

INTRODUCTION

Forecasting Infectious Diseases:

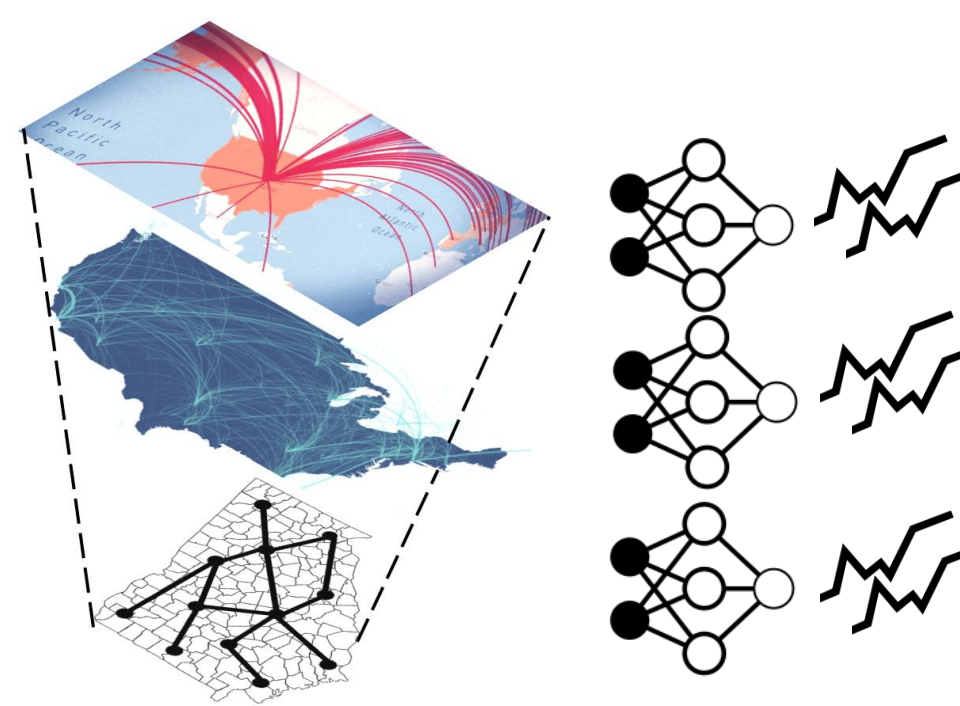
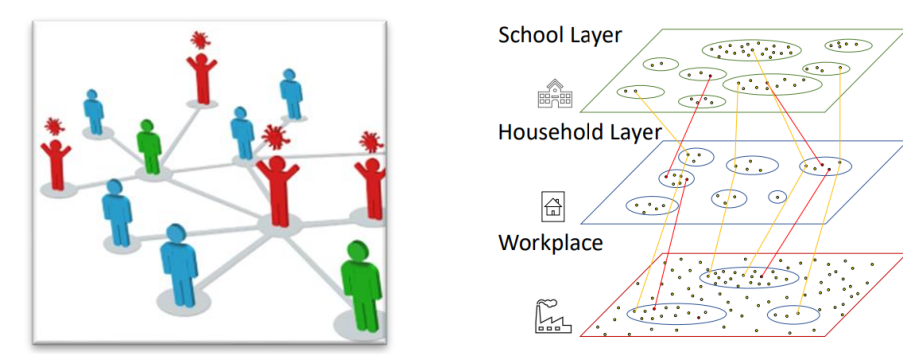
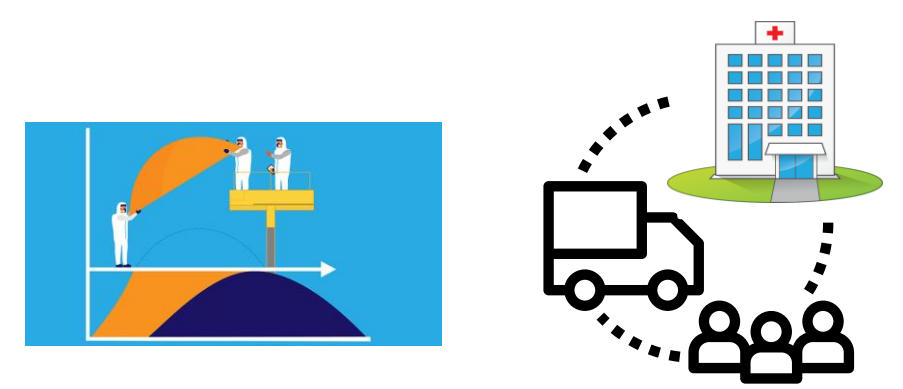
- Allows communities to allocate resources/budget, inform public policy, improve preparedness.

- Traditional methods are based on ordinary differential equations and agent-based models. Calibration is non-trivial.

- Data collection has increased, but traditional methods have difficulties ingesting these data sources.

Why computational data-driven models?

- Epidemic spread is a spatiotemporal phenomena over multi-scale networks.
- New end-to-end methods available capable of modeling data with minimal assumptions.



CHALLENGES

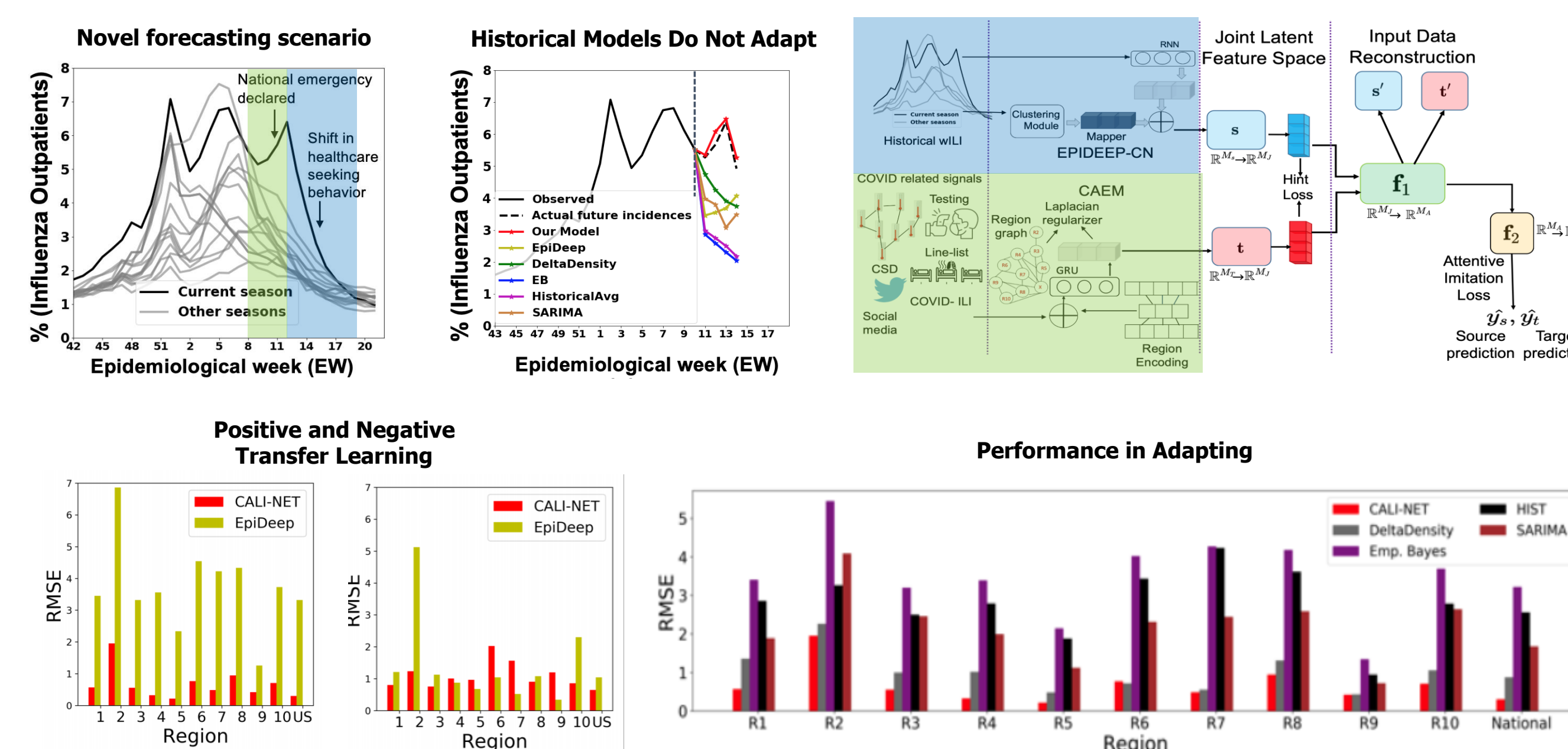
During our real-time forecasting experience, we have identified multiple challenges, which we study in our work:

Aspect	DISEASE SPREAD	DATA	UTILIZATION
Challenges	Spatial Transmission	Sparse data	Interpretability
	Mobility	Data revisions	Uncertainty quantification
	Mask adoption Social distancing	Anomalies	Actionable forecasts

DEEP LEARNING FRAMEWORKS

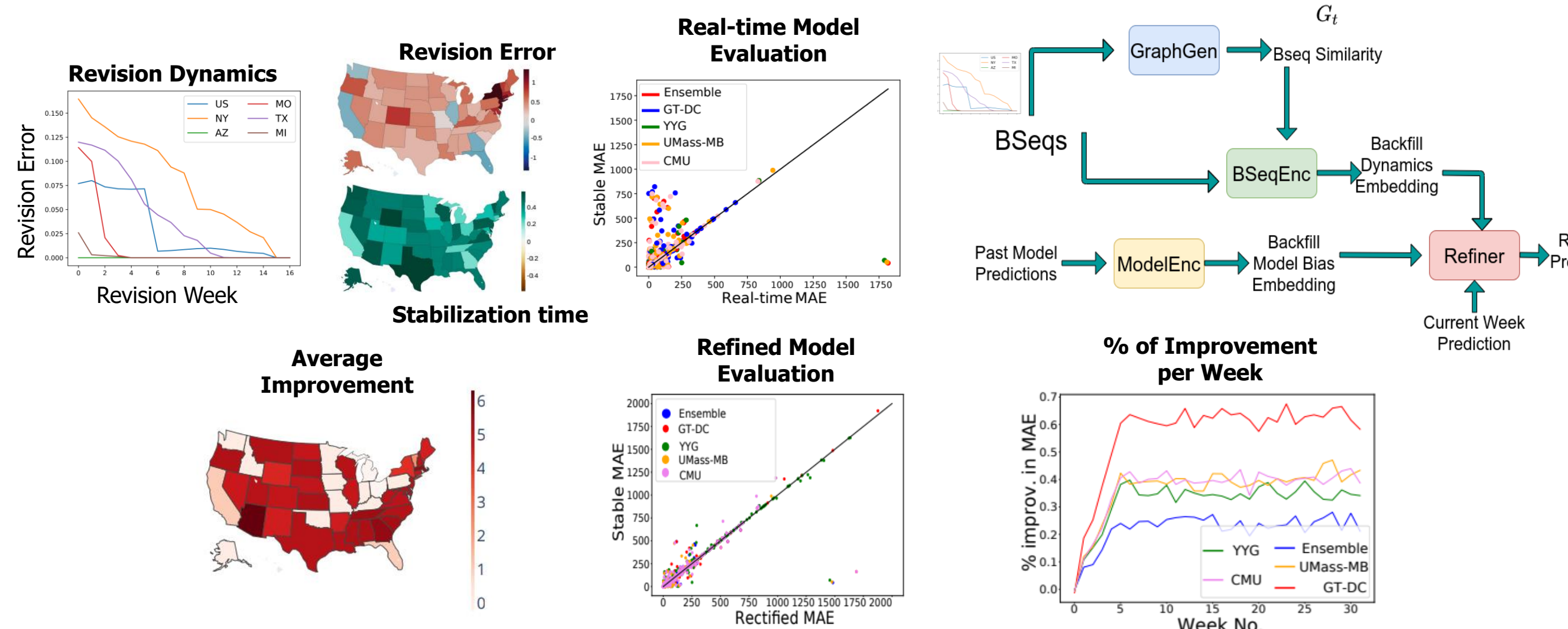
[1] Steering a historical influenza model for the COVID pandemic

Spatio-temporal modeling + heterogenous domain transfer learning



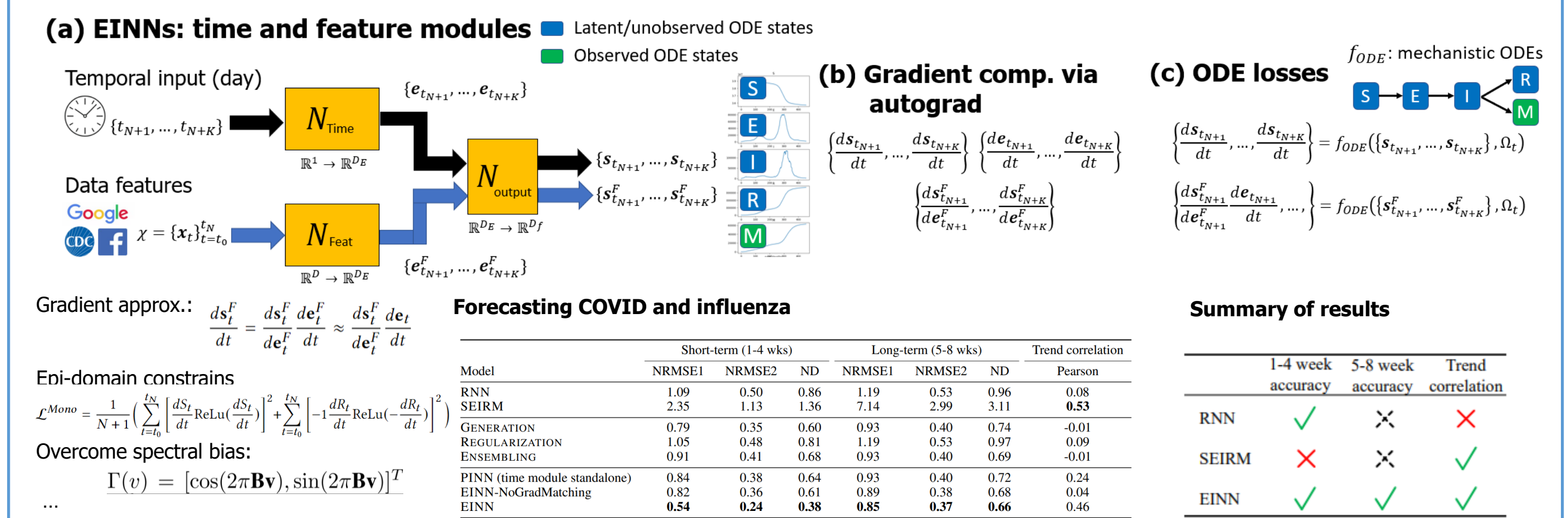
[2] Leveraging data revision dynamics to refine forecasts

Recurrent graph neural networks



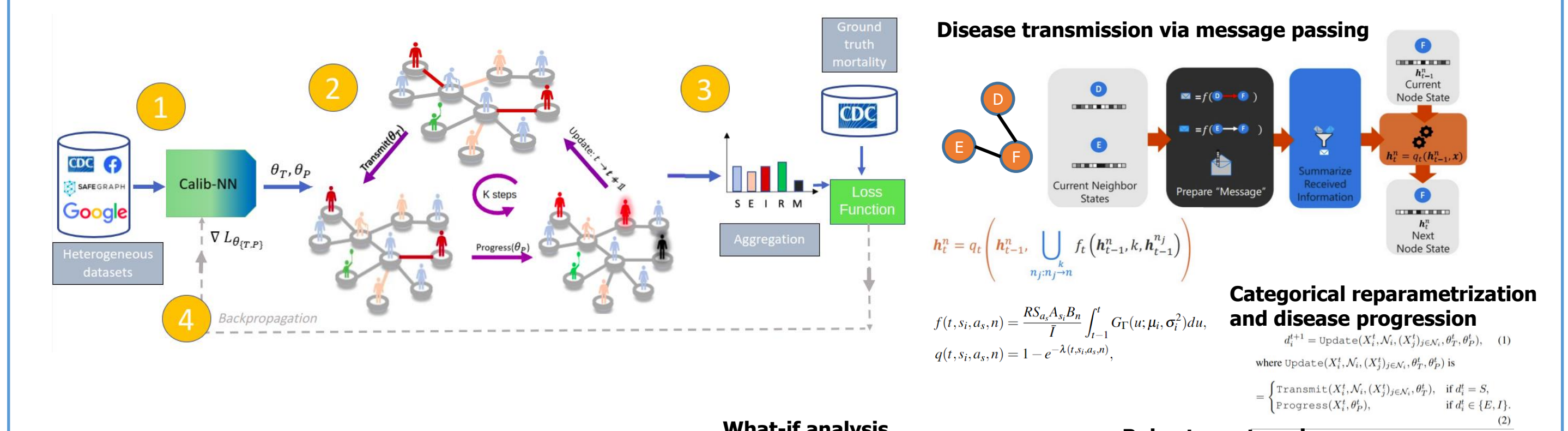
[3] Epidemiologically-informed neural networks

Physics-informed neural networks + sequential networks



[4] Differentiable Agent-based Epi Modeling for End-to-end Learning

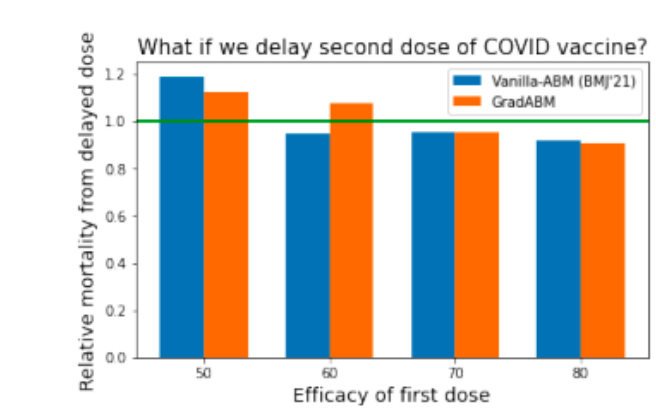
Differentiable ABM+ deep neural networks Best paper award at AI4ABM@ICML



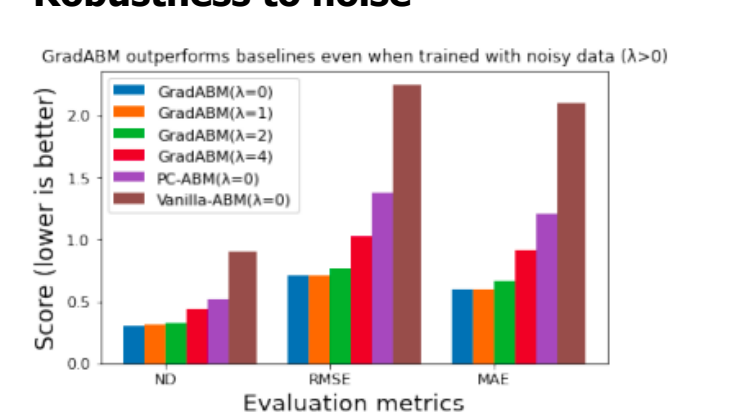
Forecasting COVID-19 and Influenza

Model	COVID-19			Influenza		
	ND	RMSE	MAE	ND	RMSE	MAE
Variational Autoencoder	6.71	48972	2703.1	0.27	2.01	1.72
GRU4Rec	23.0	11.36	121.87	0.37	0.84	0.65
GRU4Rec+LSTM	8.97	8.18	56.99	0.42	1.47	1.06
GRU4Rec+LSTM+CAUSAL	1.28	0.44	78.22	0.34	0.88	0.64
GRU4Rec+LSTM+CAUSAL+LSTM	2.39	0.55	205.14	0.34	0.88	0.64

What-if analysis



Robustness to noise



CONCLUSIONS

We have showed different facets of the utility of data-driven and theory-informed neural models in epidemic forecasting, even in emerging pandemics. Our methods have enabled applications and moved forward the state-of-the-art performance in epidemic forecasting.

REFERENCES

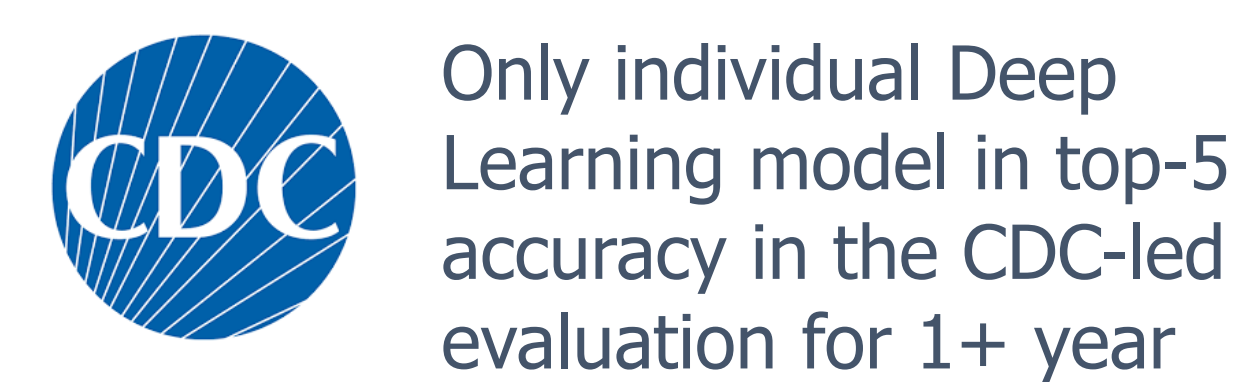
- Alexander Rodríguez, Nikhil Muralidhar, Bijaya Adhikari, Anika Tabassum, Naren Ramakrishnan, B. Aditya Prakash. Steering a Historical Disease Forecasting Model Under a Pandemic: Case of Flu and COVID-19. In AIAI-21.
- Alexander Rodríguez, Anika Tabassum, Jiaming Cui, Jiajia Xie, Javen Ho, Pulak Agarwal, Bijaya Adhikari, B. Aditya Prakash. DeepCOVID: An Operational DL-driven Framework for Explainable Real-time COVID-19 Forecasting. In AIAI-21.
- Alexander Rodríguez et al., Data-Centric Epidemic Forecasting: A Survey (under review)
- Alexander Rodríguez et al. Differentiable Agent-based Epidemiology (under review)
- Harshavardhan Kamarthi, Linghai Kong, Alexander Rodríguez, Chao Zhang, B Aditya Prakash. When in Doubt: Neural Non-Parametric Uncertainty Quantification for Epidemic Forecasting. In NeurIPS 2021.
- Alexander Rodríguez, Bijaya Adhikari, Naren Ramakrishnan, and B. Aditya Prakash. "Incorporating Expert Guidance in Epidemic Forecasting." In epidAMIK @ KDD 2020.
- Harshavardhan Kamarthi, Alexander Rodríguez, B. Aditya Prakash. Back2Future: Leveraging Backfill Dynamics for Improving Real-time Predictions in Future. In submission.
- Ester Cramer, et al. Evaluation of individual and ensemble probabilistic forecasts of COVID-19 mortality in the US. In submission.

GRANT ACKNOWLEDGEMENTS



IMPACT & OUTREACH

Top-5 in CDC Forecast Hub

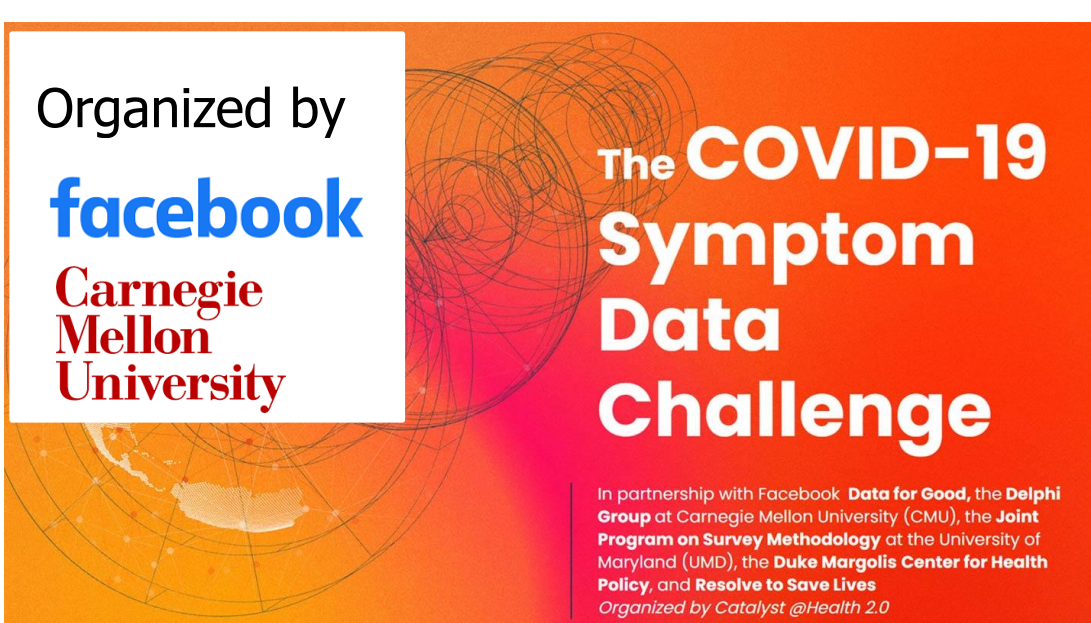


Workshops and Tutorials



1st place

Out of 115 global participants



2nd place

Out of 777 participants

