JOINT INSTITUTE 交大密西根学院

VE444 • Networks
Group# Course Project

HFSSG: A Hybrid Framework combining SIR pandemic model and Spatio-temporal Graph neural network forecasting the COVID-19 Impact in the United States

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Overview

In this work, we propose a novel hybrid framework aimed at COVID-19 case examination and feature prediction. We mainly user **SIR model** for parameter learning and **Graph Neural Network** for temporal-spatial interaction study.

Motivation

Accurate real-time pandemic forecast is always a core technological problem against the implementation for policy makers and healthcaring system.

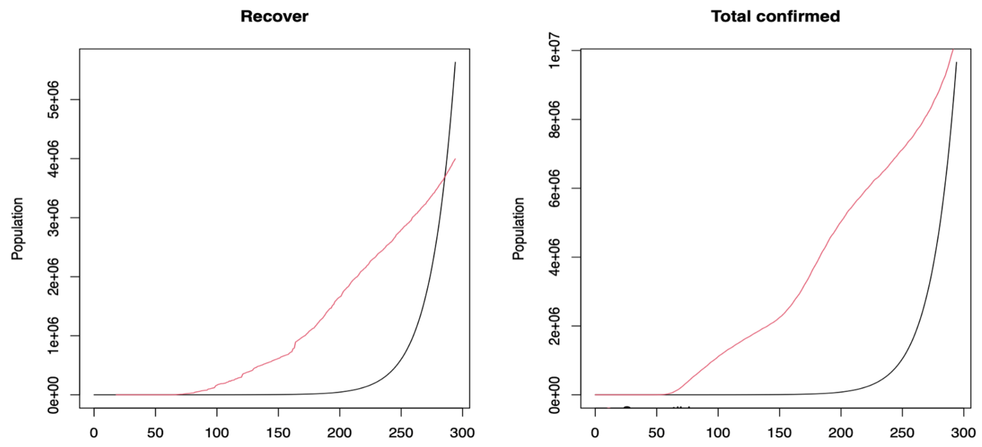

Fig 1. The Stable SIR model Fitting

However, existing forecasting models such as SIR(**Fig.1**) cannot address the information of the interaction dynamically, and it remains challenging considering the complex spatial and temporal dependencies among traffic flows.

Problem Statement

In this project, we combine two powerful models into one integrate framework to perform better prediction capabilities in COVID-19 cases with lower cost. We propose a novel hybrid multi-network based framework named HFSSG capturing geographical and temporal trends and predict the number of cases for a fixed number of days into the future.

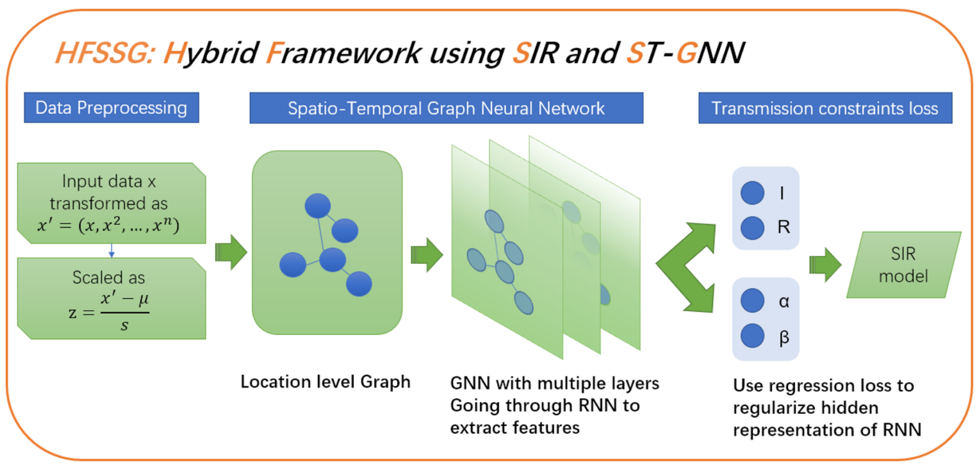

Fig 2. The Flowchart of HFSSG framework

Algorithm Design

Use GCN to Extract Spatial Features

The Two Layer GCN:

$$z_t = \hat{A}\,\mathrm{Relu}\left(\hat{A} X_t W_0\right) W_1$$

Graph attention mechanism (GAT):

$$e_{ij} = a\left(\mathbf{W}_a \mathbf{z}_t^i, \mathbf{W}_a \mathbf{z}_t^j\right)$$

Node representation:

$$\tilde{z}_t^i = \sigma\left(\frac{1}{K}\sum_{k=1}^{K}\sum_{j=1}^{N} a_{ij}^k \mathbf{W}^k z_t^i\right)$$

Use RNN to Extract Temporal Features

Node Embeddings:

$$\tilde{Z}_t = \mathrm{maxpool}(\tilde{Z}_t^0, \tilde{Z}_t^1, \ldots, \tilde{Z}_t^N)$$

GRU's hidden representation:

$$h_t = \mathrm{GRU}(\tilde{Z}_1, \tilde{Z}_2, \ldots, \tilde{Z}_t)$$

Modeling and Analysis

We model the nodes in our graph as each state in the U.S., with features of strong and weak representing the travel availability compared among others. Training our custom GNN simply start with iterating the constructed training set and propagate the loss function.

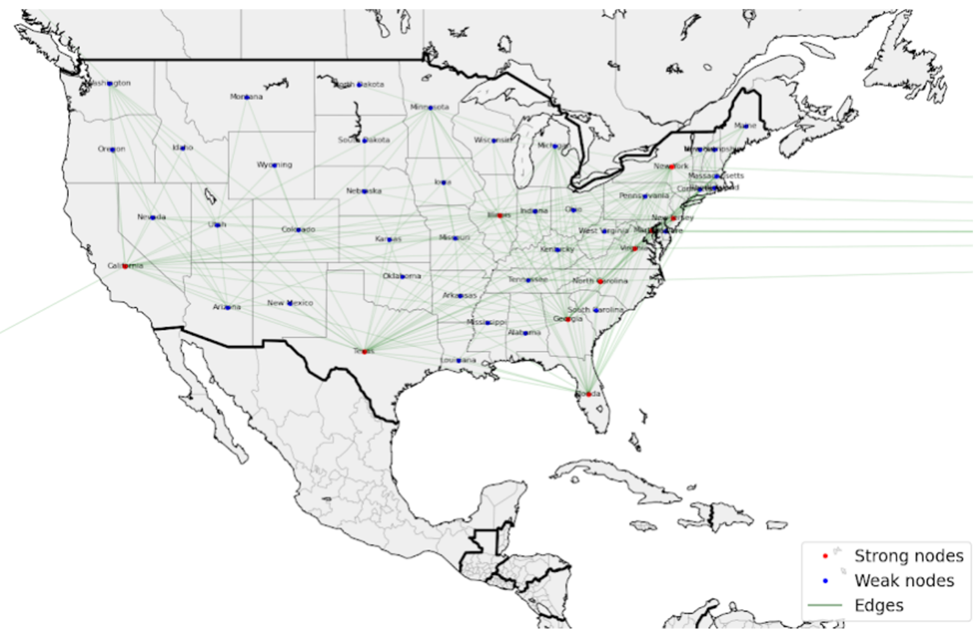

Fig 3. The Spatio-Graph Neural Network Model

The hyper-parameters of our HFSSG model includes learning rate, epoch, and number of hidden units. In the experiment, learning rate and epoch were manually set on the basis of experiences as 0.01 and 2000 for both datasets. As for the number of hidden units, we set it to 50 for the nodes in each layer.

Results

Dataset description

NYT COVID-19 dataset: US state-level and county-level dataset includes active cases, confirmed cases and deaths since 21/01/2020
IQVIA's claim data: 453,089 records of hospotal visits and medical code

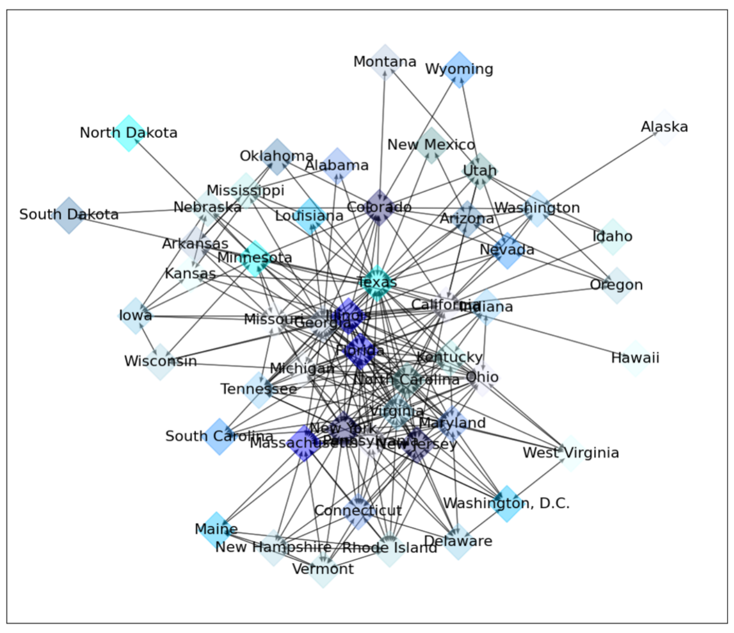

Fig 4. Locate Aware Graph Embedding

Compared approaches

SIR: An epidemiological model separates people into susceptible, infected, and removed. Differential equation is used to simulate transmission.
SEIR: Similar to SIR, add exposed partition.
HFSSG: Best performance under various prediction time length in state-level and county-level

Evaluation strategy

Commine mean square error(MSE) and mean absolute error (MAE) together through agreement measurement.

Evaluation results

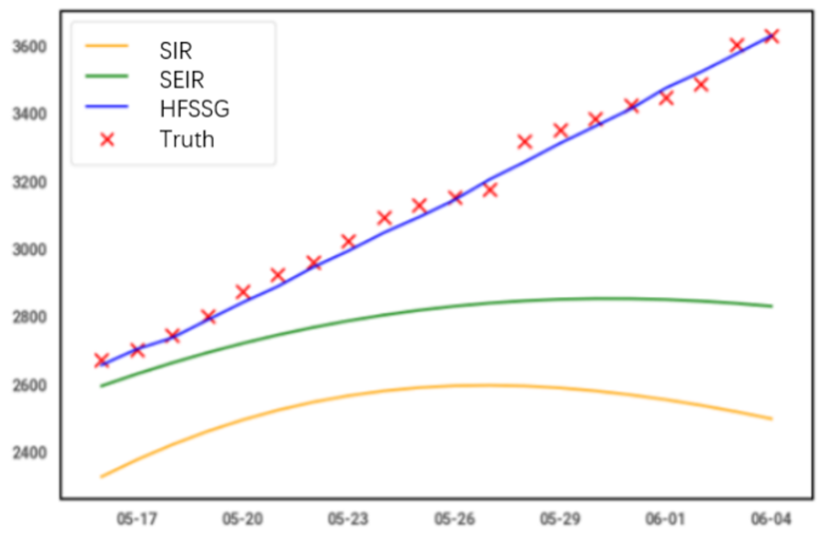

Fig 5. Predicted curve comparing 3 approaches

References

1. Alex Reinhart et al. 2018. A review of self-exciting spatio-temporal point processes and their applications. Statist. Sci. 33, 3 (2018), 299–318.
2. Zulong Diao, Xin Wang, Dafang Zhang, Yingru Liu, Kun Xie, and Shaoyao He. 2019. Dynamic spatial-temporal graph convolutional neural networks for traffic forecasting. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 33. 890–897.