

A Game Theory Model of Scapegoating in Social Networks

Opinion Dynamics and Graph Centrality

Qinyang Yu (MSEC' 26)

Department of Economics & Computer Science
Duke University

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Motivation

- New interdiscipline: Graph Analysis + Game Theory \implies Network Economics
- Scapegoating: A community transfers the blames to an innocent person
- Significance:
 - Topic-wise: Social justice and humanitarianism
 - Method-wise: Network framework



Figure: Scapegoating



Figure: Witch Hunts

Literature Review and Research Gap

Why using networks?

- Political Science: 1. Strategies for political and social control
- Social Psychology:
 - 2. Groupthink, peer influence, and imitation behavior
 - 3. Targeting marginalized individuals or minority groups
- Economics:
 - Models with 1 and 3
 - No models with 2 \implies Opinion Dynamics and Social Learning!

Opinion Dynamics

- Firstly introduced by DeGroot (1974)
- Naive updating, not Bayesian updating

$$E.g., T = \begin{pmatrix} 0 & \frac{1}{2} & \frac{1}{2} \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}, \lim_{t \rightarrow \infty} T^t p(0) = \left(\lim_{t \rightarrow \infty} T^t \right) p(0) = \begin{pmatrix} \frac{2}{5} & \frac{2}{5} & \frac{1}{5} \\ \frac{2}{5} & \frac{2}{5} & \frac{1}{5} \\ \frac{2}{5} & \frac{2}{5} & \frac{1}{5} \end{pmatrix} p(0)$$

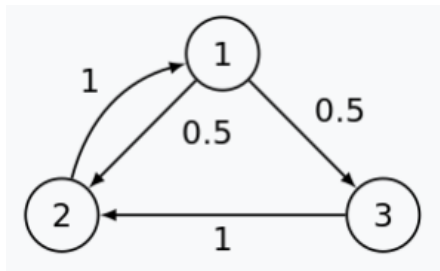


Figure: DeGroot Learning

Opinion Dynamics

A game-theoretic version of Opinion Dynamics:

- Proposed by Bindel et al. (2015) and Ghaderi and Srikant (2014)
- Given internal belief b_i , agent i chooses a public opinion $x_i \in [0, 1]$

$$u_i(x_i, x_{-i}) = \underbrace{-(x_i - b_i)^2}_{\text{Penalty 1: Disagreement with true self}} - \underbrace{\sum_{j=1}^n A_{ij}(x_i - x_j)^2}_{\text{Penalty 2: Disagreement with others' opinions}}$$

The Networked Game Model

- A community: one leader; n agents forming a social network $G(V, E)$
- A problem or a crisis hit!
- Two possible states: 0-innocent, 1-guilty
- Agents are innocent in nature
- Agent i holds a prior belief that agent k is guilty with probability $\pi_i^{(k)}$
- Agents believe the leader may also prosecute an innocent agent with probability $p \in [0, 1] \implies$ social trust in leader

The Networked Game Model

Strategies:

- Phase 1: Scapegoat Selection
 - The leader will either self-blame (game ends)
 - or choose $k \in V$ to scapegoat (game proceeds)
- Phase 2: Opinion Dynamics
 - Agent i updates belief about agent k 's guilt using Bayes' rule to form internal belief
$$b_i^{(k)} = \frac{\pi_i^{(k)}}{\pi_i^{(k)} + p(1 - \pi_i^{(k)})}$$
 - Agent i forms a public opinion $x_i^{(k)} \in [0, 1]$ about agent k 's guilt through the network

Utilities:

- For agents: $u_i^{(k)}(x_i^{(k)}, x_{-i}^{(k)}) = -(x_i^{(k)} - b_i^{(k)})^2 - \sum_{j=1}^n A_{ij}(x_i^{(k)} - x_j^{(k)})^2$
- For the leader
 - Self-blame: fixed cost C
 - Scapegoat k : reputational cost $R^{(k)} = \sum_{i=1}^n (1 - x_i^{*(k)})$

Nash Equilibrium

Phase 2:

$$FOC : \frac{\partial u_i^{(k)}}{\partial x_i^{(k)}} = 0, \forall i \in V$$

$$(x_i^{(k)} - b_i^{(k)}) + \sum_{j=1}^n A_{ij}(x_i^{(k)} - x_j^{(k)}) = 0, \forall i \in V$$

$$(1 + \sum_{j=1}^n A_{ij})x_i^{(k)} - \sum_{j=1}^n A_{ij}x_j^{(k)} = b_i^{(k)}, \forall i \in V$$

$$(I + D)x^{(k)} - Ax^{(k)} = b^{(k)}$$

$$(I + L)x^{(k)} = b^{(k)}$$

$$x^{*(k)} = (I + L)^{-1}b^{(k)}$$

Nash Equilibrium

Lemma 1 (Conversation Principle)

Using $x^{*(k)} = (I + L)^{-1}b^{(k)}$, it follows that $\sum_{i=1}^n x_i^{*(k)} = \sum_{i=1}^n b_i^{(k)}$ for all $k \in V$.

- L : row stochastic
- Opinion Dynamics redistributes and adjusts individual opinions
- But the overall “mass” of opinions remains unchanged!
- Intuitions?

Phase 1:

- Scapegoat \iff reputational cost \leq fixed cost $\iff R^{(k)} \leq C \iff \sum_{i=1}^n (1 - x_i^{*(k)}) \leq C \iff \sum_{i=1}^n (1 - b_i^{(k)}) \leq C \iff \sum_{i=1}^n (1 - \frac{\pi_i^{(k)}}{\pi_i^{(k)} + p(1 - \pi_i^{(k)})}) \leq C$
- Choose to scapegoat k with smallest $R^{(k)}$

Discrete Network Effects

Assume

$$\pi_i^{(k)} = \begin{cases} 0 & \text{if } i \in N(k), \\ \frac{1}{2} & \text{if } i \notin N(k). \end{cases}$$

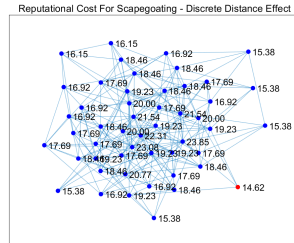
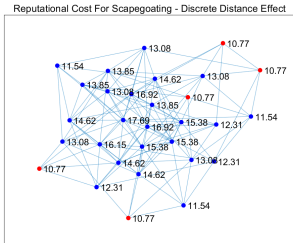
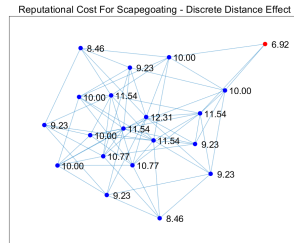
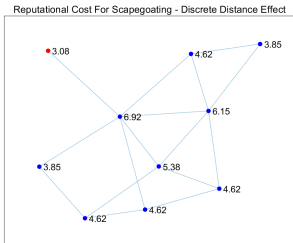
Then,

$$b_i^{(k)} = \begin{cases} 0 & \text{if } i \in N(k), \\ \frac{1}{1+p} & \text{if } i \notin N(k). \end{cases}$$

$$\begin{aligned} R^{(k)} &= \sum_{i \notin N(k)} \left(1 - \frac{1}{1+p}\right) + \sum_{i \in N(k)} (1 - 0) \\ &= \left(1 - \frac{1}{1+p}\right) + \frac{\text{deg}(k)}{n(1+p)} \end{aligned}$$

\implies The leader scapegoats the agent with the lowest **degree centrality**!

- $n = 10, 20, 30, 50$
- $p = 0.3$
- Red nodes: selected scapegoats



Discrete Network Effects

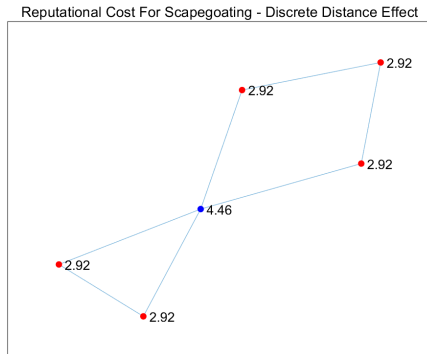


Figure: A poor scapegoat prediction with $n = 6$, $p = 0.3$, and discrete priors (red nodes as selected scapegoats)

Decay Network Effects

Let l_{ik} denote the geodesic/shortest path length between i and k . Assume

$$\pi_i^{(k)} = \frac{1}{2} - \left(\frac{1}{2}\right)^{l_{ik}} = \begin{cases} 0 & \text{if } l_{ik} = 1, \\ \frac{1}{2} & \text{if } l_{ik} \rightarrow \infty. \end{cases}$$

Algorithm 1 Scapegoat Selection Algorithm with Decay Distance Effect

Require: Graph $G(V, E)$, parameter p

Ensure: Selected nodes with the lowest D_k

```
1: for each node  $k \in V$  do
2:   Initialize vector  $\pi_k \in \mathbb{R}^{|V|}$ 
3:   for each node  $i \in V, i \neq k$  do
4:     Calculate the shortest path length  $l_{ki}$  between  $k$  and  $i$  using Breadth-First Search (BFS) for unweighted  $G$  and Dijkstra's or Bellman-Ford Algorithm for weighted  $G$ 
5:      $\pi_i^{(k)} \leftarrow 0.5 - 0.5^{l_{ki}}$ 
6:   end for
7:    $\pi_k^{(k)} \leftarrow 0$ 
8:   Generate vector  $b_k$  by  $b_i^{(k)} = \frac{\pi_i^{(k)}}{\pi_i^{(k)} + p \cdot (1 - \pi_i^{(k)})}$  where  $\forall i \in V$ .
9:   Calculate  $D_k = \sum_{i \in V} (1 - b_i^{(k)})$ 
10: end for
11: Select the nodes with the lowest  $D_k$  values
12: Output the selected nodes
```

\implies The leader scapegoats the agent with the lowest D_k !

Decay Network Effects

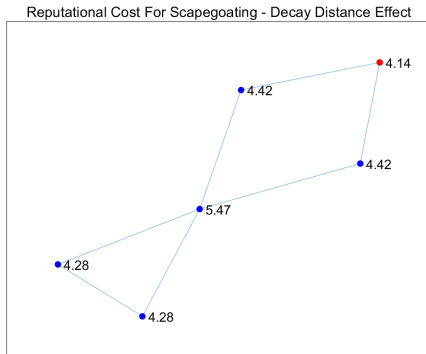
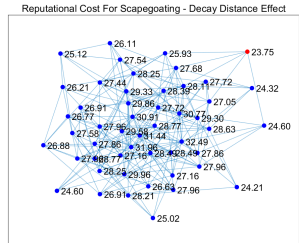
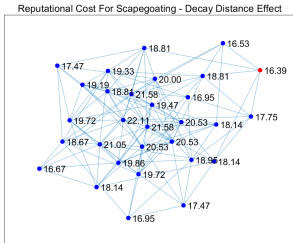
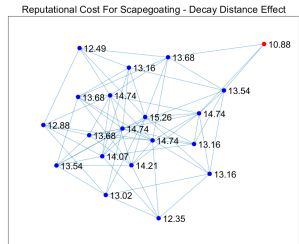
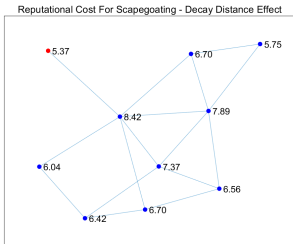


Figure: An improved scapegoat selection with $n = 6$, $p = 0.3$, and decay priors (red nodes as selected scapegoats)

Decay Network Effects

Numerical Simulations:

- $n = 10, 20, 30, 50$
- $p = 0.3$
- Red nodes: selected scapegoats



Decay Network Effects

About the metric D_k :

- A component-wise convex transformation of **decay centrality** $C_k = \sum_{i=1}^n \alpha^{l_{ik}}$ with $\alpha = \frac{1}{2} \in (0, 1)$
- Specifically, when $p = 1$, $D_k \sim C_k$.
- Advantage: **global structure** instead of local connectivity
- Disadvantage:
 - Harder to interpret
 - Computationally inefficient
 - Unweighted graph: $O(nm + n^2)$; Weighted graph: $O(nm + n^2 \log(n))$

Extensions

Main Conclusion:

Marginalized individuals \implies lower centrality \implies lower information exposure in networks
 \implies more likely to become scapegoats

Centrality Measures:

- Degree: local connectivity
- Decay, Closeness: global connectivity, ease of reaching other nodes
- **Betweenness**: importance as an intermediary connector
- **Eigenvector, Bonacich**: influence, prestige, power

The End

“The best way to bring folks together is to give them a real good enemy.”

— The Wonderful Wizard of Oz, in *Wicked*



Reference

- Bindel, D., Kleinberg, J., and Oren, S. (2015). How bad is forming your own opinion? *Games and Economic Behavior*, 92:248–265.
- DeGroot, M. H. (1974). Reaching a consensus. *Journal of the American Statistical association*, 69(345):118–121.
- Ghaderi, J. and Srikant, R. (2014). Opinion dynamics in social networks with stubborn agents: Equilibrium and convergence rate. *Automatica*, 50(12):3209–3215.