香港浸會大學 HONG KONG BAPTIST UNIVERSITY | DEPARTMENT OF COMPUTER SCIENCE 計算機科學系 | 35 YEARS OF EXCELLENCE

Epidemiology-aware Deep Learning for Infectious Disease Dynamics Prediction

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1. Target and Motivations

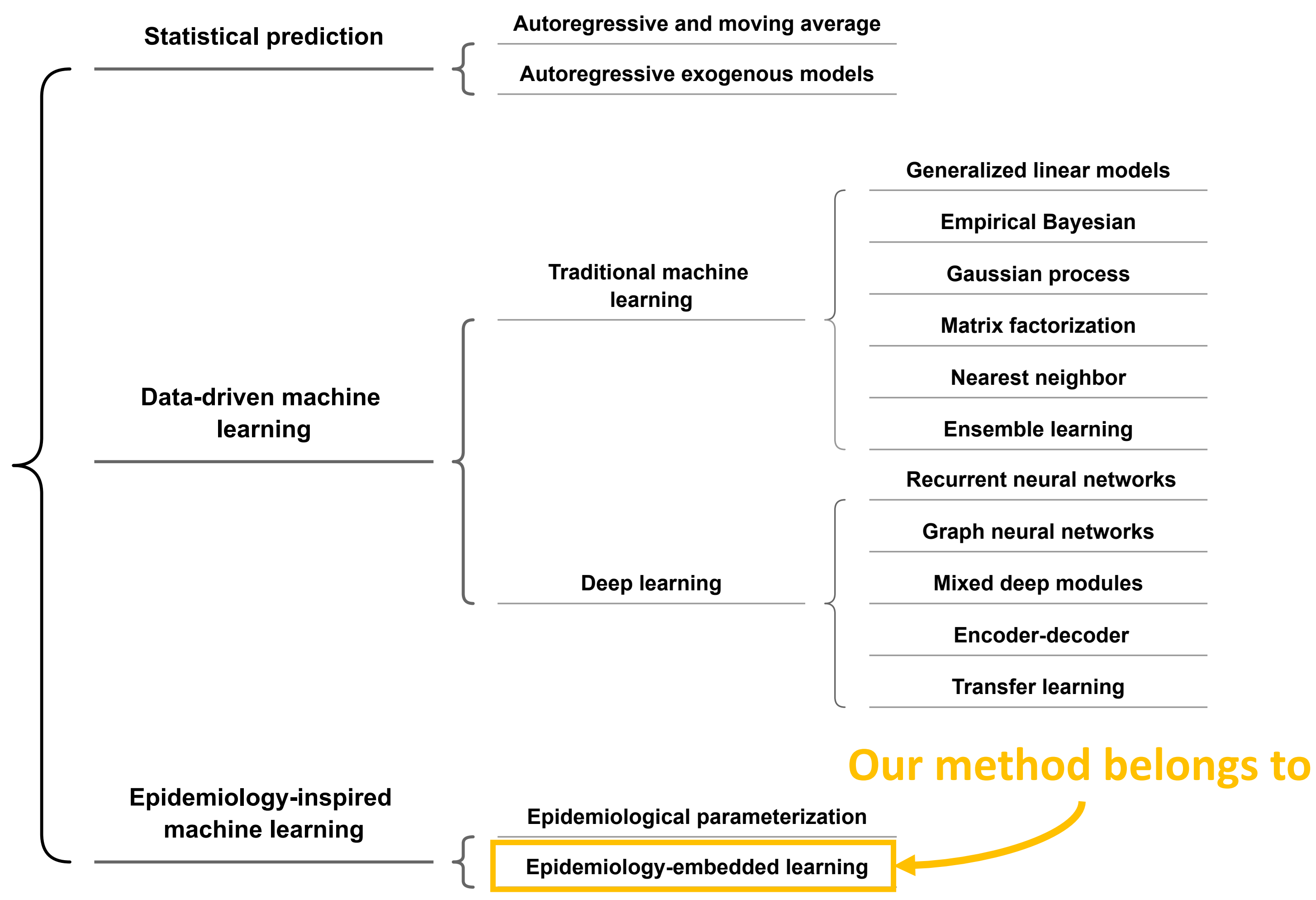
Target:

Integrating the epidemiological component into the deep learning architecture with spatial and temporal modules to enhance the performance of epidemic prediction.

Motivations:

1. Currently, most epidemiology-embedded learning methods only combine with the epidemiological model for a single location rather than considering the cross-regional disease transmission bought by human mobility.
2. In addition to infected information, most of them need to be given more information, such as the susceptible and recovered case number, to calibrate the epidemiological parameters or optimize the loss function.

2. A Big Picture of Methods for Epidemic Prediction



3. Proposed Framework

Formulation of SIR model with human mobility:

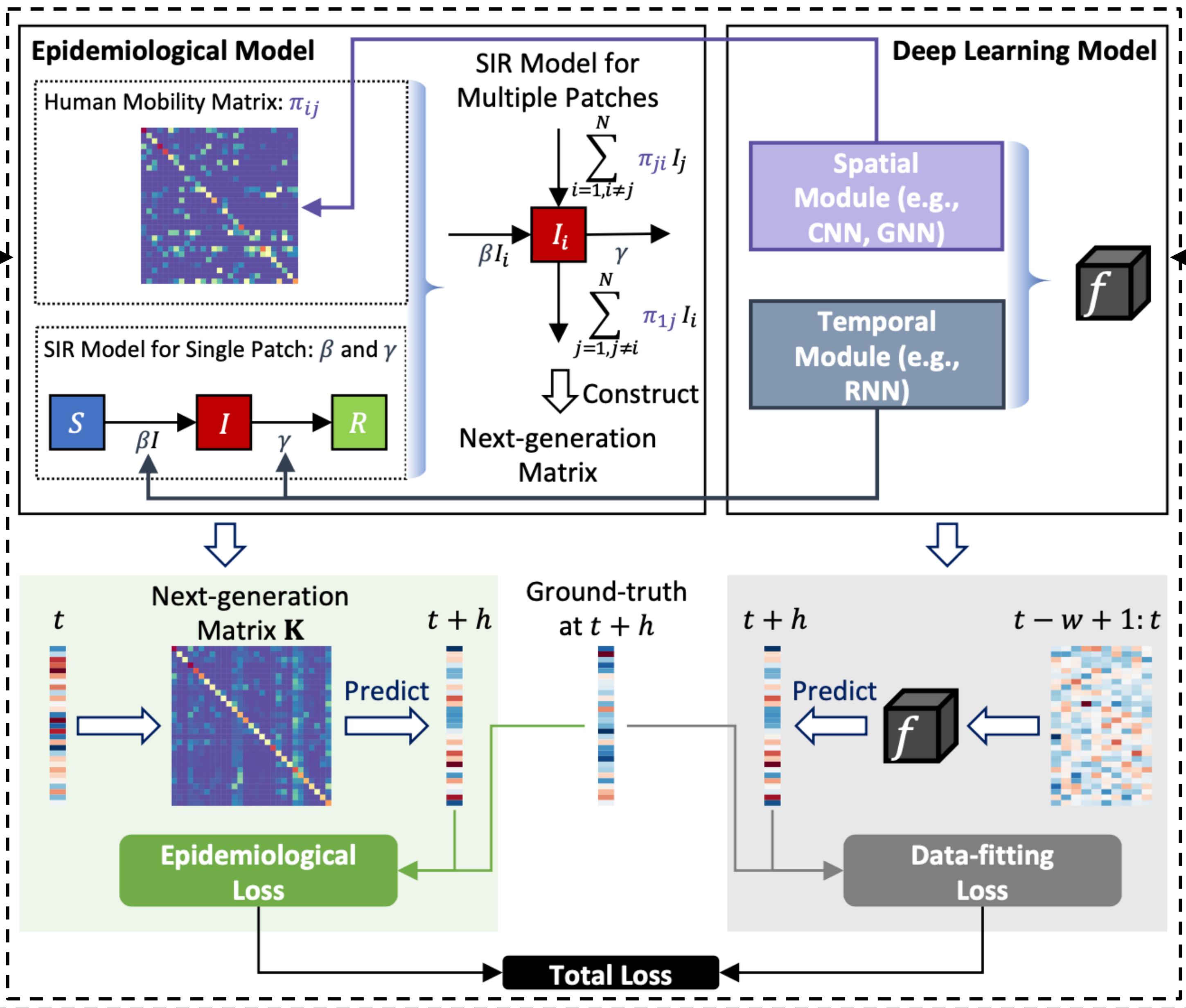
$$\frac{dI_i}{dt} = \beta_i I_i - \gamma_i I_i - \sum_{\substack{j=1 \\ j\neq i}}^{N} \pi_{i,j} I_i + \sum_{\substack{j=1 \\ j\neq i}}^{N} \pi_{j,i} I_j$$

Construction of NGM $\mathbf{K}$ [1]:

$$\mathrm{K} = \boldsymbol{\beta} \cdot (\boldsymbol{\gamma} + \mathrm{A})^{-1}$$

Prediction generated by epidemiological component:

$$\mathbf{d}_{t+h} = \mathbf{K}\mathbf{d}_t$$



Applied to two representative deep learning models:

- CNNRNN-Res [2]
  Spatial: CNN
  Temporal: RNN
- Cola-GNN [3]
  Spatial: RNN and attention
  Temporal: dilated CNN

Prediction generated by deep learning component:

$$\mathbf{d}_{t+h} = f_d(\mathbf{d}_{t-w+1:t})$$

$$\min \sum_{t=w}^{T_{train}+w} \left(\|\mathbf{d}_{t+h} - f(\mathbf{d}_{t-w+1:t})\|_2^2 + \lambda \|\mathbf{d}_{t+h} - \mathbf{K}\mathbf{d}_t\|_2^2 \right)$$

4. Experimental Results

H	Metrics	AR	GAR	VAR	CNNRNN-Res	Cola-GNN	Epi-CNNRNN-Res	Epi-Cola-GNN
1	RMSE	0.2616	0.2593	0.3031	0.2514	0.2444	**0.2402**	0.2430
	MAE	0.1832	0.1790	0.2163	0.1751	**0.1601**	0.1615	0.1602
	CORR	0.9430	0.9422	0.9301	0.9508	0.9510	0.9499	**0.9511**
2	RMSE	0.3639	0.3797	0.4142	0.3467	0.3415	**0.3091**	0.3284
	MAE	0.2580	0.2623	0.2818	0.2429	0.2256	0.2093	**0.2135**
	CORR	0.8938	0.8819	0.8677	0.9121	0.9154	**0.9291**	0.9161
4	RMSE	0.4718	0.5230	0.5042	0.4369	0.4989	**0.3952**	0.4094
	MAE	0.3449	0.3862	0.3402	0.3088	0.2954	0.2670	**0.2626**
	CORR	0.8227	0.7710	0.8070	0.8430	0.8262	**0.8812**	0.8773

- H denotes the prediction horizon
- Root-Mean-Square Error (RMSE) ↓
- Mean Absolute Error (MAE) ↓
- Pearson's Correlation Coefficient (CORR) ↑
- The best and the second-best results in each setting are highlighted using **boldface** and underlining, respectively

5. Conclusions

1. Deep learning based methods, i.e., CNNRNN-Res, Cola-GNN, Epi-CNNRNN-Res, and Epi-Cola-GNN, consistently perform better than the classical AR, GAR, and VAR.
2. By integrating the epidemiological component into the learning framework, the proposed Epi-CNNRNN-Res and Epi-Cola-GNN further outperform original algorithms (CNNRNN-Res and Cola-GNN), achieve the best or second-best performance among all methods in most scenarios.

6. References

1. Diekmann, O., Heesterbeek, J. A. P., & Roberts, M. G. (2010). The construction of next-generation matrices for compartmental epidemic models. *Journal of the royal society interface*, *7*(47), 873-885.
2. Wu, Y., Yang, Y., Nishiura, H., & Saitoh, M. (2018, June). Deep learning for epidemiological predictions. In *Proceedings of the 41st international ACM SIGIR conference on research & development in information retrieval* (pp. 1085-1088).
3. Deng, S., Wang, S., Rangwala, H., Wang, L., & Ning, Y. (2020, October). Cola-GNN: Cross-location attention based graph neural networks for long-term ILI prediction. In *Proceedings of the 29th ACM international conference on information & knowledge management* (pp. 245-254).