Modeling lane changes using parallel learning

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1 INTRODUCTION

Lane change (LC) is a fundamental driving behavior wherein a vehicle moves from its current lane to adjacent ones, exerting a considerable influence on traffic flow dynamics. Extensive research highlights the substantial impact of lane changes on both traffic safety and efficiency. Accurate modeling of lane changes is crucial for developing traffic simulators that achieve enhanced precision and traffic control strategies that manage traffic flows more effectively.

The process of a vehicle's lane change is inherently complex, typically involving two main steps. Initially, a vehicle decides to change lanes, driven either by the necessity to alter its route (referred to as mandatory lane change) or the perception of another lane being faster or more comfortable (referred to as discretionary lane change). This decision-making process is known as the Lane Change Decision (LCD) process. Once the lane change decision is made, the subsequent transition of the vehicle from its current lane to the target lane is referred to as the Lane Change Implementation (LCI) process. Both the LCD and LCI processes play a crucial role in traffic flow dynamics.

The endeavor to model vehicles' lane change behavior has spanned several decades. LC models can be broadly categorized into two types: knowledge-based behavioral models and data-driven learning models (Hidas, 2002, Zheng, 2014, Ali *et al.*, 2022). This contribution introduces an innovative approach to model the LC process of vehicles by employing parallel learning (PL), seamlessly integrating conventional physical or behavioral models with data-driven counterparts. For the LCD model, a utility-based model is embedded into a neural network. Simultaneously, the LCI model incorporates a conventional car-following model, replicating the behavior of the new follower of the lane-changer, within the training process of a long-short-term memory model. Empirical trajectory data collected from unmanned aerial vehicles, which provides detailed information on the vehicles' lane-changing process, serves as the basis for training and testing the proposed models. Additionally, data from a different site is employed to assess model transferability. Results demonstrate that the proposed models adeptly predict both LC decisions and implementations, outperforming baseline physical and behavioral models, as well as pure data-driven models, in terms of prediction accuracy. These findings highlight the significant potential of these models in improving the precision of microscopic traffic simulators.

2 PARALLEL LEARNING-BASED LANE CHANGE MODELS

2.1 LCD MODEL

In general, a PL-based model should comprise two components: a physical or behavioral model and a data-driven model. In the proposed LCD model, the physical/behavioral aspect employs a discrete choice model proposed by Ahmed (1999). This model uses logistic distribution to calculate the lane-changing probability, which is represented as,

$$p_{\text{beh}} = \frac{e^{U_{\text{TL}}}}{e^{U_{\text{CL}}} + e^{U_{\text{TL}}}}. \tag{1}$$

where U_{TL} and U_{CL} denote the utility of target lane and current lane. Each lane's utility is a linear equation related to variables such as relative spacing between vehicles, velocity, etc. Each variable has a different weight to represent their varying influence on lane-changing decisions.

The data-driven component of the proposed LCD model utilizes the neural network (NN) and is referred to as knowledge-informed NN (KINN) in the context of the PL-based LCD model. The NN frames the LCD problem as a classification task, distinguishing between lane-changing and lane-keeping scenarios. It receives the incorporated features including speed, acceleration, and relative distance as input, and predicts lane change probability, denoted as p_{nn}. Figure 1 illustrates the full architecture of the PL-based LCD model.

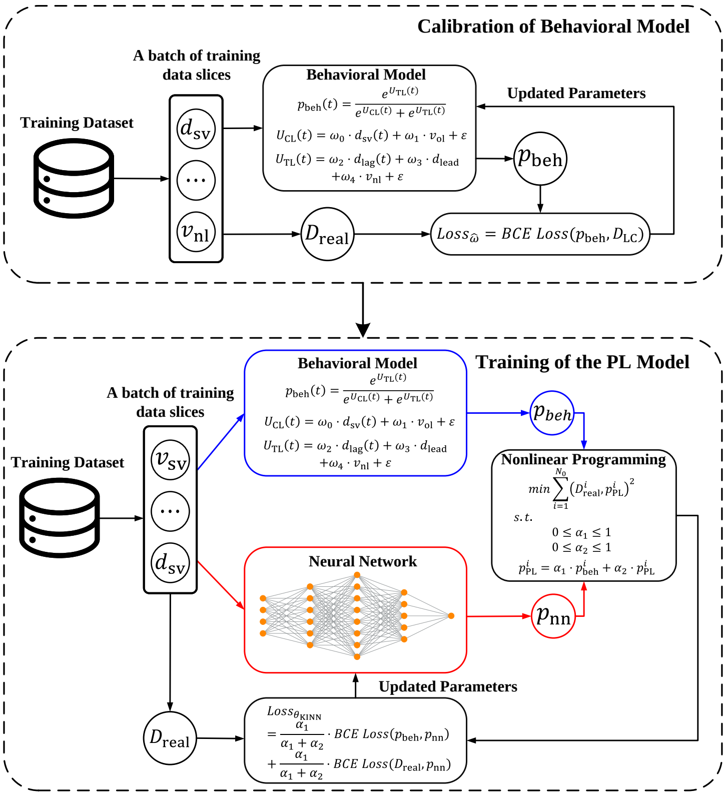

Figure 1 – *Illustration of the PL-based LCD model*

The behavior model is calibrated against real dataset D_{real} before being embedded into the NN, the training of the PL-based model occurs after the calibration. For each training data slice i, the LC probability predicted by the PL-based LCD model is given by:

$$p^i_{\text{PL}} = \alpha_1 \cdot p^i_{\text{beh}} + \alpha_2 \cdot p^i_{\text{nn}}. \tag{2}$$

Where α_1, α_2 are the weights of each component. The weights are adjusted dynamically by solving the nonlinear equation with the objective function of minimizing the Mean Square Error

(MSE) between the D^i_{real} and p^i_{PL} among the samples. The parameters of the KINN, θ_{KINN} are updated using the combination of Binary Cross Entropy (BCE) loss functions with the aforementioned weights:

$$\min \text{Loss}_{\theta_{\text{KINN}}} = \frac{\alpha_1}{\alpha_1+\alpha_2} \cdot BCE \text{ Loss}(p_{\text{beh}}, p_{\text{nn}}) + \frac{\alpha_2}{\alpha_1+\alpha_2} \cdot BCE \text{ Loss}(D_{\text{real}}, p_{\text{nn}}). \tag{3}$$

2.2 LCI MODEL

The LCI model proposed in this paper encompasses two components, a physical car-following model and a data-driven model. The physical model utilizes the model proposed in Laval & Leclercq (2008), while the data-driven model employs a LSTM model. Therefore, the physical model in the PL-based LCI model replicates the driving trajectory of the new follower rather than the lane-changer. Since the lane-changer's trajectory significantly affects that of the new follower, the accuracy in predicting the lane-changer's trajectory will also impact that of the new follower. Hence, we choose to jointly minimize the prediction errors of both the lane-changer and the new follower in our PL-based LCI model to enhance prediction accuracy.

The physical model is calibrated using real data before incorporated into the PL-based model. The LSTM within the PL-based model is referred to as the knowledge-informed LSTM (KILSTM). In each training iteration, distinct inputs are supplied to both the physical model and the KILSTM model. The KILSTM's loss function consists of two distinct components, expressed as

$$\text{Loss}_{\theta_{\text{KILSTM}}} = MAE_1 + MAE_2 \tag{4}$$

The introduction of a physical term in the loss function serves as an additional constraint for the KILSTM. The physical model simulates the position updating of the following vehicle, relying on the position of its leading vehicle. Consequently, the predictions made by the KILSTM significantly influence the LL model's predictions. In other words, inaccuracies in the KILSTM's predictions regarding the new leader's position can amplify errors within the LL model, leading to a deterioration in overall performance. Therefore, improving the precision of the KILSTM's predictions is crucial for enhancing the overall effectiveness of the model. The loss function of the proposed model captures this inter-dependency between the new follower and the lane-changer, making the training more efficient.

3 MODEL EVALUATION

Data were collected from two distinct sites in Nanjing, a provincial capital city in China. Trajectory data from both sites were obtained using high-resolution 4K cameras mounted on two unmanned aerial vehicles, employing state-of-the-art trajectory extraction algorithms. The trajectory data contains detailed information on the traffic state variation of every lane-changing vehicle, including lateral and longitudinal positions, speed, and acceleration. Data collected from site 1 will be utilized for training testing the models, while data from site 2 will be used for testing the transferability of the models.

We compare eight different LCD prediction methods, including utility-based model (UT), support vector machine (SVM), light gradient boosting machine (LGBM), extra tree (ET), deep belief networks (DBN), neural network (NN), parallel learning-based method with fixed weight (PL-Fix) and parallel learning-based method (PL). The performance test and transferability test (F1 score and Accuracy) results of the baseline models and the proposed model are summarized in Figure 2.

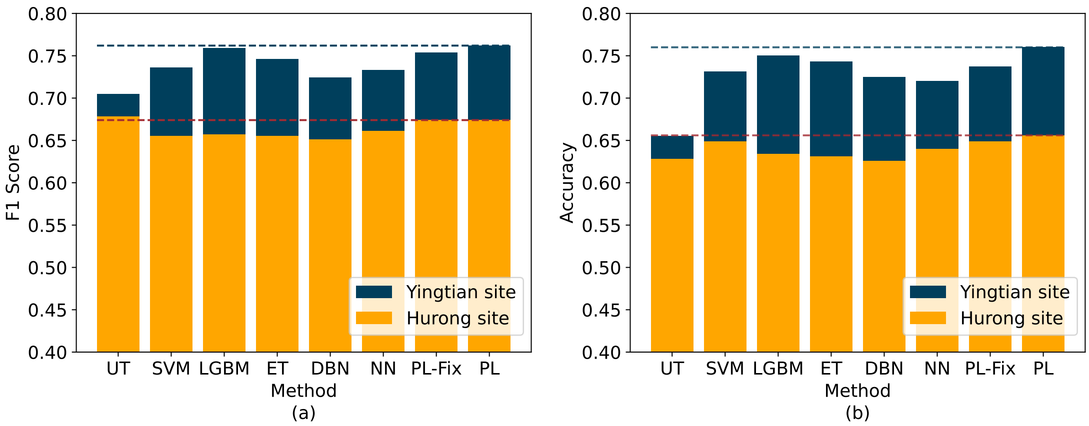

Figure 2 – *Performance of all LCD models: (a) F1 Score and (b) Accuracy*

In Figure 2(a), all machine models outperformed the utility-based model, and the proposed model achieved a correct prediction rate of 76%, surpassing other baseline models. Notably, the PL methods (both PL-Fix and the proposed method) outperformed NN, highlighting the enhanced performance achieved by incorporating behavioral models into the NN. Additionally, the proposed method surpassed PL-Fix, highlighting its efficiency compared to existing methods that assign fixed weights to behavioral and data-driven components. In Figure 2(b), the performance of all the models declined after directly transferred to the new site. However, the proposed model still achieved the best performance compared to the baselines.

The performance of PL-based LCI model was primarily compared with the LSTM model without incorporating the physical model. The prediction errors of the proposed model decreased by 22.0% for predicted position of the lane-changer when the LC maneuver ends, and by 13.7% in terms of the predicted time of the lane-changer when the LC maneuver ends.

4 CONCLUSIONS AND DISCUSSIONS

This paper explores the modeling of vehicle lane-changing behavior using parallel learning, which integrates knowledge-based physical or behavioral models with data-driven approaches. We introduce two distinct models within the lane change process: a lane change decision model and a lane change implementation model. The proposed models outperform existing approaches in terms of prediction accuracy, as demonstrated through a thorough analysis using high-resolution trajectory data gathered from real-world field observations.

References

Ahmed, Kazi Iftekhar. 1999. *Modeling drivers' acceleration and lane changing behavior*. Ph.D. thesis, Massachusetts Institute of Technology.

Ali, Yasir, Hussain, Fizza, Bliemer, Michiel CJ, Zheng, Zuduo, & Haque, Md Mazharul. 2022. Predicting and explaining lane-changing behaviour using machine learning: a comparative study. *Transportation Research Part C: Emerging Technologies*, **145**, 103931.

Hidas, Peter. 2002. Modelling lane changing and merging in microscopic traffic simulation. *Transportation Research Part C: Emerging Technologies*, **10**(5-6), 351–371.

Laval, Jorge A, & Leclercq, Ludovic. 2008. Microscopic modeling of the relaxation phenomenon using a macroscopic lane-changing model. *Transportation Research Part B: Methodological*, **42**(6), 511–522.

Zheng, Zuduo. 2014. Recent developments and research needs in modeling lane changing. *Transportation Research Part B: Methodological*, **60**, 16–32.