1 Evaluating the Limits of Zero-Shot Learning Models for Multi-Task Traffic Prediction: A Case Study on Lyon

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Context

Traffic forecasting is a crucial area of research for urban mobility, enabling effective management of road networks, public transport, and other infrastructure. Accurate traffic prediction also plays a vital role in real-time traffic control, allowing urban planners and traffic management systems to dynamically adjust signals, routes, and transport schedules in response to predicted congestion or disruptions.

Traditionally, traffic prediction models have been developed using full-shot training, where models are extensively trained on large datasets and evaluated in the same context. Examples of such approaches include recurrent neural networks (RNNs), temporal convolutional networks (TCNs), and graph convolutional networks (GCNs) (Jiang et al., 2023; He et al., 2024), which have shown strong performance in predicting traffic flow, vehicle trajectories, and ride-hailing demand... However, these models often face challenges in generalizing across different regions or timeframes, making them less effective in new or unseen contexts. Specifically, they struggle with Cross-Regional Model Spatial Generalization, which is the ability to predict traffic conditions in new geographic areas, and Temporal Generalization for Long-term Forecasting, which refers to maintaining predictive accuracy over extended periods in the face of changing patterns or seasonal trends. These models are also typically specialized in one specific task, such as traffic flow or vehicle trajectory prediction, and have difficulty handling multiple types of predictions simultaneously.

Recent advancements in foundation models offer a new paradigm for traffic prediction, allowing for zero-shot or few-shot learning, where models trained on diverse datasets can generalize to new cities or transport systems without additional training. A recent example is the OpenCity model (Li et al., 2024), which combines transformer architecture with graph neural networks to capture complex spatio-temporal dependencies in traffic data. This foundation model is designed to generalize across regions, predicting various traffic-related tasks such as vehicle trajectory, traffic flow, and taxi demand in new environments. This reduces the need for full-shot retraining and enhances both Cross-Regional Model Spatial Generalization and Temporal Generalization for Long-term Forecasting.

In this research, we will test the robustness and resilience of this zero-shot predictive mode, using real-world data from Lyon to evaluate their capacity to handle multi-modal disruptions (e.g., metro breakdowns) and environmental variations (e.g., weather changes) (Rochas et al., 2023).

Objectives and steps

The expected workflow is as follows:

- **Familiarization with Research:** Review literature on zero-shot and few-shot learning methods for traffic prediction.
- **Exploration of OpenCity:** Study the OpenCity model's capacity for spatio-temporal traffic prediction, with attention to its generalization ability and resilience to disruptions.
- **Evaluation on Lyon City Data:** Apply OpenCity to traffic data from Lyon to assess its generalization across prediction tasks (e.g., vehicle trajectories, traffic flow) and its resilience to disruptions (metro breakdowns, weather impacts), as well as its performance on long-term predictions.
- **Comparison and Analysis:** Compare OpenCity's resilience, generalization, and long-term prediction performance on Lyon data with traditional full-shot and few-shot models. Provide a comprehensive analysis of its strengths and limitations in multi-modal and long-term forecasting contexts.

Materials

- Traffic datasets from Lyon, including vehicle trajectories, traffic flow, and public transport schedules.
- Python and PyTorch.
- Source code and pre-trained models of OpenCity for experimentation.

Competencies

- Basic knowledge in data science, machine learning, or transport engineering.
- Comfortable with programming in Python and using tools like PyTorch.
- Interest in urban mobility and traffic prediction is a plus.

Internship location

ENTPE (Vaulx-en-Velin)

Application Process

To apply, please send your ZIP folder named `[MobilityTransferability_NameSurname]` to `rim.slamasalmi@entpe.fr` and in copy `angelo.furno@univ-eiffel.fr`.

This folder should contain your **CV**, a **motivation letter academic transcripts** from high school (post-baccalaureate) to the most recent year of your master's program, and any **certifications in deep learning** if you have any.