1. Introduction

- Accurate forecasting of COVID-19 in regional level can facilitate local lockdowns and effective resource allocation.
- The spread exhibits differing patterns throughout regions in the same country.
- Irregular testing and latent cases forms bursty time series that are hard to predict.

- We combine the history of the disease in each region with the mobility between and inside the regions to forecast the number of cases in the near future.

2. Methods

- Each country at day $t$ is a graph of its regions represented by a weighted mobility matrix $A$ and a feature matrix $x$ with the number of cases in the last $l$ days.
- Message passing creates a $z_u$ representation of the number of new latent cases in a node $u$.
- A stack of 2 residual MPNNs is used to predict the future number of cases for each of the next 14 days.

3. Comparison

- We compare with several baselines (AVG, LAST DAY) and time series methods (LSTM, PROPHET, ARIMA).
- The plot shows the most competitive benchmarks.
- MPNN+TL clearly outperforms the rest, especially in long-term forecasting.

4. Results

- We define a relative error based on the difference between the average predicted cases in the next five days, and the real number of cases.
- The results indicate that regions with many cases have low relative error and vice versa.

- If we start predictions from the first two weeks, we have very few samples.
- The pandemic spreads asynchronously in different countries.

- Given a set of previously infected countries, use transfer learning to improve the predictions for a newly infected one.

- We develop a MAML-based approach, and leave each country out as target set with the rest as source set in a leave-one-out evaluation.

5. Conclusion

- The disease spreading can be better predicted through the combination of mobility and disease history.
- Meta learning can improve models based on knowledge from countries hit previously by the pandemic.
- In the future, we plan to include numerous information such as demographics, test rates, temperature etc.

6. References


George Panagopoulos, Giannis Nikolentzos, Michalis Vazirgiannis
AAAI 2021
github.com/geopanag/pandemic_tgnn