Spatio-Temporal Information and Communication Technologies Supporting Sustainable Personal Mobility

Dominik Christoph Bucher

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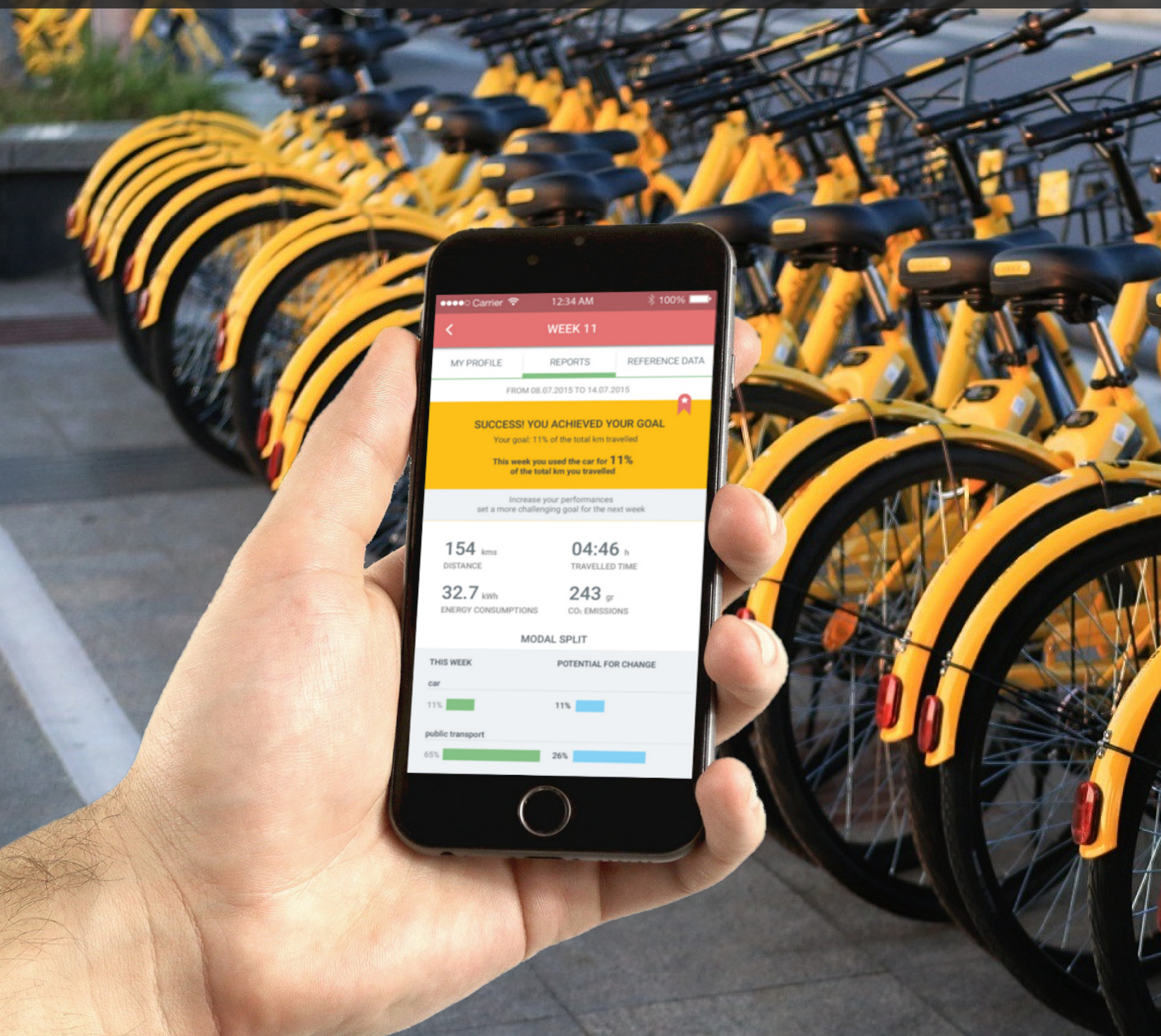

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SPATIO-TEMPORAL INFORMATION AND COMMUNICATION TECHNOLOGIES SUPPORTING SUSTAINABLE PERSONAL MOBILITY

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presented by
DOMINIK CHRISTOPH BUCHER
Master of Science in Electrical Engineering and
Information Technology (ETH Zurich)
born 22 October 1988
citizen of Mühlau, AG, Switzerland

supervised by
Prof. Dr. Martin Raubal, examiner
Prof. Dr. Harvey Miller, co-examiner
Prof. Dr. Krzysztof Janowicz, co-examiner

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ABSTRACT

Mobility and transport are responsible for approx. 30% of the total Greenhouse Gas (GHG) emissions caused by humanity, primarily due to the fact that 95% of the required energy is provided by non-renewable fossil fuels. Reducing this dependence on crude oil and optimizing mobility will not only increase its sustainability, but will also positively impact the climate, our health and environment, and, if implemented correctly, ease the use of mobility and ensure equal access for everyone. This dissertation focuses on soft incentives enabled by ongoing advances in Information and Communication Technologies (ICT). Next to technological advances and policy changes, such incentives have the potential to foster changes in mobility consumption and behavior. This is especially important in the short term, as other measures often take decades to implement. The persuasive applications treated within this work are based on automatically and passively recorded mobility data that not only give insights about the use of a transport system, but also allow giving feedback and interacting with individual people directly.

To extract information useful within a persuasive application, we first propose several methods to process mobility data to uncover individual mobility descriptors, preferences and progress along various stages of behavior change. Based on this information, we present route computation algorithms that can supply people with feasible and meaningful proposals of alternative behaviors (i.e., route options). The presented formalism and the related methods allow integrating a wide range of transport modes into high-level route planners. The proactive computation of transport options (including less commonly used transport modes such as carpooling) reduces the burden of finding means of travel and thus facilitates trying out and adopting more environmentally sustainable mobility behaviors. Finally, we propose a set of (gamified) elements to be used within persuasive (smartphone) applications to effectively support people in making sustainable choices. The resulting framework is evaluated using the large-scale study *GoEco!*, and we find significant changes in mobility along systematic routes and for groups of people that rely on the car as their predominant means of transport.

ZUSAMMENFASSUNG

Mobilität und Transport sind für ca. 30% der durch die Menschheit verursachten Treibhausgasemissionen verantwortlich, primär weil 95% der benötigten Energie durch nichterneuerbare fossile Energieträger zur Verfügung gestellt werden. Eine Reduktion der Abhängigkeit von Rohöl und eine Optimierung des Mobilitätsgebrauchs erhöhen nicht nur die Nachhaltigkeit, sondern haben auch positive Auswirkungen auf das Klima, unsere Gesundheit und Umwelt, und können die Nutzung von Mobilität vereinfachen. Diese Dissertation fokussiert auf Anreizsysteme, die durch Fortschritte im Bereich der Informations- und Kommunikationstechnologie ermöglicht werden. Neben technischen Fortschritten sowie gesetzlichen Vorgaben (welche oft Jahrzehnte zur Umsetzung brauchen) haben diese Anreizsysteme vor allem in naher Zukunft ein grosses Potential, das Verhalten und den Mobilitätsgebrauch positiv zu beeinflussen. Die Anreizsysteme basieren auf automatisch und passiv aufgezeichneten Mobilitätsdaten, welche nicht nur aufzeigen, wie ein Transportsystem benutzt wird, sondern auch erlauben, einzelnen Nutzern Feedback zu geben und mit ihnen zu interagieren.

Um die notwendigen Informationen aus Mobilitätsdaten zu extrahieren, stellen wir zuerst verschiedene Methoden zur Erfassung von Indikatoren, individuellen Präferenzen, sowie Stufen von Verhaltensänderungen vor. Basierend darauf präsentieren wir eine Formalisierung von Transportangeboten, welche mittels geeigneter Algorithmen zur Erstellung von Routenplänen benutzt werden kann. Das pro-aktive Vorschlagen von Routenalternativen und die Integration von weniger weit verbreiteten Transportmitteln (wie z.B. Carpooling) unterstützt Verhaltensänderungen, da dadurch der Planungsaufwand sinkt. Um die Informationen und Routenalternativen effektiv einzusetzen, präsentieren wir ein Set an "Gamification"-Elementen, welche zur Unterstützung von nachhaltigem Verhalten benutzt werden können. Die Evaluation anhand des Forschungsprojekts *GoEco!* hat gezeigt, dass insbesondere auf regelmässig zurückgelegten Strecken und bei Personen, die sich grösstenteils auf das private Auto verlassen, signifikante Unterschiede im Mobilitätsverhalten nach der Benutzung eines solchen Anreizsystems festgestellt werden können.

PUBLICATIONS

The following publications are included in parts or in an extended version in this dissertation:

- Paul Weiser, Dominik Bucher, Francesca Cellina, and Vanessa De Luca (2015). „A Taxonomy of Motivational Affordances for Meaningful Gamified and Persuasive Technologies.“ In: *Proceedings of the EnviroInfo and ICT for Sustainability (ICT4S) 2015*. Copenhagen: Atlantis Press.
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- Francesca Cellina, Dominik Bucher, Roman Rudel, Martin Raubal, and Andrea E Rizzoli (2016). „Promoting Sustainable Mobility Styles using Eco-Feedback and Gamification Elements: Introducing the GoEco! Living Lab Experiment." In: *4th European Conference on Behaviour and Energy Efficiency (BEHAVE 2016)*.
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- David Jonietz and Dominik Bucher (2017). „Towards an Analytical Framework for Enriching Movement Trajectories with Spatio-Temporal Context Data." In: *Societal Geo-Innovation: Short Papers, Posters and Poster Abstracts of the 20th AGILE Conference on Geographic Information Science. Wageningen University & Research 9-12 May 2017, Wageningen, the Netherlands*. Association of Geographic Information Laboratories for Europe (AGILE), p. 133.
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- Dominik Bucher, Francesca Mangili, Claudio Bonesana, David Jonietz, Francesca Cellina, and Martin Raubal (2018). „Demo Abstract: Extracting eco-feedback information from automatic activity tracking to promote energy-efficient individual mobility behavior." In: *Computer Science-Research and Development* 33.1-2,

pp. 267–268.
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- Francesca Cellina, Dominik Bucher, José Veiga Simão, Roman Rudel, and Martin Raubal (2019). „Beyond Limitations of Current Behaviour Change Apps for Sustainable Mobility: Insights from a User-Centered Design and Evaluation Process.“ In: *Sustainability* 11.8, p. 2281.
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1 INTRODUCTION

Importance and challenges of mobility

Mobility and transport are tightly linked to economic wealth and to the future local and global development (Blumenstock, Cadamuro, and On 2015; Church, Frost, and Sullivan 2000). With better access to mobility, faster and more convenient modes of transport, and dropping costs for transport, people and goods travel ever farther, be it for business or leisure (Pooley et al. 2017; Litman 2006). However, the enormous increases in mobility usage challenge existing transport infrastructures and are responsible for major shares of the environmental impacts of humanity. Studies show that transport and mobility are at the root of around 30% of the total energy demand, thus putting them on par with industrial processing (approx. 35%) and slightly ahead of household energy demands (20%) (Taptich, Horvath, and Chester 2016; Wolfram, Shelef, and Gertler 2012; Keshavarzian et al. 2012). In developed and wealthy countries like Switzerland, this rises up to approx. 38% (Bundesamt für Energie BFE 2019; Froemelt, Dürrenmatt, and Hellweg 2018), which is an indication that the relative share of mobility energy demand will rise globally in the future (cf. Wolfram, Shelef, and Gertler 2012). In large parts of the world, mobility is mostly provided by personal vehicles (Kenworthy 2003; Wright and Fulton 2005). Even in regions that offer many alternatives to Private Motorized Transport (PMT), fossil fuels are primarily responsible for energy production. For example, in Switzerland, 94.0% of all the energy consumed by transport and mobility is produced using fossil fuels such as gasoline, diesel or natural gas (Bundesamt für Energie BFE 2019).

In parallel, there is a positive trend for urbanization, as can be seen by the increasing numbers of mega-cities around the world (Taubenböck et al. 2012) or the movement of young people towards cities (Bretzke 2013; Cohen 2006; Garschagen and Romero-Lankao 2015). While the ultimate effects of this urbanization on mobility are not yet clear, it definitely poses additional burdens on the transport infrastructure in the short term, as more people need to travel within and between cities (Madlener and Sunak 2011). Even though private companies and governmental institutions continuously propose and construct new transport infrastructure, much of the traffic is passed on to existing infrastructure for PMT, especially in cities with large urban catchments (Bretzke 2013; Ichimura 2003). Ultimately, this increase and condensing of mobility and transport not only affects our environment, but also the health and well-being of each individual (Künzli et al. 2000; Levy, Buonocore, and Stackelberg 2010; Miller, Tribby, et al. 2015). In many large cities, people spend hours blocked in traffic jams, are surrounded by constant noise and have to wear protective masks against dust and exhaust particles (Zhang and Batterman 2013).

Sustainability

In particular as a response to the adverse effects of humanity on our environment, many countries agreed upon energy strategies that dictate reductions in Greenhouse Gas (GHG) emissions and energy demands. For example, the *Swiss Energy Strategy 2050* envisions a net reduction of GHG emissions from mobility and transport by 50-80% by the year 2050 (Griggs et al. 2013; EnergieSchweiz and Bundesamt für Energie BFE 2015; Kesselring and Winter 1995). After their rather recent introduction, these strategies provoked and stimulated a number of new mobility technologies and business models.

Autonomous mobility

Two of the most widely known and discussed technologies are autonomous resp. electric mobility. While true autonomous mobility still seems to be several years or even decades away (Hussain and Zeadally 2018), low-degree autonomy technologies such as lane- or distance-keeping are becoming available to more and more people. When considering the effects of autonomous vehicles on mobility and transport, full autonomy will have the largest impact, as it may optimize existing transport systems and open new avenues for businesses, such as renting out individual vehicles, improved taxi services or bus-on-demand schemes (Maurer et al. 2016; Rosenzweig and Bartl 2015; Hars 2010). Yet even lower levels of autonomy may influence the mobility behavior of people, as they potentially reduce stress caused by PMT and allow people to travel for longer distances (Cunningham and Regan 2015).

Electric mobility

On the other hand, electric mobility is in full swing; prices of electric vehicles are dropping quickly and their adoption increases steadily, in particular in countries that actively subsidize them (Zhou, Wang, et al. 2015; Du and Ouyang 2017; Propfe et al. 2013; Yang 2010). Electric vehicles allow decoupling the energy production from its consumption, which makes them suitable for reducing GHG emissions when fueled with renewable energies. Additionally, they help reduce direct exhaust from mobility, which especially plays a central role in bigger cities and along frequently traveled roads (such as highways).

Shared mobility

Among the novel yet already somewhat established mobility concepts we find shared mobility with all its facets. For example, while carsharing (or simply car rentals) has been available for decades, the field recently gained attention due to an increased number of privately owned cars participating in carsharing schemes and due to progress in Location Based Services (LBS) that enables flexible and free-floating models (Shaheen and Cohen 2007; Kortum et al. 2016). Similarly, while carpooling (i.e., the sharing of a ride with a common origin and destination using a personal vehicle) is as old as cars themselves, recent technological advances made it more accessible and convenient to use, thus increasing its reach and allowing even people unknown to each other to share their rides and costs (Kissling 2017; Bresciani et al. 2018).

ICT support

All these new forms of mobility are heavily supported by Information and Communication Technologies (ICT), which is commonly referred to as an increasing digitization (transforming analog information into a digital format) and digitalization (using digitized information to simplify operations) of the mobility sector (Kessler and Buck 2017; Kagermann 2015). While ICT acts as an enabler for autonomous mobility (providing the necessary technology for object recognition, path planning, vehicle communication, etc.), it is more supportive (yet still as disruptive) in other fields. For example, the miniaturization of communication and the standardization of interfacing technology allow retrofitting cars with remotely controllable locks, thus opening avenues for sharing of private cars (Rahier, Ritz, and Wallenborn 2015). The increased ease of use of web platforms and smartphone applications makes finding carpooling partners easy and convenient (Buliung et al. 2010). Arguably the largest immediate effect of ICT on our daily life has come from improved mapping and routing technologies. While these initially focused on automotive route planning and navigation, they have been supporting other modes of transport for a while, such as Public Transport (PT) or Slow Mobility (SM) (e.g., walking or bicycling), and recently started integrating more immediate forms of transport, such as taxis, carpooling or bikesharing (Balan, Nguyen, and Jiang 2011; Huang, Bucher, et al. 2018; Caggiani, Camporeale, and Ottomanelli 2017). Their ongoing developments prominently support another mobility concept that changed heavily with the introduction of ICT and continues to evolve: integrated mobility. Integrated mobility denotes multi-modal traveling, i.e., the use of multiple transport modes to reach a certain destination, that is actively supported by mobility and transport providers (i.e., they, or associated third-party service providers, implement access to transport modalities in an integrative manner; cf. Willing, Brandt, and Neumann 2017; Shaheen and Christensen 2014; Müller et al. 2004). To provide an integrative service, a train operator could, for example, work together with a local bikesharing provider that solves the first/last mile problem from the train station to the final destination. Users of such a service would automatically receive offers and schedules from the integrated providers that conveniently get them from their origin to a chosen destination.

Mobility behavior

It is often claimed that to change mobility in the short term (and thus to reduce GHG emissions, traffic jams, etc.), people have to actively change their behavior (Banister 2008; Prillwitz and Barr 2011; Jonietz and Bucher 2018). One possible behavioral change (among a general reduction in travels or a switch to SM) is a transition to a more integrated use of mobility, as it potentially increases the utilization of various transport modes. This higher utilization, and the fact that almost all transport modes are more "eco-friendly" than PMT, will likely cause a reduction of the environmental impacts of mobility and the related stress on transport systems.

Mobility as a service

Building heavily on technology supporting integrated mobility, the new business model of Mobility as a Service (MAAS) aims at reducing the burden on mobility consumers even further (Goodall and Dovey 2017): It essentially offers automatic cost computation and billing for several (in a perfect scenario, all) modes of transport for travel, or even reduces their cost to an upfront fixed one, reducing the variable costs of mobility to zero, and thus paving the way for an increased commoditization of mobility. This means that while previously people had to ensure they had a properly maintained personal motorized vehicle or all the necessary PT passes, they now simply purchase mobility itself, irrespective of the actually used means of transport. This recent development resp. the term "as a service" originated from the ICT sector, where it became more and more cumbersome to keep soft- and hardware up to date, and maintainers started looking for ways to externalize this infrastructure. In similar ways, MAAS also offers benefits to the maintainers, as they can highly standardize and optimize processes like maintenance, purchase of new vehicles or ensuring their availability (cf. Nemtanu et al. 2016; Li and Voege 2017).

Tracking

In parallel to these new or renewed forms of mobility, ICT were recently developed that support automated and passive location tracking (cf. Yuan, Raubal, and Liu 2012; Schüssler and Axhausen 2009; Cellina, Förster, et al. 2013; Stenneth et al. 2011). These technologies are currently primarily used for LBS such as local search or routing and navigation, but increasingly serve other mobility purposes as well, in particular in combination with spatio-temporal analyses (Huang, Gartner, et al. 2018). One basic example is data collection for statistical purposes, e.g., to replace survey-based mobility censuses. Other use cases of location tracking include improved transport infrastructure and city planning (Liu, Biderman, and Ratti 2009; Shoval 2008), personalization of route planners (Cui, Luo, and Wang 2018), or the creation of (eco-)feedback that can be used to guide a person in his or her mobility choices, in particular with respect to ecological sustainability of individual mobility (Gabrielli et al. 2014; Froehlich, Dillahunt, et al. 2009b; Jylhä et al. 2013; Bie et al. 2012), thus playing an essential role in the short-term reduction of GHG emissions. While theoretically not required for MAAS, tracking can be employed for billing and statistical purposes (e.g., to know how much individual mobility providers have to be paid, or which routes are frequently used).

1.1 MOTIVATION

Current research

Giving mobility (eco-)feedback to people to promote sustainable personal mobility behaviors as well as the combination of MAAS offers with location tracking are currently in the focus of research, and mostly exist as part of pilot studies, proof-of-concept applications and recently founded startups. Under the premise that more optimized mobility choices lead to reduced GHG emissions (and well aware of the Jevons paradox that describes potential rebound effects; Jevons 1865), we must determine how to best support people in these mobility choices. In particular integrated mobility largely builds upon support by ICT, be that through spatio-temporal analyses of automatically tracked data (with the aim of improving the support, e.g., by providing better or more personalized route planning) or through the integration of more transport modes, eco-feedback, or personalization and context in applications and systems. While the ongoing research on route planners provides us with quicker routes, for example by respecting the momentary traffic situation, holistic support that takes into account the ecological impacts of travel, personal context or new forms of mobility is lacking.

Research gap

We need to integrate sustainability goals next to personal goals and preferences such as comfort, speed or price, to include novel forms of mobility into route planning, and to provide feedback to the individual user in order to properly support people in making sustainable mobility choices. Spatial and temporal information about movement and mobility usage allows us to increasingly focus on individual people and their mobility needs. Knowing about the impact of mobility usage allows them to reflect on their behavior, and to assess mobility options accordingly. Providing such (eco-)feedback within persuasive (smartphone) applications requires us to automatically process passively tracked mobility data, extract relevant information (in privacy-preserving ways) and use motivational elements to support people in meaningful ways. For the integration of novel forms of mobility (which do not all simply provide a means to get from an origin to a destination, but include different peculiarities or constraints, such as spatial or temporal flexibility) and to enable collective outcomes, we need to adapt our current route planning systems to take into account a whole population, where each individual has its own goals and preferences. Especially concepts such as shared mobility rely on the communication between users, and not just between users and transport agencies (or to put it in another way, "each user becomes a transport agency"). As shared mobility, and in particular MAAS, are important concepts for future mobility, its supporting ICT must be built with these points in mind.

1.2 PROBLEM STATEMENT AND RESEARCH QUESTIONS

Given the issues mobility and transport are currently facing, it is widely argued that ICT must support sustainable and integrated mobility. To this end, sustainability criteria have to be combined with personal contexts and preferences, as people are seldom willing to consider mobility options if they are misaligned with their personal requirements. As this support should be as unobtrusive as possible, only giving people choices and recommendations when asked for, the inclusion of personal context and preferences has to be automatic and passive. We can thus summarize the problem treated within this dissertation as follows:

In light of recent goals to reduce the ecological impacts of mobility and to *optimize its use, a wealth of novel mobility options and concepts were developed. To reach these goals, ICT must support these mobility options in an integrated manner, taking sustainability criteria into account. It is yet unclear which processes are involved in this support, how they act together, and how their combination ultimately supports a transition towards a more ecological and convenient use of mobility.*

This problem statement can be broken up into several research questions, which will be refined and treated in later chapters:

1. What are the principal information processes and structures involved in supporting sustainable personal mobility and Mobility as a Service (MAAS)?

2. What are the components and traits of automatically recorded movement data that can be used to support mobility needs in an ecologically sustainable way (e.g., by providing eco-feedback that people can base their future decisions upon)?

3. How can we facilitate multi-modal route planning involving less commonly used modes of transport (such as carpooling or free-floating bicycles)? How can we assess the quality of the (potential) fulfillment of a transport need, taking into account personal preferences, contexts and potential sustainability goals?

4. How should transport options and choices be communicated to users to support sustainable mobility behavior? Do people adjust their mobility behavior upon receiving (eco-)feedback based on their previous choices?

While the first question takes a very high-level view on the topic of sustainable personal mobility and MAAS, building upon several research projects carried out during the work on this dissertation, questions two to four consider individual processes in greater detail. Question two considers location tracking and how it can be used to support personal mobility, especially in combination with question four, the communication of the tracked mobility choices and the associated extracted behavioral information. Question three considers the personalization and collaborative nature of various mobility concepts, and how to find meaningful mobility options, in particular when considering (currently) less frequently used modes of transport such as carpooling or free-floating bicycles, as well as potential future transport options such as buses-on-demand. Finally, to effectively support sustainable personal mobility, these generated mobility choices must be communicated to users alongside the individual feedback on mobility (question four).

1.3 CONTRIBUTION AND SCOPE

In essence, this dissertation aims at the development and assessment of technology supporting sustainable personal mobility and MAAS. The core problem studied here is how to integrate automatically and passively tracked movement and mobility data, and route planning with the aim of providing people with sustainable and convenient mobility options.

The contributions of this dissertation can be summarized as follows:

1. *Based on previous research and experience from several studies concerning the support of sustainable mobility through ICT, we propose a model encompassing the information processes and structures involved in this support.* While this model is targeted at sustainable personal mobility, its individual components can be employed for a wide range of future mobility problems, such as giving meaningful feedback on mobility or creating personalized routing services for integrated mobility.

2. *We demonstrate how to process movement trajectories with the aim of generating meaningful eco-feedback and personalized information for further use within route planning applications.* Basing feedback and personalization on passively tracked location data (though not exclusively) provides an unobtrusive way of interaction with the user, which is central when striving for a high adoption of a technology.

3. *We present novel high-level route planning methods that take into account a variety of transport modes, personal context, and are able to account for sustainability goals.* In contrast to a large body of research on route planning, which aims at finding novel resp. faster algorithms that work on large transport graphs, our focus is on integrated mobility and personalization.

4. *Based on the research in the previous chapters, we provide a set of communication strategies to nudge people towards more sustainable*

mobility behaviors. On the one hand, eco-feedback has the potential to influence the mobility behavior of people; on the other hand, mobility options have to be communicated correctly for people to choose sustainable ones. Using the large-scale mobility study *GoEco!*, we evaluate the proposed methods and strategies.

The presented technology, its evaluation, and the resulting societal impacts provide a step towards a more energy-efficient use of mobility, thus reducing GHG emissions and helping to reach the sustainability goals we set ourselves.

1.4 STRUCTURE

The dissertation is organized as follows: Chapter 2 introduces key concepts and provides definitions for the rest of the dissertation. It ends with a discussion of information processes involved in the support of sustainable personal mobility and MAAS. Chapter 3 provides background for all the processes and different emerging forms of mobility introduced in chapter 2. Chapters 4 to 6 each cover one part of the required processes in supporting sustainable personal mobility. As shown in Figure 1.1, this starts by dissecting tracked mobility, and building models that capture individual mobility preferences and behavior. Based on this information, we can generate a set of alternative transport options and evaluate them with regards to their suitability for a single person. The last step involves communicating the unraveled aspects of a user's mobility behavior with the intent of nudging the person towards a more sustainable use of mobility. Finally, chapter 7 discusses all the parts in aggregation, and chapter 8 summarizes the findings and contributions of this dissertation.

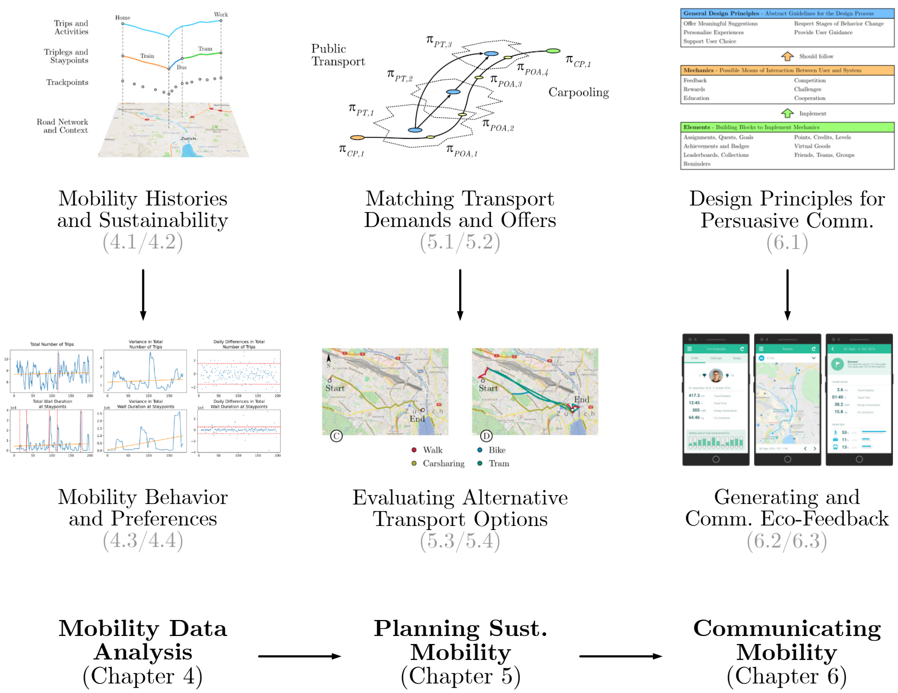


Figure 1.1.: An overview of the topics covered in this dissertation and how they relate to each other. The figures were taken from one of the scientific publications on which the respective section builds.

2 INFORMATION AND COMMUNICATION TECHNOLOGIES SUPPORTING SUSTAINABLE PERSONAL MOBILITY

Within this chapter, we first develop and elaborate on the core concepts used throughout this thesis, namely *sustainable mobility*, *integrated mobility*, and *Mobility as a Service*. In the second part, we identify how ICT supports mobility, and in particular which processes and structures are involved in supporting *sustainable personal mobility* and *sustainable Mobility as a Service*. To facilitate the explanations, to give concrete examples and to evaluate our methods, we use data from four sources: the *GoEco!* project, the *SBB Green Class* study, the Swiss Mobility Census (SMC), as well as the US National Household Travel Survey (NHTS).

Data Sources

The idea behind the *GoEco!* project (cf. Bucher, Cellina, et al. 2016; Bucher, Mangili, Cellina, et al. 2019; Cellina, Bucher, Veiga Simão, et al. 2019; Cellina, Bucher, Mangili, et al. 2019) was to assess if and how smartphone applications can influence the mobility behavior of people. Inspired by applications to monitor and improve one's own fitness and health, *GoEco!* tracked peoples' movement using the built-in GPS sensor of smartphones, and used motivational affordances such as gamification and eco-feedback to influence their mobility choices. As part of the experiment, around 200 people were interacting with the *GoEco!* app for three project phases: in the first and last (each lasting six weeks), "baseline" mobility behavior was recorded, while during the treatment phase in between (lasting three months), gamification was employed to nudge people towards more sustainable mobility behavior.

The *SBB Green Class* study (cf. Martin, Becker, et al. 2019) involved approx. 140 people who were given a general Public Transport (PT) pass (valid for unlimited travels throughout Switzerland), a private Electric Vehicle (EV), as well as access to several mobility offers (car- and bikesharing, park and ride parking spaces, etc.) as part of a MAAS offer. The idea of the Swiss Federal Railways (SBB) was to identify how

This chapter is based on Weiser, Scheider, et al. 2016; Bucher, Cellina, et al. 2016; Bucher, Weiser, et al. 2015; Bucher, Scheider, and Raubal 2017; Bucher, Mangili, Cellina, et al. 2019.

people would use mobility if they were given commoditized access for an upfront fixed cost: Would they stop using trains and shift their mobility consumption towards PMT resp. their newly available EV? Ultimately, the study aimed at answering the question if it would still be possible for SBB to position itself as a railway operator in the future, or if, due to the increasing digitalization and appearance of MAAS offers, it would have to shift its focus on becoming a mobility provider.

The SMC[1] (cf. Biedermann et al. 2017) and NHTS[2] (cf. McGuckin and Fucci 2018) are censuses conducted by the governments of Switzerland and the United States of America, respectively. They both involve a representative and statistically significant number of citizens that were asked for their travel patterns during a single day. We primarily use the census data to put the developed methods into a bigger perspective.

2.1 THE ROLE OF INDIVIDUAL CIRCUMSTANCES

To exemplify and facilitate the understanding of the impact of individual circumstances on mobility choices, we introduce three personas. These personas correspond to real people from the *GoEco!* project, but are used in an exemplary way here, standing for respective groups of the population. This means that while their movement and mobility was recorded (using a tracking app on their smartphone) as shown in the next sections, they represent hypothetical users in similar geographical contexts, and their individual journeys and demographic attributes are not uncovered here. Where applicable and appropriate, we will refer to the corresponding groups of the population by using data from the SMC and NHTS instead of the individual personas.

Mobility Personas

Alice is a typical city dweller, living in a city with good public transport, comparably short distances, but restricted freedom for private motorized vehicles (i.e., many limited speed areas, one-way streets, traffic lights, etc.). Alice does not own a car nor does she participate in any particular (car-, bike-)sharing programs. She owns a public transport pass for the city, offering her fixed-cost access to trams and buses. *Bob* lives in a suburban area of the same city. In addition to owning a private car, he has a public transport pass allowing him fixed-cost access to the city. *Charlie* lives in a rural area far from any major city,

1 The mobility census can be requested from www.bfs.admin.ch.
2 The US National Household Travel Survey can be downloaded from nhts.ornl.gov.

and thus mostly relies on a car for travel. He does not have access to any other mobility tools except an irregularly running bus, for which he owns no pass, thus inducing a variable cost for him.

Figure 2.1 shows the daily distances each of these personas covers on top. On the bottom, the transport mode resp. modal split of the three personas (in terms of distance covered) is displayed. As can be expected, Alice mostly relies on public transport, Bob uses a mixture between public and private motorized transport, while Charlie almost solely travels by car (note that he did not participate in the first project phase). While we make no statements about the correlation of the modal split and weekly distances here, this figure is intended to show that all of them cover significant distances each week, which is in line with findings from studies analyzing the travel behavior in developed countries (Metz 2012) as well as the SMC (Biedermann et al. 2017).

General Mobility Context

As is already implied from these personas, individual context and circumstances play a large role when planning and choosing mobility next to personal attitudes, values and goals (e.g., Ferdous et al. 2011; Atasoy, Glerum, and Bierlaire 2013; Kim and Ulfarsson 2008). In particular the *general mobility patterns* of a person (depicted in Figure 2.1 on the bottom) are primarily defined by a few often-traveled routes that usually involve the home and work locations (Do and Gatica-Perez 2014; Schneider, Belik, et al. 2013). Their distances and connections to public transport, and the availability of transport passes or MAAS offers drive the overall mobility consumption (Lachapelle and Frank 2009; Yang et al. 2015). We thus introduce a measure of individual circumstances by looking at a person's mobility options in a holistic manner to generalize from the three introduced personas. Based on the locations of home and work, we use a location classification that assigns each location on the map a value of either *city*, *suburb* or *rural* to define a user's *general mobility context*:

$$C_{GM} = (u(\boldsymbol{f}_H), u(\boldsymbol{f}_W)) \tag{2.1}$$

where $\boldsymbol{f}_H$ and $\boldsymbol{f}_W$ are features resp. properties of the home and work location, and $u(\cdot)$ is the function that maps any given location (specified by longitude and latitude) to an "urbanization class". This classification into a set of locations $L = \{city, suburb, rural\}$ is commonly found in the literature (cf. Zhou, Xu, et al. 2004; Short Gianotti et al. 2016; Renski 2008) and is also used in a similar form by various travel censuses. Using this formalism, we can build nine different user groups that are

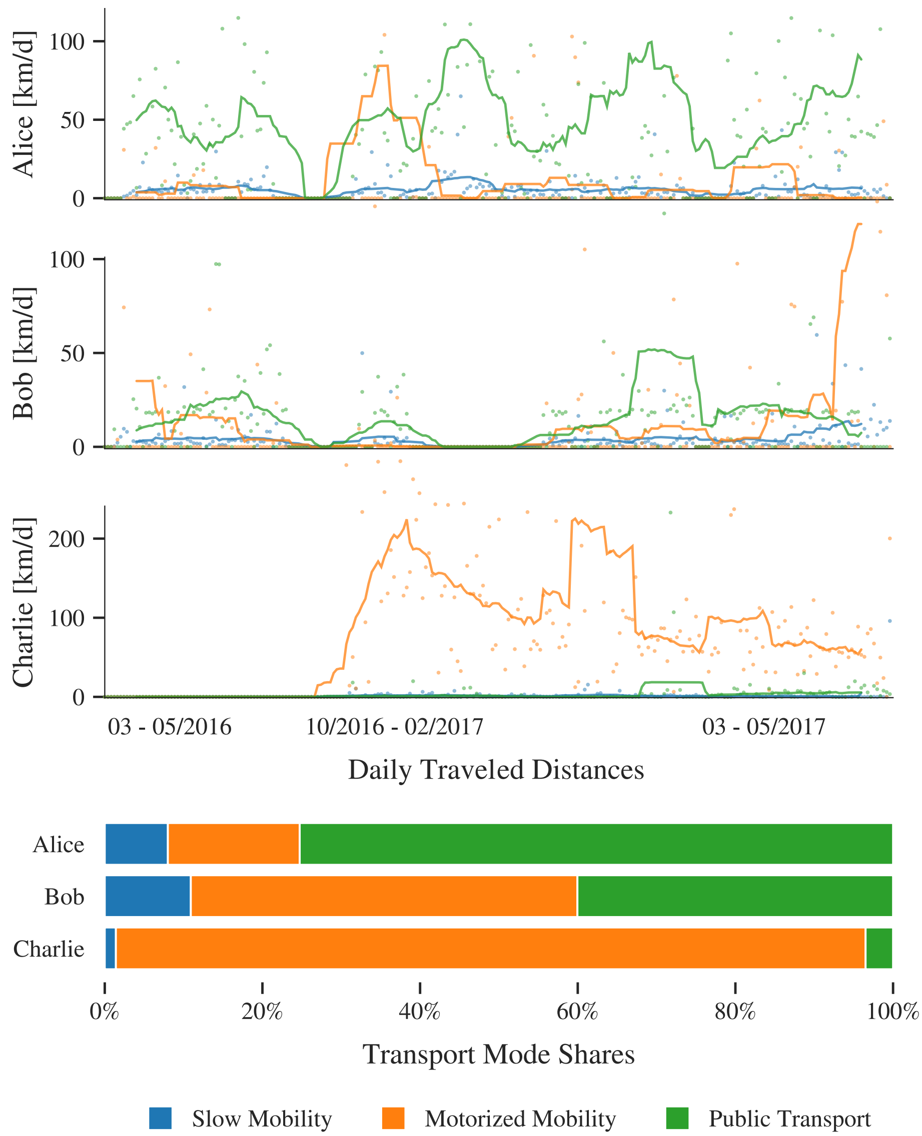


Figure 2.1.: The mobility patterns of the three personas introduced.

related to our archetypes of *city dweller* (Alice), *suburban citizen* (Bob), and *rural citizen* (Charlie), working either in the *city*, the *suburbs*, or in a *rural* area.

Urbanization Classification

Within this chapter, $u(\cdot)$ is computed by relying on the population density of the municipalities in Switzerland, as well as the public transport availability classes introduced by the Swiss federal office for statistics ARE (Bundesamt für Raumentwicklung ARE 2011) which classify each location within Switzerland into one of the five classes A-E[3]. However, as it is not in the focus of this chapter to derive an urbanization classification, we refer to section A.1 and the respective literature for an in-depth explanation of how to compute if someone lives or works in any of the denoted classes. Figure 2.2 shows the number of people being part of the respective class (based on $u(\boldsymbol{f}_H)$) for the four datasets used throughout this thesis: Data from the *GoEco!* project, from the *SBB Green Class* project, from the Swiss Mobility Census (SMC) 2015, as well as from the NHTS. It is clearly visible that the shares of the population in different areas are comparable, indicating that at least three different population groups have largely different mobility needs and thus different needs of support through ICT.

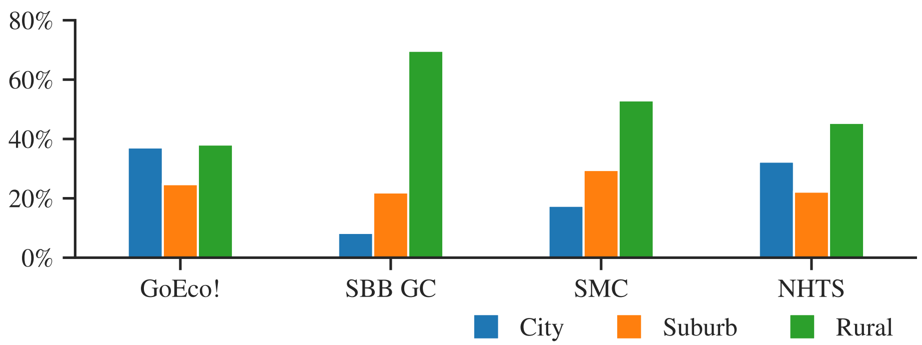


Figure 2.2.: Share of people living in different urbanization classes.

To get into more detail, Figure 2.3 shows the share of the population living in each of the urbanization classes, as well as their average mobility mix for the four datasets. A similar pattern to the above introduced three personas emerges: in rural areas, people mostly rely on PMT, which changes with increased access to PT resp. in more urban areas. It is important to highlight the differences between the Swiss transport system and the US American one, as this largely influences the transport mode choice distributions as depicted in Figure 2.3. As Switzerland is a densely populated country, it was historically always important to have mass transit alternatives to PMT. As such, the general access to PT is much higher, leading to a more prevalent use of PT.

3 As the NHTS does not provide PT accessibility classifications, but directly classifies each location into one of five classes, we use those directly; cf. section A.1.

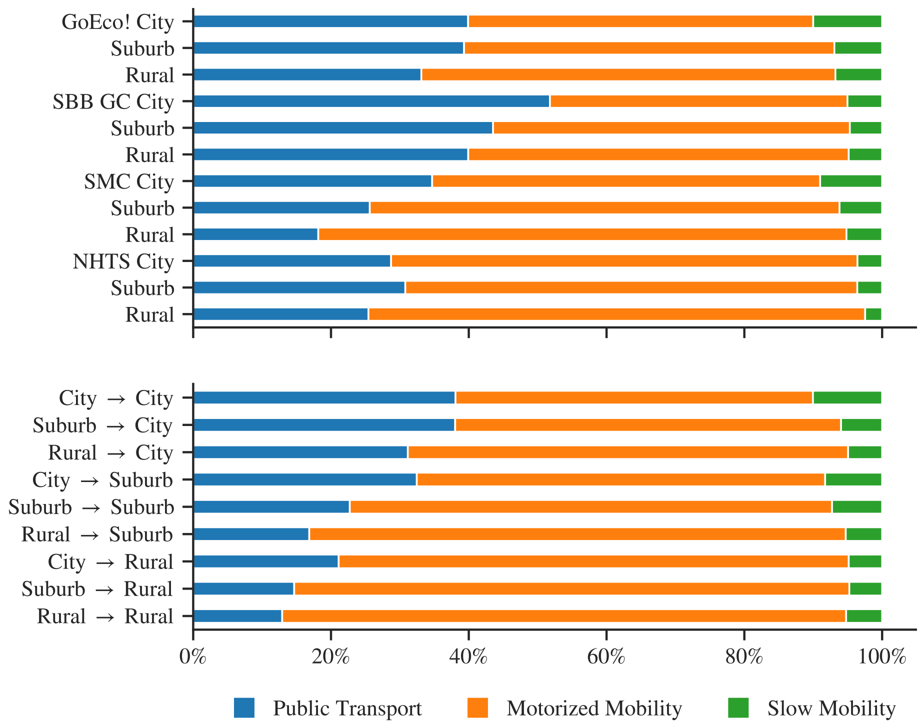


Figure 2.3.: Top: Transport mode choices for different groups of people in the four datasets (based on the $u(\boldsymbol{f}_H)$ classification). Bottom: Commuter transport mode choices for different general mobility contexts $C_{GM} = (u(\boldsymbol{f}_H), u(\boldsymbol{f}_W))$ in the SMC.

Looking at the groups represented by the three personas, they all have different support needs to reach a sustainable mobility behavior. People like Alice who already use PT for a large number of their trips could be supported in a transition to Slow Mobility (SM) (i.e., walking and bicycling), when appropriate. Bob is typically supported by offsetting more of his mobility to PT, in addition to similar support as Alice. Finally, people like Charlie usually do not have many choices for their regular trips. They can, however, be supported by giving them facilitated access to Carpooling (CP), carsharing, PT (within the bounds of its availability, e.g., by promoting *park and rail* offers), integrated forms of mobility, as well as SM for shorter trips (e.g., within a village). To get a more in-depth understanding of the impact of their mobility lifestyles, we have to define ecological sustainability within the context of mobility.

2.2 SUSTAINABLE MOBILITY

While the term sustainability has been used for a long time (originally within the context of forestry, cf. Wiersum 1995), its modern use was coined by a report from the World Commission on Environment and Development (Keeble 1988) where it is described as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (Keeble 1988, p.41). Since then, however, its meaning has evolved and the term is primarily interpreted along three dimensions: *social*, *economic* and *environmental* (Kuhlman and Farrington 2010; Kates, Parris, and Leiserowitz 2005).

2.2.1 *Types of Sustainability*

Being *socially sustainable* can refer to the maintenance of law and order, meaning that societies do not deteriorate, but also to various societal characteristics such as income distribution, employment or access to medical services (Kuhlman and Farrington 2010). *Economic sustainability* is a term commonly used within the context of companies and governments and describes the concept of healthy investments, i.e., the long-term management and securing of a business' value and monetary resources. In a wider context, it also describes the relationships between economies and (sustainable) societal and environmental developments (Spangenberg 2005; Goerner, Lietaer, and Ulanowicz 2009). Within the context of this dissertation, we are mainly concerned with *ecological sustainability*, i.e., the continuous use of natural resources without impacting future generations' possibilities to use them (Perrings 1991). In a broader and currently more used context this also refers to bounding the emission of GHG, with the aim of keeping the effects of humanity on the global environment within certain bounds. Occasionally, cultural, technological and political dimensions are added to this list, which refer to the maintenance of cultural heritage, technological progress resp. a political climate that allows future generations to have the same choices as we do today (Gibson 2001).

The differentiation between social and economic sustainability is disputed, as it can be argued that ultimately they measure the same and "weighting" social and economic aspects twice as much as environmental factors results in a bias towards "the well-being of the present generation, [while weighting] environmental [factors stronger would] mean caring about the future" (Kuhlman and Farrington 2010, p.3439). Kuhlman and Farrington 2010 go even further, and equate sustainability defined based on these three pillars with the concept of being "good", arguing that this definition obscures its definition and meaning. Instead, it is proposed to define sustainability in terms of maintaining well-being, which is easier to measure (e.g., by considering access to food, shelter, education, etc.), over an indefinite amount of time. While the discussion of what constitutes sustainability is important and will continue to be led, we primarily focus on ecological sustainability within this thesis.

Strong and Weak Sustainability

A second dimension contrasts *strong* and *weak* sustainability. While weak sustainability equates *human* (infrastructure, labor, knowledge, etc.) and *natural capital* (fossil fuels, biodiversity, etc.), the concept of strong sustainability sees them as complementary and argues that certain parts of nature can never be made up for by human capital (e.g., the ozone layer should never be compromised, as no gain in human capital can compensate for the lack of its crucial service). A large share of trips are made to increase human capital (e.g., for business meetings, to transport goods, or as part of a high quality of life), which makes a detailed contrasting juxtaposition between effects on human and natural capital necessary. In line with current trends (that favor the concept of strong sustainability, cf. Pelenc, Ballet, and Dedeurwaerdere 2015; Barua and Khataniar 2016) and to keep this thesis focused on the support of mobility choices using ICT, we primarily view the problem from the point of strong sustainability, arguing that the exhaustion of fossil fuels and the emission of GHG should be avoided in any case. However, to provide a more in-depth understanding of the trade-offs from the standpoint of weak sustainability, we highlight the juxtaposition of human and natural capital within this chapter and present ways to assess the sustainability of trips in chapter 4.

Before this background, it is necessary to consider the GHG emissions of various transport modes. Table 2.1 shows emission values for various transport modes taken from the Switzerland-specific mobitool (Tuchschmid et al. 2010). The direct CO_2 emissions result solely

Transport Mode	Direct CO_2 Emissions [gCO_2-equiv./pkm]	Total CO_2 Emissions [gCO_2-equiv./pkm]
Walking	0.00	**0.00**
Train	0.91	**7.32**
Cycling	0.00	**7.64**
Electric Bicycle	0.15	**15.26**
Bus	134.35	**145.41**
Airplane	178.70	**184.58**
Car	149.59	**197.23**

Table 2.1.: CO_2 emissions of a variety of transport modes, as reported by mobitool[4](Tuchschmid et al. 2010). The actual values heavily depend on the transport mode used, the number of people traveling in the vehicle, as well as the distance covered.

from using the respective vehicle, while the total includes a Life Cycle Assessment (LCA) that incorporates the emissions from production and disposal of the vehicle as well as the infrastructure necessary to operate it (e.g., streets or a rail network).

As expected, SM transport modes are particularly "eco-friendly", though especially for bicycles the *indirect emissions* (stemming from production, maintenance and disposal of products) put them on par with transport modes such as trains. While these values are averages for the Swiss transport sector, the actual emissions per person always depend on the individual trip: How many people are riding the tram at the same time? How many people are carpooling with me? If I use a bus at midnight and am the only one riding, it is clearly worse than if I would drive by car. Nonetheless, it can clearly be seen that shifts towards PT and SM are beneficial in terms of ecological sustainability. Thus, we either have to support people in a transition towards increased use of PT and SM, raise the number of people traveling in the same vehicle, or try to make physical trips obsolete, e.g., by replacing business trips with teleconferencing.

Considering the three personas introduced before, we can compute their current GHG emissions using the emission values from Table 2.1.

4 The mobitool values can be retrieved under www.mobitool.ch. Mobitool reports emission values for *direct operation*, *energy supply*, *vehicle maintenance*, *vehicle production and disposal*, *infrastructure maintenance* and *total*.

Persona	Current GHG emissions [kg/week]	Potential GHG emissions [kg/week]	Average GHG emissions (SMC) [kg/week]
Alice (City)	12.90	5.70	57.22
Bob (Suburban)	14.15	11.57	71.84
Charlie (Rural)	84.66	42.60	71.42

Table 2.2.: GHG emissions of the personas introduced, and their potential for change.

Table 2.2 shows their energy requirements and GHG emissions during the time their mobility was recorded, a potential lower bound of their emissions according to the methods presented in this dissertation (cf. Bucher, Mangili, Cellina, et al. 2019) and an average generated from the respective class in the SMC. While the potential emissions shown in the middle column are based on the availability of PT and SM alternatives of similar duration, thinking about the potential circumstances that influence a person in his or her mobility choices makes it apparent that it is non-trivial to decide when someone could use a more sustainable means of transport, and when not. In our support of (transitions to) sustainable personal mobility, we thus have to consider the momentary situation a person is in. One of the related aspects is the current stage in a behavior change process that someone is in.

2.2.2 *Reaching Sustainable Behavior*

Stages of Behavior Change

Changes in behavior do not happen immediately, but are processes that take place over a certain amount of time. Many studies (mostly) from the field of psychology are concerned with the various stages that people go through during this process. For example, the Transtheoretical Model of Behavior Change (TTM) (Prochaska and DiClemente 2005) uses the following five (resp. six in the newer version; cf. Figure 2.4) stages: *precontemplation*, *contemplation*, *preparation*, *action*, *maintenance* (and *termination*). People undergoing a change in behavior will start out not knowing about the problems nor the new behavior that could alleviate them. After being educated, they start contemplating change, preparing it, and finally performing the new actions, until they are internalized and solely have to be maintained.

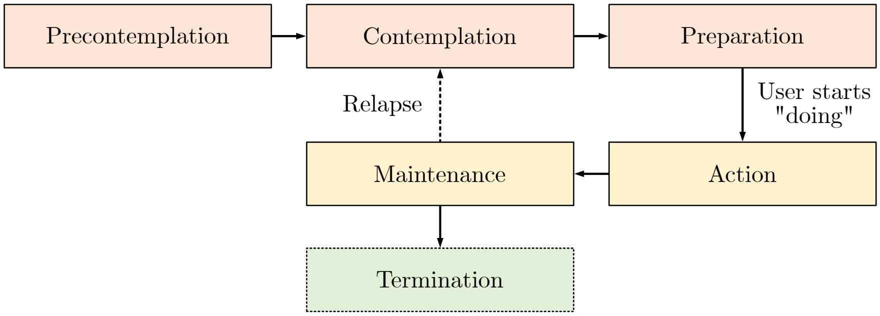


Figure 2.4.: The different stages making up the Transtheoretical Model of Behavior Change (TTM) (Prochaska and DiClemente 2005).

These stages map to similar other models, such as Li, Dey, and Forlizzi 2011's phases of reflection (where people switch back and forth between a *discovery* and a *maintenance phase*) or Dreyfus and Dreyfus 1980's model of mental activities involved in directed skill acquisition. Chapters 3 and 6 will refer to these in more detail.

While it might not be clear in which stage a particular person is without extensive interaction, we can in general assume that people's mobility behavior is relatively stable, i.e., whenever they start interacting with a new ICT service or tool, they are in one of the beginning stages (precontemplation, contemplation or preparation). In these stages, it is important to educate people about the available options and about the impact of their original behavior and possible improvements. Later on, suggestions have to become more concrete and the whole process should be supported by extrinsic motivators such as gamification elements or monetary incentives. To provide effective support, an application should thus be able to identify how a person progresses through different stages (for example by interpreting the passively tracked mobility data, or by asking the user explicit questions) and adapt support to the momentary situation. Looking at Figure 2.1, we can, for example, see that Charlie uses PMT primarily in the beginning when he uses the app for the first time. After a couple weeks of usage, we see an increased use of PT. While this might well stem from a change of circumstances, it is also possible that Charlie was contemplating a switch to more sustainable means of transport for a while, and started to change his behavior once he received constant feedback about his mobility. To make a distinction between voluntary behavior changes and effects that arise due to a change in circumstances, it is important that the context can be captured by an application in one way or another. These circumstances are often also the primary precondition to support people in a meaningful way.

2.2.3 *The Role of Immediate Context*

Context has been defined in a number of domain-specific ways (Bazire and Brézillon 2005; Keßler, Raubal, and Janowicz 2007), and as already highlighted before, plays a central role when choosing mobility options, in a similar way as goals, expectations, attitudes, beliefs and values do (e.g., Ferdous et al. 2011; Atasoy, Glerum, and Bierlaire 2013; Kim and Ulfarsson 2008). While the latter are related to the behavior in a very general way, and can usually be changed at varying speeds by taking into account the models of behavior change introduced in the previous section, context is more immediate and requires or enables *sparks* and *facilitators* (Fogg 2009) to help a person choose the most optimal transport option in a given situation. In the model by Fogg 2009, a spark is a motivational trigger that increases the motivation of a user at the decision point, while a facilitator increases a person's ability (this can also include the provision of new or different mobility options that the user is unaware of). In the context of mobility, a spark could be given by a mobile app by offering an immediate reward for using a sustainable transport mode once a person starts moving somewhere. A facilitator could be the provision of a carpooling opportunity or if an app points to a bikesharing station close by.

Immediate Mobility Context

As already introduced above, there are various scopes of context we have to consider. The *general mobility context* can be used to determine the potential support for a user on a holistic level. The *momentary* or *immediate context*, on the other hand, is primarily important for immediate (i.e., real-time) support of a person. Considering these personal and spatio-temporal circumstances, we adopt a formalization of a user u's *immediate context* when searching for transport options to perform a trip θ (from an origin O to a destination D) as:

$$C_{u,\theta} = (\boldsymbol{f}_O, \boldsymbol{f}_D, \Phi) \tag{2.2}$$

where $\boldsymbol{f}_O$ and $\boldsymbol{f}_D$ describe properties (or features) of origin (the person's momentary position) and destination, and Φ denotes the personal context (such as luggage currently being carried, other people traveling alongside the user, or the overall goal of the trip). Of course, many computed properties can be derived from this context, such as the distance $d_{O,D}$ between origin and destination, or the availability of certain (shared) transport modes at the origin (both by using the geographical location of origin resp. destination). In addition, an individual's attitudes, beliefs and values have to be included in any kind of support, but it is important to see that the support ultimately aims at aligning behavior and attitudes, beliefs and values, and not to change them. This is primarily of concern in order to prevent technology parenting and thus risk that people do not feel supported but patronized instead (cf. Weiser, Bucher, et al. 2015; Huber and Hilty 2015).

To get an impression of the influence of the immediate context on mobility choices, let us look at the behavior of Alice, Bob and Charlie (resp. the corresponding groups from the SMC) when doing trips for different purposes. In Figure 2.5, the influence of different purposes on the transport mode choice is depicted (e.g., "Errand City" describes the transport mode choices of people like Alice when running an errand). Of course, the purpose is only a small subset of all contextual factors; in reality, further trip constraints and requirements (such as weather, access to different transport modes, or the requirement to travel with luggage) can influence the transport mode choice as well.

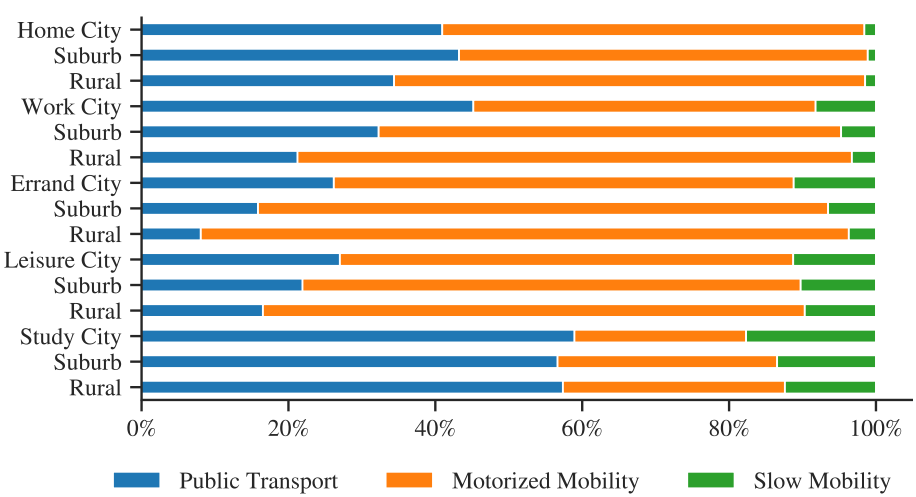


Figure 2.5.: The influence of trip purposes on transport mode choices.

Source	Cost
OECD report (OECD 2018) low end estimate 2020	30 €/t
OECD report (OECD 2018) mid-point estimate 2020	60 €/t
High-Level Commission on Carbon Price 2017 2020-2030 estimates	40-100 $/t
Voluntary Carbon Markets 2016 Report (Hamrick and Goldstein 2016)	3.3 $/t
Voluntary Carbon Markets 2019 Report (Donofrio et al. 2019)	3.01 $/t

Table 2.3.: Different CO_2 offsetting / compensation costs. Note the large carbon pricing gap (between the carbon cost estimates and the actual market values), indicating that current markets and regulations are not able to mitigate the truly caused negative effects by GHG emissions.

2.2.4 *Definition of Sustainable Mobility*

In summary, when defining sustainable mobility (on the level of an individual trip), we have to balance the relative gain in human capital with the decrease in natural capital. If we measure natural capital in terms of CO_2 emissions, we can assign a value to the decrease in natural capital by looking at current CO_2 offset costs. For reference, a number of currently available costs are given in Table 2.3.

Assigning a concrete value to human capital is difficult and a detailed derivation is out of the scope of this dissertation, as it is a multi-faceted problem that involves a lot of information usually unavailable when simply looking at travel patterns and basic demographics of people. However, as introduced in the previous sections, to assign a value to the human capital gained by a certain trip, we should consider the following points:

1. A user's goal that is fulfilled by performing a certain trip (resp. the value created for him- or herself).

2. A society's general mobility patterns, travel demands, and ultimate goals (as reaching sustainability is a collective effort that requires balancing between activities of different people).

3. A user's momentary context, including travel requirements as well as access to various transport modes, both physical as well as from an economic point-of-view.

Formalizing this, we can capture the dependency of the human capital gain $G_h(\theta)$ of a single trip θ on the various introduced factors as follows:

$$G_h(\theta) = f(C_{u,\theta}, G_u, G_S) \tag{2.3}$$

where G_u and G_S represent the goals of an individual resp. the society the person is part of, and $C_{u,\theta}$ is defined as above. Adopting a *weak* interpretation of sustainability, a trip θ can be considered "sustainable", if the gain in human capital $G_h(\theta)$ is larger than the loss in natural capital $L_n(\theta)$:

$$G_h(\theta) \geq L_n(\theta) \tag{2.4}$$

It follows trivially that we either must reduce L_n, increase G_h, or do not engage in "unimportant" journeys. Even though it is not strictly necessary to achieve $L_n(\theta) = 0$ under the definition of weak sustainability, there are two aspects that are worthy of pointing out:

- It is generally argued that humanity needs to drastically decrease its reliance on fossil energy sources and reduce the thus caused GHG emissions. This argumentation implicitly corresponds to the fact that $L_n(\theta) \gg G_h(\theta)$ for many trips.
- Ecological sustainability must be achieved by a society as a whole. While not directly visible in the above formula, G_S incorporates the fact that some trips are of high importance to a society, yet it cannot be avoided that their $L_n(\theta)$ is very large (e.g., flights of important decision makers or stakeholders).

In chapter 4, we will further elaborate on the topic by analyzing how (and how well) we can infer the sustainability of a given trip based on recorded mobility data.

2.3 INTEGRATED MOBILITY AND MOBILITY AS A SERVICE

While people always had the freedom to shape their use of mobility as they wanted (e.g., inter-modal, namely using different modes of transport), integrated mobility denotes the concept of *actively supported inter-modal use of mobility*. This active support is primarily coming from transport providers and third-party companies that facilitate the use of different modal combinations. Of course, this is closely related to MAAS, where a provider aims to bundle all possible mobility options, and provide a seamless and integrated access to the individual transport modes.

2.3.1 *Multi-Modal Transport and Integrated Mobility*

Multi-modality has always been important especially for public transport, where people usually combine multiple transport modes (at least walking plus a form of public transport, but often also multiple forms of PT, such as bus and train). More densely populated urban areas and newly created mobility offers (which have their origin in the increased digitalization of the mobility sector and in the sustainability goals set by many governments) further increased the use of multi-modal mobility. Many ICT companies additionally started offering mobility planning in an integrative manner: while for some third-party providers this mostly consists of combining multiple transport options within a single application, the transport providers themselves try to increase the usage of their transport modalities by offering people easy access to various first-/last-mile providers (e.g., the SBB integrate their train route planners with bikesharing offers in order to get people to/from the train stations).

Considering the three personas introduced above and the groups they stand for, multi-modal travel traditionally primarily concerns Alice (city-dweller) and Bob (living in a suburb), as Charlie (in a rural area) mostly drives by car (door-to-door). Looking at their use of multi-modal transport, we can see that Charlie does not often combine multiple transport modes (except for *car* and *walking*), while Alice uses various forms of transport in combination to satisfy her travel needs. Figure 2.6 shows their use of various transport mode combinations.

The integration of various transport modes was supported early on by multi-modal route planners, either developed and supported by the public transport providers themselves or by third-party travel and transport companies. Recently, transport agencies have been focusing even stronger on the integration of mobility: SBB, for example, launched several offers in cooperation with other (complementary) providers with the idea that people who have facilitated access to first-/last-mile transport modes would also be more likely to use their train network for

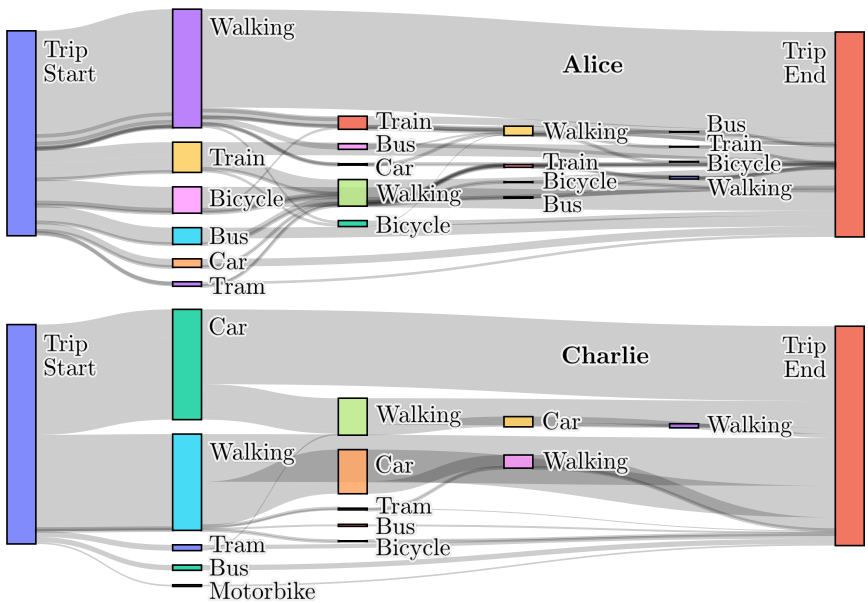


Figure 2.6.: (Multi-modal) transport mode choices of Alice and Charlie.

longer-distance travel. However, while there are plans to support these transport modes within a personalized smartphone app (that takes into account the available transport modes for an individual person), this has not been put into place yet.

2.3.2 *Commoditization of Mobility*

Commoditization describes the process during which previously distinguishable products become a commodity for the consumer (a Marxist view also denotes the process of assigning a value to a previously non-valued object as commodification; here, we adopt a non-Marxist view, cf. Kopytoff 1986; Larson 2016). A good example for a commoditized good is electricity: as a regular customer I usually do not know nor care which power plant produces the energy I use to power devices at home (it has to be noted that consumers can often choose an energy mix nowadays; however, the energy could still come from any power plant connected to the grid). In the mobility domain, while people currently often still decide for one primary transport mode or another, commodiziation will blur the borders between transport providers and transport modes, letting people choose whichever option satisfies their transport needs best, irrespective of brand or price. Looking at how most people have access to mobility nowadays, one could argue that mobility already is a commoditized good, at least as far as it will ever get (as there will always be significant differences, e.g., between a car and a train). However, we can see a novel view on mobility especially with younger people living in cities. Many of them do not own a car nor a driver's license, and increasingly use a diverse mix of mobility options to satisfy their travel needs (Metz 2012).

Mobility as a Service

While public transport providers have cooperated for a long time to offer transport passes including various means of transport at a fixed cost, recently, alongside a new wave of novel mobility concepts, they have gone further, including not only public but also private means of transport (Martin, Becker, et al. 2019). These are commonly referred to as MAAS offers, and encompass several competing models, e.g., paying an upfront fixed price, or involving automatic billing systems. MAAS is a term coined by the "XX-as-a-Service" construct from software businesses (Xin and Levina 2008), where the main selling point is that it is easier and more cost-effective to "outsource" certain functionality to an external supplier (who is specialized in this service). In a similar way the idea of MAAS is that the consumer does not have to think about mobility (and in particular which mobility supplier to choose) anymore, but just consumes it like any other commodity.

Looking at the example of SBB, their primary MAAS offer is called *SBB Green Class*, and includes a general public transport pass, an EV (out of a selection of four different models), a parking space at the train station, as well as access to several car- and bikesharing platforms for a fixed monthly cost (in the range of CHF 1070 to 2290, depending on the electric vehicle and the general public transport pass). If we look at Figure 2.7, we can see that the use of mobility changes after people start using MAAS, mostly due to the newly available EV. The data in this figure stems from the pilot study that was used to evaluate the *SBB Green Class* offer before making it available to the general public[5].

5 Note that the participants of the pilot received their EV at the start of the study (approximately in week 3 of 2017) which explains the sudden increase in EV usage.

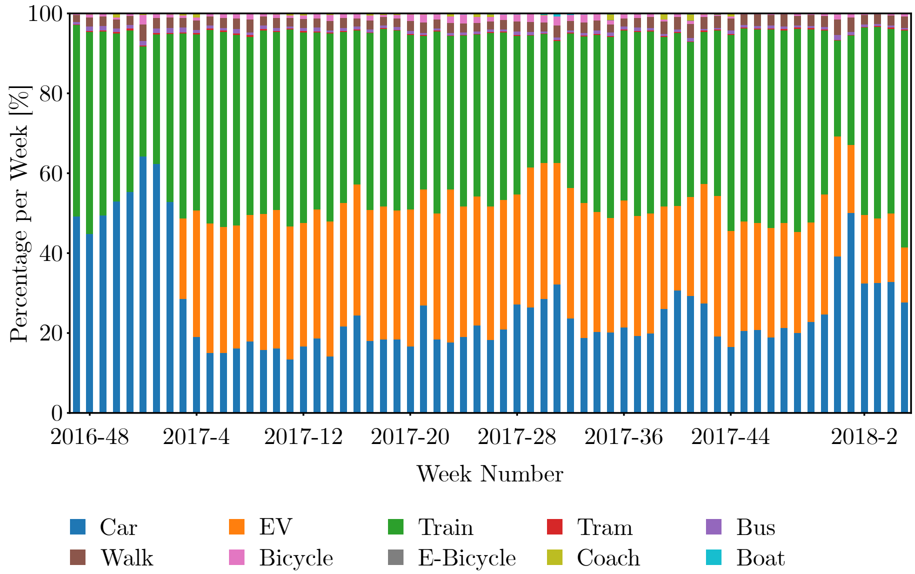


Figure 2.7.: Impacts on mobility usage after starting to use MAAS (based on pilot study participants of *SBB Green Class*). Figure from Martin, Becker, et al. 2019.

2.3.3 *Definition of Mobility as a Service*

As we have seen previously, MAAS heavily builds on the concepts of multi-modal transport and integrated mobility, and fosters the commoditization of mobility. In their review paper, Jittrapirom et al. 2017 assess various definitions and implementations of MAAS, provide their own set of attributes to define Mobility as a Service (MAAS), and propose an outline of future innovations that are necessary to (truly) deliver MAAS. In essence, MAAS "presents a shift away from the existing ownership-based transport system toward an access-based one" (Jittrapirom et al. 2017, p.13) and "is a mobility distribution model in which a customer's major transportation needs are met over one interface and are offered by a service provider" (Hietanen 2014, p.3). In other words, it is the *packaging and offering of a range of mobility options, with the goal of making mobility use more accessible and more comfortable to use*, enabled by the new interaction and aggregation possibilities that ICT and in particular the internet offer (cf. Finger et al. 2015).

Characteristics of MAAS

Building on work by Hietanen 2014, Kamargianni, Li, et al. 2016, Kamargianni and Matyas 2017, Jittrapirom et al. 2017 further elaborate on the need of personalization, integration of subscription-based consumption, collection and processing of data to identify the best transport solutions, mediation between providers and consumers, the impact of Internet of Things (IOT), as well as the relation of MAAS to the concept of a smart city. Their identified core characteristics of MAAS are given in Table 2.4. Note that we did not show the *registration requirement* (common for most internet-based services), the *inclusion of other services* (part of *multiple actors*) and the *mobility currency* (independent of MAAS), as we argue they are not central to a definition of MAAS. It is interesting to see that they additionally identified *decision influence* as a separate characteristic by reviewing various case studies, similar in spirit to the support of certain mobility behaviors as treated within this thesis. Such influence systems have been part of several MAAS (pilot) offers, but an extensive treatment of supporting technology is not given. Similar to Pangbourne et al. 2018, Jittrapirom et al. 2017 point out several aspects of MAAS that have to be considered carefully, such as its relation to sustainable mobility (which, according to Holmberg et al. 2016, must be ensured by proper tariffs, and according to other authors forms a core element of MAAS), its sociological implications (in particular with respect to low-density areas and low-income households), or operational impacts. Additionally, Pangbourne et al. 2018 provide a more in-depth treatment of the issue of resilience (what happens if a large mobility provider goes out of business and there are no alternatives) and the "false promise of freedom" (it will be difficult to offer a trip from any place to another at an arbitrary time, given the physical limitations of the transport networks and infrastructure).

Breaking down the actors, we can classify them into three types of stakeholders: a large number of *transport providers* (which can also be individuals participating in the *gig economy*, cf. Prassl 2018), *ICT providers* (that offer the integrative parts of the system as well as ticketing and pricing), as well as users consuming the MAAS offers. While the transport providers are responsible for providing the physical means of transportation (including infrastructure, vehicles, potentially required human operators, maintenance, etc.), the ICT providers integrate transport options from multiple providers and handle access to their services, reservations, billing, etc. In the case of SBB in Switzerland, they (as one of many transport providers) also try to position themselves as the ICT

Characteristic	Description
Integration of Transport Modes	The integration of various transport modes (both public and private) should facilitate multi-modal trips.
Tariff Option	Offering mobility at fixed price or through a "pay-as-you-go" model makes pricing transparent, tailored to the actual need, and in the end commoditizes mobility.
One Platform	Having only one platform to plan, book, pay, and interact with the service facilitates the consumption of mobility.
Multiple Actors	MAAS is characterized by a large number of involved actors: people with mobility needs, transport providers, and platform and third-party service providers.
Use of Technologies	MAAS is primarily enabled by technological advancements: mobile computers/smartphones, fast mobile networks, tracking and IOT technologies, interoperability standards and technology integration.
Demand Orientation	MAAS offers are highly targeted towards the individual resp. his or her demand. There is no strict preference for certain transport modes and demand-responsive transport modes (e.g., taxis) are part of it.
Personalization	Due to the wealth of options, personalization in the form of recommendations (based on preferences and context) for certain transport mode chains is necessary.
Customization	Users can freely combine mobility offers to get their preferred travel experiences.
Decision Influence	People can actively choose how the system computes the personalization for them, e.g., by favoring ecologically sustainable transport modes.

Table 2.4.: The core characteristics of Mobility as a Service (MAAS) according to Jittrapirom et al. 2017.

provider; an example of a traditional ICT provider positioning itself as a transport provider could be Google resp. its holding company Alphabet, who started developing their own cars (with the potential aim of having autonomous taxis one day).

2.4 INFORMATION AND COMMUNICATION TECHNOLOGIES IN SUPPORT OF MOBILITY

As we have shown, the recent developments in the areas of transport, ICT, but also the need to become more (ecologically) sustainable enable and entail changes in the way ICT supports our future mobility consumption. In the following we will provide an overview of the current developments in the ICT sector that help in supporting MAAS and sustainable mobility behavior.

2.4.1 *ICT and GIS in the Mobility Sector*

Information and Communication Technologies (ICT) support mobility in a wide range of tasks: From direct interaction with mechanical parts (e.g., motor or traction control in cars or electric battery charge management), over systems orthogonal to but supportive of mobility itself (e.g., entertainment systems in cars and airplanes), to advanced routing and high-resolution mapping, autonomous driving, vehicle area networks, logistics planning, booking and accounting, timetable optimization and real-time adjustment systems, and many more, there is barely a component within the general mobility domain that has not been touched by ICT. Yet, one can argue that the mobility and transport sector is still far from being completely digitalized: most vehicles are still operated by humans, choosing a route (resp. a means of transport) and buying a ticket are still manually performed steps, the integration of personal context data with publicly available transport data is in its infancy, etc. Among various impacts of digitalization on urban transport and smart cities, Creutzig et al. 2019 point out several key innovation areas of ICT in relation to transport in the next decades: For one, the increasing amount of data and processing capabilities can help city planners to plan more efficient transport systems. Innovative business models (enabled through ICT) such as bike- and carsharing have the potential to greatly reduce the number of cars, thus also freeing up space previously needed for parking vehicles, and reducing congestion, air pollution, and GHG emissions. Automated driving has the potential to substantially lower energy demands, and relies heavily on ICT both for routing and navigation purposes as well as to interpret and utilize sensor readings (Goodchild 2018). Miller 2020 summarizes the recent progress in analytics of individual and collective movement, and points at scientific and societal challenges related to achieving sustainable mobility: We are currently undergoing a "grand, real-world experiment with profound impacts on cities that will be difficult to unwind" (Miller 2020, p. 118). How ICT assist this experiment, from planning over monitoring to provision of support to the individual, will largely impact its outcome. It is thus crucial to improve the collection, integration and analysis of mobility-related data and use *tactial urbanism* to quickly iterate on potential improvements to the mobility sector (Miller 2020; Silva 2016).

Risks of Using ICT to Optimize Mobility

In line with this, Creutzig et al. 2019 also mention that "several social and environmental risks emerge from the massive and mostly unregulated use of big data and artificial intelligence" (Creutzig et al. 2019, p.2), and, arguably more important with respect to ecological sustainability, that "efficiency gains in mobility could be rendered meaningless by induced demand for additional mobility [and shifts to] automotive travel" (Creutzig et al. 2019, p.2). Several studies highlight that the impacts of a wide deployment of the mentioned technologies and business models does not necessarily impact GHG emissions in a positive way (Pakusch et al. 2018; Walnum, Aall, and Løkke 2014). Examples of other emerging problems are the control of a population using a social scoring system, or the requirement for taxi drivers to work longer shifts for costs that barely finance the ongoing costs of their cars (Creutzig et al. 2019). In essence, Creutzig et al. 2019 state that there are high risks of an unsustainable outcome of a digitalization of the mobility sector, and that it thus is of paramount importance that decision-makers need to properly leverage the new ICT technologies to reach urban sustainability goals. Among their recommendations we find a push for integrative platforms that foster multi-modal and sustainable transport, and might result in a cooperative transport system as envisioned by Miller 2013.

GIS and Mobility

Within this dissertation, we primarily look at how geospatial technologies and Geographic Information Systems (GIS) (under the umbrella term of ICT) are able to support sustainable personal mobility and MAAS, with a particular focus on human mobility behavior. Miller and Shaw 2015 describe a vision of GIS for transportation in the 21st century that is in parts driven by a shift to data-abundant environments in recent years (fostered by advancements in ICT and Location-Aware Technologies (LAT)), but also simply by continuing developments over the last twenty years. Next to technical developments such as moving objects databases, this includes a shift to individual-level data (in essence looking at individual activities instead of aggregate flows), more refined heuristics or problem-adapted algorithms to solve prevalent problems in transportation (such as vehicle routing or route planning), more elaborate analysis and optimization methods, a focus on real-time or dynamic data, heterogeneous data (e.g., from social media, videos, individual tracking devices, or IOT devices), and the adaption of open GIS and data standards. We argue that in particular the focus on individuals, combined with an ever-more accurate tracking of their activities, can help us in supporting them in their mobility choices.

2.4.2 *Automatic Tracking*

With the increased accuracy of location estimation technologies based on Global Navigation Satellite Systems (GNSSs), Wi-Fi (based on Wireless Local Area Network (WLAN) routers), cellphone towers, Bluetooth, etc., and the wide availability and miniaturization of sensor technology found in smartphones, vehicles and tracking equipment, a wealth of spatio-temporal data on the location of vehicles and people has become available. Often, these data are used within a user-centric commercial setting, e.g., to offer LBS, to improve a product such as roadside assistance or route planning, but just as often the data is used for planning (e.g., location allocation or transport infrastructure planning), for statistical purposes or for real-time updates on schedules (e.g., airplane arrivals/departures or public transport delays). Recent (prototypical) uses concerned automatic billing of transport usage, feedback on mobility behavior (as in the focus of this dissertation) or facilitating the access to different mobility options. For example, Binu and Viswaraj 2016 describe and evaluate an Android-based system for improved safety in carpooling, or Luo et al. 2019 discuss the dangers of tracking and routing technologies in relation to autonomous driving.

Smartphone Tracking

The data used throughout this dissertation primarily stems from app-based smartphone tracking. The apps performing this tracking use the functionality exposed by the Application Programming Interface (API) of the operating system, which usually automatically tries to infer the best possible location source (most commonly either cellphone towers, Wi-Fi access points or GNSS (Global Positioning System (GPS)) sources). Figure 2.8 shows the reported tracking accuracies of a range of smartphones that participated in a study in 2017. For more details on tracking accuracy, the reader is referred to subsection 4.1.1.

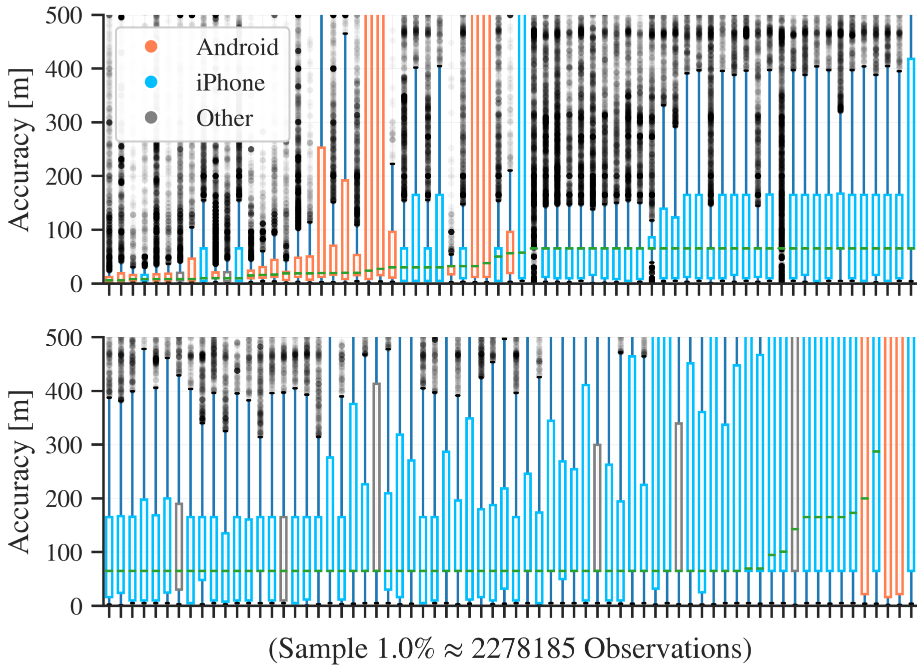


Figure 2.8.: The location accuracy reported by a range of smartphones as part of the *SBB Green Class* study in 2017.

2.4.3 *Route Planning*

Looking at the digitalization of the mobility sector from a user perspective, route planning is likely the technology that people are most in touch with. Through applications such as Google Maps, in-car navigation assistants, public transport booking systems, or carpooling platforms we are nowadays constantly supported in finding ways from one place to another. Most of these applications focus on particular criteria, e.g., the duration to reach the destination, the involved trans-

Feature	Share of Answers [%]
Available mobility alternatives (real-time)	51.5 %
Health-related impacts	36.4 %
Costs and economic impacts	36.4 %
Information about energy impacts	30.3 %
Climate and environmental impacts	30.3 %
Games and fun activities	24.2 %
Collaboration with other participants	24.2 %
More possibilities to interact with people from my real life circles (family and friends)	18.2 %
Competition with other participants	12.1 %
More tangible prizes	9.1 %
An increased sense of community	3.0 %

Table 2.5.: Responses of *GoEco!* participants to the question how future apps like *GoEco!* could support them in a transition towards a more sustainable usage of mobility ($n = 33$).

port modes, communication with transport providers, etc. While there are some route planners that focus on ecological aspects (e.g. Ferreira 2014; Guo et al. 2015), they are most often only implicitly regarded by integrating low-emission transport modes into the route planning system. Taking the recent focus on sustainable living and transport into account, it becomes important that route planners also explain the impacts on ecological sustainability of a route choice, and present users with alternatives. In the *GoEco!* study, we asked participants about their attitudes towards sustainability, and how ICT would potentially support them in becoming more sustainable. Table 2.5 shows their responses to various questions regarding these topics. While there is certainly a bias in the sample of the *GoEco!* participants, it still highlights some important future directions.

2.4.4 *Mobility Feedback*

Recently, there has been a range of new ideas and projects concerning the idea of giving people feedback on their mobility behavior (based on automatically tracked movement data; e.g., Froehlich, Dillahunt, et al. 2009b; Jylhä et al. 2013). Many of these ideas come from the health and fitness domain, where a wealth of apps is available to support people in their sports activities or eating behavior. They frequently use elements from gamification (Weiser, Bucher, et al. 2015) to give people a playful way of interacting with the respective topic.

Concerning the mobility domain, transferring these strategies to "gamify" the exposure to mobility is difficult, though, as mobility is highly individual and driven not only by attitudes and beliefs, but also by the immediate context, the availability of certain transport modes and the financial circumstances. As such, it is, for example, problematic to have a contest on "who travels least" (which would be the equivalent of, e.g., a fitness cycling app that has a contest on "who cycles the furthest"), as it would imply that noone was forced to use mobility for work or personal reasons (e.g., to visit family members).

But even within this context, it was shown that (eco-)feedback on mobility has an influence on the transport and mobility behavior of people (Cellina, Bucher, Mangili, et al. 2019). The respective applications usually do not employ any competitive components nor any numerical quantification of behavior (except the raw GHG emissions, which are often still displayed in a qualitative way to the users), but instead use personal goals, challenges, or visualization strategies to provide feedback and steer people towards a more sustainable behavior. Similarly, augmentations of existing transport apps (especially for public transport) show the CO_2 emissions of different travel options or try to quantify the ecological impact by offering monetary offsets from within the app. Other forms of feedback are not necessarily related to ecological reasons, but can be given to decrease costs, avoid congested areas, or shift trips in time in order to avoid overcrowded means of transport.

While feedback is not paramount for MAAS, it plays an important role for the sustainability of the mobility sector. It is argued that in the short term, GHG emission reductions in the mobility sector will have to come from modal and behavioral shifts, as new technologies take decades to become widely available—time that is not necessarily available if the transport sector should be increasingly and urgently decarbonized. To achieve these sustainability goals, more sustainable transport options (where available) should be shown to people, and they need to become aware of the scales of impact of one mode choice versus another.

2.4.5 *Purchasing Mobility*

Last but not least, as MAAS is about the commoditization of mobility, billing should be transparent yet mostly hidden from a user. Future ICT systems that support sustainable personal mobility and MAAS should thus integrate the negotiation and purchase of mobility, e.g., by automatic billing via the use of tracking data. The integrative aspect of MAAS requires a wide range of mobility and transport providers to interact, not only in terms of multi-modal route planning, but also in terms of context integration (e.g., when a traveler has certain requirements, these need to be fulfilled by the transport providers in an integrative way, for example, by transporting luggage with other means of transport) and financial aspects. As such, an essential part of future ICT support in the mobility domain will concern the standardized publishing of transport offers and demands, and their automatic processing with respect to finding the best possible transport options for any given person.

2.5 INFORMATION PROCESSES SUPPORTING SUSTAINABLE MOBILITY AS A SERVICE

Figure 2.9 shows the ICT processes involved in supporting sustainable personal mobility and MAAS, as identified and outlined in this chapter. Starting from the user, we can analyze his or her mobility behavior, in order to generate (and communicate) eco-feedback based on mobility patterns and usage, but also to infer the personal attitudes, goals, and circumstances. In combination with additional spatio-temporal context data (such as POIs in the vicinity, or weather data), we can further refine the analysis, and identify purposes for certain trips, assign transport modes to raw GPS trajectories, or classify the users into different mobility usage types.

On the other hand, it is important that users and transport providers specify their mobility offers and demands/needs. Currently, this is mostly a one-way process, where various public transport and specialized mobility providers publish their schedules and availabilities either using a standardized format such as General Transit Feed Specification (GTFS)[6], or within a confined web platform. Even if people are

6 The General Transit Feed Specification (GTFS) is a data exchange format that allows PT providers to publish their transport schedules. More details can be found under gtfs.org.

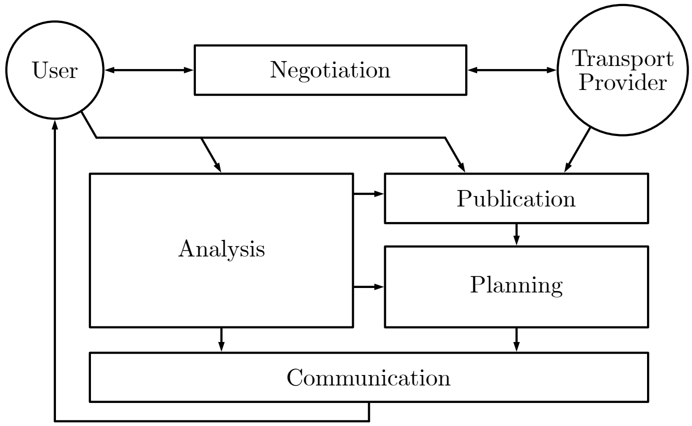


Figure 2.9.: The main information processes involved in systems supporting sustainable personal mobility and MAAS. The primary actors are the users requesting transport, and the providers offering them ways to reach the indicated destinations.

not willing to specify each of their transport demands manually, by analysis of their tracking data we can infer common ones, and use them to suggest sustainable transport options. Closely related is the process of negotiation, which is essential for the rising sharing economy. For example, when booking a shared car trip (carpooling), a price has to be negotiated, and it is important that both parties get insight about the other person (e.g., through reviews and ratings). But even for more traditional transport modes, if they should be offered as part of a MAAS package in an integrative way, it is important to easily see the total cost, and potential benefits from the combination of certain modes.

Solely from a user perspective, this leads to the component of planning, which is essential for any trip, but even more so for irregular ones, where transport modes are usually not known in depth. Based on the transport offers and demands publications and the profiles extracted from mobility analysis, we are able to personalize plans much more than ever before. The communication, finally, includes the generated eco-feedback as well as potential transport plans or options for upcoming trips.

The following chapters will mainly cover the *analysis*, *planning* and *communication* parts and present methods to process (tracking) data to support people in increasing the sustainability of their mobility behavior.

3 BACKGROUND

3.1 HUMAN MOBILITY BEHAVIOR

In this section, we provide background on human mobility behavior and choices, and how they evolve over time. A particular focus is on the choice of transport modes and routes, as understanding those is an essential part for using ICT to support sustainable personal mobility and MAAS.

3.1.1 *Human Behavior and Its Change*

Behavior is essentially grounded in the psychology of motivation. The base needs driving motivations can change over time and can be supported by ICT at different stages and on various scales.

3.1.1.1 *Theory of Motivation*

Motivational needs

Motivation "concerns those processes that give behavior its energy and direction" (Reeve 2014, p.22). Most theories argue that motivation is emerging from a variety of base needs. Figure 3.1 shows the needs discussed in detail below.

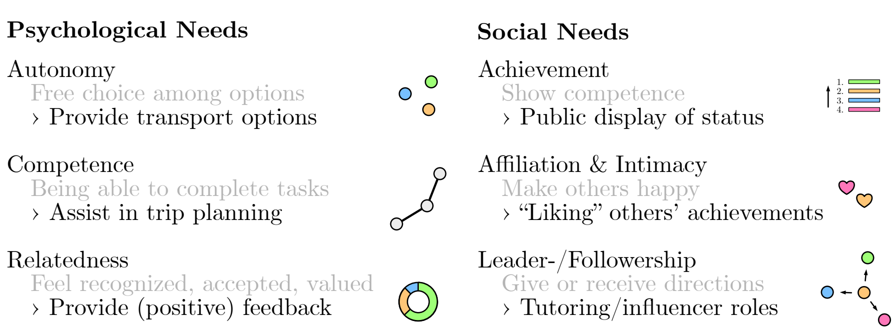


Figure 3.1.: Various motivational needs and examples how ICT can satisfy them (with regards to supporting sustainable mobility).

Psychological needs emerge without any exterior influence (Reeve 2014; Deci and Ryan 2004), and include the desire for autonomy, competence and relatedness (Weiser, Bucher, et al. 2015).

- The desire for *autonomy* describes the need resp. desire to have choices available, and the power to choose freely and independently of others (e.g., by providing a person with multiple transport options).

- *Competence* expresses our need to feel able to complete given tasks, and to improve the skills necessary for our actions (Reeve 2014; Csikszentmihalyi, Abuhamdeh, and Nakamura 2014; Werbach and Hunter 2012). This means that our tasks should neither be too easy nor too difficult, in order not to bore or frustrate us. Keeping the difficulty of a task at a level corresponding to a person's skills can keep her in a state of "flow", in which one is completely absorbed in a task and does not feel how time passes (Csikszentmihalyi, Abuhamdeh, and Nakamura 2014). ICT often employ a so-called "on-boarding" phase, during which the difficulty of a system is greatly reduced to match the (non-existent) skill of a user, e.g., by providing a tutorial phase. Gradually increasing the complexity of a system is an effective way to keep someone interested, and is, for example, heavily used in computer games.

- *Relatedness* describes the "need of engaging in relationships with others" (Weiser, Bucher, et al. 2015, p.272). Relatedness can be invoked simply by interacting with other persons, but to satisfy this need, one has to feel recognized, accepted and valued. It is interesting that people not only personally relate to ICT, but also interact with them in a way that resembles their interaction with other humans (Fogg 2002). ICT thus can fulfill the role of providing the needed recognition and acceptance, and can make humans feel valued. In addition, it can greatly facilitate the interaction between humans (also across large distances, cf. Miller 2013; Weiser, Scheider, et al. 2016; Jennings et al. 2014), thus making people feel related who otherwise might have difficulties connecting with other human beings. An example of ICT facilitating these interactions are the various social network platforms where people can group and exchange themselves based on their interests, and not solely on their physical location.

Social needs emerge from interactions with other people and are learned over the course of our life. They encompass achievement, affiliation, intimacy and leadership and followership (Reeve 2014).

- *Achievement* denotes the desire to show competence, in particular in relation to a societal norm or direct competitors. Typical elements from ICT that cater for our need for achievement are public displays of status, e.g., in the form of a leaderboard in a computer game.

- *Affiliation* and *intimacy* relate to everything that lets us make other people happy, resp. that other people do to make us happy and satisfied. These desires are heavily used by online social networks, where one can "like" other people's content, or "tag" friends in one's own postings. While the first one shows an affiliation, the second signals a special friendship and thus can be interpreted as a form of intimacy between two persons.

- *Leadership and followership* are complementary concepts that either relate to "the desire to impact, control, and influence others" (Weiser, Bucher, et al. 2015, p.272) (cf. Winter 1973) or to the need of direction given by someone in a leading position (Goffee and Jones 2001). Interestingly, ICT can take an authoritarian role over humans, for example when taking the role of an online tutor that encourages people to study more (Fogg 2002). Leader- and followership are also closely related to power, which is often exercised utilizing ICT, e.g., using leaderboards or score systems to depict particularly powerful individuals.

Motivational sources

An often made additional distinction is between *external* and *internal* (resp. extrinsic and intrinsic) motivation (Sansone and Harackiewicz 2000). While internal or intrinsic motivation is generated by one's *own goals*, *expectations*, *beliefs* and *the self*, external motivation stems from environmental, social or cultural circumstances and influences (Reeve 2014). The arguably best-known example of an extrinsic motivator is money, but there exists a wealth of others. When ICT are used to generate motivation (e.g., using gamification elements), they usually take the form of an external motivational source (Weiser, Bucher, et al. 2015).

- *Goals* and *expectations* represent desired outcome states, events, or processes (Austin and Vancouver 1996). While goals direct and influence our behavior, expectations help us manage the choice of actions (i.e., to evaluate efficacy and outcome). In order to execute an action, both efficacy (the "ability to do something") and outcome (the "likelihood that something succeeds") have to be high (Fogg 2009).

- A second form of internal motivators are *attitudes*, *beliefs* and *values*. They are all closely related, and build upon each other. Values are core ideals and preferences that lie at the base of our personality and thus are difficult and slow to change. Beliefs are personal views on "what is true and what is false" (Weiser, Bucher, et al. 2015, p.273), mostly based on experiences. They can change once we experience new situations related to a belief. Attitudes, finally, are quickest to change and describe our likes and dislikes. They are usually formed on the basis of beliefs and values.

- The *self* describes the mental representation we have of ourselves. It is usually built through interaction with other people resp. the inspection of their reactions on our behavior (Markus 1983). Ultimately, people strive to an idealized perception of one's self, behaving according to the conceptualization of one's self along the way ("confirmation bias", cf. Kahneman 2011).

Cognitive dissonance

Humans usually try to keep their actions in line with their values, beliefs, and attitudes. This can either mean to adjust behavior so it fits with one's values, or to adjust beliefs and attitudes to better reflect the actions performed. If it is not possible to reach this alignment, people fall into a state of "cognitive dissonance" (Festinger 1962). Using education, values, beliefs and attitudes can be influenced (Rokeach 1973), in turn leading to such a "cognitive dissonance" which can result in inducing behavior change.

3.1.1.2 *Behavior and Its Change*

Requirements for behavior change

Whether we decide to exhibit a certain behavior in a given situation primarily depends on our motivation and ability, as well as the concrete prompt for us to execute an action (commonly refered to as *trigger*, cf.

Fogg 2009). While our motivation and ability (i.e., skill to successfully execute the action) are given by previous experiences, motivational needs, as well as contextual factors, the trigger itself has the potential to increase motivation (becoming a *spark*; e.g., by offering a financial reward) or ability (becoming a *facilitator*; e.g., by providing information about how to successfully perform a task). Figure 3.2 shows the interplay between motivation and ability, and highlights the conceptual border between a trigger succeeding or failing as a blue line. By increasing either motivation or ability, a trigger is more likely to induce a desired behavior.

Regarding context in particular, researchers have classified it into many different areas (cf. Abowd et al. 1999). We here adopt a classification by Brimicombe and Li 2009, pp. 214, that provides the classes of *environmental*, *technological*, and *individual context* (the latter consisting of *user characteristics*, *knowledge*, *preferences* and *situation*). The situation context here includes the actions to be performed, but also individual characteristics like the emotional state or the well-being (Brimicombe and Li 2009; Consolvo, McDonald, and Landay 2009). Within ICT supporting sustainable mobility behavior, especially the environmental and individual contexts are of importance.

Stages of behavior change

On a general level, behavior change is classified into two stages: *discovery* and *maintenance* (Li, Dey, and Forlizzi 2011). During the discovery phase, people educate themselves about factors that influence a certain behavior and try to evaluate which potential new goals they could adopt. Once new goals are defined and first actions are undertaken, a person moves to the maintenance stage, where she strives towards the newly set goal, and performs and internalizes behavior. At any point during the maintenance phase, one could fall back to discovery, to learn more about the behavior and the factors that influence it.

The Transtheoretical Model (Prochaska and Velicer 1997) splits these two phases up into finer categories. People in the discovery phase start by *precontemplating*. During this time, they are not aware of a potential new behavior, and will require external stimuli to transition into a *contemplation* stage (He, Greenberg, and Huang 2010). As such, people in the precontemplation phase are best served by continuous education, which might lead them to contemplate a new behavior. Through continuing self-evaluation, they can transition into a *preparation* phase, during which concrete plans for behavior change are formed.

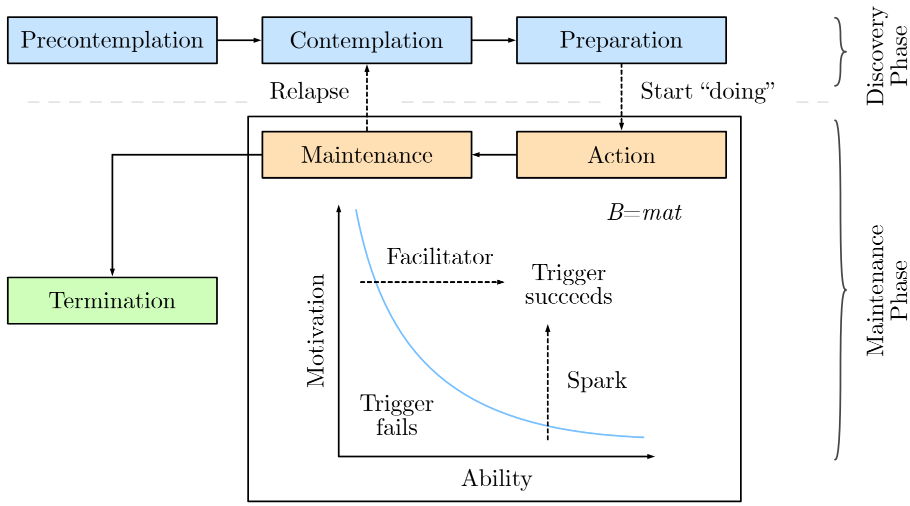


Figure 3.2.: Behavior change models according to Prochaska and Velicer 1997 and Li, Dey, and Forlizzi 2011. During the action (and maintenance) stages, behavior has to be triggered. Fogg 2009 states that the execution of a certain behavior B depends on the motivation m, ability a and trigger t itself ($B = mat$).

Once a person starts performing actions with a certain target behavior, she transitions into the maintenance phase according to Li, Dey, and Forlizzi 2011. During the *action* phase, repeatedly carrying out the new behavior leads someone from being a novice to an expert (cf. Dreyfus and Dreyfus 1980). Experienced users will transition to a *maintenance* phase, in which they still have to be kept motivated to exhibit the new behavior, in order not to *relapse* back into the contemplation phase. Only when a behavior is truly "internalized" we can consider a new habit to be formed, a process that can take a long time (Stawarz, Cox, and Blandford 2015). Figure 3.2 visualizes the explained concepts.

3.1.1.3 *ICT Supporting Behavior Change*

Information and Communication Technologies (ICT) are used to great effect in supporting certain behaviors and the change of them. Well-known examples range from electronically assisted customer loyalty programs (where all spendings are tracked and rewarded with bonus points, miles, discounts, etc.), over websites and applications rewarding people for their participation in discussion forums and for generating content, to the infamous "likes" of many social media platforms that have been shown to exhibit addictive characteristics and have recently been under a lot of scrutiny due to their potentially disheartening nature (Scissors, Burke, and Wengrovitz 2016; Blease 2015).

Motivational affordances

ICT usually support behavior change by offering *motivational affordances*. Originally invented by Gibson 1977, and based on the verb *to afford*, an affordance describes what a thing offers to an entity, i.e., the "perceived and actual properties of a thing, primarily those functional properties that determine just how the thing could possibly be used" (Salomon 1997, p. 51). Norman 2013 discusses good design of affordances (but also signifiers, constraints, mappings and feedback) by taking into account the psychopathology of everyday things and the psychological traits influencing human actions. In his book, human centered design as a philosophy is promoted: Instead of designing from a completely technical point of view, we should start "with a good understanding of people and the needs that the design is intended to meet" (Norman 2013, p. 9). To adopt this philosophy, understanding the seven stages of action are central: defining goals, planning, specifying, performing, perceiving, interpreting, and comparing. As can be seen, these stages mostly fit into the preparation and action phases introduced in the previous section. Taking the example of a planning a mobility behavior change and thus defining a corresponding goal, we might plan to use a persuasive application to reach it. For this, the application does not only have to afford motivation (cf. Zhang 2007), but it needs to be designed in a way that is *understandable* and easily *discoverable* (Norman 2013). This example also highlights that ICT supporting sustainable mobility has to go beyond offering motivational affordances, e.g., by offering educative measures or giving feedback.

Within the context of ICT, affordances are primarily studied in the subfield of Human-Computer Interaction (HCI). Norman 1999 provides an interesting discussion of how the term affordance was originally adopted within this field: an affordance was understood as a way to signify that the interaction with a (virtual) object leads to some planned outcome. However, this is not adhering to the original definition, where neither the signaling nor the planned outcome are of significance. To distinguish between these different definitions, he introduces the terms real affordances and perceived affordances (which loosely correspond to the later introduced term *signifiers*, namely indicators of possible affordances, cf. Norman 2013). Raubal and Moratz 2008, based on Raubal 2001, extend the concept of affordances by dividing it into *physical*, *social-institutional*, and *mental* affordances. Whereas the first require physical requirements to be met (e.g., an object size must match a person's hand to grab it), social-institutional affordances revolve around interactions between people and are thus often not bound to a location (e.g., one can talk to another person via telephone), and mental affordances spring into existence when a person is in a situation and needs to decide upon an action plan to reach his or her goals. Janowicz and Raubal 2007 use affordances to determine the similarity of objects and use it within a case study involving an agent that has to reach a certain goal (e.g., changing a light bulb). To proceed towards the goal, the agent chooses entities that have similar affordance descriptors to a one that is chosen based on internal knowledge. A similar case can be made when an agent has several transport modes available to reach a physical location.

He, Greenberg, and Huang 2010 mention five different models that can be used to describe how we decide between different behaviors and that thus should be respected when designing motivational affordances: the attitude model (favorable attitudes will lead to pro-environmental behavior), the rational-economic model (monetary costs determine everything), the information model (if you know enough about a problem, you will act in the best possible way), the positive reinforcement model (actions have to be rewarded), and the elaboration likelihood model (we act according to logic and rationale, but are influenced by emotional responses to problems). Froehlich, Findlater, and Landay 2010 extend this list with a model of responsible environmental behavior (which includes economic constraints and social pressure in addition to the intention to act), and norm-activation models (that are similar to attitude models, but root behavioral choices deeper in personal norms). Within this dissertation, we primarily rely on the information and positive reinforcement models, arguing that in the mobility sector, economically driven choices require policy changes (and are thus not tightly linked to ICT; note that they can be actively promoted and motivated using ICT, however) and attitudes are difficult to change in short time frames (but will over time adjust themselves in accordance with the received information and rewards).

Analyzing current and past behavior and presenting it in an interpretable form can help users become aware of their own behavior, thus forming a motivational affordance for introspection and the induction of change. This effect can be strengthened by providing alternatives for past and future behavior, as well as by offering comparisons to defined norms, goals, or other people (cf. Weiser, Scheider, et al. 2016). This form of support is rooted in the fact that people are often not aware of the impacts of their routine behavior, which is carried out subconsciously. By presenting viable alternatives, the difficult step of aligning multiple goals of people can be alleviated—otherwise, a large effort is needed to evaluate all the potential impacts on reaching different goals and balancing them against each other. In similar ways, ICT is used to simply educate people about different behaviors, and thus highlight potentially "bad" behaviors, and/or how other people behave.

Other motivational affordances include social elements, such as collaborative or competitive elements of an application. Cooperation describes all processes in which multiple individuals try to achieve something by working together. They primarily target our need for relatedness, but can also satisfy the needs for affiliation or leader- and followership; the latter when there are exclusive groups people can belong to, and/or if there are special roles within a community that manage and lead it. For example, Gustafsson, Katzeff, and Bang 2010 evaluate a game targeting a reduction in domestic energy use that builds upon cooperation within families and report that such persuasive games show a lot of promise for demand management. Jung, Schneider, and Valacich 2010 look at how to enhance HCI interfaces for collaborative applications and find that by building applications specifically including motivational affordances, significant performance gains can be achieved. Competition, on the other hand, appeals to our needs of achievement and leadership (Weiser, Bucher, et al. 2015), and mainly works for people in comparable situations. Sepehr and Head 2013 performed a study with college students and found that while competition is highly motivating, it can also have a detrimental effect on the enjoyment of a task.

Finally, elements fostering challenge or rewarding certain behaviors can both also be used as motivational affordances. Challenges primarily satisfy our need for competence, as we get the chance to evaluate our performance. They work well for people who do not have a concrete goal or do not know how to reach one (Gustafsson, Katzeff, and Bang 2010). Rewards relate to the needs of achievement and competence and are the prototypical example of extrinsic motivators (Reeve 2014; Weiser, Bucher, et al. 2015). However, as Deci, Betley, et al. 1981 point out, while rewards can provide a strong motivational source, they are less effective for changing behavior in the long term. This is similar to most extrinsic motivators, as they are not able to generate intrinsic motivation, and thus the behavior is only changed as long as the motivator exists. Munson and Consolvo 2012 find that rewards should have a surprising aspect in order to be effective, and Frederick and Loewenstein 1999 point out that the rewards must be increasing over time to give people the same amount of satisfaction.

Location-Aware ICT

Focusing on geospatial and location-aware technologies, we primarily find applications that assist people in living a healthy lifestyle, employing game-like elements (Yoganathan and Kajanan 2013). Often, these applications come in the form of fitness trackers that record the movement of people and let them evaluate their behavior over a longer period of time or in comparison with other people. Along the same line, so-called exergames similarly stimulate (young) people to perform moderate to vigorous physical activity (Boulos and Yang 2013). The focus here is more on the game itself, and the healthy lifestyle is a (desired) by-product. An in-depth review of research combining location-aware ICT and mobility behavior will be given in section 3.4.

3.1.2 *Transport Mode Choice*

To know how to best support people in making sustainable mobility choices, it is important to understand why people choose a certain mobility behavior, especially since these choices are usually not only determined by transport mode availability (resp. the built environment), but also by a variety of socio-demographic, -economic and -psychological factors (Acker, Wee, and Witlox 2010). Figure 3.3 highlights the different choices and influencing factors, as explained in this section.

Built environment

A wealth of studies analyze the dependencies between the built environment and travel behavior. Ewing and Cervero 2010 published a meta-analysis of over 200 studies in 2010, building upon qualitative work from numerous authors (Ewing and Cervero 2001; McMillan 2007; Pont et al. 2009; Stead and Marshall 2001). In essence, these studies intend to quantify the "potential to moderate travel demand by changing the built environment" (Ewing and Cervero 2010, p. 267), including density, diversity (of land uses), design (of street network), destination

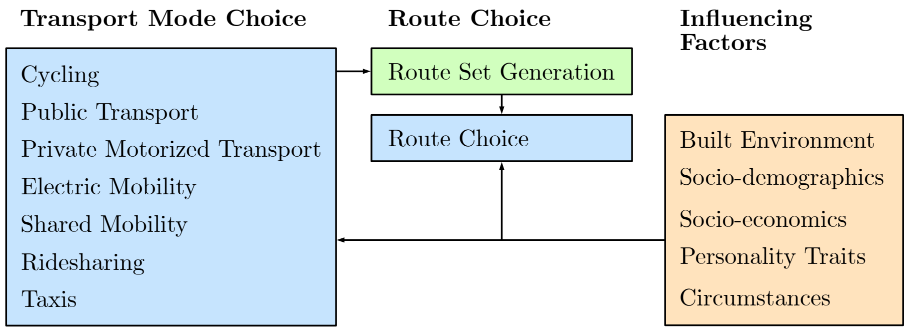


Figure 3.3.: Different choices available to people when planning mobility and factors that influence their decisions.

accessibility, distance to transit, demand management (mostly parking supply and cost) and demographics (Ewing and Cervero 2001; Ewing, Greenwald, et al. 2009; Ewing and Cervero 2010). To evaluate, they measure the travel outcome elasticity (e.g., the number of walking trips) with respect to one of the listed variables. They find that the distance to the center of town correlates positively with the PMT vehicle miles traveled, the street density correlates with the use of Slow Mobility (SM) (whereby they only refer to walking), and the distance to transit as well as the number of 4-way intersections positively influence the likelihood of taking PT. Several recent studies examined the effects of city planning and the built environment on the ecological sustainability of cities, and argue that shifts towards more dense, mixed-use urban designs will cause people to rely less on PMT (Sallis et al. 2016; Stevens 2017).

Socio-economic factors

Similar to research on the impact of the built environment, researchers studied the correlations between socio-demographic and -economic factors and travel behavior. Metz 2010 states that in recent years, even though private car ownership and average income have increased, people still spend roughly the same share of time and money for their travel needs, numbers that show "relatively stable patterns of variation as a function of life stage, socio-economic status, and geographical location" (Metz 2010, p. 670). Gatersleben, Steg, and Vlek 2002 contrast psychological and socio-economic variables regarding their impact on household energy consumption, and find that while attitudes correlate with pro-environmental behavior, the household energy demand is mainly driven by socio-economic factors such as the income or household size. Within the mobility domain, Hunecke et al. 2007 find a contradictory trend: psychological variables seem to influence both intent- as well as impact-oriented behavior (however, the socio-economic variables have to be controlled for). They explain these differences by their more accurate recording of mobility-related attitudes. Regarding the geographical differences, Buehler 2011 analyzed the differences in PMT use between the USA and Germany. Even when controlling for factors of the built environment and the socio-economic background, people in the USA travel at least 70% using PMT, whereas in Germany "only the most car-oriented groups of society display such high levels of car use" (Buehler 2011, p. 654), a difference that can potentially be explained by varying transport policies and factors of the built environment such as the availability of walkways or PT. Meng, Koh, and Wong 2016 build a multimodal logit model that highlights the dependencies between socio-demographic features and the choice for the first/last mile transport mode in Singapore. By interviewing 851 participants, they find a range of significant predictors, such as age, gender, household income, and a range of factors of the built environment.

Circumstance and personality

Within the context of this dissertation, it is also important to consider the effects of circumstantial factors and personal traits on transport choices. Krygsman, Arentze, and Timmermans 2007 investigate correlations between performed activities and mode choices. They find that people are more likely to include intermediate activities for simple transport mode chains (such as solely taking PMT), and that complex mode chains in turn lead to simple activity chains. Similarly, they note that the spatial and temporal constraints before heading to work are much tighter, leading to the result that discretionary activities are usually scheduled after work, and only mandatory activities appear before. In a study involving Swedish commuters, Vredin Johansson, Heldt, and Johansson 2006 found that while time and cost play a significant role, personality traits such as the preference for flexibility or comfort are able to explain some of the transport mode choices. Similarly, they state that personality traits determine our attitudes towards the environment, safety, comfort, convenience and flexibility (Vredin Johansson, Heldt, and Johansson 2006). Contrasting the results by Hunecke et al. 2007, Vredin Johansson, Heldt, and Johansson 2006 find no correlation between the environmental stance of a person and the choice between car or bus; however, they note that in general a pro-environmental attitude lets a person prefer PT and SM. Collins and Chambers 2005 performed a similar study with students in Australia and conclude that due to the relatively strong influence of personal beliefs on mode choice, policy should "address situational and psychological factors in attempting to encourage a commuter transport mode shift toward more use of PT" (Collins and Chambers 2005, p. 658). Donald, Cooper, and Conchie 2014 regard the problem utilizing theory of planned behavior (Ajzen et al. 1991), under which they find that the *perceived behavioral control* (the perception that the individual can perform the intended behavior) is the most impactful variable to predict a travel choice, in contrast to subjective, moral and descriptive norms. Habits, on the other hand, may, if existent, "override" all mentioned factors. An important take-away is that "it may be necessary to break habits prior to implementing attitude-based campaigns" (Donald, Cooper, and Conchie 2014, p. 46), something that could be done by changing the built infrastructure, or forcing people to (re-)make a conscious decision for a transport mode choice in a previously habit-driven setting.

In the following, we will assess research results regarding choices of various transport modes.

3.1.2.1 *Cycling*

Conventional Bicycles

With the recent focus on environmentally friendly transport modes, both electric as well as conventional bicycles came under investigation. Commutes are often subject of study, as they are regular and usually of comparatively short distances. Heinen, Maat, and Wee 2013 unveil correlations between work-related factors and the choice of an individual to commute by bicycle. They find that next to the personal attitude, the expectations of coworkers, infrastructure (availability of storage and changing facilities) and the availability of a bicycle drive the choice. Heinen, Maat, and Wee 2011 perform a similar study, finding that for shorter commutes, the opinion of others is an influencing factor, yet for longer trips one's attitudes have to be pro-cycling. Mostly, though, the direct benefits of cycling (time, comfort, flexibility) determine if someone commutes by bicycle or not. As weather and seasons might determine the choice to travel by bicycle, Bergström and Magnusson 2003 preformed a study that evaluated the attitudes towards cycling at low temperatures. While people who only cycle in summer were primarily influenced by environmental factors such as temperature, precipitation or road conditions, people who cycle the whole year round are mostly driven by the desire to exercise and lead a healthy

Electric Bicycles

lifestyle. The implications of their research include that health could be a proxy to achieve environmentally friendly behavior, but also that by increasing road maintenance during winter the number of bicycle trips could be increased. In similar spirit, Bucher, Buffat, et al. 2019 looked at which energy savings would be possible, given that people are willing to travel (by electric bicycle) at certain temperature and precipitation levels. They find that roughly 10% of all emissions from fossil fuel based commutes could be saved in Switzerland under the assumption that people would be willing to replace commutes of up to approx. 15 minutes by bicycle. However, one has to be careful when promoting e-bicycle choices, as often the involved people are more likely to transition from PT than from PMT, thus not necessarily largely changing the environmental impacts (Cherry and Cervero 2007).

3.1.2.2 *Public Transport*

When it comes to Public Transport (PT), people's choices are mostly driven by its frequency, the access and egress times, as well as the number, location, and context of transfers (whereas waiting and walking during a transfer is particularly burdensome) (Anderson, Nielsen, and Prato 2017). In their work, Anderson, Nielsen, and Prato 2017 generated public transport alternatives and found that while people are willing to wait a substantial amount of time during long trips, the transfer penalty similarly increases, indicating that travelers prefer to stay on a single mode of transport (e.g., to work during a train trip without transfer). Hensher and Rose 2007 built a nested logit model for both work-related as well as non-work trips and similarly found that the number of transfers, the fares (for PT) and costs (for PMT), followed by in-vehicle and waiting times correlate with the choice for a certain mode of (public) transport. Vrtic and Axhausen 2002 find that travel time and the number of transfers are highly decisive, and that one (train) transfer is equated with 19 minutes in-vehicle time. Another interesting finding consists of the fact that car owners value the in-vehicle time higher than people who do not own a car. Ye, Pendyala, and Gottardi 2007 observe that people tend to choose trip chains before they choose a mode, and that users of PT prefer simpler trip chains. This in turn implies that PT providers should not only improve service amenities along their routes, but also have to "cater to a multi-stop oriented complex activity agenda" (Ye, Pendyala, and Gottardi 2007, p. 111), which might call for more flexible and individual access to PT (e.g., by using bus-on-demand systems or autonomous taxis). Looking at the choice process, Bovy and Hoogendoorn-Lanser 2005 additionally find that usually people first choose a particular station to access PT (based, among previously identified factors, on personal preferences), after which they select an access mode. Eluru, Chakour, and El-Geneidy 2012 examine home-to-work/-school travel patterns, and conform the findings of the previously mentioned studies: They highlight that in comparison with trips by train and metro, travel by bus is least favorable; that women are less sensitive to travel time and that a reduction in bus travel times would greatly increase the likelihood that people travel by bus.

3.1.2.3 *Private Motorized Transport*

The use of Single Occupant Vehicles (SOVs) is examined from various points of view. Klöckner and Friedrichsmeier 2011 represent car choice using a two-level structural equation model: On the first level, trip attributes are considered; on the second, person-specific information about the individual, such as attitudes or personal norms. They find that the person-specific attributes explain a large share of the variance in the data, stating that it is thus important to not only consider trip features, but also individual characteristics. Their findings are supported by Klöckner and Blöbaum 2010 who mention that situational constraints explain most of the variance in transport mode choice models, but that habits and intentions can not be neglected. Regarding situational constraints, Klöckner and Friedrichsmeier 2011 observe that car access (which might itself be a "bad" predictor, as car ownership usually requires a previously undergone decision process of similar form), trip duration, and the trip purpose are strong predictors for car choice. The immediate context affects car usage in different ways: Weather and small disruptions of PT only marginally influence the transport mode choice, while major disruptions have significant impacts. Finally, they note that habits and perceived behavioral control show correlations with easily available trip information (such as the purpose or length of a trip) (Klöckner and Friedrichsmeier 2011). Opposite interactions between intentions, norms and attitudes, and information that is difficult to obtain, were established. This means that for habitual behavior, people tend to rely on simple rules, and that people with high levels of intention are willing to evaluate more complex decision scenarios. For persuasive ICT, it might thus make sense to break down complexity in new situations, and/or increase the levels of intention, e.g., to travel in sustainable ways. Taking an intra-household point of view, Scheiner and Holz-Rau 2012 analyze the gender differences in households containing more drivers than cars. They find that the "economic power" within a household (i.e., who earns money) does not affect car usage, however, there are indicators that the use of a car is driven by the (gendered) social role someone takes in a household (e.g., the person looking after children and being responsible for running errands might always use the car or vice versa).

3.1.2.4 *Electric Mobility*

Buying Decisions

A large field of research is concerned with the question who buys an electric car. Using a large-scale online survey in Norway, Klöckner, Nayum, and Mehmetoglu 2013 find that EVs are commonly bought as a second car, a finding that contrasts the one by Haan, Mueller, and Peters 2006, which was, however, specifically targeted at the Plugin Hybrid Electric Vehicle (PHEV) Toyota Prius. In contrast to Battery Electric Vehicles (BEVs), PHEVs can also be refueled during a journey at a regular gas station. In their study, Nayum, Klöckner, and Mehmetoglu 2016 clustered ICE car owners into five groups and contrasted them with EV owners, finding that there are large socio-psychological differences between ICE car buyers and EV buyers. EV owners are generally more environmentally friendly and show an increased perceived behavioral control alongside attitudes and intentions to buy fuel-efficient cars. However, in summary across all groups, social and personal norms had little influence (probably due to the comparably high costs involved in buying a car that made the activation of personal norms inappropriate), and the buying decision mostly relied on a car's performance and convenience attributes. In a 2011 study involving residents of San Diego county, USA, Axsen and Kurani 2013 found that a large share of the population would consider a PHEV as their next car, as they are worried about the limited range and recharging facilities as well as the high price of EVs. Haan, Mueller, and Peters 2006 point out the potential rebound effects from buying an electric car: these can manifest as direct and indirect effects, and macro-level effects (taking a whole society into account; cf. Berkhout, Muskens, and W. Velthuijsen 2000), both in terms of money as well as sustainability. Interestingly, they do not find any rebound effects regarding vehicle size nor vehicle ownership. It is pointed out that this might also be due to Prius buyers being "early adopters", and thus one might not generalize across the entire population (Haan, Mueller, and Peters 2006). Similarly, there might be a bias towards environmentally or financially overly aware people and/or people who do not consider cars as status symbols.

Range Anxiety

As EVs exhibit some different properties than ICE cars (such as longer recharging/refueling durations, shorter ranges, possibility to recuperate energy, etc.), researchers studied the differences between people using ICE cars and people using EVs for travel. Klöckner, Nayum, and Mehmetoglu 2013 note that especially in households that own an EV as their only car, the expected annual mileage is substantially lower than for households with multiple cars. This might be due to the fact that BEVs show limited ranges, or that people replacing an ICE car with a EV are actively trying to reduce their mileage. Range anxiety is a psychological phenomenon that occurs either during a drive when one realizes that not enough energy is remaining to complete the trip, or during the planning phase when one has to drive further than maximally possible with a BEV (Noel et al. 2019). Several researchers argued that range anxiety "may be an over-stated concern" (Saxena et al. 2015, p. 275) as most of the regular trips can easily be covered by BEVs, even after battery degradation or for low-cost models with little range. Rauh, Franke, and Krems 2015 analyzed the differences in range anxiety between experienced BEV users and people who never drove a BEV before, showing that experienced drivers exhibit much lower range anxiety, confirming the findings of Franke and Krems 2013. They conclude by stating that "teaching users relevant knowledge and skills [...] could be one fruitful approach to reduce the experience of range anxiety." (Rauh, Franke, and Krems 2015, p.14). Similarly, when traveling by BEV, it was found that the initial State of Charge (SOC) has a large effect on range anxiety, and that unambiguous displays (e.g., showing the remaining range at an accuracy of meters) are perceived as untrustworthy (Jung, Sirkin, et al. 2015).

3.1.2.5 *Shared Mobility*

Private carsharing

Various factors contribute to the likelihood for someone to carshare: Efthymiou, Antoniou, and Waddell 2013 find that younger and low-income people are more likely to share their car with others, alongside people who are more environmentally aware. It is also noted that carsharing often replaces PT, similar to bikesharing replacing journeys previously performed on foot. Their findings coincide with research by Kortum et al. 2016, who not only point out the generally increasing usage of carsharing, but also how residential density and the number of people per household influence both the daily bookings (negatively) as well as their growth rate (positively). Becker, Ciari, and Axhausen 2017 analyze the use of free-floating carsharing offers and find that they are primarily used for discretionary trips where no suitable PT exists; a finding that contrasts with the use of station-based carsharing, which is frequently used in areas that have good accessibility to PT and relatively high car ownership levels. In their case, free-floating carsharing was found to scale with the population density as well as the number of carsharing members living in a region. Shaheen, Schwartz, and Wipyewski 2004 note that joining a carsharing program also affects mobility use: In Europe, Vehicle Miles Traveled (VMT) drop between 30% and 70%, and from 10% to 60% of all people sell a vehicle after joining a program. Other benefits of carsharing include the fact that it reduces the frequency of impulsive trips and makes people more aware of the actual costs of a trip, which are often concealed for PMT (Zheng, Scott, et al. 2009). Next to the psychological and socio-economic resp. -demographic factors, features of the trip itself also determine the use of carsharing: Most important is usually the distance as well as the availability of parking at the destination (Fleury et al. 2017). In their study, Fleury et al. 2017 particularly focus on corporate carsharing, which describes the concept of having a fleet of vehicles that members of a company can use at their discretion, without having individual vehicles assigned. They found that within this context, ease of use is crucial in determining the intentions of employees for using the service. Environmental views only marginally influenced these intentions, related to job performance expectancy. Finally, communication plays a large role in the adoption of carsharing. Shaheen and Novick 2005 contrast the use of a brochure resp. a video and test drive, and find that the intention to use carsharing was 33% for the first group, and 78% for the second one.

3.1.2.6 *Carpooling and Ridesharing*

Definition and development

Ridesharing or carpooling is commonly defined as two or more people sharing a common itinerary and means of transport (Furuhata et al. 2013) resp. "when two or more trips are executed simultaneously, in a single vehicle" (Morency 2007, p. 240). While there is no consensus on the differences between the different forms of ridesharing and carpooling, we here adopt the terminology introduced in the work by Agatz et al. 2012: Carpoolers unite to regularly travel to a certain location together and often take turns driving (in these cases, there is also no need for payment). Ridesharing, on the other hand, is more ad-hoc and between people who usually do not know each other beforehand (and thus often enabled of facilitated by ICT). Additionally, Agatz et al. 2012 make the distinction between dynamic and static ridesharing, where dynamic refers to short-term/en-route planning of rideshares, and static to those problems that can be planned in advance (e.g., a holiday trip). Technically, this definition includes both intra- as well as inter-household ridesharing (Buliung et al. 2010; Morency 2007; Vanoutrive et al. 2012; Teal 1987). We here put a slight focus on inter-household ridesharing, as it relies more on support from ICT than intra-household carpooling, which can be formed and planned based on verbal and informal interaction (but nonetheless should be supported, e.g., by motivational elements). Ridesharing is part of so-called Collaborative Consumption (CC) which was recently enabled through ICT and is seen as a component of the *sharing economy* (Hamari, Sjöklint, and Ukkonen 2015). Even though it is generally agreed upon that ridesharing has numerous potential benefits, such as reduced travel costs and emissions, or better utilization of vehicles and infrastructure (Furuhata et al. 2013; Amirkiaee and Evangelopoulos 2018), it still only makes up for a small share of mobility.

Characteristics

Several decades ago, Teal 1987 found that around 18 to 20% of the American people used carpooling. Out of these, over 40% were members of household carpools, which consisted of 2 people in 95% of all cases. Among the inter-household carpools, 40% were sharing driving responsibilities (i.e., they take turns as drivers and contributors of a vehicle), while 39% were only riding, and the rest was only driving. Typically, these carpools showed a high regularity, being active around four out of five days per week (which means they are fixed commuting arrangements). This stands in contrast to intra-house carpools, which are used much more infrequently (as they are less formal, and much more driven by convenience factors than economic ones). While the share of carpoolers has stagnated or even reclined after the oil crisis in 1973 (Ferguson 1997; Pisarski 1997; Benklert 2004) and a shift towards intra-house carpooling took place (Morency 2007), it recently started increasing again across several regions and contexts due to rising concerns about the environment, increased urbanization and more convenient access to carpooling through ICT.

Personal factors

To find out what drives people's choice regarding carpooling, Amirkiaee and Evangelopoulos 2018 conducted a survey with 481 undergraduate students from a large public university. They found that the "ridesharing participation intention" is largely driven by one's attitude towards ridesharing, which in turn mainly depends on *trust*, *transportation anxiety* and potential *time benefits*. While trust mostly relates to the "marketplace aspects" of ridesharing (i.e., one often has to carpool with a stranger), anxiety refers to the fact that ridesharing has a stress-migitating effect (Novaco and Collier 1994) and reduces unease due to a variety of factors such as being on time, parking spaces or traffic congestion. Time benefits mostly occur if the alternative would be to take public transport or a form of slow mobility (Amirkiaee and Evangelopoulos 2018). *Economic benefits* play a minor but significant role, while *sustainability concerns* and *social aspects* do not seem to influence choices for or against ridesharing at all (Amirkiaee and Evangelopoulos 2018). In contrast to their findings, Hamari, Sjöklint, and Ukkonen 2015 state that the attitude towards a certain CC behavior is significantly motivated by the sustainability of the activity, as well as its enjoyment. Politis, Papaioannou, and Basbas 2012 examine the influence of various behavioral stages on transport mode choice and find that people in more advanced stages are much more likely to carpool.

Corporate and geographic factors

The accessibility to carpooling resp. ridesharing plays a major role in its use. A context in which carpooling is often offered is within corporations (due to easy-to-use communication channels with potential carpoolers, a high regularity of behavior, as well as a guaranteed shared origin/destination) (DeHart-Davis and Guensler 2005; Vanoutrive et al. 2012). Canning et al. 2010 find that economic aspects are the main drivers for participating in corporate carpooling, followed by the unavailability of a personal car, and environmental and social aspects. Extending this work, Vanoutrive et al. 2012 study the effects of location, organization (sector) and promotion (i.e., marketing and management measures) on the choice behavior of commuters at several workplaces throughout Belgium. They find that psychological barriers, attitudes and perceptions correlate more with the choices to carpool than socio-demographics. Additionally, the location resp. accessibility to a workplace influences the use of carpooling, as well as organizational factors (work schedules or the sector the corporation is active in) and the amount of promotion carpooling receives from the corporate management. This is in alignment with research by Teal 1987, who found a correlation between the trip distance as well as the availability of public transport and the likelihood of participating in carpooling. Soft promotion measures (such as marketing or the creation of "pools") were found to be less effective than discouraging measures (such as parking charges) (Vanoutrive et al. 2012; Canning et al. 2010). Comparing their work to previous research conducted by others (Buliung et al. 2010; Canning et al. 2010; Ferguson 1997; Teal 1987), they also note that general patterns can be recognized. For example, households in lower income classes seem to carpool more (which might be linked to the fact that a lower income inversely correlates with vehicle ownership) and women with small children less often (due to their circumstances, where they often have to drop off/pick up the child at some place). In alignment with previous research (Wang 2011), Vanoutrive et al. 2012 thus conclude that access to carpooling should be facilitated, but not actively promoted in areas with good public transport or bicycling infrastructure (as it is less efficient).

3.1.2.7 *Taxis and Autonomous Mobility*

Taxis

Schmöcker et al. 2008 perform a transport mode choice study involving elderly people in London. They find that older people travel approx. 5% of all their trips by taxi, a number that is significantly higher than the average of around 1.5% in London, and that it involves mostly homebound trips (e.g., when returning from a shopping center carrying bags). Among the available transport modes, taxis are as popular as driving one's own car or taking bus or tram, before taking the subway or railway, or being a passenger in another person's car (the latter is an indication that people do not like to be dependent on friends or family). This lack of generalizability in the study of Schmöcker et al. 2008 is partially confirmed by research by Stern 1993, who found that taxis are an inferior alternative to paratransit services (smaller buses that stop on demand). Roorda, Passmore, and Miller 2009 look at minor transport modes in the Toronto area. With regards to taxis, they primarily find that these usually originate from within the city center or are frequently used to travel from/to the airport, and that people below 19 years are more likely to take public transit, most likely due to a lack of drivers license and funds for more expensive transport modes such as taxis. Another interesting takeaway is that people are approximately six times as sensitive to parking than to travel costs. Jou, Hensher, and Hsu 2011 similarly look at the use of taxis to get from Taipei (Taiwan) to the airport and find that both out-of-vehicle (to walk to the station, search for a vehicle, etc.) and in-vehicle travel time as well as the overall time savings and the ease of use primarily drive the transport mode choice. Participants of their survey indicated that intra-variation of transport mode choices is uncommon, i.e., people always take the transport mode they are used to. For all participants, financial aspects, such as parking fees, fuel cost or highway tolls played an important role and students often asked friends or family to drive them to the airport. An important takeaway is also that the computed elasticity values for Mass Rapid Transit (MRT) systems indicate that keeping the out-of-vehicle time low is especially important for the adoption of public transport. Overall, and as Roorda, Passmore, and Miller 2009 note, transport mode choice models involving taxis suffer from a lack of data as this mode is infrequently used in comparison to others.

Autonomous mobility

Even though there are only few autonomous cars on the streets yet (and those are primarily being used within pilot experiments), several researchers looked at the intentions and attitudes of people towards autonomous mobility. Becker and Axhausen 2017 performed a literature review on the acceptance and pricing of automated vehicles, and make the distinction between private Autonomous Vehicles (AVs) and shared AVs (which correspond to on-demand services on flexible routes). The outcomes of various studies indicate that a substantial share of the population (18-50%) would either use the technology or at least think its development is important. Similarly, people would be willing to pay an additional USD 3'000 to 7'253 for the addition of autonomous capabilities to their cars. However, the complete dismissal of one's own car in favor of a shared autonomous taxi service is only accepted by a few—most people would rather replace their second car and keep their primary car for themselves. Autonomous vehicles were also found to be more accepted with increasing age (which can be explained by the physical limitations of older people) and among young people (who are generally open to new technology). Finally, Becker and Axhausen 2017 summarized that people who travel inter-modally are more inclined to accept AVs, as are people from urban areas and those who often travel on highways and in congested traffic. Their findings are partially overlapping with those by Jing et al. 2019, who do a similar literature survey, and also perform a study with 906 persons in China. They particularly highlight that a lack of knowledge about AV technology and the difficulty of risk assessments are what keeps people from being highly in favor of AVs. Winter, Cats, et al. 2017 performed a stated-choice experiment to compare free-floating carsharing and AVs with PMT and PT. Their takeaway is that while early adopters would favor autonomous vehicles, there is an aversion among other groups of the population. Malokin, Circella, and Mokhtarian 2015 examined the aspects of being able to do other activities while traveling by AV. They find that this ability significantly increases the perceived utility and thus helps AVs gaining wide acceptance. However, they also point out that this might happen as a replacement of PT and carpooling—which goes against many environmental goals.

3.1.3 *Route Choice*

Prato 2009 gives an extensive overview of route choice modeling that includes numerous transport modes within a transportation network. The author particularly highlights that route choice is fundamentally different from destination or mode choice, as the number of potential routes is usually vast, and they are not "readily available" as they have to be extracted from the transport network. Usually, the problem is divided into two parts: route set generation and choice (whereas a person chooses a particular route given some utility function on incomplete information). Starting with deterministic shortest-path algorithms (that create the K best paths according to some utility function), Prato 2009 reviews labeling approaches (that have multiple optimization criteria, each assigned to a different label; e.g., shortest path, least congested roads, etc.), link elimination approaches (that iteratively search for the shortest path after removing central links from a previously found one), and link penalty approaches (similar, but instead of removing links they are heavily penalized). Among the reviewed stochastic approaches, we find simulations (that draw link travel times or costs from a chosen distribution and use it to compute different paths) and doubly stochastic generation functions (that in addition have a stochastic component that models a traveler's perception). Other approaches use behavioral rules or probabilities assigned to each possible route choice, potentially combined with a perception model that restricts the number of potential choices. Once a set of choices is available, a route choice model is used to quantify the likelihood of choosing one route over another Prato 2009. For example, (multi-nominal) logit models express a probability for each route within the choice set, based on a given utility function (that depends on the route and potentially on a person). Various correction methods exist that reduce the probability for very similar paths. Finally, Prato 2009 discusses a range of methods that cannot be expressed in closed-form, and which thus have to be estimated using simulations.

Route preferences

A large share of the research on the actual routes people take to get to a certain destination involve cyclists—probably because safety, health and route properties matter more when cycling than when taking other transport modes. Menghini et al. 2010 look at route choices of cyclists in Zurich based on GPS observations, allowing for much more fine-grained analyses compared to the traditional stated preference approaches. In their study, they consider (generated) alternatives to the chosen route path, and evaluate them with respect to length, elevation, and road network peculiarities (traffic lights, roundabouts, bicycle lanes, traffic status, etc.). They find that the most characteristic path property is its length (for 36%, people chose the shortest route), followed by properties such as the share of bicycle paths, the gradient of the route, or the number of traffic lights on the way. As most of their samples stem from Zurich, which is a comparably hilly city, they mention that it would be interesting to perform the same study in another city where people could do detours around hills to see the actual relation between length and route gradient. The study by Allemann and Raubal 2015 also features cyclists in Zurich; here, the authors search for route choice factors distinguishing "regular" cyclists from people using an electric bicycle. The find that e-bikers tend to travel on roads shared with cars, that the distance is the most distinguishing factor, and that people traveling by e-bike feel they travel more safely and conveniently. Other studies include the one by Broach, Dill, and Gliebe 2012, who analyze a sample of 164 cyclists from Portland, Oregon. They also find that cyclists are most sensitive to route length, gradient, and number of traffic lights, but also to the number of turns along the route as well as the traffic volume. Additionally, and going towards the analysis of the effects of the built environment on cycling behavior, they mention that off-street bicycle paths as well as roads with traffic calming features are preferred by cyclists. For commuting trips, cyclists were mostly sensitive to route length and disregarded other route properties.

The built environment

The last study already highlighted the importance of the built environment on route choices. Vedel, Jacobsen, and Skov-Petersen 2017 use a choice experiment among 3'891 cyclists in Copenhagen to put exact numbers to the influences of different environmental features: cycle tracks increase the willingness to cycle by 1.84 km, greenery by 0.8 km, the avoidance of crowded streets by 1 km, and the absence of stops by 1.3 km. Among the most attractive streets for cyclists are designated and segregated paths as well as shopping streets. Another important takeaway is that people who own a car yet still use the bicycle for commutes primarily do so to get exercise, followed by simply liking to bicycle, being flexible, and being fast. Caulfield, Brick, and McCarthy 2012 use a stated preference survey and get to similar results: cyclists prefer segregated routes, independent of their cycling ability, followed by routes through residential streets and parks. Regarding the latter "bicycling experience", Stinson and Bhat 2005 examined the effects of different experience levels on route preferences. Their classification into *experienced*, *inexperienced*, *interested* and *uninterested* cyclists (the latter being inexperienced as well) aligns well with the different motivational stages. The most important takeaways are that experienced cyclists are primarily interested in travel time and less in a possible separation from automobiles, which is vice versa for inexperienced cyclists. However, in general all cyclists are interested in minimizing contact with motorized traffic. Pritchard, Bucher, and Frøyen 2019 performed a study involving a structural intervention (a new contraflow bicycle lane) in Oslo, and measured the effects on cycling behavior. They observed behavioral changes in terms of route choice: the streets running parallel to the intervention street witnessed a decrease in cyclists, who instead chose the newly built road, even though it resulted in a slightly larger mean length of all routes analyzed.

3.1.4 *Relevance to this Dissertation*

The given background on psychological needs, motivation, and the various transport mode and route choices models set the frame for the research presented in this dissertation. While we will primarily rely on the presented background regarding motivation to guide the creation of motivational affordances and gamification elements in chapter 6, the transport mode and route choice models (resp. the findings on related predictor variables) are essential to generate appropriate feedback from recorded mobility data. The choices encoded in their parameters can, for example, be used to provide personalized route alternatives or to adapt supporting measures to the individual user (cf. chapter 4 and chapter 5). As such, an understanding of how they are built and how people generally choose different transport modes is relevant for the topics discussed within this dissertation.

3.2 MOVEMENT AND MOBILITY ANALYSIS

This section provides background on how individual mobility is analyzed, following the topics of chapter 4: mobility preferences and goals, systematic mobility, and behavior. As the introductory part of a special issue on *Analysis of Movement Data*, and based on Dodge 2016, Dodge et al. 2016 provide a high-level summary of the state of art in movement data analysis within the broader field of Geographic Information Science. Essentially, there are two broad areas of research, namely the understanding of movement and the modeling of it. The field of understanding movement is further divided into quantification, context, and computational analysis, while modeling movement is linked to its simulation and prediction. Between these two larger fields, we can find validation (of analytics and models) and visualization (which helps in exploration, hypothesis formulation and communication). The following literature review will loosely follow this structure, but be more adapted to the problems treated within this dissertation. Figure 3.4 shows the analyses used within the context of this dissertation to build applications that support people in sustainable mobility. The displayed analysis pipeline was found to be commonly required for persuasive applications utilizing recorded location data and has been partially implemented (and is continuously expanded) within the Python framework *trackintel*[1].

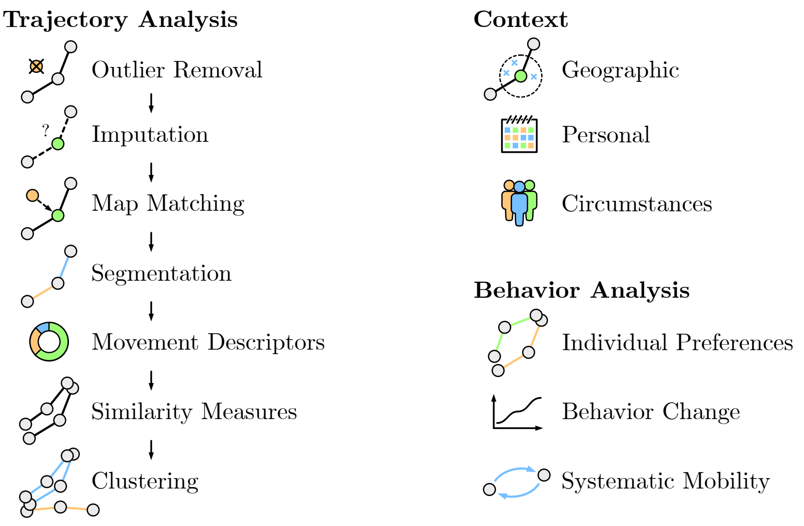


Figure 3.4.: Methods and concepts of movement and mobility analysis that are relevant for persuasive applications that support people in sustainable mobility behaviors.

3.2.1 *Trajectory Analysis*

Movement trajectories are commonly represented as sequences of time-stamped coordinates, emerging from a positioning system such as GPS, Wifi networks or cell phone towers. Smoreda, Olteanu-Raimond, and Couronné 2013 give an overview of different collection methods, and highlight that even nowadays, with accurate positioning technologies such as GPS, cellular network data can still be useful, in particular to perform studies across large geographic regions or involving many people (Yuan and Raubal 2012; Yuan and Raubal 2016). Within this dissertation, however, we mostly focus on the use of (individually collected) GPS data, as it allows assessing mobility on a much more fine-grained level (Montini et al. 2015). In the following, we summarize important work from the various stages of trajectory data processing

1 The *trackintel* framework can be found under github.com/mie-lab/trackintel.

and analysis as presented in the extensive overview paper of Zheng 2015.

Uncertainty and outliers

After collecting movement data, it is usually required to remove outliers, as the underlying data generation methods often exhibit quite large uncertainty margins. For example, GPS measurements in urban canyons suffer from low accuracy, an effect that can be countered by using more satellites, e.g., by combining position measurements from multiple GNSS (Angrisano, Gaglione, and Gioia 2013). As smartphones are able to use a wide range of positioning technologies and interpolations (cf. Brimicombe and Li 2009), their accuracies can also greatly vary (Watzdorf and Michahelles 2010). Wang, Bah, and Hammad 2019 present an overview of the current state of the art in outlier detection. They classify the available options into distance-, clustering-, density-, ensemble-, and learning-based approaches. Within the mobility domain, many outlier detection algorithms focus on identifying anomalous trajectories or (traffic) flows. In order to detect anomalous individual GPS recordings, Chen, Cui, et al. 2016 propose a method based on cubic splines (adaptively modeling the trends of trajectories) to remove individual position fixes and compare it to the more commonly applied approaches involving thresholds and Kalman filters (Gomez-Gil et al. 2013; Chen, Zou, et al. 2015; Zheng 2015). They note that the advantages of their approach lie in the adaptability (to the trajectory), the possibility to detect even small outliers, the robustness with regards to sampling rate, the increased performance, and the fact that their approach is (almost) parameter free.

Map matching and imputation

Along the same line as outlier detection are both imputation (of missing values or unknown properties, such as the transport mode taken) and map matching (the use of geographic context to improve location measurements). Barnett and Onnela 2020 argue that recording GPS traces using people's smartphones leads to a "tremendous missing data problem" (Barnett and Onnela 2020, p.1). Their approach involves resampling from previously recorded events whenever a certain interval does not contain any data. As such, these approaches are mostly suitable if the gaps in the data are short (but might be frequent). Zafar et al. 2017 present a solution to the imputation problem that works on a higher level than the actual position fixes. They essentially cluster locations (and assign semantic labels to them), which allows imputing missing locations at a later stage. Similarly, Martin, Bucher, Suel, et al. 2018 highlight another area of mobility data imputation: for some trajectories and locations a person visits, the transport mode or purpose of the visit are known. Using this information, they propose a method based on graph convolutional neural networks to infer distributions over all possible purposes for locations whose purpose is unknown.

Segmentation

A range of approaches exist to segment sequences of GPS position fixes into parts of movement (covered by a certain mode of transport) and pauses in between. For example, Li, Zheng, et al. 2008 propose an algorithm that detects staypoints within a person's movement. Their method is based on spatial and temporal thresholds that define how long a person has to stay within a certain radius before the location is considered a staypoint. Hwang, Evans, and Hanke 2017 present a similar approach, based on Density-Based Spatial Clustering of Applications with Noise (DBSCAN), that additionally is able to handle temporal gaps in GPS data. They choose a temporal threshold of 3 min, referring to other work that proposes a range of 2-30 min for important places in a person's life (Ashbrook and Starner 2002; Ye, Zheng, et al. 2009). Similarly, the spatial threshold (i.e., the ϵ in DBSCAN) is chosen as 50 m, indicating the distance within which a person has to stay in order for the location to be considered a staypoint. Biljecki, Ledoux, and Oosterom 2013 combine segmentation with identification of transport mode by using OpenStreetMap (OSM) data to extract potential transition points, and iteratively merging segments that are likely covered by the same mode of transport.

Movement descriptors

To make movement data more readily interpretable and to answer concrete questions, movement and mobility descriptors are commonly computed. For example, Laube and Purves 2011 compute speed, turning angle and sinuosity of movement, and explore how different sampling frequencies influence the individual descriptors. They show that computing these descriptors is indeed highly sensitive to the chosen sampling frequency and that GPS measurement errors tend to mask the actual measurements at high frequencies. Hasan et al. 2013 go into more detail, and propose descriptors such as rankings of different places, trip length distributions, staytime distributions, or visitation frequencies. Schneider, Belik, et al. 2013 analyze the sequential patterns appearing in a person's mobility and find that we spend most of our trips to reach up to (the same) four locations. González, Hidalgo, and Barabási 2008 compute measures such as the radius of gyration, individual travel distances, return probabilities, and visitation frequencies and find that they commonly follow some characteristic functions (often power laws).

Trajectory similarity

Detecting systematic patterns in mobility is usually done using various forms of trajectory similarity measures. Toohey and Duckham 2015 compare the most common trajectory similarity measures: longest common subsequence, Fréchet distance, Dynamic Time Warping (DTW) and edit distance. They all essentially take two trajectories (ordered sequences of individual position fixes) and return a value in $[0, \infty]$ that describes their distance in terms of the chosen metric (whereas the inverse, in $[0, 1]$, describes their similarity). Several researchers have adapted these general similarity measures to specific problems. For example, Cruz, Macedo, and Guimarães 2015 consider that in carpooling, pickup and dropoff points play an important role, and that only one of the participants has a car available. Additionally, intermediate trajectory points are usually of lesser relevance, as long as the temporal constraints can be fulfilled and the pickup and dropoff locations are along the route. He, Hwang, and Li 2014 similarly consider carpooling, and additionally take into account that in order for two trajectories to be similar they have to co-occur at roughly the same time. These problem-specific similarity measures often rely on general trajectory similarity measures, and combine them with other measures using weighted models.

Trajectory clustering

Based on the similarity values between different trajectories, it is possible to compute clusters, e.g., to determine frequently traveled trips or groups of people who could rideshare together. Nanni and Pedreschi 2006 adapt density-based clustering to explicitly consider the temporal dimension given within movement trajectories. They argue that for trajectory clustering, density-based approaches are particularly useful as clusters do not have to be of spherical nature (in parameter space), they are very robust to noise, and they do not require an upfront decision about the number of clusters. Fu, Hu, and Tan 2005, on the other hand, use pairwise similarity between trajectories and spectral and hierarchical clustering to group vehicle trajectories from traffic videos. The application of spectral clustering allows identifying an unspecified number of dominant paths, while the employed low-level hierarchical clustering first allows to detect dominant paths, which later can be refined into individual lanes of the road.

3.2.2 *Context and Circumstances*

Geographic context

Contextual data is frequently used to add additional information to georeferenced data. Purves et al. 2014 identify three types of contextual data: data that is collected alongside the movement (e.g., accelerometer data or the temperature as measured by a smartphone that also collects the movement data), data that describes the space in which a movement occurred (e.g., the precipitation or land use), and supplementary data that describes the movement or data collection process itself (e.g., a motion function that describes the physical movement of a car). Within this dissertation, and in line with the work by Siła-Nowicka et al. 2016, we primarily focus on the second type, namely data that is readily available in a wide range of geodata repositories and can be spatially and temporally linked to the movement. The reason for this choice is that such data can easily be retrieved in a post-processing stage, there is a wealth of different context data available, and it only requires limited expert knowledge to integrate (in contrast to, for example, physical models of vehicles).

In the context of Volunteered Geographic Information (VGI), Spinsanti and Ostermann 2013 use distances to other geographic entities, the population density and the predominant vegetation type within a region as context, but mention the possible use of socio-demographic parameters, historical measurements or infrastructure conditions. Getting closer to the topic at hand, Buchin, Dodge, and Speckmann 2014 argue that since context drives mobility choices and patterns, it is of paramount importance to include it within its analysis. Inspired by a case study involving hurricanes, they postulate that geographic context comes in the form of networks (e.g., trains are restricted to drive on the railway network), land cover, obstacles (that hinder the passage through a certain geographic space), terrain (i.e., changes in elevation), ambient attributes (e.g., weather), time, and presence of other agents. Further, they note that context can be discrete or continuous, as well as dynamic or static. The presence of dynamic phenomena is noteworthy as an agent moving along a trajectory will "sample" the phenomena at different points in time. Taking similarity analysis as an example, they propose to combine contextual and spatial distance. In particular, they compute a separate contextual distance based on the different context areas the original trajectory passes through and combine it with the spatial distance by introducing a context weight. As an introductory article to the special issue *Geographies of Mobilities*, Kwan and Schwanen 2016 note similarly that we have to move beyond the "traditional notion of a static, area-based geographic context" (Kwan and Schwanen 2016, p. 251) as movement takes place in space *and* time, and is tightly linked to continuously changing context. Kwan 2012 introduces the *uncertain geographic context problem*, which similarly highlights the difficulties in assigning context to movement. In this case, the uncertainty arises from a lack of knowledge about the "influence area of" resp. "duration of exposition to" a certain contextual phenomenon, a problem that is closely related to the Modifiable Areal Unit Problem (MAUP) (which describes that aggregating measurements of geographic phenomena into districts has far-reaching impacts on the resulting summary statistics). Siła-Nowicka et al. 2016 regard the analysis of human mobility, and focus on the relation between context and chosen transport modes as well as visited locations. In their work, context includes public transport data (station locations) and POI data (augmented via manual inspection through Google Maps and OSM). Especially the geographic information about PT stations as well as the timetables for buses, trains, etc. can be used well for transport mode inference. Common to all these integrations of context and movement data is that they are manually defined by experts and restricted to the problem at hand. In chapter 4, we will treat this problem by introducing a formalism for specifying how context and mobility data should be combined.

Personal context and circumstances

Next to geographic context, a variety of other, mostly temporal and personal information should be considered as circumstantial. Lovett et al. 2010 show that personal calendars in combination with social network data provide a valuable source of contextual information. They argue, however, that the calendar alone is unreliable (as meetings are often shorter than planned, get canceled, etc.), and propose a data fusion method that is able to create missing calendar entries. Their data fusion pipeline uses spatio-temporal co-occurrence of office workers, searches their communication history for potential events, and schedules or updates "missing events" accordingly. Do and Gatica-Perez 2012 use an ensemble model that is able to exploit multi-dimensional context in order to solve next-place and stay duration prediction. In their case, context consists of the *hour of day*, *day of week*, an indicator separating weekdays from weekends, visit frequencies, average stay duration, the number of Bluetooth devices in the vicinity as well as an indicator if someone was using his or her phone. Adding these variables allowed the researchers to improve both the next place as well as the duration prediction accuracy.

3.2.3 *Mobility and Transport Behavior Analysis*

The survey by Lin and Hsu 2014 groups numerous mobility analysis methods into four areas: location inference, transport mode identification, trajectory mining and activity recognition. While many of them are closely related to the above introduced trajectory analysis methods, we here consider their use to detect individual mobility preferences, systemic aspects of mobility, and how the use of mobility changes over time.

Individual preferences

Next to extracting general properties of (collective) mobility, movement trajectories are also being used to extract individual mobility preferences. Often, the aim is to improve smartphone route recommendation applications. Nack et al. 2015 propose a method to extract mobility habits that involves movement segmentation, transport mode identification and trajectory clustering. Based on the resulting clusters (and the associated travel distributions), a heuristic for destination prediction (based on visitation frequency, the weekday indicator and the distribution of departure times) is presented. The authors also introduce an approach to identify habits based on counting how often a certain trip was made within a certain time frame, which they argue could be used to help people plan their daily schedules. With a similar intent, Logesh, Subramaniyaswamy, and Vijayakumar 2018 build a travel recommender system utilizing location data and a person's social network profile. Based on individually generated POIs for each user, a recommender system proposes a route (taking into account the actions of similar users in similar situations), and a feedback loop lets the system store a user's decision for future use. Wu et al. 2018 propose a method that considers both individual preferences as well as social interactions within groups to improve location prediction. The presented two-stage approach first identifies groups of trajectories (after clustering locations into places and extracting transition edges from them) and individual moving preferences (time-dependent transition probabilities between locations), after which they are integrated using a linear regression model to yield transition probabilities that can be used for location prediction. Their results show that the prediction accuracy improves, and that the social interaction influence makes up for roughly 30% of the predicted probability. A similar split into individual and collective preferences is given by Calabrese, Di Lorenzo, and Ratti 2010, who also rely on geographical context such as land use or POIs in vicinity. While they use a similar linear regression model for combination, they do not group people according to their mobility behavior, but instead formulate general properties of mobility based on traveled distance, visited POIs and involved land use types.

Systematic mobility

Generally, many location data mining techniques aim at finding regularities (and correspondingly, irregularities) in mobility behavior of people. Within this dissertation, we are primarily interested in mining trajectories from single persons, in order to find characteristics and patterns within their individual behavior. This is in contrast to a large amount of work on general laws of mobility, such as the ones by González, Hidalgo, and Barabási 2008 describing travel distance distributions or return probabilities or the ones by Alessandretti et al. 2018 elaborating on the conserved quantity of visited places (which is approx. 25). Pappalardo et al. 2015 process a large dataset from central Italy and find that people either follow an *explorer* or a *returner* pattern in their mobility. While returners exhibit a great amount of regularity by only visiting a few preferred locations, explorers like to visit previously unseen locations. To group people into the two classes, the k-radius of gyration is introduced, namely the radius of gyration (the average weighted deviations of all visited locations by an individual from the center of mass for said individual) over the k most frequented locations. However, while this computation of radius of gyration gives valuable insights about an individual's movement, it does not say anything about the regularity of individual trips. He, Li, et al. 2012 analyze individual users' trajectory histories in order to find routes that a user frequently covers at roughly the same time of day. Their approach involves building a series of temporal grids, which are used to group trips that were taken at roughly the same time. The resulting shared trajectories are called support routes, and are matched to each other via the use of a grid-based route table (that essentially stores all the support routes' trackpoints from different users in a grid). A query for a potential ridesharing trip then simply has to search for multiple routes appearing in both the origin and destination cell of the route table. While the ultimate goal in the work of Wang, Yuan, et al. 2015 is location prediction, they split a person's mobility into regularity and conformity: regularity is essentially computed based on the visitation frequencies of various locations, and conformity is a time-dependent property that denotes if a location is frequently visited by similar people. Their results again highlight that people's mobility behavior is highly systematic, yet in those cases where they deviate from their usual patterns, considering the behavior of similar users allows inferring what they do instead.

Behavior change detection

As supporting eco-friendly behaviors play a central role within this dissertation, we argue that the detection of different stages of behavior and the transitions between them are of importance. To the best of our knowledge, only a few studies have covered the topic of intra-person mobility variations. Schlich and Axhausen 2003 examined habitual travel behavior based on a six-week travel diary and several different measures to capture the similarity of travel behavior: the frequency of similar activities within a certain period (based on Hanson and Huff 1986), the frequency of matching trips on two different days (based on Huff and Hanson 2010), a two-level daily comparison of trips (where first the order of trips is compared, and if there is a match, secondary attributes such as the mode or trip purpose are considered; cf. Pas 1983), a time budget-based measure that compares activities performed within certain intervals (based on Jones and Clarke 1988), and several others. Their results show a high variability among the different measures, especially when using the trip-based methods. Additionally, they show that for the whole 6-week survey period there are no two days that are completely dissimilar and they state that behavior is thus neither "totally repetitious nor totally variable" (Schlich and Axhausen 2003, p. 34). They conclude by saying that adapted measures that account for different groups of persons (with comparable temporal demands) could improve the measure of variability and facilitate recommending travel options that have a lower environmental impact. Pendyala, Parashar, and Muthyalagari 2001 compute some of the same measures on a dataset from 81 individuals, collected over at least three weekdays. They find that weekdays play a large role when computing the variability (on weekdays, mobility behavior varies much less); similarly, longer observation periods lead to a larger variability. Additionally, they state that using GPS data leads to higher variabilities than using travel diaries (which are a more coarse representation of mobility behavior). Stopher, Moutou, and Liu 2013 analyze the effects of a travel behavior change initiative in Australia. They measure the variability between different analysis "waves" and find that people taking part in the initiative lower their daily traveled kilometers by 5-6. Waerden, Timmermans, and Borgers 2003 use a survey to look at transport mode choice behavior after key events, such as home relocation, changing jobs, or buying a car. Among the recorded parameters within their study they looked at how a key event influenced the number of available alternatives as well as their characteristics (e.g., travel costs, comfort or reliability), how it affected the attitudes of people towards a transport mode, and how it affected the choice behavior. They found that key events significantly impact the number of alternative options as well as the key characteristics of them. While the attitudes of people were not greatly affected, their behavior changed after moving to a new place, starting to work, and experiencing a change in the work situation. Lanzendorf 2003 theoretically introduces "mobility biographies" that aim at capturing an individual's mobility behavior over his or her life time, modeled as a sequence of impactful events within the three domains life (including social and cultural environments), accessibility (of relevant locations) and mobility (availability of various transport modes). Explicitly modeling effects of age, household composition, income, professional career, leisure activities, or transport system changes allows us to put these events into relation with the corresponding mobility choices.

3.2.4 *Relevance to this Dissertation*

The given background on movement and mobility analysis is used as a foundation for the research presented in chapter 4. In particular, we build upon the research presented in this section when presenting the methods for the systematic combination of context and mobility data, the extraction of descriptors specifically tailored for eco-feedback, as well as the automatic detection of behavior changes. As was highlighted in this section, while there is a wealth of research available on these topics, the focus is seldom on supporting individuals in sustainable mobility choices. Next to considering individual circumstances, context, preferences and attitudes this also entails a stronger focus on the question of what is sustainable, which information is supportive for reaching sustainable behaviors, and how behavior (and changes thereof) can be quantified and automatically analyzed.

3.3 PLANNING TRANSPORT AND MOBILITY

To generate alternative route options and assess a person's behavior, a wide range of route computation methods are available. Bast, Delling, et al. 2015 give an extensive overview of the current state of the art in route planning on street networks, public transit graphs, as well as for inter-modal routes combining the previous two, but also more niche transport modes. In the following, we first review research in single-mode route planning for the most important transport modes, followed by a summary of the current research in multi-modal route planning as well as personalization of routes. Figure 3.5 shows the different problem settings and visualizes their characteristics.

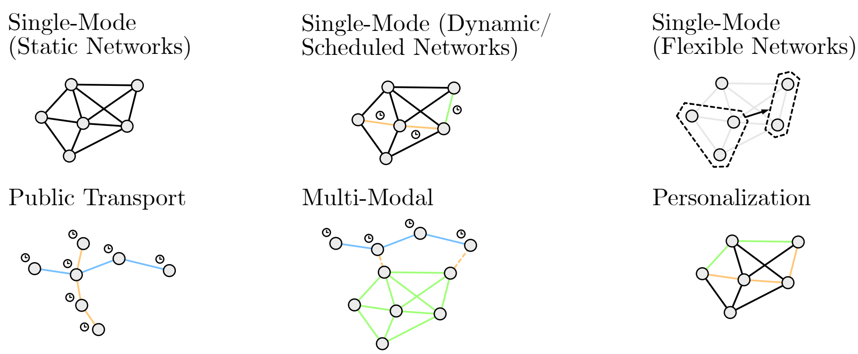


Figure 3.5.: The different characteristics of the available transport modes lead to a range of approaches to plan routes for the respective infrastructure (usually formalized as a graph).

3.3.1 *Planning Single-Mode Transport on Static Transport Networks*

Arguably the most well-researched route planning happens on static transport graphs such as street or walkway networks. What roughly started with Djikstra's (Dijkstra 1959) and Bellman-Ford's algorithms (Bellman 1958) to find the shortest path between two nodes in a graph in the 1950s was soon challenged by applying bidirectional search (Dantzig 1962) or the Floyd-Warshall algorithm to compute the all-pairs distance (Floyd 1962). In a similar fashion, heuristic approaches like A* (Hart, Nilsson, and Raphael 1968), which in its simplest form uses the Euclidean distance to the target node for greedy search, were developed to handle large graphs. More modern approaches usually involve a lengthy preprocessing phase during which nodes are sorted according to their importance. For example, approaches involving landmarks choose a set of vertices to and from which the distances to all vertices in the graph are computed (Goldberg and Harrelson 2005). Using the triangle equality, it is then possible to compute lower bounds for the distance from any vertex to the target, and iteratively choose the vertex with the lowest bound for further continuation of the algorithm. Similar, but not using individual vertices, is the approach of Arc Flags (Köhler, Möhring, and Schilling 2006). The idea here is to separate a graph into multiple (roughly equal-sized) subgraphs and note for each subgraph if it lies on a shortest path to any vertex in each of the other subgraphs. A shortest path algorithm can then quickly prune subgraphs that do not lie on the shortest path to the target subgraph. The algorithm has successfully been extended with a hierarchical component whereas the subgraphs themselves are grouped and pruned either as an aggregate or (if the subgraph lies on the shortest path to the target) individually one layer below (Möhring et al. 2007). Using separators (essentially a set of vertices whose removal splits the graph into multiple smaller subgraphs; for street networks, these could, for example, lie on roads between towns) and shortcut graphs (that preserve the distance property between any two vertices in the graph) (cf. Van Vliet 1978; Eppstein and Goodrich 2008), speedups in route computation can be achieved as it can largely be performed on the overlay graph, connecting individual separated subgraphs.

Hierarchical methods

Among the best-performing algorithms are those that make use of hierarchic structures in transport networks given by arterial roads such as highways (essentially adopting a "divide and conquer" strategy), similar to the way humans commonly plan routes (Car and Frank 1994). Highway hierarchies (Sanders and Schultes 2012) and highway node routing (Schultes and Sanders 2007) are two approaches that use the fact that long-distance queries primarily result in routes passing a few important nodes. Contraction hierarchies are a similar and widely-used approach (Geisberger et al. 2012) that inserts shortcut edges between nodes and ranks them according to their importance. The bidirectional routing algorithm then always follows edges to "more important" nodes, which will result in the shortest path while only visiting a small subset of all nodes. Bounded-hop techniques such as labeling algorithms (Peleg 2000) or transit node routing (Bast, Funke, et al. 2007) precompute distances and store them as labels or special nodes within the graph for each node in order to have very low query times which essentially consist of only a few table lookups. As most of the routing methods exploit one or another transport network property, their combination can yield further speedups. For example, the combination of landmark- and hierarchy-based methods (Goldberg, Kaplan, and Werneck 2009) allows precomputing distances only for landmarks higher up in the hierarchy, resulting in space savings. In practice, the choice between one or another algorithm is usually driven by several properties: preprocessing time, disk storage space, and query time, which have to be traded off against each other. For a wide range of realistic scenarios, other properties come into focus, such as dynamism, time-dependence, or multiple objectives.

3.3.2 *Dynamic Networks*

Considering routing on street networks, dynamism plays an important role: traffic jams lead to lower average speeds, accidents can block routes, etc. A straightforward approach to using the above methods is simply to rerun the preprocessing on the updated graph. As this can be exhaustively costly, approaches were developed to selectively update the routing graph (Delling and Wagner 2007; Schultes and Sanders 2007). It is also possible to have a resilient algorithm that still yields correct routing results after updating weights, albeit with longer query times (Delling and Wagner 2007; Geisberger et al. 2012). Probably the most successful approaches nowadays split preprocessing into a metric-independent phase, followed by a metric-dependent phase that can be run much quicker (Efentakis and Pfoser 2013; Dibbelt, Strasser, and Wagner 2014). Similarly, for many networks the dynamism is (approximately) known in advance (e.g., traffic jams tend to happen regularly at the same locations). Instead of using scalar edge weights in the transport graph, they can be modeled as functions of time. With slight adaptations, most of the presented approaches still work, albeit with longer query times (Cooke and Halsey 1966; Delling and Nannicini 2011; Batz et al. 2013), and often under the condition that the First In First Out (FIFO) property holds (departing later cannot lead to an earlier arrival). Closely related are range queries, whose purpose is to find the best shortest path through a time-dependent network both in space as well as in time (i.e., the departure and arrival times are not given, cf. Dehne, Omran, and Sack 2012).

3.3.3 *Public Transport*

A large difference between road and public transport networks is the schedule-based nature of the latter. Most PT systems around the world follow the same structure: a number of vehicles drive along given routes, stopping at predefined stations at specific points in time. To enable integration into PT route planners, they usually publish their timetables in the GTFS format, which follows the same structure (Google Inc. 2020; Barbeau 2013). The two main approaches to model PT networks are *time-expanded* and *time-dependent* (Bast, Delling, et al. 2015). The former models all the possible departures from stops (at different times) as individual vertices and uses directed edges to connect them, taking into account time (e.g., departures at a certain stop can only be taken when coming from edges that arrive earlier) (Pallottino and Scutellà 1998; Schulz, Wagner, and Weihe 2001). Various approaches exist that refine this model, e.g., by introducing minimal transfer times at stops, or by using the periodicity of a timetable to save space by encoding multiple departures into the same nodes. The time-dependent model is similar in nature to the dynamic transport graphs for road networks described previously. To save space, transfers are not unrolled, but instead time-dependent functions encoding the possibility to transfer from one vehicle to another at a given time are used (Stølting Brodal and Jacob 2004). Closely related are frequency-based models that store the time-dependent transfers simply as the initial departure time plus the frequency along the given trip (Bast and Storandt 2014).

A variety of algorithms try to solve either the earliest arrival problem (how to get to the destination as quickly as possible), the range problem (given a departure time range, what are the quickest options to get to the destination), the latest departure problem (when does a trip have to leave at the latest to still be at the destination before a given time), or a range of multicriteria problems (e.g., to minimize the number of transfers) (cf. Bast, Delling, et al. 2015). While many algorithms are comparable to their counterparts on road networks, some different approaches like the Connection Scan Algorithm (Dibbelt, Pajor, Strasser, et al. 2013) or Round-based Public Transit Optimized Router (RAPTOR) (Delling, Pajor, and Werneck 2014) exist. They use the fact that by involving a temporal component the graphs become directed and acyclic, and can be stored in different structures such as departure-time-sorted arrays that can be scanned to get a PT route (Dibbelt, Pajor, Strasser, et al. 2013). The approach by (Delling, Pajor, and Werneck 2014) is essentially a dynamic program operating on arrays of trips and routes. Each of these arrays is scanned to retrieve reachable stops, which in turn lead to subsequent scans at the next iteration of the algorithm.

3.3.4 *Carpooling and Ridesharing*

Fuzziness, flexibility, dynamism

Rideshare and carpooling trips are generally longer than regular trips (Ferguson 1997), partially due to the required detours to pick up and drop off passengers which make up around 17% of the trip distance (Rietveld et al. 1999). These detours make rideshare planning a non-trivial problem, especially considering the flexibility of the drivers and riders, the fuzziness of the itinerary descriptions, and the potential to pick up and drop off multiple people (Huang, Bucher, et al. 2018). Of further importance for a rideshare planning system are the facts that the involved entities are independent (thus both have to access the same system to find each other), they usually have a financial incentive (i.e., a matching system should account for potential costs), there is a base "fear" of traveling with a stranger (which can be alleviated by introducing a rating system), and that there are several ways how people can be matched (single driver, single rider, multiple drivers, multiple riders, and combinations thereof).

The focus of this dissertation on dynamic and inter-household ridesharing also means that the origins and destinations do normally not exactly correspond to each other, and suggests solutions globally optimizing driver and rider assignments. However, this global perspective on the ridesharing problem (which can be optimized for minimal system-wide vehicle-miles, minimal system-wide travel times, or maximal number of riders; cf. Agatz et al. 2012) is of little interest to the individual traveler, for which reason we focus here more on the planning steps for an individual route request. Raubal, Winter, et al. 2007, based on the theoretical model presented in previous work (Winter and Raubal 2006), provide a solution based on short-range communication between individual agents that uses concepts from time geography to bound the number of possibly shareable trips. Depending on the intended travel distance, drivers usually only denote pickup and drop-off regions, as they are able to move much quicker than the rider, and thus are flexible in their pickup and dropoff locations. These fuzzy descriptions and the flexibility of drivers and riders lead to the fact that even though there are many specialized web platforms that facilitate access to carpooling, there is usually much manual planning and negotiation involved. To extend the use of carpooling into persuasive mobility support systems, it is important to develop planning systems that combine various transport modes (esp. public transport) with carpooling (Aissat and Varone 2015; Bit-Monnot et al. 2013; Huang, Bucher, et al. 2018).

Linking

In general, multi-modal routing is achieved by linking several transport networks using, for example, a nearest-neighbor approach (Bast, Delling, et al. 2015; Pajor 2009). In this case, every node of one transport network is linked to the closest node of another (e.g., a train station would be linked to a footpath close by). Aissat and Varone 2015 propose a method (based on previous work by the same authors, cf. Varone and Aissat 2015) that tries to replace sub-paths of a multi-modal planner with carpooling offers. Their method involves a way to determine the suitability of a certain rideshare offer for the completion of a user's itinerary, a substitution process to select the best driver, and a pruning of offers based on their arrival time. Bit-Monnot et al. 2013 present the 2 *synchronization points shortest paths problem* and propose an efficient computation of itineraries, using a heuristical landmarks-based approach. Huang, Bucher, et al. 2018 extend the idea of nearest-neighbor-based linking with the concept of Drive Time Areas (DTAs). A DTA denotes the area that someone can realistically reach within a certain amount of time. By linking transport networks based on drive time area, the flexibility and fuzziness of carpooling can be incorporated into the planning problem. Referring again to the work by Agatz et al. 2012, the authors state that there are still many open points regarding rideshare planning: In particular, optimization (to handle a large number of potential rideshare participants), incentives to attract people to ridesharing systems, and the inclusion of people's preferences in order to give them meaningful choices, are open problems.

3.3.5 *Electric Mobility*

Related to the different characteristics of EVs (e.g., shorter ranges inducing range anxiety, longer recharging times), many researchers started adapting route planning methods to account for the State of

Charge (SOC). Within this context, the elevation profiles, road types, as well as the braking behavior resp. energy recuperation functionality gain in importance. Yao et al. 2013 use floating car data collected by cars in Beijing to determine the impact of road type on the energy consumption of vehicles. Their findings correlate vehicle speed with road type and energy consumption, and can be used as input for a route planning on a dynamic graph. However, as they do not include elevation, their model is mostly applicable to flat areas. Graser, Asamer, and Ponweiser 2015 explicitly study the impact of different Digital Elevation Models (DEMs) and interpolation methods on the energy consumption estimation and find that high-resolution DEM can explain up to 30% of the used energy by changes in elevation. Baum et al. 2014 similarly consider elevation, but focus on finding routes that trade off speed in favor of energy conservation (i.e., they evaluate multiple different speeds on the same road segment). They propose heuristics to speed up computation times by several orders of magnitude. Another interesting problem is the consideration of recharging stations for extremely long trips or for vehicles that are operated for many consecutive hours (e.g., taxis or delivery vehicles). Schneider, Stenger, and Goeke 2014 consider a special case of the Vehicle Routing Problem with Time Windows (VRPT), whereas delivery vehicles have a number of recharging stations available to deliver goods to a number of clients (within given time windows). They essentially solve a mixed-integer program that optimizes the traveled distance but respects the fact that the SOC never can get below zero, next to the usual boundary conditions (essentially to serve all customers within their time window).

3.3.6 *Autonomous Mobility and On-Demand Offers*

On-demand mobility is often regarded from a holistic optimization point of view, commonly termed as Dial-A-Ride Problem (DARP) (Cordeau and Laporte 2007; Berbeglia, Cordeau, and Laporte 2010). The problem consists of multiple vehicles that should serve a set of clients, expressing route requests from a given origin to a destination, and will likely gain in importance with an increasing autonomy of vehicles. The problem itself is a generalization of a number of other problems such as the pickup and delivery vehicle routing problem, the traveling salesman problem or the VRPT introduced above (however, these are mostly concerned with non-human cargo). In general, these problems are solved using dynamic, linear or mixed-integer programming with a number of constraints (Cordeau 2006). Usually the optimization is only solved on the subgraph of direct links between pickup and dropoff locations. Garaix et al. 2010 propose a more flexible approach involving a number of alternatives that can be used within a multi-criteria optimization. This is especially important if not only travel time, but also cost should be globally minimized. Closely related is the Demand Adaptive System or Mobility Allowance Shuttle Transport (MAST) problem (Malucelli, Nonato, and Pallottino 1999; Quadrifoglio, Hall, and Dessouky 2006), which arises from having fixed-route transport that is allowed to deviate slightly in order to pickup and dropoff people along the route (often, this is employed during phases of low demand to reduce the number of vehicles and routes in operation). Quadrifoglio, Hall, and Dessouky 2006 look at the problem by (theoretically) evaluating the impact of deviation corridor size on the throughput and transportation speed and providing a formalism to compute upper and lower bounds. Zhao and Dessouky 2008 perform a similar analysis and find that the optimal length of a MAST service corridor is roughly half of the distance that the shuttle could travel within one service cycle.

3.3.7 *Planning Multi-Modal Mobility Options*

Looking at the problem of getting from one location to another from an individual traveler's point of view, it becomes clear that the integration within a larger transport network (and especially other transport modes) has to be considered. Generally, the combination of multiple transport mode graphs can be done by inserting transfer edges (Bast, Delling, et al. 2015), whereas the same model as introduced above can be used for the different transport modes. In particular, the restricted networks (PT, bikesharing, ridesharing, etc.) are connected by unrestricted transport modes (walking, driving by car, taxis, etc.). Often, the computed routes are selected due to some combined criterion: monetary cost, travel time, number of transfers, walking duration, etc. (Bast, Delling, et al. 2015; Delling, Dibbelt, et al. 2013). Because simply applying one of the above introduced algorithms can lead to high query times in multi-criteria optimization settings, some of them have been explicitly adapted to the problem. Delling, Dibbelt, et al. 2013 present multimodal multicriteria RAPTOR that operates in rounds during which either a separate algorithm for PT or an unconstrained transport mode is run, after which the criteria are recomputed for all reached vertices. Bast, Brodesser, and Storandt 2013 formulate a set of axioms that determine trips that a user would unlikely take, which can be used at query time to filter out unlikely routes.

Another approach to yield feasible routes was introduced by using label constraints, whereas the labels denote different transport modes and enforce a certain order in the mode sequences (Barrett, Jacob, and Marathe 2000). Having their roots in regular language concepts, the label constraints can be combined with a range of routing algorithms to retrieve shortest paths along combined networks. Many of the previously presented algorithms have been adopted to work with label constraints, e.g., contraction hierarchies (Dibbelt, Pajor, and Wagner 2015) by only contracting vertices which belong to the subgraph of the same transport mode. Querying then consists of both a query in the contracted subgraphs, as well as running Djikstra's algorithm on the uncontracted core graph.

Horn 2004 considers the combination of fixed-schedule and demand-responsive modes. He classifies transport modes into four classes: fixed route modes (conventional PT), smart shuttles (on-demand buses that are either zone- or point-based), roving buses (free-range service with pickup and dropoff restricted to PT stops), and taxis (door-to-door, may carry multiple passengers). The journey planner, which is orchestrated by a request broker (that can book on-demand services), essentially searches the route solution space in a breadth-first way, whereas one-legged journeys are considered first, followed by two-legged journeys, and so on. The reasoning behind this is that in reality preferred routes often involve the least number of legs, as waiting times or walking during mode transitions is badly perceived by travelers. As the resulting solution space can potentially be huge, various speedup techniques are proposed, such as not considering nodes with later arrival times, introducing time limits for waiting at intermediate nodes, etc. Horn 2004 also mentions the importance to include user preferences and even more flexible on-demand services in the future.

Brands et al. 2014 build a multimodal router that additionally uses route, stop and line choice models (logit) to consider how many and which people would choose a certain route over another. Using a similar approach, Ambrosino and Sciomachen 2014 use a multi-criteria objective function and focus on "commuting points" that aggregate many of the routes within the network through them. Their heuristic approach yields a sequence of commuting points, but does not consider more niche transport modes (on-demand, sharing, etc.) and different user perceptions or preferences.

3.3.8 *Personalization*

Single-mode transport

With the increase of available data about individual's mobility choices and preferences, personalization gains in importance and new methods and approaches become feasible. Personalization is possible within individual routes traveled by a single mode of transport, as for example shown in the work of Letchner 2006. The authors use historical GPS traces to predict possible travel times (based on a speed extraction) and user preferences (by introducing an inefficiency ratio that denotes how far the chosen route deviates from the shortest one). The latter are incorporated into the routing algorithm by defining a utility function that prefers previously traversed road segments, arguing that people are likely to choose the same paths that they did before. Priedhorsky et al. 2012 rely on the concept of "bikeability", which denotes for each street segment and user how well it is suited for traversal by bicycle. They introduce various algorithms (clustering-based, collaborative filtering, machine learning) that predict the bikeability along a certain road segment for a given user and find that even simple approaches like taking the average of a user within a cluster leads to promising results. Funke and Storandt 2015 similarly provide single-mode route personalization, but pay more attention to the fact that commonly used routing algorithms on large graphs assume that the graphs are mostly static, thus they cannot easily account for personalization. Their approach is based on the notion of k-path covers of graphs (essentially sets of nodes where each path of length k in the graph will pass at least one node in the set), on which various properties are computed that can be weighted during routing. The result is that the routing graph becomes much smaller, which in combination with pruning methods (that remove parts of the graph that would always be dominated by others) lead to speed-ups of around 20 to 100 over regular Djikstra. Dai et al. 2015 introduce (evolving over time) travel preference distributions that balance various features of trajectories against each other and are computed on historical data (e.g., distance vs. travel time, distance vs. fuel consumption, etc.). The routing algorithm then uses these preferences by looking for similar users that traveled from the chosen origin to the destination and weighting their routes with the preferences of the user under consideration.

Multi-modal transport

Another form of personalization happens in multi-modal routing. Bouhana et al. 2013 use historical interactions of a user with a routing system (whereas each of these interactions consists of some problem data like demographics of the user or the trip's origin and destination as well as some solution data, i.e., the actually proposed and/or chosen trip). In their case, the personalization consists of selecting a solution based on the similarity of the problem data. Campigotto et al. 2017 present an approach that initially uses a similar classification into user groups based on socio-demographic attributes, after which a stated preferences survey further refines their profile. During interaction with a routing system, their continuous route choices can be used to further update their profiles. The actual routes are then computed with any graph-based routing algorithm that allows dynamic updating of edge weights (according to the users' profiles).

3.3.9 *Relevance to this Dissertation*

The given background on route planning will primarily be used within chapter 5, where we try to overcome some of the limitations given by the current state of the art: Bast, Delling, et al. 2015 note that even though the progress in route planning in the last decade has been substantial, we are still not at the point where we have a worldwide multimodal journey planner that takes into account "real-time traffic and transit information, historic patterns, schedule constraints, and monetary costs [and combines them] in a personalized manner" (Bast, Delling, et al. 2015, p. 64). We especially argue that personalization and context-dependence is important within the setting of persuasive applications supporting sustainable mobility behaviors, as it allows proactively interacting with users (e.g., by providing gamification elements or providing route alternatives) which is more difficult when only considering universally applicable choices (as they will often not fit individual perferences or contexts).

3.4 MOBILITY FEEDBACK AND ITS INFLUENCE ON CHOICES

Based on the previous sections, we provide a background on how tracking data was previously used to influence the mobility choices and behaviors of people, and which data processing methods were applied therein. With regards to the topics covered within this dissertation, an emphasis will be put on persuasive and in particular gamified systems. Figure 3.6 highlights the central elements for which this section gives background information.

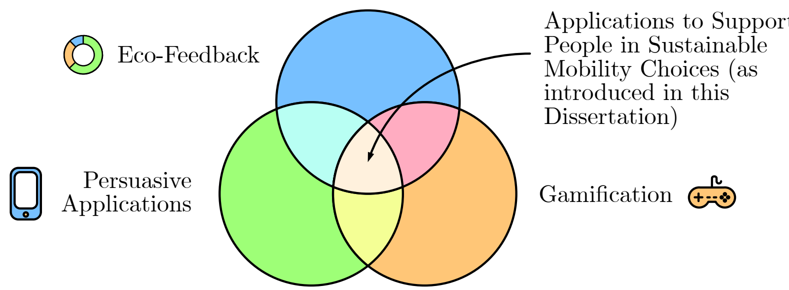


Figure 3.6.: Central elements for supporting people in sustainable mobility choices using applications that build upon automatically and passively collected tracking data.

3.4.1 *Eco-Feedback*

Roughly starting with Fogg's work on "computers as persuasive technologies" (Fogg 1998), computers and more recently smartphones have been increasingly popular for habit formation, especially in the health and wellness domain (West et al. 2012) and within the context of household energy saving (Fischer 2008). Froehlich, Findlater, and Landay 2010 focus on the questions of how HCI, and in particular computer-assisted eco-feedback should build on research from environmental psychology and which role it can take in making people become more ecologically sustainable. They provide a classification of different (technology-assisted or -enabled) means to promote pro-environmental behavior: information, goal-setting, comparison (with other individuals or within groups), commitments, incentives/rewards and "plain" feedback (which can be on a very fine-grained level or of a summarizing nature). Froehlich, Findlater, and Landay 2010 further provide an extensive review of the literature involving eco-feedback, and mention a lack of focus on HCI issues within the environmental psychology field, and vice versa a lack of psychological understanding of researchers in the HCI field. The resulting conclusion is that HCI and UbiComp (ubiquitous computing) researchers should study research from environmental psychology for proven methods and inspiration. DiSalvo, Sengers, and Brynjarsdóttir 2010 provide a similar review, focusing on identifying different research fields (within sustainable HCI) and emerging issues. Next to "plain" persuasive technology, they find researchers mostly explore ambient awareness (non-intrusive forms of feedback), sustainable interaction design, formative user studies, and pervasive sensing. Further, they highlight interesting questions such as whether we see the users as the problem or whether we intend to solve their problems, or whether we want incremental improvement or fundamental changes in lifestyle, leading to their conclusion that to advance the field of sustainable HCI it is important to foster debate, and tie it more strongly to other fields such as professional design or computer science.

Stawarz, Cox, and Blandford 2015 review 115 apps that give feedback in the form of self-monitoring and reminders, but find that their efficiency would improve if they relied on event-based cues more often (e.g., coupling a new habit to fixed events such as taking medication right after breakfast), as self-tracking "plays an important role in the behavior change process, [but] does not support habit formation [and turning] the new behavior into a daily routine" (Stawarz, Cox, and Blandford 2015, p. 2659). The authors argue that the list of included features indicates that these apps actually support motivation, and not the change of behavior, which would be best supported by letting users create routines, send back-up notifications if these routines change, and provide post-completion checks. Focusing more on ecological points of view, He, Greenberg, and Huang 2010 argue that most technologies motivating sustainable practices feature the same simple feedback on energy use. Based on work from psychology, they propose concepts and give recommendations that follow the stages of the transtheoretical model to optimally use technology for people in different phases of behavior change. Examples are to include both benefits and consequences of a certain behavior in the feedback, referring to social norms, provide examples for small actions, inform about discrepancies between attitudes and behavior, provide links to other people's behavior, support people in setting goals and plans to achieve them, provide positive reinforcement immediately after performing an action, provide prompts for habit-forming, foster self-reflection, and more.

Brynjarsdottir et al. 2012 take a more critical stance and argue that the definition of sustainability is often too narrow, for example, focusing only on measures of behavior that can be sensed (and not the underlying issues that cause said behavior). Often the focus is solely on individuals and their behaviors, and formulated from the point of view of an expert. A consequence is also the treatment of single points in time, and the related inability to account for changes (in behavior and circumstances). Their conclusion is that it might be worthwhile to think about how we can re-frame the issues and opportunities of sustainability, instead of focusing on how to provide "technical solutions to social problems" (Brynjarsdottir et al. 2012, p. 954). Li, Dey, and Forlizzi 2011 argue along the same lines, but emphasize the needs of the individual (with regards to information retrieved from sensed data). Their already previously introduced two phases of *discovery* and *maintenance* split the questions about status, history, goals, discrepancies, context and factors that users have in relation to their behavior.

3.4.2 *Inducing Mobility Behavior Change*

Several researchers looked at the impacts of persuasive technologies and in particular eco-feedback on mobility behavior. Early on, Froehlich, Dillahunt, et al. 2009b performed a study involving dedicated GPS sensors in combination with smartphones to measure and analyze movement and mobility behavior, and to study the effects of eco-feedback related to mobility. As the number of people involved in the study was comparatively low (13), the results presented in the paper mostly include qualitative statements given by users of the app during interviews. In general, the feedback was very positive, and especially the focus on a visual representation that is not tightly linked to the exact CO_2 emissions or kilometers driven gave the users a way to playfully interact with the problem at hand. Froehlich, Dillahunt, et al. 2009a report that even though the small study cannot make any statement about the behavioral changes achieved, 7 out of the 13 participants continued to use the app after the experiment was finished, indicating that people at least valued the feedback on mobility behavior and tried to use it to monitor and improve their mobility behavior. Gabrielli et al. 2014 summarize three user studies and highlight future areas of research: due to the lack of holistic research that also considers the impact of persuasive interventions on citizens' lives over a long term and due to the focus on individual behavior instead of collective mobility choices, it still remains largely unclear if the proposed measures lead to long-term changes and if they are better or worse, or simply complementary to, collective, societal, or policy measures. The presented three studies confirm that persuasive technologies can help users reach the maintenance stage in the TTM. The second presented study, MatkaHupi (Jylhä et al. 2013), featured an app including a journey planner, movement tracking, and various ways of eco-feedback. In particular the *challenge* functionality was liked by users, followed by knowing the impacts on CO_2 emissions of driving a car. Superhub (Carreras et al. 2012) was more focused on goal-setting and started out with 695 participants. As filling in the travel diaries every day was a cumbersome task, eventually only data from 65 participants could be used, however. Similarly, the rigor with which surveys were answered dropped throughout the study, which makes drawing conclusions difficult. However, in general people liked the goal-setting features and CO_2 reporting. Bie et al. 2012 present *tripzoom*, a living lab performed in several cities. They similarly use mobile sensors to detect mobility patterns, provide incentives, and additionally employ social networks where people can share their individual performances within the tripzoom community. The outcome of the project is unclear, however, several supplementary documents provide valuable insights into the creation and evaluation process. For example, Diana et al. 2013 state the evaluation metrics, and mention that behavior can be measured by indicators such as the number of trips, the distance traveled, the travel time, travel cost, and CO_2 emissions. Anagnostopoulou, Magoutas, et al. 2017 argue that personalization is an important trait of persuasive applications. They present the results of applying different persuasive strategies on people with different personality (based on the Big Five: *openness*, *conscientiousness*, *extraversion*, *agreeableness* and *neuroticism*) and mobility traits (*devoted drivers*, *image improvers*, *malcontented motorists*, *active aspirers*, *practical travelers*, *car contemplators*, *public transport dependents*, *car-free choosers*; cf. Anable and Wright 2013). Based on the eight persuasive strategies[2] and evaluated with 120 people by

2 Comparison, self-monitoring, suggestion, simulation (of potential impacts of a certain behavior), cooperation, praise, personalization and competition.

means of survey, they find that all persuasion strategies work well for all mobility types with only minor differences.

Recently, Anagnostopoulou, Bothos, et al. 2016 and Klecha and Gianni 2018 reviewed the current state of the art in behavior change for sustainable urban mobility. Anagnostopoulou, Bothos, et al. 2016 provide a summary of ten persuasive apps (some described above) and recommend to explore or incorporate the following mechanics in future system design: personalization (increases the impact and acceptability), localization (providing support at the appropriate location), timing (similar, but for time), and wearable devices (for unobtrusive interaction methods). Klecha and Gianni 2018 review 13 applications (some described above) and additionally analyze if the end-users were involved in application development. This "citizen participation" can be valuable as the resulting application is tailored to the needs of its users. In the reviewed applications, it was mostly performed via questionnaires, interviews, focus groups and diaries. As it is in the best interest of citizens to travel sustainably, "an ideal solution would create conditions that empower and inform citizens, enabling them to create their own change through social innovation" (Klecha and Gianni 2018, p. 147).

3.4.3 *Gamification*

A popular strategy for persuasive applications is "the use of game design elements in non-game contexts" (Deterding, Dixon, et al. 2011, p. 10), commonly referred to as *gamification* of an application. According to Deterding, Dixon, et al. 2011, gamification is closely related but distinct from concepts such as serious games (where entertainment is not the primary goal, but rather education or passing on information), pervasive games (where the real world plays a central role), alternate reality games (that mix events from the real and a fictitious world), and also playful design (the adaptation of user interfaces based on learnings from games). Their definition makes strict assumptions about the nature of gamified systems: In contrast to playful approaches, gamification follows structured rules and contains competitive elements (which can also include competing with "one's self"); in contrast to serious games, gamification only uses certain elements to increase the motivation of interacting with a system in a desired way; gamification does not involve the use of gaming technology (e.g., engines or controllers), but rather its design elements; gamification necessarily takes place in a non-game context. In Deterding 2011, the author makes a link to motivational affordances: This essentially means that a system affords interactions that satisfy some psychological needs of the user—in the game context this could be the need for achievement as given by a leaderboard.

Lister et al. 2014 reviewed gamification usage in 132 health and fitness apps found on the Apple App Store in 2014, and found that while gamification principles were widespread, they mostly did not adhere to professional guidelines or industry standards (i.e., gamification was only sporadically applied and did not follow health behavior theory). Around 45% of the apps used some form of passive tracking of data, and most apps either used gamification to have the user interact with the app more (57.6%), or perform completions of the desired behavior (75.8%). Going more towards sustainability, Shih and Jheng 2017 perform a literature review of persuasive strategies for energy-saving behavior and a questionnaire that relates demographic features to persuasiveness of different strategies. They find that over their whole sample, the reduction of complex behavior into simple tasks, rewards and simulation (of potential behaviors) exhibit the largest persuasiveness, while social comparison and normative influence (education or peer pressure) are less useful in persuading people. However, this differs across different ages and demographics. As a result of their work they present a list of game design elements that can be used to implement each persuasive strategy. Kazhamiakin et al. 2015 link gamification and sustainable urban mobility, and present a framework that allows implementing gamification on top of existing services. Their case study involved 40 participants in northern Italy and featured elements involving sustainability, health, as well as rewards for using Park&Ride facilities and resulted in a reduction of PMT after the gamified intervention. Similarly, Buningh, Martijnse-Hartikka, and Christiaens 2014 aimed at shifting people from using their PMT towards slow mobility, and found that their gamification mechanics (digital coach, team coherence, peer pressure, competition and awards) lead to a reduction of approx. 20% during rush hour. Wells et al. 2014 use goal-settings, behavior tracking and challenges (involving points and levels) to foster sustainable mobility behavior within the SUPERHUB project.

3.4.4 *Relevance to this Dissertation*

The presented research on persuasive applications influencing mobility behavior is mostly focused on qualitative and explorative research. Structured approaches how to build such applications and which motivational elements are available are missing, as are larger-scale and long-term studies. Additionally, there is little focus on comprehensive analyses of mobility behavior and the generation and presentation of potential (more sustainable) alternative behavior. Within chapter 6, we build upon the background presented in this chapter to overcome some of these limitations and evaluate a persuasive application within a large-scale real-world study.

4 ANALYZING MOBILITY FROM TRAJECTORY DATA

Information about individual mobility behavior increases the range and effect of potential supporting measures that we can provide in an automated fashion, as they can be tailored to individual cases and adapted to the current behavior. Recent advances in ICT enable us to record the movements of vehicles and people using a variety of devices. Of particular importance are smartphones, as their ubiquity and increasingly powerful sensors allow tracking mobility of and interacting with almost any interested person. The data gathered can be used for a wide range of applications, from planning more efficient transport infrastructure, over automated ticketing for public transport to support of individuals in their mobility choices. While previous work thoroughly studied many aspects of processing mobility, we focus on the analysis with regards to providing better support for reaching sustainable mobility. Next to sustainability criteria, this includes the identification of transport modes from GPS data of varying quality, combining context and mobility data, distinguishing systematic from non-systematic behavior, identifying mobility goals and preferences, as well as grouping different behaviors and detecting changes thereof. But how do we best record, process and analyze movement data of people in order to support them in sustainable mobility choices?

We propose a framework for mobility data processing revolving around four primary goals: the use of these data to directly *communicate* the effects of past mobility, to *identify* potential future mobility needs, to use past choices for improved *planning* of future mobility options, as well as to *provide motivational support* for making sustainable mobility choices. Figure 4.1 shows the primary data structures and information processes involved in our framework.

Starting from the user who carries a smartphone having a tracking app installed, we first have to convert the sensor information to a movement trajectory. The following preprocessing steps convert the raw

This chapter and its contents, algorithms and figures are based on Bucher, Cellina, et al. 2016; Jonietz and Bucher 2017; Jonietz and Bucher 2018; Jonietz, Bucher, et al. 2018; Bucher, Mangili, Cellina, et al. 2019; Bucher, Martin, Hamper, et al. 2020.

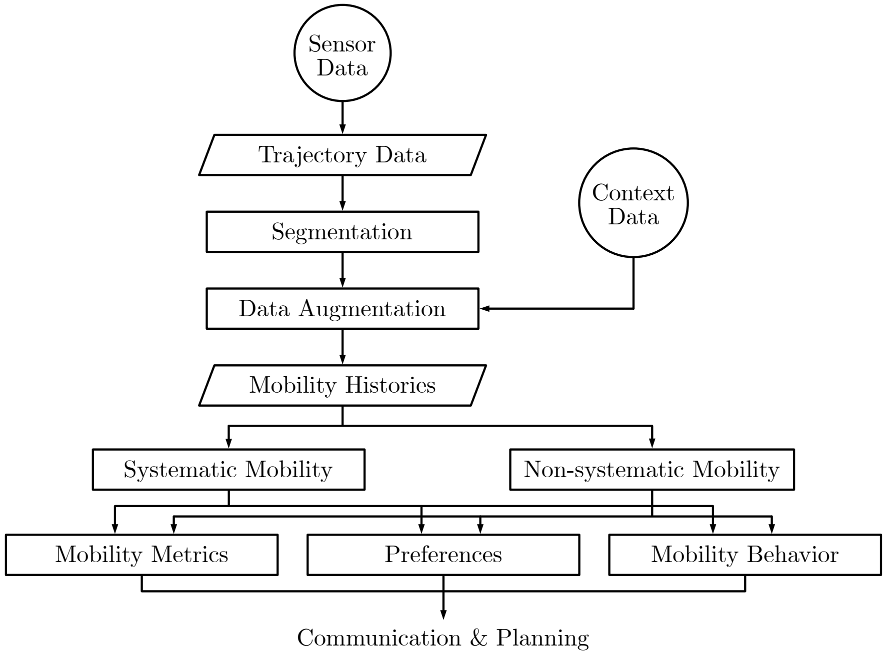


Figure 4.1.: The main information processes involved in the analysis of individual mobility with the goal of supporting sustainable mobility behaviors.

trajectories into higher-level structures, such as parts of a trajectory covered with a single mode of transport or frequently visited places. Further, the raw data is augmented with context data, such as points of interest along a route or in the vicinity of a location, weather information, or matching PT schedules. The resulting mobility histories form the basis to extract mobility metrics, preferences, as well as behaviors (and changes thereof) from a person's movement data, which in turn are required for communicating the impacts of past mobility, planning meaningful and sustainable mobility alternatives, and supporting people in choosing sustainable mobility options. These analyses (and also the exhibited behaviors) often differ between systematic and non-systematic mobility, whose detection forms another important process within the framework.

4.1 mobility histories

Historical measurements of mobility (automatically and passively collected movement data) form the basis of the support framework presented within this dissertation. Based on previous research and technologies developed within several projects that are part of this dissertation, we here present the most important preprocessing steps to arrive at a consistent and useful representation of mobility.

4.1.1 *Movement and Mobility Tracking*

Tracking applications become increasingly powerful as the power consumption of passively running location estimation technologies drops. At the same time, more data can be sampled using a wide range of sensors, e.g., the number of Bluetooth devices close by (to inform the likelihood of being in a PT vehicle) or the momentary acceleration (whose patterns greatly vary depending on the mode of transport). We distinguish between movement data (the "raw" location recordings) and mobility data (where additional information, such as the mode of transport or intermediate stops are identified). While more fine-grained data gives us the possibility of having a more accurate picture of the mobility behavior of a person, it is not necessarily required to know someone's location at all times, as much can be inferred by interpolation and augmentation with context data.

Characteristics of Mobility Tracking

Table 4.1 summarizes the most important characteristics of automatically tracked mobility data with respect to supporting sustainable personal mobility. Even though the exact route resp. movement trajectory is not necessarily of great interest (in contrast to the distance covered or the start and end locations, which are needed to determine goals of mobility and its systematic nature), it is usually easier to retrieve than, for example, the transport requirements (which have to be stated explicitly, or derived from similar situations). This is due to the fact that passive location tracking is becoming more and more standardized, and for the majority of smartphones it is relatively easy to release an app that collects movement trajectories. Usually, these trajectories consist of a sequence of individual, time-stamped *trackpoints* (also commonly denoted as location or position fixes, cf. Laube, Dennis, et al. 2007).

Functionality	Description
Location (Coordinate) Recording	Recording a person's location every few seconds and with an accuracy in the order of meters allows estimating mobility usage at a very detailed level. By using additional spatio-temporal information, less frequent and accurate data can still be used as input for the methods described here.
Start/Stop Detection	An accurate identification of the start and end of trips allows us to better estimate durations and distances, as well as have more reliable features to automatically infer transport characteristics and activity purposes.
Transport Mode Inference/Validation	Reliably knowing the transport mode is a necessity for estimating the sustainability impact of a person as well as to detect changes in behavior. Letting users validate a detected transport mode helps retraining and thus improving classifiers.
Travel Purpose Recording	Knowing why someone traveled somewhere is helpful to infer circumstantial requirements and/or preferences. Similar to transport modes, letting users validate proposed purposes increases the usefulness of data.
Transport Requirements and Additional Sensory Information	Letting users specify requirements during a certain trip improves sustainability assessments. Similarly, additional sensory information (e.g., the number of Bluetooth devices in the vicinity) can increase the accuracy of transport mode or purpose prediction.

Table 4.1.: Requirements for a tracking application to be used within the presented framework for the support of sustainable personal mobility and MAAS. The requirements are ordered by importance; in essence, only *location recording* is required. However, additional data (e.g., from the accelerometer of a smartphone) can improve the quality of several of the functionalities when performed on the recording device.

Definition 4.1 (Trackpoint)**.** A *trackpoint* p is a time-stamped coordinate pair (x, y) that denotes the location of an entity at a certain point in time t with an accuracy η: $p = (t, x, y, \eta)$.

In our definition we omit the direct relation to the entity e (usually a person whose movement is being recorded), but instead say that $p \in P_e$ if a trackpoint belongs to the set of points that correspond to the movement of e. As the location tracking usually is not perfectly accurate, most tracking technologies specify an η as the radius (in meters) of a circle around (x, y) in which the actual position of e falls with a likelihood of $p_\eta = \Pr(\sqrt{(\hat{x} - x)^2 + (\hat{y} - y)^2} \leq \eta | x, y) = 95\%$ (where $(\hat{x}, \hat{y})$ is the true location of entity e at time t). We omit the altitude z as it is not commonly required for the following methods; it needs to be noted that it can easily be added using a DEM, e.g., for energy consumption models or to compute more meaningful bicycle routes. Based on trackpoints, we can now define *trajectories*.

Definition 4.2 (Trajectory)**.** A *trajectory* τ is a sequence of trackpoints that are logically grouped due to some underlying characteristic and sorted by their timestamp: $\tau = (p_1, \ldots, p_n)$.

Of course, ordering P_e (all trackpoints of an entity e) as a sequence yields the complete movement trajectory of e (which we refer to as *track* within this dissertation). However, it is often more interesting to consider smaller segments of this complete movement as trajectories, such as the path taken from one POI to another. Note that we take a purely *Lagrangian* perspective on movement within this dissertation (i.e., movement is measured within an absolute reference system). In contrast, a substantial share of previous research considered the *Eulerian* perspective, where movement is recorded using "check-ins", e.g., at cell phone towers or Bluetooth beacons (cf. Laube, Dennis, et al. 2007).

4.1.2 *Data Segmentation*

As a first step of processing the raw trackpoints, they are segmented into various higher-level structures. When looking at mobility in a simplistic way, we can state that we consume mobility to get from one point of (personal) interest to another. At these points, we usually spend much more time than at any intermediate stops, such as when waiting to change the mode of transport or until a traffic light turns green. We formalize this idea as *staypoints*, *activities*, *triplegs* and *trips*.

Definition 4.3 (Staypoint)**.** A *staypoint* s is a coordinate pair (x, y) and an according arrival time t_s and departure time t_e at which an entity e arrives at resp. departs from the location: $s = (t_s, t_e, x, y)$.

Staypoints denote any location where a person spends a minimal amount of time, e.g., while waiting for a PT vehicle or taxi to arrive. Several researchers proposed methods to extract staypoints from raw trackpoints. A frequently used method is given by Li, Zheng, et al. 2008, who define a distance threshold θ_d and a duration threshold θ_t, which are used by sequentially iterating through all trackpoints to find sequences of trackpoints during which neither θ_d nor θ_t were crossed. Such a sequence of trackpoints $p_i \in P_s$ is then assigned to a staypoint $s = (\min_i(p_i.t), \max_i(p_i.t), \sum_i p_i.x/|P_s|, \sum_i p_i.y/|P_s|)$ (where we use the notation $p_i.x$ to denote the x coordinate of trackpoint p_i), in essence assigning the mean coordinate of all associated trackpoints to staypoint s. Due to this averaging we also drop the reference to the accuracy of a single trackpoint. From a higher-level perspective on mobility, and especially considering support for sustainable mobility, knowing when someone waited for a bus or train is not necessarily of interest, as it is not the ultimate goal of a trip. Instead, we introduce activities—essentially staypoints with a purpose.

Definition 4.4 (Activity)**.** An *activity* a, similar to a staypoint s, is a coordinate pair (x, y) and an according arrival time t_s and departure time t_e at which an entity e arrives at resp. departs from the location. In contrast to staypoints, activities denote the goals of trips, i.e., they are associated with a certain purpose ω: $a = (t_s, t_e, x, y, \omega)$.

As activities are a (in most cases strict) subset of staypoints (i.e., every activity is a staypoint, but not vice versa), they are commonly extracted by introducing additional, more restrictive duration thresholds and/or contextual requirements such as being close to the home/work location. If not noted otherwise, we consider staypoints that were not clearly generated due to being forced to *wait* for something (e.g., a connecting train) and staypoints whose duration is longer than 35 minutes as activities (where the 35 minute threshold was chosen based on experience with GPS recordings from various projects and following the argumentation that someone has to spend more than half an hour at a certain location for it to be considered a purposeful visit). The adopted definition is in line with the common interpretation of activities as "events that comprise a person's existence [...] having a temporal duration and spatial extent" (Miller 2004, p. 648). As both staypoints and activities take place at different points in space and time, they must be connected by some form of mobility consumption, namely triplegs and trips.

Definition 4.5 (Tripleg)**.** A *tripleg* l is a segment (of a longer trip) between two staypoints s_s and s_e, covered with a single mode of transport m: $l = (s_s, s_e, m, P_l)$. Each tripleg has an associated geometry, denoted by the trajectory P_l.

Triplegs are extracted from the total sequence of trackpoints $P_e \setminus (\cup_s P_s)$ (where all the trackpoints belonging to a staypoint are removed), by splitting the sequence into subsequences delimited by the staypoint start and end times. While we do not restrict the possible means of transport here, a selection of interesting ones from the perspective of a tracking app intending to support sustainable mobility is given in Table 4.2. Finally, similar to how we created triplegs from staypoints, we can create trips from activities.

Definition 4.6 (Trip)**.** A *trip* θ is the connection between two consecutive activities a_s and a_e, made up of a sequence of triplegs L_θ: $\theta = (a_s, a_e, L_\theta)$.

Based on triplegs, staypoints, and activities, the trips can be extracted as any consecutive sequence of triplegs that does not contain any intermediate activity. The resulting hierarchical segmentation is displayed in Figure 4.2. Note that the presented segmentation is in line with previous definitions, e.g., by Axhausen 2007 (albeit triplegs are referred to as *stages* and staypoints are not considered in the cited work).

4.1.3 *Augmenting Movement Data with Spatio-Temporal Context*

A big advantage of geographical spatio-temporal data is that they are embedded in the real world, for which an enormous wealth of additional data are available. Given tracking data in the previously defined format, we thus should add additional contextual data in order to increase their usefulness. A commonly used data source for improving the accuracy of the trajectories are the various transport networks, e.g., streets or railroad tracks. The so-called process of *map matching* "snaps" individual trackpoints to the transport network, and performs a routing between all consecutive snapped trackpoints in order to have a more accurate view of the route that an entity took

Map Matching

Transport Mode	Characteristics
Walk	A form of SM that is available to (almost) everyone and can be used in any situation (not or only marginally bound to a street network).
Car/Bicycle	Forms of private mobility that are available within a street network and only at the location where the car/bicycle was previously parked.
Train/Bus/Tram	PT that runs along given routes and stops at scheduled times (except when there are delays).
Taxi	A form of shared transport that is available within regions and restricted to the street network.
Carsharing/ Bikesharing	(Usually) station-based shared transport that is available whenever there are enough (non-reserved) vehicles at the station.
Ridesharing/Bus-on-demand	A spatio-temporally semi-restricted form of mobility that has to be booked in advance.
Airplane	Long-distance travel at high speeds.

Table 4.2.: Characteristics of transport modes from the point of view of a tracking application. The highlighted spatio-temporal restrictions not only determine when and where transport modes are available as potential mobility choices, but also help in identifying the transport mode solely from recorded trackpoints.

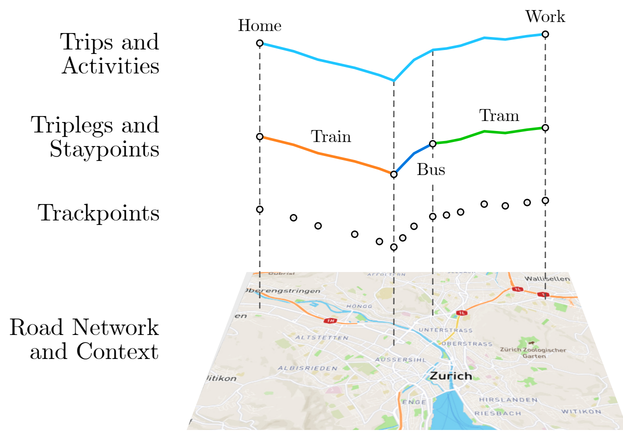


Figure 4.2.: The different layers of segmentation of human mobility.

(cf. Quddus, Ochieng, and Noland 2007). The reasoning behind this is that people usually require appropriate infrastructure, in particular when using any transport mode of a higher level than just walking, and thus necessarily have to follow valid paths in the transport network. A commonly applied technique is to build a probabilistic Hidden Markov Model (HMM), as, for example, outlined in Newson and Krumm 2009 and exemplified in Figure 4.3. The idea is to use the trackpoint accuracy η to retrieve nodes from the transport network that were likely visited along the trip (i.e., they fall within the 95% probability radius indicated by η), and assign a probability of visitation to each of them. Doing this for all $p \in P_e$ and connecting nodes of consecutive trackpoints leads to a large directed graph, where each edge in this new graph is given a transition probability, e.g., based on the distance along the road network, or the difference in travel time and tracked time. The resulting probability transition graph can then simply be used to compute the most likely transitions along the road network from the start of a tripleg to its end. More elaborate methods are also able to exclude outliers by adding skip connections or using Kalman filters, working with data that are sampled at low frequencies or simplifying resp. segmenting the trajectory before map matching (e.g., Obradovic, Lenz, and Schupfner 2006; Lou et al. 2009; Brakatsoulas et al. 2005).

Next to increasing the data quality, context data can be used to improve transport mode identification, modal choice models, or per-

Trajectory Algebra

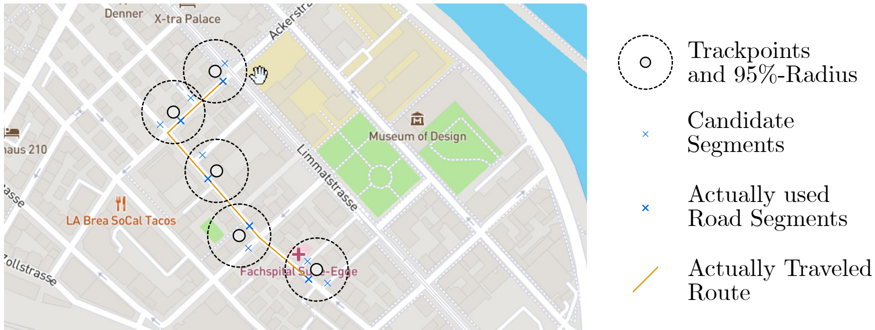


Figure 4.3.: Exemplary map matching process: For each trackpoint, a set of candidate road segments is identified. The candidate segments of consecutive trackpoints are connected in a directed acyclic graph. Finally, the actually traveled route is computed as the path through the graph that best corresponds to the recorded timestamps $p.t$.

sonalized recommender systems. To add arbitrary context data (such as the temperature, precipitation or also the number of POIs at a certain location), we introduce a trajectory algebra (based on and inspired by the more commonly known *map algebra*, cf. Tomlin 1990, and closely related to the *lifeline context operators* introduced by Laube, Dennis, et al. 2007). Context addition is usually done by retrieving discrete geographical elements within a radius around trackpoints, or by overlaying the trackpoint layer with a raster-based one (and extracting the raster value for each trackpoint). We argue, however, that this is not sufficient, as depending on the feature under investigation, it might make more sense to consider measurements along the whole trajectory (which can, for example, be averaged, or taken the maximum/minimum of), to consider measurements within a region around each trackpoint, or to combine measurements taken at the same location but at different points in time. Classical map algebra comprises a set of arithmetic operations that operate on raster data, and commonly is used as a function:

$$O = f(I_1, \dots, I_n) \tag{4.1}$$

where O denotes a grid-based output layer that is computed by applying a function f to a set of input layers I_i. Among the operators used within f, we find *local* (only considering values in I_i from the same raster cell), *focal* (considering values in I_i that correspond to some neighborhood of

Context Operator	Movement Data	Context (Spatial Dimension)	Context (Temporal Dimension)
Local	Position	Location	Instant
Focal	Interval	Neighborhood	Time Interval
Zonal	Trajectory	Zone	Era
Global	Track	Layer	Total Time

Table 4.3.: The proposed trajectory algebra operators along the three dimensions *movement data*, *spatial context* and *temporal context*.

the cell currently being computed, e.g., a 3×3 neighborhood) and *zonal* (considering values from cells that logically correspond to the cell under investigation, e.g., by belonging to the same land use class) ones. Note that originally, Tomlin 1990 defined an *incremental* operator that would consider values along geoinformation objects like a chain of pixels; in recent publications, this operator is less commonly discussed (cf. Tomlin 2017). Different to solely combining raster-based data, movement data has its own mobility-based aggregates (cf. Laube, Dennis, et al. 2007, who define these mobility-based aggregates as *instantaneous*, *interval*, *episodal* and *total*), next to the spatial and temporal dimensions of the context data we would like to join with it. In our terminology, we distinguish along the three dimensions presented in Table 4.3 and combine them, inspired by classical map algebra, using four levels of operators: *local*, *focal*, *zonal* and *global*.

In the movement data dimension, this corresponds to either aggregate context data for a single point, along a certain interval (i.e., a sliding window), along a complete trajectory (a semantically defined segmentation), or along a track (the complete data $p_i \in P_e$ available for a given entity). In the spatial dimension of the context data, this corresponds to classical map algebra, whereas we renamed *global* to *layer* to emphasize that there are multiple layers of data (denoting different time stamps), yet that we only consider a single (complete) one of them. Finally, in the temporal dimension, the operators correspond to aggregating data from a single *instant* (a single temporal layer), a *time interval* (similar to the movement operator, this is essentially a sliding window), an *era* (a semantically defined region of layers adhering to some condition, e.g., all weekends), and the *total time* (all available time layers). Figure 4.4 shows the different context operators along the three dimensions.

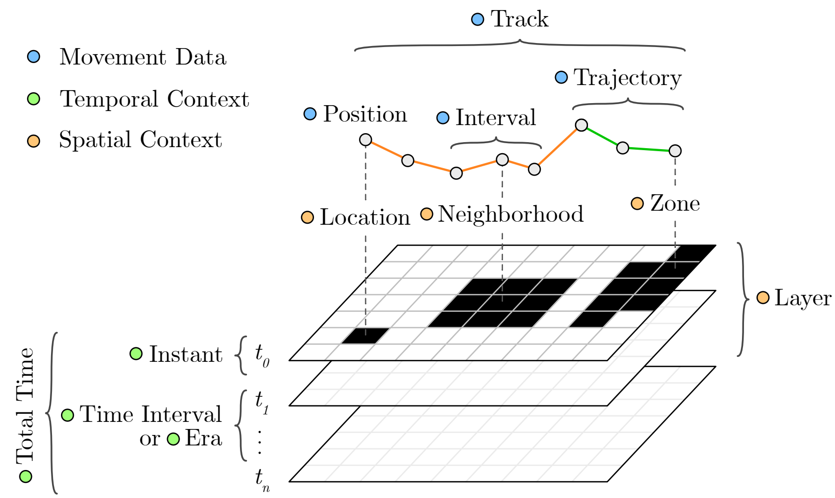


Figure 4.4.: Different combinations of trajectory algebra dimensions: movement data, spatial dimension of context data, and temporal dimension of context data.

In addition to specifying the context operators, we also have to define the aggregation functions, such as the *average*, *sum*, *maximum* or *minimum*. We propose a notation following classical map algebra statements, here given as an example that uses the focal operator in the movement dimension (with an averaging function), the zonal one in the spatial dimension of context (with a minimum function), and the global one in the temporal dimension (with a maximum function), and where the movement and context data and the specification of parameters for the context operators are given using typical map algebra statements such as *and*, *at* or *within*:

$$\begin{aligned} \mathfrak{C} = {} & \text{Focal } \textit{Avg} \text{ Zonal } \textit{Min} \text{ Global } \textit{Max} \\ & \text{OF } \textit{Movement Data} \text{ AT } \textit{Sliding Window} \\ & \text{AND } \textit{Context Data} \text{ WITHIN } \textit{Zone} \end{aligned} \tag{4.2}$$

Using the trajectory algebra presented, we can now easily assign a variety of features to each *tripleg* and *staypoint* (which is sufficient for all following steps). In line with our focus on personalization to meaningfully support sustainable mobility, we assign the features described in Table 4.4 to triplegs and staypoints.

Feature	Symbol	Description
Temperature	$f_{\{l,\theta\},\, temp}$	The temperature at the start of each tripleg/trip.
Precipitation	$f_{\{l,\theta\},\, precip}$	The precipitation at the start of each tripleg/trip.
PT Stops	$f_{\{l,\theta\},\, \{s,e,\tau\},\, PT}$	The number of $PT \in \{train, tram, bus, ...\}$ stops within vicinity r_{PT} of the start and end locations, as well as along the trajectory.
POI Category Distr.	$f_{\{l,\theta\},\, \{s,e\},\, POI}$	The distribution of POIs within vicinity r_{POI} of the start and end locations of a tripleg/trip ($POI \in \{$ *office*, *restaurant*, *sports*, ...$\}$).

Table 4.4.: Context variables assigned to triplegs and staypoints for further use within this dissertation.

4.1.4 *Extracting Basic Mobility Descriptors*

An important step in the support of sustainable personal mobility and MAAS is the provision of feedback on individual mobility behavior. Much of this feedback can be given by aggregating the mobility histories in various ways, thus making people aware of their current behavior and potentially inducing a transition towards a (motivational) contemplation or preparation stage. In the following, the most important basic mobility descriptors for providing feedback, but also to evaluate behavior change are given. While for fine-grained purposes, descriptors such as speed, acceleration, changes in azimuth, sinuosity, or the approaching rate towards a destination (cf. Laube, Dennis, et al. 2007), and for holistic analyses of mobility, measures like the radius of gyration, the jump length, or the distribution of visited places (cf. González, Hidalgo, and Barabási 2008) are commonly employed, we focus on easily interpretable descriptors that have a strong relation to sustainability and intermodality (resp. more environmentally friendly transport modes).

DISTANCE Summaries of the distances traveled within certain time periods and with different transport modes give a person a measure of how personal mobility is in relation to familiar geographical extents, the mobility behavior of other people, and its change over time (e.g., in Google Maps, the totally traveled distance is compared to the distance to the moon, or in an app by SBB, distances are given in comparison to extents of various administrative boundaries within Switzerland). The distance is computed as the sum of all distances between consecutive trackpoints (which are optimally *map matched*):

$$\begin{aligned} d(P_e, t_s, t_e, m) = \sum d_{i,i+1} \\ d_{i,i+1} = dist(p_i, p_{i+1}), \quad t_s \leq p_i.t \wedge p_i.t < t_e \wedge \\ l.m = m \wedge p_i \in P_l \end{aligned} \tag{4.3}$$

In Equation 4.3, the distances are broken down per mode. Considering behavior change towards more sustainable uses of mobility, knowing the shares traveled with each mode (and the changes thereof) gives people a sense of impact of different choices and lets them compare different behaviors over time and among each other, and quantify potential impacts of certain behaviors.

DURATION Potentially more influential than distance when regarding individual mobility choices, feedback on the duration a person spends traveling has a large impact on the mobility behavior, as it is a measure that is used by many people to optimize their mobility choices (next to financial aspects; cf. Mokhtarian and Chen 2004).

$$\begin{aligned} \Delta(P_e, t_s, t_e, m) = \sum \Delta_{i,i+1} \\ \Delta_{i,i+1} = p_{i+i}.t - p_i.t, \quad t_s \leq p_i.t \wedge p_i.t < t_e \wedge \\ l.m = m \wedge p_i \in P_l \end{aligned} \tag{4.4}$$

Similar to the distance computations, the duration (given in Equation 4.4) is usually computed per mode, in order to give people insights about the differences in temporal requirements of different modes.

MODAL SPLIT In its most simple form, the modal split helps classifying people in different mobility usage groups (cf. chapter 2) and giving them an overview of their general mobility use tendencies. The modal split is usually either given in terms of distance, duration or number of trips, which all emphasize different aspects of mobility: A distance-based split places faster transport modes more prominently, while a duration-based split is rooted in the fact that people have given mobility time budgets that they use irrespectively of the actual transport mode (e.g., a person's distance-based modal split often exhibits negligible shares of SM, while a duration-based split displays more equal shares). A split based on the number of trips with a given transport mode looks at mobility from the perspective of a person's choices, whereas each individual trip was preceded by a choice for a certain transport mode.

$$MS(P_e, t_s, t_e, m) = \frac{\{d, \Delta, |\cdot|\}(P_e, t_s, t_e, m)}{\sum_{\hat{m}} \{d, \Delta, |\cdot|\}(P_e, t_s, t_e, \hat{m})} \tag{4.5}$$

Here, $\{d, \Delta, |\cdot|\}(P_e, t_s, t_e, m)$ denote the distance, duration or number of trips with a given transport mode (as defined in Equation 4.3 and Equation 4.4).

TRIP AGGREGATES The trip aggregates used within our work include the total number of trips within a certain time period $n_{trips}(t_s, t_e) = |\theta|,\ t_s \leq \theta.t_s \wedge \theta.t_e < t_e$, the distribution of sequences of triplegs $S_{\hat{M}} = |\hat{\theta}|/|\theta|,\ \hat{\theta}.L_\theta.m = \hat{M}$ (where $\hat{M}$ describes a sequence of mode choices and $\theta.L_\theta.m = \hat{M}$ denotes that the tripleg sequence L_θ corresponds to the sequence $\hat{M}$), and the number of staypoints per trip $n_{s/\theta} = |s|/|\theta|,\ \theta.t_s \leq s.t_s \wedge s.t_e < \theta.t_e$. They allow a user to grasp his or her mobility behavior on a holistic level, give insights on the complexity of trips, and on potential room for optimization due to long waiting times.

ACTIVITY AGGREGATES To highlight which goals of mobility are responsible for unsustainable behavior, we break down the modal split based on the purposes of the activities, as this gives a person an indication of where larger potentials for change are. First, it is interesting for a person to know the number of times an activity of a certain purpose was performed $n_a(t_s, t_s, \omega) = |a_i|,\ t_s \leq a_i.t_s \wedge a_i.t_e < t_e \wedge a_i.\omega = \omega$ and the time spent performing the respective activities $\Delta(\omega) = \sum_i (a_i.t_e - a_i.t_s),\ a_i.\omega = \omega$. Targeting feedback enabling more sustainable mobility, people need to know the tripleg combinations (resp. the transport modes) used to reach activities of a certain purpose: $S_{\hat{\omega},\hat{M}} = |\hat{\theta}|/|\theta|,\ \hat{\theta}.L_\theta.m = \hat{M} \wedge \hat{\theta}.a_e.\omega = \theta.a_e.\omega = \hat{\omega}$. To give more fine-grained feedback, the distances, durations and modal shares (as defined previously) are similarly broken down by activity purposes.

4.1.5 *Transport Mode and Activity Purpose Inference*

Many tracking applications use the additional sensors available on a smartphone to estimate the transport mode someone is traveling with. While these additional data can greatly improve the transport mode recognition (e.g., Widhalm, Nitsche, and Brändie 2012; Shafique and Hato 2015), for many datasets and -sources it is not available. Instead, we can use the spatial and temporal characteristics of the recorded trackpoints, as well as the previously introduced contextual data to infer the transport mode (e.g., by considering the speed of the traveling entity, patterns that correspond to public transport timetables, etc.). Further, many mobility recording applications allow their users to specify (resp. validate) the used transport modes and/or the purpose of a certain activity. These validations of transport mode and purpose continuously supply a system with data that can be used to improve the models that predict which transport modes will likely be used to reach a certain location. We here propose a method that does not rely on very accurate GPS data nor additional sensor information (e.g., Bluetooth devices or accelerometer values), but instead uses the continuously validated data in addition to contextual data to improve its transport mode prediction. The reason for this is that many commercial smartphone-based GPS trackers prevent access to such fine-grained data, either because it is only internally used or to save battery and mobile data.

Features used for Classification

At its core, our method consists of a naïve Bayes classifier that operates on the features given in Table 4.5. These features are computed for each tripleg that was identified using the segmentation techniques introduced in subsection 4.1.2. The first four features ($f_{\bar{s}}$, $f_{\sum d}$, $f_{\max d}$ and $f_{\sphericalangle}$) do not require any additional context data and can simply be computed from the trajectories themselves. The last three ($f_{\Delta,PT}$, $f_{d,\{s,e\},PT}$ and $f_{n_s,PT}$) require computing PT alternatives resp. context data on the PT stops along the tripleg. In the experiments introduced later, the PT modes considered consist of $M_{PT} = \{train, tram, bus\}$, i.e., it is required to compute PT alternatives for these three transport modes and count the number of stops of these three transport modes along the route.

Using these features, we can formalize the transport mode identification problem as a prediction problem, taking the feature vector $\vec{f} = [f_1, ..., f_N]^T = [f_{\bar{s}}, ..., f_{n_s,PT}]^T$ (where $N = 4 + 3 \cdot |M_{PT}|$) as input and the possible transport modes $m_j \in M = \{walk, bicycle, car, bus, train, ...$

Symbol	Description
$f_{\bar{s}}$	The average speed along the tripleg.
$f_{\sum d}$	The total distance covered during traveling this tripleg.
$f_{\max d}$	The maximum distance between trackpoints.
$f_{\bar{\sphericalangle}}$	The average heading change between trackpoints.
$f_{\Delta,PT}$	The difference between the actual duration and the duration of the PT alternative.
$f_{d,\{s,e\},PT}$	The distance between the actual start/end point and the start/end point of the PT alternative.
$f_{n_s,PT}$	The number of stops in the PT solution that are closer than 50 meters to the actual trajectory.

Table 4.5.: Features used in the proposed transport mode inference method. For all features, the public transport modes considered are $PT \in \{ \textit{train}, \textit{tram}, \textit{bus} \}$.

} as output of the method. The prediction of the transport mode then essentially assigns probabilities to each class according to the Bayes' rule:

$$P(m_j|\vec{f}) = \frac{P(f_1|m_j)P(f_2|m_j)\dots P(f_N|m_j)P(m_j)}{p(\vec{f})} \tag{4.6}$$

Here, $P(f_i|m_j)$ are the conditional probabilities to observe the feature values f_i given the transport mode m_j, $P(m_j)$ is the probability of choosing transport mode m_j, and $p(\vec{f})$ is the overall probability to observe $\vec{f}$. To account for the correlation of individual itineraries and transport mode choices (i.e., if a certain transport mode was taken on a given itinerary before, it is more likely to be taken again), we introduce a factor that captures the probability of taking a transport mode m_j on a certain itinerary. To assign probability mass to previously unseen transport modes on a given itinerary, we apply additive smoothing to this factor (also called Laplace or add-one smoothing, cf. Manning, Raghavan, and Schütze 2009). To identify if two triplegs follow the same itinerary, we first compute the distances between their start and end points. If both of them are smaller than 150 meters, the triplegs are considered to follow the same itinerary.

$$P(m_j|\text{itinerary}) = \frac{n_j + \alpha}{n + |M|\alpha} \tag{4.7}$$

Here, n denotes the number of triplegs corresponding to the itinerary under consideration, n_j the number of triplegs traveled with mode m_j (following the same itinerary), $\alpha > 0$ is a smoothing parameter, and $|M|$ corresponds to the number of transport mode choices that our model can predict. The total probability is then computed as

$$\hat{P}(m_j|\vec{f}) = \frac{1}{K} P(m_j|\vec{f}) P(m_j|\text{itinerary}), \tag{4.8}$$

where K is a normalizing constant. Finally, it might not always be possible to find a corresponding PT alternative (for the features $\vec{f_{PT}} = [f_{\Delta,PT}, ..., f_{n_s,PT}]^T$). Thus, we model the conditional probability for these features as:

$$P(\vec{f_{PT}}, \mathrm{PT} = 0|m_j) = P(\mathrm{PT} = 0|m_j) \tag{4.9}$$

$$\begin{aligned} P(\vec{f_{PT}}, \mathrm{PT} = 1|m_j) &= P(\mathrm{PT} = 1|m_j) \cdot P(\vec{f_{PT}}|m_j, \mathrm{PT} = 1) \\ &= P(\mathrm{PT} = 1|m_j) \cdot \prod_{f_i \in \vec{f_{PT}}} P(f_i|m_j, \mathrm{PT} = 1) \end{aligned} \tag{4.10}$$

Where $\mathrm{PT} = 0$ means that the respective PT was not found, and $\mathrm{PT} = 1$ means it was found. This means that if there is no PT alternative found, we simply take the probability of not finding a PT alternative for a transport mode m_j, and only otherwise consider the values of $\vec{f_{PT}}$.

Formulating the transport mode prediction as a naïve Bayes problem, incorporating new data is straightforward if we can model the distribution of individual features as conjugate priors (i.e., adding a new sample does not change the shape of the distribution and its effects on the distribution parameters are well known). Here, we assume Gaussian probability distributions for all features, and choose a Gamma prior for the parameters of all distributions, except $P(\mathrm{PT} = 1|m_j)$, which uses a Beta prior. The resulting model is able to start (by computing the priors) from a small set of users/triplegs that formulate a base assumption about the dependence between features and outcome variables, which is then continuously updated for each user individually. As the transport mode choices depend a lot on the individual, we train a model for each user individually (that might start by using the priors computed from other users though).

4.2 SUSTAINABILITY METRICS

Given the basic mobility descriptors, contextual features, as well as a transport mode, we can compute more advanced metrics such as the involved costs, environmental impacts, relations to geographical features, or personal circumstances.

4.2.1 *Environmental Impact*

A commonly applied method to measure the environmental or ecological impact is the projection of all influences on the environment onto GHG emissions, in particular CO_2. Table 2.1 shows the emission of CO_2 caused by actively using a mode of transport. In addition to these values, LCA gives an estimate of the totally emitted CO_2 during the whole life cycle of a vehicle (including production and disposal of the vehicle, the processes involved in the energy supply chain, as well as the emissions caused by infrastructure provision). In line with the method given in subsection 2.2.4, we both present the ecological impact in terms of GHG emissions, and also the corresponding monetary equivalent. The produced GHG equivalent can be expressed in terms of average LCA values:

$$c_{\text{GHG}}(\theta) = \sum_{m \in L_\theta.m} d_m \cdot (c_{\text{production},m} + c_{\text{disposal},m} + c_{\text{energy},m} + c_{\text{infrastructure},m} + c_{\text{direct},m}) \tag{4.11}$$

Here, d_m stands for the distance traveled by transport mode m (i.e., the mobility descriptor $d(P_e, t_s, t_e, m)$, cf. Equation 4.3). The resulting value $c_{\text{GHG}}(\theta)$ describes the CO_2 emissions stemming from a single trip θ. To facilitate comparisons with potential gains from performing the trip, we compute a monetary equivalent under the (arguably not perfectly accurate) assumption that money is a fair representation of value. We use CO_2 offsetting costs $c_{€/tCO_2}$ as shown in Table 2.3 (note that we do not take the actual market values but the estimated true costs of GHG emissions, i.e., the values in the range of \$30-100/tCO_2) to compute this monetary equivalent. Assuming these costs include all the (potentially) occurring costs in the future, the conversion is simple:

$$c_{\text{Eco. Impact}}(\theta) = c_{\text{GHG}}(\theta) \cdot c_{€/tCO_2} \tag{4.12}$$

When considering an individual trip or an individual person on its own, the resulting monetary costs (due to GHG emissions) are often comparatively low (especially when putting them into relation with the monetary costs and gains due to salaries, personal and/or social gains, etc.). This might be an indication that a) purely self-regulated and market-driven approach at reaching sustainable mobility will have difficulties reaching net-zero emissions and b) that to induce behavior change we should lean towards adopting the concept of strong sustainability, where human capital gains cannot make up for the loss of natural capital.

4.2.2 *Monetary Cost*

The monetary cost of individual trips mostly depends on contextual and personal factors, such as prices for gas, PT passes, or the value of one's own car. However, these values are often available for different regions as averages over the whole population or certain demographic sub-populations. The monetary cost can thus be approximated similarly by using a distance-based average cost per mode:

$$c_{\text{Monetary}}(\theta) = \sum_{m \in L_\theta.m} d_m \cdot c_{\text{average},m} \tag{4.13}$$

$$c_{\text{average},m} = c_{\text{fixed},m} / d_{\text{tot},m} + c_{\text{variable},m} \tag{4.14}$$

As these averages are computed over a large population, they include both fixed ($c_{\text{fixed},m}$) as well as variable costs ($c_{\text{variable},m}$), which in reality can influence mobility choices (e.g., Thøgersen 2009). For example, a person having paid the (upfront) fixed cost of a personal car is more likely to use it than someone who would first have to buy one, even though the averaged cost for them would essentially be the same. Considering the example of Switzerland, Table 4.6 highlights some of the costs associated with various transport modes. Note that these are approximate average values; most transport providers do not calculate their prices based on the actual kilometers driven, but rather based on zones, occupancy, time of day, etc. As such, to get the most accurate cost estimation, the prices would have to be computed for each trip individually. However, for many persuasive strategies an approximation using the given values is sufficient.

Transport Mode	Average Cost [CHF/km]
Private Motorized Transport (PMT)†	0.71
Public Transport (PT)	0.25
Carpooling	0.025
Carsharing	(2.50 CHF/h) + 0.65
Airplane	0.23

Table 4.6.: Costs of various transport modes in Switzerland. †Assuming an average car price of CHF 35'000 and 15'000 km driven per year. Sources: TCS 2020, Kissling 2017.

4.2.3 *Financial and Social/Personal Capital Gains*

Most journeys are done with some purpose in mind that either has a business value or brings about personal and/or social (capital) gains. Capturing these gains solely from trajectory data is essentially impossible, as it heavily depends upon circumstances and purposes, and the related gains in financial or personal/social capital. We here propose a purpose-based method employing concepts from human capital theory (Becker 1993) to compute the various gains under the assumptions that salaries are a fair measure of a person's (financial) contribution to a business (which allows us to provide a lower bound on the business value gains) and that there is a fixed admissible budget for personal and social (capital) gains (which are the same for any demographic class). This is in line with "generalized cost" measures (resp. utility functions) that combine time and cost into a single value and achieve comparability between regions by scaling the costs according to the real incomes (Gunn 2001). These measures are rooted in random utility theory (Thurstone 1927), where the utility is given as $U = V + \epsilon$, i.e., a deterministic component $V = f(a, S, \beta)$ (depending on choice attributes a as seen by the individual, its socio-economic attributes S as well as parameters β) and a random component ϵ. Note that there are several downsides to the assumptions mentioned above: For example, financial representations often do not include costs induced in the future, and are thus an inaccurate representation of reality; income differences should actually scale the importance of cost, and not the value of time (Gunn 2001); basing business gains solely on salary does not capture the complete contribution of a person's activities to society (the Covid-19 situation highlighted well that many low-wage workers are in reality *essential* for society); the split into (salary-based, thus not equally distributed) business gains and (equally distributed) rights for personal/social gains creates a bias towards the rich that is debatable. However, the presented approach is comparably easy to implement in practice, as in addition to tracking data only an approximate value of a person's salary is required (which is often readily available in mobility studies), and it yields reasonable approximations to rank trips (in particular intra-personally) according to their sustainability.

The financial gains of a work-related activity are given by the time spent performing the activity (incl. the trips required to get to/from the location) and the salary of the traveling person.

$$g_{\text{Financial}}(a) = \Delta_{\text{work}}(a) \cdot g_{\text{salary}} \tag{4.15}$$

Similarly, the personal gains can be computed for leisure-related activities, and by considering the fixed admissible budget for personal gains (e.g., per week).

$$g_{\text{Personal}}(a) = \Delta_{\text{leisure}}(a) \cdot g_{\text{average}} \tag{4.16}$$

$$g_{\text{average}} = g_{\text{fixed}} / \Delta_{\text{tot, leisure}} \tag{4.17}$$

Here, $\Delta_{\text{tot, leisure}}$ denotes the total duration spent on leisure activities within a certain time frame, and g_{fixed} the fixed gains associated with the same time frame (e.g., a weekly "budget" for leisure activities of $g_{\text{fixed}} = \text{CHF } 500$).

These quantifications of financial and social/personal gains allow us to reason if the use of a certain transport mode (or the travel itself) is justified for a given activity. The formulas might also give indications about the tradeoffs made between travel speed and activity purpose. For example, when having to travel somewhere for work, many people choose faster yet more expensive means of transport as the corresponding financial gains are higher (or at least we are led to believe so).

4.2.4 *Combined Sustainability Indicators*

There are several ways in which we can determine whether a certain journey should be considered "sustainable". We here propose two methods: 1) A more accurate one that takes into account both the ecological as well as the monetary cost/gains as previously introduced. 2) A heuristic approximation that relies on the fact that most people have a certain time budget for overall travel (which remains relatively constant across different demographic groups as well as countries, cf. Metz 2008; Jang 2017) as well as for individual trips.

The first method is essentially captured in the following equation:

$$S(\theta) = \omega_s \cdot (g_{\text{Financial}}(a_\theta) + g_{\text{Personal}}(a_\theta)) - (c_{\text{Monetary}}(\theta) + c_{\text{Eco. Impact}}(\theta)) \tag{4.18}$$

Here, the sustainability value $S(\theta)$ (of a trip θ) is measured in financial terms resp. as overall (financial) gain (a_θ denotes the activity enabled by performing trip θ). If $S(\theta)$ is negative, the trip should have been avoided (resp. if choosing another transport mode reduces the ecological impact in such a way that the net $S(\theta)$ is positive again, the respective transport mode should be preferred). On the other hand, if $S(\theta)$ is positive and if we operate under the interpretation of weak sustainability (which can be adopted for eco-feedback in order to adhere to the meaningfulness criterion), a trip can be regarded as sustainable. Using ω_s we can make a trade-off between weak ($\omega_s = 1$) and strong sustainability ($\omega_s = 0$): In the case of strong sustainability, independently of potential gains, any trip that is not performed by SM (and thus not exhibiting any negative environmental impacts) should be avoided. On the other hand, under an interpretation of weak sustainability, many of the trips can still be regarded as being sustainable, as their overall (positive) impacts outweigh the negative environmental influences. Note that we refrain from individually weighting the different costs (as is commonly done based on stated preference data in order to have a more accurate representation of the generalized cost from a person's point of view; cf. Kumar, Basu, and Maitra 2004; Nour, Casello, and Hellinga 2010; Chintakayala and Maitra 2010), as we are not interested in a subjective assessment of cost, but look at the problem from the point of view of sustainability.

Rule-Based "Sustainability" Assessment

The second approach was used in the *GoEco!* project (Bucher, Mangili, Cellina, et al. 2019) and involved three rules: A trip is regarded as non-sustainable iff. 1) the user has access to an alternative transport mode, 2) whose usage for the given trip reduces its CO_2 emissions by at least 5%, and 3) which does not lead to an excessively long trip duration. The last criterion is defined using the threshold $d_{th} = (d_o + t_{max}) - t_{max}/(1 + d_o t_{max})$, where t_{max} denotes the maximal increase in duration (set as 1.2 hours under the assumption that this is an acceptable prolongation for longer trips; for shorter trips, the maximal prolongation is of course less) and d_o the duration of the original route. If the alternative mode of transport leads to a trip duration of more than d_{th}, it is rejected as a potential alternative.

As highlighted before, we here introduced concepts that are primarily of value within the *weak* sustainability interpretation. Taking the position of *strong* sustainability, one must always argue that any trip that leads to (non-negligible; e.g., a trip by bicycle can usually be considered negligible, even though CO_2 was emitted as part of the bicycle production) CO_2 output should be avoided. This also means that any person performing such trips should be nudged towards CO_2 neutral travels, irrespective of the potential gains. We thus propose to use the introduced sustainability indicators primarily to determine when a (more sustainable) alternative should have been chosen (which in turn can of course be used to compute "optimal" mobility behavior or potentials for change), and not to exclude any trips from within a persuasive application.

4.3 SYSTEMATIC MOBILITY AND MOBILITY PREFERENCES

Systematic mobility plays a central role for behavior change, as it is commonly responsible of for a substantial share of the overall impacts of mobility, its regularity prevents people from actively thinking about change, but once a change is implemented it can more easily lead to long-lasting effects (Jager 2003). In this section, we first elaborate on how to extract systematic patterns from mobility and how they can be used for mobility feedback, after which we look at more concrete examples of predictability of transport mode choices as well as groups of people who travel in similar ways.

4.3.1 *Geometrical, Topological and Platial Aspects of Systematic Mobility*

Usually, people perform the same activities multiple times over a longer time period (e.g., going to work usually happens on a daily basis). This recurrence is commonly used to cluster activities by specifying, for example, that an activity has to be performed at a given location more than three times in a month in order to be considered systematic. We capture this concept by the notion of a *place*. Note that the definition adopted here technically differs from common geographic interpretations of "place" (cf. Miller 2007), which do not include clear (spatial or temporal) boundaries nor scales, but instead define a place as an arbitrary "space that is filled with meanings and objectives by human experiences" (Tuan 1977, p. 4). From a movement data perspective, however, those spaces often coincide with locations that are regularly visited, for which reason we adopt this definition.

Definition 4.7 (Place)**.** A *place* Π is a geographical region (e.g., defined by a polygon) in which a given person regularly spends time. For methods which rely on a single point for computations, the center of mass of the area Π is used.

The identification of places is commonly performed using a clustering approach like DBSCAN (Ester, Kriegel, and Xu 1996), hierarchical clustering or disk-based clustering (cf. Xu and Wunsch 2005). In general, it is easier to identify places using a method that does not require the specification of the number of clusters beforehand, as this can vary between persons. Commonly, *home* and *work* are regarded as "special" places, as they are changing infrequently and the transitions between them make up for a large share of mobility needs. Based on places (which, in the most extreme cases have to be visited at least twice), we can start identifying regular patterns of mobility.

Definition 4.8 (Tour)**.** A *tour* Θ is a sequence of trips that start and end at the same place Π: $\Theta = (\Pi, L_\Theta)$. If $\Pi = home$, the tour is called a *journey*.

Most tours are actually journeys, as most people start their daily routines in the morning by going to work or do errands, and return home later in the day. However, tours can be arbitrarily nested and overlapping. For example, going to a restaurant during lunch break creates a sub-tour *work* $\rightarrow$ *restaurant* $\rightarrow$ *work*, embedded in the longer journey starting and ending at home (cf. Figure 4.5). Tours are crucial for meaningful suggestions of route alternatives, as they help keeping transport mode use consistent (e.g., if someone leaves by car in the morning, the car should be returned in the evening; on the other hand, if someone does not leave by car, the car is not available later during the tour).

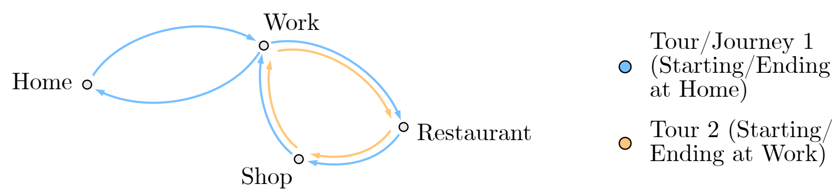


Figure 4.5.: Exemplary tour, which is also a journey (starting/ending at home), and embedded subtour.

While trips and tours themselves do not necessarily appear multiple times in a person's mobility history, we define their systematic equivalents to get insights about the regularity of a person's mobility behavior.

Definition 4.9 (Systematic Trip/Tour)**.** A *systematic trip* $\hat{\theta}$ is a transition from one activity to another that regularly appears in a person's mobility history. Similarly, a *systematic tour* $\hat{\Theta}$ is a collection of trips starting and ending at the same place that regularly appears in a person's mobility history.

Note that in practice we usually compute the regularity of a trip or tour by imposing a minimal number of trip/tour occurrences over a certain time period (e.g., a minimal frequency of three times in two weeks). Many of these descriptors of systematic mobility naturally capture behavior induced by work, regular errands, and social desires and demands. Due to their regularity, people often build habits that are simply being followed without too much thought. While this is an indication that irregular behavior is easier to change (as it is always preceded by an active decision for a certain transport mode), the regularity of systematic mobility ensures that a behavior change has a long-term and substantial impact. In addition, these regular trips are often less restricted by circumstances, as the requirements of transporting goods or other people are often not given. As such, we will put an emphasis to supporting people in transitions of their regular/systematic mobility behavior towards more sustainability.

4.3.2 *Transport Mode Choices*

Next to a spatio-temporal regularity, many people show high regularities in their transport mode choices. Here, we will particularly highlight two areas of interest to persuasive technologies: 1) How people individually choose between different transport modes, exemplified by the choice between car and e-car, an increasingly important question as EVs become more prevalent and show potential to greatly reduce the ecological impact of mobility. 2) How people's similarity in behavior change can be identified and used to group them according to their behavior, which in turn can be used to provide them different support, but also for political incentives or targeted marketing.

4.3.2.1 *Factors Influencing the Choice between Internal Combustion Engine Cars and Electric Vehicles*

Transport mode choices can either be analyzed from a individual tripleg perspective, or from the point of view of tours. The former provides more insights regarding all individual transport mode choices, while the latter offers an arguably more realistic view from the perspective of the individual, who usually plans travel "as a whole", also taking into account how to return from a certain activity. We here present a choice model regarding the problem from both the tripleg as well as the tour perspective, and taking socio-demographic variables, tripleg/tour descriptors, as well as spatio-temporal context into account. Table 4.7 shows the features used within our choice model. As noted in the table, the features for the tripleg and tour models slightly differ due to their different underlying characteristics. For the purpose features, the purposes of the next activity (for triplegs) resp. a majority vote of all involved activities' purposes (for tours) are used. The spatio-temporal context is always computed using the starting point (in space and time) of the respective tripleg or tour.

Using these features as a base, we can apply a range of models to predict transport mode choices. As a straightforward (but more difficult to explain) model, we use a Random Forest (RF). RFs are non-linear classifiers that consist of an ensemble of decision trees, and are fast to train, robust to outliers, and in general yield high prediction accuracies even without extensive hyperparameter tuning (Ho 1995). For better explainability (of the influence of different features), we also train a

Feature	Type	Coding
Tripleg/Tour descriptors		
Tripleg length*	Ratio	$[0, \infty)$
Tripleg duration*	Ratio	$[0, \infty)$
Length of all triplegs in tour covered either with *car* or *e-car*	Ratio	$[0, \infty)$
Tour length	Ratio	$[0, \infty)$
Tour duration	Ratio	$[0, \infty)$
Previous staypoint duration*	Ratio	$[0, \infty)$
Next staypoint duration*	Ratio	$[0, \infty)$
Purpose of trip*	Nominal	{home, work, errand, leisure, wait, unknown}
Purpose of tour	Nominal	{home, work, errand, leisure, wait, unknown}
Socio-demographic data		
Sex	Nominal	{male, female}
Age	Ratio	$[0, \infty)$
Cars in household**	Ratio	$[0, \infty)$
Employment status	Nominal	{working, not working}
Household income	Ratio	$[0, \infty)$
Household size	Ratio	$[0, \infty)$
Spatio-temporal context		
Hour of day***	Ordinal	$\{0, 1, ..., 23\}$
Weekday/weekend	Nominal	{weekday, weekend}
Month of year***	Ordinal	$\{1, ..., 12\}$
Temperature at start	Interval	$[-273.15, \infty)$
Precipitation at start	Ratio	$[0, \infty)$

Table 4.7.: Features (and variable types) used for the ICE car/EV choice model. Nominal variables are encoded as dummy variables, each denoting the presence of one of the labels. *For tour-level analyses these features are not used. **Prior to the start of the study. ***Normalized to lie in $[0, 1]$.

logit model. Logit models are commonly used for transport mode choice models (as their output is a multinomial variable and they can incorporate both mixed integer as well as continuous input variables). In essence, the multinomial logit model is defined by the probability of a target variable being 1:

$$p_{lr}(x_i) = \frac{1}{1 + \exp(-x_i^T \beta)} \tag{4.19}$$

Here, x_i is a vector of predictors, β a vector of (learned) parameters, and p_{lr} is the probability (e.g., of choosing the EV). The corresponding model can be trained using a regularized total loss function as follows:

$$L_{\text{sample}} = -y_i \log(p_{lr}(x_i)) - (1 - y_i) \log(1 - p_{lr}(x_i)) \tag{4.20}$$

$$L_{\text{ridge}} = \sum_i^n L_{\text{sample}}(x_i, y_i) + \lambda \sum_j^m \beta_j^2 \tag{4.21}$$

In these formulas, L_{sample} stands for the sample loss that is minimized as part of the machine learning procedure (using, for example, ordinary least squares), and could already be used without employing ridge regression. Minimizing the term L_{ridge}, however, ensures that the parameters β_j are constrained, which in turn helps against over-fitting, with problems involving many (possibly correlated) predictors, and thus improves predictions on new datasets. The probability $p_{lr}(x_i)$ is finally used to either choose the ICE car or EV for each prediction (i.e., a value $p_{lr}(x_i) \geq 0.5$ corresponds to choosing the EV).

As the logit model is essentially a linear model, we transform some of the features that exhibit a non-Gaussian distribution, e.g., the temperature (that shows a periodicity over the day as well as the year) or the distance traveled (that follows a power law). A further important distinction is between models that are trained and tested on different groups of users, or taking all users into account for both training and testing. We hypothesize that an individual's behavior is more predictable if some previous behavior of the same individual is known, as most people's mobility behavior is regular up to some stochastic component. We test this by training models both on the same users they are later predicting choices for, as well as on distinct sets of users (i.e., the users the models are trained for do not appear in the test dataset).

4.3.2.2 *Grouping Individuals According to their Transport Mode Choice Behavior*

Knowing about groups of people exhibiting similar mobility behavior patterns allows persuasive applications to target them differently and to incorporate ongoing behavior change processes. To identify such groups, we propose a clustering framework that relies on the autocorrelation of a range of features that represent individual transport mode choice behavior. In essence, we compute the autocorrelation of the daily traveled distances and durations (with different transport modes) at various time lags, and use the resulting values to cluster people. This lets us identify, for example, a group of person that uses mobility in a very regular way (exhibiting a strong autocorrelation at a time lag of 7 days) and distinguish them from people who use mobility in a more flexible way, changing the places they visit or the transport modes they use (as the resulting autocorrelations will be low). We denote the daily traveled distances and durations as:

$$D_i = [d_i^1, d_i^2, ..., d_i^N] \tag{4.22}$$

$$\Delta_i = [\delta_i^1, \delta_i^2, ..., \delta_i^N] \tag{4.23}$$

Here, $i \in M = \{bicycle, boat, bus, car, coach, e\text{-}bicycle, e\text{-}car, train, tram, walk\}$ denotes the transport mode and N corresponds to the number of days for which we have data available.

On each of these time series, we then compute the autocorrelation, defined as follows:

$$\rho_{i,r} = \frac{\sum_{t=r+1}^{N}(x_i^t - \bar{x}_i)(x_i^{t-r} - \bar{x}_i)}{\sum_{t=1}^{N}(x_i^t - \bar{x}_i)^2} \tag{4.24}$$

Here, x_i^t is a placeholder for either d_i^t or δ_i^t, r denotes the time lag (in days), i identifies the feature for which we compute the autocorrelation, N is the length of the time series (i.e., the number of days), and $\bar{x}_i$ is the mean of the time series. To make up for the fact that some people will not use some of the transport modes very often (or not at all), we introduce a scaling factor $\omega_i = x_i / \sum_{j \in M} x_j$ for each autocorrelation value. Finally, the similarity (resp. distance in feature space) between two users a and b for a number of autocorrelation values and weights is computed as:

$$d_{a,b}^2 = \sum_{i \in M} \sum_{r=1}^{R} (\rho_{a,i,r} \cdot \omega_{a,i} - \rho_{b,i,r} \cdot \omega_{b,i})^2 \tag{4.25}$$

where we distinguish between the two users using the subscripts a resp. b. This is essentially the squared difference of all autocorrelation values over all transport modes and time lags up to R.

Based on this distance, which is used to compute a distance matrix incorporating the distances between all pairs of users, we apply a hierarchical clustering method (e.g., Rokach and Maimon 2005) that results in a dendrogram representing how similar different users behave, and how they are hierarchically arranged. We compute a suitable number of clusters from this dendrogram by using the Calinski-Harabasz Index (CH-index; Caliński and Harabasz 1974), which in turn is based on the sum of squares (of distances) within and between clusters (SSW and SSB):

$$SSW = \sum_{k=1}^{K} \sum_{i \in I_k} ||x_i - C_k||^2 \tag{4.26}$$

$$SSB = \sum_{k=1}^{K} n_k ||C_k - \bar{C_X}||^2 \tag{4.27}$$

$$CH = \frac{SSB/(K-1)}{SSW/(N-K)} \tag{4.28}$$

Here, K stands for the number of clusters, I_k identifies all samples within cluster k, x_i is a single sample (i.e., all scaled autocorrelation values of a user), $N = \sum_{k=1}^{K} n_k$ the total number of samples resp. users, C_k denotes the center of cluster k, n_k the number of samples in the cluster and $\bar{C_X} = \sum_{i=1}^{N} x_i/N$ the center of all samples.

Considering both within and between cluster values, the Calinski-Harabasz Index strives to find an optimal tradeoff, minimizing the variance within a cluster, and maximizing it between clusters. It takes its maximum value at the best possible number of clusters for a given dataset (i.e., to find the optimal number of clusters, we maximize the CH-index).

4.4 INFERRING USER BEHAVIOR

Automatically detecting behavior changes is desirable for persuasive approaches and technologies as it allows adapting or reevaluating the persuasive strategy upon larger changes, sending out notifications that encourage or discourage a certain behavior or informing an expert about the changes.

4.4.1 *Mobility Choices over Time*

To analyze and utilize evolving mobility choices over time, we propose a processing pipeline that extracts features and applies pattern mining to detect anomalies in behavior (which in turn are an indication of an occurring change). The pipeline is built upon the assumption that tracking data is continuously fed into a system that processes it at certain checkpoints, e.g., once every week. Based on the mobility features introduced earlier, (anomalous) changes from one week to the next can be identified. As commonly used algorithms for anomaly detection do not indicate which feature led to the classification as anomaly (which is crucial if the response should be tailored to the behavior that changed), we propose a detection algorithm based on weighted standard deviations:

$$|f_i - \mu_i| > \lambda \cdot \sigma_i \tag{4.29}$$

For each feature f_i shown in Table 4.8 except the frequently visited places, we compute the mean μ_i and standard deviation σ_i (essentially fitting a Gaussian distribution to the feature vector). If a newly recorded feature deviates more than $\lambda \cdot \sigma_i$ from the previously recorded features, it is considered as an anomaly. Note that the average distance and duration are based on daily aggregates while the other features are either totals for a week, or averages over all recorded triplegs within a week.

Place Anomalies

For the visited places (i.e., locations that were visited multiple times within a week), we apply a comparable approach, whereas each visit at a given place within a certain week is encoded by $v_{w,p} \in \{0, 1\}$, where 1 denotes a visit. The resulting sequences are then analyzed in a two-step approach: First, anomalies in the visit sequences are identified using Equation 4.29. The resulting anomalies are then summed over all the places (as taking each place as its own feature would lead to a large number of additional features, and thus heavily bias the method towards place anomalies), which in turn yields another sequence of the number of place-related anomalies per week. In the second step, another anomaly detection (as described in Equation 4.29) is applied to this sequence of place-related anomalies, which allows extracting sudden changes in place-visiting behavior (e.g., if someone frequently visits new places, the person will have many first-level anomalies; if

Feature	Day	Week
Total number of trips		✓
Average number of triplegs per trip		✓
Total distance traveled		✓
Total distance travelled (per trip purpose)		✓
Total distance travelled (per traffic mode)		✓
Average distance travelled	✓	✓
Total duration spent travelling		✓
Total duration spent travelling (per trip purpose)		✓
Total duration spent travelling (per traffic mode)		✓
Average duration spent travelling	✓	✓
Total CO_2 emissions		✓
Average travel speed		✓
Average travel speed (per traffic mode)		✓
Frequently visited places		✓

Table 4.8.: Features used to detect anomalies in weekly exhibited behaviors.

that person suddenly stops visiting new places, the two-level detection method will flag this as behavior change).

The resulting summary of anomalies stemming from different features let a persuasive application detect when behavior might have changed, and by looking at the anomalies in detail how to best respond to the detected changes. For example, an increase of the number of anomalies related to frequently visited places in combination with anomalies of features such as the total distance or duration might be an indication that the mobility behavior changed due to differing circumstances (such as a relocation to another home). On the other hand, if only anomalies involving a small set of transport modes are detected, it can be assumed that the user tried out a new behavior, which can be supported appropriately (if the behavior is desirable).

4.4.2 *Behavior Change*

In a similar manner as before, finding individual behavioral changes and grouping people according to those changes can be beneficial both for individual support (to adapt the persuasive strategy, send notifications, etc.), as well as to get a holistic view on the mobility behavior of a group. To detect such change, we propose a two-level data mining method that in the first level (L1) computes similar features as previously introduced (the actually used features are shown in Table 4.9). On the second level (L2), descriptors that are based on the temporal variation of the first-level features are computed. These L2 features essentially capture the changes in behavior:

- We fit a first-order approximation to each of the L1 features: $v_t = a \cdot t + b$. The trend line intercept b and the trend line slope a capture the initial behavior of a person and a general change trend, and are used as L2 features.
- The minimum and maximum deviation between consecutive samples (here, we propose to take the 5th and 95th percentile).
- The number of anomalies as computed in subsection 4.4.1. Here, we take the total number of anomalies within the period of interest as the L2 feature.
- The variance σ^2 captures the volatility resp. steadiness of a given feature over the period of interest.
- Similar to the first L2 feature, we also fit a first-order approximation to σ^2 that captures general trends in the change of mobility usage.

The resulting $n \times N_{L2}$ matrix (where n is the number of users in the study sample and $N_{L2} = 8 \cdot N_{L1}$ describes the number of L2 features) is then used as input for a clustering algorithm that determines groups of people that exhibit similar behaviors.

As the high dimensionality induced by the large number of L2 features makes clustering difficult, we first select a subset of features based on the interquartile ratio, which measures relative dispersion in a robust way:

$$v_q = \frac{X_{0.75} - X_{0.25}}{X_{0.25} + X_{0.75}} \tag{4.30}$$

Here, $X_{0.25}$ and $X_{0.75}$ are the first resp. third quartile. We select all features whose interquartile ratio is above the average of all ratios. Based on the pair-wise Pearson correlation coefficient r (Benesty et al. 2009), we then remove all the features which appear in pairs where $|r| > 0.8$

Feature Description	No. Resulting Features
Duration-based modal split by purpose	$n_m \cdot n_p$
Distance-based modal split by purpose	$n_m \cdot n_p$
Duration per stay point by purpose	n_p
Total number of trips	1
Total distance travelled	1
Total number of trip legs	1
Duration of trip legs, sum over all purposes	1
Duration of stay points, sum over all purposes	1
Total duration of triplegs and stay points	1
Total CO_2 emissions	1

Table 4.9.: Features used to detect behavior changes from recorded mobility data.

and that exhibit the smaller v_q of the respective pair. The latter is done to reduce the number of strongly correlated features, which would not add additional information for the clustering. As a clustering method, we apply DBSCAN with a carefully tuned neighborhood distance ϵ and minimal number of points within this distance n_{minPts} (based on the resulting number of detected clusters and their silhouette score).

Finally, we train a (class-weighted) decision tree classifier to get interpretable results (i.e., each decision node in the tree will help understanding which feature mainly was responsible for the split, all the way down to the individual classes). The resulting (explainable) clustering can help a persuasive application in similar ways as described before. For example, a group of people showing an increasing trend of using the bicycle to go to work can be targeted by reinforcing measures, while a group showing the opposite behavior can be targeted using educative measures that highlight the benefits of cycling.

4.5 DATA AND EXPERIMENTS

In the following, we provide concrete examples for the introduced concepts and methods, and use them to argue about the applicability of the proposed approaches to enable persuasive technologies that induce more sustainable mobility behaviors. The examples are based on data collected during the *GoEco!* and *SBB Green Class* projects, as introduced in chapter 2, and implemented in Python using various supporting libraries. For many of the methods and metrics discussed, we will provide aggregate examples resp. examples highlighting the differences between individual users. Of course, when using them in a persuasive setting, the metrics are used to give a single user feedback (i.e., no information about other individual users is revealed). This and the corresponding use of metrics and methods will be discussed in detail in chapter 6.

4.5.1 *Mobility Histories*

4.5.1.1 *Augmenting Movement Data with Spatio-Temporal Context*

In section 4.1, we introduced a trajectory algebra, which is useful to assign context data to movement trajectories. For the purpose of supporting people in sustainable mobility choices, we are particularly interested in knowing about the surroundings whenever someone is in the situation where he or she has to choose a certain mode of transport, and weather-related factors, as they are among the most prevalent influencing factors. Note that, as explained in chapter 3, it is important to keep in mind that the strongest influencing factors are still the ones grounded in psychology, e.g., attitudes or habits. Figure 4.6 shows the temperature ($f_{l,temp}$) and precipitation contexts ($f_{l,precip}$) retrieved by applying the following trajectory algebra statement to the trajectories τ resp. triplegs l of the *SBB Green Class* study:

$$\begin{aligned} f_{l,\{temp,precip\}} = \text{Zonal } \textit{First} \text{ Local } \cdot \text{ Local } \cdot \\ \text{OF } P_e \text{ AT } p \in l.P_l \end{aligned} \tag{4.31}$$

To retrieve the values, both temperature and precipitation were available as raster data with a cell size of roughly 5×5 km (cf. Bucher, Buffat, et al. 2019 for a more detailed description of the meteorological data). It can clearly be seen how the temperature recorded at the start of each tripleg rises during summer, while the precipitation remains roughly constant throughout the year (in Switzerland, there are no particularly rainy seasons). These precipitation and temperature values are, for example, used in the ICE car / EV choice model introduced in subsection 4.3.2 (and examined using real tracking data in subsection 4.5.3).

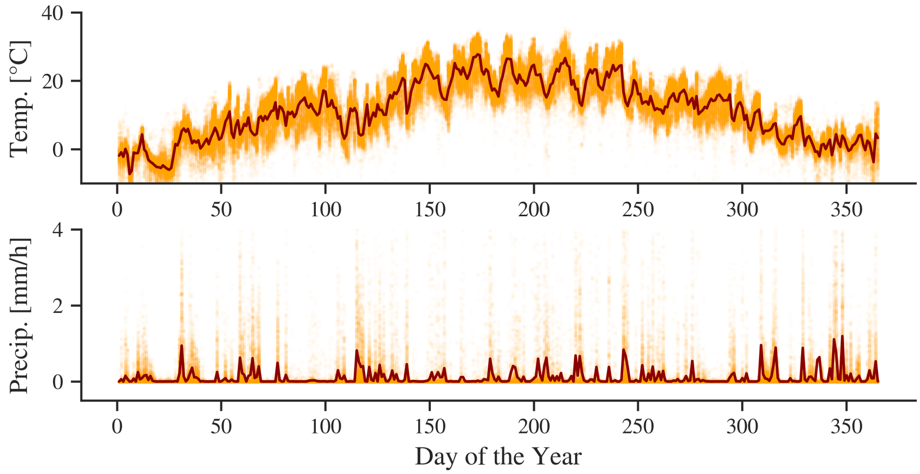


Figure 4.6.: Temperature and precipitation context added to each tripleg using trajectory algebra.

Similarly, Figure 4.7 shows the distribution of POIs (of types *restaurant*, *education*, *transport*, *errand* and *leisure*) at both the origin and destination of triplegs, as well as the number of PT stops (of types *train*, *tram* and *bus*) along the route. In this case, the POI and PT distributions were retrieved using:

$$f_{l,POI} = \text{Zonal } \textit{First/Last} \text{ Focal } \textit{Count} \text{ Local} \cdot \quad \text{OF } P_e \text{ AT } p \in l.P_l \text{ WITHIN } 100m \tag{4.32}$$

$$f_{l,PT} = \text{Zonal } \textit{Avg} \text{ Focal } \textit{Count} \text{ Local} \cdot \quad \text{OF } P_e \text{ AT } p \in l.P_l \text{ WITHIN } 50m \tag{4.33}$$

Note that in contrast to the temperature and precipitation values, POI and PT stops are available as point resp. vector data (and do not contain a temporal dimension). The proposed trajectory algebra can incorporate such data as well, as long as the spatial selection methods are unambiguously defined. As is visible from Figure 4.7, the number of PT stops along the route is an indicative feature of triplegs involving a PT mode (*train*, *tram* and *bus*). Similarly, the POI distribution can be an indication of the activity purpose.

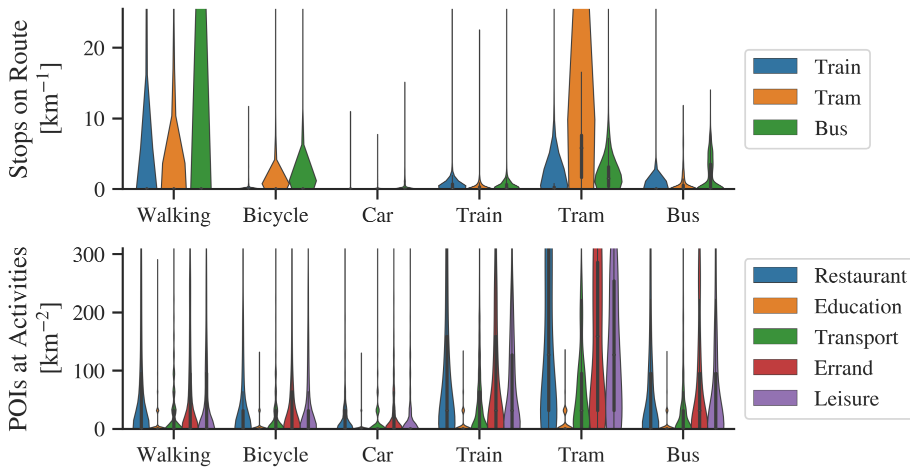


Figure 4.7.: Distribution of PT stops along the route and POIs in the vicinity of an activity location.

4.5.1.2 *Extracting Basic Mobility Descriptors*

The computed distance and duration per tripleg (according to Equation 4.3 and 4.4) are shown in Figure 4.8. Plotting the distance and duration on one axis each allows fitting a trend line that describes a characteristic speed of the given transport mode, which in turn is (implicitly) used to infer the transport mode of a given tripleg within a prediction model such as the one introduced in subsection 4.1.5. Further, knowing about the duration resp. distance of a tripleg allows arguing about the total mobility budget of a person, and how the transport modes of individual triplegs could be replaced. Last but not least, persuasive applications commonly communicate these values to users as part of given eco-feedback (either directly or embedded within some gamified elements).

Figure 4.9 shows the modal split of all participants of *SBB Green Class*, computed according to Equation 4.5. While this is a general impression of the modal split of a larger sample, it is clearly visible that by computing the modal split in different ways, the emphasis can be put on different transport modes: If we want to highlight the negative aspects of flying, a distance-based modal split easily gives the impression that flying is responsible for the largest shares of the ecological impact (a similar effect can be achieved with a CO_2-equiv.-based modal split, as discussed later in this section), which is much

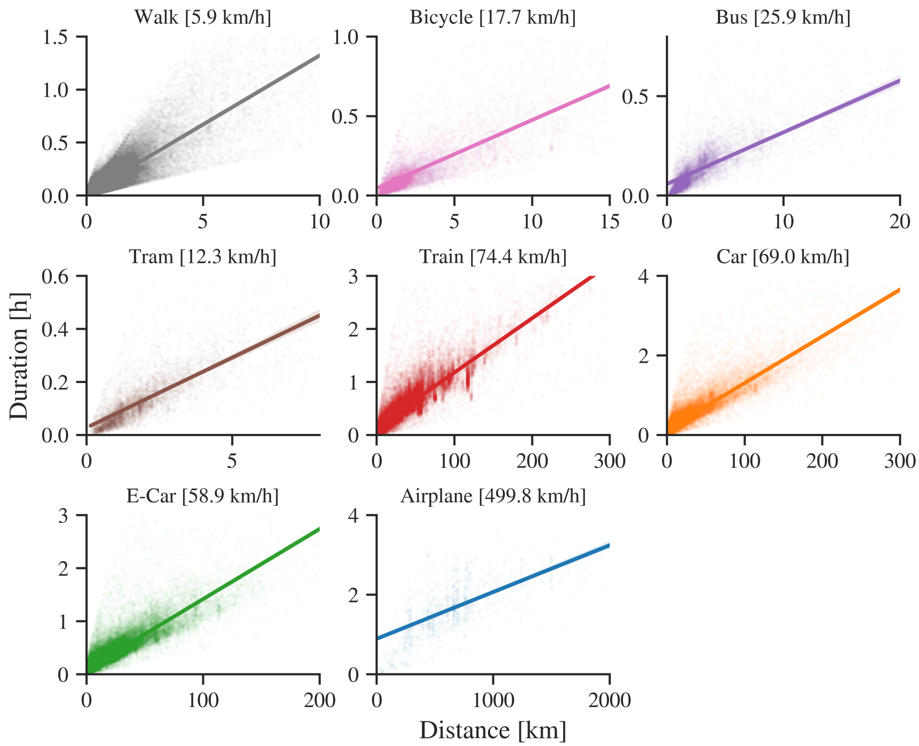


Figure 4.8.: Distances and durations of each tripleg of the *SBB Green Class* study.

less prominent in a duration-based split (that gives all transport modes approximately the same weight, which is in accordance with the fact that most people have a fixed mobility budget). The occurrence-based modal split captures the number of transport mode choice decisions a person needs to take, and is thus more important for the creator of a persuasive system, as it highlights the share of "unfavorable" choices.

Similar to the introduced transport mode splits, the activity purpose splits (introduced in subsection 4.1.4) highlight characteristics of individual people and the resulting mobility needs. Figure 4.10 shows the activity purpose splits of the participants of *SBB Green Class*. From a duration-based split, it is clearly visible that most people spend their time at home, followed by work and leisure activities. Presenting activities based on the number of occurrences again focuses more on the number of mobility decisions a person needs to make (namely to reach the given activity), and thus not only helps the developer of a persua-

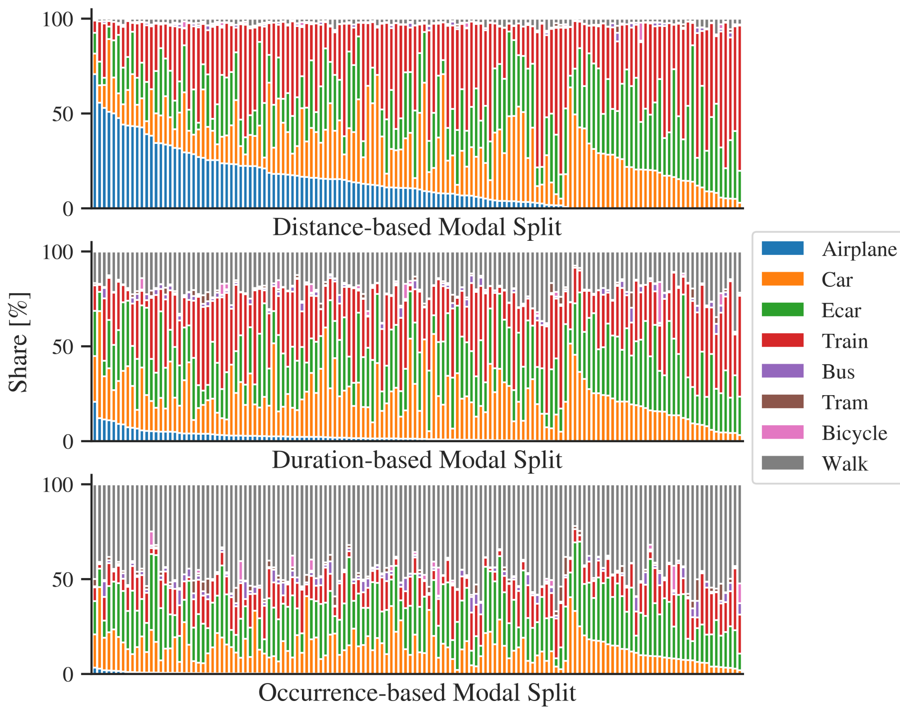


Figure 4.9.: Different ways to compute the modal split change the perception of mobility use.

sive system, but can also foster a re-evaluation of mobility choices by the user of the system (especially when the occurrence-based modal split is backed up by information about how sustainable the mobility choices to reach each of the activity purposes are).

4.5.1.3 *Transport Mode and Activity Purpose Inference*

Using features like the ones introduced in the previous sections, we can identify the transport mode of a given tripleg. Figure 4.11 shows the prediction accuracy of the naïve Bayes inference model introduced in subsection 4.1.5. As the model is continuously "re-trained" (resp. the Bayesian priors are updated), the prediction accuracy increases. The prediction accuracies shown in Figure 4.11 are averaged over all participants of the *GoEco!* project (as we train a separate model for each user to account for the individual differences in mobility use) using a sliding window of size 20 to smoothen the curves.

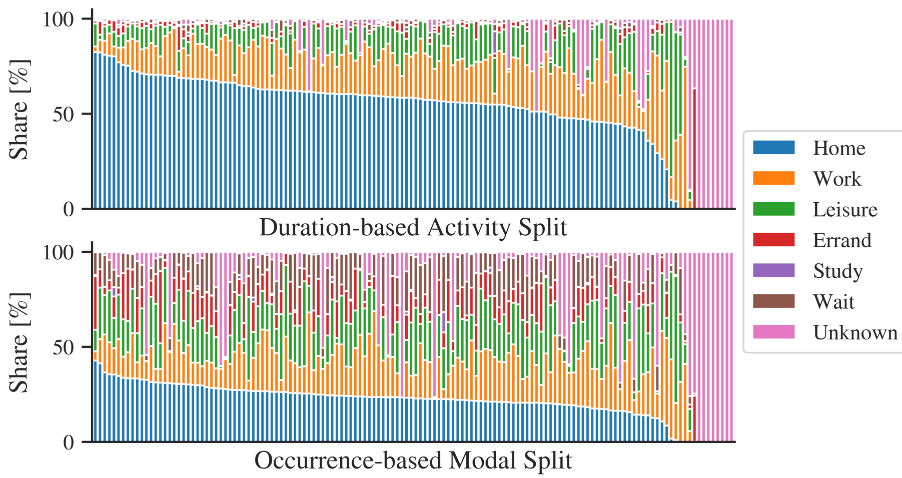


Figure 4.10.: Activity splits of users participating in the *SBB Green Class* study. The activity purposes *unknown* could not be univocally identified by the tracking app and were not separately validated by the users.

On the left side of Figure 4.11, only the features directly computed from the triplegs are used, while on the right side additional spatio-temporal context is introduced by considering available public transport alternatives for *bus*, *tram* and *train* (cf. Table 4.5). It can be seen that there are large differences in the predictability of different transport modes. *Walking* is the most easy one, likely due to its very characteristic (slow) speed. Driving by *car* is recognized fairly well, but is more easily confused with traveling by *bus*, *tram* or *train* (depending on the speed). Here, the usefulness of the added spatio-temporal context becomes visible, as the accuracies substantially increase on the right side. Note that the sudden "drops" in accuracy stem from the fact that there are only a few users remaining that recorded the respective number of triplegs, and as such misclassifications of their transport modes lead to large changes in the aggregate accuracy.

4.5.2 *Sustainability Metrics*

Once the mobility data are preprocessed and available as histories, applying the methods introduced in section 4.2 lets us determine which

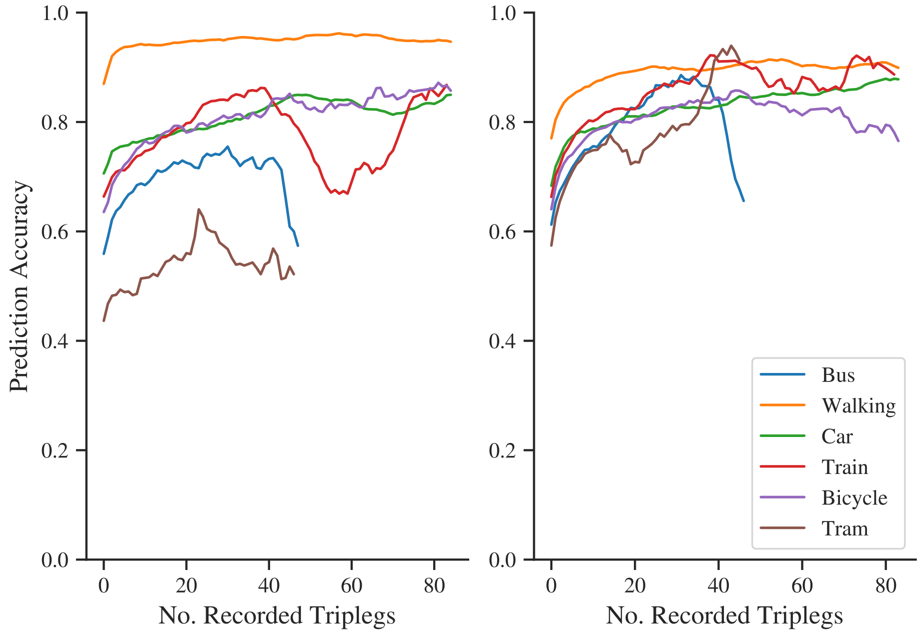


Figure 4.11.: Prediction accuracy of the transport mode prediction model introduced in this chapter. On the left side, no (geographic) context given by the PT alternatives is used; on the right side, all features introduced in subsection 4.1.5 are used.

trips resp. triplegs should be considered non-sustainable and should possibly be replaced by more eco-friendly alternatives.

4.5.2.1 *Environmental Impact*

Foremost, we are interested in knowing if a trip should or can be considered sustainable, which in turn requires determining its ecological impact, and balancing this against any potential monetary or personal/social gains acquired by performing the trip. Figure 4.12 shows the average daily ecological impact as recorded during the *SBB Green Class* study and computed according to Equation 4.12, using a price of CHF 80/tCO_2 for the offsetting costs. It can be seen that for most people, the daily ecological impact measures in monetary terms is low. The largest (individual) contributions stem from airplane trips, whose ecological impact is in the order of several dozen CHF per trip. There are two important takeaways here: First, offsetting the negative environmental impacts would be feasible for most people, as it is in the order of several hundred Swiss Francs resp. USD yearly. Second, the still relatively small ecological impacts require us to shift our thinking towards the concept of *strong* sustainability, as in most cases the generated capital gains will outweigh the environmental "costs" by far.

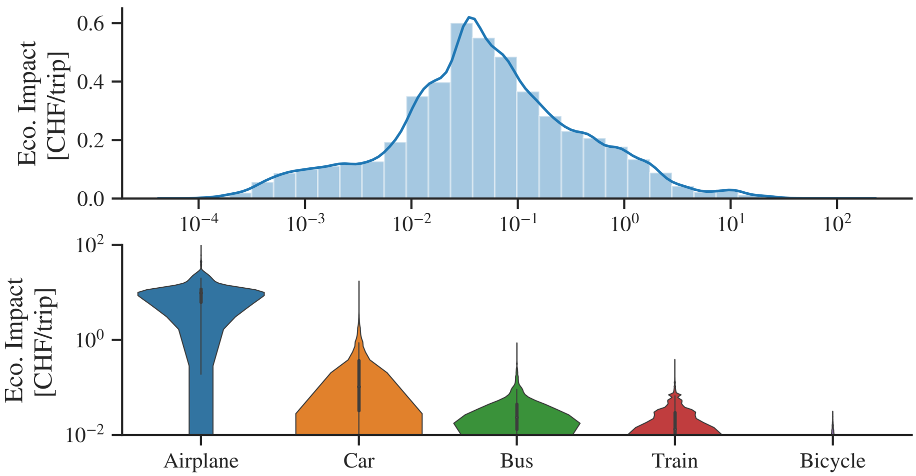


Figure 4.12.: Environmental impacts (measured in terms of monetary equivalents) of the mobility behavior of the participants of *SBB Green Class*.

4.5.2.2 *Monetary Cost and Capital Gains*

Similarly, we can compute the monetary costs resp. capital gains according to Equation 4.13, 4.15 and 4.16. Figure 4.13 shows the average daily costs for mobility for the *SBB Green Class* sample, as well as the corresponding gains from performing the respective activity (which can be either financial as measured using a person's salary, or personal by considering a fixed hourly gain across all users). Naturally, the gains are substantially larger than the corresponding costs. It can be seen, though, that they are of approx. two orders of magnitude larger than the environmental impacts.

4.5.2.3 *Combined Sustainability Indicators*

In order to combine the environmental impacts and monetary costs resp. gains as explained in the previous sections, we thus have to

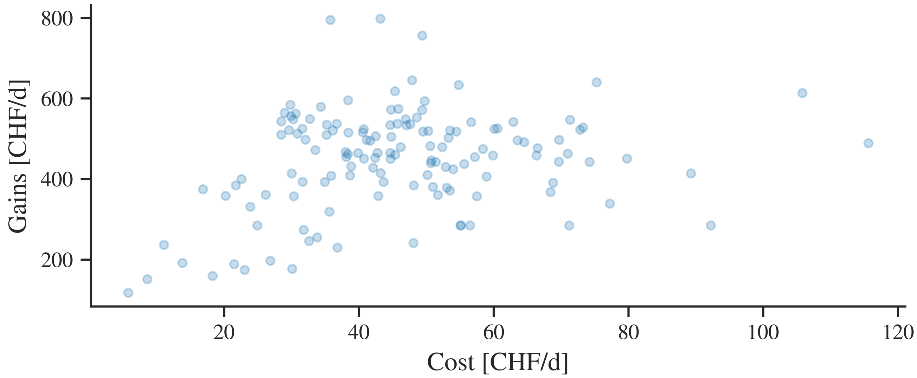


Figure 4.13.: Gains and costs of mobility as computed using the tracking data of the participants of *SBB Green Class*. We assumed an average salary of CHF 8916/month and a fixed "leisure budget" of CHF 2000/week.

carefully consider if we adopt a position of *strong* or *weak* sustainability, or some tradeoff between the two. Given by differences in the orders of magnitudes between environmental impacts and associated costs and gains, considering mobility from a point of view of weak sustainability, practically all trips can be considered sustainable, as they result in net gains (either financially or personally). Taking the point of view of strong sustainability, the opposite happens, and only those trips completely covered by SM can be considered sustainable. Figure 4.14 shows the trade-offs between different interpretations of sustainability as measured using the environmental impacts and costs/gains introduced before. We used a fixed "leisure budget" of CHF 2000/week to roughly balance the monthly salary with the budget for leisure activities. Analyzing the sensitivity of this parameter yielded that changing it in the range of CHF 500/week to CHF 5000/week does not substantially change the sustainability assessment as shown in Figure 4.14. Reducing it to 0 CHF/week, however, reduces the maximal number of sustainable trips (at $\omega_s = 1$) to approx. 25%, corresponding to the 24% of all travels in Switzerland that are performed for work reasons (Biedermann et al. 2017).

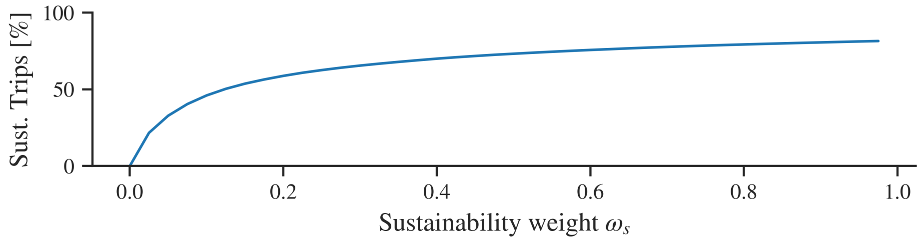


Figure 4.14.: The share of sustainable trips as a function of the sustainability weight ω_s (where $\omega_s = 0$ corresponds to the concept of *strong* sustainability and $\omega_s = 1$ to *weak* sustainability).

4.5.3 *Systematic Mobility and Mobility Preferences*

Knowing about systematic behavior and preferences of individual people lets persuasive applications specifically target these regularities (which is helpful as changes in regular behavior lead to long-term effects and are difficult to achieve without external stimuli) and further personalize the provided support.

4.5.3.1 *Geometrical, Topological and Platial Aspects of Systematic Mobility*

While estimating personal circumstances from trajectory data alone is difficult, contextual factors such as the time can lead to valuable insights. Figure 4.15 shows the transport mode choices at different times during the day (where the upper part of the figure shows the choices during the week and the lower part shows them on the weekends). It is clearly visible that in the morning and evening rush hour, trains are more frequently chosen, indicating that they are often used to travel to/from work (note that due to the comparably high price the *SBB Green Class* sample primarily consists of working middle-aged, middle-class men, cf. chapter 2). Trains are also used less on the weekend in favor of cars, indicating that trips undertaken on the weekend either require more space (e.g., to accommodate a family or transport goods) or flexibility (in terms of reachability of destinations and/or time).

Systematic mobility behavior is important for persuasive applications targeting sustainable mobility behavior, as people usually do not think much about their choices on these trips, which in turn means that their habitual behavior is potentially responsible for large ecological impacts,

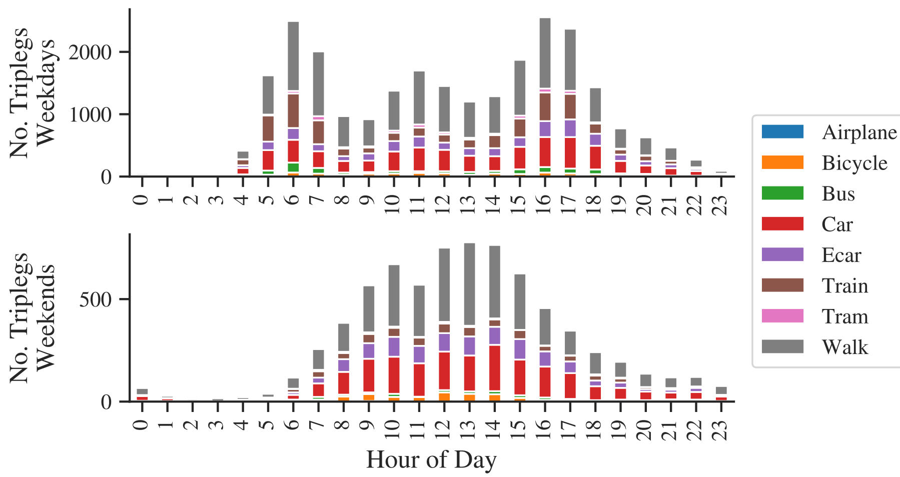


Figure 4.15.: Transport mode choices at different times, as recorded throughout the *SBB Green Class* study.

even though there would be suitable alternatives available. In addition, a change of mobility behavior on a systematic trip can easily be turned into a new habit which will have a long lasting effect. Figure 4.16 shows the shares of systematically visited locations (denoted as places within this dissertation), computed using the methods presented in subsection 4.3.1. It can be seen that on average roughly half of all trips and activities are performed on a regular basis. However, representing these systematically visited places based on their duration indicates that a large share is made up by one's home and workplace, making up for substantially more than 50% of a user's visited locations.

4.5.3.2 *Transport Mode Choices*

Knowing about all the previously introduced properties and factors gives us the possibility to build transport mode choice models. Here, we present the results of the transport mode choice model (predicting the choice between an ICE car and an EV) introduced in subsection 4.3.2. Knowing how people would choose between these two transport modes (if they had both available) is becoming more and more important with the increasing prevalence of EVs. For example, it is commonly argued that buying an EV might be a bad idea, as their limited range impacts the usefulness of the vehicle, in particular when going on holiday or doing longer leisure trips. Studying the transport mode choice model,

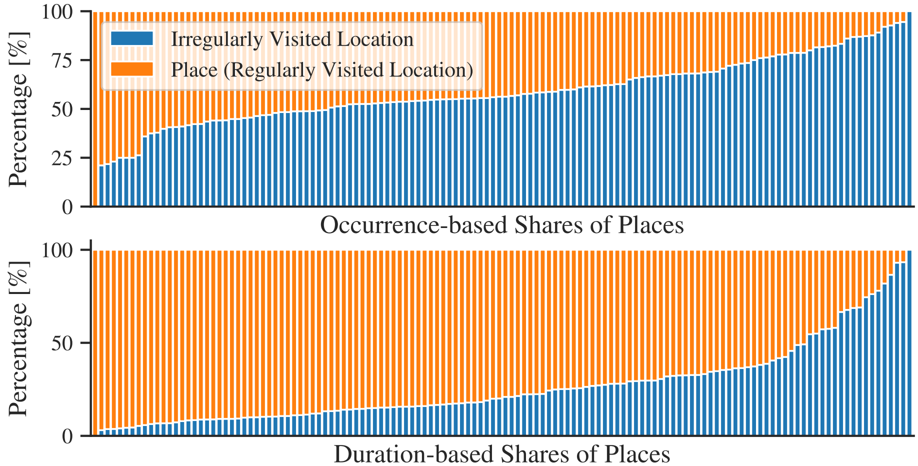


Figure 4.16.: The share of places (cf. Definition 4.7) within the set of all staypoints.

we can argue if this would indeed be problematic for most people, or if in reality, people choose the transport mode irrespective of the trip length (and instead either choose randomly or based on features that are more difficult to observe using a location tracking app, such as the number of people traveling, or the amount of luggage transported).

To evaluate these questions, we trained a logit model as well as a Random Forest (RF) on the data from the *SBB Green Class* study (where all participants had access to both an ICE car as well as an EV). Both models were trained on triplegs and tours, and considering a completely random split of data (i.e., the predictions happen on the same users as the training) as well as a user-based split (where the models were fitted on one set of users, and evaluated on another). The latter was done to study how well we can predict transport mode choices if we do not know about the previous behavior of a user (which naturally occurs, for example, when a person uses a persuasive application for the first time), and how much prediction improvement we can achieve once we know more about the mobility behavior of that person.

Figure 4.17 shows the feature importances of the RF model. While these importances confirm that the length of a trip has the largest impact on the transport mode choice, its relative increase in importance is marginal, indicating that when faced with the choice in a real setting, the tripleg length does not become a crucial factor. Table 4.10 and

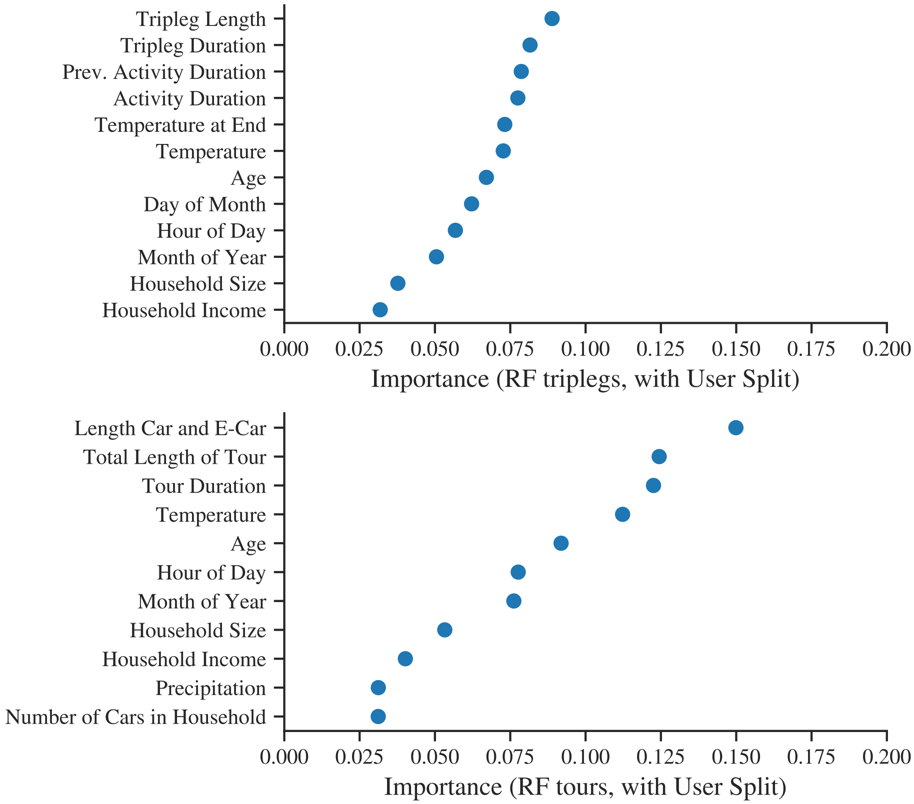


Figure 4.17.: The feature importances as used within a RF model fitted to the triplegs and tours recorded within the *SBB Green Class* study.

4.11 show the logit models both fitted on triplegs as well as tours. The long-distance factor indicates if a tripleg or tour was longer than 100 km in a binary fashion. Looking at the choice between ICE car and EV on a tour level is a more natural representation of a planning process a person might undergo.

Studying the weights of the logit models similarly shows that while the impact of the tripleg/tour length (resp. the logarithm thereof) is significant, its effect size is small (e.g., the difference between a 1 km and a 100 km tripleg/tour has approximately the same effect as a change in work status or the change from weekdays to weekends). It is also interesting to see that temperature and precipitation have very small effect sizes and are not even significant in the case of the tours logit model. This stands in contrast to statements of study participants

Feature	Coefficient	Std. Error	z-Value	p-Value
Intercept	3.7693	0.310	12.175	0.000*
Weekday/weekend	-0.4806	0.017	-27.879	0.000*
Temperature	0.0078	0.001	7.719	0.000*
Precipitation	0.0394	0.012	3.244	0.001*
Sex	-0.1872	0.025	-7.638	0.000*
Age	0.0086	0.001	8.037	0.000*
Number of cars in household	-0.0636	0.012	-5.425	0.000*
Work status	0.3381	0.023	14.635	0.000*
Household size	0.0689	0.006	11.811	0.000*
Long-distance tripleg	-1.7695	0.064	-27.848	0.000*
log(duration of next activity)	0.0776	0.005	14.868	0.000*
log(duration of prev. activity)	0.0852	0.005	15.984	0.000*
log(duration of tripleg)	-0.3136	0.018	-17.038	0.000*
log(length of tripleg)	0.2011	0.014	14.614	0.000*
log(household income)	-0.4286	0.031	-14.023	0.000*
sin(hour of day)	0.0928	0.011	8.359	0.000*
sin(month of year)	0.2385	0.011	21.001	0.000*

Table 4.10.: Model parameters and predictor significances for the tripleg logit model. *Significant at the $p < 0.05$ level.

who indicated that during cold weather the range of EVs is reduced, either due to battery limitations or to increased energy demands from heating.

Feature	Coefficient	Std. Error	z-Value	p-Value
Intercept	-1.7069	0.611	-2.792	0.005*
Weekday/weekend	-0.4440	0.035	-12.632	0.000*
Temperature	-0.0018	0.002	-0.850	0.395
Precipitation	-0.0357	0.029	-1.238	0.216
Sex	-0.1451	0.049	-2.975	0.003*
Age	0.0078	0.002	3.503	0.000*
Number of cars in household	-0.0250	0.024	-1.030	0.303
Work status	0.6985	0.260	2.689	0.007*
Household size	0.0900	0.012	7.509	0.000*
Long-distance tour	-0.5116	0.053	-9.670	0.000*
log(length of all triplegs by car or ecar)	0.0464	0.009	5.206	0.000*
log(length of tour)	0.1006	0.020	5.066	0.000*
log(duration of tour)	0.0620	0.017	3.704	0.000*
log(household income)	-0.0584	0.062	-0.940	0.347
sin(hour of day)	0.1443	0.024	6.043	0.000*
sin(month of year)	0.1223	0.023	5.282	0.000*

Table 4.11.: Model parameters and predictor significances for the tour logit model. *Significant at the $p < 0.05$ level.

Finally, to answer the question if we can predict the choice between the ICE car and the EV without knowing anything about the previous user behavior, we computed the prediction accuracy and the Madden (pseudo) R^2 (McFadden 1973) for all the different models. This alternative R^2 score is defined as $R^2 = 1 - \frac{\ln L_1}{\ln L_0}$, where L_0 is the likelihood of a model only containing the intercept and L_1 the likelihood of the complete model, and offers a meaningful substitute for binary classification tasks.

Table 4.12 shows that the RF trained on data of all users is able to predict the choices well and the model explains much of the variance

Model	Triplegs Acc.	Triplegs Ps. R^2	Tours Acc.	Tours Ps. R^2
Random Forest	78.86%	0.3060	74.04%	0.2198
Logit Model	59.00%	0.0195	58.46%	0.0328
Random Forest (User Split)	65.40%	0.1032	59.96%	0.0273
Logit Model (User Split)	52.43%	0.0055	52.43%	-0.0072

Table 4.12.: The accuracy and explanatory power of the ICE car/EV choice models presented in this chapter.

(0.3060 for triplegs resp. 0.2198 for tours). If we train on one set of users and test on another, the accuracy drops substantially and becomes only marginally better than a random prediction (which would yield 50%). Similar characteristics can be observed for the logit model, which generally exhibits lower accuracies and R^2 values. These findings support the hypothesis that the choice between an ICE car and an EV heavily depends on the person under consideration (i.e., people show a high regularity in these choices), but cannot easily be transferred from one person to the next. This in turn is an indication that in general, choices between ICE cars and EVs are rather random, and thus the negative associations with EVs are not problematic in reality.

4.5.4 *User Behavior*

The following experiments use the recorded mobility data to extract information about the exhibited mobility behavior. This information can be used by application developers to specifically target different groups of people.

4.5.4.1 *Mobility Choices over Time*

As introduced in subsection 4.3.2, we can use the introduced mobility metrics to group people into different classes of similar mobility choice behavior, which is useful for targeting people with measures adapted to their behavior. Based on the introduced autocorrelations (of daily distances traveled and duration spent traveling), displayed in Figure 4.18, we compute a similarity value for all users according to Equation 4.25. Figure 4.18 very well shows the weekly peaks in autocorrelation of the participants of the *SBB Green Class* study (i.e., they show a very regular weekly behavior). It is also visible that there is a (small) exponential dropoff with increasing lag. This highlights that our mobility behavior is constantly changing and thus everything within roughly three weeks shows a higher autocorrelation than choices further away.

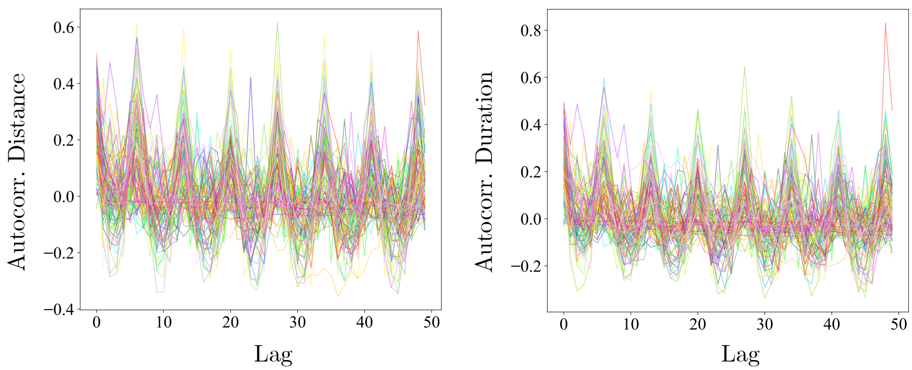


Figure 4.18.: Variations of the autocorrelation coefficients at different time lags for all users.

Clustering people according to the autocorrelations (of different transport modes) using a hierarchical clustering method, we can identify people that exhibit similar transport mode usage and regularity. To determine an optimal number of clusters, we use the CH-index given in Equation 4.28. The resulting index values are shown for up to 30 clusters in Figure 4.19. As the maximum value of the CH-index indicates the optimal tradeoff between intra-cluster and inter-cluster variance, we would be inclined to choose a low cluster number of three clusters. However, looking at the figure, we observe that there is a prominent peak at 14 clusters (duration), as well as at 7 clusters (distance). The latter become acceptable choices when considering that we might want to have a more fine-grained assessment of people and their mobility usage, thus being able to tailor a persuasive application to a larger number of groups with differing mobility usage.

In Figure 4.20, the top-2 clusters of applying hierarchical clustering to the autocorrelations computed for the participants of the *SBB Green Class* study are shown. It can be seen that people in cluster two use trains for substantially longer distances and durations, at the expense of car usage. This different use of mobility is also reflected in the CO_2 emissions which are lower for the people in cluster two.

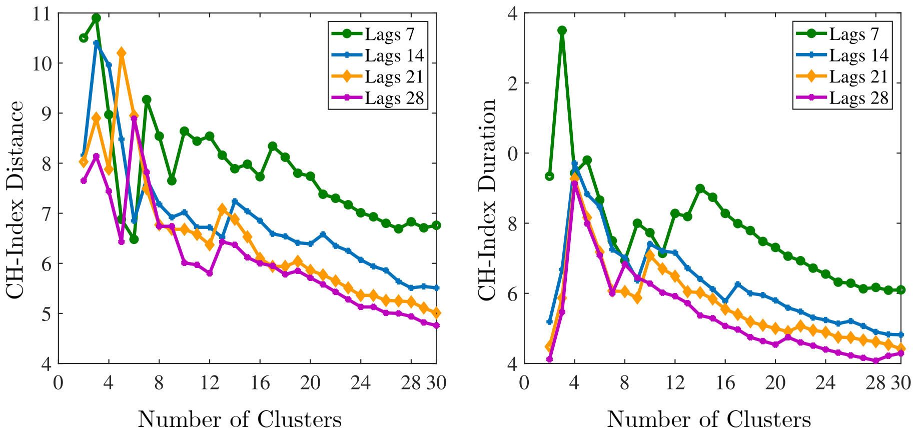


Figure 4.19.: Relation graph of the number of clusters and CH-index.

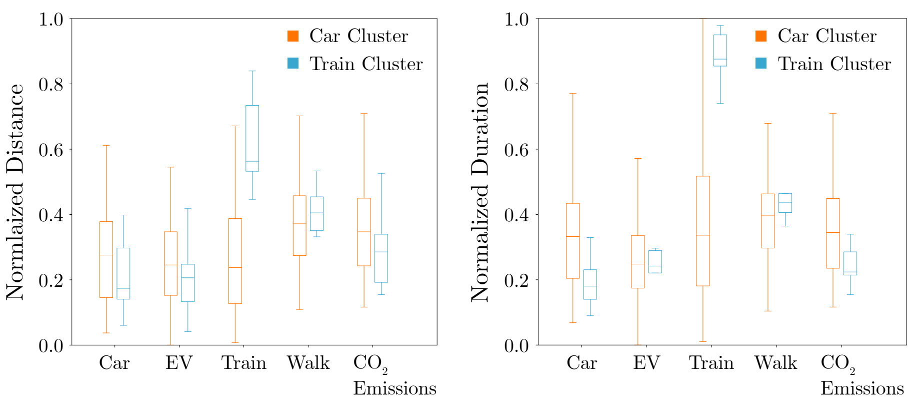


Figure 4.20.: Boxplots of five mobility indicators in different clusters.

Looking from the point of view of a persuasive application, cluster group two should be predominantly targeted with measures supporting SM, while group one should be assisted in transitioning from the use of ICE cars to more ecologically friendly modes of transport such as trains or (up to some degree) EVs.

4.5.4.2 *Behavior Change*

While the previously introduced methods allow both extracting metrics that are useful to be presented directly to the user as well as to make decisions about how to support different individuals, we here present the outcomes of applying the methods introduced in section 4.4, targeted at a longitudinal analysis of behavior and detecting the related changes. This in turn is important to identify when an applied measure shows effect as well as to know when the measures (e.g., within a persuasive application) should be adapted due to changing behavior.

Figure 4.21 and Figure 4.22 show the behavioral anomalies of two users of the *SBB Green Class* study as identified using the approach presented in subsection 4.4.1 and in particular Equation 4.29. In both figures, the yellow points indicate place-related anomalies (i.e., the number of previously unseen places visited in that week) and the blue points indicate the total number of anomalies in the respective week (i.e., considering all features). The user corresponding to Figure 4.21 exhibits a constant behavior (i.e., there are no anomalies detected) up until around week 2017-06, after which we see an increase in the total number of anomalies. These anomalies stem from an increase in distance and duration of walking and bicycling trips (however, this is not shown in Figure 4.21). In combination with the fact that the place-related anomalies (indicated in yellow) remain roughly constant, it can be concluded that this user indeed changed his or her behavior. A persuasive system should make use of this information, e.g., by reinforcing the new behavior and providing incentives to continuously exhibit it.

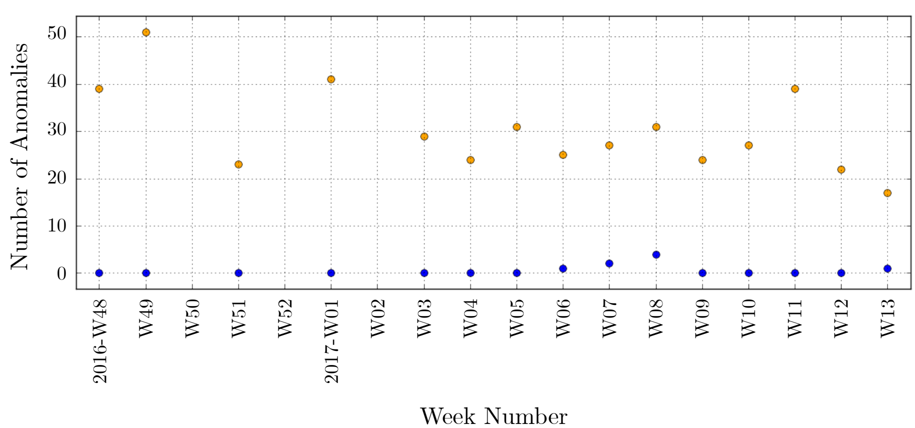


Figure 4.21.: All (blue) and only place-related (yellow) anomalies for user A of our test sample. In weeks 2016-50, 2016-52, and 2017-02, the data completeness was found insufficient to reliably assess mobility behaviour patterns.

In contrast, the user corresponding to Figure 4.22 shows an increase in the totally traveled distance (starting from week 2017-05), made up of increases in car, bike and walking distances (again, this is not shown in the figure, but analyzing the anomalies reveals this information). In combination with the increase of place-related anomalies around the same time, one has to conclude that the behavior change in this case is more likely caused by varying circumstances (e.g., a holiday trip), and thus a persuasive system should not introduce any shifts in the supporting measures.

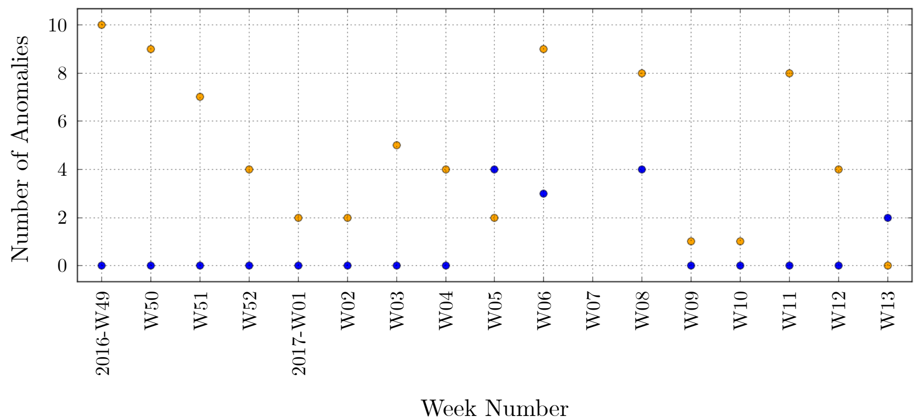


Figure 4.22.: All (blue) and only place-related (yellow) anomalies for user B of our test sample. In week 2017-07, the data completeness was found insufficient to reliably assess mobility behaviour patterns.

To identify groups of people who change their behavior similarly, we introduced a two-level behavior change method in subsection 4.4.2. Figure 4.23 shows a selection of the features extracted from the metrics introduced previously in this chapter. In blue, the "raw" level 1 (L1) features are displayed, while in orange and red the level 2 (L2) trend lines, anomalies, and quantiles are represented, which are used to cluster the people according to their behavior. For example, the total number of trips as well as the total wait duration at staypoints both contain trend lines that highlight the increases over the whole study period. They also contain anomalies, where a large increase from one day to the next was found. The variances (shown in the middle) are solely represented by a trend line, while the differences from one day to another are used to generate the 0.25- and 0.75-quantiles as L2 features.

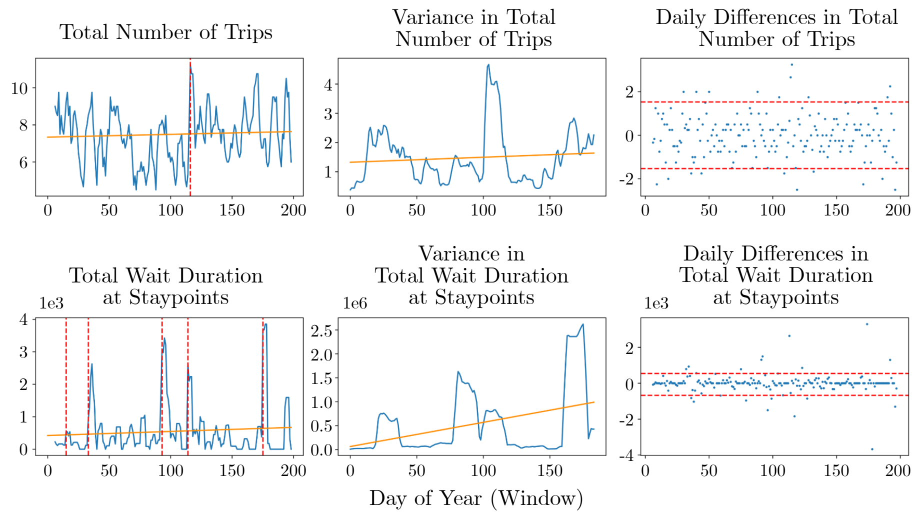


Figure 4.23.: Exemplary L1 and L2 features used to cluster people according to similarities in their behavior (resp. the change thereof).

Figure 4.24 shows the clustering results along the five primary features that led to the clustering result. It can be seen that for example cluster group 1 exhibits increases in the variance of several transport mode usage patterns, indicating that this group in the beginning of the study period showed a more regular behavior than towards the end. Group 2, on the other hand, exhibits a relative increase in regularity. A persuasive application should be aware of these trends, as for example the first group can be targeted with measures that persuade someone to try out more sustainable alternatives (e.g., by proactively showing these alternatives), while the second group seems to be more in a habit-forming process and thus (in case it is a non-sustainable habit) can be supported by educative measures that highlight the impacts of the behavior.

Clustering the people according to their mobility change behavior using a decision tree also lets us inspect the different features that led to a given clustering result. Figure 4.25 shows the decision tree responsible for clustering people as displayed in Figure 4.24, and highlights cluster 3 in red and cluster 4 in pink. It can be seen that people in cluster group 4 show a higher increase in variance of the duration spent on taking the train to get home, and further exhibit a lower increase in

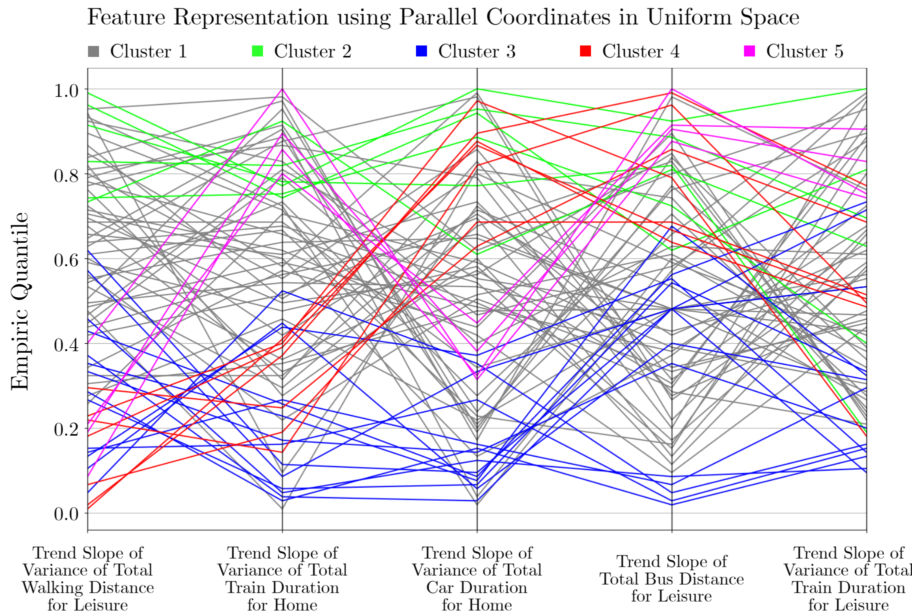


Figure 4.24.: Visualization of clusters along five features of interest. It can be seen that all members of clusters exhibit similar feature values.

variance of leisure-related walking activities. In addition to being used within a persuasive application, these results can guide mobility and movement analyses, in this case highlighting that changes in mobility pattern within the *SBB Green Class* project mainly revolve around how people use mobility for home- and leisure-related activities.

4.6 CHAPTER SUMMARY

In this chapter, we highlighted the processes and methods involved to transform automatically and passively tracked movement data into information that can be used to build persuasive applications that support people in reaching sustainable mobility. In particular, we presented a method to automatically infer transport modes using spatio-temporal context data, a collection of sustainability indicators that provide a way to determine if a given trip should be avoided or replaced by a more sustainable transport mode, a model that describes the factors influencing the choice between an ICE car and an EV, as well as a set

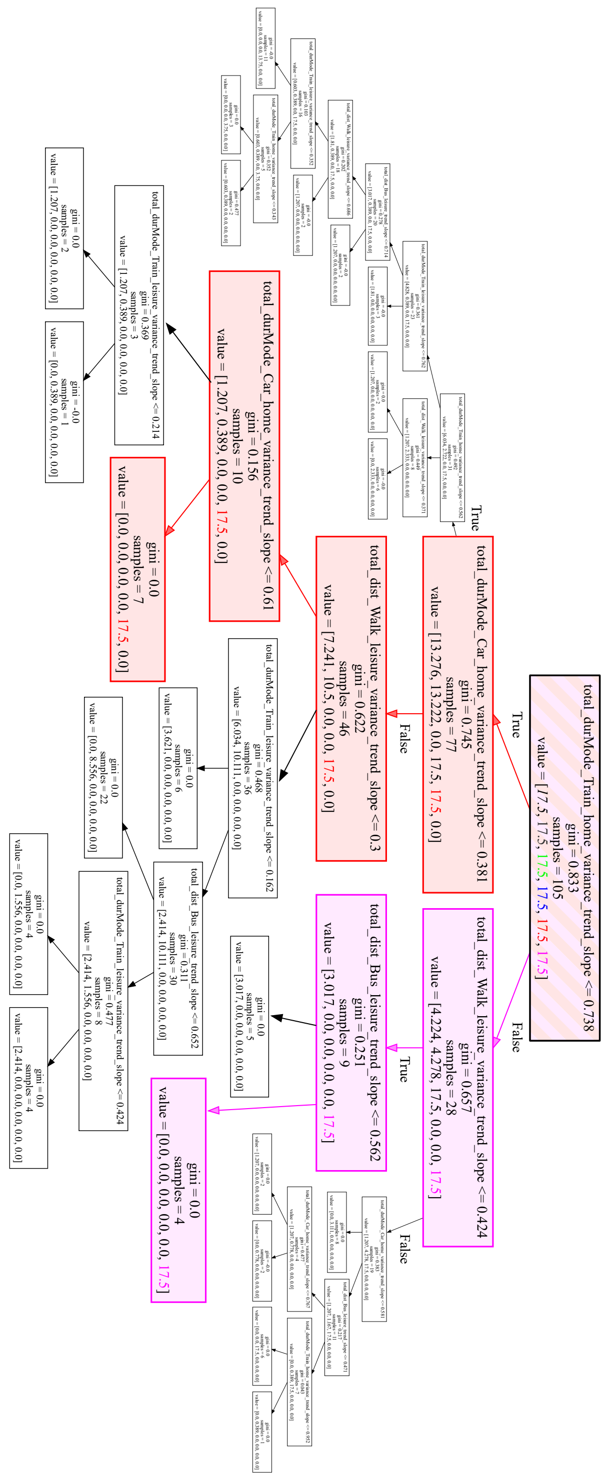


Figure 4.25.: The decision tree that leads to the classification of users into different mobility behavior change clusters. Highlighted in red and pink are two exemplary clusters.

of methods to automatically identify behavioral patterns and changes thereof. The information can be used mainly in three ways: 1) to guide an expert or an automated system in choosing which groups or individual people to support with which measures, 2) to be directly presented to users of persuasive applications or to form the basis for persuasive techniques and personalization as outlined in chapter 5 and chapter 6, as well as 3) to facilitate and guide the analysis of tracking data with respect to knowing if and how a certain persuasive intervention affects the mobility behavior and choices of people. The following chapters will build upon the here retrieved information to compute and propose meaningful alternatives as well as to communicate the information to people in a way that supports them in a transition towards more sustainable mobility behavior.

5 PLANNING INTEGRATED AND SUSTAINABLE MOBILITY

In the previous chapter, we have looked at how tracking data can be used to identify individual mobility behavior, mobility needs and demands, as well as changes thereof. The focus of this chapter lies on the development of methods and approaches to use this information to support people by giving them personalized and meaningful route alternative suggestions and by extending previous research on route planning. This will be done by incorporating personalization and providing a generalized model of high-level route computations that unify more niche and/or novel transport options (such as free-floating sharing services, carpooling or buses-on-demand). Figure 5.1 gives a high-level overview of the processes involved in the planning of integrated and sustainable mobility options, as presented within this chapter. Starting from a specification of mobility offers (e.g., for Public Transport (PT), Carpooling (CP) or free-floating micromobility services), we will present approaches to refine the specifications and extract transfer graphs which describe when and where people can transfer from one mode of transport to another. Following this, there are several ways we can use the graphs to compute high-level and/or completely specified route options that in turn can be utilized to improve persuasive applications that support people in achieving sustainable mobility.

We differentiate between two main approaches to compute route alternatives. On the one hand, we can create high-level transfer graphs that are useful for personalized routing as the number of nodes in the graphs is substantially lower than in a time-expanded (or time-dependent) graph covering a complete transport network (in particular containing all the individual streets, footpaths, and so on). This second approach, however, is useful to more quickly compute non- (or marginally) personalized routes, as it allows relying on a wealth of research speeding up graph computations on static graphs and does

This chapter and its contents, algorithms and figures are based on Bucher, Weiser, et al. 2015; Bucher, Jonietz, and Raubal 2017; Bucher, Scheider, and Raubal 2017; Huang, Bucher, et al. 2018; Bucher, Mangili, Cellina, et al. 2019.

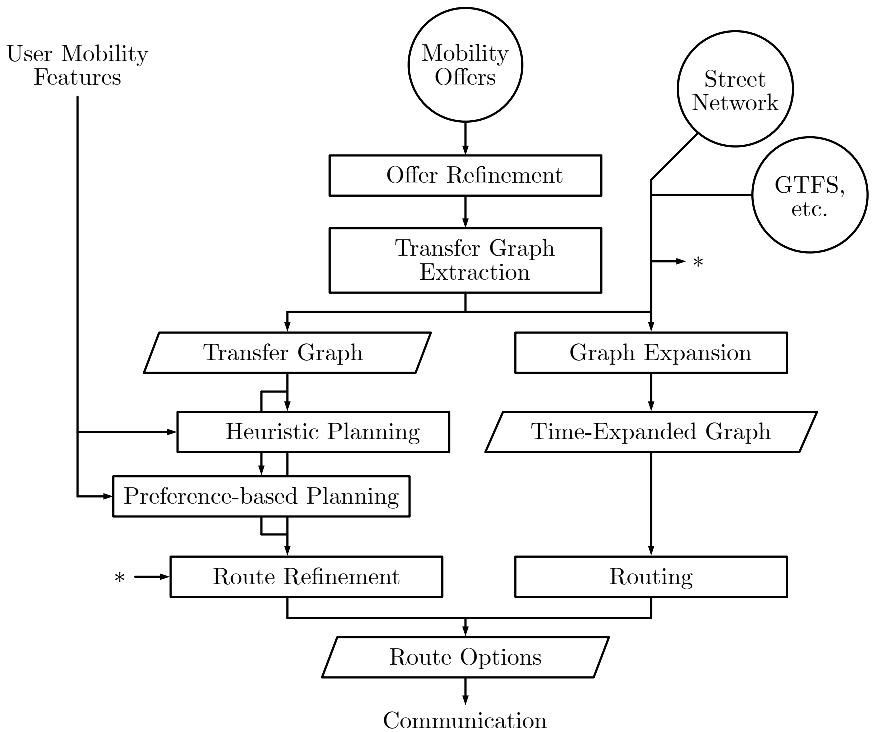


Figure 5.1.: The information processes involved in matching transport demands with offers, resp. aligning mobility and transport needs.

not require route refinement in a follow-up step. Within our framework of persuasive applications supporting sustainable personal mobility, all the resulting route options then undergo a similar sustainability assessment as presented in chapter 4 and are used to give users feedback resp. to assess potential alternative behaviors and tailor the application content appropriately.

5.1 FORMALIZING MOBILITY OFFERS

If we want to travel somewhere, there are often numerous transport modes (and combinations thereof) available. In addition, considering that a "simple mode" such as a car can not only be used for Private Motorized Transport (PMT), but also for CP, ridesharing, carsharing, car rentals, taxi services, on-demand services, etc., it becomes obvious that route planning cannot only take into account the fastest way from one location to another on a static road network, but must be flexible in terms of pickup and dropoff locations, routes, networks, schedules, etc. In this section, we provide a generalized formalization encompassing a wide range of transport modes (as used nowadays) that is flexible enough to incorporate potentially appearing future means of transport, as long as they adhere to some basic assumptions and spatio-temporal constraints. Specifying transport offers within this formalism enables applying a range of routing techniques as introduced later in the chapter without further modification or adaptation of the routing methods.

The most basic premise of our formalization is that people can change transport modes at certain points or regions in space. For many transport modes, this is easy to grasp conceptually: we can only access a train at a train station it stops at, our car can only be used at the point where it is currently parked, a taxi operator only operates in a certain (though potentially large) region, micro-mobility vehicles can only be dropped off in a certain area, and so on. This is particularly important for planning routes, where this spatial flexibility has to be taken into account: We cannot assume to always know the exact point in space where someone changes a transport mode, as it is often possible within a larger region. We denote such points or regions as *transfer locations*.

Definition 5.1 (Transfer Location)**.** A *transfer location* $\pi \in \Pi_m$ is the geographic area within which one can change to resp. from a certain transport mode $m \in M$.

Note that the set of transfer locations Π_m in this definition is not related to the places Π from Definition 4.7. As already indicated, transfer locations can often be approximated as single points in space (consider, for example, a large train station: even though it comprises a substantial area within which people can transfer to/from trains, it usually suffices to reduce it to one or a few access points for the purpose of mobility planning). We denote the function telling us for each transfer location π if it is a single *P*oint or an *A*rea as $type(\pi)$:

$$type(\pi) : \Pi \to \{A, P\} \tag{5.1}$$

Building on the formalization introduced in chapter 4, a tripleg l defines a transition from one transfer location (where the person started using transport mode m) to the transfer location where the person started using the transport mode of the following tripleg. As such, when generating mobility plans, we will refer to the same formalism of trajectories, triplegs, trips and tours, and features resp. context associated with them. Within the context of this chapter, we will focus on the following set of transport mode classes, which will be further explained in later sections: $M = \{m_{\text{wk}}, m_{\text{pmt}}, m_{\text{at}}, m_{\text{fr}}, m_{\text{sr}}, m_{\text{cp}}, m_{\text{pt}}\}$, corresponding to *walking*, *private motorized transport*, *(autonomous) taxis*, *free floating rental systems*, *station-based rental and sharing*, *carpooling*, and *public transport*. Note that *walking* is also explicitly considered a transport mode (that is available everywhere and at any time, and thus can be used to connect arbitrary transport modes), in contrast to other work that uses *walking* solely for the purpose of introducing possible transfers between other transport modes.

Pickup and Dropoff Types

While the specification of transport offers using pickup and dropoff transfer locations as given by Definition 5.1 would be sufficient for all further purposes, we here additionally introduce a schema to classify transport modes according to their *pickup* and *dropoff* types with the aim of facilitating understanding of different transport characteristics with respect to route planning. These pickup and dropoff types (specified in Table 5.1) usually do not vary within the transport mode (e.g., a free-floating scooter will always be picked up at a transfer location with $type(\pi) = P$ and can be dropped off at one with $type(\pi) = A$), determine how different transport modes are connected with each other, and also how the offers available for the individual transport mode have to be specified. Naturally, *anywhere* corresponds to a transfer location with $type(\pi) = A$ that spans the whole region (in which the route planner operates), *within area* corresponds to pickup resp. dropoff areas of $type(\pi) = A$ and *at discrete locations* corresponds to transfer locations with $type(\pi) = P$. For example, *walking* would have both a pickup as well as a dropoff type of A (anywhere), as it can be freely used irrespective of the location, and PT is often of type $P_T \to P_T$, as it only can be accessed from transfer locations π where $type(\pi) = P$.

Given the set of pickup and dropoff locations for a certain transport mode m, we can now specify individual *transport offers* (i.e., actually available means of transport to get from a pickup to a dropoff transfer location).

Definition 5.2 (Transport Offer)**.** A *transport offer* for a transport mode m is described as a bipartite graph (P, D, E_S), where the pickup locations

Spatial	Description
A	Anywhere (all transfer locations within planning region)
A_T	Within area (all transfer locations within area)
P_T	At discrete (and specified) transfer locations within region (e.g., vehicle location or (rental) station)

Table 5.1.: Pickup and dropoff types, describing for various transport modes where people can use the respective mode, and how they connect to other transfer locations in the network.

$p_i \in P \subset \mathcal{P}(\Pi_m) \setminus \emptyset$ and the dropoff locations $d_i \in D \subset \mathcal{P}(\Pi_m) \setminus \emptyset$ are sets of transfer locations that are connected according to the elements $e_i = (p_i, d_i) \in E_S$, i.e., all the dropoff locations in any set d_i are reachable from all the pickup locations in the set p_i if $(p_i, d_i) \in E_S$.

In essence, this specification tells us that we have sets of pickup (transfer) locations that can be used to reach sets of dropoff (transfer) locations. For example, we can model public transport offers by specifying that any transfer location (of mode m_{pt}) can be reached from any other (i.e., $P = D = \{\Pi_{m_{\text{pt}}}\}$ or equivalently $p_1 = d_1 = \Pi_{m_{\text{pt}}}, |P| = |D| = 1$ and $e_1 = (p_1, d_1)$, $|E| = 1$). This means that without changing the mode of transport (i.e., by keep using m_{pt}) we can reach any other part of the public transport network. Other examples are given in Figure 5.2: On the left, a PT line consisting of four transfer locations is given. As can be seen, each subsequent location can be reached by all previous ones, but the opposite is not possible (in reality, most PT lines run both ways of course, making it possible to reach each stop from any other). In the middle, the example of a private car or bicycle is given. While it is only possible to pick this up where it is currently parked, it can then be used to reach any location within a larger area. Finally, the CP example on the right is similar to the PT example, however, here each pickup and dropoff transfer location is a whole area in which transfers to other transport modes are possible. In this example, $P = \{\{\pi_{CP,1}\}, \{\pi_{CP,2}\}\}, D = \{\{\pi_{CP,2}, \pi_{CP,3}\}, \{\pi_{CP,3}\}\}, E = \{(p_1, d_1), (p_2, d_2)\}$.

Note that a drawback of this specification is that in its current form it does not include temporal components such as individual departure times. However, for many transport modes this is not strictly required for the generation of high-level mobility plans (as their schedules are highly regular) and can still be refined in a second stage where the high-level plan is refined to take into account individual vehicles and their departure times. To increase computational efficiency, the specification could be extended by only considering transport offers that are valid within a certain timeframe; the corresponding route computations can then operate on a smaller graph that represents the state of a transport network in this timeframe.

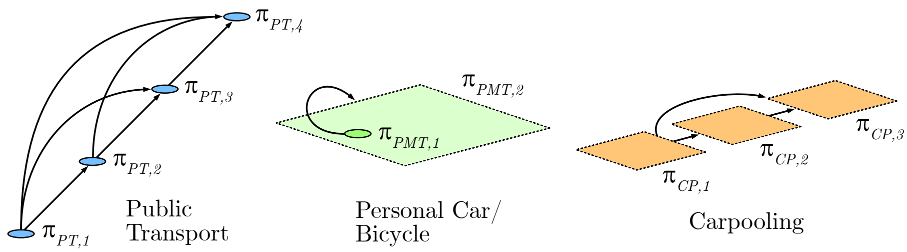


Figure 5.2.: Exemplary transport offer specifications.

5.1.1 *(Public) Transport Companies' Offers*

Public Transport Transport companies primarily offer mobility to generate revenue and/or as part of a governmental subsidy that aims at bridging gaps between the rich and the poor, and allow every citizen to travel freely. Traditionally, PT offers mobility in the form of trains, trams, buses, subways, airplanes, ferries, etc. These modes of transport commonly operate on a predefined schedule, visiting stops at well-defined geographic locations in a predetermined order. Another form of how mobility is offered by companies is by providing station-based rental services, e.g., simple car rentals, but also offers that are geared more towards short-term and -duration mobility usage, which are commonly referred to as station-based commercial carsharing. While this type of offer is similarly station-based, it is more flexible as it does not have to follow any strict schedule. However, different companies handle the vehicle return differently: While it is sometimes possible to drop off a vehicle at any station, often it has to be the one where it originally was rented from.

Taxis Taxi services are a form of mobility that has been around for a very long time, but has recently gained attraction due to several circumstances: The increasing digitalization makes (unified) access to them very easy and convenient, and manages to greatly reduce the price. In the same direction, it became much easier for people to offer taxi services with their personal vehicles and/or as side jobs (cf. the *gig economy*; Prassl 2018). Finally, the promise of level 5 autonomous cars (Driving 2014) lets us imagine scenarios where taxi services are ubiquitous and can be offered at very low prices, as no human operators need to be involved anymore. In all these forms, taxis have in common that they operate in rather large geographical regions, and can pick up and drop off people anywhere. In some cases, taxis are also not restricted to single passengers, but can pick up and drop off multiple passengers at different locations and in the process optimize their occupancy rate and driving schedules. The largest restriction is that a taxi needs to be available in the vicinity of a passenger, which can be difficult during hours of large demand.

Free-Floating Vehicles

Recently (and similarly enabled by the increasing digitalization), many companies have started to introduce free floating transport modes where transport vehicles can be picked up wherever they are currently parked, and must be returned within a larger geographic area (at any free parking spot). This is especially common for (short-term and -duration) carsharing, but even more recently also for a range of slow mobility transport modes such as (electric) bicycles, motor scooters and battery-powered scooters (footboards with steering handles). Table 5.2 summarizes the transport modes introduced as part of (public) transport companies' offers, and shows the formalized pickup and dropoff types.

5.1.2 *Private Persons' Offers and/or Available Transport Modes*

Private Transport

Private Motorized Transport (PMT) and individual Slow Mobility (SM) offer flexible and convenient travel options for most people. While the SM transport mode *walking* is available for anyone at anytime (theoretically to get anywhere, though practically limited by a maximum walking distance), taking the bicycle, car, etc. requires these modes to be present at the current location. As such, the transfer location where these modes can be taken are limited to single points in space, whereas they can be dropped off (almost) anywhere.

Ridesharing and Carpooling

It is common for people to share their individually traveled journeys with other people, e.g., to share costs on longer trips or to decrease traffic jams and/or be more sustainable (essentially by requiring less

Transport Mode	Pickup	→ Dropoff	Description
Public Transport (m_{pt})	P_T	$\to P_T$	Classical public transport follows strict lines and a predefined schedule.
Station-based Rental and Sharing (m_{sr})	P_T	$\to P_T$	Station-based rentals, e.g., for bikesharing offer vehicles that have to be returned to any of the stations.
(Autonomous) Taxis (m_{at})	A_T	$\to A_T$	Taxis usually operate within certain regions (often the pickup area is the same as the dropoff area).
Free Floating Rental Systems (m_{fr})	P_T	$\to A_T$	Vehicles of free floating systems can be picked up wherever they are parked, and have to be returned to any point within the operation area.

Table 5.2.: (Public) transport companies' mobility offers considered within this work.

individual cars). These transport offers usually come in the form of ridesharing (single-time sharing of a car) and carpooling (setting up a sharing agreement, e.g., between coworkers). We will here focus more on ridesharing as carpooling commonly requires agreements that are not necessarily possible to create in an automated fashion and thus cannot easily be incorporated into a route planner. However, the methods presented for ridesharing can be used to identify potential carpooling partners, which then can set up a "regularly running" carpool. Finally, we add buses-on-demand to this list, as they conceptually correspond well to ridesharing: both modes are semi-strict, i.e., they follow a rough schedule and route, but are flexible and allow to drive

Transport Mode	**Pickup**	**→ Dropoff**	**Description**
Walk (m_{wk})	A	$\rightarrow A$	Walking is always considered possible, and can thus be used to connect arbitrary transport modes.
Motorized Private Transport (m_{mp})	P_T	$\rightarrow A$	A private vehicle has to be available at a certain location to be used.
Carpooling, Bus-on-demand (m_{cp})	A_T	$\rightarrow A_T$	These transport modes are semi-flexible, in the sense that they follow a certain route, but are allowed to deviate from it.

Table 5.3.: Private person's mobility offers considered within this work.

detours to pick up and drop off passengers. Table 5.3 shows the private persons' transport offers used and discussed within this thesis.

The introduced transport modes correspond to currently widely used transport modes, but should be seen as categories of offers that can also be used for potentially appearing future transport modes (e.g., autonomous vehicles will roughly correspond to taxis). If a future transport mode cannot be assigned to any of the presented categories, its specification using a pickup and dropoff transfer location according to Table 5.1, defined in terms of Definition 5.1 and Definition 5.2 will still allow using the further presented methods and algorithms (e.g., a private autonomous vehicle that can pick up its owner anywhere can be modeled with a pickup type A_T).

5.1.3 *Transfer Graphs*

As the transport offers defined above are primarily used to specify actually available means of transport, we have to convert them into a structure suitable for computation of trips involving multiple means of transport. We thus model the whole transport network as a transfer graph that connects the individual transfer locations based on their geographical extent as well as the specification given as transport offers (as defined before).

Definition 5.3 (Transfer Graph)**.** A *transfer graph* $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, $\forall e = (\pi_1, \pi_2, L_e) \in \mathcal{E} : \pi_i \in \mathcal{V}$ describes how transfer locations π_i are connected with various modes of transport. L_e denotes the labels resp. properties of an edge e.

To build the transfer graph from the individual transfer locations and transport offers, we start by adding all transfer locations as nodes of the graph. For each of these vertices $\pi_i \in \mathcal{V}$, we then create an additional vertex $\pi_{i,m}$ and add one edge $e = (\pi_i, \pi_{i,m}, m(\pi_i))$ (where $m(\cdot)$ retrieves the transport mode label from the underlying transfer location π_i) to this new vertex, acting as a placeholder for transferring to mode m at location π_i. The vertices $\pi_{i,m}$ are then connected based on the transport specification given in section 5.1 by inserting an edge $e = (\pi_{i,m}, \pi_j, \cdot)$ for all pairs (π_i, π_j) that appear in pickup and dropoff combinations in E_S (i.e., $\pi_i \in p_k, \pi_j \in d_k, \forall e_k = (p_k, d_k) \in E_S$). After this step, we have a graph consisting of a number of disconnected subgraphs (one for each mode of transport resp. for each non-connected route within this transport mode).

In a second step, we connect these point locations to transfer areas to connect all subgraphs. In particular, for each (dropoff) transfer point $\pi_i \in \Pi$, $type(\pi_i) = P$ that is (geometrically) contained within a (pickup) area $\pi_j \in \Pi$, $type(\pi_j) = A$, we add a vertex $\pi_{j,m}$ and an edge $e = (\pi_i, \pi_{j,m}, m(\pi_j))$, denoting the transfer to the respective transport mode. Based on the specifications of the reachability of transfer areas (given in Definition 5.2), the vertices $\pi_{j,m}$ are then connected to all other reachable transfer points, namely those that are contained within reachable dropoff areas.

Finally, we add transfer points for any two transfer areas π_i and π_j that intersect geometrically (where π_i appears as a dropoff area and π_j as a pickup area within the bipartite transport specification graph). In this case, for intersection areas having a diameter smaller than a constant l, we add the geographic center (corresponding to the gravitational center) of the intersection polygon as a new vertex $\pi_{i,j}$, a transport mode choice vertex $\pi_{i,j,m}$, as well as an edge $e = (\pi_{i,j}, \pi_{i,j,m}, m(\pi_j))$ that denotes the transfer to the transport mode available within area π_j. We choose the geographic center as it corresponds to the mean position of all points, i.e., the expected value of a transfer point (assuming an uniform distribution of potential transfer points over the whole intersection area). However, since in practice l is chosen in the order of dozens of meters, other approximations would be viable as well. If the intersection area diameter is larger than l, we build an equidistant grid with a distance of l between points, and connect these points in a similar way as the gravitational center before. All vertices $\pi_{i,j}$ and $\pi_{i,j,m}$ are then connected to any other transfer points in $\mathcal{V}$ based on the transport specifications from section 5.1.

Figure 5.3 shows an exemplary transport offer specification containing a single public transport line, a carpooling offer, and an (area-based) taxi service. To build the transport graph, first, all transport modes are individually added to the graph ($\pi_{PT,i}$, $\pi_{CP,i}$ and $\pi_{TAXI,i}$). The public transport and carpooling offers are then connected in a second step: As $\pi_{PT,2}$ and $\pi_{PT,3}$ are contained within $\pi_{CP,1}$, a transfer from/to the respective modes is possible at these locations. As the carpooling and taxi transfer locations $\pi_{CP,3}$ and $\pi_{TAXI,1}$ are both areas (whose intersection exhibits a diameter larger than l), we create transfer points in a grid-based manner (the creation of these points is primarily done as for large intersecting transfer areas it is difficult to argue if someone would change the mode of transport without specifying an exact location). The resulting transfer points are used to connect CP and taxi in a similar manner as we linked PT and CP before.

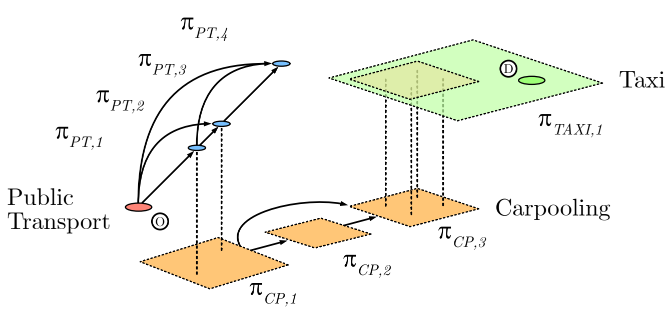


Figure 5.3.: An exemplary specification of transport offers that also highlights the spatial relations and how they determine at which locations transfers to other transport modes are available.

The transfer graph resulting from the transport specifications given in Figure 5.3 is shown in Figure 5.4. It can be seen that the individual transfer locations are added to the graph as-is, whereas (based on the spatial relationship between different transfer locations) new nodes are inserted that denote (together with the labeled edges) how one can change modes at various locations, and which other locations can be reached after performing the mode switch. The latter edges are shown as dashed grey lines—they are inserted based on the reachability specifications using Definition 5.2. Note that since there is no CP stop after $\pi_{CP,3}$, there are no dashed grey lines from the connection nodes between CP and taxi.

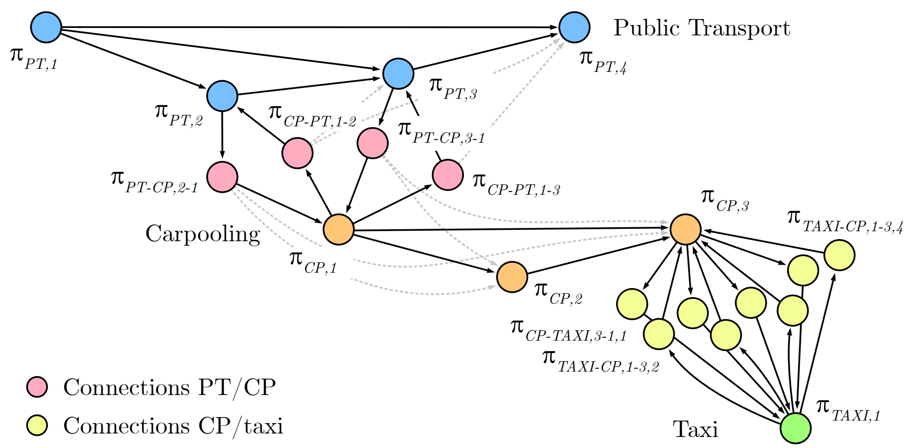


Figure 5.4.: The transfer graph extracted from the transport offer specification shown in Figure 5.3.

Within these transfer graphs we can already compute all possible mode chains (trips θ consisting of legs L_θ). However, there are some peculiarities that we will further elaborate on and develop methods for in the next sections. For one, the introduced formalism does not necessarily consider actually available transport vehicles, but only potential transfer locations. By expanding the transfer graph and adding additional nodes for each vehicle departing from a transfer location (where vehicles run on some sort of schedule), we can explicitly consider this. Second, for transport offers such as carpooling it can quickly become cumbersome to manually define all areas at which transfers are possible. The method introduced in the next section uses Drive Time Areas (DTAs) and Point of Actions (POAs) to automatically compute potential transfer areas and thus greatly reduce the complexity involved in specifying carpooling offers. Further, the graph as-is does not consider personalization at all, and can quickly lead to computationally exhaustive searches (e.g., when considering that by walking any transfer location *could* be reached at from point in the transfer graph), for which reason we add heuristic constraints and probabilistic models to compute when someone (likely) could transfer from one mode to another at a given location in the following sections.

5.2 MATCHING CARPOOLING TRANSPORT DEMANDS WITH OFFERS

Carpooling or ridesharing may help towards a short-term solution of many problems caused by PMT such as GHG emissions or traffic jams, as the cars are "already on the road", and for many popular routes there are enough drivers having roughly the same origin and destination to considerably reduce the number of individual rides along the route (cf. Correia and Viegas 2010; Deakin, Frick, and Shively 2010). However, it is difficult to bring these people together for a variety of reasons: people do not use the same matching platforms (websites), they want to be flexible about possible detours and departure times, they might be afraid to share their car with someone else or to be matched with a risky driver, or they might have neither a financial incentive nor need (as mobility is cheap). Here, we do not concern ourselves with most of these rather societal issues, and focus on the technical aspects of finding possible candidates to share a ride. The flexibility and fuzziness inherent in carpooling makes it an interesting and non-trivial problem: Drivers can make small detours or delay their departure slightly, and usually this also means that when they specify an upcoming trip (to be matched with potential riders) it is only specified very crudely, usually by publishing a list of a few stops in major towns along the route together with a departure time and rough price indication.

5.2.1 *Modeling Carpooling as Time-Expanded Graphs*

For easy integration into popular route planners (such as Google Maps), many PT providers specify their planned schedules using a standard such as the GTFS. These standards follow the structure of public transport which is (historically and due to the involved infrastructural components) centered around *routes* that describe a set of trips following the same PT line, i.e., visiting the same stops. Even though there are some differences (on which we will comment in the following sections), we here propose to model carpooling offers in a similar way, in order to easily integrate them into existing route planning systems. This integration will in particular allow us to link them to PT offers and analyze the resulting benefits. Similar to the formalization presented in chapter 4, we start with elementary connections (corresponding to triplegs):

Definition 5.4 (Elementary Connection)**.** An elementary connection l is a connection between two PT stops s_s and s_e that is served by a public transport vehicle v, starting and arriving at t_s and t_e: $l = (v, s_s, t_s, s_e, t_e)$.

Connecting multiple elementary connections leads to *trips* ($\theta = (l_1, ..., l_n)$), which in turn are collected into *routes* as described above (e.g., "Bus Line 80"). Considering that multiple routes reuse the same stops, it is now possible to connect them in a way that lets us find route options through a network involving multiple vehicles/transport modes and the respective transfers at certain stops. While the specification using GTFS differs in several ways from the generalized formalism presented in section 5.1, its basic components of *stops* and *trips* can roughly be considered the specialization of *transfer locations* and *transport offers* that does not include area-based transfer locations.

Similar to the transformation of transport offers into a transfer graph introduced in subsection 5.1.3, when transforming a specification of transport offers using GTFS into a graph suitable for route computations, we have to model all the different possible mode choices and departure times in some way. With regards to modeling departure times, we can use a time-dependent graph (where the edge weights are time-dependent, thus making it necessary to update the graph during the route computations) or a time-expanded graph (where each possible departure from any stop is modeled as its own vertex, connected to the next reachable stop). Within this section, we model the transport offers as a time-expanded graph, as it lets us use any "simple" routing algorithm (and the related speed-up techniques) such as Djikstra's, and we do not require the additional flexibility with regards to personalization given by time-dependent or high-level graphs.

Modeling of Transfers

A similar choice has to be made when modeling transfers from one mode to another. In subsection 5.1.3, we have chosen to add an additional node describing the transfer between two different modes (as this allows more easily assigning probabilities and enforcing constraints on these choices). While this is a commonly chosen approach (cf. Bast, Delling, et al. 2015), the same effect can be achieved by adding a labeled edge that directly connects the trips of two different transport vehicles or modes. We embrace this approach here, and create a labeled transition edge (carrying the label "transfer") between two elementary connections where $l_1.t_e + t_w < l_2.t_s,\ l_1.s_e = l_2.s_s$, stating that at every stop it is possible to transfer to connections departing later ($l_2.t_s$) than the arrival time of the incoming connection ($l_1.t_2$). We add additional restrictions on the creation of a transition edge: As it is often necessary to plan a minimal amount of time for the transfer itself (e.g., 3 minutes for a smaller train station), we enforce this minimum by introducing a waiting time t_w that restricts the departures to be after $l_1.t_2 + t_w$; Similarly, we add an upper bound for the waiting time ($l_1.t_e + t_u \geq l_2.t_s$, where t_u is usually in the order of 60 minutes), which reduces the number of created edges and thus the overall graph size. This is also in line with how transfers commonly happen: We wait for the first connection that gets us towards our destination, and do not arbitrarily wait for later ones. The resulting graph contains edges for all elementary connections, and thus is called a time-expanded graph (in contrast to a time-dependent graph) as all departures are explicitly modeled and the graph does not have to be updated during route computations. Algorithm 5.1 shows the algorithm used to create transfer edges between stops of elementary connections.

Summarizing, similar to regular PT schedules, we model carpooling offers utilizing a time-expanded graph, essentially using elementary connections to connect the individual stops specified by the driver. While for PT, the exact departure and arrival times are known, we have to derive them for carpooling using a routing on the network. Note that in the case of carpooling, a route nowadays commonly only consists of a single trip, as the respective web platforms are primarily used to plan one-time (and long-distance) drives.

5.2.2 *Merging Carpooling and Public Transport*

Starting from the CP model introduced in the previous section, which is in line with previous work and specifications such as GTFS, and shares the basic structure with the transfer graph specification introduced in section 5.1, we will now treat some of the peculiarities of CP (partially given by the way CP offers are commonly specified nowadays) and argue

Algorithm 5.1 Creating Transfer Edges Between Time Nodes

Input. A time-expanded graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ representing all single-ride journeys; a set of transfer conditions $tc = (s_1, s_2, t_w, t_u) \in TC$ between stops, indicating that the transfer time from stop s_1 to s_2 should be greater than t_w and no longer than t_u.
Output. A new time-expanded graph $\mathcal{G}' = (\mathcal{V}, \mathcal{E}')$ that is the original graph $\mathcal{G}$ enriched with possible transfer edges.

$\mathcal{G}' \leftarrow \mathcal{G}$
for all tc in TC **do**
    $V_1 \leftarrow$ time nodes linked to $tc.s_1$
    $V_2 \leftarrow$ time nodes linked to $tc.s_2$
    for all v_1 in V_1 **do**
        for all v_2 in V_2 **do**
            $\triangleright$ Difference between departure of v_2 and arrival of v_1.
            $dur \leftarrow v_2.t_s$ - $v_1.t_e$
            $\triangleright$ If a transfer is feasible, add a directed transfer edge with weight dur and label "transfer" from time node v_1 to v_2 to G'.
            if $dur > tc.t_w$ and $dur < tc.t_u$ **then**
                $\mathcal{E}' \leftarrow \mathcal{E}' \cup \{(v_1, v_2, w = dur, l =\text{"transfer"})\}$
return $\mathcal{G}'$

how to best resolve the resulting issues. As the flexibility and fuzziness of current approaches to match carpooling partners makes it a largely manual process (of finding each other), we here propose an approach to automatically process the route specifications resulting in a transport offer essentially corresponding to the one given in Definition 5.2. The resulting specification of pickup and dropoff areas can be used to create a transfer graph as defined in section 5.1 or a time-expanded graph (by linking the offers appropriately) as described here.

As we are particularly interested in the benefits of supplementing PT with CP offers (e.g., to reach badly connected regions), we will focus on the integration resp. linking of CP and PT graphs. Given a number of specified stops along a (potential) carpooling journey, two commonly applied linking strategies are to simply allow transfers at the closest PT stop to the given stop coordinate, or to allow transfers to any PT stop within the administrative boundary of the town or municipality. Both are not ideal, as they either do not respect the flexibility of the driver, or potentially require detours larger than the driver is willing to make. We here use the concept of *Drive Time Areas (DTAs)* to compute transfer areas for various points along the route (this concept is also commonly referred to as *potential path space* within the research field of time geography, cf. Hägerstrand 1970; Miller 1991). A DTA is a geographical space (around a point feature) that denotes the area reachable by car within a certain amount of time. As many carpooling offers only appear a single time, we compute DTAs around all PT stops (which is equivalent for our purposes) in order to reuse them when processing carpooling offers. Next to DTAs to handle the fuzziness of origin, destination and stopover specification, we introduce *Point of Actions (POAs)* to handle the flexibility of a driver along the route. A POA (also known under the term *decision point*, cf. Raubal and Winter 2002; Giannopoulos, Kiefer, and Raubal 2015) is any point along a route at which a driver has to take an action, such as leaving a highway, turning left or right, or even continuing straight after a crossing. The POAs can be retrieved by superimposing the route with the underlying transport network, and are usually also given by many route planners for turn-by-turn instructions. Once all POA along a carpooling driver's route are identified, the (PT and carpooling) networks can be linked. This would be possible with the method introduced in subsection 5.1.3 (which will create a general transfer graph). However, as we specifically treat the connection of PT and CP, we introduce a more accurate approach here (yet less personalized resp. less context-respecting) that takes into account the actual departure and arrival times at different stops along the route. Figure 5.5 shows an exemplary PT line as well as a single CP offer. As can be seen, the person offering the carpooling ride solely specified the journey in terms of $\pi_{CP,1}$ and $\pi_{CP,2}$ (origin and destination). Our method identified four POAs along the way and computed the DTAs around the PT stops which are then used to connect the individual stops to each other.

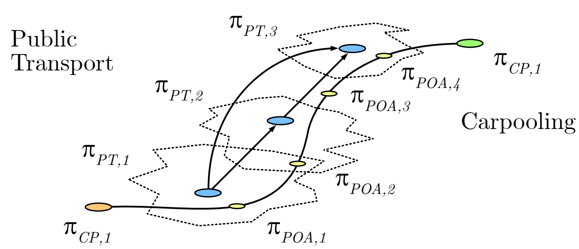


Figure 5.5.: Schematic visualization of the linking of CP and PT networks.

For each specified stop along the carpooling offer, and for each POA along the implicitly given route (e.g., computed using a route planner), we retrieve all DTAs that contain any of the stops or POAs. For each DTA thus identified, we add a transfer edge to the merged graph of the "raw" PT and carpooling specifications if the computed arrival resp. departure times of the involved PT and carpooling offers do not exceed the travel time between them (e.g., 10 min $< l^{PT}.t_s - l^{CP'}.t_e - traveltime(s^{CP'}, s^{PT}) <$ 30 min). To provide an upper bound and reduce the number of involved travel time computations, we take $traveltime(\cdot, \cdot)$ as half of the maximum detour time (note that this approximation might not hold in all cases, e.g., when one-way streets are involved; however, these cases are comparably rare and do not entail large time differences). The weight (i.e., travel time) of the thus added transfer edge is then $l^{PT}.t_s - l^{CP'}.t_e$. Similar to before, all these added edges are labeled as "transfer" to distinguish them from simply continuing to use the same mode of transport. Note that also the edges between the originally specified stops along the carpooling offer are kept to indicate that stops at POA are not required but optional. Furthermore, it should be noted that the concept of POAs allows linking different carpooling offers together at each POA, thus enabling combinations of different carpooling offers, and that picking up someone at a POA introduces delays for each of the following nodes. While the latter could be incorporated by recomputing the parts of the graph that might change due to such a detour, we here restrict the allowed detours (beyond the originally specified origin, destination and stopovers) to a single one. This is in line with how carpooling is generally used, whereas not restricting detours would quickly add up to many smaller ones which in turn introduces a large inconvenience for the driver. Algorithm 5.2 shows the complete algorithm used for merging and linking PT and carpooling graphs.

5.2.3 *Extracting Potential Matches*

The resulting time-expanded multi-modal graph can directly be used with any Dijkstra-like algorithm. Commonly, two types of queries are required to find matches between carpooling drivers and riders (potentially involving PT). *Routing with a given departure time range* describes the process of finding a multi-modal route from an origin to a destination where a person has a time window during which to depart. To answer such a query, we first identify all time nodes belonging to the origin stop that fall within the given range. A routing algorithm then finds the shortest path (in terms of total time) to any of the time nodes belonging to the destination stop. The resulting set of routes (i.e., for each of the departure time nodes, but it is also possible to "artificially" generate more routes by pruning nodes from a found path and recomputing the route again) can then be ordered according to various criteria such as the total travel time, the involved costs, the number of transfers, etc. The other predominantly used form of route queries is *routing with a given arrival time range*. In this case, the time nodes at the destination have to fall within the given range, and the search can either be performed backwards or forwards starting from all time nodes of the origin stop.

5.3 EVALUATING INTEGRATED MOBILITY OPTIONS

Commonly, route options are computed based on the total travel time or number of involved transfers (as transferring is often regarded as being more inconvenient than traveling a little bit longer). While this is

Algorithm 5.2 Merging Public Transport and Carpooling Graphs

Input. Time-expanded graphs $\mathcal{G}^{PT} = (\mathcal{V}^{PT}, \mathcal{E}^{PT})$ (representing PT trips and transfers) and $\mathcal{G}^{CP} = (\mathcal{V}^{CP}, \mathcal{E}^{CP})$ (representing a CP offer); a maximum CP detour time t_{detour}; CP stops S^{CP} (i.e., origin s_o^{CP}, destination s_d^{CP} and stopovers S_{so}^{CP}); a set of transfer conditions $tc' = (s^{PT}, min_{dur}, max_{dur}) \in TC'$ at each PT stop (defining the min. and max. time required for transferring between PT and CP).
Output. A new time-expanded graph $\mathcal{G}' = (\mathcal{V}', \mathcal{E}')$ combining the PT and CP graphs.

$\mathcal{G}' \leftarrow (\mathcal{V}^{PT} \cup \mathcal{V}^{CP}, \mathcal{E}^{PT} \cup \mathcal{E}^{CP})$ ▷ Merge the PT and CP graphs.
▷ Use an external/existing routing application to resolve CP route.
$r \leftarrow$ shortest route from s_o^{CP} to s_d^{CP} via S_{so}^{CP}
$S_{so}^{CP}.t_e, s_d^{CP}.t_e \leftarrow$ Arrival times taken from r

for all CP stop $s^{CP} \in S^{CP}$ **do**
  ▷ Filter all PT stops to only use those in approx. vicinity.
  $S^{PT} \leftarrow v^{PT} : dist(v^{PT}, s^{CP}) < (t_{detour} \cdot 100\text{ km/h})$
  for all PT stop $s^{PT} \in S^{PT}$ **do**
    $a \leftarrow$ DTA of s^{PT}, using t_{detour} as parameter
    if s^{CP} is within a **then**
      $\mathcal{E}' \leftarrow \mathcal{E}' \cup \{(s^{CP}, s^{PT}, l =\text{“transfer”})\}$
      $V^{PT} \leftarrow$ time nodes of PT stops s^{PT}
      for all $v^{PT} \in V^{PT}$ **do**
        ▷ Check for potential transfers from CP to PT.
        if $s^{CP}.t_e < v^{PT}.t_s$ **then**
          ▷ Diff. betw. departure of v^{PT} and arrival of s^{CP}.
          $dur \leftarrow v^{PT}.t_s - s^{CP}.t_e$
          if $dur > min_{dur}$ and $dur < max_{dur}$ (at s^{PT}) **then**
            ▷ Add edge ($t^{CP'}$ is the time node of s^{CP}).
            $\mathcal{E}' \leftarrow \mathcal{E}' \cup \{(t^{CP'}, v^{PT}, w = dur, l =\text{“transfer”})\}$
        ▷ Check for potential transfers from PT to CP.
        if $v^{PT}.t_e < s^{CP}.t_s$ **then**
          ▷ Diff. betw. departure of s^{CP} and arrival of v^{PT}.
          $dur \leftarrow s^{CP}.t_e - v^{PT}.t_s$
          if $dur > min_{dur}$ and $dur < max_{dur}$ (at s^{PT}) **then**
            ▷ Add edge ($t^{CP'}$ is the time node of s^{CP}).
            $\mathcal{E}' \leftarrow \mathcal{E}' \cup \{(v^{PT}, t^{CP'}, w = dur, l =\text{“transfer”})\}$
▷ Algorithm continued on next page.

▷ Exploit POAs along CP route.
$S^{CP}_{POA} \leftarrow$ POAs along r (overlap r with road network)
for all $s^{CP}_{POA} \in S^{CP}_{POA}$ **do**
  ▷ Filter all PT stops to only use those in approx. vicinity.
  $S^{PT} \leftarrow v^{PT} : dist(v^{PT}, s^{CP}_{POA}) < (t_{detour}/2 \cdot 100 \text{ km/h})$
  for all $s^{PT} \in S^{PT}$ **do**
    ▷ $t_{detour}/2$, because the driver needs to go to PT and back.
    $a \leftarrow$ DTA of s^{PT}, using $t_{detour}/2$ as parameter
    if s^{CP}_{POA} is within a **then**
      $\mathcal{V}' \leftarrow \mathcal{V}' \cup \{s^{CP}_{POA}\}$
      $\mathcal{E}' \leftarrow \mathcal{E}' \cup \{(s^{CP}_{POA}, s^{PT}, l =\text{“transfer”})\}$
      ▷ Add time node (transfer time t estimated using r).
      $\mathcal{V}' \leftarrow \mathcal{V}' \cup \{t^{CP'}_{POA}\}$
      ▷ Link time node $t^{CP'}_{POA}$ to trip node l^{CP}.
      $\mathcal{E}' \leftarrow \mathcal{E}' \cup \{(t^{CP'}_{POA}, s^{CP}_{POA}), (t^{CP'}_{POA}, l^{CP})\}$
      Add edges betw. $t^{CP'}_{POA}$ and adj. time nodes to G'
      Edge weights $\leftarrow$ travel time between corresp. stop nodes
      $V^{PT} \leftarrow$ time nodes of PT stops s^{PT}
      for all $v^{PT} \in V^{PT}$ **do**
        ▷ Check for potential transfers from CP to PT.
        if $s^{CP}_{POA}.t_e < v^{PT}.t_s$ **then**
          ▷ Diff. betw. departure of v^{PT} and arrival of s^{CP}_{POA}.
          $dur \leftarrow v^{PT}.t_s - s^{CP}_{POA}.t_e$
          $\overline{dur} \leftarrow dur - t_{detour}/2$
          if $\overline{dur} > min_{dur}$ and $\overline{dur} < max_{dur}$ (at s^{PT}) **then**
            ▷ Add edge ($t^{CP'}_{POA}$ is the time node of s^{CP}_{POA}).
            $\mathcal{E}' \leftarrow \mathcal{E}' \cup \{(t^{CP'}_{POA}, v^{PT},$
              $w = dur, l =\text{“transfer”})\}$
        ▷ Check for potential transfers from PT to CP.
        if $v^{PT}.t_e < s^{CP}_{POA}.t_s$ **then**
          ▷ Diff. betw. departure of s^{CP}_{POA} and arrival of v^{PT}.
          $dur \leftarrow s^{CP}_{POA}.t_s - v^{PT}.t_e$
          $\overline{dur} \leftarrow dur - t_{detour}/2$
          if $\overline{dur} > min_{dur}$ and $\overline{dur} < max_{dur}$ (at s^{PT}) **then**
            ▷ Add edge ($t^{CP'}_{POA}$ is the time node of s^{CP}_{POA}).
            $\mathcal{E}' \leftarrow \mathcal{E}' \cup \{(v^{PT}, t^{CP'}_{POA},$
              $w = dur, l =\text{“transfer”})\}$
return G'

often desirable, many people show regular patterns in their mobility choices and strong preferences for one mode of transport or another that are not only dependent on the travel time or distance to be covered, but depend on features as introduced in chapter 4, properties of the transport network (e.g., someone who lives close to a well-connected PT stop is likely to use PT to travel), or the availability of different modes for certain triplegs (e.g., someone might show a strong preference to take the bicycle for the "first mile" to the train station, but only if it is not raining). Using these influencing factors and thus personalizing route computations can decrease the required manual interactions with ICT before finding an appropriate route that conforms to one's own preferences. Based on the same formalization as introduced in chapter 4 and further adapted to the problem of computing route options in section 5.1, we here introduce an approach to use the passively tracked mobility data to derive mobility choice preferences that can be used to compute and/or evaluate route plans.

5.3.1 *Context and Circumstances*

To perform personalized routing on the graphs constructed in the previous sections (in particular the transfer graph from subsection 5.1.3), two functions assigning probabilities to user choices are required. First, for any location π_i that has multiple modes available (i.e., multiple connected nodes $\pi_{i,m}$), we need to determine the likelihood of a particular mode of transport m being chosen. Second, each $\pi_{i,m}$ is usually connected to several transfer locations π_j (which can be reached by using m), out of which we have to choose the most likely ones. The first function primarily depends on contextual factors (such as the time or destination of the planned trip), as well as features of the transfer location π_i. The second one additionally takes into account characteristics of the (potentially chosen) tripleg itself, such as its distance. Table 5.4 describes the features used within the prediction models in this chapter: There are basic contextual features such as the hour of day or the distances between various important locations for the trip and features related to the transfer graph itself, such as the Pagerank (Brin and Page 1998) (following the reasoning that someone might more likely choose the train for a longer trip if a well-connected PT stop is close by). While we can easily imagine other features to be added (e.g., the position of the currently being evaluated tripleg within a larger trip;

Feature	Description
m	Transport mode under consideration
t	Hour of day (at start of trip)
$d(\pi_i, \pi_j)$	Euclidean distance between start and end of tripleg
$d(\pi_j, d_\theta)$	Euclidean distance between end of tripleg and ultimate destination
$r_p(\pi_j)$	Maximal Pagerank of any public transport stop within 150 m of π_j

Table 5.4.: Features used to compute the probability of traveling from one transfer location to another.

this might emphasize walking at the start and end of a trip), having a large feature space also often entails not having enough training data to cover all cases (this is also referred to as the "curse of dimensionality").

5.3.2 *Previous Behavior and Preferences*

Given the features introduced in the previous section, we can use them to describe the probability that a person would take a certain mode at a given location or travel to a certain (intermediate) staypoint using said mode. As we do not know the statistical distributions of all involved features, we describe the probability distribution for a single user using a mixed joint density model based on multivariate kernel density estimation. To exemplify, consider that some people will likely choose PMT over PT during late evening hours as it increases their flexibility during times when PT runs infrequently. Others do not have PMT available and thus will not exhibit such a dependency. Many of the individual distributions cannot be easily modeled with commonly used statistical distributions (e.g., a Gaussian model), as they exhibit multiple peaks in the distribution (e.g., when describing a dependency on the hour of day or the total distance to the destination, in which case a transport mode such as *walk* is used both at the beginning and at the end, i.e., both when the destination is close as well as when it is far). Kernel density estimators circumvent this problem by using a kernel function to fit a probability density function to any given data. These types of models also allow combining discrete features (e.g., m, t) with continuous ones (e.g., $d(\pi_i, \pi_j)$, $d(\pi_j, d_\theta)$, c_{π_j}) and result in a probability density function that can be used to compute probabilities of all combinations of features. Thus, we model both choice functions (choosing a transport mode resp. choosing a certain intermediate staypoint) using a (parameterless) multivariate kernel density estimation (cf. Simonoff 2012):

$$\hat{f}_{\boldsymbol{H}}(\boldsymbol{x}) = \frac{1}{n}\sum_{i=1}^{n} K_{\boldsymbol{H}}(\boldsymbol{x} - \boldsymbol{x}_i) \tag{5.2}$$

Here, $K_{\boldsymbol{H}}(\boldsymbol{x}) = |\boldsymbol{H}|^{-1/2}\boldsymbol{K}(\boldsymbol{H}^{-1/2}\boldsymbol{x})$, $\boldsymbol{K}(\cdot)$ is the kernel function, and $\boldsymbol{H}$ the bandwidth matrix (that has to be chosen, usually by minimizing the mean integrated squared error). In Equation 5.2, $\boldsymbol{x}_i$ are the feature vectors computed from all previously tracked triplegs of a single user. The kernel density estimator $\hat{f}_{\boldsymbol{H}}(\boldsymbol{x})$ then describes the probability density for any combination of features of any (potentially chosen) tripleg or mode within the transfer graph. Sampling these values gives us an indication about the likelihood of a certain combination appearing in the previously recorded mobility data of a user.

Regarding the first function $p_m(\boldsymbol{x}_{-m})$ (determining the probability of choosing mode m at a given transfer location), we use the probability densities given by Equation 5.2 to compute probabilities as follows (note that $\hat{f}_{\boldsymbol{H}}(\boldsymbol{x}_{-m})$ describes a multivariate kernel density estimator not including m as a feature):

$$\begin{aligned} p_m(\boldsymbol{x}_{-m}) = \Pr(m|\boldsymbol{x}_{-m}) &= \frac{\hat{f}_{\boldsymbol{H}}(\boldsymbol{x}_{-m}|m)\hat{f}_{\boldsymbol{H}}(m)}{\hat{f}_{\boldsymbol{H}}(\boldsymbol{x}_{-m})} \\ &= \frac{\hat{f}_{\boldsymbol{H}}(\boldsymbol{x}_{-m}|m)\hat{f}_{\boldsymbol{H}}(m)}{\sum_{\pi_{i,\hat{m}}} \hat{f}_{\boldsymbol{H}}(\boldsymbol{x}_{-m}|\hat{m})\hat{f}_{\boldsymbol{H}}(\hat{m})} \\ \boldsymbol{x}_{-m} &= (t, d(\pi_j, d_\theta), r_p(\pi_j)) \end{aligned} \tag{5.3}$$

In essence, we use the Bayes' rule to compute the probability of choosing mode m (given features $\boldsymbol{x}_{-m}$) at location π_i by sampling the density estimates at different points.

As the reachable locations after choosing a mode m for travel are potentially unlimited (e.g., in the case of walking), we cannot compute a true probability for traveling to a fixed location. To exemplify, consider taking the bus to get somewhere: If there is a single stop at the destination, it is very likely that a traveler will get off at this stop (i.e., $p_l(\boldsymbol{x}) \approx 1$). However, if there were two bus stops right next to each other, the probability of leaving at one of them would be $p_l(\boldsymbol{x}) \approx 0.5$ each. Using this in a routing context (as introduced in more detail in subsection 5.4.2) would lead to lower probabilities for modes with which a large number of (intermediate) staypoints can be reached, for which reason we approximate the probability of choosing tripleg l directly using the probability density:

$$\begin{aligned} p_l(\boldsymbol{x}) &\approx \hat{f}_{\boldsymbol{H}}(\boldsymbol{x}) \\ \boldsymbol{x} &= (m, t, d(\pi_i, \pi_j), d(\pi_j, d_\theta), r_p(\pi_j)) \end{aligned} \tag{5.4}$$

This essentially corresponds to computing the probability of an infinitesimally small region around the given combination of features $\boldsymbol{x}$. As such, there are some caveats to this approach, foremost that sufficient (and sufficiently distributed) data must be available in order to prevent peaks in the distribution function (that in turn lead to large feature spaces with $p_l(\boldsymbol{x}) \approx 0$). In addition to normalizing the features this ensures that they all exhibit comparable characteristics and thus the sampled densities are in similar ranges. Further, choosing this approach prevents us from computing true probabilities (i.e., all the different travel options do not necessarily sum up to one); instead we compute a (proportional to the true probability) likelihood of traveling along a given tripleg. Within a routing context, this approximation is sufficient as it is proportional to the true probability and is applied for all transport modes equally.

Probability Surfaces

Evaluating the probability functions will give us (discrete) probability surfaces, where each transfer location is assigned a likelihood with which the user under consideration will pass by this location. We can now sample these probability surfaces at potential transfer locations in order to determine likely paths that someone could take through a routing graph. Embedding these probabilities within a transfer graph as introduced in section 5.1 and evaluating them on the fly allows us to compute personalized "most probable" route options for individual people.

5.4 DETERMINING ALTERNATIVE TRANSPORT OPTIONS

A route planning request is essentially a function that returns an ordered sequence of triplegs L_θ, based on an origin o, a destination d, at a time t:

$$L_\theta = r(o, d, t) \tag{5.5}$$

In this section, we will introduce two methods to compute personalized and context-dependent high-level mobility plans based on the transfer graphs and choice probabilities introduced before.

5.4.1 *Heuristic-based Planning Method*

First, we present a preprocessing heuristic that can be used to generate high-level mobility plans by specifying rules and constraints that have to be followed in order for routes to be considered valid alternatives. While the thus generated routes could in theory also be computed by combining various platforms or data sources and applying selected routing algorithms (cf. chapter 3), the resulting routing graphs quickly become very large and adapting them to incorporate various user constraints and preferences leads to downstream graph changes that are difficult to integrate on the fly during a routing request. Instead, we rely upon the introduced transfer graph to build possible multi-modal routes that respect various preconditions and only require updating a smaller graph during the request.

For the here presented heuristic, we add the set of user preferences P, a set of user constraints A and a description of context C to the above introduced Equation 5.5 representing a route request. In addition, the generated routes each contain summary values V_i (e.g., denoting the distance covered with each mode of transport, the overall energy consumption or the financial cost of the trip), resulting in an updated Equation 5.5:

$$\{(L_{\theta,0}, V_0), (L_{\theta,1}, V_1), ...\} = r_{\text{heuristic}}(o, d, t, P, A, C) \tag{5.6}$$

The core of the preprocessing heuristic revolves around a set of individual rules denoting preferences and constraints that adhere to the general rule form of:

$$o[condition] \rightarrow m[condition] \rightarrow d[condition] : [outcomes] \tag{5.7}$$

The rule denotes that the origin o and destination d have to fulfill some preconditions for the mode m to be available, which in turn has to adhere to some conditions for the whole tripleg to be available and chosen for a given user. Exemplary conditions include the marking of a certain location with a given transport mode, the availability of one's own car at a location, or (in the case of a mode condition) the restriction of maximum length for walking triplegs. The outcomes either involve the user, or the context (which gets updated to the next potential location if a certain tripleg is chosen for a user). An exemplary rule could thus look like:

$$
\begin{aligned}
&A[\emptyset] \rightarrow \\
&WALK[(user[distWalked] + dist(A,B) < user[maxDist]) \\
&\wedge\ (\neg\, context[rainyWeather]) \\
&\wedge\ (context[currentTime] \in user[acceptableTimeIntvlWalk])] \\
&\rightarrow B[\emptyset] : \\
&user[distWalked+ = dist(A,B)],\ context[time+ = time(A,B)]
\end{aligned}
\tag{5.8}
$$

This rule states that walking is possible at any location (i.e., the set of location requirements for both A and B is empty), but that the action of walking itself is only possible if the total distance remains below some threshold, it is currently not raining, and the time at which the walking action is performed is within some acceptable time intervals (e.g., someone might not want to walk during the night for safety reasons). The outcome statement of the rule requires an update context, by adding the traveled distance to the *distWalked* counter as well as by updating the time (i.e., in the next iteration of the route computation, the time has advanced by $time(A,B)$ for all the subsequent paths). Note that in order to not rely on an underlying transport graph and to speed up the computations, all distance computations use an Euclidean measure.

We use two functions to apply the heuristic to a transfer graph and thus compute high-level mobility plans: *checkReachability* considers all possible origin and destination locations within a graph, in combination with all potentially available modes M, and checks whether the location and mode conditions hold, i.e., if the transport mode could be used at the given location to reach a potential destination. It returns tuples (L_i, D, M) for each combination (starting at L_i) that satisfies all preconditions. *expand*, on the other hand, does not respect any preconditions but instead is used to generate a new set of locations that can be reached from a given location without any transfers (e.g., applying it on a PT stop would yield all other PT stops that are connected by the same line). The function returns a tuple (O, L_i, M, S) for every reachable location L_i that allows backtracking through the graph at the end of the algorithm to find the actual routes. The "running state" S contains additional information about the route to reach L_i which is necessary as a location L_i can usually be reached via multiple ways.

Route Plan Computation

Using the two introduced functions, we can compute the route plans as shown in Algorithm 5.3 (note that the algorithm is closely related to the way network time prisms are commonly computed, cf. Kuijpers and Othman 2009; Jaegal and Miller 2016). Starting from the origin/destination pair, we first see if there are direct ways to reach the destination from the origin, adding the resulting triples (o, d, m), $m \in M$ to the set of reachable locations S (that form the reachability graph as they consist of connections between two transfer locations). The following steps are iteratively performed (e.g., until a maximum number of transfers is reached or a minimal number of solutions has been found) from the direction of the origin (forward) as well as from the direction of the destination (backwards). This optimization is often performed in routing algorithms, as it reduces the solution space and in this case favors solutions that pass through "hubs" of mobility, which includes most trips longer than some very small distance. The iterative processing first *expand*s the space of possible solutions. For each of the thus generated potentially reachable nodes, *checkReachability* determines if a transition using a given mode m is possible. In that case, the quadruple (L_i, L_j, m) is added to the reachability graph. After a predefined number of iterations (e.g., the specification of a maximum number of transfers), the function *unfold* retrieves all possible routes from the reachability graph. In essence, *unfold* looks at all chains $(O, L_i, ..., D)$ by starting from the origin or destination and following edges in the reachability graph.

The resulting solutions respect context as well as user preferences and constraints. In contrast to performing a routing on a complete transportation network graph, the used transfer graph is much smaller and thus it becomes feasible to continuously update node and edge characteristics during the computation (essentially adopting a time-dependent graph, here applied to different mode choices).

Table A.1 shows a number of exemplary rules that can be used to compute meaningful and personalized route options by adapting various parameters to preferences of users (and that are used in the experiments later in this chapter). In this dissertation, we refrain from learning the rules based on previously recorded data, and instead assume that an expert defines a set of rules appropriate for different classes of people. After computing the route options, different ranking schemes can be

Algorithm 5.3 Generating trip plans, consisting of a number of triplegs covered with different transport modes.

Input. Origin o; destination d; departure time t; a set of user preferences P and constraints A (both in terms of rules according to Equation 5.7); a description of context C; a list of transport modes M; a minimum number of solutions s_{min}; a maximum number of transfers t_{max}.
Output. A set of route alternatives $S = \{(L_{\theta,0}, V_0), (L_{\theta,1}, V_1), ...\}$.

$L_f \leftarrow \{o\}$ ▷ Reachable transfer locations (forwards).
$L_b \leftarrow \{d\}$ ▷ Reachable transfer locations (backwards).
▷ Check if d can be directly reached from o using any of M.
$S \leftarrow S \cup checkReachability(o, d, M, t, P, A, C)$
$i \leftarrow 0$
while $|unfold(S)| < s_{min}$ and $i < t_{max}$ **do**
    $\overline{L_f} \leftarrow expand(L_f, M)$
    for $L_i \in \overline{L_f}$, $L_j \in L_b$ **do**
        $S \leftarrow S \cup checkReachability(L_i, L_j, M, t, P, A, C)$
    $L_f \leftarrow L_f \cup \overline{L_f}$
    $\overline{L_b} \leftarrow expand(L_b, M)$
    for $L_i \in L_f$, $L_j \in \overline{L_b}$ **do**
        $S \leftarrow S \cup checkReachability(L_i, L_j, M, t, P, A, C)$
    $L_b \leftarrow L_b \cup \overline{L_b}$
    $i \leftarrow i + 1$
return $unfold(S)$

applied. In our implementation, we use a distance-based GHG emission model (cf. chapter 4) in order to highlight the routes that produce the least GHG emissions. Other ranking methods compute the total travel duration, the number of transfers, or combinations thereof.

5.4.2 *Preference-based Planning Method*

The here presented second approach to compute high-level route plans from transfer graphs focuses more heavily on personalization, and in particular on using previously recorded movement and mobility data to generate meaningful route plans. To generate them, we move through the transport graph in a similar way as presented in the previous section and compute probabilities of various transitions and transfers. At each mode choice vertex, we use the policy function given in Equation 5.3, while at travel vertices, we use the tripleg choice function given in Equation 5.4. To be able to use a shortest path algorithm similar to the well-known Dijkstra algorithm (Dijkstra 1959), we transform the probabilities given by the policy functions using the logarithm function

$$w_{i,j} = -\ln(p(\cdot)) \in [0, \infty]\,, \tag{5.9}$$

after which the sum of edge weights $w_{i,j}$ to reach the destination d from the origin o is minimized. Computing route options roughly follows the computation of a shortest path using an algorithm comparable to Djikstra's. While a method such as the one used in the heuristic approach from the previous section would be possible too, we here are solely interested in the most probable paths and thus can discard any path that leads to a certain node with a lower probability than another. Algorithm 5.4 shows the complete algorithm. Initially, we assign each node a probability of zero resp. a weight of ∞, except for the origin. Starting from this origin, we then compute probabilities along all edges and update the probabilities of appearing at any of the connected nodes. This continues iteratively whereas the probabilities are summed up at each node, and the *parent* identifier is updated in case passing through another node leads to a higher overall probability at a given node (e.g., it is likely that by walking a person could reach some train station further away; the probability of passing through this train station is higher, however, if the person first walks to a closer train station and then takes the train).

Algorithm 5.4 Generating trip plans, consisting of a number of triplegs covered with different transport modes.

Input. Origin π_o; destination π_d; transfer graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$; a minimum number of solutions s_{min}.
Output. A set of route alternatives $S = \{(L_{\theta,0}, V_0), (L_{\theta,1}, V_1), \ldots\}$.

for $\pi_i \in \mathcal{V}$ **do**
    $dist[\pi_i] \leftarrow \infty$
    $parent[\pi_i] \leftarrow$ NIL
$dist[\pi_o] \leftarrow 0$

$Q \leftarrow \mathcal{V}$
while $Q \neq \emptyset$ and $|unfold(S)| < s_{min}$ **do**
    $\pi_i \leftarrow \min_q(dist[q])$
    if $label(\pi_i) =$ "transfer" **then**
        for $e_m \leftarrow M(\pi_i)$ **do**
            $p_m \leftarrow \frac{\hat{f}_{\boldsymbol{H}}(\boldsymbol{x}_{-m}|m)\hat{f}_{\boldsymbol{H}}(m)}{\sum_{\pi_{i,\hat{m}}} \hat{f}_{\boldsymbol{H}}(\boldsymbol{x}_{-m}|\hat{m})\hat{f}_{\boldsymbol{H}}(\hat{m})}$ (Equation 5.3)
            if $dist[\pi_j] > dist[\pi_i] + p_m$ **then**
                $dist[\pi_j] \leftarrow dist[\pi_i] + p_m$
                $parent[\pi_j] \leftarrow \pi_i$
    else
        for $e \leftarrow (\pi_i, \pi_j) \in E_{\pi_i,\cdot}$ **do**
            $p_l \leftarrow \hat{f}_{\boldsymbol{H}}(\boldsymbol{x})$ (Equation 5.4)
            if $dist[\pi_j] > dist[\pi_i] + p_l$ **then**
                $dist[\pi_j] \leftarrow dist[\pi_i] + p_l$
                $parent[\pi_j] \leftarrow \pi_i$
return $unfold(S)$

Similar to Algorithm 5.3, in the end we backtrack through the reachability graph (starting from the destination) to find the most probable route (using the *unfold*(S) function). In order to generate multiple route options, it is also possible to store all *parents* during the computation and backtrack along several routes. In a multi-modal setting this is particularly easy as we can simply introduce a constraint that no two (mode) label sequences may be the same in the resulting route options set (e.g., we cannot have two routes consisting of mode sequences *walk* $\rightarrow$ *train* $\rightarrow$ *walk*). This results in a useful set of route options for someone planning a journey (as they are all different), yet still allows us to sort according to the probability that someone chooses one route over another.

5.5 DATA AND EXPERIMENTS

In the following, we use various data sources to highlight the functionality and characteristics of the presented methods. The learned preferences rely on the tracked mobility data from the *GoEco!* and *SBB Green Class* projects, the PT specifications in Switzerland (published by SBB on a yearly basis[1]), transport option availability data as published by several transport providers in Switzerland (and Zurich for local ones), carpooling data crawled from a large European carpooling platform, and the general street network given by OSM[2]. The transport availability data from local providers includes carsharing[3], free-floating bicycles (from the free-floating service by *Smide*), as well as station-based bikesharing (offered by *PubliBike*). The carpooling method introduced in section 5.2 was implemented in Java, using the Neo4j graph database[4]. The heuristic and probabilistic methods from section 5.4 were implemented in Python as this allowed integrating a range of libraries to process the recorded mobility resp. the collected transport data more easily. The programs were run on commodity office computers and yielded results in the order of seconds.

1 The timetable can be downloaded from www.fahrplanfelder.ch.
2 The OSM data used within this work is downloaded from download.geofabrik.de.
3 The respective company *Mobility* publishes its available cars under www.mobility.ch.
4 The database can be downloaded from neo4j.com.

5.5.1 *Matching Carpooling Demands with Offers*

The evaluation of our proposed method to match carpoolers among themselves and with PT uses data from a large European carpooling platform as well as the railroad network data from the SBB (which could be expanded to include bus or tram networks as well). The data were retrieved in the GTFS format[5] and consist of 1'912 railway stations and 28'455 routes. As explained before, the latter are stored as individual trips, stopping at roughly 790'000 stops (at different times) throughout the year. The carpooling data consist of approx. 18'000 individual offers which were crawled from the platform within 8 months; 2'000 were randomly selected in order to reduce the computational load during the experiments. The carpooling trips often cover longer distances (a mean of 480 km), and frequently the specified origin, destination and stops along the route do not pass any railroad stop (878/2'000). The underlying street network (used to compute DTAs) was given by Esri StreetMap Premium[6]. For the implementation we used the graph database Neo4j, which offers the possibility to model directed, acyclic and labeled graphs and includes functionalities to compute shortest paths, restrict these computations to label chains, retrieve various metrics of the so generated routes, and more.

Using the data introduced, we applied the steps described in section 5.2. The time-expanded graph from the railway network was connected at stops for which $3 \text{ min} < t_b.t_e - t_a.t_s < 10 \text{ min}$, i.e., the transfer should take between three and ten minutes (while the first is to introduce a realistic time that is minimally required for the transfer, the second simply reduces the number of edges in the graph that need to be considered when computing a shortest path). The POAs for the carpooling trips were retrieved using the Google Directions API, and the respective DTAs were computed using the street network from Esri introduced before.

Nearest Neighborhood-based Approaches

Commonly, routing algorithms incorporating carpooling simply use a nearest neighbor-based approach to compute the closest PT stop that can be used for the transfer. Comparing our method (and its outcome when applied to the dataset introduced) to a nearest neighbor-based approach (with maximum distances of 1, 2 and 5 km from origin, destination and

5 The data can be downloaded from geOps via gtfs.geops.ch.

6 The ArcGIS StreetMap Premium dataset can be accessed via www.esri.com/en-us/arcgis/products/arcgis-streetmap-premium/overview.

	Our Method	**NN 1 km**	**NN 2 km**	**NN 5 km**
Links between driver-defined CP stops and railway stations	969	199	254	306
Links between CP POAs and railway stations	5'683	-	-	-
Total	6'652	199	254	306

Table 5.5.: A comparison of the number of connections when linking a PT and a CP graph using the state of the art NN and the approach introduced in this chapter.

en-route stops), we can significantly increase the number of potential stops along the route. Table 5.5 shows the difference in created links between a PT and a CP graphs when applying Nearest Neighbor (NN)-based methods with various radii in comparison to the graph merging and linking method introduced here. As can be seen, especially the POAs enable us to add a large number of links, but also simply using DTAs for origin, destination, and en-route stops increases the number of potential connections.

To investigate the effects of the approx. 5 million railway transfers, 650'000 intermodal transfers, and 125'000 carpooling transfers (that were created using the merging and linking method introduced in this chapter) on the connectedness of the resulting transport graph, we use the PageRank centrality measure (Brin and Page 1998). The PageRank algorithm was originally developed to rank websites on web search platforms. It essentially considers those nodes as important that have a high number of incoming links from other important nodes (as such, it is a measure that requires an iterative update of values until they stabilize or another stopping criterion is met). Figure 5.6 shows the density of stops with a high PageRank measure: On the left, only railroad stations are considered (and linked to each other), and on the right in addition CP stops are added. It can be seen that adding CP to a transport graph "smoothens" the resulting graph, which means that there are more well-connected stops and thus people do not necessarily have to travel to the larger hubs to get to their destination. In addition, the resulting network is more tolerant to outages, as the trips are more spread out and do not focus on a few very important stops.

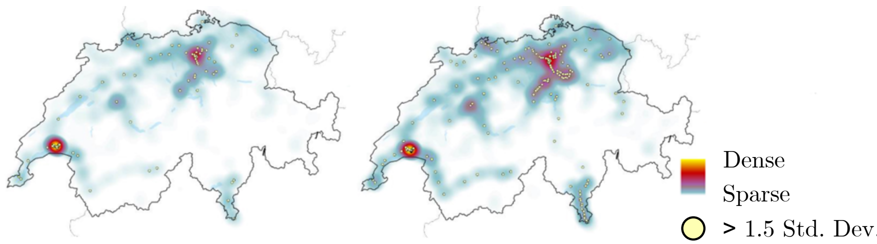


Figure 5.6.: Density map of transfer locations that exhibit a high PageRank. The right figure shows the smoother distribution of high-PageRank stops after merging and linking carpooling stops to the PT graph.

Figure 5.7 and Figure 5.8 show two exemplary routes generated by the method described within this chapter. The first figure is based upon a traveler heading back home from Bern (the capital of Switzerland) to Olten, a smaller town in the North of Switzerland. The computed route uses a carpooling offer from Sierre (Switzerland) to Liège (Belgium) which was identified to have stops in Bern as well as Egerkingen (via the use of POAs). In combination with a small train ride from Egerkingen to Olten, the resulting trip costs CHF 7.60 and takes 46 minutes. Traveling the same route solely using PT, as identified by the official route planner of the SBB, costs CHF 30 and takes 47 minutes. As can be seen, the resulting trip shows roughly the same duration yet comes at a much lower price.

The second example is based on a traveler who wants to visit the city of Milano (Italy) from Olten. As can be seen, the resulting trip combines a train journey with two different carpooling offers to get to Milano in roughly 220 minutes for the cost of CHF 27.20. The corresponding trip by SBB would cost more than CHF 103 and take around 294 minutes. In this case, not only is the price of the route involving CP roughly 25% of the corresponding PT route, but there is an additional time saving of about one hour.

Of course, it is not always possible to have carpooling offers align that well. However, by decreasing the (manual) effort that is currently required for people to specify their carpooling offers and by automatically computing feasible detours along the route, hopefully more people will

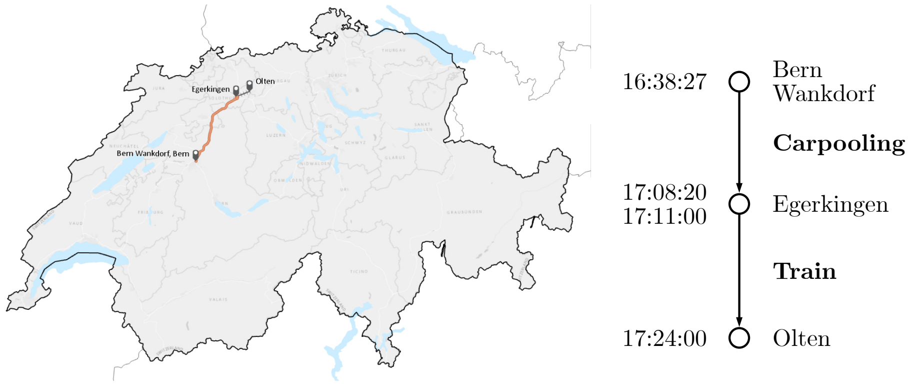


Figure 5.7.: Exemplary route from Bern to Olten.

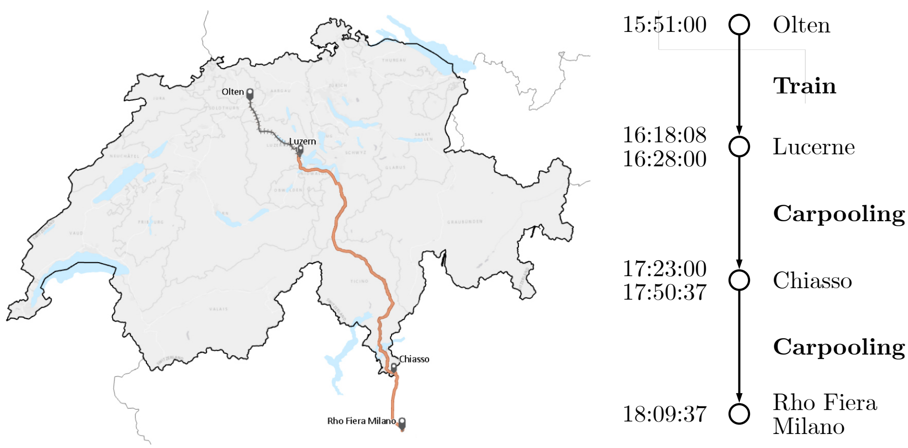


Figure 5.8.: Exemplary route from Olten to Milano.

publish their journeys by car, and thus enable a larger number of routes to be found using the method introduced here.

5.5.2 *Heuristically Generated Route Plans*

To show the applicability of the heuristic to compute personalized and context-dependent route options, we again use the GTFS data from the SBB, together with the carsharing stations of the Mobility carsharing company, all the bikesharing stations within the city of Zurich, as well as the Open Source Routing Machine (OSRM) and OSM for the underlying street networks and display on maps. We introduce a set of general rules for these transport modes, as explained in section A.2. Two exemplary case studies involving two persons each are used to highlight the presonalization and context-dependence achievable using the heuristic planning method:

1. Persons A und B intend to travel from the Northeast of Zurich to the city center. While the current weather is fine, the forecasts indicate a downpour roughly 15 minutes after the intended departure time. A likes to travel by car (and has one available), but does not like to travel more than 1 km on foot. B is willing to walk up to 3 km, and has neither a car nor a bicycle available. The general unwillingness to walk during rain is modeled by a distance decrease by a factor 5 during rain. Finally, as both are aware of their ecological impact, they would like to use the route option that causes the least amount of GHG emissions, even at the expense of longer walking distances.

2. Persons C and D intend to travel from the suburbs of Zurich to the city center late at night. Even though C has a bicycle, he or she is afraid of walking or cycling at night and thus tries to keep the distances covered with these modes small. D, on the other hand, does not mind cycling even at night, he or she even prefers cycling longer distances to exercise.

These case studies intend to represent realistic scenarios in which a flexible (and potentially adaptable, either manually by the user of a system or by automatically learning from previous behavior) system brings benefits over the current state of the art, which primarily optimizes the route choices minimizing the travel duration.

The first case study highlights the differences based on individual preferences, context such as the weather and also the availability of certain transport modes. Figure 5.9 shows the generated route plans for persons A and B. It can be seen that A only receives the suggestion to travel by car, for one because the person does not like to walk large distances on foot (even though there is a PT stop roughly 450 m from the person's home, the maximum walking distance gets reduced to 200 m due to the forecast of rain, and there is an additional segment at the end of the trip that would have to be covered by walking), and for the other because this person has a car available roughly 400 m down the road. We show two sets of route options for person B: The left side does not consider the forecast of rain, while the right side does. As can be seen, the upcoming rain prevents the user from taking any mode of transport that requires a longer walk in the end (during rain, the maximum walking distance is reduced from 3 km to 600 m), and only several bus rides remain as an option on the right side. It also needs to be noted that while there would be route choices with smaller walking distances (and thus likely smaller total travel times), these are not generated by the heuristic due to the fact that both A and B prefer more ecologically sustainable routes, which in turn precludes the use of e.g., PMT or carsharing if PT or cycling are available (this is not directly visible from the presented ruleset, but instead is achieved by ranking the generated routes before presenting them to the users). Finally, it needs to be noted that not all the route choice options in the left figure might actually be available to the user (due to the actual PT schedules resp. connections in trips with multiple PT triplegs). However, the generated output is very natural for a user in that it tells him or her about possible mode combinations and transfer locations to get to the destination, and lets the user (with the assistance of a "route refinement system") further plan the route to be chosen.

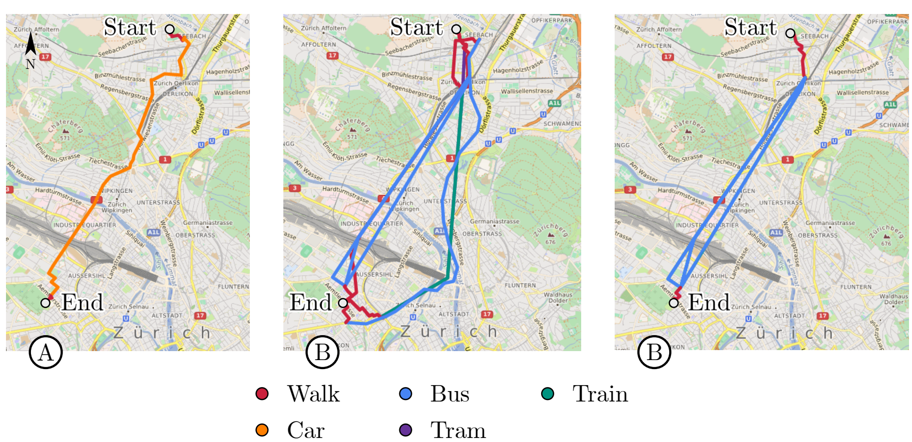


Figure 5.9.: Results from the persons A and B from the second case study to evaluate and discuss the high-level route plan heuristic presented in this chapter.

Figure 5.10 shows the results of case study two. Person C can use carsharing only, as he or she does not want to walk too far during the night, and all options involving PT also require significant walking distances of more than 200 m. Person D, on the other hand, can use the same carsharing option, as well as options involving the personal bicycle, and various trams that run to the city center. While not visible in Figure 5.10 (similar to Figure 5.9), the order of the returned options is [*bike*, *public transport*, ..., *carsharing*] as D would also like to use an eco-friendly mode of transport before resorting to transport modes that cause more GHG emissions. This is again achieved by computing the GHG emissions after generating all route choices and ordering the returned results accordingly.

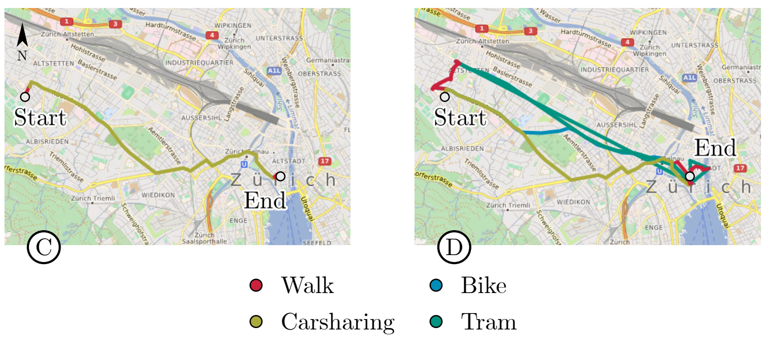


Figure 5.10.: Results from the persons C and D from the first case study to evaluate and discuss the high-level route plan heuristic presented in this chapter.

5.5.3 *Preference-based Route Plans*

To evaluate the applicability to generate personalized route plans, we use the data recorded as part of the *SBB Green Class* study. Figure 5.11 shows the empirical distributions of transport mode choices depending on various features of a single exemplary user (the actually used joint probability distributions are combinations of all these features, whereas we assume that they are all independent). It can be seen that the tripleg length is a good predictor for the chosen transport mode, as is the hour of day or the connectedness of the PT stop at which a person transfers. The distance to the destination is particularly useful for this user as it determines that the bicycle is often used if the distance is below 10 km. The increased probability to walk if the distance to the destination is between 50 and 70 km stems from the fact that for such distances we usually start a trip by walking, before switching to a transport mode such as car or train. The figure also highlights the importance of normalizing the features before using them in a routing context (i.e., to lie in the range $[0, 1]$) as the sampled densities otherwise primarily depend on the values the feature takes.

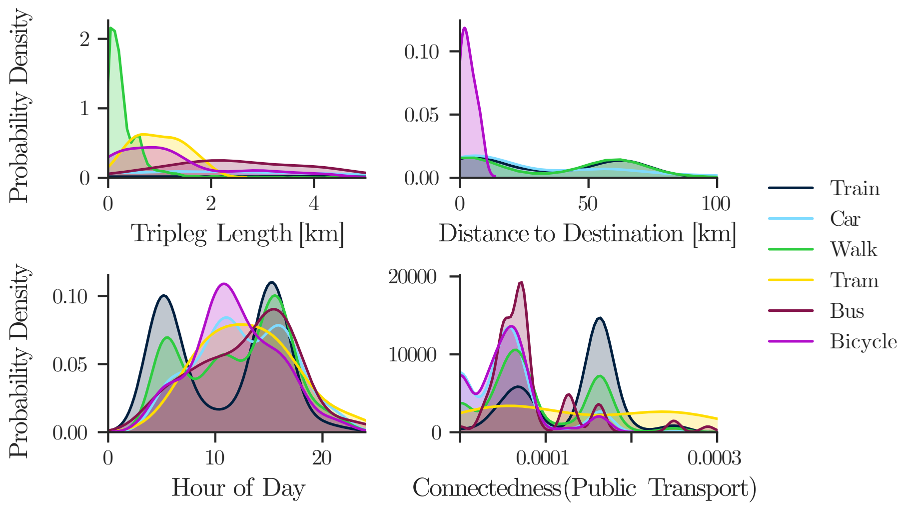


Figure 5.11.: Kernel density estimates of the probability distributions of various features.

Figure 5.12 shows the "probability surfaces" as computed during the routing procedure. In this case, we simply look at the probabilities of traveling to all transfer locations in the study region that are reachable by the chosen transport mode. As can be seen, when the person starts *walking* from the location denoted with *Start*, the probability is highest that she or he will only travel to one of the transfer locations in vicinity. For all the other transport modes (that allow traveling further distances more easily), the probability of ending up close to the *End* location (resp. destination) is high. While the *train* can only stop at a few selected stations and the evaluated *carpooling* offer only stops in the two transfer areas indicated by the grouped green dots, the *free-floating bicycle* enables the user to travel anywhere. In contrast to walking, however, this user previously recorded data that shows that he or she is willing to travel similar triplegs by bicycle, and as such the probability of ending up close to the destination (or directly at the destination) is higher. It can also be seen that the probability of stopping before the destination is higher than driving past it and walking back (i.e., there is a slight skew in the free-floating bicycle probabilities towards the *Start* position of the user).

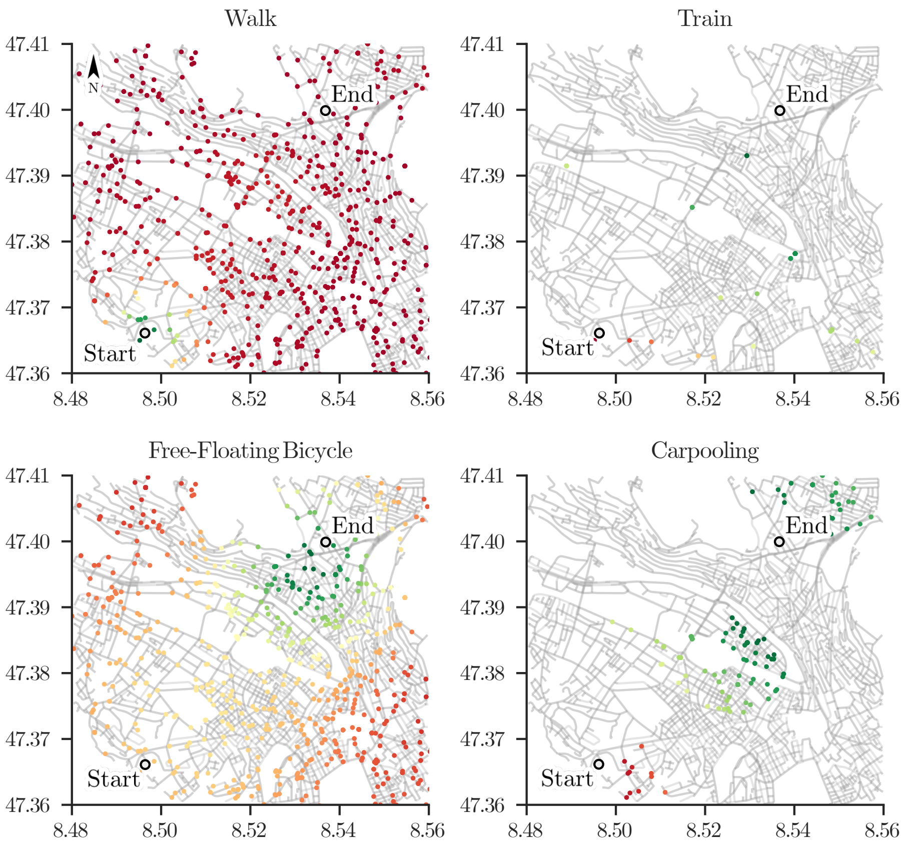


Figure 5.12.: Probability surfaces of four different transport modes.

In Figure 5.13, we show the generated route plans for three different users of the *SBB Green Class* study (exhibiting different feature distributions). In these plots, only the top two recommended routes are displayed, and routes exhibiting equal mode combinations are not shown (e.g., if a user is recommended to take a free-floating bicycle there are usually several available, each of which would generate a separate route plan; as those are very similar, they are not shown here). As can be seen, the first user commonly uses the bus for trips resembling the one from *Start* to *End*, and thus gets this as the first recommendation (followed by taking the free-floating bicycle). Similarly, the second and third users either use the bicycle or car for routes exhibiting similar features as the one that is being planned. As such, the recommendations for them either involve primarily the *bicycle* or *carsharing* (note that the private car was not available in this experiment, but that we use the same feature distributions for the individual *car* and *carsharing*; the latter was required because *SBB Green Class* did not explicitly require participants to indicate when they used carsharing and as such no training data was available).

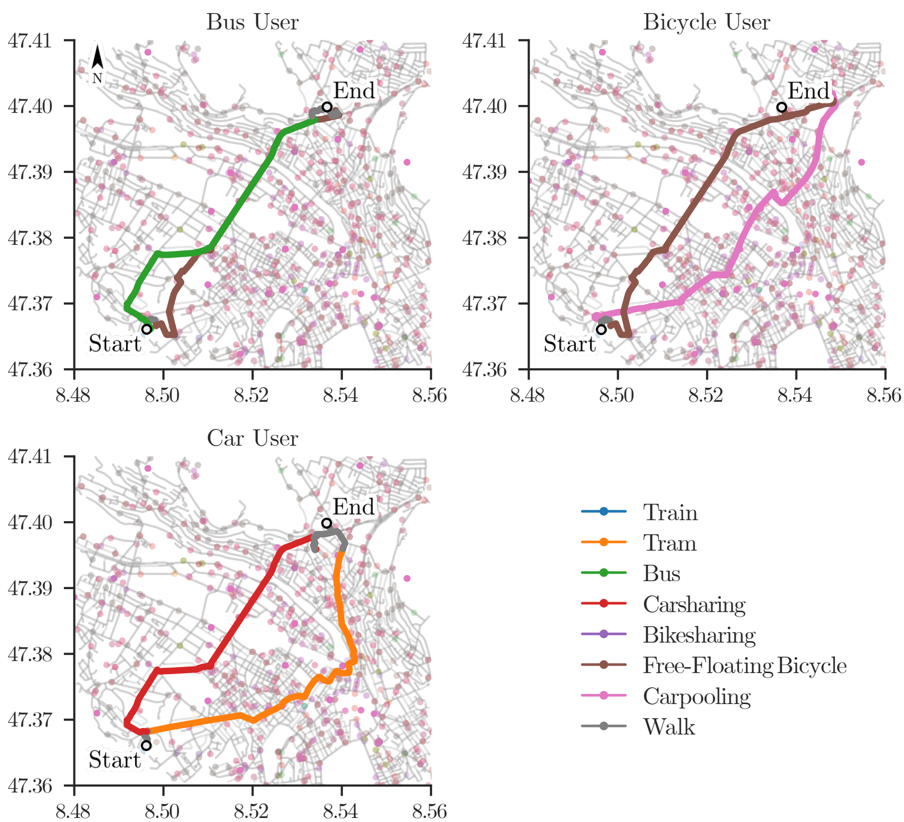


Figure 5.13.: Personalized route recommendations generated by our method for three participants of the *SBB Green Class* study.

5.6 CHAPTER SUMMARY

In this chapter, we proposed several methods to improve the personalization and inclusion of less commonly used but ecologically friendlier transport modes (such as carpooling or free-floating bicycles) within route planners. We argue that improving route planners is important for changing people's mobility behavior towards a more sustainable one, as a) the assistance by technology increases the effectiveness of *facilitators* (i.e., the work required for a person to find an eco-friendly route alternative is smaller, and thus the people are more likely to try out different alternatives), b) the resulting routes are often not only more ecologically friendly, but also lead to financial and/or temporal savings (and thus form an additional motivator) and c) the resulting routes can be used to gauge the potential for change for individual persons and thus facilitate proposing changes and improvements to people and embedding them within motivational affordances as discussed in the next chapter. The three introduced methods focus on carpooling, heuristics that can be tuned to a wide range of personal preferences and influencing context factors, and personalized route planning that relies on features as introduced in chapter 4 and the specification of mobility offers in a generalized manner involving transfer points and areas, and the respective mode availabilities between them. The following chapter will build upon the here introduced planning methods to support people in their mobility choices using a range of persuasive methods.

6 COMMUNICATING MOBILITY

In the previous two chapters, we introduced ways to process passively recorded tracking data with the aim of extracting information and generating alternative route plans that could guide persuasive applications in the choice of strategy to help a user achieving more sustainable mobility. Here, we will present different approaches to utilize this information within the context of persuasive smartphone applications, and highlight the results of their application within a large-scale user study performed in two geographically different contexts in Switzerland. Such Behaviour Change Support Systems (BCSSs) are "information systems with psychological and behavioral outcomes designed to form, alter or reinforce attitudes, behaviours or an act of complying without using coercion or deception" (Oinas-Kukkonen 2013, p. 1225). Figure 6.1 shows a high-level overview of the processes involved in processing and communicating the data in a way that is meaningful for the individual user. Starting from the mobility information extracted directly from the tracking data, and in combination with the alternative route options generated as described in chapter 5, we can score a user's past behavior, evaluate the available options, predict likely future mobility needs, and compute a set of persuasive elements based on these data. In this chapter and in line with the presented user study, many of these elements revolve around gamification, which has been used previously to foster desirable behaviors successfully (cf. chapter 3).

6.1 EFFECTIVE COMMUNICATION OF MOBILITY BEHAVIOR

A wealth of research treats the question of how to communicate behavior and incentives in ways that make them as effective as possible to support people in behavioral transitions (cf. chapter 3). Complementing this research, we here present a taxonomy of motivational affordances

This chapter and its contents, algorithms and figures are based on Cellina, Bucher, Rudel, et al. 2016; Weiser, Scheider, et al. 2016; Weiser, Bucher, et al. 2015; Cellina, Bucher, Raubal, et al. 2016; Bucher, Cellina, et al. 2016; Bucher, Mangili, Cellina, et al. 2019; Cellina, Bucher, Mangili, et al. 2019; Cellina, Bucher, Veiga Simão, et al. 2019.

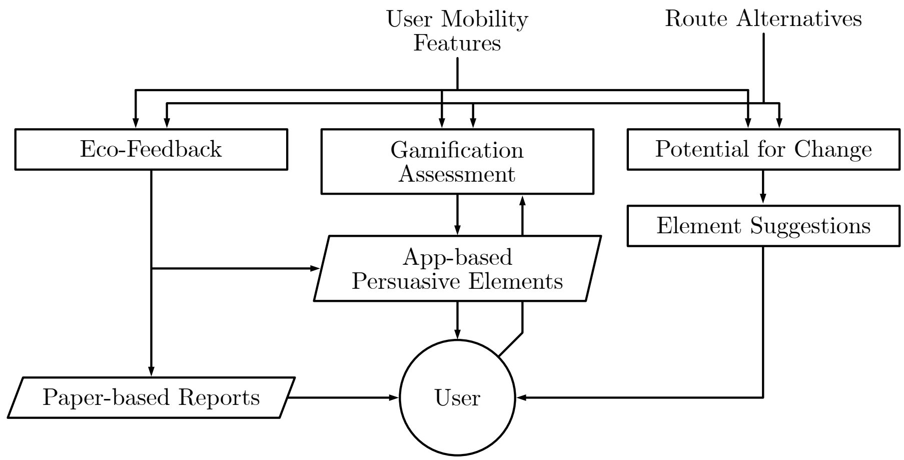


Figure 6.1.: The main information processes required for efficient mobility communication and (eco-)feedback generation.

for meaningful gamified and persuasive systems that assists application designers in choosing from a range of strategies and elements targeting behavior change. Figure 6.2 shows the three-tier taxonomy. On the uppermost level, there are five *design principles* that should always be followed in order to comply with the psychological roots of motivation, as explained in chapter 3. On the next level, several *mechanics* are available that each concentrate on a particular psychological need that generates motivation, and that should follow the overarching design principles. Finally, we specifically consider gamification *elements*, which are the building blocks that can actually be implemented within an application. While the design principles and mechanics provide generally applicable guidelines, we will use the mobility features and route options introduced in the previous chapters to evaluate and build the individual elements. The chosen gamification elements are introduced using the example of *GoEco!*, which is also used to evaluate and discuss the strengths and weaknesses of the chosen implementation.

6.1.1 *General Design Principles*

The following five general principles emerge from the theory of motivation presented in chapter 3. They should in particular be kept in mind when implementing any mechanic or element presented below.

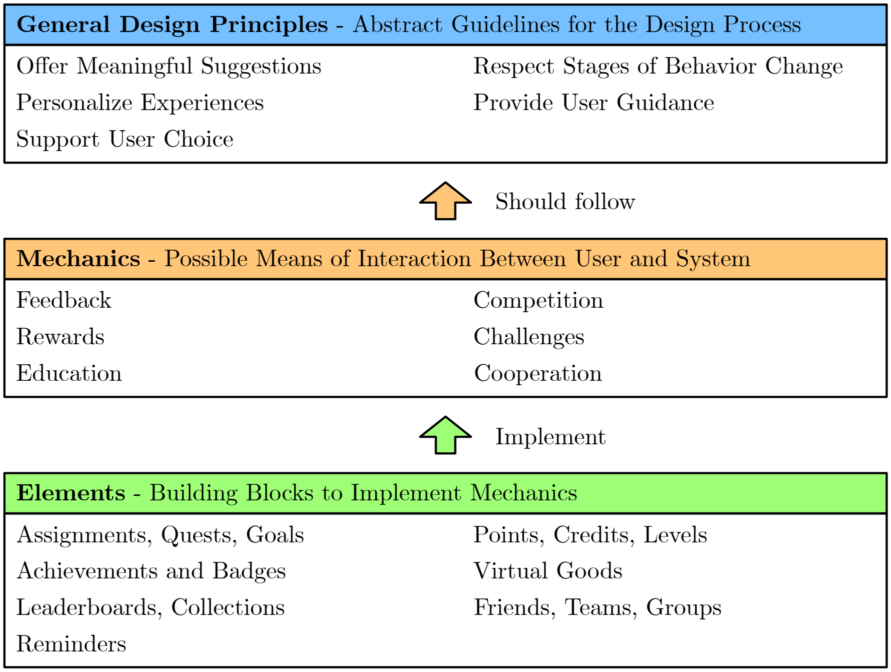


Figure 6.2.: Principles of motivational affordances that researchers and practitioners can follow to create persuasive, gamified, and meaningful applications. The gamification elements selected within *GoEco!* will be discussed in section 6.3.

OFFER MEANINGFUL SUGGESTIONS The principle of *offering meaningful suggestions* is mainly rooted in a) the fact that every decision requires an active engagement with the topic at hand (i.e., it requires cognitive effort and thus receiving proactive suggestions can increase the efficacy of the process) and that b) suggestions should not conflict with other goals a person might have (hence the requirement to be meaningful). In addition, providing suggestions helps to learn about one's own behavior by setting it in relation with the suggested behavior and thus highlighting potentially impedimental behaviors. For example, suggesting to "take the bus instead of the car" (for a certain trip) is only meaningful if there is a bus running at the time, and if the user is not required to transport heavy luggage by car. Thus, in order to create meaningful suggestions, respecting a user's context (as described in the previous chapters) is paramount. It is, however, highly difficult to capture context in its entirety, for which reason usually approximate tradeoffs are used (e.g., that an alternative would be viable for a systematically traveled route, if its duration does not exceed a certain threshold).

SUPPORT USER CHOICE Rooting in the psychological need for autonomy, the design principle of *supporting user choices* aims at letting users specify their own goals and the pace at which they work towards them. This stands in close relation to the previous principle of meaningful suggestions, essentially stating that people should be given more than "either-or" choices. Completely supporting user choice even means considering the scenario that a user does not approve of any of the options proposed by the persuasive app, and let a user adapt the system to her liking. Giving users choices also prevents "technology parenting", whereas users are discouraged because they feel that an application has too much control over them, and thus stop using it. The gained autonomy gives room for empowerment strategies, where a user can (virtually) practice a behavior or explore cause-and-effect relationships and thus become more versed at various behaviors. For example, suggesting similar transport options in different situations lets a user experience their viability in various contexts and thus gain a better understanding about the different options.

PROVIDE USER GUIDANCE *Providing user guidance* usually takes the form of task reduction or tunneling, whereas the difficulty of a task is either reduced or the experiences of a user are controlled. Providing guidance is important during the acquisition of new skills. Structuring information in an appropriate way can help people more easily grasp desired behaviors and the actions needed to achieve them. For example, presenting mobility data in an aggregated from and highlighting particular traits that run contrary to the desired behavior helps a user understand quickly where improvement is needed. Giving concrete examples of how to improve these traits, and guiding people by providing achievable steps towards the target behavior reduces the complexity of a behavior change and nudges users in the "right direction". Components that provide user guidance must be able to handle failures in exhibiting certain behaviors to prevent people from getting frustrated and relapsing to previous behavior. The latter gives a user of a system the freedom of choice, and thus again connects the process of achieving competence to the personal desire to do so (i.e., the need for autonomy).

provide personalized experience *Personalizing experiences* within a persuasive app usually takes two forms: On the one hand, letting users customize their experience within the app (e.g., by letting them modify the user interface) gives them a sense of ownership and possibility to express their self-identity. On the other hand, and more important within the context of the here studied applications, tailoring the content to the behavior of the user (or user group) satisfies our needs for relatedness, affiliation and followership. In addition to being more useful if the elements within an app are personalized, the application designer can thus foster a stronger bond between the user and the motivational artifact. It needs to be noted that personalization is often domain-dependent, though, and as such requires iterative design processes. As mobility is highly individual, personalization quickly becomes a central aspect of any non-trivial application: By analyzing someone's recorded trajectories, and giving feedback on how to improve behavior, the persuasive application already requires a deep understanding of a person's mobility (in contrast, consider a trivial app that only provides educational elements, such as (randomly timed) notifications to go to work by bicycle).

design for every stage of behavior change As already discussed previously, the path to acquiring a new behavior undergoes several stages. Optimally, applications automatically identify these stages and implement elements that respect the current stage a person is in. For example, a person who is not aware of a certain behavior that is not in line with his or her overall goals (and thus is in a pre-contemplation stage), should be given information about the behavior, comparisons with alternatives, and information that allows reflecting on it. Later, alternative behaviors and the provision of small tasks (instead of suggesting the ultimate target behavior directly) increase the ability of the user to get incrementally closer to the desired behavior. Highlighting the differences to other people and the desired outcome provides a strong motivational source, and thus can be selectively employed to "overcome" difficult situations. And as noted before, during stages where people take action in implementing certain behaviors, concrete suggestions, rearrangements of tasks, or even only informative feedback can help the user to adjust his or her actions towards the desired behavior.

In the following, we will describe the individual mechanics, which should follow the introduced design principles to ensure a high persuasiveness.

6.1.2 *Mechanics*

Mechanics describe the ways in which a user and a (persuasive) system can interact. As such, it is not required that all of them are implemented within a single system, however, those which are, should be in line with the general design principles introduced previously.

EDUCATION Education intends to provide a user with knowledge about a potentially desirable behavior, but also about how to perform tasks to reach it. It primarily targets the psychological needs for competence, but can also contain elements that satisfy the need for followership in case it is given via the role of instructors. Especially in early stages of behavior change, education plays a central role, as it can highlight differences between an idealized self and the exhibited behavior and thus induce cognitive dissonances that form a strong motivator. Similarly, it can point to normative behaviors (thus targeting the needs for affiliation and relatedness), it can create awareness, and increase a user's ability to perform certain tasks (essentially by giving instructions). In later stages educative measures can keep a topic interesting by providing additional information. Education is best used while respecting context: normative statements that lack context (such as "you must do x", without any additional reasoning) have little effect on exhibited behaviors. Examples from the sustainable mobility domain include education about the environmental effects of different transport modes, statistics on mobility use within a certain region, or the availability of different transport modes (that might previously be unknown to the user).

FEEDBACK Feedback is any information given back to a user that lets her assess the currently (or recently) performed behavior. It is either given instantly or after a short period of time (during which a larger amount of data can be accumulated into fewer representative indicators), and is mostly visual, but can also be auditory, haptic, or in a variety of other forms (e.g., commonly, a notification on a smartphone combines all three). Feedback is used in one form or another in most computer applications, in particular in pervasive systems. Next to providing motivation by showing discrepancies in exhibited and desired behavior, it can decrease the difficulty of tasks (e.g., when it contains suggestions about potential alternatives to the exhibited behavior) and thus "increase the ability" of a user. However, when feedback contains alternative behaviors, they must be meaningful and the user must be given a choice, in order to prevent technology parenting. If feedback is given instantly after a behavior was exhibited, it forms a stronger link than when given in an "offline manner" (i.e., at a later point in time). Of particular importance within the context of mobility, the system designer has to be careful that the feedback does not interfere with the activity a user is currently performing. For example, notifying a user using a visual cue while she is driving is distracting and leads to an increased risk of accidents. Giving feedback in an accumulated form at a later point has the advantage that it can be summarized well and thus more easily used to compare the current behavior to the past, and to other people in similar situations.

Indirect Feedback

More indirect forms of feedback do not necessarily require knowing anything about the user, but instead simply rephrase a situation or task in such a way that a user is inclined to exhibit the desired behavior. For example, it was found that painting perpendicular and unevenly spaced lines on the road lets people decrease their speed when passing the respective road segment (Leonard 2008). Feedback can also be given for small and (potentially) unintentional behavior changes, which leads to an adjustment of a person's belief system and thus motivates larger and intentional future behavior. However, giving feedback that is not necessarily in line with a person's belief system can also have demotivating effects, as it results in inconsistencies in one's representation of the world, and thus leads to a rejection of the imposed desirable behavior. Such "boomerang feedback" has to be considered in most cases; for example, indicating the average behavior of a user group within feedback usually leads to a regression towards said average, even if the exhibited behavior was more sustainable. Finally, it is important to note that the users of a persuasive application will not always utilize feedback given to them to change or improve their behavior, as they will often not have a complete and perfectly accurate representation of reality and will not strictly maximize sustainability. Giving correct feedback at appropriate times will increase the perceived credibility and persuasion capabilities, however.

REWARDS Rewards are mechanics that solely generate motivation, and do not change the ability of a user to perform a certain task. In addition, the generated motivation is primarily external, and as such has a range of negative associations that require a system designer to carefully evaluate if the benefits of employing rewards outweigh their negative connotations. While rewards fulfill the needs for achievement and competence in the best case, they might lead to a user performing a certain action solely for the reward in the long run, thus decreasing the overall motivation (external and internal) to perform a desired behavior. Related to this, extrinsic motivators are unsuitable to induce long-term behavior changes, as people will commonly only exhibit the behavior as long as the reward is present, and stop as soon as the extrinsic motivator disappears. In addition, for a user to continuously perform a desired behavior, the reward size has to be increased over time, and its frequency and predictability has to be changed in order to contain a moment of surprise. Failing to do both will lead to decreasing motivation and (as it is primarily an external motivator) falling back to the original (potentially undesirable) behavior.

CHALLENGES Challenges are rooted in our need for competence. Their essence is to give a (somewhat difficult) goal that allows benchmarking one's own behavior, skills, or performance. They are particularly useful when competition and cooperation is impossible, i.e., when the set of involved users and/or contexts is diverse. Additionally, they can help people without goals or people who do not know how to achieve a (potentially too difficult) goal, by providing guidance and/or reframing the desired outcome in terms of the involved steps. For example, adding upfront or intermediate goals that are easy to reach (within a larger process to achieve some desired behavior) can increase the likelihood that someone completes a task, as people feel like they are competent and making progress. Splitting up larger goals into smaller (more reachable) ones similarly relates to our need for competence, as these smaller goals seem more reachable and thus satisfy our need to feel competent more quickly. This strategy of "divide and conquer" can be found in many fields, and essentially describes how one large goal can be overwhelming, preventing a person from starting to work on it at all. When choosing challenges and/or goals, it is important to choose reasonable defaults, as people will usually not make the effort of manually adjusting them even when presented with multiple options.

COMPETITION Rooted in the needs for achievement and leadership, competition is a mechanic that works well for people who are approximately in the same situations and exhibit the same skills. These comparisons with a rival party become demotivating, however, when the differences in skills are large or when one party faces highly different circumstances. For example, giving a group of people awards based on how often they take the bicycle to work will demotivate people who need to transport baggage and thus cannot participate in the competition. Similarly, there are circumstances in which competition may be unwanted, e.g., within a family where one might follow a non-competitive ethic and want to foster cooperation and collaboration instead. Finally, it needs to be noted that the framing of a comparison is crucial, as it influences the outcomes greatly (as a very simple example consider two rankings of participants where the one who uses the bicycle the most is on top in one, and the one who uses it the least is on top in the other; the resulting motivations will greatly differ).

COOPERATION Cooperation is the opposite of competition, building upon our needs for relatedness, affiliation and leader-/followership (when roles in a cooperative setting are distributed in a way that makes individual people leaders for certain tasks). As cooperation always involves a group of people that works together in an attempt to reach a goal, it naturally works in settings where people are social and the mix of skills and knowledge within the group complements itself. This means that everyone gets to "play a part" (and thus is able to show competence), and will feel related (due to the common goal) and affiliated (due to the inalienability in the team) to others. Having anonymous teams where people do not know each other is less motivational. Often cooperation and competition are combined, whereas essentially groups of cooperative teams are formed that compete against each other. In the context of persuasive applications supporting sustainable mobility cooperation could, for example, include functionality that rewards people for carpooling together.

6.2 GENERATING AND COMMUNICATING ECO-FEEDBACK

Based on the general design principles and individual mechanics introduced above, there are several ways how to generate and communicate eco-feedback. Here (and in accordance with the chosen approaches within the *GoEco!* project), we will introduce "paper-based" mobility reports that are in particular suitable for targeted mobility studies, as well as persuasive smartphone applications. The latter enable both collecting mobility data and communicating feedback regarding the recorded behavior directly from within one device (that is available to a substantial share of people and thus theoretically allows scaling an app-based mobility behavior change intervention to the whole world).

6.2.1 *Mobility Reports*

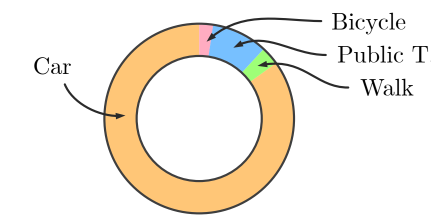
A straightforward approach to giving eco-feedback on mobility is by providing a report that summarizes the exhibited (and recorded) behaviors. The benefit of this approach is that it is independent of the mobility recording system employed, as a typical "paper-based" mobility report only requires knowing to which user a certain report must be sent. For example, simply tracking the car of a person (i.e., not recording any movement that is performed without the car) already allows gaining insights into the GHG emissions, or duration spent traveling. In addition, such reports can highlight which trips could potentially have been undertaken with a more sustainable mode of transport, thus adhering to the design principles of providing personalized experiences and user guidance (naturally, the highlighted alternatives must be meaningful in the given situation). Being paper-based and thus offering limited forms of interactivity, reports mostly generate motivation through the mechanics of *education* and *feedback*.

Figure 6.3 shows an exemplary (and slightly abstracted and simplified) report as given during the *GoEco!* experiment. After several weeks of mobility tracking, people were given a booklet that summarized their behavior in the last weeks in terms of travel distances, durations, modal shares, as well as energy requirements and GHG emissions. Next to a range of tables (not shown here) that provide a more detailed weekly overview, the report focused on highlighting the differences between the status quo, and a hypothetical, more sustainable behavior that was computed using the heuristic method introduced in chapter 5 (in combination with a PT router to evaluate the results given by our method). The second part of Figure 6.3 (denoted "Potential for Change") shows the same indicators considering the more sustainable behavior. As can be seen, in the case of this user, most trips by car could actually have been performed by PT as well, leading to a reduction of the CO_2

emissions by approx. 50%, and a decrease of the energy demand by 35%. However, this would also entail an increase in travel duration from 7 hours and 24 minutes to 8 hours and 51 minutes (an increase of roughly 20%). The "Main Energy Demand / GHG Emission Contributors" section is additionally included to put an emphasis on those transport modes whose use is particularly concerning when trying to reduce GHG emissions.

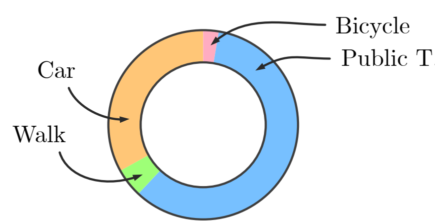
Mobility Behavior

Travel Distance	228.66	km/week
Travel Duration	7h 24min	t/week
Car	84.94	
Public Transport	9.55	
Slow Mobility	2.37	% km/week
Walking	3.14	
Other	0.00	
Energy Requirements	187.02	kWh/week
CO_2 Emissions	39.05	$kgCO_2$/week

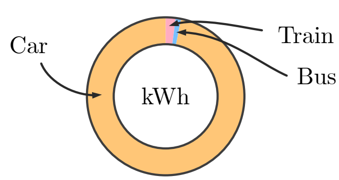


Potential for Change

Travel Distance	271.74	km/week
Travel Duration	8h 51min	t/week
Car	33.10	
Public Transport	59.35	
Slow Mobility	2.64	% km/week
Walking	4.92	
Other	0.00	
Energy Requirements	121.57	kWh/week
CO_2 Emissions	19.80	$kgCO_2$/week



Main Energy Demand / GHG Emission Contributors



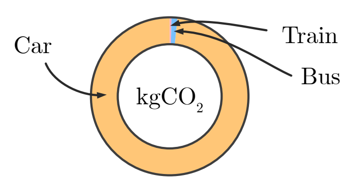
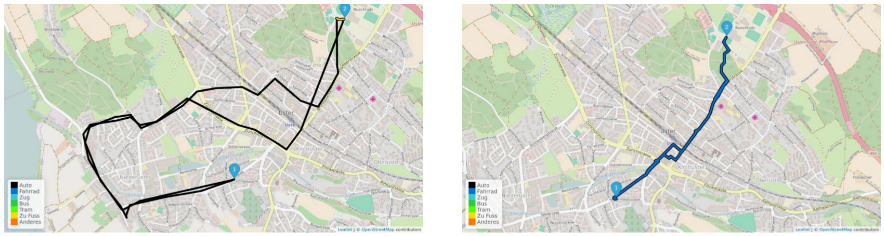


Figure 6.3.: Exemplary "paper-based" report as used within the *GoEco!* project. Next to a summary of the status quo behavior, an assessment of potential (and meaningful) changes in mobility behavior is given.

Including visual representations (as shown in Figure 6.3) allows users not only to easily compare their behavior with a potentially more sustainable one, but also with their own previous behavior (upon receiving multiple reports) and among each other. However, as those comparisons require manual efforts by users, paper-based mobility reports should be replaced by more interactive means whenever possible.

Systematic Route X

Your Route | Potential Alternative



Your Route	
Length	11.22 km
Energy Requirements	10.33 kWh
CO_2 Emissions	2.20 $kgCO_2$
Average Travel Duration	0h 26min
Mode of Transport	Car, Walking

Potential Alternative	
Length	3.97 km
Energy Requirements	0.71 kWh
CO_2 Emissions	0.07 $kgCO_2$
Average Travel Duration	0h 16min
Mode of Transport	Bicycle

Figure 6.4.: Suggestions for alternative routes as given within the "paper-based" mobility reports.

Finally, Figure 6.4 shows a second important component of the mobility reports used within *GoEco!*. For each trip that was identified as systematic (cf. chapter 4), a (more) sustainable alternative was identified and presented as a meaningful suggestion on how to change the mobility behavior.

6.2.2 *Persuasive Apps*

As paper-based mobility reports suffer from several drawbacks (most notably the restriction to non-interactive mechanics and elements), we will in the following concentrate on persuasive techniques employing interactive technologies. Nowadays, persuasive (smartphone) apps arguably offer the most convenient alternative, as they can combine tracking with (interactive and gamified) feedback elements. Figure 6.5 shows three feedback-oriented application screens, as used within the *GoEco!* app. Similar to the paper-based reports the feedback component of the *GoEco!* app revolves around the provision of summary statistics that provide a quick overview of one's own mobility behavior. In the left figure, a summary of the travel distance, time, energy consumption as well as CO_2 emissions is given. In addition, several of the gamification components (which will be introduced in section 6.3) are summarized. This summary view is supplemented by functionality that breaks down travel into individual routes, as shown in the middle of Figure 6.5. For each of the recorded triplegs, the total distance, duration and transport mode is shown, and the users are given the possibility to change or validate the detected transport mode.

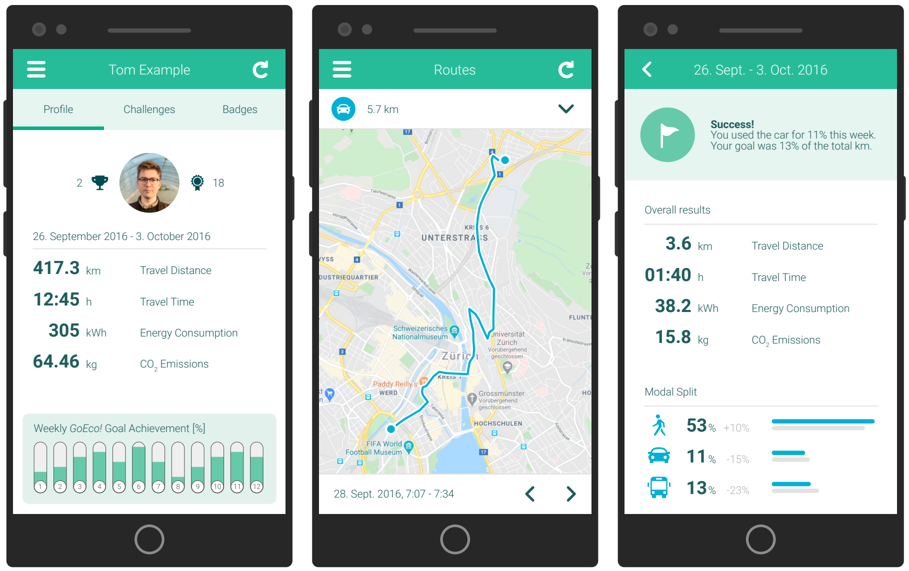


Figure 6.5.: Feedback screens used within *GoEco!*. On the left, equivalent information as given within the "paper-based" mobility reports is shown. In the middle, spatio-temporal information regarding each tripleg is available, and users are given the possibility to validate or adjust the detected transport mode. On the right, the summary for an exemplary week is given, also highlighting the changes compared to the previous week.

Finally, to enable comparisons across several weeks, the screen on the right side provides the same summary statistics as the main "profile" screen (on the left), but for each week individually. In addition, there are visual representations of the used transport modes and comparisons to their use in the previous week, as well as a summary of the achievements of that particular week (in terms of progress towards a chosen goal, cf. section 6.3).

6.3 GAMIFICATION

Gamification describes the concept of using game-like elements in non-gaming contexts. Taking mobility as an example, we can frame the process of increasing its sustainability as a game, thus "gamifying" it. Figure 6.2 shows the gamification elements available to system designers (that each implement one or more mechanics). In the following, we extend the above introduced taxonomy of motivational affordances by concrete gamification elements. Examples for the elements (as potentially used within the mobility domain) will be given by referring to the *GoEco!* app. Note that the usefulness within the mobility domain varies between elements, and not all of them are implemented within *GoEco!*. The assessment of the chosen gamification strategy will be disseminated and discussed in section 6.4.

6.3.1 *Elements*

A wealth of research exists on the motivational characteristics of various game elements (i.e., what makes games fun and what makes us keep playing them, cf. Malone 1980; Prensky 2001; Deterding, Sicart, et al. 2011; Blythe and Monk 2018). Most of them can be transferred to non-game contexts, albeit they are usually adapted to the target domain and in particular the visual aspects are often greatly reduced. Just as the mechanics should follow the general design principles, these elements implement the mechanics in different ways.

ASSIGNMENTS, QUESTS, GOALS Building upon the *challenges* mechanic, assignments, quests and goals all present users with a desired behavior that should be reached. While a user is required to complete an assignment in order to progress, quests are optional and goals describe a long-term desirable state. As such, assignments have to be employed carefully, as they are in conflict with a user's need for autonomy, risk that a user feels patronized by technology, and should often be replaced by quests altogether. Both assignments and quests are commonly used in combination with goals, whereas they break up a goal into smaller and more easily reachable parts. While assignments and quests can be completely specified by the persuasive app (resp. the system designer), goals should leave some room for fine-tuning to the user, in order to support the need for autonomy. However, proposing (and implementing) specific and challenging yet not overly difficult goals is required to yield the best motivational results. Of course, this is largely dependent on the domain and context a user is in: Within the context of sustainable mobility, proposing the goal of reducing GHG emissions by a certain amount requires knowing exactly how much was produced previously, and whether the user would have realistic alternatives to the current behavior available.

As an example, consider the two functionalities of the *GoEco!* smartphone app shown in Figure 6.6: The goal-setting screen on the left side is based on an assessment of a user's previous behavior, and his or her potential for change (as computed using the methods introduced in chapter 4 and chapter 5). However, to support user autonomy, and because it is unclear from tracking data alone, the "slider" lets a user fine-tune his or her goal (which in this case consists of reaching a lower energy consumption within the next week). On the right, a number of selectable challenges are shown. As users are not forced to compete in any of them, they fall under the quest category in the presented taxonomy. Similarly, because a user knows the possibilities of increasing sustainability best herself, the app simply offers suggestions that are in line with the previously recorded mobility data. To provide some extrinsic incentive, the challenges are coupled to receiving trophies for repeated completion (this can also be used to compete publicly against other people). In the example, the user had already completed several challenges, for which she was rewarded with a bronze resp. silver trophy.

ACHIEVEMENTS AND BADGES Achievements and badges are awarded for certain predefined behaviors. As such, they can serve several purposes: If known beforehand, they give users direction within the system (i.e., they can teach a user how to use a system), and they implicitly work in tandem with assignments, quests and goals, as they all specify a goal after reaching of which the achievement or badge is awarded. In this function, they mainly target our needs of competence. To satisfy the needs for achievement, and leader-/followership, badges are often publicly displayed. Not only can this boost a user's own motivation, but it can also signal to other people how a person interacts with the system and which desired behavior she expresses. This in turn results in the satisfaction of our need for affiliation, as it allows identifying ourselves with other people who similarly behave or interact with the system.

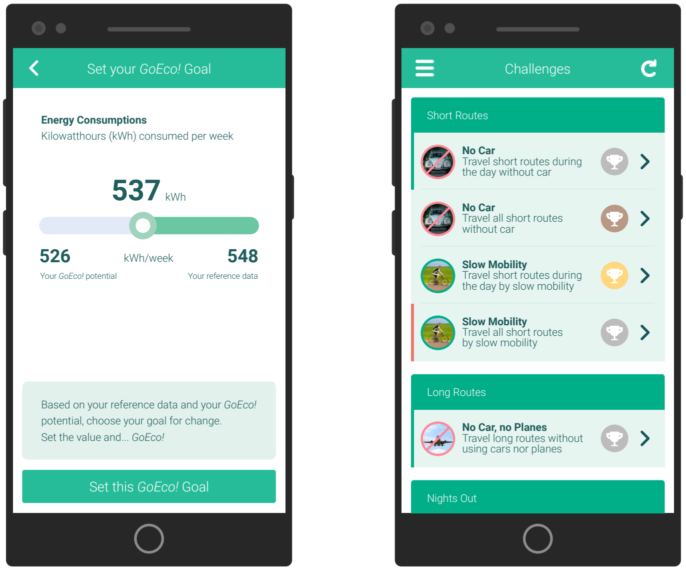


Figure 6.6.: The goal-setting and challenge selection screens in *GoEco!*. The possibility for users to choose their own goal is based on an assessment of potential behavior change, and supports the need for autonomy.

Offering badges (esp. if they are awarded at surprise moments) leads to higher exploratory and targeted usage of an application. However, to be perceived useful, badges must not be awarded for simplistic or repetitive tasks, and should require the use of contextual information (again to be specific and thus interesting).

On the left side, Figure 6.7 shows several badges as implemented within the *GoEco!* application. In this case, the available badges were known beforehand and usually existed at multiple levels (e.g., travel with a certain mode at increasing distances), to direct users into a given direction (i.e., using more sustainable modes of transport). In contrast to the challenges introduced in the previous section, however, users do not have to explicitly choose a badge to work towards, but they are simply awarded any time the related behavior has been exhibited. Similar to the trophies awarded for completing challenges, the badges are used for social comparison, primarily by considering the number of awarded badges. To summarize the difference in the implementation chosen within *GoEco!*: While challenges and goals were explicitly chosen (and thus adhere to the needs of autonomy and competence), badges were invariably available and primarily adhered to social needs (via the competitive elements explained in detail below).

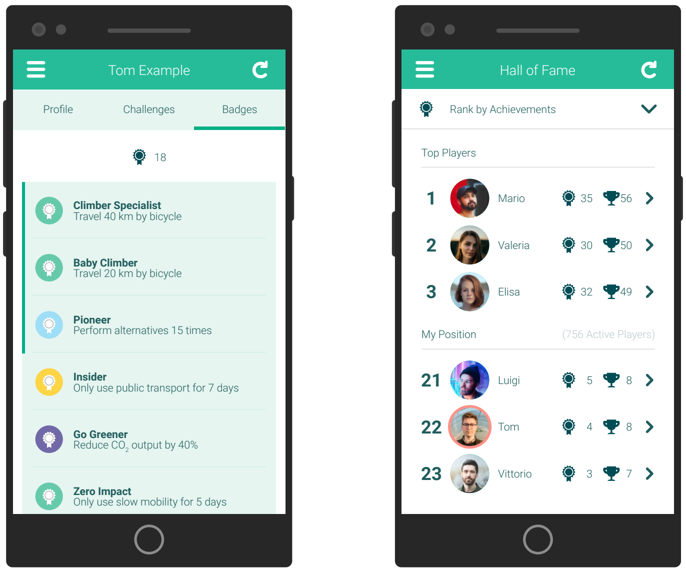


Figure 6.7.: The available badges in *GoEco!* and the leaderboard that both shows the trophies awarded for completing challenges as well as the badges received throughout the study period.

POINTS, CREDITS, LEVELS Points, credits and levels are numeric representations of behavior and the progress towards a certain behavior. As such, they contain a strong comparative (and competitive) aspect, next to giving feedback by rating different behaviors (and thus allowing comparisons with one's own previous behavior). Similar to achievements and badges, they can be used as a display of progress and status, and thus cater to our needs for achievement and leader-/followership. In contrast to points, credits can usually be traded for other components within the system, and levels are used to group point ranges and thus allow comparing users more easily and give a better sense of achievement and competence. All the mentioned numeric representations have several drawbacks: They can easily lead to behavior that opposes the desired one (e.g., awarding points or credits for traveling by PT could in extreme cases make people travel more to collect them), they should be awarded for similar behavior yet be adapted to the task at hand (which is very difficult in a highly individual setting, such as mobility—what is easy for one person might be unfeasible for another; it is neither fair giving them the same amount of points nor is it fair giving them different amounts), and their positive effects on motivation are not univocally proven (e.g., Mekler et al. 2013). Due to their controversial nature, especially within highly individual settings such as mobility, we did not include them within the *GoEco!* persuasive application.

LEADERBOARDS, COLLECTIONS Leaderboards primarily target social needs such as the need for achievement or leader- and followership. In essence, they show our achievements publicly and thus allow comparison, but also self-evaluation. Their effects on motivation are manifold, though: Especially for people in the lower parts of the leaderboard it can be motivating, as it is nearly impossible to "chatch up" and achieve the behavior of those leading the board. To circumvent this, it is possible to only show a competition with people exhibiting similar behavior. This can either be with people occupying similar positions (as is especially common for many online games, where different *leagues* separate players according to their rank), or people in similar situations (e.g., in the mobility domain this could be people living in similar regions, such as a city or a more rural area). It is also possible to only selectively show a leaderboard to users who already interact with the system frequently and are ranked towards the top, or to award people at the lower end more to make it easier for them to catch up and prevent them from stopping to use the persuasive application.

As an example, Figure 6.7 shows the leaderboard as implemented in *GoEco!* on the right side. Because mobility is highly individual, the competition is based on the rewarded badges and completed challenges. Especially the ranking in terms of challenges fosters a fairer competition, as every user is free to compete in as many as possible and as they are usually formulated in a relative way (i.e., they can be achieved by everyone similarly; for example, *travel all short routes by slow mobility* does not set a minimum or maximum number of required "short routes"). In addition, while *GoEco!* highlights the top positions, only a smaller section around the user's own position is shown which alleviates some of the negative effects associated with showing all the people who perform better or worse.

REMINDERS Reminders are used to prevent relapses into earlier stages of behavior change, can serve as feedback to a user, and encourage habit formation (though their effectiveness to this purpose is disputed). Their frequency and timeliness is important, but depends on the user and their content: For some people, reminders can quickly become a nuisance, while in other situations more frequent reminders are acceptable. For all reminders, it is better when they are generated by other human beings instead of in an automated fashion. Within *GoEco!*, reminders were provided for the weekly challenges (to choose one, but also if the progress towards the challenge goal did not proceed as fast as necessary). These reminders were chosen before the background of supporting users in their autonomy (i.e., they were reminded to choose something themselves or about a choice they had previously made). Framing reminders in this way reduces the chance that they are perceived as a nuisance.

FRIENDS, TEAMS, GROUPS Offering social elements such as connecting with friends, or forming teams and groups adheres to our needs for affiliation, relatedness and intimacy (and up to some degree to leader-/followership). Next to fostering cooperation, such functionalities offer possibilities to split up a user base into smaller groups (e.g., a large mobility user study like *GoEco!* can be split up according to the geographic region, or the personal situation of individual people), intra-group discussions on how to achieve certain goals, inter-group competition, the possibility for more advanced users to help newcomers and/or weaker players, and also to equalize large differences in users (by teaming up stronger and weaker players). Similar to competition between users, letting teams compare each other can act demotivating for weaker teams, though. Within *GoEco!*, friends, teams and groups were not explored except for real-life meetings among participants (this did not have any effect on the information displayed within the app though).

VIRTUAL GOODS Virtual goods are a special form of reward that have a real economic value (i.e., can be bought and sold from within the gamified system). As such, they share most of the characteristics with rewards such as achievements or points; in particular they adhere to our needs for achievement, competence, and leader-/followership. Similarly, they can also be used for social comparison, e.g., within a leaderboard—however, because of their economic value outside of the gamified system they go further and can be used as extrinsic motivator. Due to this and the fact that they can be bought as well, they are usually not required for intrinsically motivated people (who work towards their goals of their own accord), and can even lead to adverse effects (e.g., when people simply "buy their way up a leaderboard"). Finally, and very well visible in games that let you publicly display your purchased goods, the perceived effect you have on other players is largely influencing the decisions to buy virtual goods. Within *GoEco!*, there were no virtual goods due to their problems with the different motivation sources of people (i.e., the fact that they have detrimental effects on internally motivated people).

6.3.2 *Computation and Assessment*

For the introduced gamification elements to be unobtrusive and proactive (i.e., they must be available to a user without any specific interaction), all computations must be made on the automatically and passively tracked mobility data. As such, within *GoEco!*, we primarily relied on daily or weekly aggregates of mobility descriptors as introduced in chapter 4 and evaluated their change over time resp. their relation to descriptors exhibited under the assumption that a person would always choose a sustainable alternative (when available and if the trip was classified as unsustainable; cf. chapter 4 and 5). This periodical re-evaluation of mobility behavior and gamification elements based on aggregates suffers from the drawback that users potentially have to wait several hours after performing a trip before they get any feedback or rewards from doing so. Developers of a persuasive resp. gamified application thus have to find a balance between immediate feedback (and thus a more "game-like" experience) and ease of computation and interpretation of feedback (i.e., a daily aggregate is easily understood and computed and can take a person's complete exhibited behavior into account, while immediate feedback has to assess whether trips are completed already or if the app should withhold updating the gamified components until a later time).

6.4 DATA AND EXPERIMENTS

As introduced previously, the presented principles, gamification elements, communication strategies and computations were implemented within the *GoEco!* project, with the aim of analyzing the long-term effects of persuasive apps on mobility behavior. In the following sections, we will give a detailed account on the research questions, project setup, evaluation methods and results of the project.

6.4.1 *Project Setup*

GoEco! studied the effects of persuasive apps on mobility behavior. While both qualitative and quantitative research on these effects existed previously (cf. chapter 3), *GoEco!* envisioned a large-scale (i.e., involving several hundred participants) study performed over roughly a year in diverse geographic regions, to be able to quantify the impact of different interventions on mobility behavior at various scales and within various contexts. To this purpose, *GoEco!* followed the project setup shown in Figure 6.8. In a first phase running from March to May 2016 (8 weeks), the whole study sample installed the *GoEco!* tracker application on their mobile phones that simply recorded their movement and mobility and allowed them to validate or change the detected modes of transport.

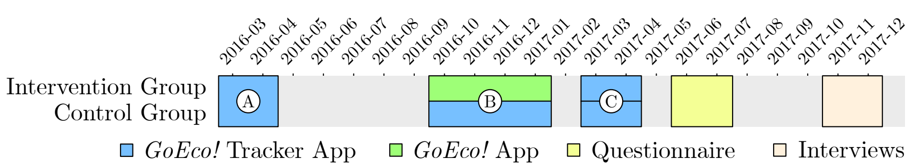


Figure 6.8.: The timeline of the *GoEco!* project, involving three phases spanning one year, a control and treatment group, as well as post-experiment questionnaires and interviews.

In the second phase, running from October 2016 to February 2017 (16 weeks), the sample of study participants was split up into two groups: While one third of the participants continued using the tracker app (solely recording mobility), the other two thirds installed the complete *GoEco!* app, including the feedback and gamification elements introduced in the previous sections. Finally, during a third phase, running from March 2017 to May 2017 (8 weeks), all participants again installed the tracker app to study whether the changes in mobility behavior remained, or if the effect of a persuasive app in the mobility domain diminishes after the intervention has ended. The three phases took place over one year and were followed by different questionnaires as well as in-person interviews during November/December 2017. Starting in Fall 2015, participants were recruited using a media campaign and advertisements on social media and in various locations around the campus of the University of Applied Sciences and Arts of Southern Switzerland (SUPSI) and the Swiss Federal Institute of Technology Zurich (ETH Zürich), the two partners who conducted the *GoEco!* experiment.

Tracking Implementation

Due to limitations imposed by the project budget and the related development resources, *GoEco!* was developed as a combination of two applications: On the one hand, we relied on the *Moves* application[1] that was a popular fitness tracking app at the time (discontinued as of August 2018). As shown in Figure 6.9, Moves tracked all movements and automatically assigned a sports-related "transport mode" to each identified tripleg (as Moves' intended use is to track activities such as *jogging*, *cycling* or *rollerskating*, the "transport modes" primarily correspond to these activities; driving by *car* was identified, but other means of transport were generally classified as *transport*). Moves published the tracked data using an API that could either be polled at regular intervals or set up as a publisher-subscriber system, enabling Moves to send notifications whenever new data was recorded and processed.

In addition to the *GoEco!* (tracker) app, the *GoEco!* application consisted of a server backend (written in Python and Scala, and running on server hardware) that regularly retrieved new data from the Moves API and processed it using several of the methods described in chapter 4 and chapter 5. In particular, we reclassified the transport mode according to the requirements of *GoEco!* (namely to be able to differentiate between transport modes that differ largely in their energy requirements and GHG emissions), computed the eco-feedback shown in the app, and updated the gamification elements used throughout the app. The results were stored in a central database, from which the app continuously read the most up-to-date data and fed back transport mode validations as well as interactions with the app (such as choosing a new challenge).

1 Information about *Moves* can be retrieved using the Wayback Machine (e.g., web.archive.org/web/20160110111352/https://www.moves-app.com) or in (Bucher, Cellina, et al. 2016).

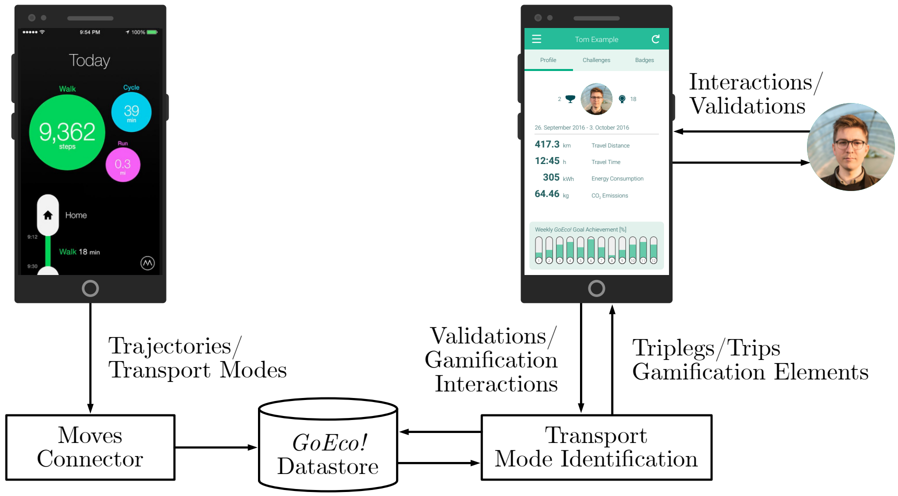


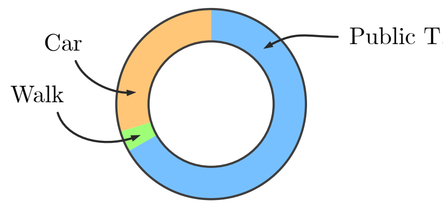
Figure 6.9.: An overview of the *GoEco!* architecture. While the Moves app tracked the movement of participants, and "pre-classified" the transport modes into sports-related modes, *GoEco!* featured its own classifier (described in chapter 4). The resulting mobility data were stored in the *GoEco!* datastore, which was accessed by the app for the computation of the gamification elements.

Additional Eco-Feedback

In addition to the reports introduced in subsection 6.2.1, which were sent to participants at the end of the first phase, a second report was sent at the end of the second phase that additionally contained information about the behavior change exhibited during the second phase. Figure 6.10 shows the additional information: The section on *mobility behavior changes* was used to give people feedback about how they changed their usage of mobility and the resulting in- resp. decreases in sustainability (as measured via the proxies CO_2 emissions and energy requirements). To further promote collaboration within the *GoEco!* project, additional in-person events were held during the second phase (this included several bicycle tours as well as visits to energy-related exhibitions). The attendance of these events was very low, though (up to approx. 10 people), for which reason they were discontinued after several weeks and are not considered further in the analyses below.

Mobility Behavior in Phase 2

Travel Distance	270.82	km/week
Travel Duration	7h 53min	t/week
Car	29.66	
Public Transport	66.78	
Slow Mobility	0.00	% km/week
Walking	3.56	
Other	0.00	
Energy Requirements	115.94	kWh/week
CO_2 Emissions	17.79	$kgCO_2$/week



Mobility Behavior Changes

Travel Distance	-28.08	km/week
Travel Duration	-21.45	t/week
Car	-13.12	
Public Transport	+12.86	
Slow Mobility	+0.00	% km/week
Walking	+0.26	
Other	+0.00	
Energy Requirements	-40.46	kWh/week
CO_2 Emissions	-46.88	$kgCO_2$/week

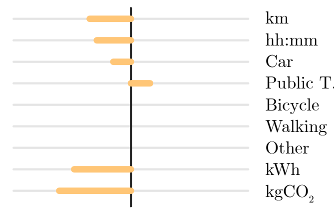


Figure 6.10.: Extract of the reports sent after the second phase. These reports intended to give the participants feedback about their changes in mobility between phase one and two.

It needs to be noted that even though it was the goal of *GoEco!* to perform a large-scale study, it turned out to be notoriously difficult to keep the users' interests high over the duration of one year. At the start of the study, 599 participants signed up for participation (out of which 277 were from Ticino, a predominantly rural region in Southern Switzerland, and 322 from Zurich, the largest city in Switzerland). 26 people could not start with the study due to incompatible smartphones. Out of the other 573, 212 fulfilled the minimal requirements of active tracking and validation for several weeks within phase A and could enter phase B. These requirements stated that a participant has to have at least three weeks of activity, where an active week was defined as having (validated) data on at least four out of seven days, and 50 recorded trips (out of which 80% needed to be validated). Ultimately, at the end of period C, we could use data from approx. 50 people (the exact number of participants varies with the analyzed property reps. hypotheses, e.g., some participants were sufficiently active for general analysis but did not exhibit a sufficient number of systematic trips for an analysis of the behavior changes within regular mobility), roughly 8.3% of the people who originally signed up. This number corresponds to app retention values found by other (commercial) projects (Guerrouj, Azad, and Rigby 2015; Sigg et al. 2019), and thus indicates that many people may not have perceived *GoEco!* primarily as a research project (in which case they would more likely have kept actively participating within the study until the end), but rather as a regular app on the market (that one removes once the novelty fades). While this reduces the explanatory power of the analyses determining the effects of a persuasive app on mobility behavior, it gives additional insights about the "real-life applicability" of a persuasive strategy centered around smartphone apps.

6.4.2 *Research Questions, Hypotheses and Evaluation Methods*

The main research question of *GoEco!* follows the fourth question given in chapter 1: *Do people adjust their mobility behavior upon receiving (eco-)feedback based on their previous choices?* To answer this question and as the main outcome of *GoEco!*, the three hypotheses stated below were analyzed:

Hypothesis 6.1. The average GHG emissions per kilometer are lower after the *GoEco!* intervention.

The main aim of a persuasive app such as *GoEco!* is to reduce the overall ecological impact caused by its users' mobility demands. Our primary proxy of the environmental impact are the GHG resp. CO_2-equiv. emissions of individuals, for which reason Hypothesis 6.1 (and the following ones) is formulated in terms of GHG emissions. Using CO_2-equiv. as a measure allows using emission factors computed within other research, and captures the entirety of GHGs that affect the environment. Of course, simply using a factor based on the distance is only an approximation, however, computing the exact emissions is usually not possible, as context such as the vehicle type, its exact velocity, or the number of passengers is generally unknown. The second hypothesis concerns the effects of the *GoEco!* app itself on the mobility behavior.

Hypothesis 6.2. The before/after difference in GHG emissions is larger for people treated with the *GoEco!* app than for those who did not use the app.

To ensure that the observed effects in Hypothesis 6.1 are not due to external effects (such as seasonality, a general shift towards more sustainable behavior in a population, or due to sample selection), the second hypothesis makes use of the control group and quantifies the differences in observed behavior between the treatment and the control group. The third hypothesis examines the effects of regularity on the potential for behavior change.

Hypothesis 6.3. Hypothesis 6.1 and Hypothesis 6.2 hold true when only regarding the subset of *systematic loops* in every person's mobility usage.

Based on our previously stated intuition that there is a difference between regular behavior (such as going to work or visiting relatives) and irregular behavior (going on weekend trips, on holidays, or for spontaneous trips), Hypothesis 6.3 states that we can observe the same behavior of a reduction in GHG emissions on regular trips. This also means that in case we have to reject Hypothesis 6.1 and Hypothesis 6.2 but cannot find any grounds upon which to reject Hypothesis 6.3, that regular behavior is indeed easier to change, and the *GoEco!* intervention had a positive effect, albeit only on the subset of more easily changeable trips.

All hypotheses were evaluated on the tracked mobility data of all the *GoEco!* participants that showed a sufficient data quality. These participants were identified based on their ground truth data, collected in phase A, and had to:

- at least have three active weeks within the first period, where an active week had to
- at least have four active days, where an active day is defined as
- any day that has at least one validated route (i.e., the user had to show some interaction with the tracking data on the given day).

6.4.3 *Effects of GoEco! on Mobility Behavior*

To test Hypothesis 6.1, we compare the total CO_2 emissions in periods A and C. As there might be some additional people stopping to use the app after phase A, we adapt the criteria from the previous section to only include people who have at least three active weeks in any of the periods, collected at least 50 routes in each phase, and validated 80% or more. Out of the remaining 52 participants, we only consider

		CO_2 Emissions per km
p-values (one-side Wilcoxon signed-rank test)	Ticino	0.21
	Zurich	0.19
Average difference between periods C and A ($X_C - X_A$)	Ticino	-12.03 gCO_2/km
	Zurich	5.96 gCO_2/km

Table 6.1.: The differences in GHG emissions (measured in terms of CO_2-equiv.) between tracking phases A and C.

the validated routes for testing the hypothesis. Out of these 52 people, 21 resp. 13 were in the treatment group in Ticino resp. Zurich, and 10 resp. 8 in the control group. As the distribution of the CO_2 emissions is not Gaussian, we used the Wilcoxon signed-rank test to compare individuals' changes from A to C, and Wilcoxon rank-sum to compare the treatment and the control group (Hypothesis 6.2 and Hypothesis 6.3).

Table 6.1 shows the resulting differences between periods A and C. It can be seen that in the more rural region Ticino the CO_2 emissions decrease after the *GoEco!* intervention, contrary to the urban region of Zurich. While this could be explained by the different context and in particular by the different perception and availability of mobility (e.g., in Zurich, driving by car is actively discouraged by the authorities and PT alternatives are much more readily available), the p-values show that neither of the results is significant. Thus, on the overall mobility behavior, *GoEco!* did not seem to have any significant impact, and Hypothesis 6.1 has to be rejected.

In line with the intuition that systematic routes are easier to change (as they often only have a few requirements such as having to carry luggage or providing space for a family, and as people often show habitual behavior and thus do not evaluate alternative options without external stimuli), we applied the same test to the CO_2 emissions generated by systematically traveled routes only. Here, systematic routes are defined according to Definition 4.9. As this restriction to regularly traveled routes changes the available data for each user, we re-evaluated the number of users fulfilling a minimal data quality criterion, resulting in 45 participants fulfilling the preconditions for testing Hypothesis 6.3.

Table 6.2 shows the differences in CO_2 emissions when only considering systematic routes. As can be seen, the differences are larger, the

		CO_2 Emissions per km
p-values (one-side Wilcoxon signed-rank test)	Ticino Zurich	0.023* 0.342
Average difference between periods C and A ($X_C - X_A$)	Ticino Zurich	-23.931 gCO_2/km -7.776 gCO_2/km

Table 6.2.: The differences in GHG emissions (measured in terms of CO_2-equiv.) between tracking phases A and C (stemming from systematic routes).

participants in Zurich also show a decreasing trend, and the change in CO_2 emissions in the rural area Ticino is significant. Taking up on the possible explanation presented previously, it seems likely that the reason for this difference are the varying circumstances in which the two participant groups are. While most people from the city of Zurich already travel by PT and SM (as the use of cars is discouraged, usually taking any other mode of transport is equally fast, and many people try to exhibit sustainable behavior), people in Ticino often have to rely on their cars even for daily commutes. This different use of mobility is rooted in the fact that many people have to rely on their cars for their daily activities, and thus also use them without much thought even if more sustainable alternatives are available.

To ensure that the observed decrease in CO_2 emissions is not due to some uncontrolled causes, we compare the treatment with the control group. Table 6.3 shows the results of this comparison. It can be seen that in Ticino the CO_2 emissions of the control group increased after the *GoEco!* intervention, leading to a total difference between phases A and C and the control and treatment group of 33.137 gCO_2/km. This difference was found to be significant, but not in Zurich, where it is much smaller as well.

6.4.4 *Evaluation of the Presented Mobility Alternatives*

To evaluate the usefulness of the presented alternatives (as part of the eco-feedback reports sent after the first and second phases), we additionally surveyed the participants of *GoEco!* regarding their systematic mobility and the applicability of the presented alternatives. Out of

		CO_2 Emissions per km
p-values (one-side Wilcoxon signed-rank test)	Ticino Zurich	0.049* 0.157
Difference between periods treatment and control group $(X_C - X_A)_{TR}$ - $(X_C - X_A)_{CTRL}$	Ticino Zurich	-33.137 gCO_2/km -1.439 gCO_2/km

Table 6.3.: The differences in GHG emissions (measured in terms of CO_2-equiv.) between tracking phases A and C and the control and treatment groups. Similar to Table 6.2, only the systematic routes were considered.

261 participants who were invited to participate in the online questionnaire, between 102 and 104 people answered (depending on the question). They were presented with the identified systematic movement patterns and generated alternatives (using a combination of the OpenTripPlanner (OTP)[2] for PT routes and the heuristic presented in subsection 5.4.1 for less frequently used combinations such as bicycle and PT) and asked several questions regarding the quality of identification and suitability of proposed alternatives. Table 6.4 shows the results of the three most important questions asked as part of the survey.

The resulting values show a positive assessment of the functionalities provided by *GoEco!*, in particular regarding the identification of reference mobility patterns and systematic mobility. In addition to the above answers, 85 users responded for 651 systematic tours of whether they would "classify this [tour] as systematic (namely, a [tour] that [they] frequently travel)" and if they think that the proposed alternative is plausible. The results (also shown in Table 6.4) indicate that most tours were identified correctly, and that the plausibility of alternatives is mostly given. Interpreting the comments given alongside the survey questions, most wrongly classified tours were simply not perceived by people as they involved shopping or leisure activities that were not considered regular behavior by the users themselves. Out of the 235 alternatives identified for tours, the survey respondents answered for 42 if the proposed alternative was plausible. 50% of the automatically found alternatives were either scored with 4 or 5 (on the 5-point Likert

2 The OTP can be retrieved from www.opentripplanner.org.

	M	SD
The reports correctly identified my reference mobility patterns, in terms of percentage of use of the means of transport (n=104).	5.81	0.98
The reports correctly identified my reference mobility patterns, in terms of systematic journeys (n=102).	5.73	1.26
The reports suggested realistic and feasible alternatives for my systematic journeys (n=102).	4.31	1.47
Individual Tour Assessments		
Would you classify this tour as "systematic" (n=550)?	3.98	1.40
Do you think the alternative is plausible (n=42)?	3.38	1.62

Table 6.4.: Assessment of systematic mobility and potential alternatives as identified by the *GoEco!* application (first three rows $n = 102 - 104$, 7-point Likert score, where 1=*totally disagree* and 7=*totally agree*; rows 4 and 5 $n = 550/42$, 5-point Likert score, where 1=*definitely no* and 5=*definitely yes*).

scale), indicating that for many people the proposed change in behavior would indeed be possible. Given that for many alternatives the circumstances are crucial (yet unknown solely from tracking data), it is a positive indication that roughly half of all tours could be improved by implementing the proposed alternative.

6.4.5 *Survey and Interview Analyses*

To answer the remaining research question given in the introduction (*How should transport options and choices be communicated to users to support sustainable mobility behavior?*), we took a closer look at the survey results and in-person interviews. The surveys were performed in an online manner between June and July 2017 (starting roughly one month after period C), and consisted of Google Forms that were sent to the participants by email. The participants were incentivized to participate by the chance to win CHF 50 vouchers for a range of services (public transport, local shopping malls, donations, etc.). Out of the 45 respondents to the questionnaire, 21 answered all questions (including non-mandatory ones). 19 respondents additionally participated

	M	SD
Climate change is a problem for society	6.47	0.84
Saving energy helps to limit climate change	6.31	0.90
The quality of our environment will improve if we use less energy	6.16	1.35
I feel responsible for pollution and climate change: it is not just a matter of governments and industries	5.67	1.22
I try to use the car as little as possible	5.56	1.39

Table 6.5.: Attitude towards environmental questions ($n = 45$; 7-point Likert score, where 1=*totally disagree* and 7=*totally agree*).

in a semi-structured interview to discuss the peculiarities of *GoEco!* and the topic of sustainable mobility in detail. The interviews were analyzed according to the *grounded theory* approach; a set of response categories was identified for each question (according to Glaser and Strauss 2017), and the interviewees' responses were classified according to this categorization.

Table 6.5 shows a basic self-assessment of the 45 questionnaire respondents regarding their environmental attitudes. It is already clearly visible that the *GoEco!* participants who remained active throughout the whole study exhibit a strong pro-environmental attitude. While we cannot compare this to the overall population of Switzerland (due to the unavailability of a representative group), and thus make no assessment about the representativeness of their statements, they can still be used as a valid feedback on the elements and mechanics used within the *GoEco!* application and project.

General Assessment of GoEco!

On a general level, the persuasive approach chosen by *GoEco!* was evaluated above average. Table 6.6 shows the corresponding survey results from the 45 respondents. The app was easy to install and use, and the overall perception is that it delivered useful results. The least positively valued aspect was the time consumption: As highlighted throughout several of the interviews conducted post-survey, this primarily referred to the amount of time required for validating routes. As one respondent put it, "validation was boring, if you did it every day. But if you forgot validating your trips for a week, and then you tried to validate them all at once... it became annoying!" (T11). While the validation of the automatically tracked data was understood as being

	Total (n = 45)									
	1	2	3	4	5	6	7		M	SD
Diff. setup	0	0	1	3	4	15	22	Easy	6.20	1.01
Diff. usage	1	0	4	5	6	18	11	Easy	5.51	1.41
Unattr.	1	3	5	8	12	13	3	Attractive	4.73	1.45
Time-consu.	4	6	6	4	8	15	2	Efficient	4.31	1.83
Uninform.	1	2	1	9	14	12	6	Informative	5.07	1.37
Useless	1	1	0	2	12	18	11	Useful	5.69	1.24
Boring	1	2	5	1	14	14	8	Interesting	5.20	1.50
Fail. expect.	1	1	3	6	14	15	5	Fulfilling	5.13	1.33

Table 6.6.: Evaluation of the *GoEco!* application ($n = 45$; 7-point Likert score, where 1=*totally disagree* and 7=*totally agree*).

necessary, the interviewees repeatedly pointed out that to be deployed universally, a persuasive app like *GoEco!* must not force people to validate their trips (at least for the more easily identifiable transport modes such as driving by car or walking), and that the identification of individual triplegs must be improved (as otherwise validating a tripleg becomes impossible as it is unclear which transport modes are involved).

Assessment of Gamification

Table 6.7 shows the assessment of the different (gamification) elements employed within *GoEco!*. Especially the "plain" feedback elements (i.e., statistics on energy consumptions and CO_2 emissions, as well as the traveled distances and the travel durations) were considered useful for stimulating sustainable mobility behaviors. The more complex elements, such as badges or the comparison with others were perceived as less useful. While this mostly aligns with the expectations (i.e., social comparisons are difficult in the mobility domain, which is naturally very diverse; receiving badges unexpectedly does not necessarily increase motivation, as the desired behavior is not known and thus no competence can be shown), it was mentioned during the interviews that *GoEco!* introduced a wealth of features directly at its inception and for all users. This was perceived as challenging, and the recommendation was given to present new users only with a few elements, and continuously expand the number of gamification elements. In addition, on-boarding phases for new elements were mentioned,

	Total (n = 25)								
	1	2	3	4	5	6	7	M	SD
Mobility footprint statistics*	0	0	2	4	6	8	5	5.40	1.23
Mobility patterns statistics**	1	0	0	5	8	8	3	5.20	1.29
Potential for change	0	1	2	9	5	5	2	4.71	1.27
Setting personal goals	3	0	1	7	7	4	3	4.56	1.71
Challenges against myself	3	2	3	3	5	4	5	4.48	2.02
Being part of a community	2	2	3	5	6	5	2	4.36	1.57
Receiving unexpected badges	2	3	2	5	7	3	3	4.32	1.77
Comparisons with others	2	4	4	5	3	5	2	4.04	1.81

Table 6.7.: Perception of various elements of *GoEco!* ($n = 25$; 7-point Likert score, where 1=*totally disagree* and 7=*totally agree*). *Weekly energy consumption and CO_2 emissions. **Weekly kilometers, transport modes, travelling time.

where a small tutorial or an experimental phase gives users time to familiarize themselves with a new feature.

Alternatives

Table 6.8 gives more detailed insights on the individual elements used within *GoEco!* and their perceived usefulness to change mobility behavior. While people were generally interested in their own behavior in order to have a base for reflection, the alternatives proposed by the paper-based reports were not commonly tried out. The interviewees primarily mentioned two causes for this: First, the suggested alternative route options did not respect the circumstances in which people are well enough. One person mentioned "how could I satisfy all my family requirements, accompanying the kids and also carrying weights?" (T2). However, as other people stated, often such statements are excuses and would not hinder a certain route alternative in reality. For them, the second cause was more prominent, namely that they were not further encouraged to take the alternatives later on during the study (while the alternatives were used to compute potential goals and other gamification elements, they were not explicitly shown in the app, for example, after a trip was undertaken for which a suitable alternative would have been available). Notifications, but also a more immediate route planning functionality (within the app) would have helped them to assess their choices either immediately before or after they made them. This primarily addresses people in the action and maintenance stages of the TTM, indicating that many of them either were motivated to make their behavior more sustainable already before participating in *GoEco!*, or that *GoEco!* managed to successfully guide them through the precontemplation and contemplation stages.

	1	2	3	4	5	6	7	M	SD
Baseline and potential mobility patterns									
I was interested in knowing about my potential for change	0	0	1	5	8	13	8	5.93	1.12
The report stimulated me to critically reflect on my mobility patterns	1	3	5	8	13	6	8	4.80	1.58
I tried out the alternatives suggested by the reports	11	4	5	8	7	6	2	3.51	1.94
I'm now regularly using some alternatives suggested by the reports	17	2	6	8	4	3	4	3.11	2.07
Goals									
The meaning of the goal for change was clear to me	1	1	3	2	5	4	8	5.21	1.79
I was stimulated to change my mobility patterns to achieve my goal	1	2	3	7	3	7	1	4.42	1.56
I was eager to know if, at the end of the week, I had achieved my goal	3	3	2	2	5	6	3	4.38	2.02
Challenges									
Challenges helped me to achieve my goal for change	4	1	3	4	6	4	2	4.13	1.90
Challenges made me critically reflect on my mobility patxterns	4	2	2	1	6	6	3	4.38	2.08
Challenges were boring: they did not stimulate me at all	4	6	7	5	1	1	0	2.83	1.31
Challenges were incompatible with constraints affecting my mobility	4	5	2	5	5	1	2	3.54	1.87
I kept replicating the mobility patterns suggested by a challenge	4	1	4	5	6	3	1	3.88	1.75
Hall of Fame									
The way the ranking in the Hall of fame was computed was clear to me	3	3	4	6	2	3	1	3.64	1.73
I checked my ranking in the Hall of fame every week	7	4	2	2	3	3	2	3.30	2.16
I stopped checking the Hall of fame due to lack of significant changes	2	3	1	8	3	4	0	3.90	1.58
I was encouraged to change my mobility behavior for a top ranking	8	3	4	3	1	2	2	3.00	2.05

Table 6.8.: Perception of various elements of *GoEco!* (varying n; 7-point Likert score, where 1=*totally disagree* and 7=*totally agree*).

Goals

While goals were generally understood by the participants, their helpfulness in reaching a certain desirable behavior was disputed. Around one third of the survey respondents stated that goals stimulated them to change their mobility patterns, while for the others the effects were less prominent. During the interviews, it became clear that goals were "quickly getting boring" (Z2) as they were not personalized enough (the suggested goals were always chosen from a pool of relatively generic templates, and primarily personalized in terms of the suggested desirable behavior). Challenges were similarly assessed, and their usefulness was mainly seen in helping critically reflect previous behavior. A large issue posed itself with the incompatibility of challenges with various constraints (a similar criticism as was mentioned with respect to the suggested alternatives). As such, even though challenges were not perceived as boring, in the majority of cases they did not lead to a lasting behavior change. The interview responses similarly indicated that the challenges were not personalized enough, i.e., sampling them from a pool of relatively generic challenges did not lead to enough diversity and thus reduced the interest in challenges in the long run. For example, one interviewee mentioned that she "could not increase [her] bicycle use anymore; [she] should [thus] not have been shown bicycle-related challenges". Next to an increased personalization, it was also mentioned that an improved notification system (that for example sends messages when a challenge is almost completed) could increase the motivation generated by challenges. Along the same line, reframing challenges in terms of the benefits ("do that, you save ten minutes" instead of "do that, it is a challenge") would have made it clearer that the challenges actually lead to the desired behavior.

Numerical Representations

During the interviews, it was also highlighted that while the eco-feedback was generally perceived useful, its presentation as a collection of numbers expressing CO_2 emissions and energy usage in kWh was difficult to understand. A range of suggestions was given, such as to "back kWh up with gasoline liters" (T10), "relate tonnes of CO_2 with other activities we are used to perform at home—for example, what about providing us with the amount of corresponding washing machine cycles?" (T1), "thanks to your use of the bicycle today, x liters of oil have not been consumed" (T5), or "the CO_2 emissions you saved are equal to y trees being planted" (T10). Additionally, feedback in terms of health benefits or monetary impact was mentioned as a useful addition—often, sustainable behavior correlates well with positive changes of these measures, which can provide additional strong incentives to use mobility in a sustainable way. Summarizing the insights from the interviews, it is difficult to grasp one's environmental impact solely from CO_2 emission and energy usage numbers. While we explicitly chose this approach to give people autonomy in their interpretation of the tracked values, they mentioned that they optimally "would have liked to receive some 'red/green light' indications" (Z1), simply to more quickly understand their behavior and not have to spend too much time manually assessing it.

Badges

When asked about badges, the interviewees generally responded with low interest. It was mentioned that they could be made more tangible by associating rewards such as planting trees somewhere in the world with them: "I would like to get a badge notifying me I have contributed to saving a certain amount of CO_2 emissions and that as a reward a number of trees will be planted somewhere in the world" (T10). This would not only increase their perceived value, but also frame them in a collective (instead of individual) setting. Similarly, the interviewees expressed a low interest in individual rewards (such as the prizes awarded for the successful validation of routes), which might be explained by the fact that many *GoEco!* participants were already intrinsically motivated, progressed beyond the precontemplation and contemplation stages, and thus did not feel the need to be incentivized by external motivators. As such, we cannot univocally state that rewards do not work within persuasive applications: as previous research reports, it is likely that especially for people in earlier stages of the behavior change process and in less economically strong contexts economic rewards might help on-boarding them and providing incentives until internal motivation is built.

Social Comparisons

As the final element assessed in the surveys, the social comparisons given by the hall of fame were not perceived as particularly useful. The primary reason was the lack of dynamism, i.e., the leaderboard remained mostly constant throughout the study, and thus did not capture interest by the participants. The suggested improvements vary: One interviewee responded that users should be ranked by "who saved more petrol in absolute values over the week" (T5), which was contradicted by others as "if I am used to travel 4000 km by car every month, and I win a car-reducing challenge, are my efforts lower, higher or the same as people travelling 400 km by car every month, and winning the same trophy? If other people start from more favourable conditions than mine, but we are rewarded with the same trophy, we are ranked equally in the leaderboard. I perceive this as unfair and soon lose interest in it" (T6). Summarizing, it can be stated that while the social comparison approach chosen by *GoEco!* tried to respect the different contexts by letting users choose from a set of challenges that were tried to be universally achievable, this was not well-enough communicated and the participants were mostly confused by the hall of fame functionality (which commonly operates on easily understandable numerical quantifications, such as points). Instead, and indicated by the interviewees, the social elements within a mobility behavior change application should rather focus on community-building, e.g., by providing features that allow interacting with other app users, sharing achievements on social networks or with friends, collaborative (or competitive) challenges, more game-like challenges ("who travels furthest with an e-bike?" (Z7)), competitions among teams, or within corporate settings (similar to the "bike to work" challenge in Switzerland[3]).

6.5 CHAPTER SUMMARY

In this chapter, we looked at the question of how to best communicate eco-feedback to people and how to best use persuasive smartphone apps within the context of sustainable mobility. Based upon a taxonomy of motivational affordances for persuasive and gamified systems, we built the *GoEco!* app, which was employed within a large-scale study spanning one year. Using the app led to a significant reduction in GHG emissions stemming from regularly traveled trips for people living in more rural areas. However, likely due to the many (uncontrolled) influencing factors and potentially due to a lack of easily comprehensible goals when making mobility choices, no significant reductions were found for people living in cities and/or for a persons' mobility considered as a whole. Several surveys and interviews pointed out strengths and weaknesses of the *GoEco!* app, such as the well-working tracking and transport mode identification or the sometimes discouraging representation of all sustainability indicators as numbers, which made them difficult to understand and interpret.

3 Teams participating in www.biketowork.ch have to record the number of kilometers traveled by bicycle to work. Prizes are drawn at the end of the competition for all teams who cycled to work on at least 50% of all days.

7 DISCUSSION

In this chapter, we will discuss the introduced methods and algorithms in light of the research questions posed in chapter 1. Following the structure of the previous chapters, we will first restate the overarching research question and compare our methods and results to previous work, followed by a discussion of their relevance and the potential impacts on the mobility behavior of people. The chapter concludes with a systemic view (relating back to the first research question), a comparison to similar persuasive applications, and a discussion of the limitations uncovered during this research.

7.1 ANALYZING MOBILITY

RQ2: What are the components and traits of automatically recorded movement data that can be used to support mobility needs in an ecologically sustainable way (e.g., by providing eco-feedback that people can base their future decisions upon)?

Comparison to Previous Work

In chapter 4, we presented methods to process trajectory data with the aim of creating applications that support people in sustainable personal mobility. In contrast to a substantial share of research on mobility analysis, we assume that detailed trajectories are collected using a GNSS, and do not consider call record data (utilizing cell phone towers to locate people) or (paper-based) mobility surveys (cf. Smoreda, Olteanu-Raimond, and Couronné 2013). While it would be possible to use these less accurate resp. different data sources (e.g., using mobility surveys, researchers have the possibility to ask more detailed questions about each performed trip), we argue that the prevalence and ubiquity of smartphones (with built-in GNSS tracking and large batteries enabling continuous location recording) will foster a continuous shift towards high-accuracy data collection. Recording mobility at high levels of detail allows assessing individual differences and preferences better and thus increasingly tailoring persuasive applications to individuals (whereas call record data and mobility surveys are commonly used to study mobility behavior of a whole population or a larger study sample, e.g., González, Hidalgo, and Barabási 2008; Alessandretti et al. 2018; Pappalardo et al. 2015). Indeed, we know of several countries and cities that have been evaluating the suitability of smartphone tracking to either replace or at least support the traditional phone- or paper-based mobility census data collection. In addition, a range of small companies started to sell products that enable automatic data collection at low cost and effort (these applications can usually be used without any custom integration, whereas they simply record mobility, or within a larger application context using a Software Development Kit (SDK))[1].

The presented data abstractions and methods to analyze mobility data contain two preprocessing steps that are of special interest for high-accuracy mobility data and of particular importance for the subsequent steps. First, the segmentation procedures are usually not required for paper-based surveys (and to a different extent for call record data), as the collected data come in a segmented form already. Second, map matching is important for GPS traces that are already available at a high level of accuracy, as it allows to further increase the reliability of measurements (for lower-accuracy trajectories, one usually resorts to routing instead). For less accurate data sources, a reconstruction using data from other people or the underlying transport graph can be performed (e.g., Li, Gao, et al. 2019), but just as often the Euclidean distance (resp. jump length) is used, in particular if the research aims at comparing relative differences between different trips (e.g., González, Hidalgo, and Barabási 2008). Considering that we mostly rely on higher-level abstractions (staypoints and triplegs) for the further processing of mobility data, one has to ask whether GNSS data come at an unnecessarily high level of detail. This discussion tightly links to privacy considerations, where we might only want to store the bare minimum of information required to provide meaningful feedback to a person (cf. Giannotti and Pedreschi 2008). However, as we have seen, not only does accurate location data provide us with very fine-grained mobility descriptors, it also lets us make better use of geographical context, e.g., to infer the transport modes by considering PT stops along a trajectory. In combination with the increased ease of use of location tracking SDKs, the recent focus of large smartphone Operating System (OS) manufacturers on clearly highlighting the potential privacy risks

1 As examples, consider the MotionTag application (motion-tag.com) or the POSMO application (datamap.io).

of various tracking applications, and novel (exploratory) data sharing concepts (e.g., data cooperatives, where people self-host their data and give selective access to third-party applications or service providers), we are convinced that for many purposes high-detail location tracking will be the standard in the future. To alleviate privacy issues, system developers should adhere to the fair information practices (Wachowicz et al. 2008): limiting the data collection to necessary information, keep data only as long as required, specify the purpose of data collection, limit its use to a predefined purpose, safeguard it appropriately, inform people about the stored data (upon request), and be accountable for adhering to these principles.

Trajectory Algebra

The introduced trajectory algebra to add contextual information to tracking data can be seen as a combination resp. advancement of the concepts of *map algebra* (Tomlin 1990; Tomlin 2017) and *lifeline context operators* (Laube, Dennis, et al. 2007). In contrast to classical map algebra that works on (temporally invariant) raster data, and the lifeline context operators that work by summarizing properties of the mobility data themselves, the combination of the two allows specifying the ways context data interact with mobility data in a standardized way (and thus ensures transferability, quick exploratory iterations when designing new context features, and potentially user-friendly implementations directly within a GIS). As with every abstraction, there are certain cases that cannot well be handled by it. For example, the trajectory algebra primarily targets contextual data in a raster format (which is available at every point in space, in contrast to vector data that is only available at discrete locations), and while its usefulness for vector datasets is not disputed (as also highlighted by the exampe given in Figure 4.7), the corresponding specification would have to be expanded substantially, in particular when considering non-point vector data (such as other trajectories, or areas resp. polygons) or operations such as retrieving the k nearest neighbors. One can imagine scenarios where context should be retrieved from other mobility data, e.g., similarity measures could be used to automatically assign contextual data based on semantically or geometrically similar trajectories (cf. Janowicz, Raubal, and Kuhn 2011), or context values could be integrated along the area a trajectory passes through.

Transport Mode Identification

Extracting mobility features and augmenting trajectories with contextual data enables the application of transport mode identification (and similarly, activity purpose imputation, cf. Martin, Bucher, Suel, et al. 2018) models to further enhance the data. In the case of the transport mode identification model presented in subsection 4.1.5 and evaluated in subsection 4.5.1, we can clearly see that the inclusion of mobility-related context features leads to performance gains in the model outputs (in particular regarding the PT modes). Comparing this to similar models, the accuracy of roughly 85% is in line with other research that solely relies on mobility descriptors and contextual features (and not more fine-grained data as provided by accelerometers, Bluetooth sensors, etc.). For example, Zheng, Liu, et al. 2008 compare four inference models (Decision Tree, Bayesian Net, Support Vector Machine and Conditional Random Field) based on the GeoLife trajectories and find that walking, driving by car, bus or bicycle can be distinguished with an accuracy of 74%. More recent work by Stenneth et al. 2011 reaches 93.5% based on features such as the average accuracy, speed, heading change, acceleration and geospatial context (distances to bus and rail lines). Currently, researchers evaluate the suitability of neural networks for transport mode inference, e.g., Dabiri and Heaslip 2018 use an approach based on convolutional neural networks (reaching an accuracy of 84.4%) that has the benefit that features do not need to be engineered explicitly. Our method differs in that we use a PT router to assess whether a given PT alternative would have been available at the time of travel, thus giving us the chance of integrating potential delays and deviations from the regular schedule in PT. However, the increased complexity of having to employ a PT router specifically for transport mode inference could also be seen as a drawback of our approach, as it not only necessitates a larger and more complex overall system, but also leads to longer inference times. In addition, our method was developed with a specific use case in mind (and evaluated within the *GoEco!* project, cf. Bucher, Cellina, et al. 2016): To infer transport modes from tracking data of unreliable quality (in our case, recorded using the third-party app *Moves*), to be able to differentiate between a large number of transport modes, and as input to a further validation step by the users themselves (that in turn can be used to continuously retrain the model). All the transport mode inference models (only relying on location and context data) usually also benefit from a combination with models that additionally process the raw sensor data recorded by a smartphone. For example, Jahangiri and Rakha 2015 and Fang et al. 2017 both use machine learning approaches on sets of features including accelerometer and gyrocsope data, and reach accuracies of approx. 95% in differentiating between standing still, walking, running, cycling and traveling in a vehicle. However, and as was the case for *GoEco!*, such data might not readily be available, as the complexity of collecting, storing and processing of this data is more complex and often not provided by location tracking SDKs.

Mobility Histories

Summarizing mobility in terms of distances covered, durations spent traveling, modal splits and activity aggregates is performed with the aim of supporting sustainable mobility behaviors resp. highlighting which choices and trips are responsible for the largest shares of negative environmental impacts. In contrast to other mobility descriptors, as for example introduced by Laube, Dennis, et al. 2007 (who mention speed, acceleration, azimuth, sinuosity, navigational displacement, approaching rate, and derivatives and standard deviations thereof) these values are all tightly linked to sustainability as defined in chapter 2 and 4 and are easily understandable also when given as feedback to non-experts. Other metrics such as the radius of gyration, jump length, or frequently visited places (cf. González, Hidalgo, and Barabási 2008; Alessandretti et al. 2018) are primarily valuable to study mobility patterns of a population, and are similarly valuable for experts who understand their exact meaning and the laws they follow. However, as shown in section 4.5, there are still valuable insights for researchers and experts studying a certain sample to be gained from the introduced mobility descriptors. Within the *SBB Green Class* project, the temporal development of modal splits was one of the main points of study, as it enabled gaining insights on the usage of a MAAS offer over the duration of a year, and in particular highlighted that people behave more sustainable because of it. As such and in line with the survey responses given as part of the *GoEco!* dissemination activities (cf. chapter 6), we argue that to enable self-reflection on mobility behavior and to provide a basis for gamification elements, the extracted mobility histories are useful.

Sustainability

After the mobility descriptors have been extracted, and the respective transport modes are known, it is important to assess the sustainability of different trips (with regards to personal contexts and the related financial and personal gains) in order to give people meaningful feedback. For example, many people do not have the possibility to work from home (though the recent Covid-19 crisis has shown that in many cases this is also an artificial restriction), and as such suggesting to avoid work-related trips is not meaningful for them as they could not realistically implement this behavior. The presented sustainability metrics are based on GHG emission data from mobility and transport (Prillwitz and Barr 2011; Lane 2019; Boulouchos et al. 2017), as well as on human capital theory (cf. Becker 1993), and try to balance the necessity of performing a trip with its ecological impacts (given the limited information available from tracking data). Due to the fact that the offsetting costs (of GHG emissions from mobility) only correspond to a small share of the overall mobility costs, and (usually) the overall costs are only a small share of the financial and personal gains acquired by performing the trip, we have to carefully consider if we want to support people from a point of view of *weak* or *strong* sustainability (where *strong* sustainability argues that no gain in human capital can make up for a loss in natural capital, thus all GHG emissions should be avoided). In most previous work revolving around using persuasive applications to support sustainable mobility, this topic is not explicitly treated, and instead a concept of *strong* sustainability is implicitly assumed, under which people are always recommended to avoid trips resp. reduce GHG emissions. The work presented in this dissertation allows us to fine-tune support of sustainable behaviors better by choosing from various strategies to compute route alternatives and to determine when a given trip should be considered sustainable and when not. Holden 2012 provides an interesting discussion regarding the topic, and formulates the requirements for sustainable mobility as follows: Sustainable mobility 1) must not threaten long-term ecological sustainability, 2) it must ensure that basic mobility needs are satisfied (e.g., everyone must be able to get to work and to access vital services), and 3) inter- and intra-generational mobility equity must be promoted (i.e., everyone must have access to the same minimum level of mobility). Our dissemination of sustainability under various interpretations fits well with the first and second points: While we have to ensure that long-term ecological sustainability is given, we still have to consider that satisfying basic mobility needs is a requirement for everyone, and thus we should adopt our support of sustainable behaviors to primarily target those trips that are non-essential or for which meaningful and easily accessible alternatives are available.

While adopting strong sustainability is a practicable approach (that is easy to adopt and works under the assumption that people will balance ecological impacts with potential gains on their own), having more information about which trip should potentially be avoided and which is necessary allows an application to provide more selective feedback and thus be more meaningful to its users. As the concluding surveys of the *GoEco!* study have shown, the participants thought it useful to know about potential alternatives and were willing to implement them as well (cf. chapter 6).

It needs to be noted that the computations of the financial and social/personal capital gains as presented within this dissertation represent a limited model. While basing the financial gains on the salary of a person is a valid approximation under the assumption that a salary is an unbiased estimator of a person's contribution towards an economy (i.e., towards the generation of value), it is easily understandable that the thus generated value is not uniformly distributed across all times (and thus across all trips) and that the salary does not manage to capture all aspects of a person's contribution to society (the current Covid-19 crisis highlights the importance of "essential workers" which often have low salaries yet are indispensable within a society). As such, a much more fine-grained evaluation would be necessary—this, however, is difficult to estimate from tracking data alone as the exact reasons for travel are usually unknown (e.g., we do not know if someone has to go to work for an important meeting that generates substantial business or societal value or simply to do administrative work). Similarly, while the proposed measure for social/personal gains tries to incorporate social equity (i.e., balance differences between rich and poor), it assumes that leisure-bound activities are necessarily "out-of-home", which is clearly violated by many people being happy to spend their leisure time in close vicinity of their homes and thus not consuming mobility as part of it (especially given the current Covid-19 situation where many people were even forced to stay at home). However, and with the same reasoning, the proposed measure essentially gives every individual a "mobility budget" for leisure, and thus can be seen as a first step into a fair assessment of the amount of GHG emissions that should be considered acceptable for leisure activities. Finally, both measures are difficult to interpret in the case of multi-purpose or even multi-day activities (e.g., traveling somewhere by plane for a holiday). In the first case, we always associate the trip leading up to the activity with the activity itself, which might distort the actual GHG emissions apportioned to different activity purposes (e.g., if someone visits a gym close to work before heading there, the potentially longer trip to the gym is associated with a leisure purpose, and the shorter trip from the gym to work is associated with the work purpose). In the second case, a separate assessment for sub-trips should be made for a more accurate estimation, and in particular the airplane trips should not only consider the first activity after reaching the destination, but all activities until the person flies back again.

EV Choice Systematic mobility forms a substantial part of our total mobility, and support of sustainable behaviors (resp. the provision of eco-friendly alternative routes) for these parts of our mobility is generally regarded as positive and important as changes in those behaviors lead to long-term and impactful results (as the behavior is repeatedly and habitually performed). Inducing behavior change for these behaviors is difficult without external support, however (as we mostly rely on habits and usually do not re-evaluate systematically performed trips on a regular basis; cf. Froehlich, Dillahunt, et al. 2009b; Cellina, Bucher, Veiga Simão, et al. 2019), for which reason it makes sense for a persuasive application to specifically treat systematic mobility. The presented identification of commonly visited places and the associated tours was found to be working well, as shown in Table 6.4. Of large interest for discussion is the mode choice model presented in subsection 4.3.2 (that uses a unique sample of persons who have access to both an ICE car as well as an EV). As presented in chapter 3, several studies highlighted the various reasons people are still reluctant to completely adopt EVs. Among these are high prices, reduced ecological friendliness (due to the high efficiency of ICEs, the high energy costs of producing batteries, and the charging of vehicles using coal and gas power) or the requirement for a (personal) charging station, but we also find that many people are worried that an EV might only cover a certain share of their mobility needs, and that they would require an ICE car to cover the rest (in particular, long journeys). Assessing this question, we found that the choices can indeed be better explained if we know how a person has chosen before (i.e., people tend to use the EV for a "typical" set of trips). However, if we do not know anything about a person before, predicting the choices almost attributes to a random guess. This also implies that we cannot make a general statement about whether an EV would lead to the dreaded situations in which its range is not sufficient without knowing more about the mobility choices of a person beforehand. This finding is in line with previous research as presented in chapter 3: While range anxiety is often brought up as a crucial argument when buying an EV (cf. Noel et al. 2019), in practice most of the trips are so short that this does not play a role in the actual decision (Saxena et al. 2015; Franke and Krems 2013; Rauh, Franke, and Krems 2015).

Behavior Change

Finally, we showed several approaches to extract behavior changes resp. classify different behaviors based on tracking data. Several studies looked at behavior (changes) from the perspective of visited places resp. using proxies such as the radius of gyration or the jump length (González, Hidalgo, and Barabási 2008; Alessandretti et al. 2018). While these measures allow us to assess the mobility behavior of a population as a whole, they are less interesting from the perspective of a persuasive application, as they can vary greatly from one week to another and are not necessarily suitable to make statements about the sustainability of a behavior (esp. in the case of looking at changes in visited places). However, searching for anomalies in these descriptors is a step towards extracting information useful for persuasive applications, and is essentially the basis for the introduced methods. The method introduced in subsection 4.4.1 looks for such deviations from the norm in a number of features and then provides the sum of found anomalies to the developer of a persuasive application (note that these deviations can also be detected in regular behavior as introduced in subsection 4.3.1, where they primarily stem from changes in transport modes). The approaches that group people either based on the autocorrelations of their traveled distances and the related durations, or on the trends of various features, on the other hand, provide the application creator with a number of groups of people that should be supported differently by the application. As is often the case when detecting anomalies, the process of responding to the respective anomaly is thus not handled by the approaches presented in this dissertation. However, we can imagine cases in which this support could be automated as well: If a behavioral anomaly is detected in one week, and a user thus switches from a group of ICE car users to a group of bicycle users, an application could focus on bicycle-related challenges in the coming week, in order to support resp. solidify this choice. On the other hand, a switch in the opposite direction could be supplemented by educational measures such as highlighting the adverse effects of car trips on the environment.

Relevance of Results

Putting the presented methods and results of chapter 4 into a bigger perspective, the interviews and surveys performed within the *GoEco!* project and various feedbacks received during the *SBB Green Class* project demonstrated that the presented information is useful for people (both app users as well as system creators resp. the decision-makers who were in charge of the *SBB Green Class* project), and generally the raw position data were processed in meaningful and correct ways (cf. chapter 6). While the extracted information was used for the planning algorithms and communication strategies in chapter 5 and 6, in particular the integration of the extracted behavior (changes) into persuasive applications is yet an unsolved problem. The directions given in this dissertation should be used as a basis for further research on automatically adapting persuasive elements to the momentary status of behavior change.

7.2 PLANNING MOBILITY

RQ3: How can we facilitate multi-modal route planning involving less commonly used modes of transport (such as carpooling or free-floating bicycles)? How can we assess the quality of the (potential) fulfillment of a transport need, taking into account personal preferences, contexts and potential sustainability goals?

Comparison to Previous Work

In chapter 5, we provided a set of route planning methods that can be used to generate alternatives for previously exhibited behavior, and use them as direct feedback to application users as well as to assess potentials for change. Our methods particularly focus on personalization and context-dependence using heuristics (e.g., defined by an expert, the user herself, or extracted from previously tracked mobility) and probabilities computed based on previous behavior, and less commonly used modes such as carpooling. We argue that personalization will become substantially more important in the future, as it can further decrease the cognitive efforts required to plan routes (cf. Raubal and Panov 2009). In addition, personalization integrates well with persuasive applications that intend to support people in sustainable choices whenever they are within the constraints exhibited by previous behavior.

The presented formalization of mobility offers (section 5.1) is an alternative to commonly used specifications such as GTFS or the Open API for distributed journey planning (Comite Europeen de Normalisation 2017). Naturally, these standards also include a wealth of information not necessary for our abstracted use cases (e.g., the names of stations or railway operators), which would be required within a real-world deployment and to reach the vision of a *Digital Earth* (Guo et al. 1998). Such a complete digital representation of our planet would not only simplify the accessibility and increase the usefulness of transport offers for route planning, but could also be used to automatically extract knowledge, e.g., to determine the similarity between different transport modes or route plans (cf. Janowicz and Hitzler 2012). Currently, however, these standards usually solely encode a time-expanded graph in textual form. While we have shown in section 5.2 that it is possible to transform carpooling offers into the same format in order to reuse existing planning applications, the proposed high-level transport offer specification provides a stronger abstraction that allows integrating a wider range of transport modes more easily, and retains the flexibility (e.g., a bus-on-demand can drive small detours if requested by a passenger) and fuzzyness (e.g., for free-floating bicycles there are no specific return locations and they can be dropped off anywhere within an area) inherent in many of them. Specifying transport offers according to this specification presented in section 5.1 primarily enables us to create high-level route plans that require later refinement (taking into consideration actual departure times, potential delays, etc.). However, we argue that this follows a natural way of how people plan their trips as well (Car and Frank 1994)—first, we look at potential high-level tripleg chains that get us to our destination, evaluate if they conform with our personal mobility preferences, and only then consider the actual transport schedules and involved partners. In addition, the introduced transport offer specification is able to handle area-based transport modes such as carpooling, taxis, free floating bicycles and cars or buses-on-demand by generating flexible transport graphs (meaning that people can transfer between the same two transport modes at different locations).

Integrating PT and CP

The method to combine carpooling offers with PT offers presented in section 5.2 advances the state of the art by merging the two transport graphs while retaining their inherent flexibility (i.e., the fact that carpool drivers can make detours and slightly advance or delay their departures) and fuzziness (i.e., the fact that carpooling route plans are usually only specified in very coarse terms), resulting in a better connectivity of both the CP as well as the PT graphs. In contrast to previous work which focused mostly on replacing a single PT tripleg with a viable CP alternative (Varone and Aissat 2015; Aissat and Varone 2015; Bit-Monnot et al. 2013), the introduced approach automatically finds the best possible CP alternative for any part of the journey. While the restriction on a maximum of one CP tripleg (from the perspective of the driver, i.e., the driver can only pick up a single passenger along the whole trip; this is introduced to avoid re-computations of the departure times in the graph) is in line with how CP is commonly used, further research is still required to incorporate multiple (smaller) CP segments, especially with regards to more ad-hoc planning of shorter CP trips. Similarly, while the chosen graph-expansion (as opposed to having a time-dependent graph) allows utilizing existing graph algorithms and optimizations, it commonly leads to very large graphs. This could become problematic when integrating numerous different transport modes, and it should be further explored how to keep the graph size within bounds, e.g., by continuously removing obsolete CP and PT offers and adding upcoming ones. Finally, it needs to be noted that most benefits from short-distance carpooling only start to appear when a lot of offers are available (as otherwise it simply will not be possible to find anyone to carpool with). This will require integration of different platforms and substantially lower barriers to publish carpooling offers (e.g., applications could pro-actively suggest upcoming drives that could be shared with someone else).

Heuristic and Probabilistic Methods

In line with existing research on time geography, it would be interesting to see how concepts from this research field could be used to bound the number of nodes that need to be processed as part of a routing algorithm. For example, while accessibility is commonly used to quantify the usefulness of a transportation system, a similar approach could be used to limit the reachable locations and thus reduce the required computations during a routing process (Miller and Wu 2000). This is not only important when considering the DTAs (that correspond to potential path spaces), but also for the high-level routing methods presented in subsection 5.4.1 and 5.4.2. While the focus of these methods is set on personalization (and to some degree, sustainability), the involved computational constructs have many parallels to concepts from time geography and navigation research (Miller 1991; Raubal, Winter, et al. 2007). For example, future research should consider using the upper bounds given by network and space-time prisms to limit the number of transfer locations that a person could realistically visit, and thus potentially substantially decrease computation time.

Notwithstanding such a line of research, the proposed routing methods are largely orthogonal to previous research. Exceptions are algorithms like RAPTOR (Delling, Pajor, and Werneck 2014) which similarly follow PT lines to retrieve all stops at which transfers are potentially available (in the case of RAPTOR, the primary reason is to use arrays and their specific memory layout on a hard disk to speed up computations). However, in contrast to these algorithms, the presented methods allow incorporating a wide range of different transport modes and enable personalization by integrating mobility metrics retrieved from tracking data. The resulting routes are of a high-level nature, and thus need to be refined in a second step. It is an unsolved question how to find a good balance in the tradeoff between yielding such high-level route plans and subsequent refinement steps (e.g., one could specify the transfer graphs on an hourly basis, and thus lower the computational complexity and false positives returned by the high-level routing algorithm). In addition, the preferences and constraints introduced as part of the heuristic method in subsection 5.4.1 are manually defined in chapter 5 (cf. appendix A). Retrieving them automatically (in a similar manner to the preferences in subsection 5.4.2) would greatly enhance the usefulness of the heuristic routing algorithm, as it could similarly "learn" from tracking data and mobility histories.

The preference-based planning method of subsection 5.4.2 uses feature distributions modeled using parameter-free functions as described in subsection 5.3.2. This allows integrating new features without knowing about the exact distributions, and automatically using them as preference values for the routing algorithm. In contrast to previous research, we thus have a very flexible way of generating personalized routes that is also not bound to a specific transport mode (a large share of previous work concerns the personalization of car or bicycle trips, for example; cf. Stinson and Bhat 2005; Menghini et al. 2010; Vedel, Jacobsen, and Skov-Petersen 2017). However, the flexibility given by the approach (e.g., when a person is walking somewhere, essentially all other transfer locations are reachable, albeit with a very low probability) can quickly lead to an exhaustive number of nodes to be visited. While choosing bounds on the probabilities can mitigate these problems, it should be further explored how to sort the nodes according to the likelihood of being visited. For example, a spatial index may be used to only process nodes that exceed a minimum visit likelihood (in the case of a quad tree (Finkel and Bentley 1974), only the immediate resp. neighboring cells could be visited for walking transfers).

Real-world Deployment

While all the introduced methods have been shown to work for the presented case studies, some points deserve further attention before a real-world deployment would be possible. First of all, we did not consider in detail how we can ensure that the data used for route planning is kept up to date. In more classical route planning applications, this data only changes infrequently (e.g., the road network only expands slowly and train schedules are known many months in advance). Many of the introduced transport modalities exhibit a high unpredictability: Ridesharing offers constantly change, free-floating vehicles continuously need to update their pickup locations, etc. Due to the focus on high-level plans (which in turn usually lead to routes with only a few hops) we can greatly alleviate the efforts required to update the routing graphs, and only locally recompute potential transfers from one mode to another. Nonetheless, the resulting graphs can quickly become highly connected, thus inducing a high computational load that leads to the second point that needs to be considered before a real-world deployment becomes possible: low system response times. The case study implementations exhibited response times in the order of seconds and were not optimized in particular, however, the extents they spanned were comparably small. A real-world (and world-wide) deployment would likely lead to much larger query times, as most of the vertices are more highly connected, leading to many more (potential) paths to a destination that need to be evaluated. A possible optimization (similar to how optimized street network routing works) is the utilization of hierarchies in the routing graph, where trips by certain modes are restricted to smaller areas (e.g., for walking, where it is unlikely that someone walks for dozens of kilometers), in combination with summary nodes that essentially group a large number of nodes (e.g., in a certain geographic region) into a single one and thus can be evaluated a lot more quickly. Conceptually, these optimizations are compatible with the introduced methods, but further evaluations are required to determine their potential efficiency gains and impacts on the routing schemes.

Relevance of Results

The presented methods are particularly useful within the context of supporting sustainable personal mobility, as they target intermodal use of mobility (which is often a preferrable alternative to ICE cars and lets people reach locations that are otherwise only reachable by a personal vehicle). Additionally, the focus on less commonly used modes of transport (such as CP or free-floating bicycles) will enable routing providers to include them into their planners, and thus make it easier to find the corresponding route options. Regarding persuasive applications supporting sustainable mobility behaviors, especially the personalization and context-dependence is beneficial, as it allows us to provide custom-tailored feedback to each individual (e.g., route alternatives that match personal preferences) and allows assessing the potential for change more realistically.

7.3 COMMUNICATING MOBILITY

RQ4: How should transport options and choices be communicated to users to support sustainable mobility behavior? Do people adjust their mobility behavior upon receiving (eco-)feedback based on their previous choices?

Comparison to Previous Work

In chapter 6, we presented ways to communicate the previously identified mobility histories and descriptors as well as the generated route alternatives to users of persuasive and gamified (smartphone) apps. Several other research studies presented prototypes for the mobility domain (inspired by other gamified systems, e.g., online community platforms or fitness applications) with different foci such as generally fostering sustainable mobility, or promoting cycling or the use of PT (Bie et al. 2012; Froehlich, Dillahunt, et al. 2009b; Carreras et al. 2012). Our work is grounded in psychological research and thus revolves around six core design principles, each adhering to several specific traits of human motivation. Based on this, we make a distinction between three main pillars: eco-feedback, which is of a more educational nature, gamification, which uses game elements to foster playful interactions with the app, and an assessment of the potential for change, based on routing alternatives retrieved by algorithms as presented in chapter 5. While (paper-based) eco-feedback is probably the easiest and most commonly used method to foster mobility behavior changes, the systematic treatment of gamification elements (within the context of mobility), as well as the foundation of them in a mobility assessment (as given by the potential for change) are setting the work presented in this dissertation apart from previous studies.

Motivational Affordances

The presented taxonomy of motivational affordances for persuasive and gamified (smartphone) applications is based on the mentioned general design principles and adds mechanics and concrete elements (how to implement mechanics within an application context) on top. While other research has studied the usefulness of gamified systems in a wide range of contexts, our taxonomy lets system designers choose appropriate elements easily. For example, in the mobility domain, point-based competitive systems are mostly unsuitable as mobility is highly individual and comparisons between different users are difficult. Remedy can be given by grouping people into classes with similar circumstances, but this is usually difficult to unambiguously identify from tracking data alone. In addition, point-based systems tend to foster behavior that maximizes the number of points, and thus could potentially lead to people traveling actually more in order to receive more points. However, and as the *GoEco!* experiment has shown, people like competitive settings within the context of apps that support behavior change. As such, studying how competitions can be made fair within a mobility setting, and how people can be grouped with others exhibiting similar potentials and circumstances should be a focus of future research. Alternatively, gamification elements that combine competitive and cooperative mechanics should be examined in greater detail (and in particular within the context of persuasive apps supporting them).

Further, among the feedback of *GoEco!* users it was often found that the timeliness of feedback is crucial. If route alternatives are given too far in advance or feedback with a too large delay, they lose their effectiveness. Similar findings were reported by Fogg 2002, and point into a direction of future research that studies the impact of timely notifications on mobility choices (e.g., by detecting when someone leaves the house, predicting where the person will likely go, and pro-actively suggesting route options). Along the same line, deeper integration with LBS would be beneficial—among the mentioned functionalities by *GoEco!* participants were tools to analyze and plan mobility alternatives or to compute economic and health impacts, but we could also imagine a deeper integration with personal planners respecting spatio-temporal constraints (Raubal, Miller, and Bridwell 2004). Finally, while the possibility for app users to set their own goals and choose challenges was generally appreciated (as it adheres to the need for autonomy), the monotony of goals and challenges was criticized. Generating such gamified elements based on previous behavior a user exhibited would increase their attractiveness and thus ensure a long-term involvement of people. For example, if the system often finds bicycle alternatives for a certain person, suggesting challenges that focus on using the bicycle or setting a goal of a minimum number of kilometers traveled by bicycle would make them more meaningful.

Gamification in GoEco!

Regarding the implementation of elements, the approaches chosen in *GoEco!* were generally liked by its users. In contrast to related research, we set a focus on supporting user choice resp. autonomy, and thus presenting most information as-is. While the idea was to foster an understanding of what different values for energy usage or CO_2 emissions mean (to enable people thinking about the respective units as they do about distance or weight measures), this proved to be not sufficiently tangible for many people to foster change. Instead, the approaches chosen by other persuasive apps (cf. Jylhä et al. 2013; Bie et al. 2012; Froehlich, Dillahunt, et al. 2009b) where GHG emissions and ecological impacts are represented using visual elements (e.g., a tree that loses leaves or an iceberg that melts) were mentioned as preferable. This points at the fact that for many people, energy usage and GHG emissions are intangible units, and we argue that future research should consider how to make people get a better understanding of these units. For example, comparisons to household activities such as running a washing machine, comparisons to commonly performed activities (such as taking a domestic flight), or comparisons to known measures (e.g., the average CO_2 emissions per kilometer of an ICE car) should be included and tested for their effectiveness in educating people about the impacts of different choices.

The presented one-year study *GoEco!*, involving initially approx. 600 people, was used to evaluate the proposed gamification concepts (and the extraction of mobility metrics and generation of route alternatives that they are based upon). It proved to be notoriously difficult to keep such a large sample motivated to interact with the app over the duration of one year (note that there were three tracking periods within this one year). In line with general numbers on app usage (cf. Guerrouj, Azad, and Rigby 2015; Sigg et al. 2019), this is to be expected though (in particular if the participants are not contractually bound to participate in the study until the end and do not receive any financial incentives for doing so). The chosen "living lab" approach led to a wealth of insights, not only about the impacts of a persuasive app like *GoEco!*, but also about the interest of various groups in the population to participate in such a research experiment, how well the developed algorithms work in practice, and on the differences between research and setting up such a project as a startup company.

Sample Bias

Regarding the interest in the population, we found that those people who participated until the end were primarily people who already travel in ecological ways and/or are interested in the topics of sustainability, energy use, and research in general. This highlights a potential bias towards eco-friendly people that was partially confirmed for the partition of the sample living in the more urban region of Zurich by comparison to the SMC. In the rural area Ticino (where also significant changes in mobility behavior after the *GoEco!* intervention were found), the average daily kilometers traveled and the average share of kilometers traveled by car correspond well to the SMC, indicating that this share of the study sample is more representative. As such, we conclude that in more rural areas a persuasive app like *GoEco!* shows larger effects than in a city like Zurich, where the self-selection bias is larger and people already travel in more sustainable ways. The responses of people given to the questions about their pro-environmental attitudes (Table 6.5) further confirm potential biases in the study sample, and point out research directions resp. strategies to involve people who are not already strongly intrinsically motivated. For example, providing more extrinsic rewards and directly recruiting participants who are known to travel often by car (e.g., via car ownership lists) could be strategies to attract a more diverse user base. External incentives like financial payments can then still be reduced after an initial onboarding period to examine the longer-term effects resp. potentially generated intrinsic motivation (that makes people keep using the app). Regarding solely the analysis of potential outcomes, it is also possible to alleviate the impacts of a biased sample by rebalancing it according to a known distribution, e.g., the demographics of a country (which are usually known from the census) (Stephan 1942). This approach was, for example, used to compare the *SBB Green Class* data with data from the Swiss Mobility Census (SMC) (Martin, Becker, et al. 2019).

Method Assessment

Looking at the evaluation of the various algorithms used within *GoEco!*, the tables in subsection 6.4.5 highlight that the provided elements were generally seen as valid and useful. However, and as discussed before, even though this was the case, the timeliness of feedback was often not given, and thus at the time of making a travel choice, support or incentives were missing. This primarily points to the direction of providing more real-time support, and thus also processing data in real-time, in particular with respect to recognizing situations in which a person will likely need to make a mobility choice and pro-actively nudging him or her into a sustainable direction. Such a provision of real-time support would require predicting movements and mobility choices of people, finding potential transport options, and communicating them in an unobtrusive (and potentially gamified) way to the user immediately. For example, in the case of determining when CP would be a viable option to travel somewhere, this would involve matching a driver with a rider without any specific interactions with them. For both the driver as well as the potential passenger, a prediction of the traveled path would have to be made, they would have to be analyzed with regards to their similarity (i.e., the potential for the driver to pick up the passenger and drop him or her off at the predicted destination), and a negotiation process would have to be started (where they both see the CP option and potentially financial and ecological costs and gains). As such a system would benefit from many people participating, Big Data (and mainly streaming) technologies should be considered to handle the real-time processing of large amounts of data (cf. Hitzler and Janowicz 2013; Tschümperlin, Bucher, and Schito 2018; Galić, Mešković, and Osmanović 2017).

GoEco! has also highlighted the differences between creating a persuasive app as a research project or within a company. The original goal of keeping 800 participants over the duration of a year was not achieved, which was partially due to the aforementioned "usual" drop outs when launching a new app (Sigg et al. 2019), but also due to technical issues, the requirements given by a research project (e.g., different study periods, required validations to keep data quality high, or the control group that did not get the full app but only a tracking version), and a strong focus on assessing if a persuasive app can have an impact on the mobility behavior of people. The last point also prevented continuous adaption of the app or starting with a smaller set of functions and gradually adding more (which is commonly done when developing a commercial application). As such, in order to keep an experiment with 800 people running over a whole year (where people are expected to interact with a system on a daily basis) would likely require large financial incentives or the flexibility to deviate from the original plan and exclude research activities.

Comparing *GoEco!* to other studies evaluating persuasive apps still points out its uniqueness, though. Most studies in the domain either consider only a small sample or let the experiments run only for a few weeks (cf. Cellina, Bucher, Mangili, et al. 2019). In addition, many of these projects either evaluate the outcomes solely qualitatively (Froehlich, Dillahunt, et al. 2009b) or not in relation to sustainability (Jylhä et al. 2013), or use other means to collect data and give feedback to people (such as web-based surveys and feedbacks). In that respect, the results of *GoEco!* are unique and show that persuasive applications that make use of automatically and passively tracked mobility data can work in settings where people naturally have room for improvement (with regards to sustainable mobility).

Relevance of Results

As the evaluation of the *GoEco!* project has shown, the deployment of a persuasive application to influence mobility behavior can lead to GHG emission savings in the order of 10-30% (cf. Table 6.1, 6.2, 6.3, as well as Cellina, Bucher, Mangili, et al. 2019). While this cannot make mobility completely sustainable in itself, the result is in agreement with the often used argument that reaching sustainability requires a large number of smaller changes. This is because it is not possible to immediately switch to completely sustainable technology, yet changes should happen fast in order to keep up with the sustainable development goals set by the United Nations (cf. UN Department of Economic and Social Affairs 2020). Many of these changes involve gradual switches to different technologies, e.g., by subsidizing photovoltaic installations which could contribute to mobility provided by EVs if they are charged at the workplace during the day (Buffat, Bucher, and Raubal 2018). Other changes are strongly related to behavior, such as switching to electric bicycles for commuter mobility (Bucher, Buffat, et al. 2019). This would likely also entail the provision of the respective infrastructure, i.e., “bicycle highways” leading from suburbs to the city center. Such changes could not only be supported by the respective subsidies, but also by laws, and last but not least by persuasive apps as presented within this dissertation.

7.4 A SYSTEMIC VIEW

RQ1: What are the principal information processes and structures involved in supporting sustainable personal mobility and Mobility as a Service (MAAS)?

Comparison to Previous Work

Looking at the proposed framework in its entirety, we can see parallels to the systems used in other persuasive studies such as UbiGreen (Froehlich, Dillahunt, et al. 2009b), tripzoom (Bie et al. 2012), or SUPERHUB (Carreras et al. 2012). Next to providing a framework encompassing the steps required to process tracking data to generate information useful for persuasive applications, in contrast to these, we put a stronger emphasis on the importance of founding the applied measures in psychological theories, and (related to that) strive for personalized and meaningful elements within the applications. While the results were generally approved by the study participants of *GoEco!*, the mentioned aspects of supporting closer to "real-time" (i.e., at the actual point of time at which a mobility decision is made) and even in more personalized ways deserve further discussion. The first could benefit from a mobility prediction component that was not included in the presented framework. Such a component could allow estimating when and with which transport mode an upcoming trip will be performed, and thus notifying the person about potential alternatives shortly before. A wide range of research is concerned with such *next place* resp. *trajectory prediction* (Bucher 2017), and the corresponding methods often rely on similar assessments of personal preferences and previous choices to determine likely future choices. The second point of more closely aligning motivational elements with previously exhibited behavior could be achieved by mapping the detected behaviors to the individual stages of behavior change, and generating challenges and goals more closely in alignment with the identified potentials for change. For example, if we detect that someone could often take the bicycle to reach his or her activity locations, the corresponding challenges should be created, and in particular for those routes for which the bicycle was found to be a viable alternative.

(Non-technological) Ways of Reaching Sustainable Mobility

Persuasive applications are not the only way to make mobility more environmentally sustainable. We can differentiate between four ways to change the mobility demands of people:

- **Soft Incentives** (as exemplified by the persuasive applications discussed within this dissertation). Targeting the choices that are made before a certain trip is performed, soft measures aim at convincing or nudging people into adopting certain behaviors. They are grounded in the theories of motivation presented in this dissertation and mainly use knowledge about attitudes, previous behaviors, context and circumstances to persuade people to adopt sustainable behaviors. Taking the example of *GoEco!*, we can see that for systematic trips (e.g., commutes) reductions of approx. 30% (cf. Table 6.3 and Cellina, Bucher, Mangili, et al. 2019) are possible using such measures (corresponding to roughly 10% of the total environmental impact of mobility).

- **Emerging Business Models**. Ultimately caused by the increasing pressure to make mobility more sustainable, novel business models such as micro-mobility, Mobility as a Service (MAAS) or various sharing schemes change the ways in which we use mobility, and thus the demands for different transport modes. Taking the example of the MAAS offer *SBB Green Class*, we can see that such business models can lead to a reduction in GHG emissions. In this case, the offer including unlimited access to PT, various sharing schemes and the provision of a compact-class EV led to an overall reduction of GHG emissions by approx. 30% (Martin, Becker, et al. 2019).

- **Policy Measures**. Laws and subsidies are steering mechanisms that work well in practice but require agreement by citizens and thus a long time to be implemented. Often these "hard" incentives are supported by educational measures and other soft incentives to create acceptance within a population. In this context, mobility is often embedded in a larger system of energy producers and consumers, and thus laws and subsidies may be put in place that support mobility in indirect ways. For example, a recent study by Buffat, Bucher, and Raubal 2018 found that a wide deployment of photovoltaic cells on people's homes (e.g., fostered by subsidies) can lead to a reduction of GHG emissions in the order of 26% of the total commuter mobility GHG emissions (corresponding to approx. 5% of the total mobility GHG emissions).

- **The (Built) Environment**. Finally, changes to the built environment can shift mobility demands, for example, due to adjustments in availability of alternative transport modes, but also due to the perceived effects of a route on health, safety or comfort (Pritchard, Bucher, and Frøyen 2019). A promising example is the construction of "bicycle highways" which facilitate access from suburbs to city centers. A study by Bucher, Buffat, et al. 2019 found that roughly 44% of the commuter GHG emissions could be saved if people would switch to electric bicycles for their commutes (corresponding to approx. 8% of the total GHG emissions by mobility).

The four discussed measures are of increasing difficulty (and thus time requirements) for implementation. For example, while deploying an application like *GoEco!* can be done comparably quickly, changing the built environment (and building new transport infrastructure) usually takes time in the order of decades. Naturally, all these measures run in parallel to technical advances that continuously improve the efficiency of our transport systems. However, it is often argued that especially in the short term, soft incentives, new business models, and policies are required to keep the impact of mobility on our environment bounded.

8 CONCLUSION

In this chapter, we summarize our work, state our contributions and give an outlook on potential future research avenues as identified as part of the presented dissertation.

8.1 SUMMARY

This dissertation presents a framework for ICT supporting sustainable personal mobility via persuasive applications. Starting from automatically and passively recorded location data, we develop methods to extract mobility histories, related preferences and behaviors (resp. the changes thereof). Building upon these structures, an assessment of potentially improved behaviors can be made, and suggestions on how to use a wide range of transport modes (intermodally) to decrease one's personal environmental impacts can be evaluated. Finally, we elaborate on the different forms of interaction between a (gamified) persuasive application and its user with the aim of nudging the person into the direction of more sustainable mobility choices. The effects and the applicability of the methods presented are examined using two large-scale mobility studies: *GoEco!*, which in essence incorporates the methods developed within this dissertation, and *SBB Green Class* that studies the impact of a MAAS offer on people's mobility, with a particular focus on the changed environmental impacts.

ICT Supporting Sustainable Personal Mobility

In chapter 2, we provide a general introduction to the topics of sustainable mobility and how persuasive applications have to respect individual contexts and circumstances in order to create meaningful support of different mobility behaviors. We exemplify this by showing that different groups of people commonly use mobility in different ways, depending on their access to both mobility itself but also to other infrastructure (e.g., for leisure activities or work). Even though it is impossible to exactly determine the circumstances and influencing factors for all trips based on tracking data alone, using such spatio-temporal context can help an application (or its developer) to favor one persuasive strategy over another. Looking at sustainability in particular, it additionally becomes crucial to define what should be considered as an acceptable environmental impact for a given activity. We distinguish between the two extremes of *strong* and *weak* sustainability, where either all trips producing GHG should be avoided, or only those whose (economic or social/personal) gains fall behind the "environmental cost". Along the same lines, we should differentiate between trips for which a reasonable alternative would be available, and those for which the chosen route was the only option. Considering this, integrated mobility and MAAS gain in importance, as they can let people use mobility in ways more closely tailored to their actual needs (e.g., constantly having commoditized access to both a car and the PT network lets people choose for each trip individually which option suits them best). We conclude the chapter by giving a high-level perspective on the information processes involved in supporting sustainable mobility using persuasive applications that sets the frame for answering the first research question. The later chapters fill in the presented building blocks in order to present a comprehensive framework for persuasive applications supporting sustainable mobility.

Background

In chapter 3, we start by providing an extensive review on the underlying psychological theories that drive human behavior. For a persuasive application to meaningfully support a person in his or her choices, it is important to know in which state of behavior change the person is, and how we commonly progress in order to achieve a new behavior. For example, people who are unaware of the consequences of a certain behavior are best supported by educative measures and comparing their behavior to other people in similar circumstances. During later stages, e.g., when trying out a new behavior, persuasive applications should decrease the efforts required to continuously exhibit the behavior. This can be done by pro-actively suggesting route alternatives or offering simple mechanisms to plan and evaluate various route options. Even later stages require motivational elements that keep a user engaged with a certain behavior (such as gamification elements) until a (new) habit is formed. In this chapter, we also provide background on the three main information processes involved in supporting sustainable behaviors via persuasive applications: the processing and analysis of movement and mobility data, planning personalized (and thus meaningful) alternatives, and creating feedback out of the previous two processes that helps people choosing sustainable mobility options. The subsequent chapters build upon this background and contribute to filling the identified research gaps.

Mobility Analysis

In chapter 4, we elaborate on the most crucial information when trying to assess the sustainability of trips and create information that is useful in supporting people in environmentally friendly behaviors. Next to basic mobility descriptors, this includes the inference of used transport modes, assessments of the environmental impacts in comparison to the financial or social/personal gains, as well as the extraction of regularly exhibited patterns and mobility choice preferences. The latter are exemplified by a choice model quantifying the predictability of choices between ICE cars and EVs. This choice is becoming more prevalent with the increasing availability of EVs and their dropping prices, but the continuing reluctance for their adoption due to range anxiety resp. fears that they cannot face one's personal mobility needs. Our findings include that even though the choices of each individual exhibit predictability, this cannot be generalized to a population (given demographic properties of the persons and descriptive features of each trip), and the choices appear random instead. This suggests that in the overall perspective, practically all trips can be covered by an EV, and issues like the range anxiety do not play a role once an EV is available. Finally, we propose several methods to extract groups of people exhibiting similar behaviors as well as changes in behavior, both of which can be used by persuasive applications to tailor the employed supportive mechanisms. These identified components and traits of automatically recorded movement data are of high importance when supporting behavioral transitions towards sustainable mobility.

Mobility Planning

In chapter 5, we provide a generalized abstraction to define point- and area-based transport offers, thus covering a large number of currently available transport modes for their integration into high-level route planners. The benefits of such high-level planners is facilitated personalization by simple adjustments of the planning graphs or restrictions on the rules evaluated during computation. This is exemplified by two route computation methods: One uses heuristic rules (that can be chosen based on an expert's assessment or by analyzing the past choices of a person) to limit the available options and generated route plans, while the other computes routes based on probabilities computed from previous choices as recorded by a tracking application. Both can be used to directly compute meaningful route options for a given person (by corresponding to previously exhibited behavior), but also to compute sustainable alternatives (e.g., by providing more stringent rules on the allowed GHG emissions or by using the preferences of people in similar situations who exhibit generally lower GHG emissions due to their mobility choices). To elaborate on the benefits of inter-modality resp. integrated mobility, we introduce a method that allows combining carpooling offers with PT, thus improving both networks in terms of connectivity. The presented methods focus on personalization and the integration of less commonly used transport modes in an inter-modal way, thus paving the way for more comprehensive and meaningful estimations of potential route alternatives.

Communicating Mobility

In chapter 6 we present a taxonomy of motivational affordances for persuasive and gamified technologies that was used to choose the elements implemented within the *GoEco!* app. Due to the differences given by the individual contexts and circumstances, persuasive applications for supporting sustainable mobility cannot rely on motivational resp. gamified elements in the same way as applications in other fields do. For example, point-based systems usually assume "equal chances" for everyone, and are thus difficult to employ in the mobility field without discouraging certain groups of people. The employed gamified motivational elements as well as the more plain "eco-feedback" are evaluated within the *GoEco!* project and are found to be helpful in supporting behavior change. *GoEco!* highlighted that behavior change using such an application is possible, albeit we only found significant changes in more rural areas (where people naturally have to rely more on cars and show less "pro-environmental" attitudes). Among the important features were the provision of timely assistance, personalized and non-generic motivational elements, as well as eco-feedback giving users the chance to learn something about their own behavior. This chapter thus answers how transport options and choices should be communicated to users to support sustainable mobility behaviors, and that people indeed exhibit changes in their behavior after interacting with a persuasive application.

8.2 CONTRIBUTIONS

Foremost, we presented a framework for supporting sustainable mobility through persuasive ICT that encompasses all processes required to generate meaningful eco-feedback (and related behavioral support in the form of mobility alternatives and gamified elements) from passively recorded mobility data. Within this framework, we highlighted three areas and presented novel processing methods, approaches to generate route plans, as well as ways to communicate the generated information persuasively to users:

- In the area of *mobility analysis and processing*, we presented a trajectory algebra to standardize the addition of context to mobility data and a related range of mobility descriptors useful for eco-feedback. Based on this context and descriptions of mobility, we presented a Bayesian model to infer transport modes that utilizes spatio-temporal data and is able to continuously improve individual predictions for all users. To exemplify the importance of mobility choices and to provide insights on the important choice between ICE cars and EVs, we presented a mode choice model and discussed the impacts of applying the model to the data recorded by the *SBB Green Class* study. Finally, we presented several methods to detect mobility behavior change and discussed their integration in and importance for persuasive applications.

- In the area of *planning integrated and sustainable mobility*, we introduced a generalized description of mobility offers (that can be used for point- and area-based modes of transport), and three methods to compute route alternatives. The first one emphasized on carpooling as a potential way to increase the occupancy rate of cars and provided an integration with PT networks. The results showed both an increased connectivity for the CP and the PT networks, highlighting the potential benefits of a combination of the two. The other approaches focused on the utilization of personal preferences and constraints to generate high-level mobility plans. Such plans can be used to assess potential alternatives (and their sustainability), as feedback for people and (in combination with lower-level routes) to generate route plans involving a large number of (previously unavailable) transport modes.

- In the area of *communicating mobility (eco-)feedback*, we presented a taxonomy of motivational affordances for persuasive applications and the synopsis of recorded mobility data within eco-feedback reports. The dissemination of the large-scale study *GoEco!* showed the applicability of the persuasive approaches (and related methods and algorithms) presented in this dissertation. We found

> that in particular in (rural) areas where people naturally rely more on their personal cars, applications like *GoEco!* can show significant effects in the mobility behavior of people. Among the primary features of interest are real-time notifications (to support sustainable behaviors immediately when the choice needs to be made), the provision of alternative routes, as well as the inclusion of non-generic gamification elements to support motivation.

Embedded within the larger framework, the presented methods and approaches provide a way to process mobility data with the aim of supporting sustainable mobility using persuasive applications and ICT.

8.3 TOWARDS OPTIMAL SUPPORT OF SUSTAINABLE PERSONAL MOBILITY

As can be seen from Figure 2.9, from a holistic perspective two large parts on optimal support of sustainable personal mobility are missing. First, the provision of alternatives requires knowing about potential transport offers that could satisfy the needs of a person. While we gave concrete examples for cases in which these offers are known (e.g., carpooling where we crawled the offers from a large European carpooling provider, or shared bicycle/car systems which were similarly crawled), to make such alternative-finding globally available requires methods to specify and process transport offers in a well-defined and flexible way (that allows incorporating a wide range of transport modes). The generalized transport offer specification presented in chapter 5 is a first step into this direction, which could be combined by using Linked Data technology (in contrast to a rigid format like GTFS), as this would allow embedding transport modes within a larger context and the automatic determination of similarities in offers (e.g., a person interested in carpooling could indicate that she needs space for luggage, and we could use information about the individual cars on offer to determine how well they would fit her need; cf. Hitzler and Janowicz 2013; Janowicz and Raubal 2007). An example of such a specification can be found in Bucher, Scheider, and Raubal 2017; in this case, it is used not only to specify the offers themselves, but also to automatically align peoples' transport needs in terms of luggage requirements and available space in cars.

Related to the automatic publication of transport offers is the integration into routing systems (and potentially systems to determine similarities between offers) which optimally would be supported by a publisher-subscriber system that continuously ingests updates of existing offers and newly available ones and passes them along to routing applications. For example, a carpooling platform that would like to see its offers integrated into a general purpose routing system like Google Maps could publish new offers using said system, upon which Google Maps would continuously integrate resp. update the transport offers. This in turn either requires the computation of high-level route plans as discussed in chapter 5 or continuous updates to the routing graphs (which must be sufficiently flexible to integrate personalization resp. mode selection). Additionally, and in particular with respect to personalizing route options, such a holistic routing system should integrate context data, e.g., from weather or as given by the traffic status.

The second larger part that was not discussed within this dissertation is the topic of negotiation. This is primarily related to shared transport modes such as CP, taxis, or (private) rental cars and describes all the processes involved in determining the sufficiency of the vehicle's properties to fulfill the transport needs, the trustworthiness of the service (resp. driver and vehicle), and the related prices. In an optimal scenario, a person with a mobility need would get transparent access to these properties and could book transport from within one application and without the need to exchange clarifying messages or financial details. Current pilot MAAS offers aim into this direction, but focus mostly on pricing and payments and thus primarily on modes of transport where this is highly standardized (e.g., carpooling is usually not available as a transport option).

8.4 FUTURE WORK

Next to the major components explained in the previous section, this dissertation highlighted several other directions for future research. First, in particular the automatic integration of extracted behavior (changes) into persuasive applications is a largely untreated field of research. While we presented potential approaches to extract behavior, and while there exists work on mobility packages (that quantify the use of transport modes in characteristic ways, e.g., taking the car for longer trips and the bicycle for shorter ones), both the automated extraction as well as the utilization of this information within persuasive applications should be further investigated. For example, it is an open question if and how transitions from one stage of the TTM to the next can be extracted from tracking data, and how an application could make use of this. We have given some examples (such as focusing on educative measures if no behavior changes are detected and the exhibited behavior is not in line with the desired one), and gradually increase feedback and motivational elements with increasing detection of behavioral anomalies.

Second, in this dissertation we introduced and discussed a potential way to generate personalized high-level mobility options. As presented here, these options are decoupled from temporal considerations and thus require a low-level routing system to validate the proposed options. To further increase the real-world applicability of such a system, it should incorporate more detailed information about transport offers and make use of the given restrictions to reduce the set of available options and thus the required processing power. With regards to carpooling, many societal and psychological factors stand in the way of a ubiquitous adoption. While we do not argue how to best overcome those, we think that by lowering the cognitive efforts required in finding a partner could greatly increase its usefulness. Especially short-distance and ad-hoc ridesharing requires the prediction of mobility, the finding of people traveling similar routes, and the proactive suggestion of these potential carpooling trips to users.

Finally, *GoEco!* has shown the positive effects of a persuasive application built from components as introduced in this dissertation. However, and as the dissemination surveys and interviews have shown, a bigger focus on real-time support, personalized motivational elements and the exploration of social elements for motivation remain largely unexplored. Follow-up studies to *GoEco!* could try to answer the questions if it is possible to determine the exact point in time at which a route choice is made, and if persuasive applications could support people in certain decisions by providing timely information and sustainable mobility options. Exploring persuasive applications within smaller communities such as families, companies or housing blocks could open up new avenues as it would allow not only to let people compete in familiar (and often similar) settings, but also to share modes of transport and optimize the performed trips and activities.

A
APPENDIX

A.1 COMPUTATION OF URBANIZATION CLASS

In the following, we describe the procedure to classify locations into one of three classes *city*, *suburb* and *rural* (as used within chapter 2). We use two datasets for this purpose:

- The division of a country into municipalities. For each of these, the number of citizens living in the municipality, the population density as well as its extent must be known.
- A classification of public transport accessibility. For the experiments in this dissertation, we relied on the classification by the Swiss federal office for statistics ARE (Bundesamt für Raumentwicklung ARE 2011), which assigns every location a class *A*-*E*, depending on its distance to PT stops and the frequency of available PT offers at the respective stops (within this classification, *A* denotes best connected, and *E* worst).

To determine locations that should be considered as *city*, we only consider the municipalities that either have a minimum number of citizens living within its boundaries, or that exceed a certain population density threshold. In the case of Switzerland, we used a minimum of 40'000 citizens or a minimum density of 20 people per hectare to consider a municipality "city-like". The combination of these two criteria is required due to the fact that municipalities in Switzerland have irregular extents (as such there are small municipalities bordering city municipalities that still have very large population densities yet a small number of citizens). The resulting municipality boundaries are then intersected with all the locations classified into classes *A* or *B* (by the ARE classification), resulting in a set of locations that lie within a highly populated area and are well-accessible by PT. We classify these locations as *city*.

Similarly, we determine suburban regions as having a minimum of 15'000 citizens or a minimum density of 5 people per hectare, and being classified by the ARE classification as either *A*, *B* or *C*. From the resulting polygon describing people in suburban areas, all regions classified as *city* are subtracted. Finally, all remaining regions (that lie neither within *city* nor within *rural* boundaries) are classified as rural. The approach was evaluated using data from Switzerland and was necessary as the PT transport classifications alone are not sufficient, as they still classify many locations in rural areas as the highest PT accessibility class *A*). Figure A.1 shows an example of the resulting classification from the city of Zurich.

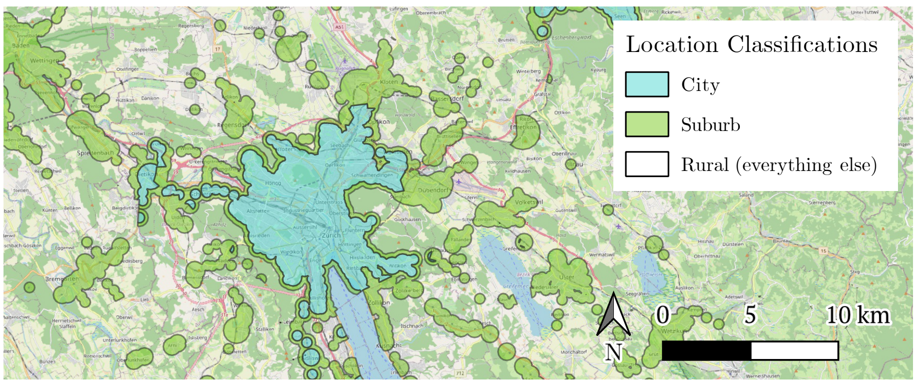


Figure A.1.: Exemplary location classifications around the city of Zurich. Map data © OpenStreetMap.

The NHTS already classifies all locations into one of five classes: *urban*, *city*, *suburb*, *town* and *rural*. As the exact locations are not given by the NHTS (thus an approach like the one presented before is not possible), these classes were directly used, whereas *urban* and *city* were interpreted as *city*, *suburb* as *suburb*, and *town* and *rural* as *rural* (in chapter 2).

A.2 RULESET FOR ROUTE COMPUTATION HEURISTIC

Table A.1 and Table A.2 show an exemplary ruleset of the high-level route planning heuristic (cf. chapter 5) as used within the *GoEco!* project and the case studies presented in chapter 5. Note that the tables do not show context variables that are automatically updated, such as the distances traveled with the respective mode or the number of transfers taken.

The ruleset also contains some factors that are in line with how people usually use different modes of transport and allow reducing the solution space greatly. For example, it can be assumed that people would not take the car to drive close to their destination, only to switch to a shared bicycle for the last few kilometers. To prevent these cases, we constrain the *expand* function in such a way that it only creates transfer locations for car journeys that are maximally half the total distance between origin and destination long. This does not prevent the heuristic from finding journeys such as *walk* $\rightarrow$ *car* $\rightarrow$ *walk* (where the *car* tripleg basically covers the whole distance), as these routes can still be found in the *checkReachability* function.

Mode	Rule	Description
WALK	$d_w = user[distWalked] + dist(A, B)$ $A[\emptyset] \rightarrow WALK[(d_w < user[maxDist]) \wedge (\neg context[rainyWeather] \vee (d_w < user[maxDistRain])) \wedge (context[currentTime] \in user[acceptableTimeIntvlWalk])] \rightarrow B[\emptyset]$: $user[distWalked+ = dist(A, B)], context[time+ = time(A, B)]$	Every node provides walking, however, a user can only walk up to a maximal distance (which gets decreased if it is raining), and if the current time is within an accepted time interval for walking. As a result of walking, the total walked distance is updated as well as the context.
BIKE	$A[user[bikeLocation] = A] \rightarrow BIKE[(\neg context[rainyWeather]) \wedge (context[currentTime] \in user[acceptableTimeIntvlWalk])] \rightarrow B[bikeParking = true]$: $user[bikeLocation] = B, user[distBiked]+ = dist(A, B), context[time+ = time(A, B)]$	A user can only take the bike, if her bike currently is at the location. Further, the destination needs to have a bike parking spot available. Concerning contextual variables similar to walking.
CAR	$A[user[carLocation] = A] \rightarrow CAR[\o] \rightarrow B[\#parkingSpots > 0]$: $user[carLocation] = B, context[time+ = time(A, B)]$	Taking the car is only possible from the location where the user currently has parked her car to locations with a parking spot available. As a result, the car is at location B.
BUS	$A[connectsLineX = true] \rightarrow BUS[\emptyset] \rightarrow B[connectsLineX = true]$: $[\o], context[time+ = time(A, B)]$	Taking a bus is only possible between locations that are served by the same line.

Table A.1.: A selection of rules implemented in the presented prototype system. Table from (Bucher, Jonietz, and Raubal 2017).

Mode	**Rule**	**Description**
TRAIN	$A[connectsLineX = true] \rightarrow TRAIN[\emptyset] \rightarrow B[connectsLineX = true] : [\emptyset], context[time+ = time(A, B)]$	Similar to BUS.
TRAM	$A[connectsLineX = true] \rightarrow TRAM[\emptyset] \rightarrow B[connectsLineX = true] : [\emptyset], context[time+ = time(A, B)]$	Similar to BUS.
CARSHARE	$A[carSharing = true, \#cars > 0] \rightarrow CARSHARE[\emptyset] \rightarrow B[\#parkingSpots > 0] : A[\#cars- = 1], context[time+ = time(A, B)]$	Carsharing is possible from carsharing locations, where enough cars are available. The destination needs to have free parking spots.
CARPOOL	$A[intersects(A, C) = true] \rightarrow CARPOOL[\emptyset] \rightarrow A[intersects(B, D) = true] : [ø]$	Carpooling is possible from locations that intersect with a spatio-temporal corridor of a carpooler.
BIKESHARE	$A[bikeSharing = true, \#bikes > 0] \rightarrow BIKESHARE[context[weather]! = \text{``}rain''] \rightarrow B[bikeParking = true] : A[\#bikes- = 1], user[distBiked]+ = dist(A, B), context[time+ = time(A, B)]$	Bikesharing is possible from bikesharing locations, where enough bikes are available.

Table A.2.: A selection of rules implemented in the presented prototype system (cont.). Table from (Bucher, Jonietz, and Raubal 2017).

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NOTATION

GENERAL NOTATION

SYNTAX	MEANING
$x.y$	Selection of (named) attribute of tuple $x = (y, ...)$

MOBILITY HISTORIES

SYMBOL	MEANING
e	Entity (e.g., a person or a car)
$p = (t, x, y, \eta)$	Trackpoint with timestamp t, coordinate pair (x, y) and accuracy η
$P_e = (p_{e,1}, \ldots, p_{e,n})$	Trackpoints of entity e (track)
$\tau = (p_1, \ldots, p_n)$	Trajectory, consisting of a list of trackpoints
$s = (t_s, t_e, x, y)$	Staypoint with arrival/departure times t_s/t_e and location (x, y)
$a = (t_s, t_e, x, y, \omega)$	Activity with arrival/departure times t_s/t_e, location (x, y) and purpose ω
$l = (t_s, t_e, m, P_l)$	Tripleg with starting/ending time t_s/t_e, transport mode m and trajectory P_l
$\theta = (a_s, t_s, a_e, t_e, L_\theta)$	Trip with starting/ending time t_s/t_e and activity a_s/a_e, and list of triplegs L_θ
Π	Place (geographical region defined by polygon) at which person regularly spends time
$\Theta = (\Pi, L_\Theta)$	Tour, i.e. a sequence of trips starting and ending at the same place Π
$\hat{\theta} = (L_\theta)$	Systematic trip
$\hat{\Theta} = (\Pi, L_\Theta)$	Systematic tour

mobility descriptors

symbol	meaning
$d(P_e, t_s, t_e, m)$	distance along trackpoints $p \in P_e$ that fall between t_s and t_e and are covered with transport mode m
$\Delta(P_e, t_s, t_e, m)$	duration of all travels by transport mode m between t_s and t_e
$MS_{\hat{m}}$	modal split of transport mode $\hat{m}$
$n_{trips}(t_s, t_e)$	number of trips in time period t_s to t_e
$S_{\hat{M}}$	distribution of sequences of triplegs $\hat{M}$
$n_{s/\theta}$	number of staypoints per trip
$n_a(t_s, t_s, \omega)$	number of times activity of purpose ω was performed
$\Delta(\omega)$	time spent on activities of purpose ω
$S_{\hat{\omega},\hat{M}}$	distribution of tripleg combinations $\hat{M}$ used to reach activities with purpose ω

spatio-temporal context and features

symbol	meaning
$C_{GM} = (u(\boldsymbol{f}_H), u(\boldsymbol{f}_W))$	General mobility context
$C_{u,\tau} = (\boldsymbol{f}_O, \boldsymbol{f}_D, \Phi)$	Immediate context (when planning a trip)
$\boldsymbol{f}_l$	Features of location l
Φ	Personal context
$\mathfrak{C}$	Trajectory algebra statement
m	Mode of tripleg
t	Hour of day
$f_{\{l,\theta\},\ temp}$	Temperature at start/end of tripleg/trip
$f_{\{l,\theta\},\ precip}$	Precipitation at start/end of tripleg/trip
$f_{\{l,\theta\},\ \{s,e,\tau\},\ PT}$	Number of PT stops in vicinity of start/end of tripleg/trip
$f_{\{l,\theta\},\ \{s,e\},\ POI}$	Distribution of Point of Interest (POI) in vicinity of start/end of tripleg/trip
$f_{\bar{s}}$	Avg. speed along tripleg
$f_{\sum d}$	Total distance of tripleg

SPATIO-TEMPORAL CONTEXT AND FEATURES (CONT.)

SYMBOL	MEANING
$f_{\max d}$	Maximum distance between trackpoints
$f_{\sphericalangle}$	Avg. heading change between trackpoints
$f_{\Delta,PT}$	Duration difference between trip and PT alternative
$f_{d,\{s,e\},PT}$	Distance between start/end point of trip and PT alternative
$f_{n_s,PT}$	Number of stops in PT alternative close to actual trajectory
$r_p(\cdot)$	Maximum Pagerank of PT stop close to location $\cdot$

SUSTAINABILITY

SYMBOL	MEANING
$G_h(\theta) = f(C_{u,\theta}, A_u, G_u, G_S)$	Human capital gain
$L_n(\theta)$	Loss in natural capital
$c_{\text{GHG}}(\theta)$	Produced GHG emissions
$c_{\text{Eco. Impact}}(\theta)$	Financial costs of GHG emissions
$c_{\text{Monetary}}(\theta)$	Monetary costs of travel
$g_{\text{Financial}}(a)$	Financial (business) gains from activity
$g_{\text{Personal}}(a)$	Personal/social gains from activity
$S(\theta)$	Sustainability indicator for trip

ROUTE PLANNING

SYMBOL	MEANING
$\pi_i \in \Pi_m$	Transfer location
$type(\pi) : \Pi \to \{A, P\}$	Mapping transfer locations to points or areas
(P, D, E_S)	Transport offer
P, D	Pickup and dropoff transfer locations
E_S	Reachability of locations in D from P
A, A_T, P_T	Pickup and dropoff types
$\mathcal{G} = (\mathcal{V}, \mathcal{E})$	Transfer graph describing connections of π_i
$l = (v, s_s, t_s, s_e, t_e)$	Elementary connection (corresponding to *tripleg*, cf. Mobility Histories)
$L_\theta = r(o, d, t)$	Route request from o to d at time t

ACRONYMS

API	Application Programming Interface
AV	Autonomous Vehicle
BCSS	Behaviour Change Support System
BEV	Battery Electric Vehicle
CC	Collaborative Consumption
CP	Carpooling
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DARP	Dial-A-Ride Problem
DEM	Digital Elevation Model
DTA	Drive Time Area
DTW	Dynamic Time Warping
EV	Electric Vehicle
FIFO	First In First Out
GHG	Greenhouse Gas
GIS	Geographic Information Systems
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GTFS	General Transit Feed Specification
HCI	Human-Computer Interaction
HMM	Hidden Markov Model
ICE	Internal Combustion Engine

ICT	Information and Communication Technologies
IOT	Internet of Things
LAT	Location-Aware Technologies
LBS	Location Based Service
LCA	Life Cycle Assessment
MAAS	Mobility as a Service
MAST	Mobility Allowance Shuttle Transport
MAUP	Modifiable Areal Unit Problem
MRT	Mass Rapid Transit
NHTS	US National Household Travel Survey
NN	Nearest Neighbor
OS	Operating System
OSM	OpenStreetMap
OSRM	Open Source Routing Machine
OTP	OpenTripPlanner
PHEV	Plugin Hybrid Electric Vehicle
PMT	Private Motorized Transport
PT	Public Transport
POA	Point of Action
POI	Point of Interest
RF	Random Forest
SBB	Swiss Federal Railways
SDK	Software Development Kit
SM	Slow Mobility

SMC	Swiss Mobility Census
SOC	State of Charge
SOV	Single Occupant Vehicle
TTM	Transtheoretical Model of Behavior Change
VGI	Volunteered Geographic Information
VMT	Vehicle Miles Traveled
VRPT	Vehicle Routing Problem with Time Windows
WLAN	Wireless Local Area Network

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CURRICULUM VITAE

PERSONAL DATA

Name	Dominik Christoph Bucher
Date of Birth	October 22, 1988
Place of Birth	Luzern (Switzerland)
Citizen of	Mühlau (Switzerland)
Contact	dobucher@ethz.ch, dominik.bucher@gmail.com
Website	http://dominikbucher.com

EDUCATION

2015 – 2020	ETH Zurich, Chair of Geoinformation Engineering *Doctor of Sciences (Dr. sc. ETH Zurich)*
2011 – 2013	ETH Zurich/The University of Edinburgh *Master of Science in Electrical Engineering and Information Technology* Focus on Computer and Networks
2007 – 2010	ETH Zurich/The University of California, Berkeley *Bachelor of Science in Electrical Engineering and Information Technology*
2001 – 2007	High School Oerlikon (KSOe) *Matura (University Entrance Diploma)* Focus on Applied Mathematics and Physics

Professional Experience

2016 – Now	MIE Lab *Co-Founder* Mobility research lab within the Group of Geoinformation Engineering at ETH Zurich.
2015 – Now	BetaFarm GmbH *Co-Founder* Company-builder hosting several projects.
2014 – Now	earlyhire.ch *Tech Lead / Co-Owner* Leading Swiss startup job platform.
2010	Levitronix *Internship (Electrical Engineer)* Specializes in bearingless electric motors.
2008	ETH Zurich *Undergraduate Student Instructor* In Digital Circuits (Prof. G. Tröster).
2007 – Now	Community of Bassersdorf/Kloten *Organist* Playing the organ on weekends.

Research Projects

2019 – Now	SCCER Rideshare *Project Proposal, Primary Researcher* Generating automatic ridesharing suggestions.
2019 – Now	SBB Mobility Initiative *Advisor (within MIE lab)* Analyzing a new MAAS offer by SBB.
2019 – Now	SCCER Smart Charging *Project Proposal, Advisor (within MIE lab)* Individual mobility needs and charging EVs.

2018 – Now	COMMIT *Project Proposal, Researcher* Context-Aware Mobility Mining Tools (COMMIT) providing methods to process spatio-temporal data.
2017 – 2019	alpinavera *Project Proposal, Primary Researcher* Optimizing delivery schedules for farmers in mountain regions of Switzerland.
2017 – 2019	SBB Green Class I & II *Project Proposal, Researcher* Analyzing a new MAAS offer by SBB.
2015 – Now	SCCER Mobility *Advisor (within MIE Lab), Researcher* Improving individuals' access to different forms of mobility and transport.
2015 – 2018	*GoEco!* *Researcher* Studying the potential of gamified apps to convince people to travel more sustainably.

DISTINCTIONS

2019	Runner-Up traffic4cast Competition *NeurIPS 2019 Competition by IARAI* Predicting traffic status using neural networks
2019	Best Poster Award Nominee *6th Annual Conference SCCER Mobility* Analysis framework and results of the SBB Green Class pilot studies

2019	Best Poster Award Nominee *6th Annual Conference SCCER Mobility* The future of logistics: How will electric trucks shape the future energy demand and distribution of Switzerland?
2018	Hack Zurich Challenge Winner *Siemens Challenge* Tracking of people on railway platforms.
2018	Cover Story Feature *International Journal of Geo-Information* Assessing the Influence of Spatio-Temporal Context for Next Place Prediction using Different Machine Learning Approaches (Urner et al. 2018).
2017	Best Paper Award Nominee *D-A-CH+ Energieinformatik 2017* Using Locally Produced Photovoltaic Energy to Charge Electric Vehicles (Buffat, Bucher, and Raubal 2018).
2017	Best Paper Award *AGILE 2017* Energy-based Routing and Cruising Range Estimation for Electric Bicycles (Haumann, Bucher, and Jonietz 2017).
2016	Hack Zurich Challenge Winner *SBB Challenge* Using Bluetooth Beacons to provide indoor localization and app-based navigation.
2015	Best Paper Award Nominee *ICT for Sustainability (ICT4S), 2015* A Taxonomy of Motivational Affordances for MeaningfulGamified and Persuasive Technologies (Weiser, Bucher, et al. 2015).
2012	IET Present Around the World Europe *IET Europe – Paris, France* Second place at the European IET Present around the World finals in Paris (*Local Browsing*).

PUBLICATIONS

Only publications that are not part of this dissertation (and thus mentioned at the beginning of this dissertation) are listed here.

- Dominik Bucher, Henry Martin, David Jonietz, et al. (2021). „Estimation of Moran's I in the Context of Uncertain Mobile Sensor Measurements." In: *11th International Conference on Geographic Information Science*. Ed. by Krzysztof Janowicz and Judith A. Verstegen. Schloss Dagstuhl–Leibniz-Zentrum fuer Informatik.
- Martin Raubal, Dominik Bucher, and Henry Martin (2020). „Geosmartness for personalized and sustainable future urban mobility." en. In: *Urban Informatics*. Accepted: 2020-04-20T08:49:11Z. Springer.
- Henry Martin, Dominik Bucher, Ye Hong, et al. (2020). „Graph-ResNets for short-term traffic forecasts in almost unknown cities." In: *Proceedings of Machine Learning Research* 123, pp. 153–163.
- Ray Pritchard, Dominik Bucher, and Yngve Frøyen (May 2019). „Does new bicycle infrastructure result in new or rerouted bicyclists? A longitudinal GPS study in Oslo." en. In: *Journal of Transport Geography* 77, pp. 113–125.
- Henry Martin, Henrik Becker, et al. (2019). „Begleitstudie SBB Green Class - Abschlussbericht." de. Zurich.
- Henry Martin, Ye Hong, et al. (Oct. 2019). *Traffic4cast-Traffic Map Movie Forecasting – Team MIE-Lab*. en. Working Paper. Accepted: 2020-01-09T06:18:52Z Publication Title: arXiv. Cornell University, p. 1910.13824.
- Dominik Bucher, René Buffat, et al. (2019). „Energy and greenhouse gas emission reduction potentials resulting from different commuter electric bicycle adoption scenarios in Switzerland." In: *Renewable and Sustainable Energy Reviews* 114, p. 109298.
- Henry Martin, Dominik Bucher, Esra Suel, et al. (Dec. 2018). „Graph Convolutional Neural Networks for Human Activity Purpose Imputation." en. In: *NIPS Spatiotemporal Workshop at the 32nd*

Annual Conference on Neural Information Processing Systems (NIPS 2018). Accepted: 2019-08-13T09:18:58Z.

- Roswita Tschümperlin, Dominik Bucher, and Joram Schito (2018). „Using Stream Processing to Find Suitable Rides: An Exploration based on New York City Taxi Data." In: *Spatial Big Data and Machine Learning in GIScience Workshop at GIScience 2018*. Schloss Dagstuhl–Leibniz-Zentrum fuer Informatik.
- Paolo Fogliaroni et al. (2018). „Intersections of Our World." In: *10th International Conference on Geographic Information Science*. Vol. 114. Schloss Dagstuhl–Leibniz-Zentrum fuer Informatik, p. 3.
- Henrik Becker, Allister Loder, et al. (July 2018). „Usage patterns and impacts of a mobility flat rate traced with a Smartphone App." en. In: *Proceedings of the 15th International Conference on Travel Behaviour Research, (IATBR2018)*.
- Dominik Bucher, David Rudi, and René Buffat (2018). „Captcha Your Location Proof—A Novel Method for Passive Location Proofs in Adversarial Environments." In: *LBS 2018: 14th International Conference on Location Based Services*. Springer, Cham, pp. 269–291.
- René Buffat, Dominik Bucher, and Martin Raubal (2018). „Using locally produced photovoltaic energy to charge electric vehicles." In: *Computer Science-Research and Development* 33.1-2, pp. 37–47.
- Jorim Urner et al. (2018). „Assessing the Influence of Spatio-Temporal Context for Next Place Prediction using Different Machine Learning Approaches." In: *ISPRS International Journal of Geo-Information* 7.5, p. 166.
- Dominik Bucher (2017). „Vision Paper: Using Volunteered Geographic Information to Improve Mobility Prediction." In: *Proceedings of the 1st ACM SIGSPATIAL Workshop on Prediction of Human Mobility*. ACM, p. 2.
- Ray Pritchard and Dominik Bucher (2017). „Targeted sensing technology for bicycle research-early results from a longitudinal study in Oslo." In: *International NTNU Sustainability Science Conference*. NTNU, pp. 31–32.

- Simon Tobias Haumann, Dominik Bucher, and David Jonietz (2017). „Energy-based Routing and Cruising Range Estimation for Electric Bicycles." In: *Societal Geo-Innovation: Short Papers, Posters and Poster Abstracts of the 20th AGILE Conference on Geographic Information Science. Wageningen University & Research 9-12 May 2017, Wageningen, the Netherlands*. Association of Geographic Information Laboratories for Europe (AGILE), p. 145.

SUPERVISED THESES

2020	*Conserved Quantities in Transport Mode Choices and Mobility Patterns of People* Ye Hong, MSc thesis supervised by Dominik Bucher, Henry Martin and Prof. Martin Raubal.
2020	*Traffic Map Forecasting using Graph Convolutional Neural Networks* Konstantin Arbogast, MSc thesis supervised by Henry Martin, Dominik Bucher and Prof. Martin Raubal.
2020	*Evaluation and Implementation of Trajectory Similarity Measures within the Context of a Mobility Processing Framework* Sven Ruf, BSc thesis supervised by Jannik Hamper, Dominik Bucher and Prof. Martin Raubal.
2019	*The Future of Logistics: How will Electric Trucks Shape the Future Energy Demand and Distribution of Switzerland?* Keyuan Yin, semester thesis supervised by Dominik Bucher, Henry Martin, Dr. René Buffat and Prof. Martin Raubal.
2018	*Real-Time Processing of Spatio-Temporal Data* Roswita Tschümperlin, MSc thesis supervised by Dominik Bucher and Prof. Martin Raubal.

2017 *Renewable Power Production Potential in Car Parking Areas*
Janis Münchrath, semester thesis supervised by René Buffat, Dominik Bucher and Prof. Martin Raubal.

2017 *Assessing and Predicting Mobility Behavior using Neural Networks*
Jorim Urner, MSc thesis supervised by Dominik Bucher, Jing Yang, Dr. David Jonietz, Prof. Ross Purves and Prof. Martin Raubal.

2016 *Carsharing and Carpooling in Multi-Modal Routing*
Julian Kissling, MSc thesis supervised by Dominik Bucher, Dr. Kai-Florian Richter, Dr. Haosheng Huang, Prof. Robert Weibel and Prof. Martin Raubal.

2016 *Optimizing the Operation Range of E-Bikes in Routing Systems*
Simon Haumann, MSc thesis supervised by Dominik Bucher and Prof. Martin Raubal.

2015 *Das Traveling Salesman Problem und die Optimierung von Auslieferungszeiten*
Katharina Henggeler, BSc thesis supervised by Dominik Bucher, Ioannis Giannopoulos and Prof. Martin Raubal.

VARIOUS

- Took part in the organization of the 14th Conference on Location Based Services (LBS 18) and the Spatial Big Data and Machine Learning in GIScience workshop at GIScience 2018.

- Reviewed articles in Intelligent Transport Systems (IEEE), Journal of Location Based Services, Journal of Transport Geography, Sensors, Knowledge and Data Engineering, The Open Transportation Journal, and for various conferences and workshops.

- Taught classes within the following courses: GIS I, GIS II, GIS III, GIS and Geoinformatics Lab, Mobile GIS, Geodata Analysis, Geomatics Seminar, CAS Mobilität der Zukunft.

COLOPHON

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