Personalized Trajectory Prediction for Driving Behavior Modeling in Ramp-Merging Scenarios *

Siyan Li, Chuheng Wei, *Graduate Student Member*, *IEEE*, Guoyuan Wu, *Senior Member*, *IEEE*, Matthew J. Barth, *Fellow*, *IEEE*, Amr Abdelraouf, Rohit Gupta, and Kyungtae Han

***Abstract*—Despite numerous studies on trajectory prediction, existing approaches often fail to adequately capture the multifaceted and individual nature of driving behavior. In recognition of this gap and based on DenseTNT, an end-to-end and goal-based trajectory prediction method, our study developed a new version of DenseTNT that incorporates personalized nodes within the graph neural network in VectorNet as context encoder. Throughout the neural network computations, these nodes represent individual driver labels, allowing a more granular understanding of diverse driving behaviors to be gained. Based on comparative analysis, our model has a 11.4% reduction in minADE when compared to baseline models that do not have personalized labels.**

Keywords—connected and automated vehicles (CAV), trajectory prediction, personalized driving behavior, ramp merging

I. Introduction

A. Background

Connected and Automated Vehicles (CAVs) are rapidly emerging as transformative elements in modern transportation, promising significant advancements in road safety, efficiency, and convenience [1, 2]. As their adoption surges, the future of transportation is expected to involve not only CAVs but also the simultaneous presence of human-driven vehicles and other road users [3, 4], this coexistence demands a profound understanding of diverse driving behaviors.

Due to the unique nature of driving, generic trajectory prediction algorithms face significant challenges. These algorithms, such as DenseTNT [5], designed for a broad spectrum of drivers, often operate under the assumption that driving behaviors are generally uniform across the board [6]. In consequence, while they may perform adequately at a macroscopic level, their predictions may be misaligned when applied to specific drivers with unique characteristics.

As a result of this realization, it is imperative to develop more personalized prediction algorithms in place of one-size-fits-all models. The central contribution of this paper is to bridge this existing gap. We aim to customize the trajectory prediction model by introducing personalized nodes representing individual driver labels into the DenseTNT algorithm. In summary, this paper makes several contributions:

- We introduce an enhanced version of the DenseTNT trajectory prediction method that incorporates personalized nodes within the graph neural network.
- We conduct experiments on a SUMO/Unity simulation platform, equipped with Logitech driving sets, to collect a personalized dataset.
- Qualitative analysis show that our personalized model outperforms traditional trajectory prediction models, particularly for specific drivers.

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Siyan Li, Chuheng Wei, Guoyuan Wu and Matthew J. Barth are with the Department of Electrical and Computer Engineering, University of California at Riverside, Riverside, CA 92507 USA (*Corresponding author: Siyan Li, e-mail: sli442@ucr.edu*).

Amr Abdelraouf, Rohit Gupta and Kyungtae Han are with Toyota North America InfoTech Labs at Mountain View, CA 94043 USA.

II. Related Work

A. Trajectory Prediction

Latent-variable-sampling-based Approach. Future predictions in the context of autonomous driving are inherently uncertain due to the unknown intents and behaviors of agents [7, 8]. SocialGAN [9] incorporates adversarial learning to enhance the realism of predictions.

Goal-based Approach. TNT [10] predicts goals on lane centerlines and generates trajectories based on these goals, using predefined sparse anchors as references. Social-LSTM [11] is a recurrent neural network-based approach that models social interactions between agents to predict their future trajectories.

B. Personalized Driving Behavior Modeling

Abdelraouf et al. [12] presents a novel personalized trajectory prediction model that leverages temporal graph neural networks, combining GCN and LSTM networks to capture intricate spatio-temporal interactions. For personalized lane-change behaviors, some researchers pioneered the concept of a Driver Digital Twin (DDT) [13], it allows CAVs to anticipate the actions of surrounding vehicles with the assistance of digital twin technology.

Recognizing driver preferences needs vehicle states, surrounding context as well as vehicular interactions. To capture the intricacies of human behavior, Ziebart et al. [14] employed Inverse Reinforcement Learning (IRL), under the assumption that human actions are driven by the optimization of an undisclosed reward function.

III. Methodology

A. Specification and Assumptions

To maintain the focus and relevance of our experiments, we've established certain specifications and assumptions:

- We employ the proposed method concentrating on detecting and analyzing ramp-merging scenarios.
- We assume that a driver's preferences remain relatively consistent over time.
- All our experiments take place in a simulated environment, and we plan to explore real-world applicability in future research.

B. Personalized Behavior Modeling Process

In DenseTNT algorithm, VectorNet [15] serves as the sparse context encoding method. In this paper, we introduce personalized nodes seamlessly within the graph neural

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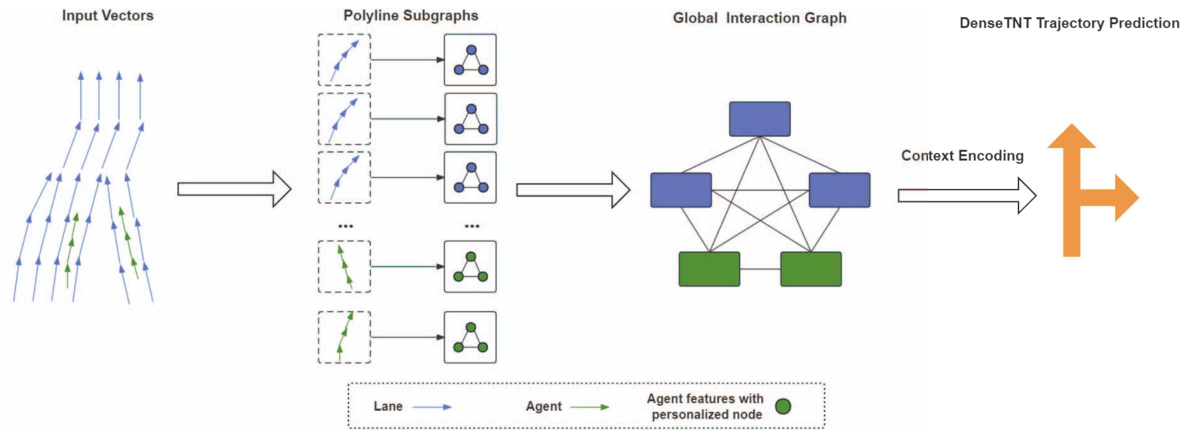


Fig. 1. The framework of proposed personalized modeling.

network component in VectorNet, as shown in Fig.1. These personalized nodes, during neural network computations, serve as unique driver labels. In the following trajectory prediction algorithm, each personalized node represents the driving characteristics, preferences, and idiosyncrasies of a specific driver, thereby creating a comprehensive driver behavior model.

C. Trajectory Prediction Based on DenseTNT

In this study, we use DenseTNT [5] as the prediction head, Fig.2 illustrates the personalized driving behavior prediction framework, which introduces the overall structure of proposed model. It begins by employing a sparse encoding technique, which captures the essential structural features of maps. VectorNet is used in this part because of its outstanding ability to add nodes with personalized characteristics. The following goal set predictor uses the probability distribution of goals to generate s set of direct goals, which then produce a diverse set of trajectory predictions.

1) Dense Goal Probability Estimation: Initially, the 2D coordinates of the goals are encoded using a multi-layer perceptron (MLP) to obtain the initial feature matrix F . The local information between the goals and the lanes can be obtained by attention mechanism:

$$Q = FW^Q, K = LW^K, V = LW^V \tag{1}$$

$$A(Q,K,V) = soft\max\left(\frac{QK^\top}{\sqrt{d_k}}\right)V \tag{2}$$

where W^Q, W^K, $W^V \in \mathbb{R}^{d_h \times d_k}$ are the matrices for linear projection, d_k is the dimension of query / key / value vectors, and F, L are feature matrices of the dense goal candidates and all map elements respectively. The predicted score of the i^{th} goal can be written as:

$$\phi_i = \frac{\exp(g(F_i))}{\sum_{n=1}^{N}\exp(g(F_n))} \tag{3}$$

By optimizing the loss term, the model can effectively update the parameters of the MLP and improve its ability to estimate the dense probabilities of the goals:

$$\mathcal{L}_{goal} = \sum_i \mathcal{L}_{CE}(\phi_i, \psi_i) \tag{4}$$

where ϕ is the predicted goal scores and ψ is the ground truth goal scores.

2) Goal Set Predictor: Our objective is to identify the most probable goals across various modalities by identifying distinctive peaks in the heatmap generated by dense probability estimation. These peaks correspond to locations with high probabilities, indicating potential positions for the final trajectories.

The goal set predictor in DenseTNT employs multiple heads for simultaneous prediction of N goal sets. During inference, we take the head with the highest confidence as the output of the goal set predictor.

3) Training Procedure: During training, a teacher forcing technique [16] is employed in DenseTNT by providing the ground truth goal as input during the training process. The loss term is then calculated as the difference or offset between the predicted trajectory $\hat{s}$ and the ground truth trajectory s :

$$\mathcal{L}_{completion} = \sum_{t=1}^{T} \mathcal{L}_{reg}(\hat{s}_t, s_t) \tag{5}$$

where $\mathcal{L}_{reg}$ is the smooth ℓ_1 loss between two points.

D. Simulation and Data Collection

Building on previous research [17, 18], we've implemented a ramp-merging model in a human-in-the-loop co-simulation platform [19] (Fig. 3 a and b). This platform seamlessly integrates a real-world track created in Unity, with mixed traffic flows generated using SUMO, including conventional and CAVs. Logitech driving sets in Unity enable human input for immersive simulations, offering insights into mixed traffic scenarios with varying CAV penetration and congestion levels. To model merging behavior accurately, we collected personalized driving data from two drivers, each contributing data from 20 ramp-to-mainline merging trips, with 5-second prediction windows at a frequency of 50Hz for performance evaluation.

E. Map Representation

We transfer ramp-merging maps into two formats: Vector Map and Rasterized Map.

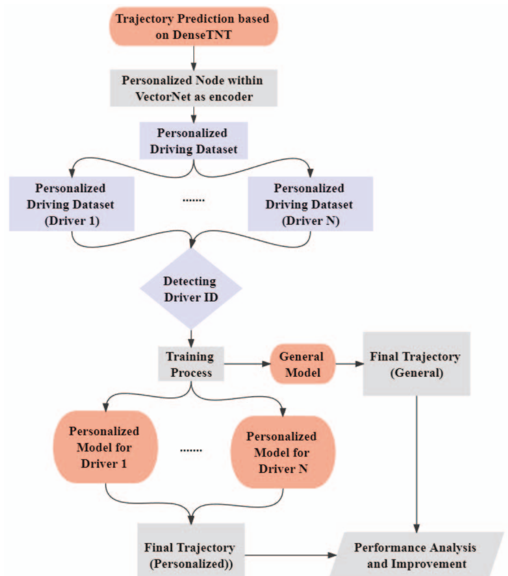


Fig.2. The framework of the personalized driving behavior prediction.

Vector Map. In Fig. 3(c), our Vector Map creation process revolves around "Nodes" and "Ways". "Nodes" are pivotal points within linear features like roads, while "Ways" represent road axes formed by ordered sequences of "Nodes", each with unique attributes like traffic specifications and neighboring lanes.

Rasterized Map. Conversely, the Rasterized Map focuses on binary drivable area labels at one-meter grid resolution, distinguishing drivable zones from non-drivable ones.

IV. RESULTS AND ANALYSIS

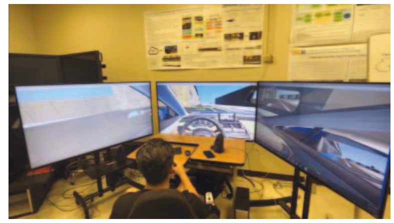
A. Metrics

We assess our models with three key metrics: minADE (average displacement error), minFDE (minimum final displacement error), and MR (Miss Rate). These metrics evaluate trajectory prediction accuracy by measuring the average displacement between predicted and ground-truth points (minADE), the minimum displacement to the actual endpoint (minFDE), and cases where predicted trajectories don't fall within a 2.0-meter threshold of the true final position (MR), reflecting prediction precision.

B. Trajectory Prediction Results

We trained the model on the personalized dataset collected from our ramp-merging simulation model on SUMO/Unity. Three different models are generated: personalized model for Driver A, Driver B and a generic model. To compare the different between two driving behaviors, we present the visualized trajectory prediction results, two different runs for each driver, which are shown in Fig. 4.

From the visualized trajectory prediction, we can easily learn different behaviors between two drivers when ramp-merging scenario occurs. In the next section, we will show the performance of the generic trajectory prediction as well as improvement when using the personalized driving model other than the generic model.



(a) Unity engine and driving set.

(b) SUMO platform

(c) Ramp-merging vector map.

Fig. 3. Ramp-merging simulation platform.

C. Performance Analysis

In Table I, we initially present an overview of the prediction results' overall performance. Crucial performance metrics such as minADE, minFDE, and MR exhibit a gradual stabilization trend. This observed trend signifies that the proposed model's performance is improving, indicating a higher level of accuracy and reliability. Furthermore, the results indicate that in all the metrics, the performance of personalized DenseTNT model outruns the generic model, which proves that it is essential to use personalized model for specific driver.

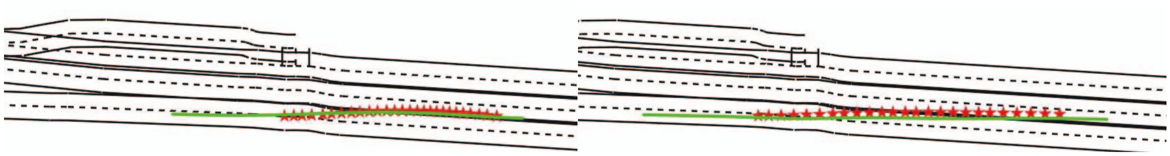
TABLE I. OVERALL MODEL PERFORMANCE

Method	Metrics		
	minADE	***minFDE***	***MR***
Generic DenseTNT	1.808	2.449	0.274
Personalized DenseTNT	**1.653**	**2.303**	**0.269**

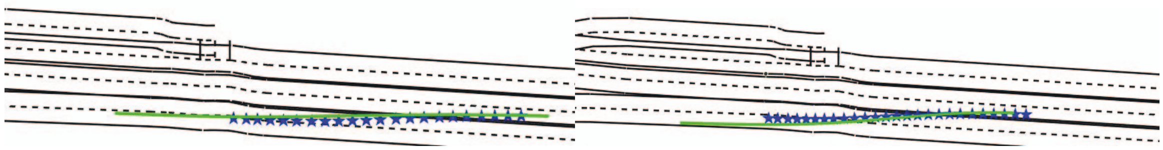
Personalized models can fit and only be used on a specific driver. In the study, our main goal is to evaluate the new version of DenseTNT can detect different driving behavior and achieves a better performance when using the personalized model for a specific driver. The accuracy and improvement evaluation is shown in Table II. The prediction of Driver B is better than Diver A using either the generic model or personalized model. The improvement of Driver A is not as significate as Driver B since the behavior is more predictable. Overall, all the metrics improves using personalized model, minADE improves the most, by 11.4% on average.

TABLE II. ACCURACY AND IMPROVEMENT EVALUATION

Driver	Metrics	Generic	Personalized	Improvement
Driver A	minADE	1.952	1.833	6.1%
	minFDE	2.791	2.663	4.6%
	MR	0.294	0.290	1.3%
Driver B	minADE	1.663	1.473	**11.4%**
	minFDE	2.107	1.943	7.8%
	MR	0.254	0.248	2.2%



(a) Predicted trajectory (two different runs) for Driver A.



(b) Predicted trajectory (two different runs) for Driver B.

Fig. 4. Visualization of predicted trajectories: Driver A in red stars, Driver B in blue stars and ground truth in green.

V. CONCLUSION AND FUTURE WORK

This paper presents an enhanced iteration of the DenseTNT trajectory prediction method, incorporating personalized nodes into VectorNet's graph neural network within the DenseTNT algorithm. This approach improves trajectory prediction by up to 11.4% on average, with a focus on ramp-merging scenarios. However, further research is needed to extend the model's applicability to complex scenarios like intersections. Additionally, refining the collection of personalized datasets to better simulate real-world driving conditions is crucial for increasing public trust and expanding the utility of personalized driving behavior models.

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