

End-to-End Risk-aware Reinforcement Learning to Detect Asymptomatic Cases in Healthcare Facilities

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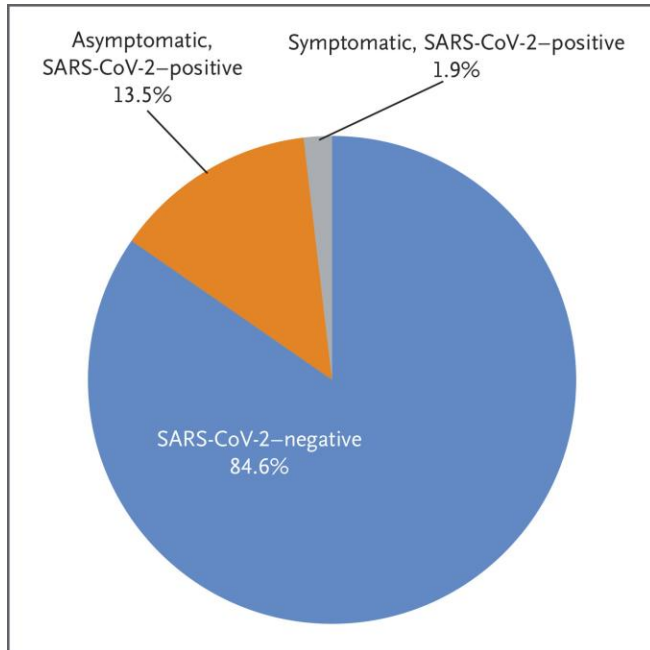
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Outline

- **Background & Challenges**
- **Problem Formulation**
- **Our Method**
- **Experiment**
- **Conclusion & Future Work**

Asymptomatic cases drives outbreak



[1] Asymptomatic cases are common

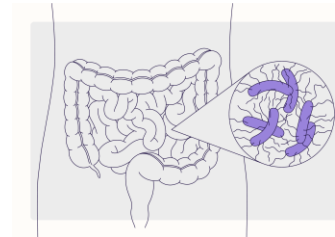
chicago news



At least 50% of COVID-19 infections come from people who aren't showing symptoms, study finds

[2]

They contribute to the outbreak



[3]

C. Difficile is another example

Detecting asymptomatic cases is crucial in combating pandemic outbreak!

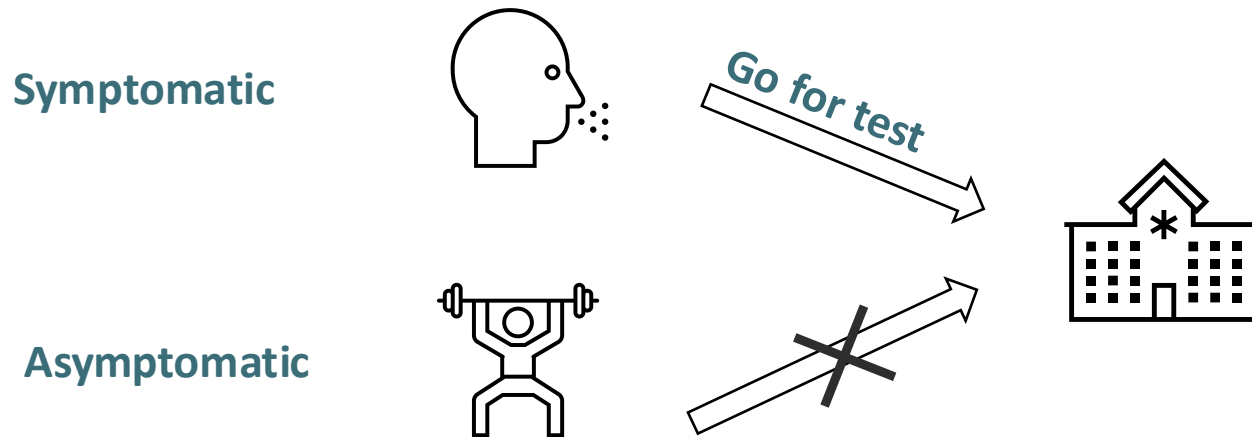
[2] Subramanian, Rahul, Qixin He, and Mercedes Pascual. "Quantifying asymptomatic infection and transmission of COVID-19 in New York City using observed cases, serology, and testing capacity." *Proceedings of the National Academy of Sciences* 118.9 (2021): e2019716118.

[3] Ziakas, Panayiotis D., et al. "Asymptomatic carriers of toxigenic *C. difficile* in long-term care facilities: a meta-analysis of prevalence and risk factors." *PLoS one* 10.2 (2015): e0117195.

Challenges in Detecting Asymptomatic Cases

▪ Challenge 1: Data Scarcity

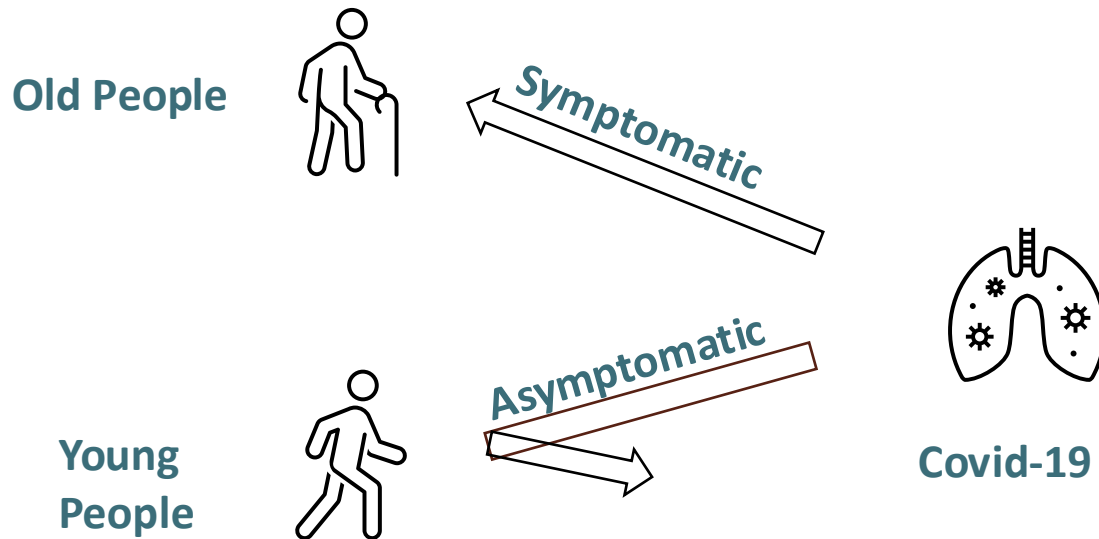
Most data don't include symptomatic information



Challenges in Detecting Asymptomatic Cases

▪ Challenge 2: Bias on Risk Factors

The *risk factors* for symptomatic infections *differ* from those of asymptomatic infections.



Challenges in Detecting Asymptomatic Cases

▪ Challenge 3: Systematic Bias

Severe cases get more attention when it comes to testing when *capacity is limited*.



Scope of This Paper

- Goal

Given *interactions* between people and some *positive* cases, *infer* the *asymptomatic* cases.

- But ...

Such *interactions do not exist* for most scenarios.

- Health Care Facilities

Well-documented

Outline

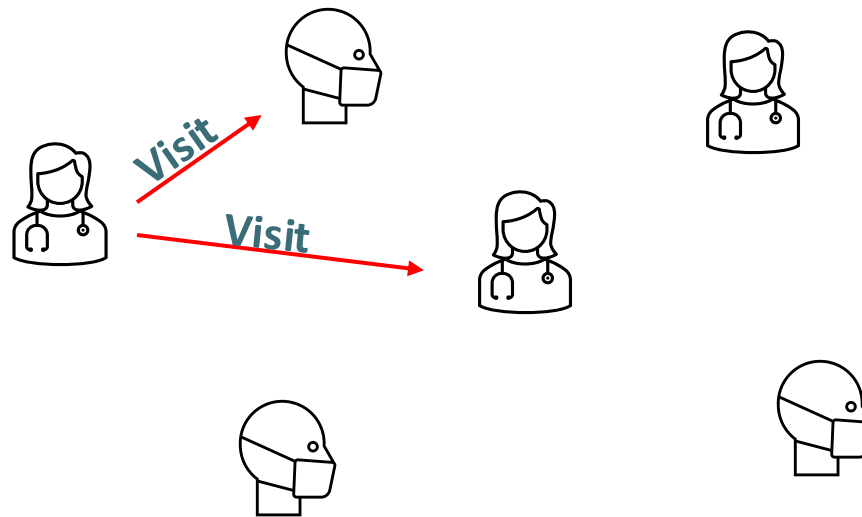
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Construct Graph from Interactions

- Health care facilities

Interactions between *patients* and *HCPs*.

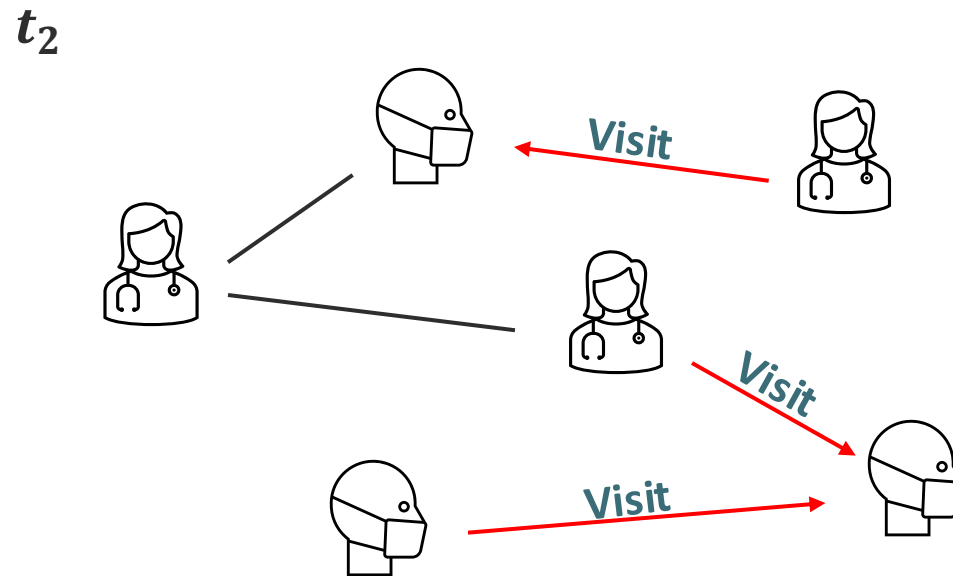
t_1



Construct Graph from Interactions

- Health care facilities

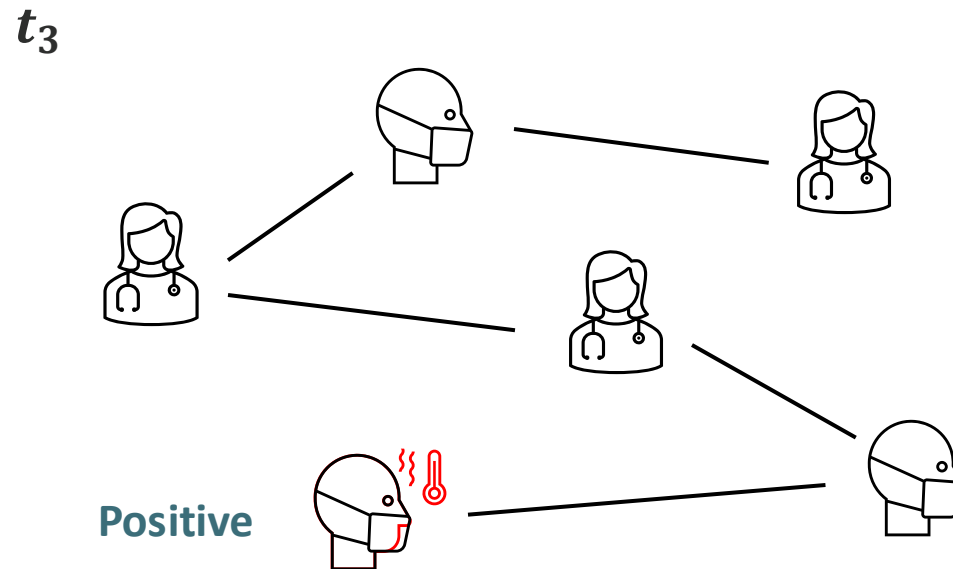
Interactions between *patients* and *HCPs*.



Construct Graph from Interactions

- Health care facilities

Interactions between *patients* and *HCPs*.

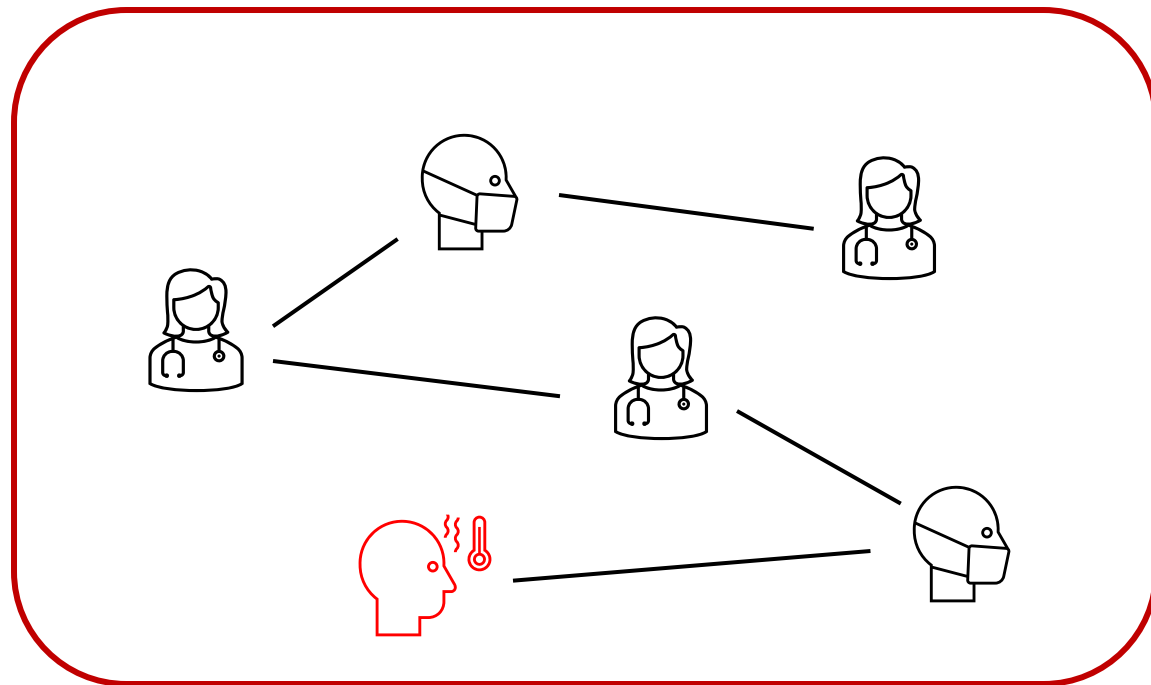


Construct Graph from Interactions

- Health care facilities

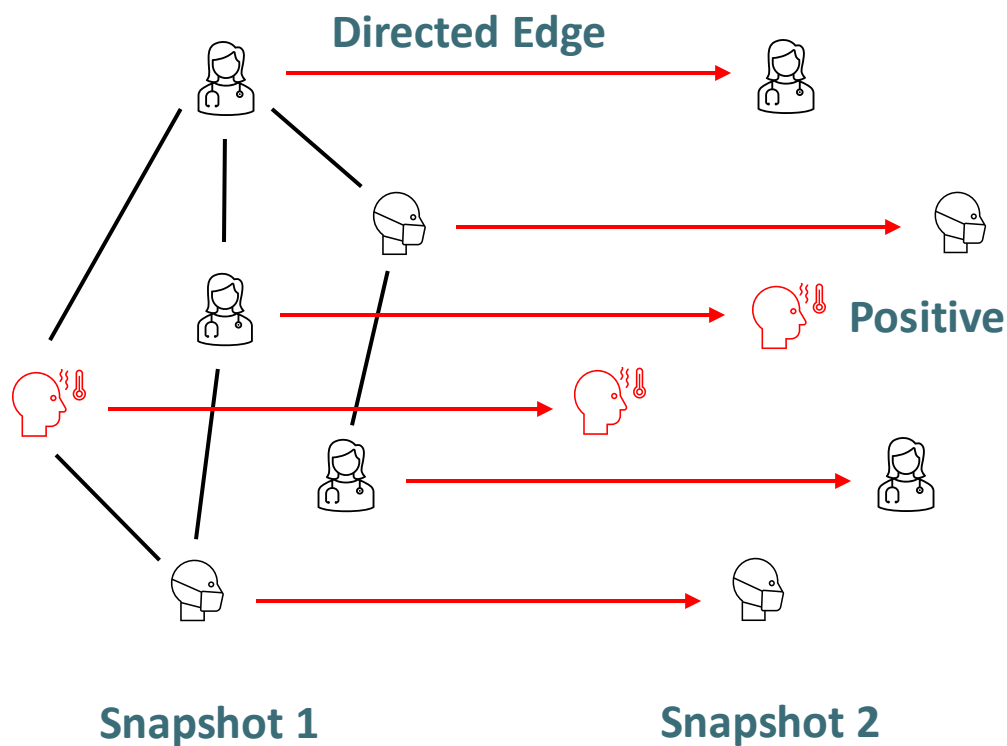
Interactions between *patients* and *HCPs*.

A Snapshot



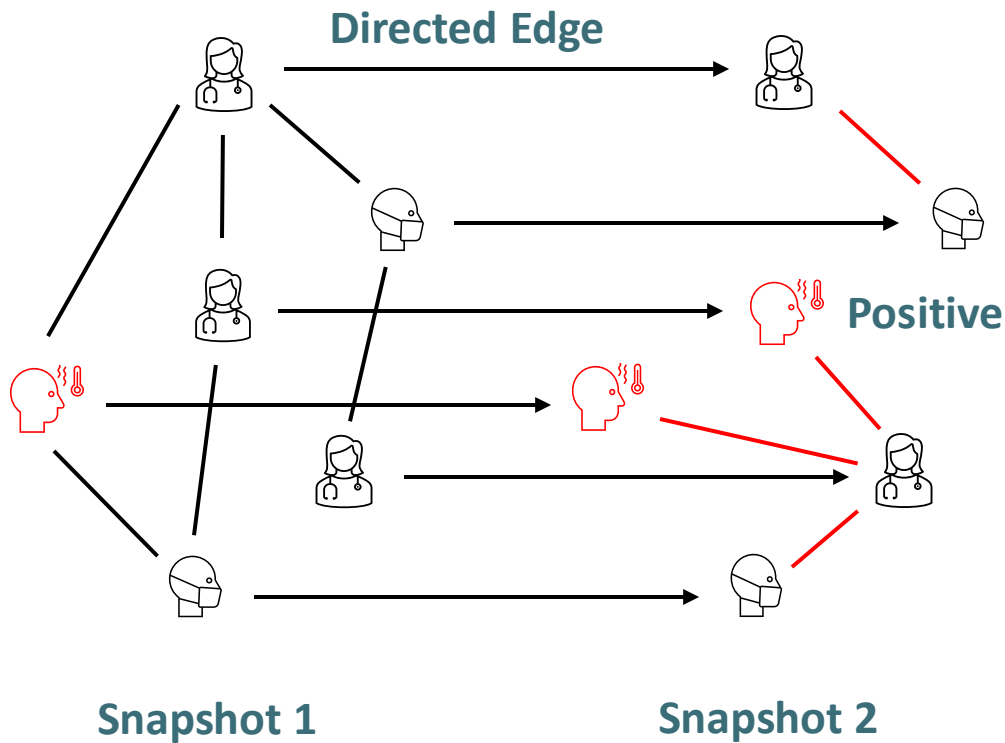
If we have more interactions ...

- Build snapshot upon previous ones



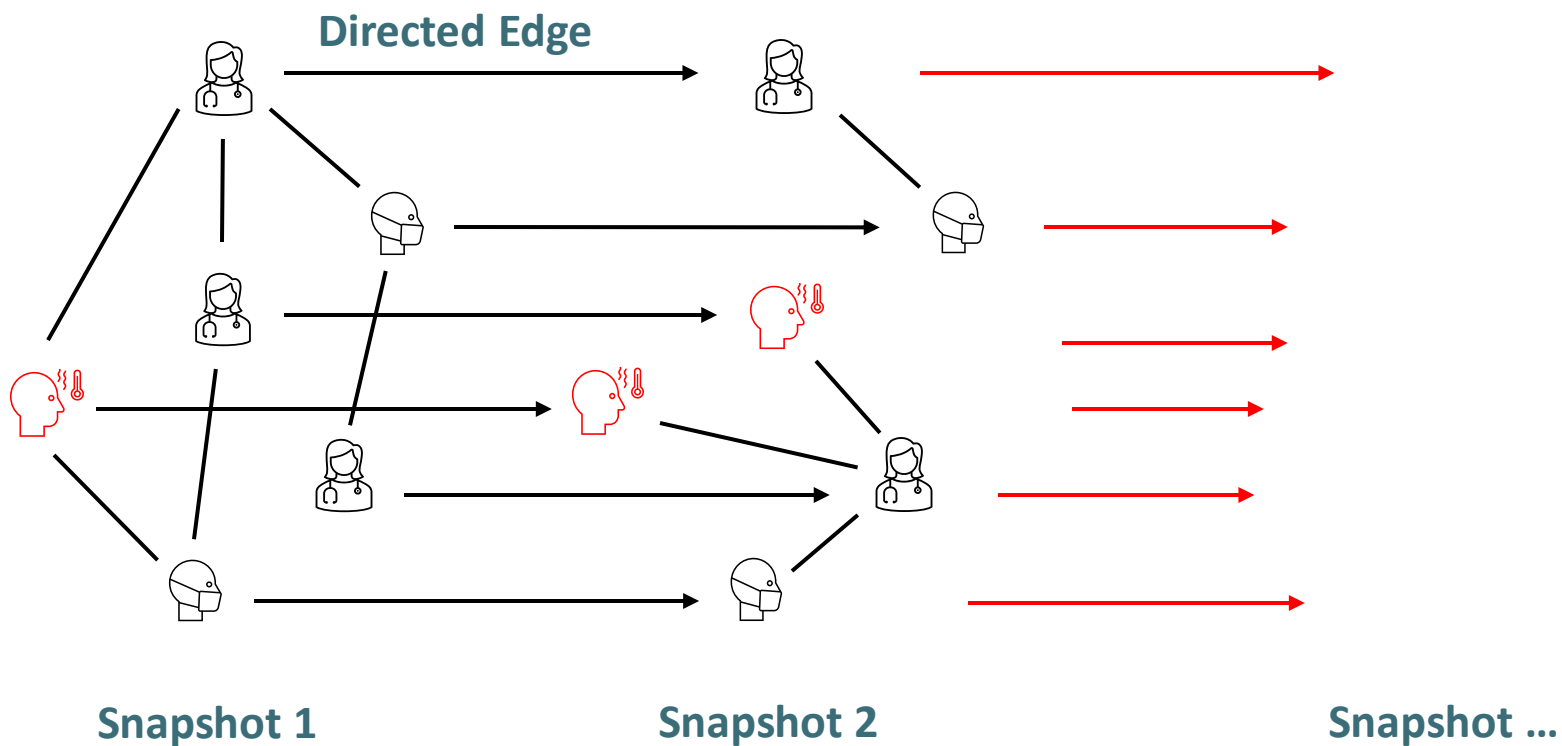
If we have more interactions ...

- Build snapshot upon previous ones



Still have more interactions ...

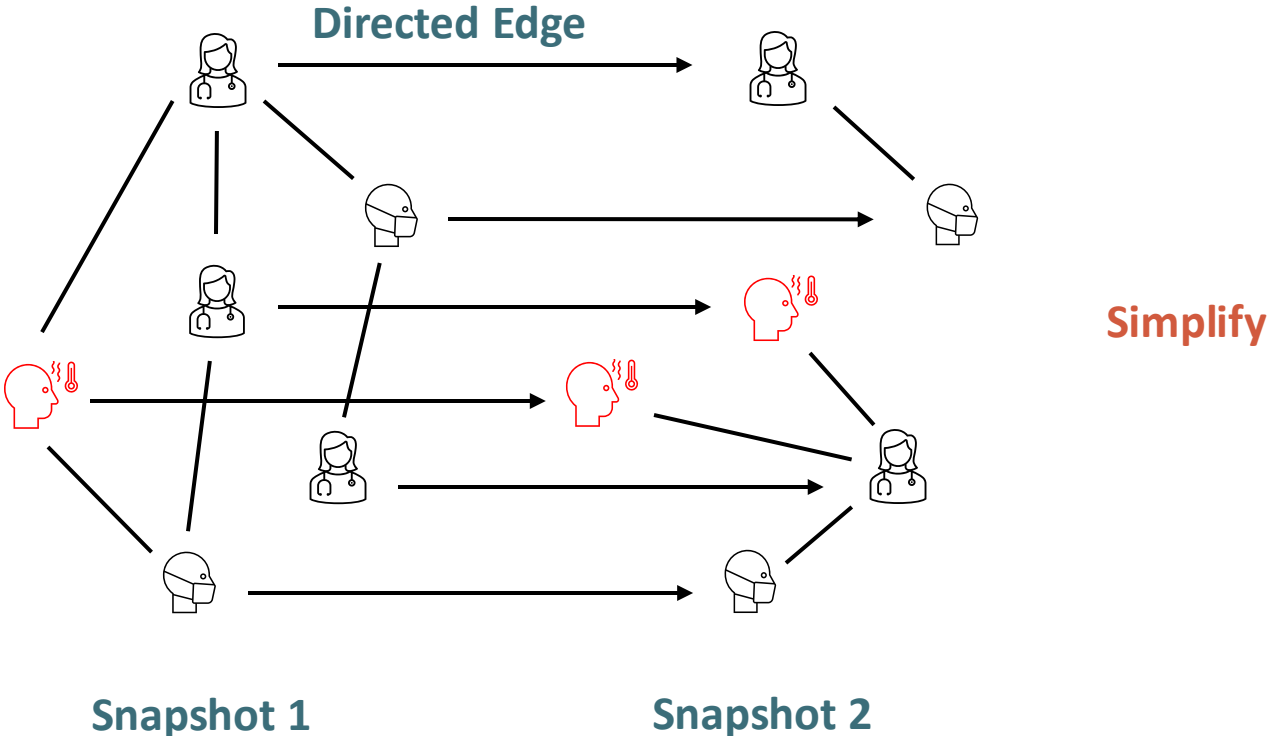
- Build snapshot upon previous ones



Such network also called *time-expanded network*

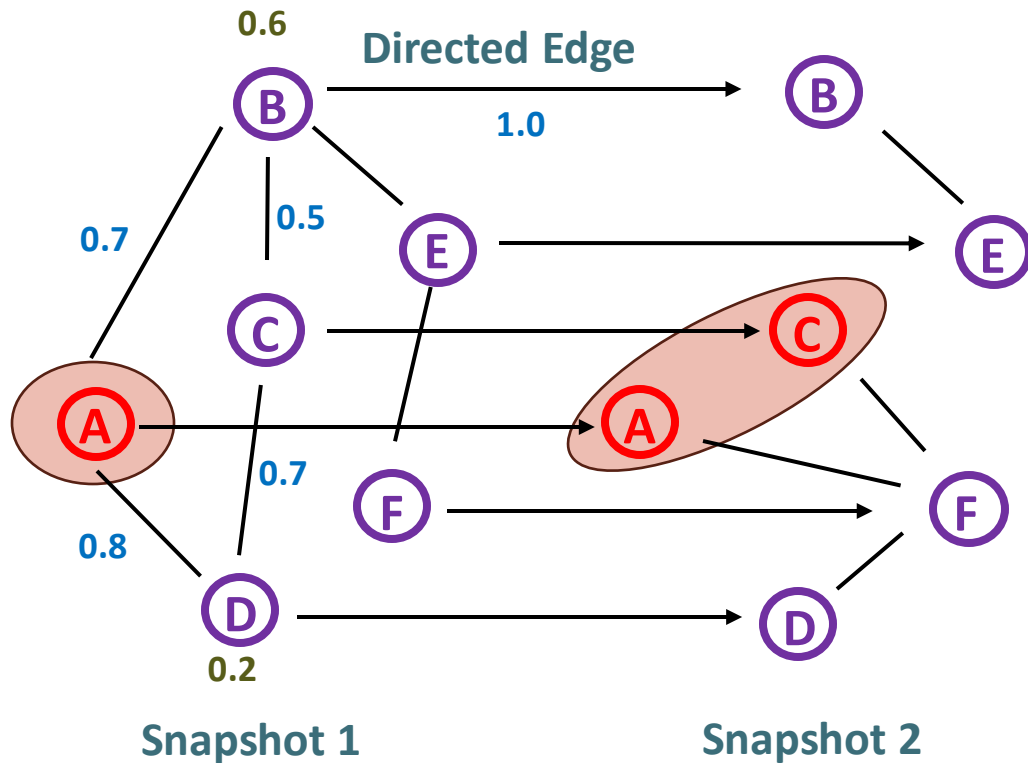
Problem Formulation

- Take 2 *snapshots* as an example. We are focusing the following problem.



Problem Formulation

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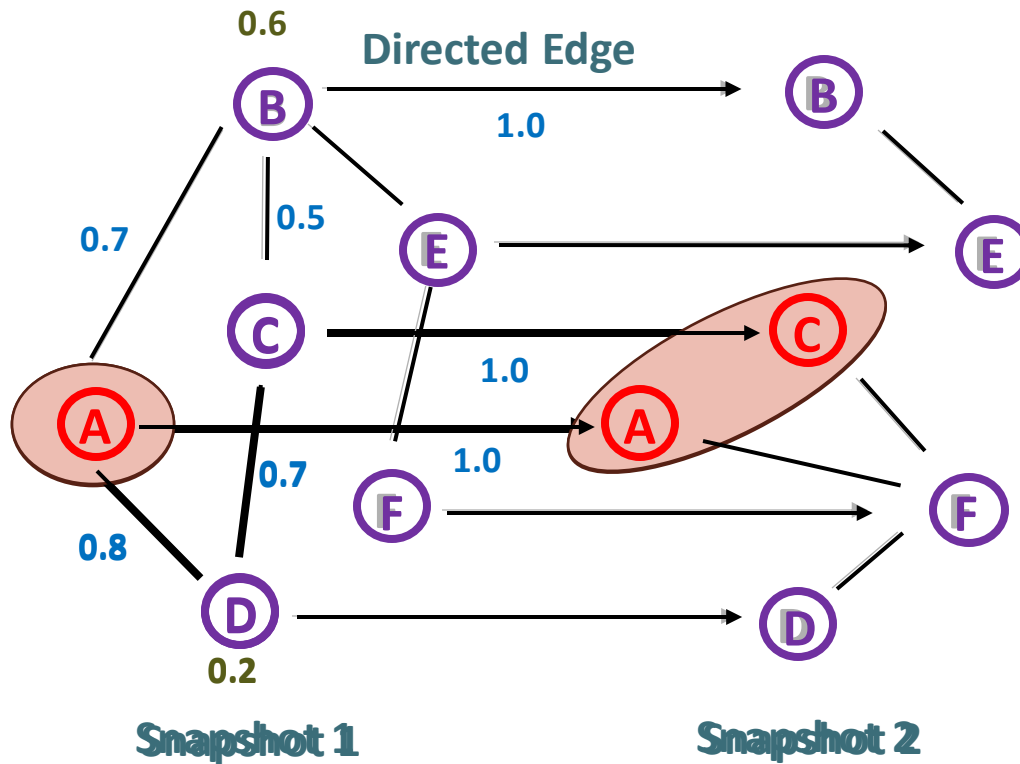
Edge Weight: Probability of transmission

Node Prize: Probability of being asymptomatic

Goal: Cover positive nodes by a *tree*, and *maximize* the weight and prize

One Solution

$$\text{Obj} = 0.7 + 0.5 + 1.0 + 1.0 + 0.2 = 3.4$$



Edge Weight: Probability of transmission

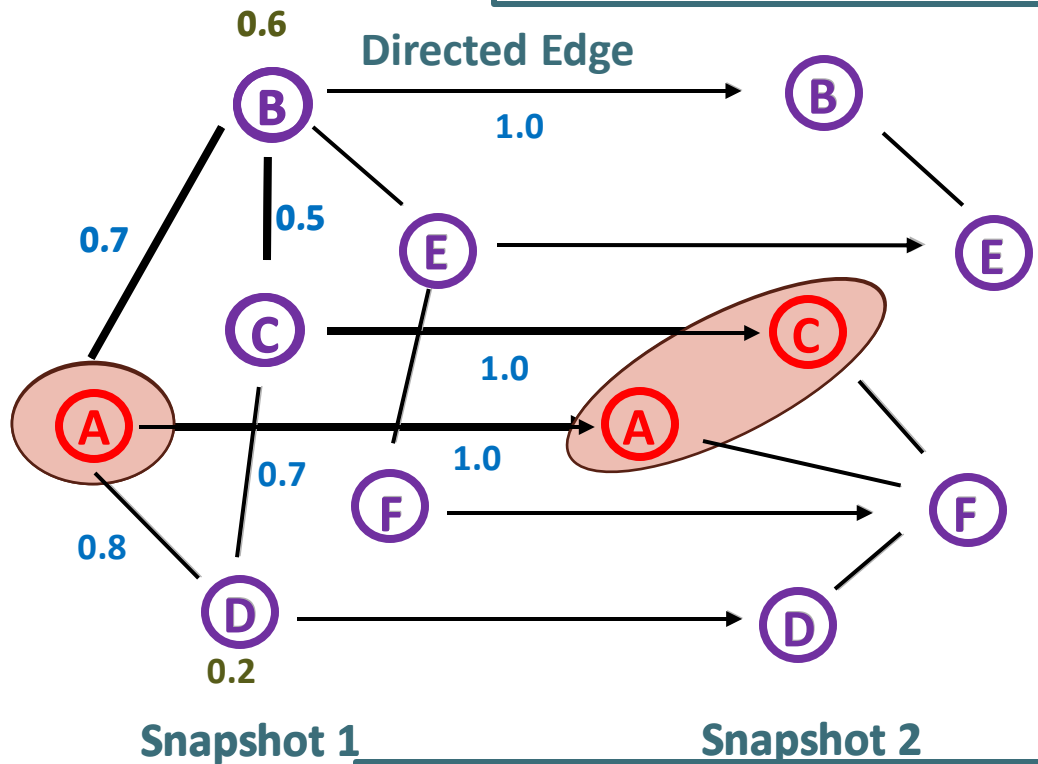
Node Prize: Probability of being asymptomatic

Goal: Cover positive nodes by a *tree*, and *maximize* the weight and prize

Another Solution

$$\text{Obj} = 0.7 + 0.5 + 1.0 + 1.0 + 0.6 = 3.8 > 3.4$$

B should be asymptomatic!



Edge Weight: Probability of transmission

Node Prize: Probability of being asymptomatic

Goal: Cover positive nodes by a *tree*, and *maximize* the weight and prize

Snapshot 1

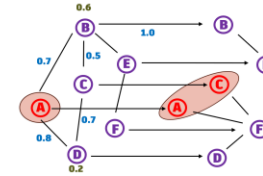
Snapshot 2

This problem is Prize-collective Steiner Tree.

Directed Prize-collecting Steiner Tree

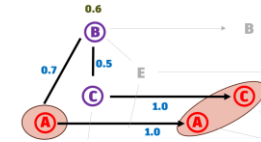
□ Given

- Time-expanded Network
- Positive Cases



□ Output

- Steiner Tree, and satisfies



$$T^* = \arg \min_T \sum_{(v_a, v_b) \in T} W_s(v_a, v_b) + \alpha \sum_{v_c \in V_s \setminus T} f(F_{v_c})$$

1 - Edge Weight

Node Prize of excluded nodes

Challenge 1: Estimate the Probability

Challenge 2: Construct the Tree

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Related Works

- ❑ MCA [Jang et al.]
 - Prize-collecting Steiner Tree
 - Fixed prize, sub-optimal

- ❑ CuLT [Rozenshtein et al.]
 - Steiner Tree
 - Assume SI model, ignore risk-factors

- ❑ TopoLSTM [Wang et al.]
 - Cascade
 - Ignore risk-factors

Methods	Cascade	Steiner Tree	Risk Factors	End-to-end
TopoLSTM	✓	✗	✗	✗
CuLT	✓	✓	✗	✗
MCA	✓	✓	✓	✗
Ours	✓	✓	✓	✓

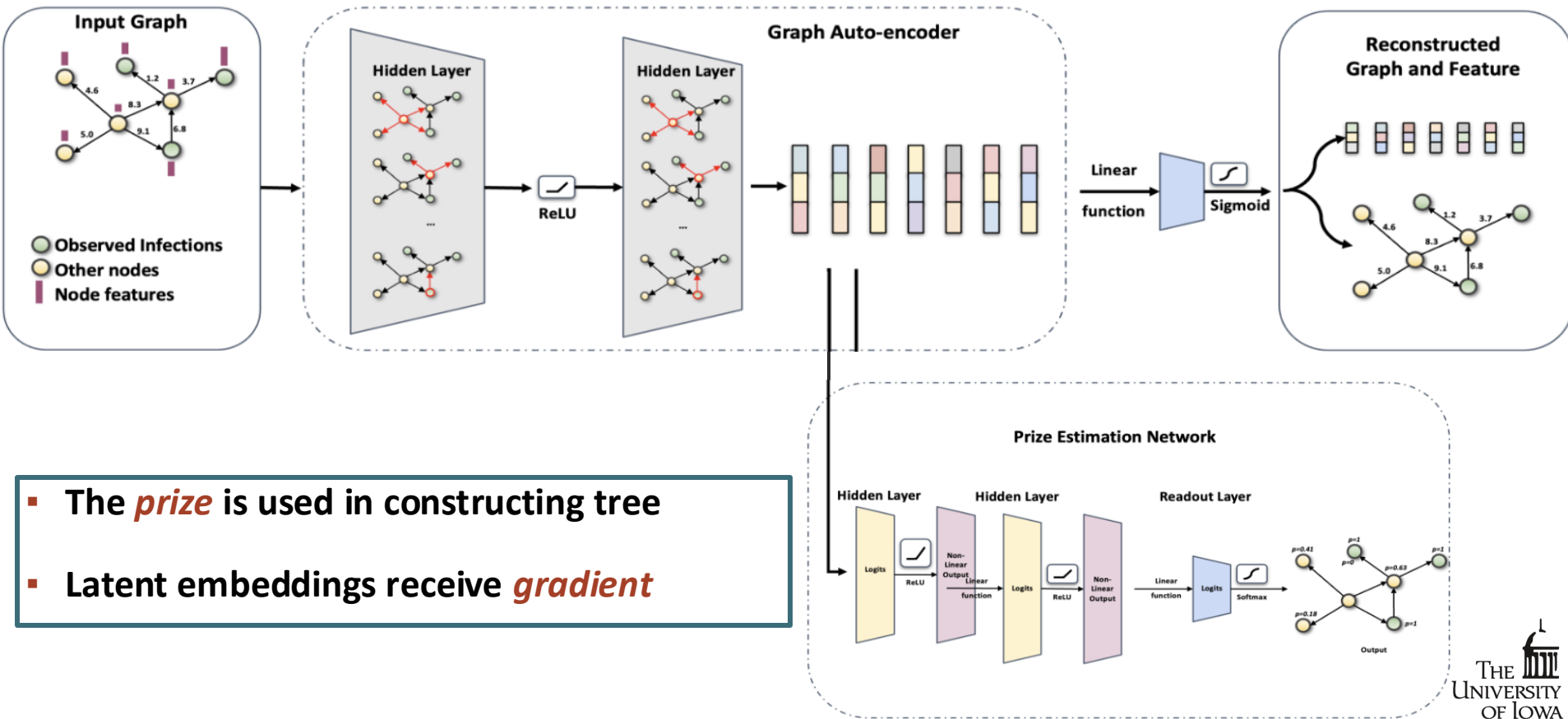
Main contribution:
jointly optimize for
estimating and
constructing.



[1] Jang, Hankyu, et al. "Risk-aware temporal cascade reconstruction to detect asymptomatic cases: For the cdc mind healthcare network." 2021 IEEE International Conference on Data Mining (ICDM). IEEE, 2021.
 [2] Rozenshtein, Polina, et al. "Reconstructing an epidemic over time." Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. 2016.
 [3] Wang, Jia, et al. "Topological recurrent neural network for diffusion prediction." 2017 IEEE international conference on data mining (ICDM). IEEE, 2017..

Estimate Probability

Graph Autoencoder



- The *prize* is used in constructing tree
- Latent embeddings receive *gradient*

Construct the Tree – Reinforcement Learning

□ State:

- The state space is *all the possible Trees*. The starting state is $\{r\}$ for some random node.

□ Action:

- The action is to *select edge (u, v)* and $u \in S_t, v \notin S_t$. Then, the state will transit to $S_t \cup \{v\}$ with probability 1. We include one more node for each step.

□ Reward:

$$\alpha f(F_v) - \sum_{u \in S_t} W_s(u, v)$$

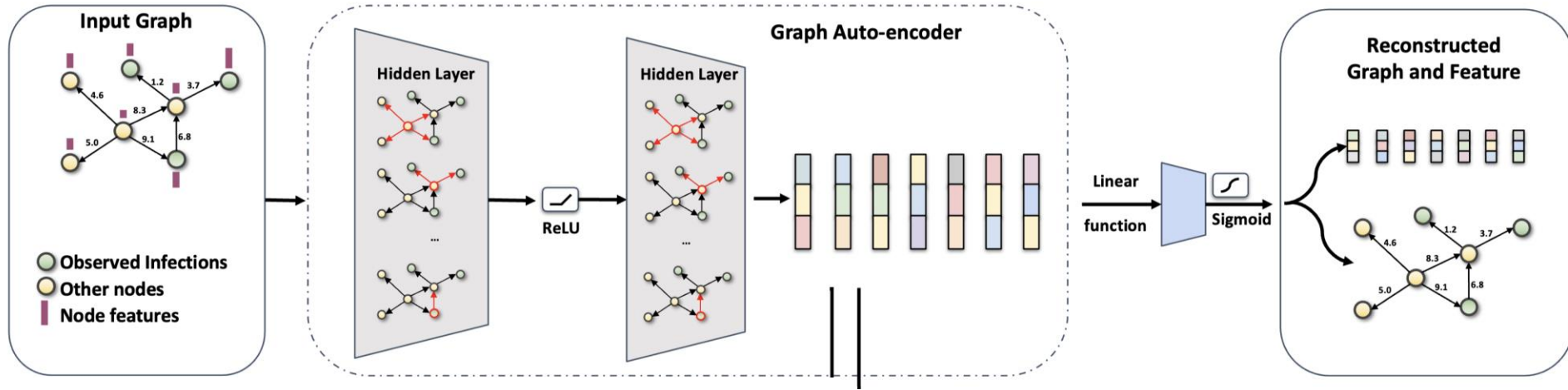


Sum up all steps

$$\alpha \sum_{v \in S_T} f(v) - \sum_{(u,v) \in S_T} W(u, v)$$

Exactly the objective!

Jointly Optimization



Content

- Background & Challenges
- Prize-collecting Steiner Tree
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Experiment

□ Data

- University of Iowa Hospitals and Clinics (UIHC)
- Interactions between **patients** and **healthcare workers**
- 500 (UIHC1), 2000 (UIHC2), and 5000(UIHC3)

□ Tasks

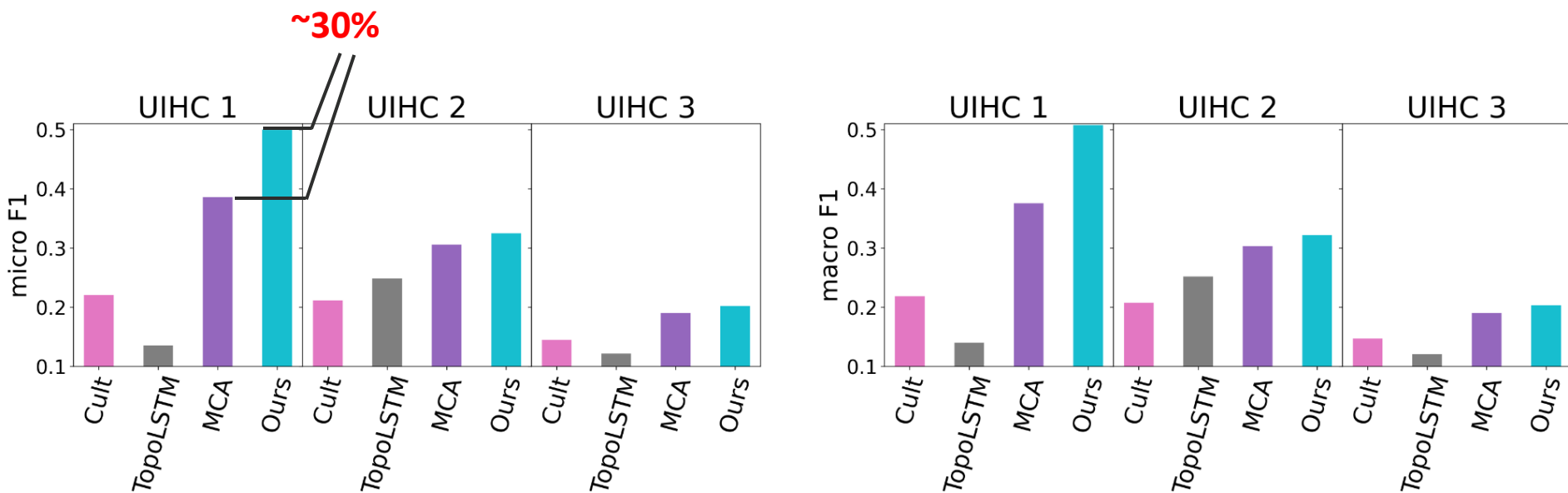
- Simulated CDI Outbreak
- Real CDI Outbreak
- Simulated Covid-19 Outbreak

No asymptomatic ground truth

Simulated CDI Outbreak - Setup

- Use *Biased-SIS* model to generate *symptomatic* and *asymptomatic* infections.
- The model used known risk factors for C. Difficile
- On 500 (*UIHC1*), 2000 (*UIHC2*), and 5000 (*UIHC3*)
- Based on *symptomatic cases*, *infer the asymptomatic*
- Use *micro-F1* and *macro-F1* to evaluate
- Run *5 time* and report the mean.

Simulated CDI Outbreak - Result



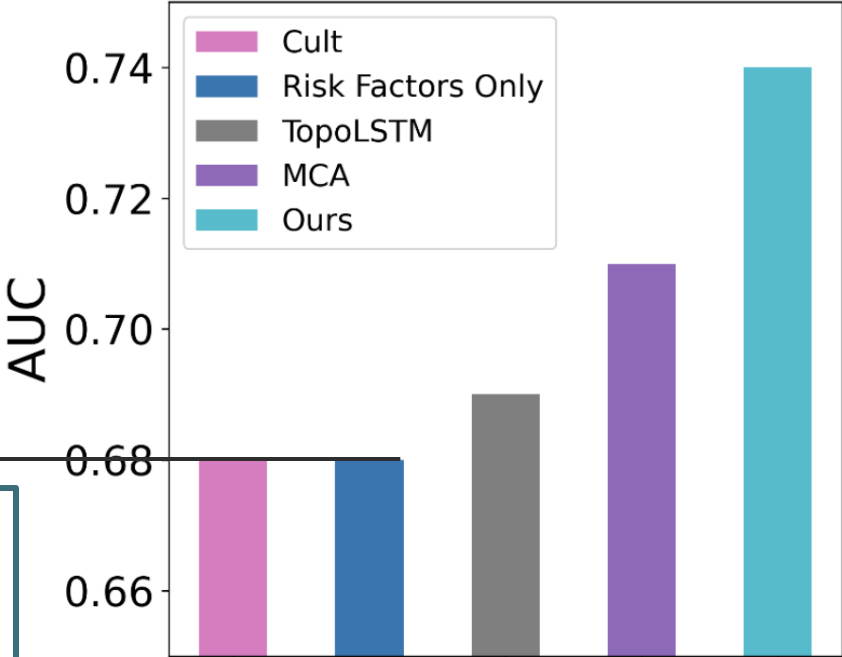
Joint optimization enables us to avoid the limitations of MCA and achieve greater accuracy.

Real CDI Outbreak - Setup

- Sample *one month of interactions* from UIHC to construct graph.
- **68** positive cases.
- **80%** training
- Each method infers the asymptomatic cases based on training set
- Based on the prediction, we compute the *asymptomatic pressure*. (i.e., a normalized metric computing interaction frequency with asymptomatic cases)
- Use the *asymptomatic pressure* as extra features, we train a MLP to predict the rest positive cases.

Real CDI Outbreak

Results



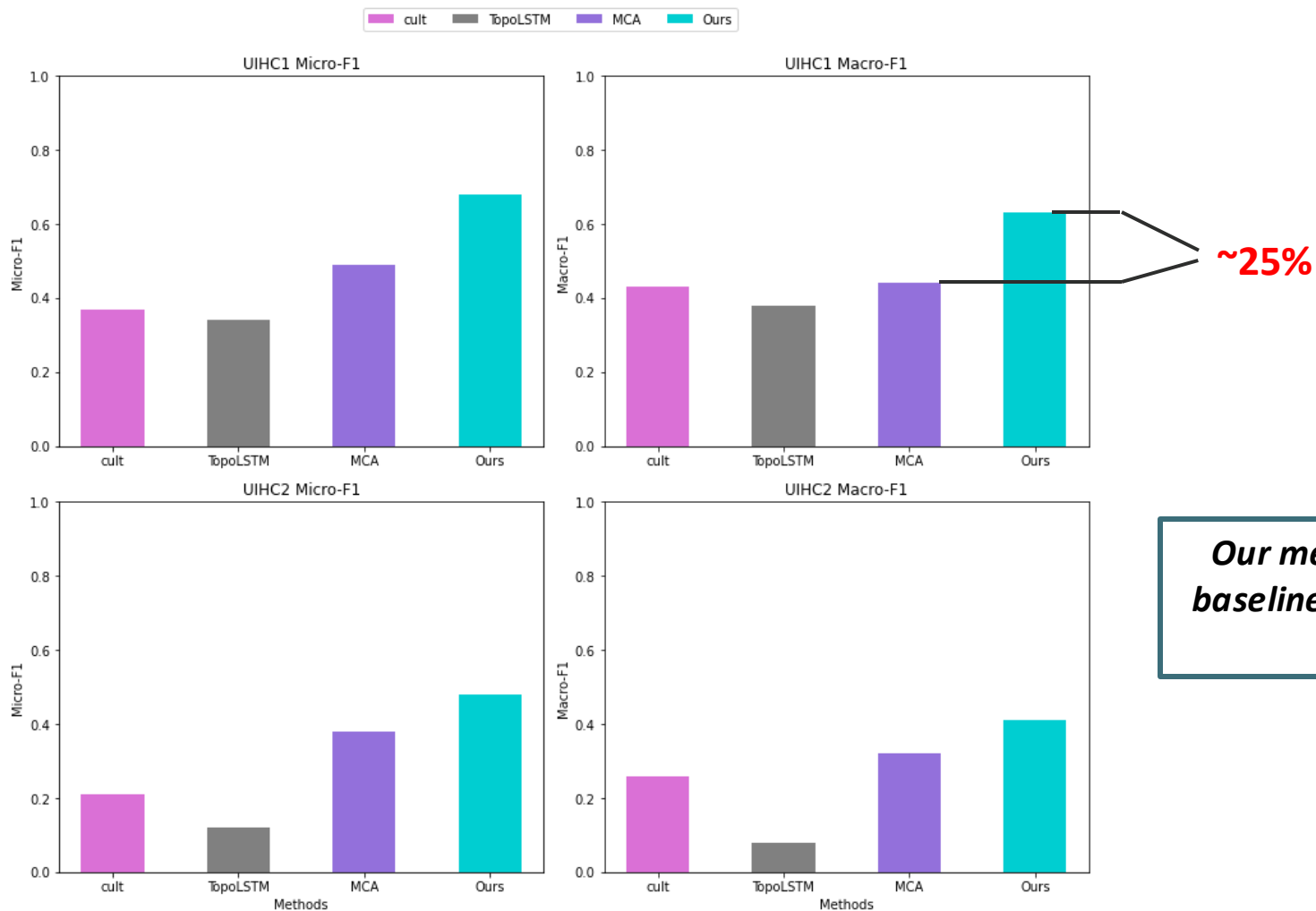
*CuLT is **unable** to improve upon the Risk-factors-only baseline*

*Inferred asymptomatic cases by our method are **more accurate***

Simulated Covid-19 Outbreak - Setup

- *CovaSim* model
- Generate **symptomatic** and **asymptomatic** infections.
- On 500 (*UIHC1*), 2000 (*UIHC2*)
- Based on **symptomatic**, models infer the asymptomatic cases.
- Use **micro-F1** and **macro-F1** to evaluate

Simulated Covid-19 Outbreak - Result



Our method outperform baselines even for another disease


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Conclusion & Future Work

- Our results on synthetic outbreaks show that the proposed approach is able to identify asymptomatic infection with high accuracy while the baseline approaches are less accurate.
- The tree affect the probability.

$$T^* = \arg \min_T \sum_{(v_a, v_b) \in T} W_s(v_a, v_b) + \alpha \sum_{v_c \in V_s \setminus T} f(F_{v_c})$$


 $f(F_{v_c}; T)$

THANKS