Co-evolution of networks and opinions

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http://www.csc.kth.se/~pholme/
Co-evolution of networks and opinions

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Phase transitions in social systems?

Co-evolution of networks and opinions

Validation

Outline

dynamics of the network

dynamics on the network
Co-evolution of networks and opinions

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phase transitions in social systems?

coevolution of networks and opinions

validation

outline

dynamics on the network
friendships, trust
business contacts

dynamics of the network
opinions, information
disease, religion, norms
outline

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

our models

verify empirically / experimentally

what can we learn?
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phase transitions

quantity describing system

system’s environment
... 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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the idea


- 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

choose one vertex randomly
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The voter model

copy the opinion of a random neighbor
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the voter model

and so on . . .
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Validation of the voter model

phase transitions in social systems?

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and so on . . .
acquaintance dynamics: precepts

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

- People of similar interests are likely to get acquainted.
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validation
choose one vertex randomly
acquaintance dynamics

rewire an edge to a vertex w same opinion
acquaintance dynamics

and so on . . .
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Validation

and so on . . .
acquaintance dynamics

and so on . . .
Start with a random network of $N$ vertices $M = \bar{k}N/2$ edges and $G = N/\gamma$ randomly assigned opinions.

Pick a vertex $i$ at random.

With a probability $\phi$ make an acquaintance formation step from $i$.

. . . otherwise make a voter model step from $i$.

If there are edges leading between vertices of different opinions—iterate from step 2.
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 $\phi$ 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.
model definition

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phases

low $\phi$—one dominant cluster
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phases

high $\phi$—clusters of similar sizes
quantities we measure

- The relative largest size $S$ of a cluster (of vertices with the same opinion).
- The average time $\tau$ to reach consensus.
quantities we measure

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Cluster size distribution

\[ P(s) \]

\[ s = 10^{-4} \]

\[ s = 10^{-6} \]

\[ s = 10^{-8} \]

\[ s = 0.01 \]

\[ \phi = 0.04 \]

\[ \phi = 0.458 \]

\[ \phi = 0.96 \]
Assume a critical scaling form:

\[
S = N^{-a} F\left( N^b (\phi - \phi_c) \right)
\]
finding the phase transition

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finding the phase transition

\[ S_1 N^{-a} = \frac{N}{N_b} \left( \frac{\phi - \phi_c}{N^b} \right) \]

\[ a = 0.61 \pm 0.05, \ \phi_c = 0.458 \pm 0.008, \ \beta = 0.7 \pm 0.1 \]

random graph percolation: \( a = b = 1/3 \)
finding the phase transition

\[ S_1 N^{-a} \]

\[ (\phi - \phi_c) N^b \]

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

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Finding the phase transition

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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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an equilibrium model
an equilibrium model
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methodology of mechanistic models

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model capturing behavior of the individual

macroscopic observations consistent with

behavior of the individual
thank you!

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