



Autonomous driver identification using vehicle trajectory data

Conference Poster**Author(s):**

Makridis, Michail ; Laverde Marín, Andrés; Fontaras, Georgios; Ramírez Quintana, María José; Kouvelas, Anastasios 

Publication date:

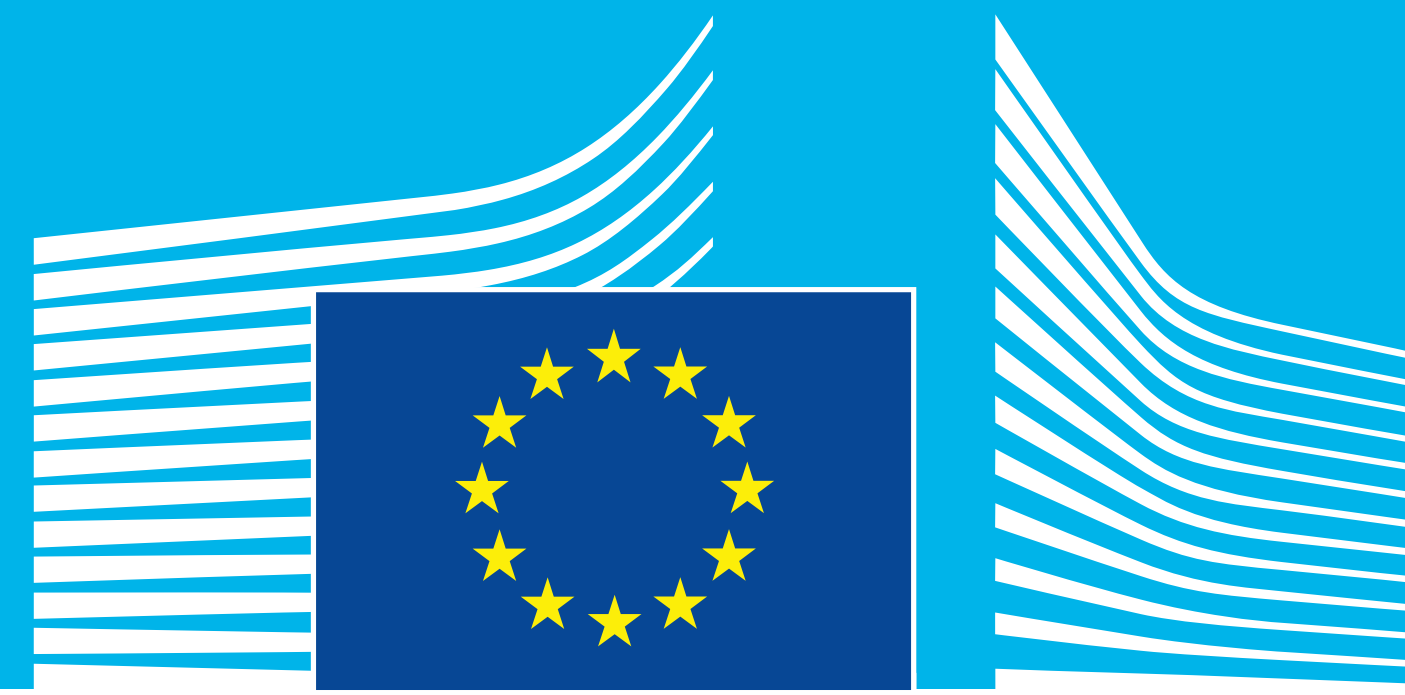
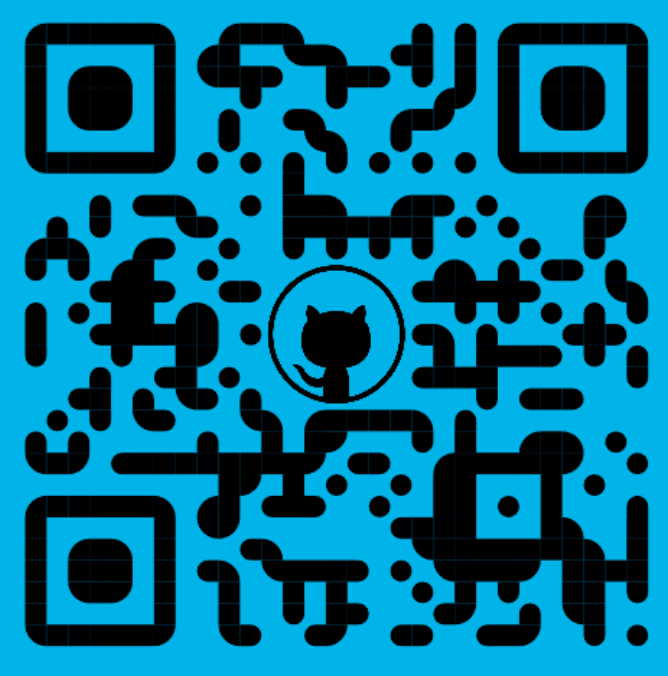
2023-01

Permanent link:

<https://doi.org/10.3929/ethz-b-000594789>

Rights / license:

In Copyright - Non-Commercial Use Permitted



Autonomous driver identification using vehicle trajectory data

Michail A. Makridis, Andres L. Marin, Georgios Fontaras, María José Ramírez Quintana, and Anastasios Kouvelas

Idea

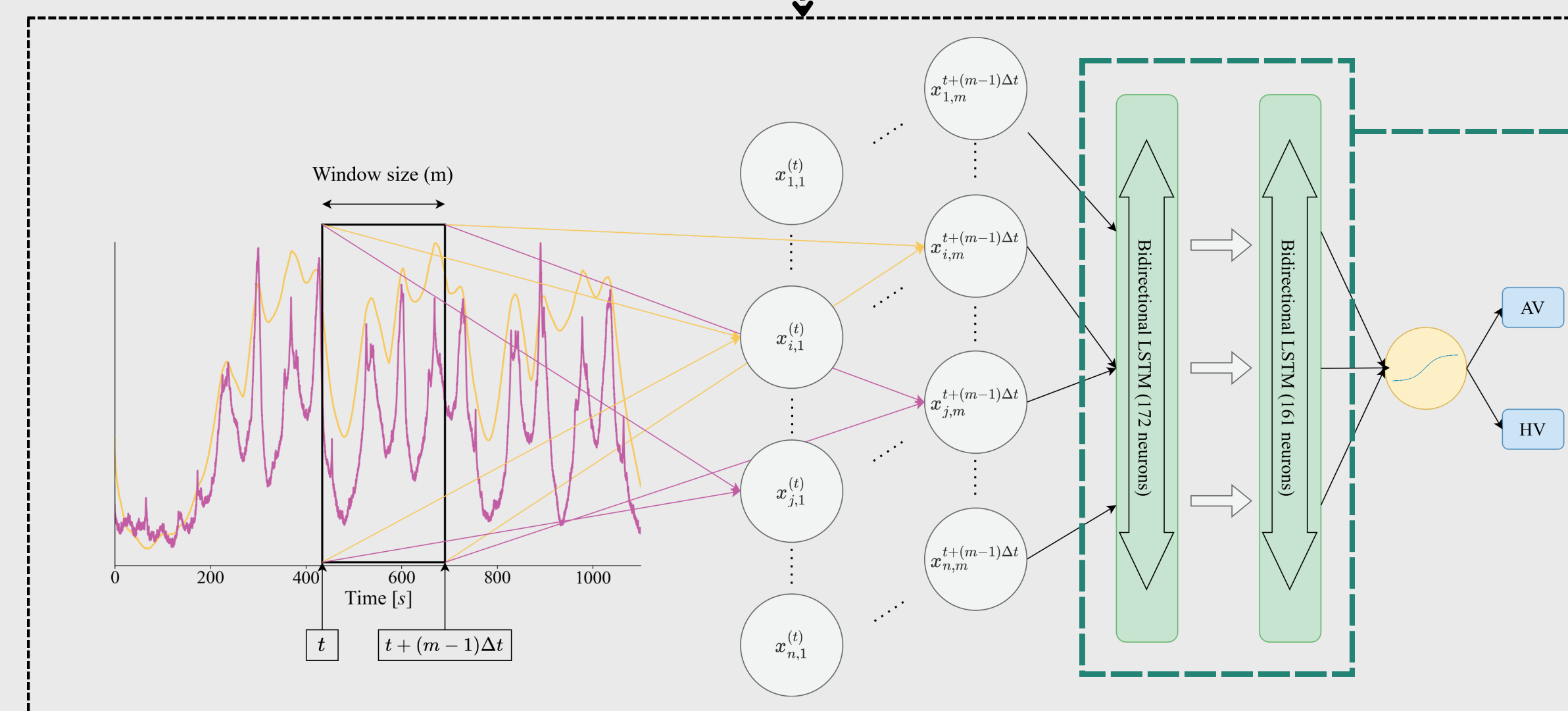
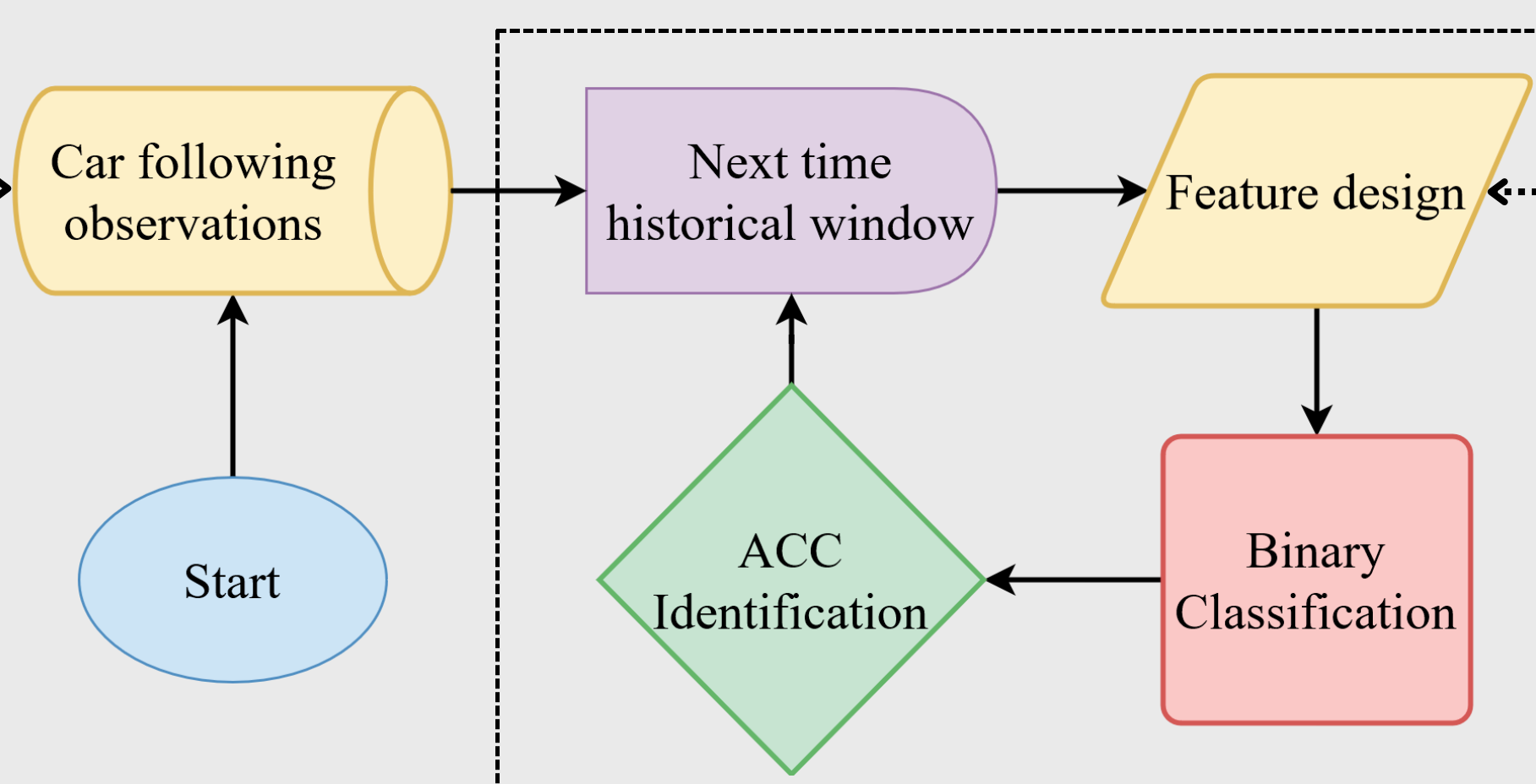
Robust identification of automated driving only by observing inexpensive raw trajectory data, i.e. speed, acceleration and spacing.

Background

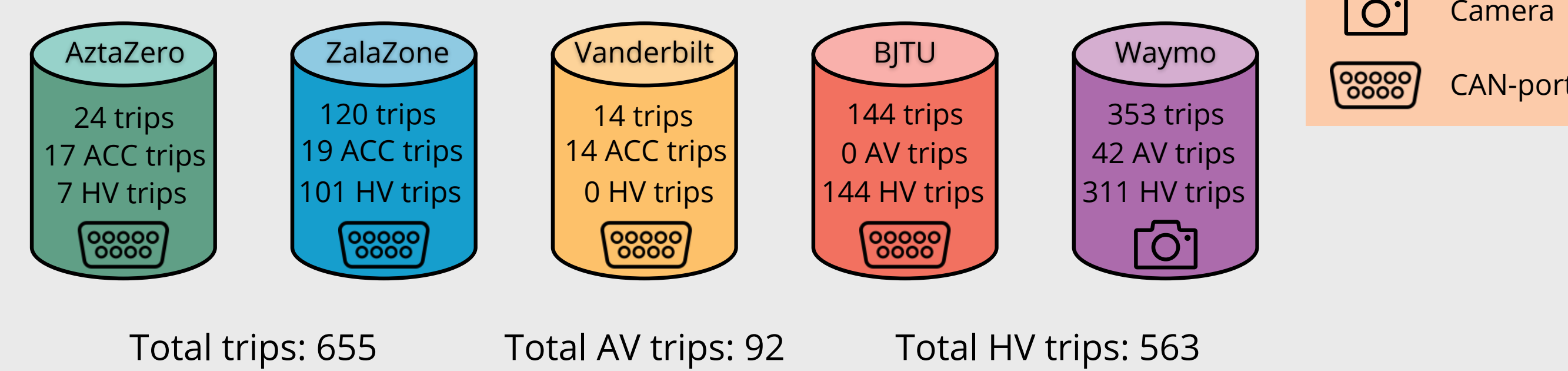
Prominent behavioral differences exist between human drivers (HV) and automated driving (AV). These differences gradually introduce unprecedented patterns in already complex road traffic dynamics. Knowledge of whether a human or a controller operates a vehicle could quantify the impact of AVs and leverage new possibilities for sustainable mobility.

Methodology

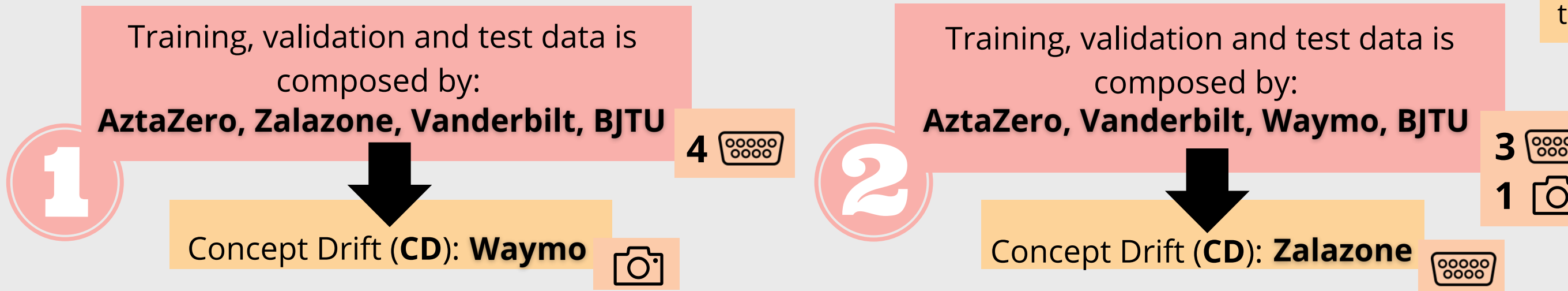
For each input signal, we calculate the **standard deviations** over a past-time step window



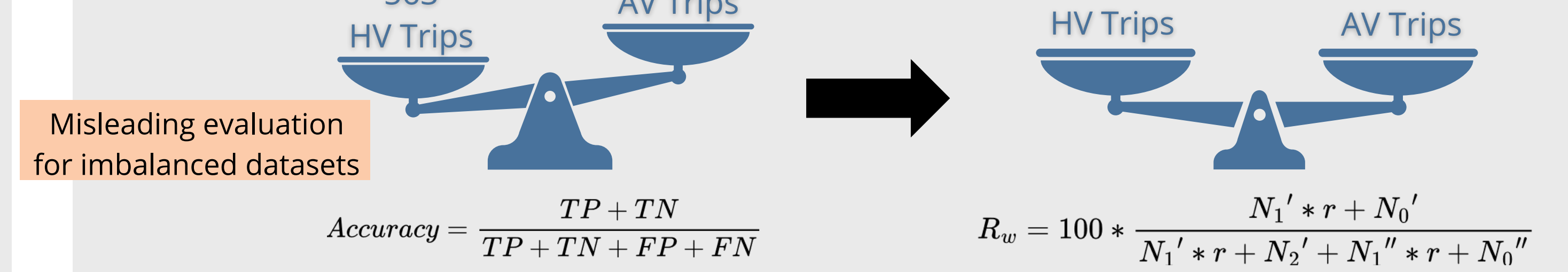
Data



Scenarios

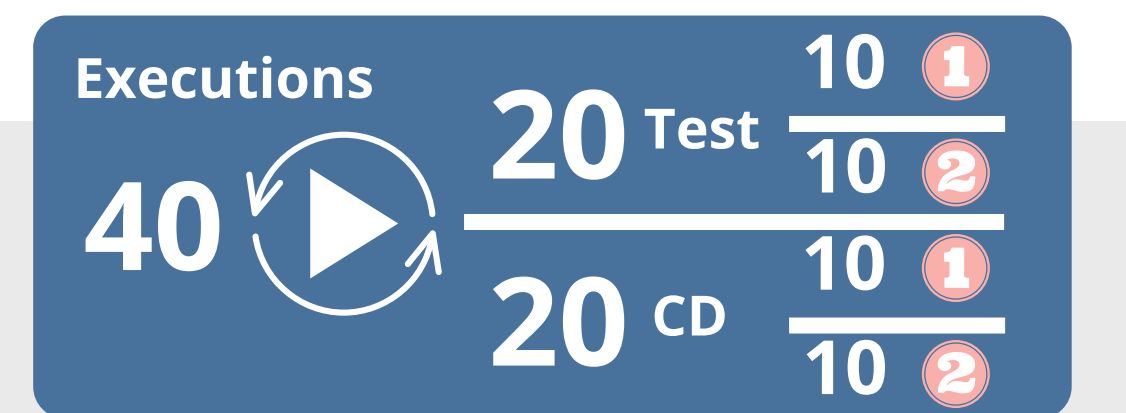


Metric

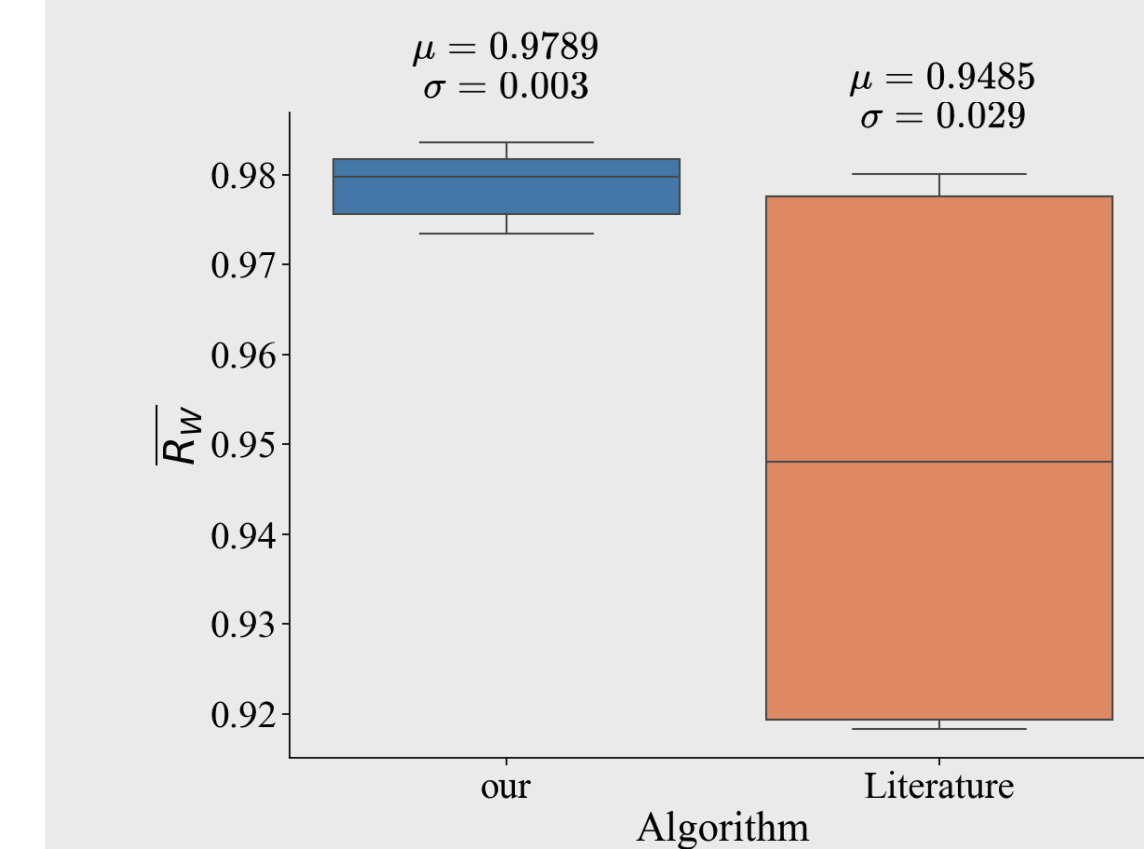


Results and Discussions

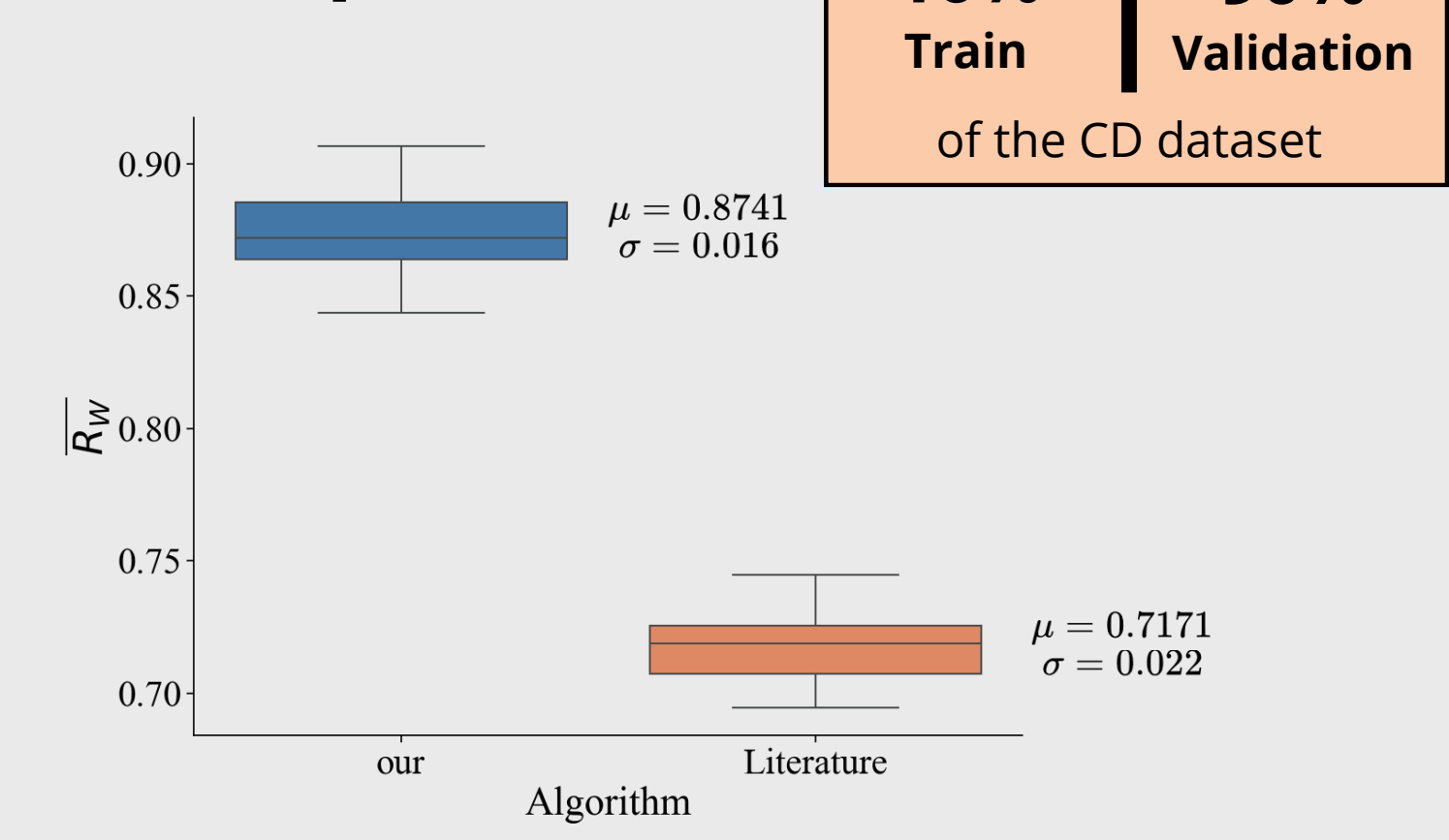
CD refers to the phenomenon in machine learning where the statistical properties of the data being processed change over time, potentially leading to decreased model performance.



Test



Concept Drift



Major Findings:

- Our method is available to identify ACC and AV.
Our method performs in a imbalance dataset without in favor of the majority class.

Method Advantages:

- Our method is available to generalise to new datasets from different sources.

Conclusion

We propose a method for identifying autonomous driving in unseen datasets that has high accuracy and reliability. It can classify ACC and AV based on speed, acceleration and Timeheadway. The LSTM considers context from previous and future frames, improving performance. This method has high accuracy and reliability for identifying autonomous driving in unseen datasets, making it a promising approach for real-world applications.

References

[1] Q. Li, X. Li, H. Yao, y. Z. Liang, «Automated Vehicle Identification in Mixed Traffic», en 2021 IEEE International Intelligent Transportation Systems Conference (ITSC), sep. 2021, pp. 1-5. doi: 10.1109/ITSC48978.2021.9564756.
[2] M. Makridis, K. Mattas, A. Anesiadou, y B. Ciuffo, «OpenACC. An open database of car-following experiments to study the properties of commercial ACC systems», Transp. Res. Part C Emerg. Technol., vol. 125, p. 103047, abr. 2021, doi: 10.1016/j.trc.2021.103047.
[3] G. Gunter et al., «Are Commercially Implemented Adaptive Cruise Control Systems String Stable?», IEEE Trans. Intell. Transp. Syst., vol. 22, n.o 11, pp. 6992-7003, nov. 2021, doi: 10.1109/TITS.2020.3000682.
[4] X. Hu, Z. Zheng, D. Chen, X. Zhang, y J. Sun, «Processing, assessing, and enhancing the Waymo autonomous vehicle open dataset for driving behavior research», Transp. Res. Part C Emerg. Technol., vol. 134, p. 103490, ene. 2022, doi: 10.1016/j.trc.2021.103490.
[5] R. Jiang, M.-B. Hu, H. M. Zhang, Z.-Y. Gao, B. Jia, y Q.-S. Wu, «On some experimental features of car-following behavior and how to model them», Transp. Res. Part B Methodol., vol. 80, pp. 338-354, oct. 2015, doi: 10.1016/j.trb.2015.08.003.

