Simple models of teens, diplomats, religious cults and more

Petter Holme

KTH, CSC, Computational Biology

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http://www.csc.kth.se/~pholme/

outline

simple mechanistic models of the micro- to macro-transition in networked social systems (toy models), of:

- group formation *w Andreas Grönlund*
- youth subcultures *w Andreas Grönlund*
- co-evolution of networks and opinions *w Mark Newman*
- agents maximizing centrality & minimizing degree *w Gourab Ghoshal*

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motivation

- *macro phenomena:* subcultures & other distinct social groups in social networks
- *micro process:* search for personal identity
- *idea:* modify the "seceder model" [Dittrich *et al.*, Phys. Rev. Lett. **84** (2000), 3205–3208] to a network model

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the seceder model

- N individuals with a real number $s(i)$ representing the traits of i
- Select three individuals i_1, i_2 and i_3 randomly.
- Pick the one of these $\hat{i}$ whose s-value is furthest from the average $[s(i_1) + s(i_2) + s(i_3)]/3$.
- Replace the s-value of a random agent j with $s(\hat{i}) + \eta$, where η is a random number from the normal distribution $N(0, 1)$.

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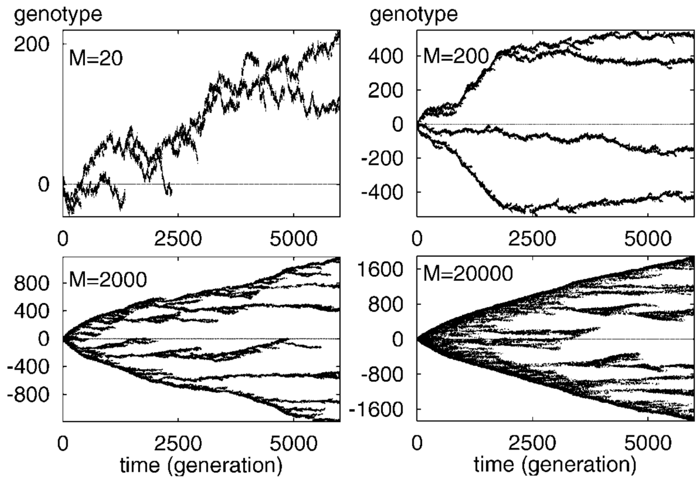
time evolution



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- Select three random (but distinct) vertices i_1, i_2 and i_3.
- Pick the one of these with highest eccentricity $\hat{i}$ (or, if the graph is disconnected, the member of the smallest group with highest eccentricity).
- Pick another random vertex j in $V \setminus \{\hat{i}\}$. Rewire as many of j's edges as possible to $\hat{i}$.
- Go through all j's edges once more and, with a probability p, rewire these to random others.

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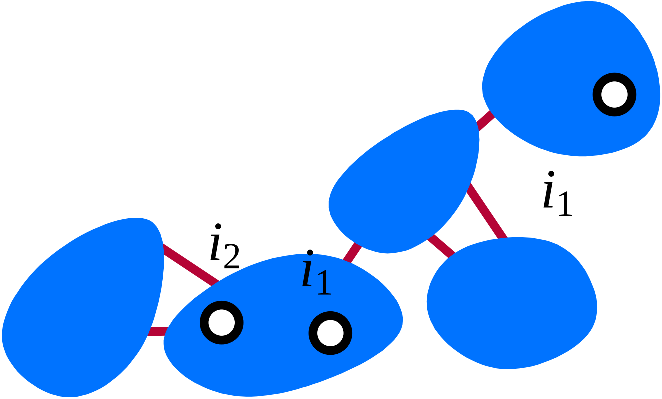
sketch



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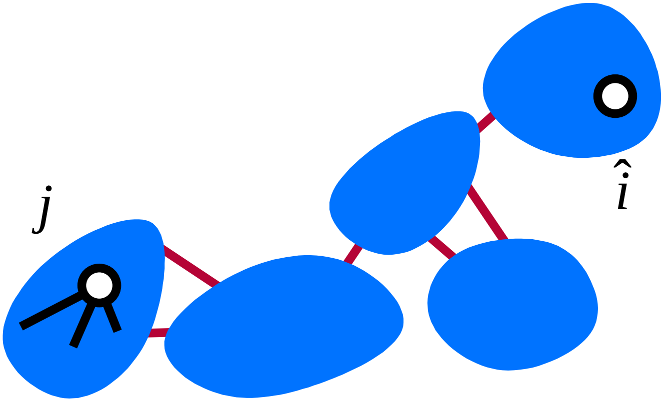

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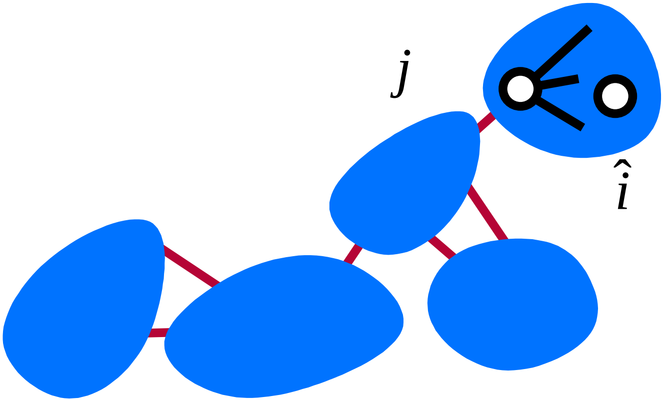

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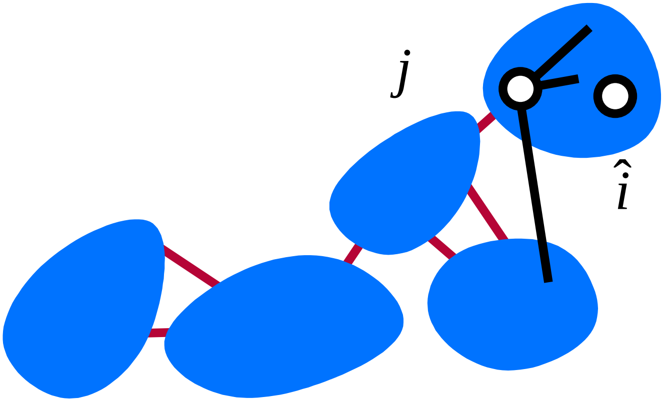
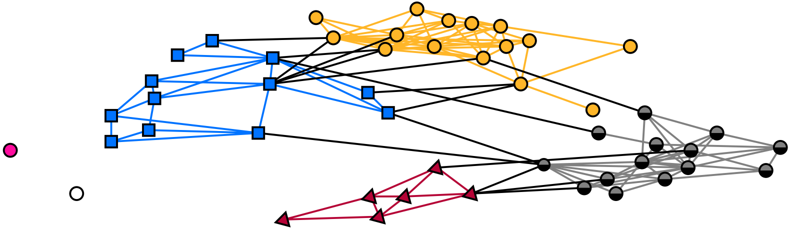
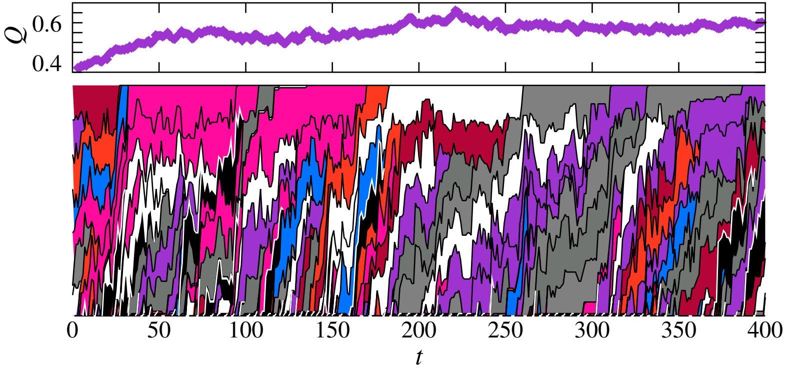


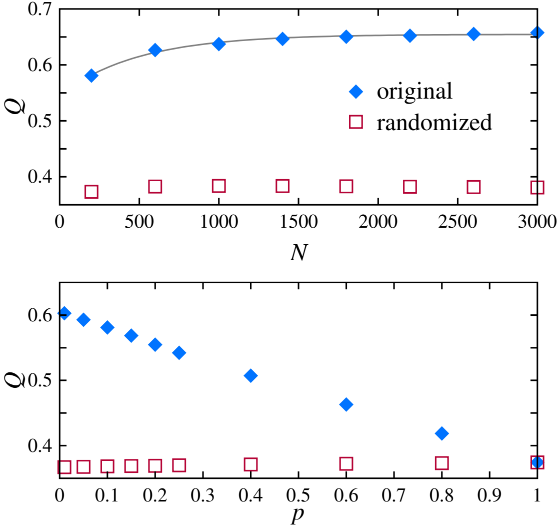
output: example network



output: time evolution



output: parameter dependence



summary

- Grönlund & Holme, Phys. Rev. E **70**, 036108 (2004)
- group formation (the desired qualitative behavior) occurs
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the idea

- to start with documented principles and derive a model for the dynamics of youth subcultures
- turn these observations into a mechanistic model

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precepts

- an adolescent belongs to one subculture at a time
- threshold behavior: if the fraction of friends that have adopted a certain subculture is big enough then an adolescent will adopt that subculture too
- the attractiveness of a subculture decreases with its age
- there is a certain resistance to changing subcultures
- the dynamics of the underlying social network is negligible

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model definition: attractiveness

attractiveness

$$s_c(t,i) = \frac{k}{k_i}\, n_i(c)\, \frac{t(c)-t(c_i)}{t-t(c_i)}$$

- where $t(c)$ is the age of c
- $k = 2M/N$ is the average degree
- k_i is the degree of i
- $n_i(c)$, the number of neighbors of i with the identity c

model definition: iterations

- For every vertex i (chosen sequentially) calculate the score $s_c(t, i)$ of all subcultures c.
- Go through the vertex set sequentially once again. If the score is higher than a threshold T for some identity c, then i change its identity to c. If more than one subculture has a score above the threshold then the individual adopts the subculture with the highest score.
- With a probability R a new identity is assigned to a vertex. (On average, NR fads are introduced per time step.)

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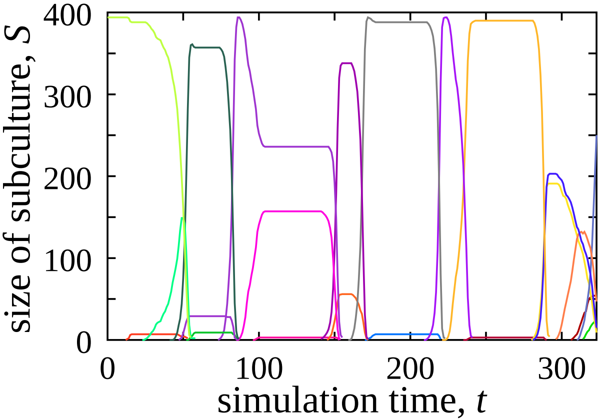

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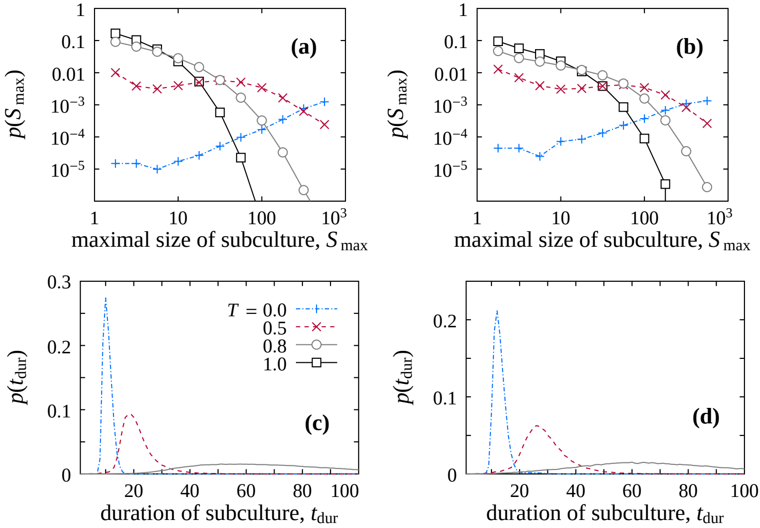

summary

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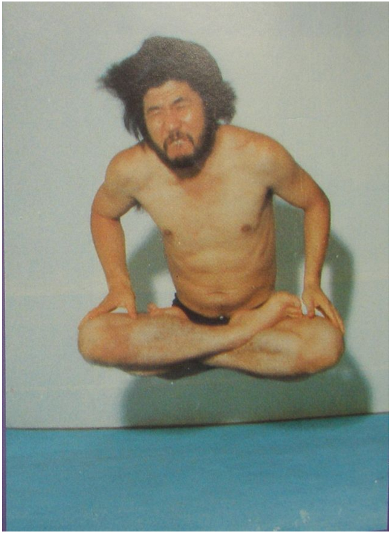

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P. Holme & M. E. J. Newman, Phys. Rev. E **74**, 056108 (2006).

- 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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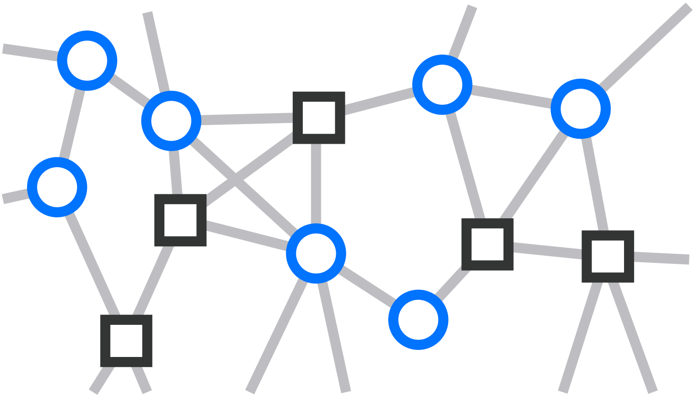

Clifford & Sudbury, Biometrika **60**, 581 (1973).
Holley & Liggett, Ann. Probab. **3**, 643 (1975).

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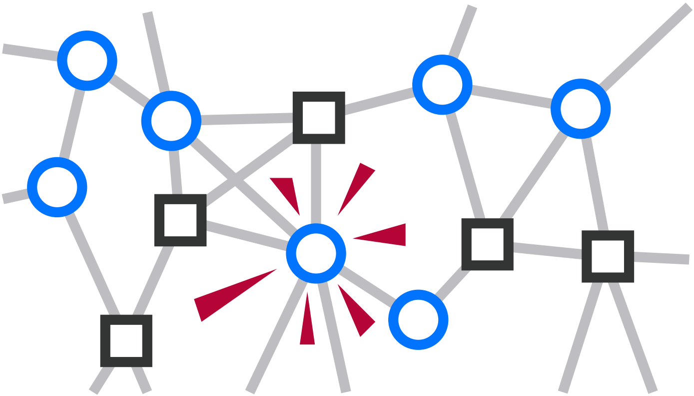

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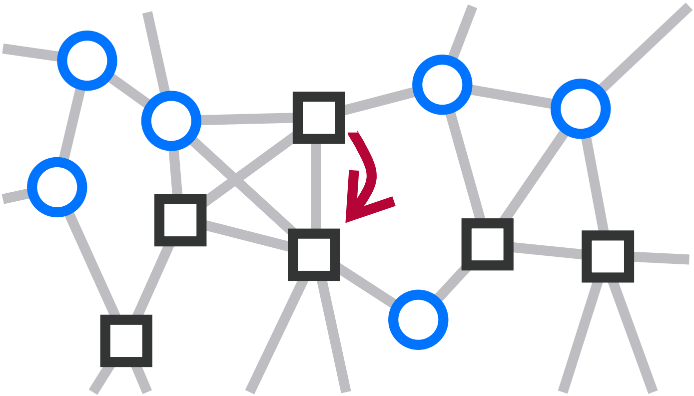

copy the opinion of a random neighbor

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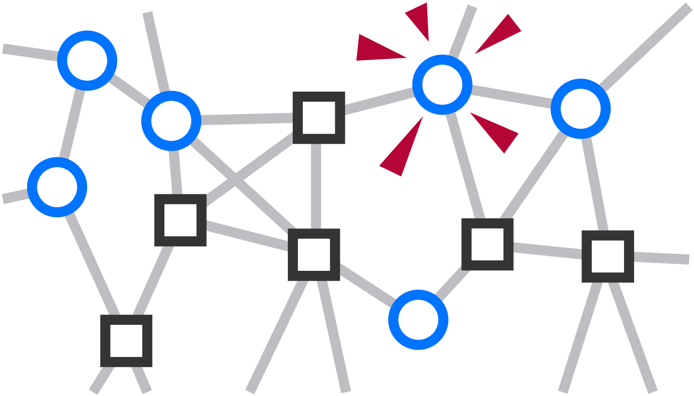

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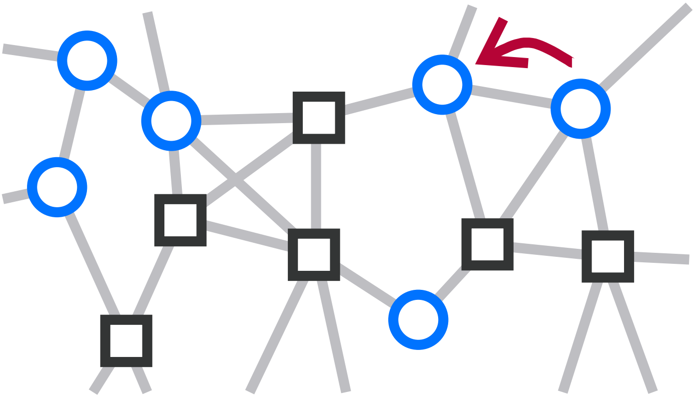

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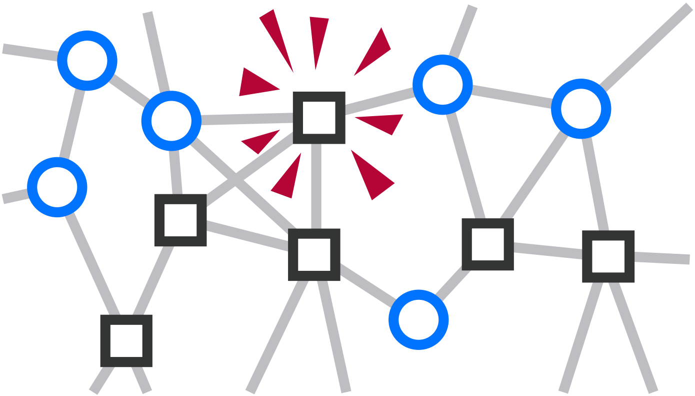

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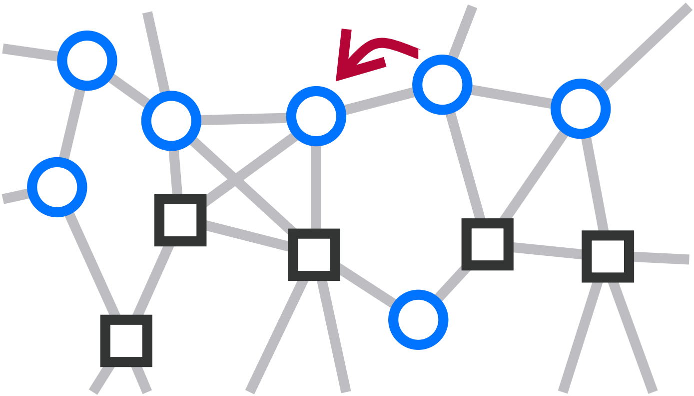

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acquaintance dynamics: precepts

- People of similar interests are likely to get acquainted.
- The number of edges is constant.

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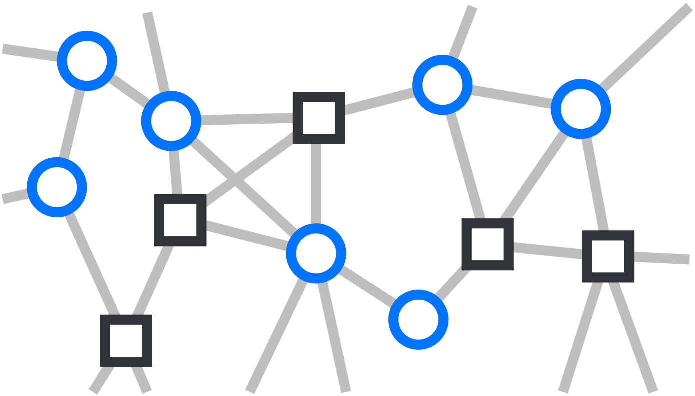

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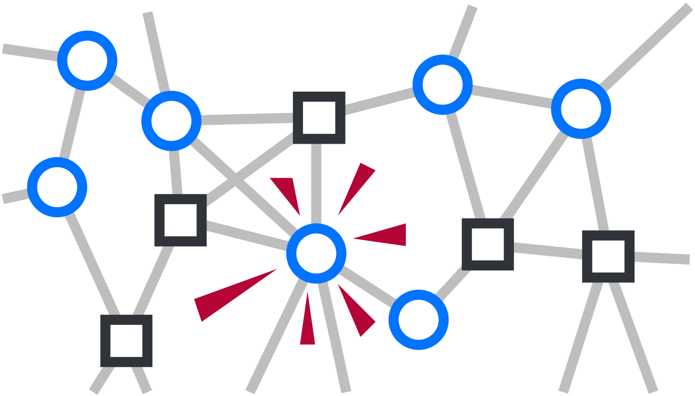

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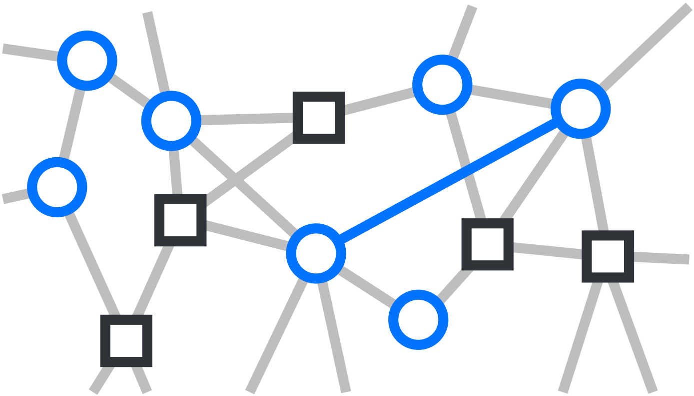
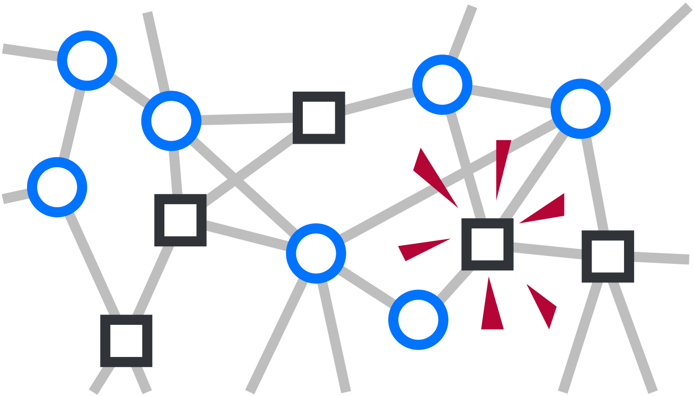


rewire an edge to a vertex w same opinion

acquaintance dynamics



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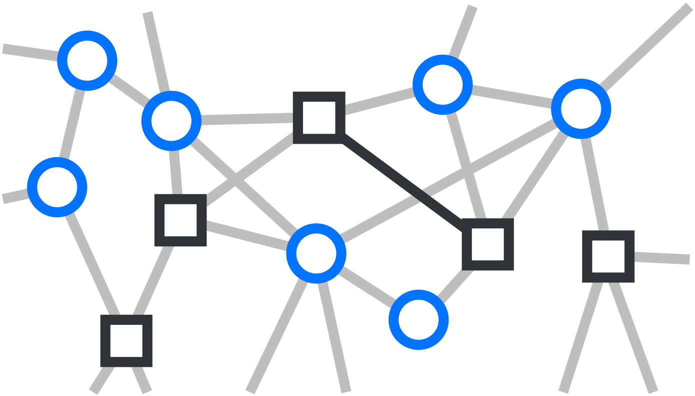

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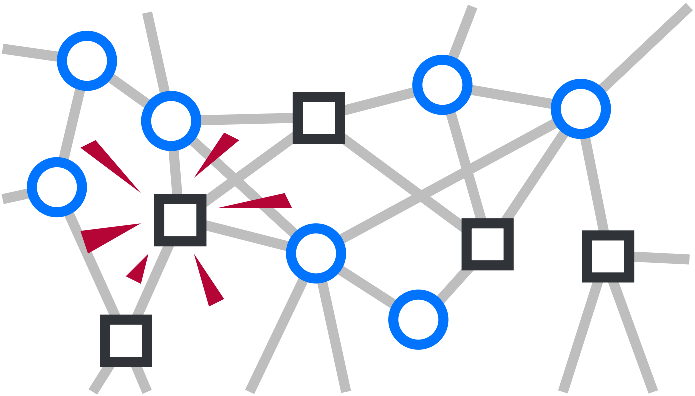

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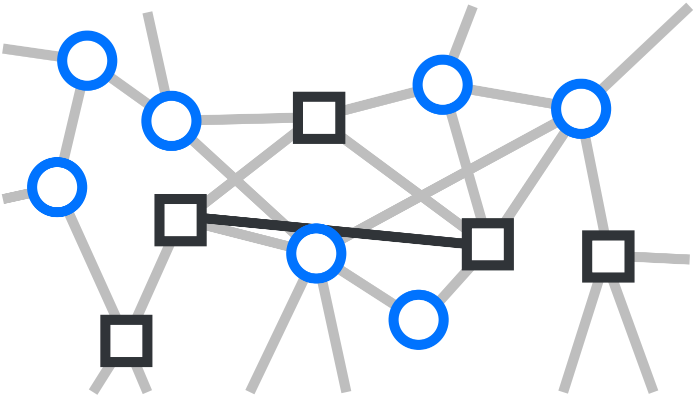

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model definition

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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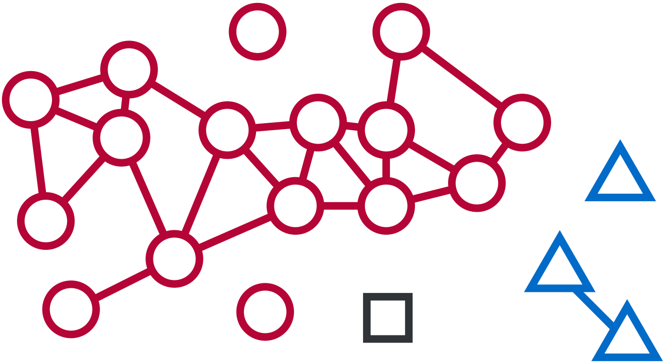
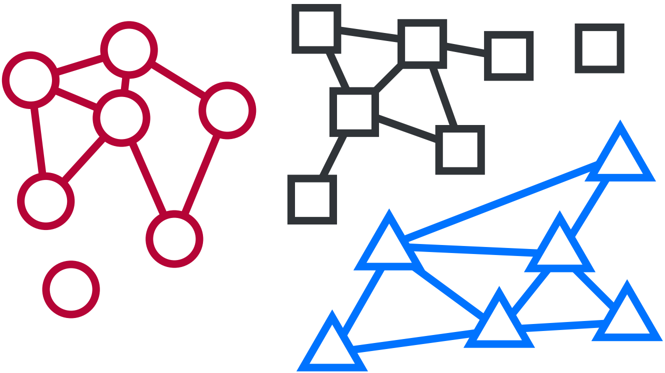


low ϕ—one dominant cluster

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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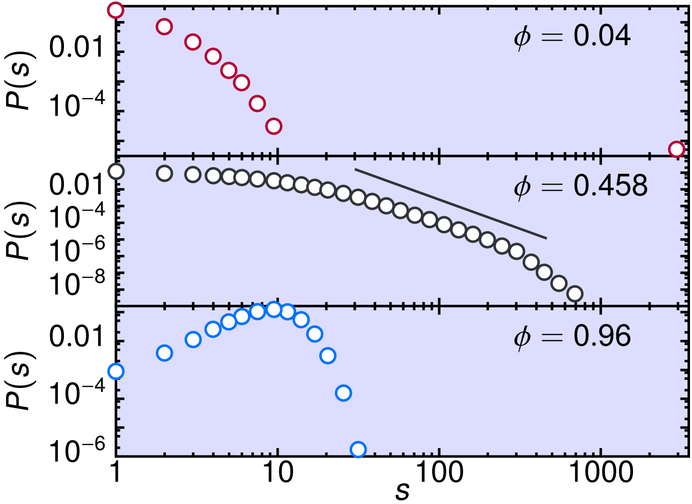
cluster size distribution



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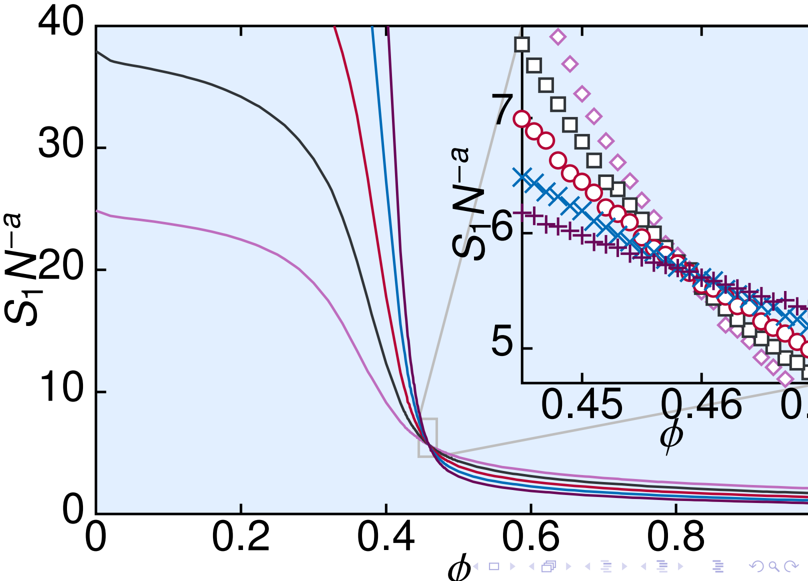
finding the phase transition

Assume a critical scaling form:

scaling form

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

finding the phase transition



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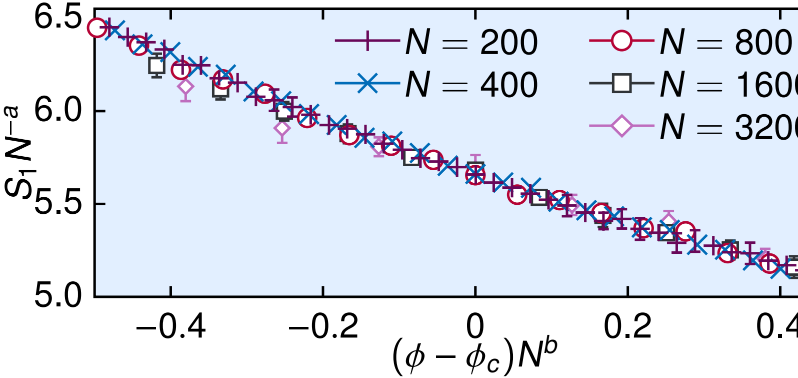

$a = 0.61 \pm 0.05$, $\phi_c = 0.458 \pm 0.008$, $b = 0.7 \pm 0.1$

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

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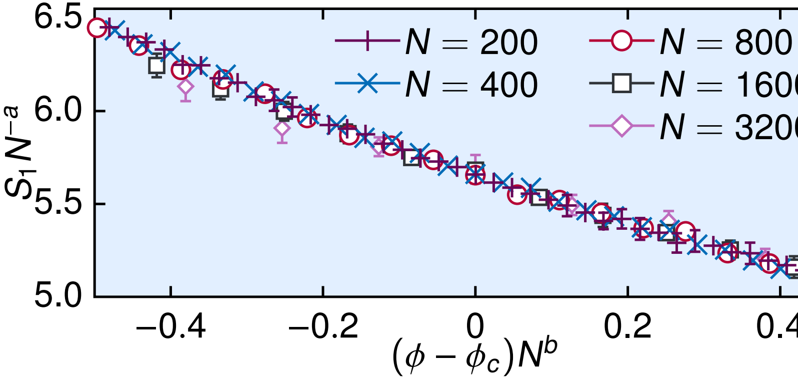

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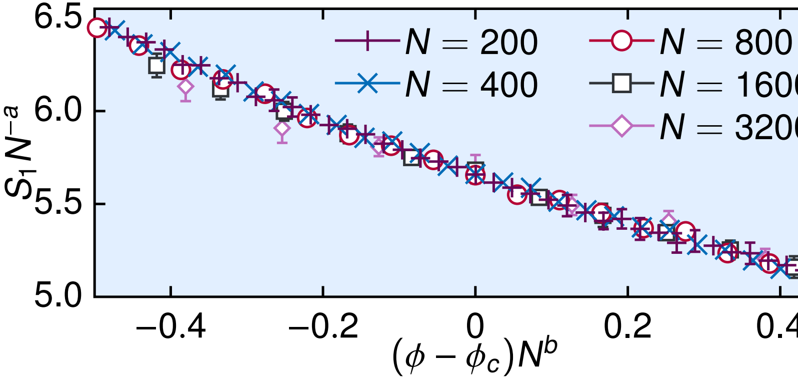

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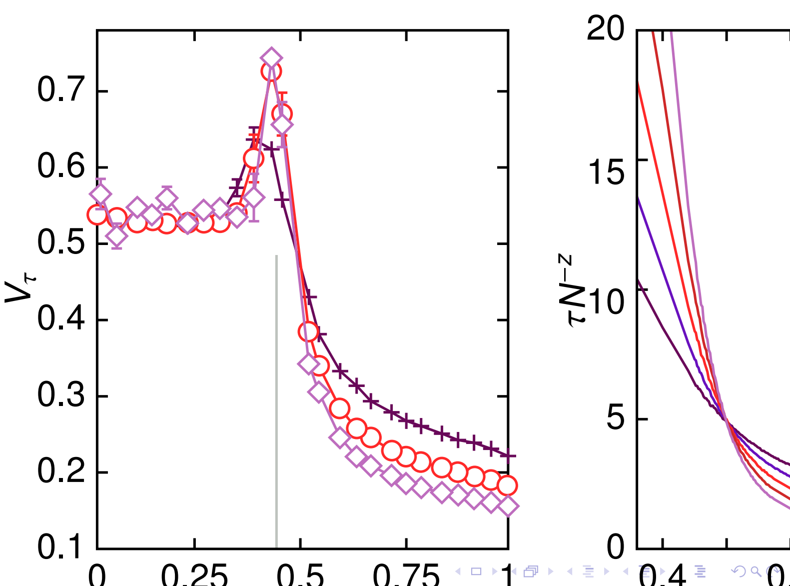
dynamic critical behavior



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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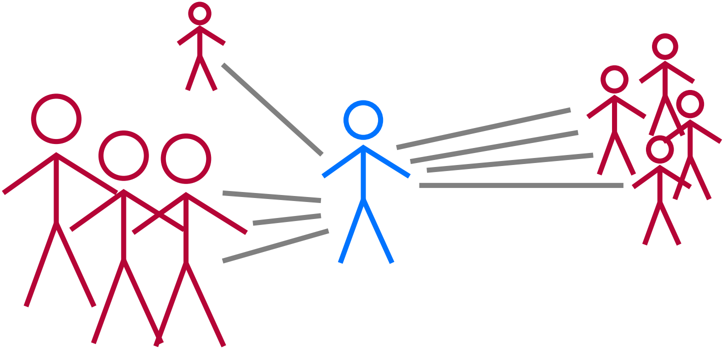
motivation

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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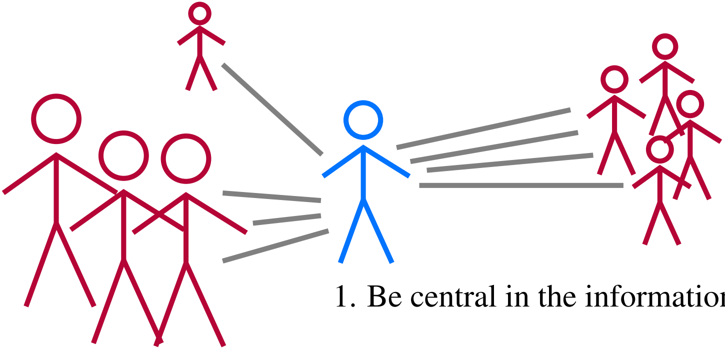

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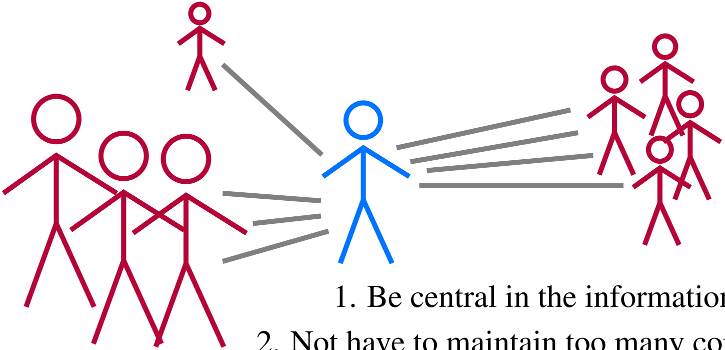

1. Be central in the information flow.
2. Not have to maintain too many contacts.

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

the object system

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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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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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- we also assume the score and degree of a vertex is known

- let the agents use a genetic algorithm to develop attachment / deletion strategies
- drive the system with noise

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time evolution

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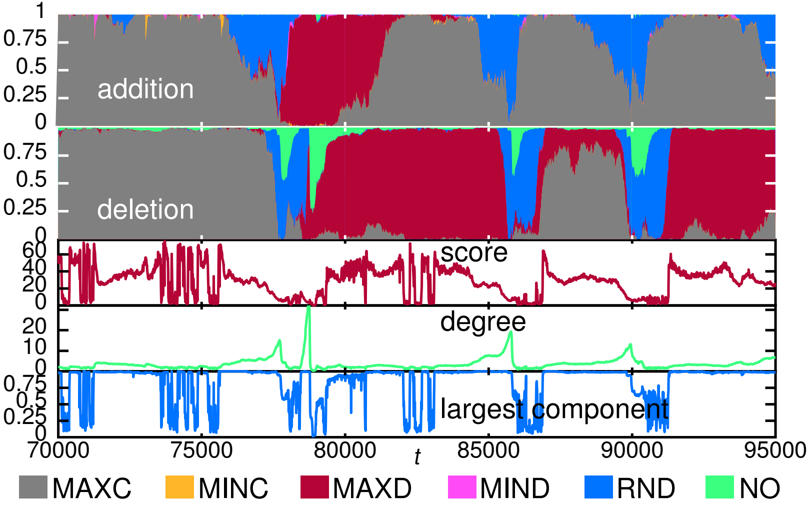
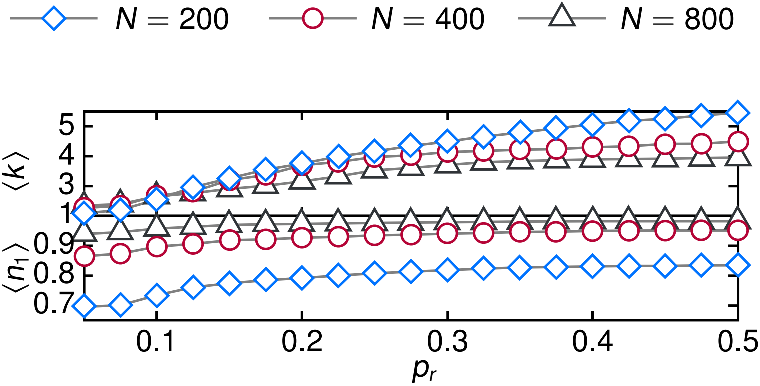


effect of random moves: degree & cluster size



conclusions

- 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
- The NO/NO strategy is not stable—Red Queen.
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