Finding Patient Zero: Learning Contagion Source with Graph Neural Networks

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Problem

- We are given an interaction graph, whose nodes indicate people, and an edge between two nodes indicates an interaction.
- We are also given a snapshot, indicating the status of each node as susceptible, infected or recovered
- Our goal is to **determine the source of the contagion** (also known as patient zero).

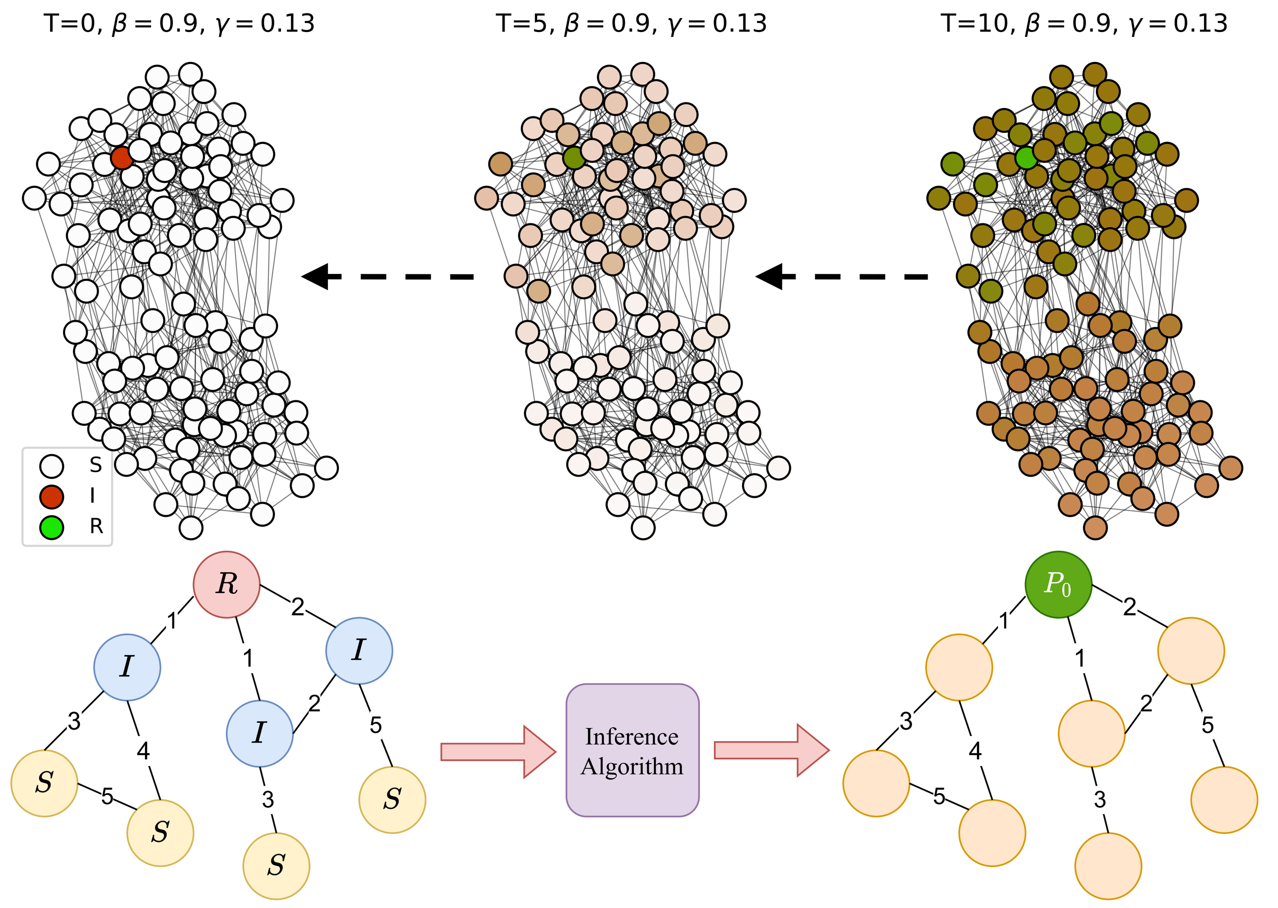


Figure: Graphical representation of our problem

Our Results

We examine GNNs (Graph Neural Networks) as an efficient and flexible inference algorithm for this problem. In particular, we:

- Detail how with residual connections, the standard Graph Convolutional Network (GCN) model can be better adapted to the problem;
- Compare against other state-of-the-art methods on different choices of graph topology for the interaction graph;
- Demonstrate the robustness of GNNs to incomplete node and edge information;
- Examine the topological entropy as a proxy measure for predicting inference performance.

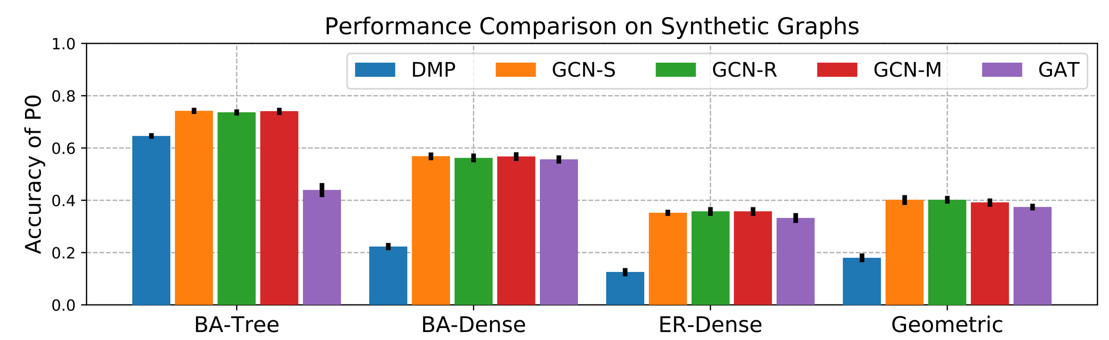
Other applications

- Rumor Source Detection on Social Networks
- Bitcoin Deanonymization
- Viruses spreading over cyber-physical networks

Related Work

- Baseline methods we compared against include Dynamic Message Passing (DMP) and Belief Propagation (`sib`).
- These methods model the likelihood of each node being the origin of the outbreak using the epidemic parameters. However, they do not scale well to large and dense graphs.
- GNNs, on the other hand, do not require knowledge of the epidemic parameters. They are also fast and efficient, and scale well with the number of nodes.
- We note here that both the message passing and belief propagation algorithms can leverage knowledge about the time of each interaction, while the GNNs do not.

Results - Accuracy on different synthetic graph topologies



Inference times

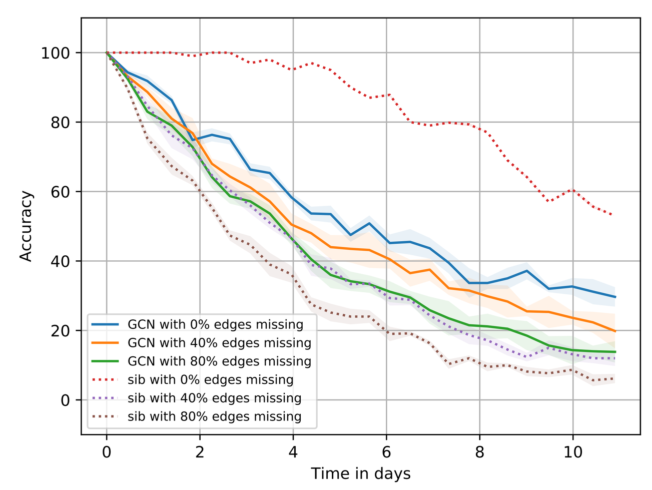
Dataset	DMP	GCN	GAT
BA-Tree	14.40 hr	3.89s	**3.18s**
BA-Dense	77.04 hr	**4.91s**	8.19s
ER-Dense	71.77 hr	**4.93s**	9.66s
Geometric	70.35 hr	**5.34s**	10.87s

The GNN-based methods perform better than the classical message-passing algorithm DMP in all settings while being several orders of magnitude faster.

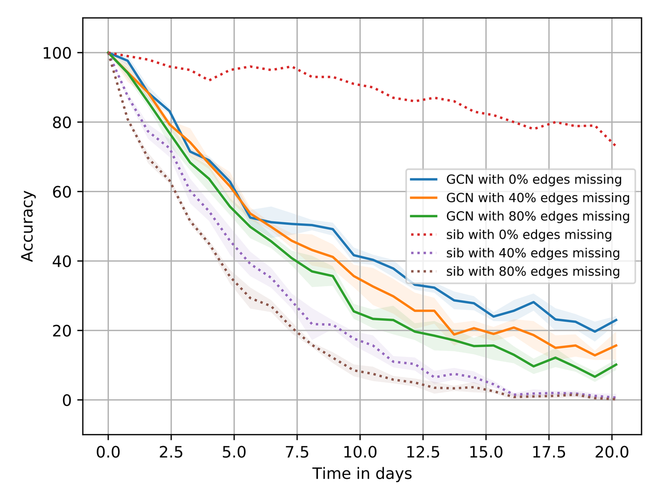
Results - Robustness

Motivation: Most real-world data is incomplete and/or inaccurately reported, e.g. missed interactions, asymptomatic cases, etc. We examine the effectiveness of the inference algorithms despite the missing information.

Missing Edge Information: Remove a proportion p of the edges, chosen randomly, from the interaction graph which is sent as input to the inference algorithm.



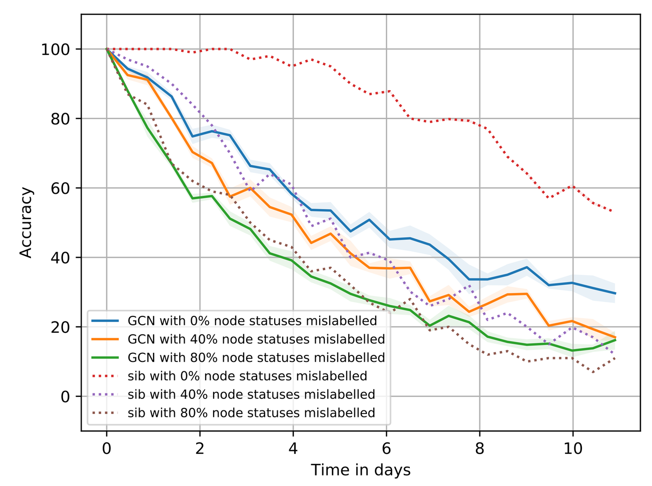
(a) Barabasi-Albert graph with $m = 7$



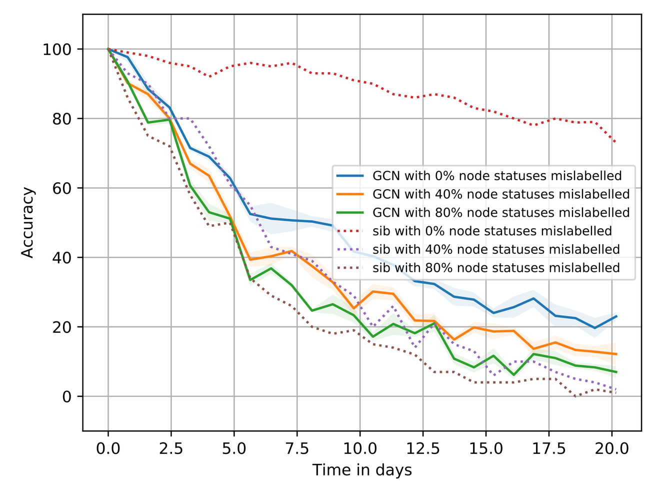
(b) Barabasi-Albert graph with $m = 3$

In figures (a)-(e), `sib` refers to the belief propagation algorithm from [1]. This method leverages time-steps from the social interaction graph during inference (which is not the case with GNNs). With 0 missing edges, `sib` outperforms the GNN methods, however, we notice that even with a small proportion of missing edges, `sib` is outperformed by the GNNs.

Missing node information: Select a proportion p of non-susceptible nodes and mark them as susceptible before the graph is sent to the inference algorithm.



(a) Barabasi-Albert graph with $m = 7$



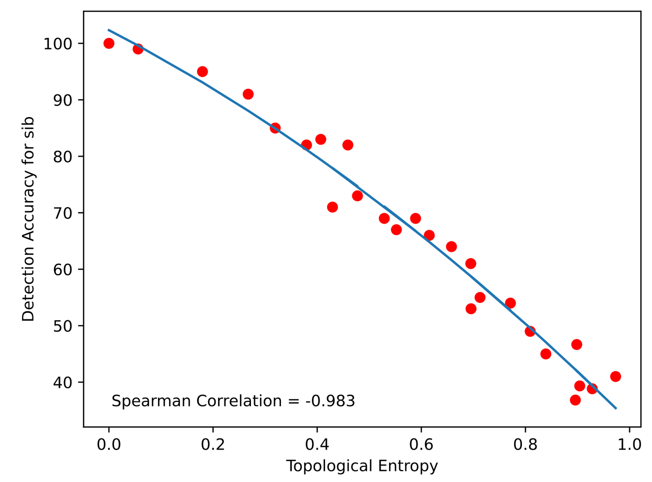
(b) Barabasi-Albert graph with $m = 3$

Again, we notice that despite superior performance when no information is missing, `sib` performs roughly as well as the GNN methods with missing node information, despite leveraging additional temporal information.

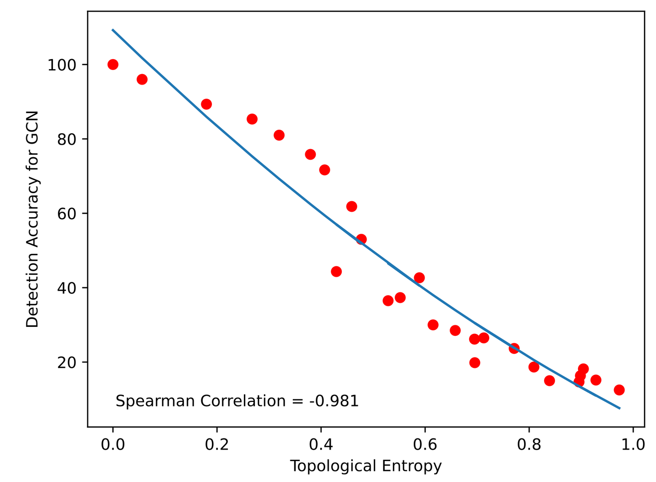
Investigating graph structure vs accuracy

Motivation:

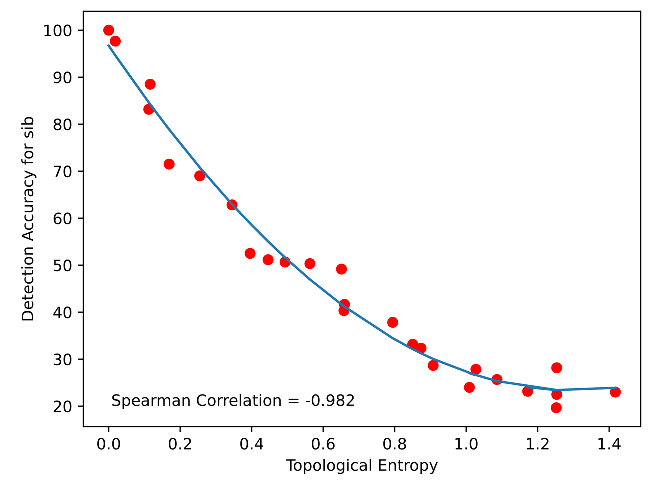
- The accuracy of the inference algorithm at different timescales depends on the topology of the underlying social interaction graph.
- We investigate what property of the graph the inference algorithm is most affected by. We examine the relationship between *topological entropy* (defined as $|\lambda|$ where λ is the largest eigenvalue of the graph adjacency matrix) [2] and patient zero detection accuracy.



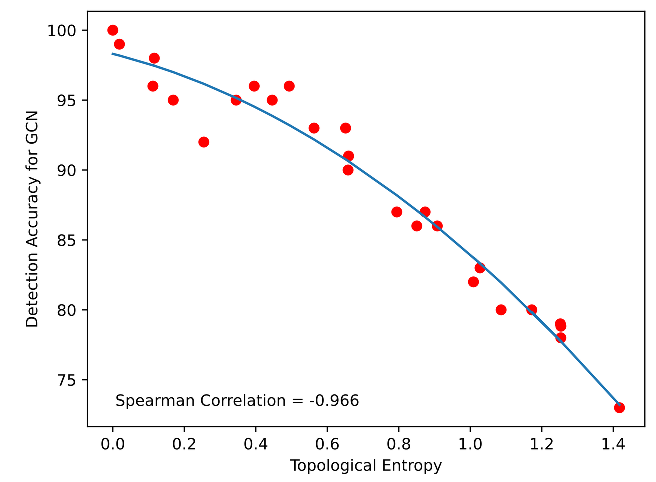
(a) Regular graph + `sib`



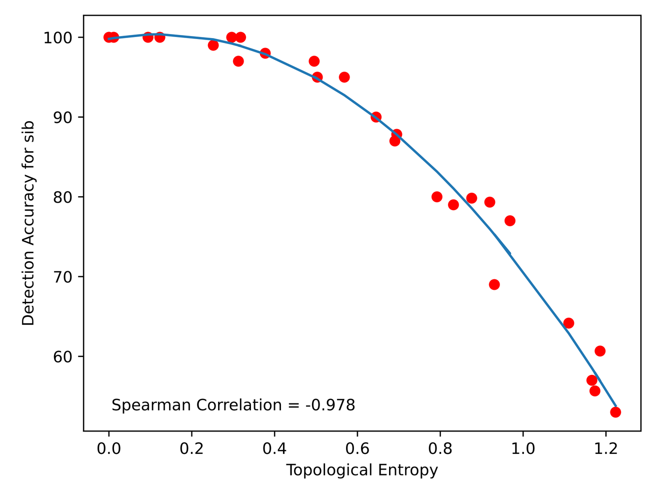
(b) Regular graph + GCN



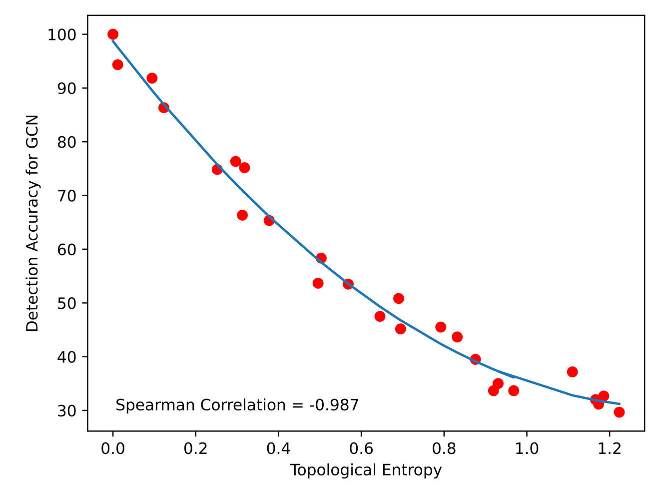
(c) Barabasi-Albert graph ($m = 3$) + `sib`



(d) Barabasi-Albert graph ($m = 3$) + GCN



(e) Barabasi-Albert graph ($m = 7$) + `sib`



(f) Barabasi-Albert graph ($m = 7$) + GCN

We notice a clear trend indicating that *increasing entropy of the social interaction graph decreases the detection accuracy* for both `sib` and GCN. Combined over all datasets, the Spearman correlation between the entropy and detection accuracy is -0.82 for `sib` and -0.86 for GCN, clearly highlighting the inverse relationship between entropy and detection accuracy.

References

[1] A. Braunstein and A. Ingrosso. Inference of causality in epidemics on temporal contact networks. *Scientific reports*, 6(1):1–10, 2016.

[2] L. Demetrius and T. Manke. Robustness and network evolution—an entropic principle. *Physica A: Statistical Mechanics and its Applications*, 346(3):682–696, 2005.

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