Co-evolution of networks and opinions

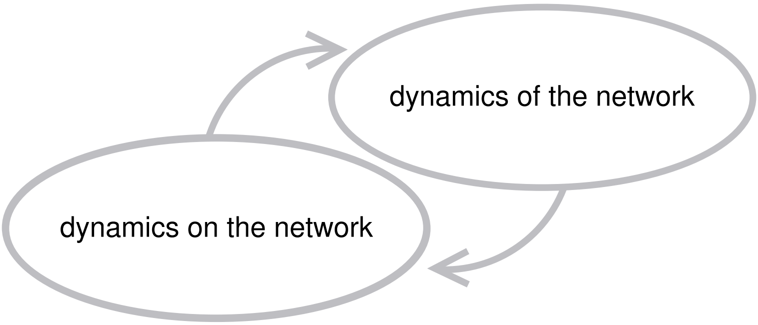
Petter Holme

KTH, CSC, Computational Biology

November 4, 2008, DIMACS

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

outline



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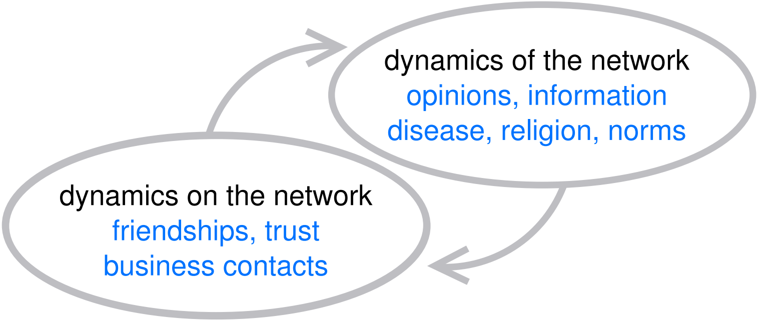
dynamics of the network
opinions, information
disease, religion, norms
dynamics on the network
friendships, trust
business contacts

outline

- phase transitions in social systems?
- our models
- verify empirically / experimentally
- what can we learn?

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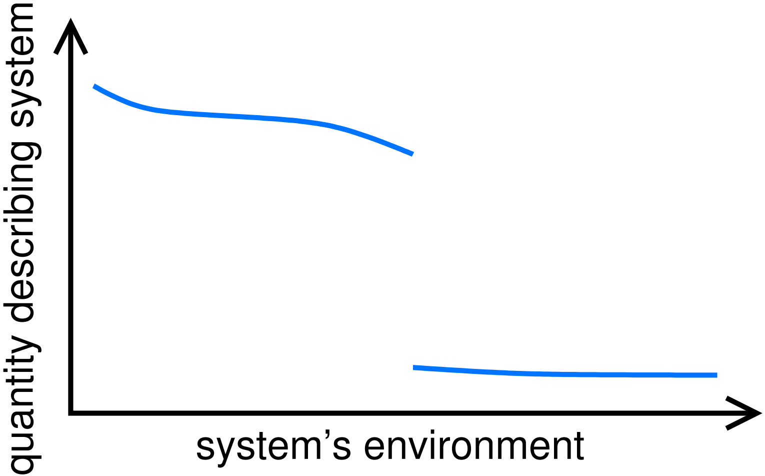
phase transitions



. . . in social systems?

- quantities describing the system — census statistics, election results, . . .
- parameters describing the environment (should be "the same" for all the agents) — gas price, . . .
- does social systems fit this framework?
- phase transitions can be categorized by their "critical exponents", which depends only on symmetries in the system (not boundary conditions, dynamic properties, etc.)

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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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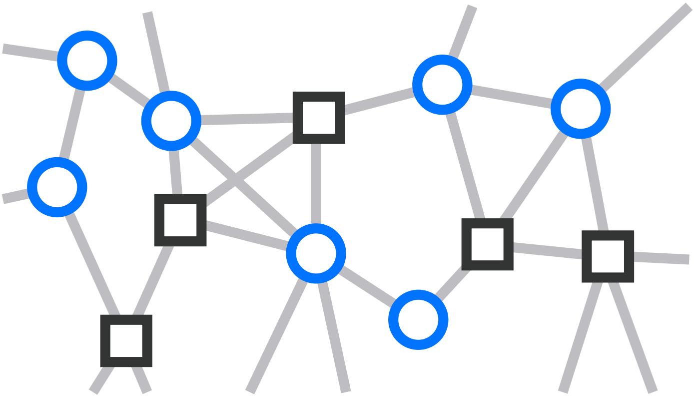
the voter model



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

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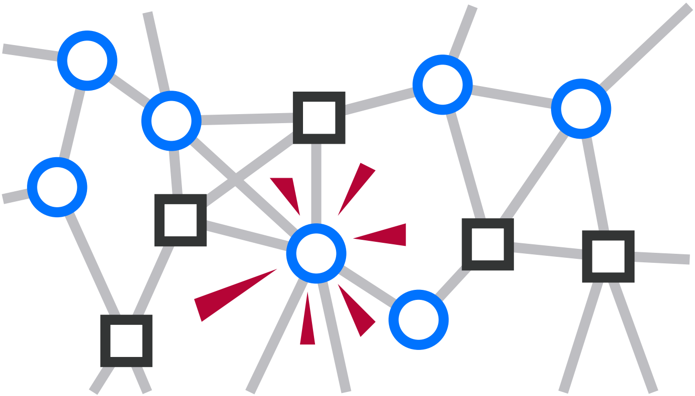
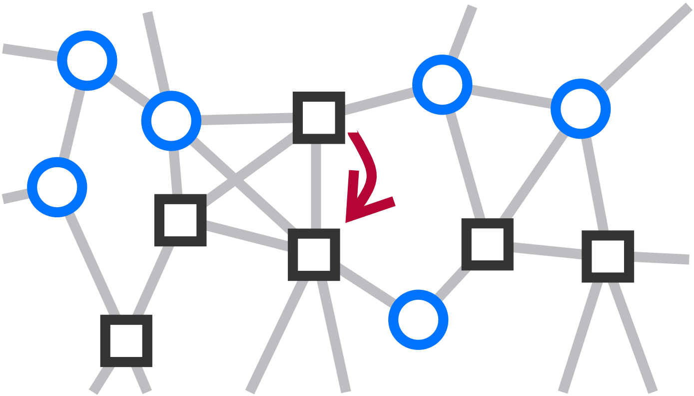


choose one vertex randomly

the voter model



copy the opinion of a random neighbor

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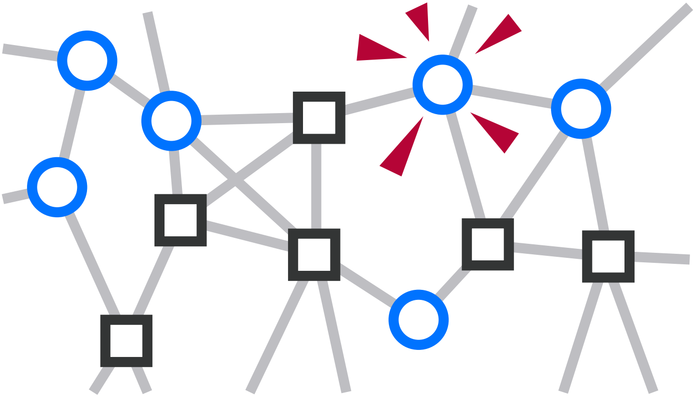

and so on . . .

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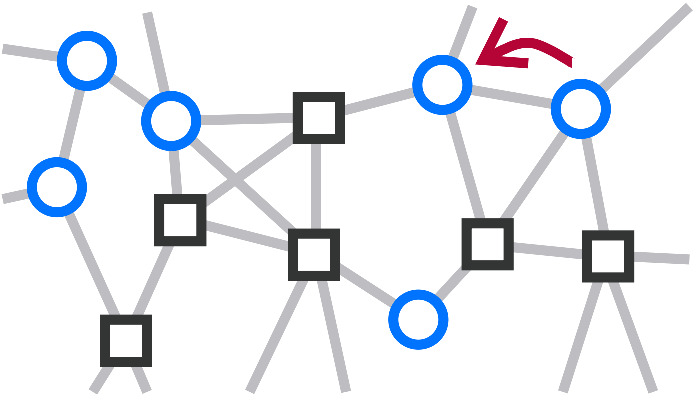

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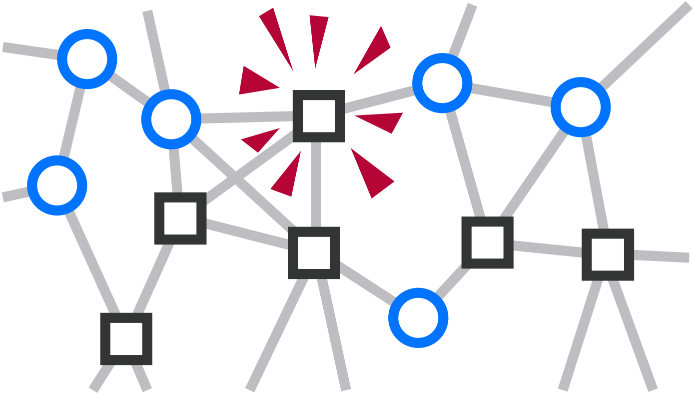

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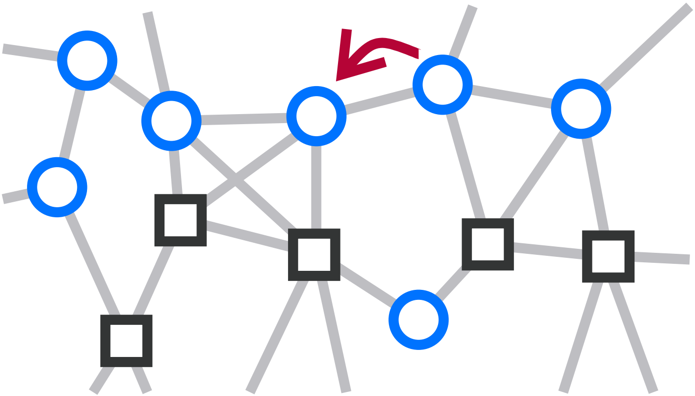

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acquaintance dynamics: precepts

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

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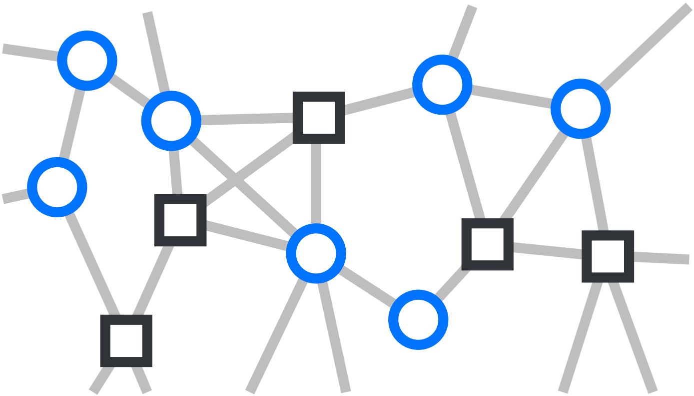

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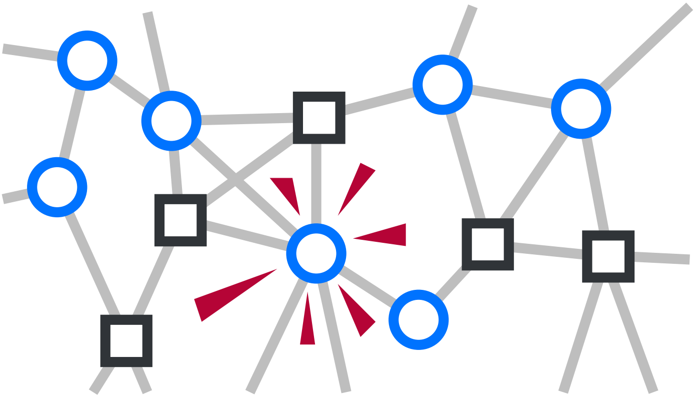

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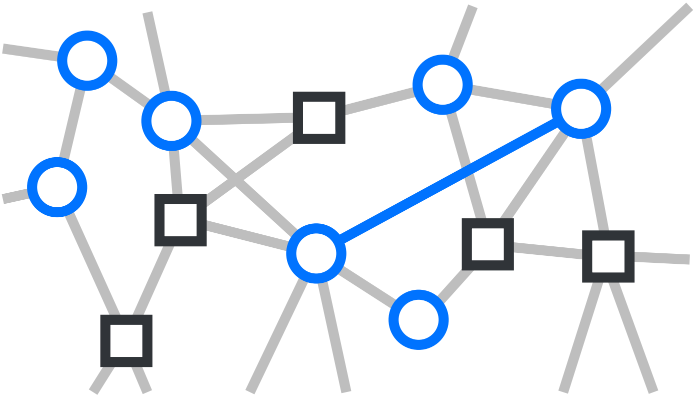
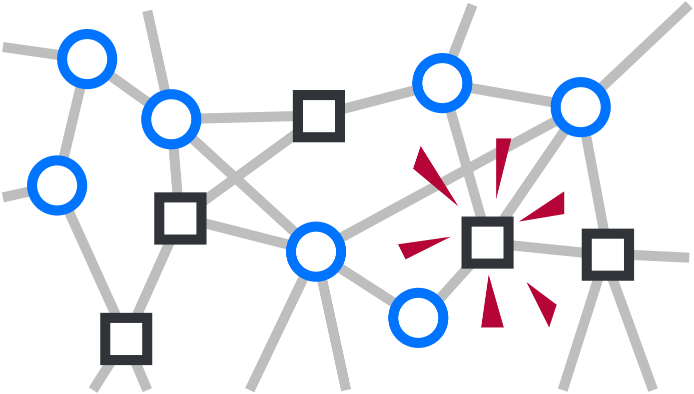
acquaintance dynamics



rewire an edge to a vertex w same opinion

acquaintance dynamics



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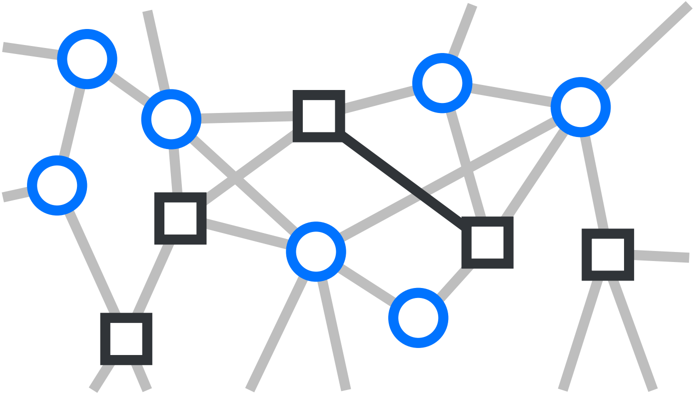

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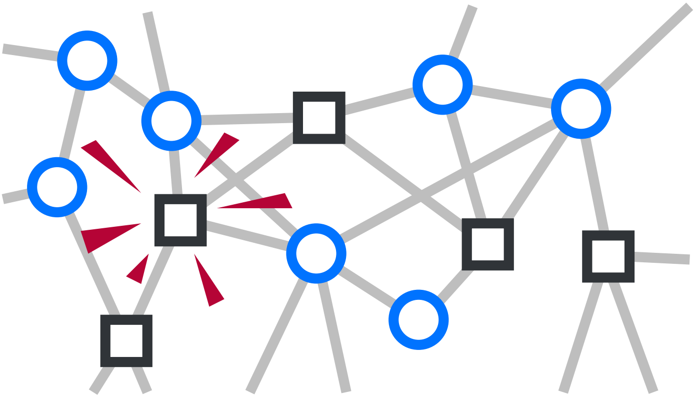

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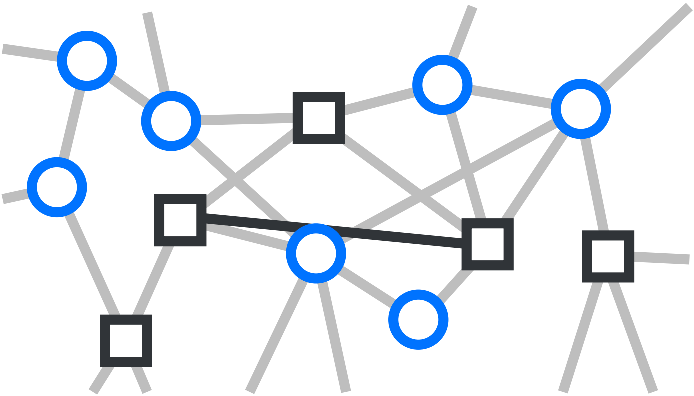

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model definition

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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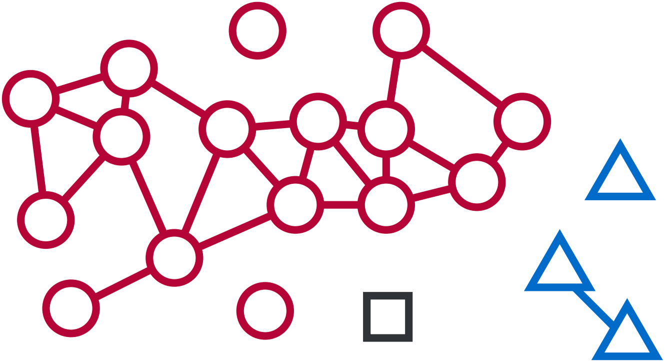
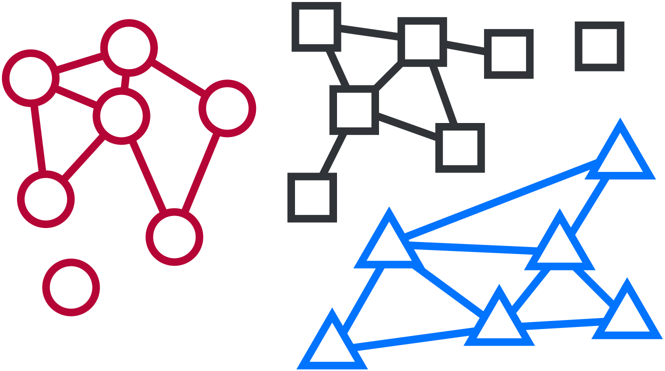
phases



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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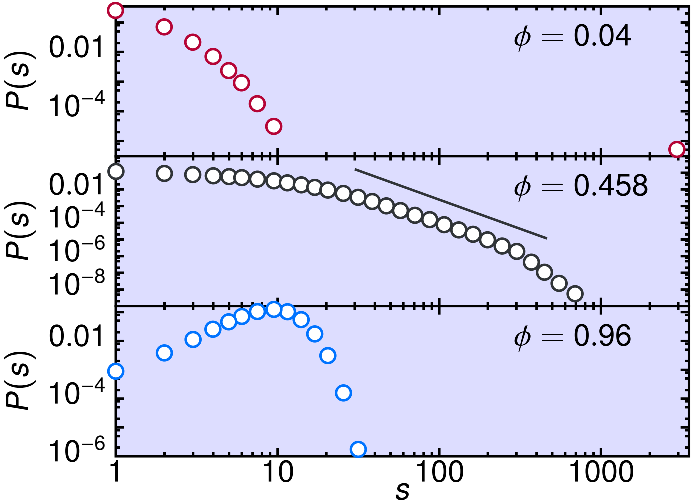
cluster size distribution



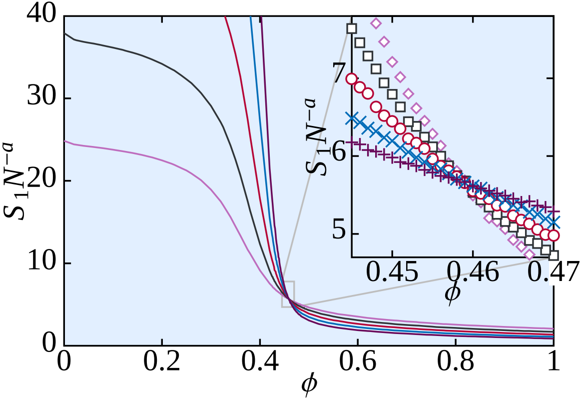
finding the phase transition

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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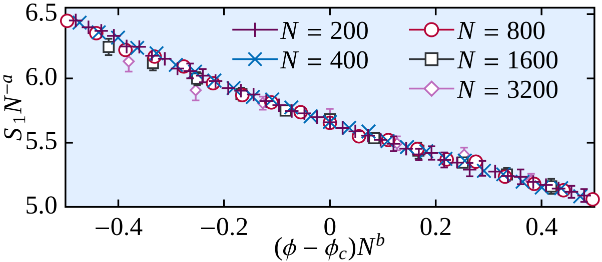
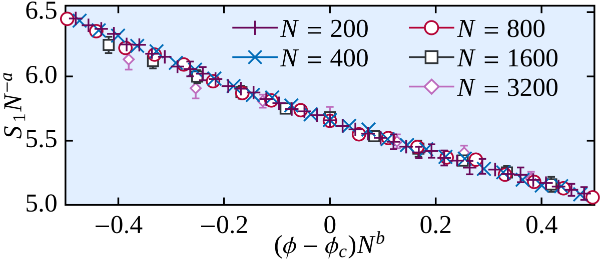


$a = 0.61 \pm 0.05$, $\phi_c = 0.458 \pm 0.008$, $b = 0.7 \pm 0.1$

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

finding the phase transition



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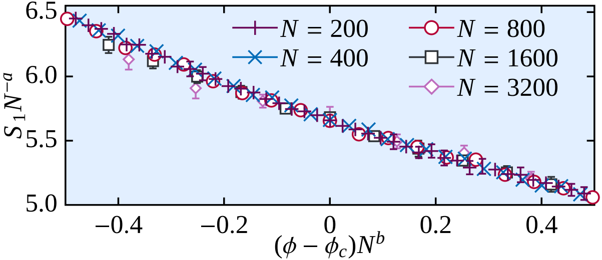

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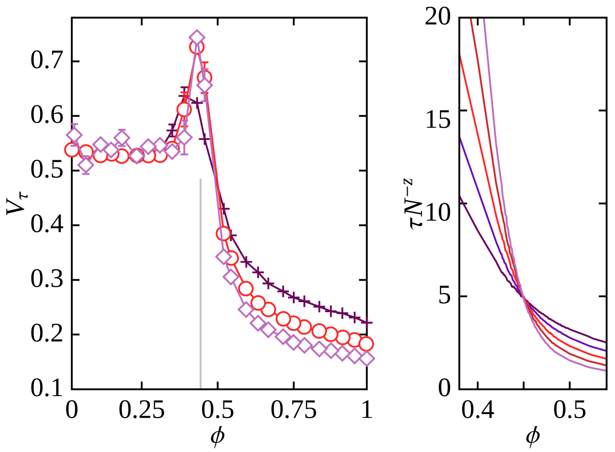
dynamic critical behavior



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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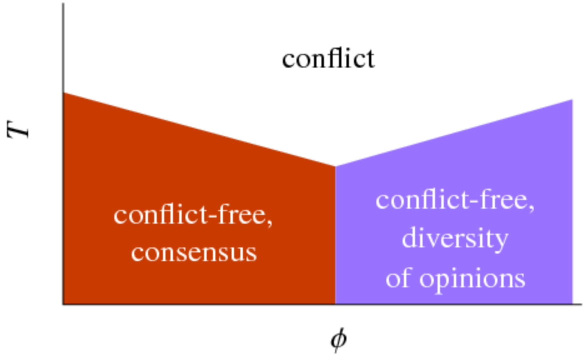

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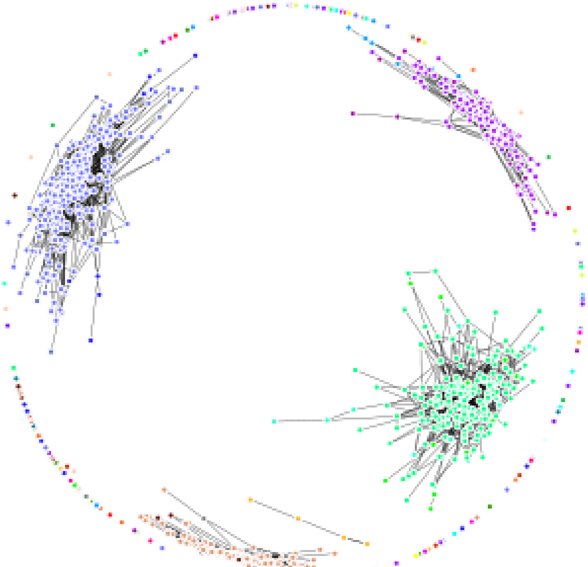

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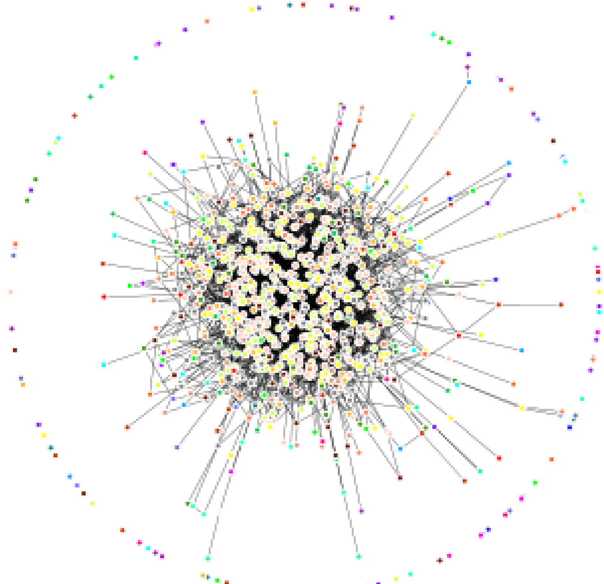

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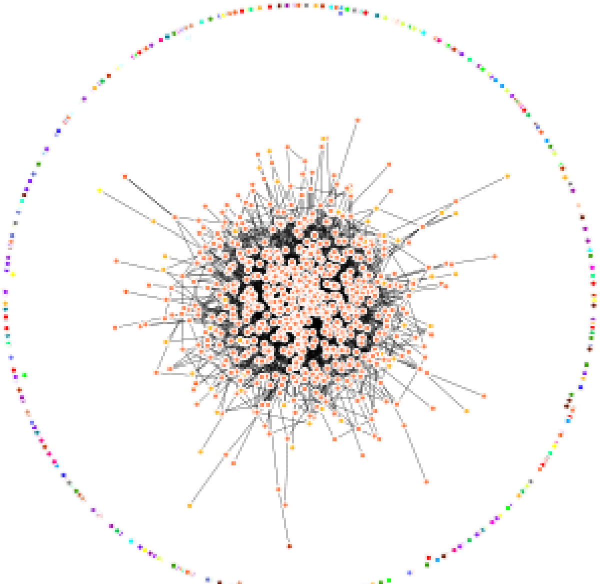
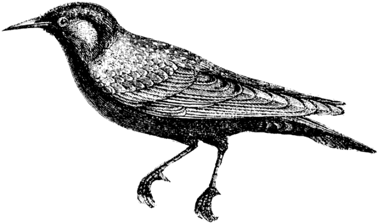
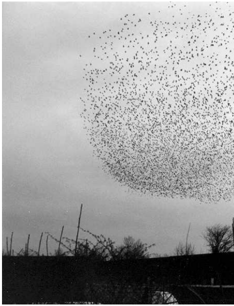


methodology of mechanistic models





model capturing
behavior of the individual

macroscop
consis

thank you!

Mark Newman
Zhi-Xi Wu

Gourab Ghoshal
Andreas Grönlund
Luís Enrique Correa da Rocha
Fredrik Liljeros