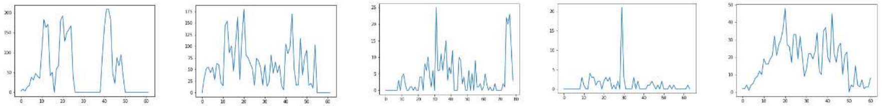
Transfer Graph Neural Networks for Pandemic Forecasting

1. Introduction

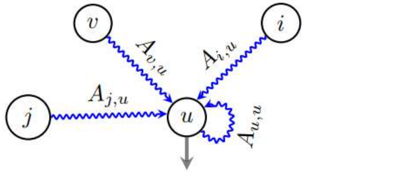
- Accurate forecasting of COVID-19 in regional level can facilitate local lockdowns and effective resource allocation.
- The spread exhibits differing patterns throughout regions in the same country.
- Irregular testing and latent cases forms bursty time series that are hard to predict.



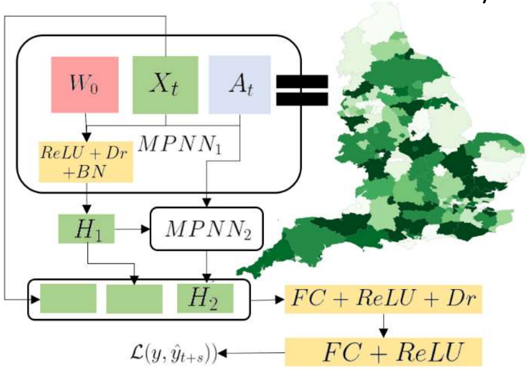
➢ We combine the history of the disease in each region with the mobility between and inside the regions to forecast the number of cases in the near future.

2. Methods

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



$$\mathbf{z}_u = (A_{j,u}\mathbf{x}_j + A_{i,u}\mathbf{x}_i + A_{v,u}\mathbf{x}_v) + A_{u,u}\mathbf{x}_u$$

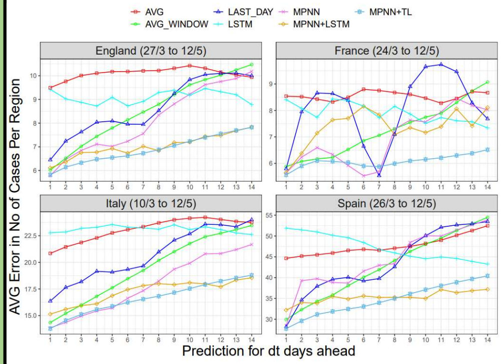


- If we start predictions from the first two weeks, we have very few samples.
- The pandemic spreads asynchronously in different countries.

- 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.

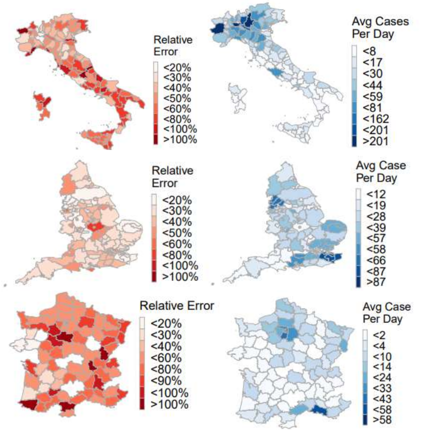
3. Comparison

- 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.



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

[1] Finn, C., Abbeel, P., & Levine, S. (2017). Model-agnostic meta-learning for fast adaptation of deep networks. In 34th ICML 70 (pp. 1126-1135).
[2] Kipf, T. N., & Welling, M. (2016). Semi-supervised classification with graph convolutional networks. arXiv preprint arXiv:1609.02907.
[3] Panagopoulos, G., Nikolentzos, G., & Vazirgiannis, M. (2020) Transfer Graph Neural Networks for Pandemic Forecasting. arXiv preprint arXiv:2009.08388.

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github.com/geopanag/pandemic_tgnn