Concept of Interactive Machine Learning in Urban Design Problems

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Author(s):
Chirkin, Artem; König, Reinhard

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Concept of Interactive Machine Learning in Urban Design Problems

Artem M. Chirkin
ETH Zürich
Wolfgang-Pauli-Str. 27, CH-8093
Zurich, Switzerland
chirkin@arch.ethz.ch

Reinhard König
ETH Zürich
Wolfgang-Pauli-Str. 27, CH-8093
Zurich, Switzerland
reinhard.koenig@arch.ethz.ch

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Abstract
This work presents a concept of interactive machine learning in a human design process. An urban design problem is viewed as a multiple-criteria optimization problem. The outlined feature of an urban design problem is the dependence of a design goal on a context of the problem. We model the design goal as a randomized fitness measure that depends on the context. In terms of multiple-criteria decision analysis (MCDA), the defined measure corresponds to a subjective expected utility of a user.

In the first stage of the proposed approach we let the algorithm explore a design space using clustering techniques. The second stage is an interactive design loop; the user makes a proposal, then the program optimizes it, gets the user's feedback and returns back the control over the application interface.

Author Keywords
MCDM; interactive machine learning; urban design; multiple-criteria optimization

ACM Classification Keywords
D.2.2 [Design Tools and Techniques]: User interfaces; H.3.3 [Information Search and Retrieval]: Selection process; H.5.2 [User Interfaces]: Interaction styles; J.6 [Computer-aided engineering]: Computer-aided design (CAD)

Generative Design as a source of creativity

Although Avital and Te'Eni mainly focus on the generative fit of a program, referring to Frazer[3] and Janssen[4], they write:
in the case of artificial intelligence and other types of smart agents, information technology can be also modelled as an antecedent or source of a creative output [1].

Incorporating certain generative design (GD) algorithms, a program can inspire or challenge a designer by creating unique design alternatives[4].

Introduction

This research presents a concept of interactive machine learning developed in an urban design context. The overall intention of the research is to improve task-related performance of the designers working with their software. Unfortunately, the nature of the application domain makes it difficult to evaluate the impact of a program on a designer's performance. One of the key performance factors in this area is the creativity of a designer. It has been argued that computer interface should be appealing, intelligent, and stimulating to endorse the creativity of an application's user[9] – thus an application is not allowed to disturb a designer focused on their work by asking too many questions in an active machine learning style. Avital and Te'Eni[1] build the concept of generativity which relates to the ability to create something new. According to Avital, two components of a task-related performance are the operational efficiency and the generative capacity; we aim at endorsing the generativity by proposing machine-generated design alternatives while trying keep the operational efficiency on a similar level with convenient CAD systems.

Background

Evaluation of a solution (design) is an important part of design space exploration or optimization. The key concept within the scope of the research is the design criteria that can be made explicit. Based on these criteria a user (designer) or a program can choose a preferable solution among available alternatives.

Quantifiable design criteria for urban design tasks include purely geometrical or topological measures, such as the length of roads or space accessibility[10], as well as social aspects, especially the perception of space, e.g. streetscape security[7]. We do not restrict the way the criteria are estimated; we state explicitly that the qualitative or subjective nature of some underlying aspects introduces an uncertainty into the evaluated criteria.

Obviously, criteria formed by the evaluation methods are interdependent and sometimes contradictory. Thus, the designer faces a complex multiple-criteria design problem (MCDP) and wants to find the best compromises between the criteria. An approach to a MCDP that is widely used in design synthesis methods is the exploration of Pareto-optimal solutions[11]. The decision as to which of the Pareto-optimal solutions is best suited for a particular problem depends on qualitative criteria or non-operational human preferences.

A way to find a desirable solution in a Pareto-front is to estimate the designer's priorities over the design criteria. This problem lies in the area of multiple-criteria decision making (MCDM) [6]. MCDM methods vary in a way they relate criteria to each other. The simplest approach is to make a single utility function as a linear combination of criteria; then the problem reduces to a search of weights (importance) for each criterion. This approach has a number of extensions that treat the weights as probabilities of being the most important criterion [8]. Many sociological studies argue that people tend to underestimate low probabilities [8, 6], thus more recent developments introduce uncertain method and the fuzzy logic to utility models (e.g. [2]).

Interactive design process

Figure 1 shows a UML diagram of the proposed machine learning and user interaction process. Process B on the figure describes the unsupervised part of the machine learning process. As an initial dataset for the unsupervised learning we can use existing spatial configurations, which are freely available through OpenStreetMap. An unsupervised phase of the learning labels initial data; but, after that,

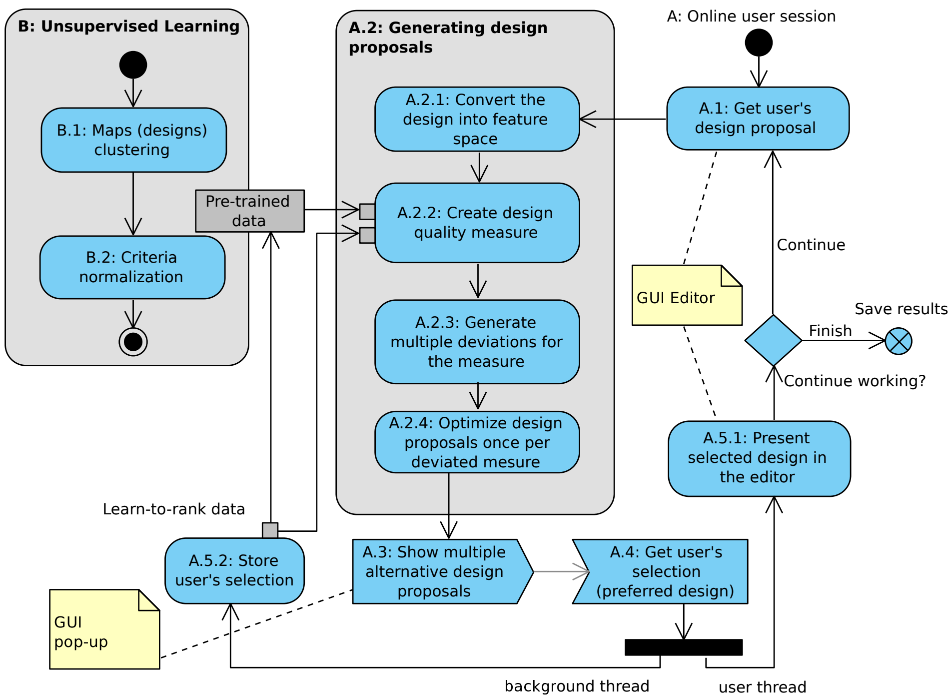

Figure 1: Learning cycle embedded into a design process

any new data must be classified into one of the available clusters. This can be done by a variety of supervised learning methods. Once we have a label assigned to a particular design layout, we can assume that a design goal does not change a lot within an assigned cluster. Thus we optimize a likelihood function on a data subset from this cluster to estimate preference parameters of a designer in a given case.

The research does not aim at providing fully machine-generated urban design proposals. Instead, we want to develop a recommendation system that could be integrated into a design process conducted by a human. Process A on Figure 1 shows the interaction:

- A.1 A designer creates the first version of a design;
- A.2 The program analyzes the design assuming it to be preferable for the designer. This allows making a hypothesis on the design goals;
- A.3 According to the created (machine) model of the designer's goals, the program suggests a small set of the machine-generated alternatives;
- A.4 The designer chooses one of the alternatives, thus giving additional information for refining the machine's model;
- A.5.1 The designer finishes the work, or continues to step A.1 creating a new design version.

The interaction cycle described above does not require providing any information besides the input it takes by observing a standard human design process: the only additional action the designer does is selecting the preferred solution among the proposed ones, which is itself the reason to use the application and the aim of the project.

Further research

The core ideas of the approach are the declaration of the data sources and the communication loop between a user and a program. We have developed the learning model based on changes to designs submitted by the user. This approach resembles a reinforcement learning model with human reward, which is a rapidly developing topic in machine learning (such models are described in e.g. [5]). We

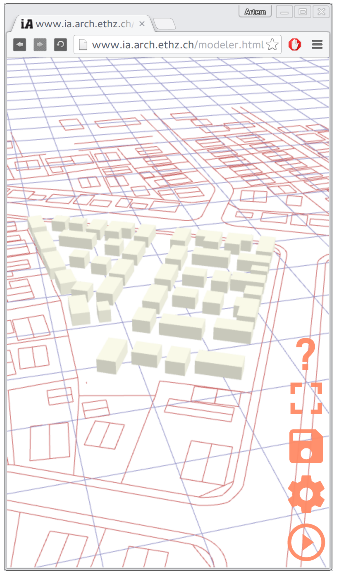

Figure 2: A prototype of a web-based geometry editor. The program is to be available for a wide range of users; thus, gives a tool to learn urban design for audience and collects data for the research.

have also mentioned that the program may propose multiple design alternatives (Figure 1 A.3). Since the program can control generation of the alternatives, it can use active learning exploration-exploitation approach to improve its estimates. This reveals a lot of opportunities for further research.

A designer's priorities usually change during the design session as their proposal advances, hence a design session can also be modelled, for instance, as Markov decision process.

At the current stage of the project we are working on simplified geometries. Moving to real-world districts is a principle step towards completion of the project, and is to be done in near future.

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