Knowledge-Driven Lane Change Prediction for Secure and Reliable Internet of Vehicles

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***Abstract*— Ensuring the smooth operation of road traffic is a momentous target in Intelligent Transportation Systems, which can be expedited by a secure and reliable Internet of Vehicles (IoV). As prominent carriers of the IoV, intelligent vehicles (IVs), that bear the promising potential for alleviating traffic congestion, have become the core road traffic participants. However, the mixed-traffic environment escalates the risk of IVs, as the discretionary lane change behaviors of nearby human-driven vehicles may result in collisions with IVs, compromising the robust performance of the IoV. Recent studies have utilized advanced deep learning techniques to achieve proactive lane change intention prediction, including Recurrent Neural Networks and Transformer. Although attaining reasonable prediction performance, they adopt the *data-driven* paradigm, which excessively focuses on learning from data while neglecting the domain knowledge. Against this background, we propose to employ the *knowledge-driven* paradigm and design KLEP, a knowledge-driven lane change prediction framework. KLEP incorporates driving knowledge into lane change modeling, presenting the top-down hierarchical cognitive process of drivers when performing lane change maneuvers. Extensive experiments conducted on two real-world natural driving datasets demonstrate the effectiveness of KLEP. Compared to state-of-the-art lane change prediction baselines, KLEP consistently outperforms them and achieves average improvements of 6.2-7.1% and 53.0-67.2% on intention classification and intention forecast tasks across different datasets, respectively. We also validate that KLEP has strong interpretability that aligns with real-world physical laws in lane change scenarios and is lightweight enough to fulfill online prediction.**

***Index Terms*— Lane change prediction, knowledge-driven, heterogeneous graph, Internet of Vehicles, driving safety.**

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I. INTRODUCTION

IN THE new era of Intelligent Transportation Systems (ITS), enhancing the capacity of road traffic is a pressing imperative as it directly concerns the efficiency, productivity, comfort, and safety of society [1]. The Internet of Vehicles (IoV) is considered promising for warranting the smooth operation of road traffic, however, its security and reliability are intertwined with the driving safety of its carriers, intelligent vehicles (IVs). Benefiting from the rapid development of artificial intelligence and information communication technologies, intelligent vehicles (IVs) have been progressively advancing and are on the verge of becoming the key component in road traffic [2], [3]. Therefore, there will be an extended period where human-driven vehicles (HDVs) and IVs coexist on roads, constituting a mixed-autonomy traffic landscape [4], [5]. To ensure driving safety and social compliance, IVs necessitate the capability to timely detect surrounding traffic environments so that they can proactively make sensible decisions. In particular, the ability to predict the driving behaviors of HDVs in their vicinity is remarkably essential for the smooth and safe operation of IVs. Among various driving behaviors, the lane change maneuver is a much frequent and safe-critical behavior for both IVs and HDVs. Recent studies have shown that over 50,000 traffic accidents in the U.S. each year result from discretionary lane change maneuvers [6], [7]. Accordingly, accurately predicting the lane change intention of surrounding HDVs is crucial for the establishment of IVs.

IVs are capable of collecting the driving states of nearby HDVs in real time, generating large quantities of driving features. The advent of deep learning techniques furnishes the prospect of achieving lane change prediction by leveraging the potential of such big data. Recurrent Neural Network (RNN) and its variants, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), have been employed to accommodate the temporal variation in driving features and yield favorable lane change intention prediction performance [8], [9], [10]. To further elevate the ability of RNNs to capture lane change patterns, hierarchical learning is introduced to complement prediction information presented in different lane change scenarios [11], [12]. Transformer is a groundbreaking architecture for natural language processing that has extended its applications to computer vision and autonomous driving [13]. It exhibits strong competence in capturing the correlations among input elements with the attention mechanism. Inspired by this regard, Transformer is also applied in lane change prediction, resulting in better performance than the RNN family [14].

Although the methods mentioned above realize satisfactory lane change prediction performance to some extent, they focus on modeling the relationships between driving features and thus cause the dependency-dominant embedding space. This study refers to these methods as the *data-driven* paradigm, meaning they only adapt to the plain representation of driving data. Recently, *knowledge-driven* paradigm has been increasingly prevailing in behavior prediction literature [15], [16], [17]. Unlike the bottom-up information flow in the data-driven paradigm, the knowledge-driven paradigm maintains top-down message propagation, in conformity with the hierarchical cognitive process of drivers in lane change scenarios, thereby facilitating the interpretability of lane change prediction. Simultaneously, the knowledge-driven paradigm can mitigate data biases by directly modeling lane change semantics, an issue inevitably encountered by the data-driven paradigm.

Against this background, we propose a Knowledge-Driven Lane Change Prediction (**KLEP**) framework, complying with the philosophy of the knowledge-driven paradigm. KLEP is designed to incorporate driving knowledge into the lane change prediction process. Specifically, the raw driving data is first transformed and categorized into two types of driving features at the data preparation stage. Then a knowledge-driven lane change prediction model is devised, containing: 1) a heterogeneous driving graph is constructed to represent the hierarchical driving knowledge, referring to the logic of symbolism [18] and the cognitive process of the perceived safety under lane change circumstances [19]; 2) a temporal information extractor is conceived to refine the time series features and avert the data noise; 3) a heterogeneous graph Transformer is developed to capture correlations between nodes in the hierarchical driving graph, enabling the lane change prediction with the driving knowledge. Finally, we implement KLEP in the manners of offline training and online prediction.

The main contributions of this study are summarized as follows:

1) We revisit the problem of lane change intention prediction and point out the drawbacks of current methods that are limited to the data-driven paradigm. Therefore, we propose to accomplish the knowledge-driven paradigm in lane change prediction.
2) We propose KLEP, a knowledge-driven lane change prediction framework, designed to incorporate the driving knowledge into the lane change prediction process. It not only boosts the intention prediction performance but also improves the interpretability of lane change maneuvers.
3) We conduct a thorough evaluation of KLEP, comparing it with a sizeable collection of state-of-the-art baselines on two real-world natural driving datasets. The experimental results demonstrate the superiority of KLEP in lane change prediction. For the intention classification task, KLEP achieves average improvements of 6.2-7.1% over the best-performing baseline across different datasets. Furthermore, on the intention forecast task, KLEP still outperforms the best-performing baseline, yielding average improvements of 53.0-67.2% across different datasets. In addition, KLEP exhibits forceful interpretability and is lightweight enough to execute online prediction.

The rest of this article is organized as follows. Section II reviews some relevant works. Section III elaborates on the proposed framework. Section IV presents detailed experimental results. Finally, Section V concludes the research and provides some future works.

II. Related Work

In this section, we systematically review the evolutionary process of lane change intention prediction and trace the trajectory of efforts aimed at accurate prediction.

At first, researchers holistically analyzed the details of lane change maneuvers and proposed to precisely model the behaviors of vehicles before executing lane change. Reference [20] employed the steering wheel angle as a crucial signal for predicting the lane change intention of drivers. It discovered the common disengagement behavior of drivers before straying away from the original lane and associated such behavior with the steering wheel angle. Reference [21] further utilized more kinds of vehicle dynamic features collected by a wealth of vehicle sensors. The combination of rich sensor information facilitates lane change prediction. Reference [22] considered the temporal variation of driving features and characterized the lane change behavior with a potential field that adapts to temporal fluctuations in feature distributions. However, these maneuver-based methods only focus on the individual dynamics of vehicles and neglect the influence of surrounding vehicles, resulting in poor prediction performance.

Afterward, researchers proposed to model interactions between vehicles, incorporating inter-vehicle correlation features. Reference [23] constructed Bayesian Networks to describe the causal effect between driving features. It also captured the traffic scenes about lane change with occupancy grids and merged the scene characteristics with Bayesian Networks to better accommodate the interactions. Reference [24] applied a Support Vector Machine to classify the lane change intention. The speed and position of vehicles were adopted as two important indicators for identifying the boundary. Reference [25] exerted the Hidden Markov Model to distinguish left and right lane change intention from the mixed lane change and lane keeping behaviors. In addition to the steering wheel angle, it also considered the lateral acceleration to obtain the optimal model structure. Although these methods capture the interactions to some extent, they lean toward the interpretability of lane change behaviors and grapple with the generalization to large-scale driving data.

With the emergence of advanced artificial intelligence techniques such as deep learning approaches, researchers put forward diverse methods to achieve lane change prediction on big data. Reference [26] referred to Random Forest (RF), setting a new high watermark to account for a large amount of spatial and temporal driving features. Reference [8] followed the RNN architecture for time series and employed LSTM to capture the temporal dynamics hidden in lane change maneuvers. Reference [9] extended [8] by using Bidirectional LSTM (Bi-LSTM) to enhance the extraction of temporal features and improve the lane change pattern representations. Reference [27] chose Temporal Convolutional Network to capture temporal variation in lane change-related features, realizing the same utility as [8] and [9]. Reference [10] combined different RNN-based methods and only drew out their essences with the help of ensemble learning. References [11] and [12] considered the hierarchical structure of lane change behaviors and modified the vanilla LSTM into the double-level classifier. Reference [14] used Transformer to capture correlations among inter-vehicle interaction features. The powerful capability of multi-head attention in extracting lane change context renders it to achieve better prediction performance than RNN-based methods.

Although the above data-driven methods achieve fabulous lane change prediction performance, the knowledge-driven philosophy has become increasingly prevalent as it aligns with the cognitive process of drivers in lane change scenarios and holds great promise for more accurate prediction. Reference [15] first proposed to consider the driving knowledge when predicting lane change intention. Nevertheless, it failed to model the intricate relationships between driving features and was restricted by superficial prior knowledge. Therefore, we propose KLEP to comprehensively model lane change-related driving knowledge.

III. Knowledge-Driven Lane Change Prediction Framework

This section depicts KLEP, a knowledge-driven lane change prediction framework. In Section III-A, we present the problem formulation and the overall architecture of KLEP. Section III-B outlines the data preparation process for lane change behavior modeling. Subsequently, we elaborate on the approach to lane change intention inference in Section III-C. Finally, the training and prediction paradigm is exhibited in Section III-D.

A. Problem Formulation and Framework Overview

In this study, we focus on predicting lane change intentions. Within the context of the IoVs, the driving states of surrounding vehicles–such as positions, velocities, and accelerations–can be obtained for a target vehicle. Based on the historical states of these vehicles, the objective of lane change intention prediction is to forecast future lane change maneuvers of the target vehicle, including left lane changes, right lane changes, and lane keeping. Fig. 1 illustrates the flowchart of KLEP. Firstly, data preprocessing is implemented to forge appropriate input features for the following lane change prediction model. Meanwhile, the curated dataset is partitioned into historical data for model training and real-time data for model testing (prediction). Afterward, a novel knowledge-driven graph Transformer method for lane change prediction is developed. Lastly, the proposed lane change prediction model is optimized in the offline training phase and then is employed to achieve real-time forecasting in the online prediction phase. The details of KLEP are elucidated in the following sections.

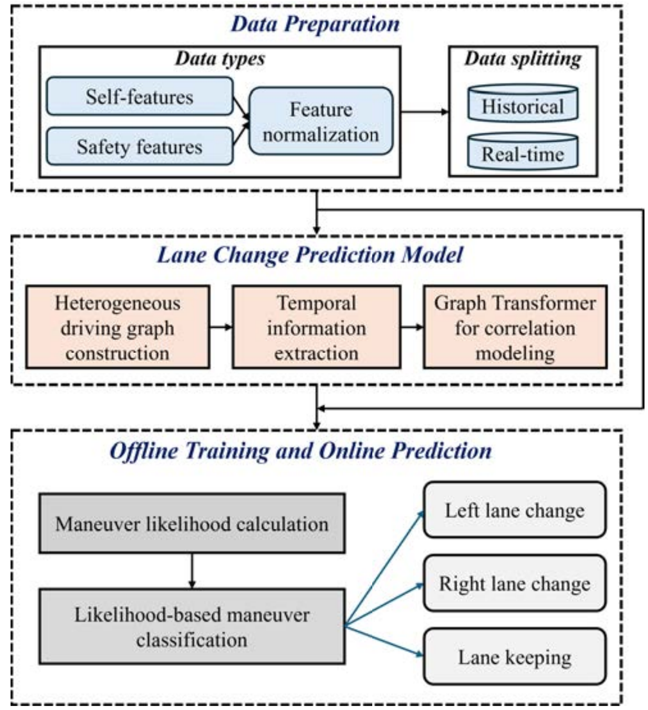


Fig. 1. The architecture of the proposed KLEP framework.

B. Data Preparation

The intention of a vehicle to change lanes is influenced by its current driving state [5], [28] and the perceived safety of its driving environments [29], [30], [31]. For example, a vehicle tends to switch from the slow lane to the fast lane when it wants to increase the driving speed on freeways. However, the decision to change lanes will only be made after a deliberate inspection of the surrounding environment to ensure driving safety. Therefore, we convert the driving data into two types of lane change-related features, namely self-features and safety features.

For self-features, the velocity and acceleration of vehicles are recognized as indicators reflecting their individual driving states. As for safety features, we employ the Time-To-Collision (TTC) metric to represent the perceived safety of a vehicle in dynamic driving environments. TTC is a commonly used traffic safety metric to measure the remaining time before two vehicles collide if they maintain their original driving states. Given the velocity of a target vehicle v_{target}, the TTC

TABLE I

ILLUSTRATION OF INPUT FEATURES AND THEIR RESPECTIVE FEATURE CODES

Feature types	Feature code	Feature description
Self-features	Velocity	The velocity of the target vehicle
	Accel	The acceleration of the target vehicle
Safety features	ttcFr	The TTC between the target vehicle and its direct front vehicle
	ttcLeftFr	The TTC between the target vehicle and its left front vehicle
	ttcRightFr	The TTC between the target vehicle and its right front vehicle
	ttcLeftRe	The TTC between the target vehicle and its left rear vehicle
	ttcRightRe	The TTC between the target vehicle and its right rear vehicle

between the target vehicle and its front vehicle is calculated by:

$$\mathrm{TTC}_f = \frac{d_f}{v_{target} - v_f} \tag{1}$$

where v_f denotes the velocity of the front vehicle and d_f is the distance between the target vehicle and its front vehicle. Also, the TTC between the target vehicle and its rear vehicle is computed by:

$$\mathrm{TTC}_r = \frac{d_r}{v_r - v_{target}} \tag{2}$$

where v_r refers to the velocity of the rear vehicle and d_r denotes the distance between the target vehicle and its rear vehicle. The complete input features are presented in Table I. Referring to some advanced lane change prediction methods [12], [14], [28], [32], surrounding vehicles in five positions (shown in Table I) are selected to compute safety features since they have direct impacts on the lane change intention of the target vehicle. Our lane change prediction model also accommodates the scenario where the number of surrounding vehicles is less than five, which will be further discussed in the following section.

To mitigate the repercussions of numerical differences for lane change prediction performance, we apply min-max normalization to the obtained input features. The minimum and maximum values of a certain feature are determined by reviewing historical data. When making on-the-fly predictions, values smaller than the minimum are mapped to 0 while values larger than the maximum are mapped to 1. Notably, the calculation of TTC may yield negative values indicating the zero collision risk, and thus these negative TTC values are mapped to 1 accordingly.

C. Lane Change Prediction Model

This section illuminates the developed knowledge-driven graph Transformer method for lane change prediction. We first present the construction of the heterogeneous driving graph, which explicitly models driving knowledge. Then we introduce a temporal information extractor that accounts for the temporal dynamics in input features. Finally, we showcase a novel heterogeneous graph Transformer, which captures correlations in the heterogeneous driving graph.

1) Heterogeneous Driving Graph Construction: From the viewpoint of Symbolism, knowledge originates from the connections between symbols and then evolves into a cognitive graph (or network) to interpret the real world [18].

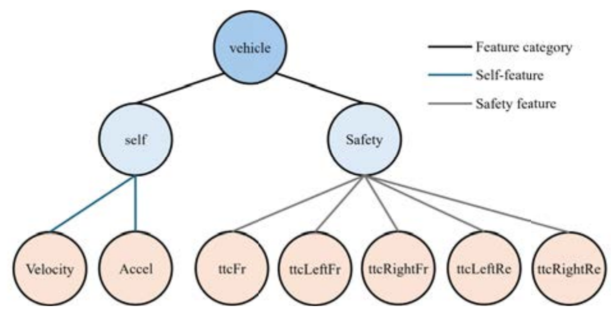


Fig. 2. Illustration of the heterogeneous driving graph, which symbolizes the hierarchical structure of lane change-related driving knowledge. Orange nodes correspond to the feature code in Table I. Edges do not have a direction.

Inspired by this, we resort to the heterogeneous graph to embody the driving knowledge under the circumstances of lane change. Furthermore, we refer to the cognitive process of perceived safety [19] and incorporate the hierarchy into the heterogeneous driving graph. Specifically, the undirected heterogeneous driving graph $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$ is shown in Fig. 2, wherein $\mathcal{V}$ denotes the node set and $\mathcal{E}$ refers to the edge set. There are three edge types: *Feature category* represents the vehicle-feature type connection that anchors the hierarchical structure in driving knowledge, maintaining the hierarchical cognitive process toward lane change; *Self-feature* and *Safety feature* represent the respective feature type-feature connections that depict the elementary knowledge in the lane change scenario. This hierarchical structure can well represent the top-down cognitive process of drivers in lane change scenarios, concretizing the lane change-related driving knowledge.

2) Temporal Information Extraction: Each input feature is typically expressed in the form of a time series vector:

$$\mathbf{h}_i^{t_0} = \left(h_i^{t_0-T+1}, h_i^{t_0-T+2}, \ldots, h_i^{t_0}\right) \tag{3}$$

where $\mathbf{h}_i^{t_0}$ denotes the time series vector of the i-th feature at timestamp t_0. T refers to the traceback time window. $h_i^{t_0}$ denotes the value of the i-th feature at timestamp t_0. The long-range time series vector inclines to instill irrelevant information into the downstream model and thus impair the model performance. In this context, we consider extracting the refined temporal information from the time series vector in advance to avert model degradation while reducing the dimension of the vector to promote model efficiency. Here, we use 1D-CNN [33] as the temporal information extractor:

$$\overline{\mathbf{h}}_i^{t_0} = \text{1D-CNN}\left(\mathbf{h}_i, \mathbf{W}_{i,c}\right) \tag{4}$$

where $\overline{\mathbf{h}}_i^{t_0}$ is the updated feature vector of the i-th feature at timestamp t_0. $\mathbf{W}_{i,c}$ is learnable parameters of the convolutional filters for the i-th feature. Compared to the RNN family (including RNN, LSTM, GRU, etc.) and attention-based methods (such as Transformer), 1D-CNN bears the merits of the global receptive field over RNNs and the lightweight configuration against attention mechanisms, rendering it more suitable for the real-time temporal information extraction.

3) Heterogeneous Graph Transformer: To enable the driving knowledge to inform the lane change prediction, it is requisite to capture correlations between nodes in the heterogeneous driving graph. This process allows these intricate relationships to be encoded so that the updated node features can be exploited to generate future lane change intentions. Transformer has proven to achieve commendable performance in eliciting correlations between lane change-related features and accomplish superb intention prediction performance [10], [14], [28], [34], [35]. Nevertheless, the essence of global information exchange in multi-head attention enlarges the computational overhead, resulting in the strain on timely lane change prediction. Simultaneously, such global multi-head attention fails to account for the structure of the heterogeneous driving graph and thus leads to cumbersome information in correlations. To surmount the above issues, we propose a heterogeneous graph Transformer (HGT) to fulfill efficient and exact multi-head attention on the heterogeneous driving graph.

Following the philosophy of GNNs, message passing on the heterogeneous driving graph is realized by aggregation function and update function [36]. Specifically, the aggregation function merges a set of feature vectors and compresses them into a single vector, which is expressive of aggregated features. It is required to allow for an arbitrary number of input vectors and ensure independence of their permutations. Next, the update function transforms each feature vector derived from the aggregation function into the required size for the subsequent lane change prediction.

In HGT, we apply multi-head attention to the aggregation function. However, the vanilla multi-head attention is designed for homogeneous elements (such as words in a sentence), which is unsuitable for the heterogeneous driving graph since the connections (edge types) between nodes vary. Hence, we adopt a type-aware strategy to implement multi-head attention. For a node $v \in \mathcal{V}$ in the heterogeneous driving graph $\mathcal{G}$, the input feature vector of v to the l-th layer is $\mathbf{v}^{l-1}$ obtained from the last layer. Notably, the input feature vectors to the first layer originate from the feature vectors obtained through temporal information extraction. We denote the neighboring nodes of v that connect to v with the edge type j by N_v^j and their feature vectors to l-th layer by $\mathbf{N}_v^{j,l-1}$. The attention score of the edge type j for the node v is calculated by:

$$\mathbf{a}_j = \sigma\left(\frac{\mathbf{q}_j \mathbf{K}_j}{\sqrt{d}}\right) \tag{5}$$

where $\mathbf{q}_j = \mathbf{v}^{l-1}\mathbf{W}_{Q_j}$, $\mathbf{K}_j = \mathbf{N}_v^{j,l-1}\mathbf{W}_{K_j}$. $\mathbf{W}_{Q_j}$ and $\mathbf{W}_{K_j}$ are the query and key linear transformation matrices for the edge type j, respectively. $\sigma(\cdot)$ denotes the Softmax function and d refers to the stable factor used in multi-head attention. In doing so, the attention score is type-aware and conforms with the

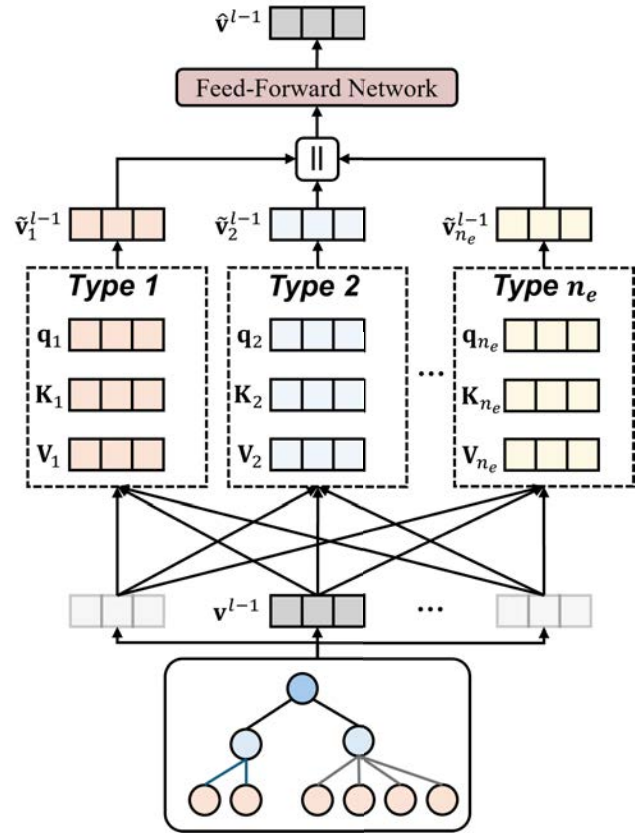


Fig. 3. Overview of the proposed heterogeneous graph Transformer.

heterogeneity in the driving graph. Moreover, the aggregated feature vector of the edge type j for the node v is obtained:

$$\tilde{\mathbf{v}}_j^{l-1} = \mathbf{a}_j^{\mathrm{T}}\mathbf{V}_j \tag{6}$$

where $\mathbf{V}_j = \mathbf{N}_v^{j,l-1}\mathbf{W}_{V_j}$. $\mathbf{W}_{V_j}$ denotes the value linear transformation matrix for the edge type j. In this way, the number of heads in multi-head attention equals the number of edge types in the driving graph, capturing more precise correlations between nodes while hastening the robustness of node representations. Finally, the obtained aggregated feature vectors are concatenated and processed by the update function:

$$\hat{\mathbf{v}}^{l-1} = \mathrm{FFN}\left(\left[\tilde{\mathbf{v}}_1^{l-1} || \tilde{\mathbf{v}}_2^{l-1} || \cdots || \tilde{\mathbf{v}}_{n_e}^{l-1}\right]\right) \tag{7}$$

where $\mathrm{FFN}(\cdot)$ is the feed-forward network inherited from the vanilla multi-head attention, where the residual connection [37] and layer normalization [38] are both tapped into for stable training. $||$ denotes the concatenation operator and n_e is the number of edge types. More specifically, the pseudo-code for HGT is presented in Algorithm 1.

To sum up, HGT harnesses the advantages of both GNNs and Transformer: 1) adheres to the aggregation and update functions in GNNs, exquisitely accommodating the hierarchical structure of driving knowledge and capturing the heterogeneous information innate in the driving graph; 2) utilizes multi-head attention in Transformer to bolster node representations while alleviating the computational burden with type-aware aggregation strategy. Fig. 3 presents the workflow of HGT. Notably, the message passing of HGT

Algorithm 1 The Pseudo-Code for Heterogeneous Graph Transformer

Input: The node feature $\mathbf{v}^0$ ($v \in \mathcal{V}$) obtained from temporal information extraction

Output: The updated node feature $\widehat{\mathbf{v}}^L$

Initialize query, key, and value linear transformation matrices $\mathbf{W}_{Q_j}|_{j=1}^{n_e}$, $\mathbf{W}_{K_j}|_{j=1}^{n_e}$, and $\mathbf{W}_{V_j}|_{j=1}^{n_e}$

for $l = 1, 2, \ldots, L$ **do**

  for $j = 1, 2, \ldots, n_e$ **do**

    $\mathbf{N}_v^{j,l-1} \leftarrow$ concatenate features of neighboring nodes of v that connect to v with the edge type j

    $\mathbf{q}_j \leftarrow \mathbf{v}^{l-1}\mathbf{W}_{Q_j}$

    $\mathbf{K}_j \leftarrow \mathbf{N}_v^{j,l-1}\mathbf{W}_{K_j}$

    $\mathbf{V}_j \leftarrow \mathbf{N}_v^{j,l-1}\mathbf{W}_{V_j}$

    Calculate the attention score of the edge type j by Eq. (5)

    Calculate the aggregated feature vector of the edge type j by Eq. (6)

    Calculate the updated feature vector $\widehat{\mathbf{v}}^{l-1}$ by Eq. (7)

  end

end

is only imposed on nodes since we focus on obtaining the informative and knowledgeable node embeddings for lane change prediction. Through confining message updates to nodes, we effectively prevent information spillovers to edges, thereby maintaining the integrity and relevance of the node features [14], [15].

D. Offline Training and Online Prediction

After building the lane change prediction model, we design offline training and online prediction procedures for the practical application of KLEP. Since we focus on the lane change intention of the target vehicle, only the feature vector of the vehicle node in the heterogeneous driving graph is read out to make the prediction. Assume that the node v corresponds to the target vehicle. The final feature vector of v learned by HGT is denoted by $\widehat{\mathbf{v}}^L$. Wherein, L refers to the number of layers in HGT. A fully connected layer with Softmax activation function is applied to acquire the likelihood of driving maneuver:

$$\omega = \sigma\left(\mathrm{FC}\left(\widehat{\mathbf{v}}^L\right)\right) \tag{8}$$

The dimension of ω corresponds to the number of driving maneuver categories. In this study, the maneuver categories are defined as lane keeping, left lane change, and right lane change. Therefore, the lane change prediction problem here is formulated as a classification problem, and the cross entropy loss is employed for offline training:

$$\mathcal{L} = -\sum_{i=1}^{C} y_i \log \omega_i \tag{9}$$

where C is the number of maneuver categories. y_i is the ground-truth label for the i-th category and ω_i denotes the predicted maneuver likelihood of the i-th category.

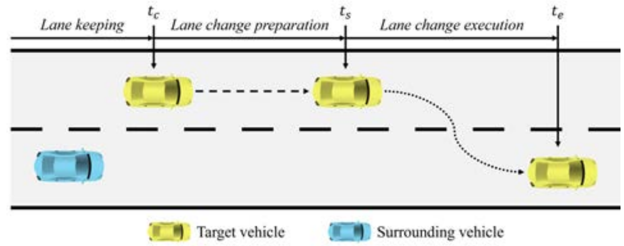


Fig. 4. The example of lane change scenarios.

TABLE II

DETAILS OF THE DATASETS. THE COLUMNS RESPECTIVELY DENOTE THE NUMBER OF TRAINING SEQUENCES, TEST SEQUENCES, THE PREDEFINED LANE CHANGE PREPARATION TIME, AND THE COLLECTION FREQUENCY

Dataset	Training	Test	Preparation time	Frequency
NGSIM	11,430	2,856	2s	10 Hz
HighD	16,446	4,110	2s	25 Hz

When making online predictions, the category with the highest value in ω indicates the most likely maneuver the target vehicle will perform shortly.

IV. EXPERIMENTS

In this section, we evaluate the proposed universal framework KLEP on two real-world datasets. We first introduce the experimental setup and then exhibit experimental results and analyses, including overall performance comparison, model ablation study, computational efficiency comparison, and interpretability verification.

A. Experimental Setup

1) Datasets: To validate the intention prediction performance of KLEP, two large-scale real-world datasets, NGSIM [39] and HighD [40], are used for offline training and online testing. NGSIM stems from the simulation program inaugurated by the U.S. Federal Highway Administration. It collects data on the I-80 freeway with a sampling frequency of 10 Hz including vehicle coordinates, velocities, accelerations, types, and lane information. HighD garners natural driving data on German highways with a sampling frequency of 25 Hz. This dataset records the trajectories of 110,000 vehicles on 6 highway segments spanning 16.5 hours. To label the datasets, we first investigate the realistic lane change process. Fig. 4 shows an example of lane change scenarios, consisting of three momentous time spans: 1) before t_c the target vehicle maintains the lane keeping process; 2) from t_c to t_s, the target vehicle observes surrounding environments and prepares to execute the lane change maneuver; 3) from t_s to t_e, the target vehicle executes the lane change process and finishes the lane change at timestamp t_e. As only t_s and t_e are presented in datasets while t_c is undefined, we need to identify the t_c for the labeling of the lane change process. Referring to previous works [41], [42] on the temporal analyses of the lane change procedure, we assume that the period between t_c and t_s is 2 seconds and label the time frame (t_c, t_e) as lane

TABLE III

OVERALL DRIVING INTENTION PREDICTION PERFORMANCE. COMPARISON OF LANE CHANGE AND LANE KEEPING PREDICTION RESULTS OF VARIOUS METHODS ON NGSIM AND HIGHD DATASETS

Paradigm	Method	NGSIM Dataset				HighD Dataset			
		Lane Change		Lane Keeping		Lane Change		Lane Keeping	
		Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
Data-driven	RF	67.13%	66.25%	75.23%	73.98%	58.24%	59.31%	64.77%	65.56%
	LSTM	74.88%	73.98%	81.27%	80.96%	68.05%	67.28%	74.21%	75.19%
	Bi-LSTM	77.82%	76.93%	84.27%	83.99%	73.54%	73.21%	80.19%	80.57%
	TMMOE	76.31%	78.24%	83.29%	82.46%	74.98%	74.71%	80.98%	81.35%
	MMAE	79.43%	80.84%	86.77%	88.10%	76.98%	78.54%	84.31%	83.27%
	VWC	82.46%	85.77%	90.32%	91.27%	79.56%	80.43%	86.98%	88.81%
	H-LSTM	81.78%	86.24%	89.38%	90.56%	80.07%	80.39%	87.04%	87.19%
	PRNN-GHMM	84.37%	85.29%	91.29%	92.46%	82.95%	82.58%	88.31%	88.76%
	Transformer	87.89%	87.44%	93.77%	93.26%	86.79%	85.98%	92.13%	91.90%
Knowledge-driven	KLEP	**93.78%**	**94.56%**	**98.15%**	**98.07%**	**93.29%**	**93.21%**	**97.84%**	**97.57%**

TABLE IV

OVERALL LANE CHANGE INTENTION PREDICTION PERFORMANCE. COMPARISON OF LEFT LANE CHANGE AND RIGHT LANE CHANGE PREDICTION RESULTS OF VARIOUS METHODS ON NGSIM AND HIGHD DATASETS

Paradigm	Method	NGSIM Dataset				HighD Dataset			
		Left Lane Change		Right Lane Change		Left Lane Change		Right Lane Change	
		Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
Data-driven	RF	69.24%	68.37%	65.33%	63.64%	59.78%	60.42%	56.32%	58.17%
	LSTM	77.41%	75.68%	70.36%	72.03%	70.31%	68.25%	67.42%	65.99%
	Bi-LSTM	79.87%	80.31%	75.24%	73.54%	76.45%	75.27%	71.12%	71.53%
	TMMOE	78.32%	80.34%	75.21%	76.94%	76.75%	76.37%	72.69%	72.56%
	MMAE	82.17%	78.65%	76.39%	82.31%	78.42%	79.27%	74.63%	77.65%
	VWC	84.31%	86.54%	80.62%	84.11%	80.37%	81.27%	78.46%	79.53%
	H-LSTM	80.29%	85.74%	82.64%	86.75%	82.57%	81.30%	78.24%	79.07%
	PRNN-GHMM	83.26%	83.69%	85.18%	86.72%	81.45%	83.64%	83.37%	81.09%
	Transformer	88.46%	86.38%	87.10%	88.35%	88.37%	86.59%	85.10%	84.99%
Knowledge-driven	KLEP	**94.32%**	**94.76%**	**93.47%**	**94.29%**	**93.87%**	**92.95%**	**92.83%**	**93.58%**

change sequence while the same length of time frame before t_c as lane keeping sequence.

At last, we obtain 7,143 lane change/lane keeping sequences for the NGSIM dataset and 10,278 lane change/lane keeping sequences for the HighD dataset. Among them, 80% is used for offline training whereas 20% is utilized for online testing. For clarity, the details of the statistics are shown in Table II.

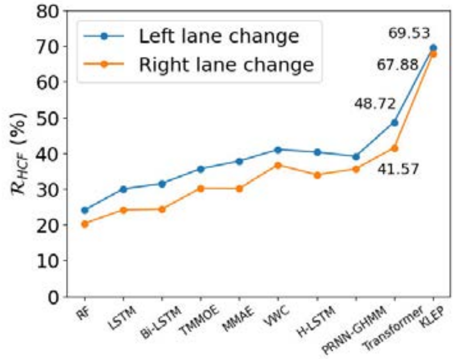
2) Baselines: We compare KLEP with a sizeable collection of state-of-the-art baselines:

1) **RF** [26]. Random Forest is a rudimentary model for lane change prediction. It incorporates various spatial and temporal driving-related features to classify diverse lane change decisions.
2) **LSTM** [8]. Long Short-Term Memory is employed to accommodate the temporal variation of driving features and further extract the hidden embeddings at different timestamps for lane change prediction.
3) **Bi-LSTM** [9]. Bidirectional LSTM is an updated version of LSTM, which models bidirectional information flow to facilitate the representation of dynamic behavioral patterns of lane change.
4) **TMMOE** [27]. Temporal Multi-task Mixture Of Experts applies Temporal Convolutional Networks to capture temporal dynamics among lane change-related features, enlarging the perception field toward driving interactions.
5) **MMAE** [10]. Multiple Model-Based Adaptive Estimator integrates multiple time series extractors to achieve strengthened lane change pattern recognition and outputs the mixed likelihood of lane change behaviors.
6) **VWC** [15]. Variable Weight Combination introduces the concept of driving knowledge and selects the perceived speed and comfort as indicators to quantify the impact of driving features on lane change intention.
7) **H-LSTM** [11]. Hierarchical LSTM learns from driving data with a hierarchical structure, seamlessly accounting for the interactions between lane change maneuvers and vehicle trajectories.
8) **PRNN-GHMM** [12]. Parallel Recurrent Neural Networks are used as the upper module to model lane change behaviors and Gaussian Hidden Markov Model in the lower module absorbs the learned behavioral patterns to generate intention likelihood.
9) **Transformer** [14]. Transformer is used to model correlations between varied driving features and the multi-head attention mechanism enhances its capability of extracting lane change-related context.

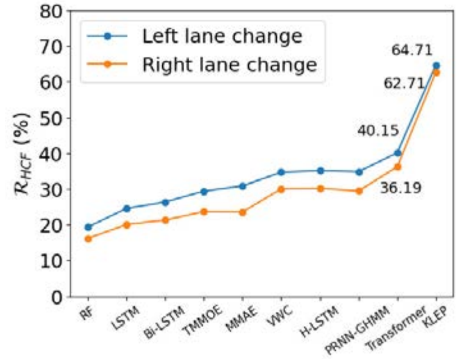
Notably, these baselines are all fine-tuned on the datasets, and their best prediction results are reported in the experiments.

3) Evaluation Metrics: Some widely adopted evaluation metrics are presented below.

a) Classification: To thoroughly measure the prediction ability, we exert precision and recall metrics to characterize



(a) Forecast ability comparison on NGSIM dataset.



(b) Forecast ability comparison on HighD dataset.

Fig. 5. Visualization of the lane change forecast ability for disparate methods.

the classification performance of lane change intention:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{10}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{11}$$

where TP denotes the number of correctly predicted samples with positive labels, FP denotes the number of wrongly predicted samples with negative labels, and FN denotes the number of wrongly predicted samples with positive labels.

b) Forecast: Despite classification metrics effectively reckoning the lane change intention prediction performance, we also aim to measure the forecast ability of the models, specifically, how early the model can detect the lane change intention of target vehicles. According to [43], the high-level correct forecast $\mathcal{R}_{HCF}$ is defined:

$$\mathcal{R}_{\text{HCF}} = \frac{1}{N_{\text{LC}}} \sum_{i=1}^{N_{\text{LC}}} \delta_{\text{HCF}}(R_i)$$
$$\delta_{\text{HCF}}(R_i) = \begin{cases} 1, & \text{if } R_i \geq 80\% \\ 0, & \text{else} \end{cases} \tag{12}$$

where R_i is the recognition rate. For a lane change sequence in (t_c, t_e) (as shown in Fig. 4), R_i is the ratio of the period from the first correctly predicted timestamp to t_s to the time frame (t_c, t_s).

4) Implementation Details: There are two key hyperparameters in KLEP: the traceback time window T for temporal information extraction is set to 50 and 125 for NGSIM and HighD, respectively; the hidden dimension of HGT is set to 128 for both datasets. The offline training of KLEP is implemented by Adam optimizer [44] with the batch size $BS = 256$ and the learning rate $l_r = 0.0001$ on both datasets. KLEP is instantiated by PyTorch and both offline training and online prediction are carried out on benchmark hardware (Intel Xeon5320@2.20GHz, 512GB RAM@4800Hz, NVIDIA GeForce RTX 4090 24GB, Ubuntu 21.04).

B. Overall Performance

In this experiment, we compare the intention prediction performance of KLEP against all state-of-the-art baselines on both NGSIM and HighD datasets. Table III presents the overall driving intention prediction results and Table IV exhibits the breakdown of lane change intention prediction results. The best prediction result on each task and for each dataset is highlighted in bold, while the best baselines are underlined.

We observe that RF achieves suboptimal performance, due in large part to its limited capability of only capturing correlations among static driving features. By contrast, LSTM and Bi-LSTM can adapt to more intricate temporal-varied features, resulting in better prediction performance across all cases, including left lane change, right lane change, and lane keeping. MMAE combines the benefits of LSTM and TMMOE, generating an ensemble model that consistently performs better than the single LSTM or TMMOE. VWC accounts for the lane change-related driving knowledge and reinforces the prediction ability of vanilla LSTM with the knowledge semantics, thereby yielding better performance than MMAE on all tasks. This indicates that driving knowledge avails the modeling of lane change behaviors and thus enhances driving intention prediction performance. H-LSTM and PRNN-GHMM are two hierarchical learning methods that stratify the process of lane change, achieving on-par prediction performance with VWC. Aligning with the above two discoveries, KLEP incorporates the driving knowledge while retaining its hierarchical structure. Transformer is the best-performing baseline, profiting from the vigorous ability of multi-head attention in capturing correlations between dynamic driving features. In general, KLEP consistently outperforms all baselines, achieving average improvements of 6.2% and 7.1% over Transformer on NGSIM and HighD datasets, respectively, highlighting the superiority of the knowledge-driven paradigm over the data-driven paradigm. Additionally, KLEP is extremely robust to diverse lane change scenarios, which can be corroborated by the tiny variance between prediction results on NGSIM and HighD datasets.

Apart from the gauge of classification ability mentioned above, we also investigate the forecast ability of KLEP over baselines and show their performance in Fig. 5. We discover that KLEP still consistently outperforms all baselines, yielding average improvements of 53.0% and 67.2% over the best-performing baseline (i.e., Transformer) on NGSIM and HighD datasets, respectively. Likewise, KLEP accomplishes stable performance whether predicting the left or right lane

TABLE V

ABLATION STUDY ON OVERALL INTENTION PREDICTION. COMPARISON OF LANE CHANGE AND LANE KEEPING PREDICTION RESULTS OF DIFFERENT KLEP VARIANTS ON NGSIM AND HIGHD DATASETS

Method	**NGSIM Dataset**				**HighD Dataset**			
	Lane Change		**Lane Keeping**		**Lane Change**		**Lane Keeping**	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
KLEP	**93.78%**	**94.56%**	**98.15%**	**98.07%**	**93.29%**	**93.21%**	**97.84%**	**97.57%**
w/o temporal	92.76%	92.99%	96.63%	96.42%	92.84%	92.65%	96.03%	96.13%
w/o hierarchy	90.45%	90.66%	96.81%	96.20%	89.76%	90.03%	96.35%	96.24%
w/o type	90.21%	90.37%	96.45%	96.27%	88.94%	89.36%	96.21%	96.07%
w/o normalization	93.08%	93.24%	97.13%	97.05%	92.87%	92.88%	96.83%	96.90%

TABLE VI

ABLATION STUDY ON LANE CHANGE INTENTION PREDICTION. COMPARISON OF LEFT LANE CHANGE AND RIGHT LANE CHANGE PREDICTION RESULTS OF DIFFERENT KLEP VARIANTS ON NGSIM AND HIGHD DATASETS

Method	**NGSIM Dataset**				**HighD Dataset**			
	Left Lane Change		**Right Lane Change**		**Left Lane Change**		**Right Lane Change**	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
KLEP	**94.32%**	**94.76%**	**93.47%**	**94.29%**	**93.87%**	**92.95%**	**92.83%**	**93.58%**
w/o temporal	93.27%	93.28%	92.49%	92.76%	93.41%	92.29%	92.44%	93.01%
w/o hierarchy	91.02%	90.71%	90.15%	90.19%	90.37%	89.57%	89.45%	90.31%
w/o type	90.84%	90.55%	90.03%	90.06%	89.56%	89.02%	88.63%	89.47%
w/o normalization	93.91%	93.78%	92.45%	92.83%	93.77%	92.81%	92.34%	92.97%

change maneuver. The tremendous prominence of KLEP is attributed to the inventive design of the whole framework, especially the philosophy of knowledge-driven lane change prediction. The incorporation of driving knowledge extends beyond the perceptual capabilities of the data-driven paradigm in lane change forecasting.

C. Ablation Study

In this experiment, we further dissect the lane change prediction model in KLEP to delve into the effectiveness of its components. We design four variants to quantify the impact of the temporal information extractor, the hierarchical structure of the driving graph, the type-aware multi-head attention, and the TTC normalization, on lane change prediction. Each variant is individually fine-tuned and the best prediction results are presented in Table V-VI.

w/o temporal variant is devised by removing the whole temporal information extractor from KLEP. We observe that the *w/o temporal* variant is slightly inferior to the complete KLEP. This means the temporal information extractor dampens the raw data noise induced by long-range time series features, resulting in better prediction performance. *w/o hierarchy* variant is designed through eliminating the hierarchical structure of the heterogeneous driving graph, directly connecting specific feature nodes to the vehicle node. It can be found that the lane change prediction performance of *w/o hierarchy* dramatically declines compared to the complete KLEP. This implies that the hierarchical structure of driving knowledge is essential for boosting lane change prediction, which is reasonably modeled in KLEP. Also, we develop *w/o type* variant by replacing the type-aware strategy with vanilla multi-head attention. We also notice the distinct plunge in lane change prediction performance of the *w/o type* variant, which substantiates the efficacy of type-aware multi-head attention in distilling the message passing on the heterogeneous driving graph. Finally, we derive the *w/o normalization* variant by removing the mix-max normalization on TTC. The results show that normalizing TTC elevates model performance across all cases on both datasets, largely due to the reduction of numerical variations.

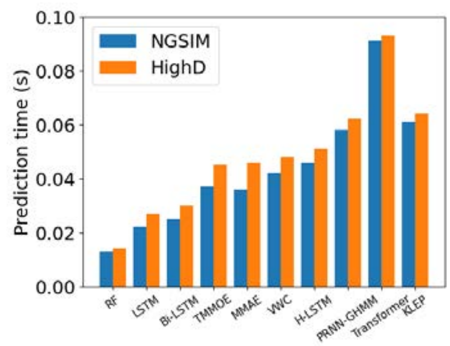
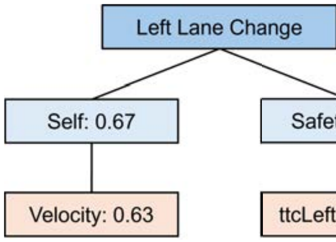


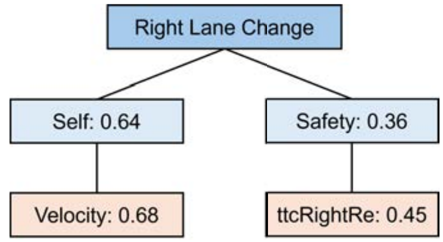
Fig. 6. Time consumption comparison of different methods in online prediction on NGSIM and HighD datasets.

D. Computational Efficiency

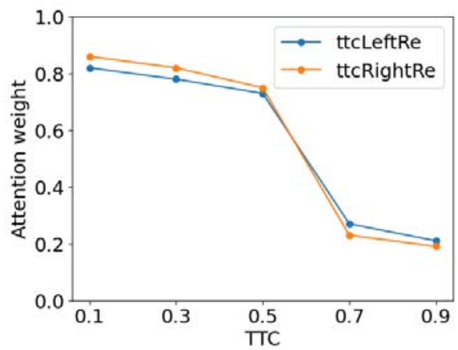
Prediction time is critical to the practical application of KLEP, as online prediction requires responsive outputs. Thus, we compare the prediction time consumption of KLEP with several baselines, and the results are presented in Fig. 6. Notably, the benchmark hardware used in this experiment is elaborated on in Section IV-A.4, the computing power of which is much weaker than the industry, such as Tesla's Full Self-Driving (FSD) computational platform. In Fig. 6, we observe that the prediction time of KLEP is less than the best-performing baseline Transformer, even comparable to the prediction time of PRNN-GHMM, which means the proposed KLEP is a lightweight framework that can achieve real-time lane change prediction. The lightweight architecture is realized by the type-aware strategy in HGT, which releases redundant computations thereby raising the potential of computational ability.



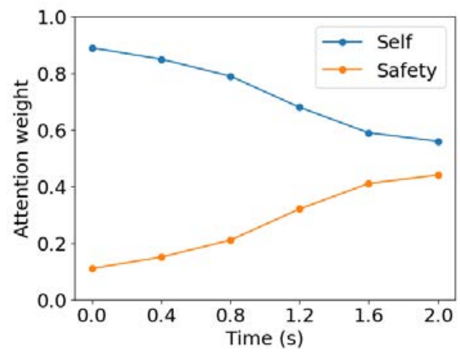
(a) Attention weights on left lane change.



(b) Attention weights on right lane change.



(c) The variation of attention weights over TTC.



(d) The variation of attention weights in safety-critical scenarios.

Fig. 7. Interpretability analyses in lane change scenarios.

E. Interpretability

Finally, we decipher the attention weights acquired by HGT to favor the comprehension of realistic lane change characteristics. We plot the attention weights pertaining to left and right lane change scenarios in Fig. 7a-7b. Whether left or right lane change, the self features have a larger effect than safety features, which is plausible since the lane change intention is first generated from the dissatisfaction with the current driving state. For left lane change, the ttcLeftRe feature influences driving safety the most while the ttcRighRe feature has the largest impact among safety features. This indicates that the degree of the perceived safety of the target vehicle mainly hinges on the driving state of its rear vehicles, which is also verified in lane change safety literature [30], [45], [46].

To further analyze the effect of ttcLeftRe and ttcRighRe, we visualize the variation trends of their attention weights in Fig. 7c. Both attention weights strictly decrease with the increase of TTC, which is in accord with real-world physical laws. This attests to the strong interpretability of KLEP. We also discover that the change in both attention weights is not smooth but rather presents a sharp drop around TTC $=$ 0.5. This threshold quantitatively characterizes the trade-off in driving safety, providing insight for downstream IV tasks, such as decision-making and trajectory planning.

We further investigate the significance of safety features in safety-critical scenarios. Specifically, we examine several lane change cases for overtaking and plot the variation in attention weights of both self and safety features throughout the lane change preparation process, as illustrated in Fig. 7d. Our observations indicate that as the lane change decision-making process progresses, the attention weight of safety features gradually increases. This trend is logical, as ensuring driving safety during overtaking necessitates careful monitoring of the surrounding environment. This manifests that safety features indeed reflect the cognitive aspects of driving safety during lane change maneuvers.

TABLE VII
THE OPTIMAL HYPERPARAMETER SETTINGS FOR KLEP AND ITS VARIANTS

Method	**NGSIM Dataset**		**HighD Dataset**	
	T	d_H	T	d_H
KLEP	50	128	125	128
w/o temporal	50	64	125	128
w/o hierarchy	50	128	125	128
w/o type	50	128	100	128

F. Hyperparameter Settings

Two key hyperparameters of KLEP are the traceback time window T for temporal information extraction and the hidden dimension of heterogeneous graph Transformer d_H. We employ the grid search strategy to identify the optimal hyperparameter settings. The range of candidate values for hyperparameters T and d_H are $\{25, 50, 75, 100, 125, 150\}$ and $\{32, 64, 128, 256\}$, respectively. Afterward, the optimal hyperparameter setting of a model is identified by comparing the lane change prediction performance under different hyper-parameter combinations. The final hyperparameter settings for KLEP and its variants are shown in Table VII.

V. CONCLUSION

In this study, we propose KLEP, a knowledge-driven lane change prediction framework. KLEP constructs the heterogeneous driving graph to represent the hierarchical driving knowledge following the top-down cognitive process of drivers when performing lane change maneuvers. Also, a heterogeneous graph Transformer is devised to accommodate the correlations between nodes in the heterogeneous driving graph, where a type-aware strategy is developed and enforced on the vanilla multi-head attention to achieve efficient and exact information propagation, resulting in the coherent representation of lane change behaviors. Experimental results demonstrate the superiority of KLEP, achieving average improvements of 6.2-7.1% and 53.0-67.2% on intention classification and intention forecast tasks across different datasets, respectively. Furthermore, the interpretability is substantiated by analyzing the attention weights that reflect the physical laws in the lane change process. Also, the KLEP is lightweight enough to achieve online prediction, whose prediction time consumption is even less than the best-performing baseline.

In the future, we plan to further investigate the problem of lane change trajectory prediction and design an integrated approach that simultaneously generates accurate intention and trajectory predictions.

References

[1] P. K. R. Maddikunta et al., "Industry 5.0: A survey on enabling technologies and potential applications," *J. Ind. Inf. Integr.*, vol. 26, Mar. 2022, Art. no. 100257.

[2] W. Wang et al., "Realizing the potential of the Internet of Things for smart tourism with 5G and AI," *IEEE Netw.*, vol. 34, no. 6, pp. 295–301, Nov. 2020.

[3] Y. Lu, W. Wang, X. Hu, P. Xu, S. Zhou, and M. Cai, "Vehicle trajectory prediction in connected environments via heterogeneous context-aware graph convolutional networks," *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 8, pp. 8452–8464, Aug. 2023.

[4] Y. Lu, H. Ding, S. Ji, N. N. Sze, and Z. He, "Dual attentive graph neural network for metro passenger flow prediction," *Neural Comput. Appl.*, vol. 33, no. 20, pp. 13417–13431, Oct. 2021.

[5] Y. Lu, Q. Lin, H. Chi, and J.-Y. Chen, "Automatic incident detection using edge-cloud collaboration based deep learning scheme for intelligent transportation systems," *Int. J. Speech Technol.*, vol. 53, no. 21, pp. 24864–24875, Nov. 2023.

[6] W. Wang et al., "Vehicle trajectory clustering based on dynamic representation learning of Internet of Vehicles," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 6, pp. 3567–3576, Jun. 2021.

[7] H. Ding, Y. Lu, N. N. Sze, T. Chen, Y. Guo, and Q. Lin, "A deep generative approach for crash frequency model with heterogeneous imbalanced data," *Analytic Methods Accident Res.*, vol. 34, Jun. 2022, Art. no. 100212.

[8] Q. Shi and H. Zhang, "An improved learning-based LSTM approach for lane change intention prediction subject to imbalanced data," *Transp. Res. C, Emerg. Technol.*, vol. 133, Dec. 2021, Art. no. 103414.

[9] Y. Xing, C. Lv, H. Wang, D. Cao, and E. Velenis, "An ensemble deep learning approach for driver lane change intention inference," *Transp. Res. C, Emerg. Technol.*, vol. 115, Jun. 2020, Art. no. 102615.

[10] J. Do, K. Han, and S. B. Choi, "Lane change–intention inference and trajectory prediction of surrounding vehicles on highways," *IEEE Trans. Intell. Vehicles*, vol. 8, no. 7, pp. 3813–3825, Jul. 2023.

[11] X. Liao et al., "Online prediction of lane change with a hierarchical learning-based approach," in *Proc. Int. Conf. Robot. Autom. (ICRA)*, May 2022, pp. 948–954.

[12] Z. Li, Y. Wang, Z. Zuo, and C. Hu, "A hierarchical intention inference model for connected and automated vehicles," *IEEE Trans. Intell. Vehicles*, early access, Mar. 28, 2024, doi: 10.1109/TIV.2024.3382872.

[13] A. Vaswani et al., "Attention is all you need," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 30, Jun. 2017, pp. 5998–6008.

[14] K. Gao et al., "Dual transformer based prediction for lane change intentions and trajectories in mixed traffic environment," *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 6, pp. 6203–6216, Jun. 2023.

[15] X. Wang et al., "Variable weight combination model for lane-changing prediction of human-driven vehicle," *IEEE Trans. Intell. Vehicles*, early access, Jun. 31, 2024, doi: 10.1109/TIV.2024.3360417.

[16] L. Wen et al., "DiLu: A knowledge-driven approach to autonomous driving with large language models," in *Proc. 12th Int. Conf. Learn. Represent.*, 2023, pp. 1–20.

[17] J. Zhang, Z. Huang, A. Ray, and E. Ohn-Bar, "Feedback-guided autonomous driving," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2024, pp. 15000–15011.

[18] T. Todorov, *Symbolism and Interpretation*. Ithaca, NY, USA: Cornell Univ. Press, 1986.

[19] S. I. Kronemer et al., "Human visual consciousness involves large scale cortical and subcortical networks independent of task report and eye movement activity," *Nature Commun.*, vol. 13, no. 1, p. 7342, Nov. 2022.

[20] K. Schmidt, M. Beggiato, K. H. Hoffmann, and J. F. Krems, "A mathematical model for predicting lane changes using the steering wheel angle," *J. Saf. Res.*, vol. 49, p. 85, Jun. 2014.

[21] B. Morris, A. Doshi, and M. Trivedi, "Lane change intent prediction for driver assistance: On-road design and evaluation," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2011, pp. 895–901.

[22] H. Woo et al., "Dynamic potential-model-based feature for lane change prediction," in *Proc. IEEE Int. Conf. Syst. Man Cybern. (SMC)*, Oct. 2016, pp. 838–843.

[23] D. Kasper et al., "Object-oriented Bayesian networks for detection of lane change maneuvers," *IEEE Intell. Transp. Syst. Mag.*, vol. 4, no. 3, pp. 19–31, Fall. 2012.

[24] Y. Dou, F. Yan, and D. Feng, "Lane changing prediction at highway lane drops using support vector machine and artificial neural network classifiers," in *Proc. IEEE Int. Conf. Adv. Intell. Mechatronics (AIM)*, Jul. 2016, pp. 901–906.

[25] H. Hou, L. Jin, Q. Niu, Y. Sun, and M. Lu, "Driver intention recognition method using continuous hidden Markov model," *Int. J. Comput. Intell. Syst.*, vol. 4, no. 3, pp. 386–393, 2011.

[26] Q. Sun, C. Wang, R. Fu, Y. Guo, W. Yuan, and Z. Li, "Lane change strategy analysis and recognition for intelligent driving systems based on random forest," *Exp. Syst. Appl.*, vol. 186, Dec. 2021, Art. no. 115781.

[27] R. Yuan, M. Abdel-Aty, Q. Xiang, Z. Wang, and X. Gu, "A temporal multi-gate mixture-of-experts approach for vehicle trajectory and driving intention prediction," *IEEE Trans. Intell. Vehicles*, vol. 9, no. 1, pp. 1204–1216, Jan. 2024.

[28] T. Huang et al., "Driver lane change intention prediction based on topological graph constructed by driver behaviors and traffic context for human-machine co-driving system," *Transp. Res. C, Emerg. Technol.*, vol. 160, Mar. 2024, Art. no. 104497.

[29] M. Rubagotti, I. Tusseyeva, S. Baltabayeva, D. Summers, and A. Sandygulova, "Perceived safety in physical human–robot interaction—A survey," *Robot. Auto. Syst.*, vol. 151, May 2022, Art. no. 104047.

[30] H. Liu, T. Wang, W. Li, X. Ye, and Q. Yuan, "Lane-change intention recognition considering oncoming traffic: Novel insights revealed by advances in deep learning," *Accident Anal. Prevention*, vol. 198, Apr. 2024, Art. no. 107476.

[31] Y. Lu et al., "Hyper-relational interaction modeling in multi-modal trajectory prediction for intelligent connected vehicles in smart cites," *Inf. Fusion*, vol. 114, Feb. 2025, Art. no. 102682.

[32] M. Liu, Y. Li, Q. Yang, and W. Wu, "Peril set-aided lane-change intention inference on highway," *IEEE Internet Things J.*, vol. 11, no. 9, pp. 16647–16659, May 2024.

[33] S. Kiranyaz, O. Avci, O. Abdeljaber, T. Ince, M. Gabbouj, and D. J. Inman, "1D convolutional neural networks and applications: A survey," *Mech. Syst. Signal Process.*, vol. 151, Apr. 2021, Art. no. 107398.

[34] M. Peng, X. Guo, X. Chen, M. Zhu, and K. Chen, "LC-LLM: Explainable lane-change intention and trajectory predictions with large language models," 2024, *arXiv:2403.18344*.

[35] N. Zhao, B. Wang, K. Zhang, Y. Lu, R. Luo, and R. Su, "LC-RSS: A lane-change responsibility-sensitive safety framework based on data-driven lane-change prediction," *IEEE Trans. Intell. Vehicles*, vol. 9, no. 1, pp. 2531–2541, Jan. 2024.

[36] P. W. Battaglia et al., "Relational inductive biases, deep learning, and graph networks," 2018, *arXiv:1806.01261*.

[37] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2016, pp. 770–778.

[38] J. Lei Ba, J. R. Kiros, and G. E. Hinton, "Layer normalization," 2016, *arXiv:1607.06450*.

[39] V. Punzo, M. T. Borzacchiello, and B. Ciuffo, "On the assessment of vehicle trajectory data accuracy and application to the next generation simulation (NGSIM) program data," *Transp. Res. C, Emerg. Technol.*, vol. 19, no. 6, pp. 1243–1262, Dec. 2011.

[40] R. Krajewski, J. Bock, L. Kloeker, and L. Eckstein, “The highD dataset: A drone dataset of naturalistic vehicle trajectories on German highways for validation of highly automated driving systems,” in *Proc. 21st Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2018, pp. 2118–2125.

[41] T. Chen, X. Shi, and Y. D. Wong, “Key feature selection and risk prediction for lane-changing behaviors based on vehicles’ trajectory data,” *Accident Anal. Prevention*, vol. 129, pp. 156–169, Aug. 2019.

[42] Y. Li, F. Liu, L. Xing, C. Yuan, and D. Wu, “A deep learning framework to explore influences of data noises on lane-changing intention prediction,” *IEEE Trans. Intell. Transp. Syst.*, vol. 25, no. 7, pp. 6514–6526, Jul. 2024.

[43] F. Wirthmüller, J. Schlechtriemen, J. Hipp, and M. Reichert, “Teaching vehicles to anticipate: A systematic study on probabilistic behavior prediction using large data sets,” *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 11, pp. 7129–7144, Nov. 2021.

[44] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” 2014, *arXiv:1412.6980*.

[45] T. Chen, Y. Lu, X. Fu, N. N. Sze, and H. Ding, “A resampling approach to disaggregate analysis of bus-involved crashes using panel data with excessive zeros,” *Accident Anal. Prevention*, vol. 164, Jan. 2022, Art. no. 106496.

[46] Y. Zhang, Y. Chen, X. Gu, N. N. Sze, and J. Huang, “A proactive crash risk prediction framework for lane-changing behavior incorporating individual driving styles,” *Accident Anal. Prevention*, vol. 188, Aug. 2023, Art. no. 107072.