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Review article

Continual driver behaviour learning for connected vehicles and intelligent transportation systems: Framework, survey and challenges☆

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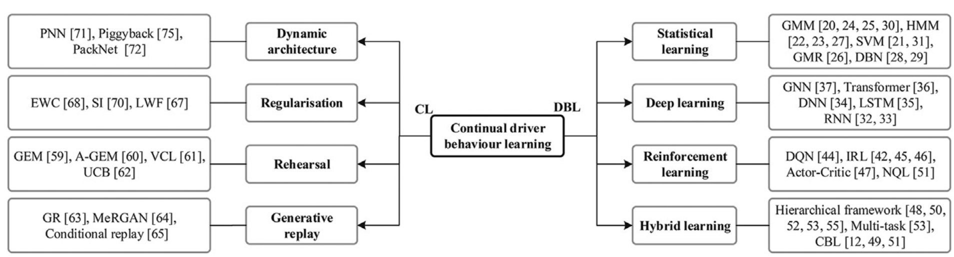
HIGHLIGHTS

- A comprehensive review of state-of-the-art driving behaviour learning (DBL) is presented.
- A framework for continual driver behaviour learning (CDBL) is proposed by leveraging continuous learning technology. The proposed CDBL framework is demonstrated to outperform existing methods in behaviour prediction through a case study.
- Future works, potential challenges and emerging trends in continual driver behaviour learning area are discussed and summarized.

GRAPHICAL ABSTRACT



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ABSTRACT

Modelling, predicting and analysing driver behaviours are essential to advanced driver assistance systems (ADAS) and the comprehensive understanding of complex driving scenarios. Recently, with the development of deep learning (DL), numerous driver behaviour learning (DBL) methods have been proposed and applied in connected vehicles (CV) and intelligent transportation systems (ITS). This study provides a review of DBL, which mainly focuses on typical applications in CV and ITS. First, a comprehensive review of the state-of-the-art DBL is presented. Next, Given the constantly changing nature of real driving scenarios, most existing learning-based models may suffer from the so-called "catastrophic forgetting," which refers to their inability to perform well in previously learned scenarios after acquiring new ones. As a solution to the aforementioned issue, this paper presents a framework for continual driver behaviour learning (CDBL) by leveraging continual learning technology. The proposed CDBL framework is demonstrated to outperform existing methods in behaviour prediction through a case study. Finally, future works, potential challenges and emerging trends in this area are highlighted.

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1. Introduction

1.1. Background

In conjunction with the evolution of intelligent transportation systems, developing novel technologies, such as autonomous driving and vehicle-to-everything (V2X) communication, is increasingly regarded as a crucial solution for enhancing traffic efficiency and reducing accident rates [1,2]. Meanwhile, we have witnessed the rapid advancement of autonomous driving perception, planning, and control algorithms in recent years [3]. However, on the way towards fully automated driving, connected and autonomous vehicles (CAVs) are expected to coexist with human-driven vehicles (HVs) for a considerable duration. For autonomous vehicles (AVs) and advanced driver assistance systems (ADAS), accurately understanding and predicting the behaviour of human drivers is of paramount importance for ensuring safety. With the development of deep learning technologies, an increasing number of deep learning-based driving behaviour methods have been proposed [4], which are termed driver behaviour learning (DBL) methods. These include predicting the driver's manoeuvring behaviour or anticipating the trajectories of surrounding vehicles. The inherent advantages of neural networks enable them to model the mapping from complex environmental information to driving behaviour [5]. For DBL models deployed in real-world intelligent systems, it is desirable that the models adapt to continually changing scenarios while achieving continual adaptation and maintaining strong performance for previously learned situations. This machine learning paradigm is known as continual learning (CL) [6–8].

This paper proposes a taxonomy of DBL methods and presents a comprehensive review of related works. It divides DBL methods into four categories: statistical learning-based, deep learning-based, reinforcement learning-based, and hybrid learning-based approaches. Meanwhile, a continual driver behaviour learning (CDBL) framework is proposed based on the overview of continual learning methods. The outperformance of CDBL is demonstrated based on case study in interactive driver behaviour prediction. Finally, reflecting on existing research, critical challenges and future works are discussed to provide guidance to researchers in the related fields.

1.2. Related reviews

Several reviews and perspectives have reviewed and discussed modelling driver behaviours from different perspectives [2]. provided a review of the motion prediction and risk assessment problems in intelligent vehicles. Its focus lies in risk assessment methods based on predictions of human driver behaviour, seeking to enhance the safety of intelligent vehicles through application in planning and control modules. However, the majority of the literature mentioned in Ref. [2] is outdated, offering limited guidance for contemporary research [9]. presented an overview of human motion trajectory prediction, which was a critical component in various applications such as robotics, surveillance, and autonomous vehicles. It covered a wide range of approaches, including physics-based, pattern-based, and interaction-aware methods, as well as deep learning techniques. The paper highlighted the strengths and weaknesses of each method and discusses the challenges faced in accurately predicting human motion trajectories, such as dealing with complex interactions, diverse environments, and real-time implementation requirements. , this survey only discusses human trajectory prediction in ITS, which does not involve DBL methods. In Ref. [5], a comprehensive survey on trajectory-prediction methods used in autonomous driving was proposed. It categorizes current techniques into three main groups: physics-based, manoeuvre-based, and interaction-aware methods. The paper also discussed the advantages and disadvantages of each method to provide insights for researchers and practitioners. Nonetheless, this paper mainly concentrated on trajectory-level driving behaviour modelling and does not encompass the modelling of drivers' decision-making and planning. As for deep learning-based behaviour prediction [4], reviewed deep learning techniques for vehicle behaviour prediction in autonomous driving applications. It provided a comprehensive overview of various deep learning architectures, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and graph neural networks (GNNs). The paper discussed how these architectures have been utilized to address different aspects of vehicle behaviour prediction, including trajectory, manoeuvre, and intention prediction [4]. focused on the deep learning-based approach, statistic learning and reinforcement learning-based methods are not included [10]. presented a comprehensive overview of deep reinforcement learning (RL) and imitation learning (IL) techniques applied to policy learning for autonomous driving. It reviewed algorithms, architectures, and applications of both learning paradigms, focusing on how they contribute to the development of intelligent driving policies. The paper also investigated the challenges and limitations related to these approaches, such as the need for large amounts of data, exploration-exploitation trade-offs, and computational complexity. By highlighting the current state of the art and future research directions, the survey aims to support researchers and practitioners in further advancing the field of autonomous driving policy learning using deep RL and IL methods [11]. reviewed social interactions for autonomous driving, emphasizing the importance of understanding and modelling the complex interactions between various road users. It discusses different approaches for capturing these interactions, including rule-based, probabilistic, and deep learning methods, and their applications in various aspects of autonomous driving, such as intention recognition, trajectory prediction, and decision-making. The paper also highlights challenges in modelling social interactions, such as diverse behaviours, dynamic environments, and real-time constraints, while suggesting potential future research directions to improve the understanding and incorporation of social interactions in autonomous driving systems [11]. mainly concentrated on the social interactions for autonomous driving, which can be seen as a part of DBL. Moreover, there are also studies utilising transfer learning to model the driver behaviour and realise different transfer learning abilities [12–19].

Although several DBL techniques are more or less discussed in the aspect of risk assessment [2], trajectory prediction [5,9], and policy learning [10], none of these works comprehensively addressed the methods and problems in DBL [4,11]. separately discussed vehicle behaviour and road interaction modelling, but Ref. [4] focused only on deep learning based techniques while Ref. [11] focused only on interactive behaviours. In contrast to the aforementioned reviews, this paper concentrates on comprehensively discussing different driver behaviour modelling techniques. Furthermore, based on an analysis of DBL techniques in continuous scenarios, a CDBL framework is proposed in this paper. To the best of our knowledge, there are no similar reviews specifically addressing DBL. The challenges and future works related to this topic, as drawn from existing research, are also summarised.

1.3. Contributions and outlines

The contributions of this paper are listed as follows.

- This paper presents a comprehensive survey of DBL methods. According to the proposed taxonomy, four kinds of approaches are introduced: statistical learning-based, deep learning-based, reinforcement learning-based and hybrid learning-based solutions;
- Building upon the review of continual learning methods, the DBL framework (CDBL) in continual scenarios is proposed. To illustrate the outperformance of CDBL, a case study in interactive driving behaviour prediction is demonstrated. It achieves consistently high prediction accuracy in continuous scenarios without re-training, which mitigates catastrophic forgetting compared to non-continual learning approaches;

- The proposed CDBL framework is newly developed in driving behaviour modelling. We summarise the challenges encountered by existing CDBL models and promising future works.

The paper is organised as follows. Section 2 presents the taxonomy and comprehensive review of DBL methods. Then, The overview of continual learning and the proposed CDBL framework are detailed in Section 3. Next, challenges and future works are discussed in Section 4. Finally, the conclusion is summarised in Section 5.

2. Learning-based driver behaviour models

Many taxonomies can be used to study DBL, for instance, model mathematical formulations, modelling time scales, and model representations. In this paper, we build a taxonomy based on machine learning methods used for modelling driver behaviour, which is shown in Table 1. More specifically, DBL methods are classified into four categories: statistical learning-based, deep learning-based, reinforcement learning-based, and hybrid learning-based methods. A summary of the DBL taxonomies is presented in Table 1.

Table 1
A taxonomy of the literature in DBL.

Learning method	Advantage	Disadvantage	Method	Driver modelling task	Reference
Statistical learning-based models	Model simplicity enables fast learning and deploying; accurate modelling for scene-specific tasks	Poor generalization ability; unable to deal with high-dimensional model input; degraded performance in continuous modelling tasks	GMM ([20,24,24,25,30]), HMM ([21,23]), GMM-HMM ([27]), SVM ([21,31]), DBN ([28,29]), GMR([26])	Pedal operation in car-following scenario	[20]
				Violating driving behaviour at intersections	[21]
				Personalized path planning in lane change scenario	[23]
				Acceleration behaviour in car-following scenarios	[28,29]
				Personalized path tracking control method	[26]
				Driver behaviour in lane keeping scenarios	[25]
				Driver brake behaviour in lane keeping scenarios	[27]
				Driver heterogeneity in car-following scenarios	[30]
				Driving styles in lane following scenarios	[31]
Deep learning-based models	High-accuracy model; capable of modelling time series and continuous tasks	Weak reasoning; high computational cost; model compexity	CNN([34,37]), Transformer([35]), MS-HARA ([36]), RNN([32,33])	Driver trajectory planning in urban scenario	[34]
				Driver's steering torque and steering posture	[35]
				Driver intention and activity	[36]
				Driver's abnormal behaviour	[37]
				Driver intention at intersections	[32]
				Driver intention in lane change scenarios	[33]
Reinforcement learning-based models	Enable driver model to be trained in an interactive manner; high model accuracy;	High training cost	DQN ([44]), IRL ([45,46]), Actor-Citric ([47]), Q-learning ([43])	End-to-end driver model	[44]
				Driver trajectory planning in urban scenario	[45]
				End-to-end driver model	[47]
				Personalised path planning in lane change scenario	[42]
				Driver interaction behaviour	[43]
				Driving action	[46]
Hybrid learning-based models	Take advantage of sub-methods	Low generality; difficult architecture design		Driver braking intensity	[50]
				Personalised driver behaviour in overtaking scenarios	[12]
				Personalised driver behaviour in adaptive cruise scenario	[51]
				Driver anomalous lane change	[52]
				Driver intention and trajectory probability	[53]
				Driving style evaluation and abnormal detection	[48]
				Imitation learning of driver behaviours	[49,54,55]

2.1. Statistical learning-based models

The statistical learning-based driver model is a data-driven approach that aims to model and predict driver behaviour by leveraging statistical and machine learning techniques. Drawing upon large-scale datasets collected from various driving scenarios, this method captures the driver characteristics underlying statistical patterns and relationships between driver behaviour and different observations, such as vehicle state, traffic conditions, and environmental factors. By employing regression, clustering, and classification algorithms, statistical learning-based methods can be used to analyze and model complex driving behaviours, including vehicle manoeuvring, trajectory prediction, and driver intention recognition.

A Gaussian mixture model (GMM) is employed in Ref. [20] to model the driver pedal operation pattern in the car-following scenario, where two GMM models are separately built to learn the gas and brake pedal operation from driver behaviour. The models are learned and compared with three different drivers with respective driving characteristics, and the results show the great potential of the statistical learning method for extracting and fitting with different driving characteristics. Two statistical learning methods are introduced in Ref. [21] for driver behaviour recognition at intersections, they separately are support vector machines (SVM) and hidden Markov models (HMM). The driver's violating behaviours are learnt using a large naturalistic data set, where the statistic learning methods show their superiority over traditional methods such as TTI-based methods. A driver intention model is modelled in Ref. [22] by incorporating a hybrid-state-system (HSS) representation with an HMM model for intersection decision estimation. The HSS representation can capture driver behaviour and vehicle dynamics as a continuous-state system and feed the HMM for discrete driver decisions near intersections. The driver's decision near intersections is also modelled in Ref. [23], which uses HMM to model the driver's “stop or pass” decision-making process. The study also reveals that the driver's decision to pass or stop at an intersection and be time-varying, and HMM shows great advantages over the binary logit model in such scenarios.

To tackle continuous driver modelling, such as personalised trajectory generalisation [24], integrate a GMM for driver preference learning with a kinematic method for lane change trajectory generating. The statistical model GMM is employed to provide personalized parameters for generating a sinusoidal lane change trajectory. The effectiveness of employing a regenerative stochastic driver model for lane departure correction systems is investigated in Ref. [25]. This model captures the inherent variability and uncertainty in human driving behaviour, providing a realistic assessment of the performance of lane departure correction systems. By simulating different driving scenarios and incorporating factors such as road conditions, driver attentiveness, and vehicle dynamics, the study comprehensively evaluates the driver model's ability to prevent lane departures and enhance road safety. The results highlight the potential benefits of integrating lane departure correction systems in vehicles and emphasise the importance of considering stochastic driver models when evaluating ADAS. The development of two driver models is presented in Ref. [26], which aims to capture individual driver behaviour in path-tracking tasks. Utilising machine learning techniques, the study focuses on replicating the unique characteristics of individual drivers in a pure pursuit scenario. The models are evaluated based on their ability to accurately predict individual driving behaviours and their performance in comparison to a generalised driver model. The results demonstrate the potential of learning-based personalised driver models for improving the understanding and modelling of human driving behaviour, which could ultimately enhance the performance of autonomous vehicles in real-world driving situations. Based on the combination of the Gaussian mixture model and hidden Markov model (GMM-HMM), a driver behaviour prediction model structure integrating the perception-decision-decision process was proposed in Ref. [27]. The driver longitudinal control behaviour can be predicted with the driver's foot movements, light intensity and EEG signals, which greatly expands the range of signal type selection for driver behaviour modelling and improves the prediction accuracy of the model.

Since different driving preferences may be presented by different drivers, the difference between drivers should be identified, and the driver behaviour model needs to be more personalized for better accuracy. A scene-aware driver behaviour model based on a dynamic Bayesian network (DBN) is introduced in Refs. [28,29], which models the driver states as a discrete hidden variable. Facilitated with a stimulus-response model (SRM) behaviour representation, the combined model can provide more accurate acceleration prediction in car-following scenarios. Two types of driver heterogeneity for car-following behaviour are also modelled in Ref. [30] using GMM, achieving 82.3% accuracy for the identification of 8 drivers. To solve the problem of excessive data annotation in supervised learning [31], proposes a classification method of driving styles based on a semi-supervised support vector machine, which divides driving styles into the aggressive type and the normal type. This method can improve the success rate of classification and reduce the consumption of manual labelling effort.

The driving behaviour learning model based on statistical learning has the advantages of model simplicity and fast reasoning speed in discrete scenarios. However, when considering complex dynamic and static information around intelligent vehicles, statistical learning methods often struggle in modelling mapping from high-dimensional environmental observation to driver decision-making, planning and control.

2.2. Deep learning-based models

DBL emerges advanced deep neural networks based on deep learning, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks. Capitalizing on the ability of deep learning algorithms to process large-scale, high-dimensional data and automatically extract complex features, this approach aims to capture the intricate patterns and relationships governing driving behaviour, including vehicle dynamics, traffic context, and environmental factors. The DL-based DBL method can be applied to many driving tasks. For example, intention recognition, trajectory prediction, and safety control.

A driver intention prediction method is proposed in Ref. [32] for predicting driver target destinations at unsignalized intersections using RNN. By considering a time sequence data of the vehicle's previous observation as input, the model can predict the driver's crossing strategy with good accuracy and provide a 1.3 s prediction window before conflicts. An ensemble RNN method is proposed in Ref. [33] for driver lane change intention recognition. By extracting and incorporating multi-modular observation including both driver and driving environment, the ensemble learning method is capable of recognising driver lane change intention before the lane change manoeuvre and achieving high accuracy. Deep neural strategy networks are proposed in Ref. [34] to map the perceptual information directly to the planned trajectory. Considering that the output of the neural network model is difficult to ensure the safety of the vehicle, a safety-enhanced controller is proposed to avoid driving risks. A multi-task sequential learning framework is proposed in Ref. [35] for the driver's steering torque and steering posture. It builds accurate predictions ranging from upper limb neuromuscular Electromyography (EMG) signals to steering behaviour. In order to realize multi-scale identification and prediction of driver activity. In Ref. [36], a two-stream multiscale human activity recognition and anticipation model is proposed to simultaneously represent the temporal and spatial characteristics of the driver, achieving good accuracy in the short-term, medium-term and long-term driving behaviour prediction. A contrastive learning approach is proposed in Ref. [37] to solve the problem of abnormal driver behaviour evaluation. A novel clustering supervised contrastive loss is introduced to optimise the distribution of the extracted representation vectors to improve the model performance. It can realise the continuous evaluation of the driver's abnormal behaviour.

In DBL, it is very important to predict the driver's estimation in a complex interactive environment. This helps to guarantee ITS safety and improve the social compatibility of smart vehicles. With the release of naturalistic driving datasets, such as NGSIM [38], INTERACTION dataset [39], Waymo [40] and Argoverse [41]. A lot of studies have been proposed and applied to interactive driving behaviour prediction. The driving behaviour learning method based on deep learning has advantages in the representation of complex interactive information and heterogeneous perception information from multiple sources. However, deep learning-based driver planning and control behaviour learning requires the manual design of network structure. For example, multi-source information and dynamic and static information fusion strategies. Meanwhile, the DBL model based on supervised deep learning requires a large amount of marked training data, which requires a large amount of cost. Therefore, some researchers propose reinforcement learning methods.

2.3. Reinforcement learning-based models

By combining with deep learning technology, reinforcement learning technology has made breakthroughs in recent years. Models trained in reinforcement learning have outperformed humans in games like Go and Star Wars, which is also prominent in capturing driver interaction behaviour through automated interactions with the environment. Considering that reinforcement learning can be automated through interaction with the environment, it can define and simulate a variety of tasks, even including some safe-critical scenarios.

To learn driver behaviour in dynamic environments, spatiotemporal state lattice is employed as representation for learning demonstration with IRL in Ref. [42]. The lattice-based representation greatly reduced the state space and computational burden of the learning and deploying process and is capable of learning driver demonstrations for trajectory planning in dynamic environments A driver interaction model is proposed in Ref. [43] through RL for verification and validation of AV in interactive environments. The interaction model assumes different drivers have different levels of reasoning, and the model of the higher level of reasoning can be iteratively trained in simulation when agents with the minimum level of reasoning are manually composed.

A control strategy for autonomous vehicles in complex environments based on model-free reinforcement learning is proposed in Ref. [44]. A new output feature representation form is designed to transform high-dimensional visual features into low-dimensional features into reinforcement learning algorithms. This method can well realise the safe and efficient control of the autonomous vehicle. Inverse reinforcement learning is used in Ref. [45] to transform the continuous space driving behaviour learning problem into a discrete space strategy selection problem. It models the coefficient of the personalised loss function through the maximum entropy reinforcement learning strategy. Experimental results show that this method can better learn and generate the driver's planned trajectory. To model driver behaviour, Generative

Adversarial Imitation Learning (GAIL) is also adopted and extended in Ref. [46], which is capable of imitating driver models with large state and action space. Three modifications of GAIL are also proposed to address the limitation in multi-agent interaction, rules of road impact, and disentanglement of latent variability in demonstrations. The above research use simulation environment or offline data generation methods to realise driving behaviour learning. In Ref. [47], a human-in-the-loop autopilot system is proposed. The driver can actively modify or intervene in the training process of reinforcement learning. This method can enhance training efficiency and improve performance. Further, it prioritised experience-based reinforcement learning with human guidance for autonomous driving. Prioritised experience-based reinforcement learning with Human guidance for autonomous driving The improvement of driving strategies guided by a driver.

Reinforcement learning can simulate many dangerous scenarios through the design of training strategies. Avoiding the cost of collecting data from natural driving scenarios. However, the algorithm based on reinforcement learning has some problems, such as difficulty in designing reward functions and difficulty in training convergence.

2.4. Hybrid learning-based models

The above three categories of DBL methods have their own advantages, and several research also tries to integrate two or more methods, such as deep learning, reinforcement learning, statistical learning and other methods, for better model representation and performance of the DBL model.

To evaluate the driving style quantitatively [48] propose a neural network-based personalised driver model, which utilised the K-means clustering result to verify the detection of abnormal driving behaviours. In Ref. [49], human driving behaviour is modelled and simulated by employing multi-agent reward augmented imitation learning (MARAIL). By leveraging both imitation learning and reinforcement learning, this method effectively captures the complex interactions between human drivers in a dynamic and realistic manner. The authors conduct extensive experiments and analyse various emergent properties, such as the formation of traffic jams and the impact of aggressive driving on traffic flow. The results demonstrate that MARAIL offers a robust and versatile framework for understanding and predicting human driving behaviour. In Ref. [50], a driver braking intensity prediction model is proposed, which integrates the statistical learning model GMM and deep neural network. Firstly, the braking behaviours of drivers are divided into three categories based on the unsupervised method, and a multi-layer neural network is constructed in each category to achieve continuous, accurate and real-time prediction of braking intensity. By combining natural actor-critic (NAC) learning and general regression neural network (GRNN), a strategy for driver personalised behaviour learning in overtaking scenarios is proposed in Ref. [12] to integrate driver general history data and online personalised data for learning. This method can better learn drivers' personalised overtaking behaviour and learn new drivers' driving behaviour faster. Similarly, this blended learning strategy has been applied to adaptive cruise Control [51]. A hybrid method is proposed in Ref. [52] for driver anomalous lane change identification, which integrates three unsupervised learning methods for feature extraction, anomalous lane change recognition, and latent space visualisation. By adopting hybrid unsupervised methods, the model can efficiently capture heterogeneity between drivers and between abnormal lane change behaviours without prior labels. A prediction model of driver intention and trajectory probability based on MDN is proposed in Ref. [53]. It uses a probabilistic prediction framework to estimate the intention and target location of multiple vehicles at the same time. In Ref. [54], generative adversarial imitation learning (GAIL) is extended to the optimisation of RNN, which is combined with reinforcement learning to learn highway driver behaviours. It rivals rule-based controllers and maximum likelihood models in realistic highway simulations [55]. propose to imitate driver behaviours by concurrently learning the policy and inferring latent state variables. This method effectively addresses the challenges posed by the partially observable nature of human driving and the complex interactions that occur on the road. The authors propose a novel algorithm that combines deep neural networks with Bayesian inference techniques to capture and reproduce the intricacies of driver behaviour effectively. Through rigorous experiments and evaluation, the paper demonstrates the superior performance of this approach compared to traditional imitation learning methods, highlighting its potential for enhancing autonomous vehicle development and improving traffic safety.

3. Continual driver behaviour learning

In Sections 1 and 2, we have introduced the taxonomy of driver behaviour learning and provided comparisons of various methodologies, emphasising driver behaviour learning approaches based on deep learning. Concurrently, the application of driver behaviour modelling in ITS has been thoroughly discussed [56,57]. Almost all machine learning models assume random sampling within a stable data distribution and are validated within the same data distribution (or scenario). However, for real-world situations, this assumption is overly solid and uncommon. For machine learning-based models applied in the real world, connected vehicles are expected to possess stable learning capabilities within continuously changing tasks or scenarios (see Fig. 1).

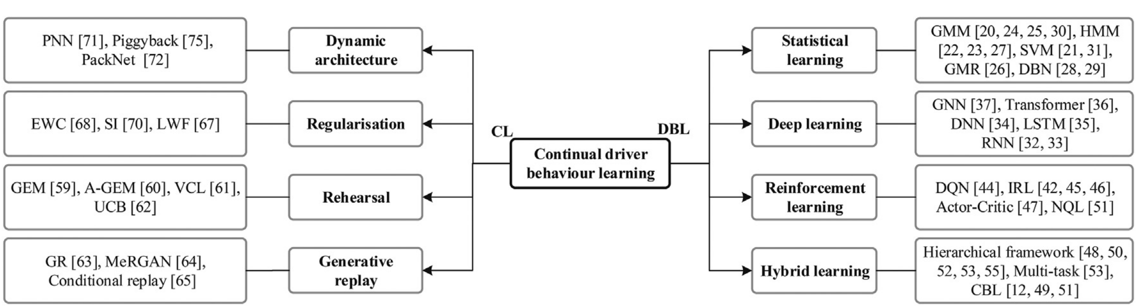

Fig. 1. The overall illustration of continual driver behaviour learning.

A common approach to address such problems is to store all data received from continuous data streams, cache it, and utilise traditional DBL methods for training. Nonetheless, these strategies are not always practical due to limitations in accessing historical data. In this section, we will primarily raise the issue of the continuous evolution of learning-based driving behaviour models in continuous scenarios and propose the CDBL model. Firstly, the fundamental assumptions and problem formulation of CDBL are introduced. Them, since the continual learning (CL) method is the main strategy to realise CDBL, four different CL methods are presented. The summary of reviewed CL methods is shown in Fig. 2. Finally, this work proposes a continual driving behaviour learning framework and demonstrates its performance through a case study.

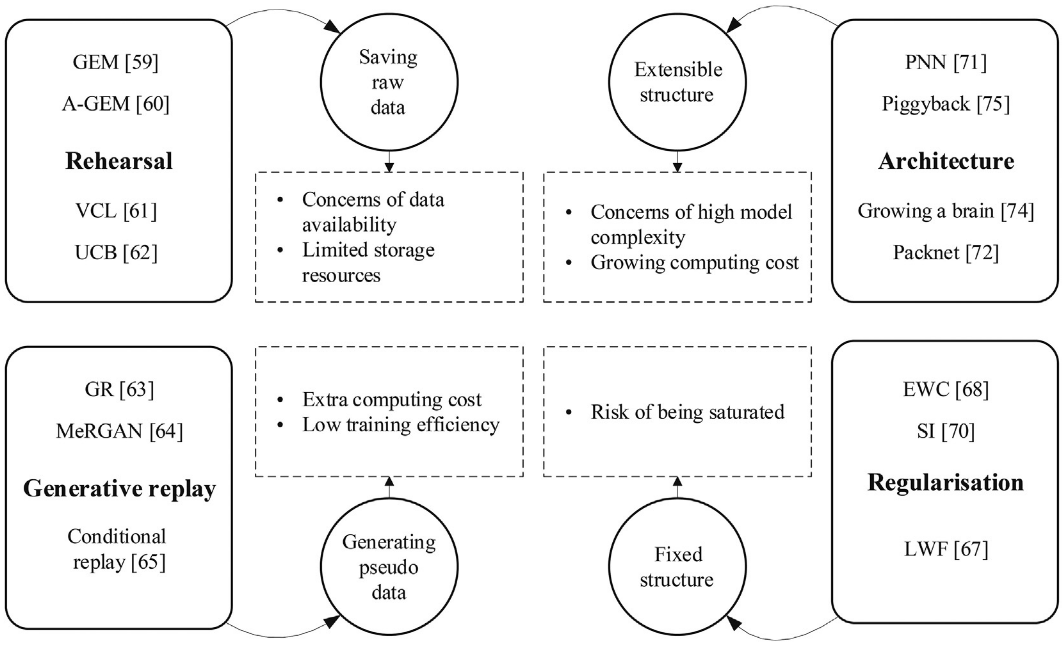

Fig. 2. The overall illustration of continual driver behaviour learning.

3.1. *Definition of continual driver behaviour learning*

In order to better introduce the CDBL model, we first describe the fundamental concepts within continual learning. Specifically, these include continal tasks, catastrophic forgetting (the problem to solve in CL) [58], and constraints in real-world applications.

3.1.1. *Tasks in continual driver behaviour learning*

In terms of data for CDBL, $D = \{D_1, D_2, \ldots, D_N\}$ is a sequence of datasets from different distributions, which can be potentially unlimited. In each dataset $\boldsymbol{D}_i = (\boldsymbol{X}, \boldsymbol{Y})$ $(i = 1, 2, \ldots, N)$, $\boldsymbol{X}$ and $\boldsymbol{Y}$ are inputs and outputs of neural networks using for a specific task. At the time step t, the training set $\boldsymbol{Tr}_t$ is composed of one or several samples from D. Models need to learn task T_t based on the training set $\boldsymbol{Tr}_t$. Then, continual tasks are defined as sequential tasks $\boldsymbol{T}_{\mathrm{cl}} = \{T_1, T_2, \ldots, T_i, \ldots\}$. Specifically, in CDBL, each task can be the recognition of the driver's personalised intention or the prediction of driving behaviour. The goals of CDBL is to have consistent good performance in continual tasks. If R_i is the cost function of the ith task, the aim can be generally represented as: minimize $R = \sum_i R_i$.

3.1.2. *Catastrophic forgetting in continual driver behaviour learning*

Catastrophic forgetting [58] is a critical problem to be solved when dealing with continual tasks in CDBL. For an intelligent agent (or a learning model), catastrophic forgetting occurs when, after acquiring new knowledge, previously learned knowledge is almost entirely forgotten [58]. It results in artificial agents lacking the ability to adapt to new environments and engage in incremental (continual) learning, akin to biological entities. It is one of the main problems to handle within continual learning [6]. In CDBL, catastrophic forgetting can refer to the phenomenon that the recognition or prediction accuracy in past scenarios declines after the model learns the data of a new scenario.

3.1.3. *Constraints of continual driver behaviour learning*

Inspired by continual learning [6], it is assumed that all data are not accessible at once in CDBL. Based on the assumptions described above, the main constraints for continual driver behaviour learning are the limited memory resource and computing power. Specifically, the number of useable data samples for driver behaviour learning in the current task is required to be lower than the total number of previously observed samples. The memory and computation resource for a CL strategy is also bounded, considering the real-world applications of automated vehicles.

3.2. *Rehearsal-based methods*

Rehearsal approaches in continual learning involve storing and replaying past data to prevent forgetting previously learned tasks while learning new ones [59–62]. These approaches aim to mitigate the problem of catastrophic forgetting, where a neural network trained on multiple tasks may forget or degrade performance on earlier tasks when trained on new tasks. By replaying past data during training on new tasks, the model can retain the knowledge learned from earlier tasks and can also adapt to new tasks.

Gradient episodic memory (GEM) is a famous rehearsal algorithm that uses the data stored in an episodic memory to calculate losses on past tasks. Then, these losses are utilised to define an inequality constraint, interfering with the training process. The model trained under the constraint mitigates the catastrophic forgetting by avoiding the increment of losses on previous knowledge [59]. The shortcoming of GEM is the high computing cost since it needs to compute the losses of all learned tasks at each updating step. To handle this disadvantage, a more efficient rehearsal approach, average gradient episodic memory (A-GEM), is developed [60]. Instead of computing the overall losses of every previous task in the training process, A-GEM computes the average loss to approximate the losses on all previous tasks. As a result, A-GEM achieves similar performance to GEM but with much less computing costs.

The main disadvantages of rehearsal approaches are two-fold: First, directly saving raw data as memory resources requires the accessibility to original data, which does not consider data availability and privacy.

Second, storing the raw and unprocessed data from learned tasks may require an enormous storage resource, especially when continual tasks include numerous sub-tasks.

3.3. Generative replay-based methods

In contrast to rehearsal-based methods that require access to original data, the key idea of generative replay-based methods is to employ a generative model to produce synthetic data samples of previous tasks, which are then combined with new data to train the model [63–65]. Consequently, such methods enable the utilisation of samples from historical tasks when learning new ones. Generative replay-based methods circumvent catastrophic forgetting through this mechanism.

Generative replay-based methods have been applied in related studies of intelligent vehicles. For example [8], mitigated catastrophic forgetting for multi-agent interaction behaviour prediction in continual tasks by using a conditional generative memory system. The conditional generative memory system is designed based on graph-neural-networks(GNNs), generating pseudo-data as memory resources to construct mixed training data. Similarly [66], uses generative adversarial networks (GANs) to construct a generative memory module for vehicle trajectory predictions. The generative memory module mitigates catastrophic forgetting in continual tasks by training with both current task data and the generated data for previous tasks. Although the generative replay-based methods relax the requirement of memory storage, they consume extra computing resources for generating the pseudo-data, bringing high training costs.

3.4. Regularisation-based methods

Regularisation-based methods add additional constraints to the model to prevent it from fitting too closely to the training data, thereby improving its ability to generalise to new, unseen data. In other words, a model cannot solely focus on fitting the current new learning task, as this would lead to forgetting previously learned tasks. Regularisation-based methods in continual learning aim to retain the memory of previously acquired knowledge by influencing the updating of neural network weights by adding a regularisation term [67–70].

One common approach to regularisation in continual learning is called “elastic weight consolidation” (EWC) [68]. EWC involves adding a regularisation term to the loss function that penalises changes to the weights of the model that were important for previous tasks. This encourages the model to preserve its previously learned knowledge while still learning new tasks. However, the EWC approach does not have advantages in task order independence and computational time efficiency. Because of this, Synaptic Intelligence (SI) method is proposed. SI uses an efficient online algorithm that does not require storing and computing the Fisher information matrix for each task, making it more scalable and computationally efficient than EWC. Moreover, it can be applied to a wide range of models, including recurrent neural networks, convolutional neural networks, and generative models, while EWC is limited to feedforward neural networks with a single output [70].

Regularisation-based methods have shown advantages in classification and reinforcement learning. However, after learning a number of continuous tasks, models may become saturated. Consequently, models cannot retain the learned experience while learning more new tasks.

3.5. Architecture-based methods

Different from the regularisation-based methods, which can be saturated due to the limited model structure, architecture-based approaches in continual learning involve modifying the architecture of the model during training to adapt to new tasks or data [71–75]. These approaches aim to overcome the limitations of fixed architecture models, which may struggle to learn new tasks or suffer from catastrophic forgetting. Progressive Neural Networks (PNNs) is a typical architecture-based approach [71]. PNN creates a new model when dealing with each new task. Each developed new model is connected to all previous ones, aiming to learn a new task by utilising the obtained experience from previous models. However, it can become computationally inefficient as the number of tasks increases, as each new model adds additional computational overhead. Thus, study [74] improves this shortcoming of PNN by dynamically expanding layers in a single network without re-training previously learned model parameters.

Architecture-based approaches offer several advantages over fixed architecture models, including improved scalability, adaptability, and flexibility. However, these approaches can also be computationally expensive and require careful design and training to ensure that the model can effectively learn and generalise to new tasks.

3.6. Case study in continual driver behaviour learning

This section demonstrates a case study of continual driver behaviour learning to provide a specific application example of the proposed CL paradigm. The driver behaviour learning task in the case study is vehicle trajectory prediction. A deep learning-based trajectory predictor is required to perform well consistently over continuously changing scenarios. First, the problem formulation of the specific task in our case study is represented. Then, a novel continual driver behaviour learning approach named dynamic gradient scenario memory (D-GSM) is proposed in the case study. Finally, the performance of D-GSM is shown through CL experiments.

3.6.1. Inputs and outputs representation

This case study focuses on predicting the future trajectories of vehicles in continuously changing scenarios. The continual tasks compose of trajectory prediction tasks in different scenarios. In each task, the model observes the historical trajectories of vehicles in the scene over t_h seconds. Then, it predicts future trajectories of target vehicles over t_f seconds. In detail, the input to the predictor can be represented as $\boldsymbol{X} = \left[\boldsymbol{tr}^{(t-t_h)}, \dots, \boldsymbol{tr}^{(t-1)}, \boldsymbol{tr}^{(t)}\right]$, where $\boldsymbol{tr}^{(t)} = \left[x_0^{(t)}, y_0^{(t)}, \dots, x_i^{(t)}, y_i^{(t)}, \dots, x_n^{(t)}, y_n^{(t)}\right]$ represents x and y co-ordinates of vehicles at time t. $\boldsymbol{tr}^{(t)}$ includes $x_0^{(t)}$ and $y_0^{(t)}$, representing coordinates of the predicted vehicle. $x_i^{(t)}$ and $y_i^{(t)}$, $(i = 1, \dots, n)$ are co-ordinates of surrounding vehicles. The output is considered as the estimated bi-variate distribution over $\boldsymbol{Y} = \left[\boldsymbol{tr}_0^{(t+1)}, \dots, \boldsymbol{tr}_0^{(t+t_f)}\right]$, with $\boldsymbol{tr}_0^{(t)} = \left[x_0^{(t)}, y_0^{(t)}\right]$ are future co-ordinates of the predicted vehicle. Thus, the output can be formulated as $P(\boldsymbol{Y}|\boldsymbol{X}) \sim \boldsymbol{\Gamma}$, where $\boldsymbol{\Gamma} = \left[\boldsymbol{\Gamma}^{(t+1)}, \dots, \boldsymbol{\Gamma}^{(t+t_f)}\right]$ are parameters of a bivariate Gaussian distribution at each time step over the prediction horizon.

The predictor is required to handle continual tasks represented by predictions in a sequence of continuous scenarios. Specifically, constructing continuous scenarios as $S = \{d_1, \dots, d_c, \dots, d_n\}$, the data of the current scenario $d_c \in S$ are fully accessible for training. Conversely, the data of past scenarios $d_i \in S, (i = 1, .., c-1)$ are not fully accessible. After learning data from the current scenario, a trajectory predictor is expected to perform well among all scenarios that have been learned. The performance of prediction is evaluated on all testing sets from $d_i \in S, (i = 1, .., c)$.

3.6.2. Dynamic gradient scenario memory-based driver behaviour prediction

The proposed CL approach for driver behaviour learning in our case study is named Dynamic Gradient Scenario Memory (D-GSM) [7]. D-GSM consists of a scenario repository module, a traffic divergence measurement module, and a dynamic memory-aware continual learning module. The scenario repository module is used to store observed samples as memory data. Then the traffic divergence measurement module estimates the divergence between observed scenarios and the current scenario in order to make a reasonable allocation of memory resources. Finally, based on the divergence measurements, the dynamic memory-aware CL module utilises the memory data to apply the specific

CL strategy for model learning. The framework of D-GSM is shown in Fig. 3, and more details of the D-GSM can be obtained in the paper [7]. As a demonstration of the case study, the following of this section will mainly introduce the core module i.e., the dynamic memory-aware CL module.

$$l\left(f_\theta, m_r^{\mathrm{D}}\right) = \frac{1}{m_r^{\mathrm{D}}}\sum_{i=1}^{m_r^{\mathrm{D}}} l\left(f_\theta(\boldsymbol{X}_i, r), \boldsymbol{Y}_i\right) \tag{1}$$

where $f_{\boldsymbol{\theta}}$ is the vehicle trajectory predicting model parameterised by θ, and $(\boldsymbol{X}_i, \boldsymbol{r}, \boldsymbol{Y}_i)$ is the ith sample in the allocated memory data corre-

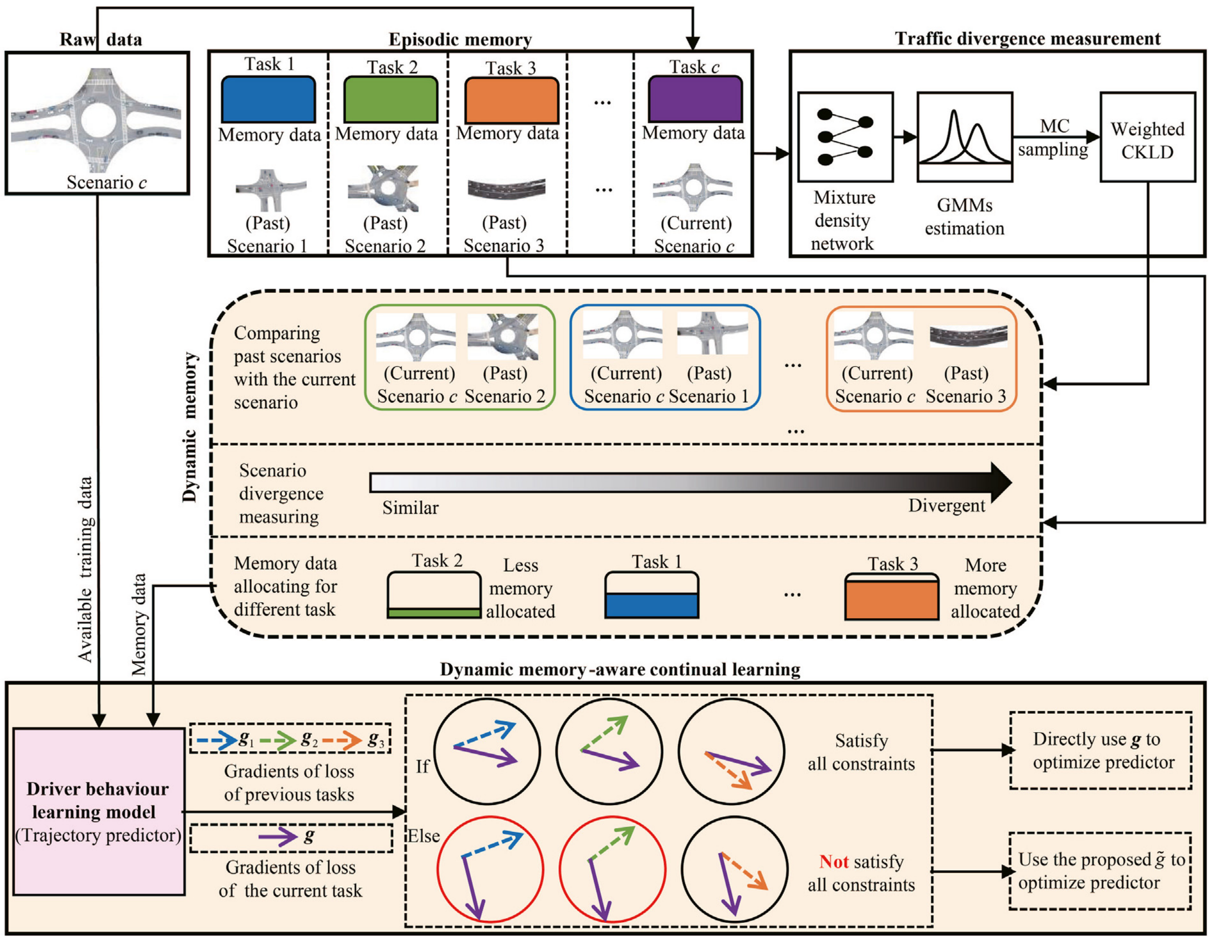

Fig. 3. Dynamic Gradient Scenario Memory (D-GSM): When a new traffic scenario arrives, the scenario repository will first store new data as memory data. Then, the traffic divergence measurement module utilizes memory data to measure the divergence between the current scenario and each past scenario. Based on the measuring of divergence, the dynamic memory module allocates memory data with different amounts for different previous tasks to the CL module. Finally, with the help of the GEM strategy, the trajectory predictor is trained in the CL module. Since more memory data bring higher computing cost, dynamic memory balances the training efficiency and performance by allocating memory data in a reasonable way [7].

In the dynamic memory-aware CL module, the dynamic memory is first used to allocate memory data to each previous task with different sample numbers. The specific number of allocated data to a past scenario depends on its traffic divergence from the current scenario. The allocated memory data from the dynamic memory module are used to apply the CL strategy in model training. Inspired by GEM [59], the CL strategy defines loss functions for previous tasks, i.e., trajectory predictions in past scenarios. Then, inequality constraints are set to interface the training process, where the model observes the training data of the current scenario. Finally, proposed gradients satisfying the inequality constraints are applied to update parameters, which avoids the increment of losses on previous tasks.

In detail, the loss functions for previous tasks are calculated using memory data. Original GEM treats all previous tasks equally without considering the similarity between tasks, which may bring an unnecessary computational burden. In our work, denoting m_r^{D} $(r = 1, .., c-1)$ is the allocated number of memory data for the rth scenario (i.e., the rth task), the loss functions for the $r^{\mathrm{th}}s$ learned task is defined as:

sponding to the r^{th} $(r = 1, .., c-1)$ past scenario. Then, in the training process of the current task, losses in Eq. (1) are used to define inequality constraints to avoid the increment of losses on previous tasks.

Supposing that $(\boldsymbol{X}, c, \boldsymbol{Y})$ are samples of the current task, and $f_{\boldsymbol{\theta}}'$ represents the predicting model state at the end of learning of the last traffic scenario, the inequality constraints are formulated as:

$$\begin{aligned} &\text{minimize}_\theta \; l(f_\theta(\boldsymbol{X}, c), \boldsymbol{Y}) \\ &\text{s.t.} \;\; l\left(f_\theta, m_r^{\mathrm{D}}\right) \le l\left(f_\theta', m_r^{\mathrm{D}}\right), \qquad \text{for all } r < c. \end{aligned} \tag{2}$$

For an efficient implementation, this paper assumes that the loss function is locally linear (when the learning rate is small) and denotes loss gradients of the current and previous tasks as $\boldsymbol{g}$ and $\boldsymbol{g}_r$, respectively. Eq. (2) can be rephrased into:

$$\langle \boldsymbol{g}, \boldsymbol{g}_r \rangle := \left\langle \frac{\partial l(f_\theta(\boldsymbol{X}, c), \boldsymbol{Y})}{\partial \theta}, \frac{\partial l\left(f_\theta, m_r^{\mathrm{D}}\right)}{\partial \theta} \right\rangle \ge 0, \quad \text{for all } r < c. \tag{3}$$

If constraints Eq. (3) are satisfied, the proposed gradient $\boldsymbol{g}$ to update parameters will not increase the loss of previous tasks. Otherwise, the gradient $\boldsymbol{g}$ will be projected to the closest gradient $g^{\sim}$ (in squared L2 norm) satisfying all constraints in Eq. (3):

$$\begin{aligned} &\text{minimize}_{\tilde{g}} \quad \frac{1}{2}\boldsymbol{g} - \tilde{\boldsymbol{g}}_2^2 \\ &\text{s.t.} \quad \langle \tilde{\boldsymbol{g}}, \boldsymbol{g}_r \rangle \geq 0, \ \text{for all } r < c. \end{aligned} \tag{4}$$

3.6.3. Experimental setting and implementation of case study

Based on INTERACTION dataset [39], continuous scenarios $S_{\text{three}} = \{d_1, d_2, d_3\}$ and $S_{\text{four}} = \{d_1, d_2, d_3, d_4\}$ are constructed for the evaluation. Each scenario d_i ($i = 1, 2, 3, 4$) is a sub-dataset collected from different traffic locations representing the divergent scenario. First, models are continually trained in continuous scenarios. Then models are tested with all scenarios that have been learned, where the last scenario d_3 and d_4 are denoted as the “current scenario” in S_{three} and S_{four}, respectively.

In the implementation, approximate 10,000 data samples from each scenario are used for training. Historical trajectories of vehicles are extracted as features for training. Models are implemented using PyTorch.[1] The training epoch is 250. The metrics used in this experiment are average displacement error (ADE) and final displacement error (FDE), commonly used in trajectory predictions [76,77]. Ref. [7] is referred for more details.

3.6.4. Experimental results of case study

The detailed experimental results are shown in Table 2. The GSM in Table 2 refers to the base model applied with the proposed approach but without dynamic memory. The memory usage for all past scenarios is equal. And the D-GSM refers to the base model applied with the entire proposed approach. d_i ($i = 1, 2, 3, 4$) denotes the ith scenario in continuous scenarios. The first row shows the performance over continuous scenarios S_{three}, where models are tested on all scenarios after learning the last scenario d_3. Similarly, the second row shows model performance over S_{four}. Compared to the vanilla base model, the proposed GSM and D-GSM models have lower ADE and FDE among three groups of continuous scenarios, indicating that the proposed CL approach for driver behaviour learning alleviates catastrophic forgetting in the continual tasks.

4.1. The combination of subjective and objective factors

Most of the existing research work focuses on separately modelling the subjective and objective factors that influence human driving behaviour. For objective factors, most DBL approaches encode objective observations (environmental perception and vehicle states) by the neural network. Then construct the mapping from objective information to driver decision-making, planning and operational behaviours. Leveraging the powerful approximation capability of the neural network, objective information-aware DBL models can effectively generate human-like driving behaviours. In Ref. [78], dynamic surrounding vehicles and static map features are encoded by GNN, which can accurately predict trajectories in 3 s based on 1 s historical information. However, driving behaviour is influenced not only by objective information but also by drivers' subjective factors, such as driving style, perceived safety perception, trust level, and emotions. Some works focus on estimating drivers' decision-making process by measuring their psychophysiological information, such as electroencephalography (EEG), electrocardiography (ECG), eye movements, and head posture [79]. create a multimodal psychological, physiological and behavioural dataset for human emotions in driving tasks. It largely supports the analysis, modelling and prediction of human driver emotions. However, few research concern the combination of subjective and objective factors in DBL. Some researchers took one-step work towards trustworthy automated driving [80]. proposed a trust-based individualizable ACC. It leveraged the driver's trust level into the control barrier function of ACC, which improved the system stability, safety and path-tracking performance. In Ref. [81], an empirical analysis was conducted to evaluate the operational design domain (ODD) by combining objective and subjective risk measures, which aided road operators in clearly describing the ODD of automated lane-keeping systems. However, at the present stage, current works remain limited explorations in some opening issues, such as the discrepancy between driver's subjective and objective risk perceptions, which is essential in guaranteeing the safety of the human-vehicle collaboration system.

4.2. The unified representation learning of driver behaviours

DBL methods focus on mapping observed (historical) state information to drivers' decision-making and control outputs. In various applications, it is necessary to design the architecture of the neural network to represent observational features based on specific driving scenarios. For example, in highway driving, a broader longitudinal range of surrounding vehicles should be taken into consideration. In roundabouts or intersections, suitable surrounding vehicles with potential interactions need to be selected in accordance with the constraints imposed by road traffic regulations. In the study of drivers’ lane-changing behaviour, current models primarily pay attention to the relative distance and speed

Table 2
Vehicle Trajectory Predicting Performance (ADE/FDE) In Continuous Scenarios: “Vanilla” represents the base model (Social-STGCNN [77]) without applying continual learning approach. “GSM” represents the base model applied with the proposed approach but without dynamic memory. The memory usage for all past scenarios are equally. “D-GSM” represents the base model applied with the entire proposed approach [7].

Continuous scenarios	Tested scenario	Vanilla	GSM (ours)	D-GSM (ours)
Continuous scenarios	The 1st past scenario: d_1	4.82/11.53	2.55/6.36	2.67/6.14
S_{three}:d_1, d_2, d_3	The 2nd past scenario: d_2	5.29/12.15	**2.96**/6.84	3.05/6.91
	Current scenario: d_3	**0.73/1.62**	**0.80/1.74**	0.90/1.97
	(Average)	(3.61/8.43)	(**2.10/4.98**)	(2.21/5.01)
Continuous scenarios	The 1st past scenario: d_1	2.74/7.29	2.03/5.73	2.01/5.60
S_{four}:d_1, d_2, d_3, d_4	The 2nd past scenario: d_2	2.23/5.83	1.95/5.13	**1.86/4.88**
	The 3rd past scenario: d_3	2.96/6.37	1.46/3.09	**1.23**/2.60
	Current scenario: d_4	1.52/3.84	**1.40/3.67**	1.44/3.76
	(Average)	(2.36/5.83)	(1.71/**4.04**)	(**1.63**/4.21)

4. Challenges and future works

In previous sections, the taxonomy, strategies and applications of DBL are presented. Based on the issues raised by ML in sequential and continual tasks, we propose the CDBL framework and demonstrate the outstanding performance of interactive driving behaviour prediction by case study. In this section, challenges and future works are highlighted.

[1] https://pytorch.org.

between the ego vehicle and the vehicles in the target lane. In scenarios involving complex interactions between vehicles, the selection of spatiotemporal features and the design of the neural network structure significantly influence the performance of DBL. From these works, it is evident that existing DBL models struggle to achieve a unified input feature representation. Feature engineering and input design based on specific scenarios can affect the adaptability in practical applications. However, there is limited research on the unified representation learning of driver behaviours. A unified representation learning model is promising in improving adaptability for DBL models that can be applied to various scenarios in ITS.

4.3. The continual and self-learning of driver behaviours

In order to enhance the performance of DBL models, current methods tend to utilise a greater volume of data during the training process. This training strategy suffers the following problems: Firstly, the cost and computational resource utilisation associated with training models based on massive amounts of data are considerable. The preparation of manually annotated data necessitates the consumption of a substantial amount of human resources. Secondly, following deployment, autonomous driving systems or ADAS needs to contend with continually changing scenarios; driving behaviour models constructed using ML technologies require adaptability and self-evolved learning capabilities for new situations. Thirdly, DBL models applied within ADAS need to progressively learn and evolve to accommodate the corresponding drivers. In summary, DBL models necessitate continual learning and self-evolution capabilities for new scenarios. At present, some studies attempt to retrain and adjust models by fine-tuning them using data from new scenarios. According to Ref. [6], this may lead to a decline in model performance for previously learned scenarios, a phenomenon referred to as catastrophic forgetting. Consequently, a promising direction for DBL models is to adapt to new scenarios while addressing catastrophic forgetting.

4.4. Benchmarking the continual driver behaviour learning

In recent years, with the advancement of deep learning technologies, numerous DBL models have been proposed. For fixed and non-continuously changing scenarios, contemporary models have introduced various evaluation metrics based on the output of driver models, such as average displacement error (ADE), final displacement error (FDE), and intent classification accuracy. Several publicly available vehicle trajectory prediction competitions have also provided updated benchmarks for DBL models [39–41,82,83]. Nonetheless, for continually changing streaming data, it is required to propose novel evaluation metrics and benchmarks based on continual learning to validate the effectiveness of CDBL algorithms. Specifically, the following indicators need to be considered: prediction performance for new scenarios, the degree of forgetting for previously learned scenarios, performance under varying streaming data sequences, learning efficiency (including the ability to achieve online continual learning), and memory utilisation. Comprehensive evaluation metrics and benchmarks facilitate fair assessments of the proposed CDBL method.

5. Conclusion

Precise understanding, modelling, and prediction of driving behaviour play an essential role in ensuring the safety of transportation systems. In this paper, we first provide a taxonomy of DBL strategies and review DBL models from the perspectives of statistical learning, deep learning, reinforcement learning and hybrid learning. Through the literature review, we demonstrate the application of DBL in various domains within intelligent transportation systems, such as CAVs and ADAS. Then, based on the survey of DBL methods and issues raised by machine learning in continual tasks, the continual driver behaviour learning (CDBL) framework is proposed. To verify the effectiveness of CDBL, a case study in interactive driving behaviour prediction is presented, which develops a dynamic memory mechanism by utilising the divergence measurement of driving scenarios. Finally, we summarise challenges in CDBL and outline future works.

CRediT authorship contribution statement

Zirui Li: Conceptualization, Methodology, Software and Writing - Original Draft. Cheng Gong: Conceptualization, Methodology, Writing - Original Draft. Yunlong Lin: Methodology, Writing - Original Draft. Guopeng Li: Writing -Review & editing. Xinwei Wang: Writing -Review & editing. Chao Lu: Methodology, Writing - Original Draft. Miao Wang: Writing -Review & editing. Shanzhi Chen: Writing -Review & editing. Jianwei Gong: Methodology, Writing -Review & editing.

Data availability

The data and materials used to support the findings of this study are available from the corresponding author upon reasonable request.

Declaration of competing interest

All authors disclosed no relevant relationship.

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References

[1] Keqiang L, Yifan D, Shengbo L, Mingyuan B. State-of-the-art and technical trends of intelligent and connected vehicles. J Automot Safety Energy 2017;8(1):1.
[2] Lefèvre S, Vasquez D, Laugier C. A survey on motion prediction and risk assessment for intelligent vehicles. ROBOMECH J 2014;1(1):1–14.
[3] Schwarting W, Alonso-Mora J, Rus D. Planning and decision-making for autonomous vehicles. Annu Rev Control Robot Auton Syst 2018;1:187–210.
[4] Mozaffari S, Al-Jarrah OY, Dianati M, Jennings P, Mouzakitis A. Deep learning-based vehicle behavior prediction for autonomous driving applications: a review. IEEE Trans Intell Transport Syst 2020;23(1):33–47.
[5] Huang Y, Du J, Yang Z, Zhou Z, Zhang L, Chen H. A survey on trajectory-prediction methods for autonomous driving. IEEE Trans Intell Veh 2022;7(3):652–74.
[6] Lesort T, Lomonaco V, Stoian A, Maltoni D, Filliat D, Díaz-Rodríguez N. "Continual learning for robotics: definition, framework, learning strategies, opportunities and challenges. Inf Fusion 2020;58:52–68.
[7] Lin Y, Li Z, Gong C, Lu C, Wang X, Gong J. "Continual interactive behavior learning with traffic divergence measurement: a dynamic gradient scenario memory approach. 2022. arXiv preprint arXiv:2212.11167.
[8] Ma H, Sun Y, Li J, Tomizuka M, Choi C. Continual multi-agent interaction behavior prediction with conditional generative memory. IEEE Rob Autom Lett 2021;6(4):8410–7.
[9] Rudenko A, Palmieri L, Herman M, Kitani KM, Gavrila DM, Arras KO. Human motion trajectory prediction: a survey. Int J Robot Res 2020;39(8):895–935.
[10] Zhu Z, Zhao H. A survey of deep rl and il for autonomous driving policy learning. IEEE Trans Intell Transport Syst 2021;23(9):14. 043–14 065.
[11] Wang W, Wang L, Zhang C, Liu C, Sun L, et al. Social interactions for autonomous driving: a review and perspectives. Found Trends Robot 2022;10(3–4):198–376.
[12] Lu C, Wang H, Lv C, Gong J, Xi J, Cao D. Learning driver-specific behavior for overtaking: a combined learning framework. IEEE Trans Veh Technol 2018;67(8):6788–802.
[13] Lu C, Hu F, Cao D, Gong J, Xing Y, Li Z. Transfer learning for driver model adaptation in lane-changing scenarios using manifold alignment. IEEE Trans Intell Transport Syst 2019;21(8):3281–93.
[14] Virtual-to-real knowledge transfer for driving behavior recognition: framework and a case study. IEEE Trans Veh Technol 2019;68(7):6391–402.
[15] Li Z, Gong J, Lu C, Xi J. Importance weighted Gaussian process regression for transferable driver behaviour learning in the lane change scenario. IEEE Trans Veh Technol 2020;69(11):12497–509.
[16] Lu C, Lv C, Gong J, Wang W, Cao D, Wang F-Y. Instance-level knowledge transfer for data-driven driver model adaptation with homogeneous domains. IEEE Trans Intell Transport Syst 2022;23(10):17 015–017 026.
[17] Li Z, Gong C, Lu C, Gong J, Lu J, Xu Y, et al. Transferable driver behavior learning via distribution adaption in the lane change scenario. 2019 IEEE Intelligent Vehicles Symposium (IV). plus 0.5em minus 0.4emIEEE 2019:193–200.

[18] Gong C, Li Z, Lu C, Gong J, Hu F. A comparative study on transferable driver behavior learning methods in the lane-changing scenario. 2019 IEEE Intelligent Transportation Systems Conference (ITSC). IEEE 2019:3999–4005.
[19] Wang L, Hu Y, Sun L, Zhan W, Tomizuka M, Liu C. Hierarchical adaptable and transferable networks (hatn) for driving behavior prediction. 2021. arXiv preprint arXiv:2111.00788.
[20] Nishiwaki Y, Miyajima C, Kitaoka N, Itou K, Takeda K. Generation of pedal operation patterns of individual drivers in car-following for personalized cruise control. IEEE Intelligent Vehicles Symposium, Conference Proceedings 2007:823–7.
[21] Aoude GS, Desaraju VR, Stephens LH, How JP. Driver behavior classification at intersections and validation on large naturalistic data set. IEEE Trans Intell Transport Syst 2012;13(2):724–36.
[22] Gadepally V, Krishnamurthy A, Ozguner U. A framework for estimating driver decisions near intersections. IEEE Trans Intell Transport Syst 2014;15(2):637–46.
[23] Tang K, Zhu S, Xu Y, Wang F. Modeling drivers' dynamic decision-making behavior during the phase transition period: an analytical approach based on hidden markov model theory. IEEE Trans Intell Transport Syst 2016;17(1):206–14.
[24] Butakov VA, Ioannou P. Personalized driver/vehicle lane change models for adas. IEEE Trans Veh Technol 2015;64(10):4422–31.
[25] Wang W, Zhao D. Evaluation of lane departure correction systems using a regenerative stochastic driver model. IEEE Trans Intell Veh 2017;2(3):221–32.
[26] Li Z, Wang B, Gong J, Gao T, Lu C, Wang G. Development and evaluation of two learning-based personalized driver models for pure pursuit path-tracking behaviors. 2018 IEEE Intelligent Vehicles Symposium (IV). IEEE 2018:79–84.
[27] Wang W, Xi J, Zhao D. Learning and inferring a driver's braking action in car-following scenarios. IEEE Trans Veh Technol 2018;67(5):3887–99.
[28] Xu D, Zhao H, Guillemard F, Geronimi S, Aioun F. Scene-aware driver state understanding in car-following behaviors. IEEE Intelligent Vehicles Symposium (IV), Conference Proceedings 2017:1490–6.
[29] Aware of scene vehicles—probabilistic modeling of car-following behaviors in real-world traffic. IEEE Trans Intell Transport Syst 2018;20(6):2136–48.
[30] Ding Z, Xu D, Tu C, Zhao H, Moze M, Aioun F, et al. Driver identification through heterogeneity modeling in car-following sequences. IEEE Trans Intell Transport Syst 2022;23(10):17143–56.
[31] Wang W, Xi J, Chong A, Li L. Driving style classification using a semisupervised support vector machine. IEEE Tran Human Mach Syst 2017;47(5):650–60.
[32] Zyner A, Worrall S, Nebot E. A recurrent neural network solution for predicting driver intention at unsignalized intersections. IEEE Rob Autom Lett 2018;3(3):1759–64.
[33] Xing Y, Lv C, Wang H, Cao D, Velenis E. An ensemble deep learning approach for driver lane change intention inference. Transport Res C Emerg Technol 2020;115:102615 [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0968090X19308332.
[34] Chen J, Yuan B, Tomizuka M. "Deep imitation learning for autonomous driving in generic urban scenarios with enhanced safety," in 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE; 2019. p. 2884–90.
[35] Xing Y, Li W, Mo X, Lv C. Multi-task driver steering behaviour modeling using time-series transformer. arXiv preprint arXiv 2022:2207.00484.
[36] Xing Y, Golodetz S, Everitt A, Markham A, Trigoni N. Multiscale human activity recognition and anticipation network. IEEE Transact Neural Networks Learn Syst 2022:1–15.
[37] Hu Z, Xing Y, Gu W, Cao D, Lv C. Driver anomaly quantification for intelligent vehicles: a contrastive learning approach with representation clustering. IEEE Trans Intell Veh 2022;8(1):37–47.
[38] Coifman B, Li L. A critical evaluation of the next generation simulation (ngsim) vehicle trajectory dataset. Transp Res Part B Methodol 2017;105:362–77.
[39] Zhan W, Sun L, Wang D, Shi H, Clausse A, Naumann M, et al. Interaction dataset: an international, adversarial and cooperative motion dataset in interactive driving scenarios with semantic maps. 2019. arXiv preprint arXiv:1910.03088.
[40] Ettinger S, Cheng S, Caine B, Liu C, Zhao H, Pradhan S, et al. Large scale i open motion dataset. In: Proceedings of the IEEE/CVF international conference on computer vision; 2021. p. 9710–9.
[41] Chang M-F, Lambert J, Sangkloy P, Singh J, Bak S, Hartnett A, et al. Argoverse: 3d tracking and forecasting with rich maps. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition; 2019. p. 8748–57.
[42] Gonzalez DS, Erkent O, Romero-Cano V, Dibangoye J, Laugier C. Modeling driver behavior from demonstrations in dynamic environments using spatiotemporal lattices. IEEE International Conference on Robotics and Automation (ICRA). IEEE, Conference Proceedings 2018:3384–90.
[43] Li N, Oyler DW, Zhang M, Yildiz Y, Kolmanovsky I, Girard AR. Game theoretic modeling of driver and vehicle interactions for verification and validation of autonomous vehicle control systems. IEEE Trans Control Syst Technol 2018;26(5):1782–97.
[44] Chen J, Yuan B, Tomizuka M. Model-free deep reinforcement learning for urban autonomous driving. 2019 IEEE Intelligent Transportation Systems Conference (ITSC); 2019. p. 2765–71.
[45] Huang Z, Wu J, Lv C. Driving behavior modeling using naturalistic human driving data with inverse reinforcement learning. IEEE Trans Intell Transport Syst 2021;23(8):10239–51.
[46] Bhattacharyya R, Wulfe B, Phillips DJ, Kuefler A, Morton J, Senanayake R, et al. Modeling human driving behavior through generative adversarial imitation learning. IEEE Trans Intell Transport Syst 2023;24(3):2874–87.
[47] Wu J, Huang Z, Hu Z, Lv C. Toward human-in-the-loop ai: enhancing deep reinforcement learning via real-time human guidance for autonomous driving. Engineering; 2022.
[48] Shi B, Xu L, Hu J, Tang Y, Jiang H, Meng W, et al. Evaluating driving styles by normalizing driving behavior based on personalized driver modeling. IEEE Trans Syst Man Cybern Syst 2015;45(12):1502–8.
[49] Bhattacharyya RP, Phillips DJ, Liu C, Gupta JK, Driggs-Campbell K, Kochenderfer MJ. Simulating emergent properties of human driving behavior using multi-agent reward augmented imitation learning. 2019 International Conference on Robotics and Automation (ICRA). IEEE 2019:789–95.
[50] Lv C, Xing Y, Lu C, Liu Y, Guo H, Gao H, et al. Hybrid-learning-based classification and quantitative inference of driver braking intensity of an electrified vehicle. IEEE Trans Veh Technol 2018;67(7):5718–29.
[51] Chen X, Zhai Y, Lu C, Gong J, Wang G. A learning model for personalized adaptive cruise control. 2017 IEEE intelligent vehicles symposium (IV). IEEE 2017:379–84.
[52] Fan P, Guo J, Wang Y, Wijnands JS. A hybrid deep learning approach for driver anomalous lane changing identification. Accid Anal Prev 2022;171:106661 [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0001457522000975.
[53] Hu Y, Zhan W, Tomizuka M. Probabilistic prediction of vehicle semantic intention and motion. 2018 IEEE Intelligent Vehicles Symposium (IV). IEEE 2018:307–13.
[54] Kuefler A, Morton J, Wheeler T, Kochenderfer M. Imitating driver behavior with generative adversarial networks. 2017 IEEE Intelligent Vehicles Symposium (IV). IEEE 2017:204–11.
[55] Morton J, Kochenderfer MJ. Simultaneous policy learning and latent state inference for imitating driver behavior. 2017 IEEE 20th international conference on intelligent transportation systems (ITSC). IEEE 2017:1–6.
[56] Li Z, Gong J, Lu C, Li J. Personalized driver braking behavior modeling in the car-following scenario: an importance-weight-based transfer learning approach. IEEE Trans Ind Electron 2022;69(10):10 704–710 714.
[57] Li Z, Lin Y, Gong C, Wang X, Liu Q, Gong J, et al. An ensemble learning framework for vehicle trajectory prediction in interactive scenarios. 2022. arXiv preprint arXiv:2202.10617.
[58] French RM. Catastrophic forgetting in connectionist networks. Trends Cognit Sci 1999;3(4):128–35.
[59] Lopez-Paz D, Ranzato M. Gradient episodic memory for continual learning. Adv Neural Inf Process Syst 2017;30.
[60] Chaudhry A, Ranzato M, Rohrbach M, Elhoseiny M. Efficient lifelong learning with a-gem. 2018. arXiv preprint arXiv:1812.00420.
[61] Nguyen CV, Li Y, Bui TD, Turner RE. Variational continual learning. In: International conference on learning representations; 2018 [Online]. Available: https://openreview.net/forum?id=BkQqq0gRb.
[62] Ebrahimi S, Elhoseiny M, Darrell T, Rohrbach M. Uncertainty-guided continual learning in bayesian neural networks–extended abstract. In: Proc. IEEE conf. Comput. Vis. Pattern recognition. CVPR); 2018.
[63] Shin H, Lee JK, Kim J, Kim J. Continual learning with deep generative replay. Adv Neural Inf Process Syst 2017;30.
[64] Wu C, Herranz L, Liu X, Wang Y, Van De Weijer J, Raducanu B, et al. Memory replay gans: learning to generate new categories without forgetting. Adv Neural Inf Process Syst 2018;31.
[65] Lesort T, Gepperth A, Stoian A, Filliat D. "Marginal replay vs conditional replay for continual learning," in artificial neural networks and machine learning–ICANN 2019: deep learning: 28th international conference on artificial neural networks. 2019. Munich, Germany: Proceedings, Part II 28. Springer; 2019. p. 466–80. September 17–19.
[66] Bao P, Chen Z, Wang J, Dai D, Zhao H. Lifelong vehicle trajectory prediction framework based on generative replay. arXiv preprint arXiv 2021:2111.07511.
[67] Li Z, Hoiem D. Learning without forgetting. IEEE Trans Pattern Anal Mach Intell 2017;40(12):2935–47.
[68] Kirkpatrick J, Pascanu R, Rabinowitz N, Veness J, Desjardins G, Rusu AA, et al. Overcoming catastrophic forgetting in neural networks. Proc Natl Acad Sci USA 2017;114(13):3521–6.
[69] Aljundi R, Babiloni F, Elhoseiny M, Rohrbach M, Tuytelaars T. Memory aware synapses: learning what (not) to forget. In: Proceedings of the European conference on computer vision. ECCV); 2018. p. 139–54.
[70] Zenke F, Poole B, Ganguli S. Continual learning through synaptic intelligence. In: International conference on machine learning. PMLR; 2017. p. 3987–95.
[71] Rusu AA, Rabinowitz NC, Desjardins G, Soyer H, Kirkpatrick J, Kavukcuoglu K, et al. Progressive neural networks. 2016. arXiv preprint arXiv:1606.04671.
[72] Mallya A, Lazebnik S. Packnet: adding multiple tasks to a single network by iterative pruning. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2018. p. 7765–73.
[73] Serra J, Suris D, Miron M, Karatzoglou A. Overcoming catastrophic forgetting with hard attention to the task. In: International conference on machine learning. PMLR; 2018. p. 4548–57.
[74] Wang Y-X, Ramanan D, Hebert M. Growing a brain: fine-tuning by increasing model capacity. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2017. p. 2471–80.
[75] Mallya A, Davis D, Lazebnik S. Piggyback: adapting a single network to multiple tasks by learning to mask weights. In: Proceedings of the European conference on computer vision. ECCV); 2018. p. 67–82.

[76] Alahi A, Goel K, Ramanathan V, Robicquet A, Fei-Fei L, Savarese S. Social lstm: human trajectory prediction in crowded spaces. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2016. p. 961–71.

[77] Mohamed A, Qian K, Elhoseiny M, Claudel C. Social-stgcnn: a social spatio-temporal graph convolutional neural network for human trajectory prediction. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition; 2020. p. 14424–32.

[78] Li G, Li Z, Knoop V, van Lint H. Uqnet: quantifying uncertainty in trajectory prediction by a non-parametric and generalizable approach. Available at SSRN 2022:4241523.

[79] Li W, Tan R, Xing Y, Li G, Li S, Zeng G, et al. A multimodal psychological, physiological and behavioural dataset for human emotions in driving tasks. Sci Data 2022;9(1):481.

[80] Hu C, Wang J. Trust-based and individualizable adaptive cruise control using control barrier function approach with prescribed performance. IEEE Trans Intell Transport Syst 2021;23(7):6974–84.

[81] Farah H, Bhusari S, Van Gent P, Babu FAM, Morsink P, Happee R, et al. An empirical analysis to assess the operational design domain of lane keeping system equipped vehicles combining objective and subjective risk measures. IEEE Trans Intell Transport Syst 2020;22(5):2589–98.

[82] Wilson B, Qi W, Agarwal T, Lambert J, Singh J, Khandelwal S, et al. Argoverse 2: next generation datasets for self-driving perception and forecasting. 2023. arXiv preprint arXiv:2301.00493.

[83] Caesar H, Bankiti V, Lang AH, Vora S, Liong VE, Xu Q, et al. nuscenes: a multimodal dataset for autonomous driving. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition; 2020. p. 11621–31.