# ShareTrace: Contact Tracing with the Actor Model

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# Motivation

- Proximity-based contact tracing relies on mobile-device interaction to estimate infection spread [2, 6, 8, 16, 18, 19, 23, 24]
- ShareTrace is a privacy-preserving, proximity-based approach that estimates a user's infection risk based on their symptoms, direct contacts, *and* indirect contacts
- Previous work [3] evaluted efficacy, but not scalability or efficiency

# Definitions

- *Risk score* $(r, t)$: a timestamped probability where $r \in [0, 1]$ and $t \geq 0$
  - *Symptom score*: prior infection probability; only considers user symptoms [21]
  - *Exposure score*: posterior infection probability; accounts for (in)direct contact
- *Factor graph* $G = (\mathcal{V}, \mathcal{F}, \mathcal{E})$: a bipartite graph [15]
  - $\mathcal{V}$: variable vertices, where a variable vertex $v \in \mathcal{V}$ represents a user
  - $\mathcal{F}$: factor vertices, where a factor vertex $f(u, v) \in \mathcal{F}$ represents a contact
  - $\mathcal{E}$: edges incident between the sets $\mathcal{V}$ and $\mathcal{F}$
- *Message* $m_{u \to v} = \{(r, t), \ldots\}$: a set of risk scores sent from vertex $u$ to vertex $v$

# Proposed Scheme

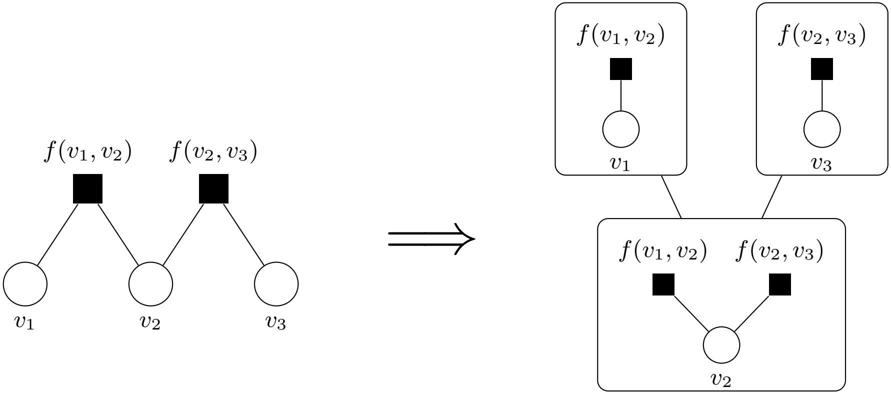



Figure: Apply one-mode projection on the factor graph (left) to get the contact network (right)

# Proposed Scheme

- Reformulate the factor graph as a *temporal contact network* [12, 14]:

$$\mathcal{C} = \{(u, v, t) \mid u, v \in \mathcal{V}; u \neq v; t \geq 0\}$$

- Partition the contact network into $K$ subnetwork *actors* $G_k \in G$ [1, 4]
- Send each actor its initial risk scores (i.e., previous exposure and symptom scores)
- Actors non-iteratively pass messages (*risk scores*) until convergence
- Assumption: risk transmission is incomplete; use a *transmission rate* of $\alpha = 0.8 \in (0, 1)$ [11]

# Proposed Scheme

- Only propagate messages if they are likely to change the risk score of other users in the network
- *Send coefficient* $\gamma$ parametrizes the trade-off between accuracy and efficiency of non-iterative message passing
- A vertex $u$ only sends a message $m_{u \to v}$ if
  - it is close in value to its initial message: $r_{u \to v} \geq \gamma \cdot r_0(u)$; and
  - it is at least as old as its initial message: $t_{u \to v} \leq t_0(u)$
- Ensures convergence when $\alpha < 1$ and $\gamma > 0$

# Message Reachability

- In temporal network theory, a *time-respecting path* (TRP) is a sequence of nondecreasing contacts.
  - Vertex $v$ is *temporally reachable* from vertex $u$ if there exists a TRP from $u$ to $v$
- Message-passing on a temporal network may not require temporal reachability
- *Message reachability* from vertex $u$ to vertex $v$ is the number of edges along the shortest path $\mathcal{P} = u \to v$ that satisfy the message-passing constraints,

$$m(u,v) = \sum_{(i,j)\in\mathcal{P}} f(u,i,j,v),$$

where $f(u,i,j,v) = 1$ if all constraints are satisfied and $f(u,i,j,v) = 0$ otherwise

# Message Reachability: Risk Propagation

Let $H(x) = \mathbf{1}_{x \geq 0}$ be the *Heaviside step function*. Then

$$m(u) = \max_{\mathcal{P}} \left\{ \sum_{(i,j) \in \mathcal{P}} f_c(u,i,j) \cdot f_r(u,i) \cdot f_t(u,i) \right\}$$

where users are enumerated $0, 1, \ldots, |\mathcal{P}| - 1,$ ; and

- Contact-time constraint: $f_c(u,i,j) = H(t_{ij} + \beta - t_0(u))$
  - *Time buffer* $\beta \geq 0$ accounts for incubation and delayed symptom reporting
- Risk-score value constraint: $f_r(u,i) = H(\alpha^i \cdot r_0(u) - \gamma \cdot r_0(i))$
  - Risk score values exponentially decrease as they propagate from their source user
- Risk-score time constraint: $f_t(u,i) = H(t_0(i) - t_0(u))$
  - Older risk scores are less likely to be propagated

# Message Reachability: Risk Propagation

- We can estimate $m(u)$ by relaxing the temporality constraints:

$$\alpha^i \cdot r_0(u) - \gamma \cdot r_0(i) = 0 \overset{\text{solve for } i}{\Longrightarrow} \hat{m}(u, v) = \log_\alpha \left\{ \gamma \cdot \frac{r_0(v)}{r_0(u)} \right\}$$

- (Estimated) message reachability of a vertex $u \in \mathcal{V}$:

$$m(u) = \max\{m(u, v) \mid v \in \mathcal{V}\}$$
$$\hat{m}(u) = \max\{\hat{m}(u, v) \mid v \in \mathcal{V}\}$$

# Message Reachability: Significance

- Generalizes temporal reachability to account for message-passing semantics
- Quantifies the communication complexity of a given algorithm
- RP: higher message reachability $\implies$ more users at risk
- RP: higher send coefficient $\gamma \implies$ higher communication cost (optimize!)

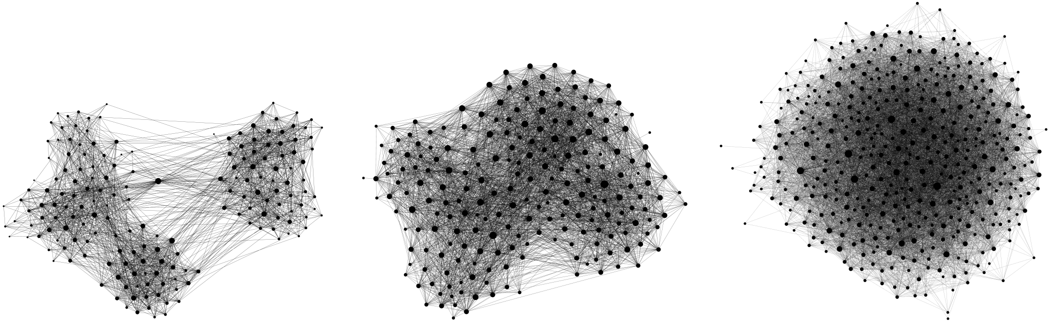
# Evaluation

- What is the optimal value for the send coefficient?
- How do the transmission rate and send coefficient affect accuracy and efficiency?
- How accurate is estimated message reachability?

$$\textit{Message-reachability ratio}: \quad \mathrm{mrr}(u) = \frac{m(u)}{\hat{m}(u)}$$

- What is the runtime performance of risk propagation?
- Synthetic graphs:
  - Random geometric graphs (RGGs) [7]
  - Benchmark graphs (LFRGs) [17]
  - Clustered scale-free graphs (CSFGs) [13]

# Evaluation: SocioPatterns Networks



(a) High school: 180/2,220 [9] (b) Workplace: 217/4,274 [10] (c) Conference: 403/9,565 [10]

Figure: SocioPatterns contact networks (number of users / number of contacts). Edges represents the most recent time of contact (duration $\geq$ 20s).

# Results: Efficiency

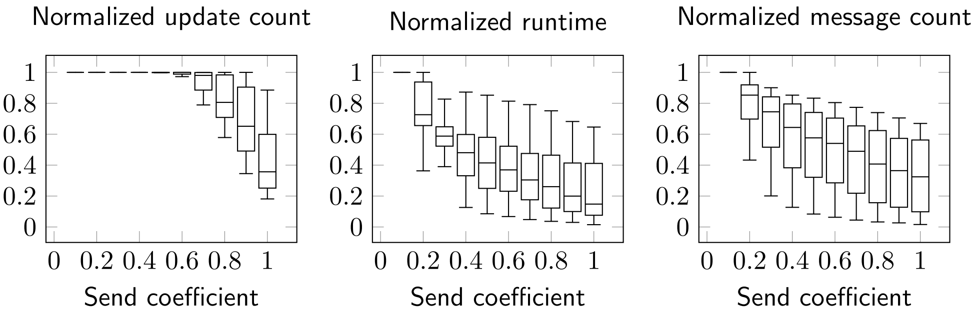



Figure: Effects of send coefficient and transmission rate on efficiency. All dependent variables are normalized across networks and transmission rates. *Update count* is the number of users whose exposure score was different from their initial score; a higher normalized value indicates better accuracy. *Message count* is the number of messages sent by actors; a lower count indicates lower communication overhead. A send coefficient of $\gamma = 0.6$ optimizes for accuracy and efficiency by permitting 99% of the possible user updates.

# Results: Message Reachability

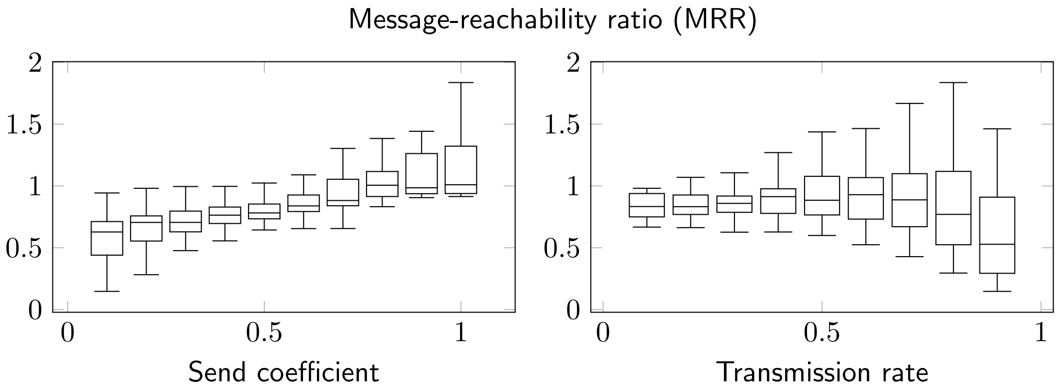



Figure: Effects of send coefficient and transmission rate on the MRR. Independent variables are grouped across networks. MRR $\geq 1$ ($< 1$) indicates overestimation (understimation).

# Results: Message Reachability

| | $\mathrm{mrr}(u) \pm 1.96 \cdot$ SE | | |
|---|---|---|---|
| *Synthetic* | LFR | RGG | CSFG |
| **0.85 ± 0.08** | 0.88 ± 0.14 | 0.74 ± 0.12 | 0.90 ± 0.14 |
| *Real-world* | High school | Workplace | Conference |
| **0.60 ± 0.01** | 0.58 ± 0.01 | 0.63 ± 0.01 | 0.60 ± 0.01 |

Table: Message-reachability ratio for synthetic and real-world contact networks ($\alpha = 0.8$, $\gamma = 0.6$). Synthetic (real-world) ratios are averaged across parameters (runs).

# Results: Scalability

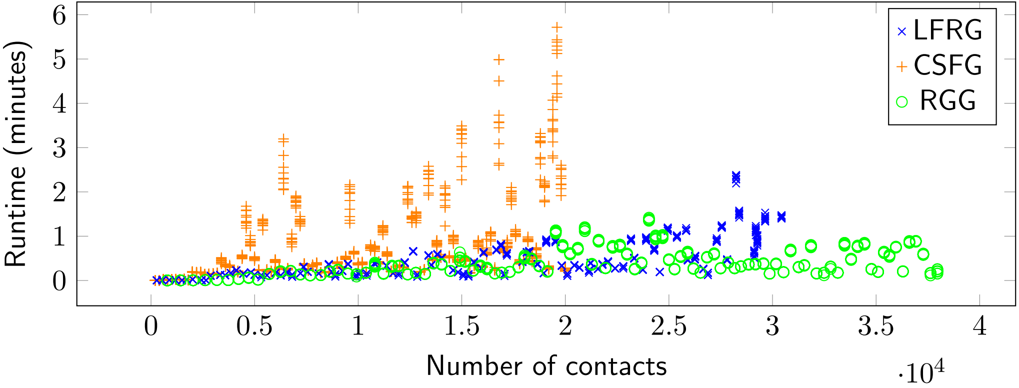



Figure: Runtime of risk propagation on synthetic networks. A linear regression fit explains ($R^2 = 0.52$) the runtime of LFRGs and RGGs with slope $m = (1.1 \pm 0.1) \cdot 10^{-3}$ s/contact and intercept $b = 4.3 \pm 1.6$s ($\pm 1.96 \cdot$ SE).

# Future Work

- Formulate risk propagation as an *online* algorithm.
  - Aligns with the message-passing semantics of risk propagation
  - Accounts for synchronization delays between a user's device and actor
  - Better scalability and fault-tolerance with Akka
  - Self-soverign identity (i.e., Web3) [22]
  - Mobile crowdsensing [5]
- How does message passing affect concurrency and network topology [20]?
- How do different risk-score and contact distributions affect risk propagation?

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