Analysis of Social Media

MLD 10-802, LTI 11-772

William Cohen

9-25-12

Administrivia

- William's office hours: **1:00-2:00 Friday** or by appointment
    - but not this week, 9/21

- Wiki access: send email to Katie Rivard (krivard@andrew)

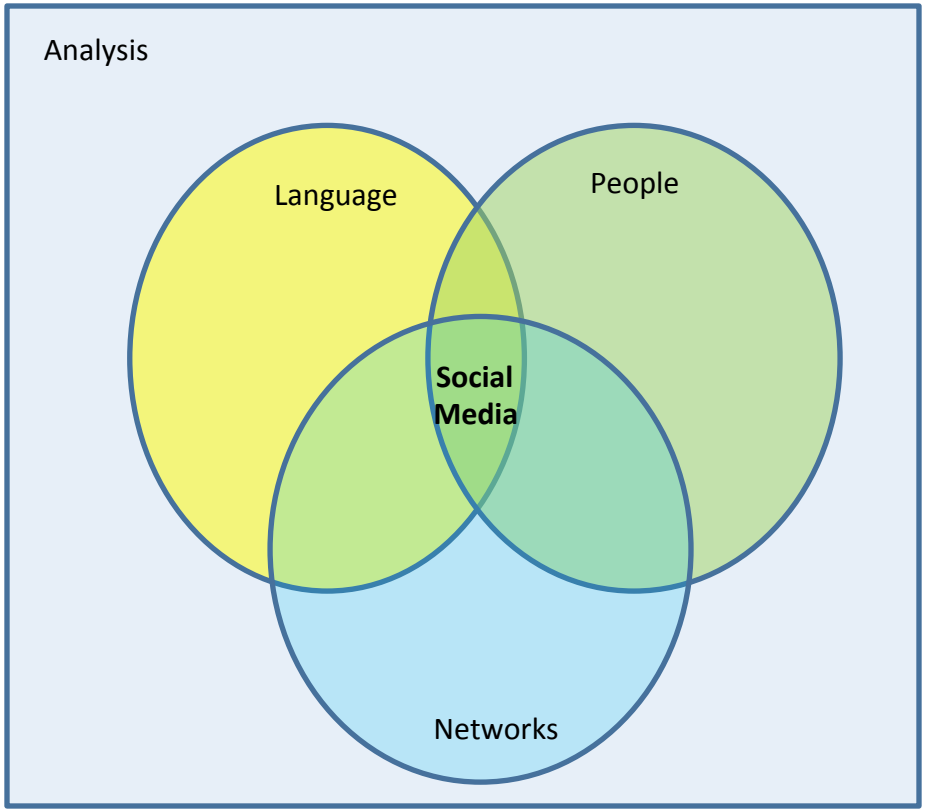
- First assignment….

Assignments

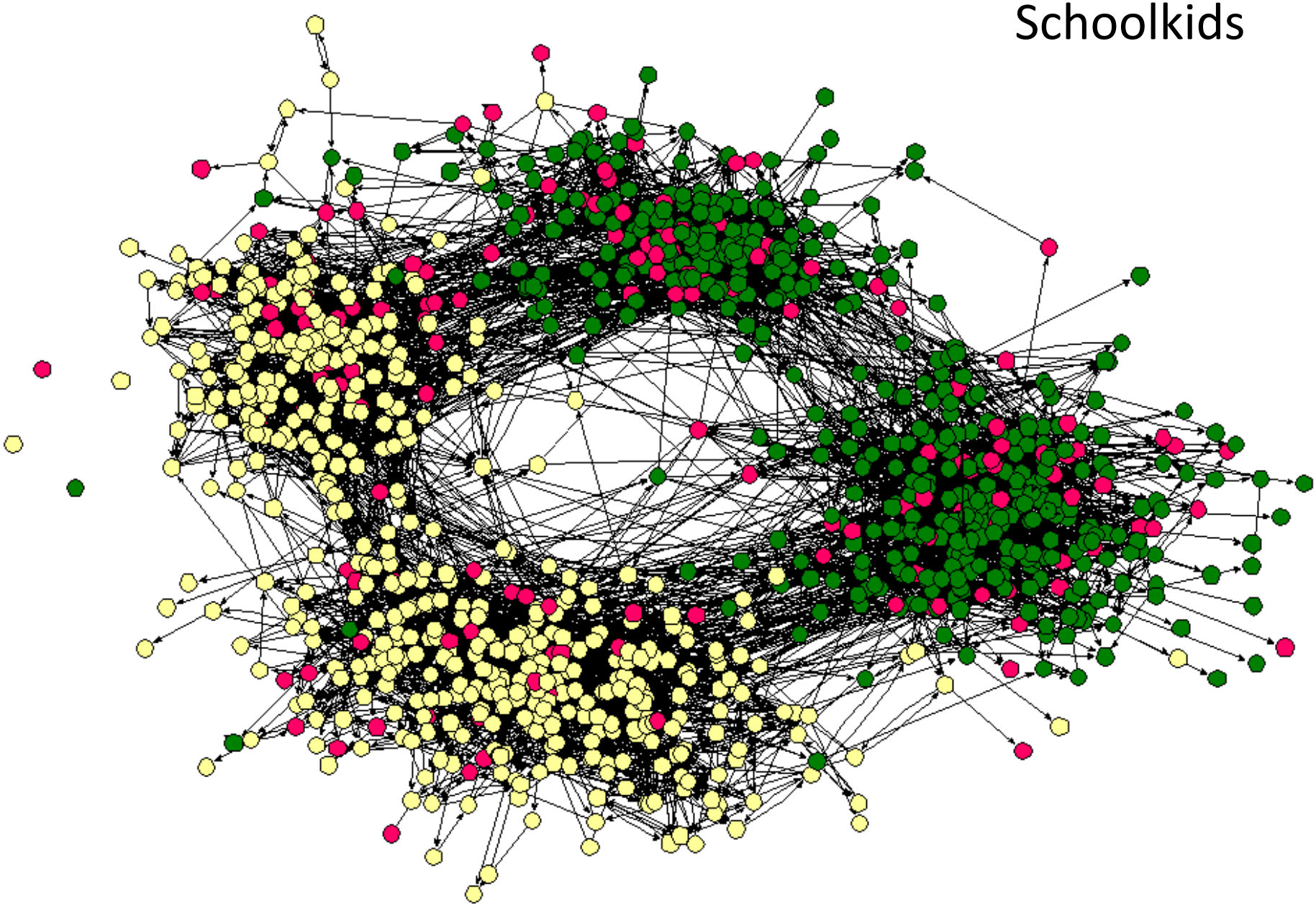
- ~~Monday 9/24, by 10am:~~ Now
  - send us 3 papers you plan to summarize
    - title, authors, ptr to on-line version
  - any not-yet-summarized papers on this years or last year's syllabus are pre-approved
    - search the wiki to make sure it's new!
    - also, don't propose papers I've presented in class
    - or, you can propose another paper I don't know about
  - you can work in groups if you like - but you still need to do 3 papers per person
    - eg if this will be a group for the project
  - hint: short papers are not necessarily easier to read
- Thus 9/27 at 10:30am:
  - first summary is due
  - structured summary + the study plan you followed
    - Example of a structured summary: http://malt.ml.cmu.edu/mw/index.php/Recent_or_influential_technical_papers_in_Analysis_of_Social_Media
    - Example of a study plan: to be posted
  - if the paper contains a novel Problem, Method, or Dataset then also add a page for it to the wiki
- Tues 10/2:
  - three summaries per student on the wiki
- Thus 10/4:
  - project proposal - first draft - one per student
  - we will allow lit review projects - more on this later
- Tues 10/9:
  - form project teams of 2-3 people

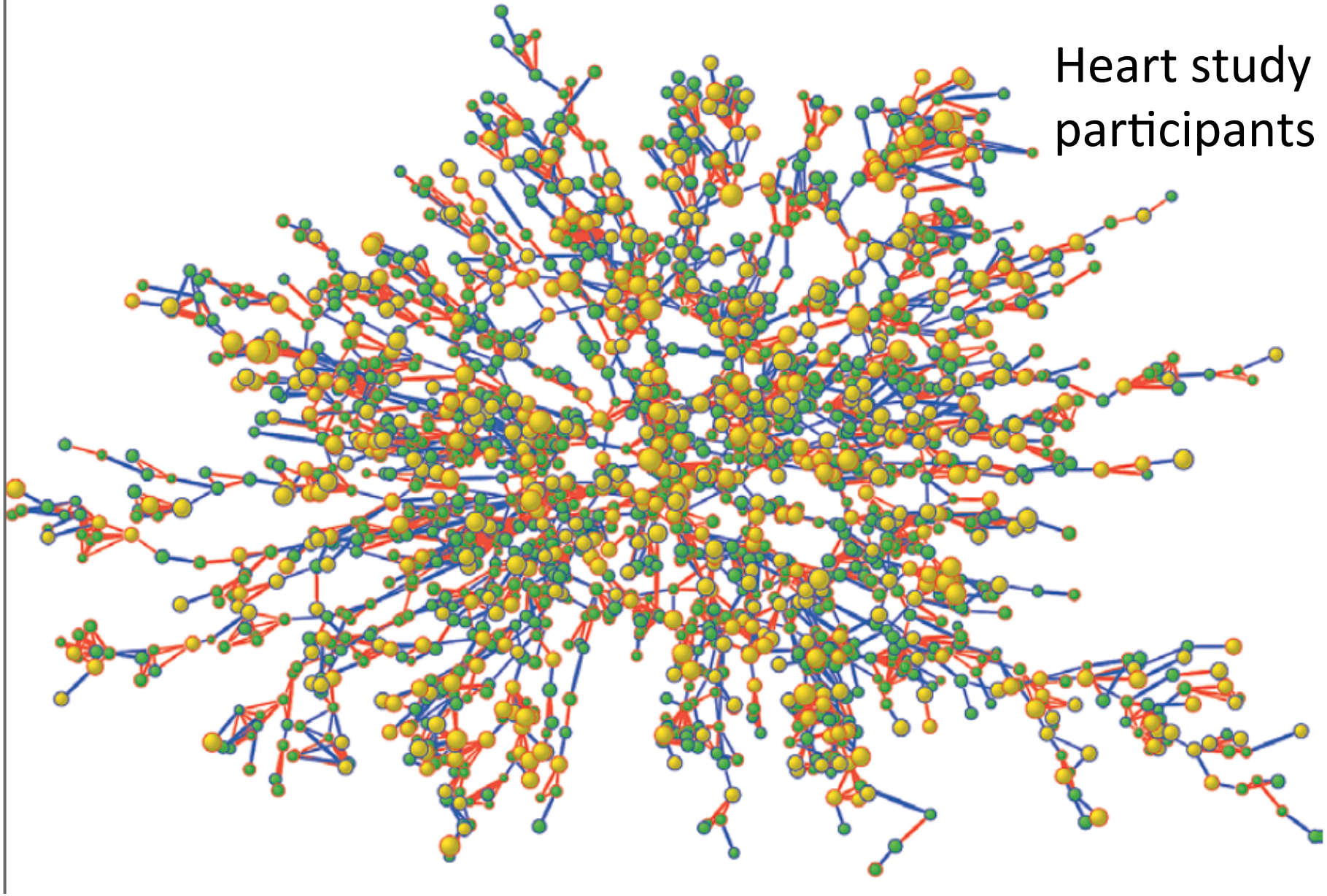
Syllabus

- 1. Background(6-8 wks, mostly me):
  - Opinion mining and sentiment analysis. Pang & Li, FnTIR 2008.
  - **Properties of social networks. Easley & Kleinberg, ch 1-5, 13-14; plus some other stuff.**
  - Stochastic graph models. Goldenberg et al, 2009.
  - Models for graphs and text. [Recent papers]

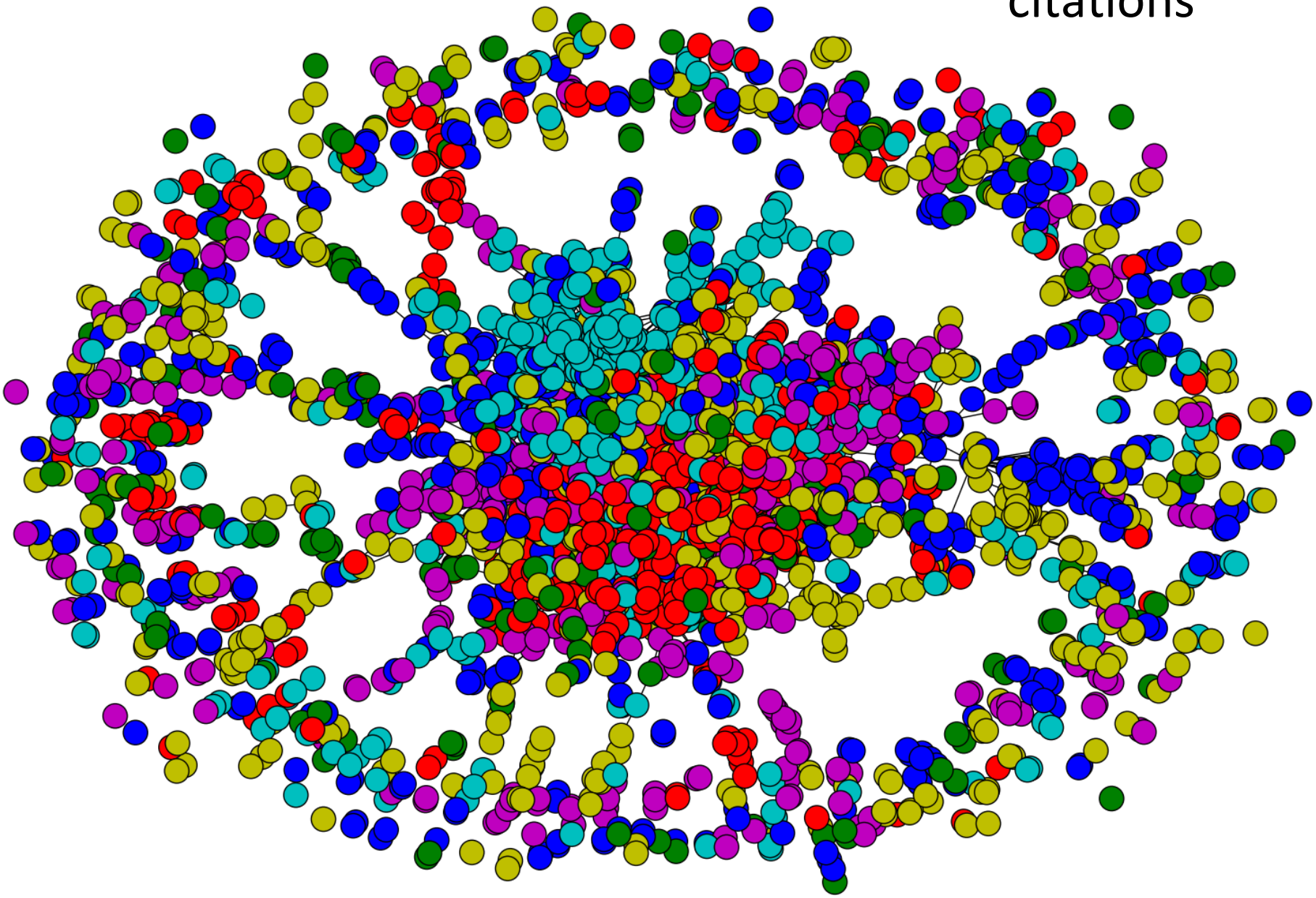


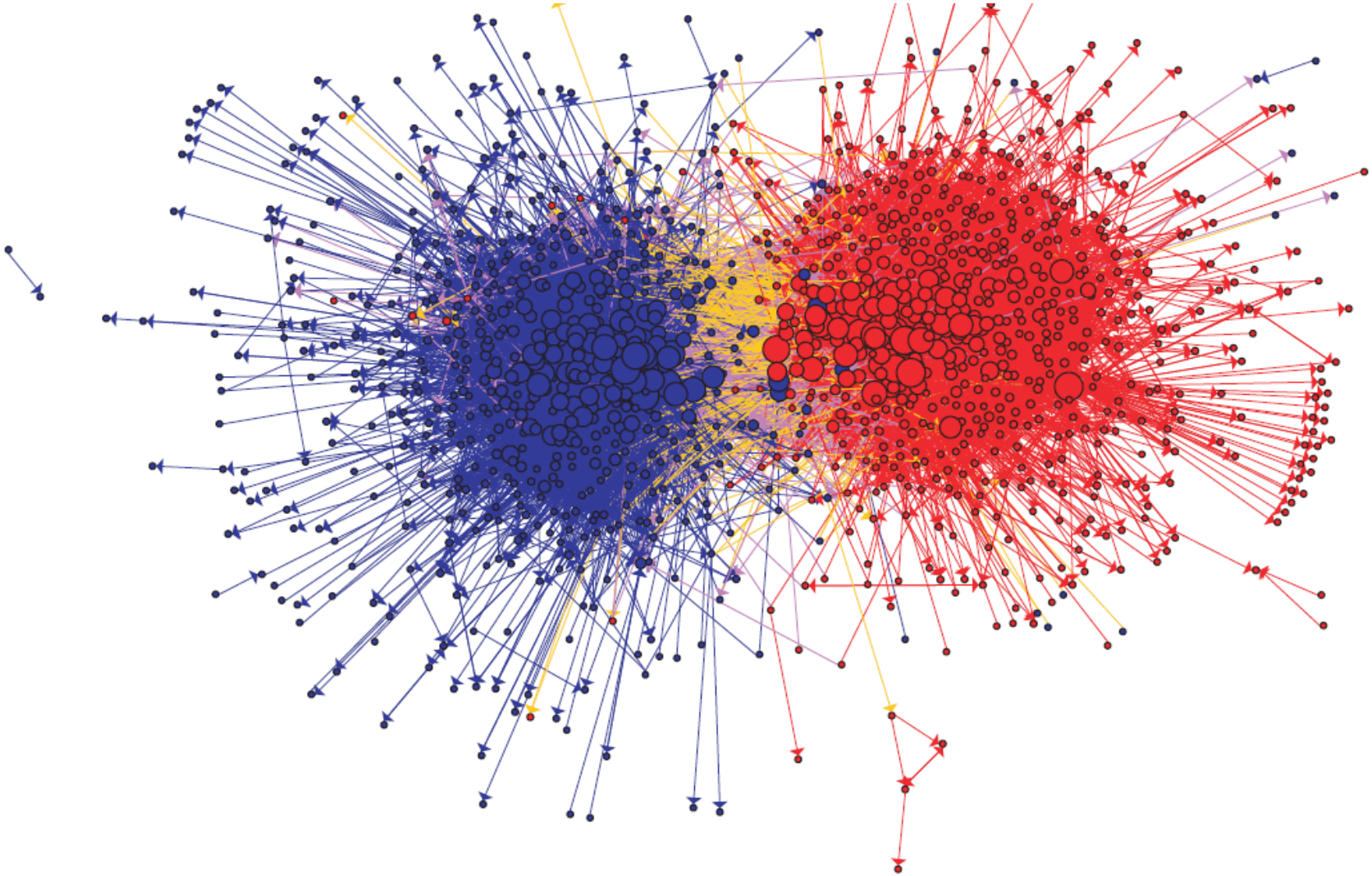
Schoolkids




Heart study
participants

citations

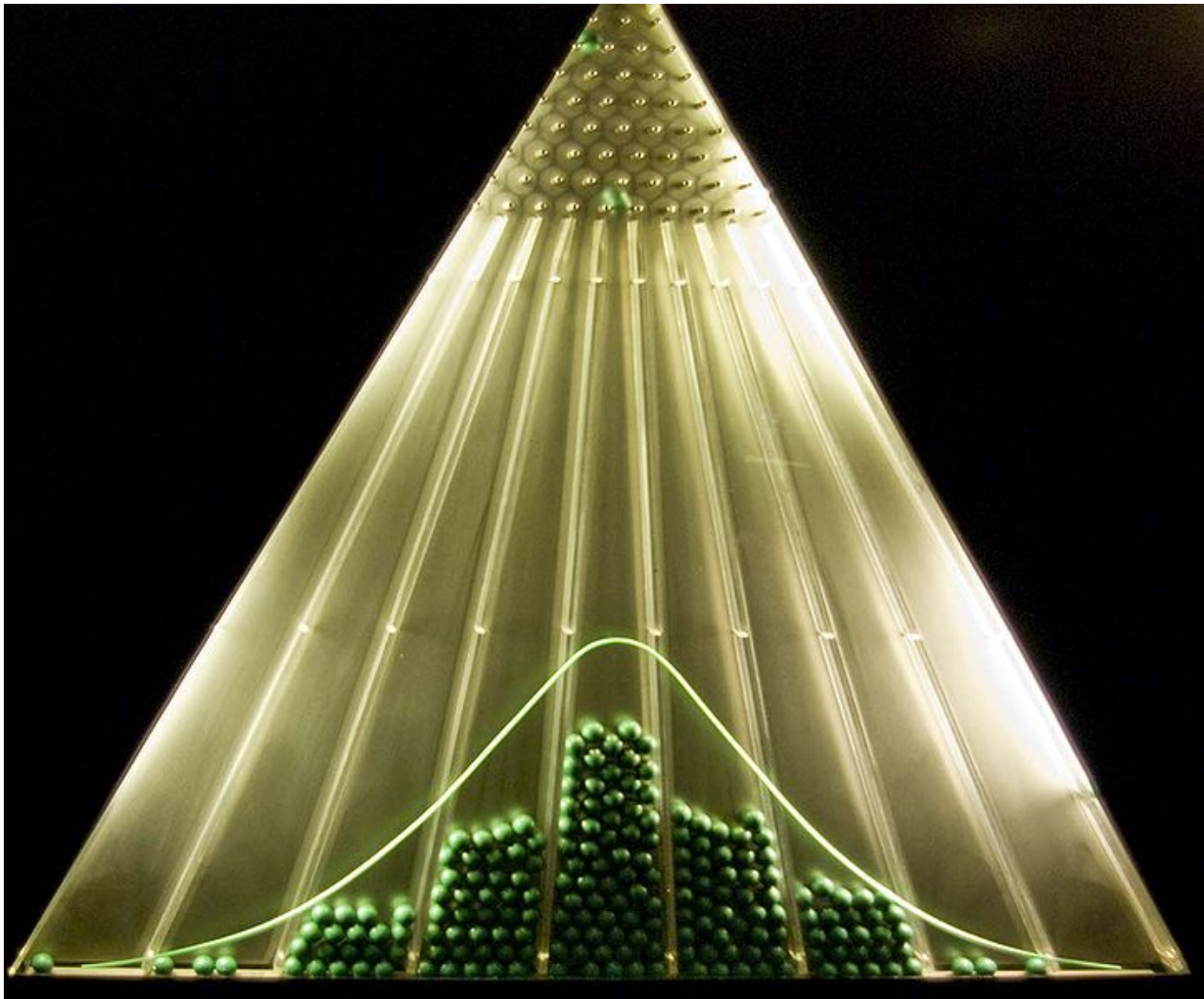




What are we trying to do?

Normal curve:

- Data to fit
- Underlying process that "explains" the data
- Closed-form parametric form $\frac{1}{\sqrt{2\pi\sigma^2}}\exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$
- Only models a small part of the data



Graphs

- Some common properties of graphs:
  - Distribution of node degrees
  - Distribution of cliques (e.g., triangles)
  - Distribution of paths
    - Diameter (max shortest-path)
    - Effective diameter (90th percentile)
    - Connected components
  - …
- Some types of graphs to consider:
  - Real graphs (social & otherwise)
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    - Erdos-Renyi "Bernoulli" or "Poisson"
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    - Barbosi-Albert "preferential attachment"
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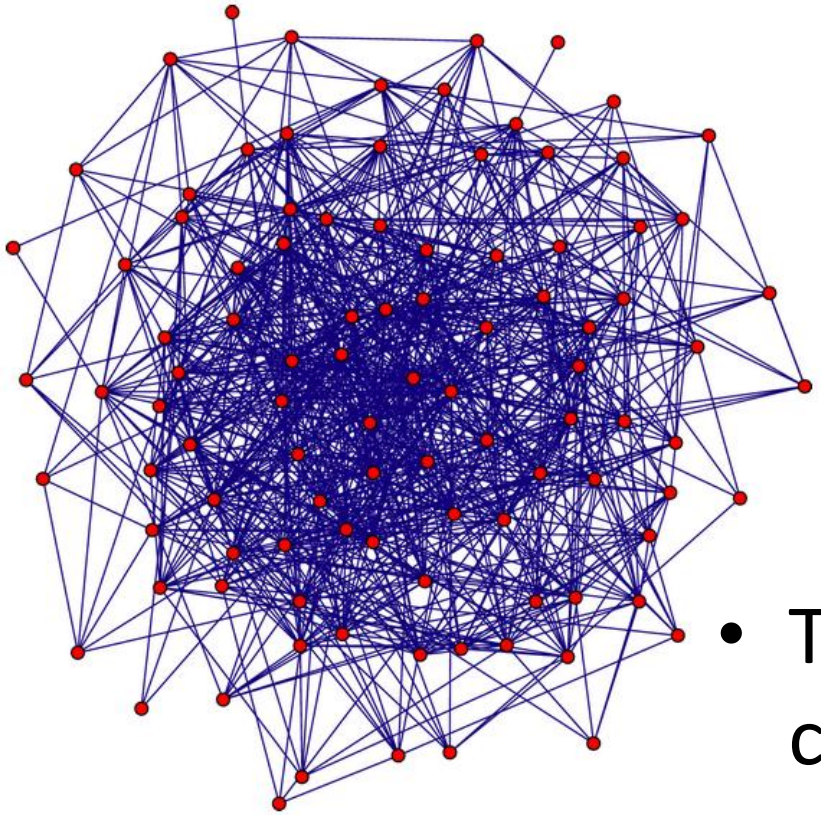
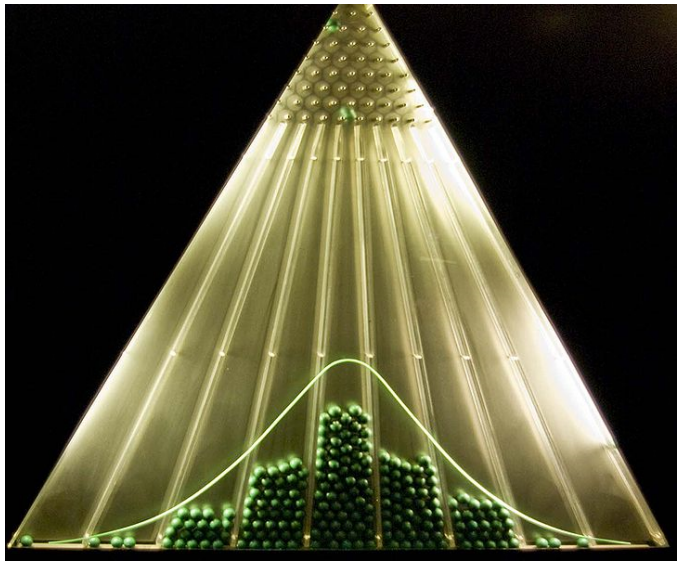


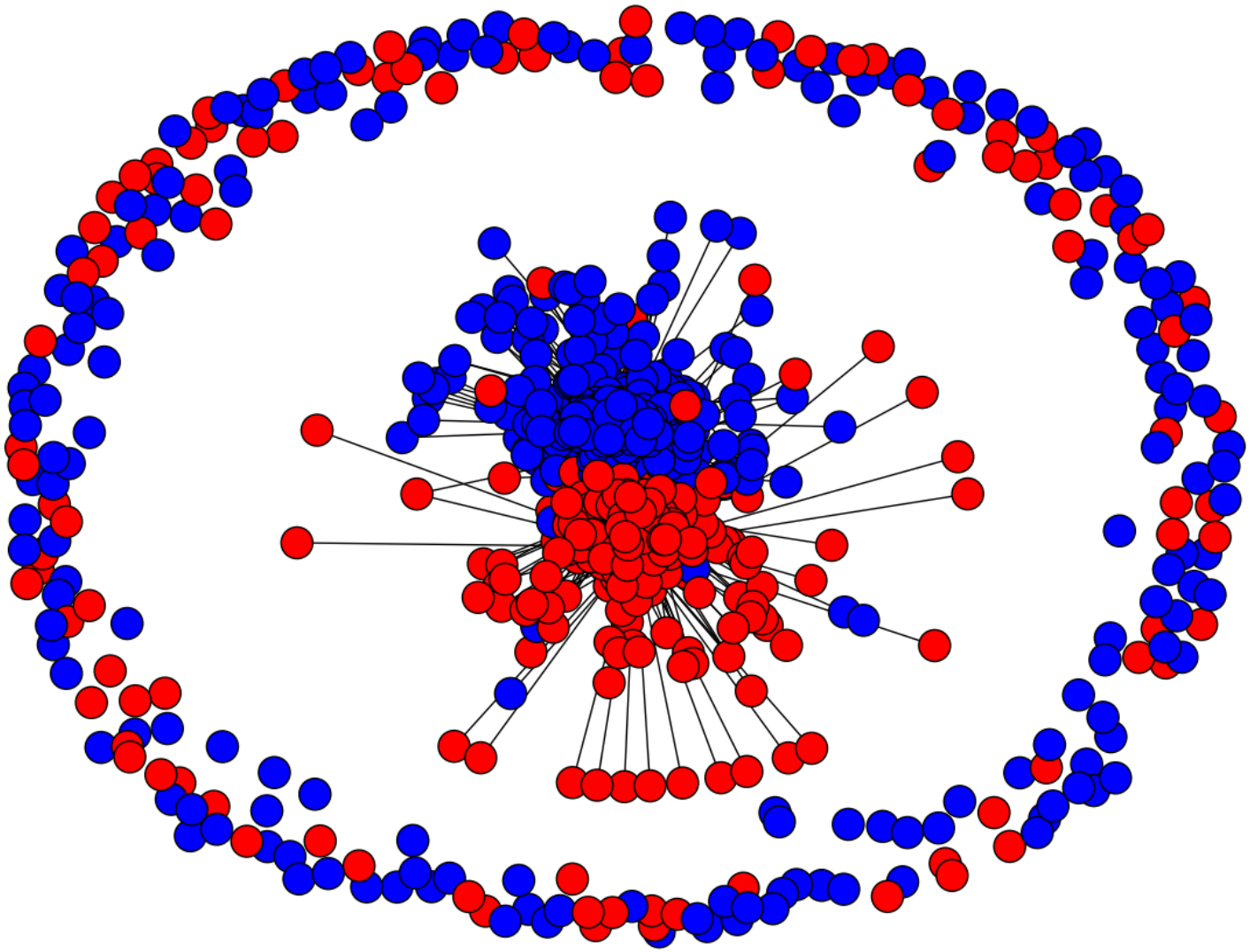
Random graph
(Erdos Renyi)

- Take *n* nodes, and connect each pair with probability *p*
  - Mean degree is $z=p(n-1)$
  - More precisely, the *distribution* of degrees is approximately *Gaussian*



Erdos-Renyi graphs

- Take *n* nodes, and connect each pair with probability *p*
  - Mean degree is $z=p(n-1)$
  - Mean number of neighbors distance *d* from *v* is z^d
  - How large does *d* need to be so that $z^d >= n$?
    - If $z>1$, $d = \log(n)/\log(z)$
    - If $z<1$, you can't do it
  - So:
    - *If z>1, diameters tend to be small (relative to n)*



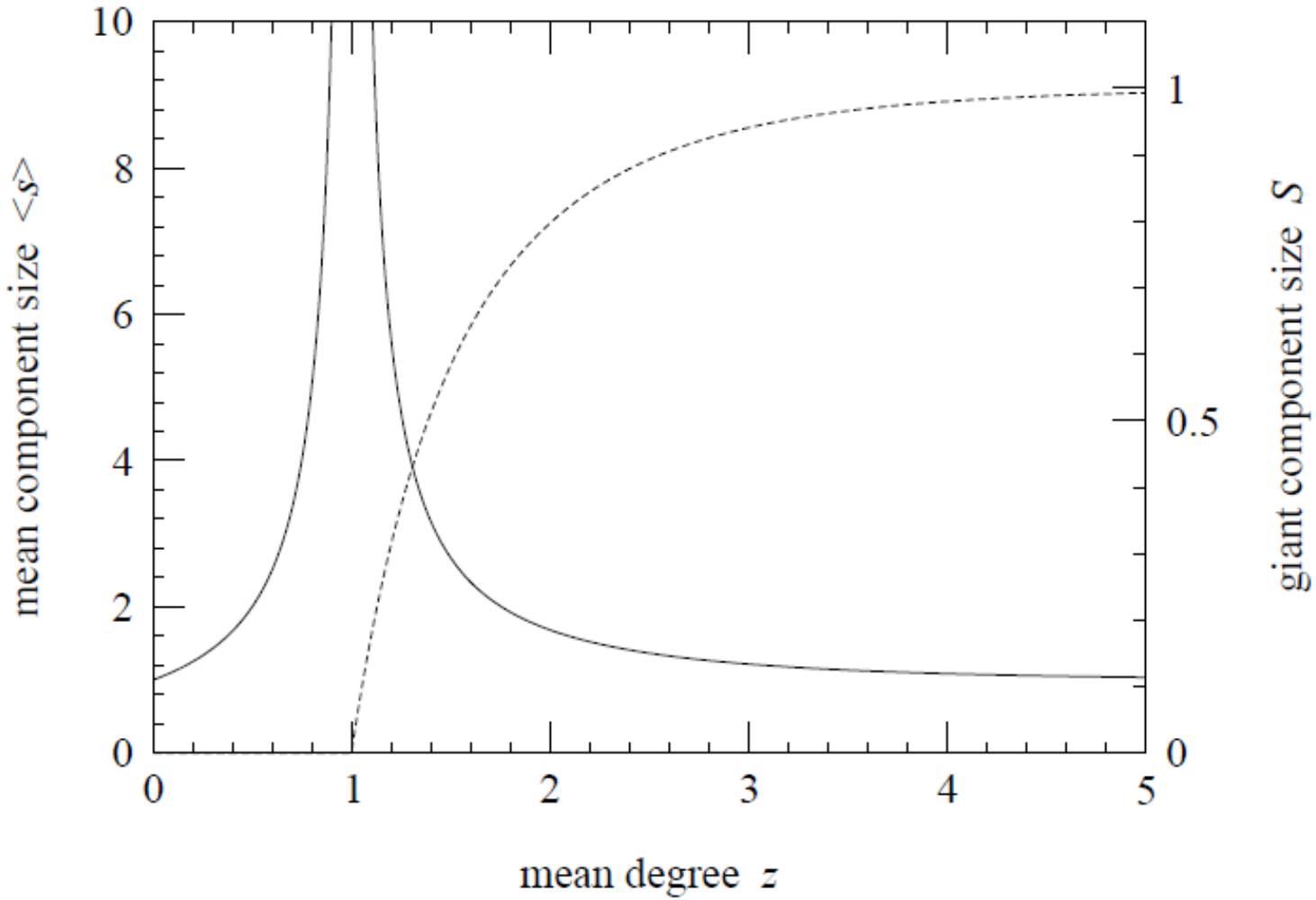


FIG. 10 The mean component size (solid line), excluding the giant component if there is one, and the giant component size (dotted line), for the Poisson random graph, Eqs. (20) and (21).

THE APOCALYPSE! THE SKIES BURN, THE SEAS TURN TO BLOOD, AND THE DEAD WALK THE EARTH!

PAUL ERDŐS?
WE NEED YOU TO SIGN THIS.
YES?

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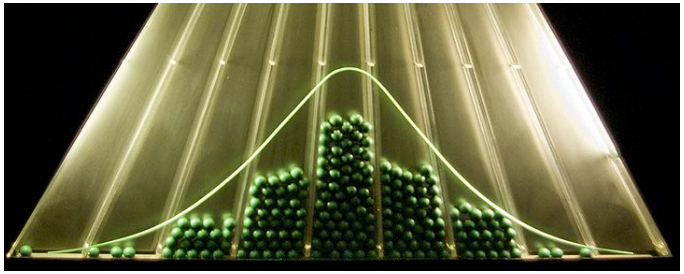
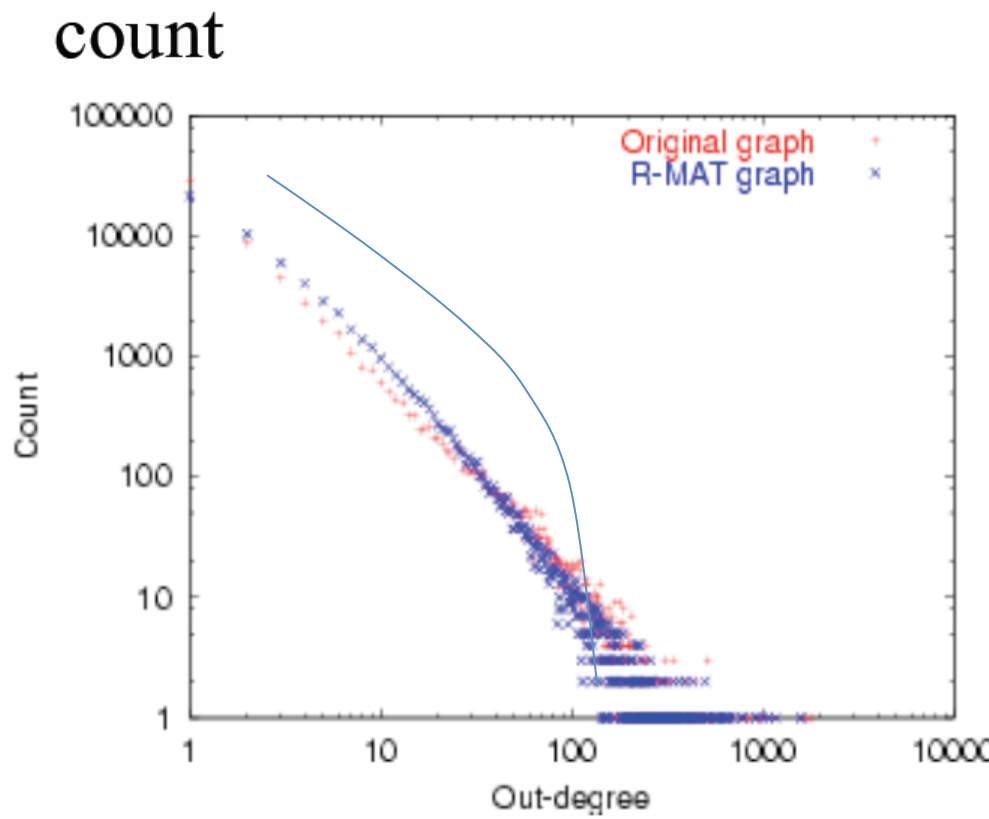


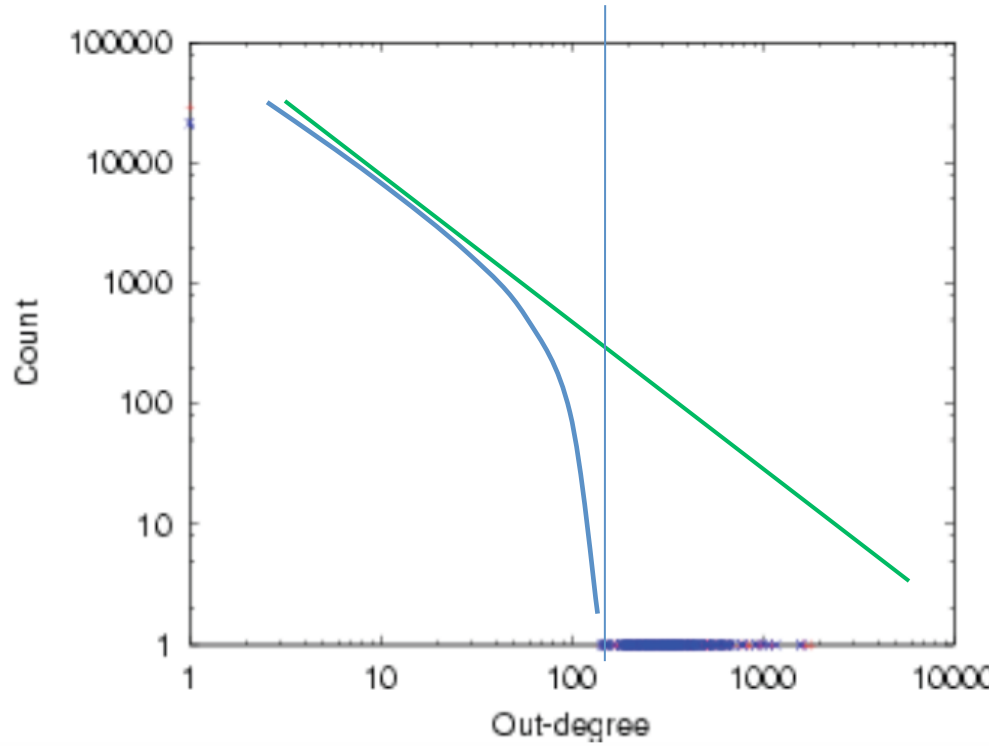
Degree distribution

- Plot *cumulative* degree
  - X axis is degree
  - Y axis is #nodes that have degree at least *k*
- Typically use a log-log scale
  - Straight lines are a power law; normal curve dives to zero at some point
  - Left: trust network in epinions web site from Richardson & Domingos



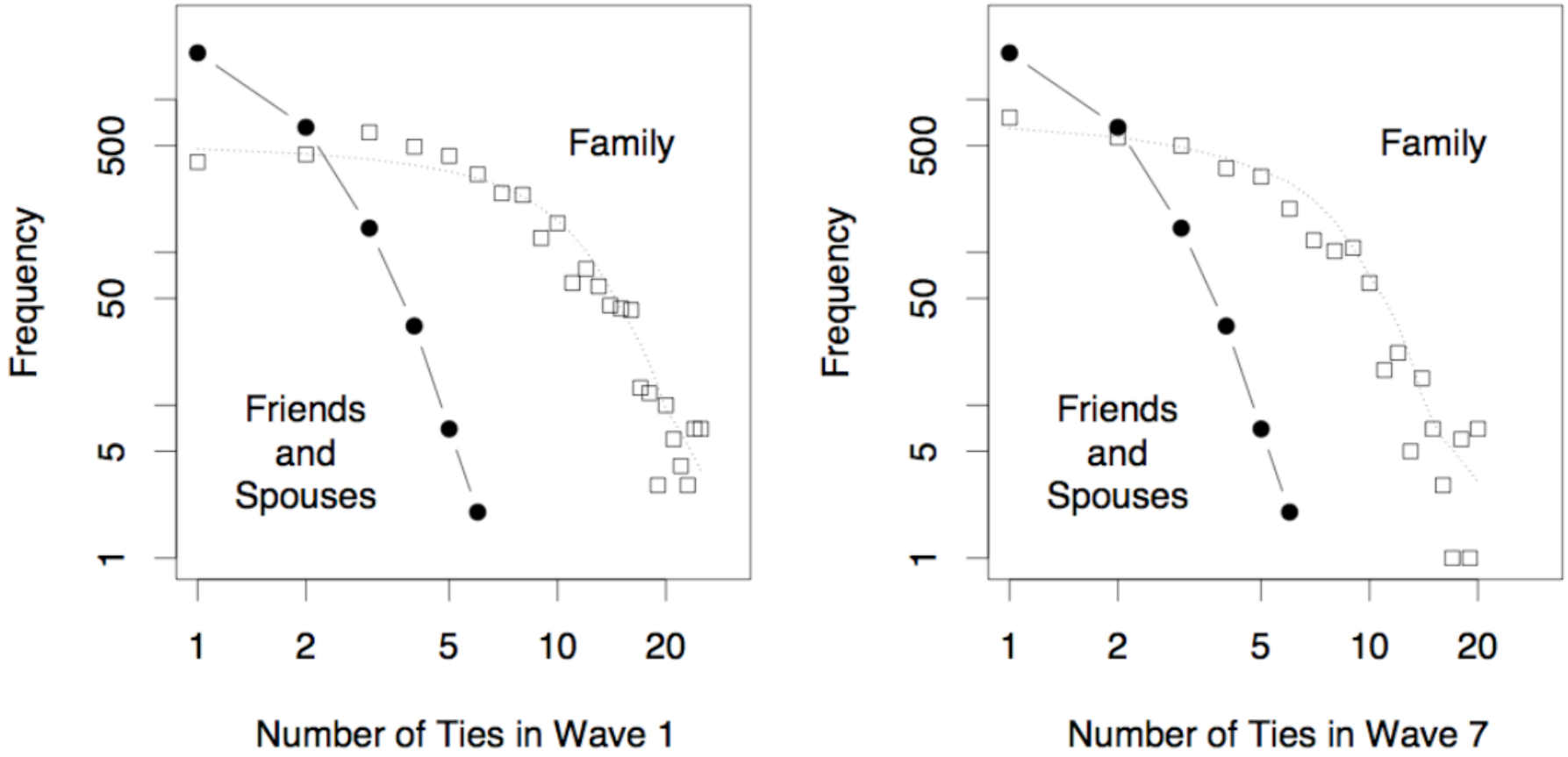
Degree distribution

- Plot cumulative degree
  - X axis is degree
  - Y axis is #nodes that have degree at least *k*
- Typically use a log-log scale
  - Straight lines are a power law; normal curve dives to zero at some point
    - This defines a "scale" for the network
  - Left: trust network in epinions web site from Richardson & Domingos



$$p_k \propto k^{-\alpha}$$

Figure S1: Degree Distribution of the FHS-Net



Friendship network in Framington Heart Study

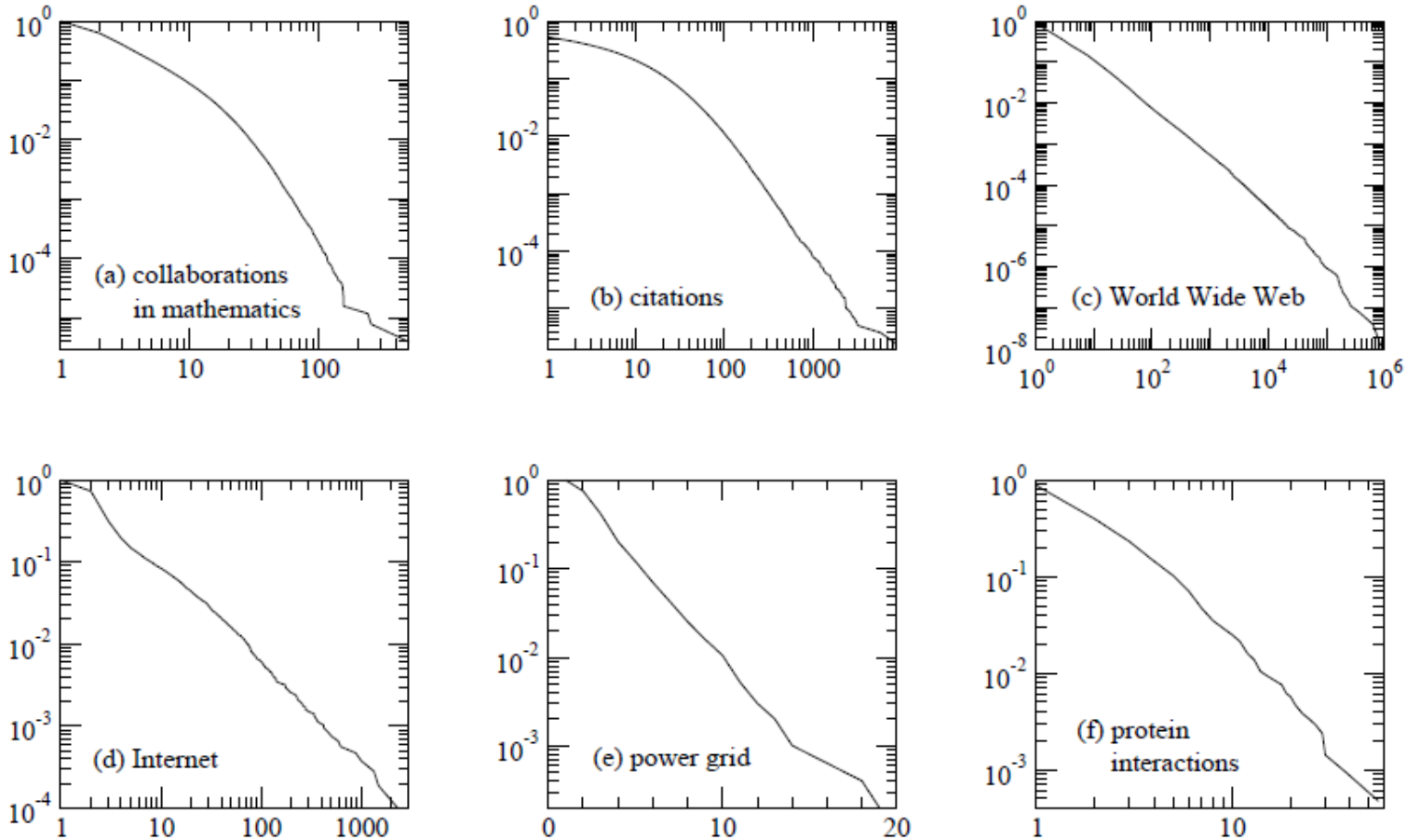


FIG. 6 Cumulative degree distributions for six different networks. The horizontal axis for each panel is vertex degree k (or in-degree for the citation and Web networks, which are directed) and the vertical axis is the cumulative probability distribution of degrees, i.e., the fraction of vertices that have degree greater than or equal to k. The networks shown are: (a) the collaboration network of mathematicians [182]; (b) citations between 1981 and 1997 to all papers cataloged by the Institute for Scientific Information [351]; (c) a 300 million vertex subset of the World Wide Web, *circa* 1999 [74]; (d) the Internet at the level of autonomous systems, April 1999 [86]; (e) the power grid of the western United States [416]; (f) the interaction network of proteins in the metabolism of the yeast *S. Cerevisiae* [212]. Of these networks, three of them, (c), (d) and (f), appear to have power-law degree distributions, as indicated by their approximately straight-line forms on the doubly logarithmic scales, and one (b) has a power-law tail but deviates markedly from power-law behavior for small degree. Network (e) has an exponential degree distribution (note the log-linear scales used in this panel) and network (a) appears to have a truncated power-law degree distribution of some type, or possibly two separate power-law regimes with different exponents.

	network	type	n	m	z	ℓ	α	$C^{(1)}$	$C^{(2)}$
social	film actors	undirected	449 913	25 516 482	113.43	3.48	2.3	0.20	0.78
	company directors	undirected	7 673	55 392	14.44	4.60	–	0.59	0.88
	math coauthorship	undirected	253 339	496 489	3.92	7.57	–	0.15	0.34
	physics coauthorship	undirected	52 909	245 300	9.27	6.19	–	0.45	0.56
	biology coauthorship	undirected	1 520 251	11 803 064	15.53	4.92	–	0.088	0.60
	telephone call graph	undirected	47 000 000	80 000 000	3.16		2.1		
	email messages	directed	59 912	86 300	1.44	4.95	1.5/2.0		0.16
	email address books	directed	16 881	57 029	3.38	5.22	–	0.17	0.13
	student relationships	undirected	573	477	1.66	16.01	–	0.005	0.001
	sexual contacts	undirected	2 810				3.2		
information	WWW `nd.edu`	directed	269 504	1 497 135	5.55	11.27	2.1/2.4	0.11	0.29
	WWW Altavista	directed	203 549 046	2 130 000 000	10.46	16.18	2.1/2.7		
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	power grid	undirected	4 941	6 594	2.67	18.99	–	0.10	0.080
	train routes	undirected	587	19 603	66.79	2.16	–		0.69
	software packages	directed	1 439	1 723	1.20	2.42	1.6/1.4	0.070	0.082
	software classes	directed	1 377	2 213	1.61	1.51	–	0.033	0.012
	electronic circuits	undirected	24 097	53 248	4.34	11.05	3.0	0.010	0.030
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biological	metabolic network	undirected	765	3 686	9.64	2.56	2.2	0.090	0.67
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    - **Connected components usually one giant CC**
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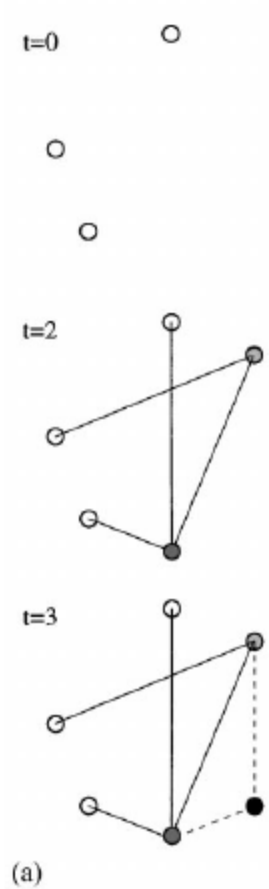
    - Watts-Strogatz "small world" graphs
    - Barbosi-Albert "preferential attachment" **generates scale-free graphs**
    - …

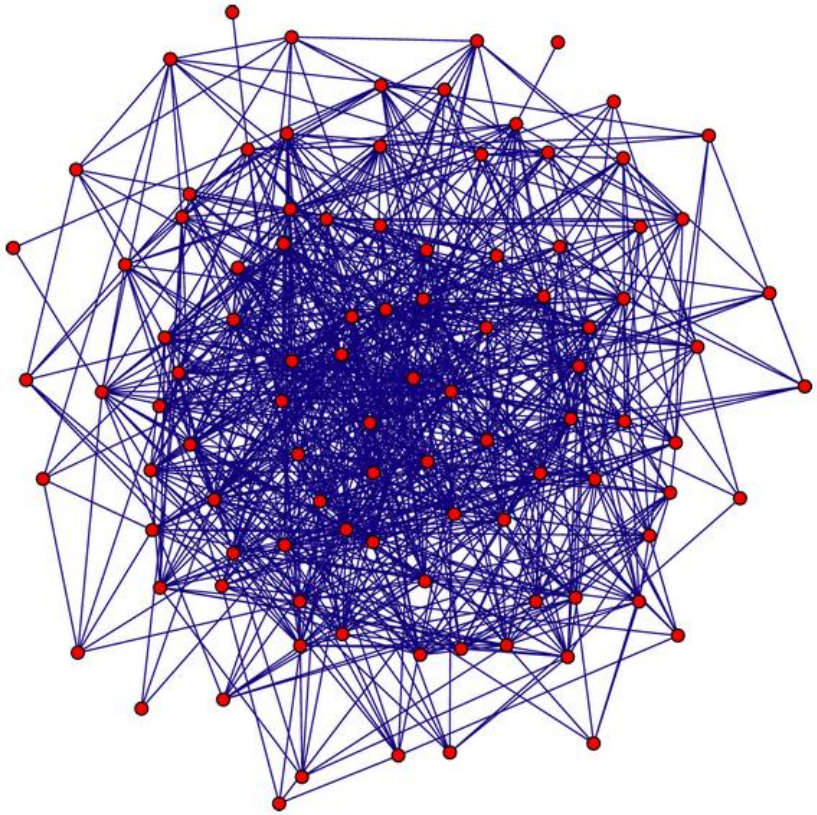
Barabasi-Albert Networks

- *Science* **286** (1999)
- Start from a small number of node, add a new node with *m* links
- **Preferential Attachment**
  - Probability of these links to connect to existing nodes is proportional to the node's degree

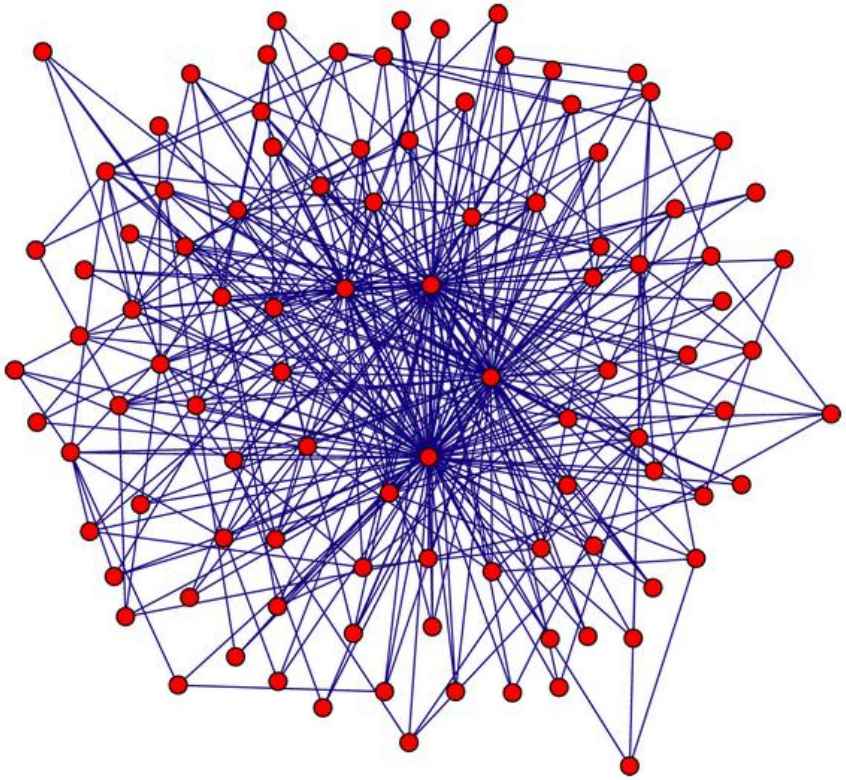
$$\prod(k_i) = \frac{k_i}{\sum_j k_j}$$

  - 'Rich gets richer'
- This creates 'hubs': few nodes with very large degrees





Random graph
(Erdos Renyi)



Preferential attachment
(Barabasi-Albert)

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Homophily

- One definition: excess edges between similar nodes
  - E.g., assume nodes are male and female and Pr(male)=*p,* Pr(female)=*q.*
  - Is *Pr(gender(u)≠ gender(v) | edge (u,v)) >= 2pq?*
- Another def'n: excess edges between common neighbors of *v*

$$CC(v) = \frac{\#\,\text{triangles connected to } v}{\#\,\text{pairs connected to } v}$$

$$CC(V,E) = \frac{1}{|V|}\sum_{v} CC(v)$$

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$$\boxed{CC'(V,E) = \frac{\#\,\text{triangles in graph}}{\#\,\text{length 3 paths in graph}}}$$

Homophily

- In a random Erdos-Renyi graph:

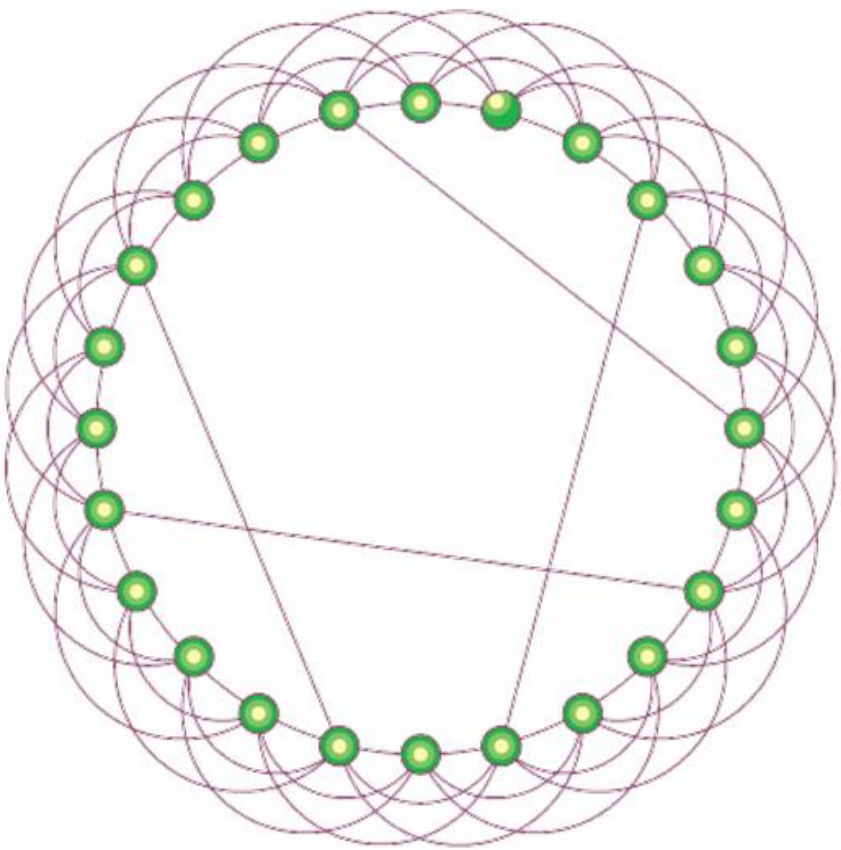
$$CC'(V,E) = \frac{\#\text{triangles in graph}}{\#\text{length 3 paths in graph}} \approx \frac{1}{n} \text{ for large n}$$

In natural graphs two of your mutual friends might well be friends:

- Like you they are both in the same class (club, field of CS, …)
- You introduced them

Watts-Strogatz model

- Start with a ring
- Connect each node to *k* nearest neighbors
    - ➔ homophily
- Add some random shortcuts from one point to another
    - ➔ small diameter
- Degree distribution *not* scale-free
- Generalizes to *d* dimensions



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A big question

- Which is cause and which is effect?
  - Do birds of a feather flock together?
  - Do you *change your behavior* based on the behavior of your peers?

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A big question

- Which is cause and which is effect?
  - Do birds of a feather flock together?
  - Do you change your behavior based on the behavior of your peers?
- How can you tell?
  - Look at *when* links are added and see what patterns emerge:

Pr(new link btwn *u* and *v* | #common friends*)*

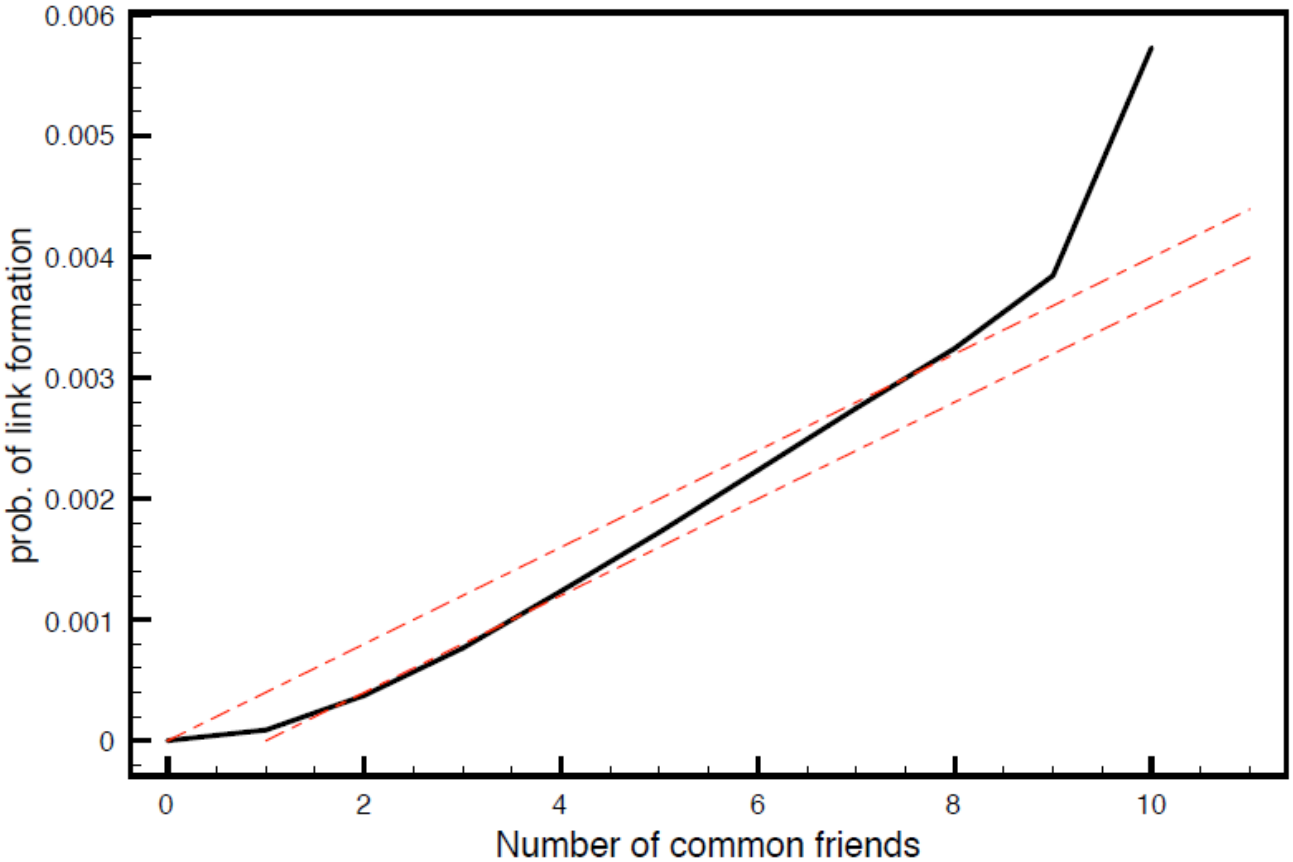


Figure 4.9: Quantifying the effects of triadic closure in an e-mail dataset [256]. The curve determined from the data is shown in the solid black line; the dotted curves show a comparison to probabilities computed according to two simple baseline models in which common friends provide independent probabilities of link formation.

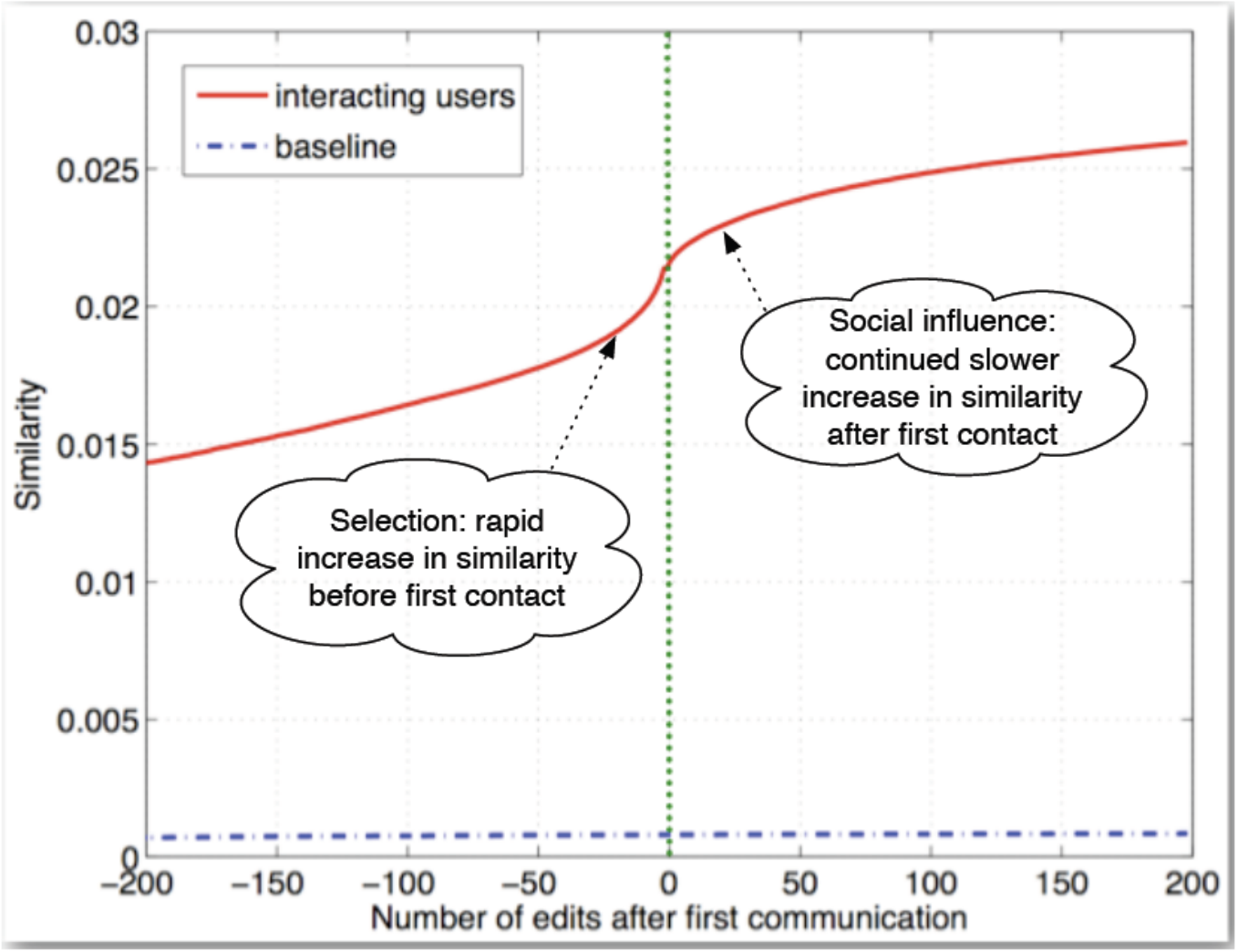
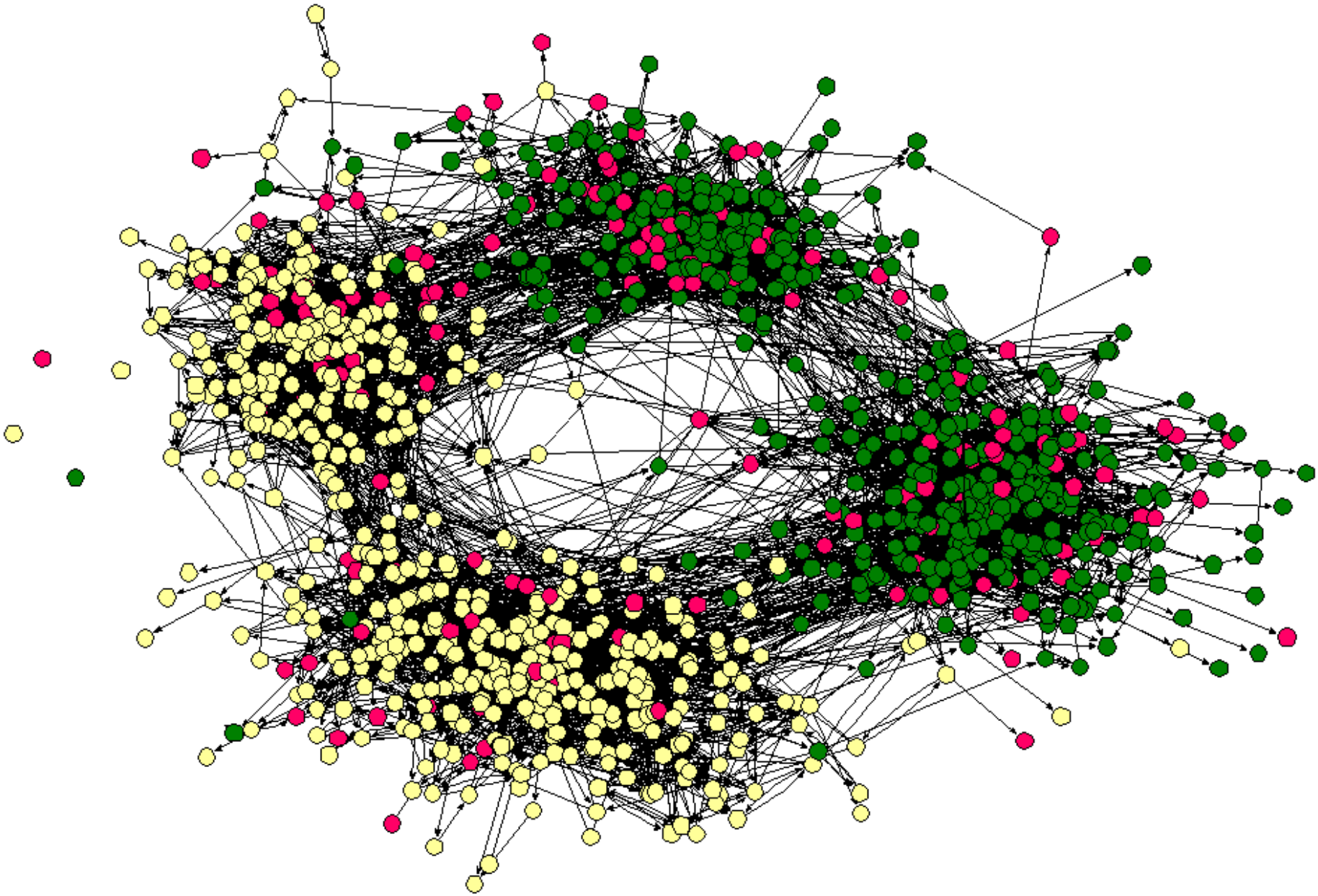
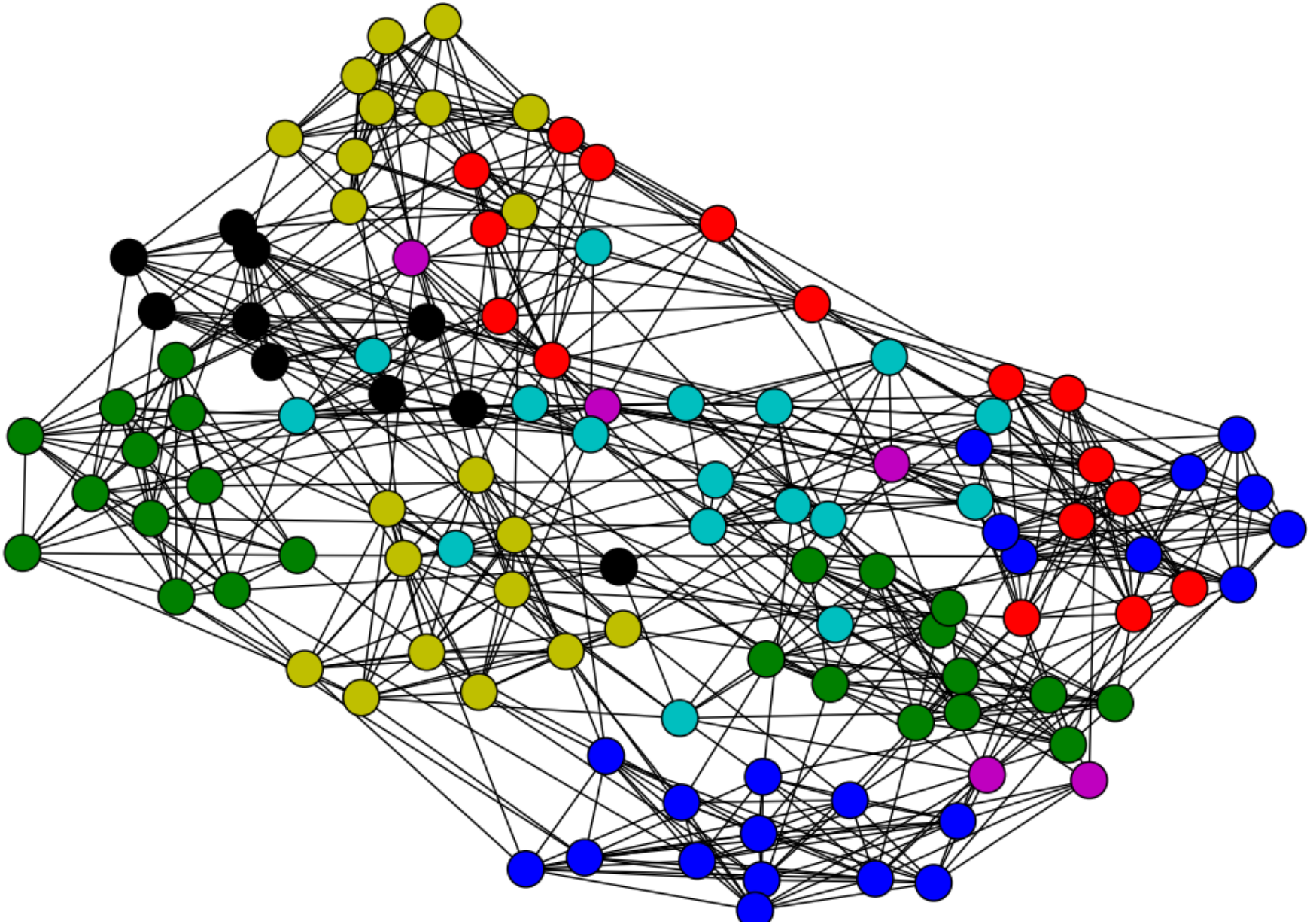


Figure 4.12: The average similarity of two editors on Wikipedia, relative to the time (0) at which they first communicated [121]. Time, on the x-axis, is measured in discrete units, where each unit corresponds to a single Wikipedia action taken by either of the two editors. The curve increases both before and after the first contact at time 0, indicating that both selection and social influence play a role; the increase in similarity is steepest just before time 0.





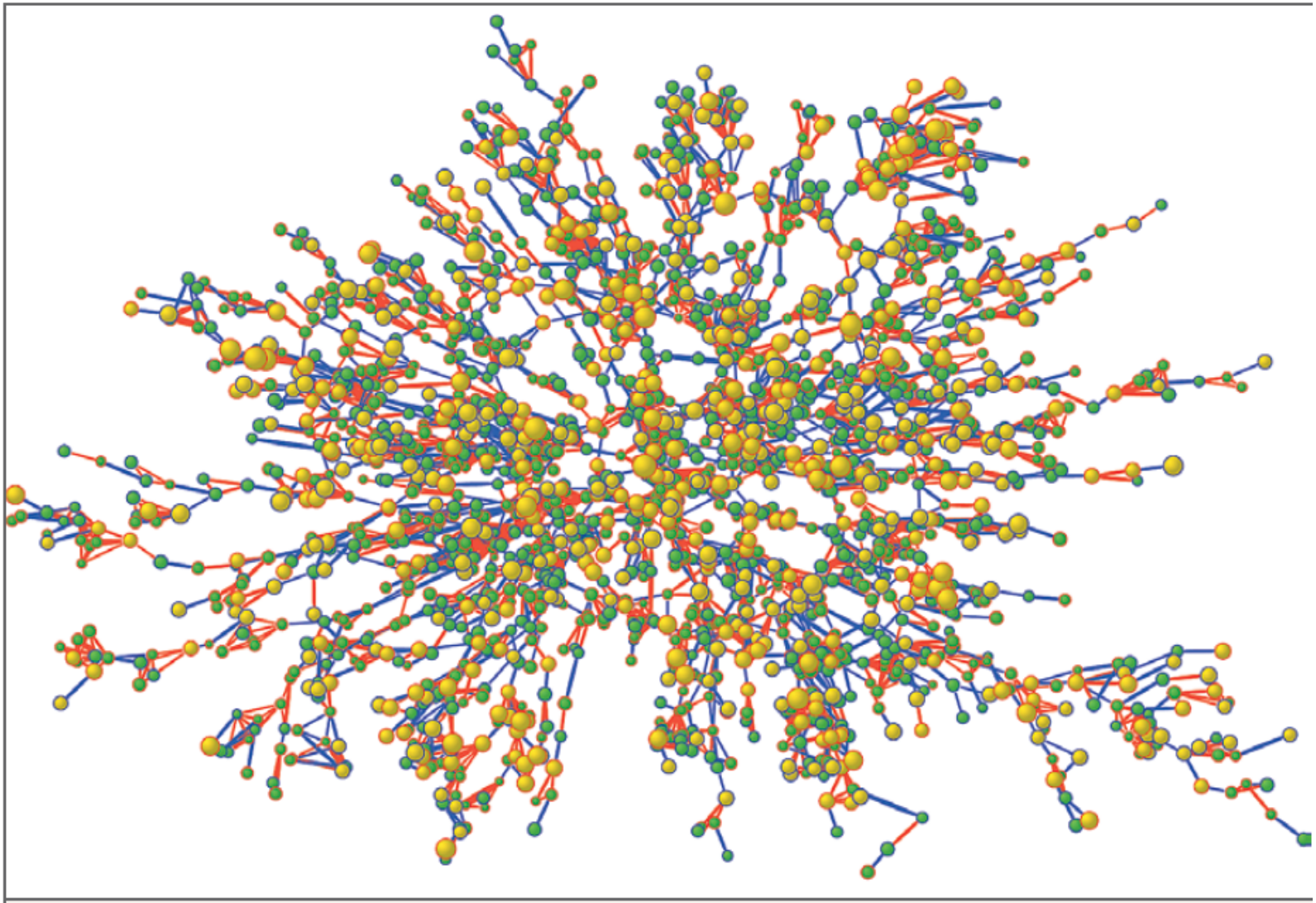


Figure 1. Largest Connected Subcomponent of the Social Network in the Framingham Heart Study in the Year 2000.
Each circle (node) represents one person in the data set. There are 2200 persons in this subcomponent of the social network. Circles with red borders denote women, and circles with blue borders denote men. The size of each circle is proportional to the person's body-mass index. The interior color of the circles indicates the person's obesity status: yellow denotes an obese person (body-mass index, ≥30) and green denotes a nonobese person. The colors of the ties between the nodes indicate the relationship between them: purple denotes a friendship or marital tie and orange denotes a familial tie.

Final example: spatial segregation

- http://names.mappinglondon.co.uk/
- How picky do people have to be about their neighbors for homophily to arise?

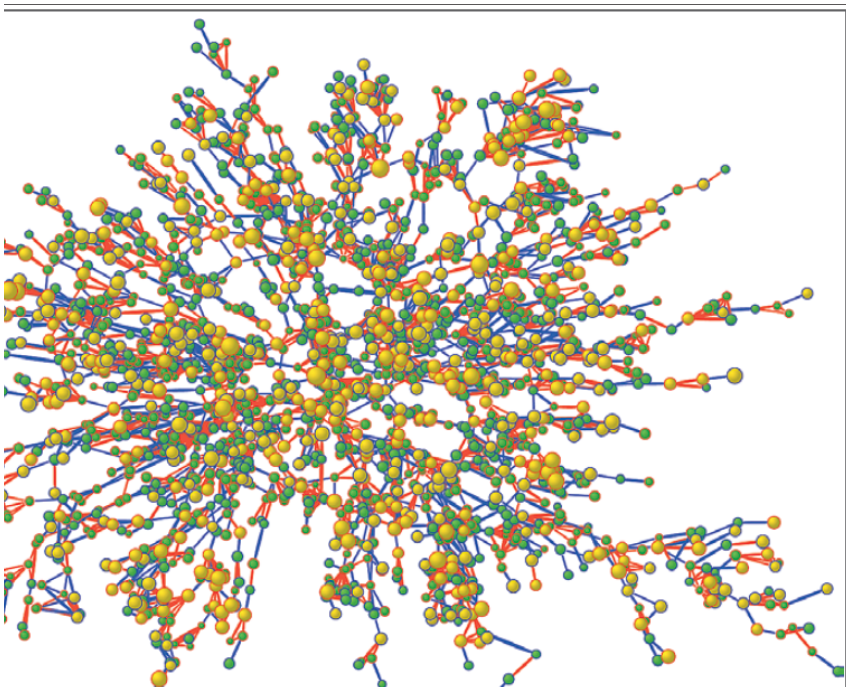
Thomas Schelling - spatial segregation models

Final example: spatial segregation

- Imagine a grid world where
  - Agents are red or blue
  - Agents move to a random location if they are unhappy
    - Agents are happy unless <k neighbors are the same color they are (k=
    - i.e., they prefer not to be in a small minority
  - What's the result over time?

  - http://ccl.northwestern.edu/netlogo/models/Segregation

First guest lecture on Thursday….

Cosma Shalizi

"it does give an accurate impression of my desk (and hair), and people recognize me from it at meetings."