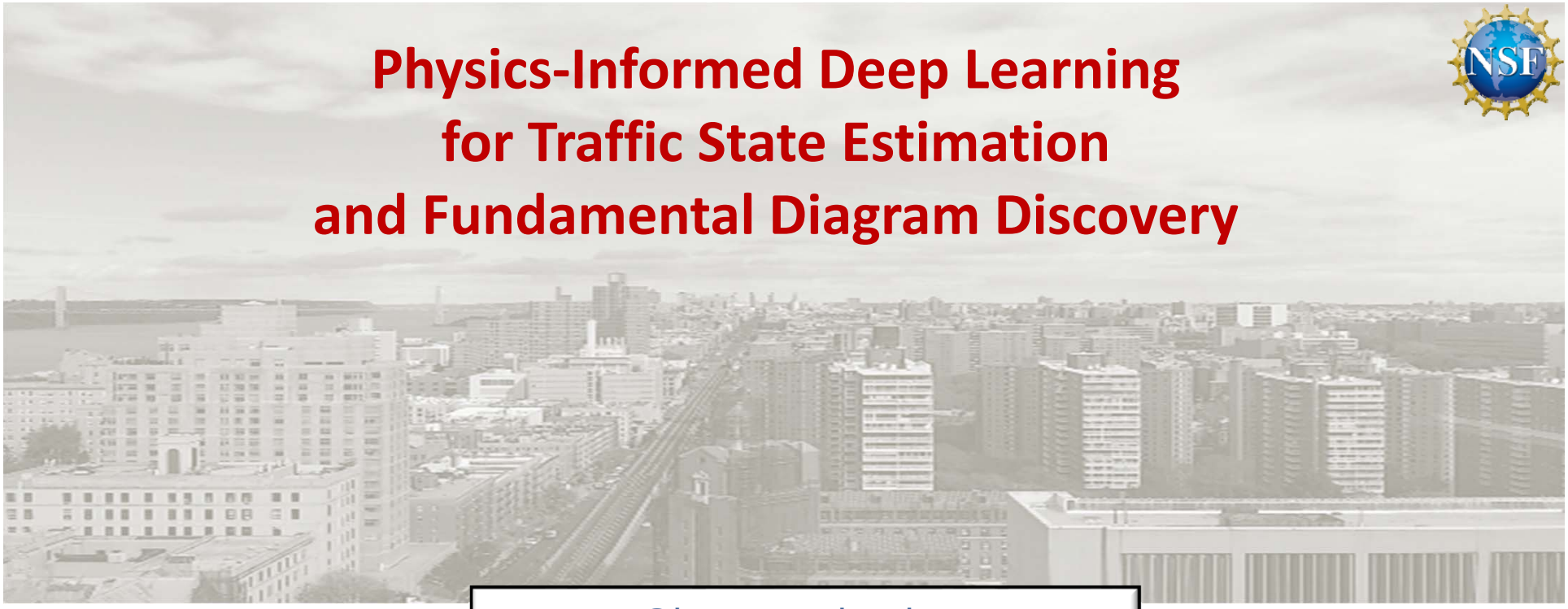
Physics-Informed Deep Learning for Traffic State Estimation and Fundamental Diagram Discovery



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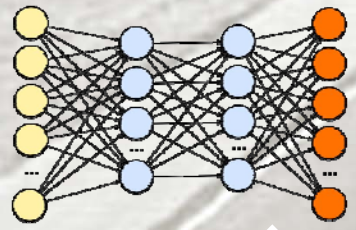
Traffic State Estimation: Highlights

Train neural network (NN) w. sparse sensors?

NN regularized by traffic models outperform w. small data



Big data

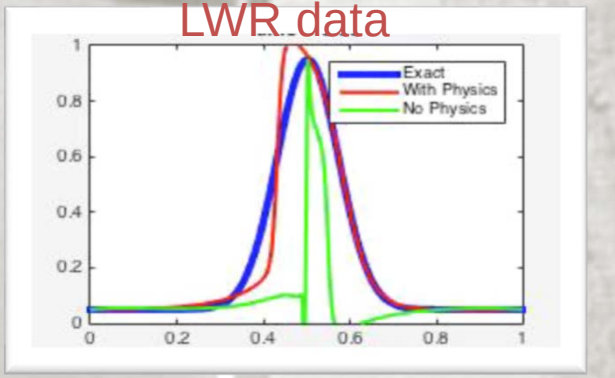
Small data

pattern discovery

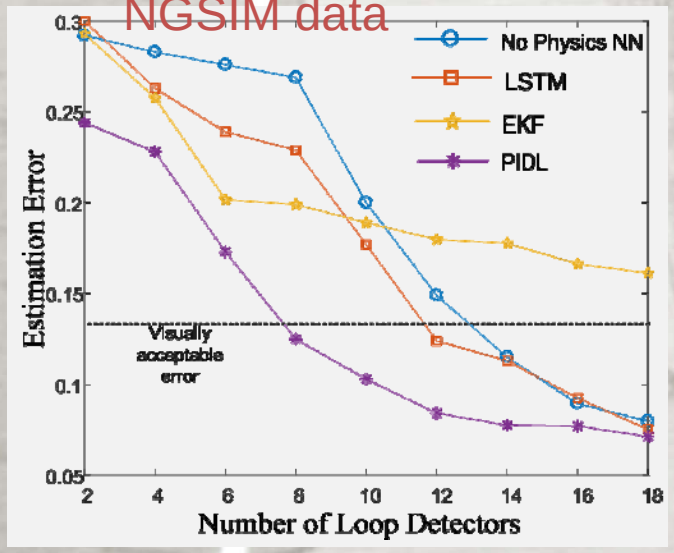
Physical constraint

Traffic Flow Model

LWR data



NGSIM data

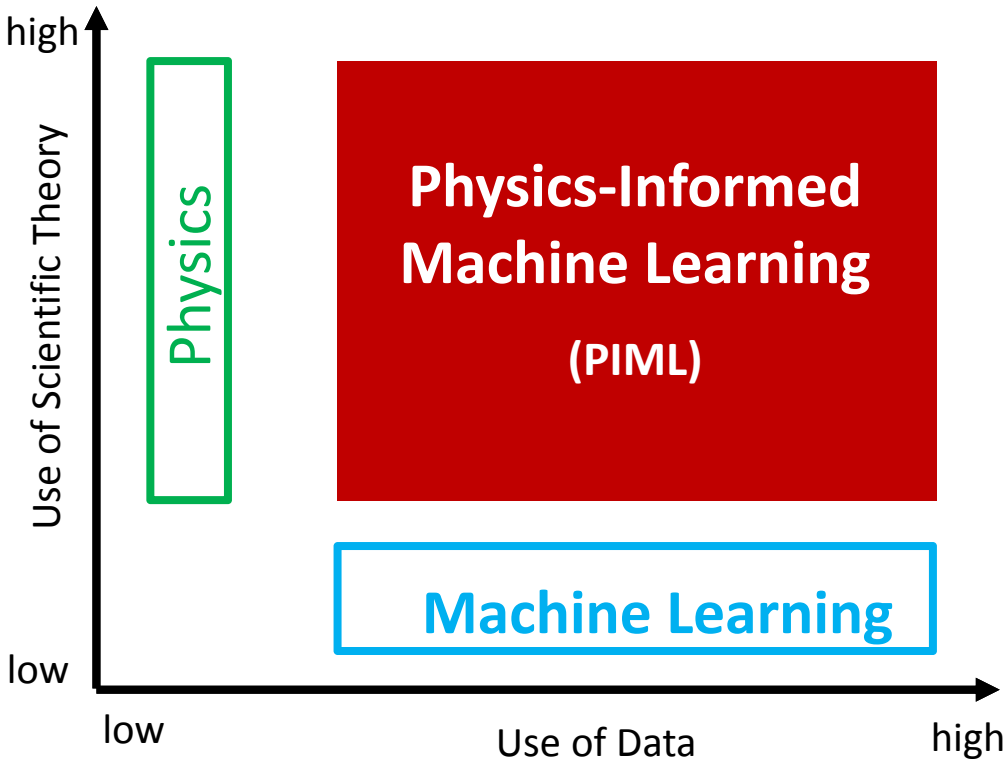


IoT: COSMOS Testbed

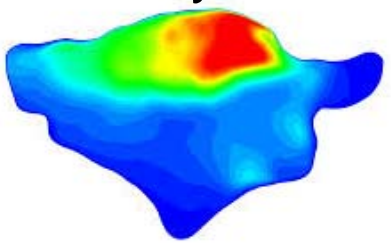
Cloud-Enhanced Open Software Defined Mobile Wireless Testbed for City-Scale Deployment

How to leverage data collected from IoT powered by CPS for real-time traffic state estimation?

Physics-Based vs. Data-Driven



Fluid Dynamics



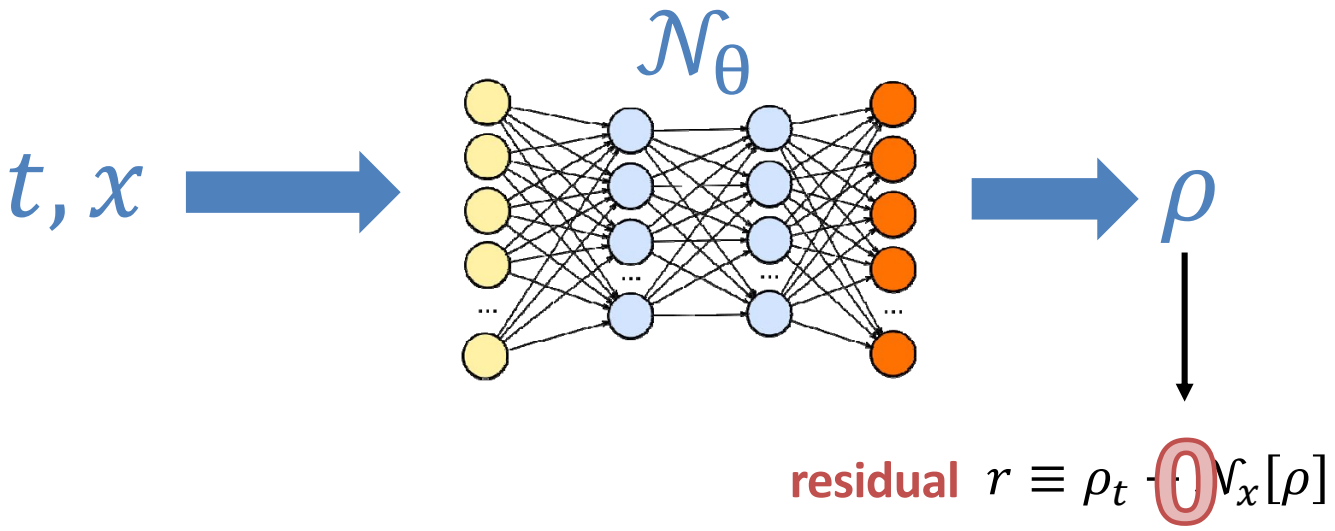
Neuroscience

Data-Driven Solutions of PDE

$$\rho_t + \mathcal{N}_x[\rho] = 0, t \in [0, T], x \in \Omega$$

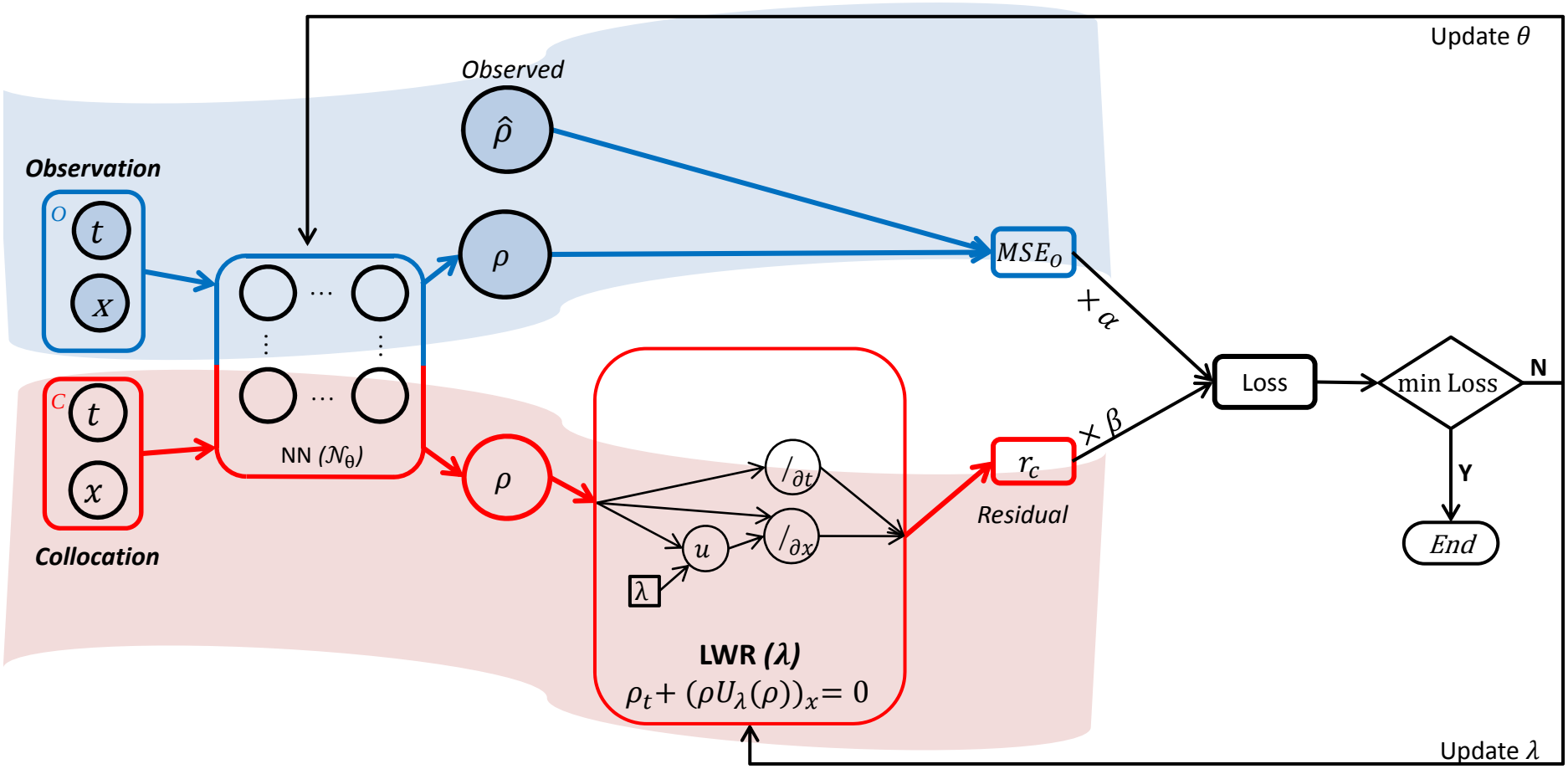
- $\rho(t, x)$: the solution of physical value (e.g., density/velocity field)
- $\mathcal{N}_x[\cdot]$: a nonlinear differential operator
- Ω: a subset of $\mathbb{R}^D$, denoting the high-dimensional physical space.

Goal approximate $\rho(t, x)$ by a neural network



[Raissi-Maziar (2017, 2019)]

Training PIML



[Shi, R., Mo, Z. and **Di, X.**, 2021. *Physics Informed Deep Learning for Traffic State Estimation: A hybrid paradigm informed by second-order traffic models*. AAAI]

Data-Driven Solution of LWR Models

$$\rho_t + (\rho u)_x = 0, \qquad x \in (0,1), t \in (0,3)$$

$$u = u_{max}\left(1 - \frac{\rho}{\rho_{max}}\right)$$

$\rho(0,x) = \hat{\rho}_0(x)$ (initial condition)

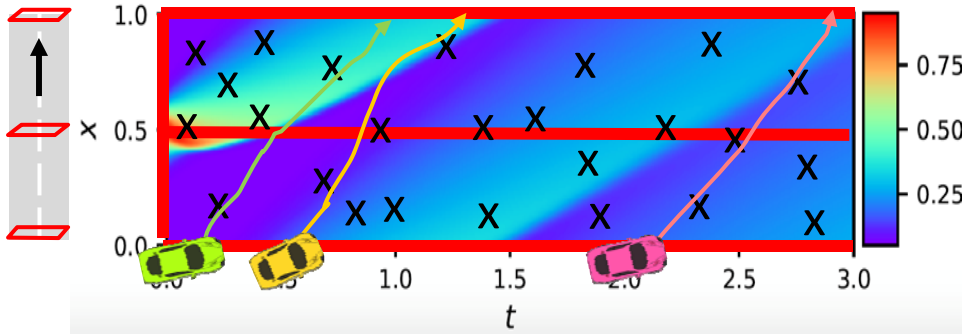
$\rho(t,0) = \rho(t,1)$ (boundary condition)

ring road

Observation (labeled) $\{(t_o^i, x_o^i), \hat{\rho}^i\}, i = 1, \dots, N_o$

Collocation (unlabeled) $(t_c^i, x_c^i), i = 1, \dots, N_c$

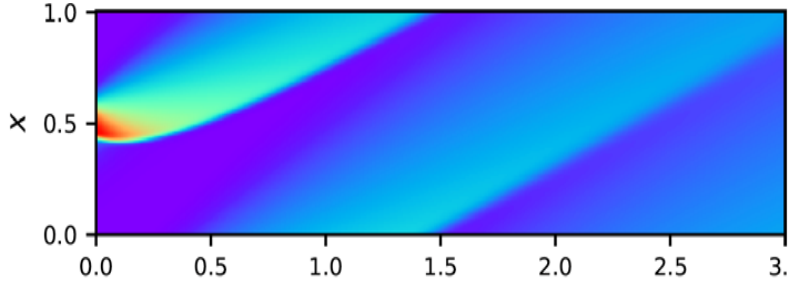
Traffic density: ground truth



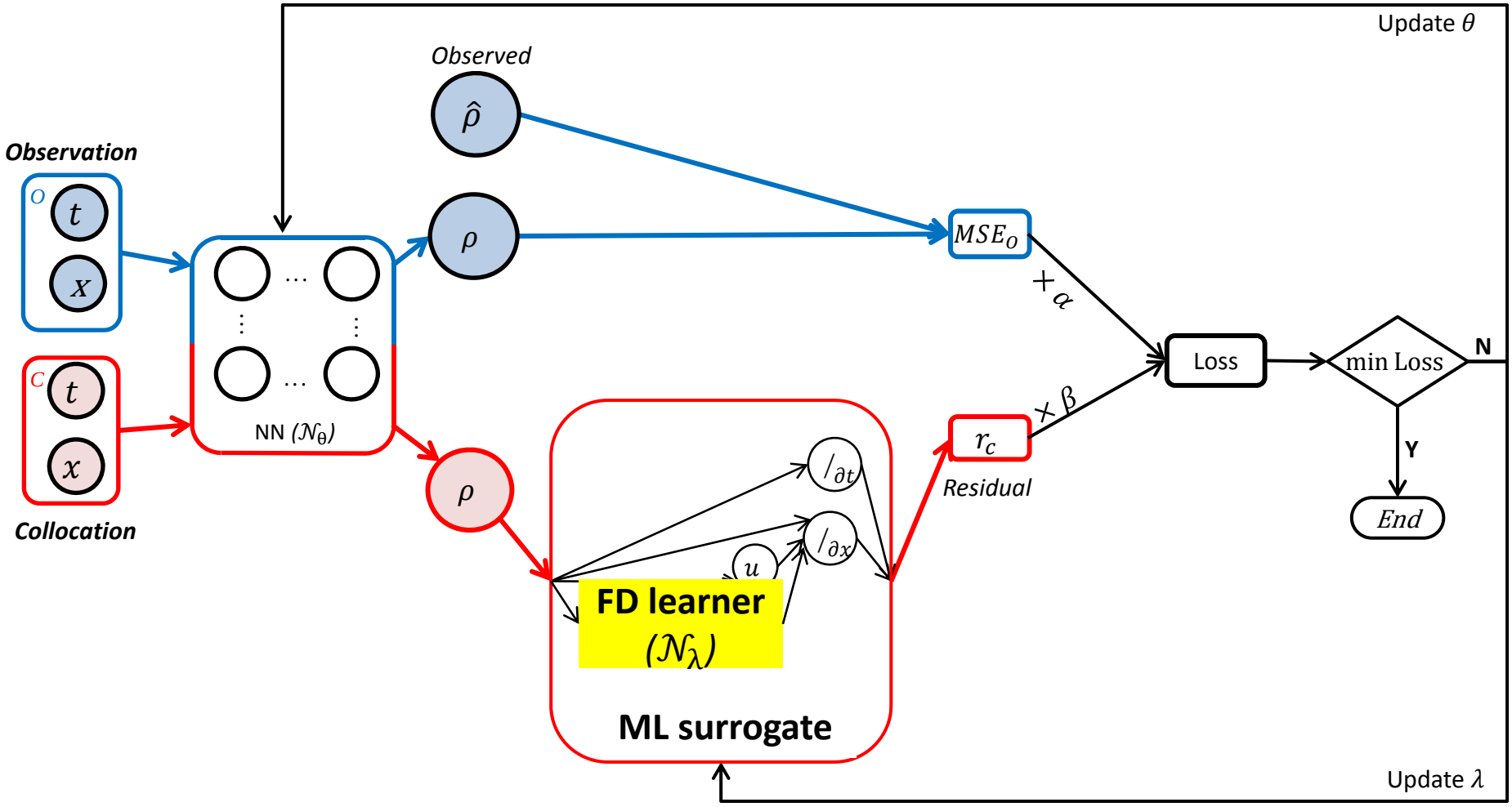
$$Loss = \alpha \underbrace{\boldsymbol{MSE_o}}_{\text{Obs. discrepancy}} + \beta \underbrace{\boldsymbol{r_c}}_{\text{Physics discrepancy}}$$

- ✓ **Initial**
- ✓ **Boundary**
- ✓ **within domain**

Traffic density: reconstructed from sparse data

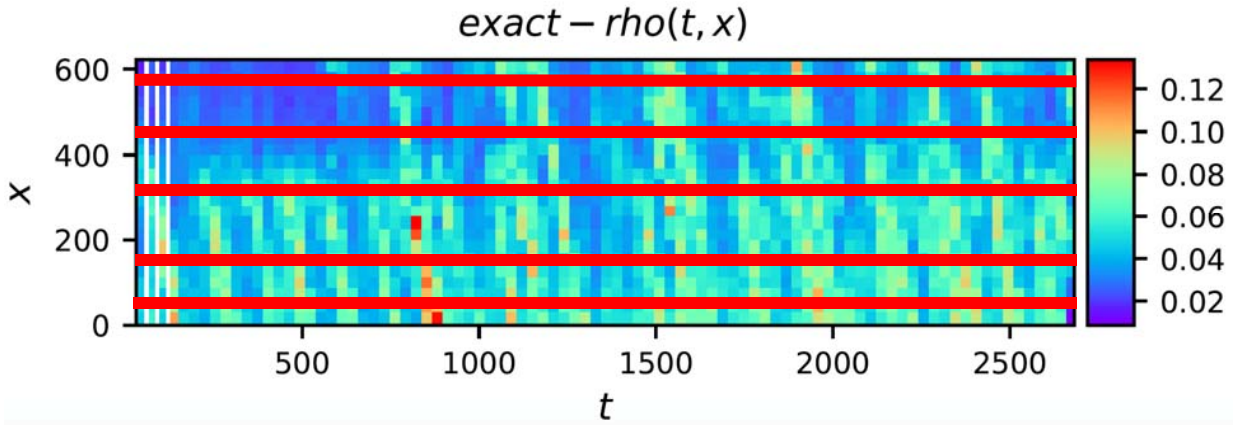


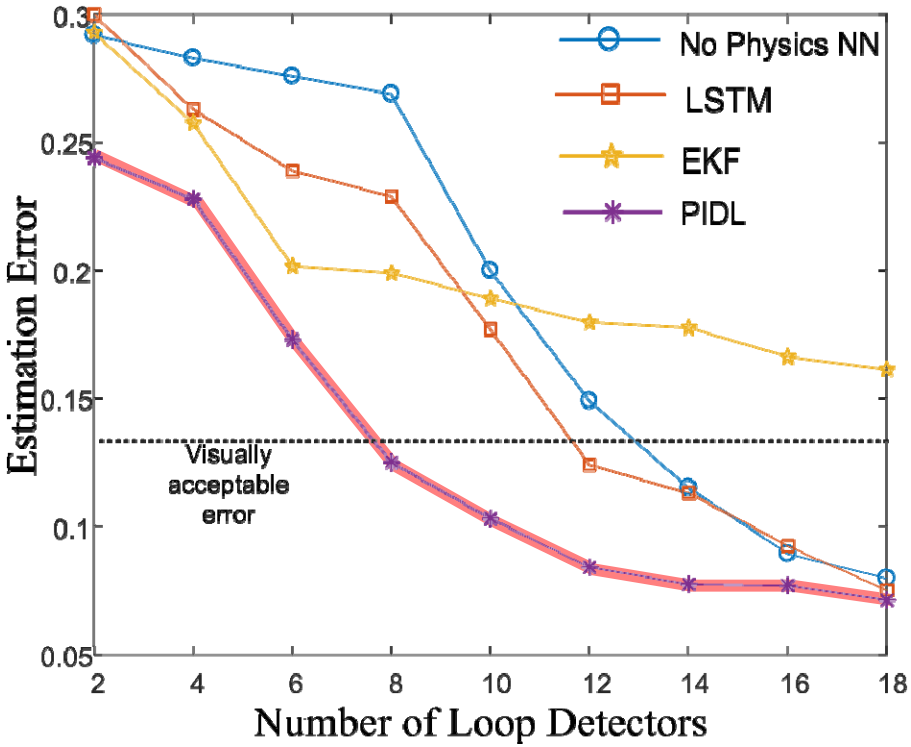
Fundamental Diagram (FD) Learner

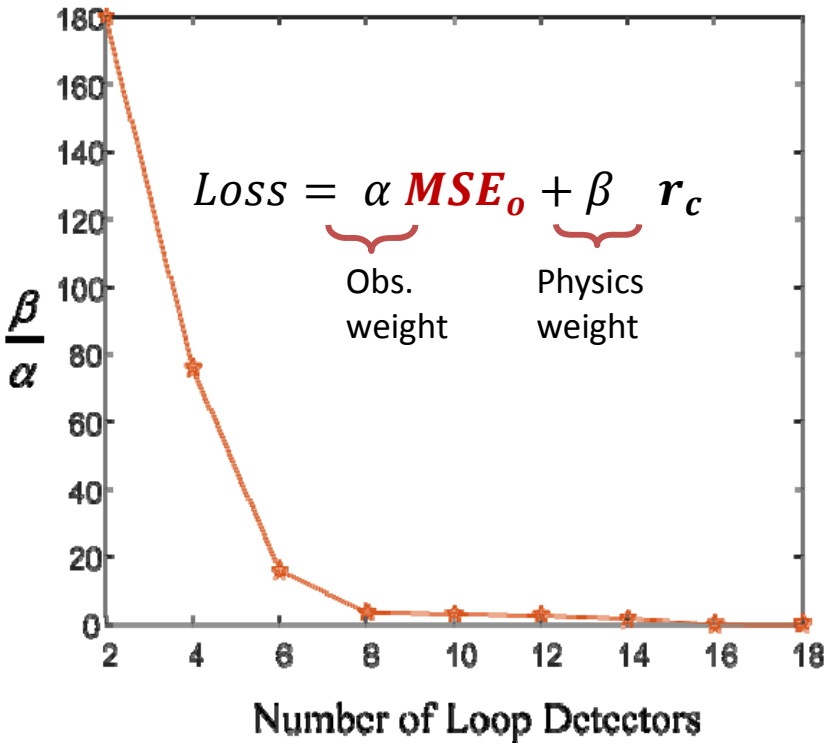


[Shi, R., Mo, Z., **Di, X.**, 2021. *A Physics-Informed Deep Learning Paradigm for Traffic State and Fundamental Diagram Estimation*. IEEE ITS]

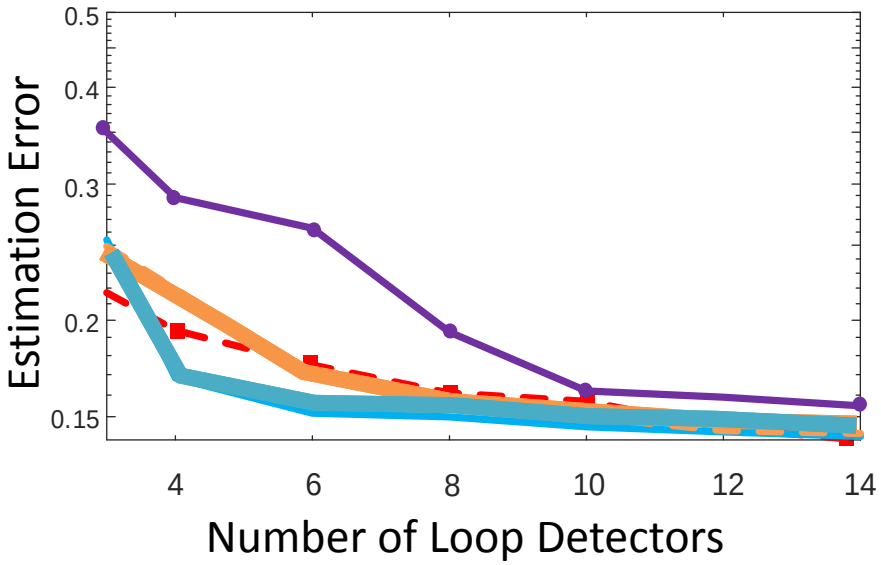
NGSIM: LWR as Physics

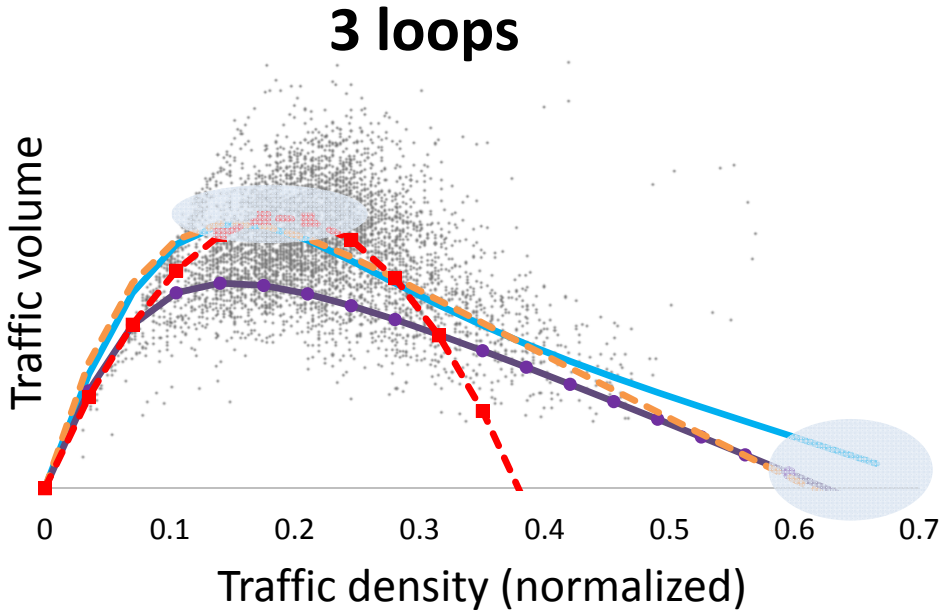






Fundamental Diagram Learner (FDL)





LWR-PIDL+FDL

LWR-PIDL(using LWR with 3-parameter FD)

ARZ-PIDL+FDL

ARZ-PIDL (using ARZ with Greenshields FD)

THANK YOU!

Questions?