**Report**

**ETA Prediction with Graph Neural Networks in Google Maps**

**Introduction**

Estimated Time of Arrival (ETA) prediction is a critical task in transportation networks, significantly impacting the functionality of web mapping services like Google Maps. Accurate ETA predictions facilitate informed decision-making for both users and enterprises, enhancing user experience and operational efficiency. The complexity of this task arises from the need to model both the topological properties of road networks and the dynamic nature of traffic conditions. This paper presents a graph neural network (GNN) estimator for ETA prediction, deployed in production at Google Maps, demonstrating substantial improvements over previous methods.

**Architecture of the Model**

The proposed model leverages Graph Neural Networks (GNNs) due to their effectiveness in handling graph-structured data, such as road networks. The architecture consists of the following key components:

* Graph Representation: The road network is modelled as a graph where nodes represent road segments and edges represent connections between these segments.
* GNN Model: The model follows the Graph Network framework, implementing an encode-process-decode paradigm. It includes three main blocks:
  + Encoder: Transforms raw input features into latent representations.
  + Processor: Applies multiple iterations of message passing to update node and edge representations.
  + Decoder: Converts latent representations into travel time predictions.
* Meta-Gradients: This method dynamically adjusts learning rates during training, enhancing model stability and performance.
* Semi-Supervised Training: Combines labelled and unlabelled data to improve robustness.

The model predicts travel times for multiple future horizons, enabling more accurate ETAs by considering both current and future traffic conditions.

**Results**

The deployment of the GNN model in Google Maps has led to significant reductions in negative ETA outcomes. Notable improvements include:

* Over 40% reduction in negative ETA outcomes in cities like Sydney.
* Consistent performance gains observed across various regions worldwide.

Offline evaluations show substantial gains over previous baselines, with improvements in Root Mean Squared Error (RMSE) metrics. The model's performance is further validated through qualitative analyses on real-world traffic scenarios, demonstrating its practical effectiveness.

**Performance Evaluation**

The performance of the GNN model was evaluated both offline and online:

* Offline Evaluation: Conducted using temporally held-out test datasets. The GNN model outperformed baselines such as real-time travel times, historical travel times, and DeepSets in terms of RMSE.
* Online Evaluation: The model's effectiveness was tested in a live production environment, confirming its superior performance in reducing negative ETA outcomes compared to traditional methods.

**Critical Analysis**

The paper highlights several strengths and weaknesses of the proposed model:

Strengths

* High Accuracy: The GNN model delivers precise ETA predictions, even in complex traffic conditions.
* Robustness: Effective handling of both spatial and temporal data enhances prediction reliability.
* Scalability: Successfully deployed in a large-scale production environment, serving global user queries.

Weaknesses

* Model Complexity: The GNN model requires significant computational resources and training time.
* Data Storage and Inference Costs: Handling large-scale graph data can be resource-intensive, impacting cost-efficiency.

**Future Work**

The paper suggests several directions for future research and development:

* Optimization: Further improvements in model architecture and training techniques.
* Feature Exploration: Investigating new data sources and advanced training methods.
* Dynamic Aggregation: Researching adaptive aggregation techniques for diverse traffic patterns.
* Real-time Feedback: Enhancing the model with real-time user feedback for continuous improvement.

**Conclusion**

The paper presents a robust and accurate GNN-based ETA prediction model, successfully deployed in Google Maps. The model's ability to handle complex spatiotemporal data and its significant performance improvements over previous baselines underscore its practical value. While the model's complexity and resource requirements present challenges, its demonstrated benefits and potential for further enhancement make it a valuable contribution to the field of transportation network analysis