A Physics-Informed Deep Learning Paradigm for Car-Following Models

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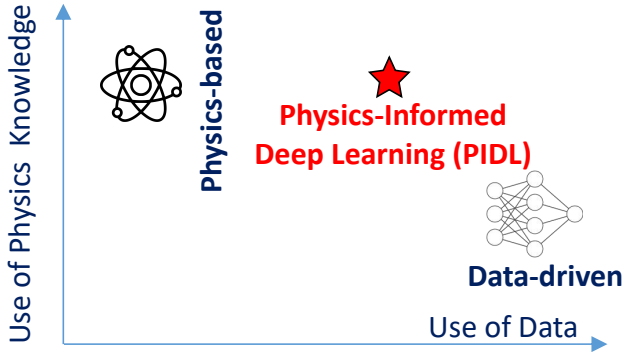
Introduction

Car-following modeling is important

Self-Driving

Simulation Platform

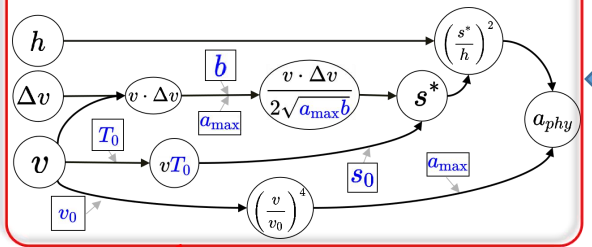
How to predict accelerations?



	Physics-based	Data-driven
Input	headway h	velocity v velocity diff. Δv
Output	acceleration a	
Param.	λ (# <10)	θ (# 1K~1M)

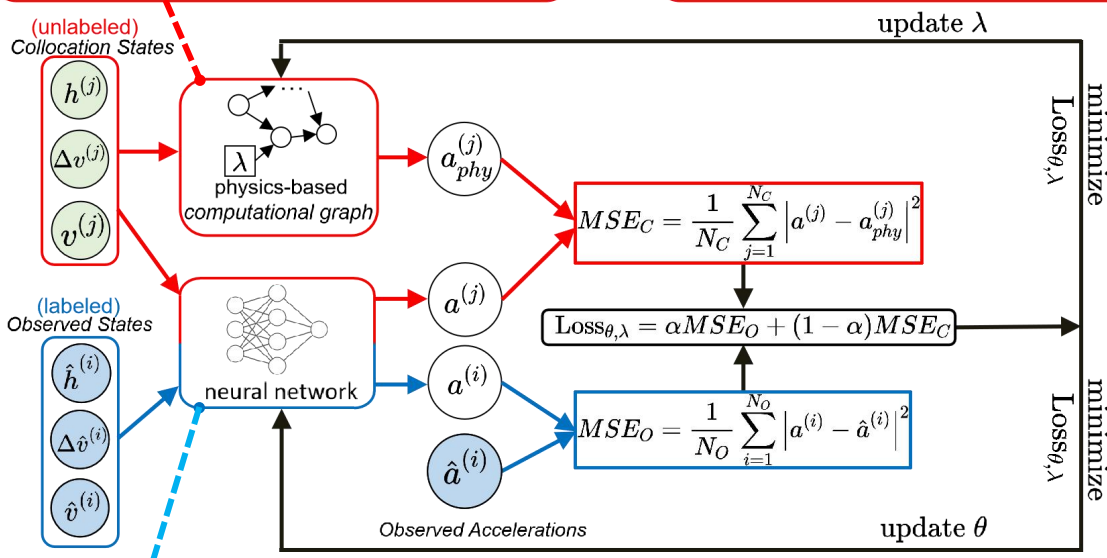
Physics-Informed Deep Learning Strucuture

An **intelligent driving model** as a computational graph



An **intelligent driving model** as a **physics** component

$$\begin{cases} a_{phy} = a_{\max}\left[1 - \left(\frac{v}{v_0}\right)^4 - \left(\frac{s^*}{h}\right)^2\right] \\ s^* = s_0 + vT_0 + \frac{v \cdot \Delta v}{2\sqrt{a_{\max} b}} \end{cases}$$



A **Neural Network** as a **data-driven** component

N_O : # of the obversation data
N_C : # of the collocation data
MSE : Mean Square Error
λ : Physics parameters
θ : Neural network parameters

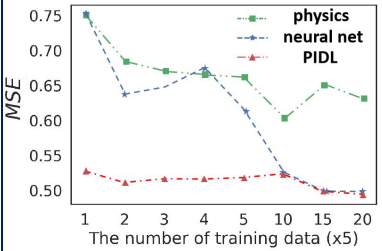
Results & Conclusions

Dataset

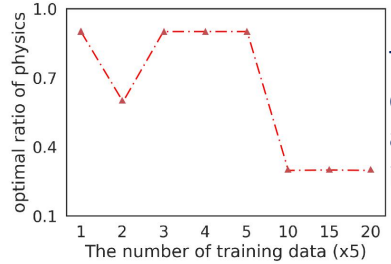
Next Generation SIMulation (NGSIM)

- Vehicle GPS trajectories collected by bird-view cameras (sampling frequency = 10 HZ)

Results



The proposed model **outperforms** the baselines especially when training data is sparse.



The optimal ratio of physics **decreases** as the training size increases.

Conclusions

- PIDL contains both **data-driven** and **physics** components
- Experiments on a real-world dataset demonstrate PIDL's advantages in both **accuracy** and **data efficiency**

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