Informative Causality-based Vehicle Trajectory Prediction Architecture for Domain Generalization

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***Abstract*—Vehicle trajectory prediction is a promising technology for improving the performance of Cellular Vehicle-to-Everything (C-V2X) applications by providing future road states. Various vehicle trajectory prediction methods have been proposed to increase the accuracy of the predicted trajectory. Although the existing vehicle trajectory prediction methods can accurately predict the future trajectory under the assumption that data comply with the Independent and Identically Distributed (IID), their performance is seriously degraded in practical implementation due to the ubiquitous distribution shifts in vehicle trajectory data. To improve the universality of the vehicle trajectory prediction method, generalizing the method to an environment that never appeared in the training data, namely, the Domain Generalization (DG) task, should be considered. Thus, we propose a plug-and-play inFORmaTive caUsality-based vehicle trajectory predictioN architecturE (FORTUNE) to improve the DG capability of vehicle trajectory prediction methods. First, a novel structural causal model (SCM) of vehicle trajectory prediction is established to simulate the causality of the data-generating process. Second, we utilize the principle of mutual information to learn the invariant representation of the SCM. Third, an invariant knowledge-transferring module is proposed to increase learning ability without destroying the structure of the original model. The results from simulation experiments demonstrate that the proposed scheme can significantly improve the DG capability of vehicle trajectory prediction methods.**

***Index Terms*—Domain Generalization, Structural Causal Model, Mutual Information, Invariant Knowledge-Transferring Module**

I. Introduction

As a promising communication technology, Cellular Vehicle-to-Everything (C-V2X) enables vehicles to be connected with every communication device [1]. In this way, massive applications for intelligent transportation systems (ITS), such as mobile vehicle computing (MVC) [2] and collision warning systems [3] can be supported by the C-V2X system. However, the performance of most existing works in these fields is restricted due to the highly dynamic road state. Vehicle trajectory prediction is known as an emerging technique to improve the performance of C-V2X applications by bringing future road insight into C-V2X services [4]. Therefore, it is crucial to ensure the excellent performance of the vehicle trajectory prediction method.

More recently, various deep learning-based methods have been proposed to extract the interaction between the vehicle and its surroundings [5] to predict future vehicle trajectories. Nevertheless, achieving precise vehicle trajectories merely based on the interaction between the vehicle and its surroundings is unrealistic due to the ignorance of the driving maneuvers. Consequently, simultaneously considering the interaction and driving maneuvers has become a major point for improving the accuracy of predicted vehicle trajectories [6]. However, these methods are all based on the assumption that the training dataset and the test dataset comply with the principle of Independently and Identically Distributed (IID). It is challenging to ensure their performance in practical implementation due to the ubiquitous distributional shifts caused by the transformation of the environment (domain) [7]. For instance, the distributions of historical and future vehicle trajectories on roads with different topologies or traffic laws are various. The distributional shifts would cause serious performance degradation in trajectory prediction because of insufficient prior knowledge. Specifically, the accuracy of vehicle trajectory prediction methods may be unexpectedly low when the test domain is not included in the training domain set. Thus, achieving the high performance of vehicle trajectory prediction methods even under the transformation of domains, namely, domain generalization (DG) capability [8], [9], is a critical issue that should be addressed.

To effectively improve the DG capability of the existing vehicle trajectory prediction methods, we propose a plug-and-play inFORmaTive caUsality-based vehicle trajectory predictioN architecturE (FORTUNE), which consists of an invariant representation learning (IRL) module and an invariant knowledge-transferring (IKT) module. First, we establish a structured causal model (SCM) to simulate the data-generating process of the vehicle trajectory prediction task and guide the learning of variant representation. Second, inspired by [10], the mutual information is utilized to formalize the optimization objective of the IRL module. To further improve the learning ability of methods and simultaneously retain concerns of the original methods for time series prediction, such as the analysis of driving style, the IKT module is devised. Thereby, FORTUNE can assist any existing traditional vehicle trajectory prediction method in improving the DG capability. The main contributions of this paper can be summarized as follows,

- An SCM of vehicle trajectory prediction is established to guide the methods to learn the invariant representation and reduce the impact of spurious features. To the best of our knowledge, this is the first work that introduces the structured causal model into the vehicle trajectory prediction task.
- An informative causality-based IRL module is devised. The mutual information is used to formalize the target of the SCM of vehicle trajectory prediction to avoid learning pseudo-invariant features and geometric skews in the data. Moreover, we derive the tractable loss function from the above-formalized optimization objective for vehicle trajectory prediction.
- An IKT module is proposed to improve the learning efficiency and avoid the reduction of basic generalization ability and the damage to original models. In this way, a plug-and-play invariant learning architecture is obtained to empower the existing vehicle trajectory prediction methods without destroying the structure of the original model.

The rest of this paper is organized as follows. Section II describes the system overview of our plug-and-play invariant learning architecture and problem formulation. The details of this architecture are presented in Section III. Experimental evaluations and discussions are presented in Section IV. The conclusion of this paper is presented in Section V.

II. System Model

A. System Overview

In order to enable the vehicle trajectory prediction model to accurately predict the future trajectories of vehicles in the case of brand-new environments, we propose an informative causal vehicle trajectory prediction architecture. The overall architecture of FORTUNE is shown in Fig. 1, which is a plug-and-play method for any existing traditional vehicle trajectory prediction method. FORTUNE consists of three components, including the encoder of input, the invariant representation learning (IRL) module, and the domain invariant knowledge-transferring (IKT) module, respectively. The encoder of input is a set of parameters θ_g for extracting the hidden features from the input, and it is a universal structure that can be replaced by any encoder in the existing vehicle trajectory prediction methods. The IRL module focuses on learning the features that are the same across domains and considers the causality of vehicle trajectory prediction. In addition, adaptors θ_{a_1} and θ_{a_2} are utilized to link to the encoder and the decoder, respectively, to suit their feature dimensions. The structure of the adaptor is different for various vehicle trajectory prediction methods. Furthermore, the IKT module is proposed to improve learning ability and avoid losing generalization ability under IID. Specifically, this module distills the invariant knowledge from the IRL module to the original decoder, as shown by the purple dotted line in Fig. 1. In this way, the data flow only passes the encoder and the original decoder in the inference process, as shown by the red line in Fig. 1. The details of those two modules will be discussed in Section III.

B. Problem Formulation

In this section, we discuss the objective of this paper and formulate the essential problem of the study. First, the input and future trajectory spaces can be presented as $\mathcal{X}$ and $\mathcal{Y}$, respectively. Their joint distribution $P^k_{XY}, XY \in \mathcal{X} \times \mathcal{Y}$ is related to the domain D_k, namely, a specific road. The set of domain is assumed as $\mathcal{D} = \{D_k\}_{k=1}^{K}$. There are a set of input-future trajectory pairs in each domain, and each pair is defined as $D_k = \{(X_i^k, Y_i^k)\}_{i=1}^{N_k}$, where N_k represents the number of input-future trajectory pairs in this domain. The $X_i^k = \{x_{i,t}^k\}_{t=t_0-l}^{t_0}$ is the input sequence of vehicle i in time t in domain k, where l represents the length of the input sequence. $x_{i,t}^k$ represents the state of itself and its surrounding vehicles, including coordinates, velocity, acceleration, vehicle type, lane number, etc. $Y_i^k = \{y_{i,t}^k\}_{t=t_0+1}^{t_0+T}$ is the future trajectory sequence of vehicle i, where T is the length of the prediction window. $y_{i,t}^k$ is the future coordinate of this vehicle in time t. The objective of traditional vehicle trajectory prediction methods is to reduce the deviation between the real and the predicted future trajectory, which is defined as,

$$\min_{\theta_\psi, \theta_f} \sum_{i}^{N} \mathcal{L}(f(\psi(X_i)), Y_i) \tag{1}$$

where N represents the total number of the dataset, and ψ and f represent the encoder and decoder, respectively. However, this optimization objective merely focuses on the overall performance of the vehicle trajectory model, which makes it unable to generalize to a new domain in practical implementation. Therefore, we propose a novel optimization objective to enable vehicle trajectory prediction methods to generalize to a brand-new environment that never appeared in the training set. The novel optimization objective is defined as,

$$\begin{aligned} &\min_{\theta_\psi, \theta_f} \sum_{k}^{K} \mathcal{L}^{D_k}(f(\psi(X_i^k)), Y_i^k), \\ &s.t.\ \theta_f \in \arg\min_{\theta_{\hat{f}}} \mathcal{L}^{D_k}(\hat{f}(\psi(X_i^k)), Y_i^k), \end{aligned} \tag{2}$$

where $\hat{f}$ is an optimal vehicle trajectory predictor in the domain k. However, it is not a tractable optimization objective because it is a bi-level optimization. Accordingly, we transform it into a tractable optimization function. The details will be discussed in Section III.

III. The Solution

This section exhaustively presents each component of FORTUNE. First, a structural causal model of vehicle trajectory prediction is discussed from the aspect of data-generating. Second, we transfer the optimization objective in Eq. (2) into a tractable optimization function by using mutual information. Finally, we detail the IKT module.

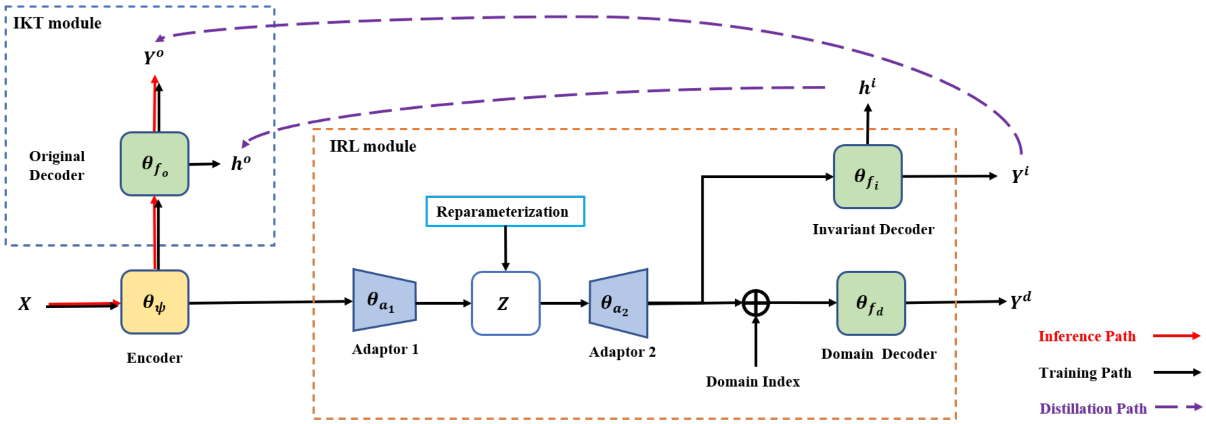


Fig. 1. The overall architecture of the FORTUNE.

A. Invariant Causal Model

In this section, we propose a causal view of the data-generating process in terms of vehicle trajectory to formalize the DG problem of vehicle trajectory prediction. As shown in Fig. 2, we establish an SCM to represent the causality of generating vehicle trajectories. The full line with the arrow represents the causal relationship between two nodes and the dotted line denotes the non-causal correlation. Each node in this SCM denotes a feature of the process of generating vehicle trajectories. D represents the domain information of the road, such as lane number and traffic rulers. I denotes the driving state that is unobservable, which includes the vehicle state and the driving style, for instance, prudence and aggressiveness. The input X is mainly generated based on two kinds of variables, namely, the causal feature Z_c that is the same across the domain and the domain-dependent feature Z_a that is impacted by both environments and driving states. Z_c is the only causal feature of the future vehicle trajectory Y. Z_a is related to D, I, and Y, but Z_a is not the reason for Y. Therefore, we can get three important conditional independence relations for the crucial nodes from the SCM based on the concept of $d-$separation. First, the marginal distribution of the future trajectory Y is related to the domain D, which can be defined as $Y \not\perp\!\!\!\perp D$. Thus, it is difficult to generalize the prediction model to a novel domain by directly learning the relation between X and Y. Second, the marginal distribution of Y is dependent on the domain D if it is conditioned on both Z_a and Z_c, which can be defined as $Y \not\perp\!\!\!\perp D|Z_a, Z_c$. Accordingly, the predicted trajectory depends on the domain D if the encoder simultaneously extracts the causal feature Z_c and the domain-dependent feature Z_a, which causes the vehicle trajectory prediction methods to fail to generalize to the novel domain. Finally, the crucial conditional independence relation for learning the invariant representation from Fig. 2, namely, $Y \perp\!\!\!\perp D|Z_c$, which means that Y is independent of the domain D if only conditioned on Z_c. Thus, it is possible to generalize vehicle trajectory methods into a novel environment by extracting Z_c. In other words, $Z = \psi(X)$ should represent the invariant representation Z_c rather than the knowledge about Z_a. The above problem can be formalized as,

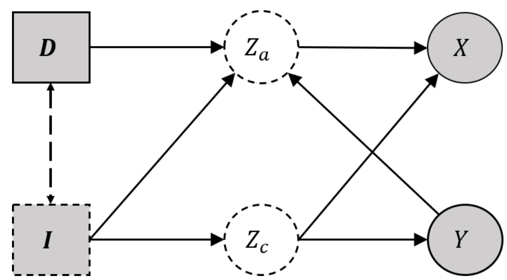


Fig. 2. Illustration of the SCM in terms of vehicle trajectory.

$$\begin{aligned} &\min_{\theta_\psi} \; dist(Z_c, \psi(X)), \\ &\max_{\theta_\psi} \; dist(Z_a, \psi(X)), \end{aligned} \tag{3}$$

where $dist(\cdot)$ denotes the distance between two distributions.

B. Optimization Objective Of FORTUNE

However, considering that Z_c and Z_a in Eq. (3) are both unobservable, it is infeasible to compute those distances of distribution. Therefore, we transform it into a tractable form by using the mutual information to learn the invariant representation of the vehicle trajectory prediction task, the Eq. (2) can be redefined as,

$$\max_{\theta_\psi} \; I(\psi(X), Y) - \beta I(Y, D|\psi(X)), \tag{4}$$

where $I(\cdot)$ means the mutual information of two random variables. The mutual information represents the relevance of those two random variables. In addition, the above optimization objective for causal invariant representation may fail due to ignoring pseudo-invariant features and geometric skews [10]. Consequently, we also extend an extra penalty function into the optimization objective, which can be defined as,

$$\max_{\theta_\psi} \; I(\psi(X), Y) - \beta I(Y, D|\psi(X)) - \gamma I(X, \psi(X)), \tag{5}$$

where the penalty function $I(X,\psi(X))$ is used to avoid learning the spurious features caused by the pseudo-invariant feature and statistical geometric skews. The term $I(\psi(X),Y)-\gamma I(X,\psi(X))$ is the typical form of the information bottle [11]. Suppose the encoder obeys the distribution of $p(\psi(X)|X)=\mathcal{N}(\psi(X)|\psi_\mu(X),\psi_\Sigma(X))$, where μ and Σ represent the mean and covariance, respectively. In order to compute the tractable loss function, we use the reparameterization trick to transform $\psi(X)$ as shown in Fig. 1, and the two adaptors are used to adjust the feature dimension without changing the architecture of the original model. In this way, we have $q(\psi(X)|X)d\psi(X)=q(\epsilon)d\epsilon$, and $Z=\psi(X,\epsilon),\epsilon\sim\mathcal{N}(0,1)$. Thus, the optimization objective of the information bottle can be transformed as follows,

$$\mathcal{L}_{bottle}=\mathcal{L}_2(Y,f_i(\psi(X)))+\gamma\mathcal{L}_Z(\psi), \tag{6}$$

where the $\mathcal{L}_Z = KL[p(Z|X,r(Z))]$, and f_i denotes the predictor. The term $I(Y,D|\psi(X))$ can be represented as,

$$I(Y,D|\psi(X))=H(Y|\psi(X))-H(Y|D,\psi(X)), \tag{7}$$

Based on the principle of maximum conditional entropy [12], we have $H(Y|\psi(X)) = \mathbb{E}[Var(Y|\psi(x))]$ and $H(Y|D,\psi(X))=\mathbb{E}[Var(Y|\psi(x),D)]$, the loss function of these two terms can be respectively defined as,

$$\begin{aligned}\mathcal{L}_i&=\mathcal{L}_2(Y,f_i(\psi(X))),\\ \mathcal{L}_e&=\mathcal{L}_2(Y,f_d(\psi(X),d))\end{aligned} \tag{8}$$

where f_d is the domain-dependent predictor. To better minimize the $I(Y,D|\psi(X))$, we propose to use the form of the mean square error to optimize the equation 7, the optimization objective is defined as,

$$\min_{\theta_\psi} I(Y,D|\psi(X))=\mathcal{L}_2(\mathcal{L}_i,\mathcal{L}_e), \tag{9}$$

Finally, the overall loss function of the invariant representation learning module can be defined as follows,

$$\mathcal{L}_{inv}=\mathcal{L}_{bottle}+\beta\mathcal{L}_2(\mathcal{L}_i,\mathcal{L}_e). \tag{10}$$

C. IKT Module

Given that the invariant representation learning module could destroy the structure of existing vehicle trajectory prediction methods and impact the focus of the original methods, thereby reducing their generalization ability without domain shift, we design an invariant knowledge-transferring module to solve this problem. Inspired by the concept of self-distillation [13], we transfer the invariant knowledge from the invariant representation learning module into the original decoder. Unlike self-distillation, the objectives of the two modules in our architecture are different. In this way, the invariant representation learning module becomes a plug-and-play module to improve the DG capability of the existing methods without destroying their time series prediction structure. As shown in Fig. 1, the knowledge from the invariant decoder f_i is distilled for the original decoder f_o. In our architecture, there are two routes for transferring knowledge, hidden distillation, and output distillation. First, the loss function of hidden distillation is defined as,

$$\mathcal{L}_h=\mathcal{L}_2(h_o,h_i), \tag{11}$$

where h_o is the hidden features of the original decoder and h_i denotes the hidden features of the invariant decoder. The loss function of output distillation is defined as,

$$\mathcal{L}_o=(1-\alpha)\mathcal{L}_2(Y^o,Y)+\alpha\mathcal{L}_2(Y^o,Y^i), \tag{12}$$

where Y^o represents the output of the original decoder and Y^i denotes the output of the invariant decoder.

Finally, the total loss function of FORTUNE can be defined as,

$$\mathcal{L}_{total}=\mathcal{L}_{inv}+\mathcal{L}_o+\lambda\mathcal{L}_h. \tag{13}$$

IV. Result And Discussion

This section demonstrates the performance of FORTUNE. First, the basic settings of the experimental environment are discussed. Then, we conduct sufficient experiments to evaluate the performance of FORTUNE.

A. Evaluation Scenarios And Performance Metrics

To evaluate the performance of FORTUNE in terms of DG of the vehicle trajectory prediction, extensive experiments in the HighD [14] and NGSIM [15], [16] datasets are conducted in this section. The HighD dataset contains 60 different roads on German highways. The NGSIM dataset consists of data on two roads, namely, the US101 highway and the I80 highway. Our experiments are conducted on a machine with an Intel Xeon Gold 6226R CPU@2.90GHZ, 128GB memory, and the platform is based on Python 3.8 and Pytorch 1.12.1. Moreover, the simulation parameters are shown in Table I.

TABLE I
Simulation Parameters

Parameter	Value
γ	5×10^{-8}
β	0.1
α	0.3
λ	0.02
learning rate	0.0005
batch size	128

Then, the performance metrics for evaluating FORTUNE are introduced as follows,

- *Root Mean Square Error* (RMSE): It is used to measure the root mean square deviation between the predicted vehicle trajectory and the real vehicle trajectory. RMSE is more sensitive to the large deviation compared with MAE. RMSE is defined as,

$$\text{RMSE}=\sqrt{\frac{1}{N}\sum_{i=1}^{M}\left(\hat{Y}_i-Y_i\right)^2} \tag{14}$$

  where M denotes the number of vehicles, $\hat{Y}_i$, and Y_i represent the real future trajectory and predicted future trajectory of vehicle i, respectively.

- *Mean Absolute Error* (MAE): It measures the mean absolute error between the generated and real future vehicle trajectory. MAE is defined as,

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\hat{Y}_i - Y_i\right| \tag{15}$$

We evaluate the effectiveness of FORTUNE for improving the model ability of DG by comparing it with the following different methods.

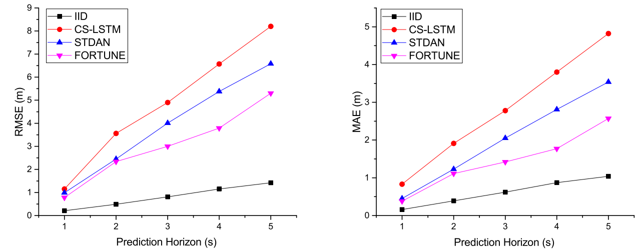
- *Convolutional Social-LSTM (CS-LSTM) [17]*: This paper proposes an LSTM encoder-decoder model that learns the interdependencies in vehicle motion by using convolutional social pooling layers.
- *Dual Learning Model (DLM) [18]*: this paper proposes to use lane occupancy and risk maps for predicting future vehicle trajectories. These two features are used in the encoder-decoder model.
- *Spatial-Temporal Dynamic Attention Network (STDAN) [6]*: This basic model comprehensively considers the temporal and social patterns in vehicle trajectory prediction, and it fuses the driving intention-specific feature into the extracted temporal and social features. In this way, this model has achieved excellent performance in predicting the future vehicle trajectory.

Moreover, we design two types of experimental settings to evaluate the DG ability of FORTUNE.

- *Independently and Identically Distributed (IID)*: It trains and tests the model in the training domain set.
- *Domain Shift*: It trains the model in the training domain set and tests the model in the test domain set, where the dissimilarity between the domain in the training domain set and the test domain set is higher than that between the domain in the same domain set.

B. Ablation Experiments

This section demonstrates the effectiveness of each component in FORTUNE for improving the DG ability of the existing vehicle trajectory prediction methods, including the IRL module and IKT module. In order to verify the DG capability, we conduct FORTUNE in two kinds of domain sets, which are the training domain set and the test domain set. The training domain set contains three domains from the US101 highway of the NGSIM dataset. The test domain set consists of three domains from the I80 highway of the NGSIM dataset. In both the training domain set and test domain set, data over each period denotes a domain. In addition, the original method is STDAN in this part. As shown in Table II, the RMSE of the predicted trajectory of STDAN is 3.96m in the 5th second when testing the method in the training domain. However, the RMSE of the predicted result of STDAN degrade to 4.26m in the 5th second when testing the method in the test domain. The average RMSE of the predicted result decreases from 2.17m to 2.14m by adding the IRL module into the original method under the setting of domain shift. By simultaneously adding the IRL module and the IKT module to the original method, the average RMSE in 5s continues to decrease to 2.09m. Thus, the IRL module and IKT module can effectively improve the DG capability of the original method.



(a) RMSE (b) MAE

Fig. 3. The predicted error in the first kind of domain shift.

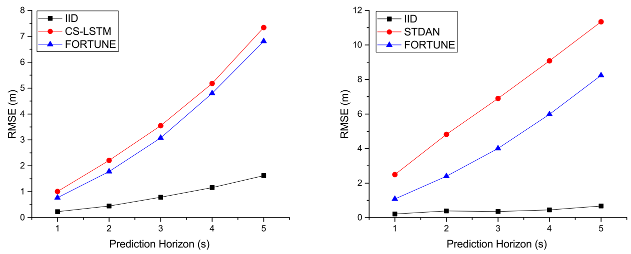
TABLE II
ABLATION STUDY RESULT (RMSE)

Source / Target	Measures	1s	2s	3s	4s	5s	Average
US101 / US101	STDAN	0.4	1	1.73	2.7	3.96	1.96
	STDAN	0.5	1.15	1.95	2.99	4.26	2.17
US101 / I80	STDAN + IRL	0.51	1.14	1.94	2.94	4.17	2.14
	STDAN + IRL + IKT	**0.49**	**1.13**	**1.89**	**2.87**	**4.07**	**2.09**

C. Experimental Results and Performance Analysis

To demonstrate the effectiveness of FORTUNE in improving the DG capability of the existing vehicle trajectory prediction methods, we test the performance of FORTUNE under two kinds of extreme domain shifts in this section. In the first domain shift, we chose 10 roads with 2 lanes as the training domain and 10 roads with 3 lanes as the test domain from the HighD dataset. The baseline method of FORTUNE in this part is STDAN. As shown in Fig. 3, the RMSE and MAE of the predicted trajectory of the baseline method are no more than 1.5m under the setting of IID. However, serious accuracy degradation in the baseline method can be observed when being tested in the test domain, where the RMSE and the MAE of STDAN are 6.58m and 3.54m in the 5th second, respectively. Moreover, the RMSE and the MAE of CS-LSTM are up to 8.2m and 4.82m in the 5th second, respectively. By adding the FORTUNE into the STDAN, the RMSE, and the MAE respectively be decreased to 5.3m and 2.57m, which shows that FORTUNE can significantly improve the DG capability.

In the second kind of domain shift, the above 20 roads, including 10 roads with 2 lanes and 10 roads with 3 lanes, from the HighD dataset are set to be the training domain set, and the test domain set is the two roads from the NGSIM dataset. In this part, we test the performance of FORTUNE based on CS-LSTM and STDAN, respectively. As shown in Fig. 4, CS-LSTM and STDAN all suffer from varying degrees of accuracy degradation in the second kind of domain shift, where the accuracy degradation of STDAN is more serious from 0.67m to 11.34m and the performance of CS-LSTM degrades from 1.62m to 7.34m in the 5th second. The performance of these



(a) FORTUNE for CS-LSTM (b) FORTUNE for STDAN

Fig. 4. The predicted error in the second kind of domain shift.

methods in the second kind of domain shift is all improved by FORTUNE in 5s, where the RMSE of CS-LSTM is reduced from 7.34m to 6.81m and that of STDAN is reduced from 11.34m to 8.24m in the 5th second. Therefore, FORTUNE can significantly improve the DG capability of the existing vehicle trajectory prediction methods.

In addition to improving the model ability of DG, it is also essential to ensure the predicted accuracy under the setting of IID. Thus, we compare the performance of FORTUNE with that of the existing vehicle trajectory prediction methods under the setting of IID. In this part, the baseline method of FORTUNE is the STDAN. As shown in Table III, we test the performance of FORTUNE in the data of all roads in the NGSIM dataset. The performance of FORTUNE is slightly lower than that of DLM in the first two seconds, but better than that of the existing models in 3-5s. Furthermore, the prediction errors of FORTUNE are all lower than those of STDAN in 5s, which indicates that Fortune is also able to improve the generalization ability of the model without domain shift.

TABLE III
PREDICTION ERRORS IN NGSIM DATASET

Measures	1s	2s	3s	4s	5s	Average
CS-LSTM	0.61	1.27	2.09	3.10	4.37	2.29
DLM	0.41	0.95	1.72	2.64	3.87	1.92
STDAN	0.42	1.01	1.69	2.56	3.67	1.87
FORTUNE (ours)	0.42	1	**1.68**	**2.54**	**3.63**	**1.85**

V. CONCLUSION

In this paper, we propose an informative causality-based vehicle trajectory prediction method, namely, FORTUNE, to address the issue of domain shift during the practical deployment of the vehicle trajectory prediction model. The extensive experimental results demonstrate that FORTUNE can significantly improve the DG capability without reducing the performance under IID. Given the limitations of the existing methods in a specific scenario, as a concrete future step, we plan to investigate the proposed FORTUNE in more different operating conditions and real scenarios.

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REFERENCES

[1] G. Twardokus and H. Rahbari, "Vehicle-to-Nothing? securing C-V2X against protocol-aware dos attacks," in *Proceedings of the International Conference on Computer Communications*, 2022, pp. 1629–1638.

[2] E. Zhang, L. Zhao, N. Lin, W. Zhang, A. Hawbani, and G. Min, "Cooperative task offloading in cybertwin-assisted vehicular edge computing," in *Proceedings of the International Conference on Embedded and Ubiquitous Computing (EUC)*, 2022, pp. 66–73.

[3] C. Qu, W. Y. Qi, and P. Wu, "A high precision and efficient time-to-collision algorithm for collision warning based V2X applications," in *Proceedings of the International Conference on Robotics and Automation*, 2018, pp. 1–5.

[4] Y. Wang, P. Lang, D. Tian, J. Zhou, and D. Zhao, "A game-based computation offloading method in vehicular multiaccess edge computing networks," *IEEE Internet of Things Journal*, vol. 7, no. 6, pp. 4987–4996, 2020.

[5] Y. Cai, Z. Wang, H. Wang, L. Chen, Y. Li, M. Sotelo, and Z. Li, "Environment-attention network for vehicle trajectory prediction," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 11, pp. 11 216–11 227, 2021.

[6] X. Chen, H. Zhang, F. Zhao, Y. Hu, C. Tan, and J. Yang, "Intention-aware vehicle trajectory prediction based on spatial-temporal dynamic attention network for internet of vehicles," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 10, pp. 19 471–19 483, 2022.

[7] J. Wang, C. Lan, C. Liu, Y. Ouyang, T. Qin, W. Lu, Y. Chen, W. Zeng, and P. Yu, "Generalizing to unseen domains: A survey on domain generalization," *IEEE Transactions on Knowledge and Data Engineering*, pp. 1–1, 2022.

[8] D. Mahajan, S. Tople, and A. Sharma, "Domain generalization using causal matching," in *Proceedings of the International Conference on Machine Learning*, 2021.

[9] E. Rosenfeld, P. K. Ravikumar, and A. Risteski, "The risks of invariant risk minimization," in *Proceedings of the International Conference on Learning Representations*, 2021.

[10] B. Li, Y. Shen, Y. Wang, W. Zhu, D. Li, K. Keutzer, and H. Zhao, "Invariant information bottleneck for domain generalization," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 36, no. 7, 2022, pp. 7399–7407.

[11] A. A. Alemi, I. Fischer, J. V. Dillon, and K. Murphy, "Deep variational information bottleneck," 2016.

[12] F. Farnia and D. Tse, "A minimax approach to supervised learning," in *Proceedings of the Advances in Neural Information Processing Systems*, 2016.

[13] L. Zhang, C. Bao, and K. Ma, "Self-distillation: Towards efficient and compact neural networks," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 44, no. 8, pp. 4388–4403, 2022.

[14] 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 *Proceedings of the International Conference on Intelligent Transportation Systems (ITSC)*, 2018, pp. 2118–2125.

[15] J. Colyar and J. Halkias , "U.s. highway 80 dataset," *Federal Highway Admin., Tech. Rep. FHWA-HRT-06-137*, 2007.

[16] J. Colyar and J. Halkias, "U.s. highway 101 dataset," *Federal Highway Admin., Tech. Rep. FHWA-HRT-07-030*, pp. 27–69, 2007.

[17] N. Deo and M. M. Trivedi, "Convolutional social pooling for vehicle trajectory prediction," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, 2018, pp. 1468–1476.

[18] M. Khakzar, A. Rakotonirainy, A. Bond, and S. G. Dehkordi, "A dual learning model for vehicle trajectory prediction," *IEEE Access*, vol. 8, no. 99, pp. 21 897–21 908, 2020.