EpiGNN: Exploring Spatial Transmission with Graph Neural Network for Regional Epidemic Forecasting.

The European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases

Feng Xie, Zhong Zhang, Liang Li, Bin Zhou*, Yusong Tan

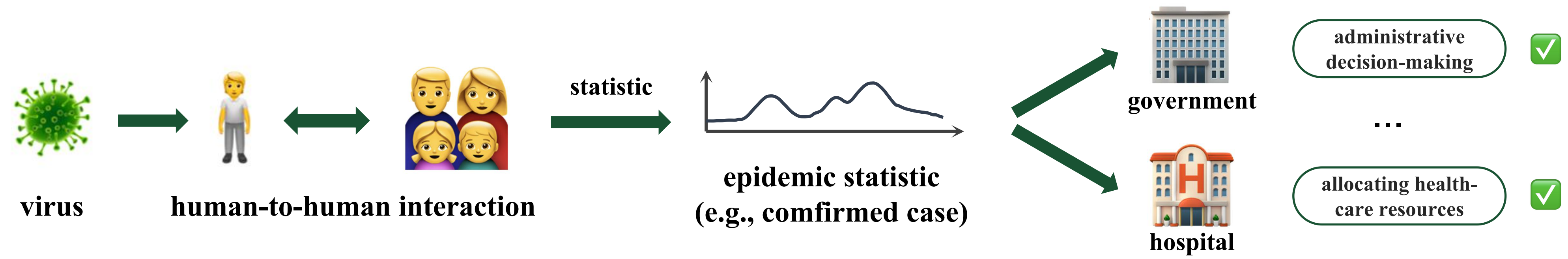
National University of Defense Technology, Hunan, China
Department of Computer Science and Technology
xiefeng@nudt.edu.cn

ECML PKDD 2022

Springer

Outline

Background & Motivations



Epidemics spread through human-to-human interaction and circulate worldwide, seriously endangering public health.

- **Seasonal influenza**: The World Health Organization (WHO) estimates that seasonal influenza annually causes approximately 3-5 million severe cases and 290,000-650,000 deaths [1].
- **Other epidemics**: In recent years, the COVID-19 has spread to more than 200 countries and territories around the world [2].

✓ Accurate Epidemiological Forecasting:

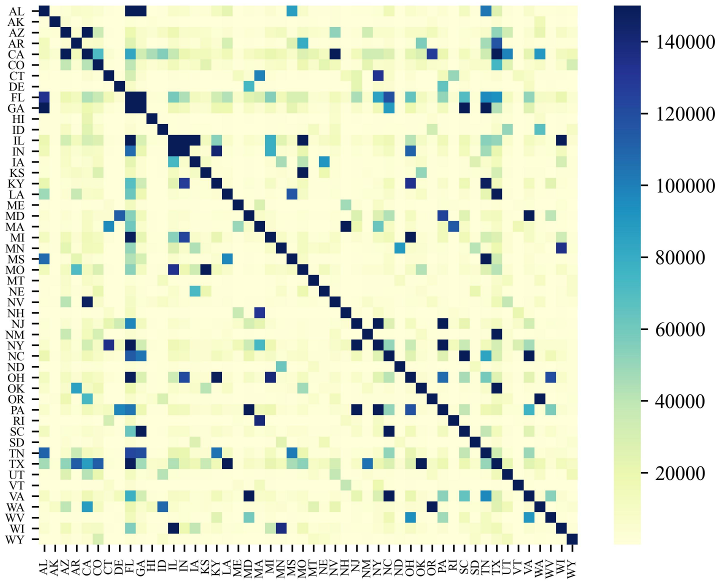
- provides opportunities for driving **administrative decision-making** and,
- timely **allocating healthcare resources**.
- helps with **drug research** (i.e., vaccines) which leads to reduce financial burdens and deaths.

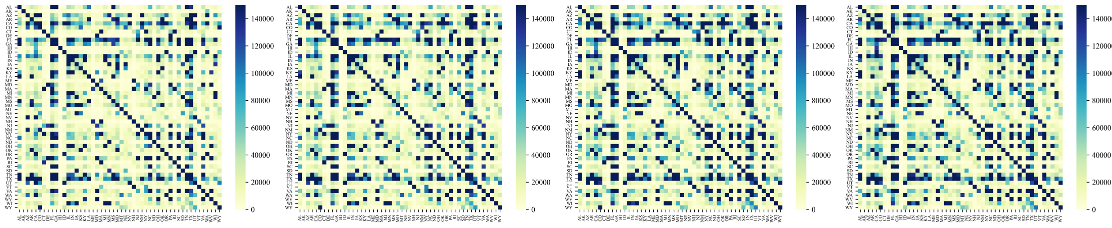
Background & Motivations

Main characteristics of this task

- The inherent difficulty of **long-term forecasting**
- Nonlinear **temporal dependencies** (e.g., seasonal influenza in Fig.1)
- dynamic **inter-dependencies between regions** (e.g., human mobility in Fig.2)

2020/5/05 - 2020/6/01





5/05-5/11 5/12-5/18 5/19-5/25 5/26-6/01

Figure 2. The overall of human mobility flow between different states within Covid-19 period in US (2020).

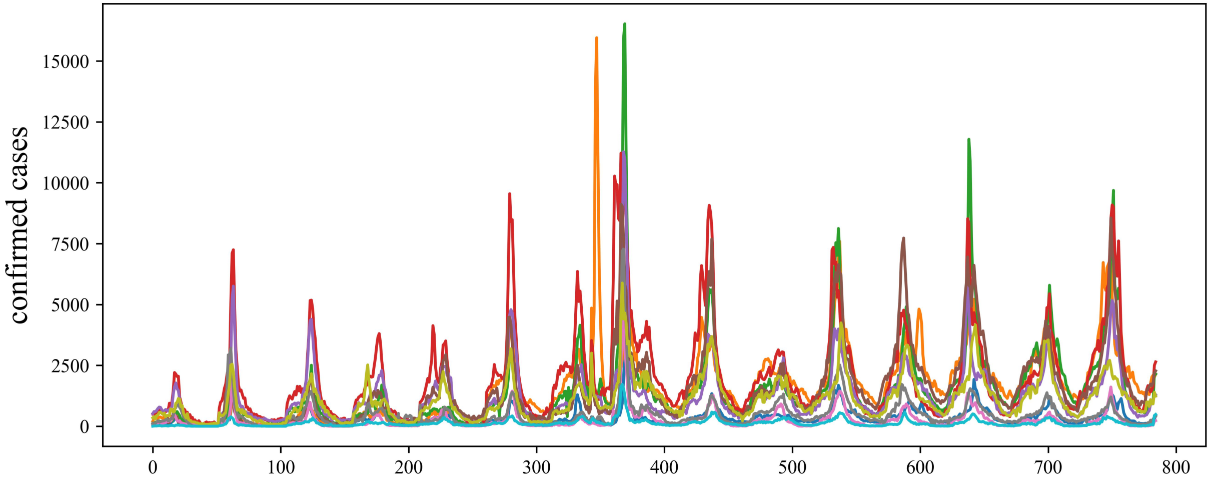


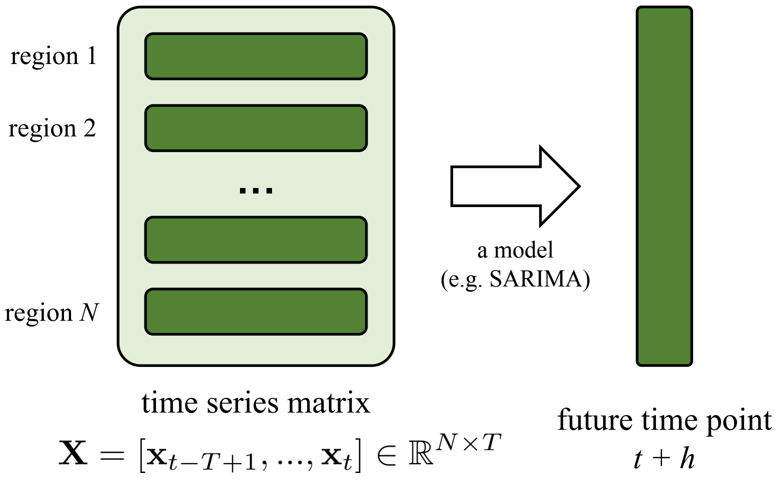
Figure 1. The overall of the flu statistic of US HHS regions.

Background & Motivations

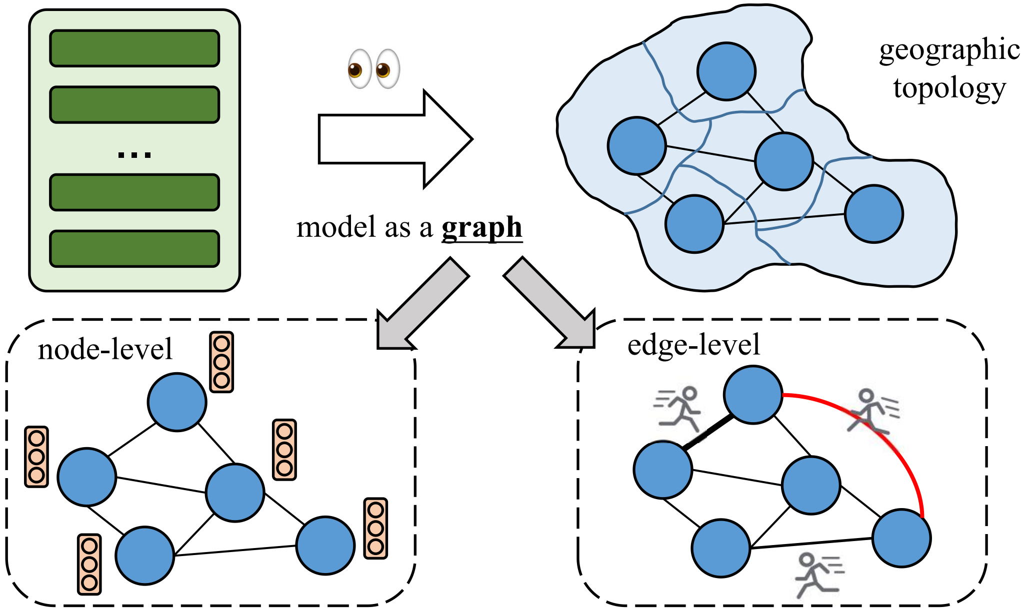
Exsiting Methods

- **Statistic Methods**: AR, ARIMA, SARIMA.
- **Compartment Methods**: SIR, SEIR, SEUIR.
- **Deep Learning-based Methods**: CNNRNN-Res, Cola-GNN, MPNN, SMART, etc.

◆ *Traditional methods*



◆ *GNN-based methods*



Background & Motivations

1. Spatio-Temporal Graph Construction

- **Explicit graph structures** (e.g., geographic topology):
  - does not necessarily reflect the true dependencies.
  - hard to capture hidden correlations.
- **Using external data** (e.g., human mobility):
  - data availability, data accuracy, and data privacy
- **Graph learning methods** (e.g., self-attention):
  - oversmoothing
  - noise propagation

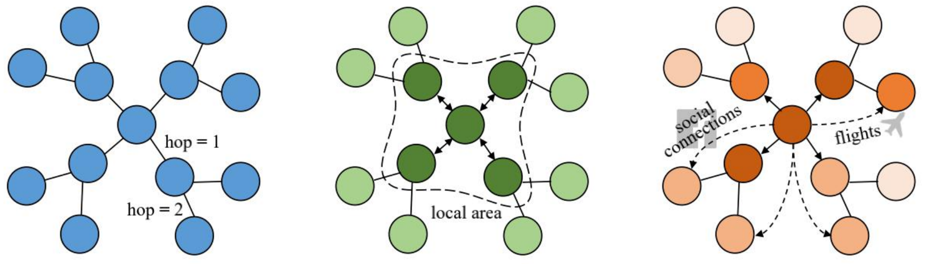
➢ Capturing underlying transmission dependencies between regions reasonably and accurately.

➢ the method should flexibly support both scenarios when rich external information can be collected or not.

2. Spatial Transmission Risk: implies a potential ability that the epidemic in one region impacts other regions from a spatial perspective.

the epidemic in one region has not only local effects but also spillover effects across regions through complicated social connections [3]

- **Local Transmission Risk:** geographically adjacent
- **Global Tansmission Risk:** complex social connections



(a) Geographic topology. (b) Local transmission effects. (c) Global transmission effects.

Fig. 1. The illustration of geographic topology, local and global spatial transmission effects, where nodes represent regions and edges represent the relationships.

Problem Formulation (Fig.1)

- ***N* regions.** We have a total of N regions (i.e., states or cities). Each region is associated with a time series for a window T.

$$\mathbf{x}_{i:} = [x_{i,t-T+1}, \dots, x_{i,t}] \in \mathbb{R}^T$$

- **Input.** Epidemic statistic with a look-back window T at time point t.

$$\mathbf{X} = [\mathbf{x}_{t-T+1}, \dots, \mathbf{x}_t] \in \mathbb{R}^{N \times T}$$

- **Goal.** The goal of this task is to predict the epidemic statistic of the future time point $t + h$.

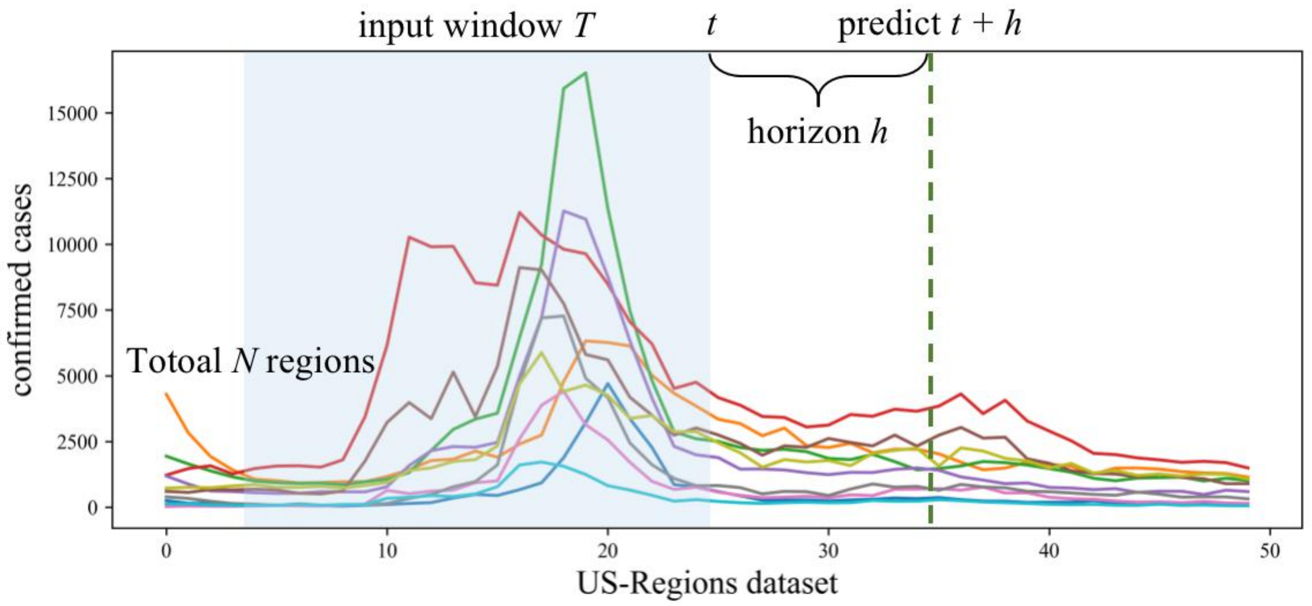
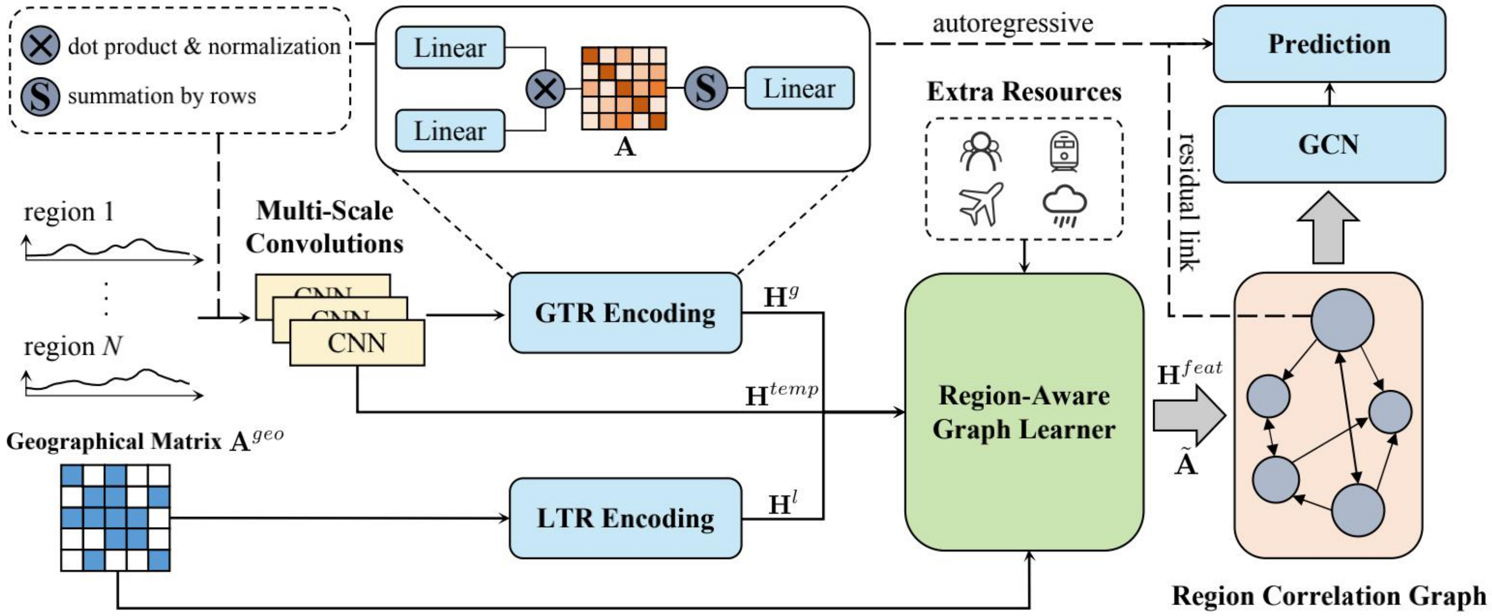


Figure 1. The illustration of problem formulation.

Methodology
Overall

- We design a novel graph neural network-based model for epidemic prediction in which a **transmission risk encoding module** is proposed that shows how we incorporate local and global spatial effects of regions into the model.

- We introduce a **Region-Aware Graph Learner** which takes transmission risk, geographical information, and temporal dependencies into account to better explore underlying spatio-temporal correlations between regions.

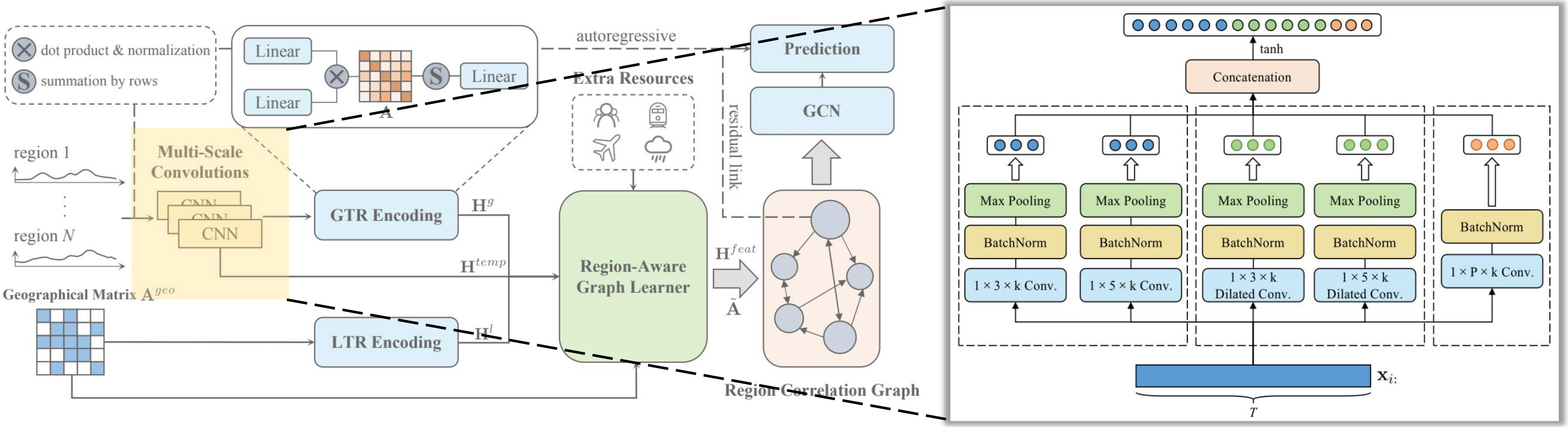


Methodology

Encoder: Multi-Scale Convolutions

Previous works [4,5] suggest that using a set of multi-scale convolutions can capture complex temporal patterns simultaneously. Therefore, in this work, we also adopt multi-scale convolutions with different filter sizes and dilated factors as a feature extractor.

$$\mathbf{x}_{i:} \star \mathbf{f}_{1\times s,d}(j) = \sum_{i=0}^{s-1} \mathbf{f}_{1\times k}(i)\mathbf{x}(j - d \times i),$$



Methodology

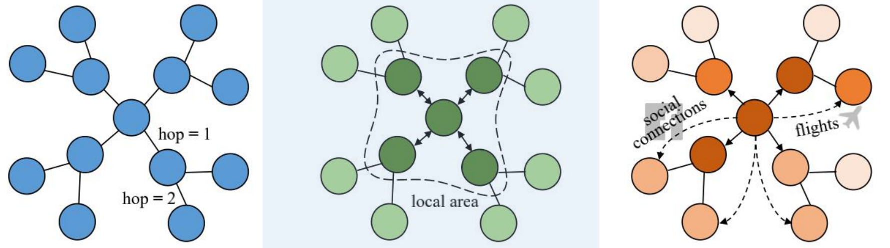
Transmission Risk Encoding Module

Local Transmission Risk (LTR) Encoding

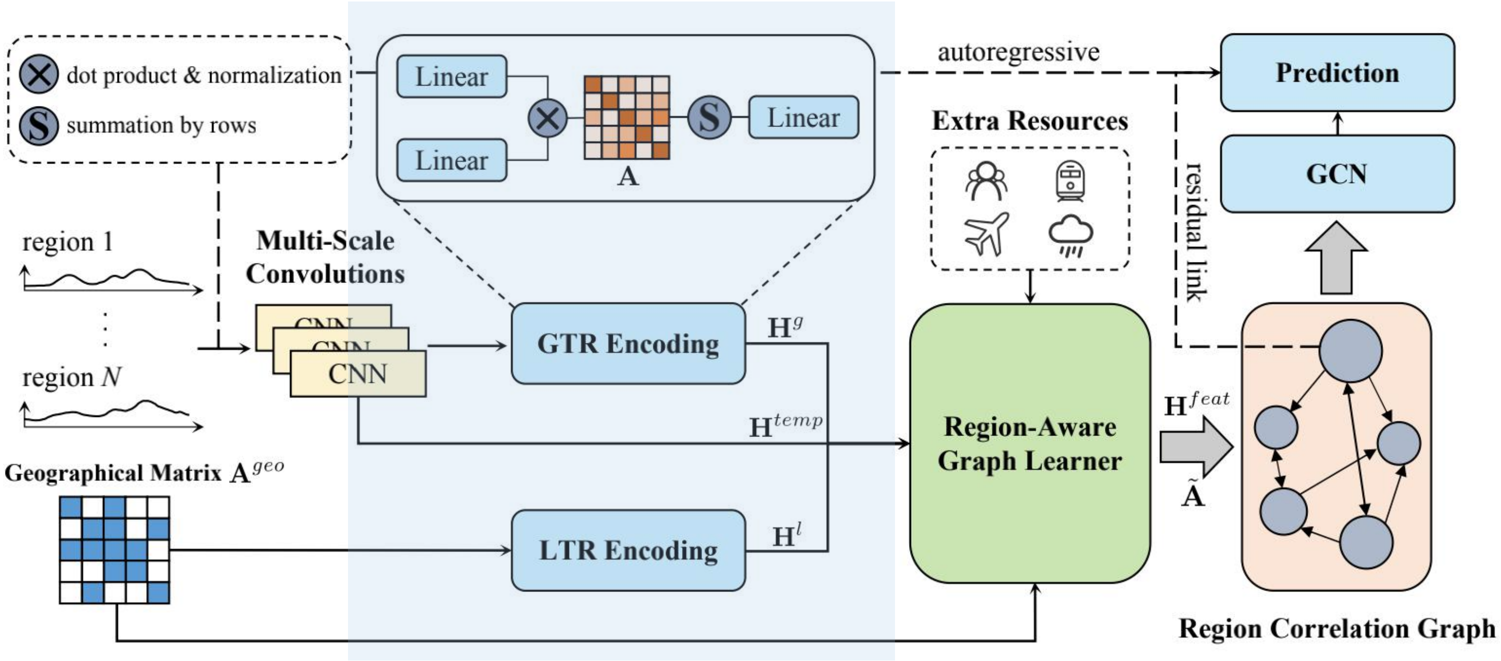
- The proximity between regions will lead to a rapid increase in the mobility of internal elements between regions (e.g., human mobility), which will exacerbate local transmission risk.

the degree of region i

$$\mathbf{h}_i^l = \mathbf{W}^l \cdot d_i + \mathbf{b}^l,$$



(a) Geographic topology. (b) Local transmission effects. (c) Global transmission effects.



Global Transmission Risk (GTR) Encoding

- Due to the complicated social connections, there are also potential correlations between disjoint regions.

attention

$$\left\{\begin{aligned} &\mathbf{A} = (\mathbf{H}^{temp}\mathbf{W}^q)(\mathbf{H}^{temp}\mathbf{W}^k)^T, \\ &a_{i,j} = \frac{a_{i,j}}{\max(\|\mathbf{a}_{i:}\|_2, \epsilon)}, \end{aligned}\right.$$

$$g_i = \sum_j a_{ij},$$

$$\mathbf{h}_i^g = \mathbf{W}^g \cdot g_i + \mathbf{b}^g,$$

Methodology

Region-Aware Graph Learner

We design a **Region-Aware Graph Learner (RAGL)**, which considers both temporal and spatial information to generate a region correlation graph, where nodes correspond to regions, and edge weights correspond to the correlations between regions.

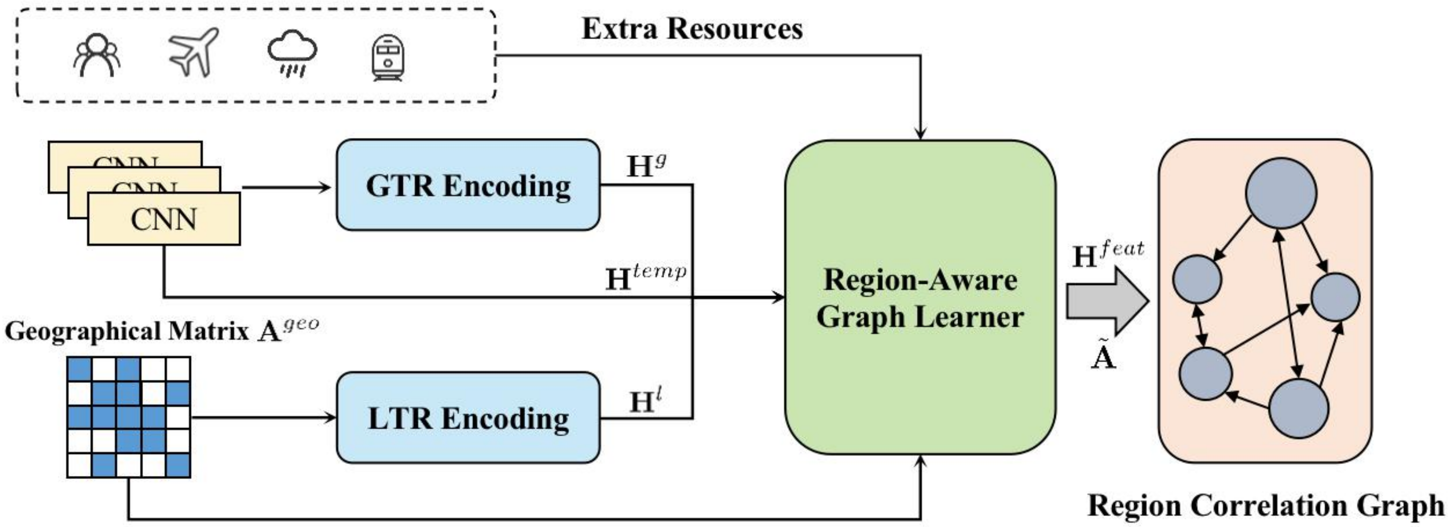


Fig. The input and output of RAGL

Temporal Correlation

$$\mathbf{M}_1 = \tanh(\mathbf{H}^{temp}\mathbf{W}_1 + \mathbf{b}_1), \quad \mathbf{M}_2 = \tanh(\mathbf{H}^{temp}\mathbf{W}_2 + \mathbf{b}_2),$$

$$\hat{\mathbf{A}} = \mathrm{ReLU}(\tanh(\mathbf{M}_1\mathbf{M}_2^T - \mathbf{M}_2\mathbf{M}_1^T)),$$

Spatial Correlation

$$\mathbf{D}^s = \mathrm{sigmoid}(\mathbf{W}^s \circ \mathbf{d}\mathbf{d}^T),$$

As a gate

$$\tilde{\mathbf{A}} = \mathbf{D}^s \circ \mathbf{A}^{geo} + \hat{\mathbf{A}},$$

External resources

$$\mathbf{A}^e = \mathbf{W}^e \circ \sum_{i=0}^{e-1} \mathbf{E}_{t-e},$$

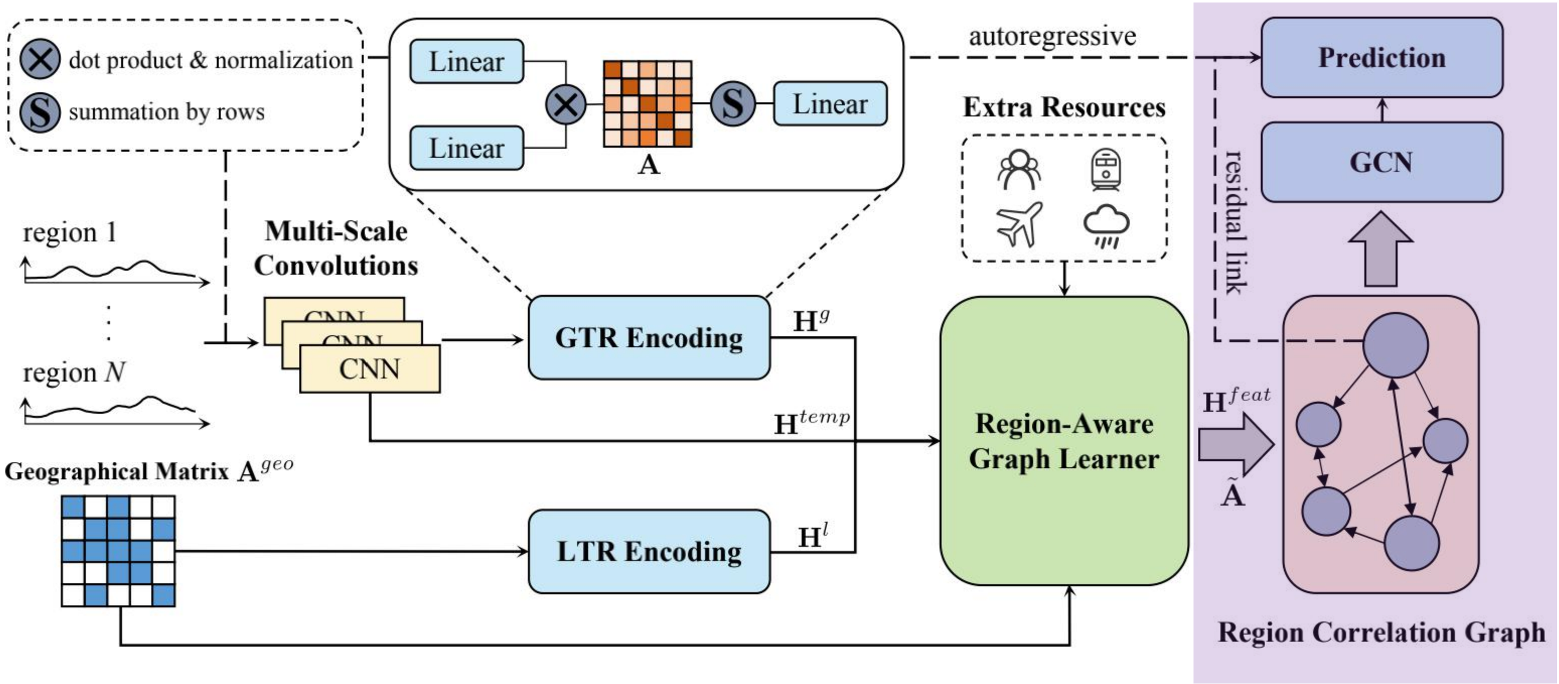
Methodology

Graph Convolution Network and Final Prediction

In this work, we apply GCN [6] to investigate the epidemic propagation among different regions. We apply the following **yellow box** to update node representations.

- **Linear Part**. Some works have incorporated a linear part to deal with the sensitivity to input and purely nonlinear modeling [7,8].
- **Nonlinear Part**. Neural networks are dedicated to handling the nonlinear characteristics of raw time series.

The final prediction of EpiGNN is obtained by summing the nonlinear part and the linear part got by an **AutoRegressive component**.



GCN

$$\mathbf{h}_i^{feat} = \mathbf{h}_i^{temp} + \mathbf{h}_i^{l} + \mathbf{h}_i^{g}.$$

$$\mathbf{H}^{(l)} = \sigma(\tilde{\mathbf{D}}^{-1}\tilde{\mathbf{A}}\mathbf{H}^{(l-1)}\mathbf{W}^{(l-1)}),$$

Final prediction

$$\hat{y}^l_{i,t+h} = \sum_{m=0}^{q-1} \mathbf{W}^{ar}_m x_{i,t-m} + b^{ar},$$

$$\hat{\mathbf{y}}^n_{t+h} = [\mathbf{H}^{(0)}; \mathbf{H}^{(l)}]\mathbf{W}_n + \mathbf{b}_n,$$

$$\hat{\mathbf{y}}_{t+h} = \hat{\mathbf{y}}^l_{t+h} + \hat{\mathbf{y}}^n_{t+h}.$$

Experimental Settings

➢ Datasets

We prepare five real-world epidemic-related datasets as follows, and their data statistics are shown in Table 1.

- **Influenza statistics datasets:**
  - **Japan-Prefectures**
  - **US-Regions**
  - **US-States**

  from Cola-GNN
- **COVID-19 statistics datasets:**
  - **Australia-COVID**
  - **Spain-COVID**

  from JHU-CSSE

Table 1. Statistics of datasets, where SD is standard deviation and granularity means the frequency of epidemic surveillance records.

Datasets	Regions	Length	Min	Max	Mean	SD	Granularity
Japan-Prefectures	47	348	0	26635	655	1711	weekly
US-Regions	10	785	0	16526	1009	1351	weekly
US-States	49	360	0	9716	223	428	weekly
Australia-COVID	8	556	0	9987	539	1532	daily
Spain-COVID	35	122	0	4623	38	269	daily

➢ Baselines

We compared the proposed model with the following methods.

- Statistic models: **HA, AR**.
- Deep Learning-based models:
  - **LSTM** [9]
  - **TPA-LSTM** [ECMLPKDD2019] [8]
  - **ST-GCN** [IJCAI18] [10]
  - **CNNRNN-Res** [SIGIR2018] [11]
  - **SAIFlu-Net** [JBHI2021] [12]
  - **Cola-GNN** [CIKM2020] [4]

➢ Metrics

- **RMSE** $$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$$
- **PCC** $$PCC = \frac{\sum_{i=1}^{N}(\hat{y}_i - \overline{\hat{y}})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{N}(\hat{y}_i - \overline{\hat{y}})^2}\sqrt{\sum_{i=1}^{N}(y_i - \overline{y})^2}}$$

For RMSE lower value is better, while for PCC higher value is better

Experimental Results

We evaluate our model in **short-term** (horizon < 10) and **long term** (horizon >=10) settings.

Our method (EpiGNN) achieves the most stable and optimal performance on all datasets.

Table 3. RMSE performance of different methods on two COVID-19 datasets with horizon = 3, 7, 14. Bold face indicates the best result of each column and underlined the second-best. - means the forecasting results are not available.

Dataset	Spain-COVID			Australia-COVID		
	Horizon			Horizon		
Methods	3	7	14	3	7	14
HA	167.20	189.90	214.19	2948.48	2777.37	2589.61
AR	165.07	179.51	203.13	85.21	237.73	309.03
LSTM	152.79	177.27	184.44	181.97	315.85	338.34
TPA-LSTM	150.74	183.52	227.95	180.14	220.82	462.78
ST-GCN	162.81	186.21	190.13	253.97	443.01	485.12
CNNRNN-Res	163.75	208.85	219.65	210.23	416.90	488.01
SAIFlu-Net	158.06	200.63	229.62	133.85	277.90	351.14
Cola-GNN	138.34	176.52	203.67	127.59	279.56	326.79
EpiGNN	135.54	162.51	186.41	**71.42**	**153.07**	**287.90**
EpiGNN_{exter}	**129.90**	**145.33**	**178.73**	-	-	-

Table 2. RMSE and PCC performance of different methods on three datasets with horizon = 3, 5, 10, 15. Bold face indicates the best result of each column and underlined the second-best. ∗ represents that the result is reported in the corresponding reference.

Dataset		Japan-Prefectures				US-Regions				US-States			
		Horizon				Horizon				Horizon			
Methods	Metric	3	5	10	15	3	5	10	15	3	5	10	15
HA	RMSE	2129	2180	2230	2242	2552	2653	2891	2992	360	371	392	403
	PCC	0.607	0.475	0.493	0.534	0.845	0.727	0.514	0.415	0.893	0.848	0.772	0.742
AR	RMSE	1705	2013	2107	2042	757	997	1330	1404	204	251	306	327
	PCC	0.579	0.310	0.238	0.483	0.878	0.792	0.612	0.527	0.909	0.863	0.773	0.723
LSTM	RMSE	1246	1335	1622	1649	688	975	1351	1477	180	213	276	307
	PCC	0.873	0.853	0.681	0.695	0.895	0.812	0.586	0.488	0.922	0.889	0.820	0.771
TPA-LSTM	RMSE	1142	1192	1677	1579	761	950	1388	1321	203	247	236	247
	PCC	0.879	0.868	0.644	0.724	0.847	0.814	0.675	0.627	0.892	0.833	0.849	0.844
ST-GCN	RMSE	1115	1129	1541	1527	807	1038	1290	1286	209	256	289	292
	PCC	0.880	0.872	0.735	**0.773**	0.840	0.741	0.644	0.619	0.778	0.823	0.769	0.774
CNNRNN-Res	RMSE	1550	1942	1865	1862	738	936	1233	1285	239	267	260	250
	PCC	0.673	0.380	0.438	0.467	0.862	0.782	0.552	0.485	0.860	0.822	0.820	0.847
SAIFlu-Net	RMSE	1356	1430	1654	1707	661	870	1157	1215	167	195	236	238
	PCC	0.765	0.654	0.585	0.556	0.885	0.800	0.674	0.564	0.930	0.900	0.853	0.852
Cola-GNN*	RMSE	1051	1117	**1372**	1475	636	855	1134	1203	167	202	241	237
	PCC	0.901	0.890	**0.813**	0.753	0.909	0.835	0.717	0.639	0.933	0.897	0.822	0.856
EpiGNN	RMSE	**996**	**1031**	1441	**1470**	**589**	**774**	**984**	**1061**	**160**	**186**	**220**	**236**
	PCC	**0.904**	**0.908**	0.739	**0.773**	**0.912**	**0.842**	**0.749**	**0.694**	**0.935**	**0.907**	**0.865**	**0.861**

Experimental Results

- ablation study

- **w/oLTR** stands for EpiGNN without local transmission risk encoding.
- **w/oGTR** represents EpiGNN without global transmission risk encoding.
- **w/oRAGL** indicates EpiGNN using self-attention [13] to capture dependencies between regions instead of Region-Aware Graph Learner (i.e., applying $\tilde{\mathbf{A}} = \mathrm{softmax}((\mathbf{H}^{feat}\mathbf{W}_1)(\mathbf{H}^{feat}\mathbf{W}_2)^T)$).

We quantitatively show that the complete EpiGNN can yield the most stable and optimal performance compared to other incomplete models.

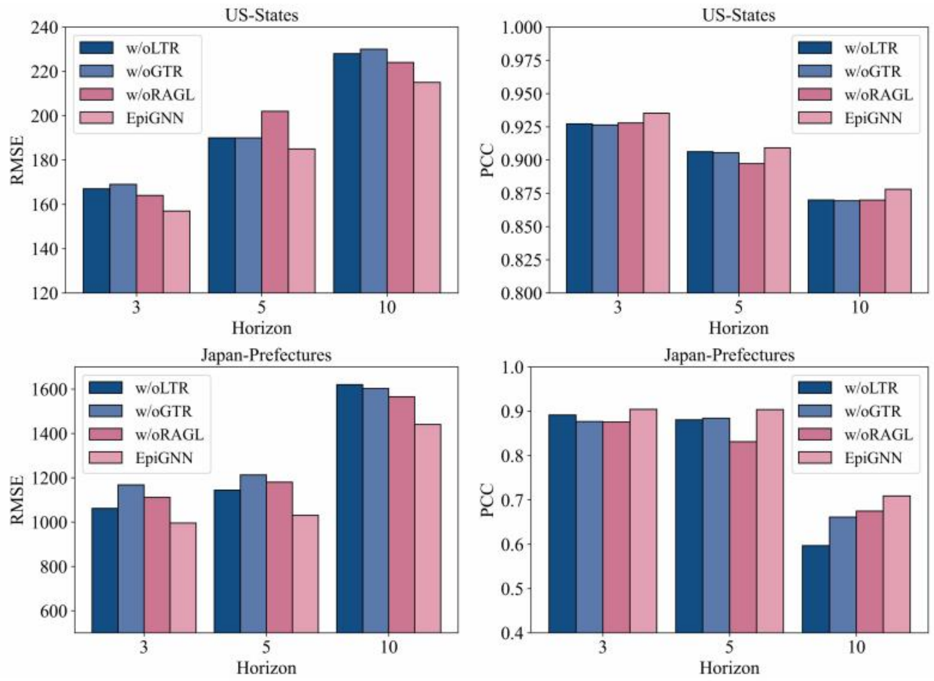
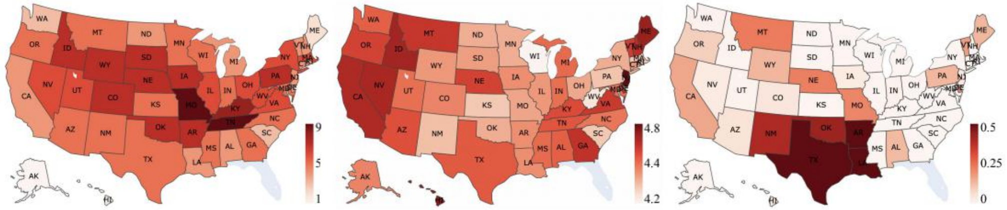


Fig. 3. Results of ablation studies on US-States (top) and Japan-Prefectures (bottom) datasets. For RMSE lower value is better, while for PCC higher value is better.

Experimental Results

We visualize an example with window=(2016/46th-2017/13th) and horizon=5 (week) in US-States dataset.

- Texas does not have dependencies with all states. Nevertheless, Texas has relatively significant dependencies with its adjacent regions and also has relationships with some non-adjacent regions.



(a) The distribution of degrees. (b) The distribution of global correlation coefficients. (c) The distribution of correlations between Texas and other states.

Fig. 5. Visualization of intermediate results.

TX's adjacent states

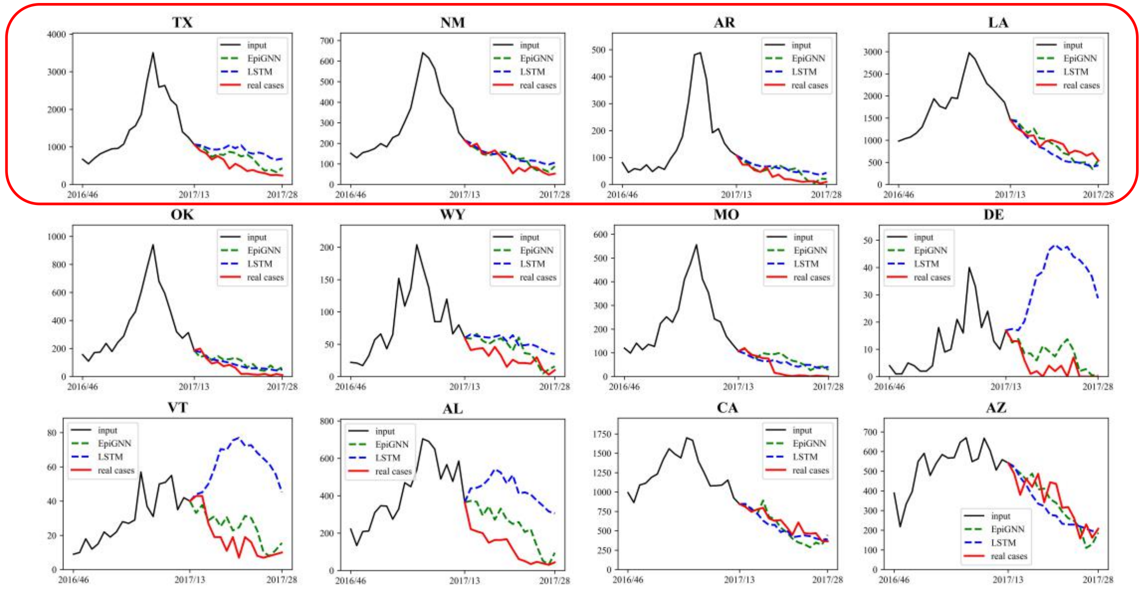


Fig. 6. Predicted curve of EpiGNN (green) and LSTM (blue) for selected states.

The predicted curve of EpiGNN and LSTM in Fig. 6:

We observe that EpiGNN fits the ground truth better, and some trends of fluctuation are also predicted better (e.g., WY/DE/VT), while LSTM yields quite inaccurate predictions in some states.

Conclusions

- In this paper, we develop EpiGNN, a novel model for epidemic prediction. In this model, we design a transmission risk encoding module to characterize local and global spatial effects of each region.
- Meanwhile, we propose a Region-Aware Graph Learner that takes transmission risk, geographical dependencies, and temporal information into account to better explore spatial-temporal dependencies.
- Experimental results show the effectiveness and efficiency of our method on five epidemic-related datasets.
- As for future work, we will devote to better predict by considering the time decay effects of spatial transmission.

EpiGNN: Exploring Spatial Transmission with Graph Neural Network for Regional Epidemic Forecasting

Feng Xie, Zhong Zhang, Liang Li, Bin Zhou(✉), and Yusong Tan

College of Computer, National University of Defense Technology
{xiefeng,zhangzhong,liliang98,binzhou,ystan}@nudt.edu.cn

Abstract. Epidemic forecasting is the key to effective control of epidemic transmission and helps the world mitigate the crisis that threatens public health. To better understand the transmission and evolution of epidemics, we propose EpiGNN, a graph neural network-based model for epidemic forecasting. Specifically, we design a transmission risk encoding module to characterize local and global spatial effects of regions in epidemic processes and incorporate them into the model. Meanwhile, we develop a Region-Aware Graph Learner (RAGL) that takes transmission risk, geographical dependencies, and temporal information into account to better explore spatial-temporal dependencies and makes regions aware of related regions' epidemic situations. The RAGL can also combine with external resources, such as human mobility, to further improve prediction performance. Comprehensive experiments on five real-world epidemic-related datasets (including influenza and COVID-19) demonstrate the effectiveness of our proposed method and show that EpiGNN outperforms state-of-the-art baselines by 9.48% in RMSE.

Keywords: Epidemic Forecasting · Graph Neural Network · Spatial Transmission Modeling · Public Health Informatics.

1 Introduction

Epidemics spread through human-to-human interaction and circulate worldwide, seriously endangering public health. The World Health Organization (WHO) estimates that seasonal influenza annually causes approximately 3–5 million severe cases and 290,000–650,000 deaths[1]. Recently, the coronavirus disease 2019 (COVID-19) has spread over more than 200 countries and territories[2], causing heavy human losses and economic burdens. Accurate prediction of epidemics is the key to effective control of epidemic transmission and plays an essential role in driving administrative decision-making, timely allocating healthcare resources, and helping with drug research.

✉ Corresponding author.
[1] https://www.who.int/en/news-room/fact-sheets/detail/influenza-(seasonal)
[2] https://covid19.who.int/

References

[1] https://www.who.int/en/news-room/fact-sheets/detail/influenza-(seasonal)
[2] https://covid19.who.int/
[3] Han, X., Xu, Y., Fan, L., Huang, Y., Xu, M., Gao, S.: Quantifying covid-19 im_x0002_portation risk in a dynamic network of domestic cities and international countries. Proceedings of the National Academy of Sciences (2021)
[4] Songgaojun Deng, Shusen Wang, Huzefa Rangwala, Lijing Wang, and Yue Ning. 2020. Cola-gnn: Cross-location attention based graph neural networks for long_x0002_term ili prediction. In Proc. of CIKM.
[5] Wu, Z., Pan, S., Long, G., Jiang, J., Zhang, C.: Graph wavenet for deep spatial_x0002_temporal graph modeling. arXiv preprint arXiv:1906.00121 (2019)
[6] Kipf, T.N., Welling, M.: Semi-supervised classification with graph convolutional networks. arXiv preprint arXiv:1609.02907 (2016)
[7] Guokun Lai, Wei-Cheng Chang, Yiming Yang, and Hanxiao Liu. 2018. Modeling long-and short-term temporal patterns with deep neural networks. In Proc. of SIGIR.
[8] Shun-Yao Shih, Fan-Keng Sun, and Hung-yi Lee. 2019. Temporal pattern attention for multivariate time series forecasting. Machine Learning (2019).
[9] Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural computation (1997).
[10] Yu, B., Yin, H., Zhu, Z.: Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting. arXiv preprint arXiv:1709.04875 (2017)
[11] Yuexin Wu, Yiming Yang, Hiroshi Nishiura, and Masaya Saitoh. 2018. Deep learning for epidemiological predictions. In Proc. of SIGIR.
[12] Seungwon Jung, Jaeuk Moon, Sungwoo Park, and Eenjun Hwang. 2021. Self-attention-based Deep Learning Network for Regional Influenza Forecasting. IEEE Journal of Biomedical and Health Informatics (2021).
[13] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, L., Polosukhin, I.: Attention is all you need. Proc. of NeurIPS (2017)

Thanks for your attention!

For more information, please refer to our paper and source codes:

paper: https://2022.ecmlpkdd.org/wp-content/uploads/2022/09/sub_829.pdf
source codes: https://github.com/Xiefeng69/EpiGNN
homepage: https://xiefeng69.github.io/

ACKNOWLEDGMENTS: This work is supported by the Key R&D Program of Guangdong Province No.2019B010136003 and the National Natural Science Foundation of China No. 62172428, 61732004, 61732022.