Centre for Data Science

MODELLING PANDEMIC TRANSMISSION DYNAMICS FOR DECISION MAKING AND POLICY RESPONSE

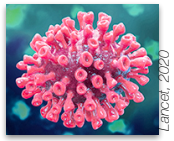
A GNN+mRNN based metamodel for Pandemic Transmission Dynamics

Stefani Sotomayor
stefani.sotomayor@hdr.qut.edu.au

Queensland University of Technology
School of Computer Science
Centre for Data Science

Motivation

Capture a detailed description of a pandemic spread using real spatiotemporal data for evaluating and testing different policy scenarios.

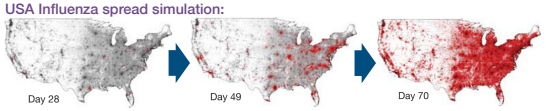


Prior work

Classical Models for Infectious Disease Transmission

$f_{(x)}$ Stochastic models Computationally expensive Hand-crafted parameters

USA Influenza spread simulation:



Red & grey: infected & susceptible population

Ferguson et.al, 2006 *Squazzoni et.al, 2020*

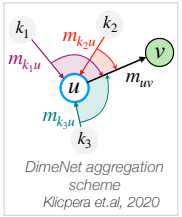
Our approach

Graph Neural Networks (GNNs)

Expressivity | Generalisation | Invariance

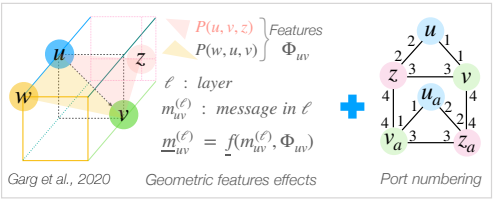
$f_{(x)}$ Powerful representation learning of complex structured data

Spatial learning in GNNs:



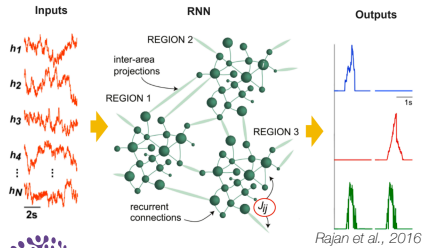
DimeNet aggregation scheme Klicpera et.al, 2020

Hierarchical Directional Message Passing Consistent Port Numbering Network (H-DCPN):



Garg et al., 2020 *Geometric features effects* *Port numbering*

Multi-region Recurrent Neural Networks (mRNNs)



Rajan et al., 2016

Mathematical model:

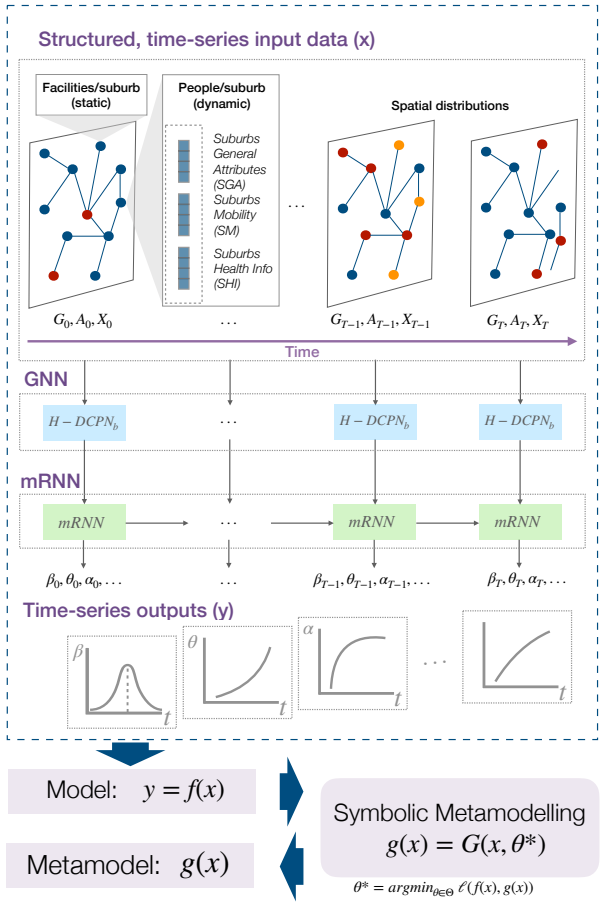
$$\tau \frac{dx_i}{dt} = -x_i + g \sum_j J_{ij} \phi(x_j) + h_i$$

Capabilities:

- High fidelity learning of chaotic dynamics in continuous time
- $f_{(x)}$ Data-driven RNN model based on experimentally-recorded data

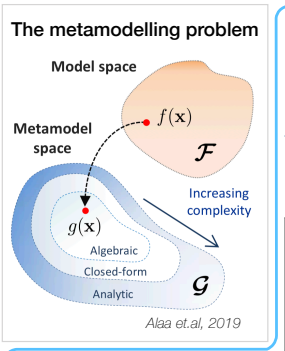
NEURAL INFORMATION PROCESSING SYSTEMS

Proposed GNN+mRNN framework

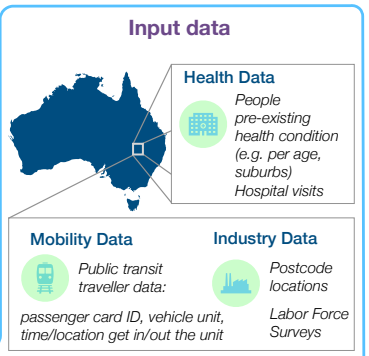


Our main contributions

- ✓ A bipartite based GNN model (H-DCPNb) that captures the transmission spread dynamics across (i) individuals and (ii) facilities with granularity descriptors (e.g. health condition, age, mobility).
- ✓ A sequence modelling that temporally integrates the GNN learnt representations using multi-region recurrent neural network (mRNN).
- ✓ A metamodel equation of the proposed GNN+mRNN model that integrates multiple, time-series spreading rate results (e.g. per age, health condition, mobility) which is capable of explaining the transmission dependency between descriptors.



Alaa et.al, 2019



References

Ferguson, N.M., Cummings, D.A., Fraser, C., Cajka, J.C., Cooley, P.C. and Burke, D.S., 2006. Strategies for mitigating an influenza pandemic. Nature, 442(7101), pp.448-452.Vancouver

Squazzoni, Flaminio, et al. "Computational models that matter during a global pandemic outbreak: A call to action." Journal of Artificial Societies and Social Simulation 23.2 (2020).

Garg, V.K., Jegelka, S. and Jaakkola, T., 2020. Generalization and representational limits of graph neural networks. arXiv preprint arXiv:2002.06157.

Klicpera, J., Groß, J. and Günnemann, S., 2020. Directional message passing for molecular graphs. arXiv preprint arXiv:2003.03123.

Rajan, K. et al., 2016. Recurrent network models of sequence generation and memory. Neuron, 90(1), pp. 128-142.

Alaa, A.M. and van der Schaar, M., 2019. Demystifying Black-box Models with Symbolic Metamodels. In Advances in Neural Information Processing Systems (pp. 11304-11314). Vancouver

Women in Machine Learning

2020 WiML Workshop at NeurIPS Conference