Updated Graph Neural Network to Predict Patient Zero(s)

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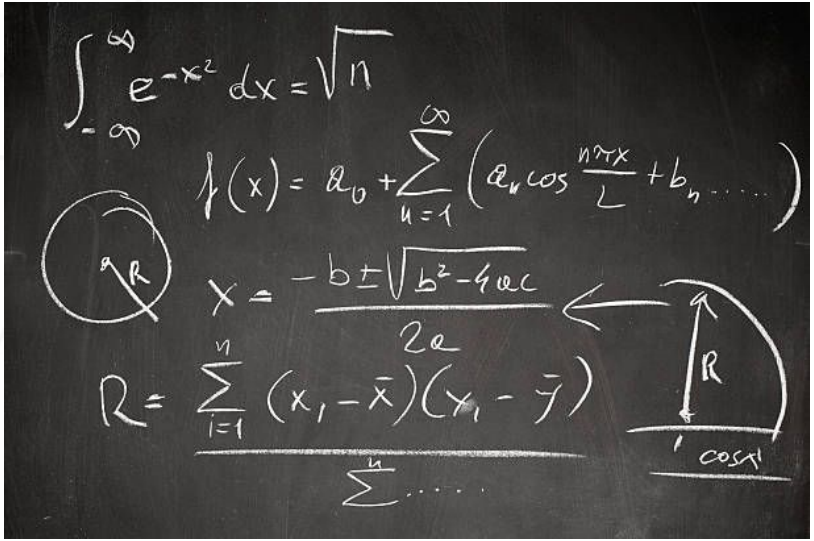
Why does it matter?

- Important to find P0s since containing them would help mitigate spread
- Knowing the sources of disease can give insight into avenues of spread
- Discovering how a disease starts can be important for vaccine development
- Finding P0s can help bring awareness of spread and we can avoid future occurrences

How do we model it better?

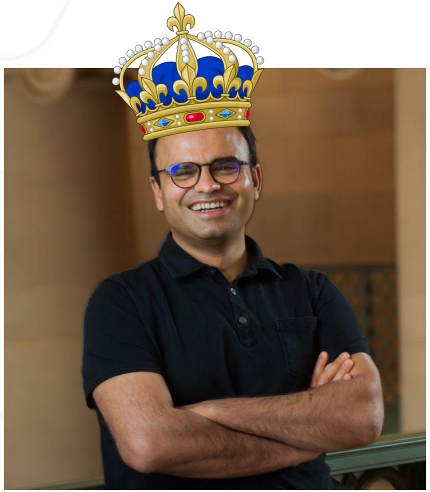
- Current practices:
  - rely on MLE for specific graph structures (Cayley trees)
  - Use GNNs on outbreaks with only one patient 0
- Our methods:
  - Utilize multiple snapshots of disease progression
  - Incorporate and train models to find multiple patient 0s

What are some complications with current methods?



- Can be mathematically complex to calculate
  - So much so that the problem has to be limited
- To train the model to recognize Patient 0s can be computationally expensive with limited data

What's been done? *Algorithm Edition*



Devavrat Shah

$$\hat{v} = \arg\max_{v \in G_N} \mathbf{P}(G_N | v^* = v)$$

The infected subgraph

Tauhid Zaman

Leveraging Maximum Likelihood Estimation to make estimates on a potential infection source

Talked about in class with Professor Prakash!

What's been done? *Graph Neural Network Edition*

Shah and others
Many-layered Graph Convolutional Network

Song and others
Graph Convolutional and Graph Attention Network

Ru and others
Backtracking graph neural network for temporal data

Song, Huang, and Lu
Out-In-Degree Graph Convolutional Network

Xu and others
Hierarchically Aggregated Graph Neural Networks

How do graph neural networks work?

GRAPH Neural Networks

GRAPH
DATA
(a lot of it too
hopefully)

How do graph neural networks work?

Graph Convolutional Network Update Formula

$$h_i^{t+1} = f\left(h_i^t W + \sum_{j \in \text{Neighbors of } i} \frac{1}{c_{ij}} h_j^t U\right)$$

h = information vector
W, U =vectors that the network can learn
c_{ij} =normalization value to weight neighbors differently

Getting information from our current information vector as well as the vectors for our neighbors for ***better representations***

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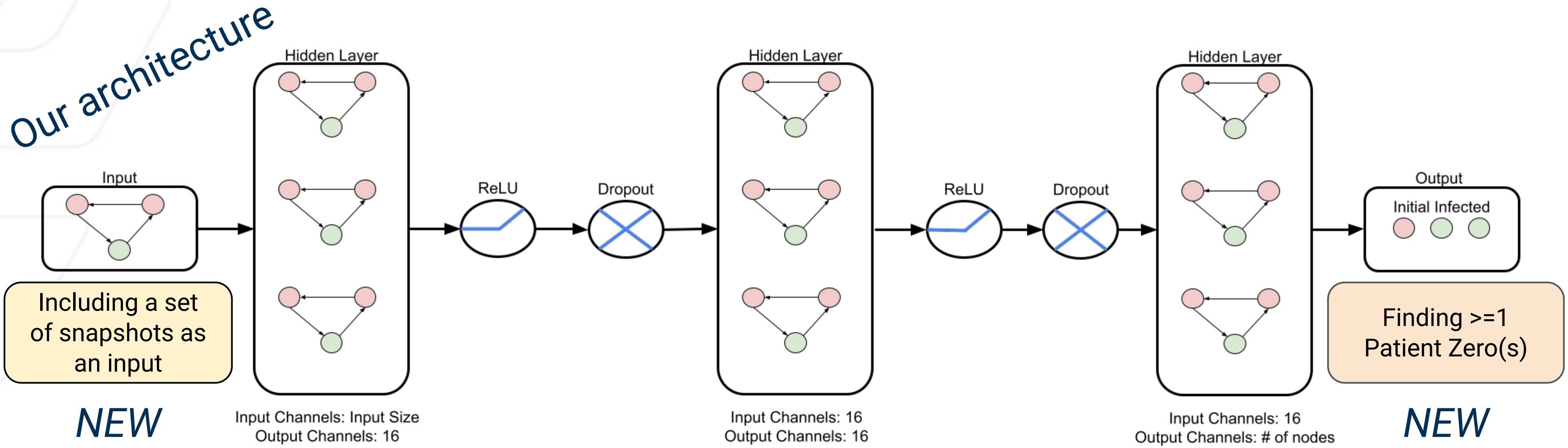
So what's our graph neural network looking like?

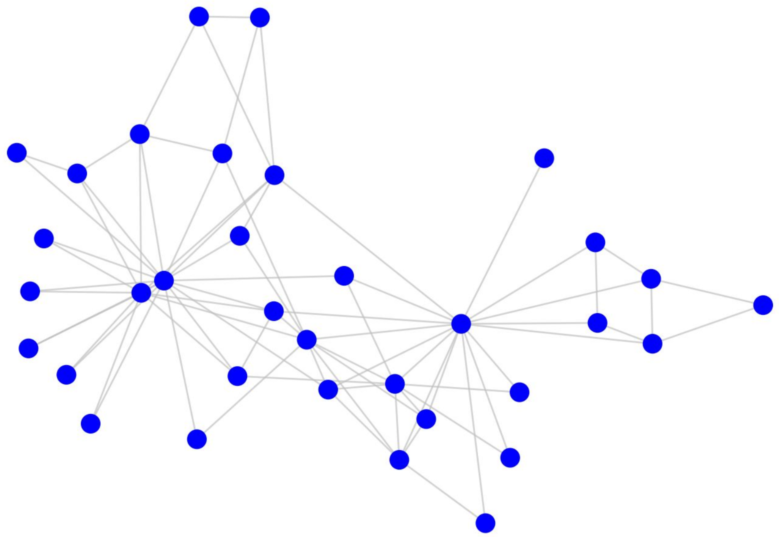


Few hidden layers, ReLUs for nonlinearity, Dropouts for generalizability… **what's new?**

Dataset

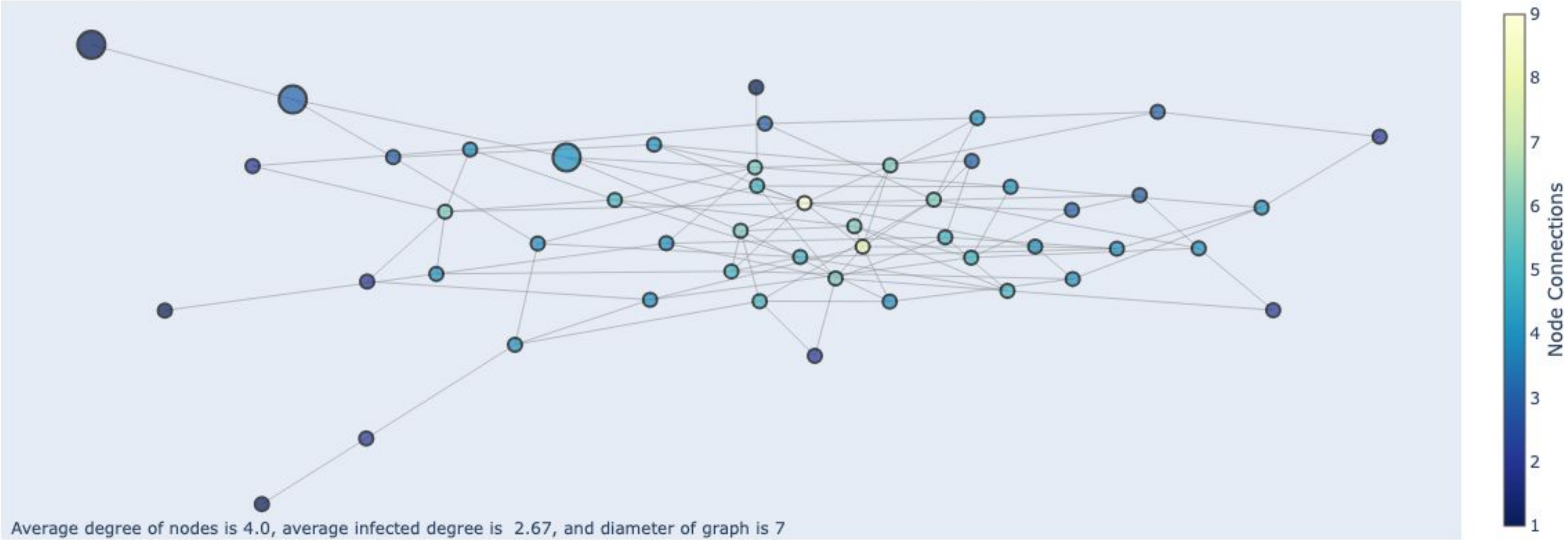
Graph and Outbreak Parameters

- Beta: 0.15
- Gamma: 0
- Number of Nodes: 50
- Number of Edges: 100
- Training/Testing Size: 10,000 graphs
    - Generated randomly with networkx
- Training/Testing split: 70/30



Dataset

Network Snapshot of Graph with 50 Nodes and 100 Edges where there is 1 p0 and t=5



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Results

Accuracy	Day 5	Day 10	Day 20
1 Snapshot	26.73%	13.47%	16.60%
2 Snapshots	33.57%	23.73%	11.60%
3 Snapshots	30.43%	22.17%	15.53%

Figure 3: Accuracy Table w/ 1 Patient Zero

Accuracy	Day 5	Day 10	Day 20
1 Snapshot	22.08%	15.08%	6.13%
2 Snapshots	19.93%	18.53%	12.88%
3 Snapshots	23.23%	19.92%	13.95%

Figure 4: Accuracy Table w/ 2 Patient Zeros

Accuracy	Day 5	Day 10	Day 20
1 Snapshot	19.92%	12.04%	8.13%
2 Snapshots	17.97%	20.93%	13.23%
3 Snapshots	18.76%	16.87%	14.38%

Figure 5: Accuracy Table w/ 3 Patient Zeros

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Trends

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Worse patient zero(s) inference as **days elapse**

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Better patient zero(s) inference with **more snapshots**

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Fairly equal patient zero(s) inference with **more patient zero(s)**

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Discussion: Why do we think the trends were happening?

Patient 0s Trend

- We only see a slight drop off in accuracy when increasing # of P0s
- Expected to see a bigger drop off since we increased model complexity
- Due to short time period, P0 outbreaks do not overlap as much

Snapshots Trend

- Snapshots are provided in equal spacing (e.g. t= 10)
    - 9
    - 4, 9
    - 3, 6, 9
- Diminishing returns for more snapshots
- Could be confusing the model

Time Steps Trend

- More time steps leads to deeper outbreak
- Creates more uncertainty and harder time predicting

Future Work

- Deeper time steps to model delayed outbreak detection
- More robust model architecture to make better use of multiple snapshots
- Introduce a recovery rate
- Running on more diverse set of networks

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