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Detecting Sources of Healthcare Associated Infections

Presenter: Hankyu Jang

Co-authors: Andrew Fu, Jiaming Cui, Methun Kamruzzaman,
B. Aditya Prakash, Anil Vullikanti, Bijaya Adhikari, *Sriram V. Pemmaraju

University of Iowa
comp|epi
computational epidemiology research

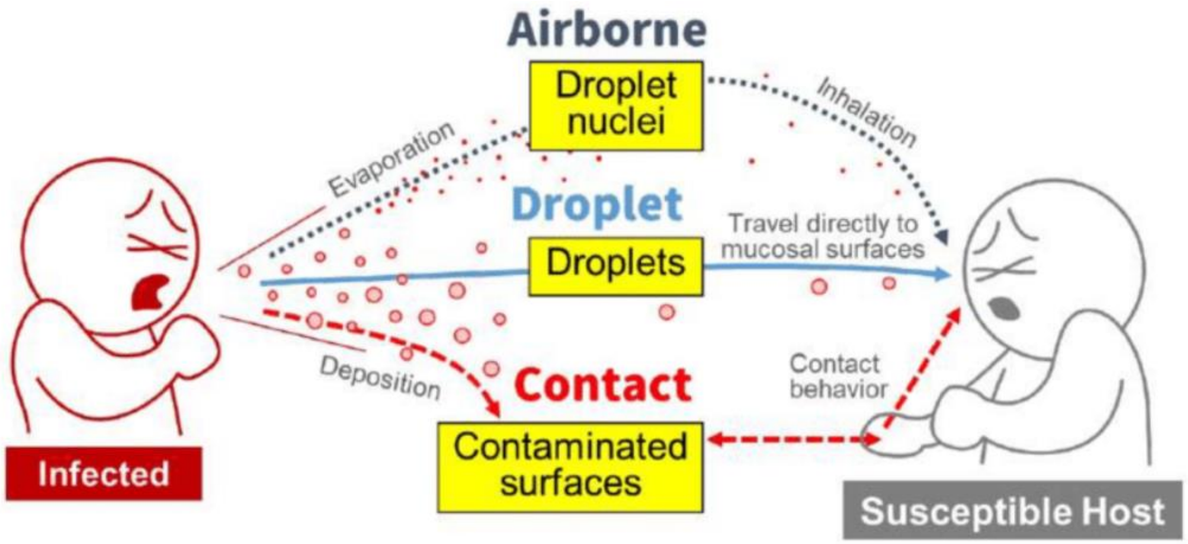
Georgia Tech

University of Virginia

The University of Iowa

Healthcare associated infections

- *Healthcare-associated infections* (HAIs): infections that spread in healthcare settings
  – Each year, roughly 4% of patients in the US are diagnosed with HAI [*]
  – Immunocompromised patients are at risk of HAI, and infections can lead to severe outcomes
- Common HAIs, such as *Methicillin-resistant Staphylococcus aureus (MRSA) infection* or *Clostridioides difficile infection (CDI)* spread via ***contact***

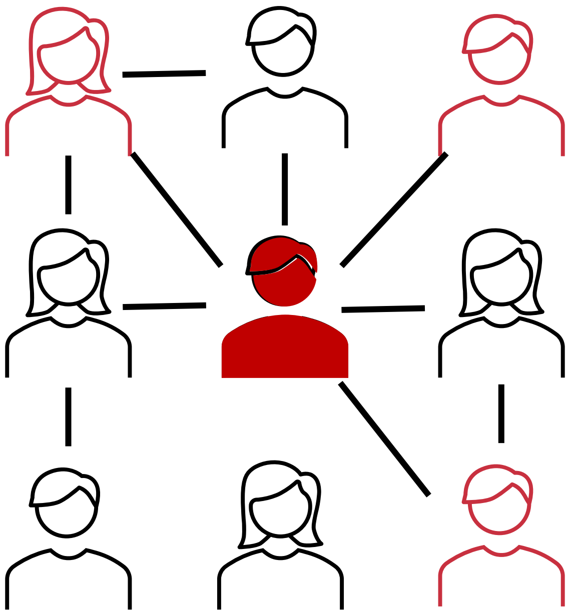


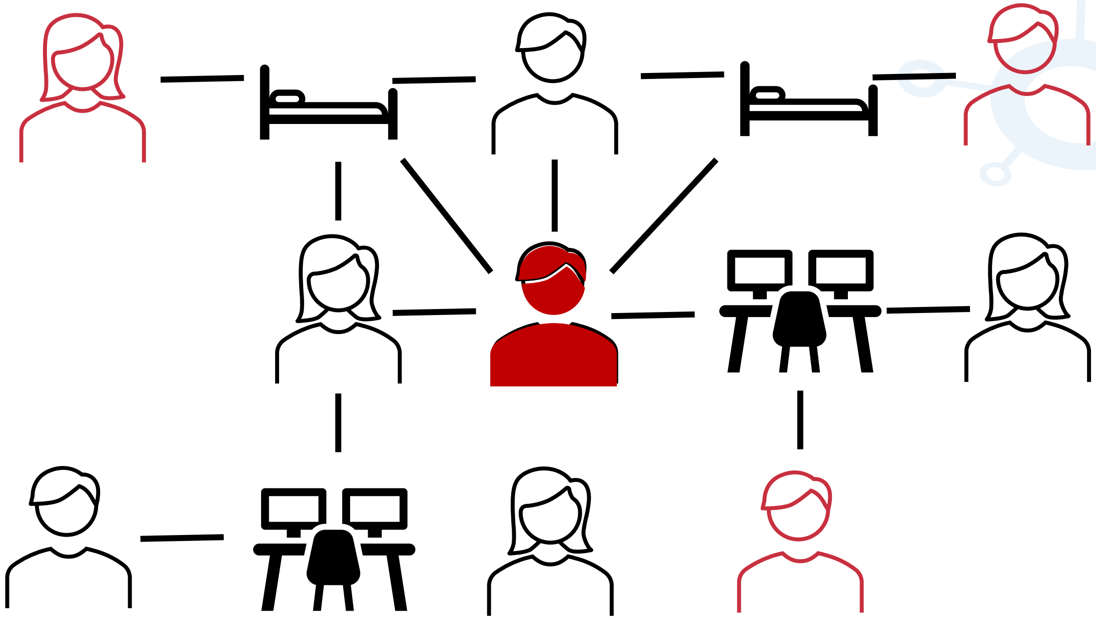
[-]

[*] CDC, "Healthcare-associated infections (hais)," https://www.cdc.gov/winnablebattles/report/HAIs.html.
[-] Gameiro Silva, M. An analysis of the transmission modes of COVID-19 in light of the concepts of Indoor Air Quality. 2020

Motivation

- When some HAIs are detected, a lot of effort is invested into rapidly identifying the source of infection
- This corresponds to the classical ***source detection*** problem [+,-,=]





Source detection problem remains open for HAIs, and is the focus of our paper

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[=] Lappas, T.; Terzi, E.; Gunopulos, D.; and Mannila, H. Finding Effectors in Social Networks. KDD 2010
[+] ***Prakash BA***, Vreeken J, Faloutsos C. Efficiently spotting the starting points of an epidemic in a large graph. KAIS 2014

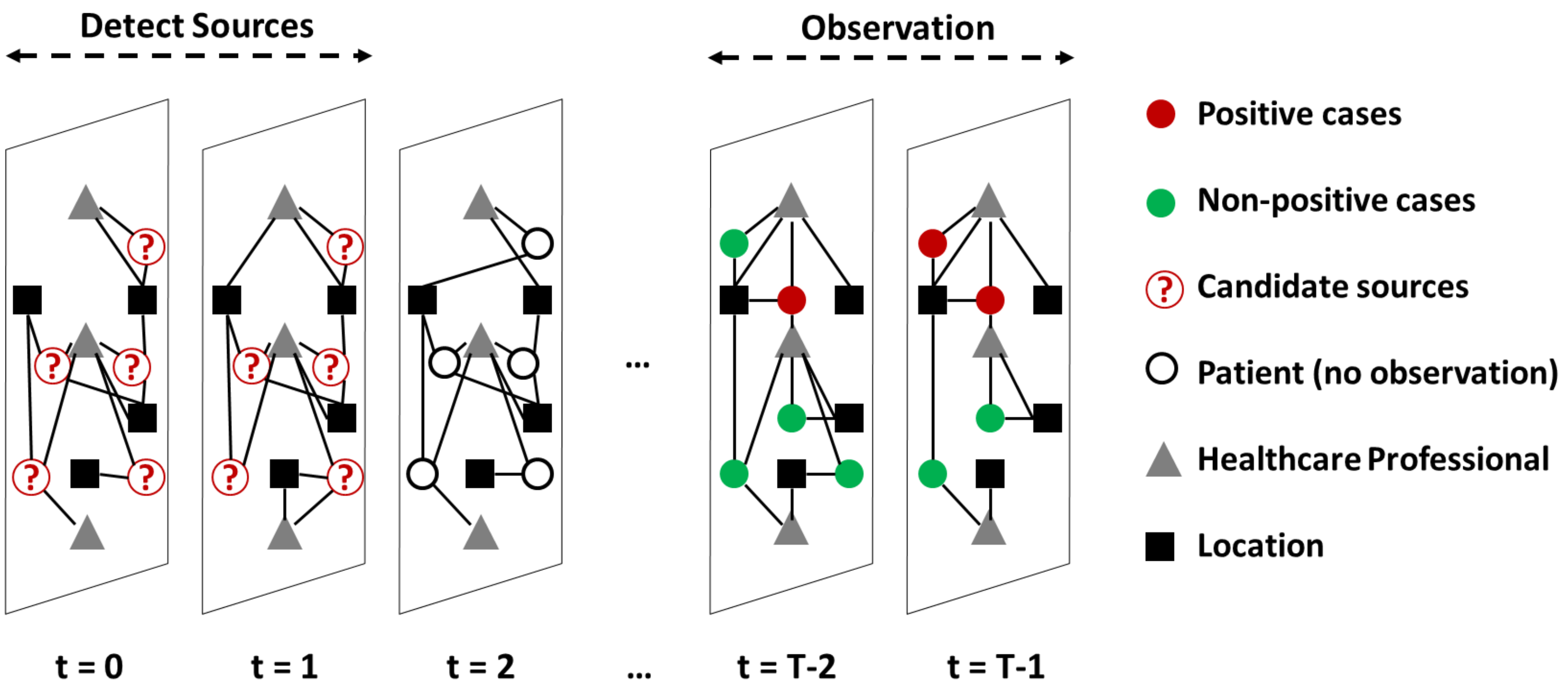
The source detection problem

- Given a temporal network $\mathcal{G} = (G_0, G_1, \dots, G_{T-1})$, a load sharing model M, and a set of observed cases
- Find a source set S
  - that makes $g(S)$ large
  - while keeping $f(S)$ small

$\alpha(v, S)$: Probability of v that get infected according to M due to disease starting at S

$g(S) = \sum_{v \in Pos} \alpha(v, S)$: Expected number of infections among **Positive cases**

$f(S) = \sum_{v \in Neg} \alpha(v, S)$: Expected number of infections among **Non-positive cases**



Background: load sharing model

- Traditional compartmental models model disease spread via person-to-person contact
- Recently, disease models that take into account the role of environments were proposed [+, -, =]
- Load sharing model [+]

$$L_y(t+1) = \underbrace{(1-d)L_y(t)}_{\text{Load remaining after natural decay}} - \underbrace{\sum_{x:\{x,y\}\in E_t} \rho_{y,x} \cdot L_y(t)}_{\text{Outgoing load}} + \underbrace{\sum_{x:\{x,y\}\in E_t} \rho_{x,y} \cdot L_x(t)}_{\text{Incoming load}} + \underbrace{I_{inf} \cdot q}_{\text{Shedding}}$$

[-] Li S, Eisenberg JN, Spicknall IH, Koopman JS. Dynamics and control of infections transmitted from person to person through the environment. American journal of epidemiology. 2009
[=] Plipat N, Spicknall IH, Koopman JS, Eisenberg JN. The dynamics of methicillin-resistant Staphylococcus aureus exposure in a hospital model and the potential for environmental intervention. BMC infectious diseases. 2013
[+] ***Hankyu Jang***, S. Justice, P. M. Polgreen, A. M. Segre, D. K. Sewell, and ***S. V. Pemmaraju***, "Evaluating Architectural Changes to Alter Pathogen Dynamics in a Dialysis Unit," IEEE/ACM ASONAM 2019

Problem formulation. **SD±PSC**

Source Detection Positive-Negative Partial Set Cover (SD±PSC)

- Given
  - a temporal network $G = (G_0, G_1, \dots, G_{T-1})$,
  - a load sharing model M
  - an observed positive set Pos in time $T-2$ and $T-1$
- Find a source set S^* in time 0 and 1
- That minimizes $\underbrace{\sum_{v \epsilon Pos}(1-\alpha(v,\ S))}$ + $\underbrace{\sum_{v \epsilon Neg}\ \alpha(v,\ S)}$

Expected number of ***positive*** cases ***not infected*** by an infection starting at source set S

Expected number of ***negative*** cases ***infected*** by an infection starting at source set S

The objective function is a simple and natural model for the Source Detection problem

However, ***no reasonable approximation exists*** for the problem

Proof of hardness of approximation is in the paper

Tractable problem formulation. **SD±KNAP**

Source Detection Positive-Negative Knapsack (SD±KNAP)

- Given
  - a temporal network $G = (G_0, G_1, \dots, G_{T-1})$,
  - a load sharing model M
  - an observed positive set Pos in time $T-2$ and $T-1$
  - Parameters $k_{T-2}, k_{T-1} \in \mathbb{R}^+$
- Find a source set S^* in time 0 and 1
- That maximizes $g(S)$
  - Such that S satisfies constraints $f_{T-2}(S) \leq k_{T-2}$ and $f_{T-1}(S) \leq k_{T-1}$

Tractable problem formulation. **SD±RATIO**

Source Detection Positive-Negative Ratio (SD±RATIO)

- Given
  - a temporal network $G = (G_0, G_1, \dots, G_{T-1})$,
  - a load sharing model M
  - an observed positive set Pos in time $T-2$ and $T-1$
  - Parameters $\gamma_{T-2}, \gamma_{T-1} \in \mathbb{R}^+$
- Find a source set S^* in time 0 and 1
- That maximizes $\dfrac{g(S)}{\gamma_{T-2} \cdot f_{T-2}(S) + \gamma_{T-1} \cdot f_{T-1}(S)}$

These tractable problem formulations depend on the ***submodularity*** of the functions f and g

Submodularity

Set function $f: 2^V \rightarrow \mathbb{R}$ is submodular if it satisfies

$$f(S \cup \{e\}) - f(S) \geq f(T \cup \{e\}) - f(T)\,, \qquad S \subseteq T \subseteq V, \qquad e \in V \backslash \mathrm{T}$$

- The core of our contribution is showing $g(S)$, $f(S)$ and $f_t(S)$ are monotone and submodular set functions
  - The key aspect is showing that if (i) *loads at nodes are monotone, submodular functions of the source set* and *(ii) the dose response function is concave*, then $g(S)$ is submodular
  - Proof uses 'coupling' technique [+]
  - We couple the stochastic decisions made from 4 source sets $S, S + \{v\}, Q, Q + \{v\}$, where $S \subseteq Q$ and $v \notin Q$
- The submodularity in the objective functions allows access to various algorithmic approaches
  - SD±KNAP : Adapted from Bilmes-Iyer, gradient ascent framework [-] Azar-Gamzu, multiplicative update [=]
  - SD±RATIO : Adapted from Bai et. al, greedy for maximizing ratio of submodular functions [*]

[+] Mossel E, Roch S. On the submodularity of influence in social networks. ACM STOC 2007
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[-] Iyer RK, Bilmes JA. Submodular optimization with submodular cover and submodular knapsack constraints. NIPS 2013
[*] Bai W, Iyer R, Wei K, Bilmes J. Algorithms for optimizing the ratio of submodular functions. ICML 2016

Data

- Daily interactions between healthcare personnel (HCP), patients, and locations
- 31 daily snapshots each of the datasets

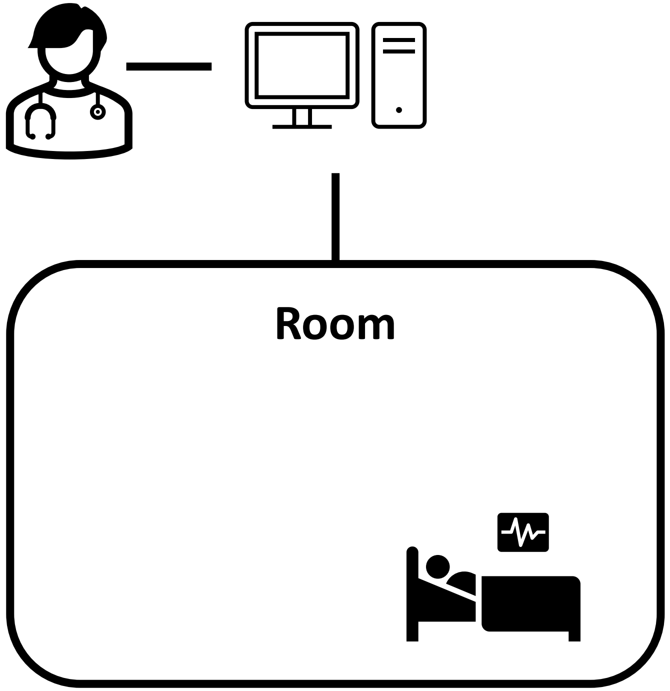
Hospital	Number of nodes	Number of edges (/ day)	Description
UIHC[1] whole graph	10.4 K	13.8 K	Interactions captured in UIHC, the whole hospital
UIHC unit	0.8 K	0.5 K	A unit in UIHC with the most number of CDI cases
UVA[2] pre COVID	2.4 K	0.4 K	Interactions recorded in Cardiology department, 2011
UVA post COVID	0.9 K	0.4 K	Interactions recorded in Cardiology department, 2020
Carilion	2.3 K	29.6 K	Public dataset. Interactions captured in Carilion Hospital in VA

[1] UIHC: University of Iowa Hospitals and Clinics
[2] UVA: University of Virginia Hospital

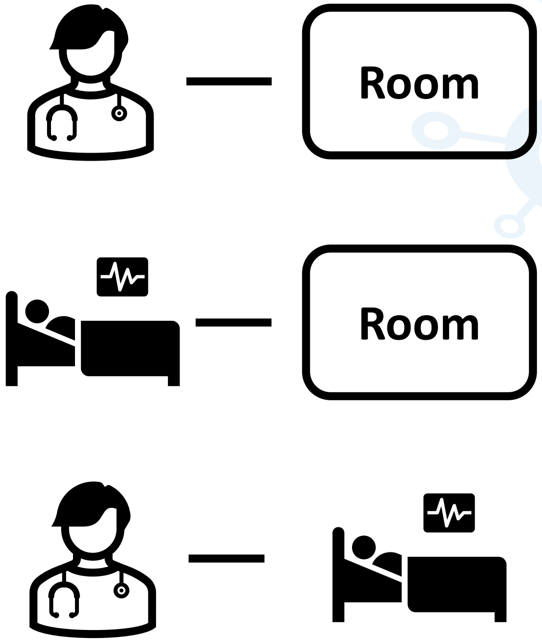
UIHC contact network

- HCP mobility: HCP terminal logins data
- Patient mobility: Admission-discharge-transfer (ADT) data

Nodes



Edges



Experiments

Experiment set up

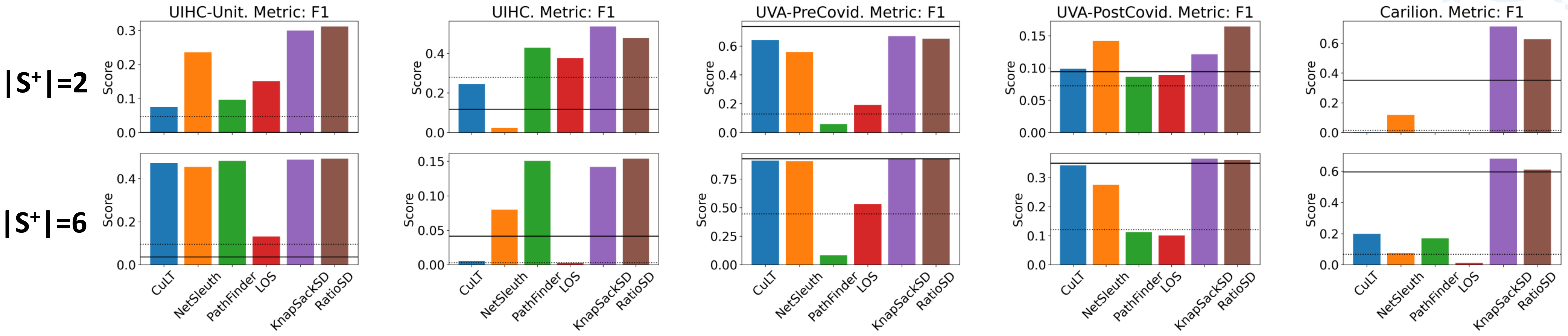
- Simulate outbreaks from randomly selected sources S_{GT}, and record observations Pos and Neg
- Then detect sources S_M using our algorithms and baselines

Evaluation

- A straightforward metric is to measure intersection of S_{GT} and S_M
  - In general, it is impossible for any algorithm M to do well w.r.t. this metric
  - S_{GT} may do poor in explaining Pos and Neg
- Hence, we use two other natural metrics
  - Pos, Neg *Overlap*: Measure overlap between "Pos and Neg" and "the positive set and negative set caused by outbreaks starting from S_M"
  - S_{GT} *Distance*: Compute distance between S_{GT} and S_M

Results. Metric: Pos, Neg ***Overlap***

- KnapsackSD and RatioSD consistently outperform all baselines
- Other baselines, e.g., CuLT [+] and NetSleuth [-] are inconsistent
  - Baselines do not capture instances where multiple pathways plays role in infections
  - In such settings, their performance may drop



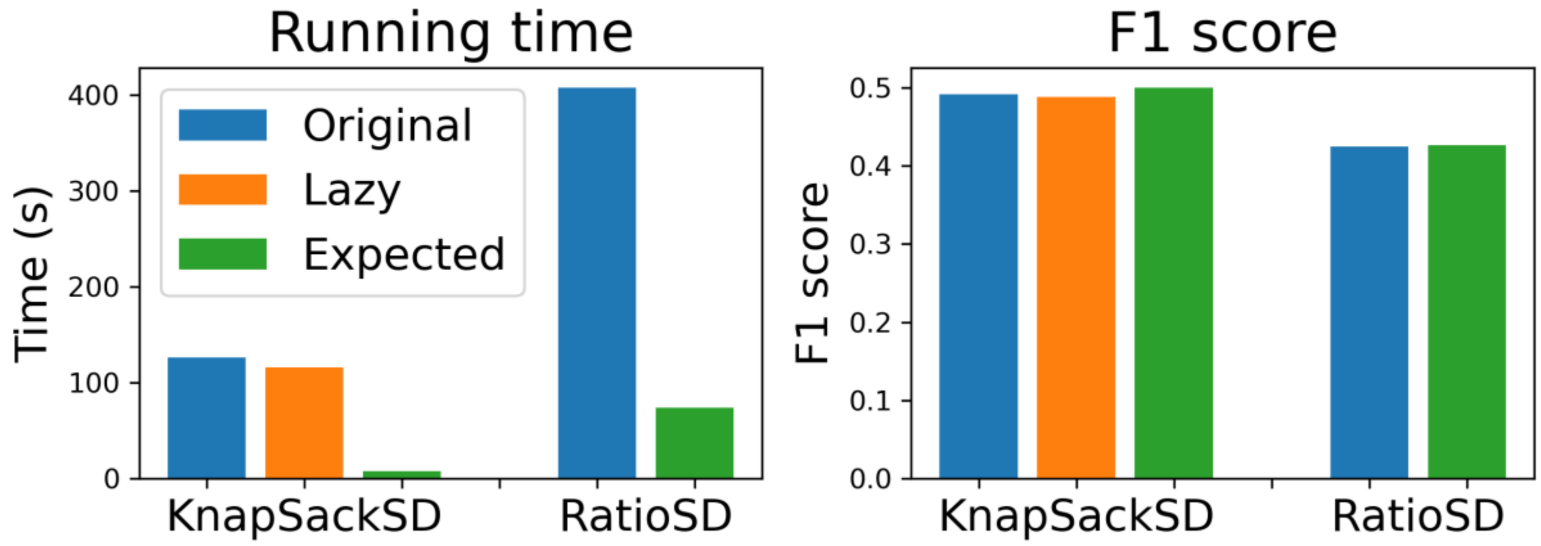
[-] ***Prakash BA***, Vreeken J, Faloutsos C. Spotting culprits in epidemics: How many and which ones?. ICDM 2012
[+] Rozenshtein P, Gionis A, ***Prakash BA***, Vreeken J. Reconstructing an epidemic over time. KDD 2016

Speed up via expected load propagation

- Since f and g are ***stochastic***, which requires a substantial number of simulations to get good estimates
- We propose ***expected load propagation*** heuristic

$$\mathbb{E}[L_y(t+1)] = \underbrace{(1-d)\mathbb{E}[L_y(t)]}_{\text{Load remaining after natural decay}} + \underbrace{\sum_x (\rho_{y,x}\mathbb{E}[L_x(t)]}_{\text{Incoming load}} \underbrace{- \sum_x \rho_{x,y}\mathbb{E}[L_y(t)])}_{\text{Outgoing load}} + \underbrace{q \cdot p(\mathbb{E}[L_y(t)])}_{\text{Probabilistic shedding}}$$

Pos, Neg **Overlap**



Thank you!

Hankyu Jang	Andrew Fu	Jiaming Cui	Methun Kamruzzaman	B.Aditya Prakash	Anil Vullikanti	Bijaya Adhikari	* Sriram V. Pemmaraju
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	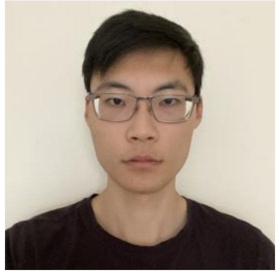						

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University of Virginia
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* **Corresponding author:** Sriram V. Pemmaraju. Department of Computer Science, University of Iowa. sriram-pemmaraju@uiowa.edu