Dynamics of Networking Social Agents: From Diplomacy to Friendship

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July 17, 2007, Statistical mechanics of distributed information system

http://www.cs.unm.edu/~holme/

COEVOLUTION OF NETWORKS & OPINIONS: the idea

P. Holme & M. E. J. Newman, Phys. Rev. E **74**, 056108 (2006).

- Opinions spread over social networks.
- People with the same opinion are likely to become acquainted.
- We try to combine these points into a simple model of simultaneous opinion spreading and network evolution.

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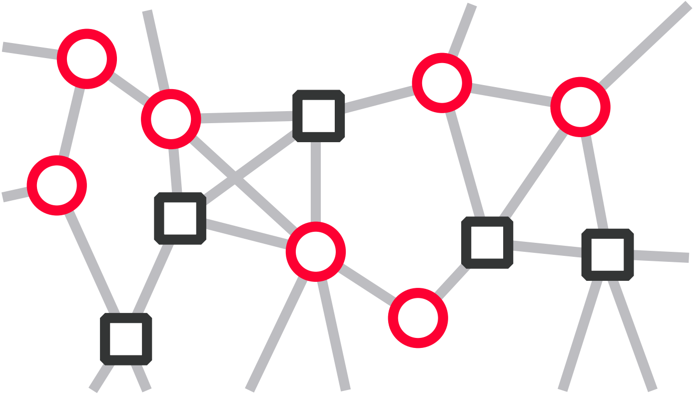

Clifford & Sudbury, Biometrika **60**, 581 (1973).
Holley & Liggett, Ann. Probab. **3**, 643 (1975).

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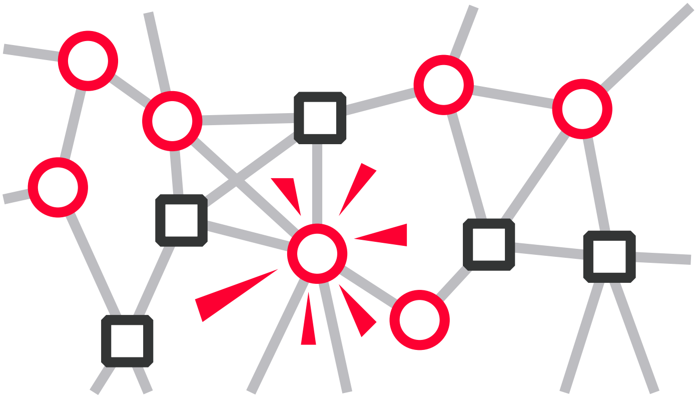
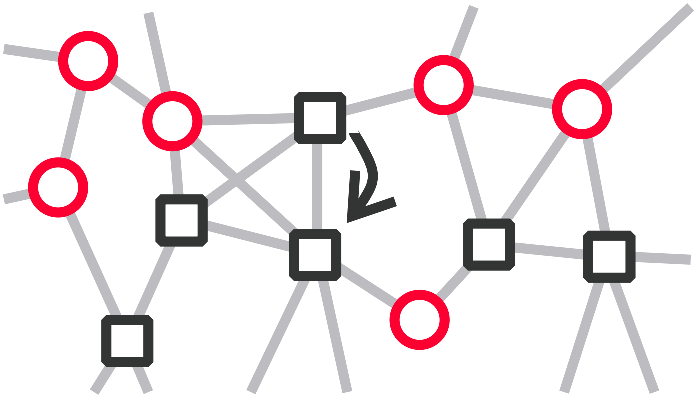


choose one vertex randomly

the voter model



copy the opinion of a random neighbor

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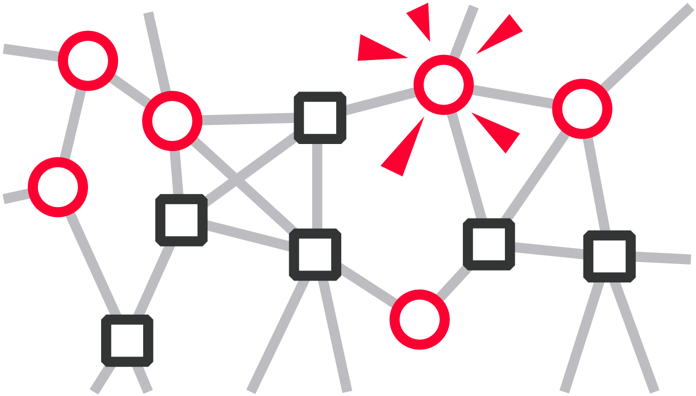

and so on . . .

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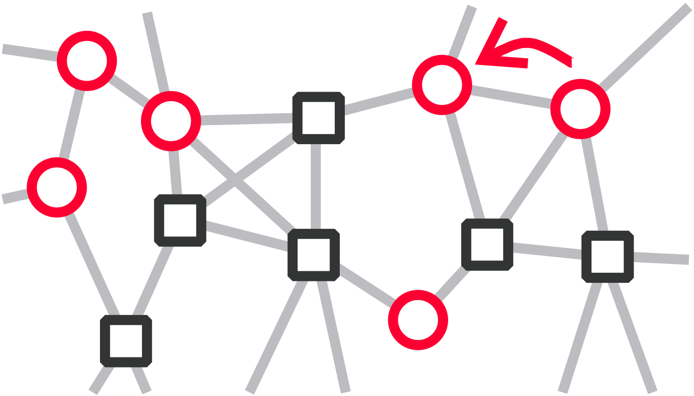

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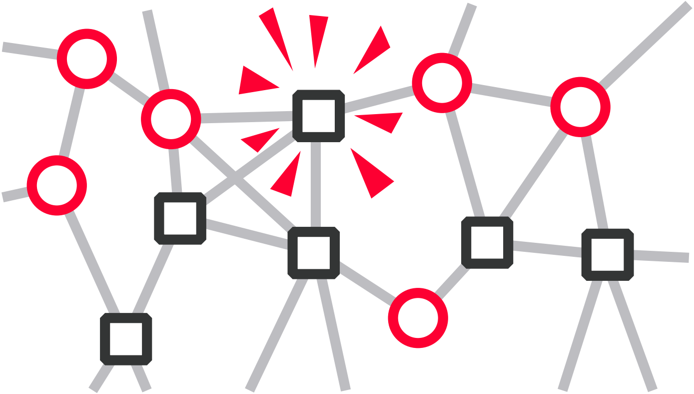

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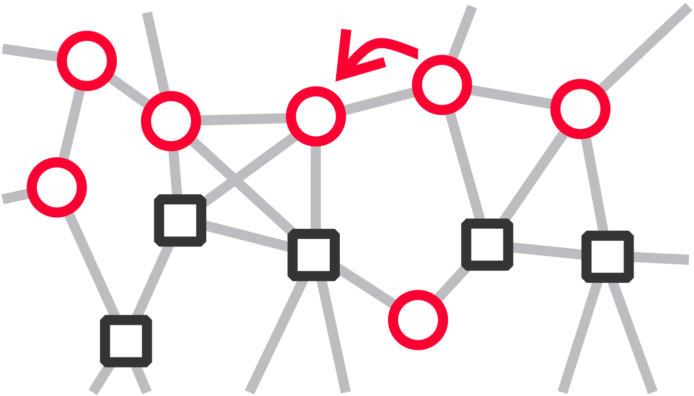

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acquaintance dynamics

- People of similar interests are likely to get acquainted. e.g.: McPherson *et al.*, Ann. Rev. Sociol. **27**, 415 (2001).
- The number of edges is constant.

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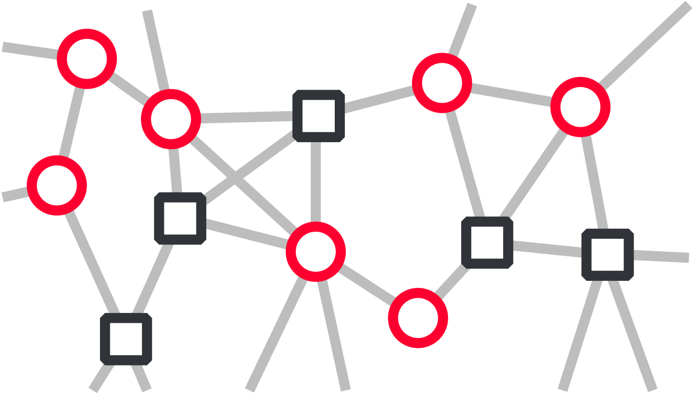

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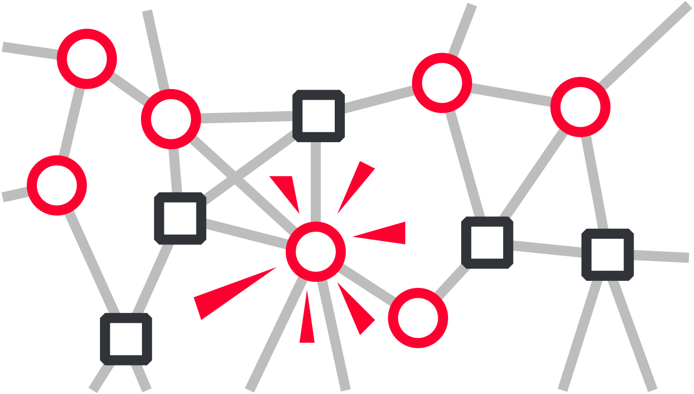

choose one vertex randomly

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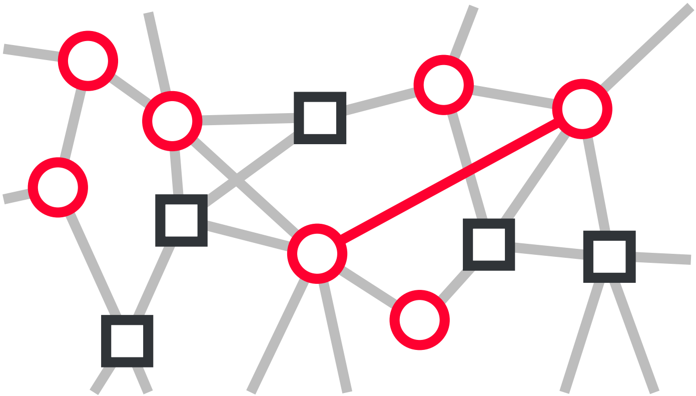
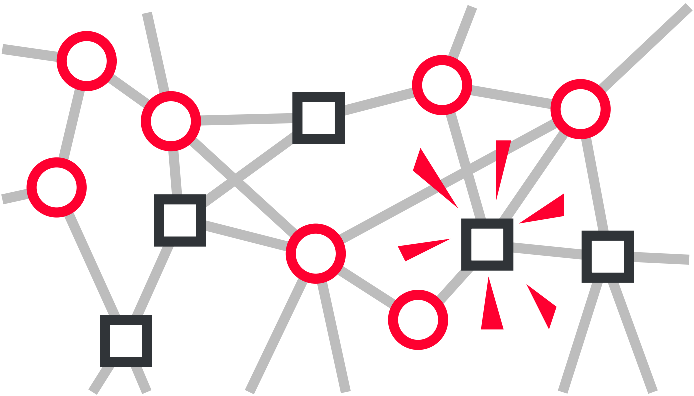


rewire an edge to a vertex with the same opinion

acquaintance dynamics



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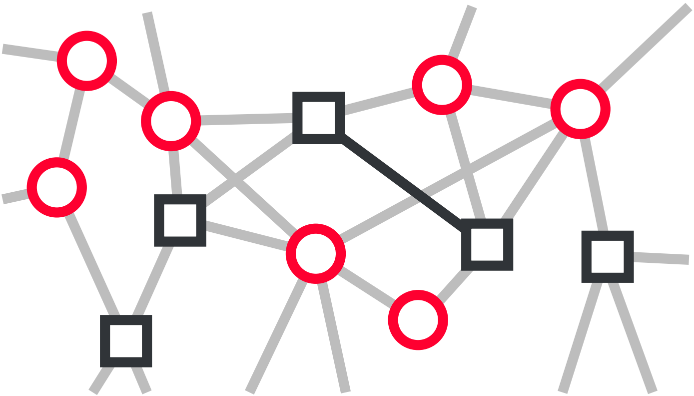

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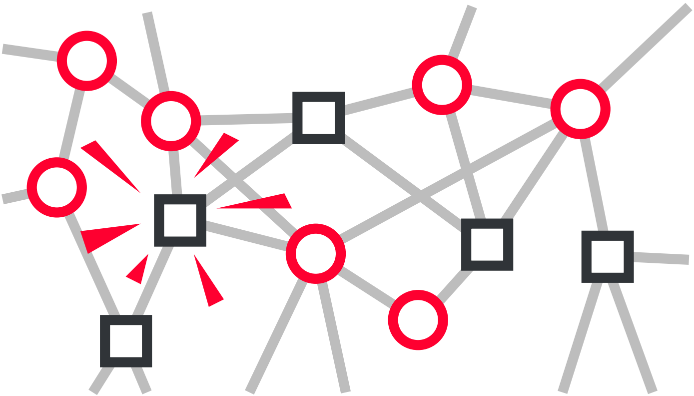

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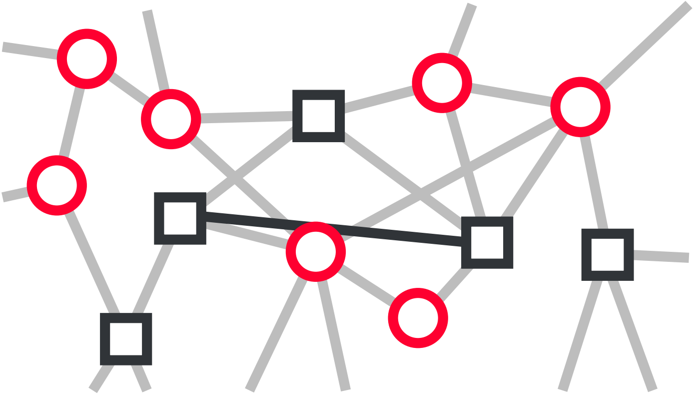

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our model

1. Start with a random network of N vertices $M = \bar{k}N/2$ edges and $G = N/\gamma$ randomly assigned opinions.
2. Pick a vertex i at random.
3. With a probability ϕ make an acquaintance formation step from i.
4. . . . otherwise make a voter model step from i.
5. If there are edges leading between vertices of different opinions—iterate from step 2.

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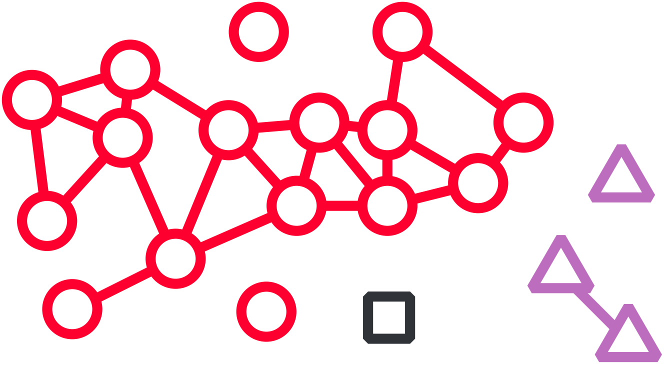
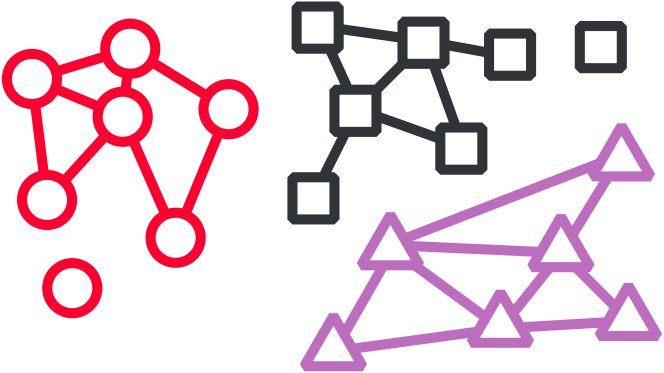
phases



low ϕ—one dominant cluster

phases



high ϕ—clusters of similar sizes

quantities we measure

- The relative largest size S of a cluster (of vertices with the same opinion).
- The average time τ to reach consensus.

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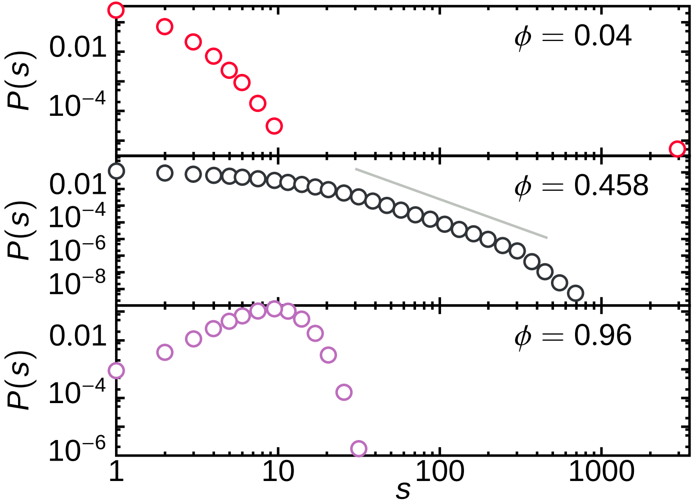
cluster size distribution



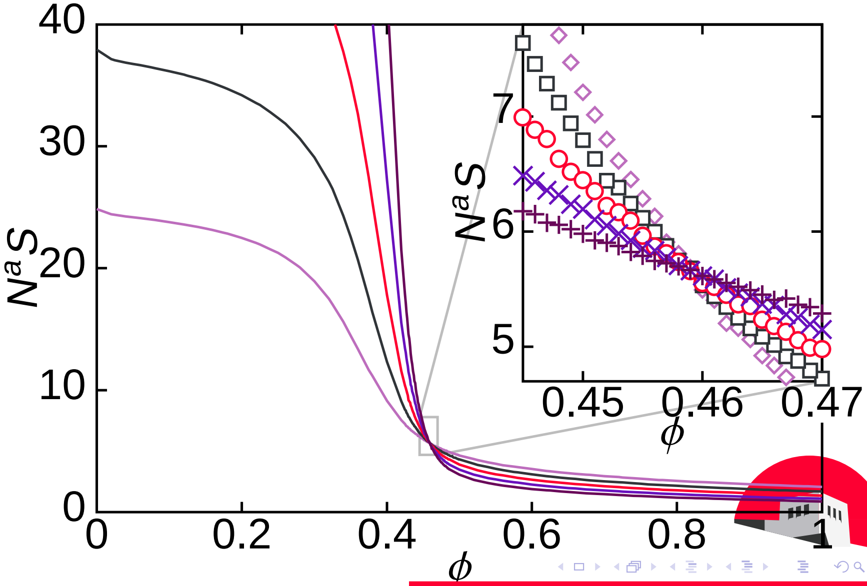
finding the phase transition

Assume a critical scaling form:

scaling form

$$S = N^{-a} F\left(N^{b}(\phi - \phi_c)\right)$$

finding the phase transition



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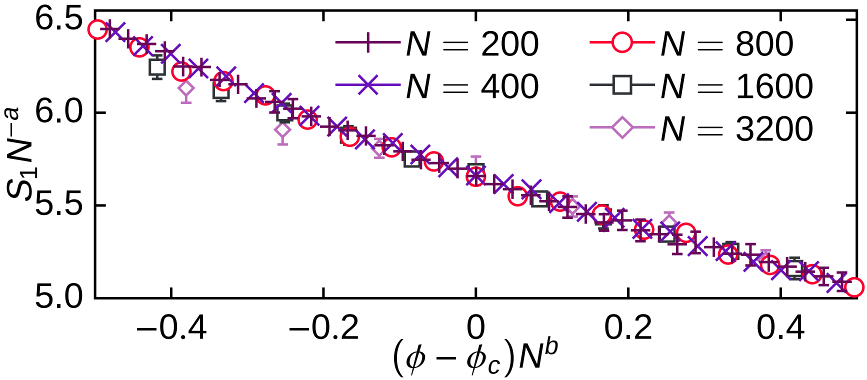
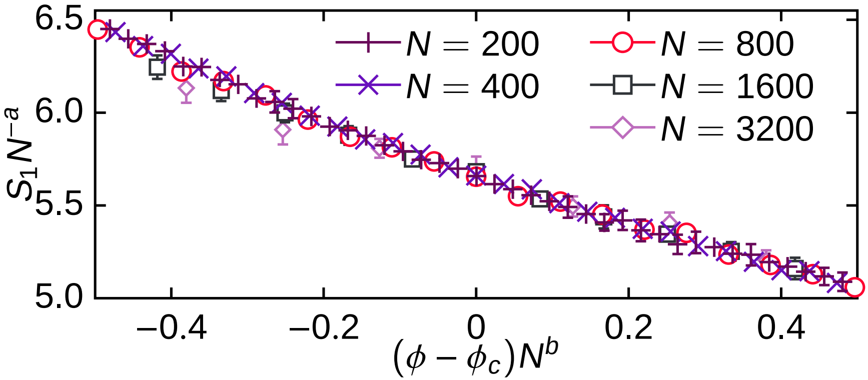


$a = 0.61 \pm 0.05$, $\phi_c = 0.458 \pm 0.008$, $b = 0.7 \pm 0.1$

random graph percolation: $a = b = 1/3$

finding the phase transition



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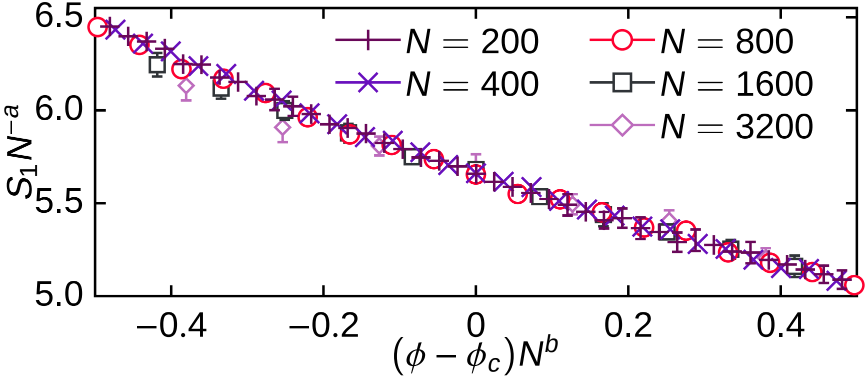

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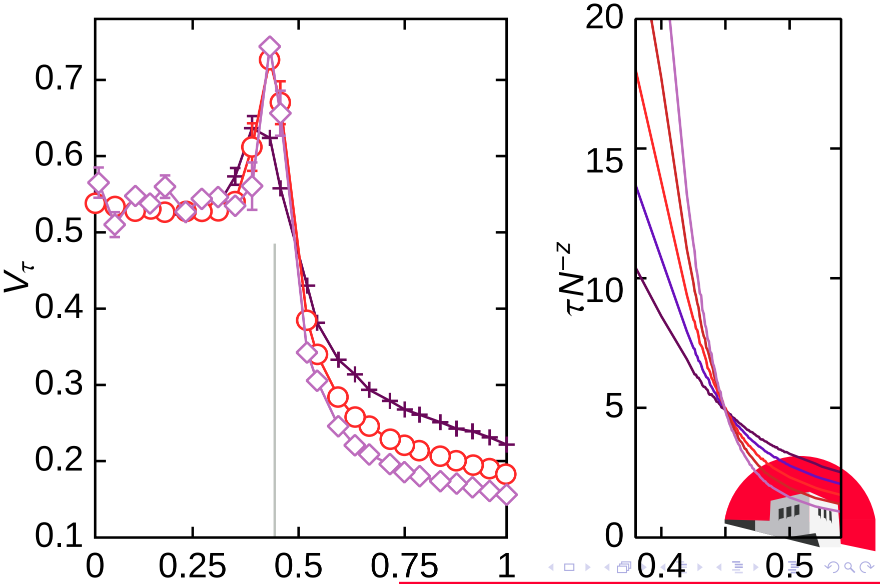
dynamic critical behavior



conclusions

- We have proposed a simple, non-equilibrium model for the coevolution of networks and opinions.
- The model undergoes a second order phase transition between: One state of clusters of similar sizes. One state with one dominant cluster.
- The universality class is not the same as random graph percolation.
- In society, a tiny change in the social dynamics may cause a large change in the diversity of opinions.

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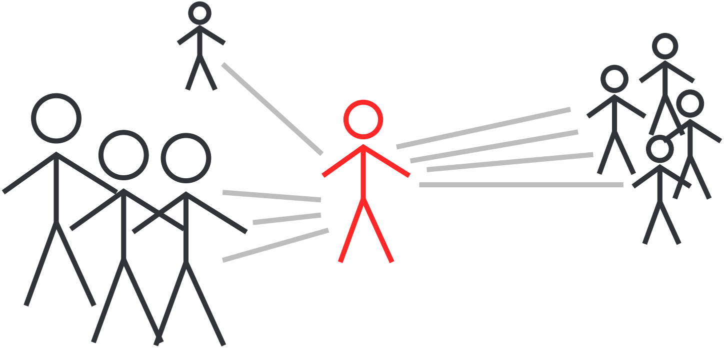
motivation

In diplomacy, lobbying or other political or corporate networking, it is important to:



Holme & Ghoshal, Phys. Rev. Lett. **96**, 098701 (2006)

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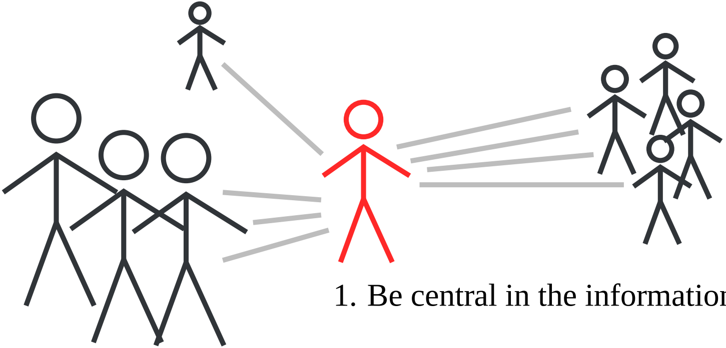

1. Be central in the information flow.

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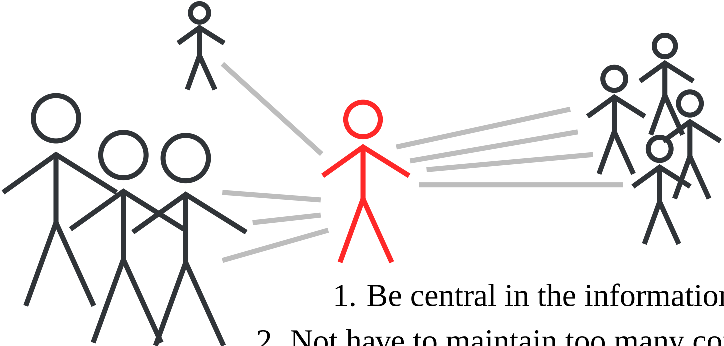

1. Be central in the information flow.
2. Not have to maintain too many contacts.

Holme & Ghoshal, Phys. Rev. Lett. **96**, 098701 (2006)

score function

- Central is good—*closeness centrality*

$$C(i) = (N-1) / \sum_{j \neq i} d(i,j)$$

- If the network is disconnected, being a part of a large component is good.
- Large degree is bad.

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score function

Component size can be incorporated by modifying the definition of closeness: If we sum the reciprocals (instead of inverting the sum), we get the score function:

Definition

$$s(i) = \begin{cases} (1/k_i) \sum_{H_i} 1/d(i,j) & \text{if } k_i > 0 \\ 0 & \text{if } k_i = 0 \end{cases} \quad (1)$$

H_i is the component i belongs to, except i

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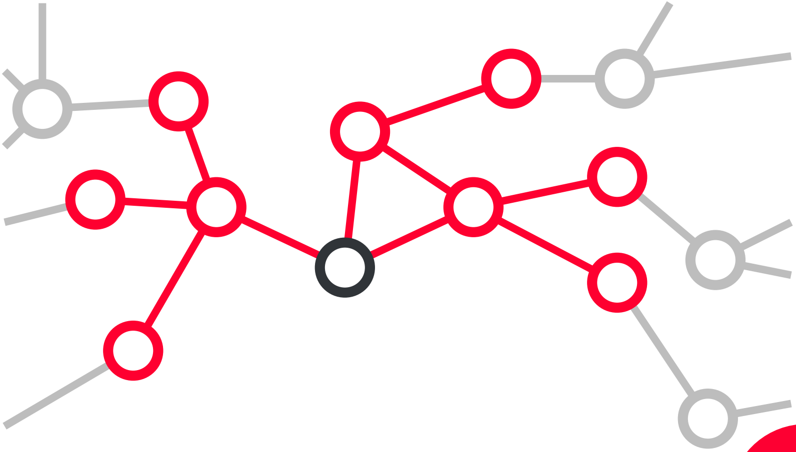
moves



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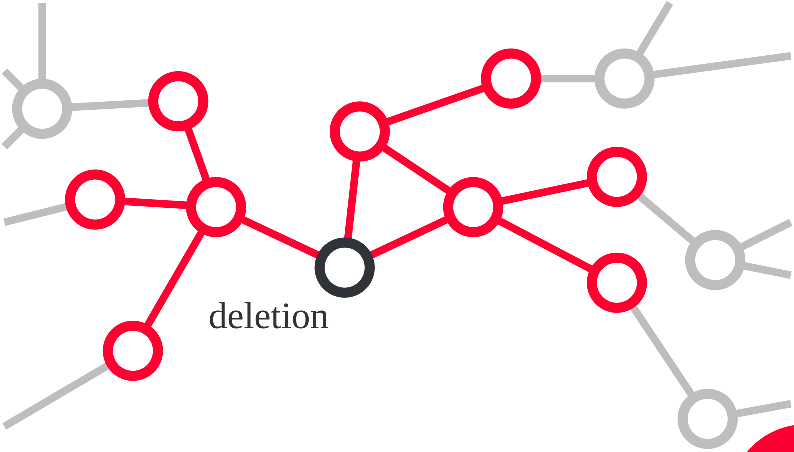

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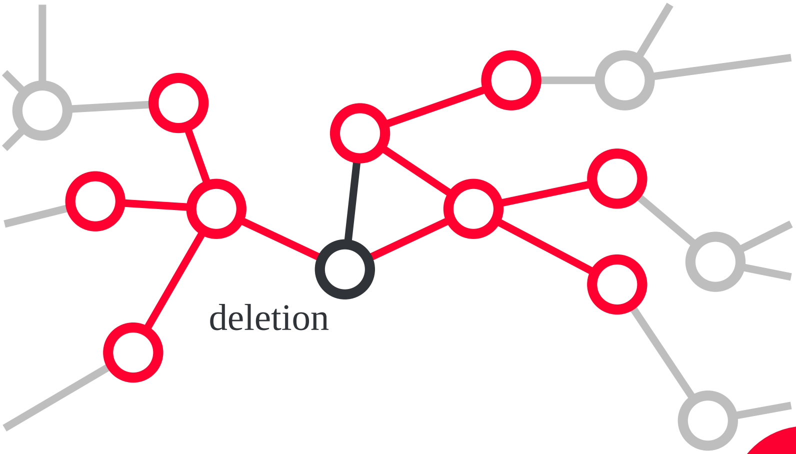

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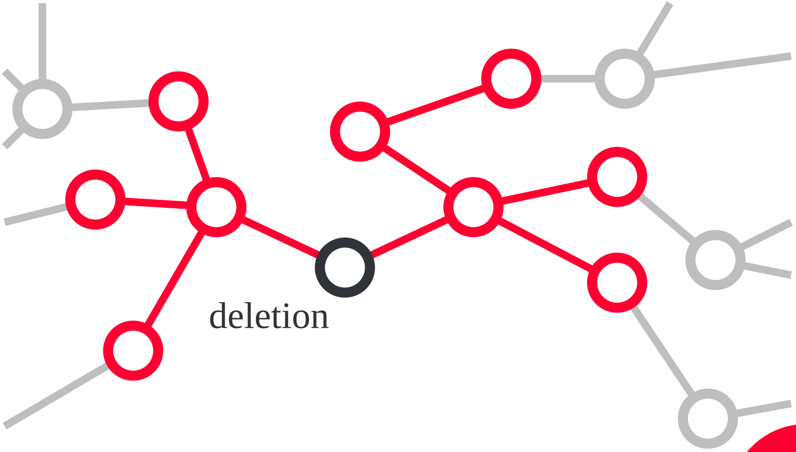

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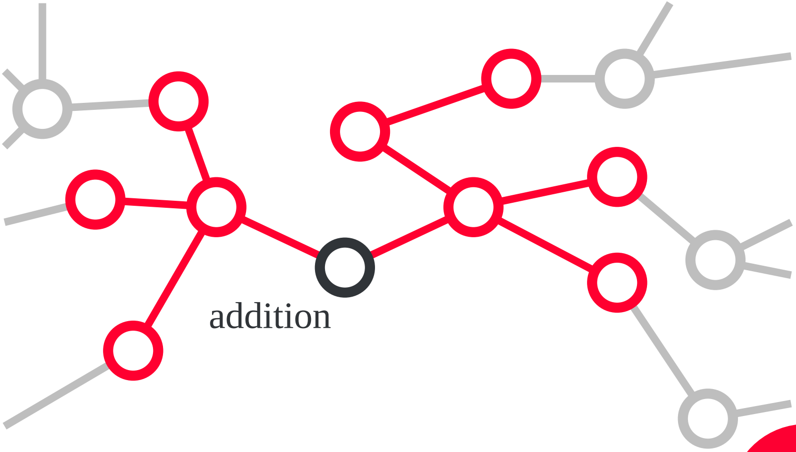

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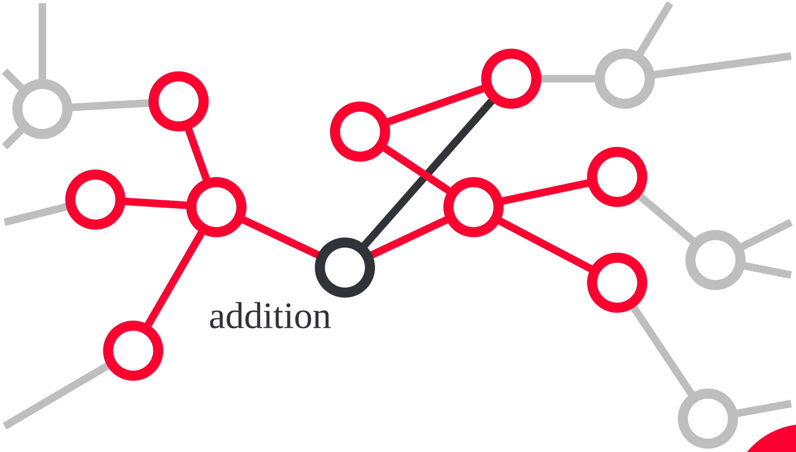

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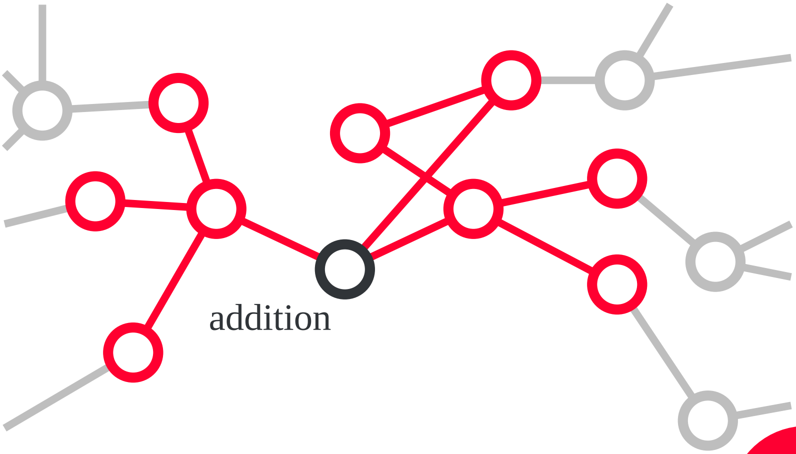
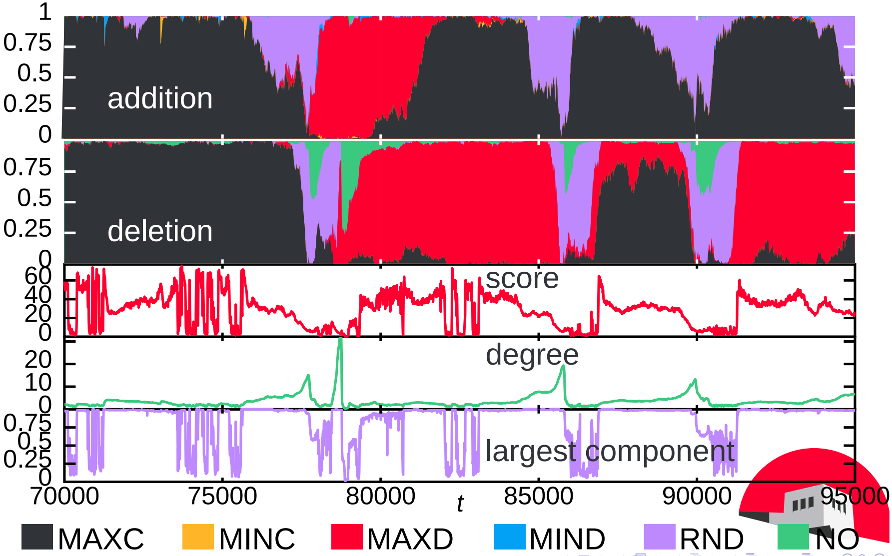
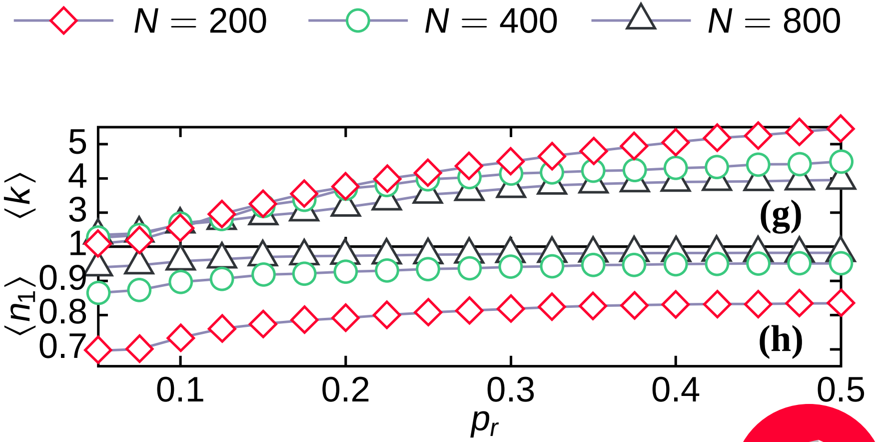


time evolution



effect of random moves: degree & cluster size



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- A simple problem that gets quite convoluted when one wants to be general.
- Complex time evolution with spikes, quasi-equilibria and trends.
- Network structure and strategy densities are correlated.
- The most common strategy, over a large range of parameter space, is MAXC.
- MAXC gives a bimodal degree distribution
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