Dynamic Route-Aware Graph Neural Networks for Accurate ETA Prediction

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***Abstract*—Accurate estimated time of arrival (ETA) is a cornerstone of navigation systems, logistics planning, and intelligent transportation operations. However, most existing methods either (i) sum time-dependent edge costs along a precomputed route or (ii) learn from trajectories without explicit knowledge of a traveler's intended path—both choices introduce mismatch with evolving congestion and ambiguity about the actual route. We propose a dynamic, intent-aware graph neural network (DGNN) for ETA prediction that (1) represents junctions and vehicles as nodes in a multi-relational spatio-temporal graph; (2) injects explicit route intent via typed edges from vehicles to upcoming junctions; and (3) employs a mixture-of-experts (MoE) with temporal memory to capture heterogeneous traffic regimes and history. On simulated urban traffic with per-trip planned routes, our approach reduces mean absolute error compared to route-unaware baselines and strong spatio-temporal graph models. Ablations show that intent edges and MoE routing are complementary: intent reduces path ambiguity while MoE specialization improves modeling capacity under varying demand patterns. The proposed formulation is compatible with standard routing stacks and can incorporate real-world route plans when available, paving the way for ETA models that are simultaneously traffic-aware and route-faithful.**

***Index Terms*—ETA prediction, graph neural networks, spatio-temporal graphs, user intent, traffic forecasting**

I. INTRODUCTION

Estimated Time of Arrival (ETA) prediction is a fundamental component of modern navigation systems and intelligent transportation applications. Accurate ETA enables commuters to make informed travel decisions, supports fleet management and logistics operations, and reduces congestion by distributing demand across the road network. With the ubiquity of GPS-enabled devices and connected vehicles, navigation platforms such as Google Maps and Waze [1]–[3] have transformed how travelers plan and adapt their journeys. However, despite significant progress, ETA estimation remains challenging due to the dynamic and stochastic nature of urban traffic.

Traditional approaches to ETA computation rely on shortest-path algorithms such as Dijkstra's algorithm [4], which provide efficient solutions under static conditions but do not account for evolving congestion or interaction effects between vehicles. As a result, travel times computed via such methods can diverge substantially from reality when traffic conditions fluctuate during the trip.

With the growth of urban mobility datasets, machine-learning approaches have been introduced. Tree-based models such as XGBoost [5] predict ETA from handcrafted features and perform well on aggregated trip records like NYC Taxi and Porto Taxi [6], [7]. Deep learning methods improve performance by modeling temporal patterns and spatio-temporal context along a route: DeepTTE learns ETA from raw GPS traces [8]; TADNM incorporates transportation-mode awareness [9]; MetaTTE applies meta-learning for cross-city generalization [10]; and STAD corrects routing-engine outputs using spatio-temporal adjustments [11].

In parallel, graph-based spatio-temporal learning has advanced traffic prediction by representing road networks as graphs and learning their dynamics with diffusion or convolution operators (e.g., DCRNN, ST-GCN, Graph WaveNet) [12]–[14]. Nevertheless, existing benchmarks (NYC, Porto, Chengdu/DiDi, Geolife) [6], [7], [15], [16] lack explicit representation of the user's pre-planned route. Models must therefore infer the likely path between origin and destination, introducing ambiguity and reducing prediction accuracy. Prior work proposed incorporating future-traffic–aware route selection to improve ETA accuracy [17]. We build on this direction by explicitly modeling user intent and the pre-planned route within a dynamic spatio-temporal graph, and by learning ETA with a graph-based mixture-of-experts architecture.

Our contributions are: (i) a dynamic graph-based dataset unifying junction states, vehicle dynamics, and explicit pre-planned route information; (ii) a DGNN architecture that combines graph attention, temporal encoding, and mixture-of-experts specialization for accurate ETA prediction; and (iii) comprehensive experiments on simulated traffic data demonstrating significant gains over route-unaware baselines.

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II. RELATED WORK

A. Classical pathfinding and routing

On static graphs $G = (V, E)$ with non-negative edge costs, shortest paths are computed via Dijkstra's algorithm [4]. Numerous speed-up techniques enable web-scale routing: A*/ALT landmarks [18], Contraction Hierarchies [19], highway-dimension theory [20], and Customizable Route Planning [21]. Multi-criteria and k-shortest paths [22] broaden the option set, but ETA still depends on exogenous edge-time models.

B. Learning-based ETA and traffic forecasting

ETA prediction leverages classic ML (e.g., gradient boosting [5]) and deep models operating on GPS traces and route contexts [8]–[11]. Spatio-temporal GNNs such as DCRNN, ST-GCN, and GraphWaveNet [12]–[14] learn dynamics over road graphs, often on benchmarks like NYC/Porto/DiDi/Geolife [6], [7], [15], [16].

C. Intent- and route-aware prediction

Route intent matters for ETA accuracy. Incorporating future-traffic–aware route selection improves travel-time estimates [17]. Recent trajectory-prediction and destination-aware works also model intent and downstream effects, complementing our focus on ETA within a dynamic multi-relational graph.

III. Methodology

We represent the transportation system at snapshot time t as a directed, multi-relational graph

$$G_t = \big(V_t, E_t, \{A_t^{(\rho)}\}_{\rho\in\mathcal{R}}\big),$$

with $V_t = V^j \cup V_t^v$ where V^j are junction nodes (static) and V_t^v are vehicle nodes present at time t. Edge relations

$$\mathcal{R} = \{\text{road, trav, inter, intent}\}$$

are encoded via binary adjacencies $A_t^{(\rho)}$ and optional weights $W_t^{(\rho)} \in \mathbb{R}_{\geq 0}^{|V_t|\times|V_t|}$.

Typed edges: 1) Road segments ($\rho = \text{road}$): for adjacent $u, v \in V^j$ with legal direction $u \to v$, $(u, v) \in E_t^{(\text{road})}$.

2) Traversal ($\rho = \text{trav}$): if vehicle v_i^t occupies directed segment (a, b), then (a, v_i^t) and (v_i^t, b) exist in $E_t^{(\text{trav})}$.

3) Interaction ($\rho = \text{inter}$): for vehicles v_i^t, v_j^t on the same segment with spacing $d_{ij}(t) \leq \varepsilon$ and aligned headings, $(v_i^t, v_j^t) \in E_t^{(\text{inter})}$ with weights $\omega\big(d_{ij}(t)\big)$ (e.g., $\omega(d) = e^{-d/\lambda}$).

4) Intent ($\rho = \text{intent}$): for planned route $\mathcal{R}_i = (e_1, \ldots, e_K)$ at departure t_0, connect v_i^t to upcoming junctions on its route with decay weights α_k.

We learn ETA from a temporal window $\mathcal{G}_{t-H+1:t} = \{G_\tau\}_{\tau=t-H+1}^{t}$. Our DGNN employs spatio-temporal encoding and a mixture-of-experts module that routes vehicles/segments to specialized experts; a memory layer captures longer-range temporal dependencies. We train with supervised ETA loss (e.g., MAE) and evaluate across trip-duration buckets and ablations of intent edges.

IV. Experiments

We evaluate on simulated urban traffic with explicit route plans per trip. We report MAE (seconds) and relative improvements vs. baselines. Baselines include: (i) static route-sum ETA; (ii) XGBoost with handcrafted features [5]; (iii) deep sequence models (e.g., DeepTTE [8]); and (iv) graph models (DCRNN, ST-GCN, Graph WaveNet) [12]–[14]. We ablate intent edges and the MoE router.

Implementation uses PyTorch Geometric [23]. Training details: optimizer, learning rate, window H, batch size, and early stopping. We stratify results by trip duration bins to analyze regimes.

V. Results

Our DGNN achieves lower MAE than route-unaware baselines across all duration bins. Intent edges consistently reduce errors for longer trips. The MoE router exhibits meaningful specialization (measured via entropy and gate usage), contributing to accuracy gains.

VI. Discussion

Route intent reduces path ambiguity and aligns ETA modeling with user plans. Limitations include simulation-to-reality gaps and potential sensor/route noise. Future work: real-world datasets with planned routes, robust intent inference, and uncertainty-aware ETAs.

VII. Conclusion

We presented a dynamic, intent-aware graph approach to ETA prediction, combining spatio-temporal encoding with a mixture-of-experts. Experiments indicate that explicit route intent and expert specialization improve accuracy. Future work will validate on real-world data and explore policy feedback between ETA and route selection.

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