Provable Sensor Sets for Epidemic Detection over Networks with Minimum Delay

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Abstract

The efficient detection of outbreaks and other cascading phenomena is a fundamental problem in a number of domains, including disease spread, social networks, and infrastructure networks. In such settings, monitoring and testing a small group of pre-selected nodes from the susceptible population (i.e., a sensor set) is often the preferred testing regime. We study the problem of selecting a sensor set that minimizes the delay in detection—we refer to this as the MinDelSS problem. Prior methods for minimizing the detection time rely on greedy algorithms using submodularity. We show that this approach can sometimes lead to a worse approximation for minimizing the detection time than desired. We also show that MinDelSS is hard to approximate within an $O(n^{1-1/\gamma})$-factor for any constant $\gamma \geq 2$ for a graph with $n$ nodes. This instead motivates seeking a bicriteria approximations.

We present the algorithm ROUNDSENSOR, which gives a rigorous worst case $O(\log n)$-factor for the detection time, while violating the budget by a factor of $O(\log^2 n)$. Our algorithm is based on the sample average approximation technique from stochastic optimization, combined with linear programming and rounding. We evaluate our algorithm on several networks, including hospital contact networks, which validates its effectiveness in real settings.

Introduction

Recurring disease outbreaks, including the COVID-19 pandemic and the emerging variants, illustrate the importance of good surveillance in order to detect the onset of a disease outbreak in the population. Diverse mechanisms exist for testing, ranging from syndromic surveillance (CDC 2021) based on symptoms to more accurate PCR based tests, which can detect fragments of the pathogen. However, such testing is expensive, both in terms of personnel and equipment needed. This is also true in a hospital setting, where hospital acquired infections, such as MRSA, pose significant health burden (Stone 2009; Leclère et al. 2017). Problems of detecting a spreading process also arise more generally in a number of other applications, such as water networks and blog networks (Leskovec et al. 2007).

Such surveillance problems involve finding a “sensor set” $S$, such that monitoring nodes in $S$ is sufficient to detect the disease in the network. As in prior work (Leskovec et al. 2007; Adhikari et al. 2019), we assume that either a set of cascades (or possible scenarios) of disease transmission in a graph are given, or the cascades are sampled from an SIR process on the network. Standard metrics for effective surveillance are probability of detection and the expected delay in detection. Submodularity has been the primary technique in finding good algorithms in prior work (Leskovec et al. 2007; Adhikari et al. 2019). While the detection probability is submodular, the detection time is not (also, it is a minimization problem). (Leskovec et al. 2007) show that a slightly different “penalty reduction” variation of the detection time objective is submodular. As a result, a greedy algorithm gives a $(1 - 1/e)$-factor approximation.

However, as we show, a solution computed by the greedy algorithm for maximizing such a penalty reduction objective can be highly suboptimal with respect to the detection time—this is especially important in regimes when the detection time is low, which is the more realistic setting in disease surveillance. No prior results are known for directly minimizing the detection time. Further, in an SIR model, minimizing the expected detection time is a stochastic optimization problem, which hasn’t been considered before.

Our Contributions.

- We study the problem MinDelSS of finding a sensor set with a given budget, that directly minimizes the detection time; the cascades can be either specified as input, or sampled, in the case of the SIR model for epidemic spread. We show that the greedy approach of (Leskovec et al. 2007) can have an approximation factor of $\Theta(n)$, in general, where $n$ denotes the number of nodes in the graph. We prove that MinDelSS is hard to approximate within an $O(n^{1-1/\gamma})$-factor, for any constant $\gamma \geq 2$, which contrasts with the complexity of maximizing the detection probability or the penalty reduction approach for detection time (Leskovec et al. 2007); this hardness holds even when the cascades are sampled from the SIR process.

- We design a bicriteria approximation algorithm, ROUNDSENSOR, which gives a rigorous worst case $O(\log n)$-factor for the average delay for a set of cascades, while violating the budget by a factor of $O(\log^2 n)$. Note that in light of the above approximation
hardness, we believe such a bicriteria approximation is the best option for finding effective algorithms. We combine this with the sample average approximation technique from stochastic optimization and derive similar bounds on the expected detection time in the SIR model.

• We evaluate our algorithms on multiple real world networks, including four contact networks between patients and health care workers in a hospital. Two of these are quite novel, and constructed using patient electronic medical record (EMR) data; additionally, we have networks for a pre-COVID and COVID period. Our results show that the empirical performance is significantly better than all our theoretical worst case bounds, including the approximation factor for the average delay, the violation in budget, and the number of sampled cascades needed in the case of the SIR model. We also find interesting structural differences in the solutions for the pre-COVID and COVID networks.

Due to space constraints, we omit some of the technical and experimental details; these are presented in the Supplementary material.

Related Work

As mentioned earlier, there has been a lot of work on surveillance and finding sensor sets in different applications, including water networks, air pollution, blogs networks and epidemic surveillance, e.g., (Leskovec et al. 2007; Shao et al. 2018; Christakis and Fowler 2010; Adhikari et al. 2019; Leclère et al. 2017; Hsieh, Lin, and Zheng 2015). (Leclère et al. 2017) describe diverse approaches for outbreak detection for hospital acquired infections—these include statistical process control, scan statistics, traditional statistical models, and data mining methods. (Christakis and Fowler 2010) introduce the problem of finding sensor sets that give good lead time for the peak time of an epidemic—they show that a sensor set chosen based on popular friends of a random set provides good lead time; this was improved by (Shao et al. 2018) using an approach based on dominator sets. Sensors have also been deployed on social networks (Lerman, Yan, and Wu 2016) like Twitter to detect major events. For example, (Kryvashey et al. 2015) studies the detectable patterns of user Twitter messages during Hurricane Sandy to track the disaster. (Sakaki, Okazaki, and Matsuo 2010) treat every user in Twitter as a sensor to construct an earthquake reporting system while (Zhang et al. 2017; Paul, Peng, and Li 2019) sense the geo-tagged tweets to detect events.

Much of the work on surveillance in the AI and ML literature that provide rigorous performance guarantees is based on using submodular optimization. (Leskovec et al. 2007) introduce different metrics for detection by sensor sets with a fixed budget, and reduce them to submodular maximization, including for detection time, as mentioned earlier; this allows a simple greedy algorithm gives a $(1 - 1/e)$-approximation (Nemhauser, Wolsey, and Fisher 1978). (Adhikari et al. 2019) extend this problem to surveillance schedules, instead of a fixed sensor sets, i.e., nodes could be tested at different times, and develop approximation algorithms using submodular functions on a lattice. More complex cost constraints for the sensor set than cardinality have also been considered, e.g., (Krause et al. 2008).

Preliminaries

Cascades and testing. A cascade $H = (V, E')$ is a subgraph of an undirected graph $G = (V, E)$ which is initiated at a node $s(H) \in V$. A node $v$ that is reachable from $s(H)$ and is at distance $t(v, H) - 1$ in $H$ is said to be infected at time $t(v, H)$ (the source $s(H)$ is infected at time 1). If $v$ is not reachable from $s(H)$ in $H$, we define $t(v, H) = n + 1$ where $n$ is the number of nodes within the graph. We consider the following setting for testing—if a node $v$ gets infected at time $t'$ and is tested at any time $t \geq t'$, its prior infection status gets detected. In the context of a disease spread, this could be viewed as a model for antibody tests. A sensor set $S$ is a subset of nodes which get tested every day; the detection time $T(S, H)$ for sensor set $S$ in cascade $H$, denoted by $T(S, H) = \min_{v \in S} t(v, H)$ is the minimum time at which any node in $S$ gets infected in $H$ (recall that the time is $n + 1$ in case no node in $S$ gets infected in $H$). We assume a set of $N$ cascades $H_1, \ldots , H_N$ are given as input. The objective of interest is the average detection time with respect to $S$, denoted by $T_{avg}(S) = \frac{1}{N} \sum H T(S, H)$.

Example. In the example in Figure 1(b) with budget $k = 1$, node $u_4$ gets infected at time $t = 3$, i.e., $t(u_4, H_1) = 3$, and so if it is tested at any time $t' \geq 3$, the infection would be detected. For the sensor set $S_1 = \{u_4\}$, we have $T(S_1, H_1) = 3$ and $T(S_2, H_1) = 2$. For $S_2 = \{u_6\}$, we have $T(S_2, H_1) = 7$ and $T(S_2, H_2) = 3$. For an input with cascades $H_1, H_2$, we have $T_{avg}(S_1) = 2.5$ and $T_{avg}(S_2) = 5$. For this instance, $S^* = \{u_2\}$ is the optimal solution with $T_{avg}(S^*) = 1.5$.

Min Delay Sensor Set (MinDelSS) Problem. Given a graph $G = (V, E)$, a set of cascades $H_1, \ldots , H_N$, and a budget parameter $k$, find a sensor set $S$ of size at most $k$ such that $T_{avg}(S)$ is minimized.

Approximation Algorithms. We say that $S$ is an $(\alpha, \beta)$-bicriteria approximation for MinDelSS if $T_{avg}(S) \leq \alpha T_{avg}(S^*)$ and $|S| \leq \beta k$, where $S^*$ is an optimal solution to the instance of MinDelSS.

Detection in an SIR Model. A specific instance of MinDelSS is in the context of the spread of a disease on a net-
work. We consider an SIR model on a graph $G = (V, E)$, in which the disease spreads from an infectious node $u$ to a susceptible neighbor $v \in N(u)$ with probability $p_{uv}$, independently. We assume $p_{uv}^0$ is the probability that the disease starts at node $u$; $\sum_{v \in N(u)} p_{uv}^0 = 1$. In this setting, a cascade $H$ is a random subgraph on which the disease spreads. In this setting, our objective is to minimize $\mathbb{E}[T(S)]$, where the expectation is over the stochastic disease outcomes $H$.

**Inefficiency of Greedy and Computational Hardness of MinDelSS**

### Greedy Can Be Very Inefficient

(Leskovec et al. 2007) propose a greedy algorithm which attempts to find a set $S$ that maximizes $\pi(S) = 1 - \sum_{i=1}^n (n+1-T(S,H_i))$ for the set of cascades, which is equal to $n + 1 - T_{avg}(S)$.

They show that $\pi(S)$ is submodular, which implies that a greedy algorithm gives a $(1-1/e)$ approximation to the optimal solution. However, maximizing $\pi(\cdot)$ does not imply minimization of the delay, as shown below; the proof is presented in the Supplementary material.

**Lemma 1.** There exist instances where the solution $S_g$ computed by the greedy algorithm of (Leskovec et al. 2007) has $T_{avg}(S_g) = \Omega(nT_{avg}(S^*))$, where $S^*$ denotes an optimal solution.

### Computational Hardness of MinDelSS

In contrast to the $(1-1/e)$-factor approximation for maximizing detection probability, or the penalty reduction approach for detection time (Leskovec et al. 2007), MinDelSS is much harder, both when the cascades are specified, and in the SIR model.

**Theorem 1.** No polynomial time $O(n^{1-1/\gamma})$-approximation to MinDelSS is possible, unless P=NP for a constant $\gamma \geq 2$.

Our proof is by a reduction from the Hitting Set problem. An instance $H$ of Hitting Set is a tuple $H = (U = \{u_1, \ldots, u_r\}, \mathcal{C} = \{C_1, \ldots, C_m\})$, where each $C_i \subset U$; without loss of generality, we can assume $m = \Theta(r)$. A subset $S \subset U$ is a hitting set for $H$ if for all $i$, we have $S \cap C_i \neq \emptyset$. The decision question is, given a bound $k$, is there a hitting set $S$ for $H$ with $|S| \leq k$? We construct an undirected graph $G = (V, E)$ from $H$ in the following manner (see Figure 2 for an illustration). We assume $\gamma$ is an integer; else we consider $\lceil \gamma \rceil$.

- We have $V = V_1 \cup V_2 \cup V_3$, where $V_1 = C$, and $V_2 = U$. For each $u_j \in V_2$, let $L(u_j)$ denote a set of $r^\gamma$ nodes. The set $V_3 = \cup_j L(u_j)$. Then $|V| = m + r + r^{\gamma+1}$.
- The set $E$ of edges is constructed in the following manner: if $u_j \in C_i$, we have edge $(u_j, C_i)$. For each $u_j$, the set $L(u_j)$ forms a path, which is connected to $u_j$.
- We construct $m$ cascades $H_1, \ldots, H_m$, with $H_i$ consisting of the subgraph induced by the set of nodes $V_i = \{C_i\} \cup C_i \cup \cup_{u_j \in C_i} L(u_j)$.

**Lemma 2.** If there exists a hitting set for $H$ of size $k$, then there exists an optimal sensor set $S^*$ for $G$ with $|S^*| \leq k$ such that $T_{avg}(S^*) \leq 2$.

**Proof.** Let $S \subset U$ be a hitting set for $H$ with $|S| = k$. Then, for each $C_i$, we have $C_i \cap S \neq \emptyset$. Due to the structure of $H_i$, it follows that $T(S,H_i) = 2$, which implies $T_{avg}(S) = 2$.

**Lemma 3.** There exists a constant $c$ such that if there exists a sensor set $S$ for $G$ with $T_{avg}(S) < cn^{1-1/\gamma}$, then there exists (1) a hitting set for $H$ of size at most $|S|$, and (2) a sensor set $S^*$ for $G$ with $T_{avg}(S^*) \leq 2$.

**Proof.** First, observe that without loss of generality, we can assume that $S \cap L(u_j) = \emptyset$ for all $u_j$; if not, and there exists a node $v \in S \cap L(u_j)$, the set $S \cup \{u_j\} - \{v\}$ has expected delay no larger than $T_{avg}(S)$.

Next, suppose there exists $C_i$ such that $(\{C_i\} \cup C_i) \cap S = \emptyset$. Then, for the sample $H_i$, we have $T(S,H_i) \geq r$, which implies $T_{avg}(S) \geq n/m \geq r^\gamma \geq cn^{1-1/\gamma}$ for a constant $c$. Thus, if $T_{avg}(S) < cn^{1-1/\gamma}$, it must follow that for each $C_i$, we have $(\{C_i\} \cup C_i) \cap S \neq \emptyset$. Construct a set $S' \subset U$ in the following manner: if $u_j \in S$, add $u_j$ to $S'$, and if $C_i \subset S$, add any $u_j \in C_i$ to $S'$. It follows that for all $C_i$, $C_i \cap S' \neq \emptyset$, and so $S'$ is a hitting set for $H$. Further, $|S'| \leq |S|$, and since $S'$ is a hitting set, $T_{avg}(S') \leq 2$. Thus, the lemma follows.

Lemma 3 implies that if $S^*$ is an optimal solution for graph $G$, then either $T_{avg}(S^*) \leq 2$ or $T_{avg}(S^*) \geq cn^{1-1/\gamma}$. 

**Table 1.** Summary of notation used in the paper.
Proof. (of Theorem 1) Suppose we have a polynomial time algorithm with approximation factor less than \( \frac{cn^{1-1/\gamma}}{2} \), where \( c \) is the constant in Lemma 3. Let \( S \) be the sensor set computed by such an algorithm for the instance \( G \). Let \( S^* \) be an optimal solution for \( G \). Let \( S^*_H \) be an optimal hitting set for \( H \). Then, \( T_{avg}(S) < \frac{cn^{1-1/\gamma}}{2} T_{avg}(S^*) \). Recall that the decision question for the hitting set problem is whether \( |S^*_H| \leq k \). From Lemmas 2 and 3, it follows that either \( T_{avg}(S^*) \leq 2 \) or \( T_{avg}(S^*) \geq cn^{1-1/\gamma} \). In the former case, we would have \( T_{avg}(S) < cn^{1-1/\gamma} \), and in the latter case we would have \( T_{avg}(S) \geq cn^{1-1/\gamma} \). Thus, if \( T_{avg}(S) < cn^{1-1/\gamma} \), it follows that \( T_{avg}(S^*) \leq 2 \), and \( |S^*_H| \leq |S^*| \leq k \). On the other hand, if \( T_{avg}(S) \geq cn^{1-1/\gamma} \), it follows that \( T_{avg}(S^*) > 2 \), and by Lemma 2, \( |S^*_H| > k \). Therefore, a polynomial time algorithm with approximation factor less than \( cn^{1-1/\gamma}/2 \) allows us to solve the hitting set problem, and the theorem follows.

**Hardness for MinDelSS in the SIR Model.** Our reduction can be adapted to show that the hardness holds even in the SIR model. The details of this reduction are presented in the Supplementary Materials.

**Theorem 2.** No polynomial time \( O(n^{1-1/\gamma}) \)-approximation to MinDelSS is possible for any constant \( \gamma \geq 2 \), unless \( \mathcal{P} = \mathcal{NP} \), even when the cascades are sampled from the SIR model.

**Our Approach**

We first present ROUNDSENSOR for the setting in which a set of cascades \( H_1, \ldots, H_N \) is given as input, and the goal is to find a sensor set \( S \) to minimize \( T_{avg}(S) \). Later, we show how this can be extended to an SIR model with the goal of minimizing \( T_{avg}(S) \).

**ROUNDSENSOR Under Given Cascades**

Our algorithm, ROUNDSENSOR, is based on linear programming relaxation and randomized rounding. We first start with the following integer program (IP) with two kinds of variables: the variables \( x_u \) indicate that node \( u \) is picked in the sensor set, and \( y_{id} \) indicates that in the sample \( H_i \), a node \( u \) in the set \( V_{id} \) is in the sensor set, where \( V_{id} \) is the set of nodes at distance \( d - 1 \) from the source \( s(H_i) \) (i.e., the detection time is \( d \)).

\[
\min \sum_{d=1}^{n+1} \frac{1}{N} \sum_{i=1}^{N} y_{id} \cdot d
\]

(1)

for all \( i, d: \sum_{u \in V_{id}} x_u \geq y_{id} \)

(2)

\[\sum_{u} x_u \leq k\]

(3)

for all \( i: \sum_{d} y_{id} = 1\)

(4)

\[x_u, y_{id} \in \{0, 1\}\]

(5)

**Algorithm 1: ROUNDSENSOR**

**Input:** \( G = (V, E), k \), \( H_1, \ldots, H_N \)

**Output:** Sensor set \( S \)

1. Solve the LP obtained by relaxing the constraints (5) of IP to \( x_u, y_{id} \in [0, 1] \) for all \( u, i, d \).
2. Let \( x, y \) be the optimal fractional solution to the above LP. For each node \( u \), add \( u \) to \( S \), with probability \( x_u y_{id} = \min\{1, x_u \log((n+1) \log(Nn))\} \)
3. Return \( S \)

The constraint (2) indicates that if \( y_{id} = 1 \) (i.e., the detection time is \( d \)), then some node in \( V_{id} \) is picked. The constraint (4) ensures that \( y_{id} = 1 \) for exactly one value of \( d \) (which will be the minimum, because of the objective).

**Lemma 4.** The above integer program (IP) is valid, i.e., if \( x, y \) is an optimal solution to the IP, then \( T_{avg}(S^*) \leq \frac{1}{N} \sum_{i=1}^{N} \sum_{d=1}^{n+1} y_{id} \cdot d \), where \( S^* \) is an optimal solution.

Proof. Consider a solution \( x^*, y^* \) corresponding to \( S^* \) defined in the following manner: if \( u \in S^* \), we have \( x_{id}^* = 1 \), else \( x_{id}^* = 0 \). If \( T(S^*), H_i \) = \( d \), we set \( y_{id}^* = 1 \), else \( y_{id}^* = 0 \). It is easy to verify that \( x^*, y^* \) is a feasible solution to (IP). Similarly, any feasible solution \( x, y \) corresponds to a sensor set \( S \). Therefore, the lemma follows.

**Relaxation and Rounding.** Solving (IP) is infeasible for large instances. We relax the difficult integrality constraint (5) to get a linear program, and use the technique of randomized rounding to get an approximate solution, as summarized in Algorithm 1.

**Main Ideas Behind the Analysis of ROUNDSENSOR**

- Let \( U_j = \{2^j, \ldots, \min\{n+1, 2^{j+1} - 1\}\} \), for \( 0 \leq j \leq \log(n+1) \). While the variables in the LP can be fractional, and \( y_{id} \) need not be 1, we can show that there is a set \( U_{d(i)} \) for each sample \( H_i \), such that the sum of \( y_{id} \) for \( d \in U_{d(i)} \) is not too small (Lemma 5).
- For each \( d(i) \), it follows that \( \sum_{u \in U_{d(i)}} x_u \geq \log(Nn) \). As a result, the randomized rounding in Step 3 of ROUNDSENSOR ensures that at least one node \( u \in \cup_{d \in U_{d(i)}} V_{id} \) is picked in the solution (Lemma 6).
- Finally, the scaling used to construct the variables \( x_u \) and the definition of the sets \( U_j \) give biformula bounds on \( |S_r| \) and \( T_{avg}(S_r) \) (Theorem 3).

**Lemma 5.** Let \( x, y \) denote the solution to the LP. Then, for all \( i = 1, \ldots, N \), there exists \( d(i) \leq \log(n+1) \) such that \( \sum_{d \in U_{d(i)}} y_{id} \geq \frac{1}{\log(n+1)} \).

Proof. The sets \( U_j \) are disjoint, and \( \sum_{d=1}^{n+1} y_{id} = \sum_{j \geq 0} \sum_{d \in U_j} y_{id} = 1 \), which implies there exists \( d(i) \) such that \( \sum_{d \in U_{d(i)}} y_{id} \geq \frac{1}{\log(n+1)} \).

**Lemma 6.** Let \( S_r \) denote the solution picked by our algorithm. For each cascade \( H_i \), let \( d(i) \) be the index, as in Lemma 5. Then, with probability at least \( 1 - \frac{1}{n} \), for all \( i = 1, \ldots, N \), we have \( T(S_r, H_i) \leq 2^{d(i)+1} \).
Proof. Let \( B_{id(i)} = \bigcup_{d \in U_{d(i)}} V_{id} \). We will show below that for all \( i \), we have \( S_r \cap B_{id(i)} \neq \emptyset \) with probability at least \( 1 - \frac{1}{n^2} \). Observe that if \( S_r \cap B_{id(i)} = \emptyset \), we have \( T(S, H_i) \leq 2^{d(i)+1} \), and the lemma follows.

Consider any fixed \( i \). Observe that \( \Pr[S_r \cap B_{id(i)} = \emptyset] = \prod_{u \in B_{id(i)}} (1 - x_u) \). We have two cases. First, suppose there is a node \( u \in B_{id(i)} \) such that \( x_u = 1 \), then \( \Pr[S_r \cap B_{id(i)} = \emptyset] = 0 \), which implies \( S_r \cap B_{id(i)} \neq \emptyset \).

Second, if \( x_u < 1 \) for all \( u \in B_{id(i)} \), we have \( x_u = \log(n + 1) \log([Nn] \cdot x_u) \). In this case, \( \Pr[S_r \cap B_{id(i)} = \emptyset] = \prod_{u \in B_{id(i)}} (1 - x_u) \leq \prod_{u \in B_{id(i)}} \exp(-x_u) = \exp(-\sum_{u \in B_{id(i)}} x_u) \). We have

\[
\sum_{u \in B_{id(i)}} x_u = \log(n + 1) \log(Nn) \sum_{d \in U_{d(i)}} \sum_{u \in V_{id}} x_u \\
\geq \log(n + 1) \log(Nn) \sum_{d \in U_{d(i)}} y_{id} \\
\geq \log(Nn),
\]

where the first inequality follows because of the constraint \( \sum_{u \in V_{id}} x_u \geq y_{id} \) in the LP, and the second inequality follows from Lemma 3.

Therefore, \( \Pr[S_r \cap B_{id(i)} = \emptyset] \leq \exp(-\sum_{u \in B_{id(i)}} x_u) \leq \frac{1}{n^2} \), using the above bound on \( \sum_{u \in B_{id(i)}} x_u \). This implies that in both the cases, we have \( \Pr[S_r \cap B_{id(i)} = \emptyset] \leq \frac{1}{n^2} \).

By a union bound over all the cascades \( i \), we have \( \Pr[\text{There exists } i \text{ such that } S_r \cap B_{id(i)} = \emptyset] \leq \frac{N}{n^2} = \frac{1}{n} \) and the Lemma follows.

\[ \square \]

Theorem 3. Let \( S_r \) be the set of nodes selected by the above algorithm. With probability at least \( 1 - \frac{1}{n^2} \), we have:

(1) \( |S_r| \leq k \cdot 2 \log(Nn) \log(n + 1) \cdot k \).

(2) \( T_{avg}(S_r) \leq 2 \log(n + 1) T_{avg}(S^*) \), where \( S^* \) is an optimal solution.

Proof. Let \( X_u = 1 \) with probability \( x_u \). Then, \( |S_r| = \sum_u X_u \), and \( \mathbb{E}[|S_r|] = \sum_u x_u \geq \log(Nn) \log(n + 1) \cdot k \).

Applying the Chernoff bound (Theorem 5 in the Supplementary Material), we have \( \Pr[|S_r| > 6k \log(Nn) \log(n + 1)] \leq 2^{-6k \log(Nn) \log(n + 1)} \leq 2^{-6 \log(n + 1)} \leq 1/n \).

For all \( i \), we have \( \sum_{d \in U_{d(i)}} y_{id} \geq 2^{d(i)} \sum_{d \in U_{d(i)}} y_{id} \geq \frac{2^{d(i)}}{\log(n+1)} \), with probability at least \( 1 - 1/n \), where the first inequality follows from the definition of the set \( U_{d(i)} \), the second inequality follows from Lemma 5, and the third inequality follows from Lemma 6. This implies that with probability at least \( 1 - 1/n \), for all \( i \), \( T(S_r, H_i) \leq 2 \log(n + 1) \cdot \sum_{d \in U_{d(i)}} y_{id} \leq 2 \log(n + 1) \cdot \sum_{d} y_{id} \).

Therefore, with probability at least \( 1 - 1/n^2 \), \( T_{avg}(S_r) = \frac{1}{N} \sum_i T(S_r, H_i) \leq \frac{1}{N} \sum_i 2 \log(n + 1) \cdot \sum_{d} y_{id} \leq 2 \log(n + 1) T_{avg}(S^*) \), since the LP value is a lower bound for \( T_{avg}(S^*) \). The probability that either the bound for \( |S_r| \) or \( T_{avg}(S_r) \) is not satisfied is at most \( \frac{1}{4n} \), and therefore, the theorem follows. \[ \square \]

Algorithm 2: ROUNDSENSOR\textsc{SIR}

Input: \( G = (V, E), k \)
Output: Sensor set \( S_r \)

1: Sample \( N = \Omega(\frac{2}{3} n(n + 1) \log n) \) cascades \( H_1, \ldots, H_N \)
2: Return \( S_r = \text{ROUNDSENSOR}(G, k, H_1, \ldots, H_N) \)

Minimizing \( \mathbb{E}[T(S)] \) in the SIR Model

In the context of disease surveillance, the disease spread is modeled by an SIR process on the network. The cascades are not specified ahead of time, but are sampled according to the SIR process, as defined in Section . We use the sample average technique from stochastic optimization and show that if we run ROUNDSENSOR on a polynomial set of cascades, we also get a good approximation for the expected detection time; we refer to this as Algorithm ROUNDSENSOR\textsc{SIR}.

Recall that \( T(S, H) \) is the delay associated with set \( S \) for the disease outcome \( H \). Let \( S = \arg\min_g T_{avg}(S) \) denote an optimal solution for the cascades \( H_1, \ldots, H_N \). Let \( S^* = \arg\min_g \mathbb{E}[T(S)] \) denote an optimal solution (which minimizes the expected detection time).

Lemma 7. Let \( N \geq \frac{2}{3} n(n + 1) \log n \) for \( \epsilon \in (0, 1) \). For any \( \epsilon \in (0, 1) \), \( \Pr[\text{there exists } S \text{ such that } T_{avg}(S) \neq \lceil (1 - \epsilon) \mathbb{E}[T(S)] \rceil, (1 + \epsilon) \mathbb{E}[T(S)] \rceil \leq 1/n^2 \)

Proof. For any fixed \( S \), we have \( N T_{avg}(S) \leq 1/n + 1 \). By the definition of \( T(S, H_i) \), we have \( Z_i = \frac{T(S, H_i)}{n+1} \in [0, 1] \). Also, \( \mathbb{E}[T(S, H_i)] = \mathbb{E}[T(S)] \), which implies \( \mathbb{E}[N T_{avg}(S)] = N \mathbb{E}[T(S)] \). Applying Theorem 5 from the Supplementary Material to \( Z = N T_{avg}(S) \), we have

\[
\Pr \left[ T_{avg}(S) \not\in \lceil (1 - \epsilon) \mathbb{E}[T(S)], (1 + \epsilon) \mathbb{E}[T(S)] \rceil \right] \\
= \Pr \left[ N T_{avg}(S) \not\in \lceil (1 - \epsilon) \frac{N \mathbb{E}[T(S)]}{n+1}, (1 + \epsilon) \frac{N \mathbb{E}[T(S)]}{n+1} \rceil \right] \\
\leq 2 \exp(- \epsilon^2 \mathbb{E}[T(S)] / (3(n + 1))) \\
\leq \exp(- n \log n)\]

if \( N \geq \frac{2}{3} n(n + 1) \log n \), since \( \mathbb{E}[T(S)] \geq 1 \). By a union bound over all \( S \subset V \), it follows that the probability that there exists \( S \) with \( T_{avg}(S) \not\in \lceil (1 - \epsilon) \mathbb{E}[T(S)], (1 + \epsilon) \mathbb{E}[T(S)] \rceil \) is at most \( 2^n \exp(-n \log n) \leq 1/n^2 \). \[ \square \]

Theorem 4. Let \( N \geq \frac{2}{3} n(n + 1) \log n \) for \( \epsilon \in (0, 1) \). With probability at least \( 1 - \frac{2}{3} \), \( |S_r| \leq k \cdot 2 \log(\frac{2}{3} n^2(n + 1) \log n) \log(n + 1) \leq (2 + \frac{2}{3}) n \log n \).
data sets, as summarized in Table 2. These include four hospital
contact networks.
1. arXiv High Energy Physics-Theory (HEP-TH) collaboration
network from January 1993 to April 2004 (Leskovec
and Krevl 2014). We only use the largest connected com-
ponent in this network.
2. Battle of the Water Sensor Networks (BWSN) (Ostfeld
et al. 2008).
3. Hospital network from Lyon: this is a temporal contact
network of a hospital based in Lyon, France (Vanhems
et al. 2013). The data set tracks 46 health care workers
and 29 patients from December 6, 2010 at 1pm to De-
cember 10, 2010 at 2pm.
4. Carilion network: constructed from patient and provider
contacts in the Carilion hospital in Roanoke, Vir-
ginia (Adhikari et al. 2019). We only use the network
data for a 2 month period.
5. UVA pre-COVID and COVID networks: these are
anonymized contact networks from electronic medical
record (EMR) data of hospitalized patients at the Uni-
versity of Virginia (UVA) hospital. Nodes are patients
and health care providers, while edges represent co-
location based contacts. The Pre-COVID network spans
the period 4/1/2018—10/28/2018, and the COVID net-
work spans the period 10/14/2020—5/21/2021.

Table 2: Data sets used for experiments

| Graph Name          | Number of nodes | Number of edges |
|---------------------|-----------------|-----------------|
| Arxiv HEP-TH        | 8638            | 24827           |
| Water network       | 12523           | 14822           |
| Lyon Hospital Ward  | 75              | 1138            |
| Carilion hospital network | 11413   | 25663           |
| UVA Pre-COVID       | 10789           | 291881          |
| UVA COVID           | 9949            | 399495          |

Table: Data sets used for experiments

Baselines. We compare with the following baselines

- Random: select k nodes randomly with uniform proba-
bility distribution
- Degree: select top k nodes with highest degrees
- GREEDY: select k nodes with greedy scheme
  (Leskovec et al. 2007).

Effectiveness

Figure 3 shows that ROUNDSENSOR performs better than
the three baselines that we have selected. While this greedy
approach does offer certainty in the budget allowance and
a deterministic outcome, we see that ROUNDSENSOR offers
increasing benefits as our budget increases, up to a 9% lower
mean detection time after rounding. Note that these base-
lines have budget k’ = |S∗| after rounding to ensure a fair
comparison.

Next, we consider the approximation ratios. Recall that
ROUNDSENSOR gives a bicriteria approximation (The-
orem 3), and we evaluate both $T_{avg}(S_*)/T_{avg}(S^*)$ (the
approximation ratio with respect to the objective), where $S^*$ is
an optimal solution, and $|S_*/k|$ (the violation in budget). We
cannot calculate the exact approximation ratio, since $S^*$ is
unknown, but the ratio between $T_{avg}(S_*)$ and the LP objec-
tive gives an upper bound on the approximation ratio. Fig-
ure 4 (left) shows that the approximation ratio achieved by
ROUNDSENSOR, with respect to the objective value is less
than 1.4 in experiments—this is a significant contrast with
the worst case $O(\log n)$ approximation factor we prove in
Theorem 3.
Figure 3: Mean detection time vs the sensor set size for the UVA COVID network, comparing ROUNDSENSOR and other baselines.

Figure 4: (Left) Upper bound on the approximation ratio achieved by ROUNDSENSOR vs $|S_r|$ in experiments across various data sets and budgets. (Right) Violation in budget for ROUNDSENSOR vs $k$, for a transmission probability of 0.15.

Finally, Figure 4 (right) shows the violation in budget for ROUNDSENSOR. Note that for all values of $k$, the violation is at most $1.8n$, which is significantly lower than the $O(\log^2 n)$ bound proven in Theorem 3.

**Number of Sampled Cascades Needed in the SIR Model**

Recall that Theorem 4 gives a bound of $N \geq \frac{5}{2} n(n + 1) \log n$ for the analysis of the SAA technique. Figure 5 shows the impact of varying $N$. For low values of $N$, the objective value is low, since choosing nodes close to the sampled sources is a good strategy. We find that the plots plateau off well before $N = n$, which suggests that linear number of samples are adequate in practice.

**Case Study**

We analyze the mean detection time in the UVA contact networks in Figure 6. We observe that the detection time reduces in the COVID period, for the same transmission probability. While there are likely many factors at play, we note that the COVID network is much denser (average density of 40.15) than the pre-COVID network (average density 27.05). Higher density generally increases the ease of disease transmission, e.g.,(Newman 2003). A deeper analysis is needed to understand this better.

Figure 6 shows how the makeup of $S_r$ (namely, the fraction consisting of patients) changed from the pre-COVID to the COVID period. There are noticeable differences in the composition of the sensor sets, which changes with $k$. In particular, during the COVID period, the fraction of patients increases with $k$, becoming a more disproportionate size of the set, while in our pre-COVID data set, we see that decrease as it gets larger.

**Conclusions**

We present the first approximation algorithms for the MinDelSS, both when the cascades are specified, or sampled from an SIR process. Our algorithms give bicriteria approximation guarantees, which is inevitable in light of the computational hardness we prove for MinDelSS. Our experiments on diverse networks, including four hospital networks show that our method is quite effective. Identifying surrogates of the nodes picked in our near-optimal solutions can be useful in designing more implementable solutions. In practice, more general surveillance strategies need to be considered, in which a node is not tested daily, but with some rate. Our approach can be extended to settings where schedules are periodic.
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