Center for Sustainable Future Mobility (CSFM)

Evaluating the Robustness of Deep Learning Models for Mobility Prediction Through Causal Interventions

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1 Introduction

Changes in the characteristics of mobility data can significantly influence the predictive performance of deep learning models. However, there is still a lack of understanding of the degree of their impacts and the robustness of deep learning models against the variability of these characteristics. This hinders the development of benchmark datasets for evaluating different mobility prediction models. In this study, we use a causal intervention approach to evaluate the robustness of deep learning models towards different interventions of mobility data characteristics [1], using both traffic forecast and individual next location prediction as case studies.

2 Methods

1. Construct **Structural Causal Model (SCM)** based on mobility simulators
2. Conduct **causal interventions** and test the difference in prediction errors before and after the intervention
3. Quantify the degree of domain shifts using **uncertainty estimation**

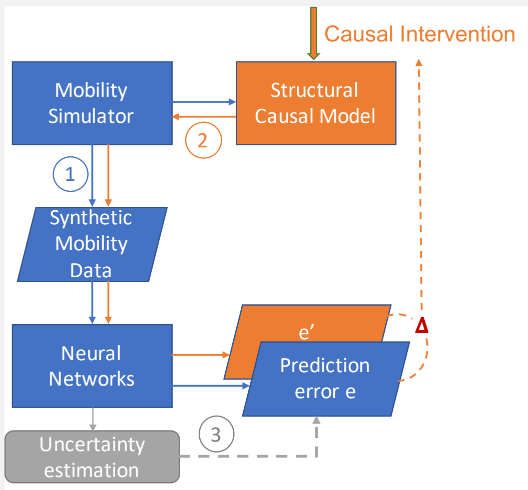

Figure 1: Workflow of the Study.

3 Case Study – Traffic Forecast

- A SCM model is constructed based on the CTM macroscopic traffic simulator.
- Causal interventions on *on-ramp flow*, *off-ramp flow*, and *free-flow speed* are used to simulate different characteristics of traffic flow.
- The changes in prediction error under different interventions are used to evaluate the impact of each intervention.

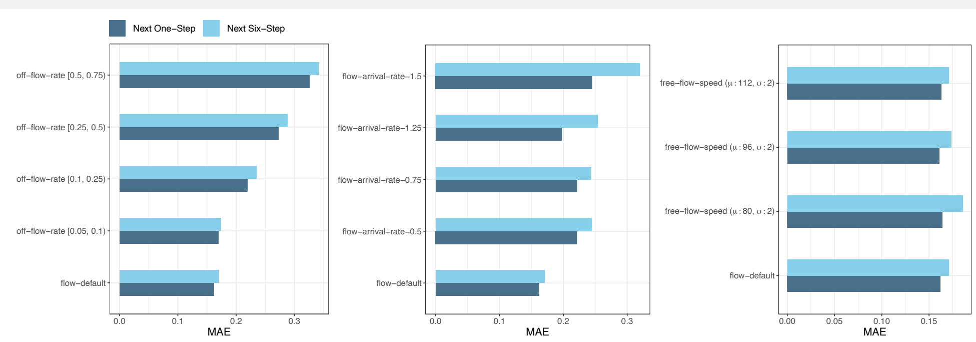

Figure 2: Impact of different interventions on the accuracy of traffic flow prediction using LSTM model.

4 Case Study – Individual Next Location Prediction

- SCM constructed with density-EPR and individual preferential transition (IPT) mechanistic simulators.
- Causal interventions on *population-level location attractiveness as well as user-specific exploration* and *return tendencies* are used to simulate changes in individual behavior.
- We quantify network's performance variations after interventions.

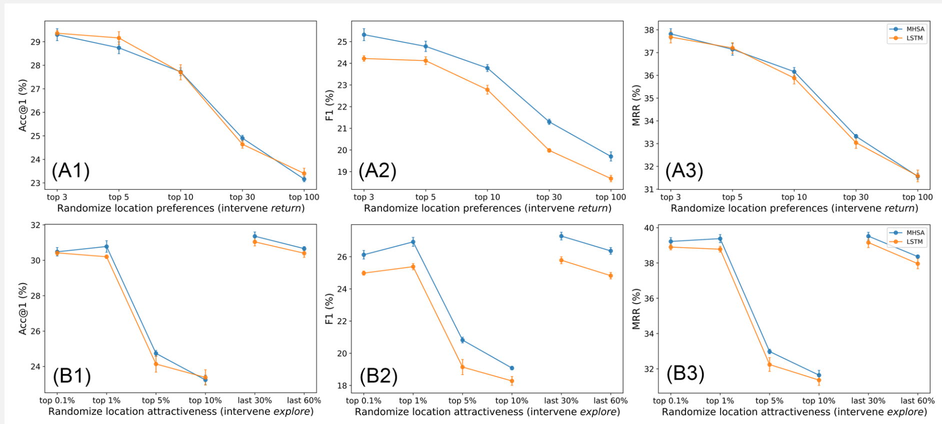

Figure 3: Location prediction performances in LSTM and multi-head self-attention (MHSA) networks [2]. (A) Intervene on individual preferences during *return*, and (B) intervene on collective preferences during *exploration*.

5 Conclusion and Expected Impact

Conclusions

- Traffic forecast: 1) The intervention on speed has minor or no impacts on the prediction accuracy. 2) The interventions on flow arrival rate and off-flow lowered the prediction accuracy and the extent of the accuracy drop generally aligns with the strength of the intervention.
- Next location prediction: 1) Prediction performance variations aligns with the strength of the intervention; 2) Interventions on Individual location preferences have more significant impacts than the ones in the overall population preference; and 3) MHSA performs better than LSTM no matter how intense the interventions are.

Impacts

- Enrich our understanding on the robustness of deep learning models towards different distribution shifts.
- Provide key insights on the specifications of benchmark datasets for evaluating deep learning models for mobility prediction.

References

1. Xin, Yanan, et al. "Vision paper: causal inference for interpretable and robust machine learning in mobility analysis." Proceedings of the 30th International Conference on Advances in Geographic Information Systems. 2022.
2. Hong, Ye, et al. "How do you go where? Improving next location prediction by learning travel mode information using transformers." Proceedings of the 30th International Conference on Advances in Geographic Information Systems. 2022.

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