New Jersey Institute of Technology

An Introduction to AI for Forecasting Epidemic Dynamics

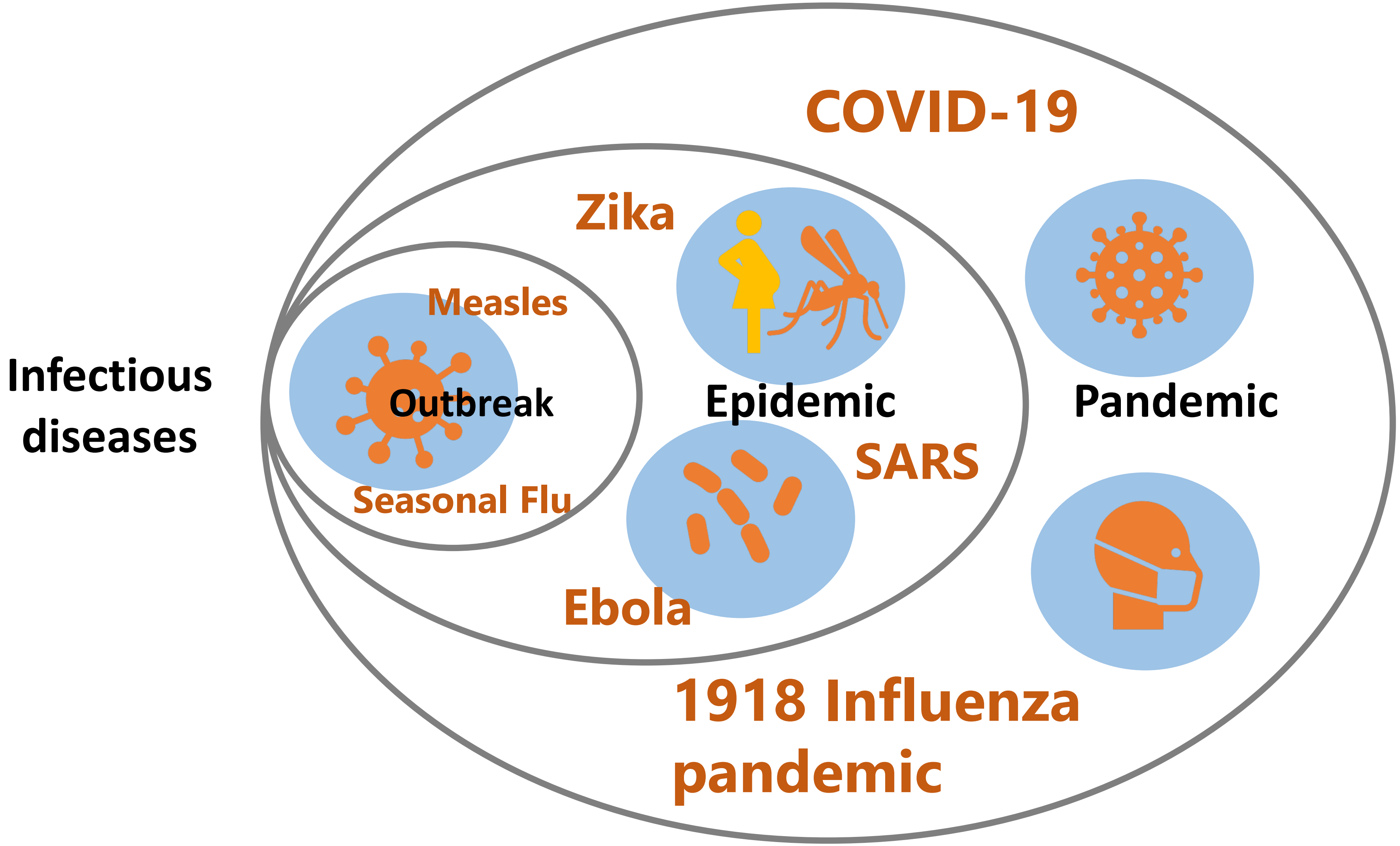
Lijing Wang
Assistant Professor, Data Science, New Jersey Institute of Technology
NJ ACTS Biostatistics and Epidemiology Workshop Series
05/12/2023

Today’s talk: 2 parts

- Part 1: Epidemic forecasting: an introduction
- Part 2: AI-based methodologies for epidemic forecasting

Part 1: Epidemic forecasting: an introduction

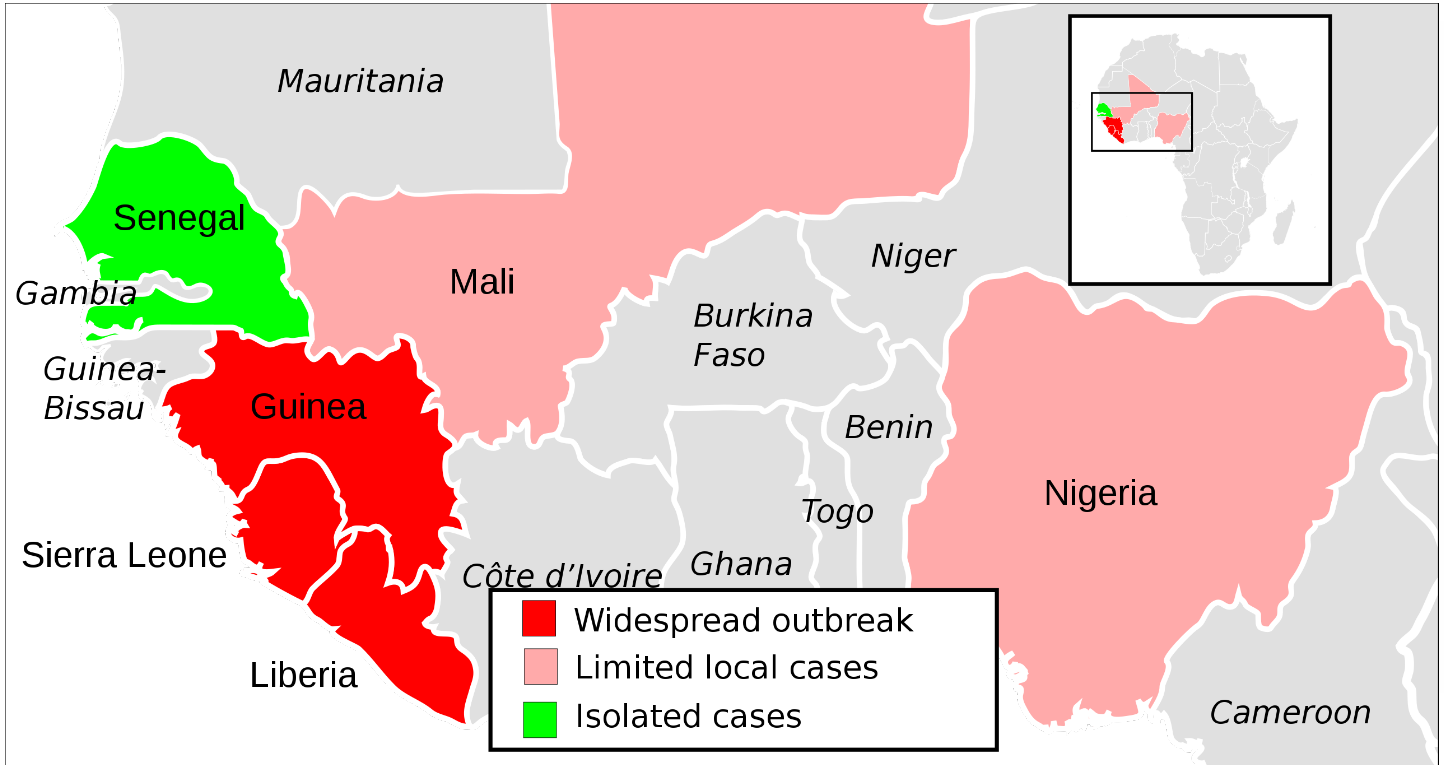
Epidemics

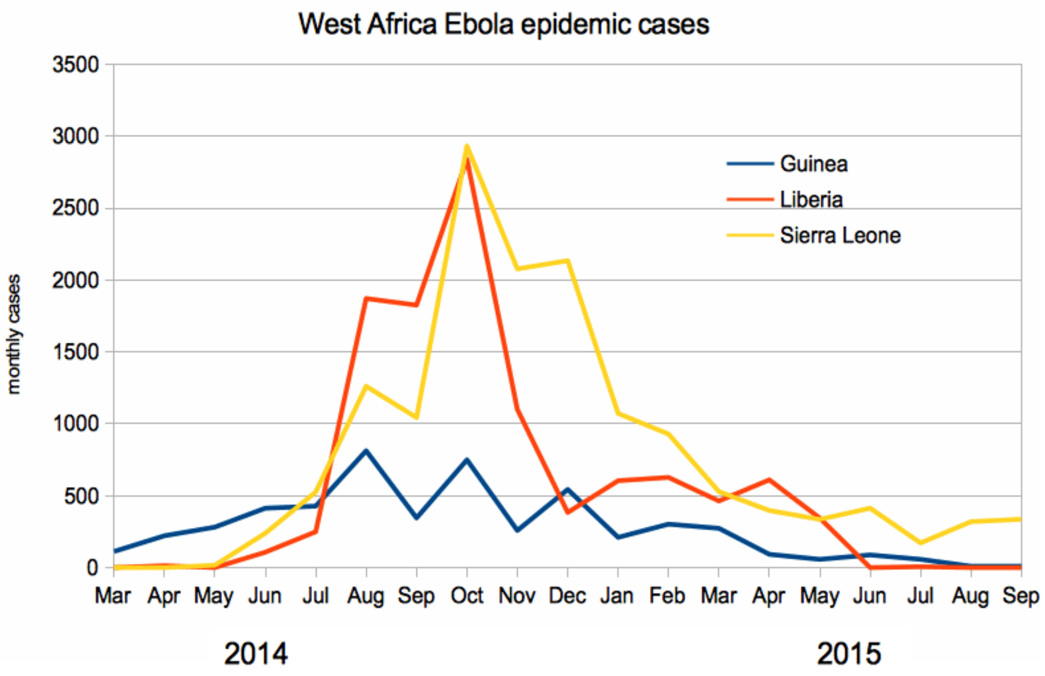

Infectious
diseases
COVID-19
Zika
Measles
Outbreak
Seasonal Flu
Epidemic
SARS
Ebola
Pandemic
1918 Influenza
pandemic

Disease Spread Dynamics

- When and where it started
- The scope and pervasiveness
- The duration of spread
- Overall severity

An Example – 2014-2016 West Africa Ebola Epidemic



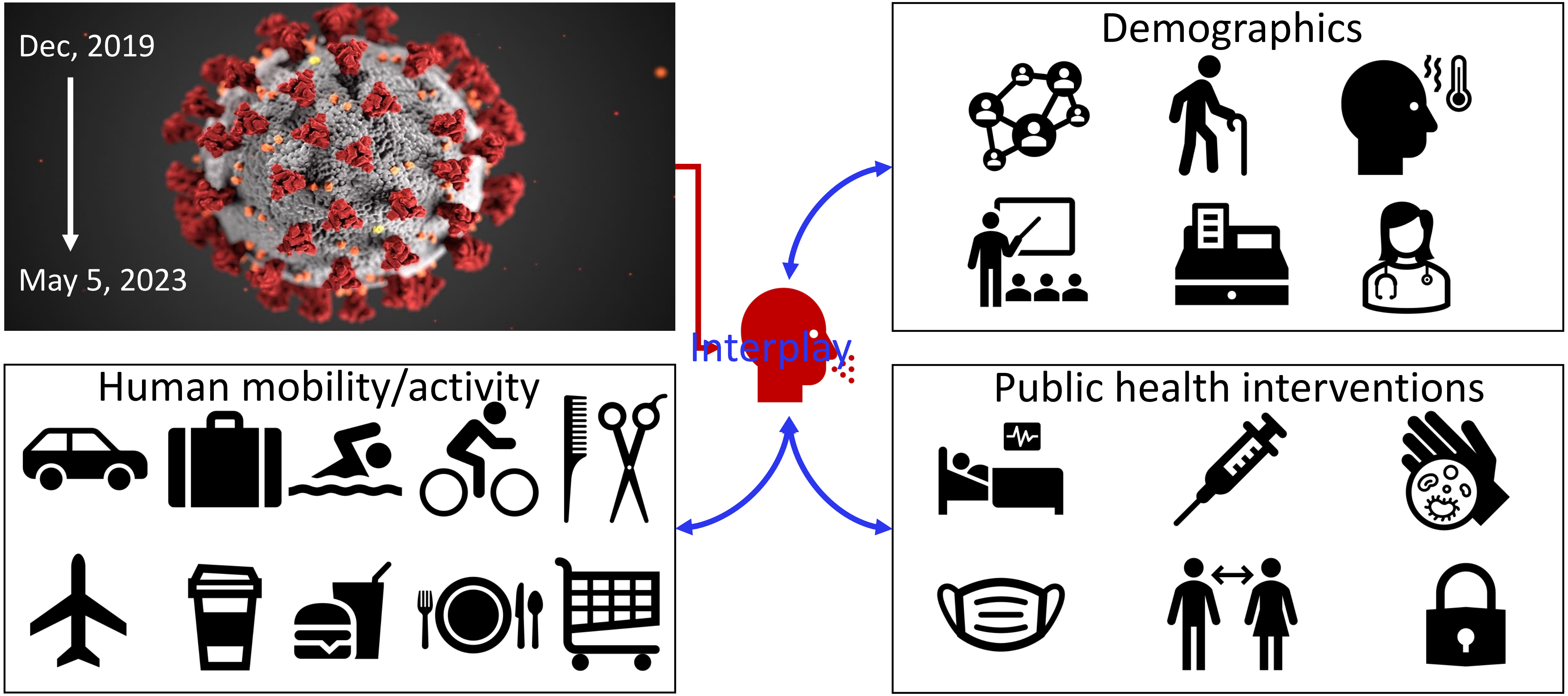


Source: https://en.wikipedia.org/wiki/Western_African_Ebola_virus_epidemic

Affecting Factors

- Human factors and demographics
  - mobility, daily activities, mixing patterns
  - age, gender, social status, economic status
- Environmental factors
  - sanitation facilities, water supply, food, and climate
- Public health interventions
  - pharmaceutical (prophylactics, antivirals, vaccines)
  - non-pharmaceutical (stay-at-home orders, mask wearing, social distancing, safe burials)

An Example – COVID 19 Pandemic

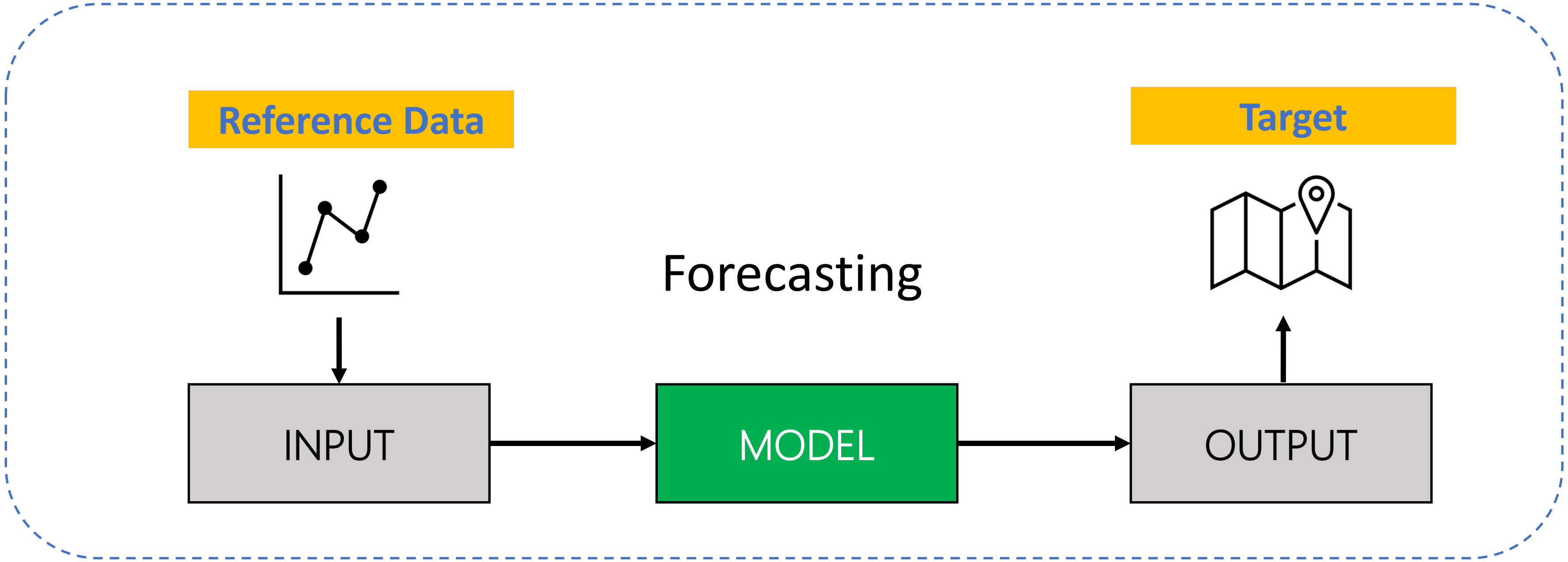


Safety

Pictures from Google Images

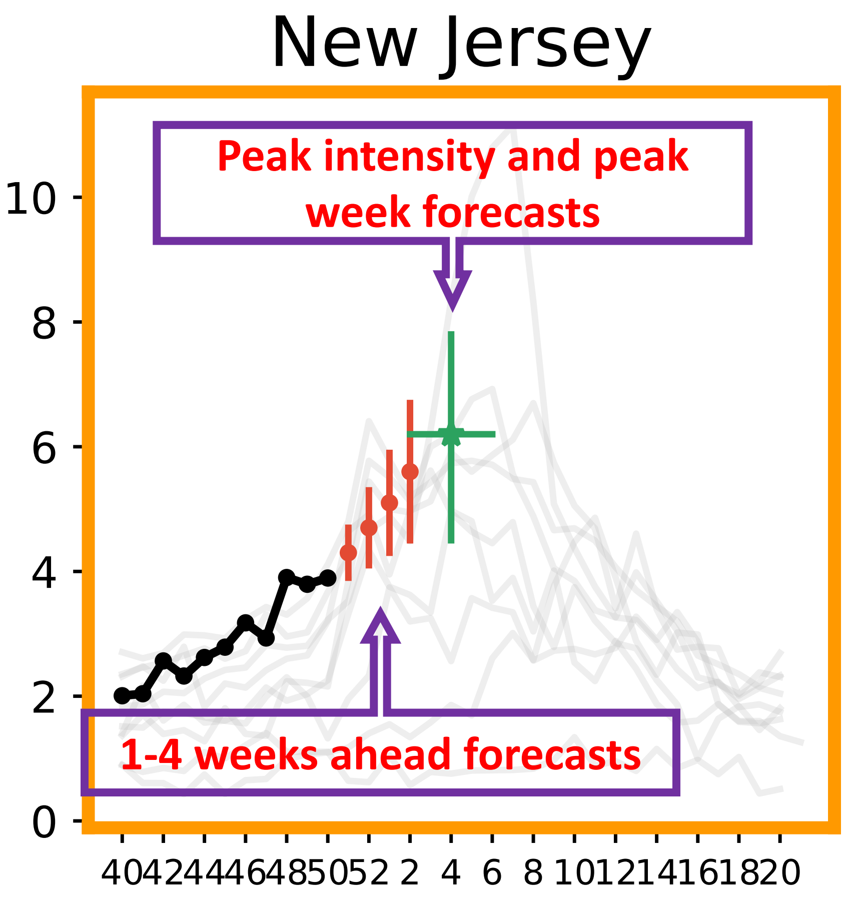
Epidemic Forecasting

- Use observed data sources as the reference data to make temporal and spatial predictions of an epidemiological target.



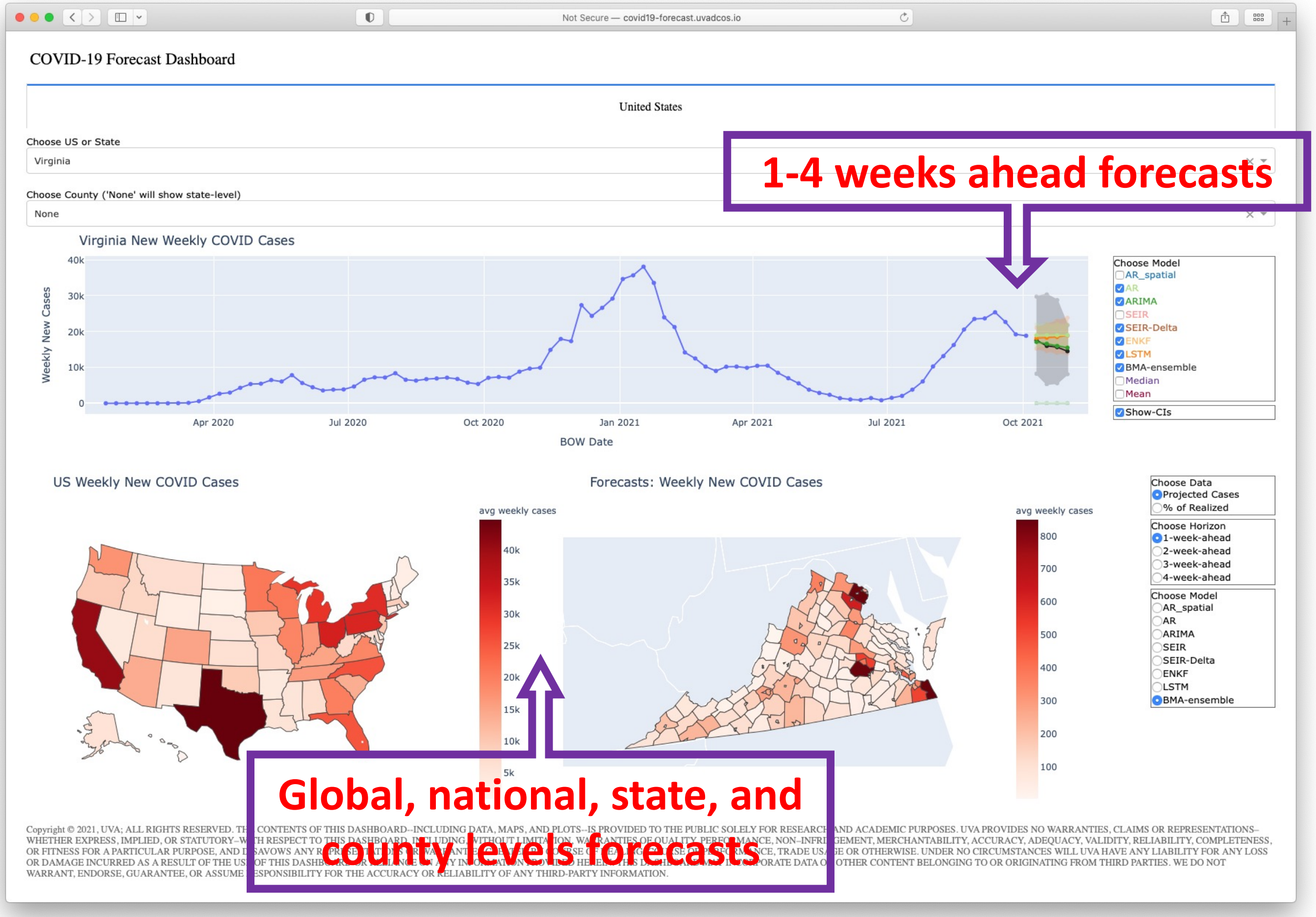
Examples – Flu/COVID Forecasting

Example-1
CDC FluSight Challenge



Centers for Disease Control and Prevention (CDC)

Example-2
CDC COVIDHub Challenge



Reference Data

- Surveillance data
  - Stable and reliable
  - Delayed, not at finer resolution
- Mobility data
  - Modeled vs. real world collected
- Social media data
  - Real time at finer resolution
  - Not representative, large collection and curation efforts
- Other reference data

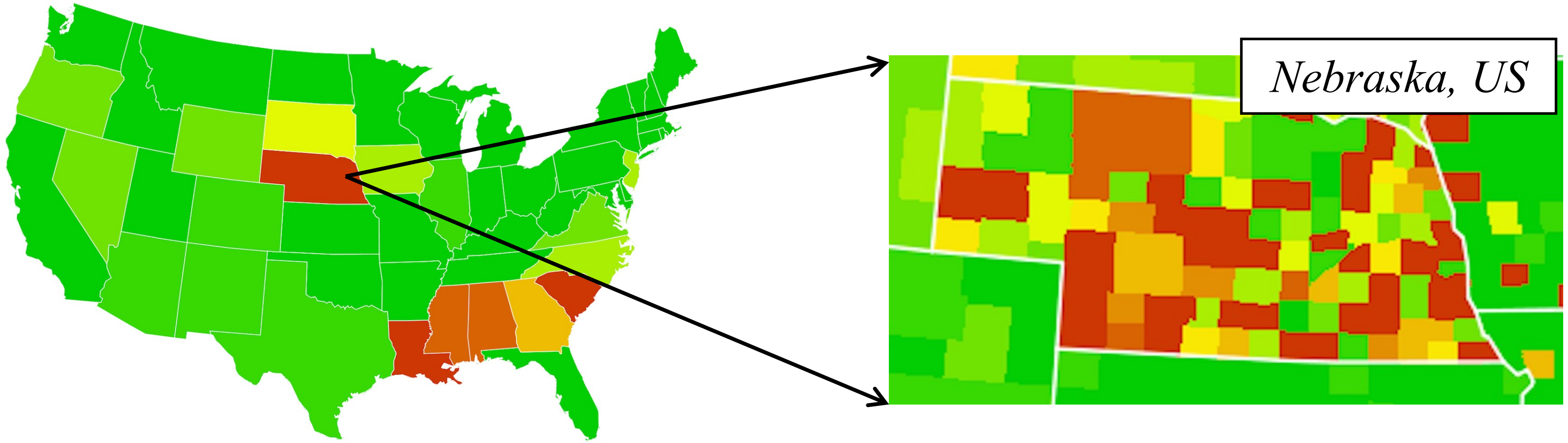
Temporal Forecasting

- Real-time forecasting
- Retrospective forecasting
- Short-term forecasting
- Long-term forecasting
- Lead time or horizon
  - at time point t, h is the horizon if predicting time point $t + h$

Spatial Forecasting

- Flat-resolution forecasting
- High-resolution forecasting
- Coarse-resolution forecasting

Influenza-like-illness (ILI)



State level surveillance data is available

County level surveillance data is NOT available

Challenges of Epidemic Forecasting

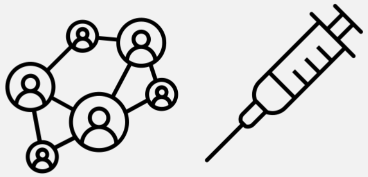
- With reference data
  - Coarse spatial resolution, delayed; sparse, noisy, rapidly co-evolving
- With spatial and temporal forecasting
  - Compute- and data-intensive
  - Hard to capture long-term patterns with limited reference data
  - Lack of spatiotemporal correlations

Evaluations

- **Point estimation**
- Popular metrics:
  - (1) Mean Absolute Error (MAE), (2) Mean Squared Error (MSE), (3) Root Mean Squared Error (RMSE), (4) Mean Absolute Percentage Error (MAPE), (5) Pearson Correlation (PCORR).
- **Probabilistic forecasting**
- Popular metrics:
  - (6) Logarithmic Score (logS), (7) Continuous Ranked Probability Score (CRPS), (8) Interval Score (IS), (9) Weighted Interval Score (WIS).

Epidemic Forecasting Methods

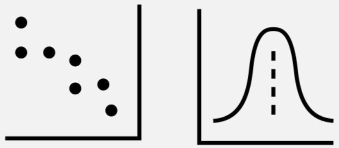
Mechanistic methods



Causal prediction

SIR, SEIR, SIRD, SEIRD, etc.

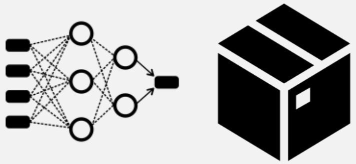
Statistical time series methods



Simplicity

AR, ARMA, ARIMA, etc.

Deep learning methods

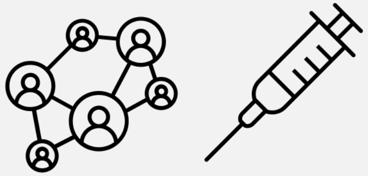


Non-linear learning power

FNN, RNN, CNN, GNN, etc.

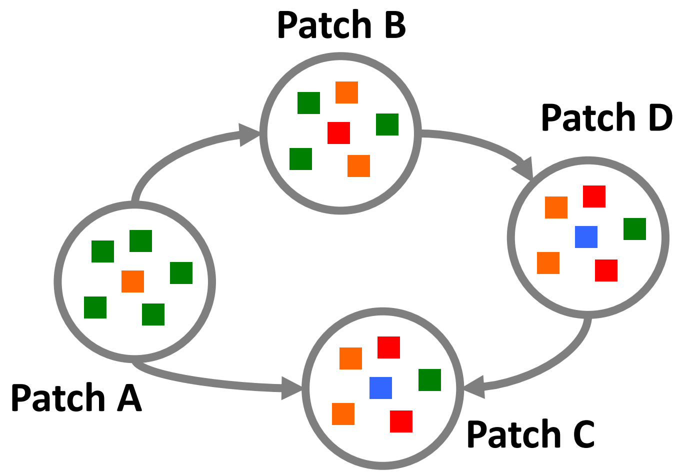
Theory-based Mechanistic Methods

Mechanistic methods

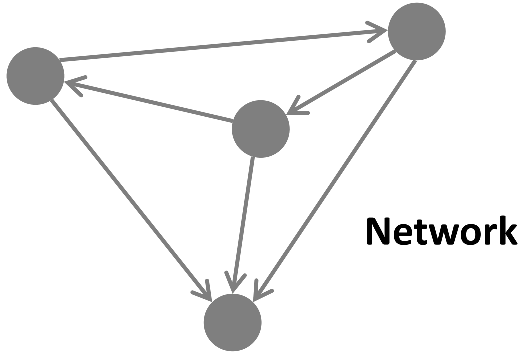


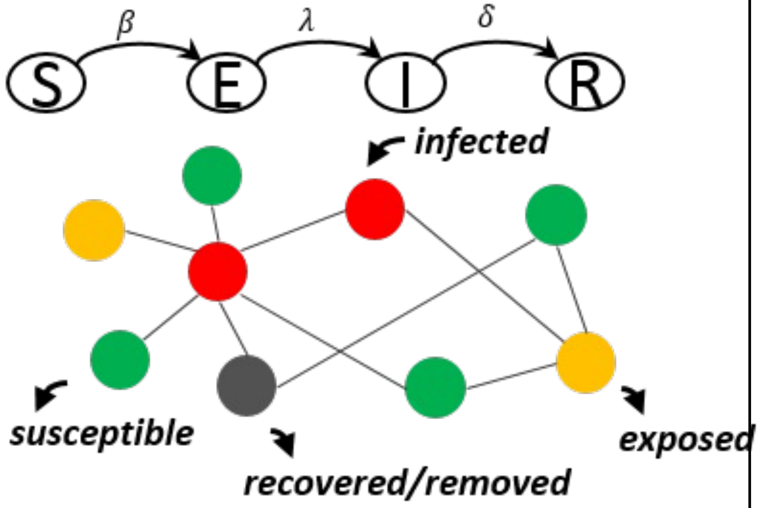
Causal prediction

SIR, SEIR, SIRD, SEIRD, etc.

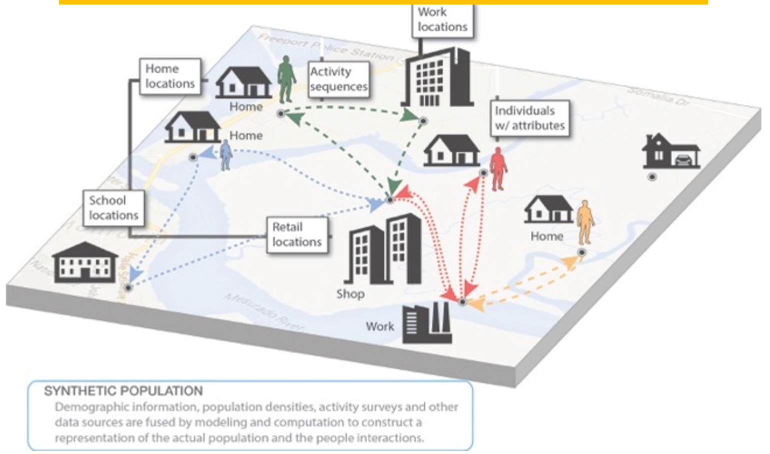


Single-patch/Network-based compartmental models





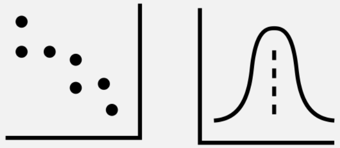
Agent-based models



Example: Susceptible-Exposed-Infectious-Recovered (SEIR)

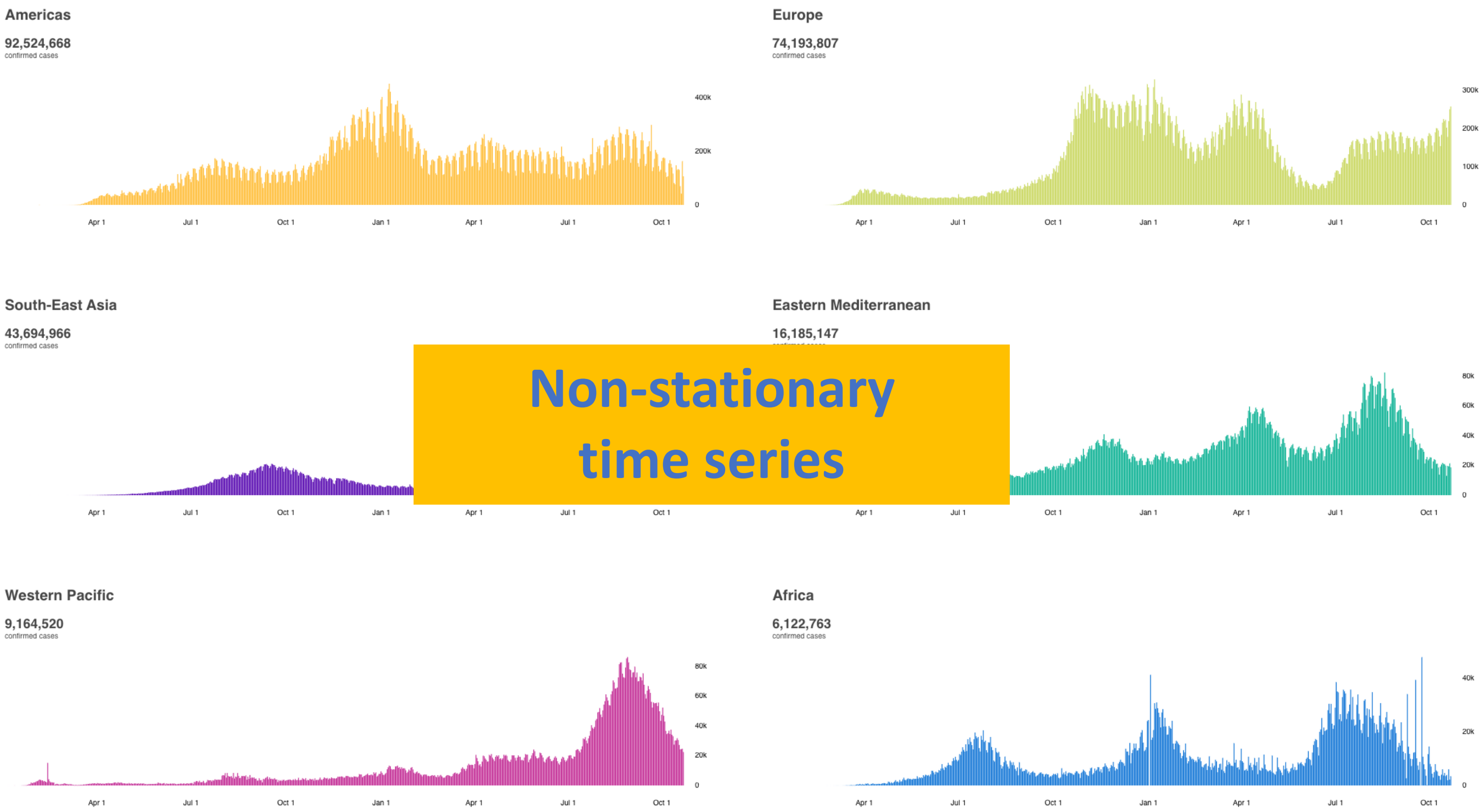
Data-driven Statistical Methods

Statistical time series methods



Simplicity

AR, ARMA, ARIMA, etc.

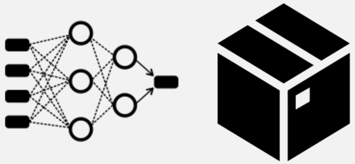


Non-stationary time series

Plots from WHO COVID-19 Dashboard

Data-driven Deep Learning Methods

Deep learning methods



Non-linear learning power

FNN, RNN, CNN, GNN, etc.

Deep learning in epidemic forecasting

Feed Forward Neural Networks (FNN)

2017.05
(Xu et al. PlosOne)
First FNNs for influenza forecasting

Recurrent Neural Networks (RNN)

2017.12
(Volkova et al. PlosOne)
First LSTMs for influenza forecasting

Convolutional Neural Networks (CNN)

(Wu et al. SIGIR)
RNN and CNNs for influenza forecasting
2018.06

Graph Neural Networks (GNN)

(Deng et al. CIKM)
First GNNs for ILI forecasting
2019.12

Part 2: AI-based methodologies for epidemic forecasting

Questions

- Can we apply recurrent neural networks to capture long-term patterns in epidemic forecasting?
- How to leverage graph neural networks to learn spatial and temporal signals for spatiotemporal epidemic forecasting?
- How to leverage theory-based mechanistic models to provide epidemiological context for deep learning-based epidemic forecasting?
- How to improve the robustness of forecasting systems?

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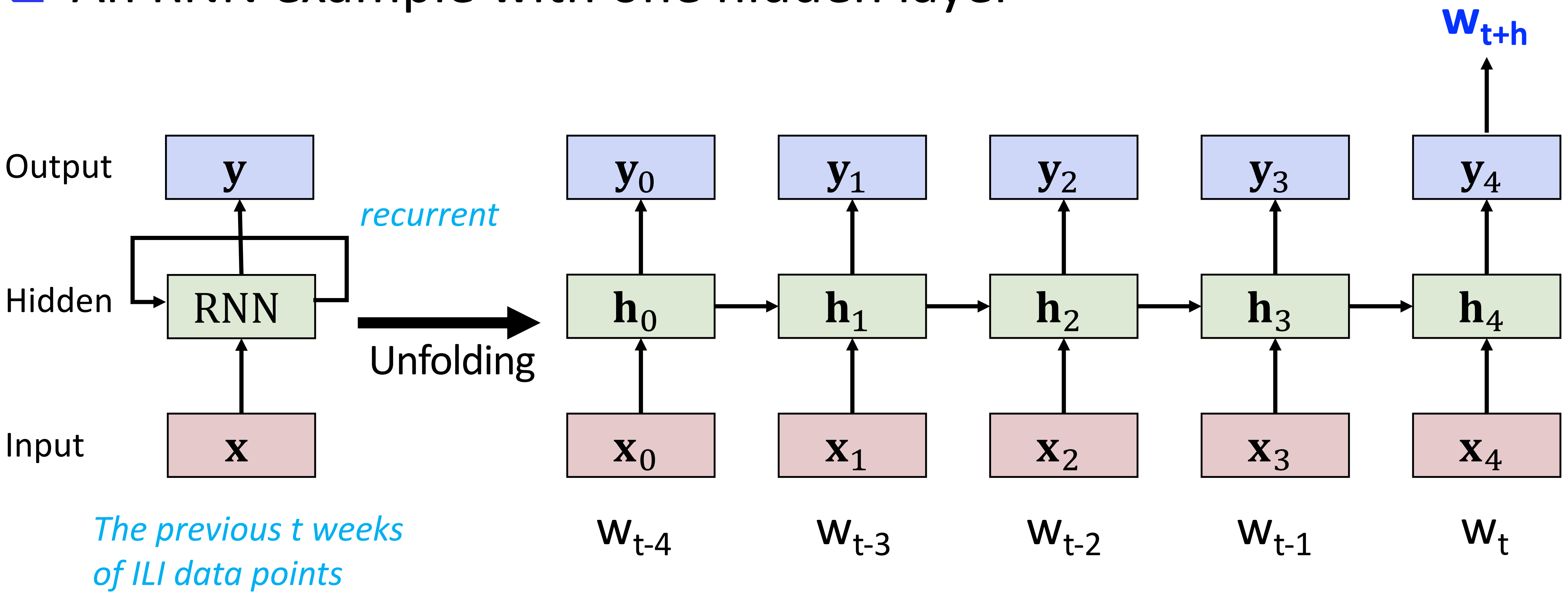
LSTM-based Epidemic Forecasting

- Challenge: capture long-term patterns
- Recurrent neural networks (RNNs), are a class of neural networks that allow previous outputs to be used as inputs while having hidden states.
- Popular applications of RNNs are machine translation, text classification, video classification, etc.
- Make use of RNN for epidemic forecasting
  - In 2018, the first LSTM-based model in seasonal influenza forecasting challenge (CDC FluSight)

Epidemic Forecasting with RNN

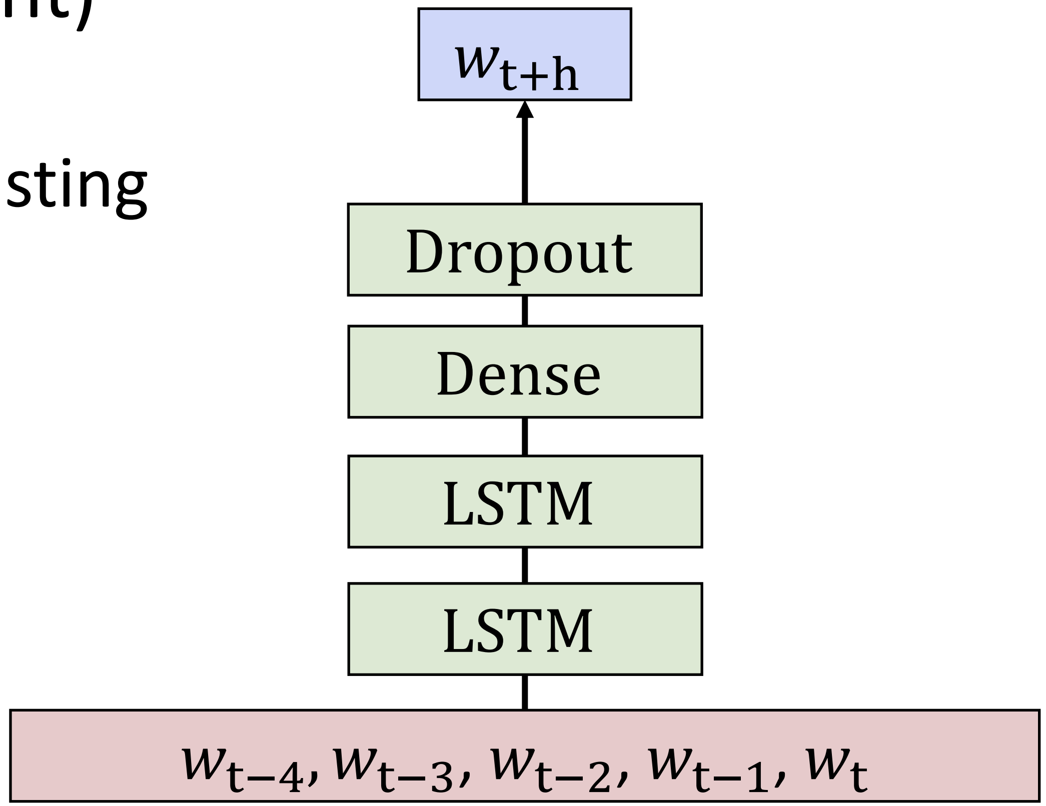
- An RNN example with one hidden layer



LSTM-based Epidemic Forecasting

- In 2018, the first LSTM-based model in seasonal influenza forecasting challenge (CDC FluSight)
  - Two-layer LSTM model
  - MCDropout for probabilistic forecasting

The previous t weeks of ILI data points



Questions

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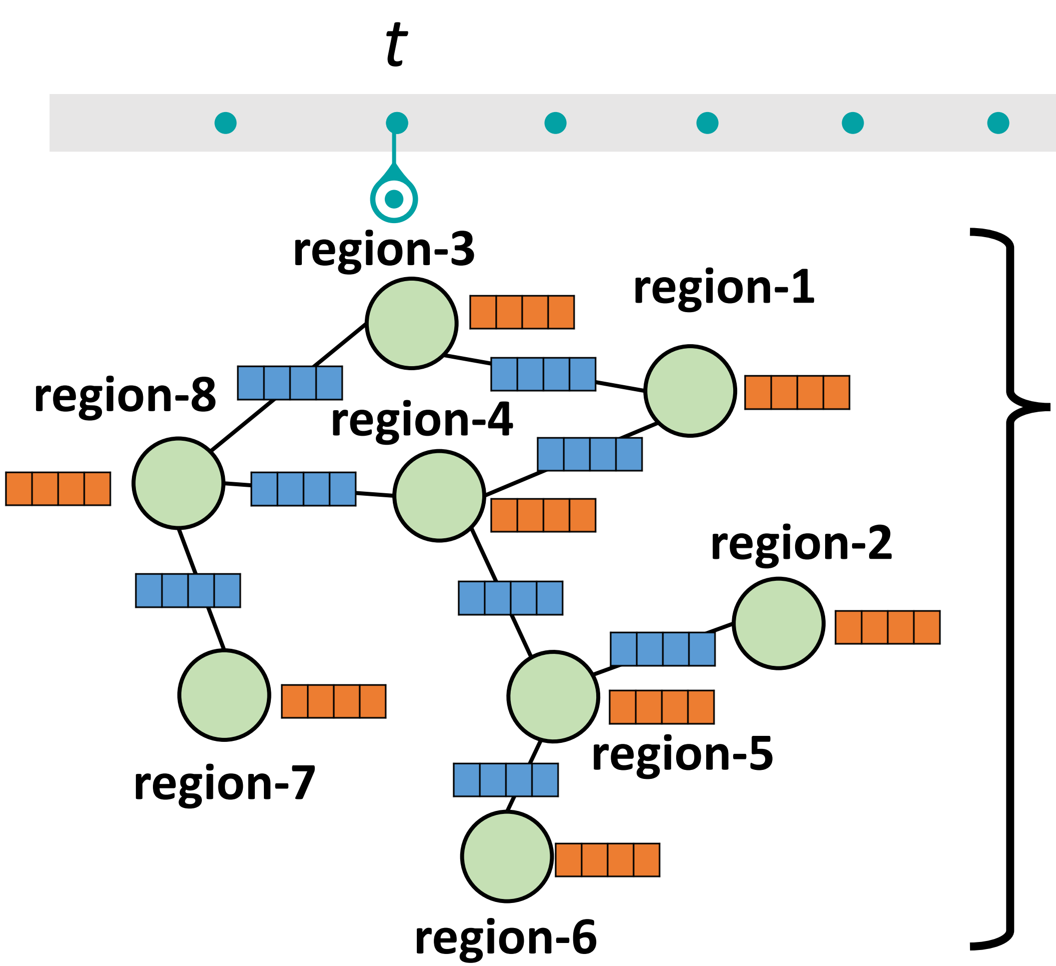
GNN-based Epidemic Forecasting

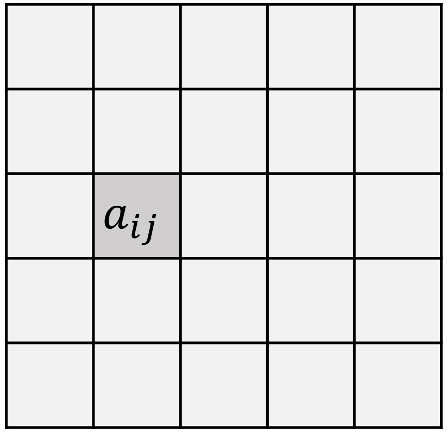
- Challenge: capture spatial and temporal signals
- Graph neural networks (GNNs), are a class of neural networks for processing data that can be represented as graphs, and provide an easy way to do node-level, edge-level, and graph-level prediction tasks.
- Make use of GNN for epidemic forecasting
  - In 2019, the first GNN-based model for seasonal influenza forecasting

Problem Formulation



Structure =
Adjacency Matrix

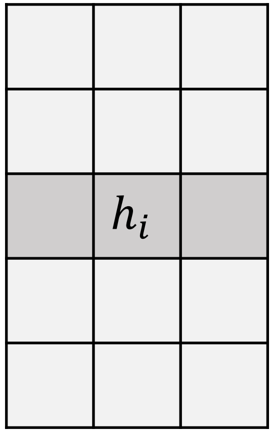
$$A_t \in \mathbb{R}^{N \times N}$$



Geo-adjacency; Commute flow;
Gravity network; Mobility flow;
Learned attention matrix

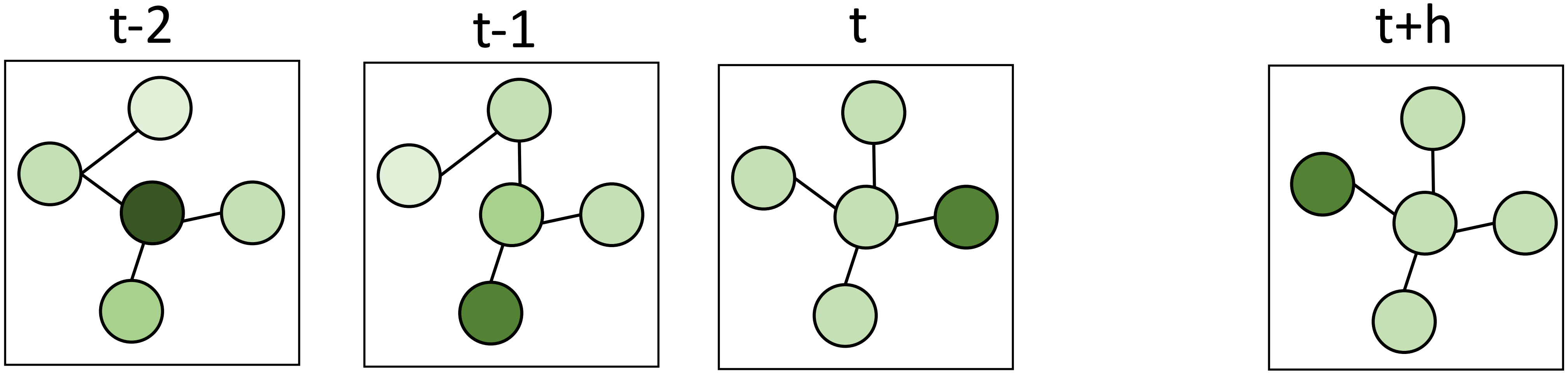
Graph signals =
Feature Matrix

$$X_t \in \mathbb{R}^{N \times F}$$



Problem Formulation

- Node level predictions
  - Dynamic adjacency matrix
  - Dynamic node features
  - Dynamic edge features



Spatiotemporal Correlations

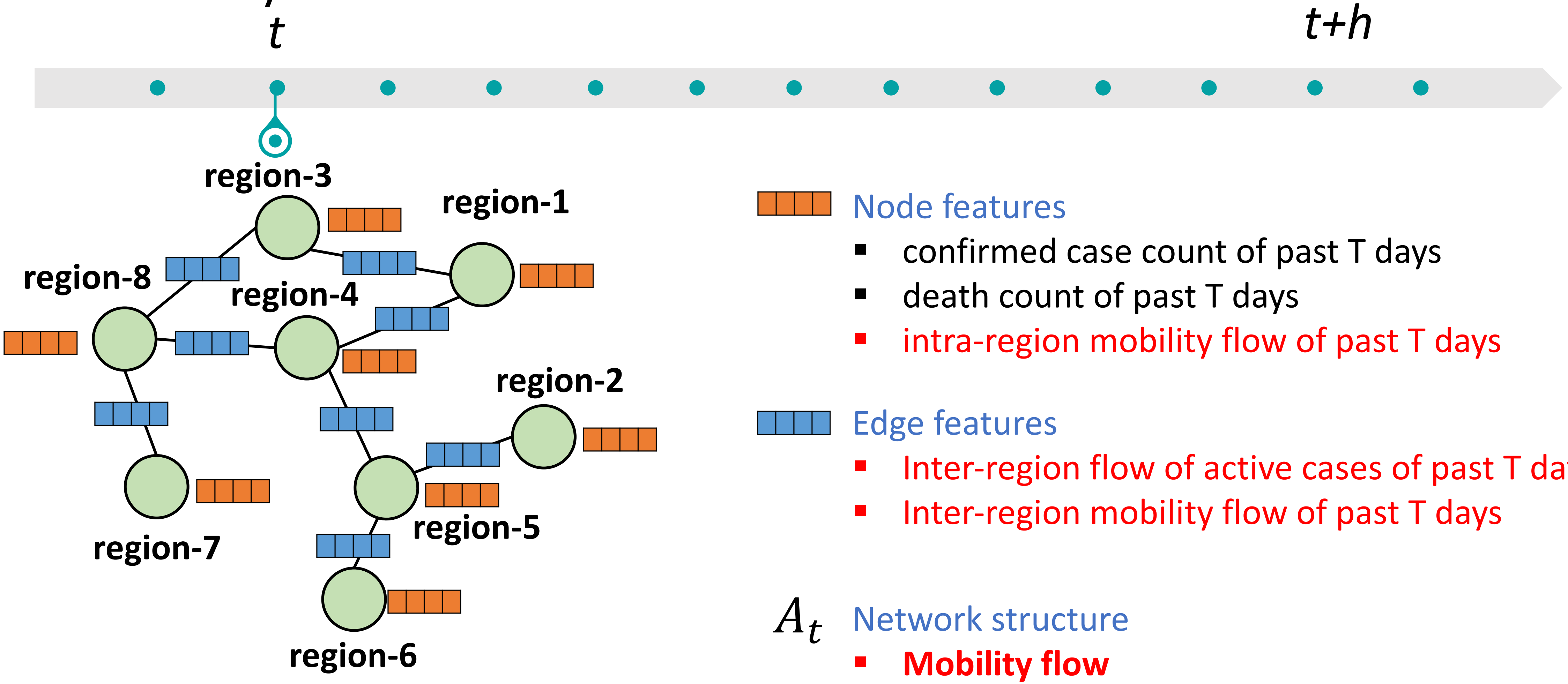
- Geo-adjacency: static
- Commute flow: not real time
- Gravity network: model-based static data
- Mobility flow: real time but not public accessible
- Learned attention matrix: dynamic with computation cost

Our methods:

Graph Neural Network + Mobility Map

Graph Neural Network + Attention Mechanism

Mobility-GNN



Node features
- confirmed case count of past T days
- death count of past T days
- intra-region mobility flow of past T days

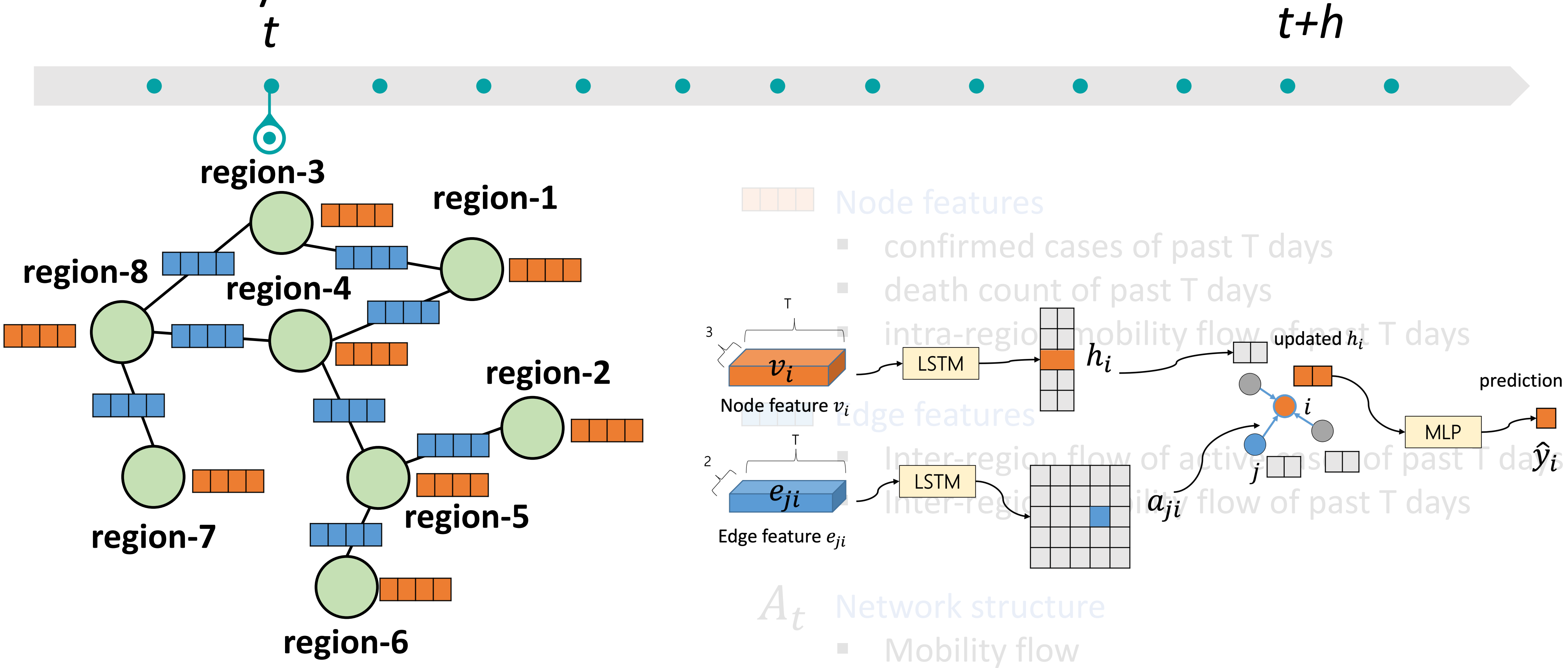
Edge features
- Inter-region flow of active cases of past T days
- Inter-region mobility flow of past T days

A_t Network structure
- **Mobility flow**

Google COVID-19 Aggregated Mobility Research Data

L. Wang et al., "Using Mobility Data to Understand and Forecast COVID-19 Dynamics", *IJCAI 2021 workshop on AI4SG, 2021.*

Mobility-GNN



Google COVID-19 Aggregated Mobility Research Data

L. Wang et al., "Using Mobility Data to Understand and Forecast COVID-19 Dynamics", *IJCAI 2021 workshop on AI4SG, 2021.*

Forecasting Performance

Target

- Point estimates
- 53 US states COVID 19 daily new confirmed cases

Setting

- Training-validation-testing: 100-25-28 days from March 1st to August 29th, 2020

Metrics

- Root Mean Squared Error (RMSE)
- Pearson Correlation (PCORR)

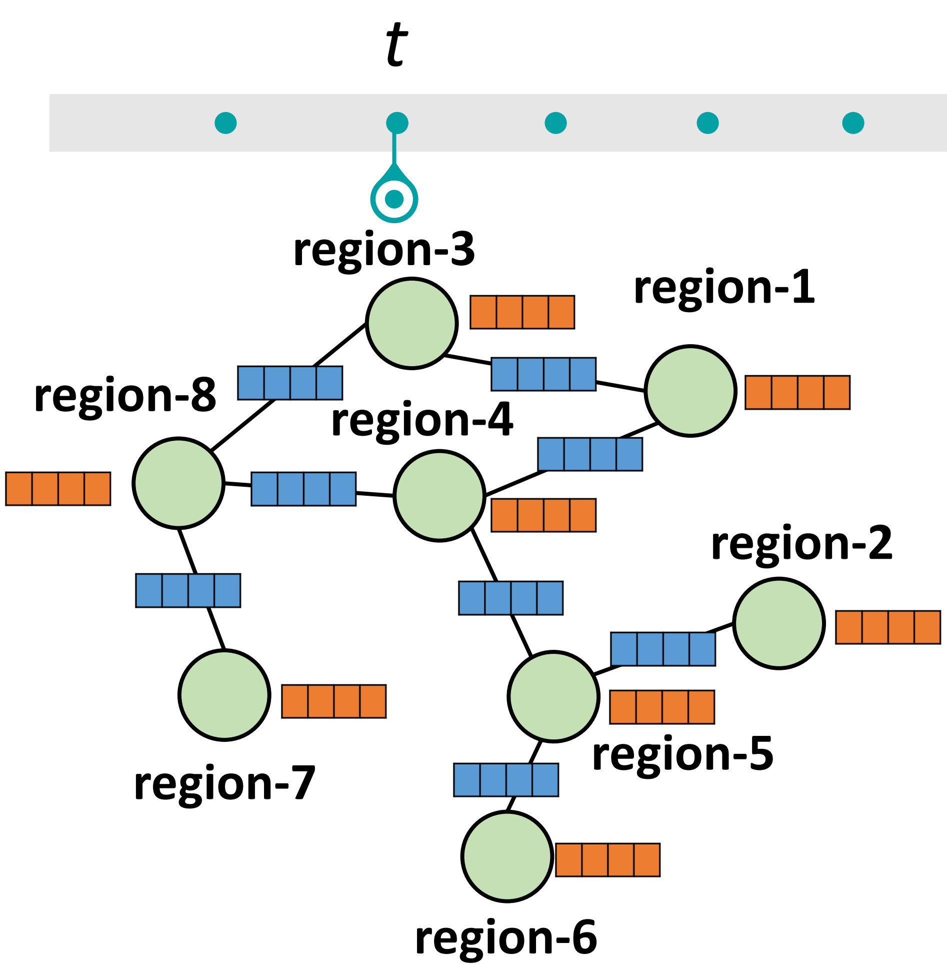
Variants

- GNN-adj: geo-adjacency matrix
- GNN-att: attention matrix
- GNN-smob: static mobility map
- GNN-dmob: dynamic mobility map

	US state				
RMSE(↓)	2	7	14	21	28
Naive	411	389	445	496	525
AR	376	634	866	975	978
ARMA	400	637	944	1107	1186
LSTM	368	504	517	567	605
CNNRNN	416	432	512	606	659
cola-GNN	320	502	451	530	714
GNN-adj	**310**	411	407	412	513
GNN-att	319	479	985	457	745
GNN-smob	313	405	410	**406**	510
GNN-dmob	313	**330**	**350**	445	**465**
MAE(↓)	2	7	14	21	28
Naive	317	303	381	454	497
AR	330	667	727	825	827
ARMA	347	675	827	988	1037
LSTM	270	353	402	533	690
CNNRNN	390	446	566	657	704
cola-GNN	258	455	420	450	675
GNN-adj	**243**	320	322	393	461
GNN-att	260	406	982	374	682
GNN-smob	246	316	351	384	460
GNN-dmob	253	**270**	**300**	**370**	**397**

Wang, et al., IJCAI AI4SG 2021

Cola-GNN



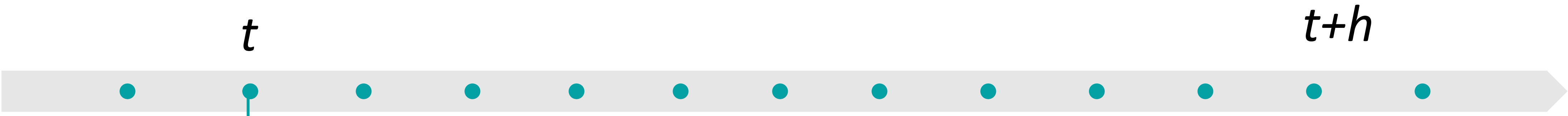
Node features
- infectious case count of past T days

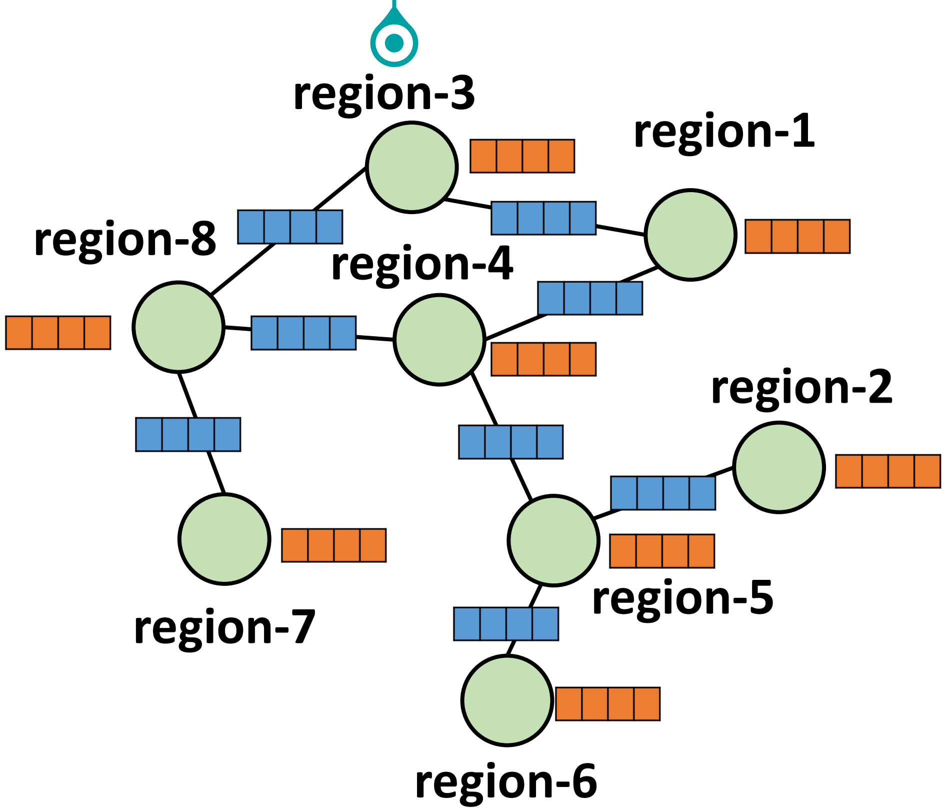
Edge features
- None

A_t Network structure
- **Geo-adjacency matrix + Attention matrix**

S. Deng et al., "Cola-GNN: Cross-location Attention based Graph Neural Networks for Long-term ILI Prediction.", *CIKM, 2020.*

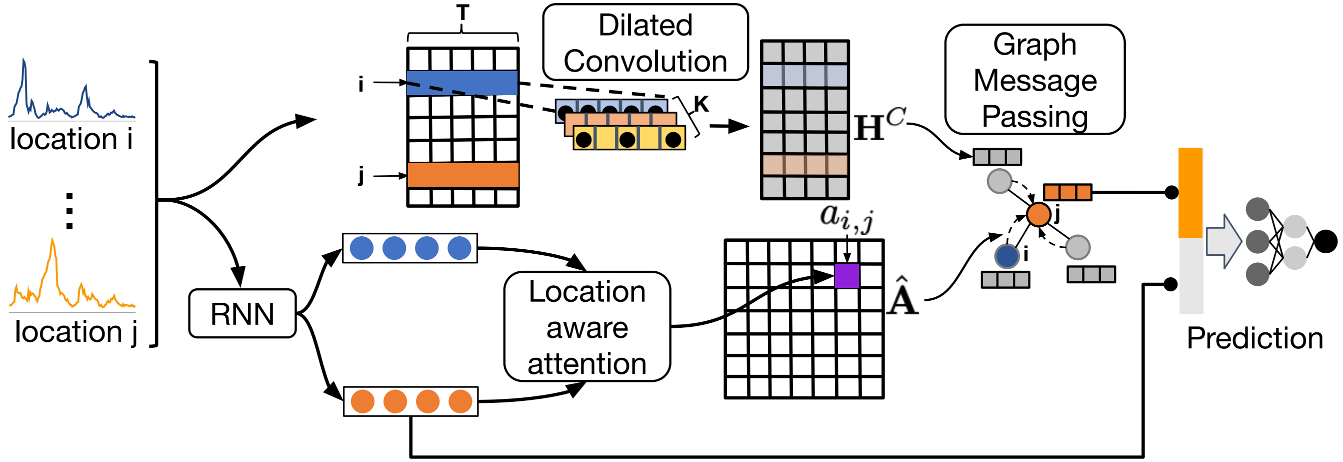
Cola-GNN





Node features

- infectious cases of past T days



A_t Network structure

- Geo-adjacency matrix + Attention matrix

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Forecasting Performance

	Japan-Prefectures					US-Regions					US-States				
RMSE(↓)	2	3	5	10	15	2	3	5	10	15	2	3	5	10	15
GAR	1232	1628	1988	2065	2016	536	715	991	1377	1465	150	187	236	314	340
AR	1377	1705	2013	2107	2042	570	757	997	1330	1404	161	204	251	306	327
VAR	1361	1711	2025	1942	1899	741	870	1059	1270	1299	290	276	295	324	352
ARMA	1371	1703	2013	2105	2041	560	742	989	1322	1400	161	200	250	306	326
RNN	1001	1259	1376	1696	1629	513	689	896	1328	1434	149	181	217	274	315
LSTM	1052	1246	1335	1622	1649	507	688	975	1351	1477	150	180	213	276	307
RNN+Attn	1166	1572	1746	1612	1823	613	753	1065	1367	1368	152	186	234	315	334
DCRNN	1502	1769	2024	2019	1992	711	874	1127	1411	1434	165	209	244	299	298
CNNRNN-Res	1133	1550	1942	1865	1862	571	738	936	1233	1285	205	239	267	260	250
LSTNet	1133	1459	1883	1811	1884	554	801	998	1157	1231	199	249	299	292	292
ST-GCN	996	1115	1129	1541	1527	697	807	1038	1290	1286	189	209	256	289	292
Cola-GNN	**929**	**1051**	**1117**	**1372**	**1475**	**480**	**636**	**855**	**1134**	**1203**	**136**	**167**	**202**	**241**	**237**
% relative gain	6.7%	5.7%	1.1%	11.0%	3.4%	5.3%	7.6%	4.6%	2.0%	2.3%	8.7%	7.2%	5.2%	7.3%	5.2%
PCC(↑)	2	3	5	10	15	2	3	5	10	15	2	3	5	10	15
GAR	0.804	0.626	0.339	0.288	0.470	0.932	0.881	0.790	0.581	0.485	0.945	0.914	0.875	0.777	0.742
AR	0.752	0.579	0.310	0.238	0.483	0.927	0.878	0.792	0.612	0.527	0.940	0.909	0.863	0.773	0.723
VAR	0.754	0.585	0.300	0.426	0.474	0.859	0.797	0.685	0.508	0.467	0.765	0.790	0.758	0.709	0.653
ARMA	0.754	0.579	0.310	0.253	0.486	0.927	0.876	0.792	0.614	0.520	0.939	0.909	0.862	0.773	0.725
RNN	0.892	0.833	0.821	0.616	0.709	0.940	0.895	0.821	0.587	0.499	0.948	0.922	0.886	0.821	0.758
LSTM	0.896	0.873	0.853	0.681	0.695	0.943	0.895	0.812	0.586	0.488	0.948	0.922	0.889	0.820	0.771
RNN+Attn	0.850	0.668	0.590	0.741	0.522	0.887	0.859	0.752	0.554	0.552	0.947	0.922	0.884	0.780	0.739
DCRNN	0.697	0.537	0.292	0.342	0.525	0.897	0.849	0.760	0.604	0.558	0.941	0.886	0.886	0.829	0.837
CNNRNN-Res	0.852	0.673	0.380	0.438	0.467	0.920	0.862	0.782	0.552	0.485	0.904	0.860	0.822	0.820	0.847
LSTNet	0.846	0.728	0.432	0.518	0.515	0.935	0.868	0.746	0.609	0.533	0.913	0.850	0.759	0.760	0.802
ST-GCN	0.902	0.880	0.872	0.735	**0.773**	0.879	0.840	0.741	0.644	0.619	0.907	0.778	0.823	0.769	0.774
Cola-GNN	**0.915**	**0.901**	**0.890**	**0.813**	0.753	**0.946**	**0.909**	**0.835**	**0.717**	**0.639**	**0.955**	**0.933**	**0.897**	**0.822**	**0.856**
% relative gain	1.4%	2.4%	2.1%	9.7%	-	0.6%	1.6%	1.7%	10.2%	3.2%	0.7%	1.2%	0.9%	0.1%	1.1%

Target

- Point estimates
- ILITotal in 47 Japan prefectures, 10 US regions, 49 US states

Setting

- Training-validation-testing: 50%-20%-30%.

Metrics

- Root Mean Squared Error (RMSE)
- Pearson Correlation (PCORR)

Questions

- Can we apply recurrent neural networks to capture long-term patterns in epidemic forecasting?
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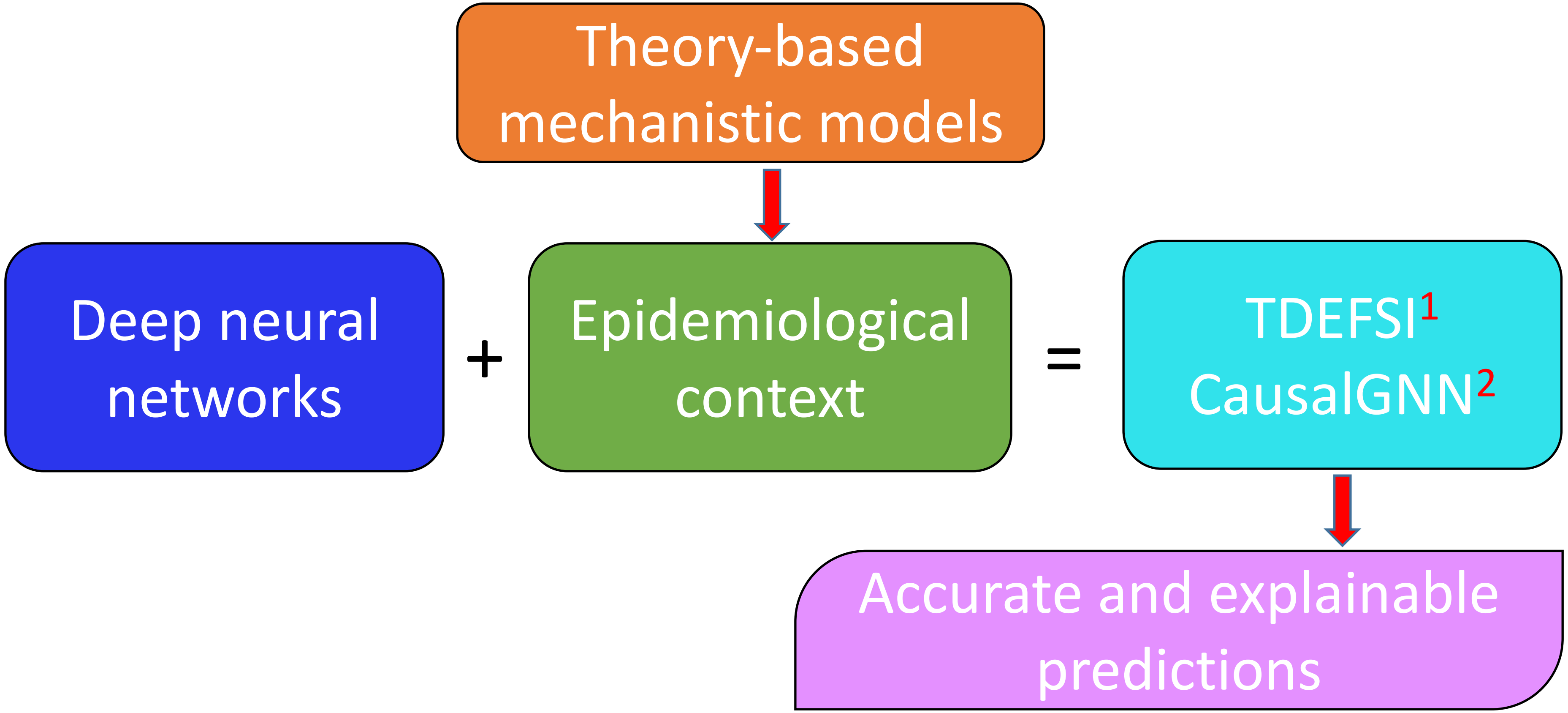
- How to improve the robustness of forecasting systems?

Theory Guided DL for Epidemic Forecasting

- Challenge: lack of epidemiological context
- Combining theory-based mechanistic models with deep learning models

Our methods:
Deep Neural Network + Mechanistic Models

Theory Guided DL for Epidemic Forecasting



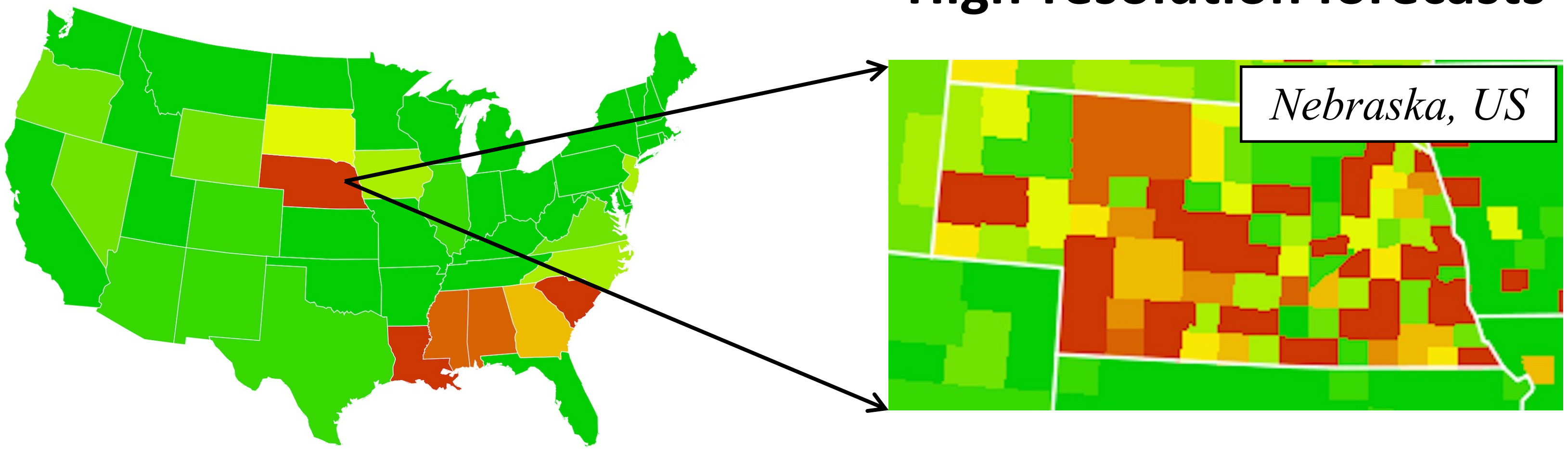
[1]**L. Wang** et al., "TDEFSI: Theory Guided Deep Epidemic Forecasting with Synthetic Information", *ACM Transactions on Spatial Algorithms and Systems, Deep Learning for Spatial Algorithms and Systems*, 2020.
[2]**L. Wang** et al., "CausalGNN: Causal-based Graph Neural Networks for Epidemic Forecasting", *AAAI 2022.*

TDEFSI Motivation

Influenza-like-illness (ILI)

Flat-resolution forecasts

High-resolution forecasts



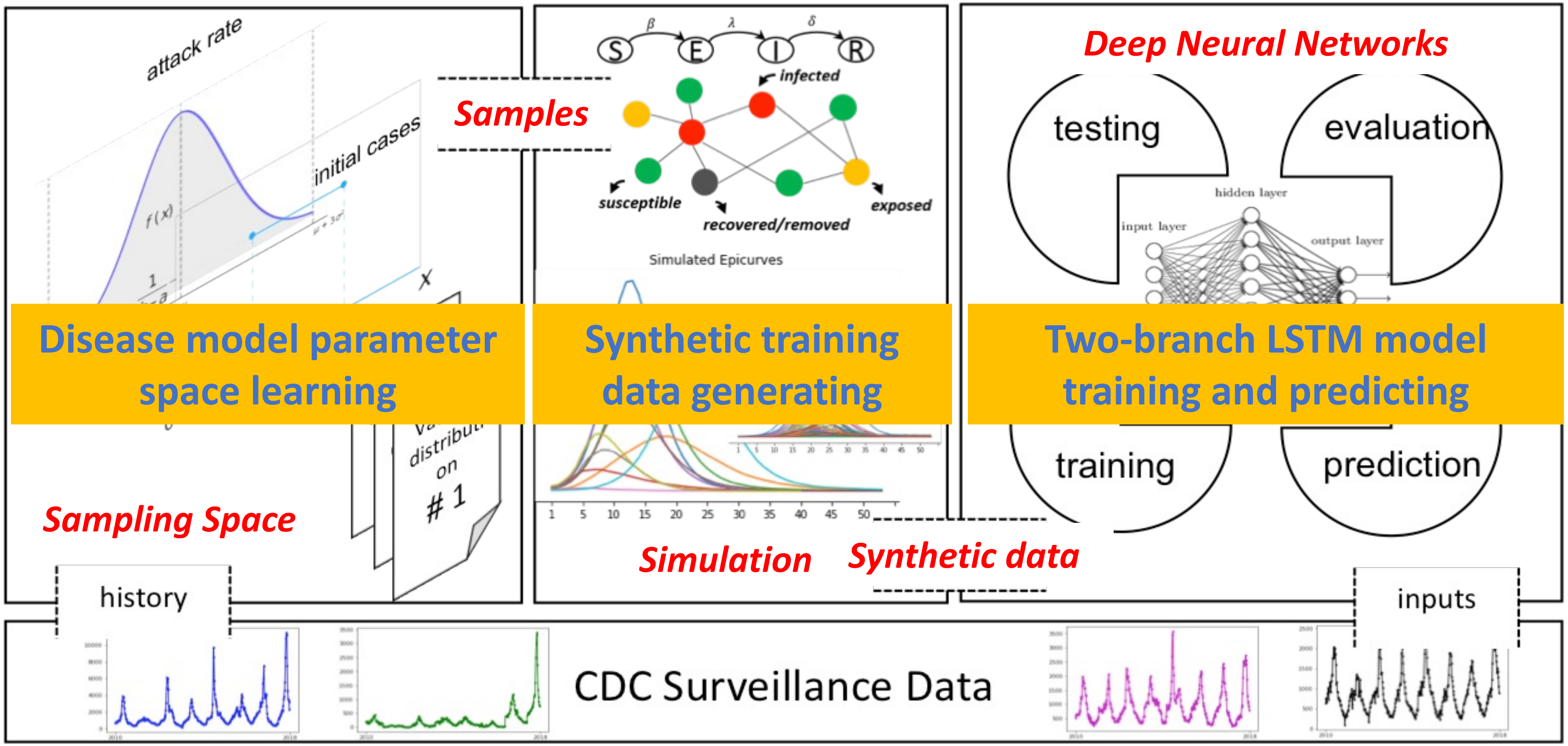
State level surveillance data is available

County level surveillance data is NOT available

L. Wang et al., "TDEFSI: Theory Guided Deep Epidemic Forecasting with Synthetic Information", *ACM Transactions on Spatial Algorithms and Systems, Deep Learning for Spatial Algorithms and Systems*, 2020.

TDEFSI Framework

TDEFSI = Agent-based SEIR + LSTM + Physical Constraints

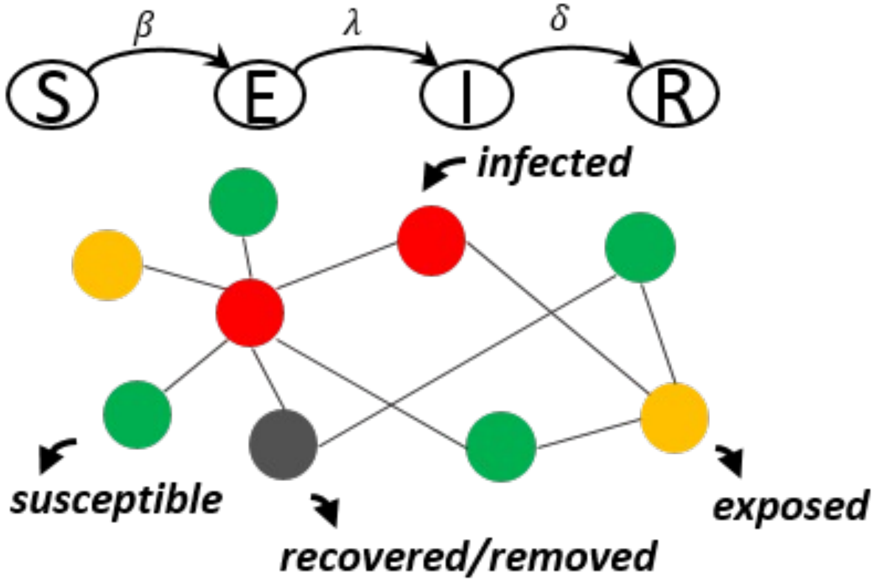


L. Wang et al., "TDEFSI: Theory Guided Deep Epidemic Forecasting with Synthetic Information", *ACM Transactions on Spatial Algorithms and Systems, Deep Learning for Spatial Algorithms and Systems*, 2020.

TDEFSI – Agent-based Simulator

EpiFast*: An SEIR-based Epidemic Simulation

- Susceptible (S) -> exposed (E) -> infectious (I) -> recovered or removed (R)



Disease Model Parameter Space

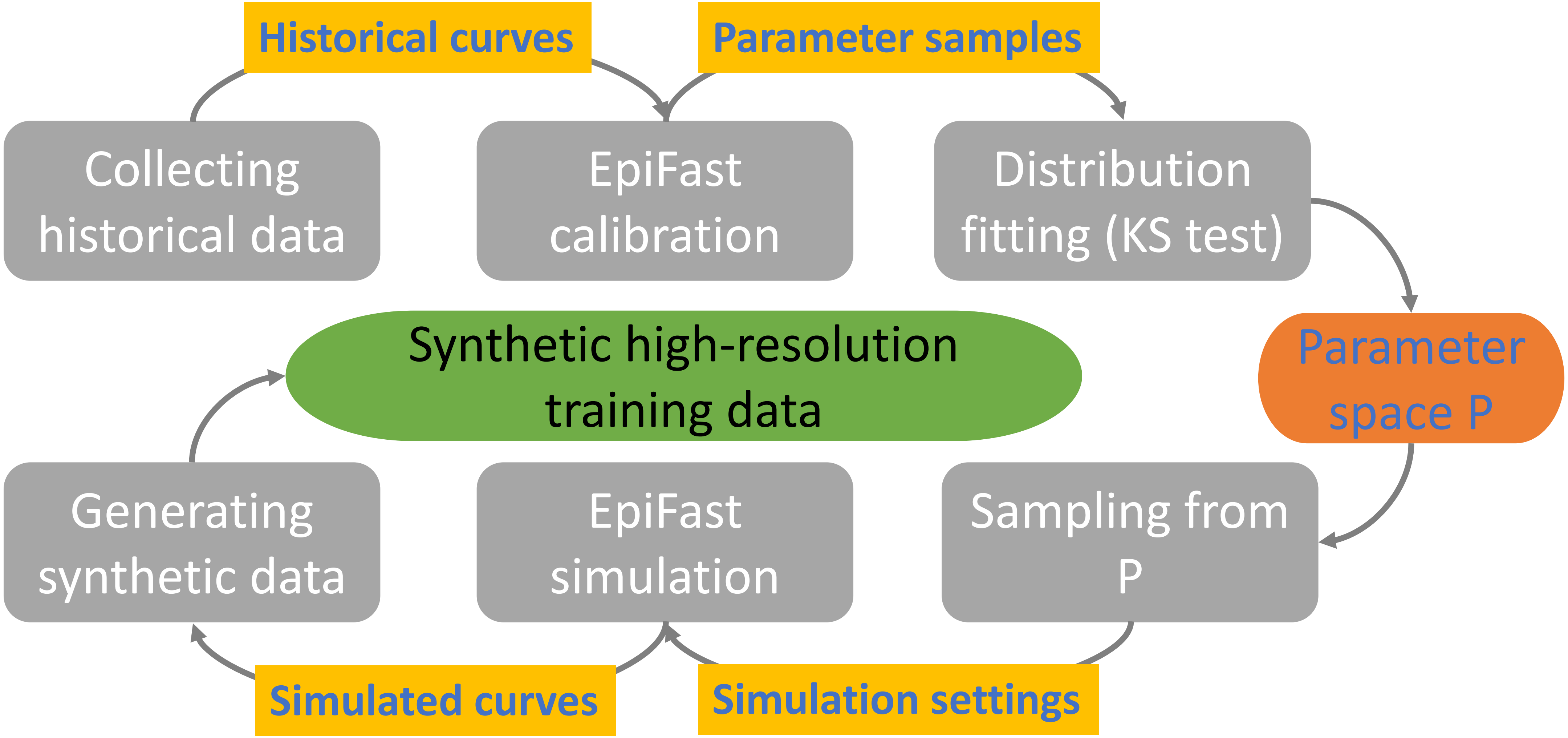
- Parameter Space = (Incubation period, Infectious period, Transmissibility, Initial case number, Vaccine intervention)

$$P = (p_E, p_I, \tau, N_I, I_V)$$

* Keith R. Bisset, Jiangzhuo Chen, Xizhou Feng, V.S. Anil Kumar, and Madhav V. Marathe. 2009. EpiFast: a fast algorithm for large scale realistic epidemic simulations on distributed memory systems. ICS '09. ACM, New York, NY, USA, 430-439.

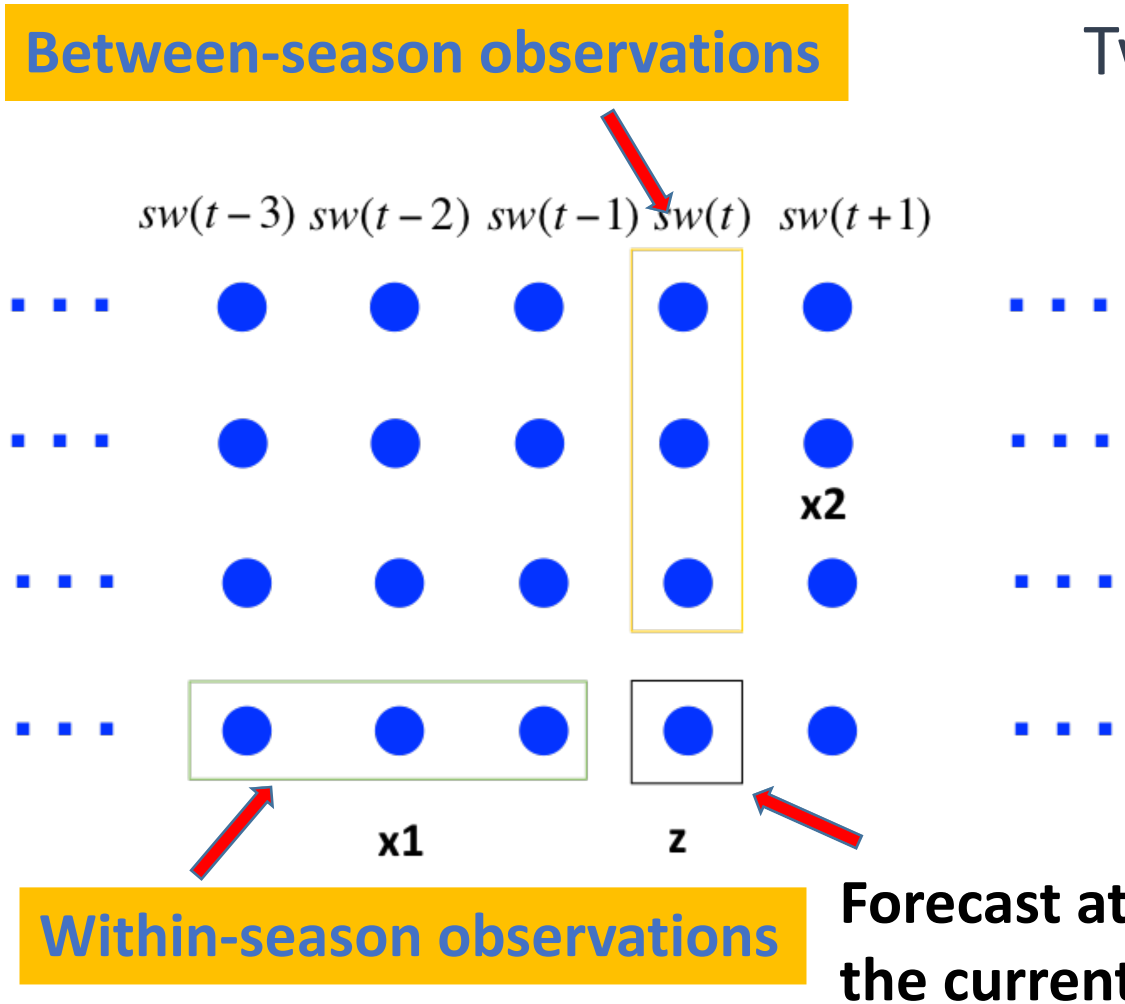
Wang, et al., ACM TSAS 2020

TDEFSI Framework

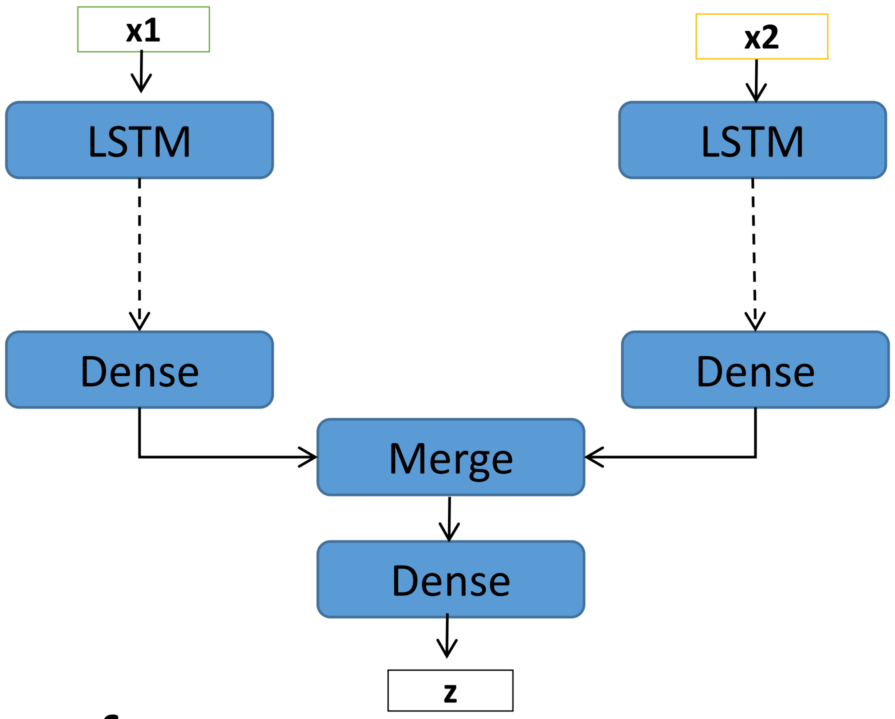


Wang, et al., ACM TSAS 2020

TDEFSI Framework



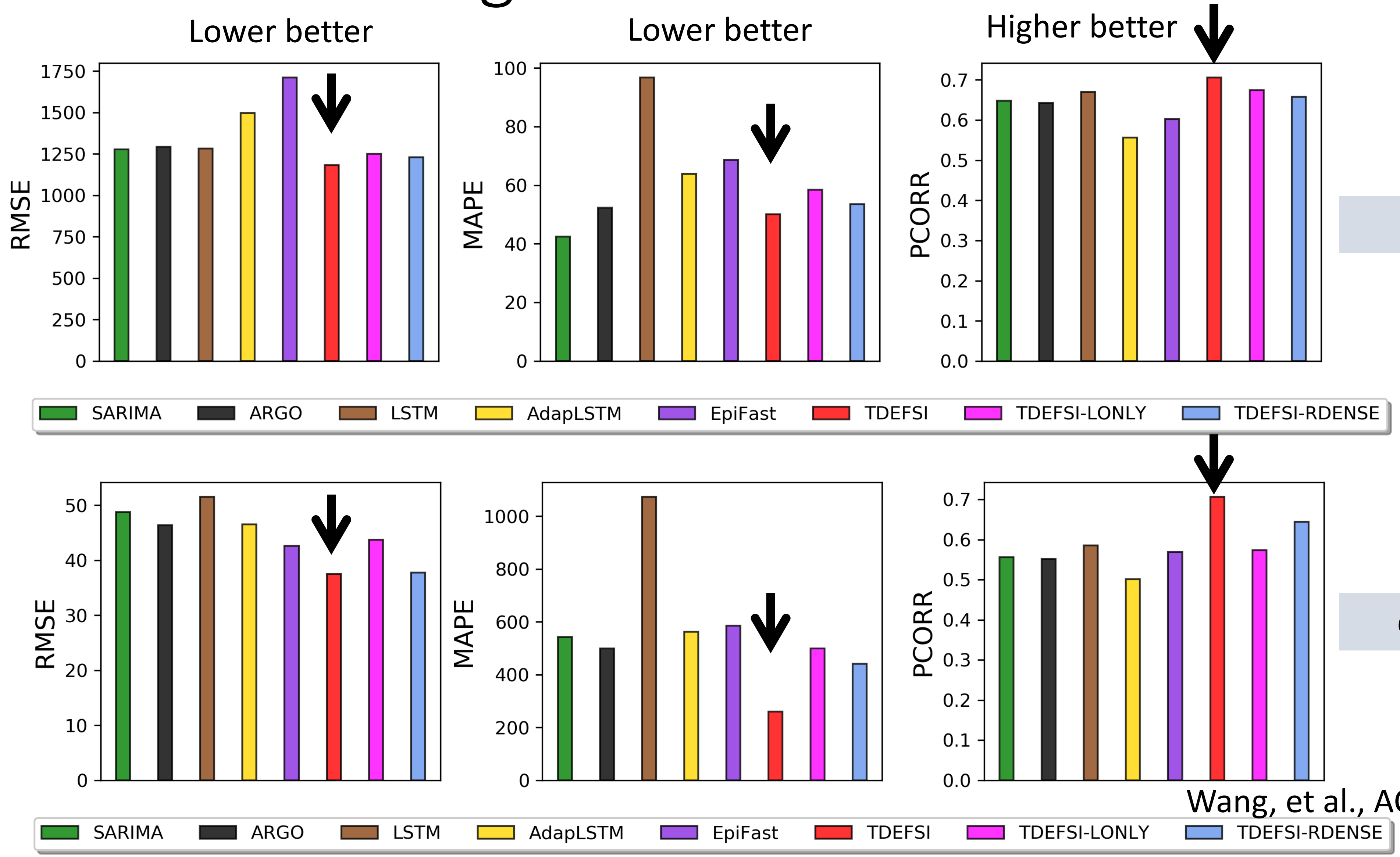
Two-branch LSTM-based model



$$\hat{\mathbf{z}}_t = f([\mathbf{x1}, \mathbf{x2}]_t, \theta)$$

Wang, et al., ACM TSAS 2020

TDEFSI Forecasting Performance



State-level

County-level

Wang, et al., ACM TSAS 2020

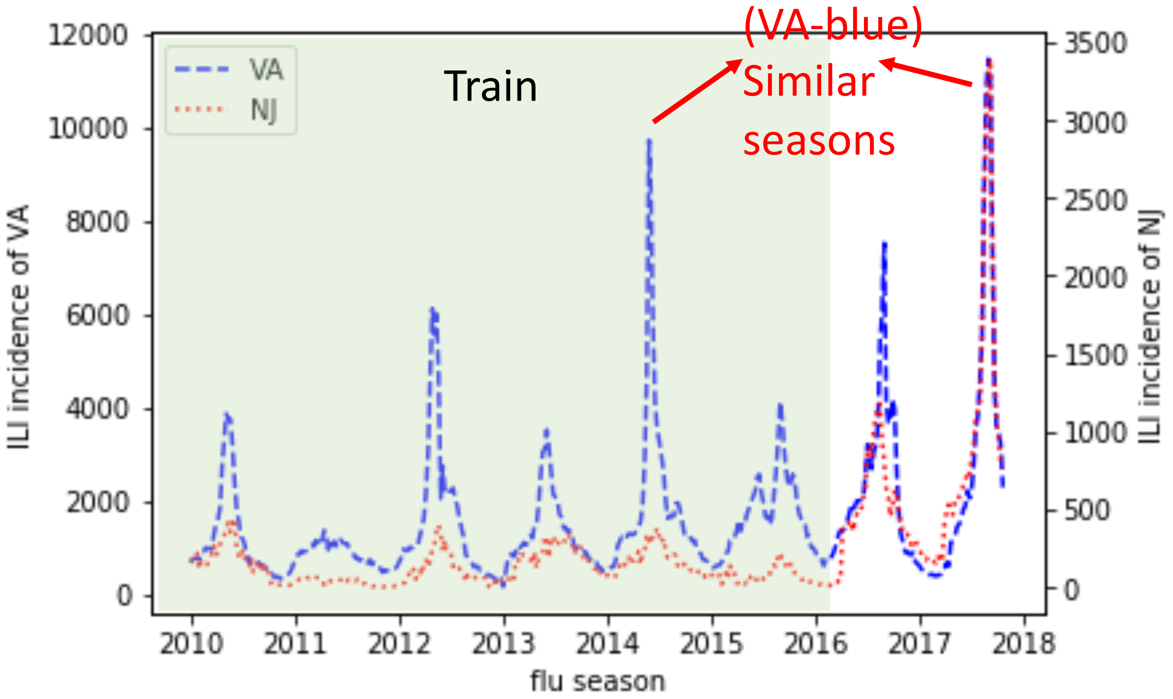
TDEFSI Forecasting Performance

Table 2. State Level Performance across Season 2016–2017 and 2017–2018 for VA and NJ with Horizon = 1, 2, 3, 4, 5

	VA					NJ				
RMSE	1	2	3	4	5	1	2	3	4	5
SARIMA	**824**	1463	2059	2440	2682	218	464	690	891	1050
ARGO	1073	1592	2072	2444	2580	313	512	717	760	874
LSTM	1083	1629	**2013**	2273	**2438**	240	470	699	902	1070
AdapLSTM	2012	2038	2264	2382	2449	586	729	640	871	1006
EpiFast	1300	2087	2989	3674	4284	238	382	567	725	871
TDEFSI	1000	**1447**	2014	**2358**	2544	**174**	**344**	511	665	757
TDEFSI-LONLY	900	1572	2119	2582	2742	197	373	531	696	801
TDEFSI-RDENSE	1109	1686	2136	2421	2540	193	358	**506**	**630**	**711**
MAPE	1	2	3	4	5	1	2	3	4	5
SARIMA	**15.96**	**32.57**	**50.62**	**65.60**	77.94	**13.28**	24.32	35.62	48.32	59.99
ARGO	31.06	54.00	73.69	78.97	77.85	24.96	33.14	44.52	50.05	54.60
LSTM	38.40	49.29	58.80	67.98	71.00	39.44	78.53	131.19	189.79	243.40
AdapLSTM	42.67	51.22	61.02	67.33	**70.60**	64.30	64.77	65.56	74.14	76.50
EpiFast	31.14	53.45	84.32	124.05	167.44	30.32	32.40	50.75	64.61	76.27
TDEFSI	25.75	40.69	58.61	74.06	88.95	18.16	29.74	43.49	55.12	66.09
TDEFSI-LONLY	22.40	35.18	59.27	89.95	123.70	15.56	32.21	45.74	60.46	72.13
TDEFSI-RDENSE	31.89	51.69	76.94	101.38	125.23	15.17	**21.74**	**29.19**	**37.95**	**44.14**
PCORR	1	2	3	4	5	1	2	3	4	5
SARIMA	0.9461	0.8271	0.6468	0.4925	0.3788	0.9541	0.8173	0.6421	0.4611	0.3195
ARGO	**0.9590**	0.8728	**0.7219**	0.4518	0.3218	0.9444	0.8005	0.6043	0.4530	0.2921
LSTM	0.9223	0.7890	0.6350	0.5050	0.4101	0.9603	0.8542	0.6995	0.5340	0.3939
AdapLSTM	0.7048	0.6397	0.5174	0.4307	0.3818	0.8113	0.5912	**0.7686**	0.4477	0.2753
EpiFast	0.8876	0.7665	0.5616	0.3906	0.2340	0.9573	0.8535	0.7044	0.3835	0.2841
TDEFSI	0.9358	0.8487	0.6892	**0.5555**	**0.4647**	**0.9683**	**0.8773**	0.7348	**0.5639**	0.4247
TDEFSI-LONLY	0.9460	**0.8776**	0.7037	0.5074	0.3266	0.9659	0.8697	0.7288	0.4946	0.3245
TDEFSI-RDENSE	0.9043	0.7824	0.6182	0.4409	0.2826	0.9654	0.8692	0.7280	0.5630	**0.4248**

The best value is marked in bold, and the second best value is marked with underline.

Compared with other data-driven methods, TDEFSI performs better on NJ than on VA. Why?

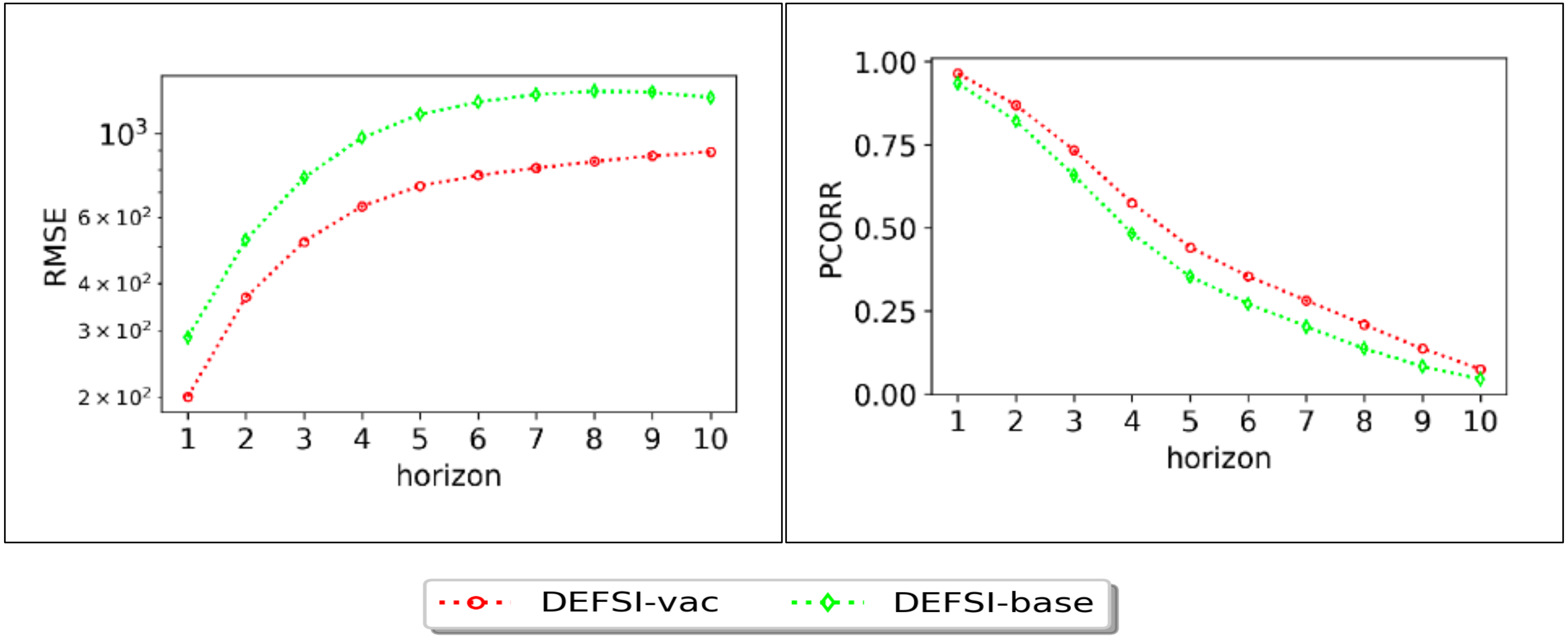


TDEFSI is trained with synthetic data which includes unseen trends in historical data!

Wang, et al., ACM TSAS 2020

TDEFSI Interpretability

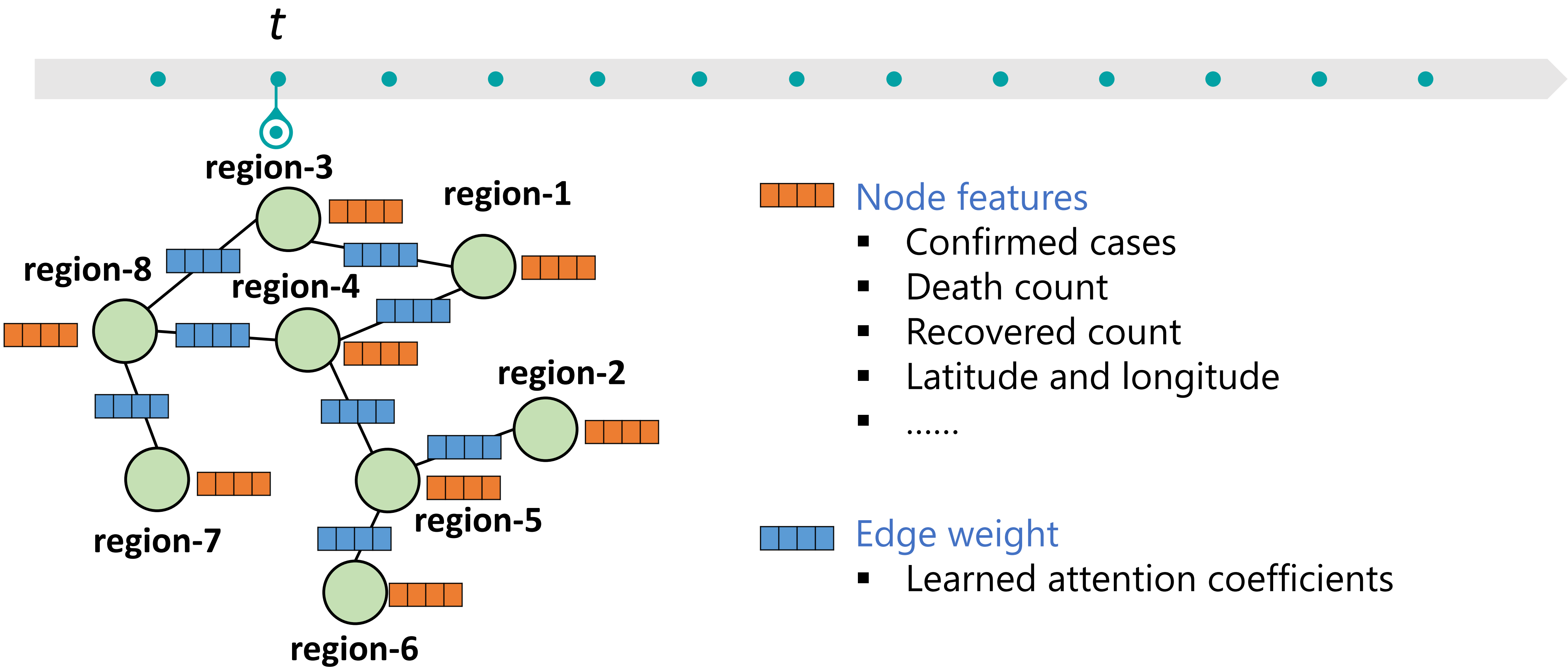
What-if forecasting



TDEFSI performs better if trained with vac-based data than non-vac-based data.

Wang, et al., ACM TSAS 2020

CausalGNN Problem Formulation

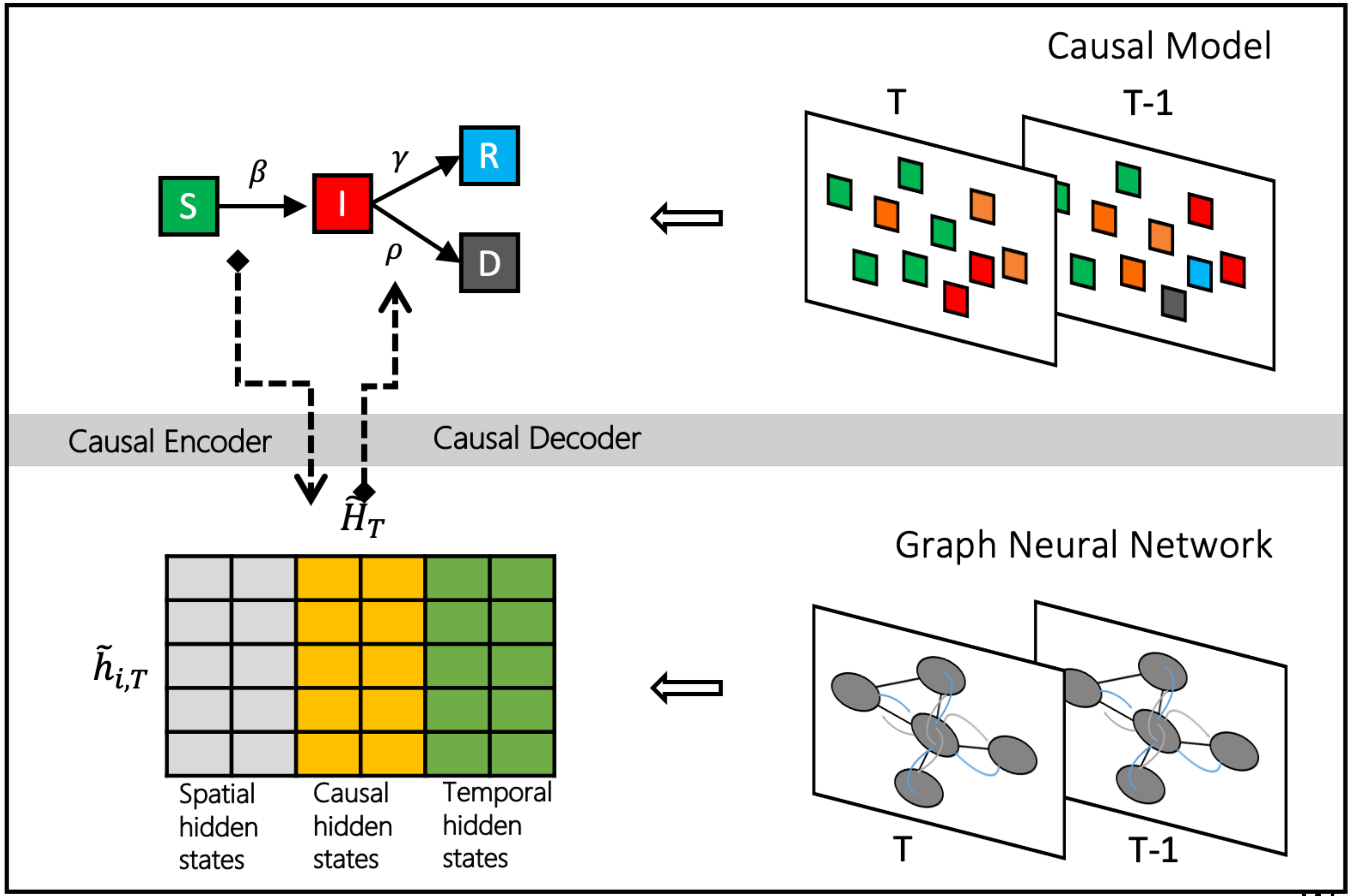


Node features
- Confirmed cases
- Death count
- Recovered count
- Latitude and longitude
- ……

Edge weight
- Learned attention coefficients

Wang, et al., AAAI 2022

CausalGNN Framework



Wang, et al., AAAI 2022

Experiments

Target

- Point estimates
- COVID 19 daily new confirmed cases at national level, US state level and county level.

Setting

- Training-validation-testing: 80%-10%-10% from May 3rd, 2020 to Mar. 21st, 2021.

Metrics

- Root Mean Squared Error (RMSE)
- Mean Absolute Percentage Error (MAPE)

Baselines

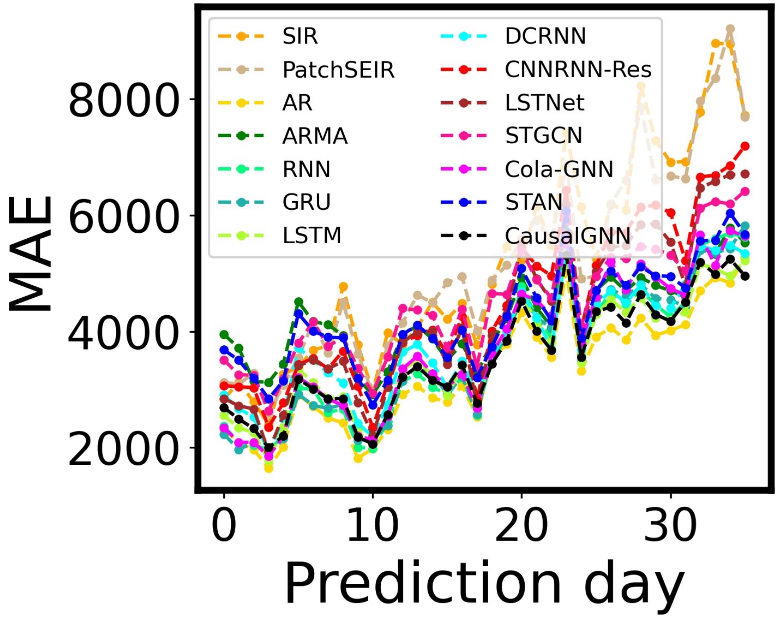
- SIR, PatchSIR
- AR, ARMA
- RNN, GRU, LSTM
- DCRNN, CNNRNN-Res, LSTNet
- STGCN, Cola-GNN, STAN

Data set	Size	Min	Max	Mean	std
Globe	93×355	0	823225	3988	15381
US-State	52×355	0	62168	1670	3192
US-County	1351×355	0	34497	59	238

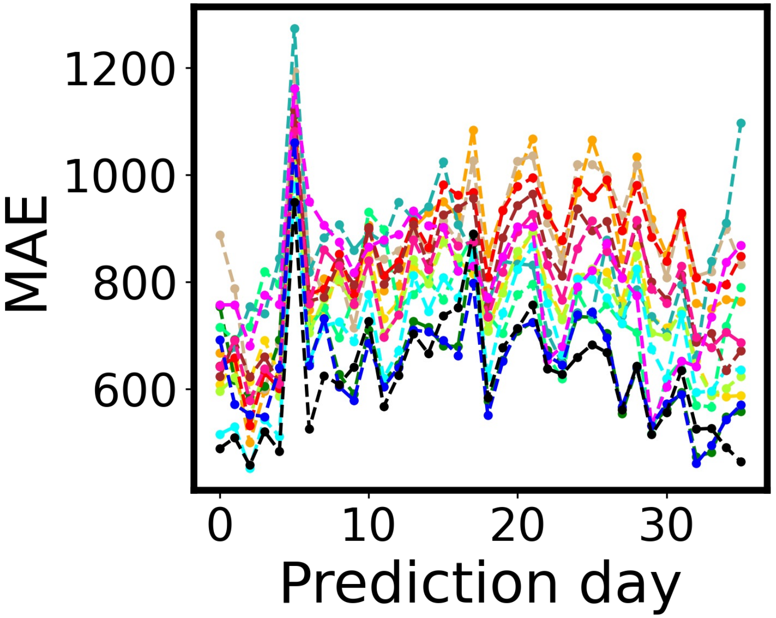
Wang, et al., AAAI 2022

Forecasting Performance

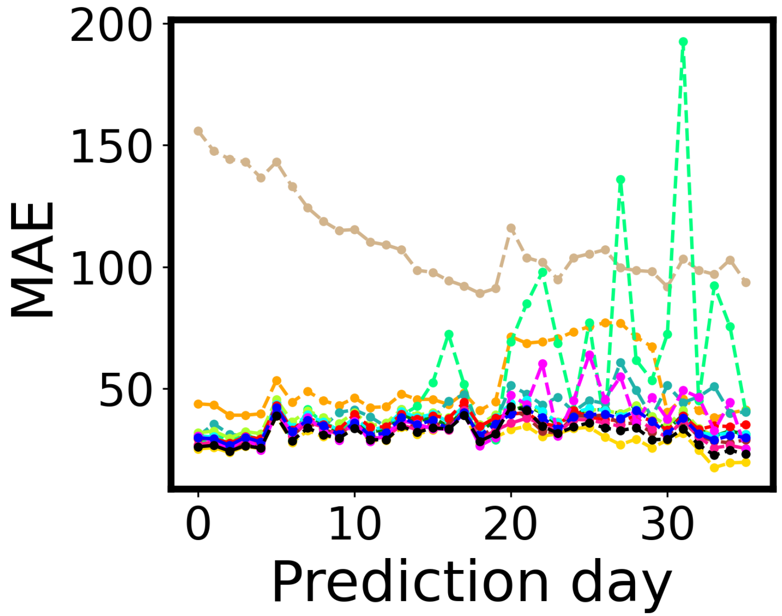
CausalGNN	1911±192	**2502±144**	**3041±211**	**3310±58**	**339±13**	**416±16**	**498±68**	640±51	**21.3±0.4**	24.1±0.1	**26.8±0.7**	**29.0±0.7**
Improvement	-	3.2%	0.3%	7.4%	1.5%	1.2%	2.7%	-	0.9%	-	6.0%	7.1%



Globe



State



County

Wang, et al., AAAI 2022

Questions

- Can we apply recurrent neural networks to capture long-term patterns in epidemic forecasting?
- How to leverage graph neural networks to learn spatial and temporal signals for spatiotemporal epidemic forecasting?
- How to leverage theory-based mechanistic models to provide epidemiological context for deep learning-based epidemic forecasting?
- How to improve the robustness of forecasting systems?

Ensemble-based Epidemic Forecasting

- Challenge: lack of robustness in different methods for forecasting at high resolution
- Ensembling different methods for a robust performance along the pandemic

Our methods:
Clustering-based Training
Bayesian Ensemble

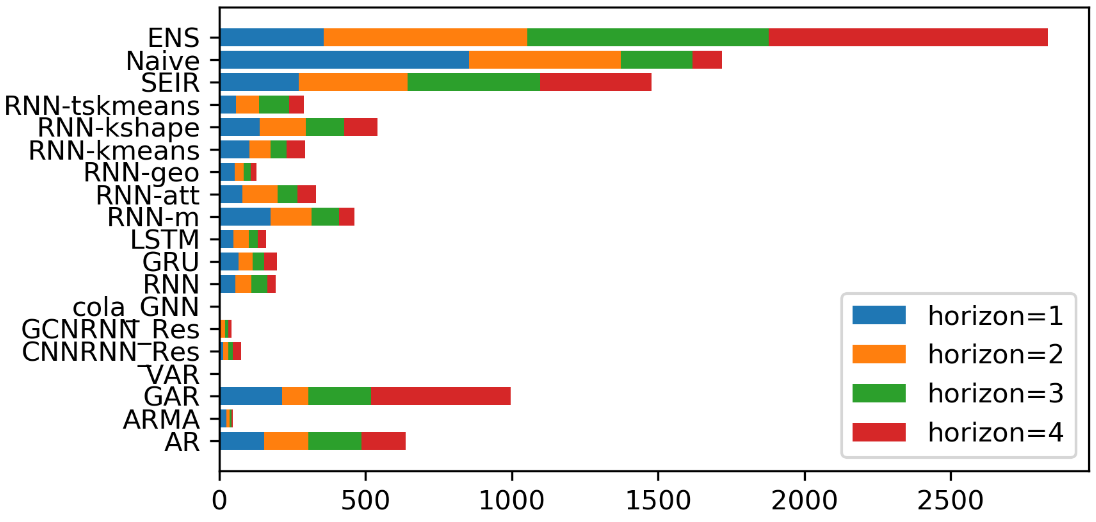
Related publications:
L. Wang, et al., "Examining Deep Learning Models with Multiple Data Sources for COVID-19 Forecasting", IEEE BigData DSMH 2020.
Adiga**, L. Wang**, et al., "All Models Are Useful: Bayesian Ensembling for Robust High Resolution COVID-19 Forecasting", *SIGKDD 2021*.
A. Adiga**,** et al., "Enhancing COVID-19 Ensemble Forecasting Model Performance Using Auxiliary Data Sources", *IEEE BigData 2022*. Best paper.

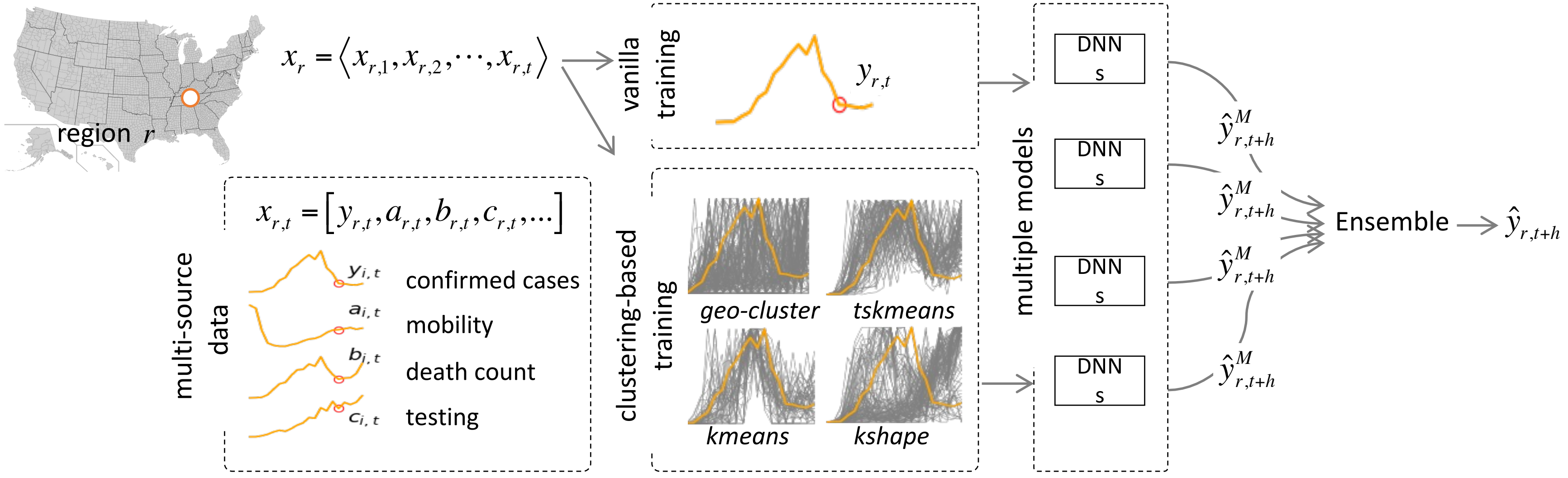
COVID-19 Forecasting Efforts

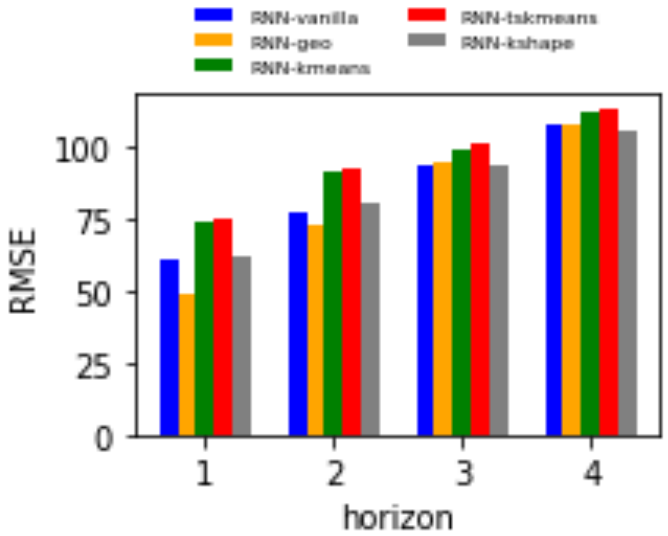
- Challenges in real-time forecasting of COVID-19 dynamics
  - There is no sufficient historical data
  - Forecast at finer spatial resolution
  - Higher noise due to lower population counts
  - Lack of exogenous observables such as mobility or testing rates at equivalent resolution
  - Greater level of connectivity across regions leading to interdependence
  - Reporting errors, back-filled cases may lead to uncharacteristic spikes not necessarily reflecting the state of the pandemic

Multi-source Ensemble

- Clustering-based training
- Stack ensemble





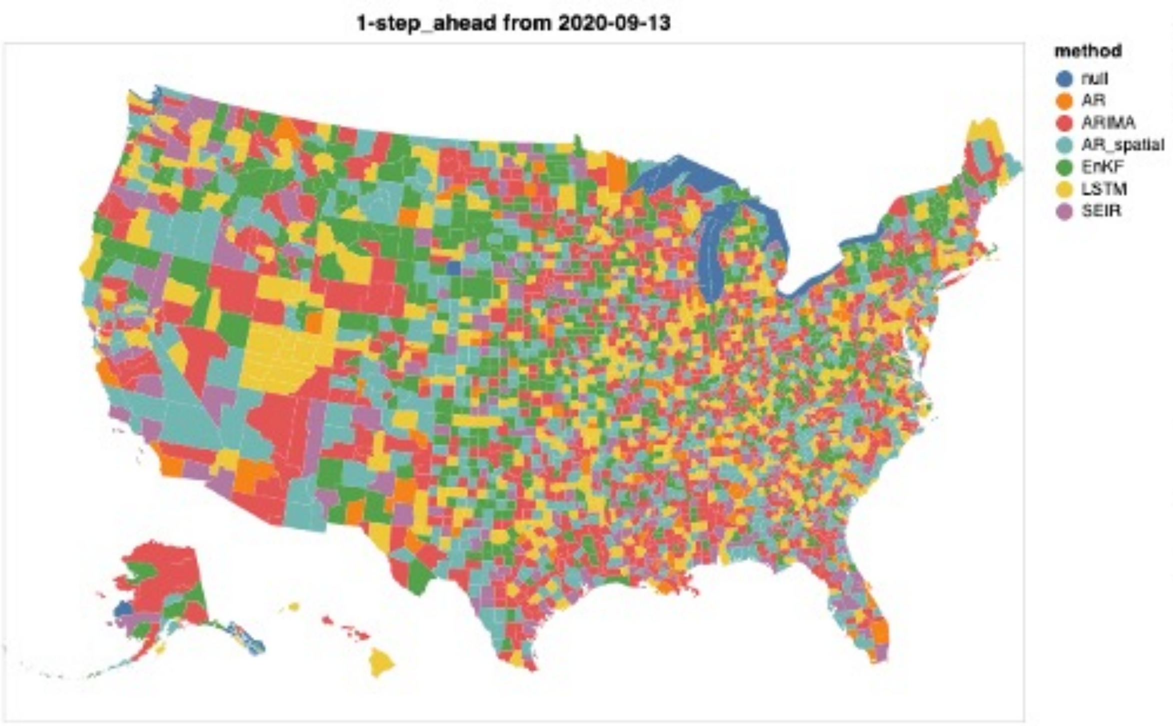


Wang, et al., IEEE BigData Workshop 2020

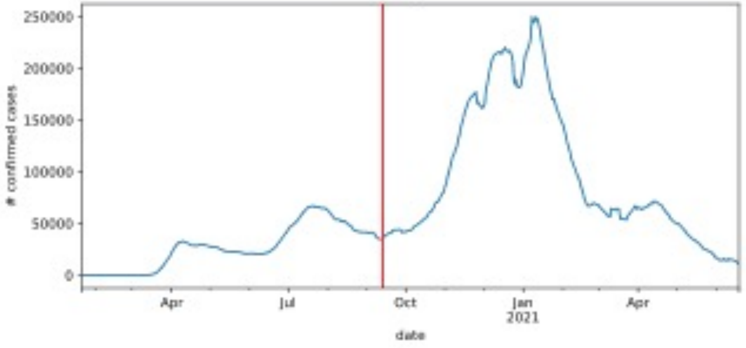
"All Models are Useful"- BMA Ensemble

Dashboard: http://covid19-forecast.uvadcos.io/

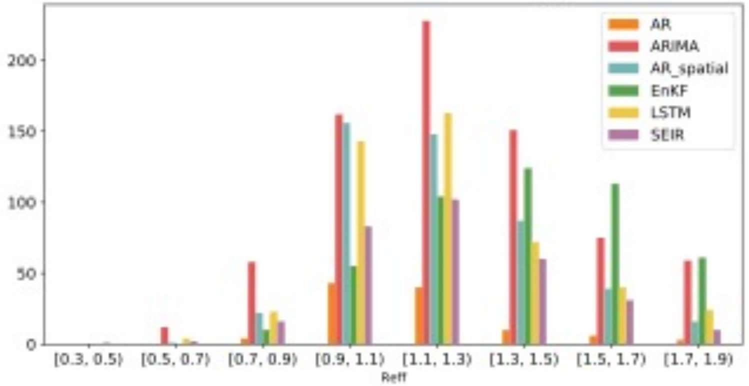
County map with colors indicating dominant method



Pandemic phase



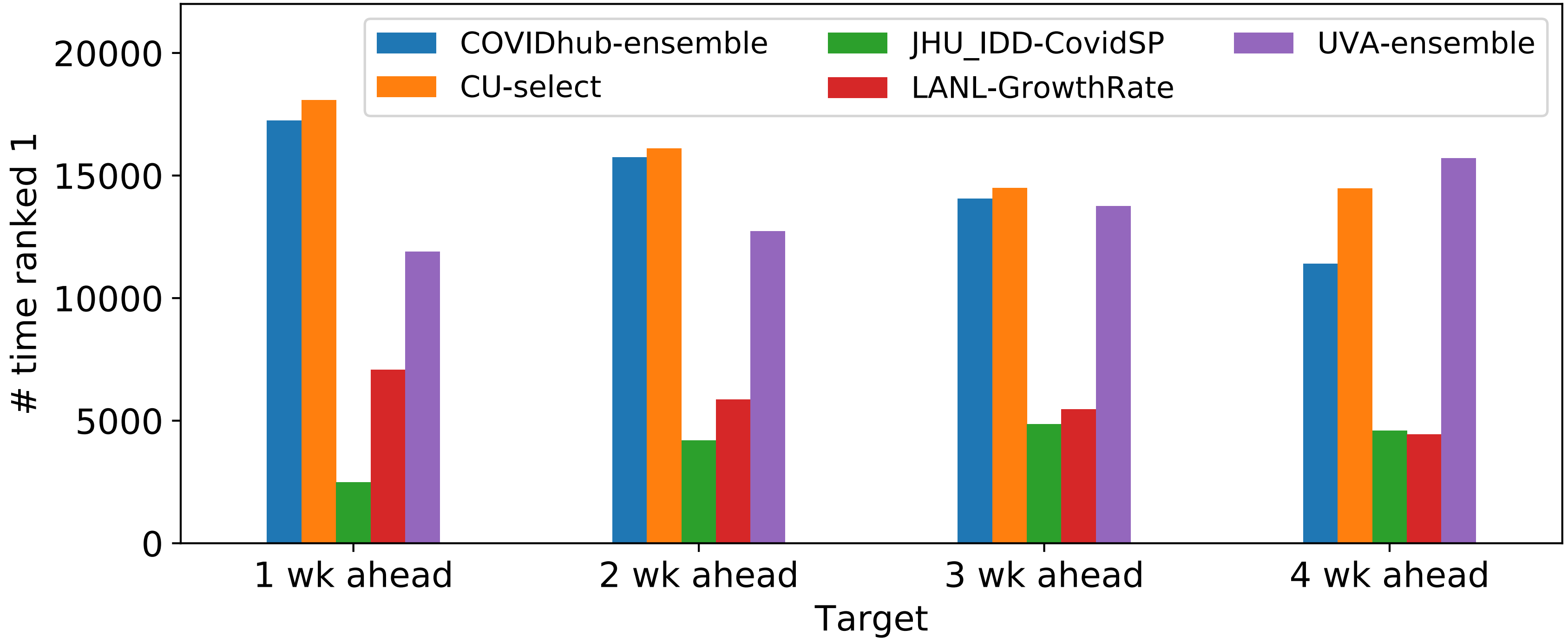
Counties binned by R_{eff}



- Plateau phase: Significant number of counties showing $0.9 < R_{eff} < 1.1$
- Mostly dominated by purely data-driven methods

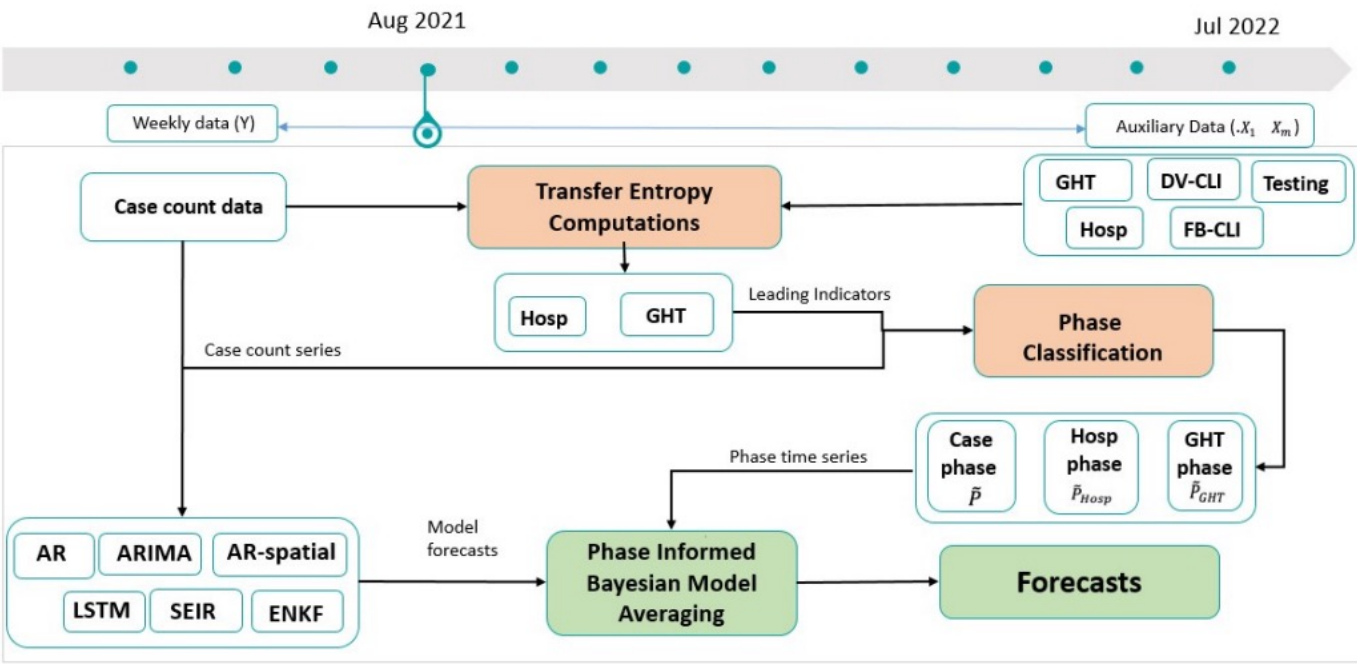
Adiga, et al., SIGKDD 2021

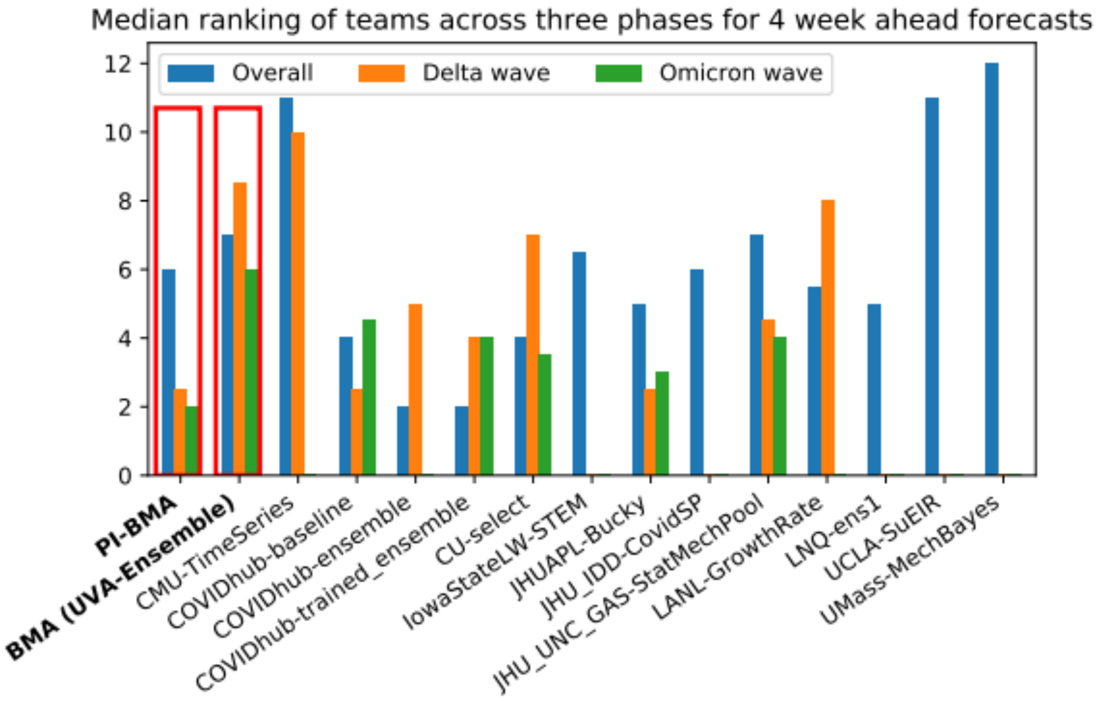
“All Models are Useful”- BMA Ensemble



Ranking of teams based on Mean WIS scores: the plot indicates the number of locations across all weeks a given model was the best.

Phase Informed BMA





Adiga, et al., IEEE BigData 2022. Best paper.

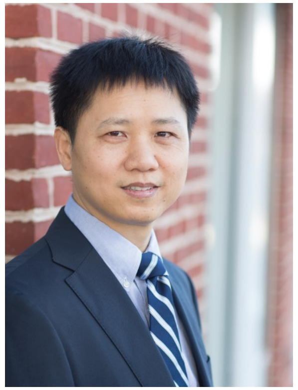
Applications

- CDC FluSight
  - Seasonal influenza forecasting challenge
  - Since 2018
- CDC COVID ForecastHub
  - COVID 19 forecasting challenge
  - Since 2020
- Biocomplexity Forecast Dashboard
  - UVA forecasting team weekly brief to VDH
  - Since 2020

Major Takeaways

- Models in research
  - LSTM, GNN can be applied for epidemic forecasting
  - Combining theory and deep learning models for explainable predictions
- Techniques in real applications
  - MCDropout for probabilistic forecasting
  - Clustering-based training for epidemics with sparse and noisy data
  - Ensembling of multiple methods for improving the robustness of forecasting systems

Many Thanks



Jiangzhuo Chen
UVA (Advisor)

Madhav Marathe
UVA (Advisor)

Aniruddha Adiga
UVA

Bryan Lewis
UVA

Srinivasan Venkatramanan
UVA

Adam Sadilek
CEO of AIM | Google[x]

Many more whose names are not listed here!

Thank You

Welcome to any discussions!

Please feel free to contact me:

Lijing Wang, PhD
Lijing.wang@njit.edu