Complex Networks

Principles of Complex Systems
CSYS/MATH 300, Fall, 2010

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Outline

net•work |ˈnetˌwərk|

noun

1 an arrangement of intersecting horizontal and vertical lines.

- a complex system of roads, railroads, or other transportation routes : *a network of railroads.*

2 a group or system of interconnected people or things : *a trade network.*

- a group of people who exchange information, contacts, and experience for professional or social purposes : *a support network.*
- a group of broadcasting stations that connect for the simultaneous broadcast of a program : *the introduction of a second TV network* | [as adj.] *network television.*
- a number of interconnected computers, machines, or operations : *specialized computers that manage multiple outside connections to a network* | *a local cellular phone network.*
- a system of connected electrical conductors.

verb [trans.]

connect as or operate with a network : *the stock exchanges have proven to be resourceful in networking these deals.*

- link (machines, esp. computers) to operate interactively : [as adj.] (**networked**) *networked workstations.*
- [intrans.] [often as n.] (**networking**) interact with other people to exchange information and develop contacts, esp. to further one's career : *the skills of networking, bargaining, and negotiation.*

Thesaurus deliciousness:

network

noun

1 *a network of arteries* WEB, lattice, net, matrix, mesh, crisscross, grid, reticulum, reticulation; Anatomy plexus.

2 *a network of lanes* MAZE, labyrinth, warren, tangle.

3 *a network of friends* SYSTEM, complex, nexus, web, webwork.

Ancestry:

From Keith Briggs's excellent etymological investigation: (⊞)

- Opus reticulatum:
- A Latin origin?

[http://serialconsign.com/2007/11/we-put-net-network]

Ancestry:

First known use: Geneva Bible, 1560

'And thou shalt make unto it a grate like networke of brass (Exodus xxvii 4).'

From the OED via Briggs:

- 1658–: reticulate structures in animals
- 1839–: rivers and canals
- 1869–: railways
- 1883–: distribution network of electrical cables
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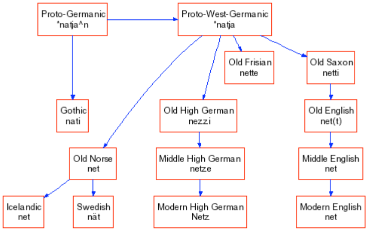
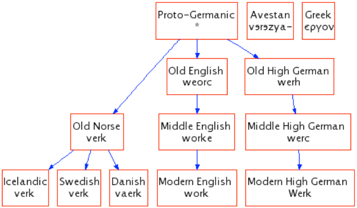
Net and Work are venerable old words:

- ‘Net’ first used to mean spider web (King Ælfréd, 888).
- ‘Work’ appear to have long meant purposeful action.



The network of Germanic `net' words



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- ‘Network’ = something built based on the idea of natural, flexible lattice or web.
- c.f., ironwork, stonework, fretwork.

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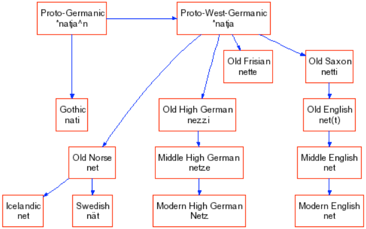

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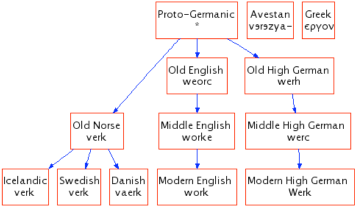

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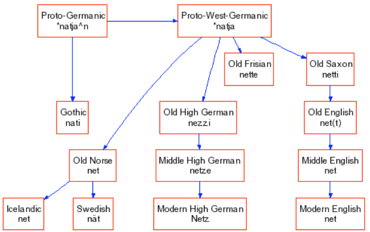

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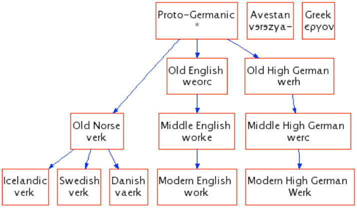

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- Opens door to mathematical and numerical analysis.
- Dominant approach of last decade of a theoretical-physics/stat-mechish flavor.
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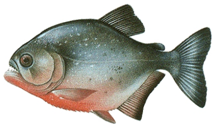

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- Hunt in packs.
- Feast on new and interesting ideas (see chaos, cellular automata, ...)

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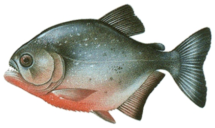

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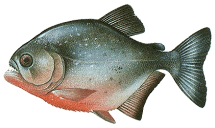

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Popularity (according to ISI)

"Collective dynamics of 'small-world' networks" [30]

- Watts and Strogatz
  Nature, 1998
- Cited ≈ 4325 times (as of June 7, 2010)
- Over 1100 citations in 2008 alone.

"Emergence of scaling in random networks" [4]

- Barabási and Albert
  Science, 1999
- Cited ≈ 4769 times (as of June 7, 2010)
- Over 1100 citations in 2008 alone.

Popularity (according to ISI)

Review articles:

- S. Boccaletti et al.
  "Complex networks: structure and dynamics" [6]
  Times cited: 1,028 (as of June 7, 2010)
- M. Newman
  "The structure and function of complex networks" [21]
  Times cited: 2,559 (as of June 7, 2010)
- R. Albert and A.-L. Barabási
  "Statistical mechanics of complex networks" [2]
  Times cited: 3,995 (as of June 7, 2010)

Popularity according to textbooks:

Textbooks:

- Mark Newman (Physics, Michigan)
  "Networks: An Introduction" ()
- David Easley and Jon Kleinberg (Economics and Computer Science, Cornell)
  "Networks, Crowds, and Markets: Reasoning About a Highly Connected World" ()

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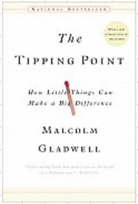
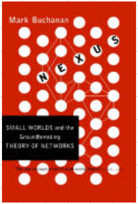


The Tipping Point: How Little Things can make a Big Difference—Malcolm Gladwell [14]



Nexus: Small Worlds and the Groundbreaking Science of Networks—Mark Buchanan

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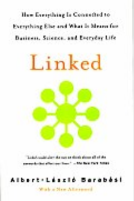
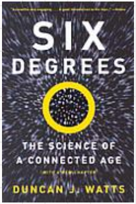


Linked: How Everything Is Connected to Everything Else and What It Means—Albert-Laszlo Barabási



Six Degrees: The Science of a Connected Age—Duncan Watts [28]

Numerous others:

- Complex Social Networks—F. Vega-Redondo [27]
- Fractal River Basins: Chance and Self-Organization—I. Rodríguez-Iturbe and A. Rinaldo [22]
- Random Graph Dynamics—R. Durette
- Scale-Free Networks—Guido Caldarelli
- Evolution and Structure of the Internet: A Statistical Physics Approach—Romu Pastor-Satorras and Alessandro Vespignani
- Complex Graphs and Networks—Fan Chung
- Social Network Analysis—Stanley Wasserman and Kathleen Faust
- Handbook of Graphs and Networks—Eds: Stefan Bornholdt and H. G. Schuster [8]
- Evolution of Networks—S. N. Dorogovtsev and J. F. F. Mendes [13]

More observations

- But surely networks aren't new...
- Graph theory is well established...
- Study of social networks started in the 1930's...
- So why all this 'new' research on networks?
- Answer: Oodles of Easily Accessible Data.
- We can now inform (alas) our theories
  with a much more measurable reality.*
- A worthy goal: establish mechanistic explanations.

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* *If this is upsetting, maybe string theory is for you...*

More observations

- Web-scale data sets can be overly exciting.

Witness:

- The End of Theory: The Data Deluge Makes the Scientific Theory Obsolete (Anderson, Wired) (⊞)
- "The Unreasonable Effectiveness of Data," Halevy et al. [15].

But:

- For scientists, description is only part of the battle.
- We still need to understand.

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Super Basic definitions

Nodes = A collection of entities which have properties that are somehow related to each other

- e.g., people, forks in rivers, proteins, webpages, organisms,...

Links = Connections between nodes

- Links may be directed or undirected.
- Links may be binary or weighted.

Other spiffing words: vertices and edges.

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Node degree = Number of links per node

- Notation: Node i's degree = k_i.
- $k_i = 0, 1, 2, \ldots$.
- Notation: the average degree of a network = $\langle k \rangle$
- Connection between number of edges m and average degree:

$$\langle k \rangle = \frac{2m}{N}.$$

- Defn: $\mathcal{N}_i$ = the set of i's k_i neighbors

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Adjacency matrix:

- We represent a directed network by a matrix A with link weight a_{ij} for nodes i and j in entry (i, j).
- e.g.,

$$A = \begin{bmatrix} 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 \end{bmatrix}$$

- (n.b., for numerical work, we always use sparse matrices.)

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Examples

So what passes for a complex network?

- Complex networks are large (in node number)
- Complex networks are sparse (low edge to node ratio)
- Complex networks are usually dynamic and evolving
- Complex networks can be social, economic, natural, informational, abstract, ...

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- Neural networks
- Trees and leaves
- Blood networks
- The Internet
- Road networks
- Power grids

- Distribution (branching) versus redistribution (cyclical)

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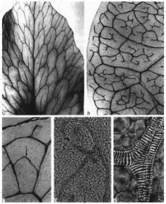

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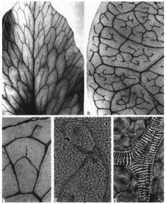

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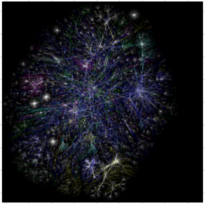

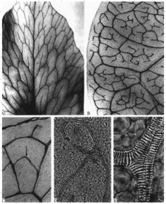

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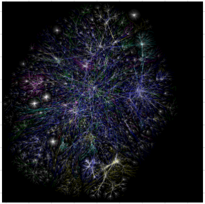

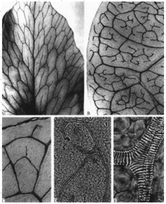

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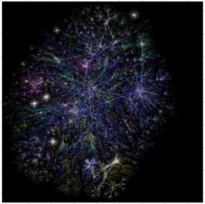

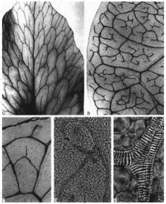

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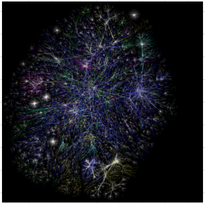

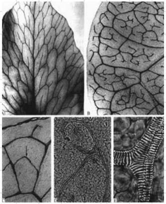

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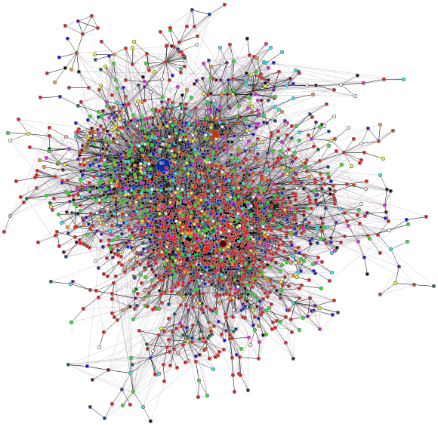

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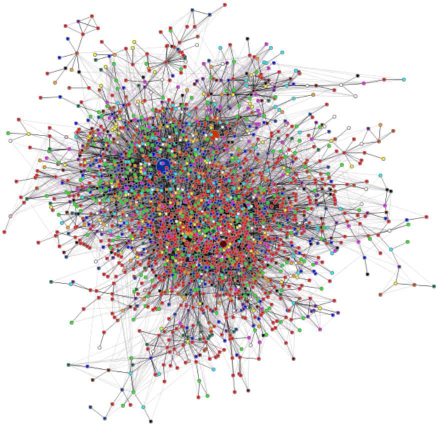

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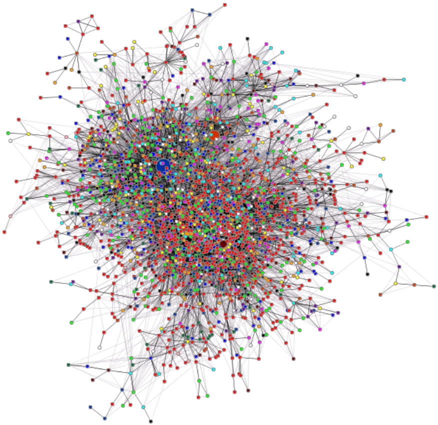

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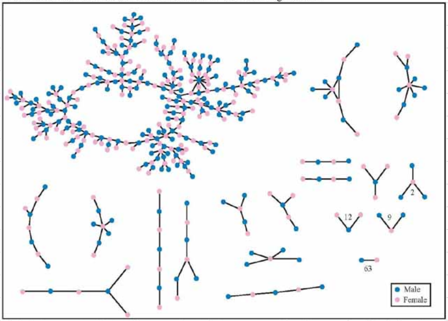

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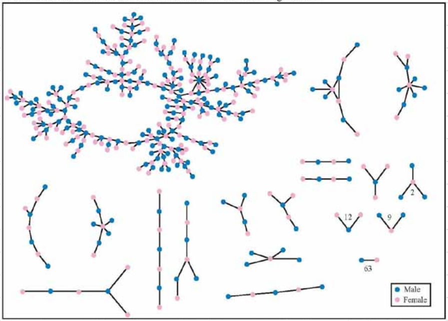

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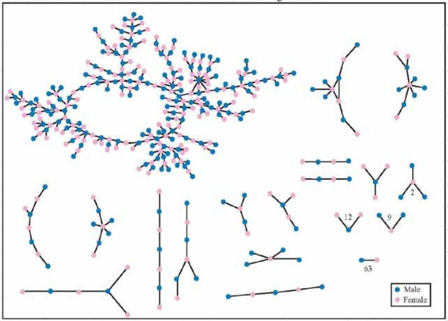

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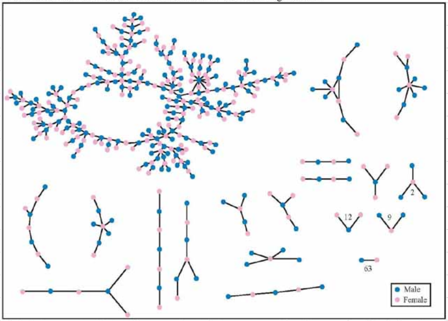

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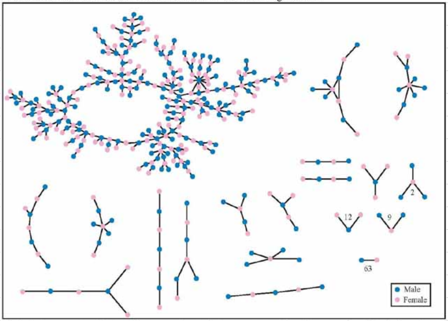

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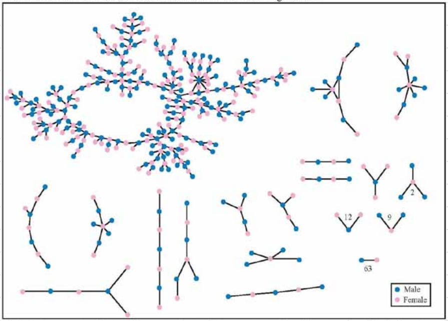

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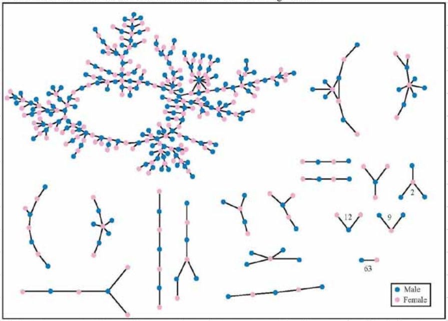

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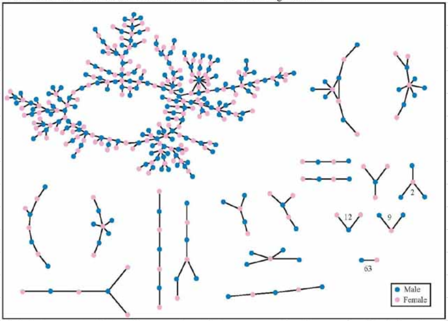

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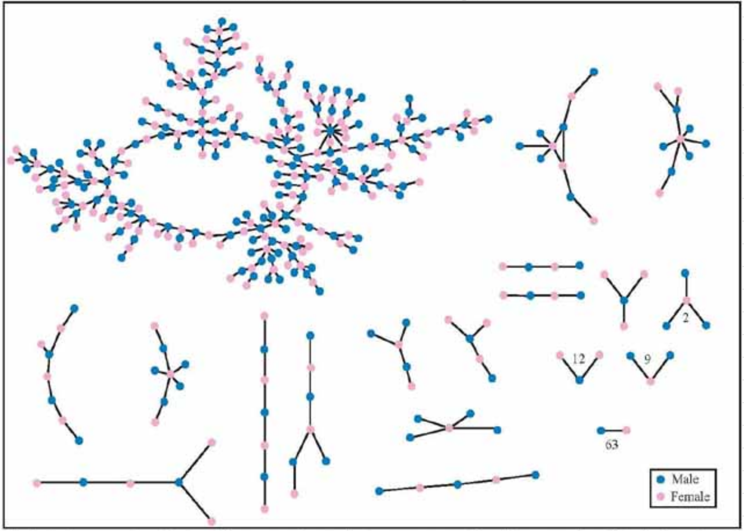

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Relational networks

- Consumer purchases
- Thesauri: Networks of words generated by meanings
- Knowledge/Databases/Ideas
- Metadata—Tagging: del.icio.us (⊞) flickr (⊞)

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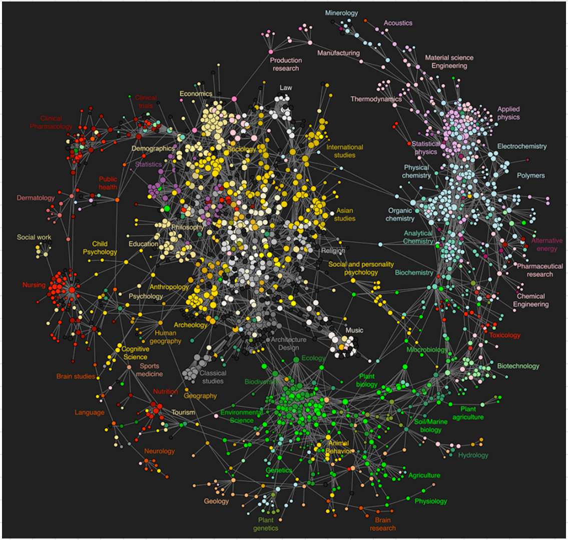
common tags cloud | list

community daily dictionary education encyclopedia english free imported info information internet knowledge learning news reference research resource resources search tools useful web web2.0 wiki wikipedia

Clickworthy Science:



Bollen et al. [7]

A notable feature of large-scale networks:

- Graphical renderings are often just a big mess.

- And even when renderings somehow look good:

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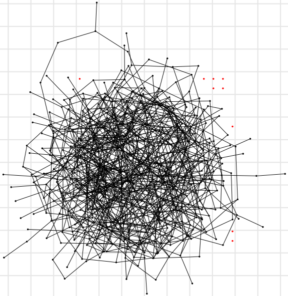

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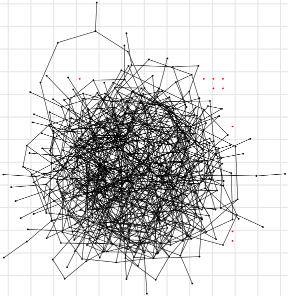

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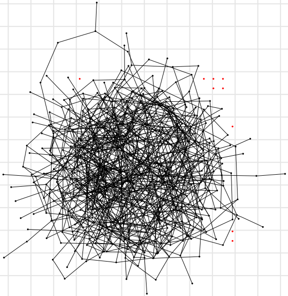

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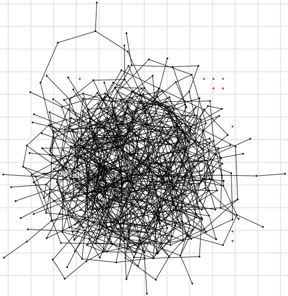

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Properties

Some key features of real complex networks:

- Degree distribution
- Assortativity
- Homophily
- Clustering
- Motifs
- Modularity
- Concurrency
- Hierarchical scaling
- Network distances
- Centrality
- Efficiency
- Robustness

- Coevolution of network structure and processes on networks.

Properties

1. Degree distribution P_k

- P_k is the probability that a randomly selected node has degree k
- Big deal: Form of P_k key to network's behavior
- ex 1: Erdős-Rényi random networks have a Poisson distribution:

$$P_k = e^{-\langle k \rangle} \langle k \rangle^k / k!$$

- ex 2: "Scale-free" networks: $P_k \propto k^{-\gamma} \Rightarrow$ 'hubs'
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2. Assortativity/3. Homophily:

- Social networks: Homophily (⊞) = birds of a feather
- e.g., degree is standard property for sorting: measure degree-degree correlations.
- Assortative network: [20] similar degree nodes connecting to each other.
- Disassortative network: high degree nodes connecting to low degree nodes.

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  - *Often technological or biological: Internet, protein interactions, neural networks, food webs.*

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4. Clustering:

- Your friends tend to know each other.
- Two measures:

$$C_1 = \left\langle \frac{\sum_{j_1 j_2 \in \mathcal{N}_i} a_{j_1 j_2}}{k_i(k_i - 1)/2} \right\rangle_i \text{ due to Watts \& Strogatz [30]}$$

$$C_2 = \frac{3 \times \#\text{triangles}}{\#\text{triples}} \text{ due to Newman [21]}$$

- C_1 is the average fraction of pairs of neighbors who are connected.
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$$C_2 = \frac{3 \times \#\text{triangles}}{\#\text{triples}} \text{ due to Newman [21]}$$

- C_1 is the average fraction of pairs of neighbors who are connected.
- Interpret C_2 as probability two of a node's friends know each other.

Properties

5. Motifs:

- Small, recurring functional subnetworks
- e.g., Feed Forward Loop:

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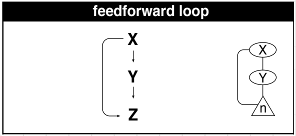

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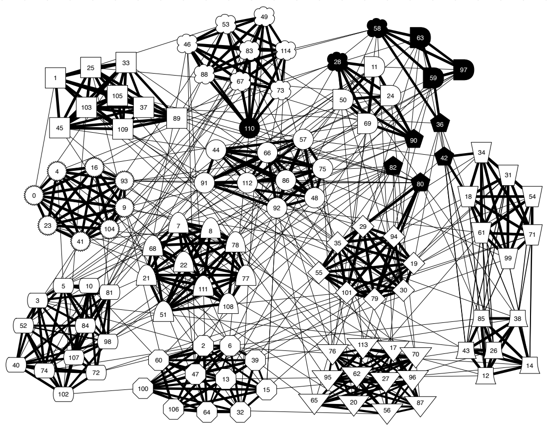

Clauset *et al.*, 2006 [10]: NCAA football

Properties

7. Concurrency:

- Transmission of a contagious element only occurs during contact [18]
- Rather obvious but easily missed in a simple model
- Dynamic property—static networks are not enough
- Knowledge of previous contacts crucial
- Beware cumulated network data!

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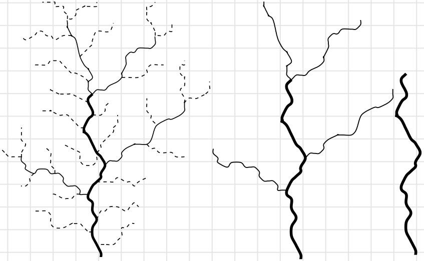
8. Horton-Strahler stream ordering:

- Metrics for branching networks:
  - Method for ordering streams hierarchically
  - Reveals fractal nature of natural branching networks
  - Hierarchy is not pure but mixed (Tokunaga). [25, 12]
  - Major examples: rivers and blood networks.



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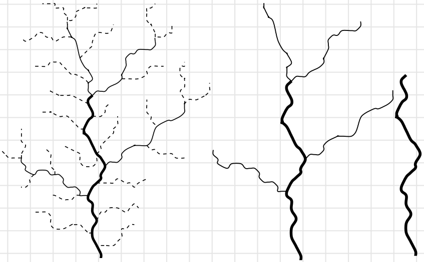

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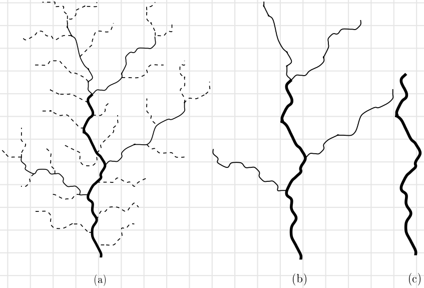

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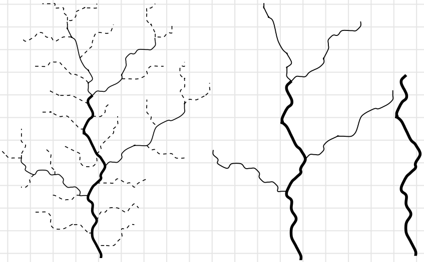

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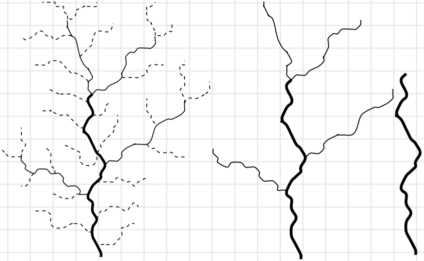

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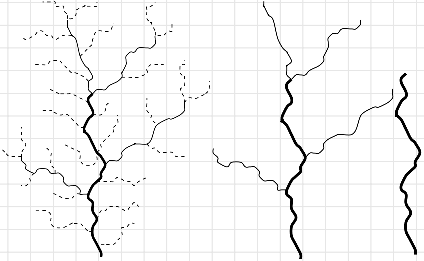

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Overview Key Points:

- The field of complex networks came into existence in the late 1990s.
- Explosion of papers and interest since 1998/99.
- Hardened up much thinking about complex systems.
- Specific focus on networks that are large-scale, sparse, natural or man-made, evolving and dynamic, and (crucially) measurable.
- Three main (blurred) categories:
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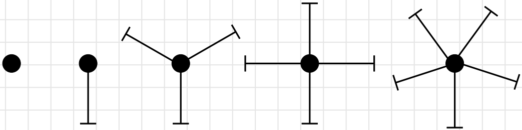
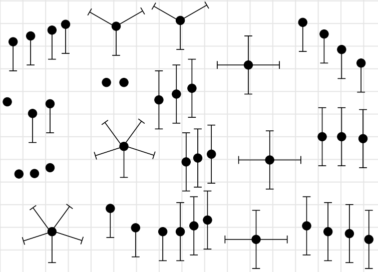
- Idea: start with a soup of unconnected nodes with stubs (half-edges):





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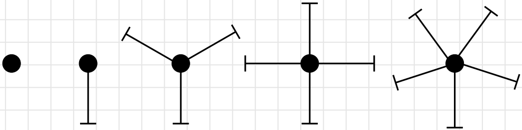

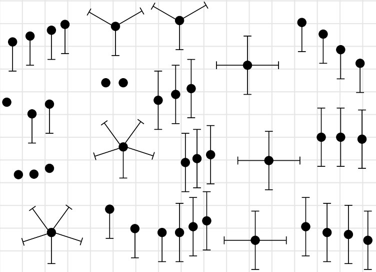

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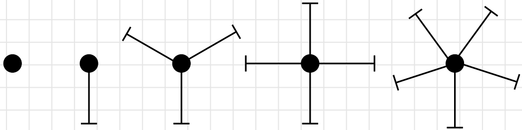

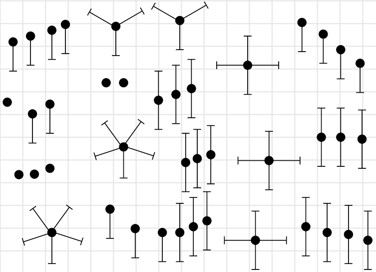

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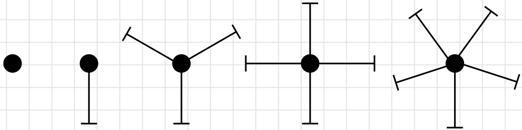

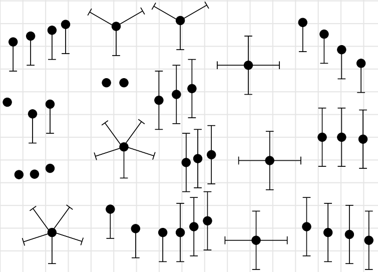

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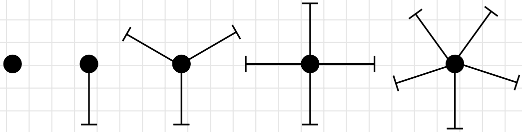

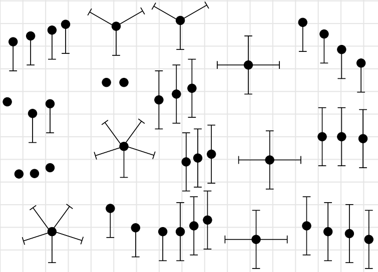

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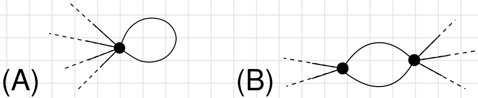
- Now find any (A) self-loops and (B) repeat edges and randomly rewire them.



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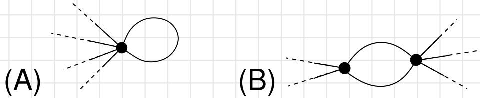

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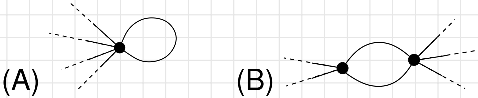

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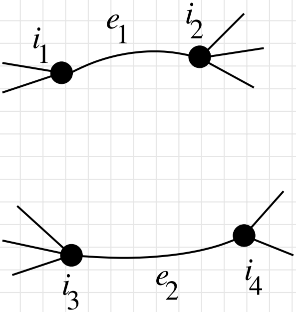
General random rewiring algorithm



- Randomly choose two edges. (Or choose problem edge and a random edge)
- Check to make sure edges are disjoint.
- Rewire one end of each edge.
- Node degrees do not change.
- Works if e_1 is a self-loop or repeated edge.
- Same as finding on/off/on/off 4-cycles, and rotating them.

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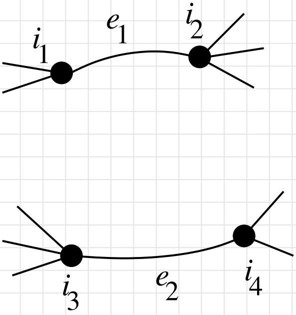
General random rewiring algorithm



- Randomly choose two edges. (Or choose problem edge and a random edge)
- Check to make sure edges are disjoint.
- Rewire one end of each edge.
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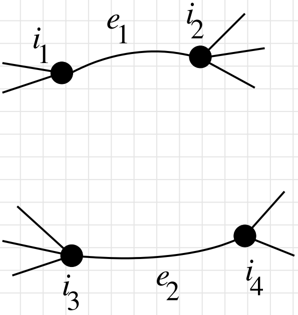

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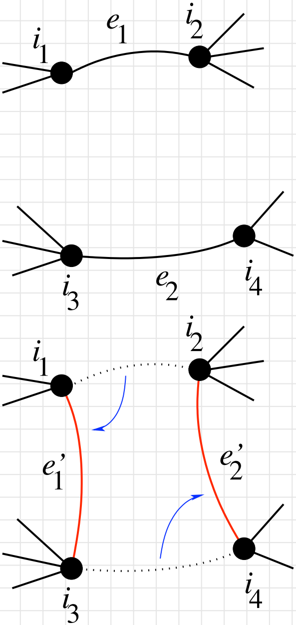

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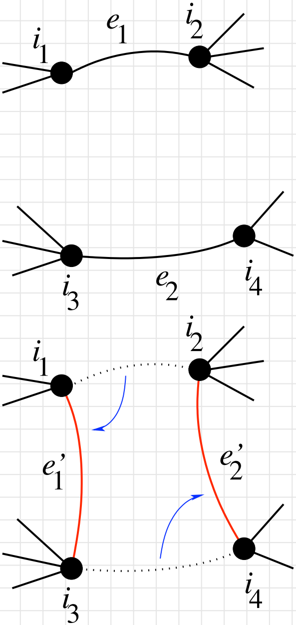

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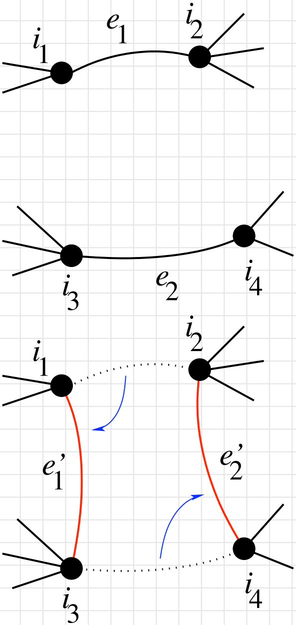

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Sampling random networks

Phase 2:

- Use rewiring algorithm to remove all self and repeat loops.

Phase 3:

- Randomize network wiring by applying rewiring algorithm liberally.
- Rule of thumb: # Rewirings $\simeq 10 \times$ # edges [19].

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Outline

Basic definitions

Examples of Complex Networks

Properties of Complex Networks

Nutshell

Basic models of complex networks
- Generalized random networks
- Scale-free networks
- Small-world networks
- Generalized affiliation networks

References

Scale-free networks

- Networks with power-law degree distributions have become known as scale-free networks.
- Scale-free refers specifically to the degree distribution having a power-law decay in its tail:

$$P_k \sim k^{-\gamma} \text{ for 'large' } k$$

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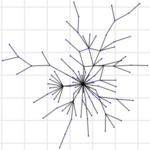
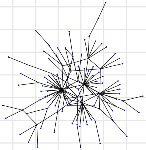
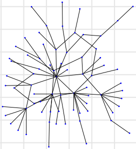


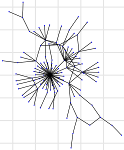
γ = 2.5
$\langle k \rangle$ = 1.8



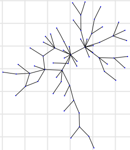
γ = 2.5
$\langle k \rangle$ = 2.05333



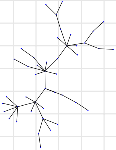
γ = 2.5
$\langle k \rangle$ = 1.66667



γ = 2.5
$\langle k \rangle$ = 1.92



γ = 2.5
$\langle k \rangle$ = 1.6



γ = 2.5
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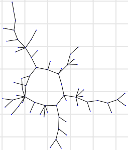

γ = 2.5
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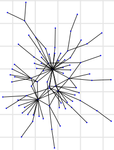

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Scale-free networks

The big deal:

- We move beyond describing networks to finding mechanisms for why certain networks are the way they are.

A big deal for scale-free networks:

- How does the exponent γ depend on the mechanism?
- Do the mechanism details matter?

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- Barabási-Albert model = BA model.
- Key ingredients:
  Growth and Preferential Attachment (PA).
- Step 1: start with m_0 disconnected nodes.
- Step 2:
  1. Growth—a new node appears at each time step $t = 0, 1, 2, \ldots$.
  2. Each new node makes m links to nodes already present.
  3. Preferential attachment—Probability of connecting to ith node is $\propto k_i$.
- In essence, we have a rich-gets-richer scheme.

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- Definition: A_k is the attachment kernel for a node with degree k.
- For the original model:

$$A_k = k$$

- Definition: $P_{\mathrm{attach}}(k, t)$ is the attachment probability.
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$$P_{\mathrm{attach}}(\text{node } i, t) = \frac{k_i(t)}{\sum_{j=1}^{N(t)} k_j(t)} = \frac{k_i(t)}{\sum_{k=0}^{k_{\max}(t)} k N_k(t)}$$

where $N(t) = m_0 + t$ is # nodes at time t and $N_k(t)$ is # degree k nodes at time t.

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- When $(N+1)$th node is added, the expected increase in the degree of node i is

$$E(k_{i,N+1} - k_{i,N}) \simeq m \frac{k_{i,N}}{\sum_{j=1}^{N(t)} k_j(t)}.$$

- Assumes probability of being connected to is small.
- Dispense with Expectation by assuming (hoping) that over longer time frames, degree growth will be smooth and stable.
- Approximate $k_{i,N+1} - k_{i,N}$ with $\frac{\mathrm{d}}{\mathrm{d}t} k_{i,t}$:

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- Deal with denominator: each added node brings m new edges.

$$\therefore \sum_{j=1}^{N(t)} k_j(t) = 2tm$$

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$$\frac{\mathrm{d}}{\mathrm{d}t} k_{i,t} = m \frac{k_i(t)}{\sum_{j=1}^{N(t)} k_j(t)} = m \frac{k_i(t)}{2mt} = \frac{1}{2t} k_i(t)$$

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Approximate analysis

- Deal with denominator: each added node brings m new edges.

$$\therefore \sum_{j=1}^{N(t)} k_j(t) = 2tm$$

- The node degree equation now simplifies:

$$\frac{\mathrm{d}}{\mathrm{d}t} k_{i,t} = m \frac{k_i(t)}{\sum_{j=1}^{N(t)} k_j(t)} = m \frac{k_i(t)}{2mt} = \frac{1}{2t} k_i(t)$$

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- Know ith node appears at time

$$t_{i,\text{start}} = \begin{cases} i - m_0 & \text{for } i > m_0 \\ 0 & \text{for } i \le m_0 \end{cases}$$

- So for $i > m_0$ (exclude initial nodes), we must have

$$k_i(t) = m \left(\frac{t}{t_{i,\text{start}}} \right)^{1/2} \quad \text{for } t \ge t_{i,\text{start}}.$$

- All node degrees grow as $t^{1/2}$ but later nodes have larger $t_{i,\text{start}}$ which flattens out growth curve.
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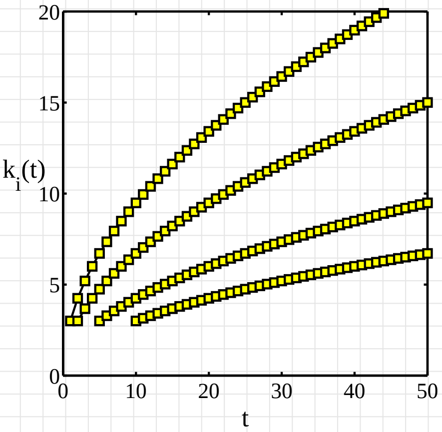

- $m = 3$
- $t_{i,\mathrm{start}} =$ 1, 2, 5, and 10.

Degree distribution

- So what's the degree distribution at time t?
- Use fact that birth time for added nodes is distributed uniformly:

$$\mathbf{Pr}(t_{i,\mathrm{start}})\mathrm{d}t_{i,\mathrm{start}} \simeq \frac{\mathrm{d}t_{i,\mathrm{start}}}{t}$$

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$$k_i(t) = m\left(\frac{t}{t_{i,\mathrm{start}}}\right)^{1/2} \Rightarrow t_{i,\mathrm{start}} = \frac{m^2 t}{k_i(t)^2}.$$

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- We thus have a very specific prediction of $\mathbf{Pr}(k) \sim k^{-\gamma}$ with $\gamma = 3$.
- Typical for real networks: $2 < \gamma < 3$.
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- $2 < \gamma < 3$: finite mean and 'infinite' variance (wild)
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The Internets is a different business...

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Real data

From Barabási and Albert's original paper [4]:

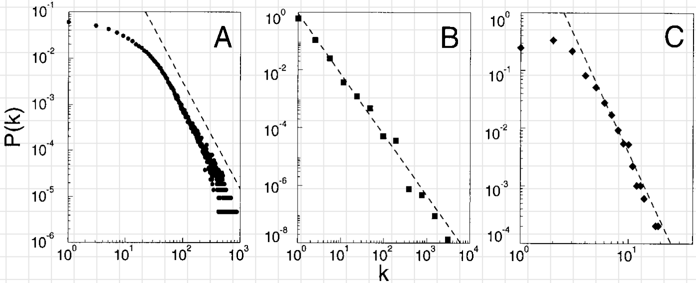

Fig. 1. The distribution function of connectivities for various large networks. (**A**) Actor collaboration graph with $N = 212{,}250$ vertices and average connectivity $\langle k \rangle = 28.78$. (**B**) WWW, $N = 325{,}729$, $\langle k \rangle = 5.46$ (6). (**C**) Power grid data, $N = 4941$, $\langle k \rangle = 2.67$. The dashed lines have slopes (A) $\gamma_{actor} = 2.3$, (B) $\gamma_{www} = 2.1$ and (C) $\gamma_{power} = 4$.

Things to do and questions

- Vary attachment kernel.
- Vary mechanisms:
  1. Add edge deletion
  2. Add node deletion
  3. Add edge rewiring
- Deal with directed versus undirected networks.
- Important Q.: Are there distinct universality classes for these networks?
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- PA implies arriving nodes have complete knowledge of the existing network's degree distribution.
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Preferential attachment through randomness

- Instead of attaching preferentially, allow new nodes to attach randomly.
- Now add an extra step: new nodes then connect to some of their friends' friends.
- Can also do this at random.
- Assuming the existing network is random, we know probability of a random friend having degree k is

$$Q_k \propto kP_k$$

- So rich-gets-richer scheme can now be seen to work in a natural way.

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- System robustness and system robustness.
- Albert et al., Nature, 2000:
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Robustness

- Standard random networks (Erdős-Rényi)
  versus
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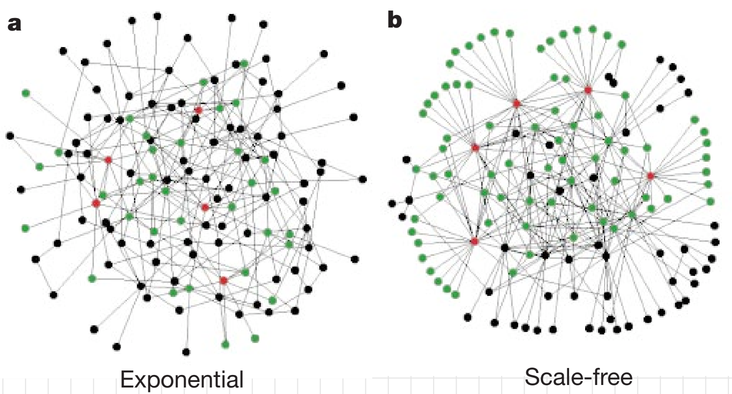

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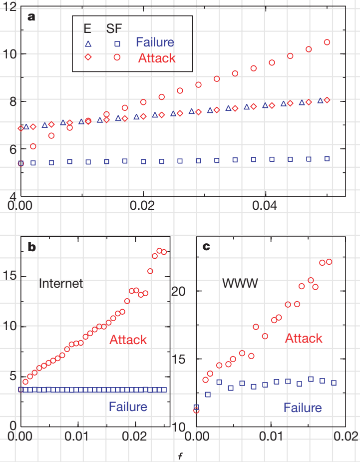

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- Plots of network diameter as a function of fraction of nodes removed
- Erdős-Rényi versus scale-free networks
- blue symbols = random removal
- red symbols = targeted removal (most connected first)

Robustness

- Scale-free networks are thus robust to random failures yet fragile to targeted ones.
- All very reasonable: Hubs are a big deal.
- But: next issue is whether hubs are vulnerable or not.
- Representing all webpages as the same size node is obviously a stretch (e.g., google vs. a random person's webpage)
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- All very reasonable: Hubs are a big deal.
- But: next issue is whether hubs are vulnerable or not.
- Representing all webpages as the same size node is obviously a stretch (e.g., google vs. a random person's webpage)
- Most connected nodes are either:
  1. Physically larger nodes that may be harder to 'target'
  2. or subnetworks of smaller, normal-sized nodes.
- Need to explore cost of various targeting schemes.

Outline

Basic definitions

Examples of Complex Networks

Properties of Complex Networks

Nutshell

Basic models of complex networks

- Generalized random networks
- Scale-free networks
- Small-world networks
- Generalized affiliation networks

References

People thinking about people:

How are social networks structured?

- How do we define and measure connections?
- Methods/issues of self-report and remote sensing.

What about the dynamics of social networks?

- How do social networks/movements begin & evolve?
- How does collective problem solving work?
- How does information move through social networks?
- Which rules give the best 'game of society?'

Sociotechnical phenomena and algorithms:

- What can people and computers do together? (google)
- Use Play + Crunch to solve problems. Which problems?

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A small slice of the pie:

- Q. Can people pass messages between distant individuals using only their existing social connections?
- A. Apparently yes...

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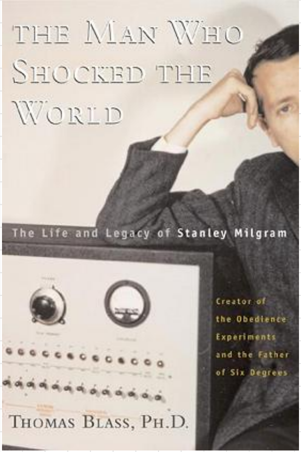
Milgram's social search experiment (1960s)



http://www.stanleymilgram.com

- Target person = Boston stockbroker.
- 296 senders from Boston and Omaha.
- 20% of senders reached target.
- chain length $\simeq$ 6.5.

Popular terms:

- The Small World Phenomenon;
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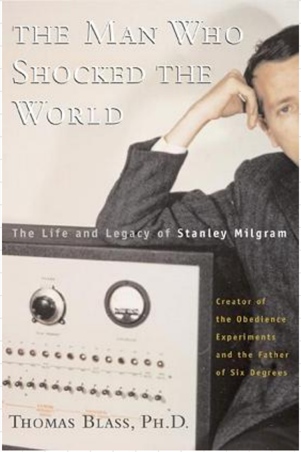

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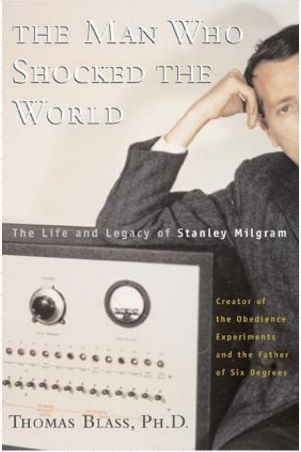

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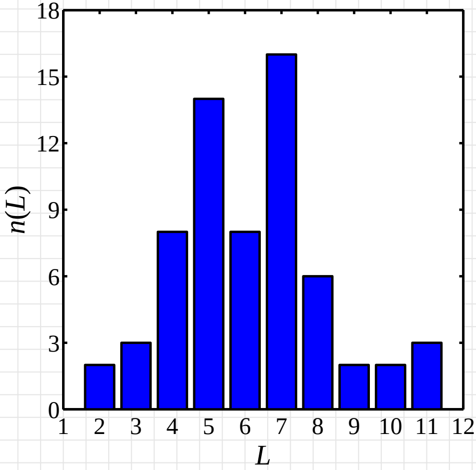
Lengths of successful chains:



From Travers and Milgram (1969) in Sociometry: [26]
"An Experimental Study of the Small World Problem."

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Two features characterize a social 'Small World':

1. Short paths exist

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Social Search

Milgram's small world experiment with email:

"An Experimental study of Search in Global Social Networks"
P. S. Dodds, R. Muhamad, and D. J. Watts,
Science, Vol. 301, pp. 827–829, 2003. [11]

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- 60,000+ participants in 166 countries
- 18 targets in 13 countries including
  - a professor at an Ivy League university,
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- Probability of a chain of length 10 getting through:

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- age, gender
- country of residence
- income
- religion
- relationship to recipient

Range of completion rates for subpopulations:

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Nevertheless, some weak discrepencies do exist...

An above average connector:

Norwegian, secular male, aged 30-39, earning over $100K, with graduate level education working in mass media or science, who uses relatively weak ties to people they met in college or at work.

A below average connector:

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Mildly bad for continuing chain:

choosing recipients because “they have lots of friends” or because they will “likely continue the chain.”

Why:

- Specificity important.
- Successful links used relevant information. (e.g. connecting to someone who shares same profession as target.)

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Basic results:

- $\langle L \rangle = 4.05$ for all completed chains
- $L_* =$ Estimated 'true' median chain length (zero attrition)
- Intra-country chains: $L_* = 5$
- Inter-country chains: $L_* = 7$
- All chains: $L_* = 7$
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Harnessing social search:

- Can distributed social search be used for something big/good?
- What about something evil? (Good idea to check.)
- What about socio-inspired algorithms for information search? (More later.)
- For real social search, we have an incentives problem.
- Which kind of influence mechanisms/algorithms would help propagate search?
- Fun, money, prestige, ... ?
- Must be 'non-gameable.'

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Red balloons:

A Grand Challenge:

- 1969: The Internet is born (⊞) (the ARPANET (⊞)—four nodes!).
- Originally funded by DARPA who created a grand Network Challenge (⊞) for the 40th anniversary.
- Saturday December 5, 2009: DARPA puts 10 red weather balloons up during the day.
- Each 8 foot diameter balloon is anchored to the ground somewhere in the United States.
- Challenge: Find the latitude and longitude of each balloon.
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Finding red balloons:

The winning team and strategy:

- MIT's Media Lab (⊞) won in less that 9 hours.
- People were virally recruited online to help out.
- Idea: Want people to both (1) find the balloons and (2) involve more people.
- Recursive incentive structure with exponentially decaying payout:
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  - $500 for recruiting a person who recruits the balloon finder.
  - etc.

Finding balloons:

Clever scheme:

- Max payout = $4000 per balloon.
- Individuals have clear incentives to both
  1. involve/source more people (spread), and
  2. find balloons (goal action).
- Gameable?
- Limit to how much money a set of bad actors can extract.

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The social world appears to be small... why?

Theory: how do we understand the small world property?

- Connected random networks have short average path lengths:

$$\langle d_{AB} \rangle \sim \log(N)$$

N = population size,

d_{AB} = distance between nodes A and B.

- But: social networks aren't random...

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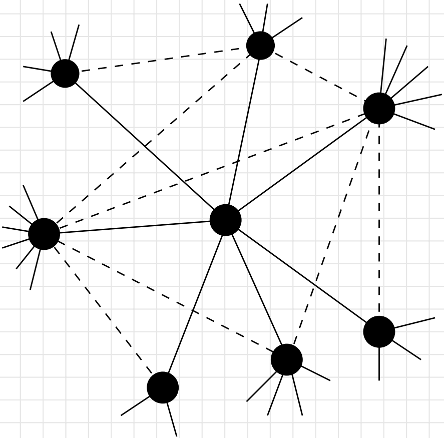
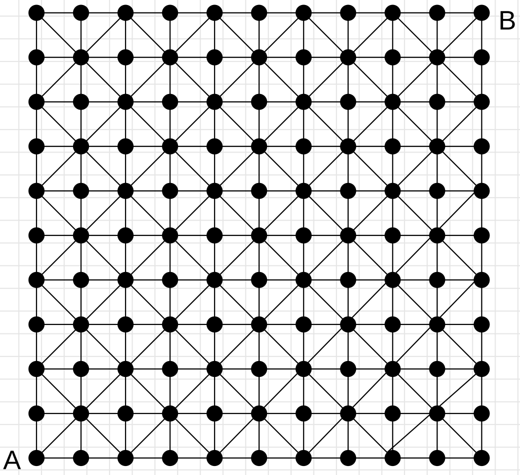
Simple socialness in a network:



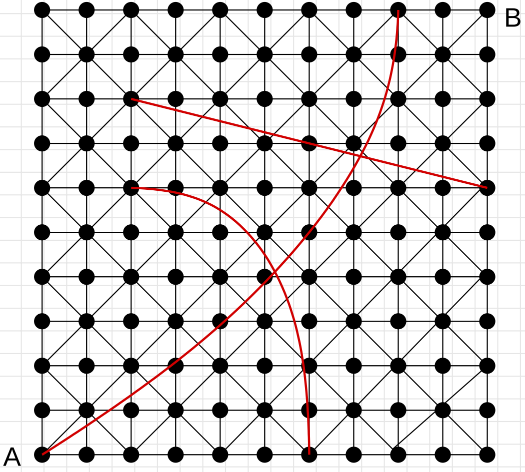
Need “clustering” (your friends are likely to know each other):

Non-randomness gives clustering:



$d_{AB} = 10 \rightarrow$ too many long paths.

Randomness + regularity



Now have $d_{AB} = 3$

$\langle d \rangle$ decreases overall

Small-world networks

Introduced by Watts and Strogatz (Nature, 1998) [30]
"Collective dynamics of 'small-world' networks."

Small-world networks were found everywhere:

- neural network of C. elegans,
- semantic networks of languages,
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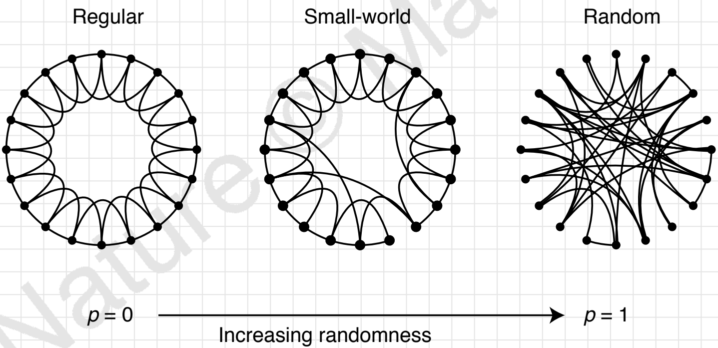
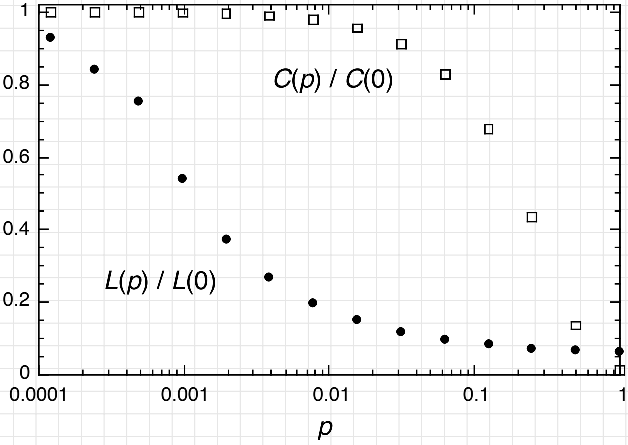
Toy model:



Nature © Macmillan

The structural small-world property:



- $L(p)$ = average shortest path length as a function of p
- $C(p)$ = average clustring as a function of p

Previous work—finding short paths

But are these short cuts findable?

Nope.

Nodes cannot find each other quickly with any local search method.

Need a more sophisticated model...

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- What can a local search method reasonably use?
- How to find things without a map?
- Need some measure of distance between friends and the target.

Some possible knowledge:

- Target's identity
- Friends' popularity
- Friends' identities
- Where message has been

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Kleinberg's Network:

1. Start with regular d-dimensional cubic lattice.
2. Add local links so nodes know all nodes within a distance q.
3. Add m short cuts per node.
4. Connect i to j with probability

$$p_{ij} \propto x_{ij}{}^{-\alpha}.$$

- $\alpha = 0$: random connections.
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Theoretical optimal search:

- "Greedy" algorithm.
- Number of connections grow logarithmically (slowly) in space: $\alpha = d$.
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But: social networks aren’t lattices plus links.

Previous work—finding short paths

- If networks have hubs can also search well: Adamic et al. (2001) [1]

$$P(k_i) \propto k_i^{-\gamma}$$

  where k = degree of node i (number of friends).
- Basic idea: get to hubs first (airline networks).
- But: hubs in social networks are limited.

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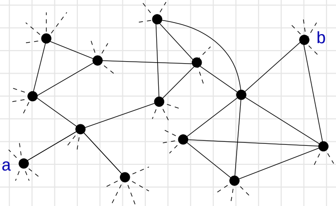
Outline

The problem

If there are no hubs and no underlying lattice, how can search be efficient?



Which friend of a is closest to the target b?

What does ‘closest’ mean?

What is ‘social distance’?

Models

One approach: incorporate identity.

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Identity is formed from attributes such as:

- Geographic location
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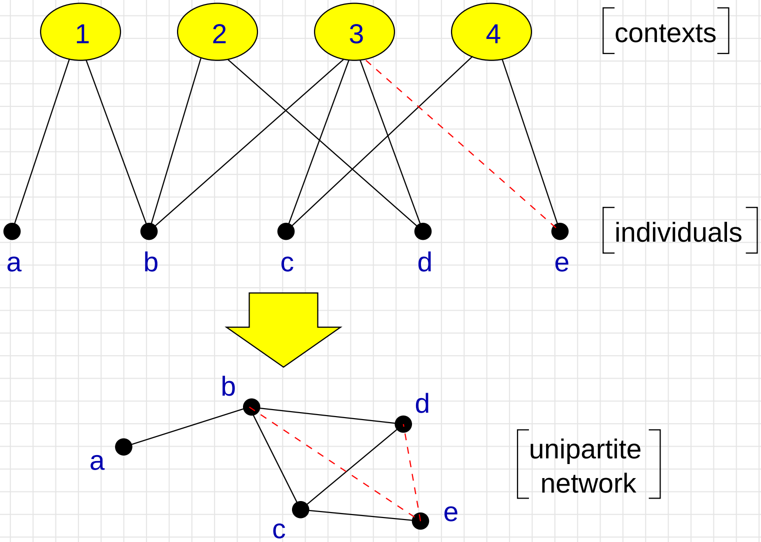
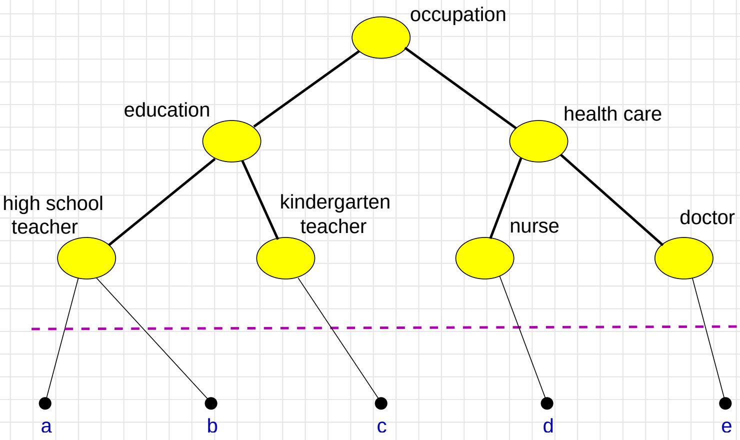
Attributes ⇔ Contexts ⇔ Interactions ⇔ Networks.

Social distance—Bipartite affiliation networks



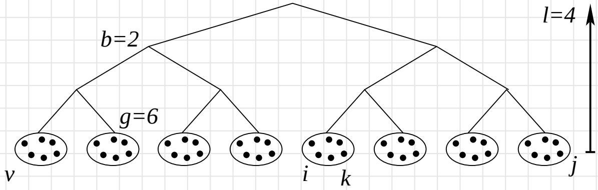
Bipartite affiliation networks: boards and directors, movies and actors.

Social distance—Context distance



Models

Distance between two individuals x_{ij} is the height of lowest common ancestor.



$x_{ij} = 3$, $x_{ik} = 1$, $x_{iv} = 4$.

Models

- Individuals are more likely to know each other the closer they are within a hierarchy.
- Construct z connections for each node using

$$p_{ij} = c \exp\{-\alpha x_{ij}\}.$$

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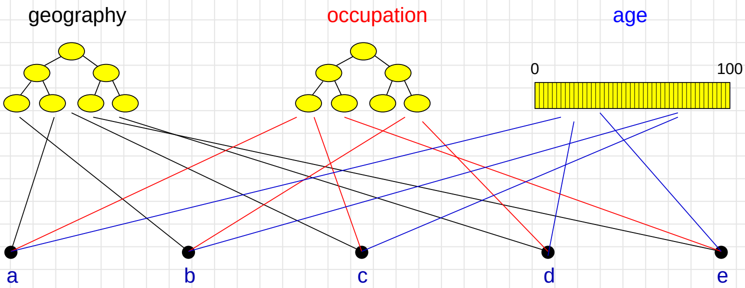
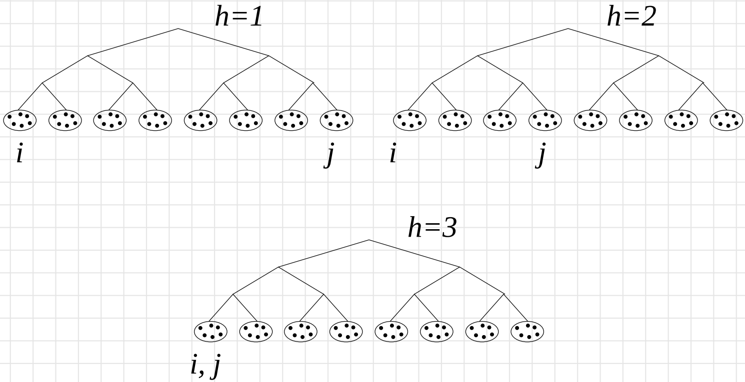
Generalized affiliation networks



- Blau & Schwartz [5], Simmel [24], Breiger [9], Watts *et al.* [29]

The model



$\vec{v}_i = [1\ 1\ 1]^T$, $\vec{v}_j = [8\ 4\ 1]^T$

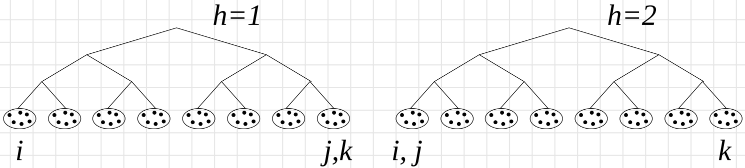
$x^1_{ij} = 4$, $x^2_{ij} = 3$, $x^3_{ij} = 1$.

Social distance:

$$y_{ij} = \min_h x^h_{ij}.$$

The model

Triangle inequality doesn’t hold:



$$y_{ik} = 4 > y_{ij} + y_{jk} = 1 + 1 = 2.$$

The model

- Individuals know the identity vectors of
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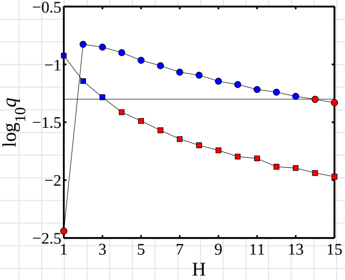
The model-results—searchable networks

$\alpha = 0$ versus $\alpha = 2$ for $N \simeq 10^5$:



$q \geq r$

$q < r$

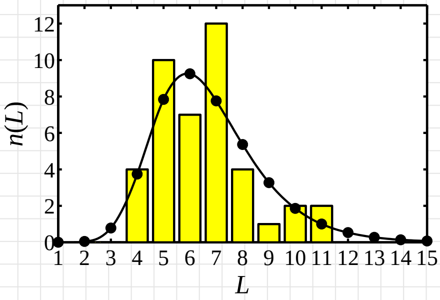
$r = 0.05$

q = probability an arbitrary message chain reaches a target.

- A few dimensions help.
- Searchability decreases as population increases.
- Precise form of hierarchy largely doesn't matter.

The model-results

Milgram's Nebraska-Boston data:



Model parameters:

- $N = 10^8$,
- $z = 300$, $g = 100$,
- $b = 10$,
- $\alpha = 1$, $H = 2$;

- $\langle L_{\mathrm{model}} \rangle \simeq 6.7$
- $L_{\mathrm{data}} \simeq 6.5$

Social search—Data

Adamic and Adar (2003)

- For HP Labs, found probability of connection as function of organization distance well fit by exponential distribution.
- Probability of connection as function of real distance $\propto 1/r$.

Social search—Data

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Social Search—Real world uses

- Tags create identities for objects
- Website tagging: `http://www.del.icio.us`
- (e.g., Wikipedia)
- Photo tagging: `http://www.flickr.com`
- Dynamic creation of metadata plus links between information objects.
- Folksonomy: collaborative creation of metadata

Social Search—Real world uses

Recommender systems:

- Amazon uses people's actions to build effective connections between books.
- Conflict between 'expert judgments' and tagging of the hoi polloi.

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- Bare networks are typically unsearchable.
- Paths are findable if nodes understand how network is formed.
- Importance of identity (interaction contexts).
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[1] L. Adamic, R. Lukose, A. Puniyani, and B. Huberman.
Search in power-law networks.
Phys. Rev. E, 64:046135, 2001. pdf (⊞)

[2] R. Albert and A.-L. Barabási.
Statistical mechanics of complex networks.
Rev. Mod. Phys., 74:47–97, 2002. pdf (⊞)

[3] R. Albert, H. Jeong, and A.-L. Barabási.
Error and attack tolerance of complex networks.
Nature, 406:378–382, 2000. pdf (⊞)

[4] A.-L. Barabási and R. Albert.
Emergence of scaling in random networks.
Science, 286:509–511, 1999. pdf (⊞)

References II

[5] P. M. Blau and J. E. Schwartz.
Crosscutting Social Circles.
Academic Press, Orlando, FL, 1984.

[6] S. Boccaletti, V. Latora, Y. Moreno, M. Chavez, and D.-U. Hwang.
Complex networks: Structure and dynamics.
Physics Reports, 424:175–308, 2006. pdf (⊞)

[7] J. Bollen, H. Van de Sompel, A. Hagberg, L. Bettencourt, R. Chute, M. A. Rodriguez, and B. Lyudmila.
Clickstream data yields high-resolution maps of science.
PLoS ONE, 4:e4803, 2009. pdf (⊞)

References III

[8] S. Bornholdt and H. G. Schuster, editors.
Handbook of Graphs and Networks.
Wiley-VCH, Berlin, 2003.

[9] R. L. Breiger.
The duality of persons and groups.
Social Forces, 53(2):181–190, 1974. pdf (⊞)

[10] A. Clauset, C. Moore, and M. E. J. Newman.
Structural inference of hierarchies in networks, 2006.
pdf (⊞)

[11] P. S. Dodds, R. Muhamad, and D. J. Watts.
An experimental study of search in global social networks.
Science, 301:827–829, 2003. pdf (⊞)

References IV

[12] P. S. Dodds and D. H. Rothman.
Unified view of scaling laws for river networks.
Physical Review E, 59(5):4865–4877, 1999. pdf (⊞)

[13] S. N. Dorogovtsev and J. F. F. Mendes.
Evolution of Networks.
Oxford University Press, Oxford, UK, 2003.

[14] M. Gladwell.
The Tipping Point.
Little, Brown and Company, New York, 2000.

[15] A. Halevy, P. Norvig, and F. Pereira.
The unreasonable effectiveness of data.
IEEE Intelligent Systems, 24:8–12, 2009. pdf (⊞)

[16] J. Kleinberg.
Navigation in a small world.
Nature, 406:845, 2000. pdf (⊞)

References V

[17] J. M. Kleinberg.
Authoritative sources in a hyperlinked environment.
Proc. 9th ACM-SIAM Symposium on Discrete Algorithms, 1998. pdf (⊞)

[18] M. Kretzschmar and M. Morris.
Measures of concurrency in networks and the spread of infectious disease.
Math. Biosci., 133:165–95, 1996. pdf (⊞)

[19] R. Milo, N. Kashtan, S. Itzkovitz, M. E. J. Newman, and U. Alon.
On the uniform generation of random graphs with prescribed degree sequences, 2003. pdf (⊞)

[20] M. Newman.
Assortative mixing in networks.
Phys. Rev. Lett., 89:208701, 2002. pdf (⊞)

References VI

[21] M. E. J. Newman.
The structure and function of complex networks.
SIAM Review, 45(2):167–256, 2003. pdf (⊞)

[22] I. Rodríguez-Iturbe and A. Rinaldo.
Fractal River Basins: Chance and Self-Organization.
Cambridge University Press, Cambrigde, UK, 1997.

[23] S. S. Shen-Orr, R. Milo, S. Mangan, and U. Alon.
Network motifs in the transcriptional regulation network of *Escherichia coli*.
Nature Genetics, pages 64–68, 2002. pdf (⊞)

[24] G. Simmel.
The number of members as determining the sociological form of the group. I.
American Journal of Sociology, 8:1–46, 1902.

References VII

[25] E. Tokunaga.
The composition of drainage network in Toyohira River Basin and the valuation of Horton's first law.
Geophysical Bulletin of Hokkaido University, 15:1–19, 1966.

[26] J. Travers and S. Milgram.
An experimental study of the small world problem.
Sociometry, 32:425–443, 1969. pdf (⊞)

[27] F. Vega-Redondo.
Complex Social Networks.
Cambridge University Press, 2007.

[28] D. J. Watts.
Six Degrees.
Norton, New York, 2003.

References VIII

[29] D. J. Watts, P. S. Dodds, and M. E. J. Newman.
Identity and search in social networks.
Science, 296:1302–1305, 2002. pdf (⊞)

[30] D. J. Watts and S. J. Strogatz.
Collective dynamics of 'small-world' networks.
Nature, 393:440–442, 1998. pdf (⊞)