



DECSAI

Departamento de Ciencias de la Computación e I.A.

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Networks

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Networks



- Network Analysis
 - Applications
 - Network Properties
- Network Models
 - Random-Graph Models
 - Growing Random Models
 - Strategic Network Formation
- Network Structure & Dynamics
 - Network Centrality
 - Community Detection
 - Diffusion through Networks
 - Search on Networks
- Bibliography



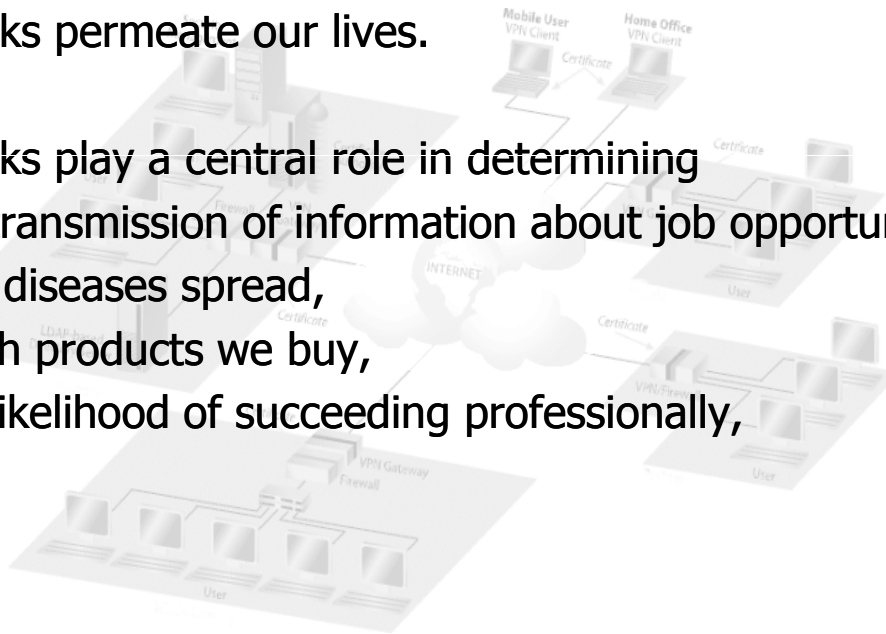
Network Analysis



Networks permeate our lives.

Networks play a central role in determining

- the transmission of information about job opportunities,
- how diseases spread,
- which products we buy,
- our likelihood of succeeding professionally,
- ...

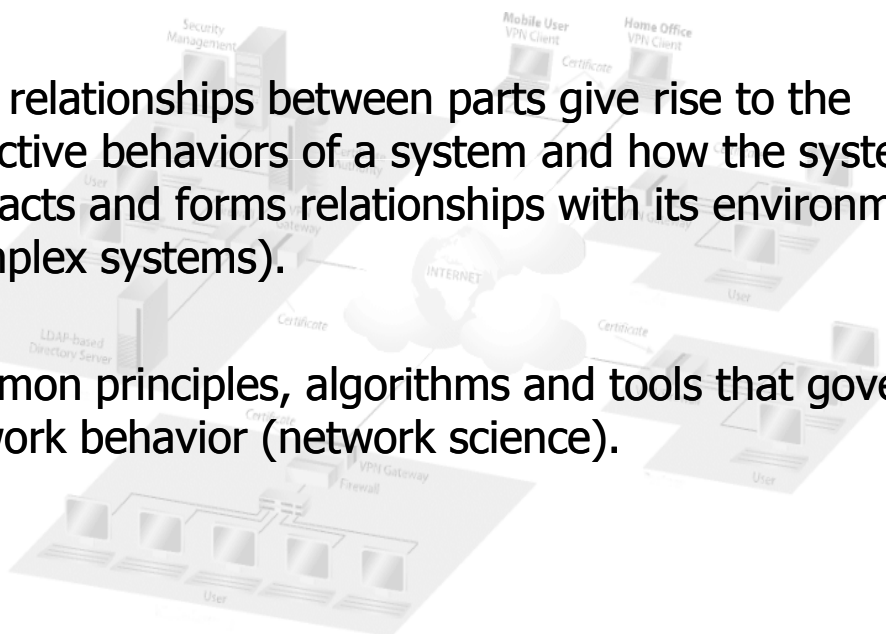


Network Analysis



As a field of study...

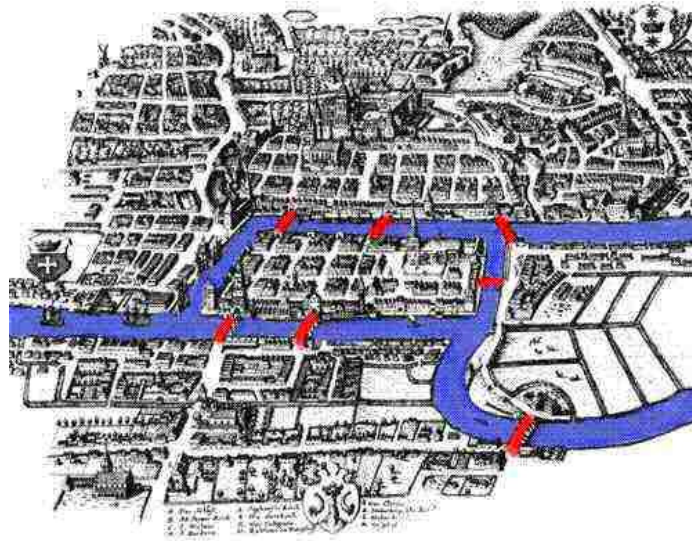
- How relationships between parts give rise to the collective behaviors of a system and how the system interacts and forms relationships with its environment (complex systems).
- Common principles, algorithms and tools that govern network behavior (network science).



Network Analysis



Origins: Graph Theory



The Seven Bridges of Königsberg
(Leonhard Euler, 1736)

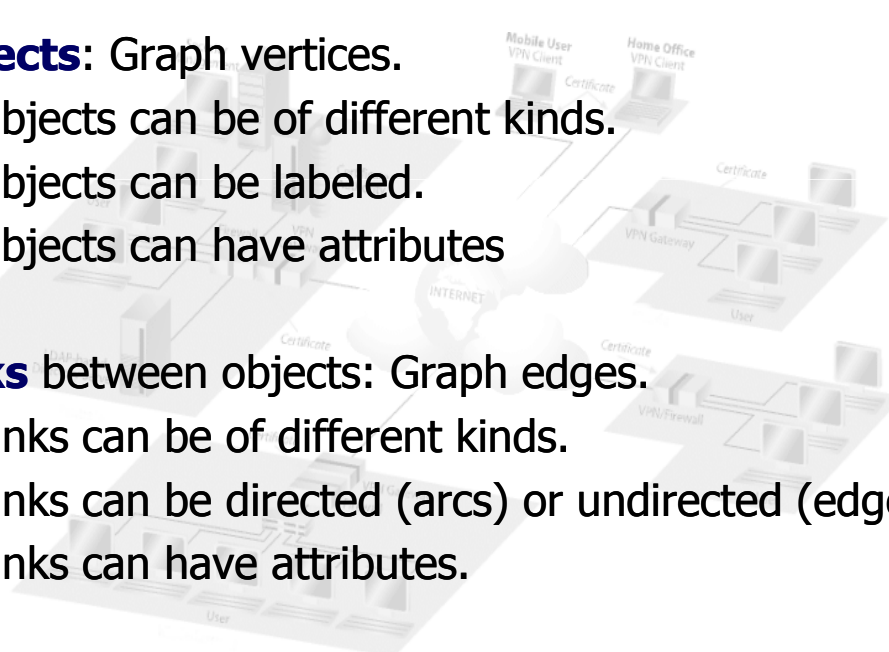


Network Analysis



Networks as graphs "on steroids" ...

- **Objects:** Graph vertices.
 - Objects can be of different kinds.
 - Objects can be labeled.
 - Objects can have attributes
- **Links** between objects: Graph edges.
 - Links can be of different kinds.
 - Links can be directed (arcs) or undirected (edges).
 - Links can have attributes.



Network Analysis



A formal definition of network

[Ted G. Lewis: "Network Science," 2009]

$$\mathbf{G}(t) = \{ \mathbf{N}(t), \mathbf{L}(t), \mathbf{f}(t) : \mathbf{J}(t) \}$$

where

- t = time (simulated or real)
- N = nodes (a.k.a. vertices or "actors")
- L = links (a.k.a. edges)
- f = topology (connections through links)
- J = behavior of nodes and links (algorithm)



Network Analysis



An interdisciplinary field: Complex systems

("networks of heterogeneous components that interact")

- Physics: **Nonlinear dynamics & chaos.**
Dynamical systems that are highly sensitive to initial conditions (a.k.a. butterfly effect).
- Economics: **Markets.**
Spontaneous (or emergent) order as the result of human action, but not the execution of any human design [Austrian perspective].
- Information theory: **Complex adaptive systems.**
(focus on the ability to change and learn from experience).



Applications



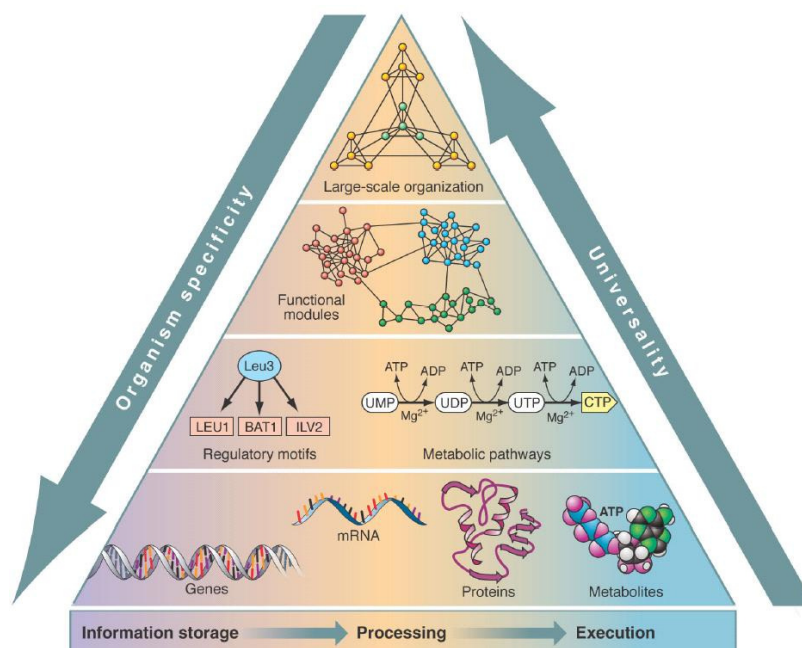
- "Cheminformatics": Chemical compounds.
- "Bioinformatics": Protein networks & bio-pathways
- Software Engineering: Program analysis...
- Network flow analysis (transport, workflows...)
- Semi-structured databases, e.g. XML
- Knowledge management: Ontologies & semantic nets
- Computer-aided design (CAD): IC design...
- Geographic information systems (GIS) & cartography
- Social networks, e.g. Web
- Economic networks, e.g. markets



Applications



"Life complexity pyramid"



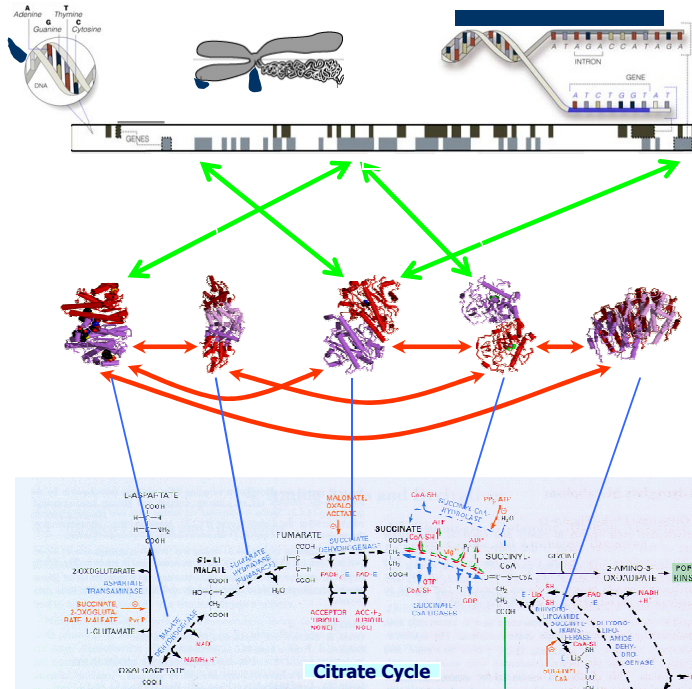
from Z.N. Oltvai and A.-L. Barabasi. Science, 2002



Applications



Biological networks



GENOME

Gene-protein interactions

PROTEOME

Protein-protein interactions

METABOLISM

Biochemical reactions



Applications



Yeast protein interaction network



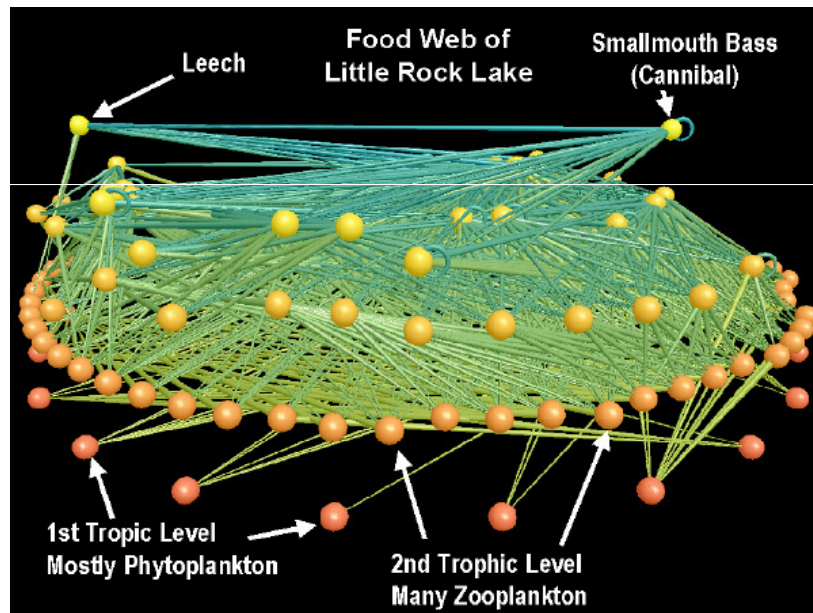
from H. Jeong et al Nature 411, 41 (2001)



Applications



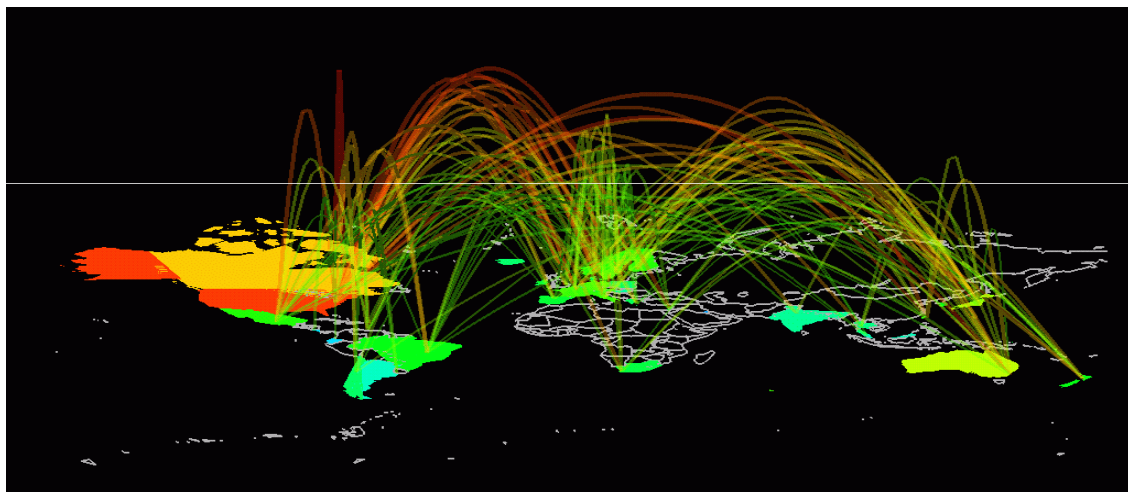
Ecological network: Trophic relationships in a food web.



Applications



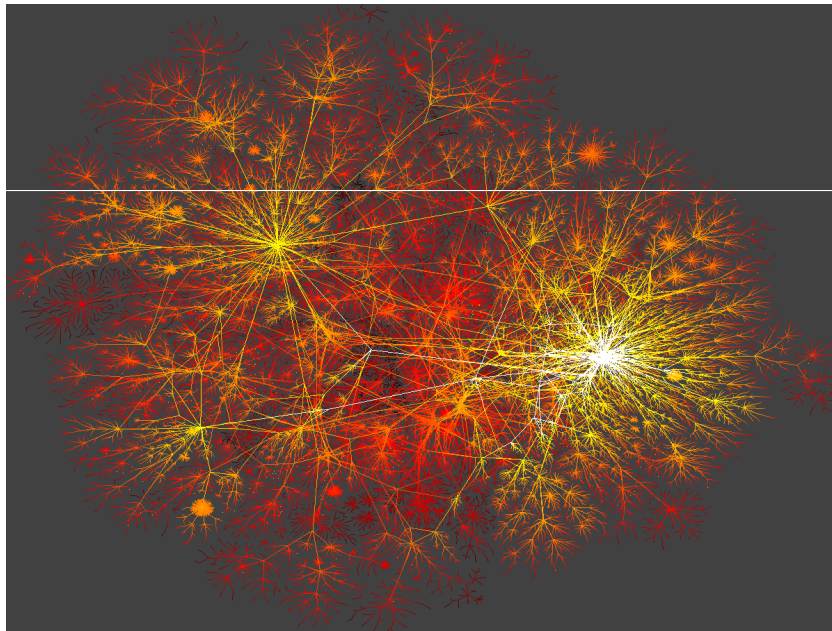
Telecommunication network



Applications



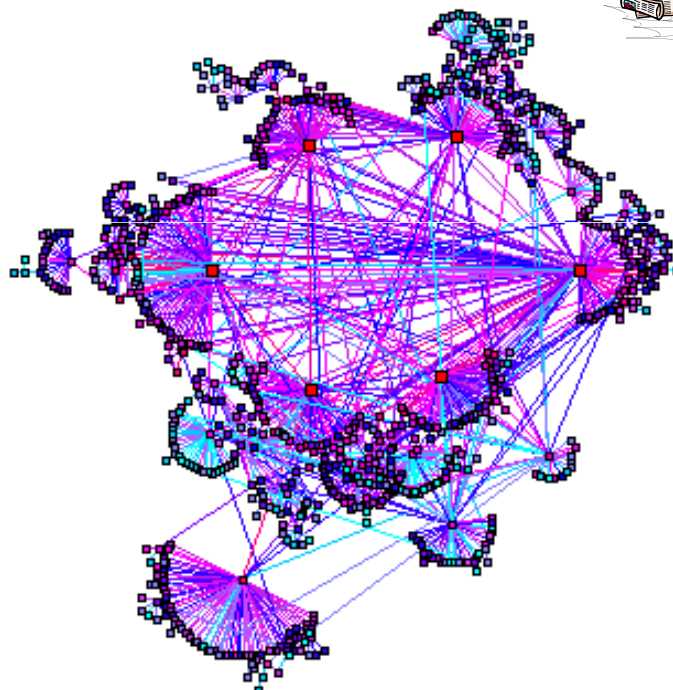
Internet



Applications



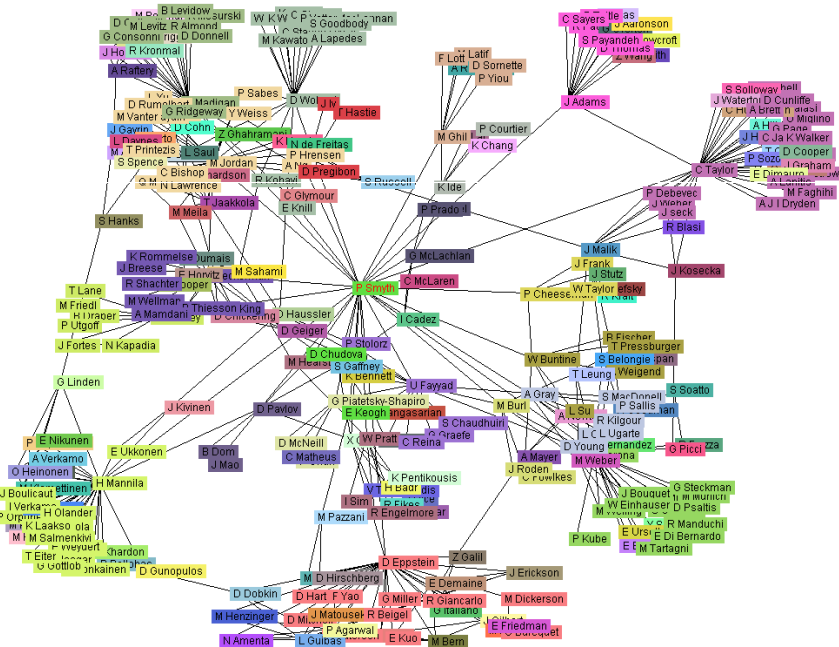
World Wide Web



Applications



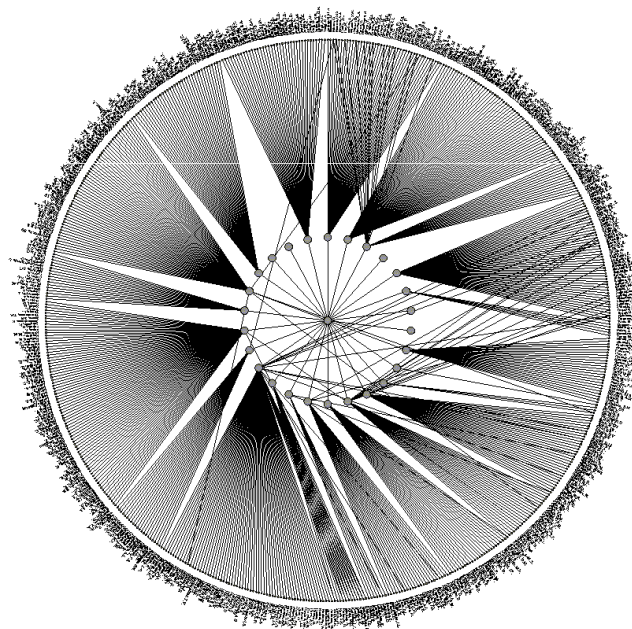
Social network: Bibliographic network (coauthors)



Applications



Social network: Bibliographic network (coauthors)

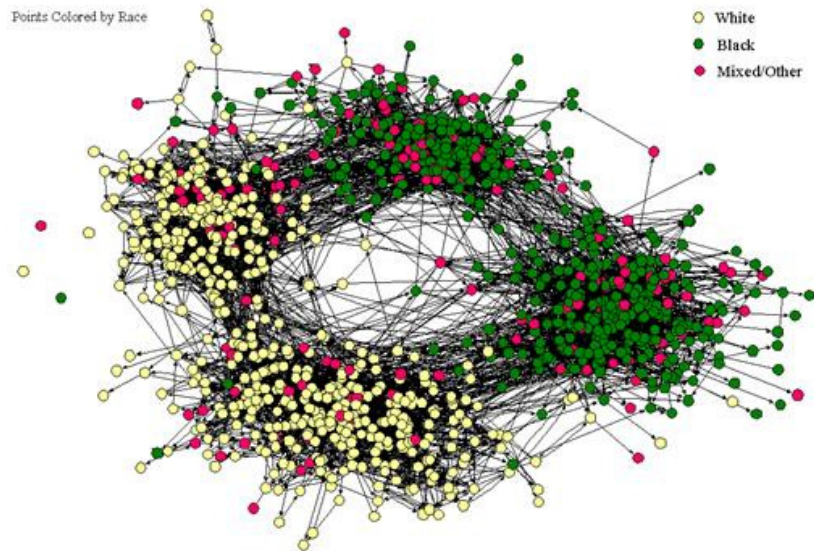


Applications



Social network: FOAF ("friend of a friend")

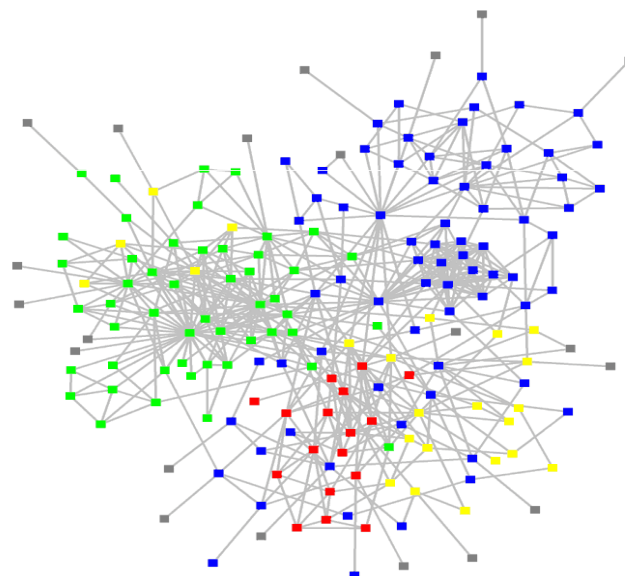
The Social Structure of "Countryside" School District



Applications



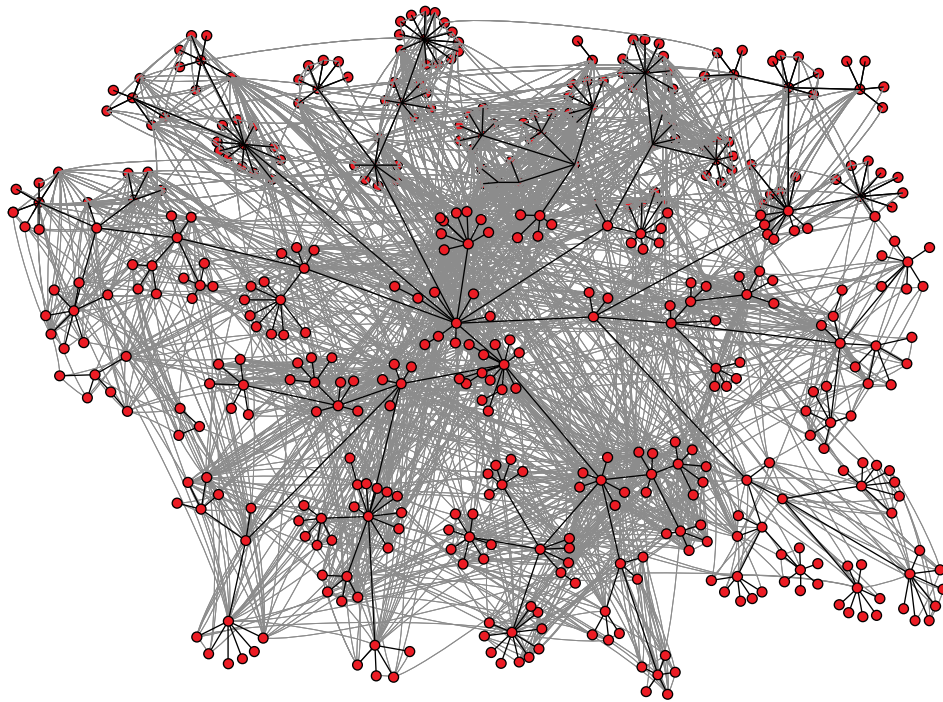
Social network: Organization



Applications



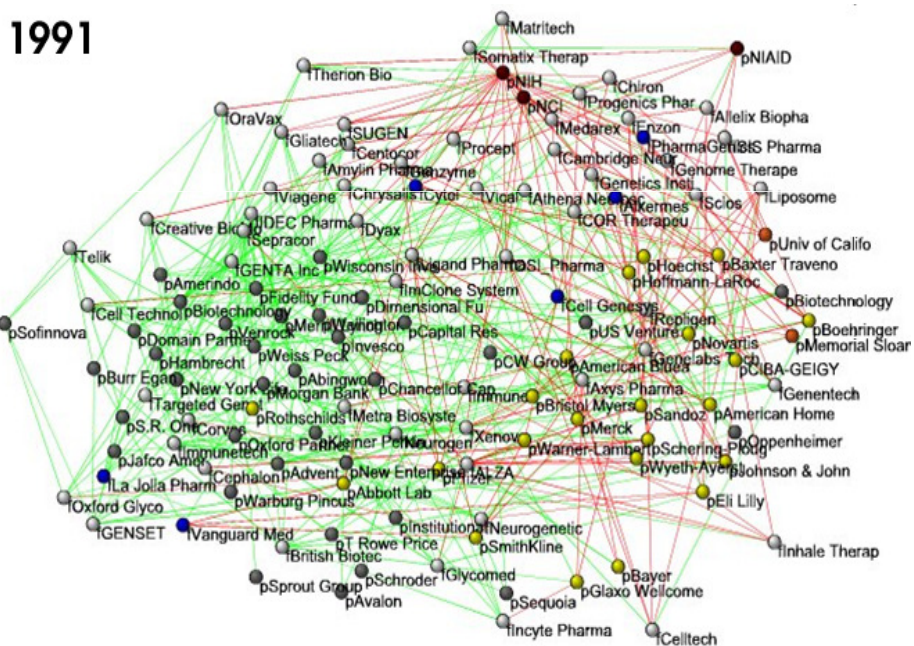
Social network: E-mail spectroscopy



Applications



Social network: US Biotech Industry

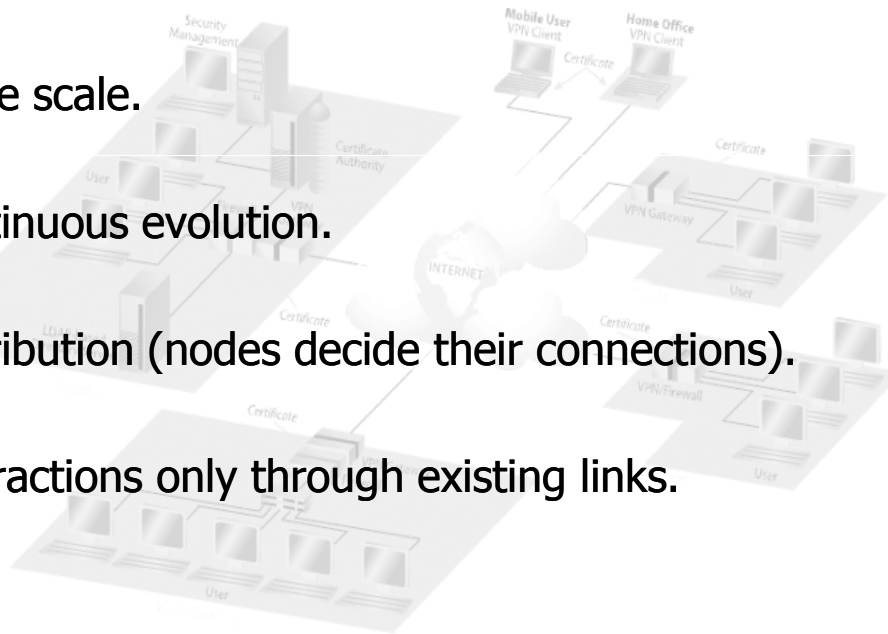


Network Properties



Common network features:

- Large scale.
- Continuous evolution.
- Distribution (nodes decide their connections).
- Interactions only through existing links.



Network Properties



Some interesting structural properties:

- Connected components: How many? Of what size?.
- Network diameter: Average distance, worst case...
- Node degree distribution & existence of "hubs" (heavily-connected nodes).
- Groupings (balance between local and large-distance connections, as well as their roles).

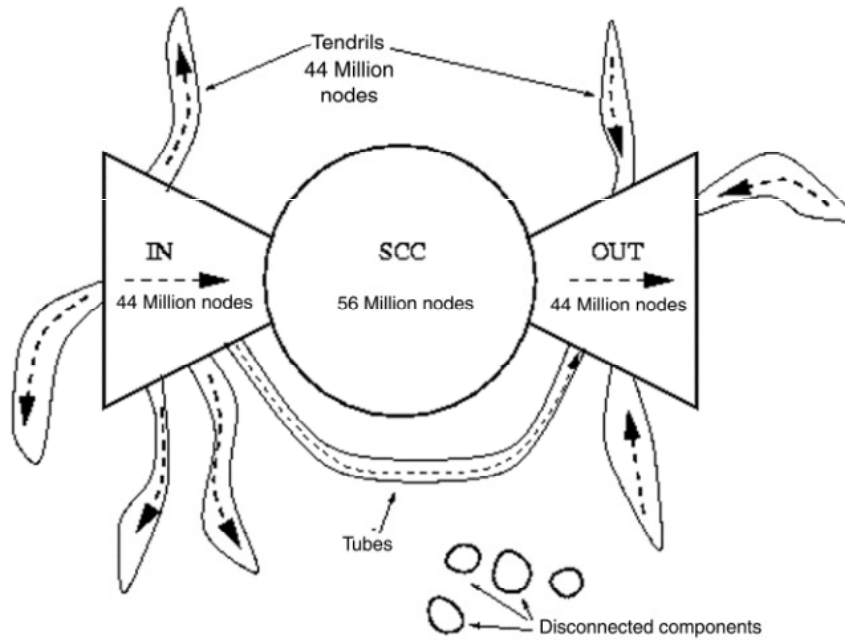


Network Properties



Network Connectivity

WWW

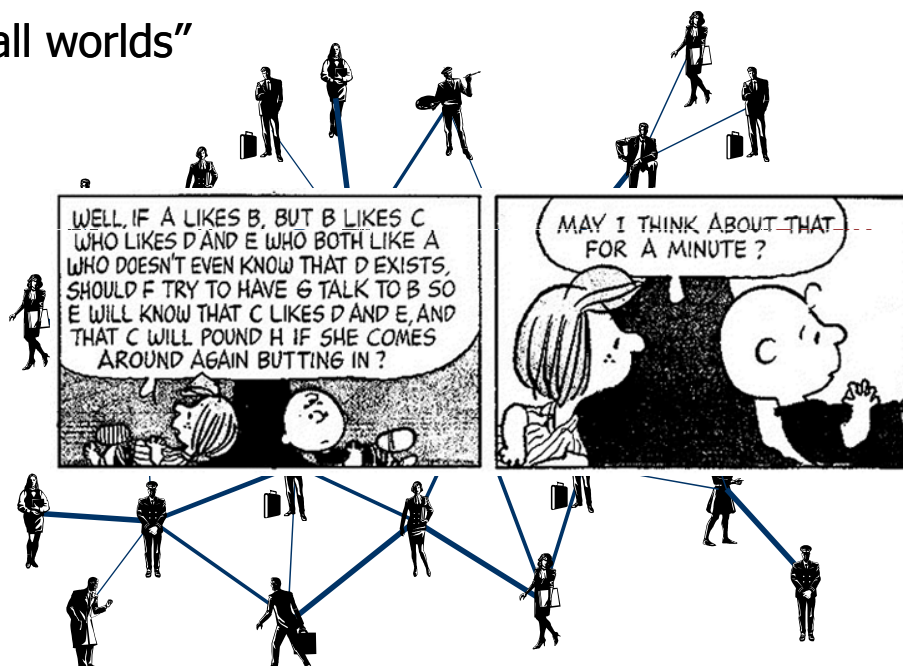


Network Properties



Network Diameter

"small worlds"



Network Properties



Clustering coefficient

- $\text{nbr}(u)$ Neighbors of the node u in the network.
 k Number of neighbors of u , i.e. $|\text{nbr}(u)|$.
 $\text{max}(u)$ Maximum number of links among the neighbors of u , e.g. $k*(k-1)/2$.

Clustering coefficient for the node u :

$$c(u) = (\text{\#links among neighbors of } u) / \text{max}(u)$$

Clustering coefficient for the graph G :

C = average of $c(u)$ for every node in G



Network Properties

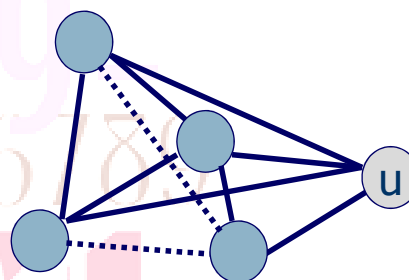


Clustering coefficient

$$k = 4$$

$$m = 6$$

$$c(u) = 4/6 = 0.66$$



$$0 \leq c(u) \leq 1$$

Similarity of u neighbors to a clique (complete graph).

Informal interpretation:

“My friends tend to be friends among them.”



Network Properties



Clustering coefficient for some real networks

Network	N	C	C_{rand}	L
WWW	153127	0.1078	0.00023	3.1
Internet	3015-6209	0.18-0.30	0.001	3.7-3.76
Actor	225226	0.79	0.00027	3.65
Coauthorship	52909	0.43	0.00018	5.9
Metabolic	282	0.32	0.026	2.9
Foodweb	134	0.22	0.06	2.43
C. elegance	282	0.28	0.05	2.65

Clustering coefficient (C):

$$C > C_{rand}$$

Path length (L):

$$L < L_{rand}$$



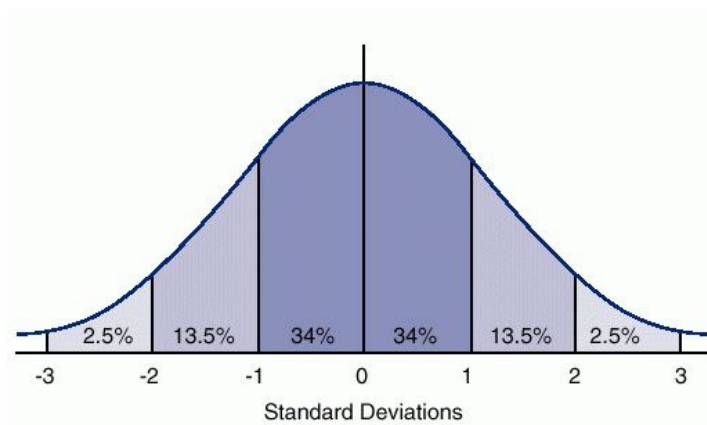
Network Properties



Node degree distribution

Normal distribution

Parameters: Average & deviation



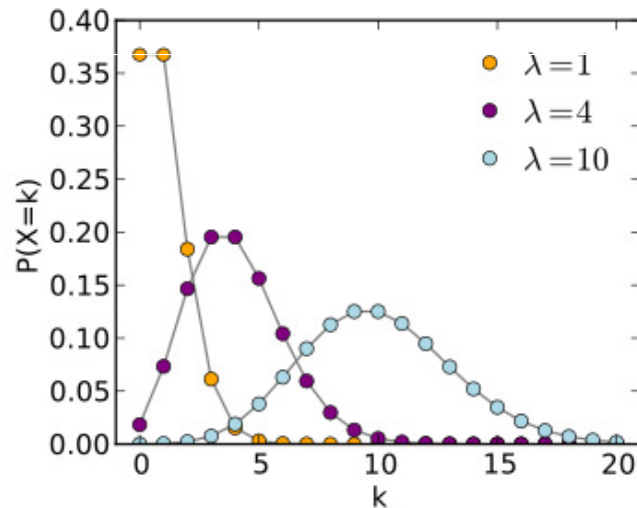
Network Properties



Node degree distribution

Poisson distribution

Single parameter: λ (mean & deviation)



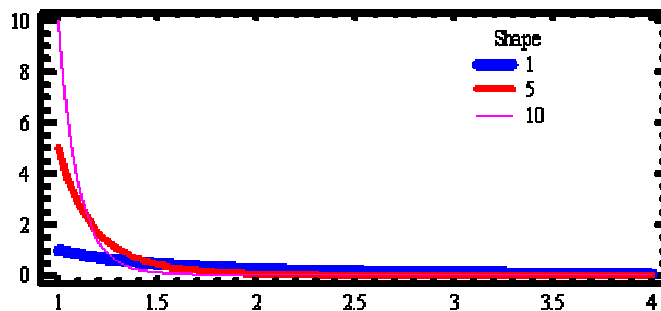
Network Properties



Node degree distribution

Pareto distribution (a.k.a. "power law")

Single parameter: α



$$P(x) \sim x^{-\alpha}$$

The Pareto principle (the "80-20 rule"):

20% of the population controls 80% of the wealth.



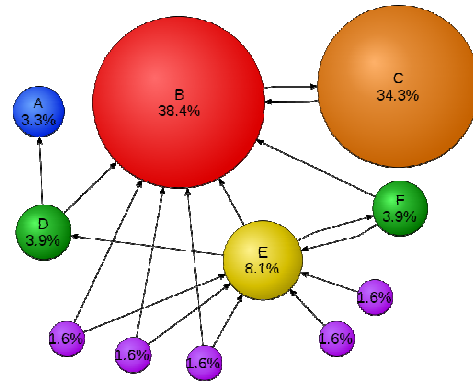
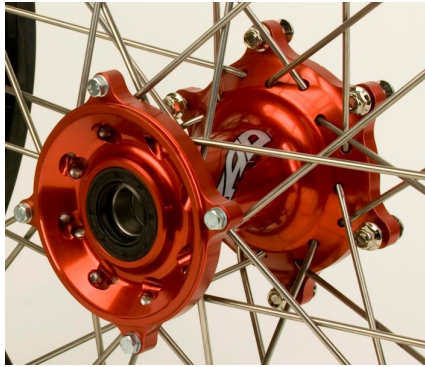
Network Properties



Node degree distribution

Hubs

Small number of nodes with a very high degree.



- Hubs appear with power laws ($P(x) \sim x^{-\alpha}$), but not with normal/binomial/Poisson distributions.



Network Properties



Node degree distribution

Log-log plot

- **Pareto distribution**

- $\log(\Pr[X = x]) = \log(1/x^\alpha) = -\alpha \log(x)$
- Linear, $-\alpha$ slope.

- **Normal distribution**

- $\log(\Pr[X = x]) = \log(a \exp(-x^2/b)) = \log(a) - x^2/b$
- Nonlinear, concave around the average.

- **Poisson distribution**

- $\log(\Pr[X = x]) = \log(\exp(-\lambda) \lambda^x/x!)$
- Nonlinear.



Network Properties



Node degree distribution

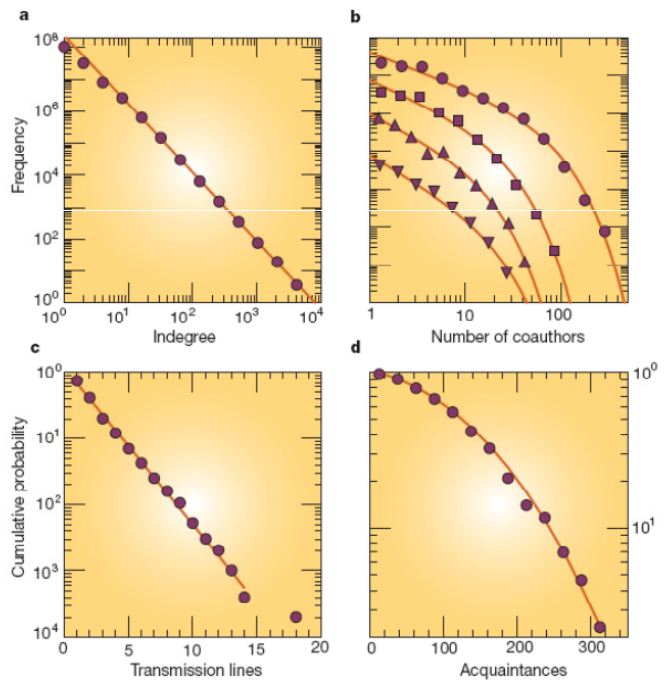
Log-log plot

a WWW
power law

b Coauthorship networks
power law with exponential cutoff

c Power grid
exponential

d Social network
Gaussian



Network Models



“Natural” networks tend to have...

- One (or a few) connected components.
 - Independent of network size.
- A small diameter (“six degrees of separation”).
 - Constant, logarithmically increasing, or even decreasing with network size.
- High clustering (“communities”).
 - Much larger than expected from a random network (and, even so, with a small diameter!).
- A mixture of connections.
 - Local vs. “long-distance” connections

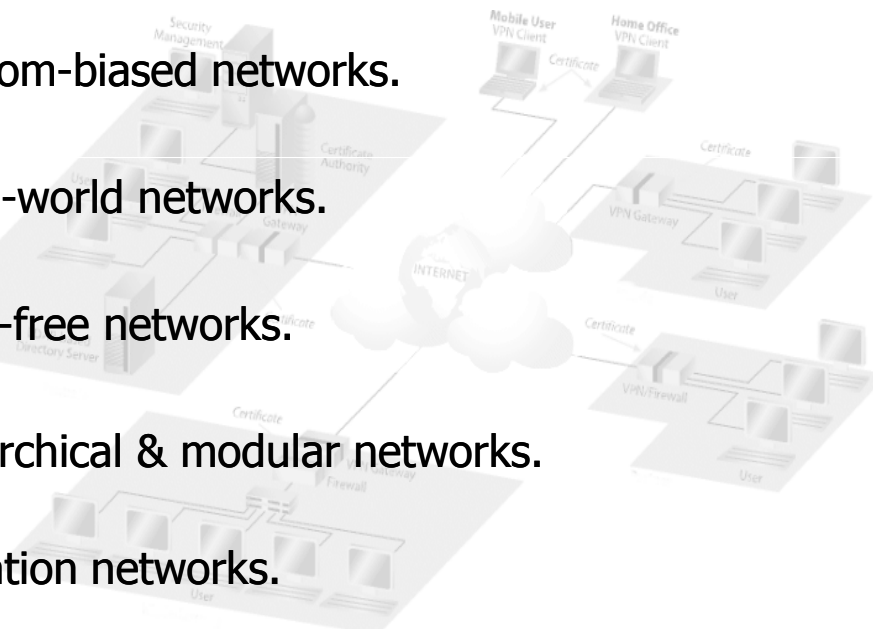
Do they share some “universal” features?



Network Models



- Random networks.
- Random-biased networks.
- Small-world networks.
- Scale-free networks.
- Hierarchical & modular networks.
- Affiliation networks.



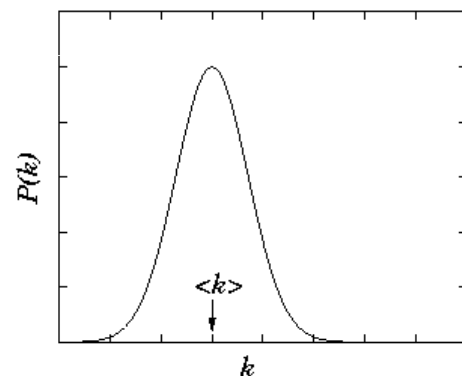
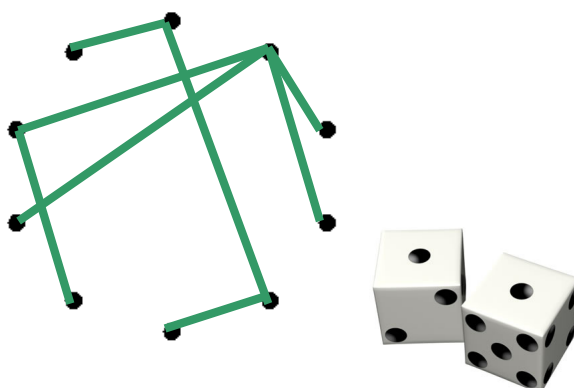
Network Models



Random Networks

Erdős-Rényi model

- Small number of connected components (typically one).
- Low clustering coefficient.
- Poisson distribution.

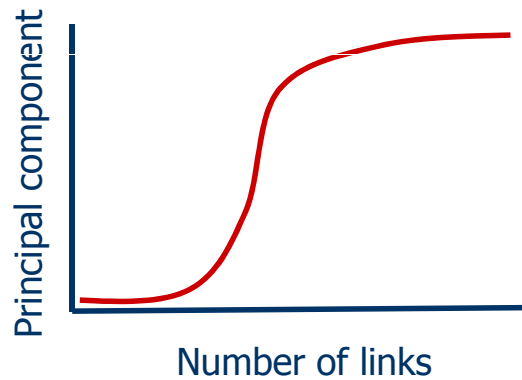
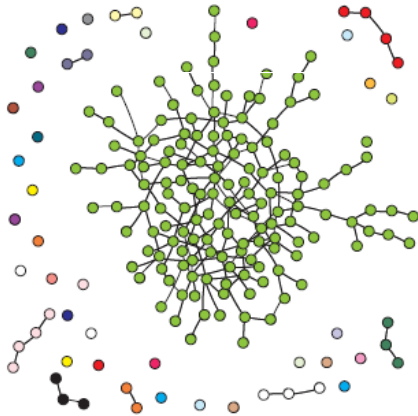


Network Models



Random Networks

Erdős-Renyi model

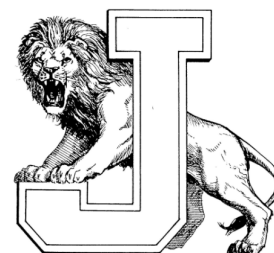
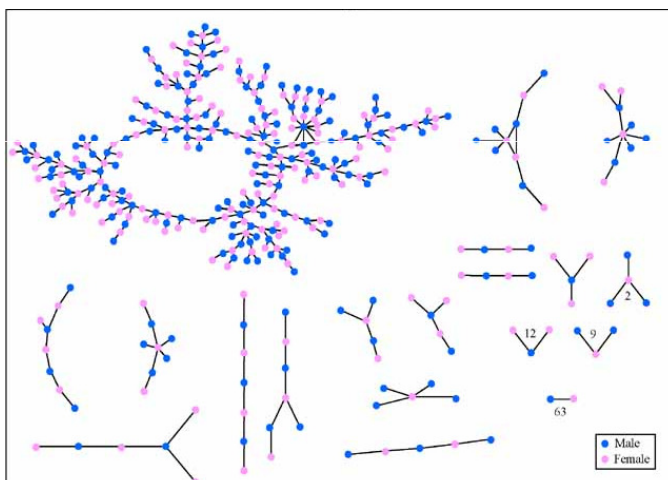


Network Models



Random Networks

Example: Romantic relationships in the Add Health data set.



Peter S. Bearman, James Moody & Katherine Stovel:
"Chains of Affection: The Structure of Adolescent Romantic and Sexual Networks"
American Journal of Sociology, 110(1):44–91, July 2004



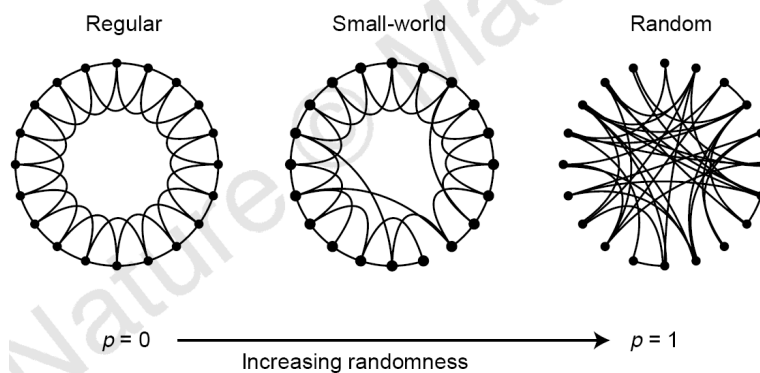
Network Models



Small-World Networks

Watts & Strogatz model

- Small number of connected components (typically one).
- **Small diameter.**
- Poisson distribution.
- **High clustering coefficient.**

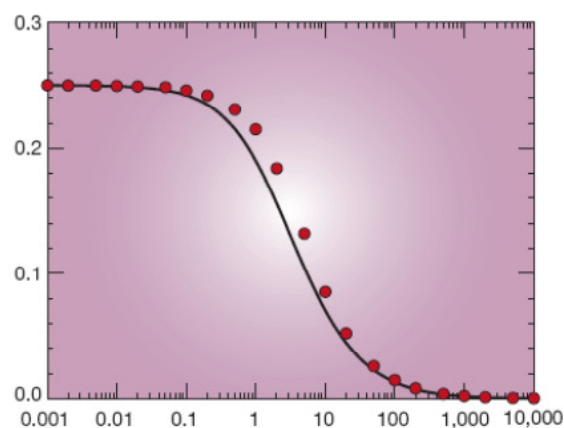


Network Models



Small-World Networks

Watts & Strogatz model



Average path length, normalized by system size, plotted as a function of the average number of shortcuts.



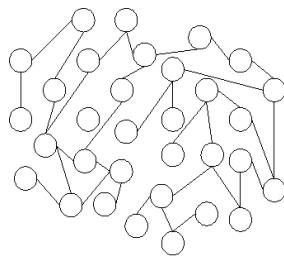
Network Models



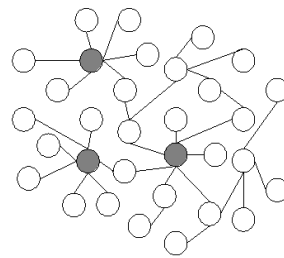
Scale-Free Networks

Barabási & Albert model

- Small number of connected components (typically one).
- Small diameter.
- **Pareto distribution.**
- **Small clustering coefficient.**
- **Hubs.**



(a) Random network



(b) Scale-free network



Network Models



Scale-Free Networks

Barabási & Albert model

“Natural” interpretation of the model:

- Variable number of nodes:
Network grows as new nodes are added.
- **Preferential attachment:**
The more connected a node is,
the more likely it is to receive new links
(“rich get richer” or Matthew effect).

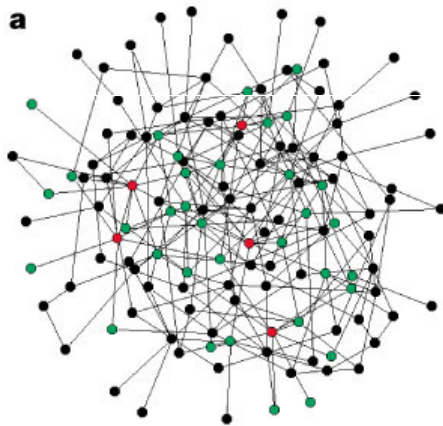


Network Models

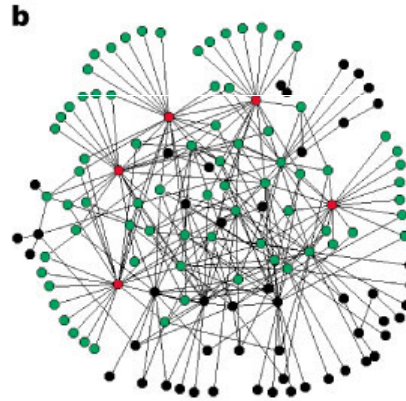


Scale-Free Networks

Barabási & Albert model



Exponential model...
... without hubs.



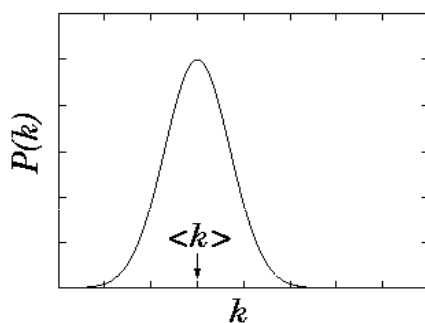
Scale-free model...
... with hubs.



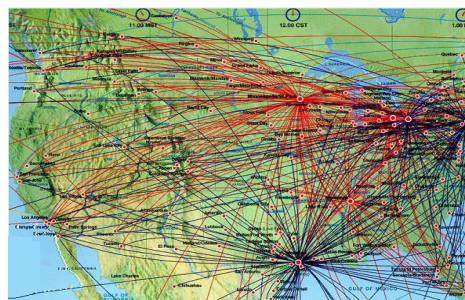
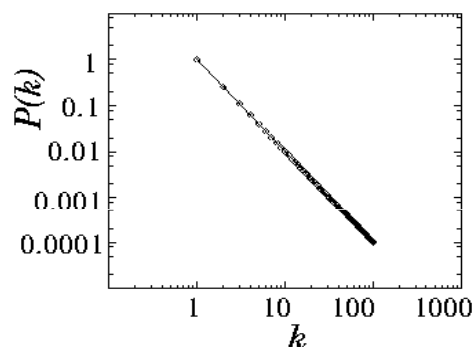
Network Models



Poisson



Pareto (power law)



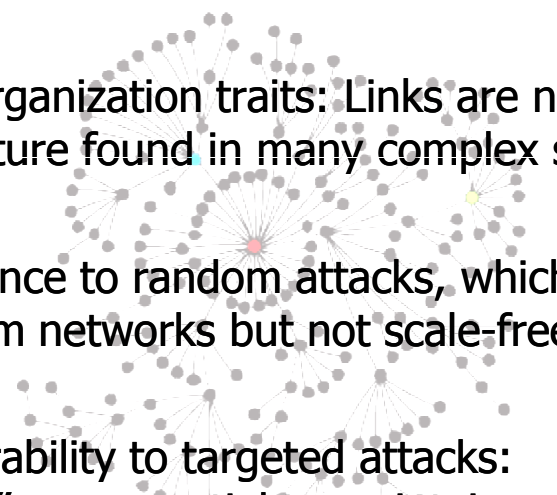
Network Models



Scale-Free Networks

Features

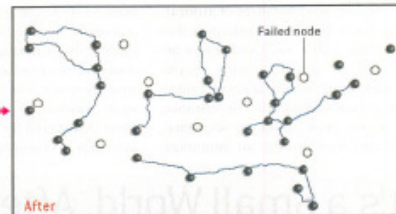
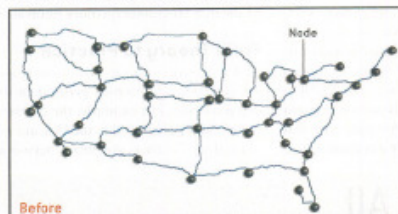
- Self-organization traits: Links are not random (a feature found in many complex systems).
- Tolerance to random attacks, which easily disrupt random networks but not scale-free networks.
- Vulnerability to targeted attacks: "Hubs" are essential to maintain connectedness.



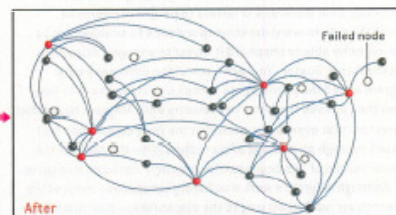
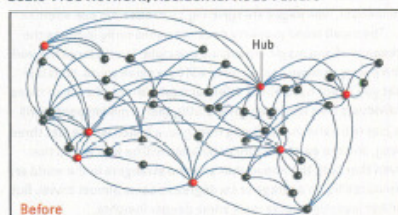
Network Models



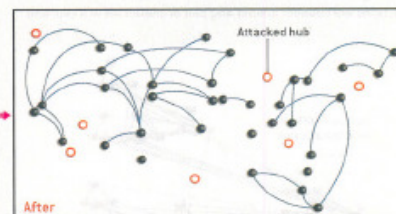
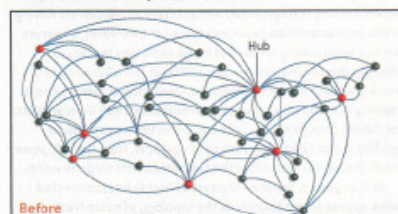
Random Network, Accidental Node Failure



Scale-Free Network, Accidental Node Failure



Scale-Free Network, Attack on Hubs

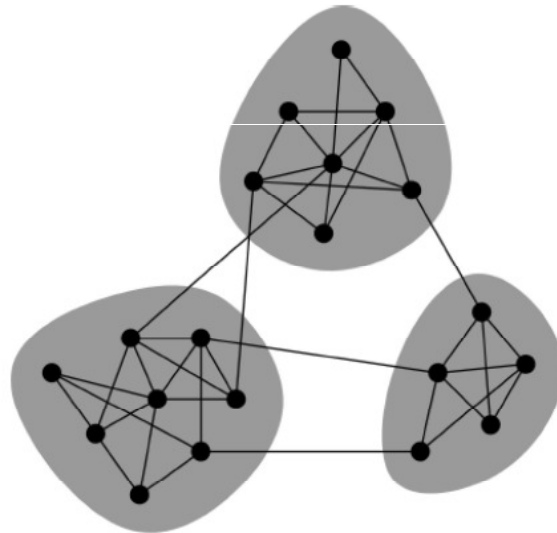


Network Models



Hierarchical/Modular Networks

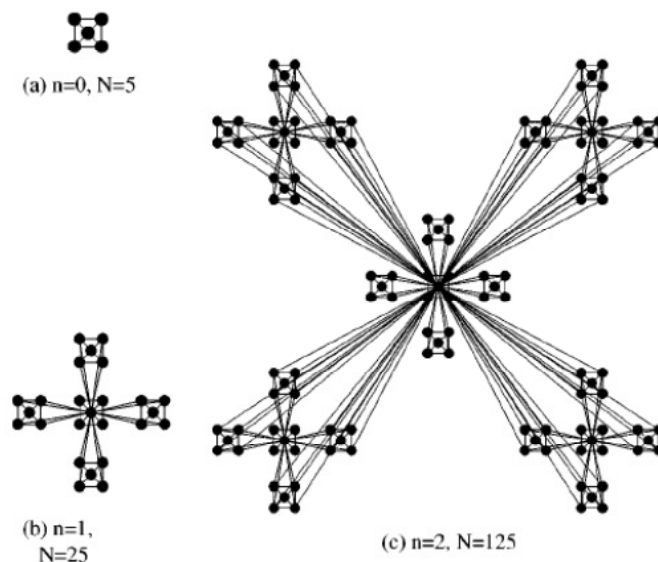
- Hierarchical organization.
- Hubs.
- **Cliques.**



Network Models



Hierarchical/Modular Networks

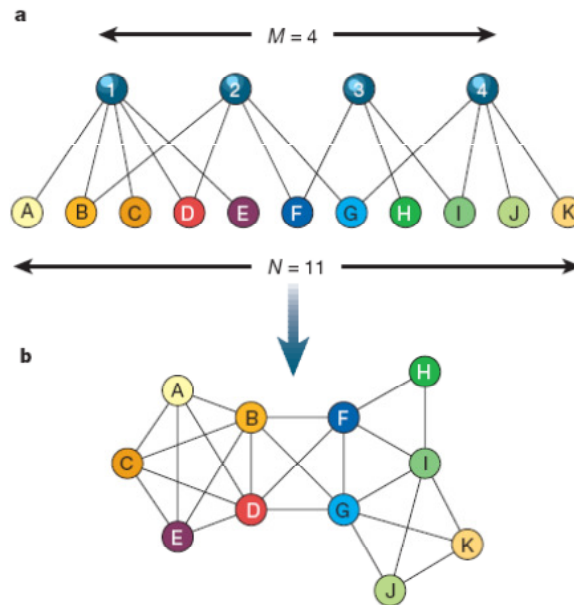


Network Models



Affiliation Networks

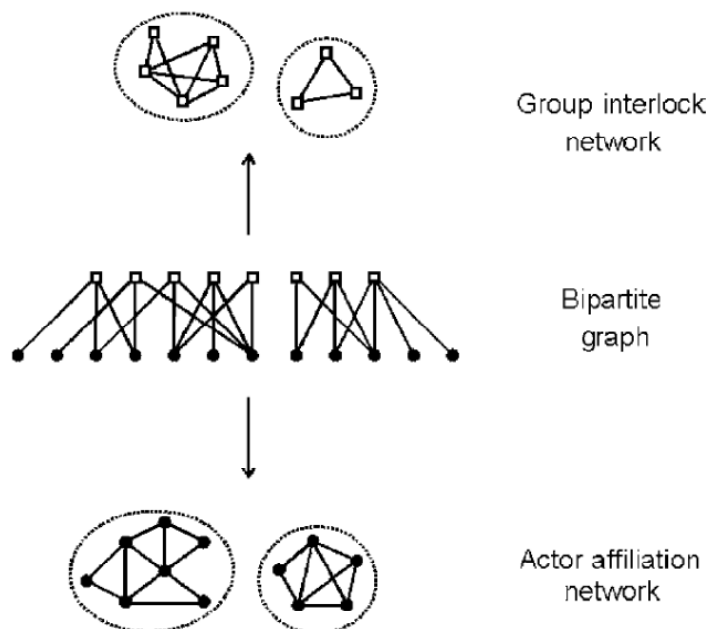
Bipartite graph to model social interactions:



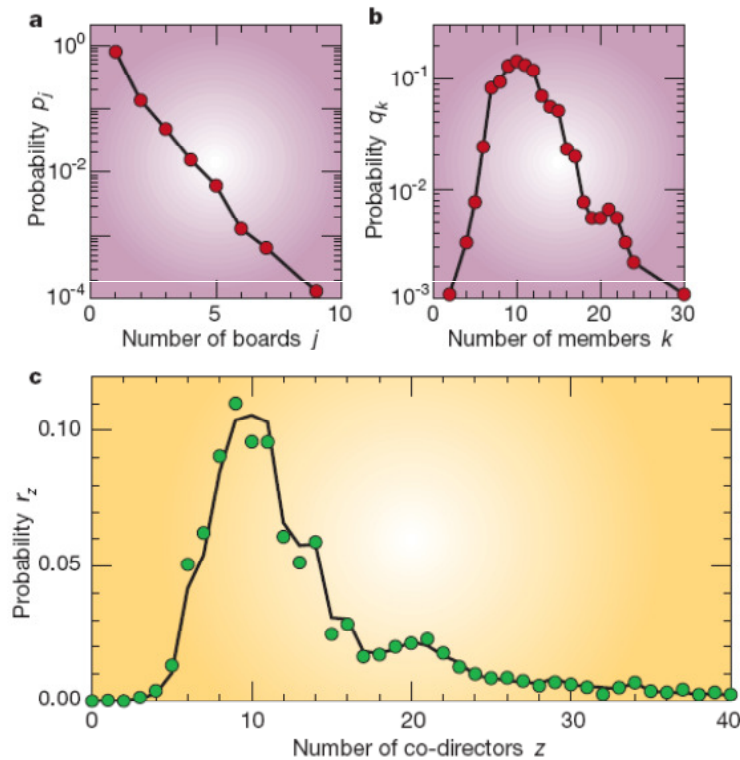
Network Models



Affiliation Networks



Network Models

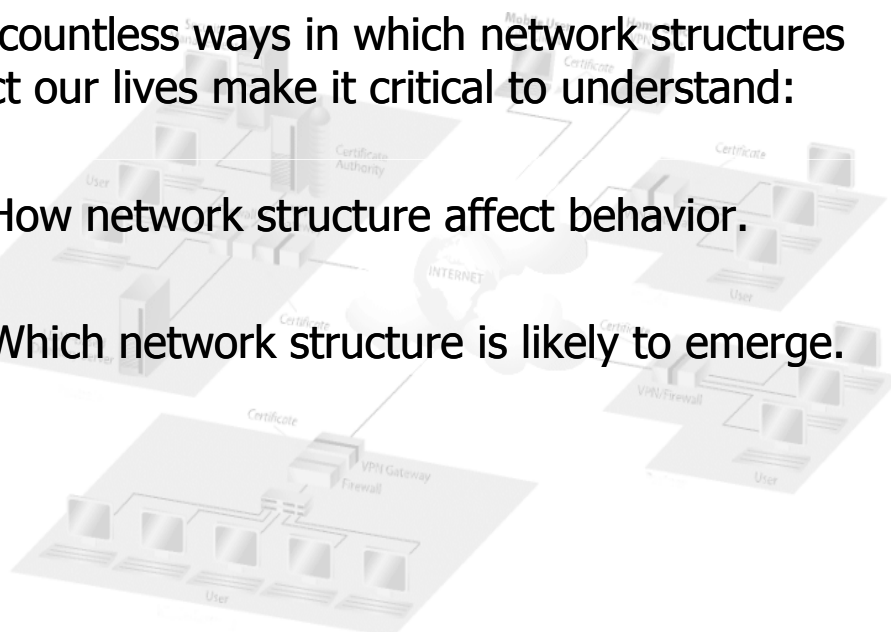


Network Structure & Dynamics



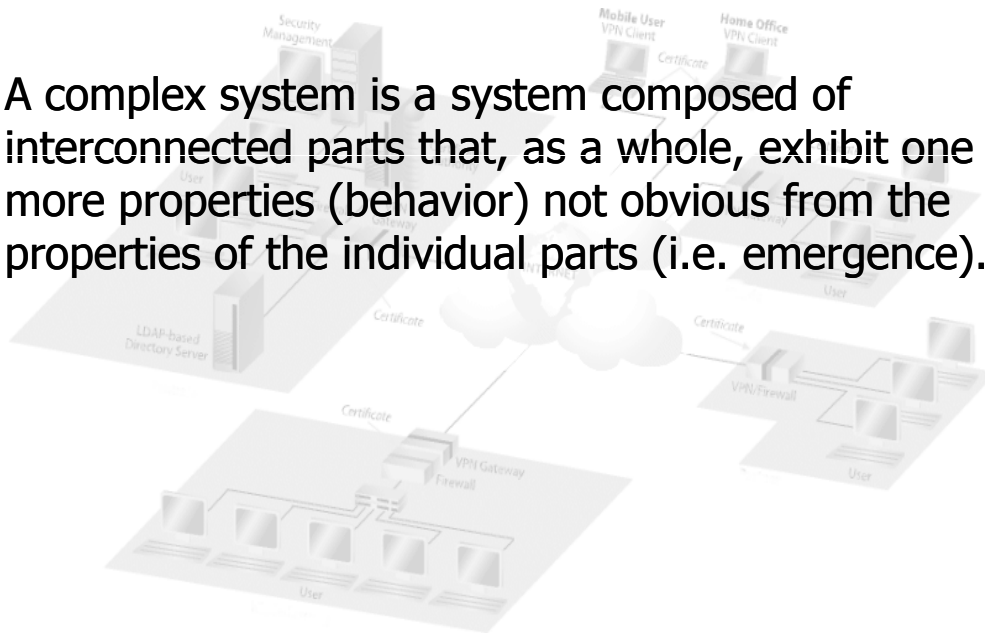
The countless ways in which network structures affect our lives make it critical to understand:

1. How network structure affect behavior.
2. Which network structure is likely to emerge.



Network Structure & Dynamics

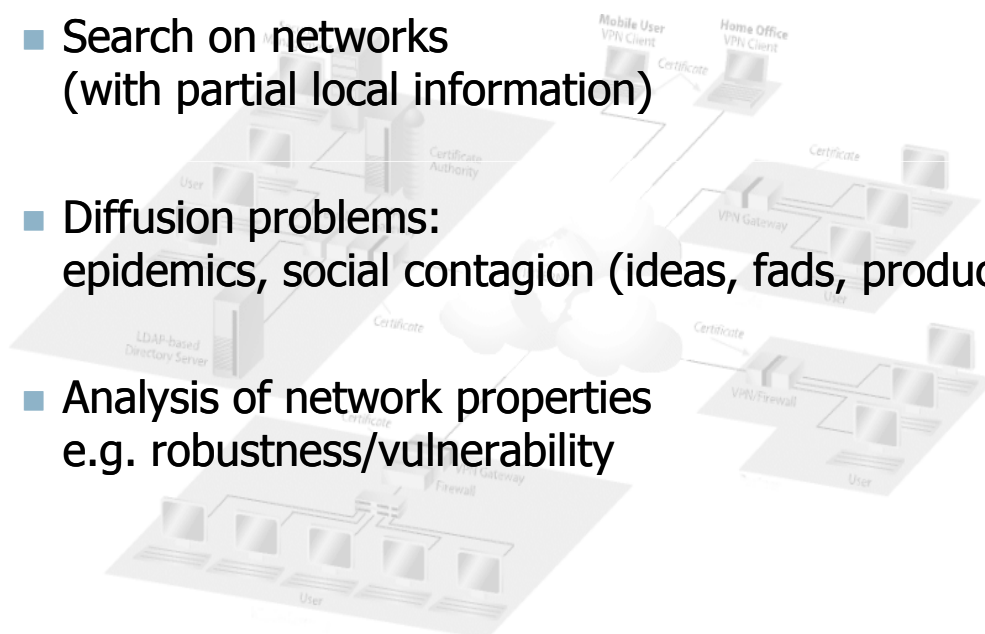
A complex system is a system composed of interconnected parts that, as a whole, exhibit one or more properties (behavior) not obvious from the properties of the individual parts (i.e. emergence).



Network Structure & Dynamics

Research problems

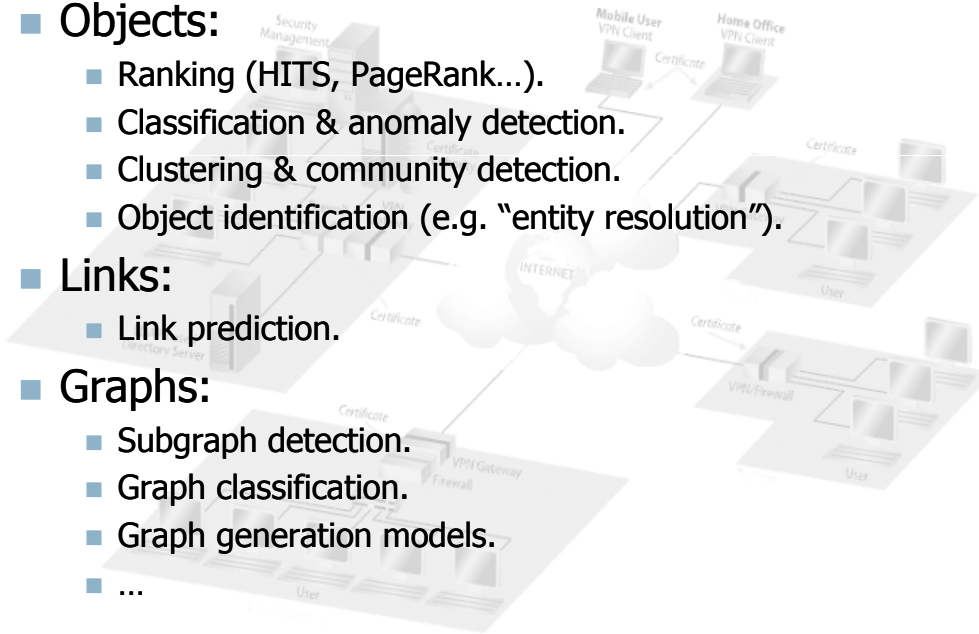
- Search on networks (with partial local information)
- Diffusion problems: epidemics, social contagion (ideas, fads, products...)
- Analysis of network properties e.g. robustness/vulnerability



Network Structure & Dynamics

From an algorithmic point of view...

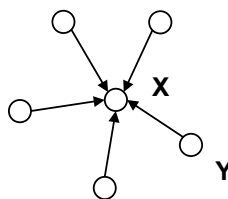
- **Objects:**
 - Ranking (HITS, PageRank...).
 - Classification & anomaly detection.
 - Clustering & community detection.
 - Object identification (e.g. "entity resolution").
- **Links:**
 - Link prediction.
- **Graphs:**
 - Subgraph detection.
 - Graph classification.
 - Graph generation models.
 - ...



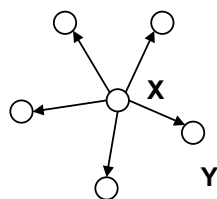
Network Structure: Centrality

Different notions of centrality

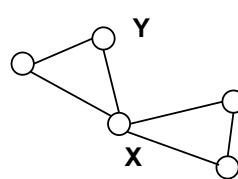
In each of the following networks, X has higher centrality than Y according to a particular measure



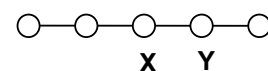
in-degree



out-degree



betweenness



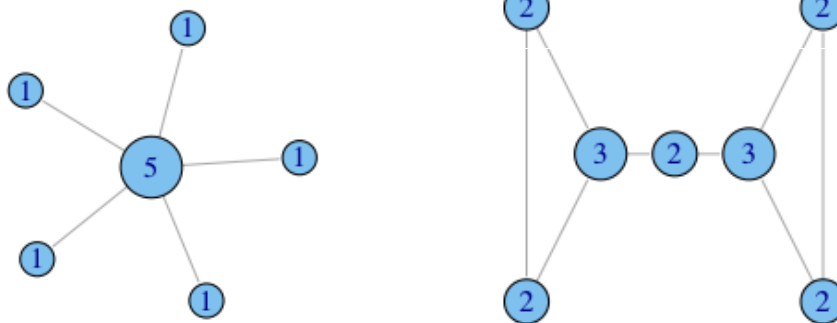
closeness



Network Structure: Centrality

Degree

Nodes with more connections are more central...



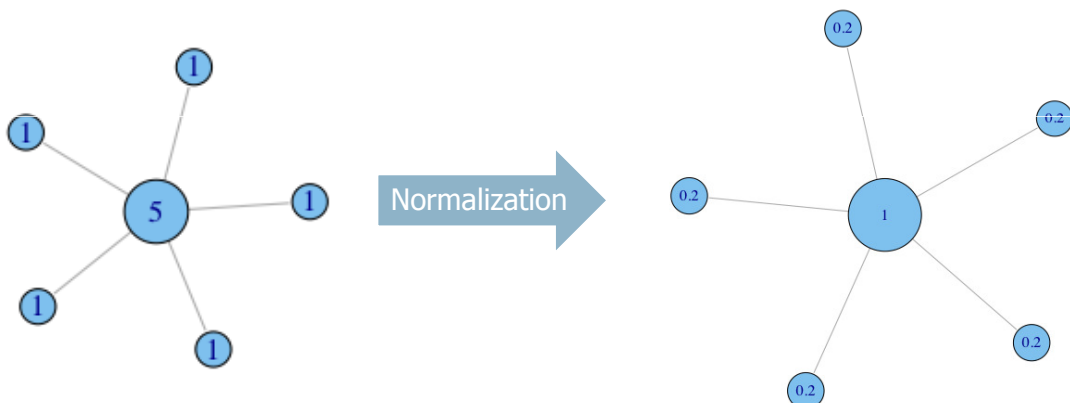
[Lada Adamic, "Social Network Analysis", <https://www.coursera.org/course/sna>]



Network Structure: Centrality

Degree

Nodes with more connections are more central...



[Lada Adamic, "Social Network Analysis", <https://www.coursera.org/course/sna>]

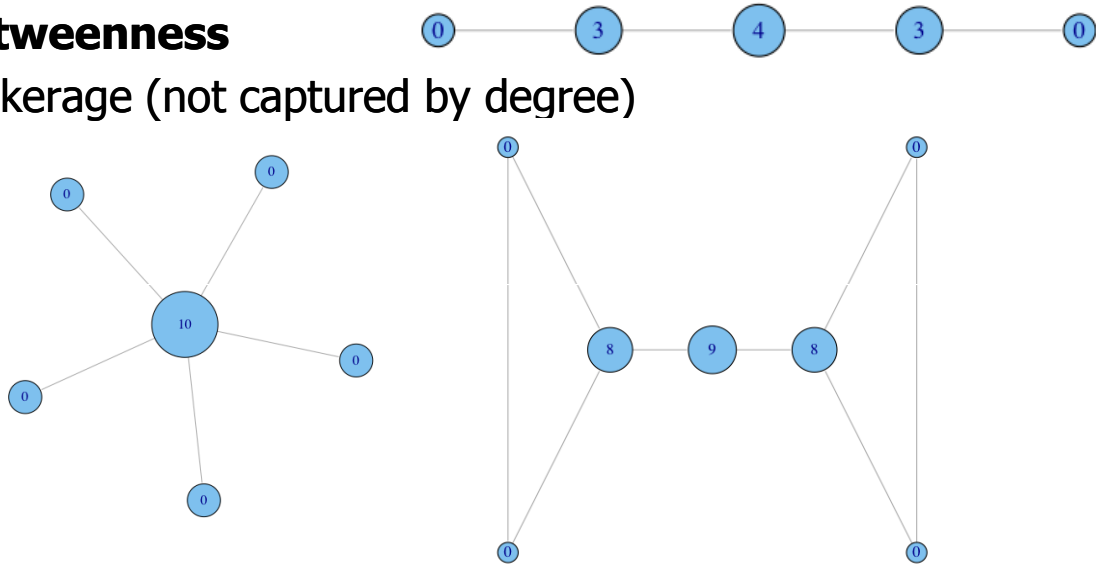


Network Structure: Centrality



Betweenness

Brokerage (not captured by degree)



IDEA: How many pairs of individuals would have to go through you in order to reach one another in the minimum number of hops?

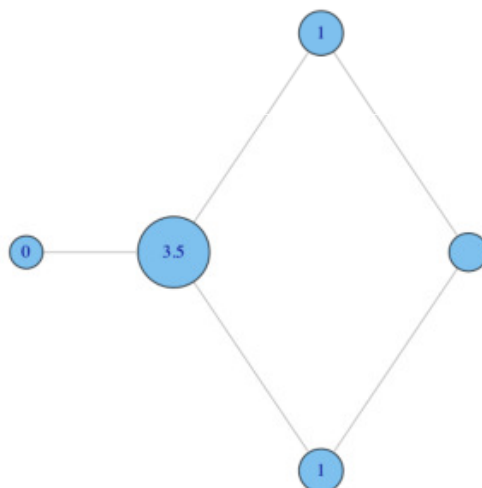


Network Structure: Centrality



Betweenness

Brokerage (not captured by degree)



Partial credit for lying in one of several shortest paths...

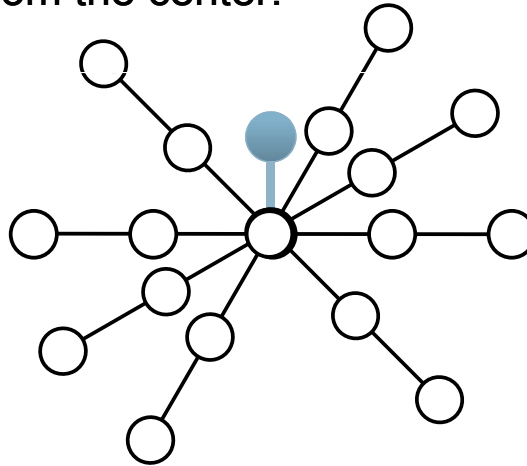


Network Structure: Centrality



Closeness

When it is not so important to have many connections, nor be between others, but be in the middle of things... not too far from the center.



[Lada Adamic, "Social Network Analysis", <https://www.coursera.org/course/sna>]

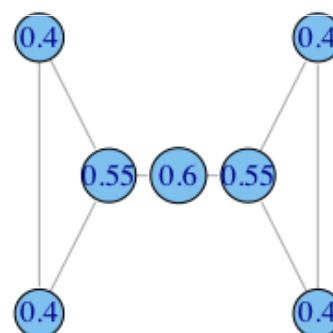
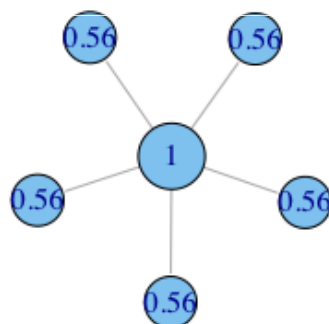


Network Structure: Centrality



Closeness

based on the length of the average shortest path between a node and all other nodes in the network.

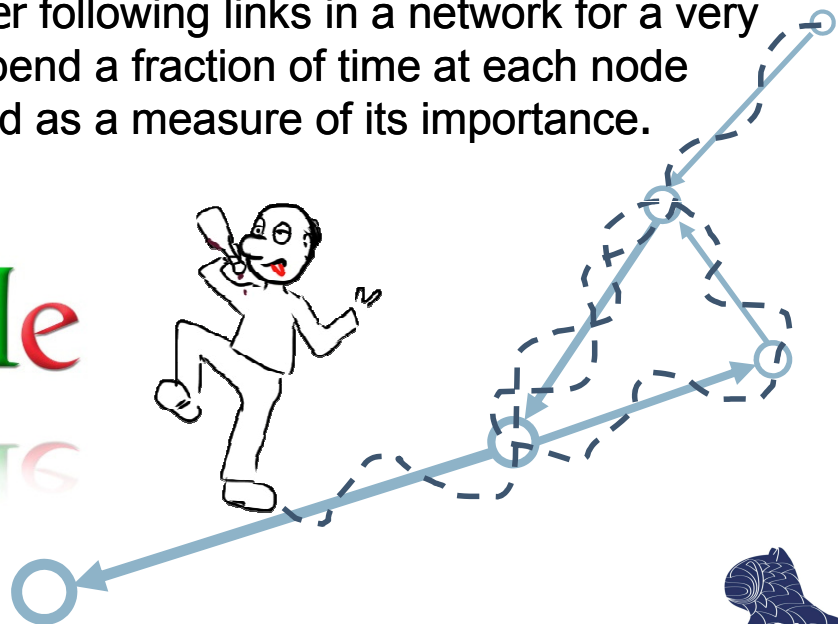


Network Structure: Centrality

PageRank

A random walker following links in a network for a very long time will spend a fraction of time at each node that can be used as a measure of its importance.

Google



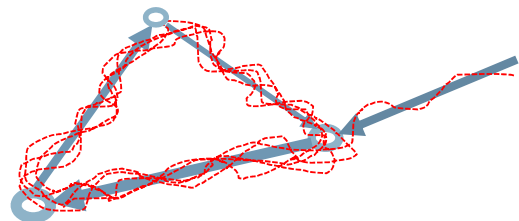
[Lada Adamic, "Social Network Analysis", <https://www.coursera.org/course/sna>]



Network Structure: Centrality

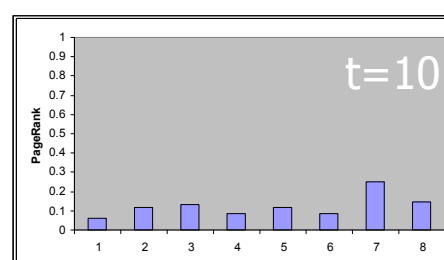
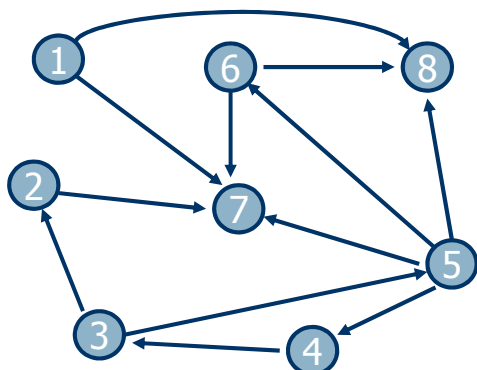
PageRank

Problem: Stuck in the network



Solution: Teleportation

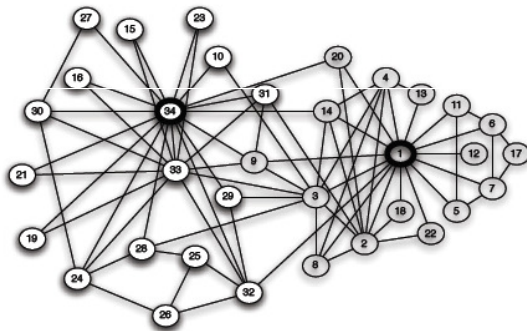
A random jump to anywhere else with a given probability.



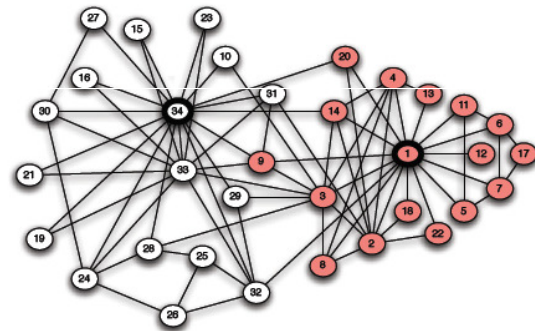
Network Structure: Communities

Community detection (i.e. clustering)

Identification of groups of nodes within a network...



(a) Karate club network



(b) After a split into two clubs

David Easley & Jon Kleinberg:
"Networks, Crowds & Markets: Reasoning About a Highly Connected World",
<http://www.cs.cornell.edu/home/kleinber/networks-book/>



Network Structure: Communities

Heuristics

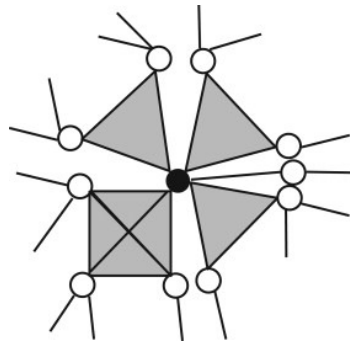
- Mutual ties
- Frequency of ties within a community (cliques & k-cores)
- Closeness/reachability of community members (n-cliques)
- Relative frequency of ties within a community (ties among members compared to ties to non-members)



Network Structure: Communities

Cliques & k-cores

- Cliques (complete subgraphs)
 - A single missing link disqualifies the clique
 - Overlapping cliques



- K-cores
(every node connected to at least k other nodes)



Network Structure: Communities

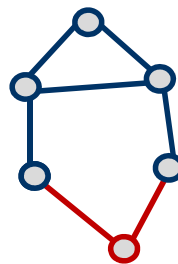
n-cliques

Maximal distance between any two nodes is n

IDEA: Information flow through intermediaries.

Problems:

- Diameter $> n$
- Disconnected n -cliques



2-clique
diameter = 3

path outside the 2-clique

Solution: **n-clubs** (maximal subgraphs of diameter n)



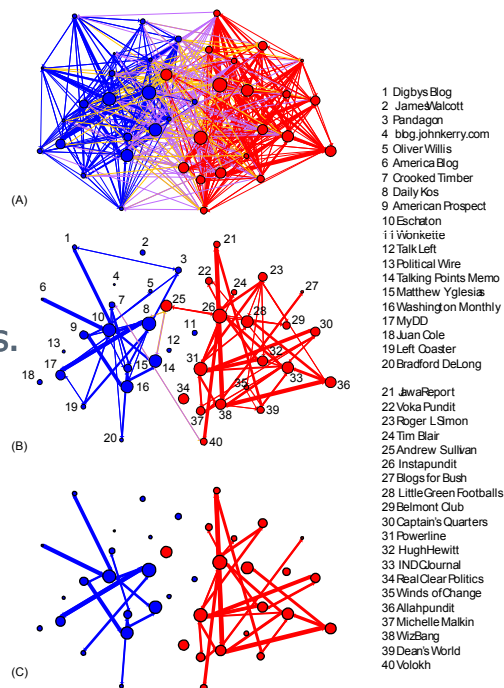
Network Structure: Communities

Example: Political blogs

- A) All citations between blogs.
- B) Blogs with at least 5 citations in both directions.
- C) Edges further limited to those exceeding 25 combined citations.

only 15% of the citations bridge communities

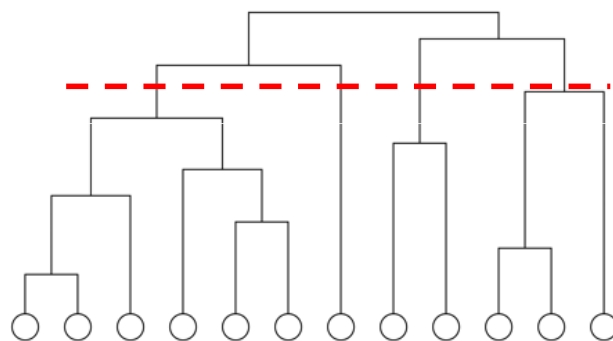
[Adamic & Glance, LinkKDD2005]



Network Structure: Communities

Community detection algorithms

Hierarchical clustering



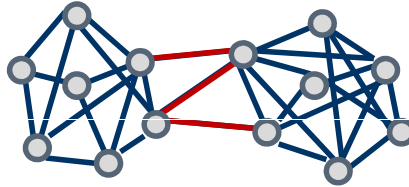
Michelle Girvan & Mark E.J. Newman:
 "Community structure in social and biological networks"
 PNAS **99**(12):7821–7826, 2002
[doi:10.1073/pnas.122653799](https://doi.org/10.1073/pnas.122653799)



Network Structure: Communities

Betweenness clustering

Hierarchical clustering using edge betweenness



compute the betweenness of all edges
while (betweenness of any edge > threshold)
 remove edge with highest betweenness
 recalculate betweenness

- Betweenness clustering is inefficient due to the need to recompute edge betweenness in every iteration.



Network Structure: Communities

Modularity clustering

- Consider links that fall within a community (vs. links between a community and the rest of the network)

Modularity Q

$$Q = \frac{1}{2m} \sum_{vw} \left[A_{vw} - \frac{k_v k_w}{2m} \right] \delta(c_v, c_w)$$

adjacency matrix

probability of an edge between two vertices is proportional to their degrees

if vertices are in the same community

NOTE: For a random network, $Q=0$



Network Structure: Communities

Modularity clustering

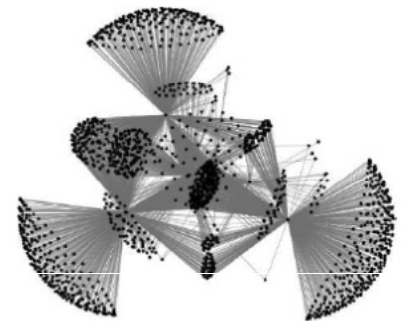
Algorithm

start with all vertices as isolates

do

 join clusters with the greatest increase in modularity (ΔQ)

while ($\Delta Q > 0$)



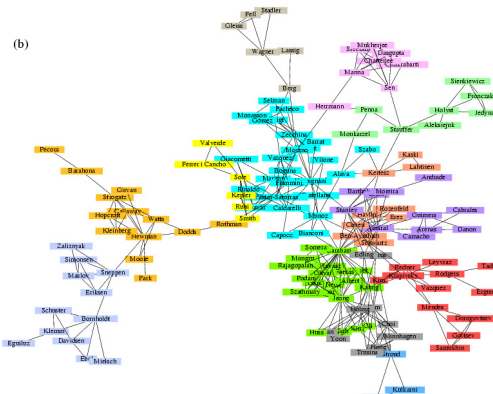
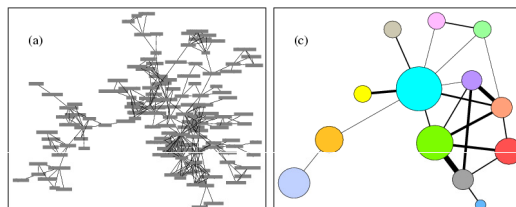
Aaron Clauset, Mark E. J. Newman, Cristopher Moore:
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Physical Review E 70(6):066111, 2004
[doi:10.1103/physreve.70.066111](https://doi.org/10.1103/physreve.70.066111)



Network Structure: Communities

Modularity clustering

An application: Visualization of large networks (Gephi)



Network Structure: Communities

Limitations of current community detection methods

- Scalability: Identification of large communities.
- Existence of overlapping communities in large networks.
- Unrealistic models (algorithms make oversimplified assumptions over the networks or community structures, but perform poorly against real world data sets).
- Heuristics without performance guarantees (for those heuristic algorithms that work well in practice, there is no performance guarantee over the quality of their output).



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Search on Networks

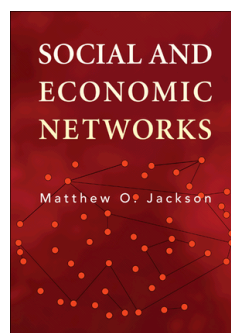
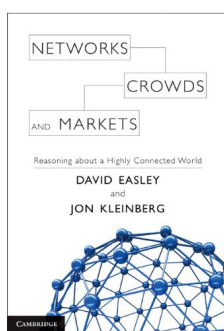
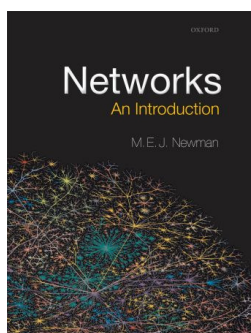
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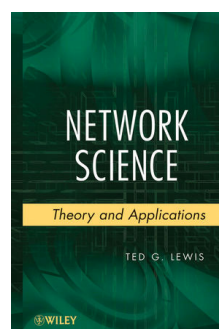
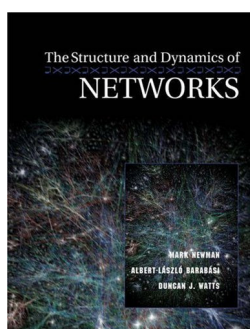
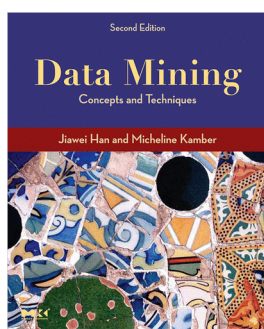
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