Dynamic Data-driven Microscopic Traffic Simulation using Jointly Trained Physics-guided LSTM

1 INTRODUCTION

This document contains supplementary materials of our paper, *"Dynamic Data-driven Microscopic Traffic Simulation using Jointly Trained Physics-guided LSTM"*, submitted to the journal, Transactions on Modeling and Computer Simulation (TOMACS) under Association of Computing Machinery (ACM).

2 REVIEW ON DATA-DRIVEN CAR-FOLLOWING MODELS

The existing works on data-driven car-following models can be categorized into – (i) classic machine learning models [3, 4, 7]; (ii) deep learning models [1, 5, 6]; (iii) deep reinforcement learning models [8, 9], and (iv) physics-informed deep learning models [2]. The summary of the existing literature is provided in Table 1.

Table 1. Summary of existing data-driven car-following models

Model Type	Ref	Year	Models Used	Hybrid Model	Main Contribution
Classic Machine Learning	[3]	2015	Loess	No	To capture more accurate car-following behaviours by using more input variables
	[4]	2018	Loess	No	To extend the model in [3] for traffics practicing weak-lane discipline
	[7]	2019	Random Forest, ANN, Gipps	Yes	To avoid vehicle collisions when using data-driven models
Deep Learning	[6]	2018	GRU, LSTM	No	To incorporate temporal dependency and driver memory effect into the model
	[1]	2019	Encoder-Decoder LSTM	No	To handle both variable input and output lengths and consider reaction delay when applying the model output
	[5]	2020	GRU, Markov Chain	Yes	To bound the model predicted value within the reasonable range
Deep Reinforcement Learning	[8]	2018	DDPG	No	To achieve better generalisation capability than deep learning models
	[9]	2019	DDPG	No	To extend the model in [8] to capture more realistic driving behaviour
Physics-Informed Deep Learning	[2]	2021	IDM, OVM, ANN, LSTM	Yes	To systematically integrate physics-based models and deep learning models

2.1 Classic Machine Learning Models

A machine learning model, namely Locally weighted regression (Loess), was proposed in [3] to model car-following behaviour. By using additional input variables, the model achieved superior performance compared to Gipps model. The same model was used in [4] and extended further to work in situations where strict lane-discipline is often not practiced (as in the cities of developing countries). In such a case, it can be very difficult to identify appropriate follower-leader pairs. Thus, temporary virtual lanes were created to help address this problem. Then, in conjunction with Loess, it was used to model car-following behaviour in mixed traffic and weak lane-discipline scenarios.

Car-following models that are based on classic machine learning have one major issue. Since these models are data-driven, they are highly biased towards the data that are used to train them [7]. Although such models could learn realistic driving patterns from the data, they could also learn inappropriate behaviours or unsafe manoeuvres found in the data. Hence, a car-following model, that combines the physics-based Gipps model and traditional machine learning techniques such as Random Forest and Artificial Neural Network (ANN), was proposed in [7] to overcome this weakness. The ring-road simulation test was conducted to evaluate the performance of different models and demonstrated the advantages of the proposed method.

2.2 Deep Learning Models

The above-mentioned models do not consider the memory effect or the temporal dependency between vehicle states. These factors are important to model driving behaviours since a driver makes decision not only based on the current state, but also based on previous driving states. A type of deep learning models, namely Recurrent Neural Networks (RNNs), can capture this temporal dependency with their internal structure. Thus, in the current literature, two kinds of RNNs: 1) Gated Recurrent Unit (GRU) and 2) Long Short-Term Memory (LSTM), are widely adopted for modelling car-following behaviour.

In [6], a GRU neural network that accounts for both memory effect and temporal dependency was proposed to capture car-following behaviour. During the simulation experiment, the leading vehicles' speed were varied to different pre-defined values and the followers' driving patterns produced by different models were compared. The proposed GRU-based model outperforms other baseline data-driven models including LSTM based on the evaluation in terms of test data and an offline what-if scenario simulation. In [1], a seq2seq model based on Encoder-Decoder LSTM architecture was proposed. The model considers both memory effect and reaction delay. Due to the nature of seq2seq models, it can handle variable input and output lengths. What differentiates their work from other existing works is the consideration of reaction delay. Instead of applying the output variable in the next immediate time step, their model accounts for reaction delay because a traffic state in the current time step may take some time to reflect in subsequent time steps. During the evaluation stage, a vehicle platoon simulation was carried out to assess the model performance.

Deep learning-based car-following models may produce implausible values such as negative speed and space headway [5]. Hence, a new model that integrates Markov Chain and GRU was proposed in [5]. The Markov Chain is used to keep the predicted value at a reasonable range and hence, it helps stabilize the trajectory prediction in simulation. During the simulation experiment, the leading vehicles' speed were varied according to sinusoidal equations. Then, the following vehicles' states produced by different car-following models were analysed whether they could produce stable car-following behaviours.

2.3 Deep Reinforcement Learning Models

The data-driven models that are based on classical machine learning or deep learning heavily depend on the diversity of the training data. In other words, the models are not able to generalize other traffic scenarios that are absent in the training dataset. To address this limitation, a deep reinforcement learning (DRL) based car-following model was proposed in [8]. It employed an extension of deep Q-learning network (DQN), namely Deep Deterministic Policy Gradient (DDPG), that can handle continuous action spaces. A simple traffic simulator was implemented to serve as the learning environment for DDPG. The proposed model was benchmarked against other car-following models ranging from IDM and Loess to RNNs. During the simulation experiment, the leading vehicles were controlled by the ground-truth data while the followers' dynamics were controlled by the proposed model. The DDPG-based car-following model outperforms other baseline methods according to their simulation results. The same model was extended to account for safe, efficient, and comfortable car-following behaviours by modifying the reward function correspondingly in [9].

2.4 Physics-Informed Deep Learning Models

An attempt to combine conventional physics-based model and sophisticated deep learning models was already made in [7]. Nevertheless, it could be considered as a shallow combination of the two approaches. Hence, for deeper coupling of the two approaches, a novel car-following modelling paradigm is proposed in [2]. During the training process, a learning-based model (either ANN or LSTM) is trained by using two types of losses – (i) data loss and (ii) physics loss. The former measures the discrepancy between the learning-based model output and the observed data while the latter accounts for the discrepancy between the learning-based model output and the physics-based model output (either from IDM or Optimal Velocity Model, OVM). This encourages the learning-based model to produce physically consistent outputs. Through experiments, their proposed physics-informed deep learning models have been shown to surpass other baselines that do not couple with physics-based models, especially when only sparse observation data are used in model training.

3 PERFORMANCE COMPARISON BETWEEN STATIC LSTM & JTPG-LSTM

In this section, we varied the amount of training data used (from 20% to 100%) to compare the performance between our physics-guided JTPG-LSTM and the pure data-driven LSTM. According to the results shown in Table 2 and 3, JTPG-LSTM outperformed static LSTM by about 3.88% in terms of acceleration prediction when using only 20% of training data. In the mean time, the former had zero collisions, but the latter led to 29 collisions. In alignment with our reference work [2], these findings suggest that the physics-guided JTPG-LSTM is also more data-efficient than the pure data-driven LSTM.

Table 2. JTPG-LSTM performance when using varying amount of training data

Training Data	$RMSE_{acc}$	$RMSE_{vel}$	$RMSE_x$	$Collisions$	v_0	T	s_0	a_{max}	b_{max}
20%	**1.2475**	**0.7813**	**0.6069**	**0**	33.3282	0.5052	1.6387	0.3724	3.4084
40%	**1.2392**	**0.7682**	**0.6062**	**0**	33.3327	0.5	2.1697	0.333	3.41
60%	1.247	0.767	0.606	0	33.3149	0.5173	2.5348	0.2806	3.41
80%	1.2335	0.7512	0.5981	0	33.3309	0.5891	1.938	0.2947	3.4033
100%	1.2374	0.7559	0.6005	0	33.3143	0.6298	1.8529	0.2803	3.4069

Table 3. Static LSTM performance when using varying amount of training data

Training Data	$RMSE_{acc}$	$RMSE_{vel}$	$RMSE_x$	$Collisions$
20%	**1.2979**	**0.8802**	**0.6404**	**29**
40%	**1.2329**	**0.7866**	**0.614**	**14**
60%	1.207	0.7343	0.5957	13
80%	1.1941	0.724	0.5948	9
100%	1.1951	0.7196	0.5897	9

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