

# Finding Optimal Strategies for Influencing Social Networks in Two Player Games

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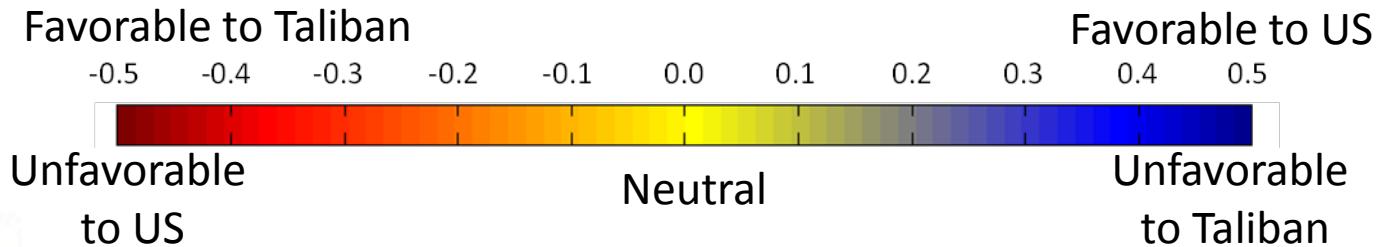


# Problem Statement

- Given constrained resources for influencing a Social Network, how best should one spend it in an adversarial system?

# Agents

- Each node in the network is an agent
- 4 classes of agents: Regular, Forceful, Very Forceful, Stubborn (immutable)
- Scalar belief for each agent:  $x_i(t) \in [-0.5, 0.5]$



# Network and Interactions

- Arcs represent communication
- Stochastic interactions occur with one of three types:

- Forceful w.p.  $\alpha_{ij}$

$$\begin{aligned} X_i(t+1) &= X_i(t) \\ X_j(t+1) &= \varepsilon_{ij} \cdot X_j(t) + (1 - \varepsilon_{ij}) \cdot X_i(t) \quad 0 \leq \varepsilon_{ij} \leq 0.5 \end{aligned}$$

- Averaging w.p.  $\beta_{ij}$

$$X_i(t+1) = X_j(t+1) = \frac{X_i(t) + X_j(t)}{2}$$

- No Change w.p.  $\gamma_{ij}$

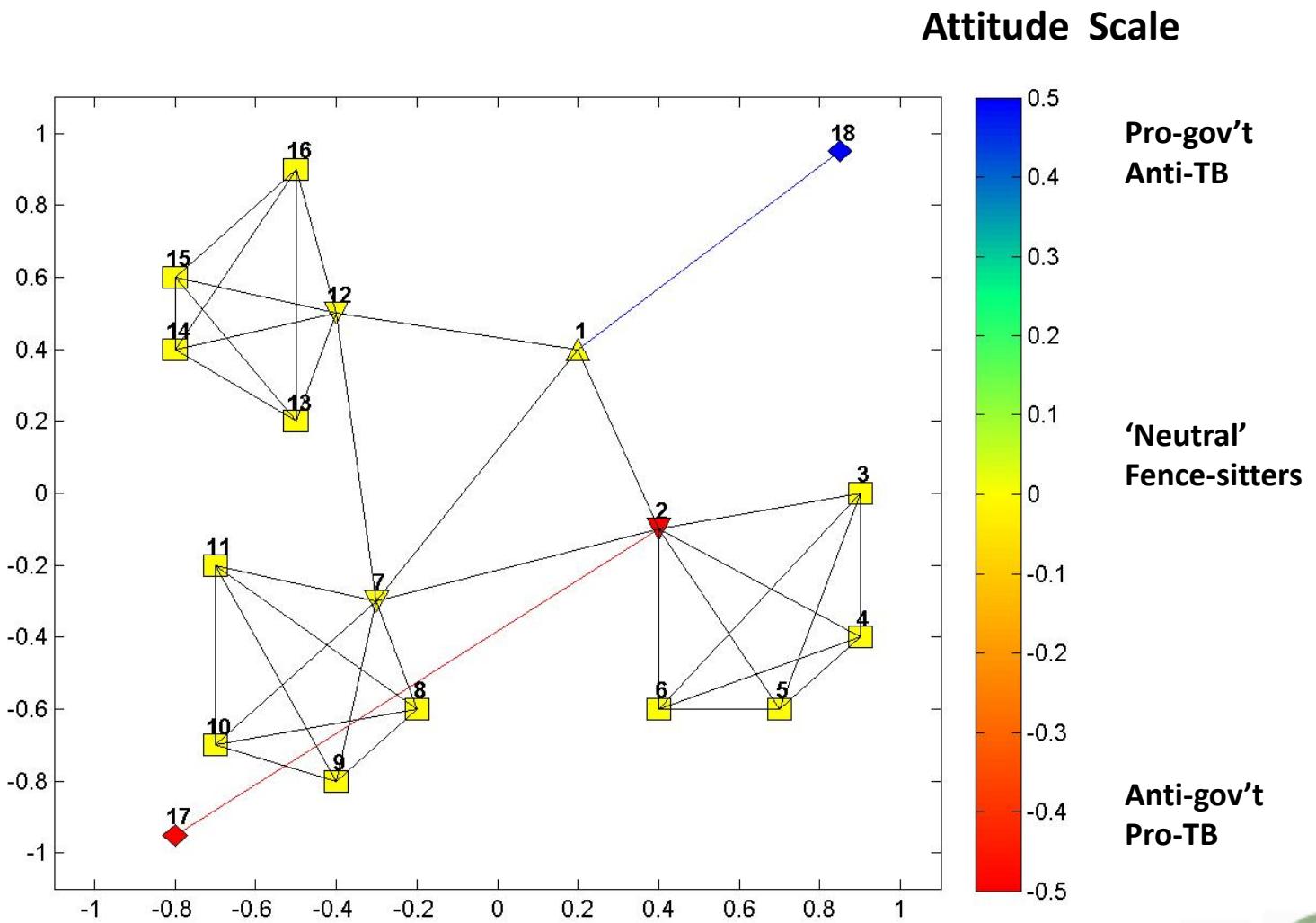
$$\begin{aligned} X_i(t+1) &= X_i(t) \\ X_j(t+1) &= X_j(t) \end{aligned}$$



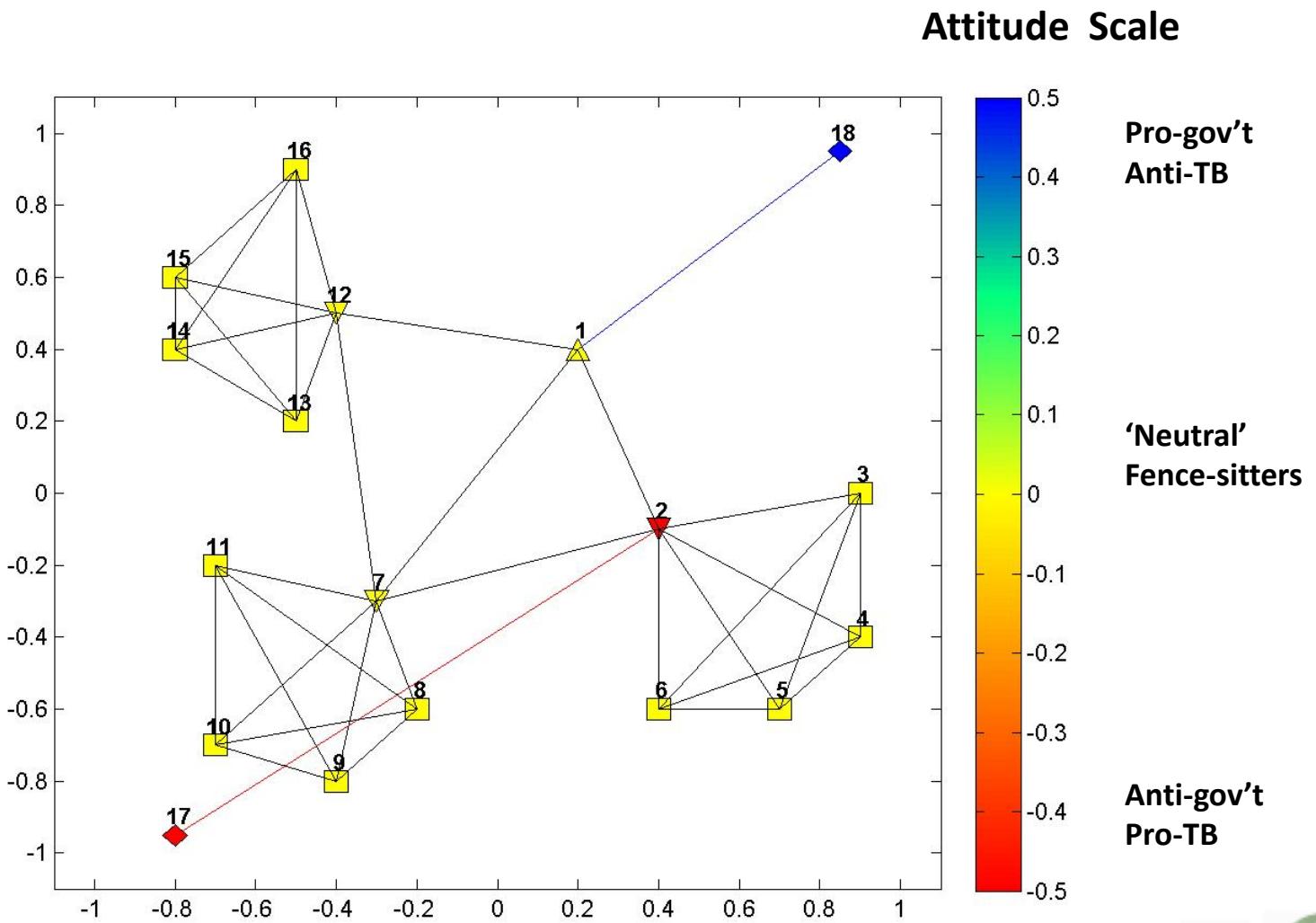
# Data Parameterization

- We choose a set of influence parameters that generally make influence flow ‘down’
- However we found through simulation that the solution to our game is highly robust to changes to these parameters.

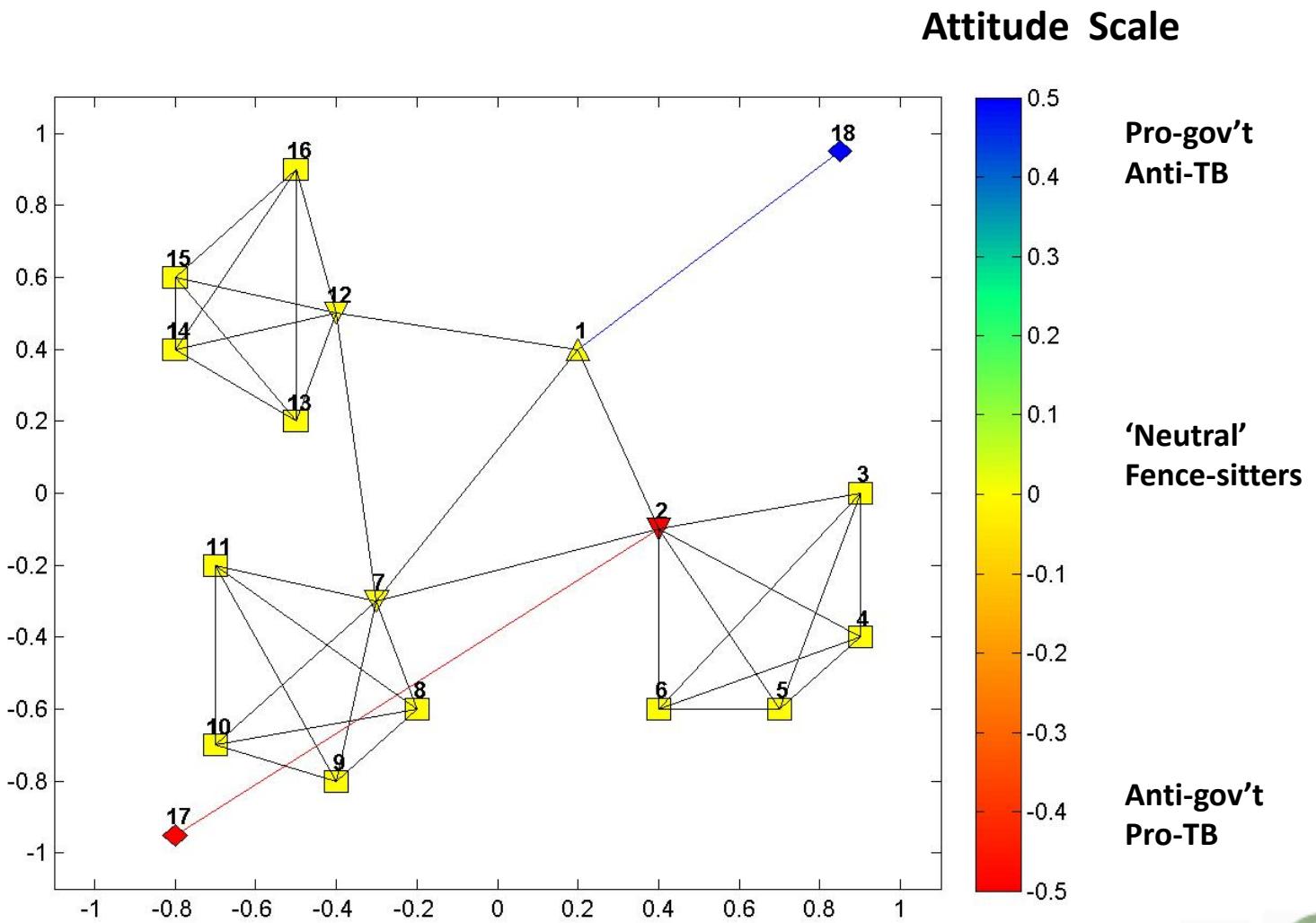
# Interaction Simulation



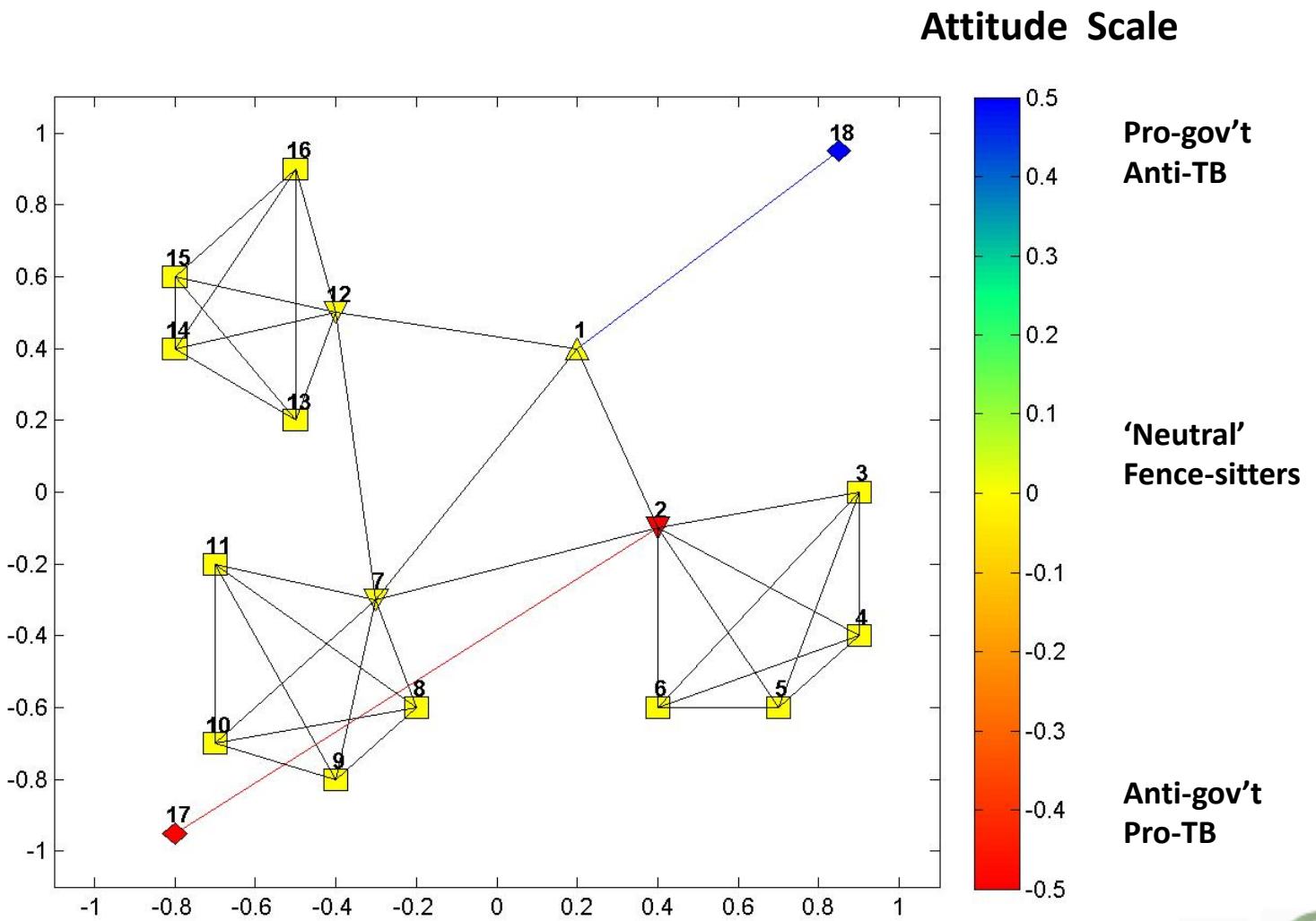
# Interaction Simulation



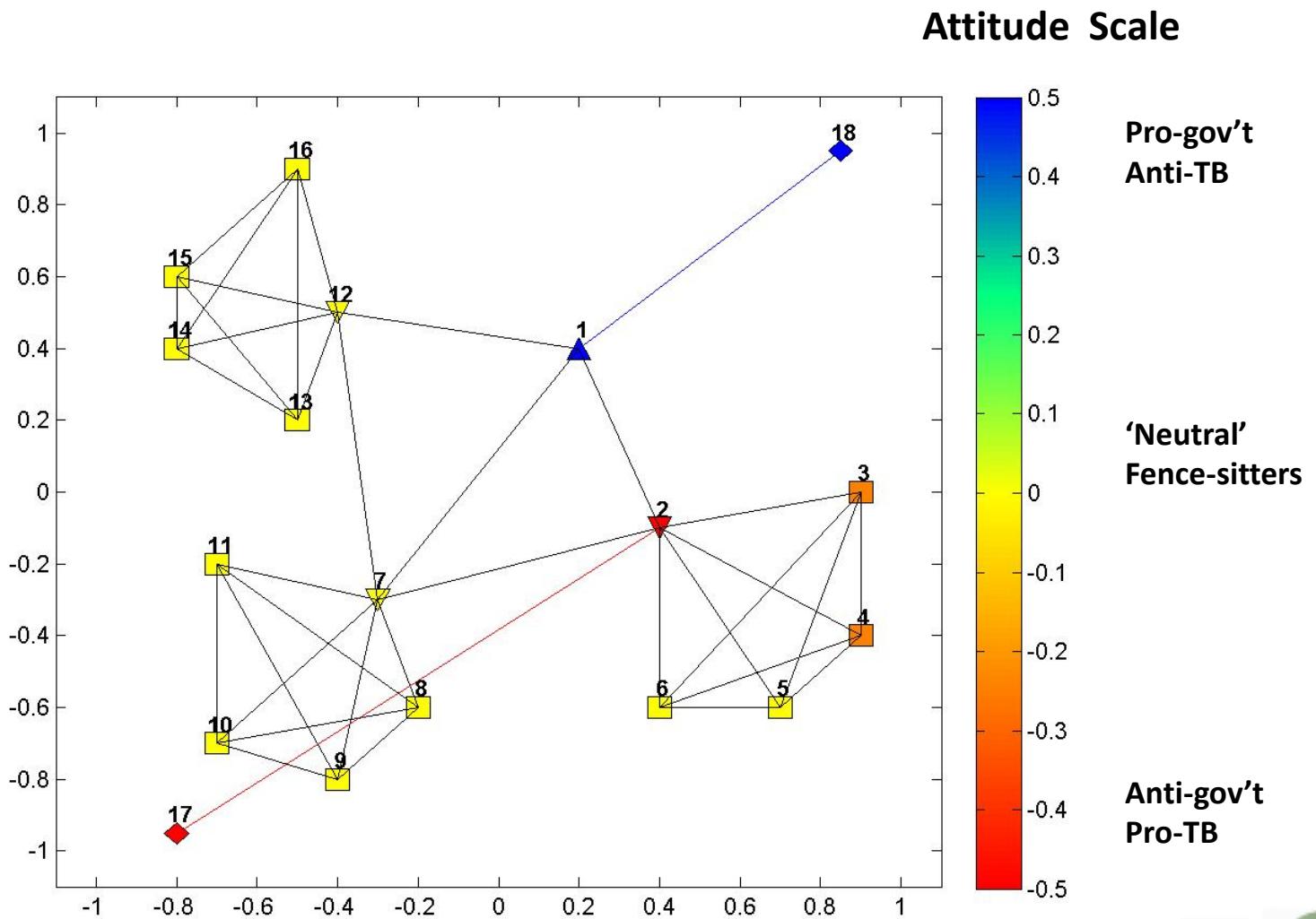
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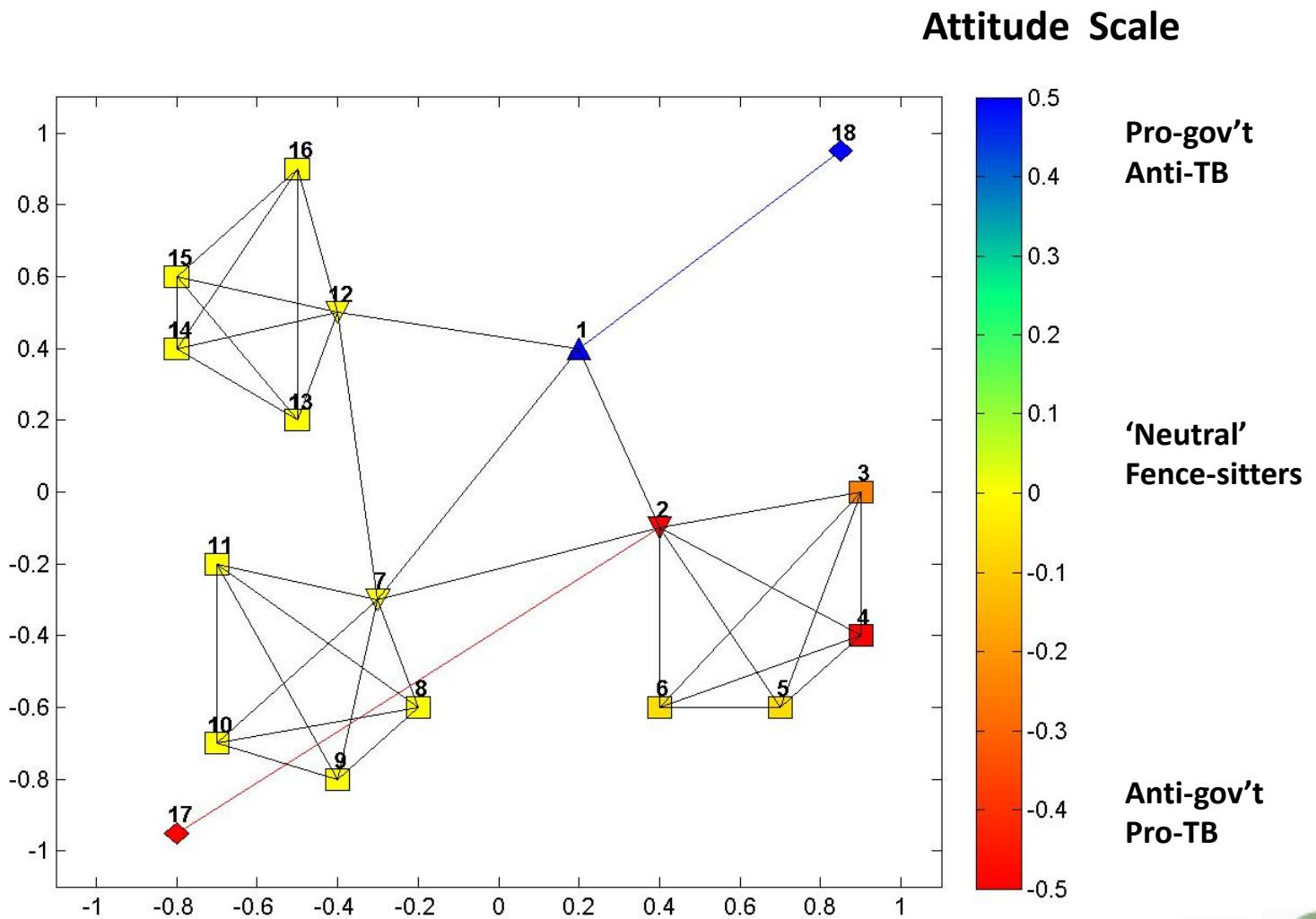
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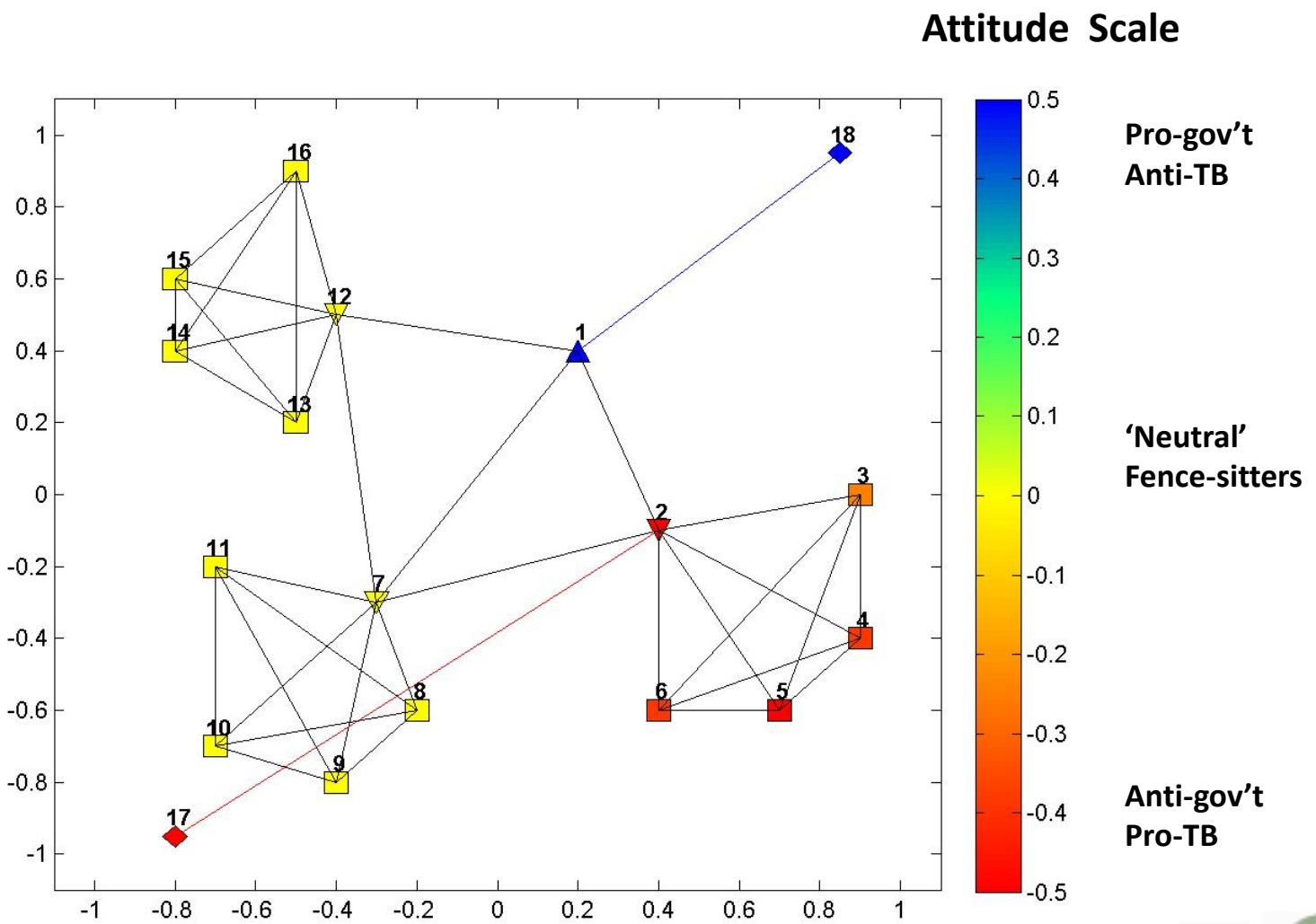
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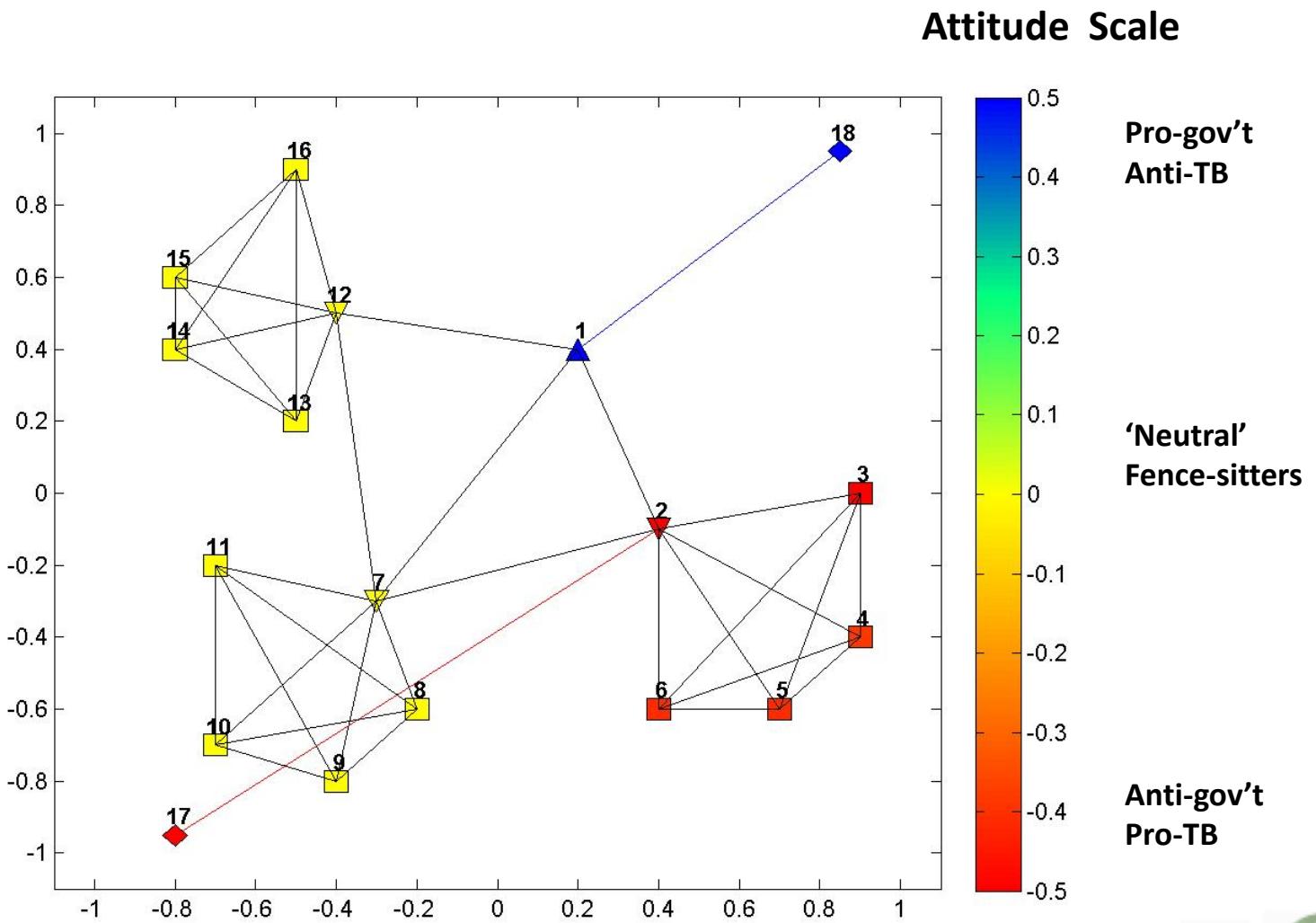
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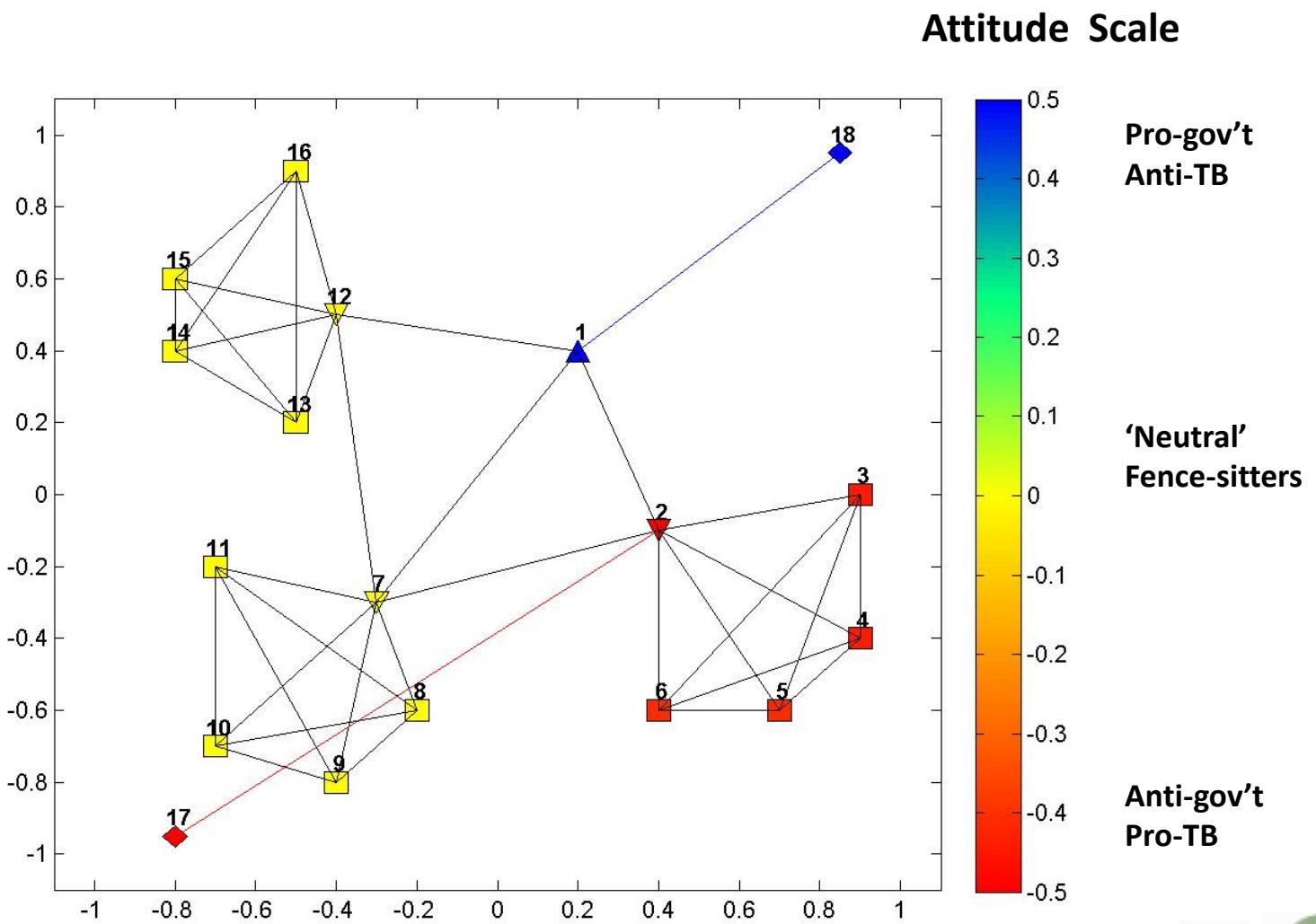
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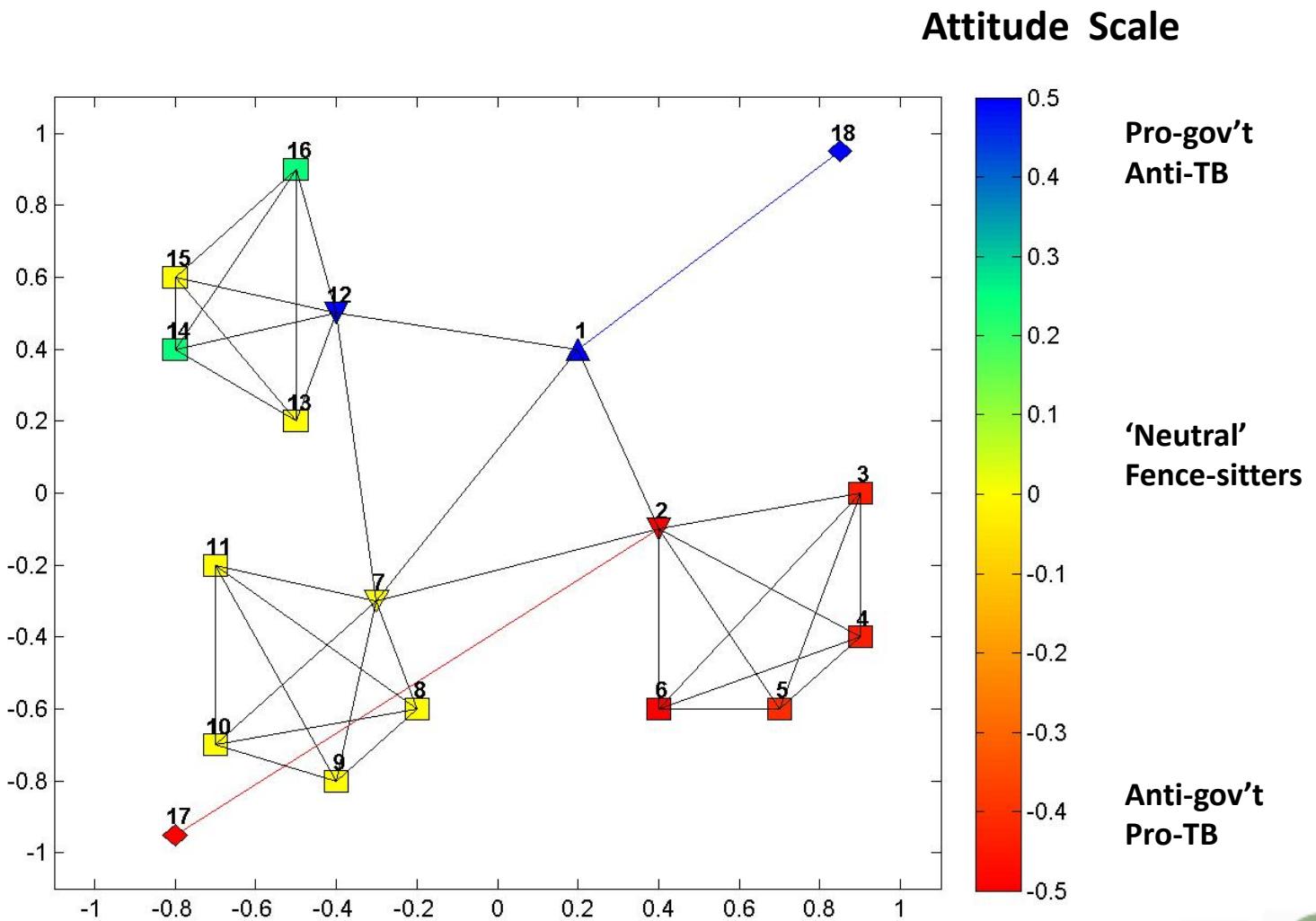
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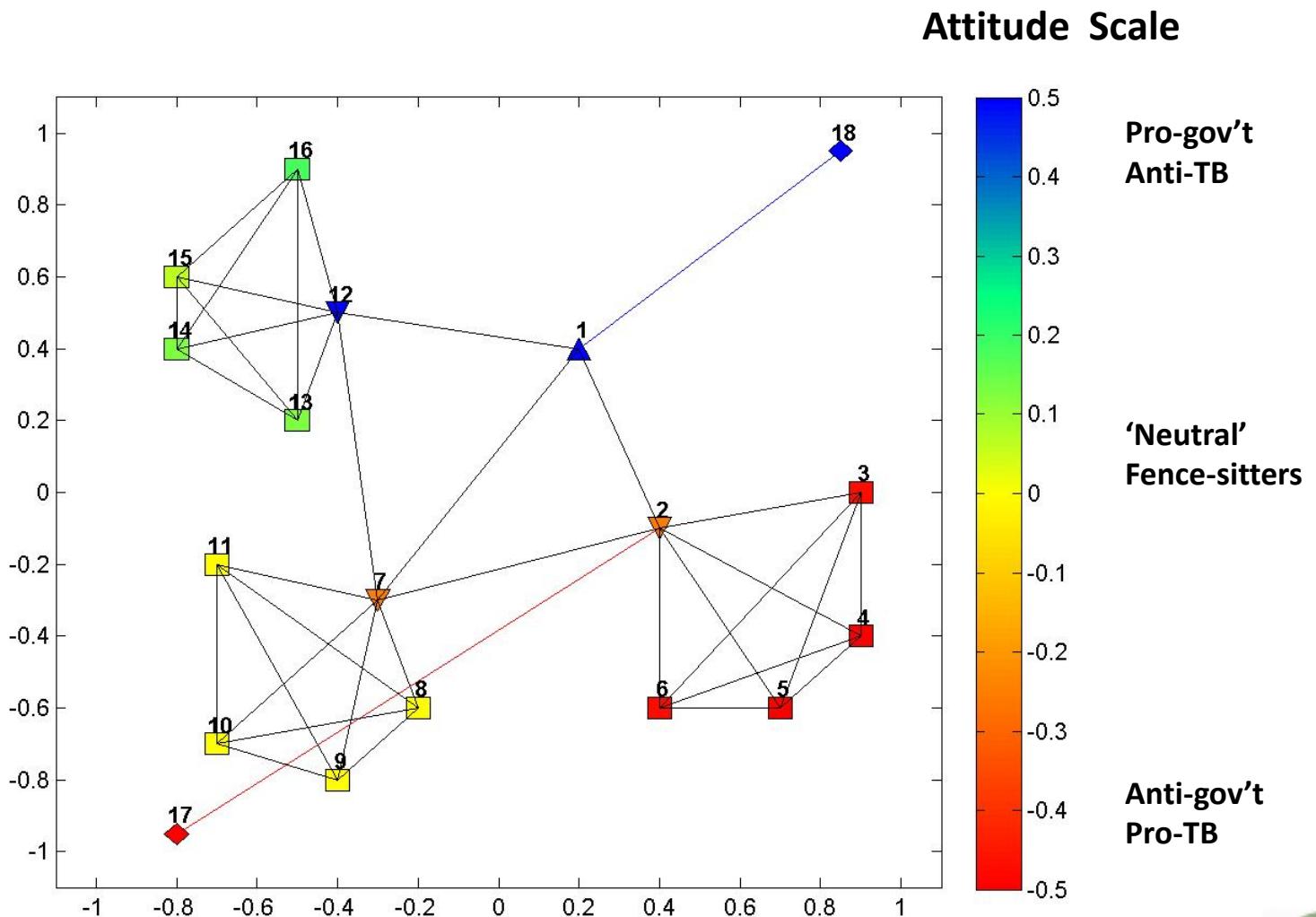
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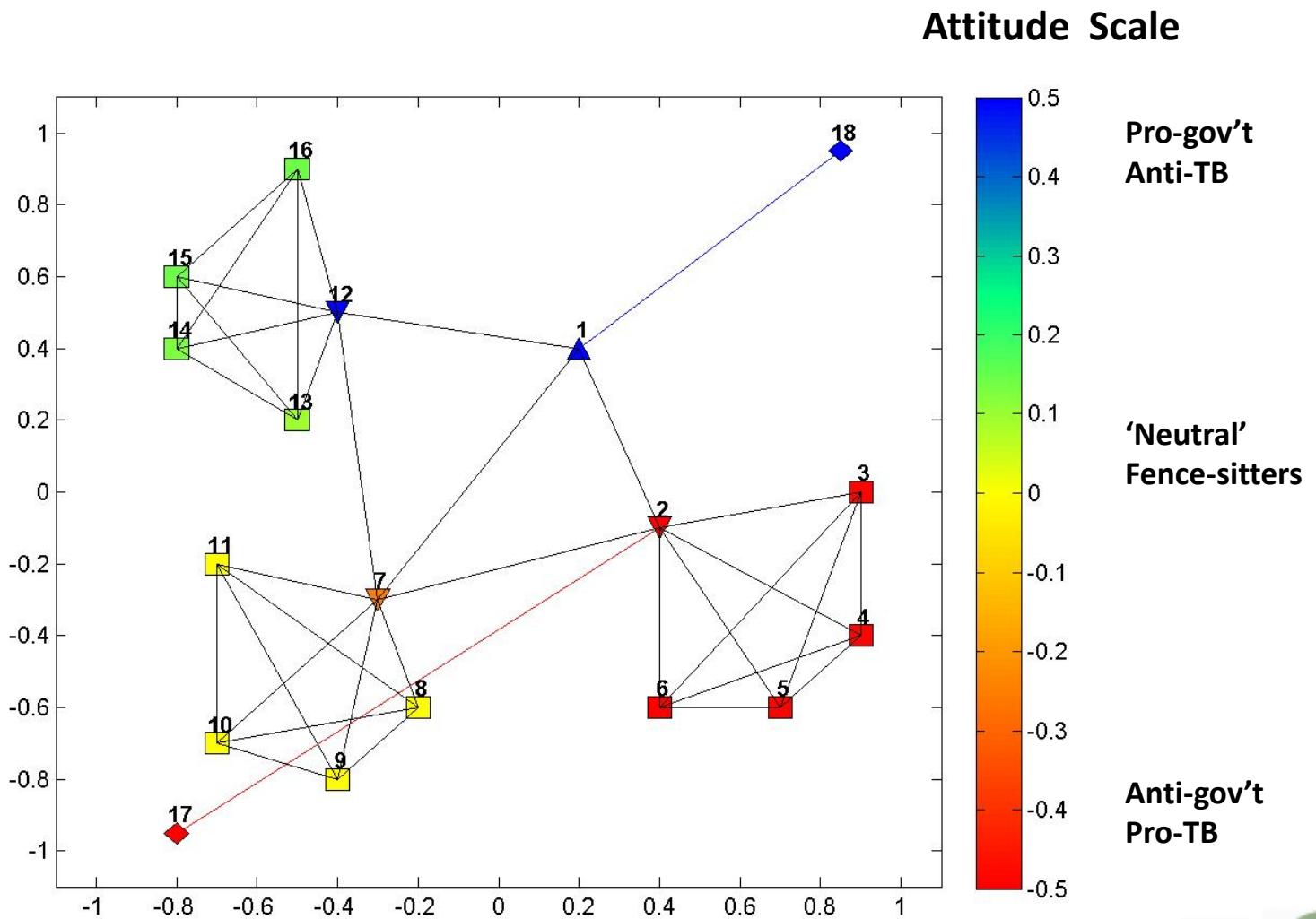
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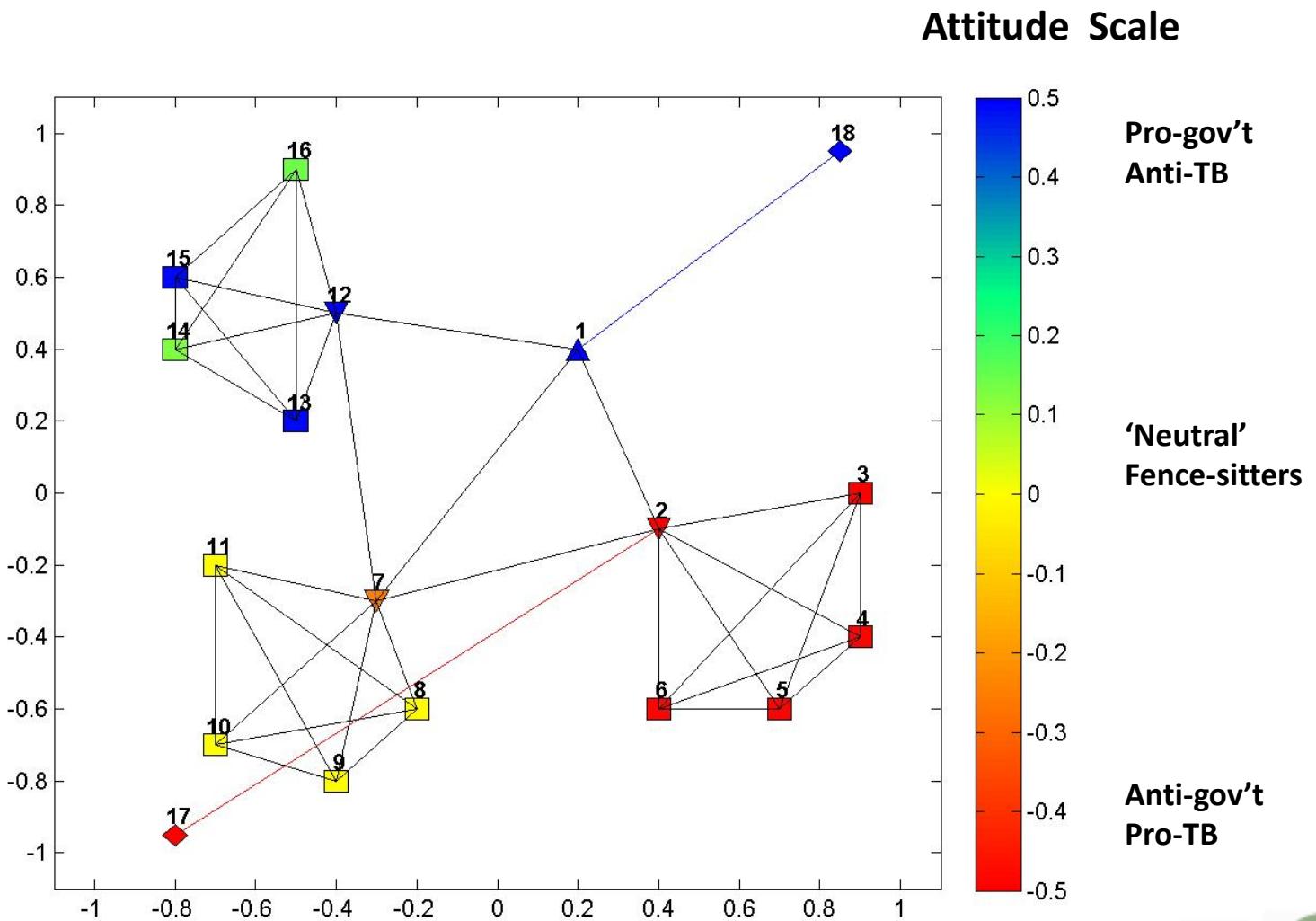
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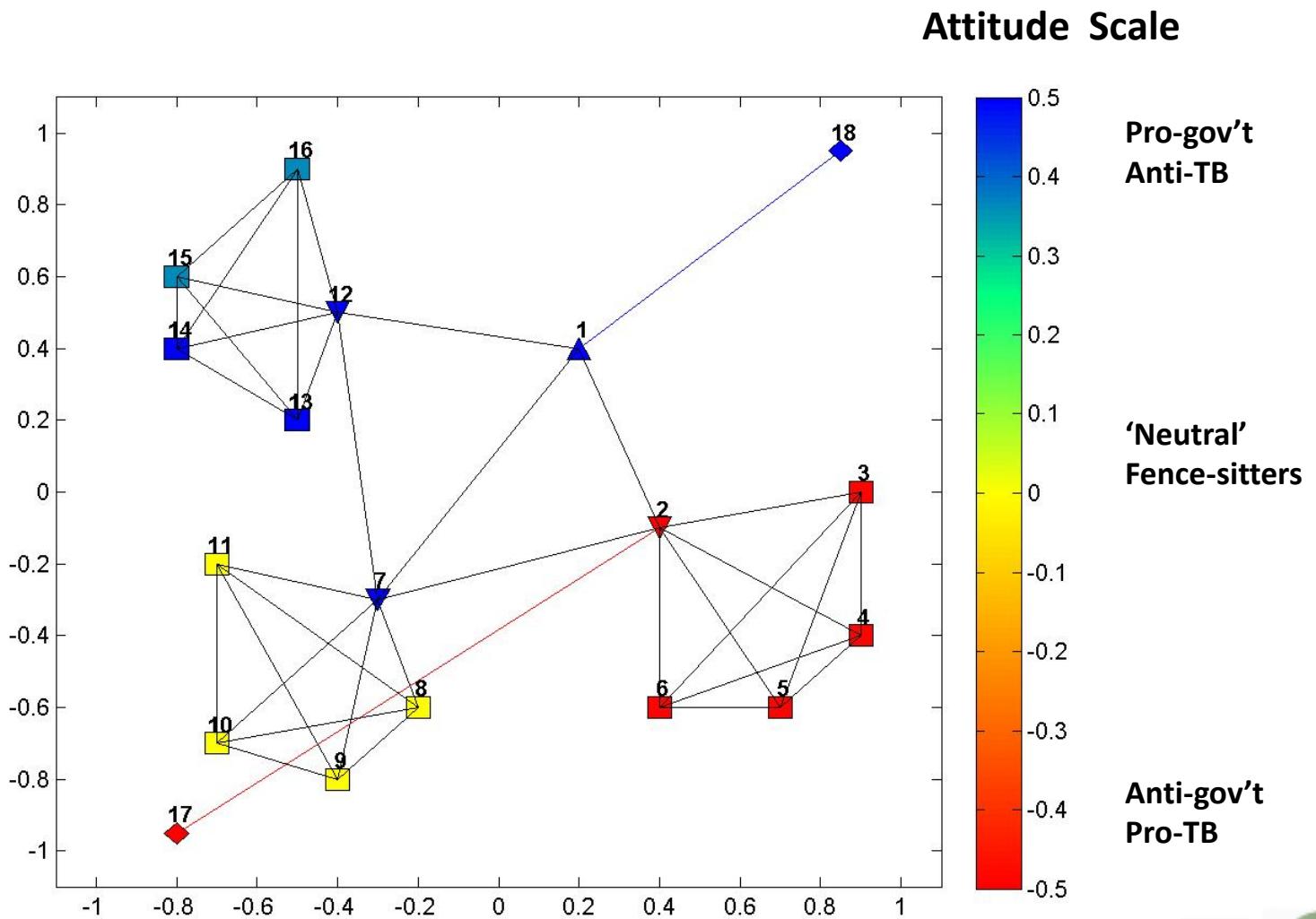
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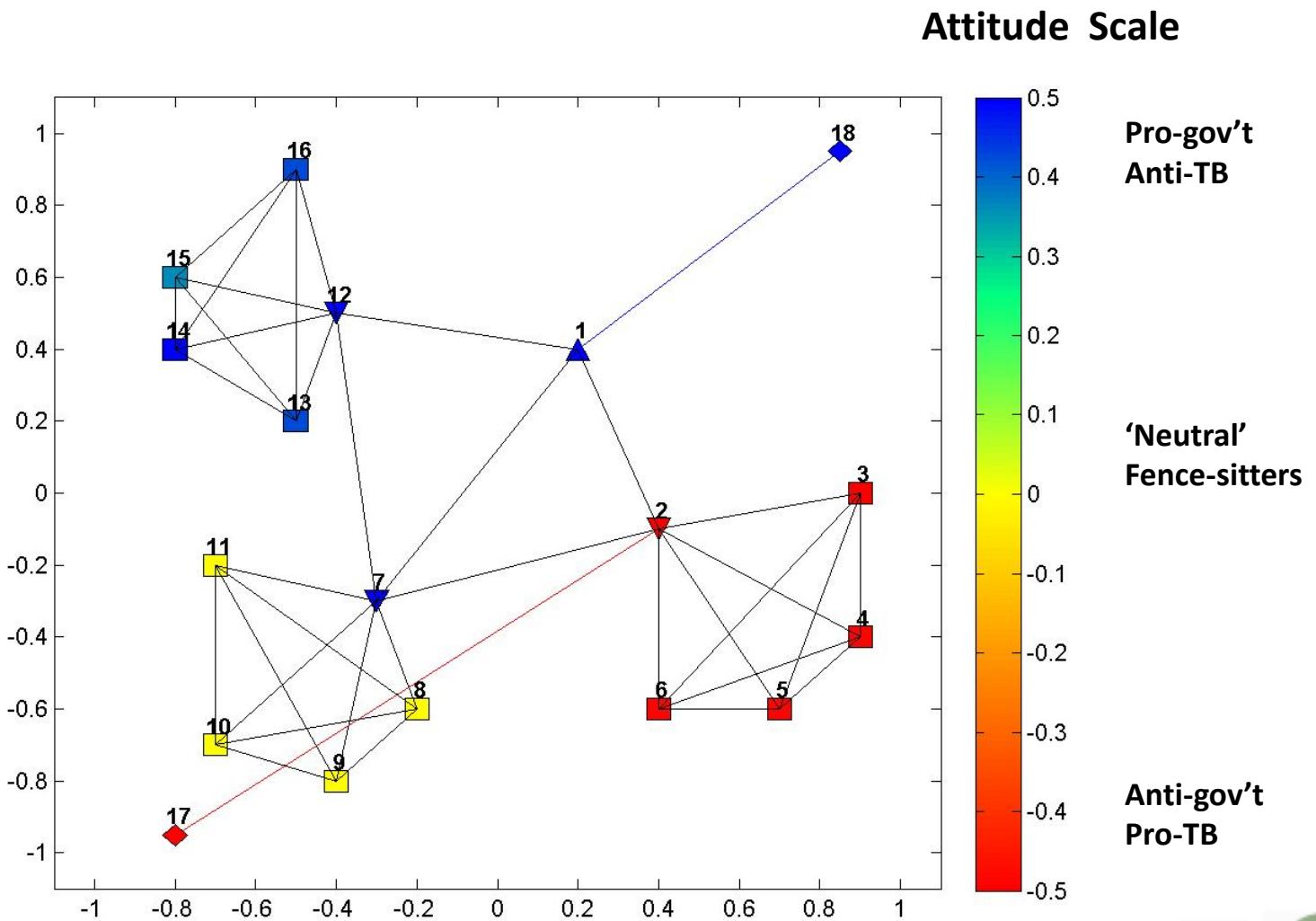
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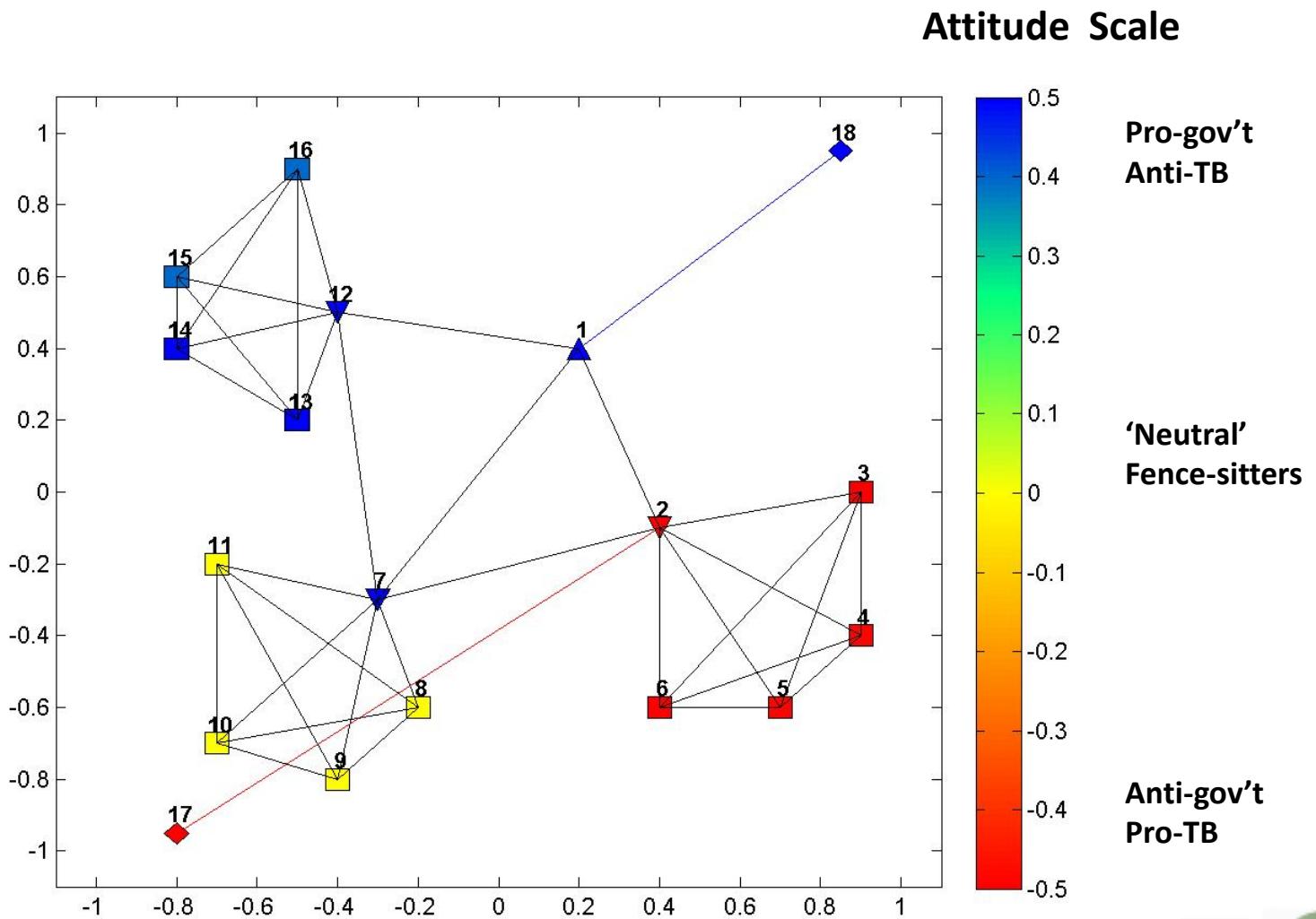
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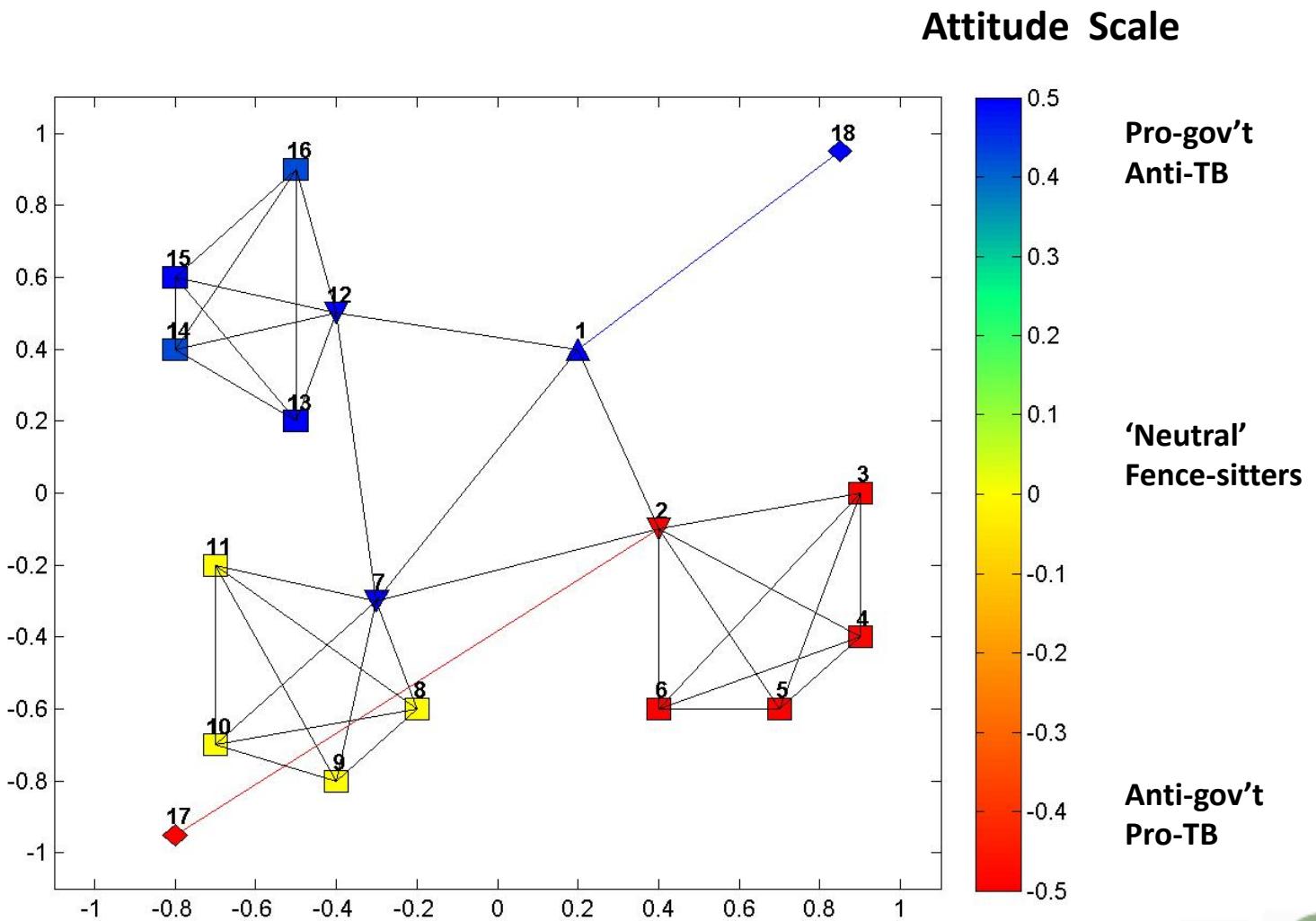
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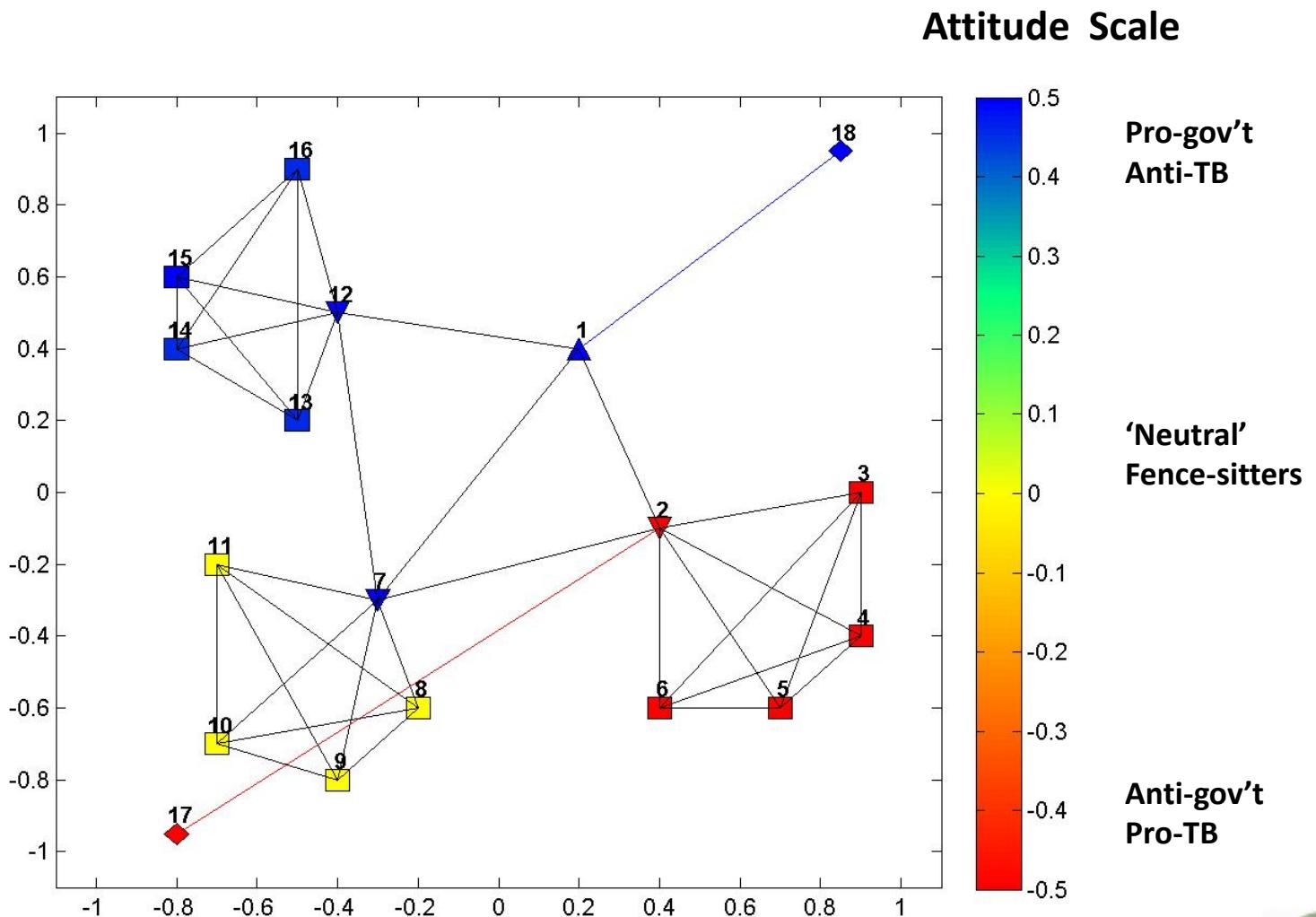
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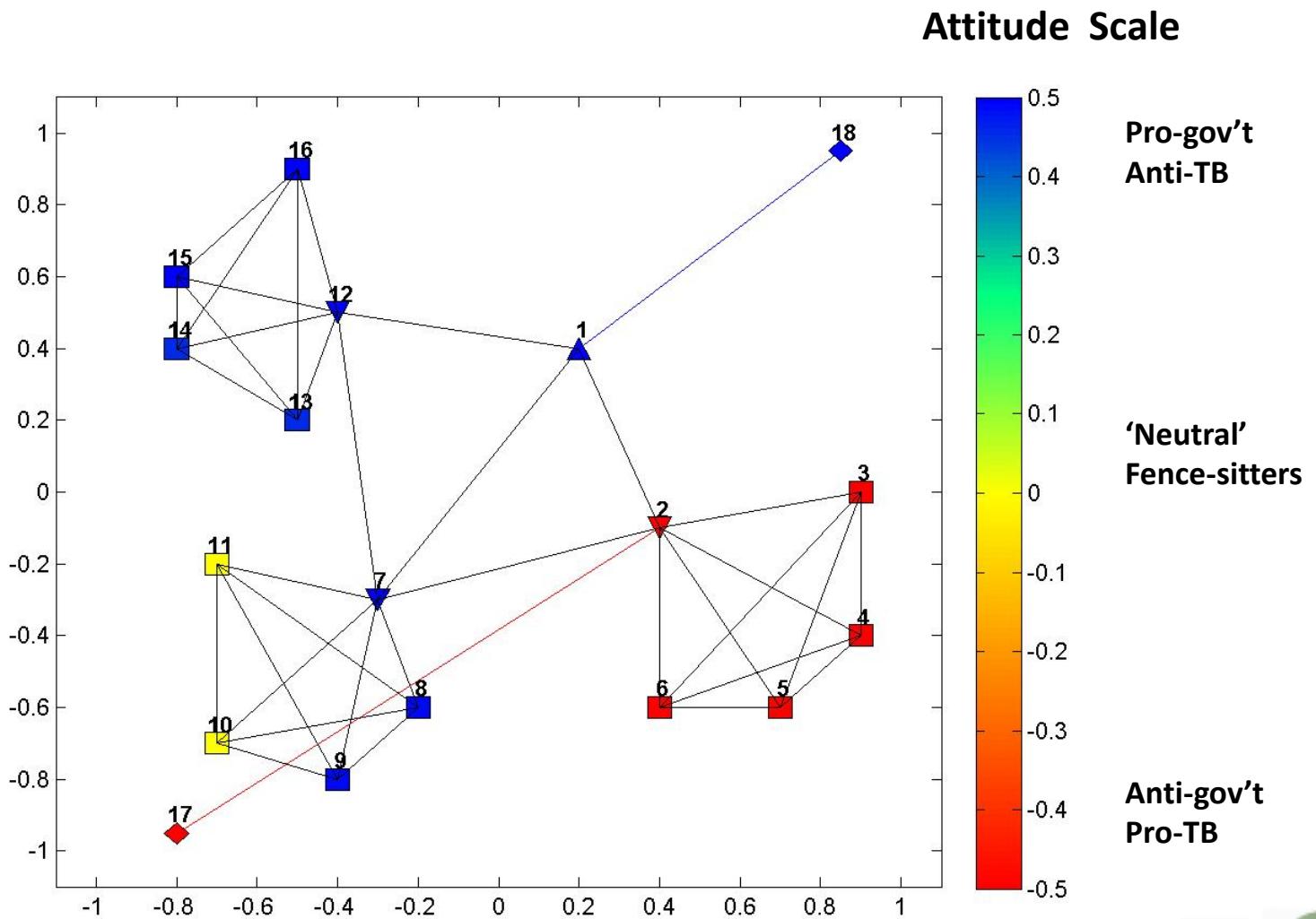
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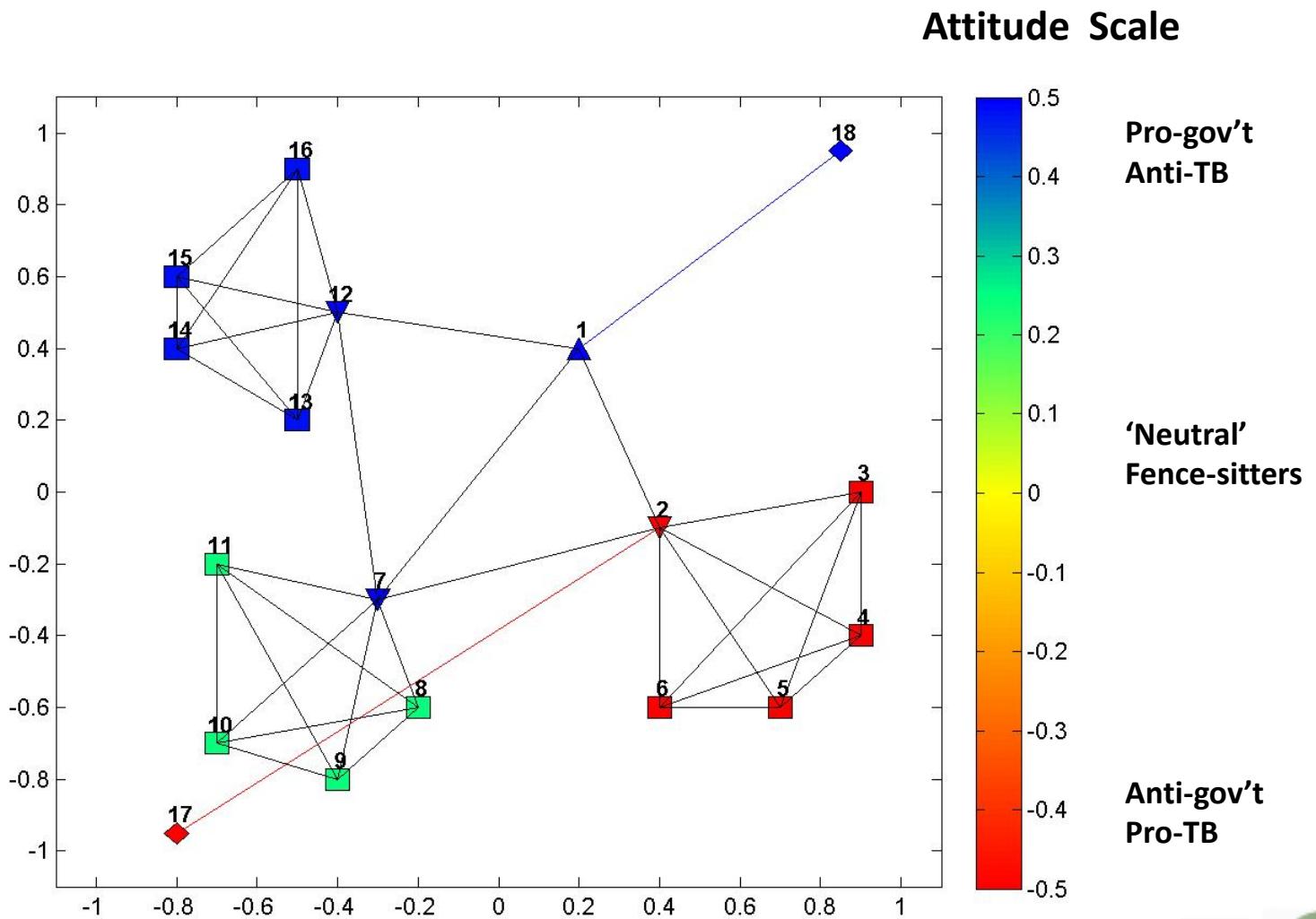
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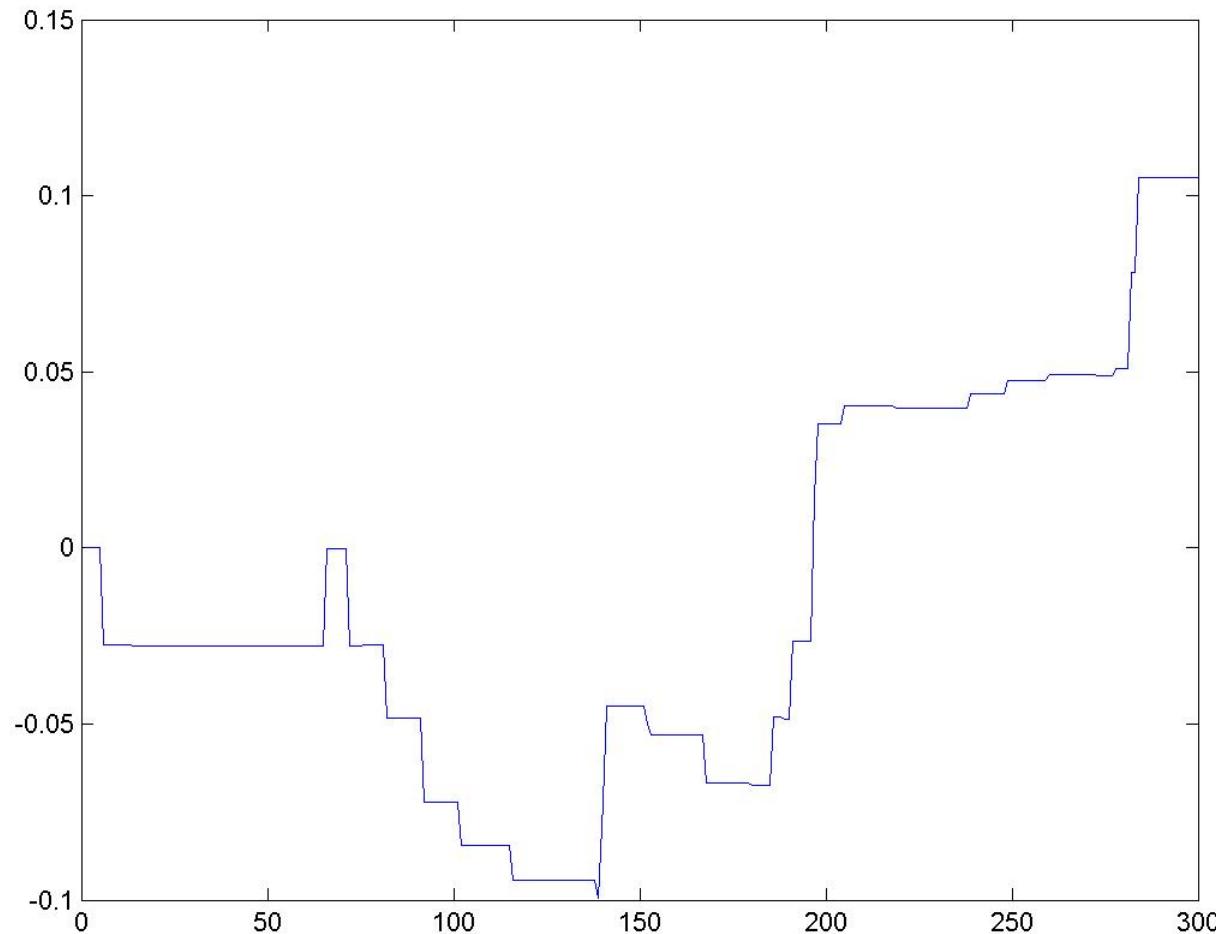
# Interaction Simulation



# Interaction Simulation



# Mean Belief of Network Over Time



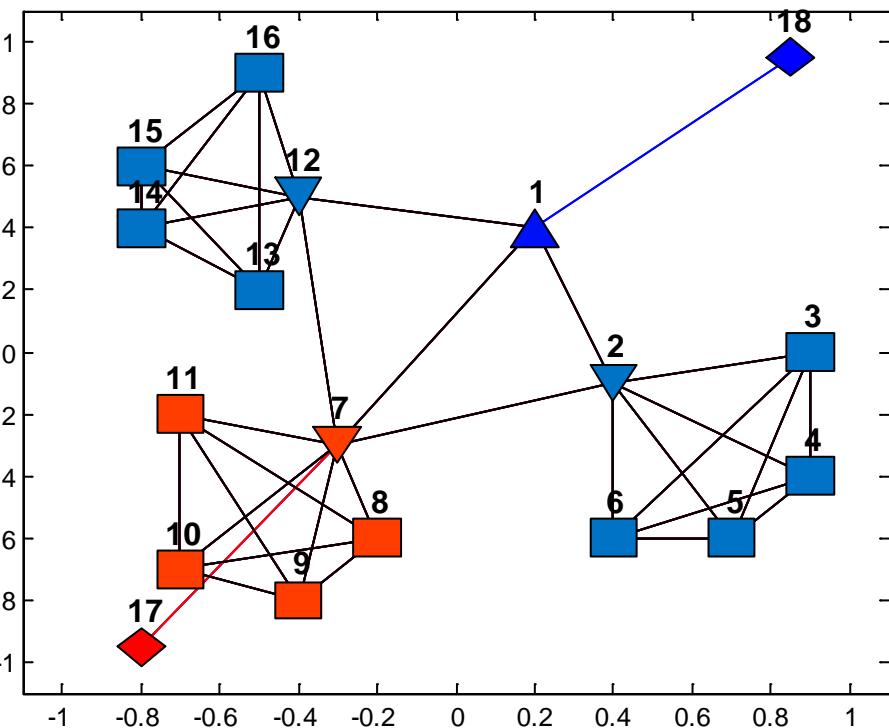
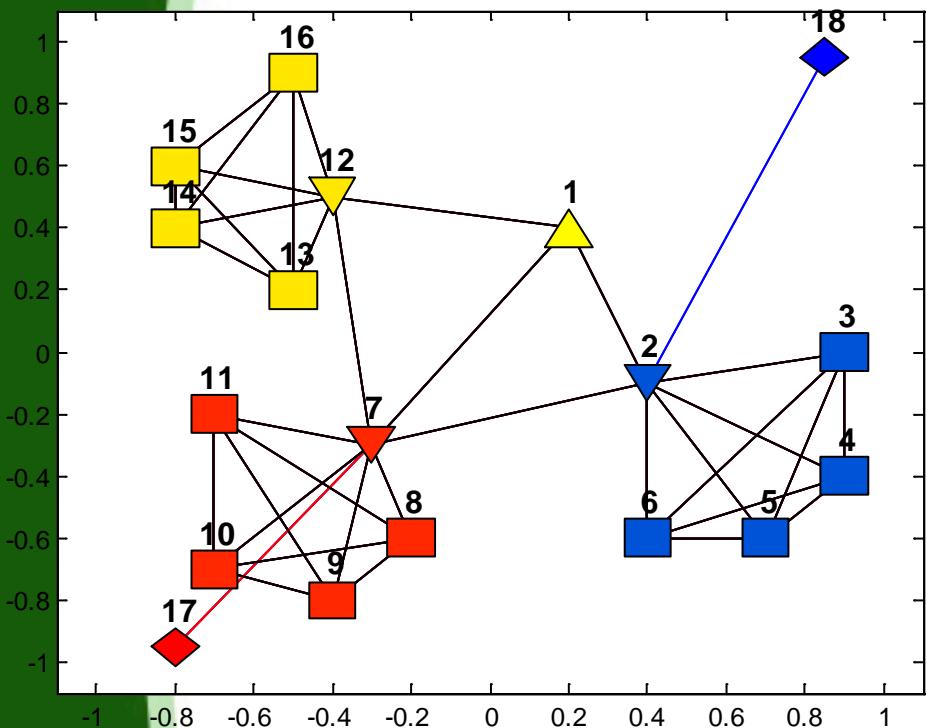
# Properties of the Network Model

- Well defined first moment
  - Beliefs converge in expectation at a sufficiently large time in the future to a set of equilibrium beliefs:
$$X^* = \lim_{k \rightarrow \infty} E[(X(t + k) | X(t))]$$
  - $X^*$  is independent of  $X(t)$
- In simulation the average belief of the network oscillates around the average equilibrium belief
- $X^*$  can be calculated in  $O(n^3)$

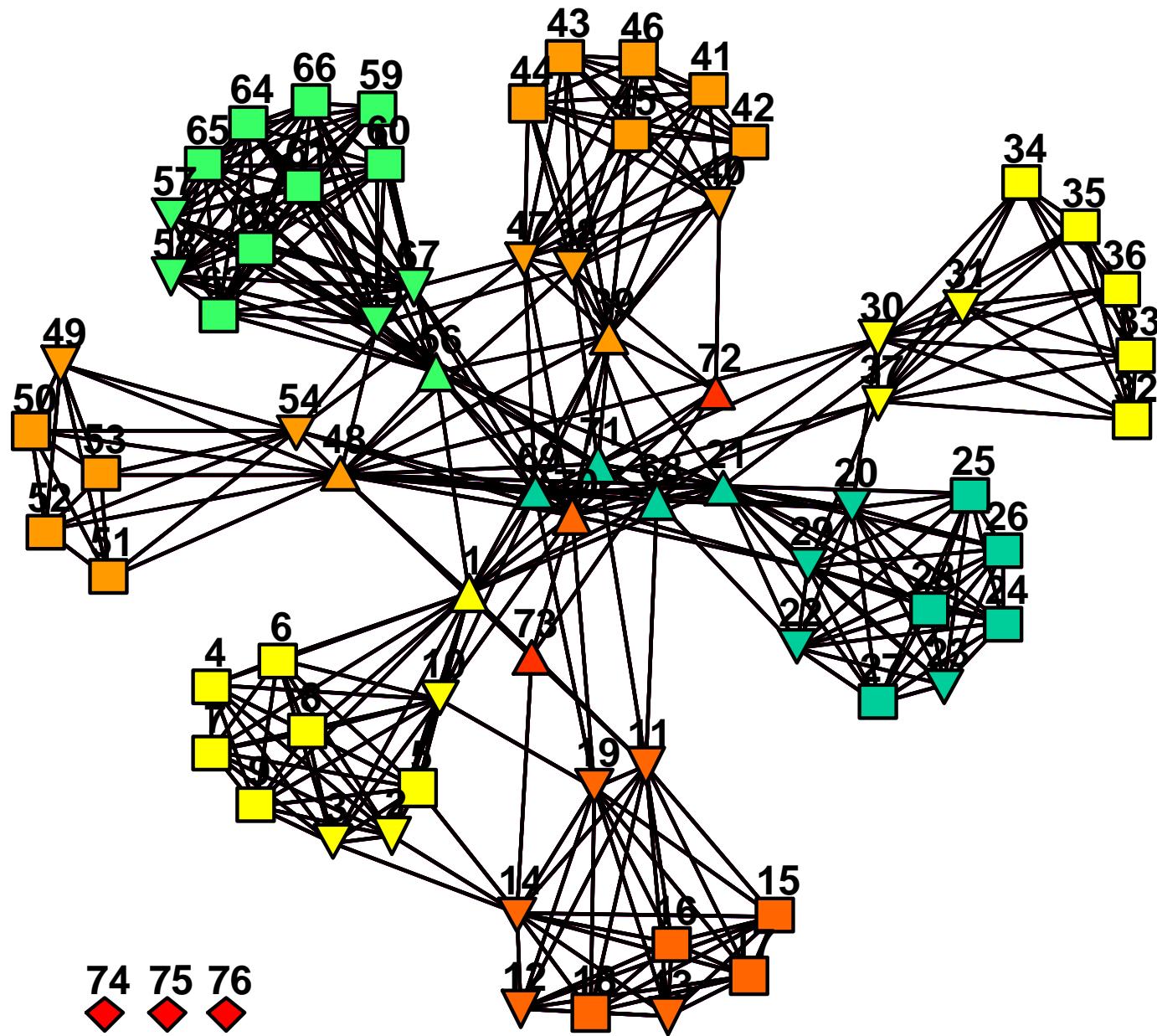
# The Game

- Complete information, symmetric
- 2 players control a set of stubborn agents, and then make connections to the mutable agents
- Payoff functions defined as a function of the expected mean belief of network (convex combination of the elements of  $X^*$ )

# Example Payoffs



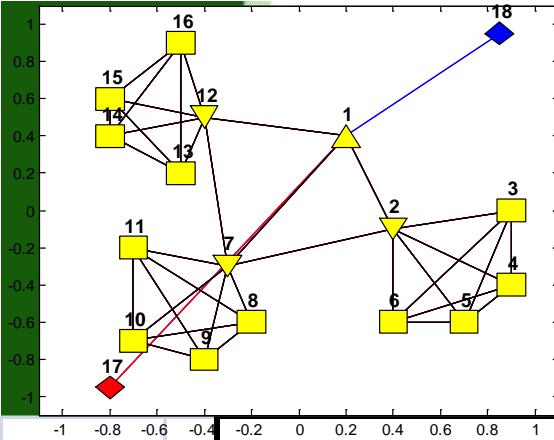
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# Finding Nash Equilibria

- Finding Nash Equilibria from a payoff matrix is straightforward
- However, given  $C$  connections for each player, it takes  $O(n^{2C+3})$  to enumerate the payoff matrix
- Simulated Annealing runs in  $O(n^3)$  to optimize a single player's strategy (vs MINLP)
- Applying the simulated annealing algorithm allows us to use Best Response Dynamics to find Pure Nash Equilibria in  $O(n^3) +$
- The equilibria turn out to be highly robust to changes of the influence parameters

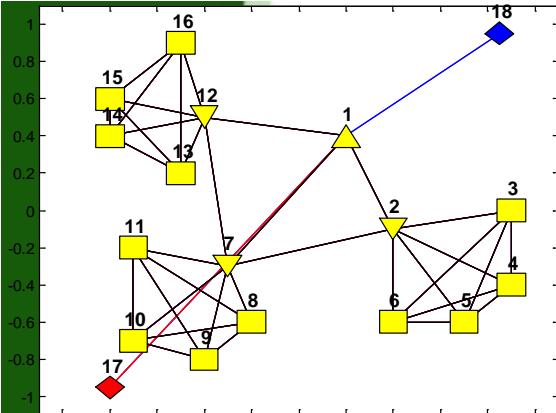




## TB Strategy

**US Strategy**

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	0.000	0.119	0.295	0.295	0.295	0.295	0.052	0.283	0.283	0.283	0.283	0.119	0.295	0.295	0.295	0.295
2	-0.119	0.000	0.310	0.310	0.310	0.310	-0.046	0.240	0.240	0.240	0.240	0.000	0.237	0.237	0.237	0.237
3	-0.295	-0.310	0.000	0.000	0.000	0.000	-0.268	-0.004	-0.004	-0.004	-0.004	-0.237	0.000	0.000	0.000	0.000
4	-0.295	-0.310	0.000	0.000	0.000	0.000	-0.268	-0.004	-0.004	-0.004	-0.004	-0.237	0.000	0.000	0.000	0.000
5	-0.295	-0.310	0.000	0.000	0.000	0.000	-0.268	-0.004	-0.004	-0.004	-0.004	-0.237	0.000	0.000	0.000	0.000
6	-0.295	-0.310	0.000	0.000	0.000	0.000	-0.268	-0.004	-0.004	-0.004	-0.004	-0.237	0.000	0.000	0.000	0.000
7	-0.052	0.046	0.268	0.268	0.268	0.268	0.000	0.304	0.304	0.304	0.304	0.046	0.268	0.268	0.268	0.268
8	-0.283	-0.240	0.004	0.004	0.004	0.004	-0.304	0.000	0.000	0.000	0.000	-0.240	0.004	0.004	0.004	0.004
9	-0.283	-0.240	0.004	0.004	0.004	0.004	-0.304	0.000	0.000	0.000	0.000	-0.240	0.004	0.004	0.004	0.004
10	-0.283	-0.240	0.004	0.004	0.004	0.004	-0.304	0.000	0.000	0.000	0.000	-0.240	0.004	0.004	0.004	0.004
11	-0.283	-0.240	0.004	0.004	0.004	0.004	-0.304	0.000	0.000	0.000	0.000	-0.240	0.004	0.004	0.004	0.004
12	-0.119	0.000	0.237	0.237	0.237	0.237	-0.046	0.240	0.240	0.240	0.240	0.000	0.310	0.310	0.310	0.310
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15	-0.295	-0.237	0.000	0.000	0.000	0.000	-0.268	-0.004	-0.004	-0.004	-0.004	-0.310	0.000	0.000	0.000	0.000
16	-0.295	-0.237	0.000	0.000	0.000	0.000	-0.268	-0.004	-0.004	-0.004	-0.004	-0.310	0.000	0.000	0.000	0.000

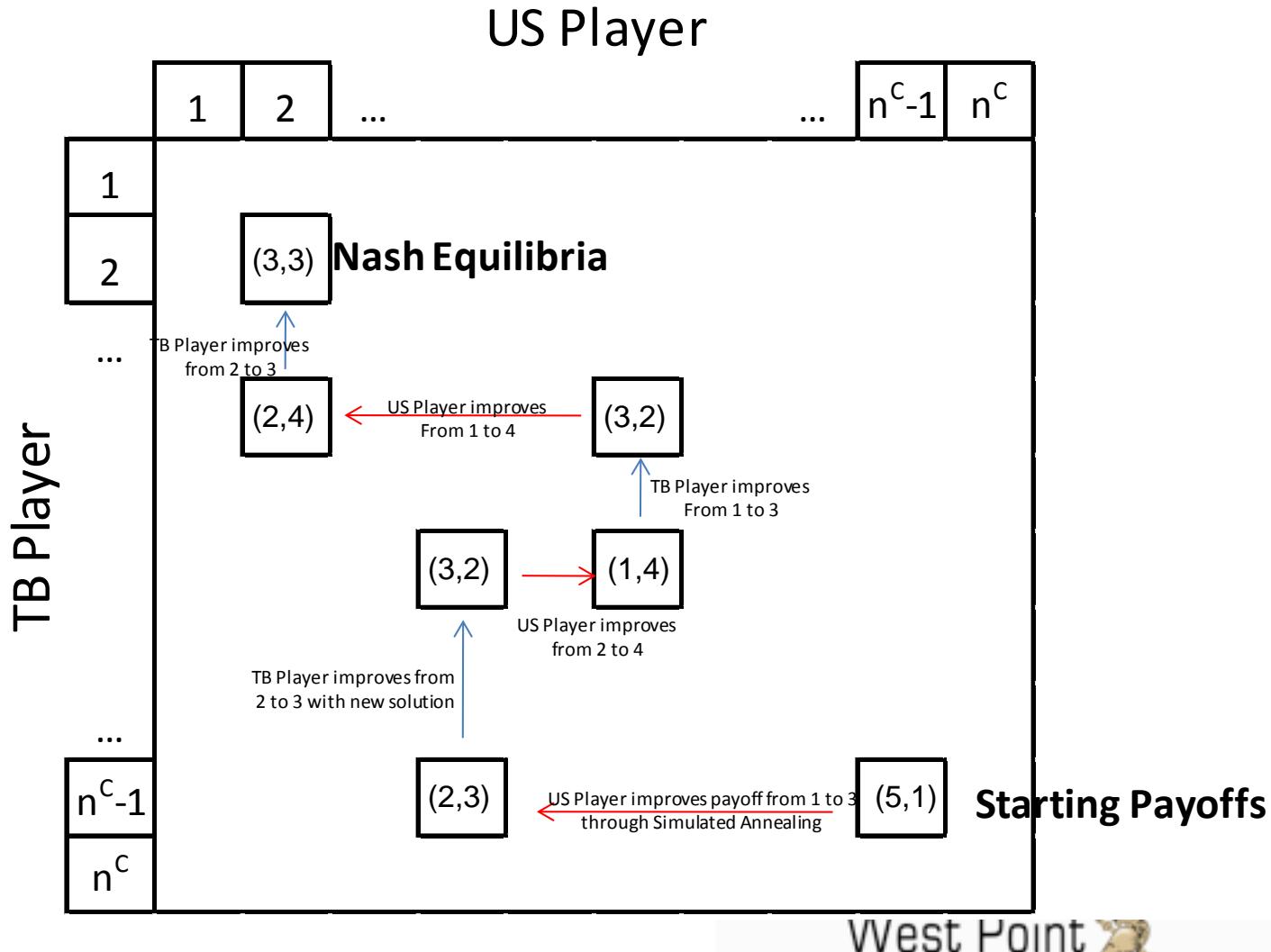


## TB Strategy

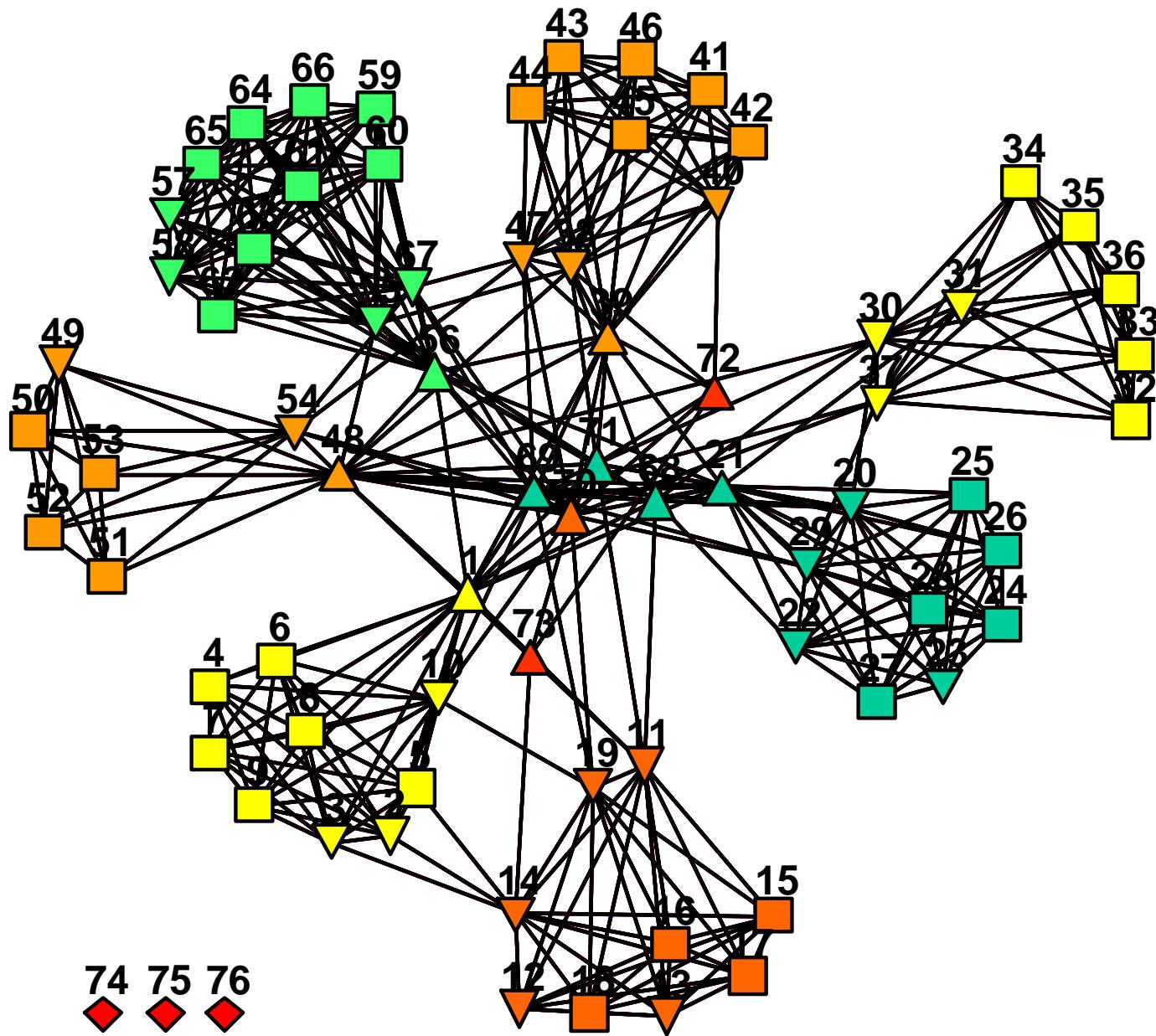
**US Strategy**

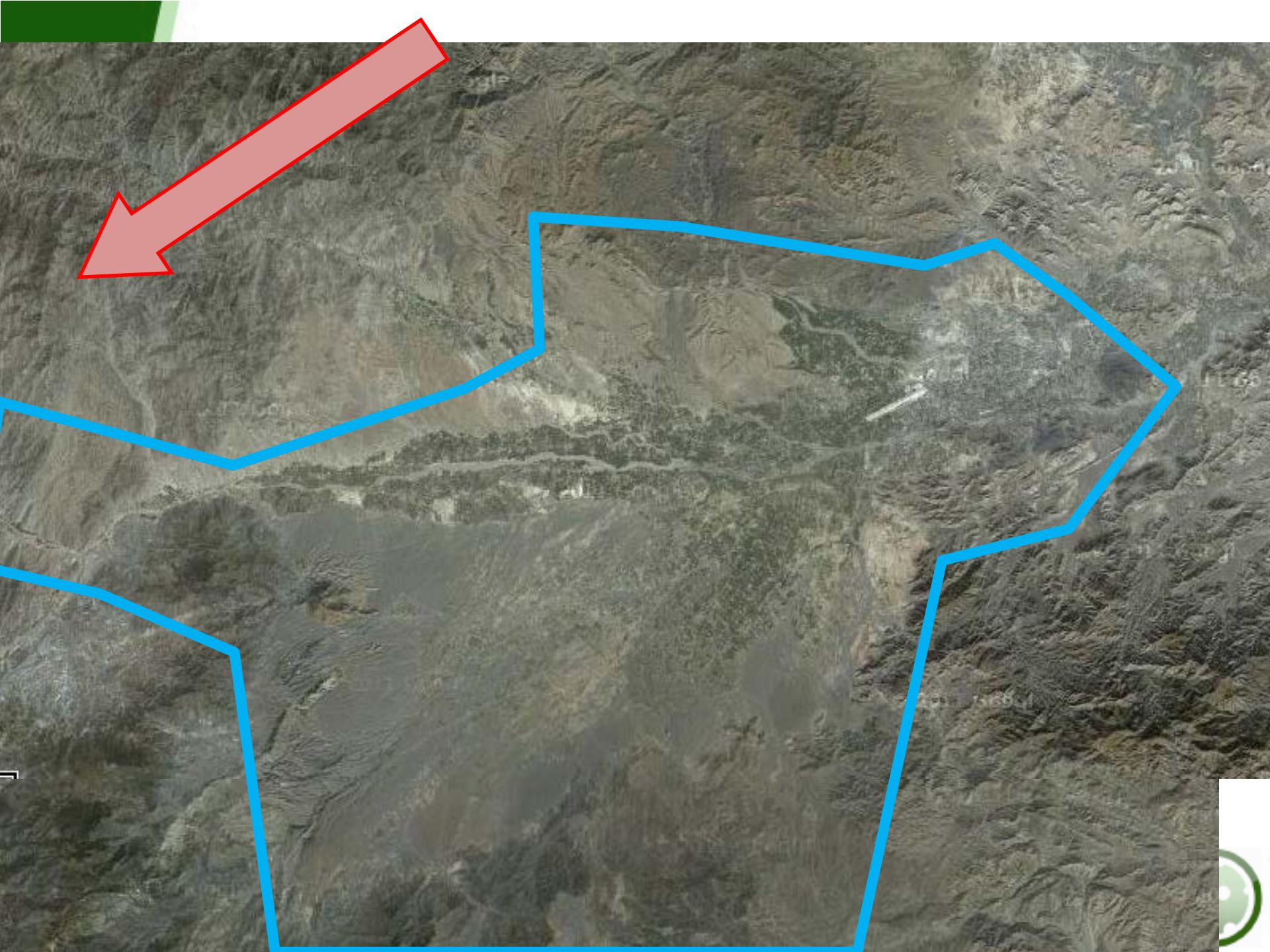
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	0.000	-0.119	0.295	0.295	0.295	0.295	0.052	0.283	0.283	0.283	0.283	0.119	0.295	0.295	0.295	0.295
2	-0.119	0.000	0.310	0.310	0.310	0.310	-0.046	0.240	0.240	0.240	0.240	0.000	0.237	0.237	0.237	0.237
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4	-0.295	-0.310	0.000	0.000	0.000	0.000	-0.268	-0.004	-0.004	-0.004	-0.004	-0.237	0.000	0.000	0.000	0.000
5	-0.295	-0.310	0.000	0.000	0.000	0.000	-0.268	-0.004	-0.004	-0.004	-0.004	-0.237	0.000	0.000	0.000	0.000
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13	-0.295	-0.237	0.000	0.000	0.000	0.000	-0.268	-0.004	-0.004	-0.004	-0.004	-0.310	0.000	0.000	0.000	0.000
14	-0.295	-0.237	0.000	0.000	0.000	0.000	-0.268	-0.004	-0.004	-0.004	-0.004	-0.310	0.000	0.000	0.000	0.000
15	-0.295	-0.237	0.000	0.000	0.000	0.000	-0.268	-0.004	-0.004	-0.004	-0.004	-0.310	0.000	0.000	0.000	0.000
16	-0.295	-0.237	0.000	0.000	0.000	0.000	-0.268	-0.004	-0.004	-0.004	-0.004	-0.310	0.000	0.000	0.000	0.000

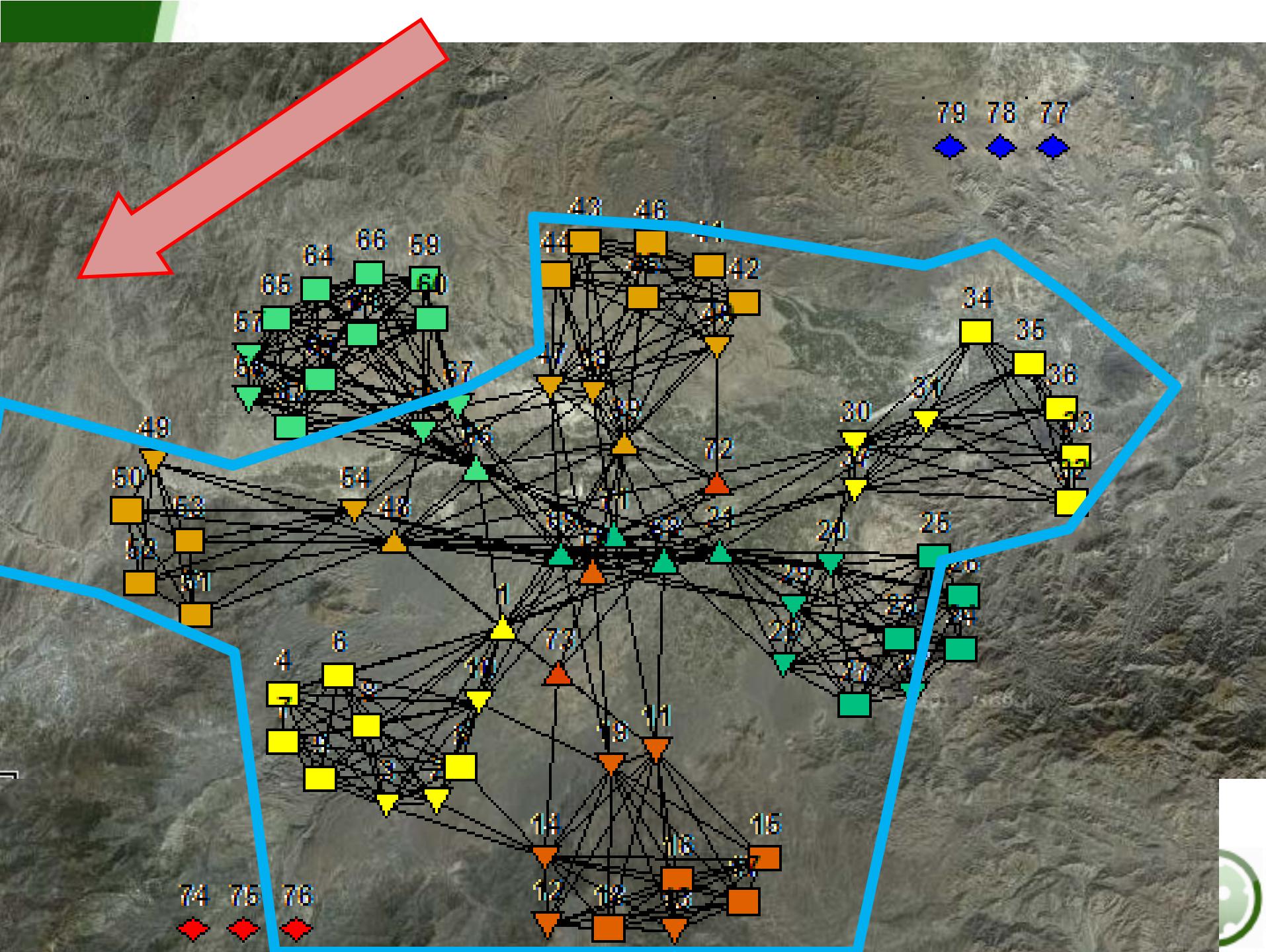
# Notional Best Response Dynamics Search Using Simulated Annealing

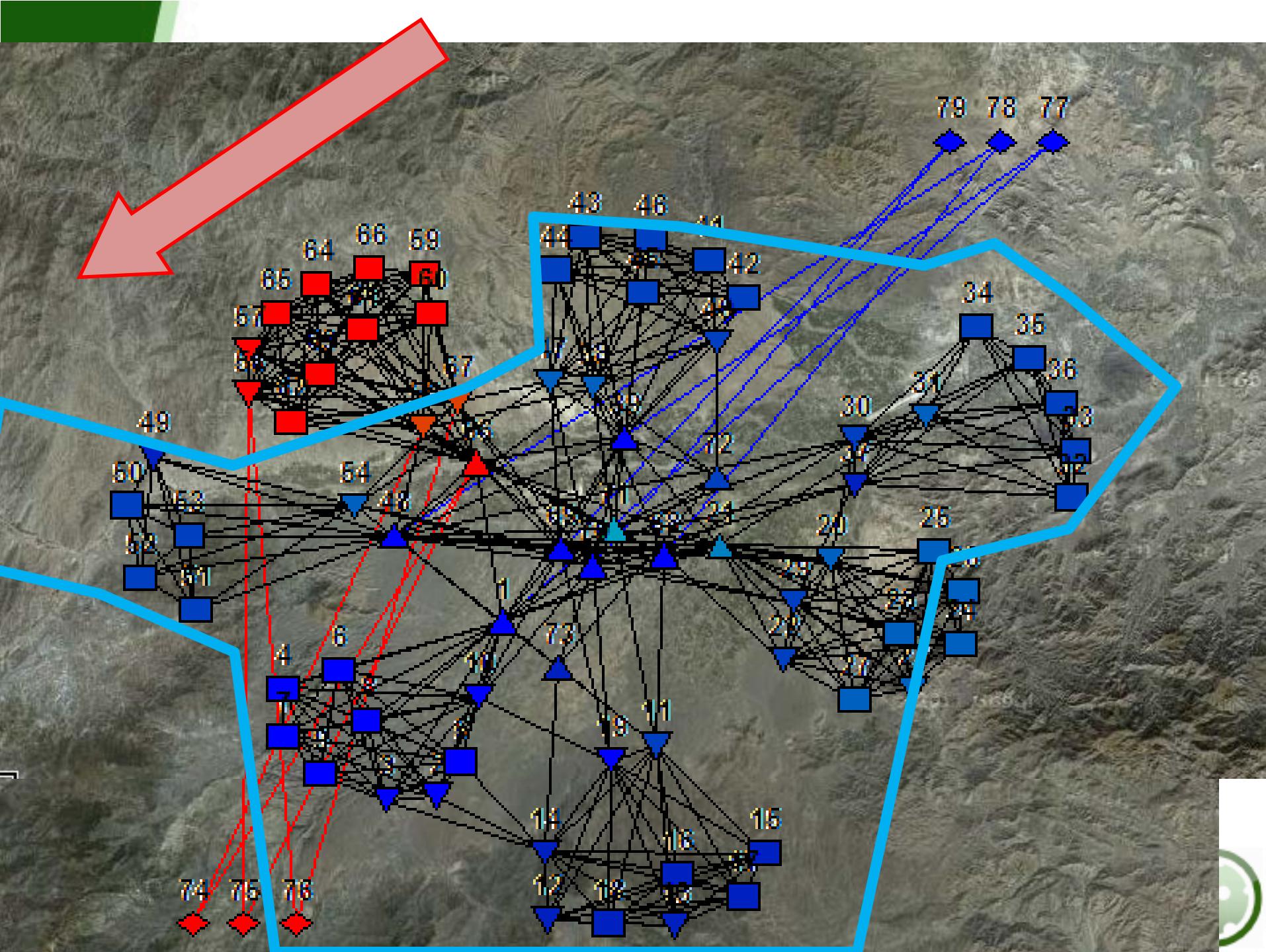


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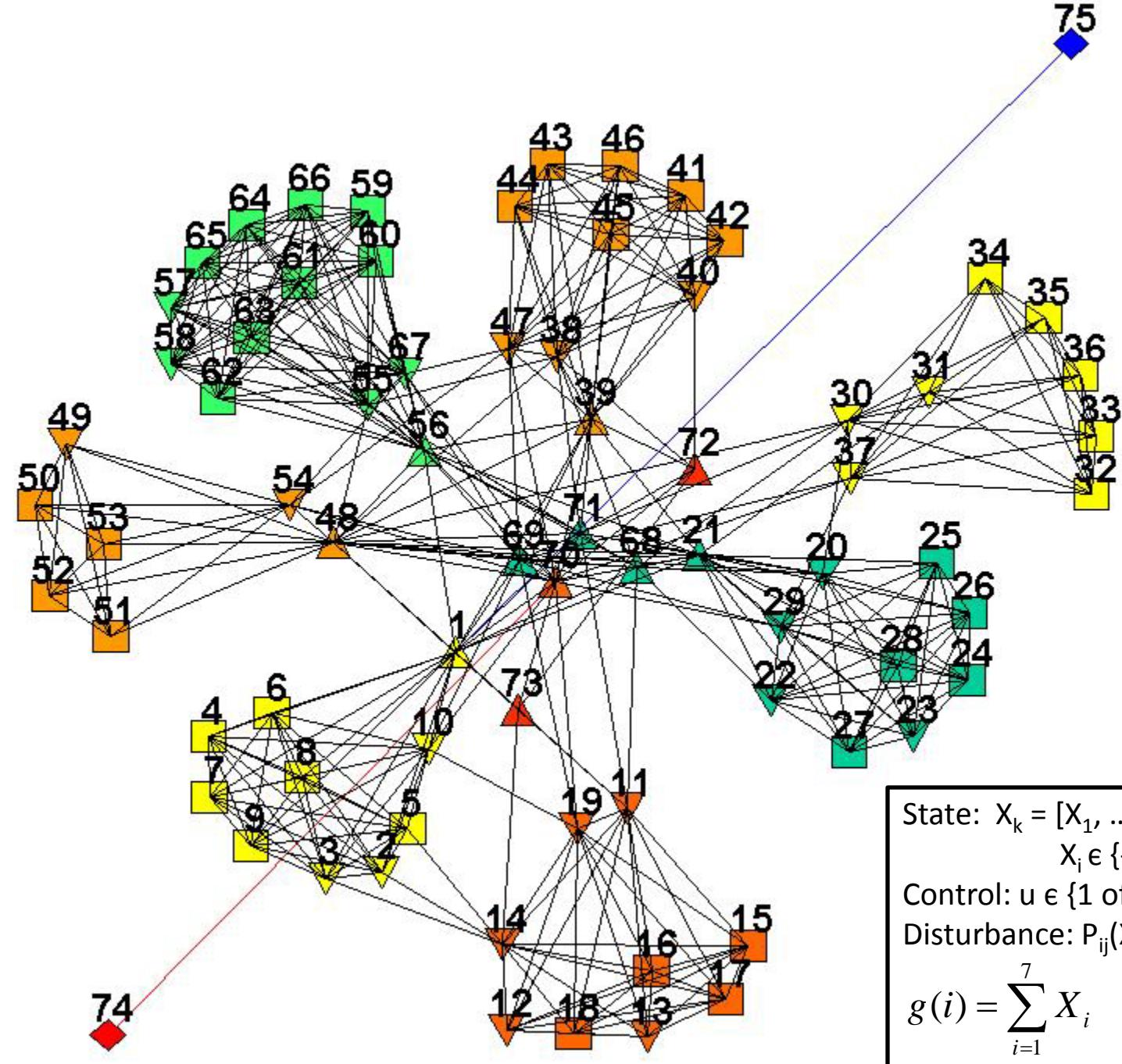




# Thoughts

- The time to find Pure Nash Equilibria increases exponentially with C
- Simulated Annealing heuristic provides a method to conduct best response dynamics
- Current equilibrium payoff functions not completely realistic, but make problem tractable
- Inverse Optimization could be used to determine the enemy's payoff function based off of intelligence reports of villages





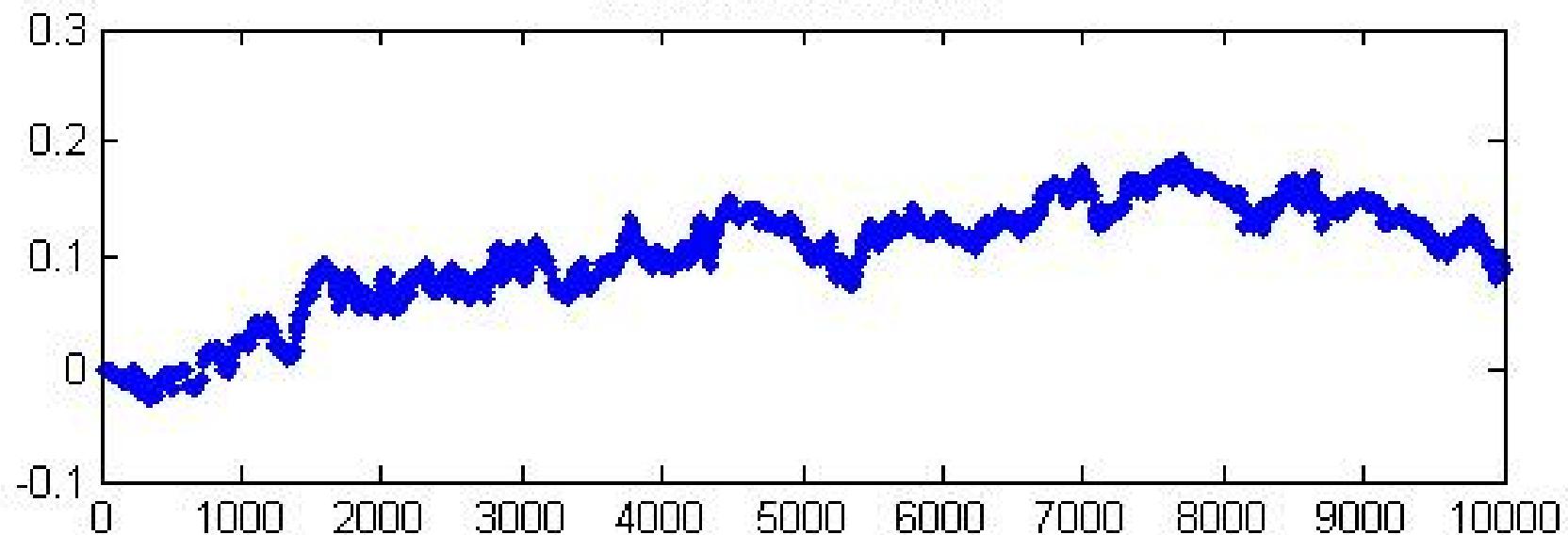
State:  $X_k = [X_1, \dots, X_7] \quad | \quad |X_k| = 3^7$   
 $X_i \in \{-1, 0, 1\}$

Control:  $u \in \{1 \text{ of the } 35 \text{ Inf. Nodes}\}$   
Disturbance:  $P_{ij}(X_k, u)$

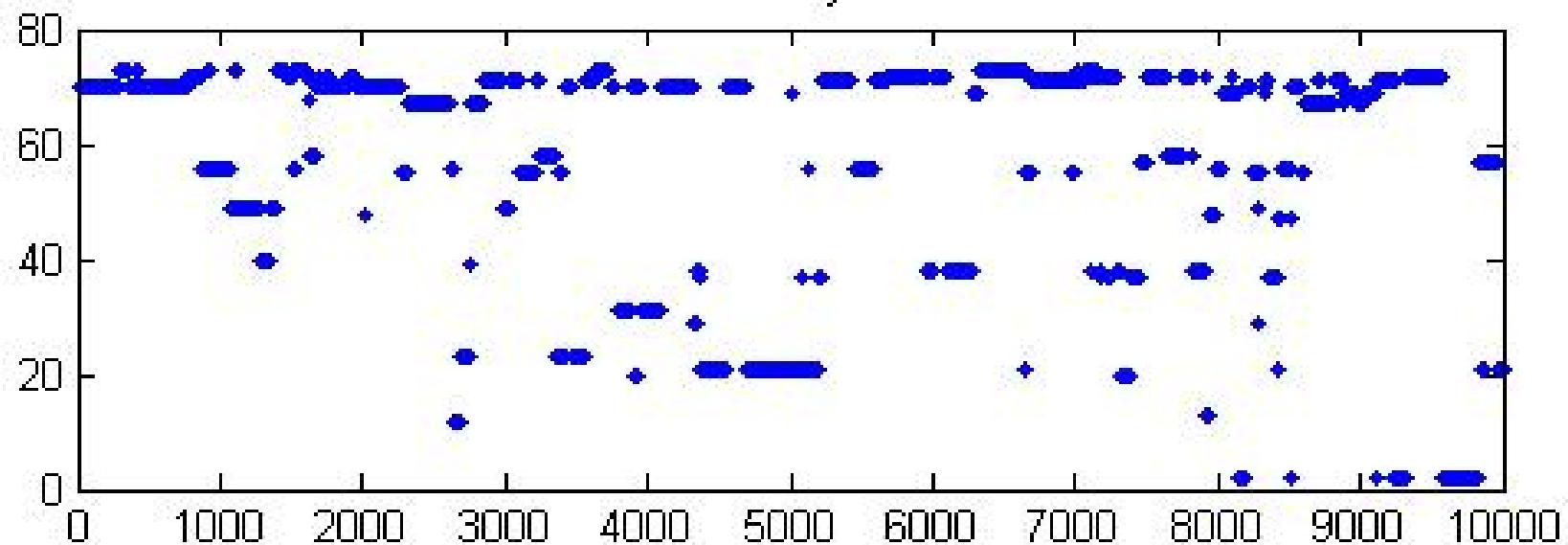
$$g(i) = \sum_{i=1}^7 X_i$$

$$J(i) = \arg \max_u (g(i) + \alpha \sum_j P_{ij}(i, u) J(j))$$

Mean Network Belief



Policy



# Conclusions

- Even with small amount of information, I can generate a set of stationary policies that do much better than a static strategy
- Once the network goes to a large positive belief, it generally stays there (self-sustaining)
- Flexibility and information have enormous utility in affecting the flow of information in this model

# Recommendations for Future Work

- Non-equilibrium payoff functions
- Different Strategy Options
- Partial information game
- Dynamic Networks