Countering Misinformation in Social Networks

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* The University of Texas at Austin

Outline

Countering misinformation

- Controlling the information flow with guarantees [ACC 2024]
- Credibility detection and community analysis through textual information [submitted to ICWSM 2024]
- Motivations for misinformation spread
- Improving information quality via optimal ranking

Network Perception

- Risk of misperception in networked autonomous systems [CDC2023]
- Fast networked feature selection to reduce uncertainty [submitted to IROS 2024]
- Effects of memory and message limitations on network perception

Pentagon on Fire 🔥

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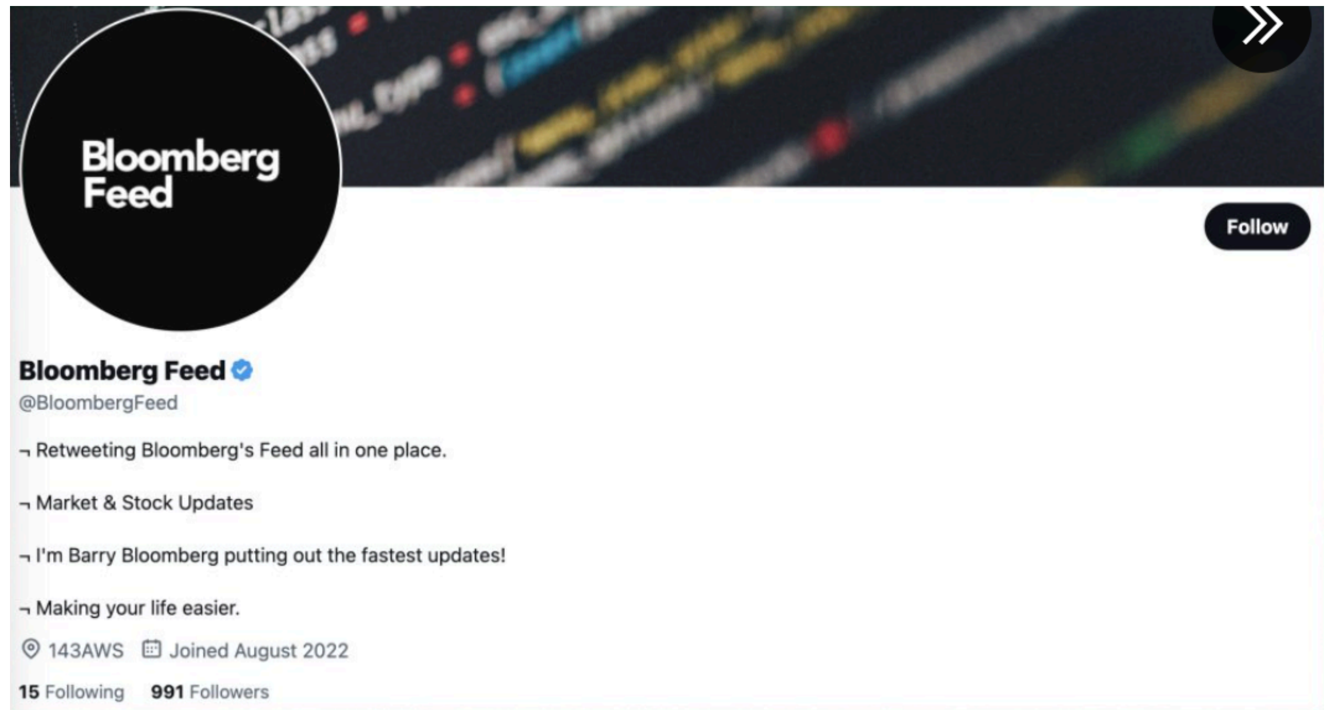

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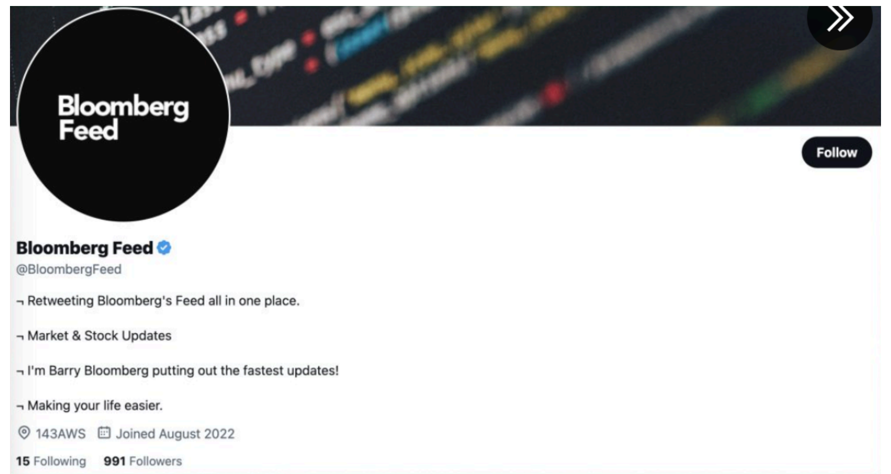

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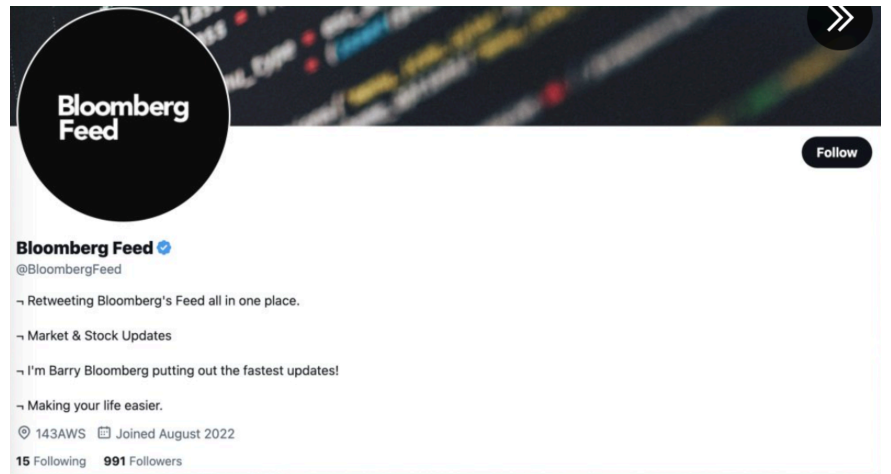

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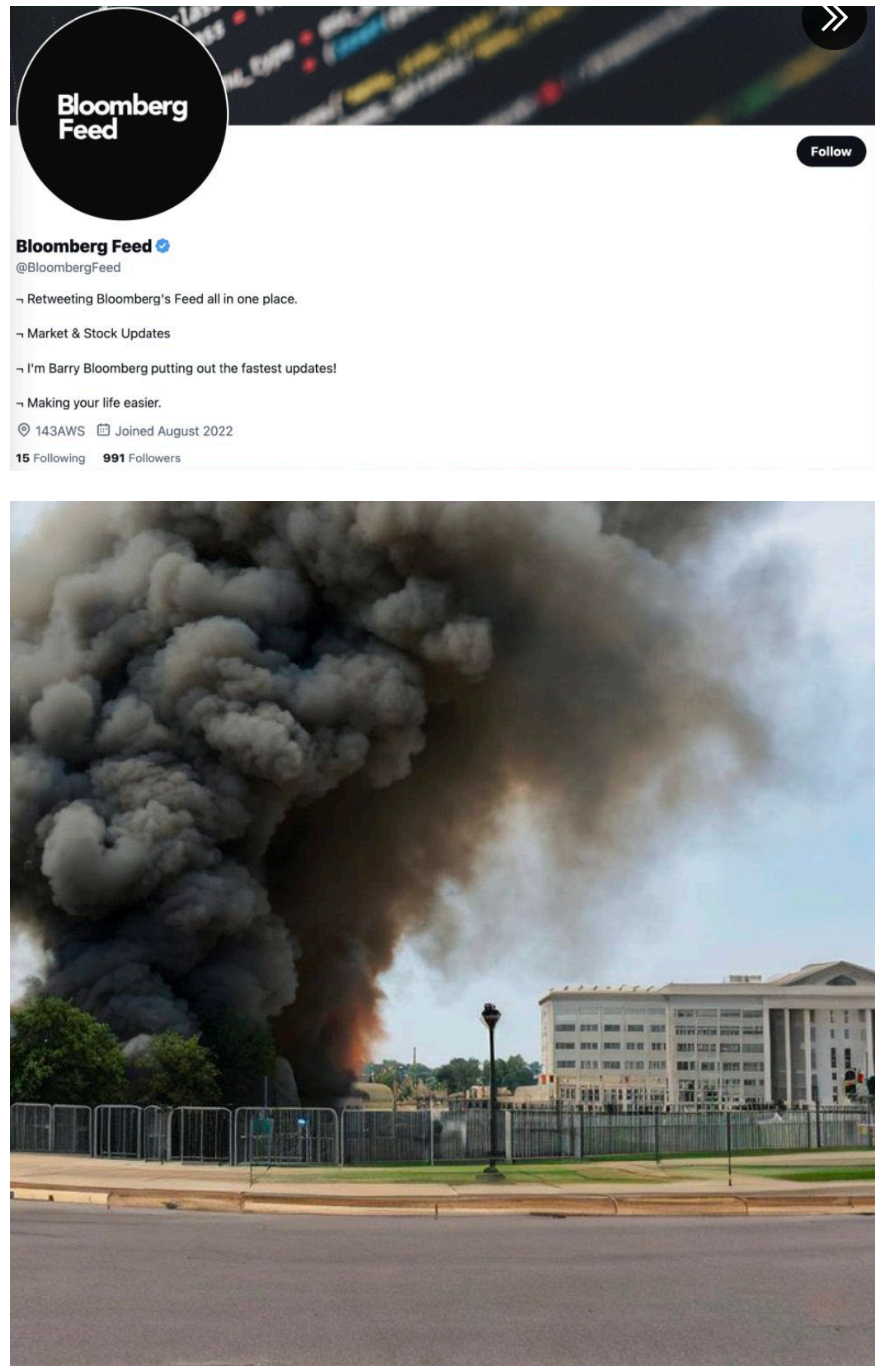

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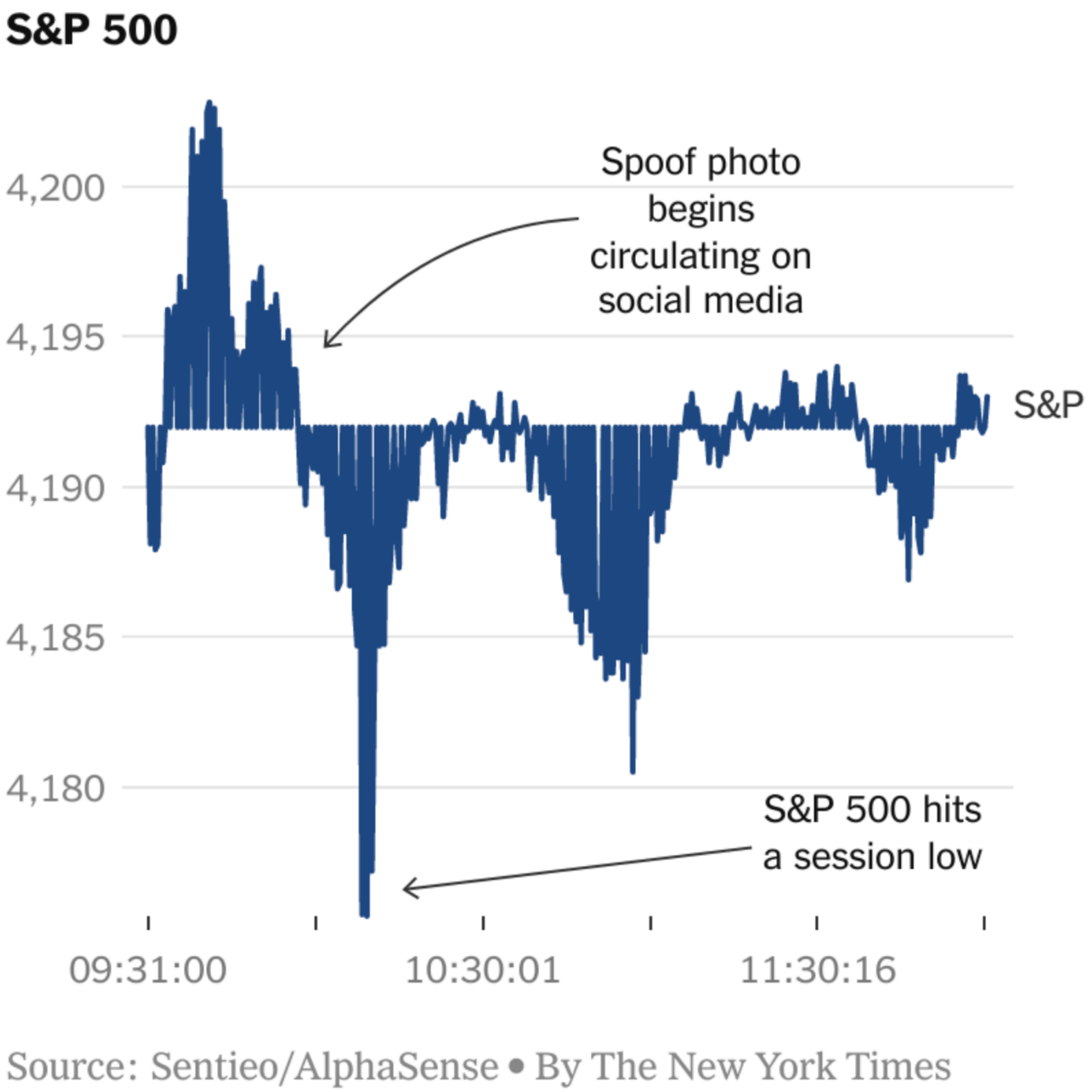

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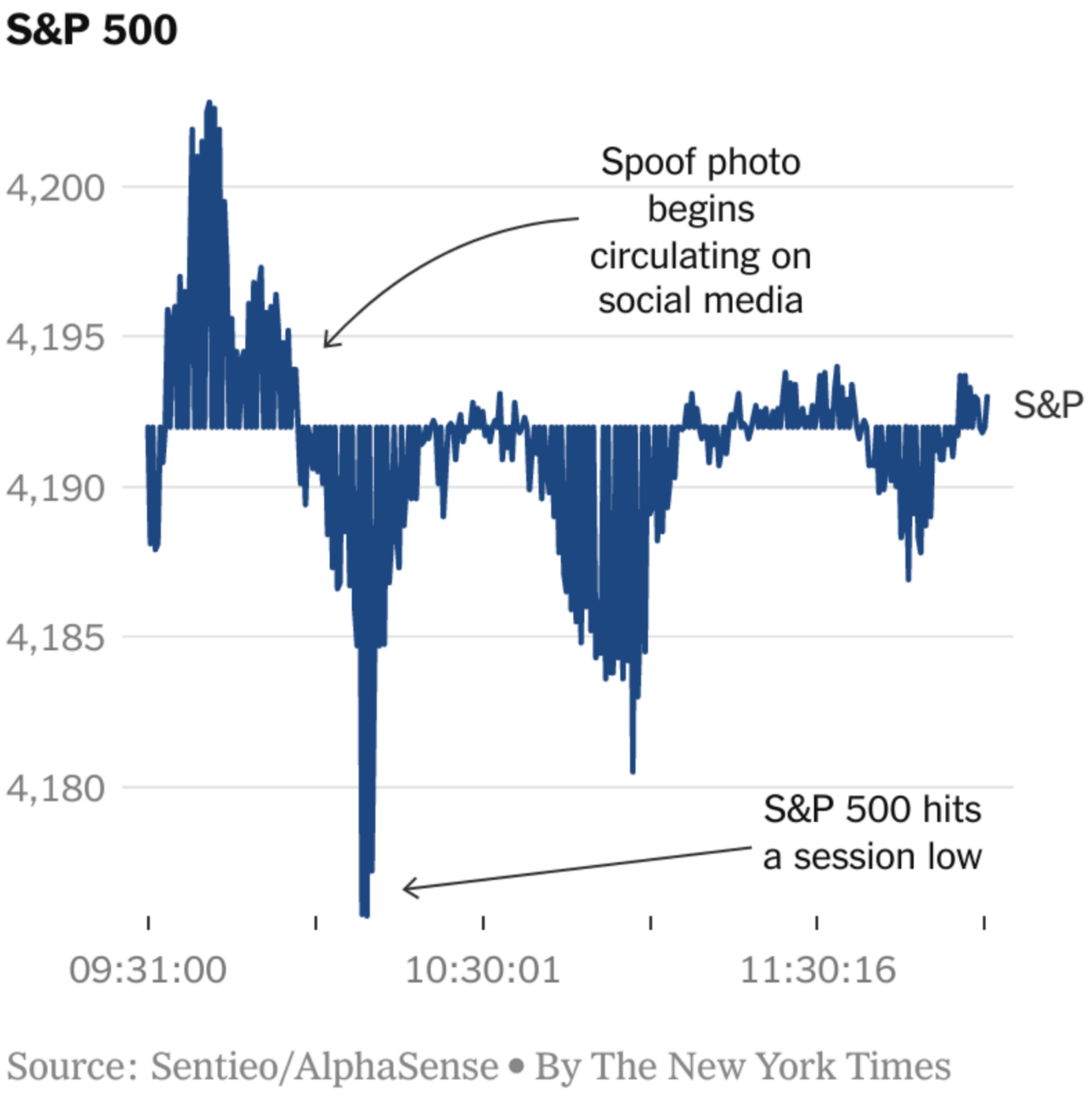

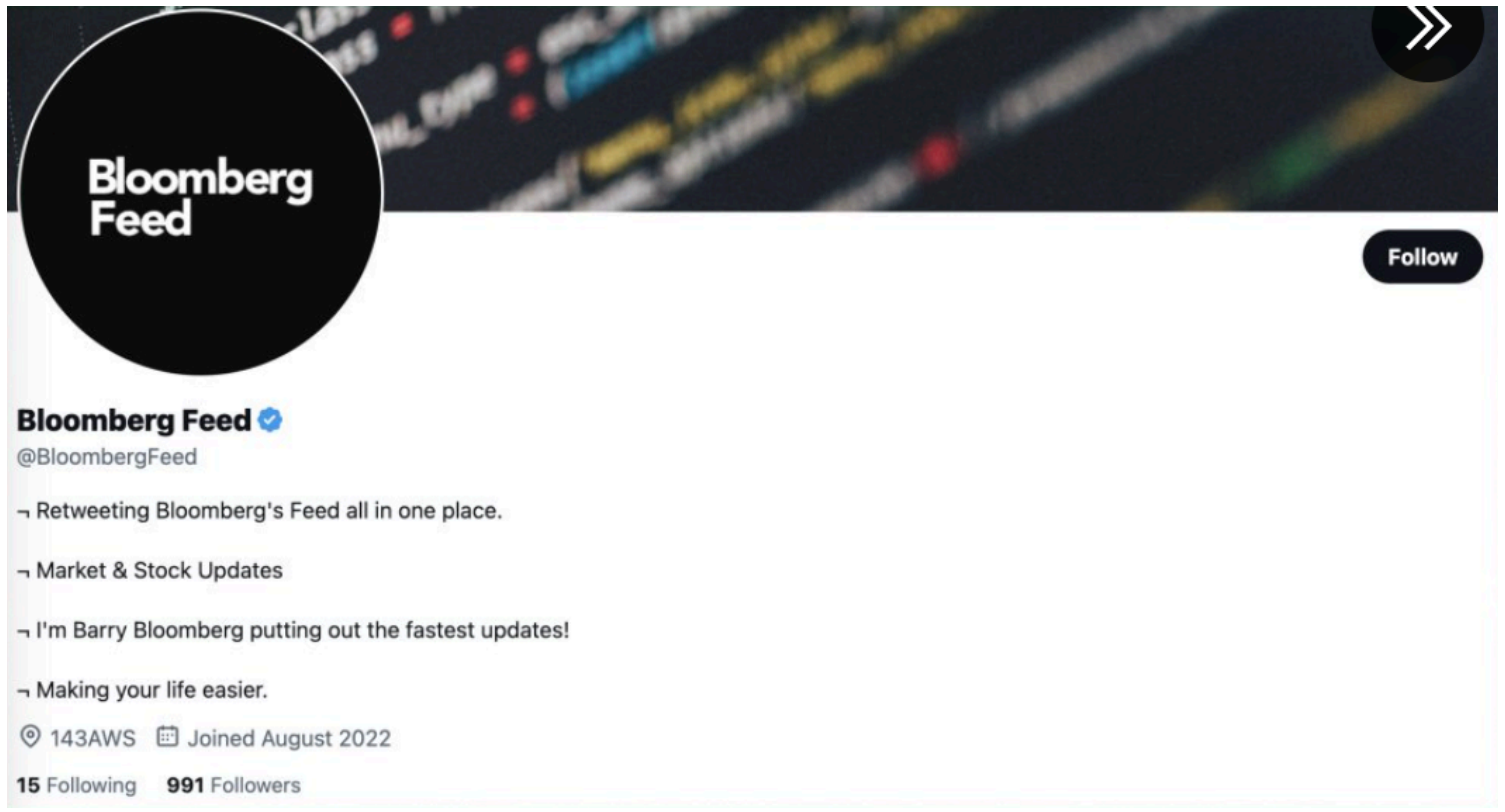

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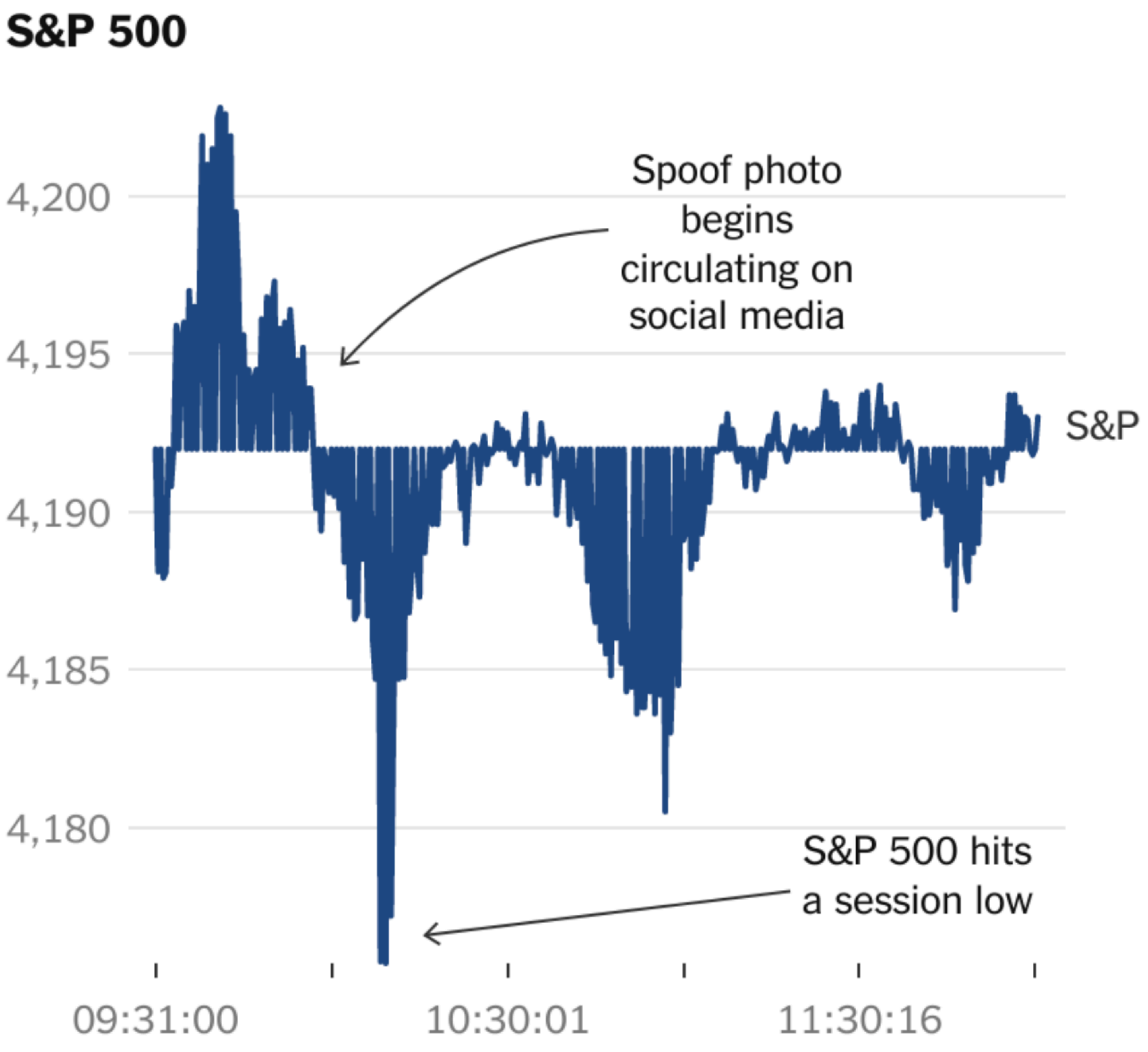
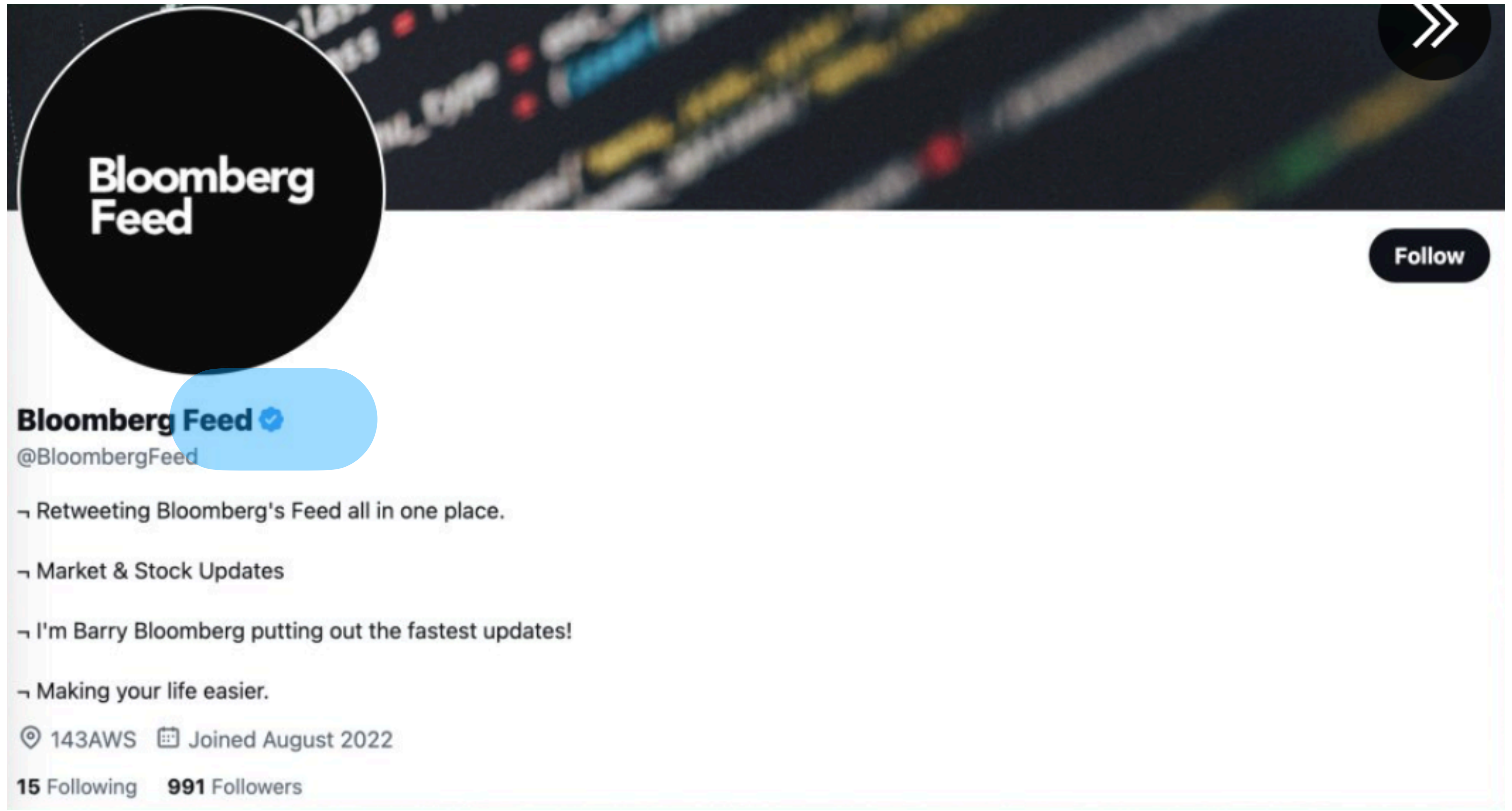


Source: Sentieo/AlphaSense • By The New York Times



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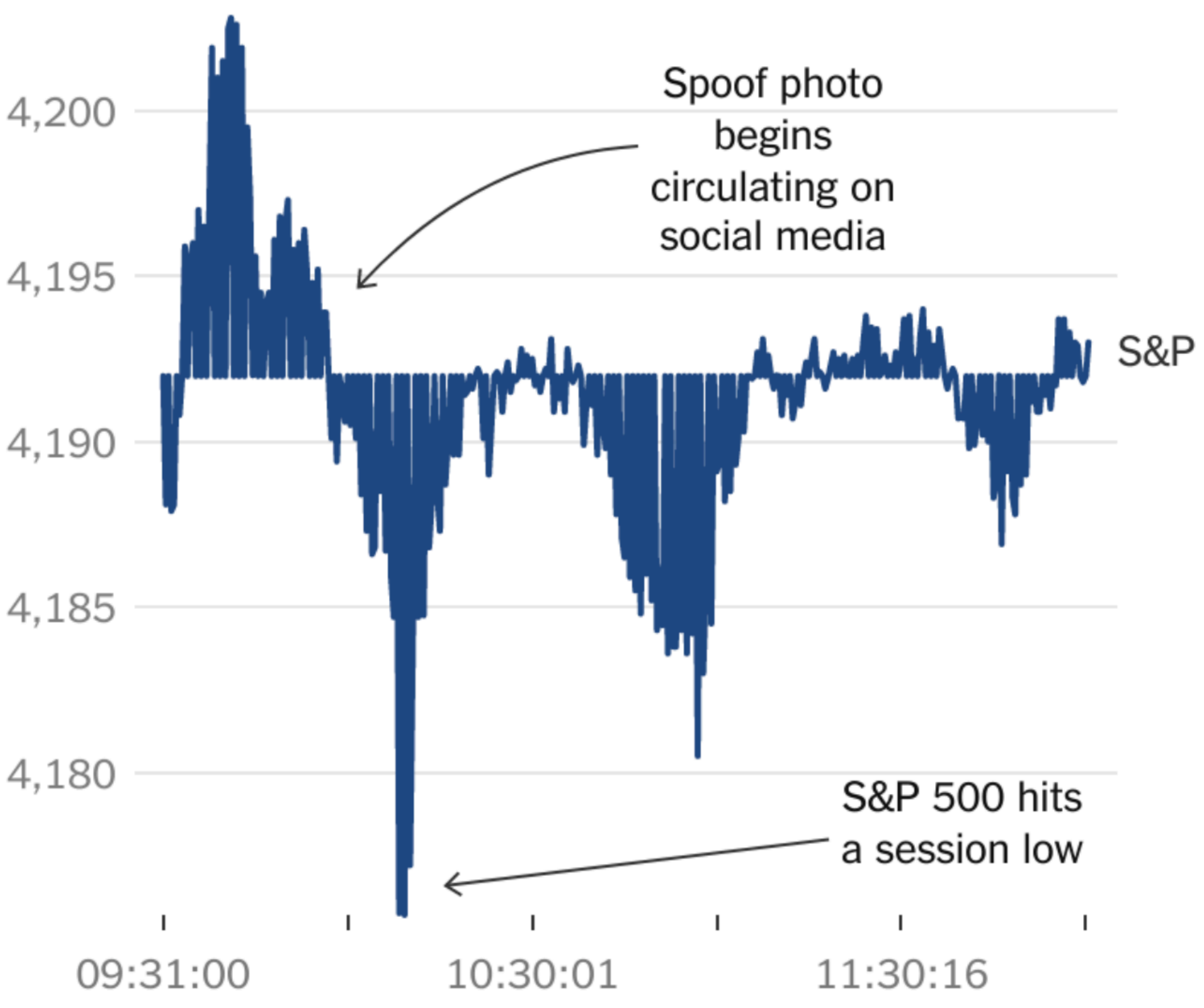

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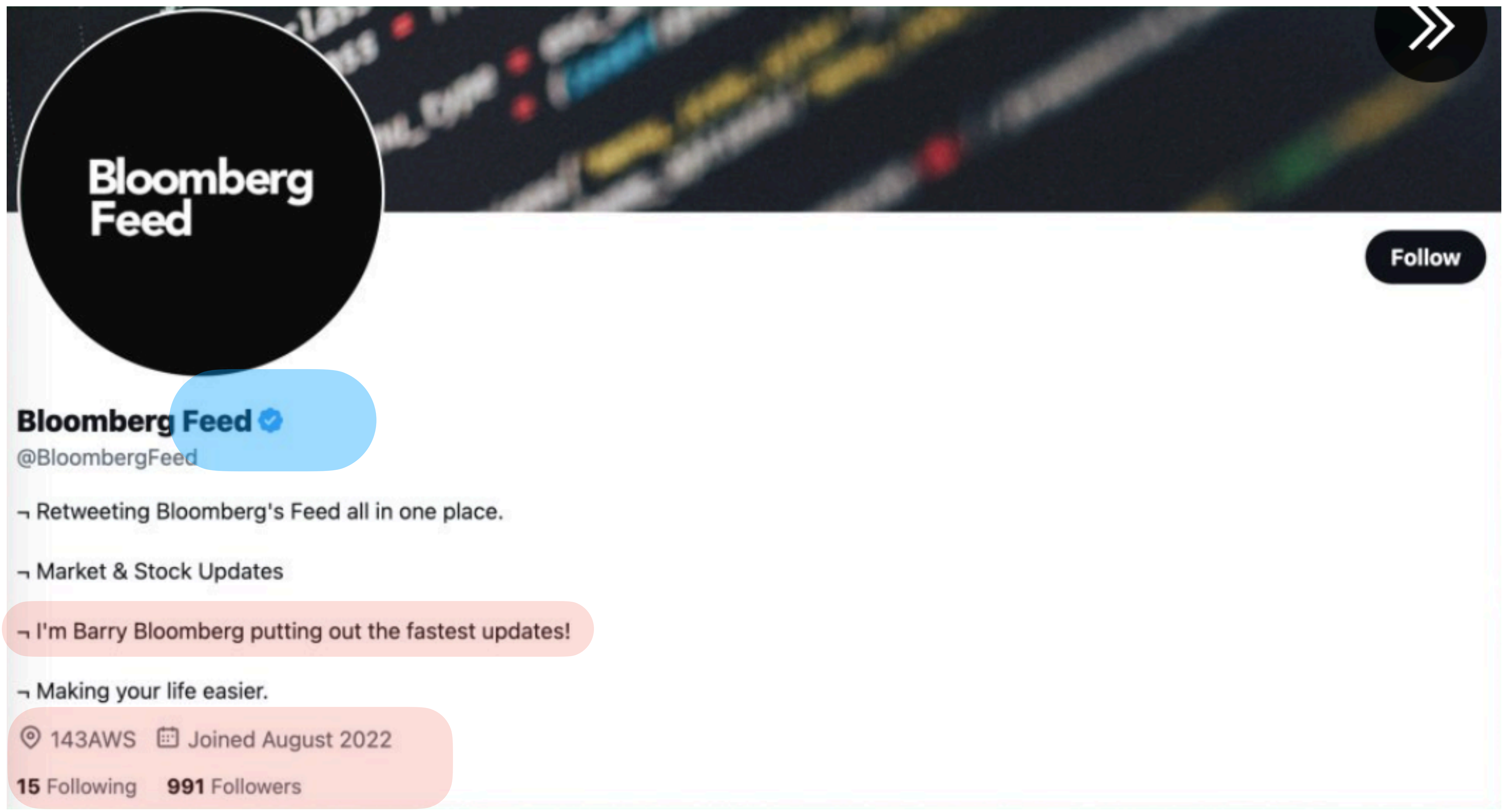

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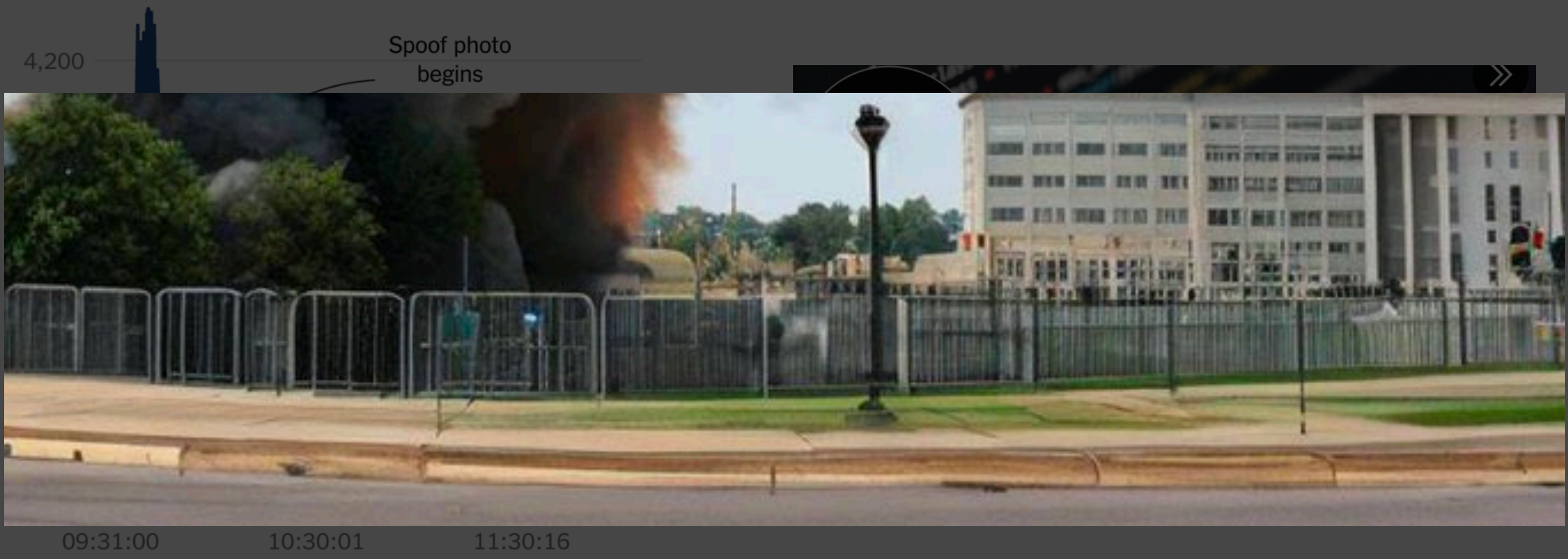

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- Propaganda
- Scams
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- Content Monitoring
- Detection by NLP
  - LLM models
  - BERT models

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Mitigation of spread

- Alternation of Social Network
- Controlling Information Flow
- Countering Spread

Twitter Algorithm

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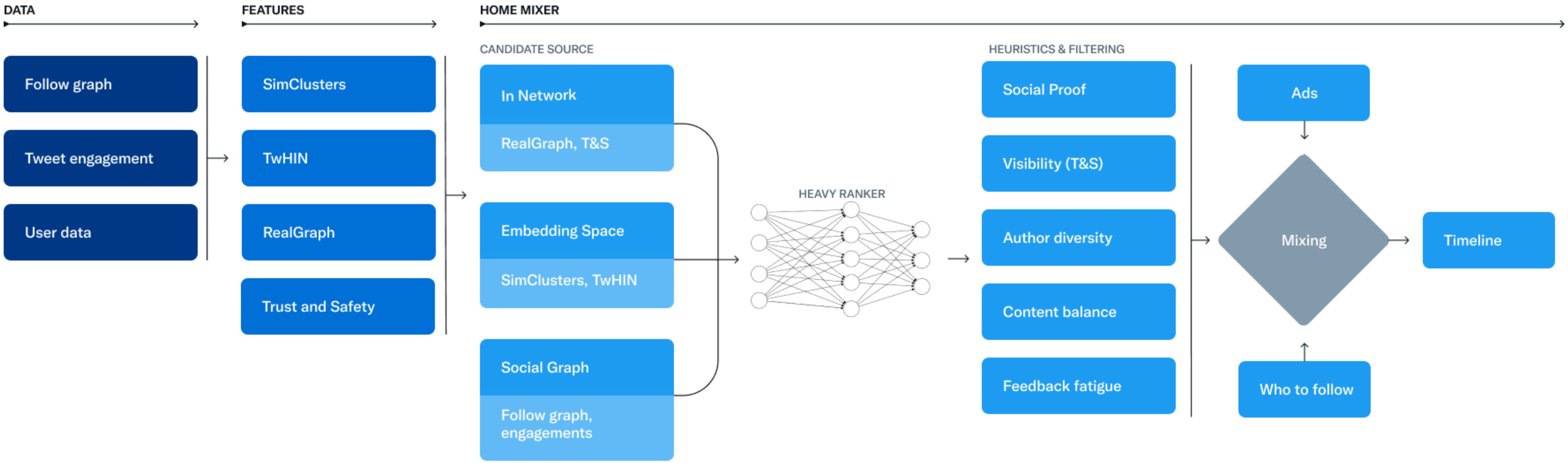

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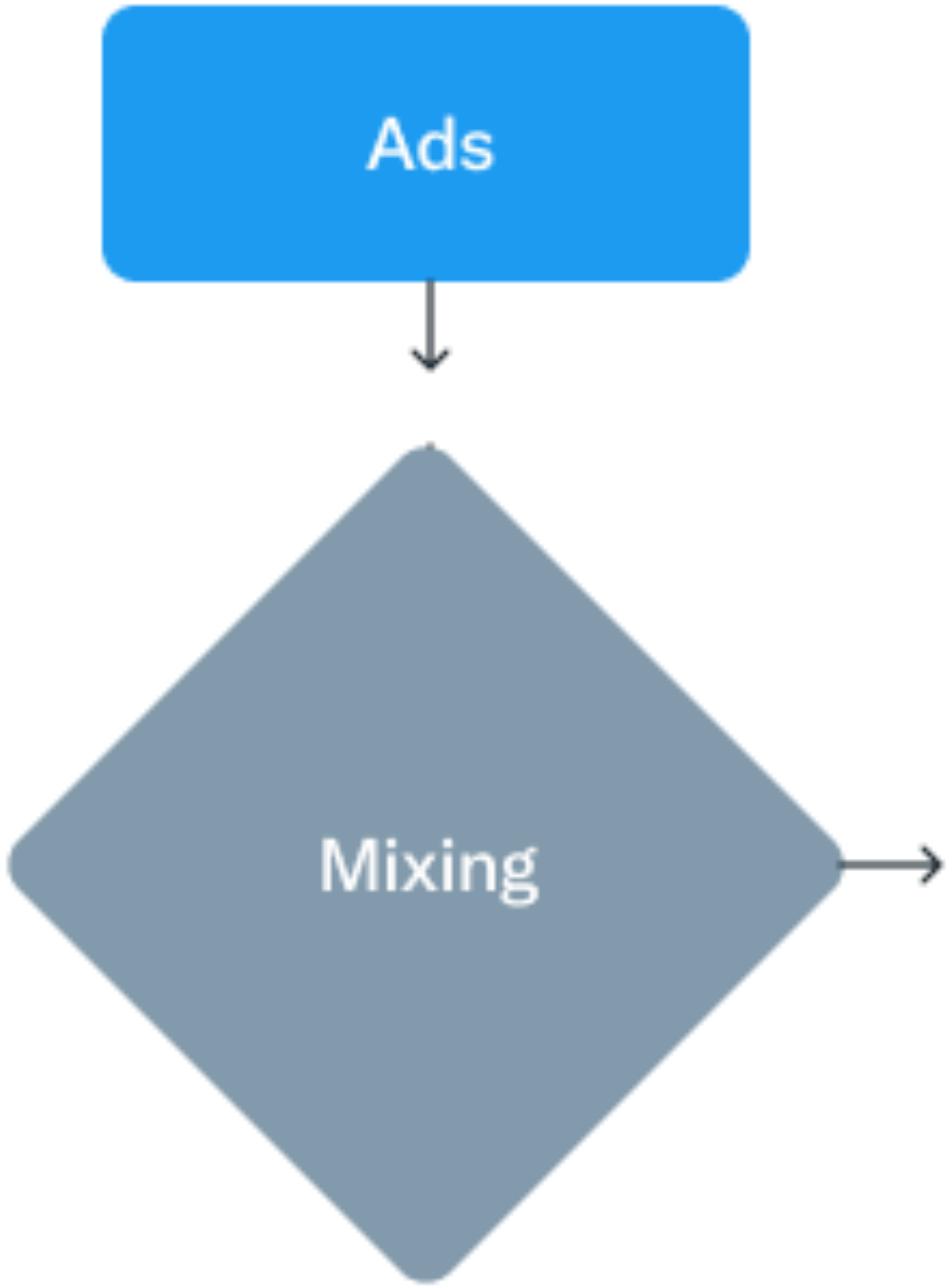

Social Media companies are **profit-driven**

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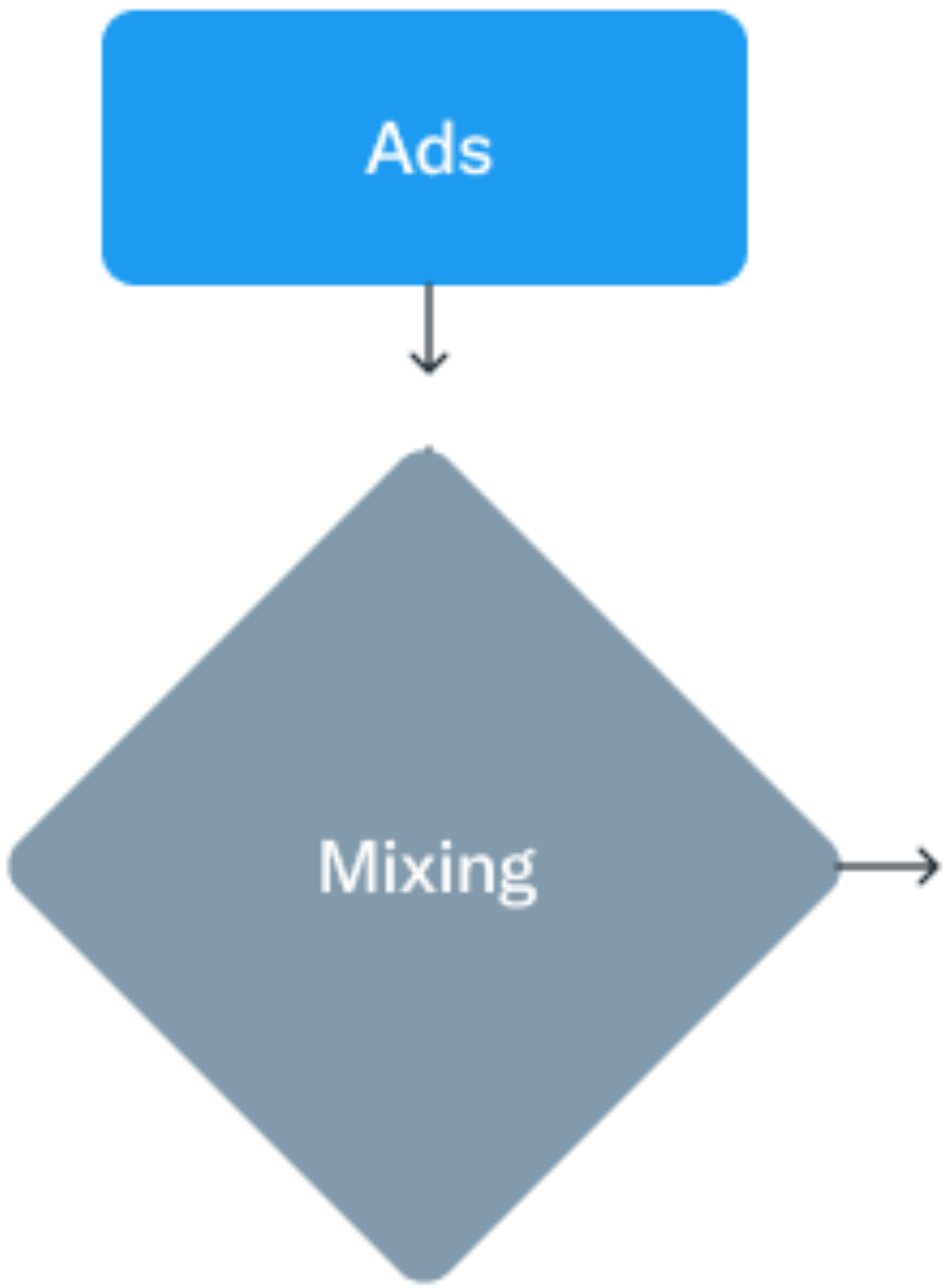

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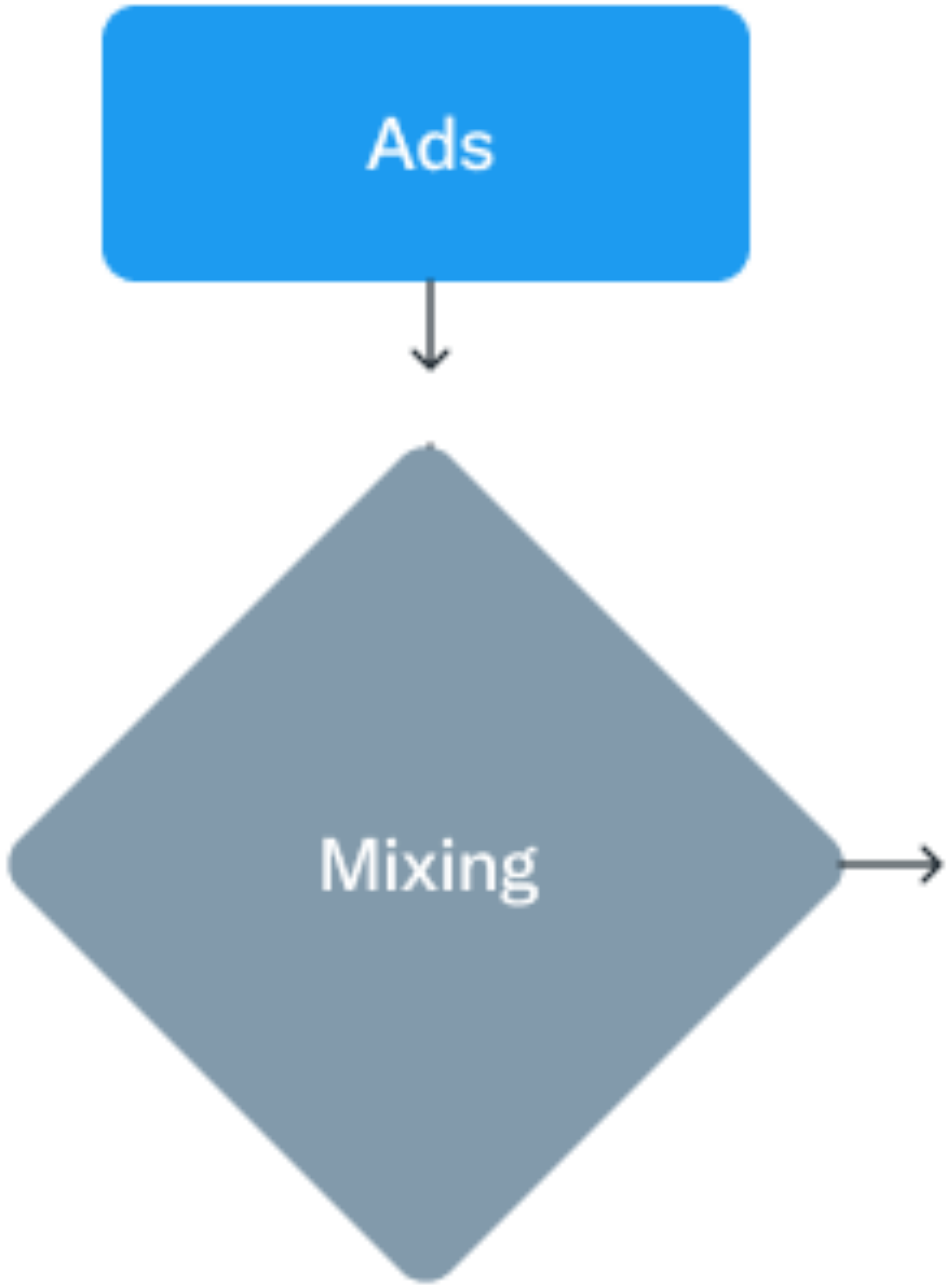

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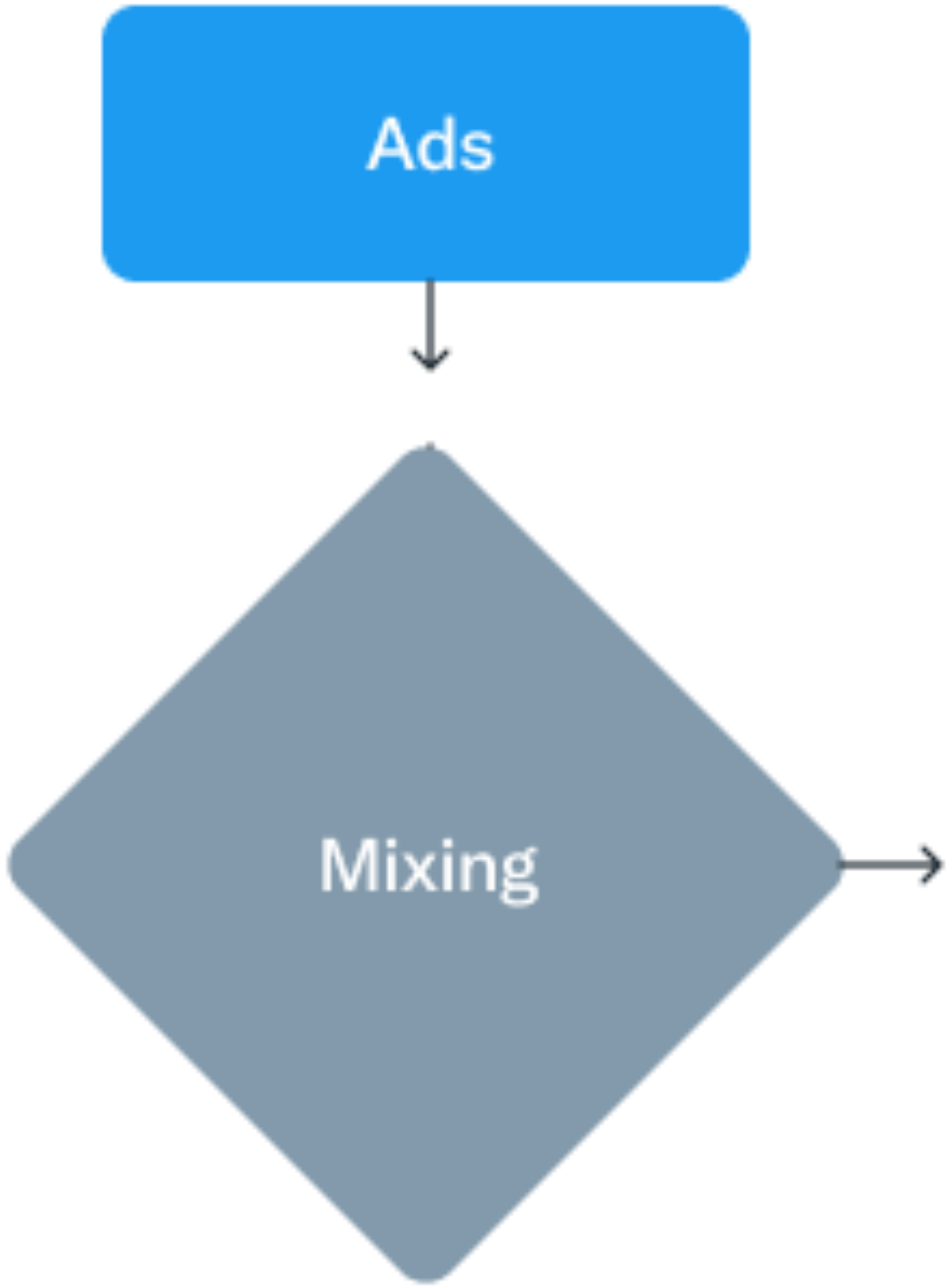

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Users = Revenue

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Social Media companies are **profit-driven**

- **Advertising:**

Fighting Misinformation is a **secondary** goal for Social Media Companies

- Controversies are interesting
- Freedom of speech

Users = Revenue

Infodemic Modeling

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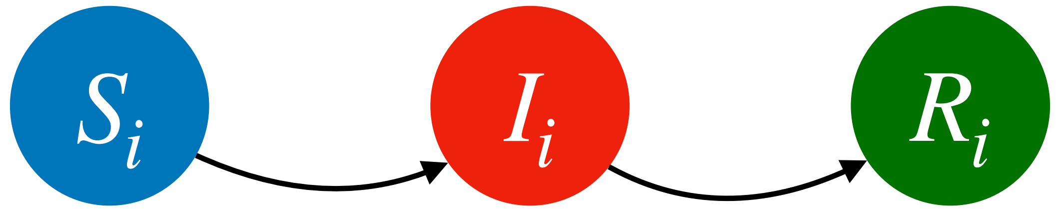
- Susceptible-Infected-Recovered Model (SIR)



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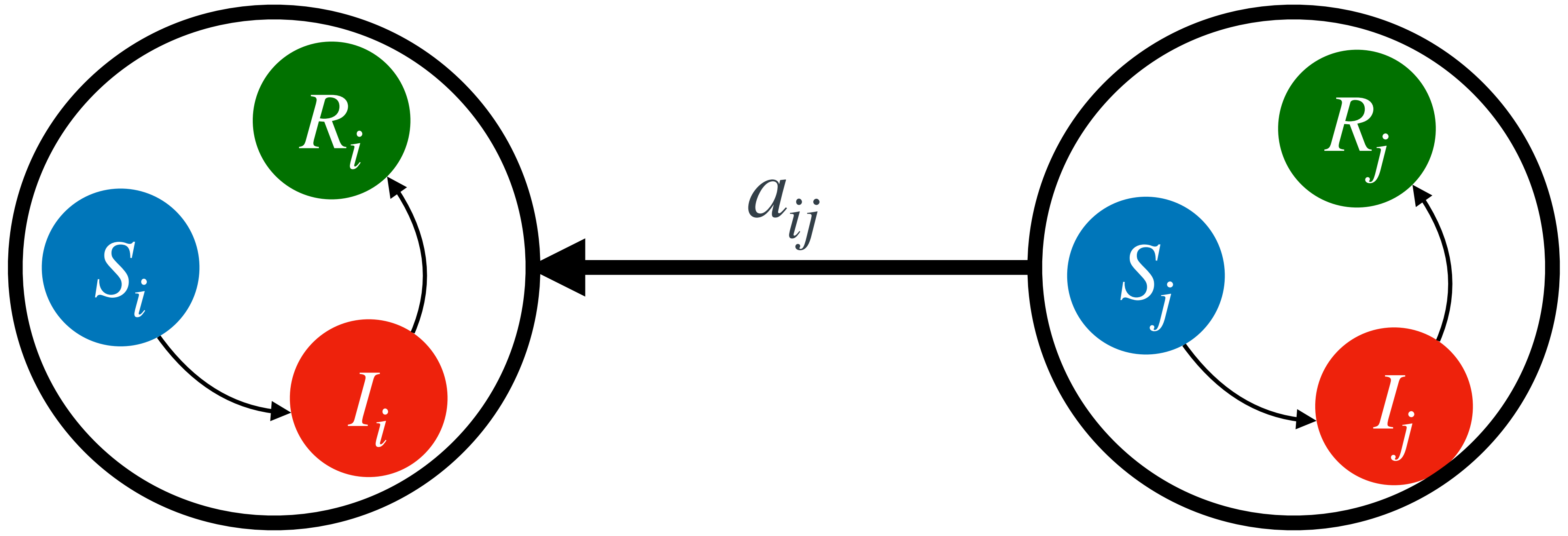

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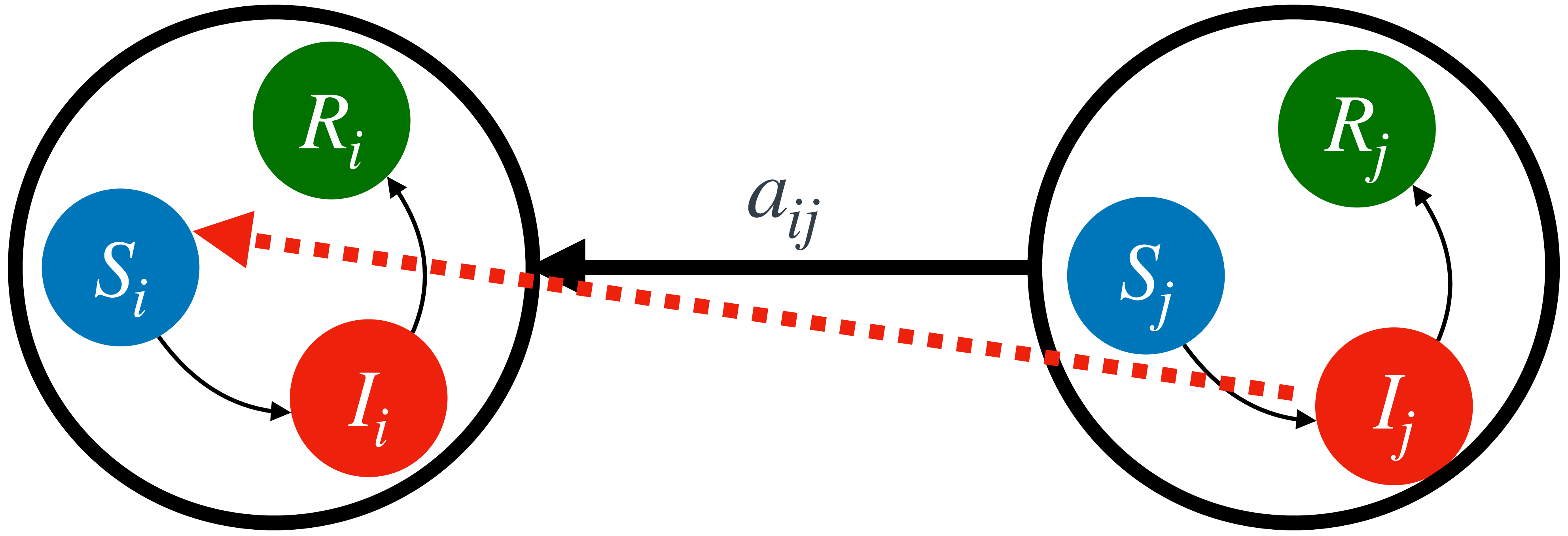

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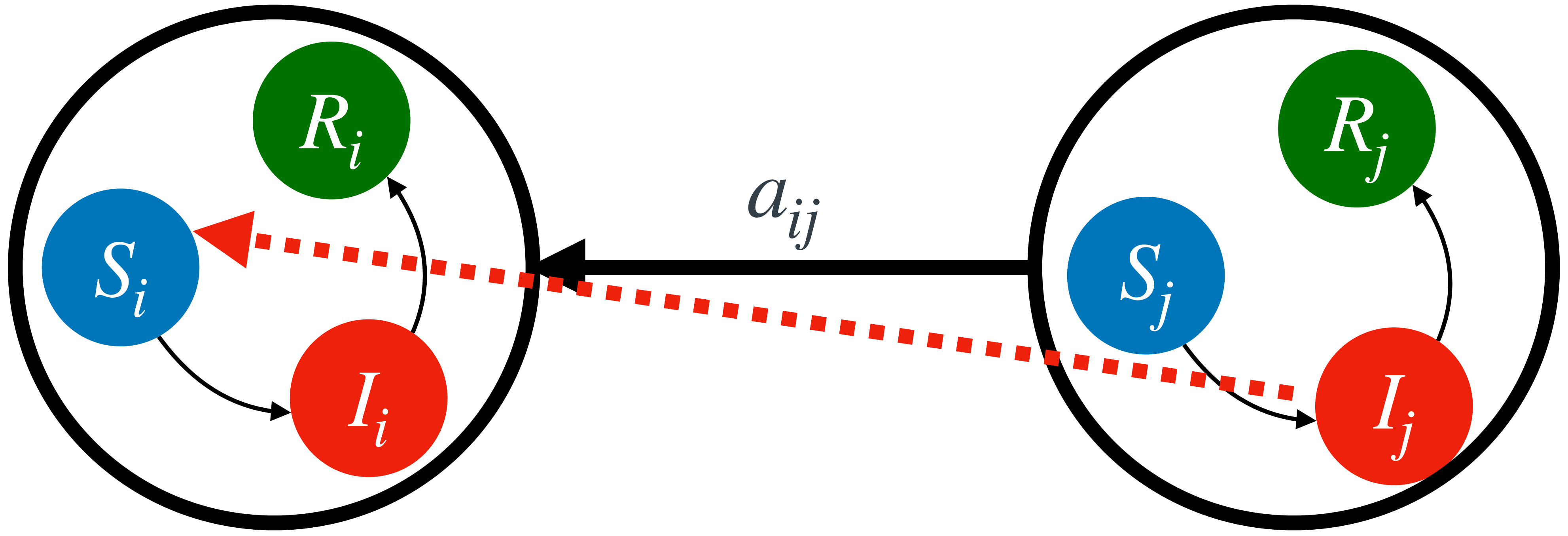

- Susceptible → Infected

$$\mathbb{P}(X^i(t+\Delta t) = I \,|\, X^i(t) = S) = \sum_{j=1}^{n} \beta^i a_{ij} \delta_{X_j}(I) \Delta t$$

- Infected → Recovered

$$\mathbb{P}(X^i(t+\Delta t) = R \,|\, X^i(t) = I) = \gamma^i \Delta t$$

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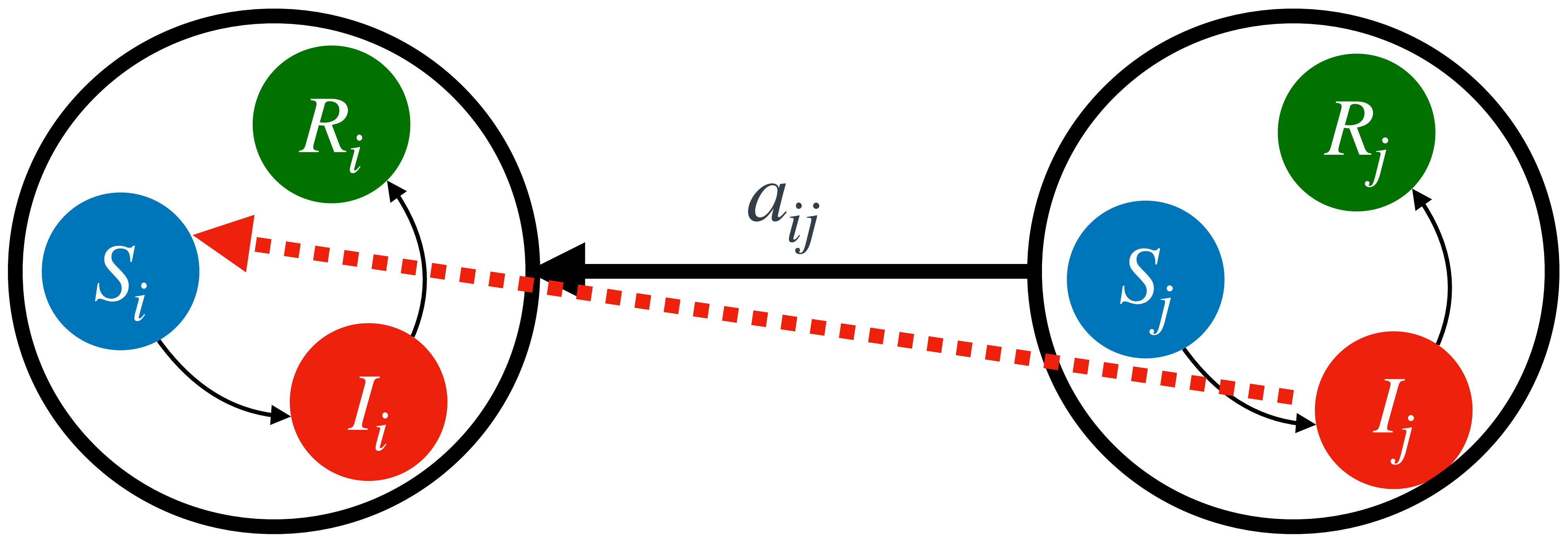

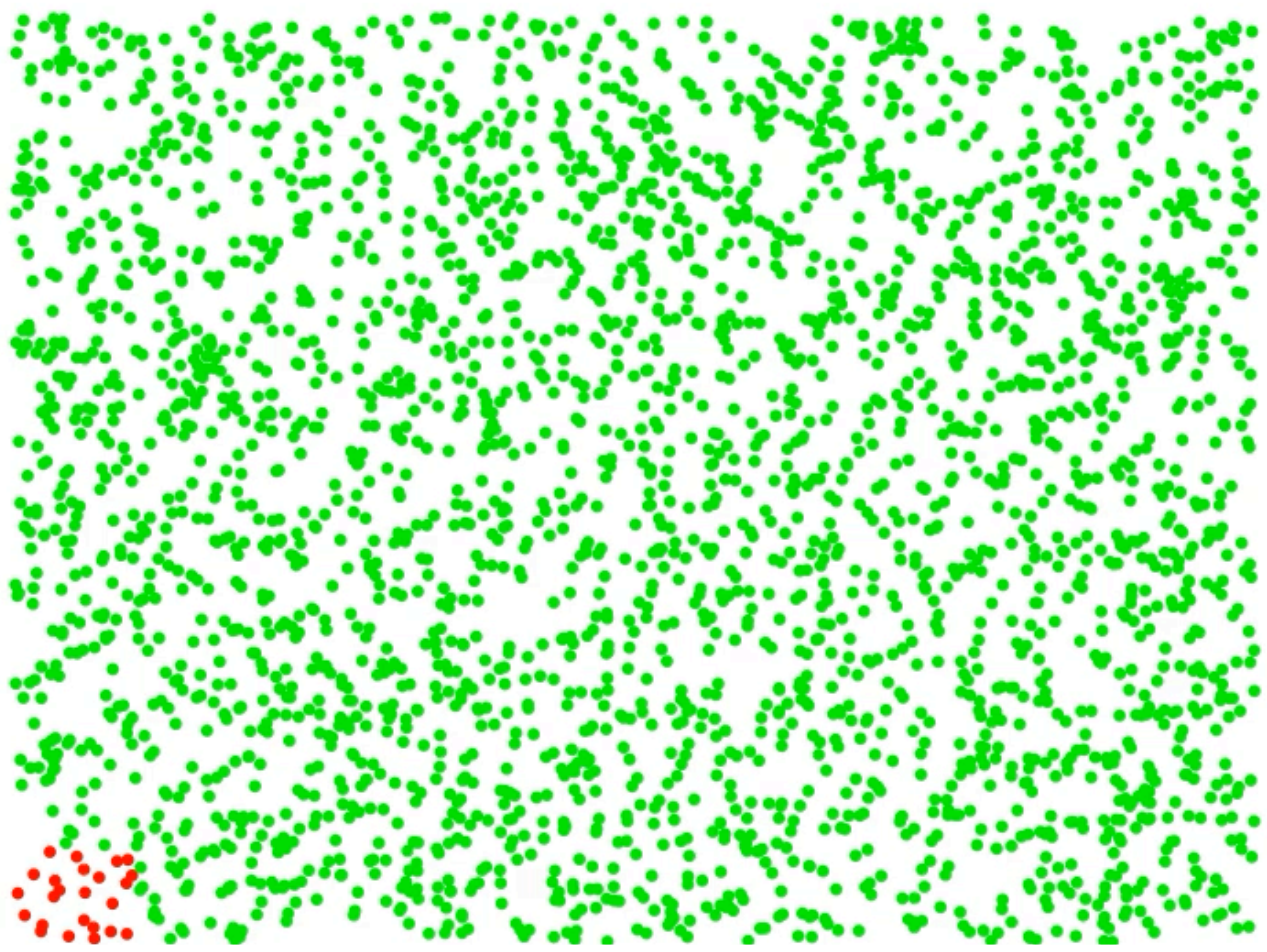

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Mean-field Approximations

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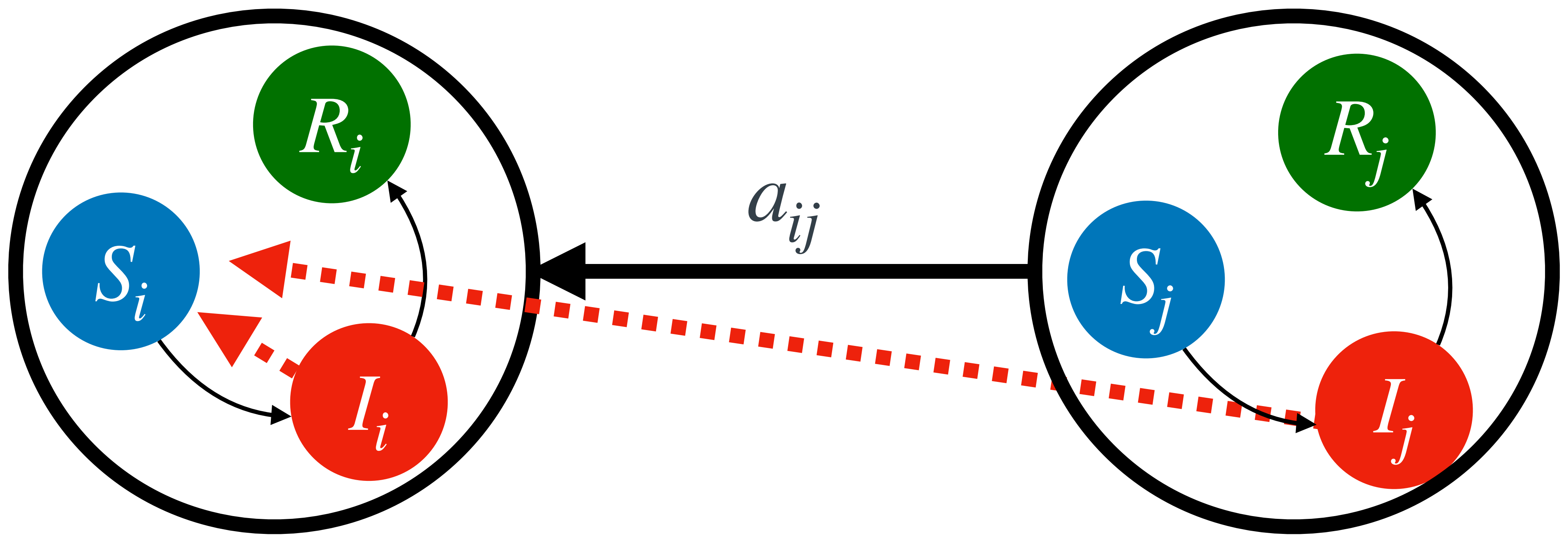
- SIR Model for communities



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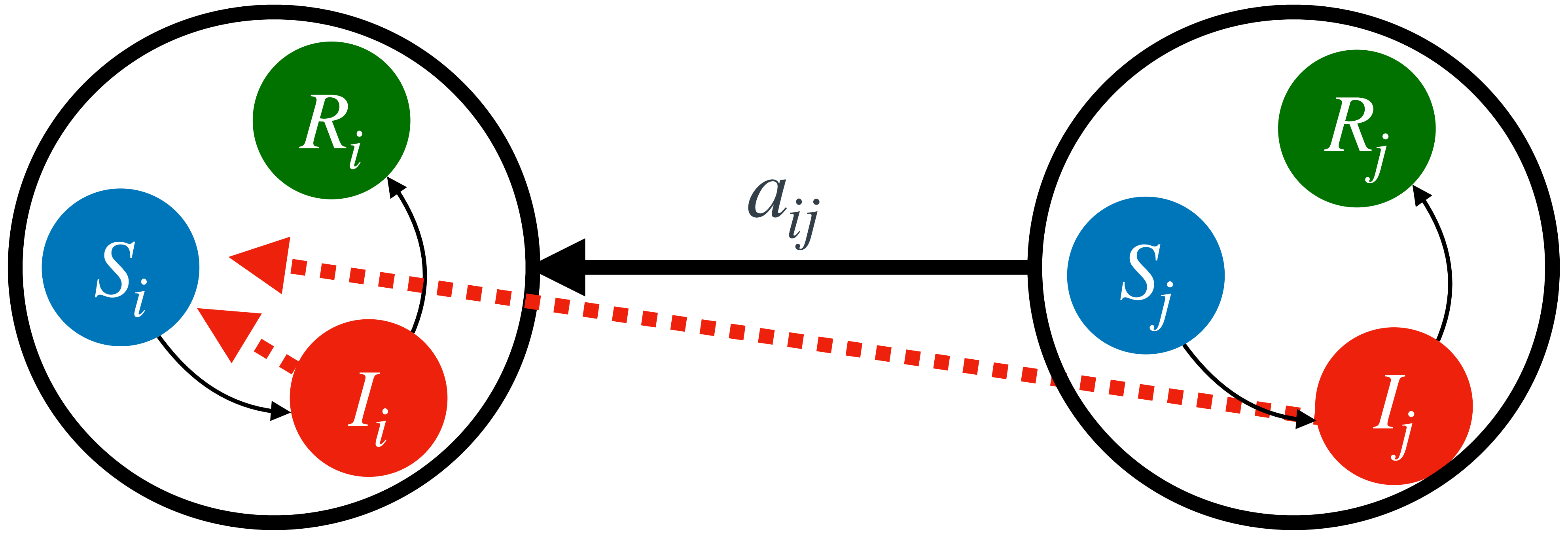

$$s_t^i = \mathbb{P}(X_t^i = S) = \mathbb{E}[\delta_{X_t^i}(S)]$$

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$$r_t^i = \mathbb{P}(X_t^i = S) = 1 - x_t^i - s_t^i$$

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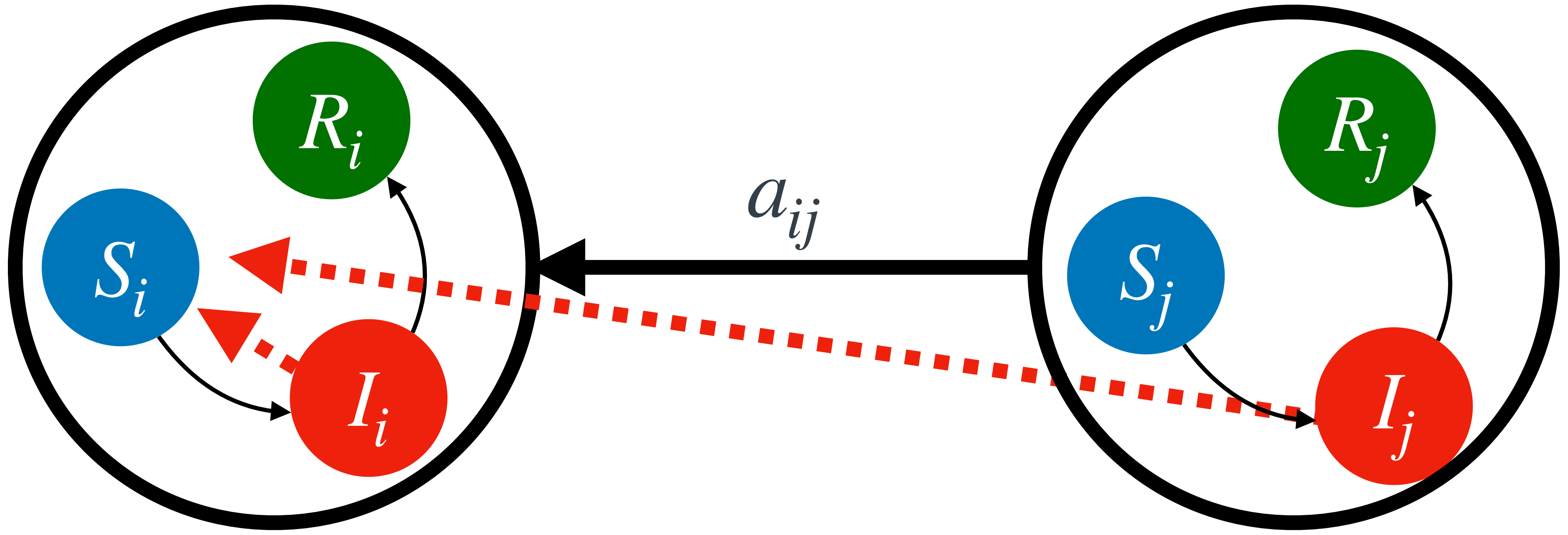

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→

$$\dot{s}^i(t) = -\beta^i s^i(t) \sum_{j=1}^{n} a_{ij} u_{ij}(t) x^j(t)$$

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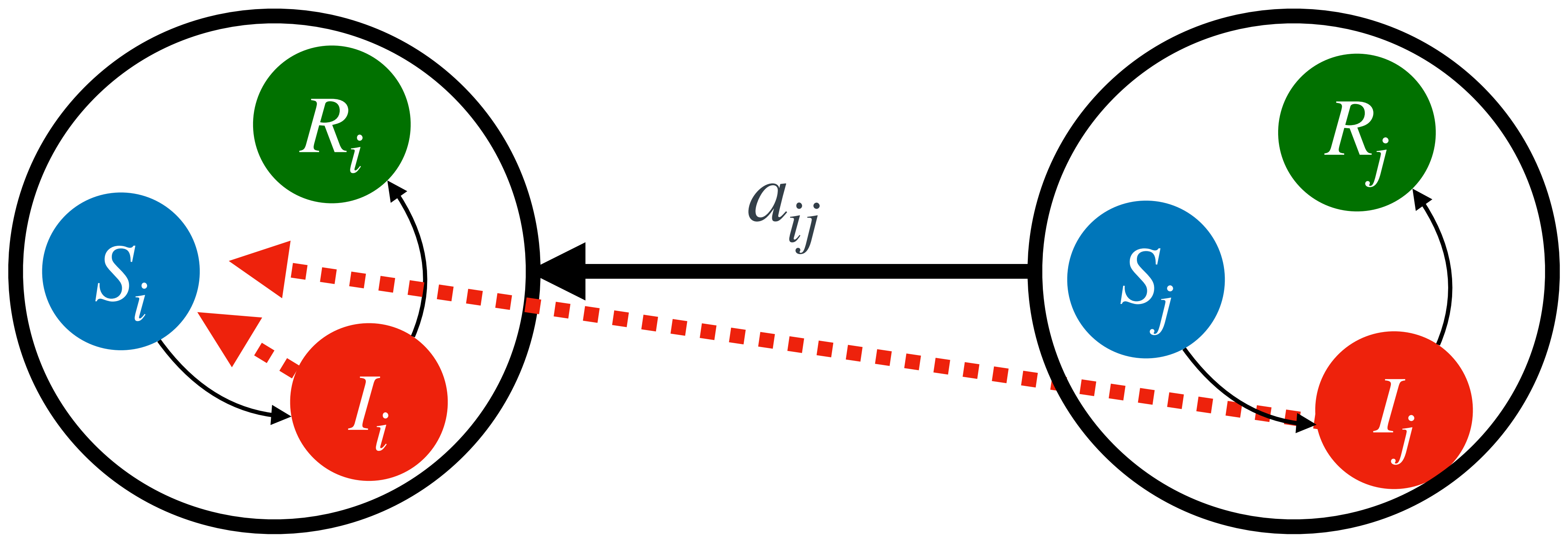

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3^n

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$2n$

Safety and Information Flow

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- Controlling information inside a community is not possible
  - **Out-of-platform** connections
  - Similar **sources**

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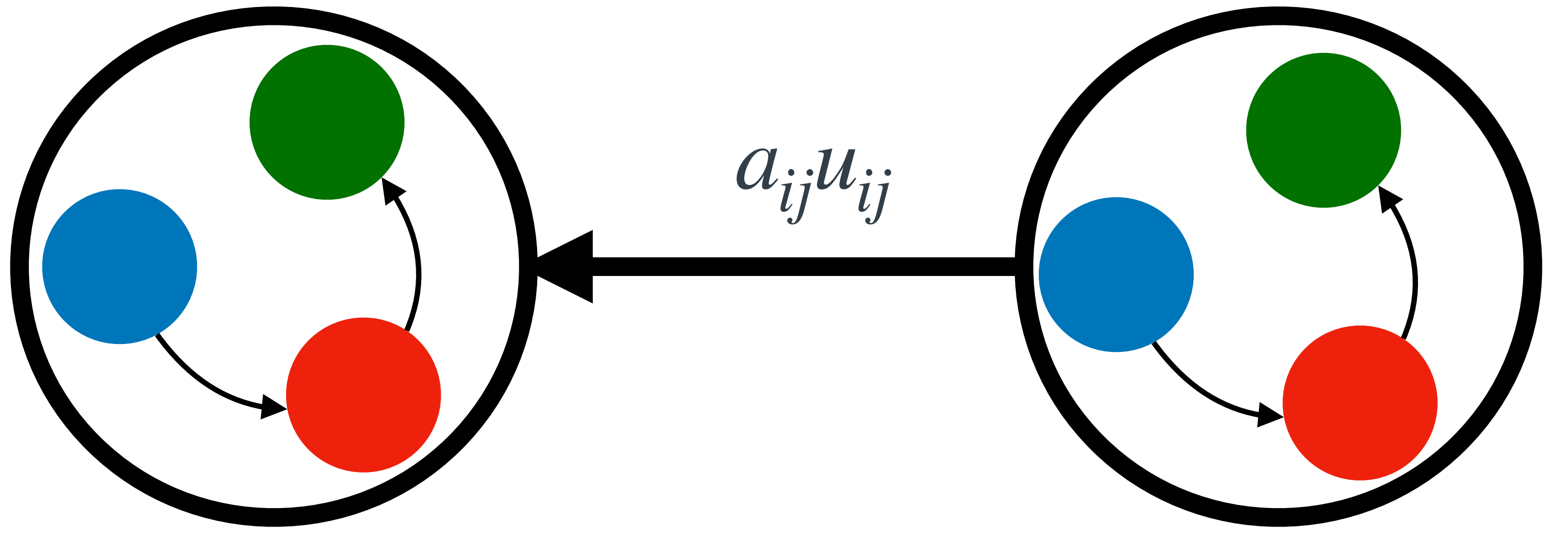

- Controlling Information between communities
    1. Minimizing the overall number of infected
    2. Minimizing the network modifications
    3. Preventing viral rumors
    4. Maintaining information flow

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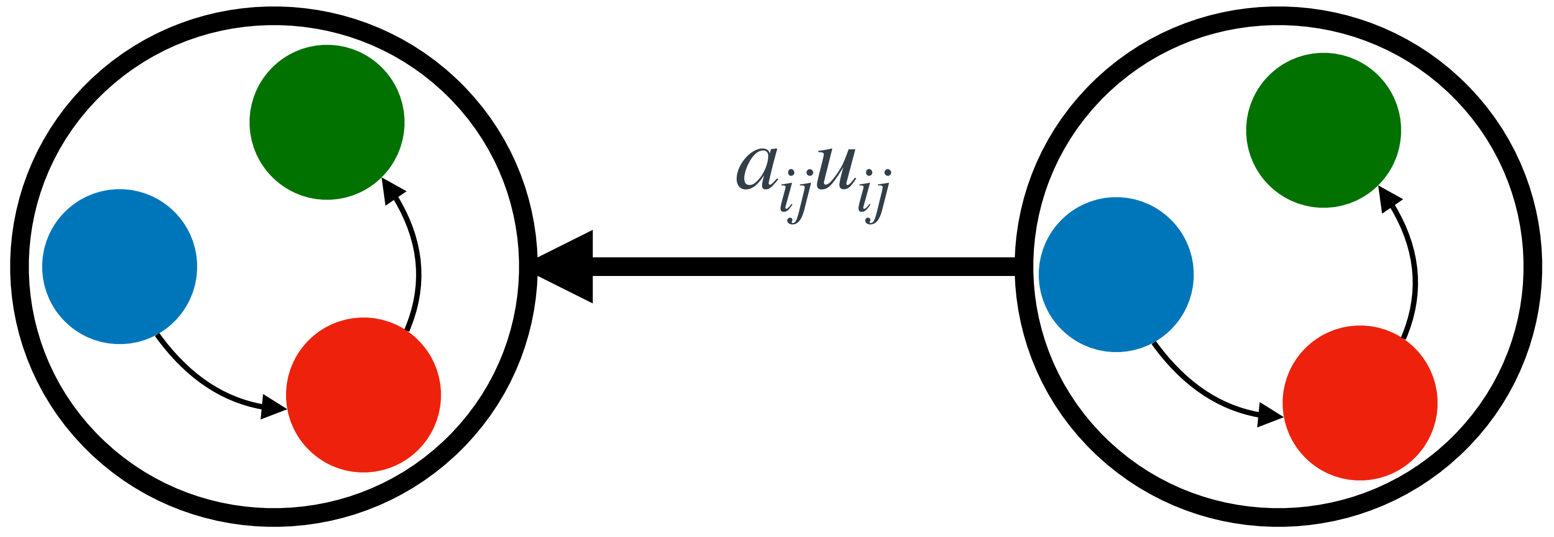

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$$\min_{[u_{ij}]_{i,j=1}^{n}} \quad \int_0^T \sum_{i=1}^{n} q_i x_i + \sum_{i,j=1}^{n} r(1-u_{ij})^2 dt$$

s.t. Dynamics , $x^i(0) = x_0^i, s^i(0) = 1 - x_0^i$

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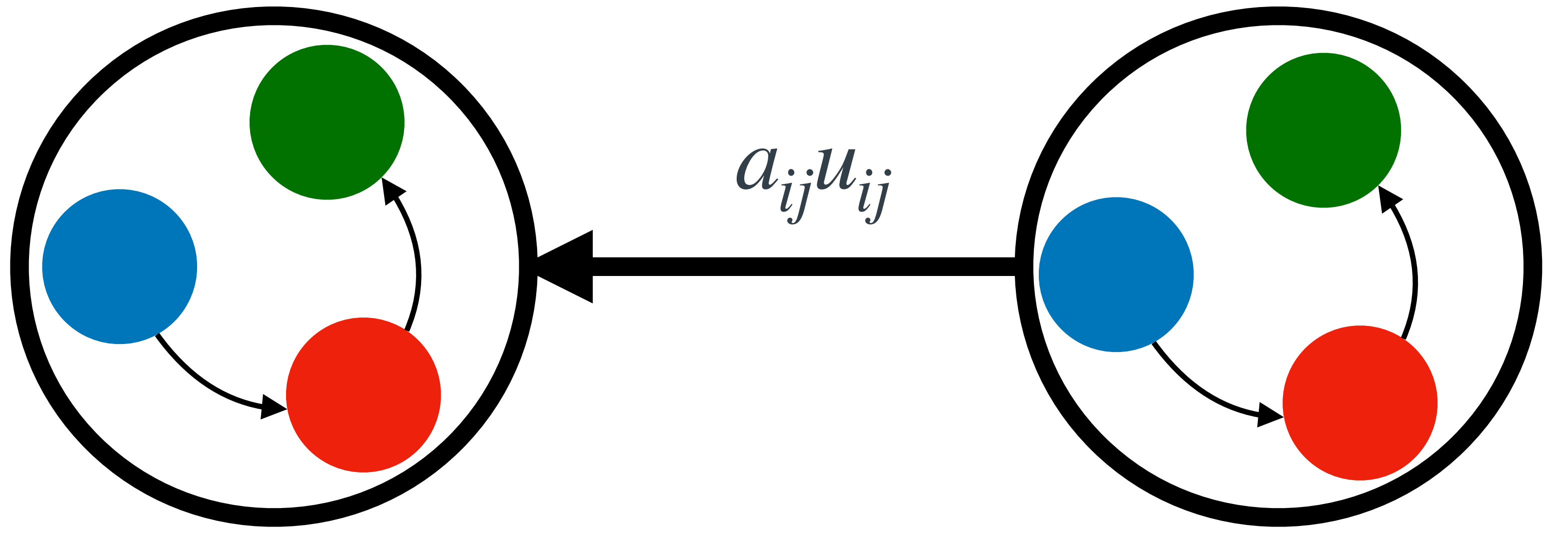

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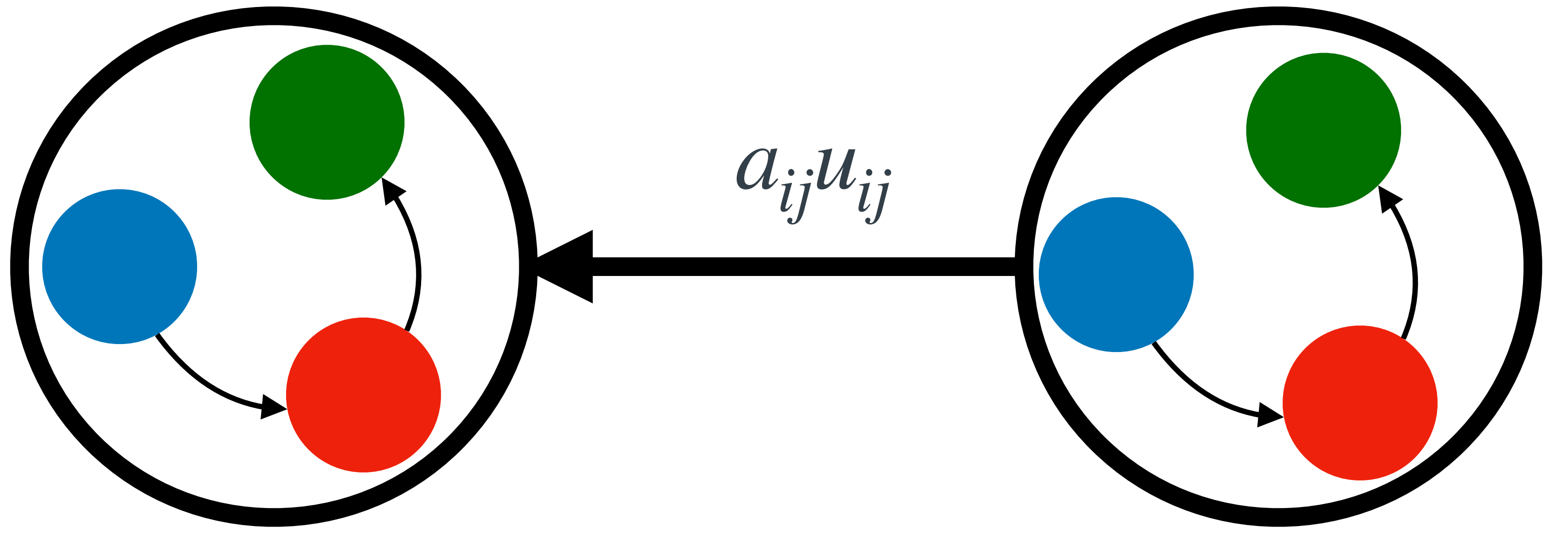

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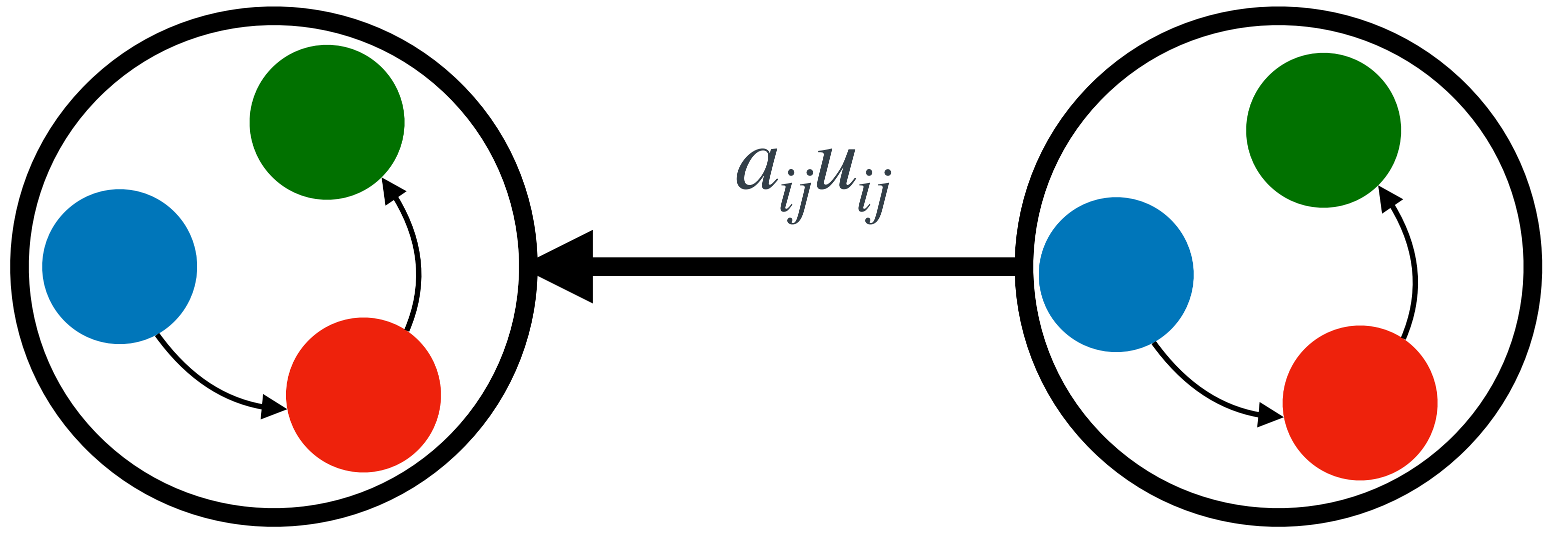

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Optimal Control Problem

Pontryagin's Maximum Principle

$$L = \sum_{i=1}^{n} \left[\lambda_s^i \dot{s}^i(t) + \lambda_x^i \dot{x}^i + \mu^i g^i - q_i x^i\right] - \sum_{i,j=1}^{n} r(1 - u_{ij})^2$$

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$$\max_{u \in \mathcal{U}} \quad L(x, u, \lambda, \mu)$$

s.t. Dynamics , $x^i(0) = x_0^i,\ s^i(0) = 1 - x_0^i,$

$$\dot{\lambda}_x^i = -\frac{\partial L}{\partial x^i},\ \lambda_x^i(T) = 0,$$

$$\dot{\lambda}_s^i = -\frac{\partial L}{\partial s^i},\ \lambda_s^i(T) = 0,$$

$$\mu^i g^i(x, u) = 0,\ \mu^i(t) \le 0$$

$$\min_{[u_{ij}]_{i,j=1}^n} \int_0^T \sum_{i=1}^{n} q_i x_i + \sum_{i,j=1}^{n} r(1-u_{ij})^2 dt$$

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Pontryagin's Maximum Principle

$$L = \sum_{i=1}^{n} \left[\lambda_s^i \dot{s}^i(t) + \lambda_x^i \dot{x}^i + \mu^i g^i - q_i x^i\right] - \sum_{i,j=1}^{n} r(1-u_{ij})^2$$

$$\max_{u \in \mathcal{U}} \quad L(x, u, \lambda, \mu)$$

s.t. Dynamics $, x^i(0) = x_0^i, s^i(0) = 1 - x_0^i,$

$$\dot{\lambda}_x^i = -\frac{\partial L}{\partial x^i}, \ \lambda_x^i(T) = 0,$$

$$\dot{\lambda}_s^i = -\frac{\partial L}{\partial s^i}, \ \lambda_s^i(T) = 0,$$

$$\mu^i g^i(x, u) = 0, \ \mu^i(t) \leq 0$$

$$\min_{[u_{ij}]_{i,j=1}^n} \quad \int_0^T \sum_{i=1}^{n} q_i x_i + \sum_{i,j=1}^{n} r(1-u_{ij})^2 dt$$

s.t. Dynamics , $x^i(0) = x_0^i, s^i(0) = 1 - x_0^i$

$$x^i(t) \leq \bar{x}(t) \quad \forall\, i \in \mathcal{V}, \forall\, t \in \mathbb{R}_+,$$

$$u_{ij}(t) \in \mathcal{U} \quad \forall\, (i,j) \in \mathcal{E},$$

$$\sum_{j=1}^{n} a_{ij} u_{ij}(t) \geq \sum_{j=1}^{n} a_{ij} \qquad \forall\, i \in \mathcal{V}$$

Optimal Control Problem

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Theorem 1. In the SIR dynamics, If $[u_{ij}(t)]$ satisfies

$$0 \leq \gamma^i \bar{x} - \beta^i s^i(t) \sum_{j=1}^{n} a_{ij} u_{ij}(t) x^j(t), \qquad \forall i \in \mathscr{V}, \forall t \in \mathbb{R}_+,$$

then $x^i(t) \leq \bar{x}$ for all $t \in \mathbb{R}_+$ and $i \in \mathscr{V}$.

Optimal Control Problem

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Theorem 1. In the SIR dynamics, If $[u_{ij}(t)]$ satisfies

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Optimal Control Problem

$$\min_{[u_{ij}]_{i,j=1}^{n}} \quad \int_0^T \sum_{i=1}^{n} q_i x_i + \sum_{i,j=1}^{n} r(1 - u_{ij})^2 dt$$

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$$0 \leq \gamma^i \bar{x} - \beta^i s^i(t) \sum_{j=1}^{n} a_{ij} u_{ij}(t) x^j(t)(t) \quad \forall\, i \in \mathscr{V}, \forall\, t \in \mathbb{R}_+,$$

$$u_{ij}(t) \in \mathscr{U} \quad \forall\, (i,j) \in \mathscr{E},$$

$$\sum_{j=1}^{n} a_{ij} u_{ij}(t) \geq \sum_{j=1}^{n} a_{ij} \qquad \forall\, i \in \mathscr{V}$$

Optimal Control Problem

The University of Texas at Austin
Oden Institute for Computational Engineering and Sciences

Constrained Quadratic Programming

$$\max_{u_i \in \mathcal{U}_i} \quad -r u_i(t)^T u_i(t) + c_i^T u_i(t)$$

$$\text{s.t.} \quad a_i^T \mathbf{1}_n \leq \quad a_i^T u_i(t)$$

$$b_i(t)^T u_i(t) \leq \gamma^i \bar{x}$$

$$a_i := [a_{i1}; a_{i2}; \cdots; a_{in}]$$

$$b_i := s^i \beta^i \,\text{Diag}(a_i)\, x$$

$$c_i := (\lambda_x^i - \lambda_s^i - \mu^i) s^i \beta^i \,\text{Diag}(a_i)\, x + 2r\mathbf{1}_n$$

Optimal Control Problem

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Forward Backward Sweep Method

Optimal Control Problem

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Forward Backward Sweep Method

Decentralize Solution

Experiments

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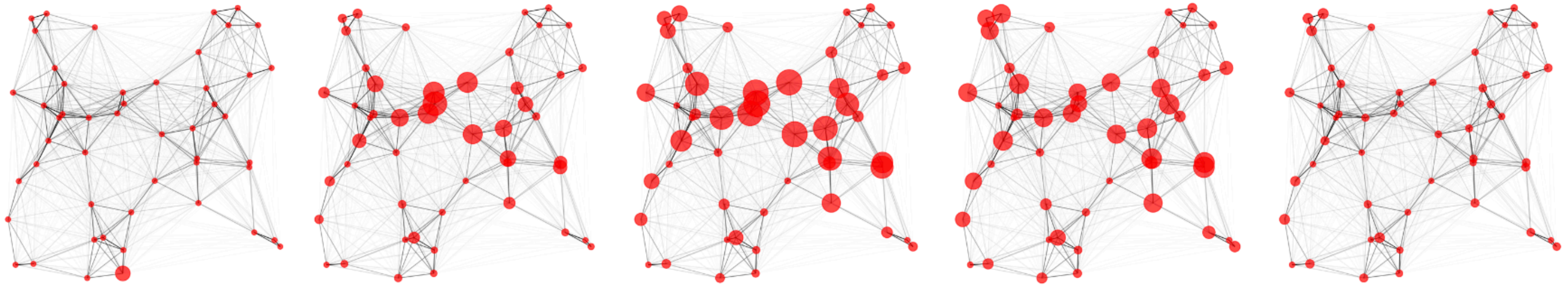
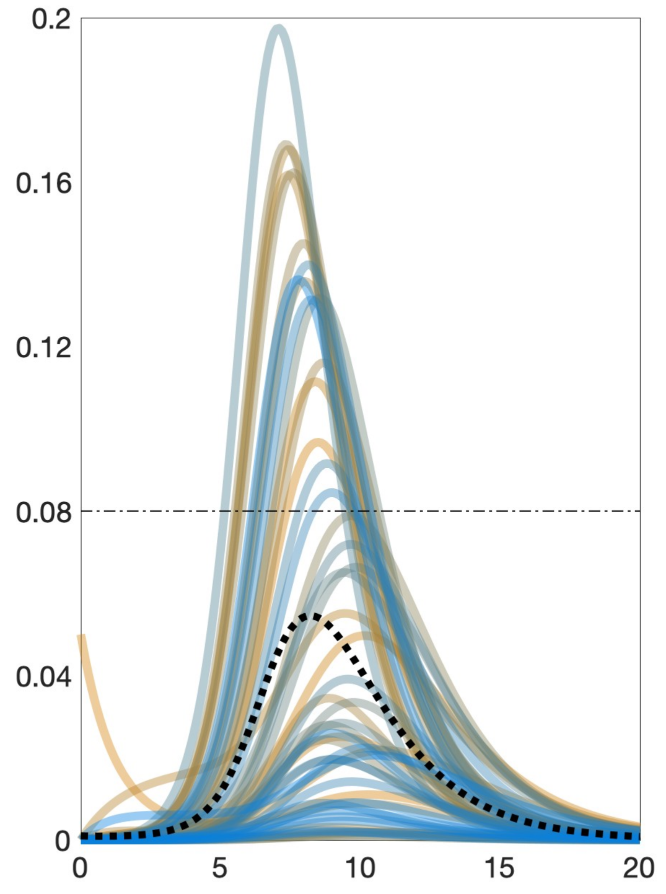
No control



(f) $t = 0$ (g) $t = 6$ (h) $t = 8$ (i) $t = 10$ (j) $t = 15$



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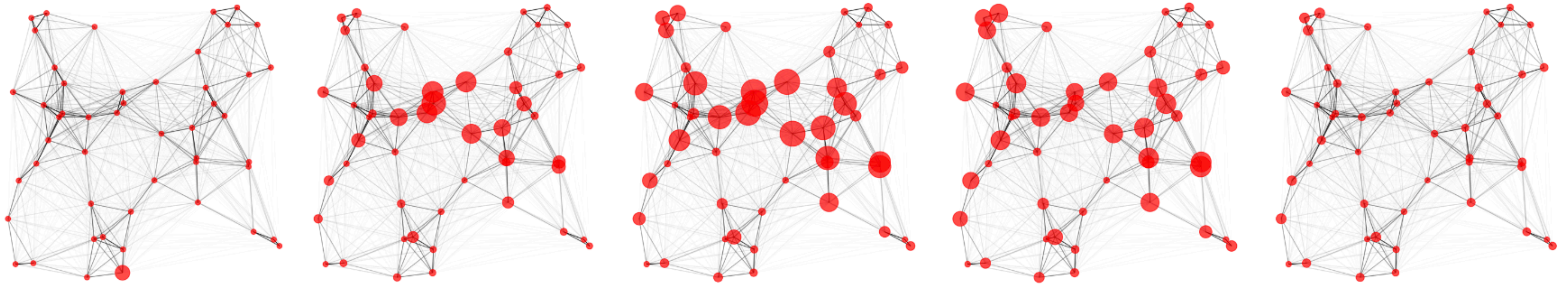

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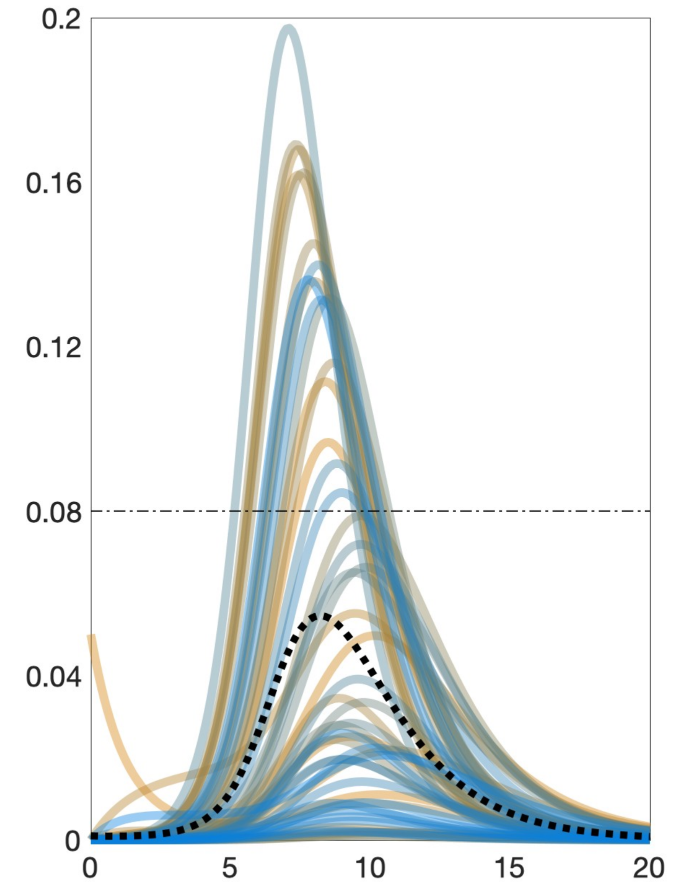
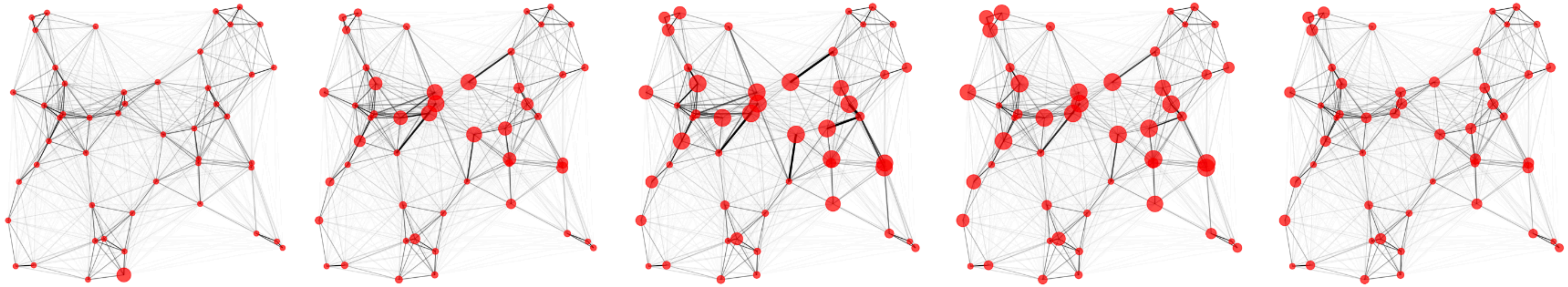
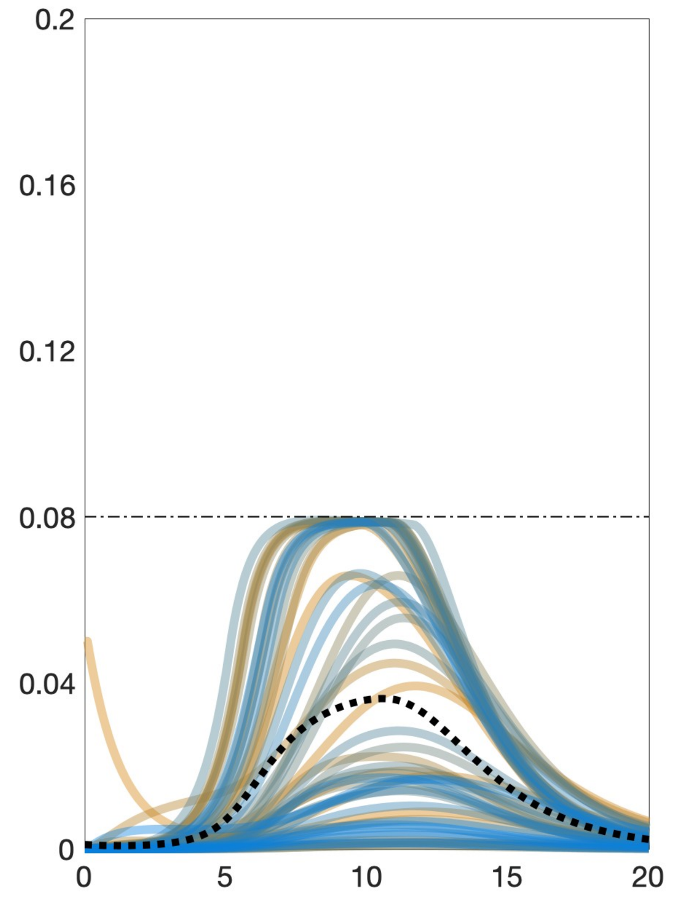


Proposed controller



(a) $t = 0$ (b) $t = 6$ (c) $t = 8$ (d) $t = 10$ (e) $t = 15$



Scalability

Scalability

The University of Texas at Austin
Oden Institute for Computational Engineering and Sciences

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- Number of nodes ~ 10^5
- The graph is almost complete
- The optimization problem is solved in polynomial time
- We need to solve the optimization for each time instant multiple times

Each node solve CQP with n parameters each time step

Scalability

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Oden Institute for Computational Engineering and Sciences

Constrained Quadratic Programming

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  mu

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This method can't handle large networks

Network Latent Space

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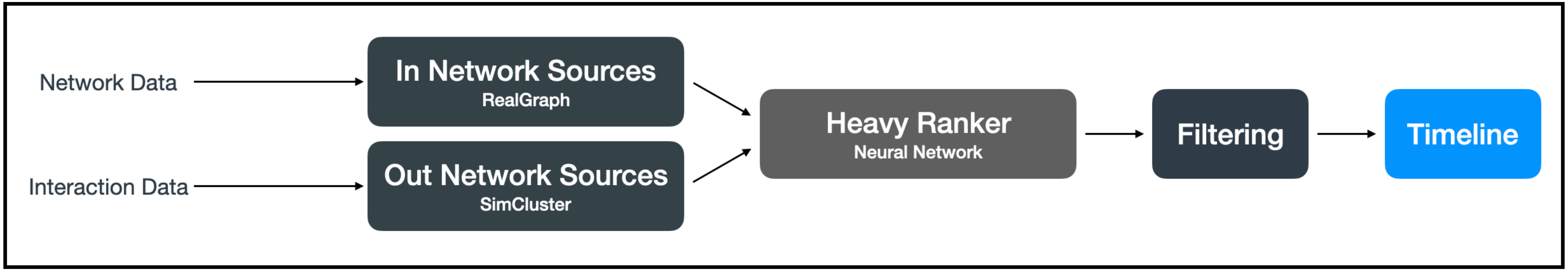

Network Latent Space

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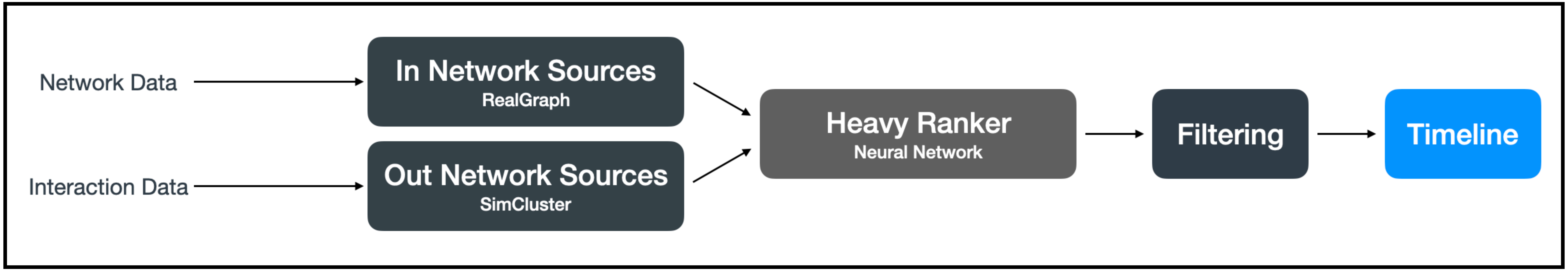

SimCluster

- Identify 145,000 community
- Clustering based on Interactions
- Updated weekly

Network Latent Space

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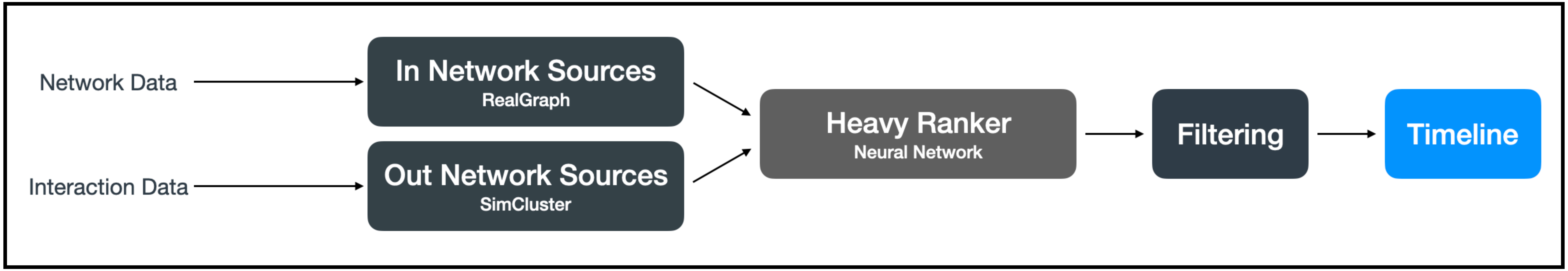
Oden Institute for Computational Engineering and Sciences



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→

Can we use the network structure to make the proposed algorithm scalable?

Graph Embedding

Micro Interaction

Using interactions such as:

- Conversation Engagements
- Mentions
- Retweets

$$\hat{p}_{uv} = \frac{\text{Number of interactions between u and v}}{\text{Number of all interactions in u and v}}$$

1. Lubold, Shane, Arun G. Chandrasekhar, and Tyler H. McCormick. "Identifying the latent space geometry of network models through analysis of curvature." Journal of the Royal Statistical Society Series B: Statistical Methodology.

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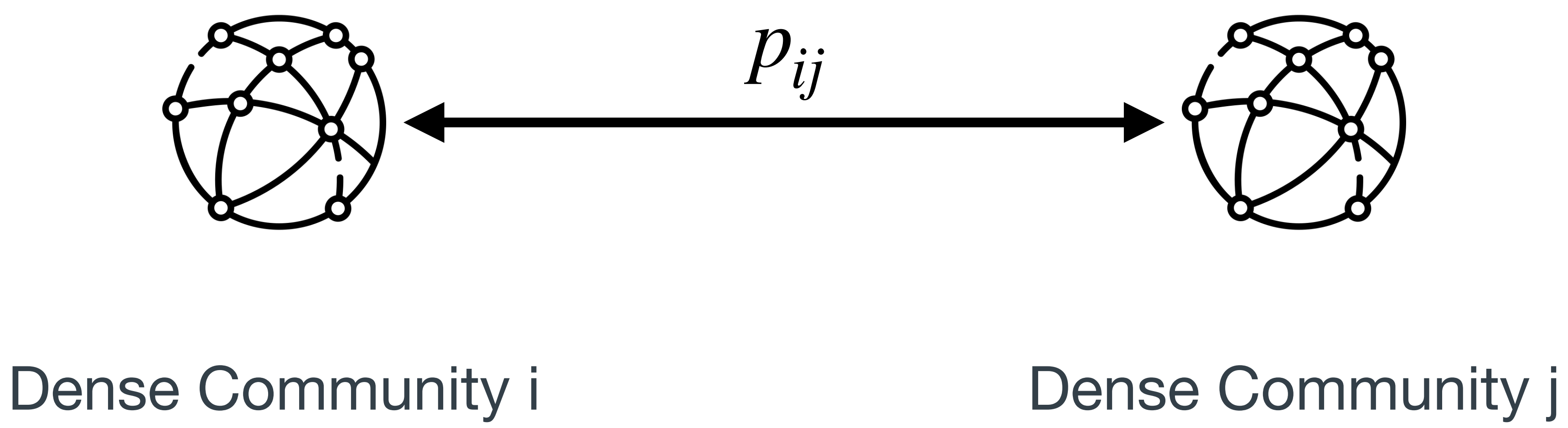
Latent Manifold Identification from Graph Data



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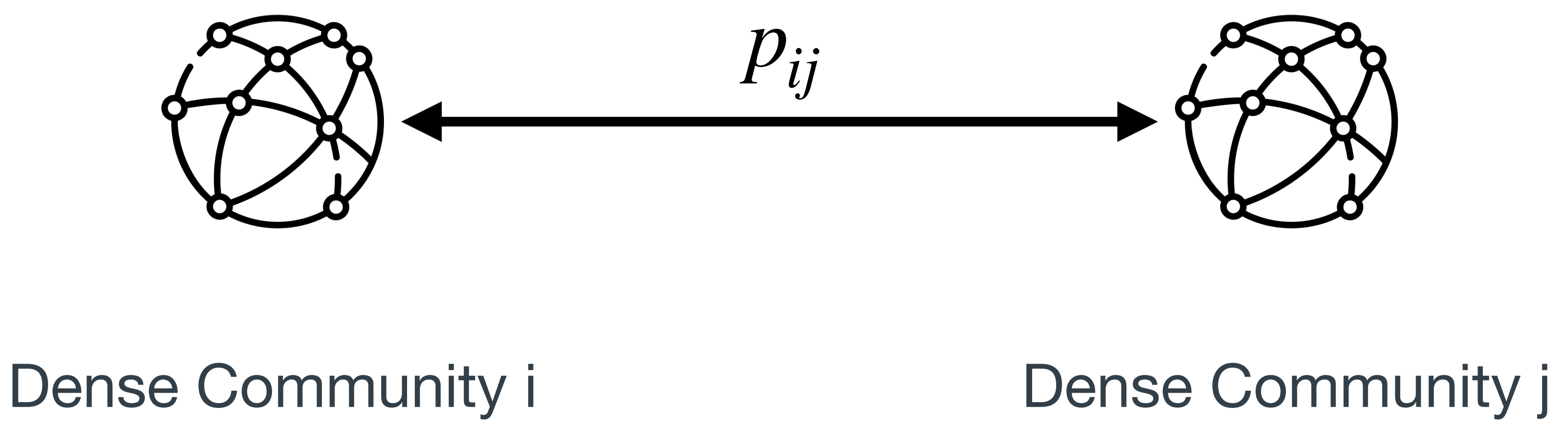

$$\hat{p}_{ij} = \frac{\nu_{ij}}{|\nu_i||\nu_j|}$$

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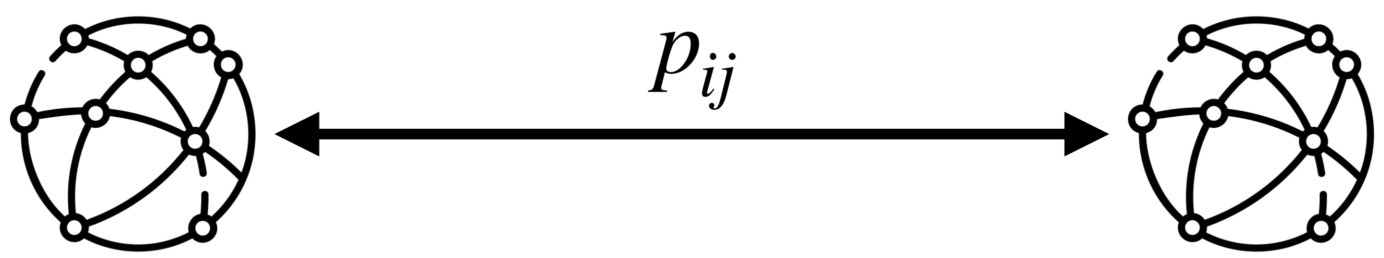

Dense Community i

Dense Community j

$$\hat{p}_{ij} = \frac{\nu_{ij}}{|\nu_i||\nu_j|} \longrightarrow p_{ij} = \phi(d(z^i, z^j))$$

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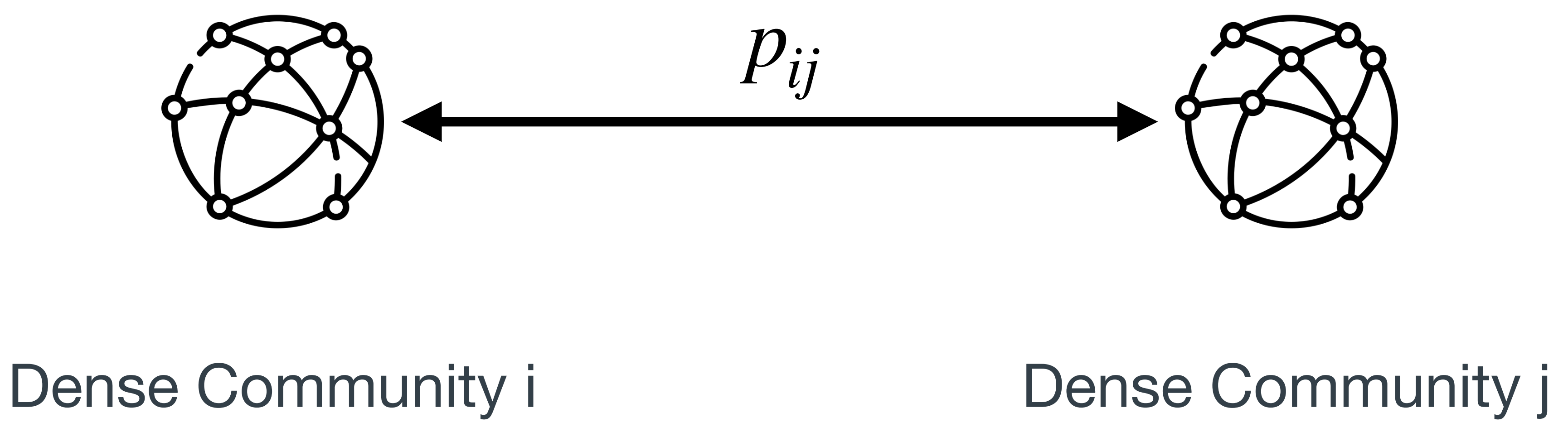

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➜ Identification of the **Latent Manifold** [1]

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Localization for Scalability

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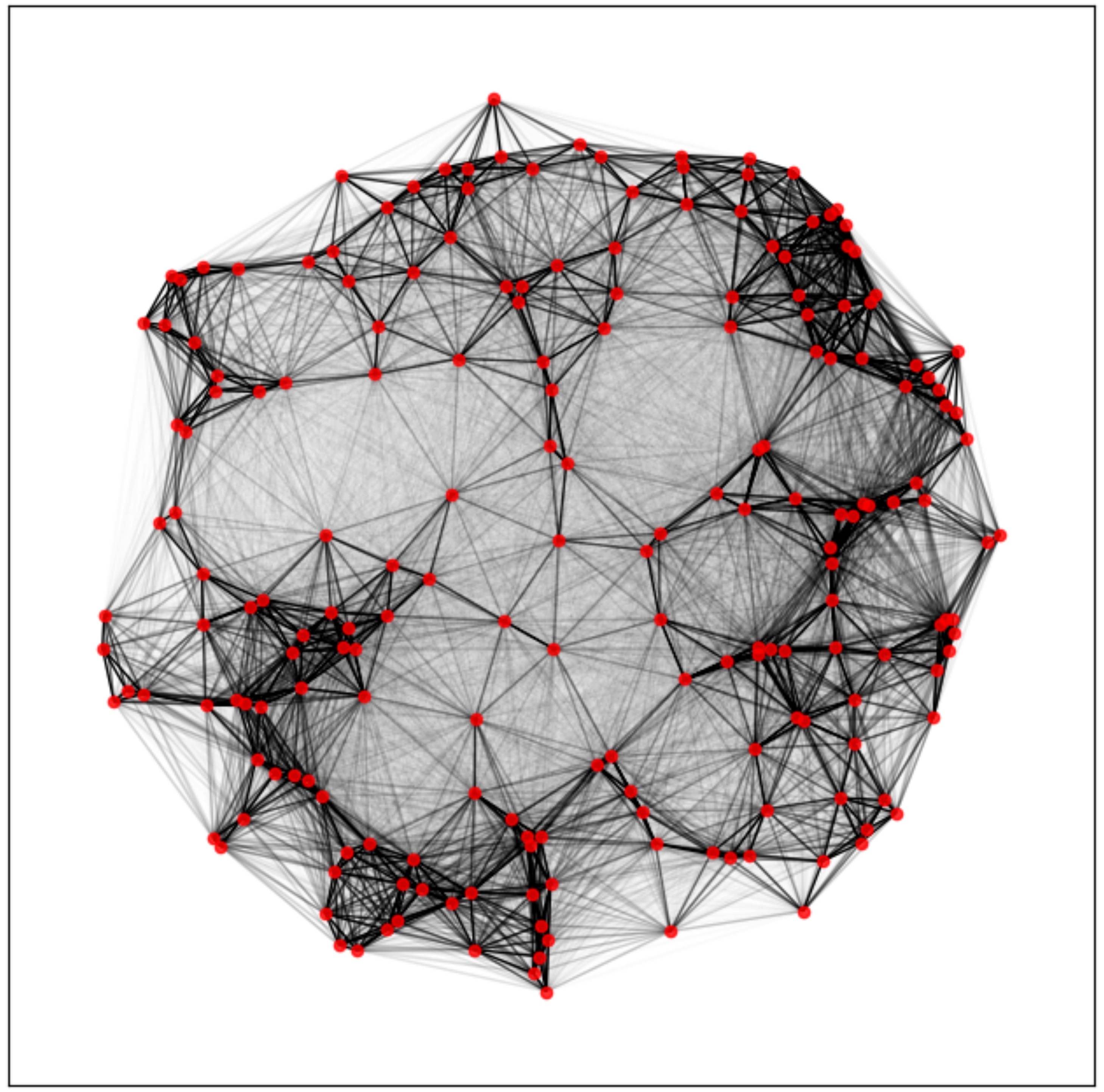
Truncating the graph

Remove links based on their latent space distance:

If $d_{ij} \leq \kappa$ **remove** the link between i and j



Original Graph

Localization for Scalability

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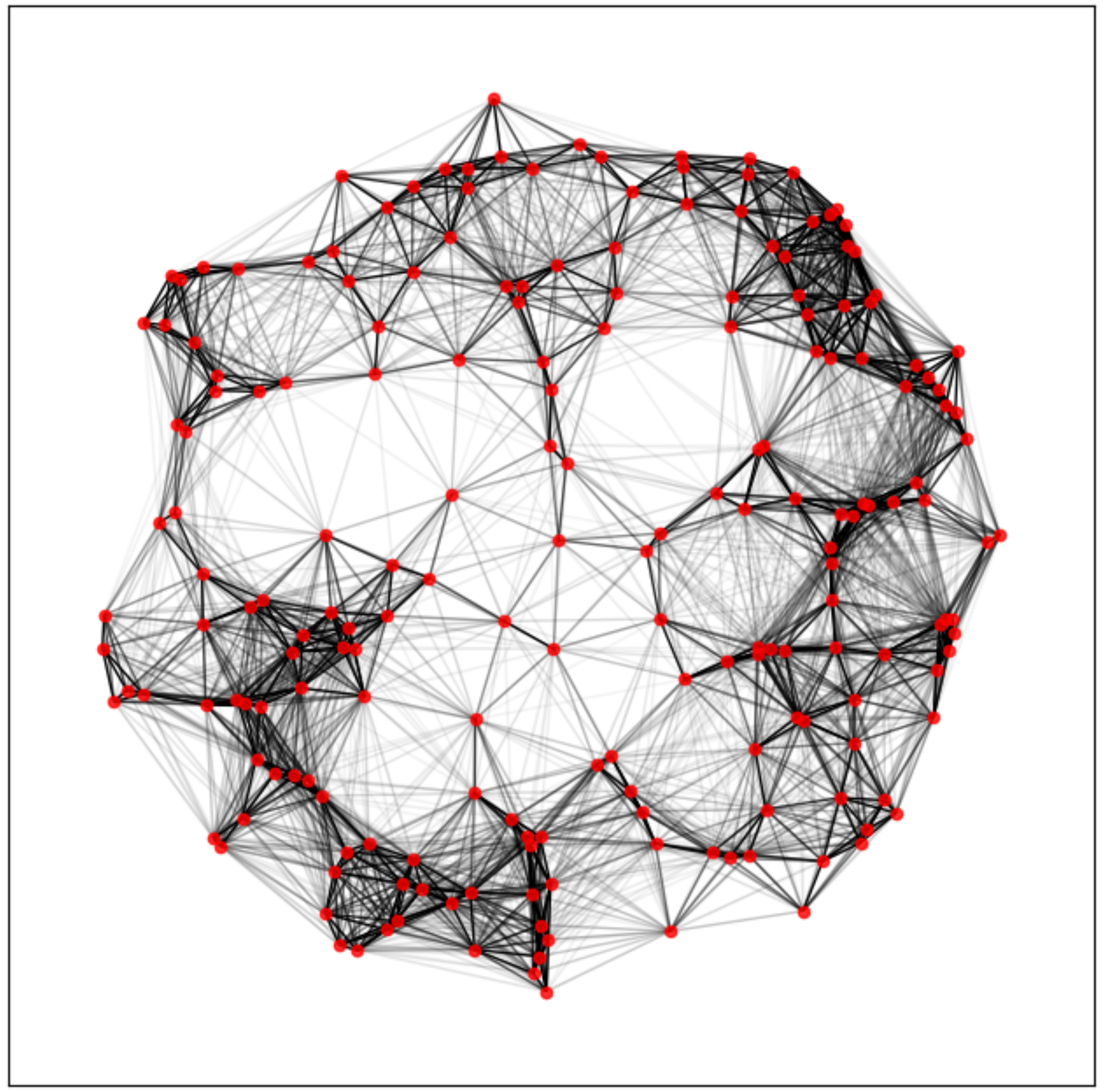

Localized Graph

Localization for Scalability

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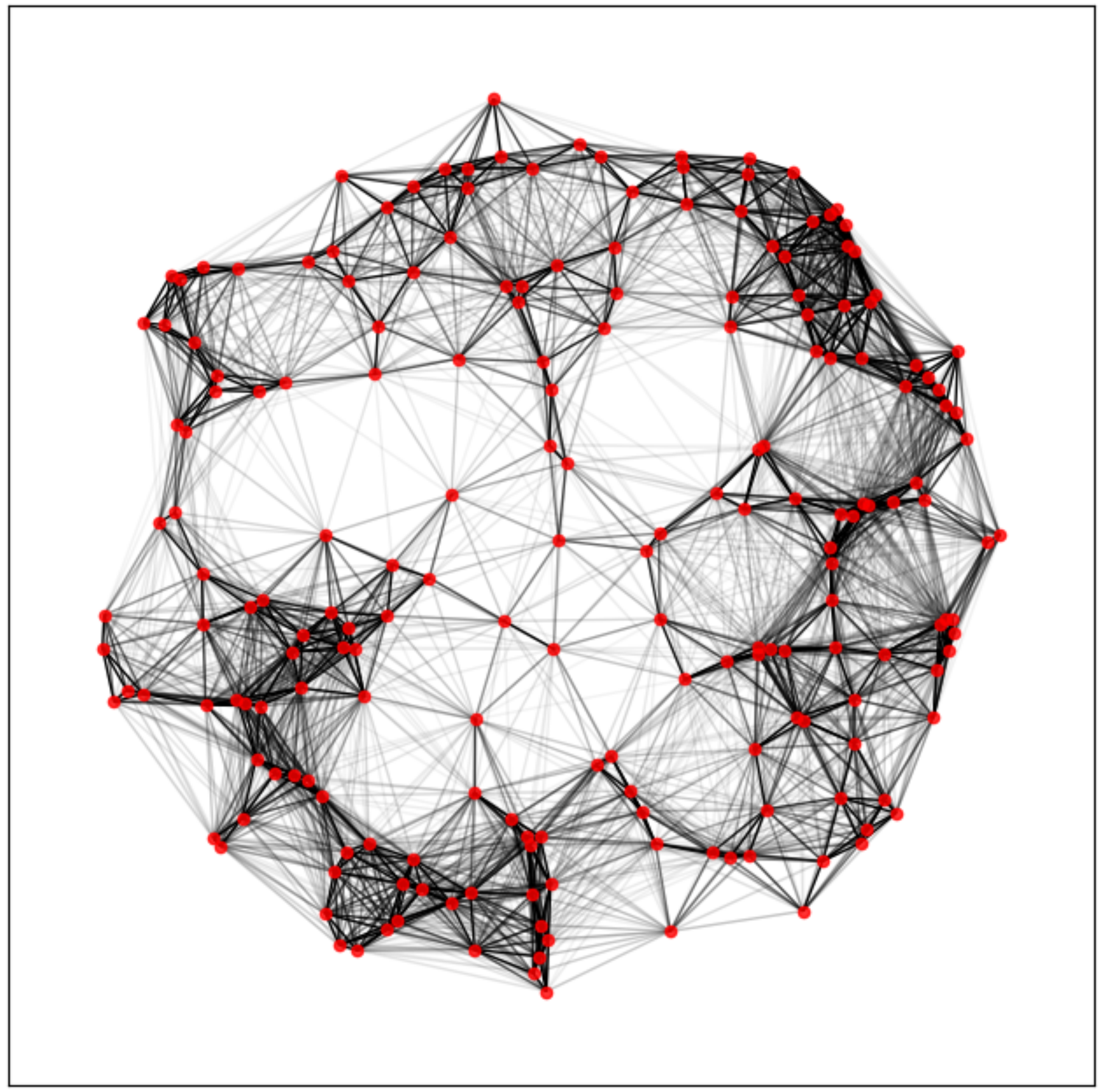
Solve the control problem for the **truncated network**



Localized Graph

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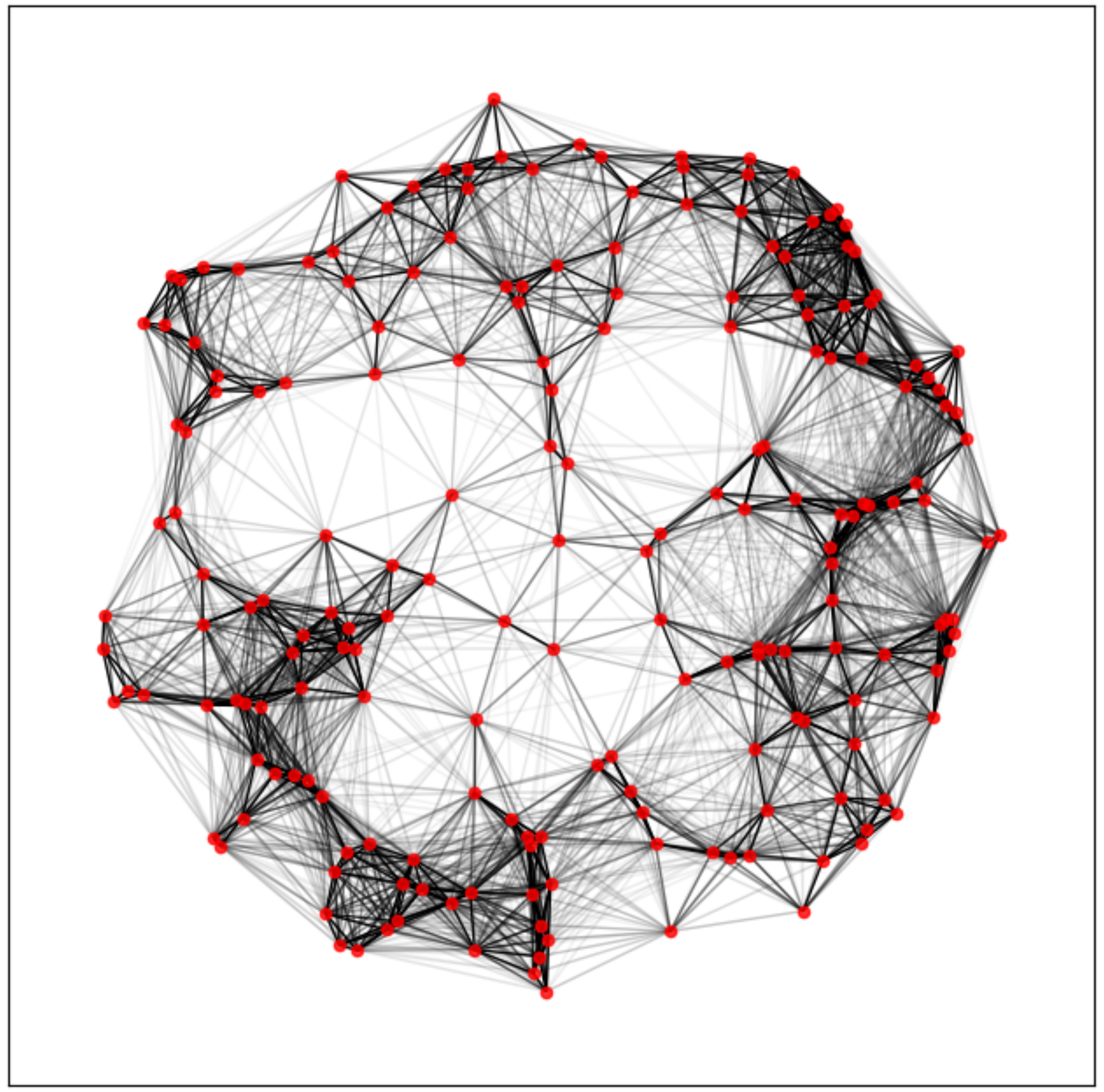

Localized Graph

Question:

Can we guarantee that the resulting policy uphold the **constraints**?

Localization for Scalability

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Lemma 1. If the nodes are uniformly distributed in the latent space with at most ρ nodes in unit space, and $a_{ij} = \alpha e^{-d_{ij}}, \quad \forall (i,j) \in \mathscr{E}$ then for any $i \in \mathscr{V}$ it follows that

$$\sum_{j \notin \mathscr{N}_\kappa^i} a_{ij} \leq \Gamma_l e^{-\lfloor \kappa \rfloor} \lfloor \kappa \rfloor^{(l+1)},$$

where $\mathscr{N}_\kappa^i$ denotes the κ-distance neighborhood of node i defined by $\mathscr{N}_\kappa^i := \{j \in \mathscr{V} \mid d_{ij} \leq \kappa\}$, and$\Gamma_l = \alpha\rho\eta(l+1)$ for some constant $0 < \eta$.

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Lemma 2. Let $\delta_\kappa^i = \sum_{j \notin \mathscr{N}_\kappa^i} a_{ij} x^j$ and $\forall (i,j) \in \mathscr{E}\kappa,\ u_{ij}^\kappa(t)$ satisfy

$$0 \leq \left(\gamma^i \bar{x} - \beta^i s^i \delta_d^i \right) - \beta^i s^i \sum_{j \in \mathscr{N}_\kappa^i} a_{ij} u_{ij}^\kappa x^j, \quad i \in \mathscr{V}$$

then $x^i(t) \leq \bar{x}$ for all $0 \leq t$. We can further simplify the constraint to be solely based on the information from $\mathscr{N}_\kappa^i$ by

$$0 \leq \gamma_\kappa^i \bar{x} - \beta^i s^i \sum_{j \in \mathscr{N}_\kappa^i} a_{ij} u_{ij}^\kappa x^j,$$

where $\gamma_\kappa^i = \gamma^i \left(1 - \frac{\beta^i s^i(0) \Gamma_l e^{-\lfloor \kappa \rfloor} \lfloor \kappa \rfloor^{l+1}}{\bar{x}}\right)$.

Localization for Scalability

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Localized Optimal Control Problem

$$\min_{u_{ij}^{\kappa}} \quad \int_0^T q^T x(t) + \sum_{i=1}^{n} \sum_{j \in \mathcal{N}_\kappa^i} r(1 - u_{ij}^{\kappa})^2 dt$$

s.t. Dynamics, $x^i(0) = x_0^i,\ s^i(0) = 1 - x_0^i$

$$u_{ij}^{\kappa} \in \mathcal{U} \quad \forall (i, j) \in \mathcal{E}_\kappa,$$

$$0 \leq \gamma_\kappa^i \bar{x} - \beta^i s^i \sum_{j \in \mathcal{N}_\kappa^i}^{n} a_{ij} u_{ij}^{\kappa} x^j \quad \forall i \in \mathcal{V},$$

$$\sum_{j=1}^{n} a_{ij} \leq \sum_{j \in \mathcal{N}_\kappa^i}^{n} a_{ij} u_{ij}^{\kappa} \quad \forall i \in \mathcal{V}.$$

Feasibility Criteria

$$e^{-\lfloor \kappa \rfloor} \lfloor \kappa \rfloor^{l+1} < \frac{\bar{x}}{\beta^i s_i^0 \Gamma_l}$$

Localization for Scalability

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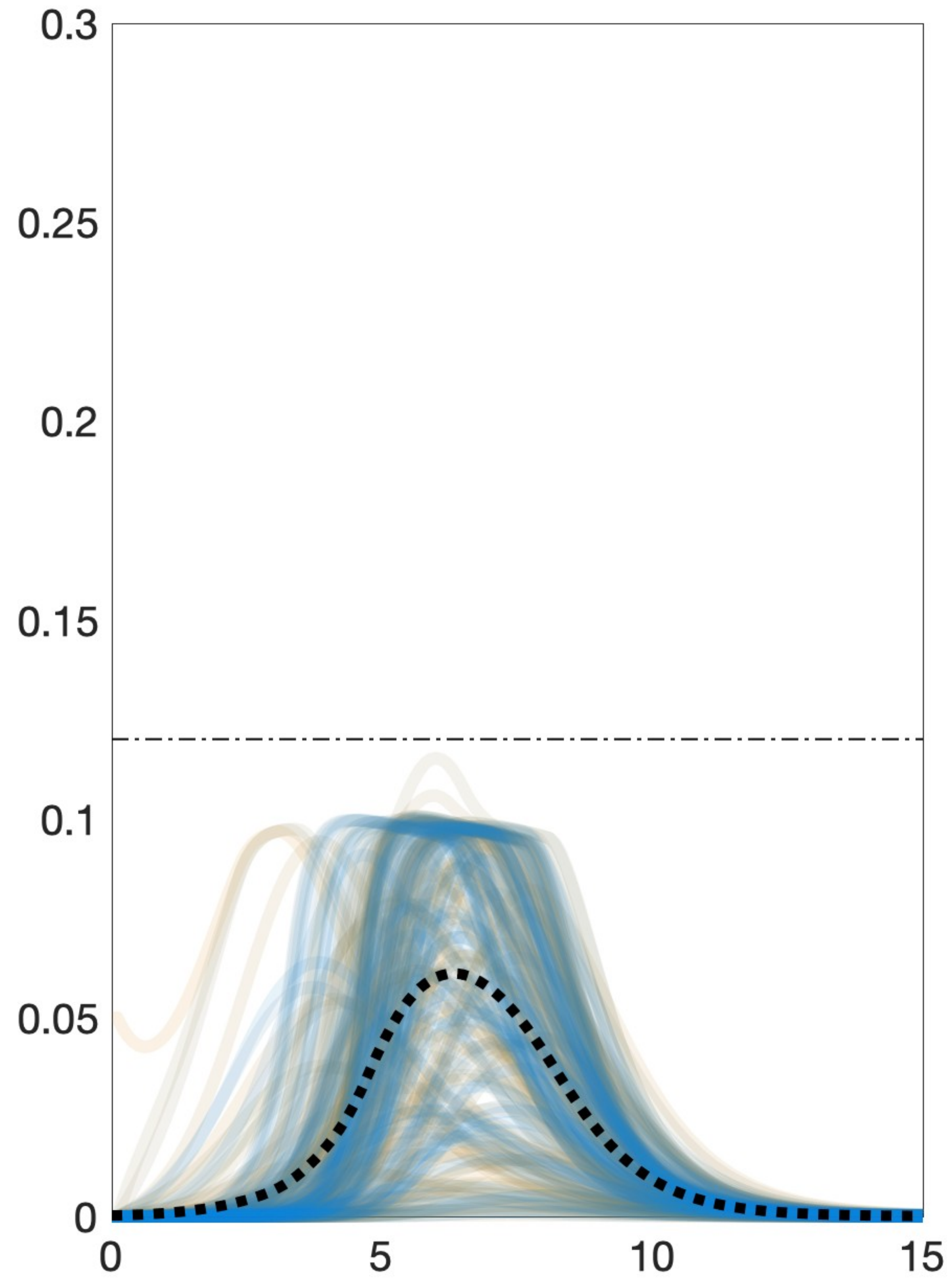
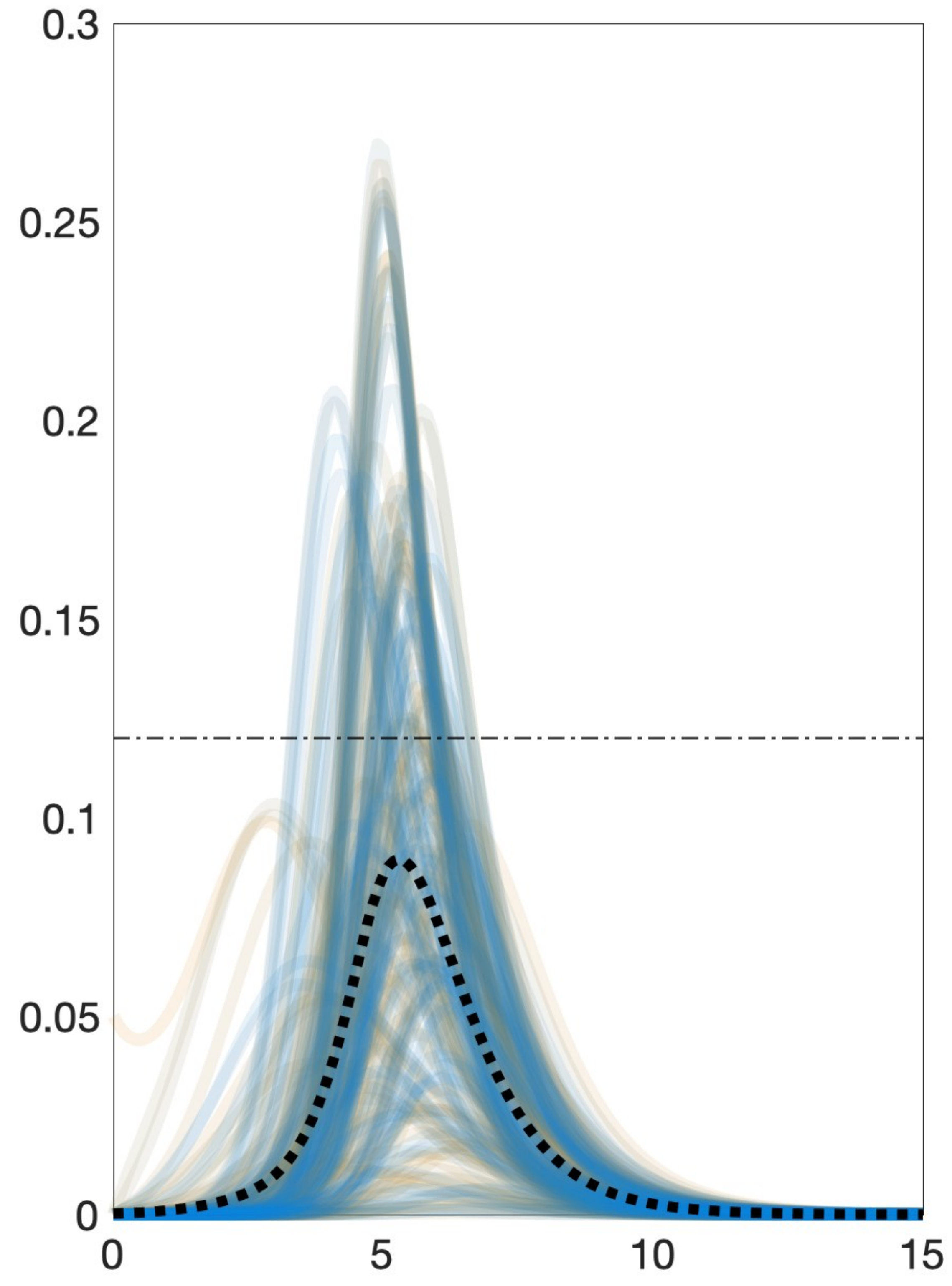
We applied the algorithm to the network extracted from 500 million tweets

- 200 Communities (~150,000 users)
- 4 dimensional manifold

κ	Convergence time	x^s_κ	m_κ
3.00	N/A	N/A	3,238
3.92	120.47 s	0.1194	4,280
4.6	149.08 s	0.1163	6,558,
5.30	185.08 s	0.1071	8,088
6.91	350.06 s	0.1027	11,990
∞	+1 hr	N/A	40,000



Localized Controller for $\kappa = 5$



No Control

Conclusion and Future Works

Conclusion and Future Works

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Conclusion

- We Introduce an edge-based controller to mitigate misinformation with safety and engagement guarantees.

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Future Directions

- Social network connections are uncertain

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Future Directions

- Social network connections are uncertain
- Misinformation disseminate randomly

Conclusion and Future Works

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