

A rapid introduction to Complex Networks



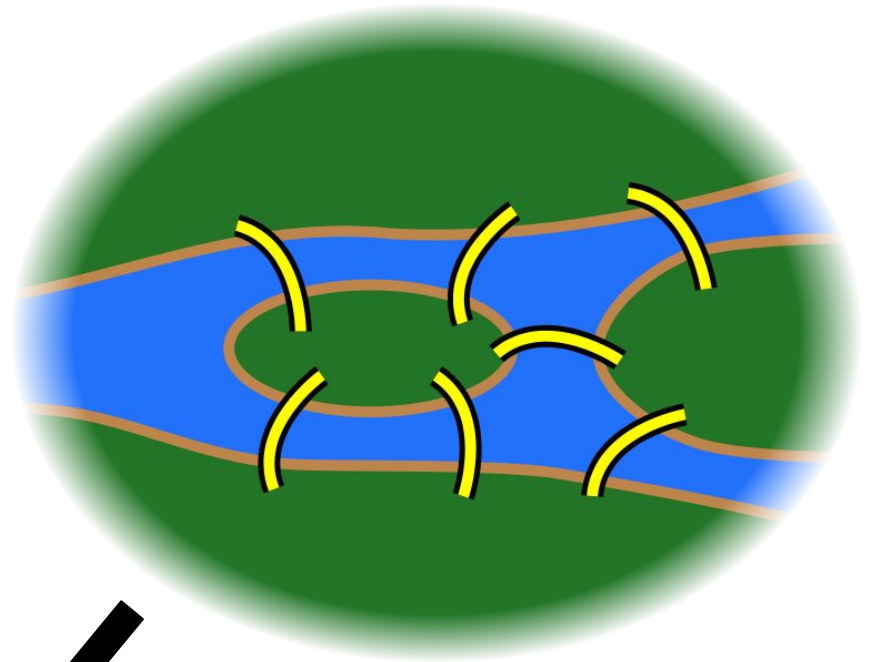
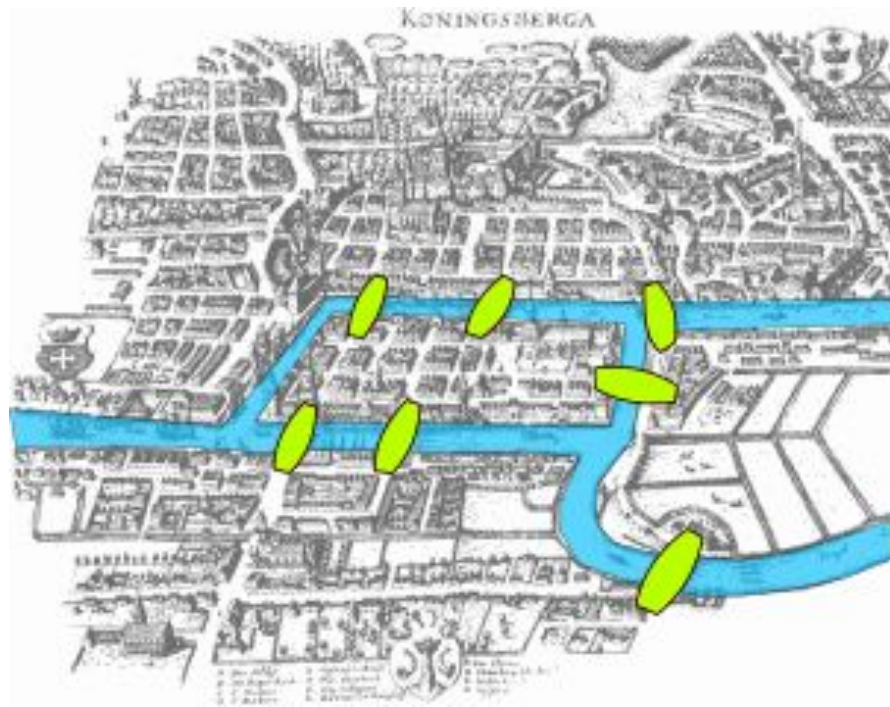
UFOP

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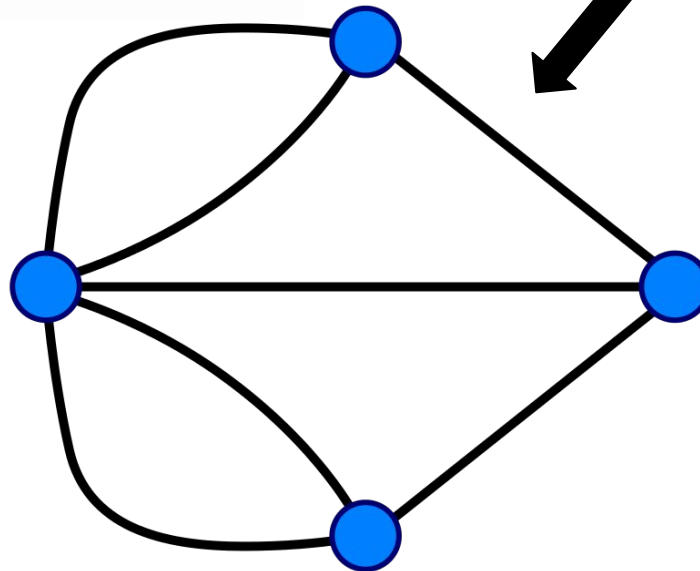
Agenda

- Introduction
- Network Models
- Degree correlations
- Robustness
- Community detection
- Spreading Phenomena
- References

Introduction - Seven Bridges of Königsberg (1736)



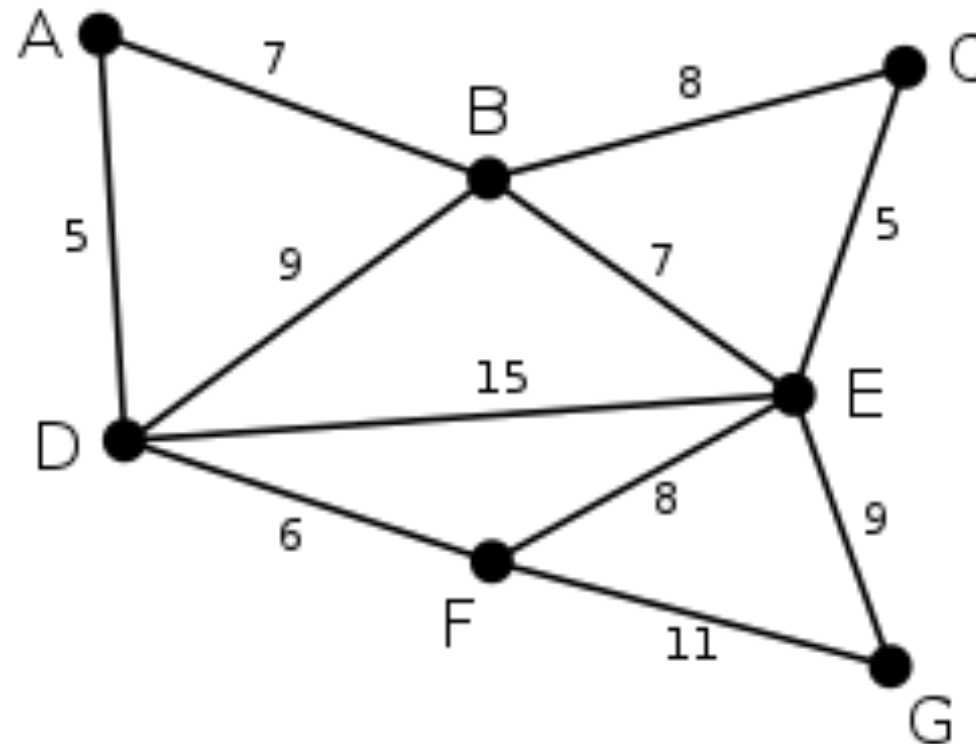
Graph: $G(V,E)$
Vertex (nodes)
and Edges (links)



Eulerian path:
connected graph
with exactly zero or
two nodes of odd
degree

Introduction

Graph (network): $G(V,E)$
Vertex (nodes) and Edges (links)
Graphs in Complex Systems: Complex
Networks



Complex

[adj., v. kuh m-pleks, kom-pleks; n. kom-pleks]

—adjective

1. composed of many interconnected parts; compound; composite: a complex highway system.
2. characterized by a very complicated or involved arrangement of parts, units, etc.: complex machinery.
3. so complicated or intricate as to be hard to understand or deal with: a complex problem.

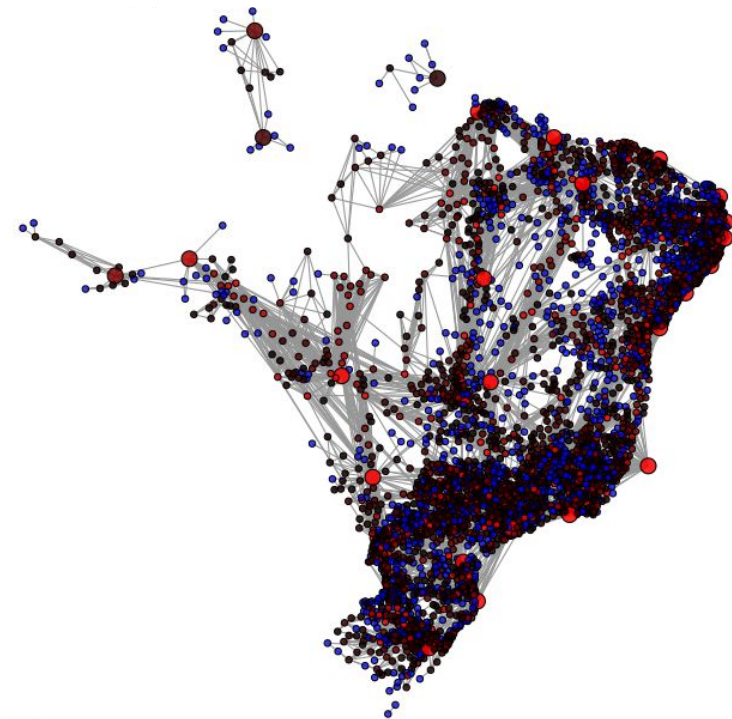
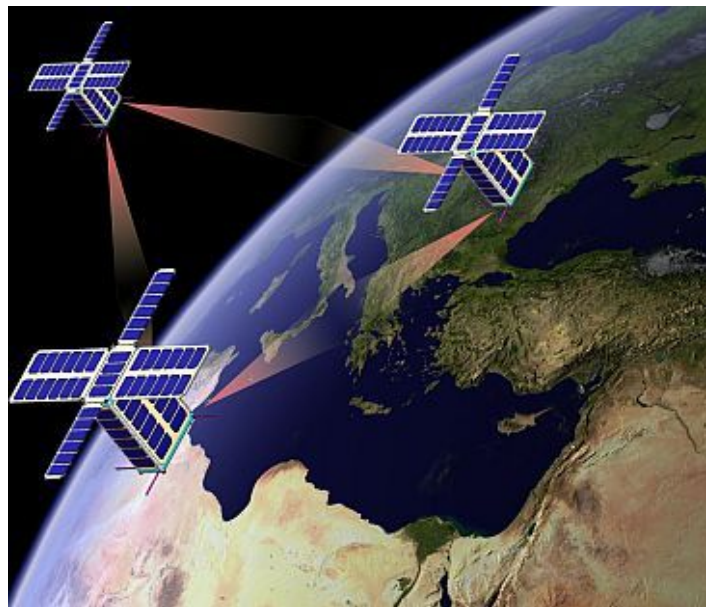
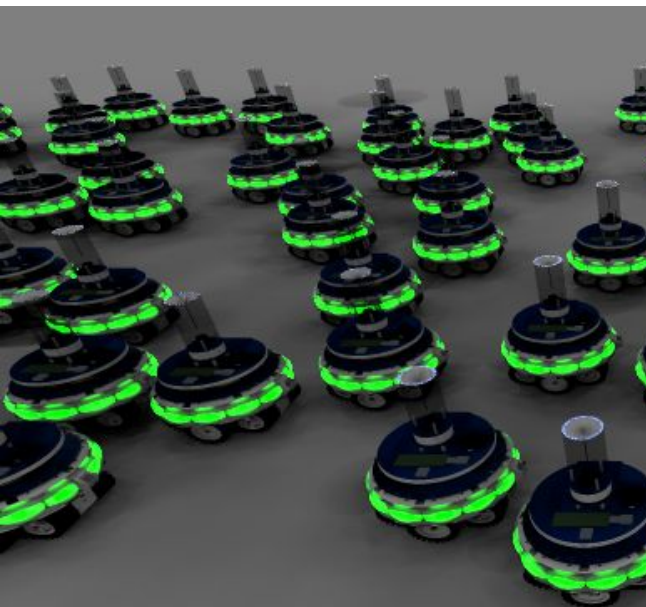
Source: Dictionary.com

Complexity

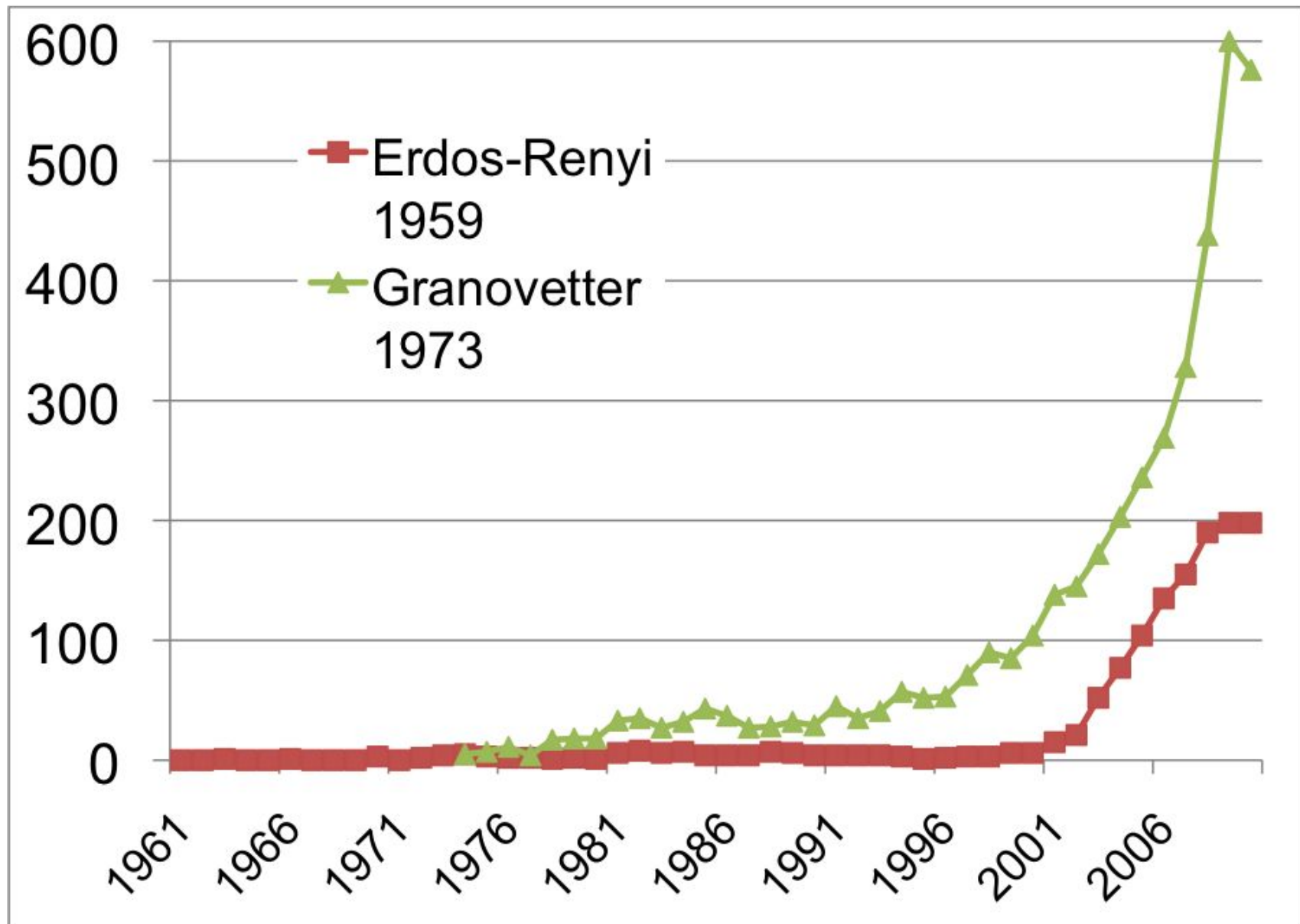
Complexity, a scientific theory which asserts that some systems display behavioral phenomena that are completely inexplicable by any conventional analysis of the systems' constituent parts. These phenomena, commonly referred to as emergent behaviour, seem to occur in many complex systems involving living organisms, such as a stock market or the human brain.

Source: John L. Casti, Encyclopædia Britannica

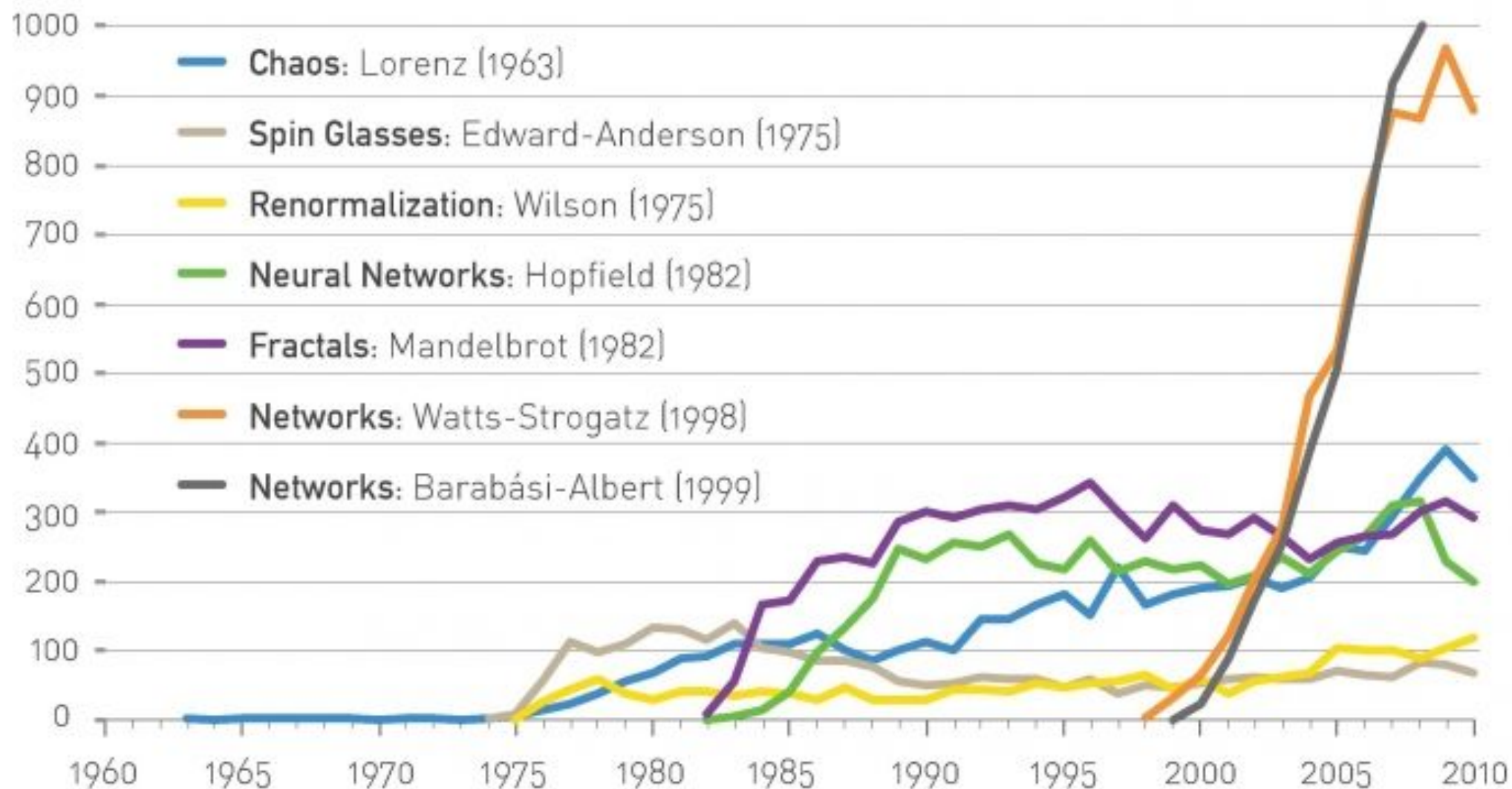
Introduction - Complex systems



Introduction



Introduction



Introduction - Important people in the field



Albert Barabasi (1967)
Romanian Physicist



Réka Albert (1972)
Romanian-Hungarian
Physicist



Paul Erdős
(1913-1996)
Hungarian
Mathematician



Alfred Rényi
(1921-1970)
Hungarian
Mathematician



Duncan Watts (1971)
American Physicist and
Sociologist



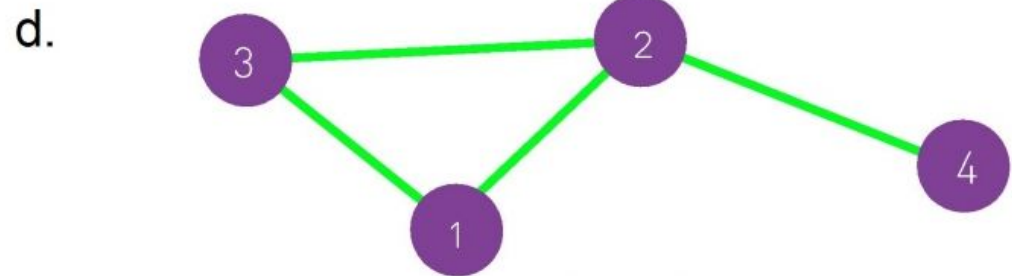
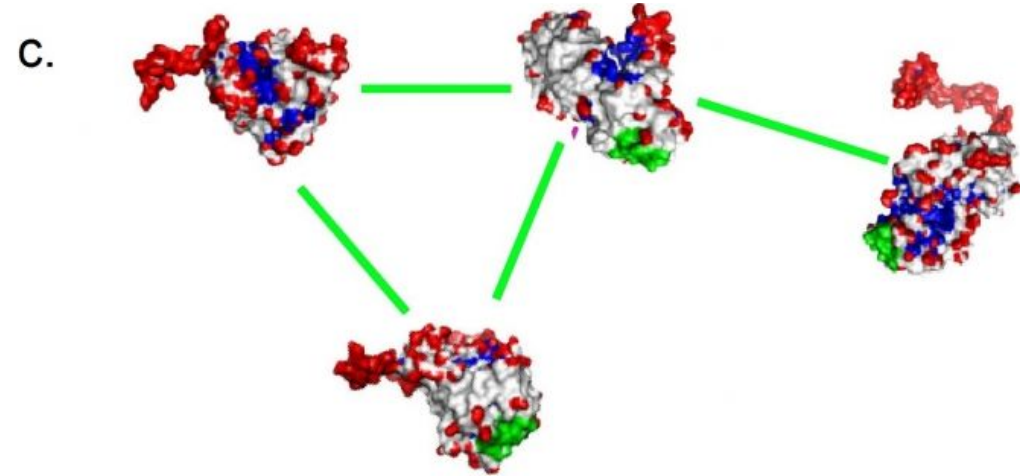
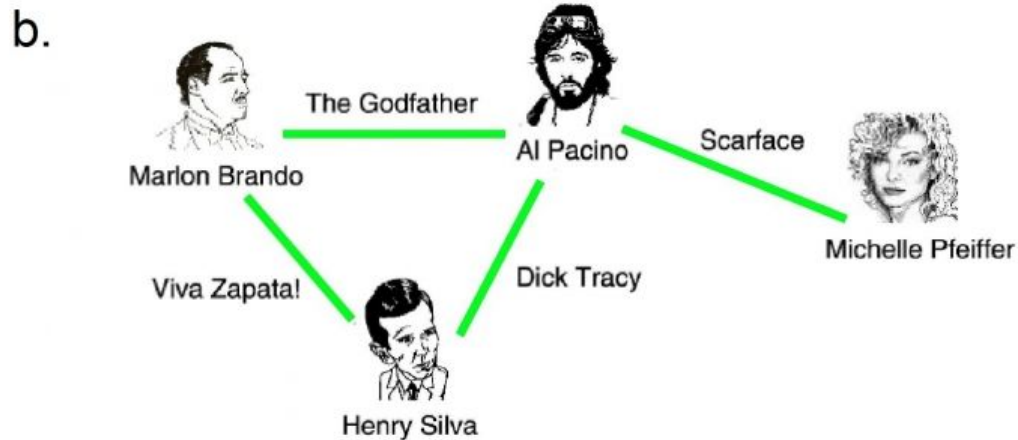
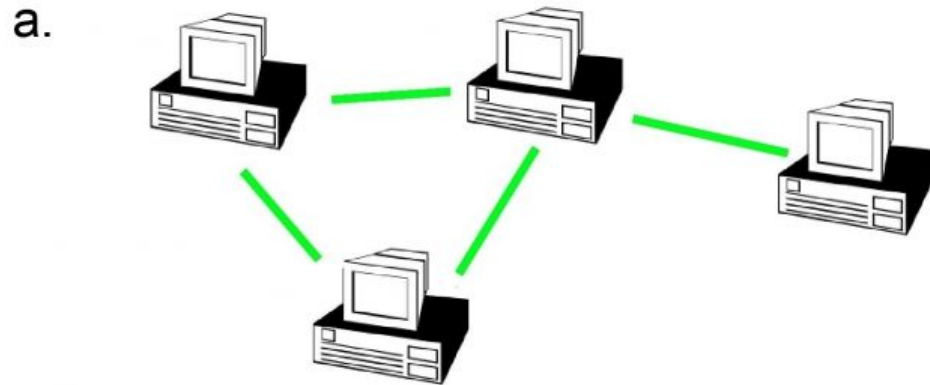
Steven Strogatz (1959)
American Physicist

- The emergence of network maps:
 - Movie Actor Network, 1998;
 - World Wide Web, 1999.
 - C elegans neural wiring diagram 1990
 - Citation Network, 1998
 - Metabolic Network, 2000;
 - PPI network, 2001

The universality of network characteristics:

The architecture of networks emerging in various domains of science, nature, and technology are more similar to each other than one would have expected.

Introduction - Different Networks, same Graph

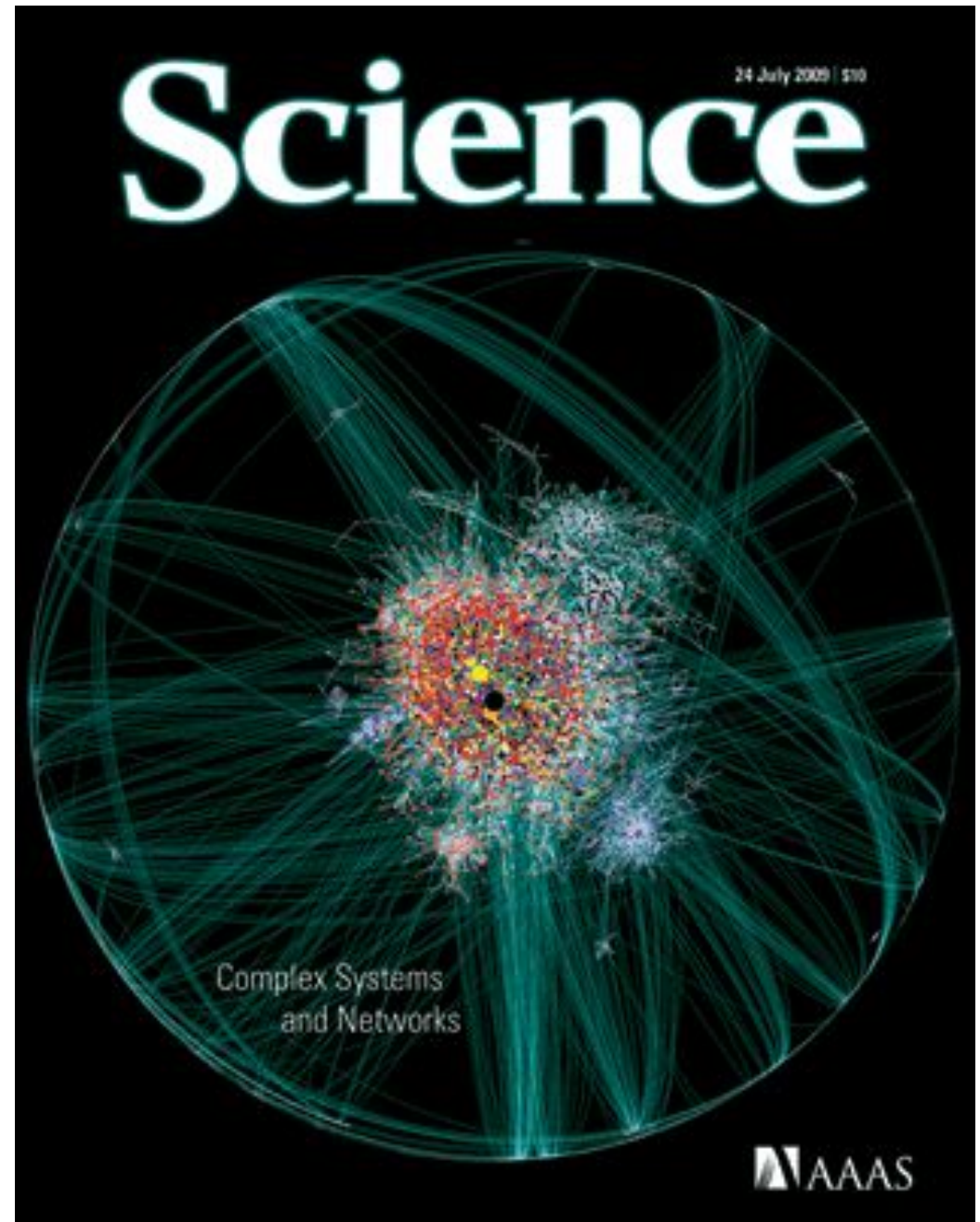


Introduction

Network	Nodes	Links	Directed / Undirected	N	L	(K)
Internet	Routers	Internet connections	Undirected	192,244	609,066	6.34
WWW	Webpages	Links	Directed	325,729	1,497,134	4.60
Power Grid	Power plants, transformers	Cables	Undirected	4,941	6,594	2.67
Mobile-Phone Calls	Subscribers	Calls	Directed	36,595	91,826	2.51
Email	Email addresses	Emails	Directed	57,194	103,731	1.81
Science Collaboration	Scientists	Co-authorships	Undirected	23,133	93,437	8.08
Actor Network	Actors	Co-acting	Undirected	702,388	29,397,908	83.71
Citation Network	Papers	Citations	Directed	449,673	4,689,479	10.43
E. Coli Metabolism	Metabolites	Chemical reactions	Directed	1,039	5,802	5.58
Protein Interactions	Proteins	Binding interactions	Undirected	2,018	2,930	2.90

Science (2009):

Special Issue for the 10
year anniversary of
Barabasi & Albert 1999
paper.



2019

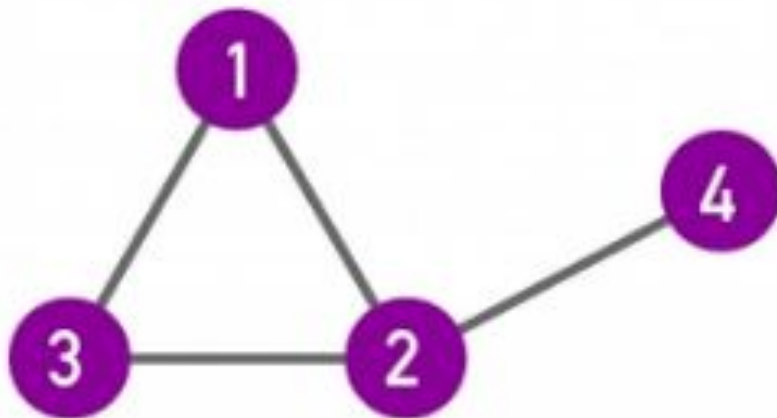


150 years of *Nature*

A century and a half of research and discovery.

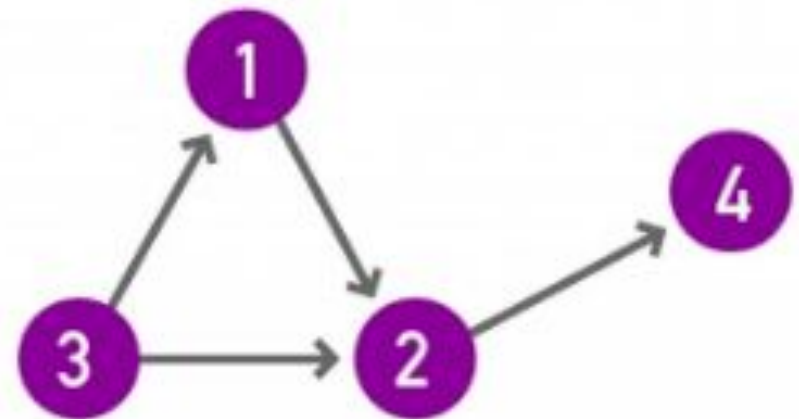
Introduction - Adjacency matrix

b. Undirected network



$$A_{ij} = \begin{bmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

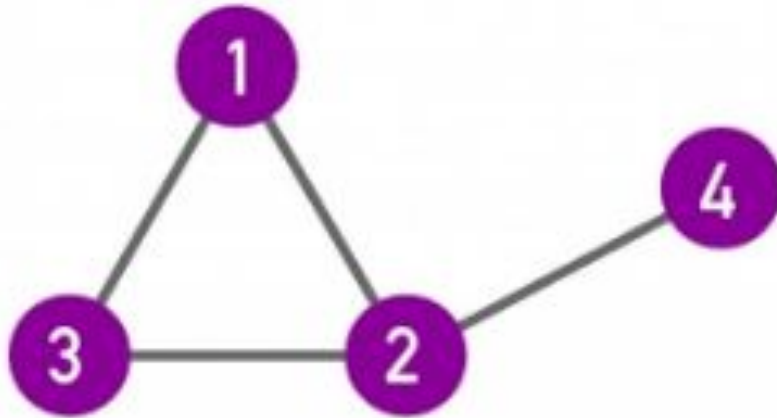
c. Directed network



$$A_{ij} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

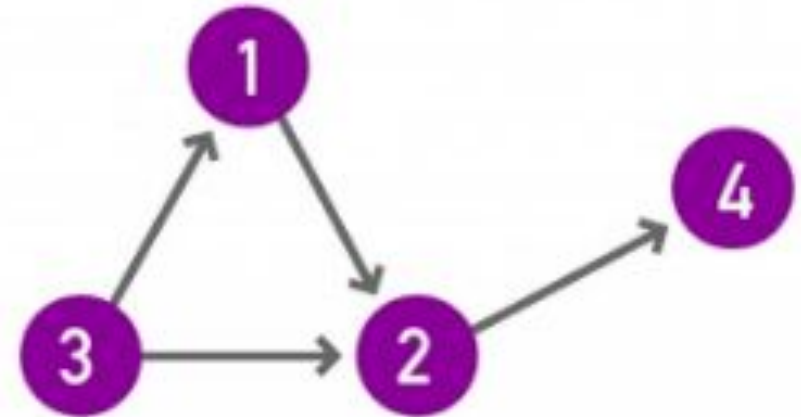
Introduction - Adjacency list

b. Undirected network



$$G = ((1,2), (1,3), (2,3), (2,4))$$

c. Directed network



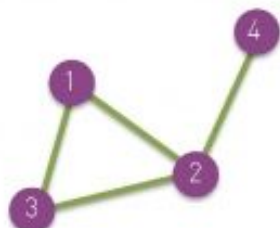
$$G = ((1,2), (2,4), (3,1), (3,2))$$

The adjacency matrix shows whether the network is undirected or not. On the other hand, the adjacency list does not.

However, the list needs **less** disk space to be stored.

Introduction - Adjacency matrix

a. Undirected

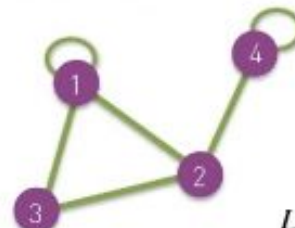


$$A_{ij} = \begin{pmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix}$$

$$A_{ii} = 0 \quad A_{ij} = A_{ji}$$

$$L = \frac{1}{2} \sum_{i,j=1}^N A_{ij} \quad \langle k \rangle = \frac{2L}{N}$$

b. Self-loops

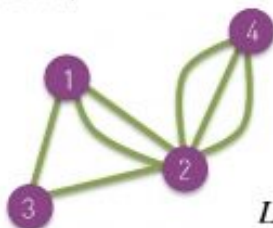


$$A_{ij} = \begin{pmatrix} 1 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 \end{pmatrix}$$

$$\exists i, A_{ii} \neq 0 \quad A_{ij} = A_{ji}$$

$$L = \frac{1}{2} \sum_{i,j=1, i \neq j}^N A_{ij} + \sum_{i=1}^N A_{ii} \quad ?$$

c. Multigraph
(undirected)

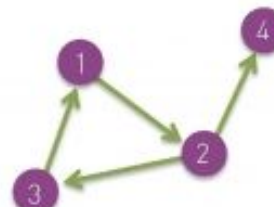


$$A_{ij} = \begin{pmatrix} 0 & 2 & 1 & 0 \\ 2 & 0 & 1 & 3 \\ 1 & 1 & 0 & 0 \\ 0 & 3 & 0 & 0 \end{pmatrix}$$

$$A_{ii} = 0 \quad A_{ij} = A_{ji}$$

$$L = \frac{1}{2} \sum_{i,j=1}^N A_{ij} \quad \langle k \rangle = \frac{2L}{N}$$

d. Directed

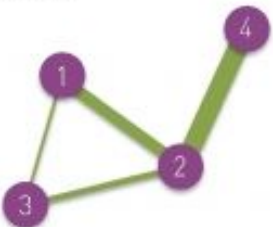


$$A_{ij} = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

$$A_{ij} \neq A_{ji}$$

$$L = \sum_{i,j=1}^N A_{ij} \quad \langle k \rangle = \frac{L}{N}$$

e. Weighted
(undirected)

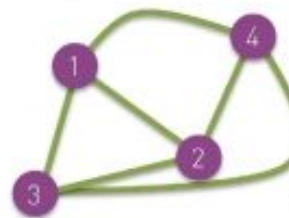


$$A_{ij} = \begin{pmatrix} 0 & 2 & 0.5 & 0 \\ 2 & 0 & 1 & 4 \\ 0.5 & 1 & 0 & 0 \\ 0 & 4 & 0 & 0 \end{pmatrix}$$

$$A_{ii} = 0 \quad A_{ij} = A_{ji}$$

$$\langle k \rangle = \frac{2L}{N}$$

f. Complete Graph
(undirected)



$$A_{ij} = \begin{pmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix}$$

$$A_{ii} = 0 \quad A_{i \neq j} = 1$$

$$L = L_{\max} = \frac{N(N-1)}{2} \quad \langle k \rangle = N-1$$

Introduction - Metrics

Degree k : Number of nodes a node is connected to.

A B C D E F G

Ex: [2, 4, 2, 4, 5, 3, 2]

Strength s : Accumulated weights from incident edges.

A B C D E F G

Ex: [12, 31, 13, 35, 44, 25, 20]

$$s_i = \sum_{j=1}^N F_{ij}$$

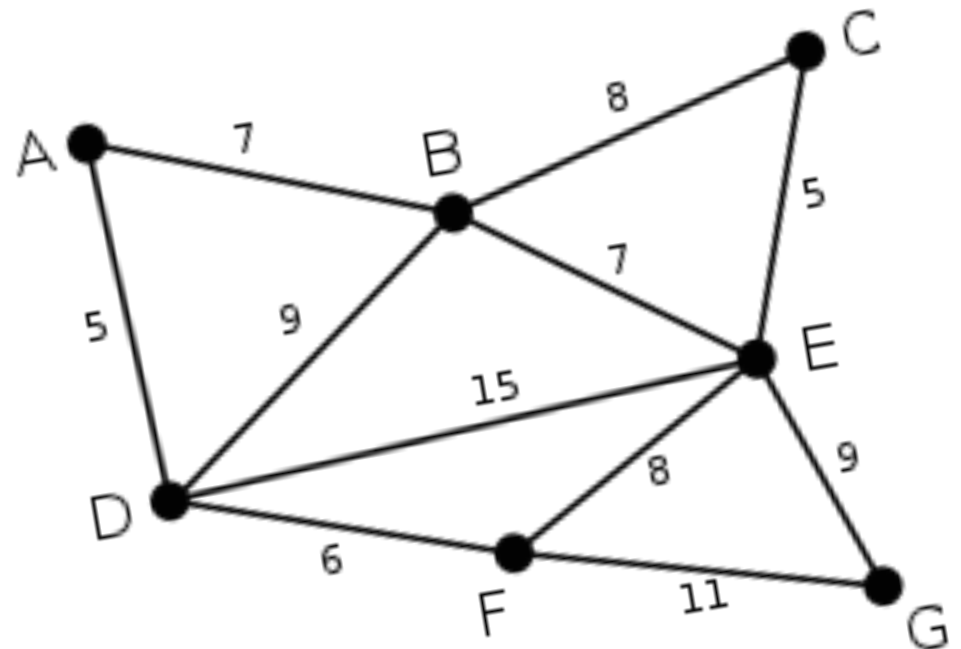
Betweenness b : Rate of shortest paths that pass through a node.

A B C D E F G

Ex: [0, 2.33, 0, 2.67, 5.17, 0.83, 0]

$$b_i = \sum_{v \neq w \neq i} \frac{\sigma_{vw}(i)}{\sigma_{vw}}$$

Diameter D : Length of the largest shortest path. Ex: [3]



Introduction

The empirical study of networks:

- Technological networks
 - The internet
 - The telephone network
 - Power grids
 - Transportation networks
 - Delivery and distribution networks
- Networks of information
 - The World Wide Web (WWW)
 - Citation networks
 - Peer-to-peer networks
 - Recommender networks
 - Keyword indexes
- Social Networks
 - Affiliation networks
 - Twitter (X), Instagram, Facebook
 - Co-workers
 - Sex
 - Friends
- Biological networks
 - Biochemical networks: metabolic, protein-protein
 - Brain networks
 - Ecological networks
 - Food web

Introduction

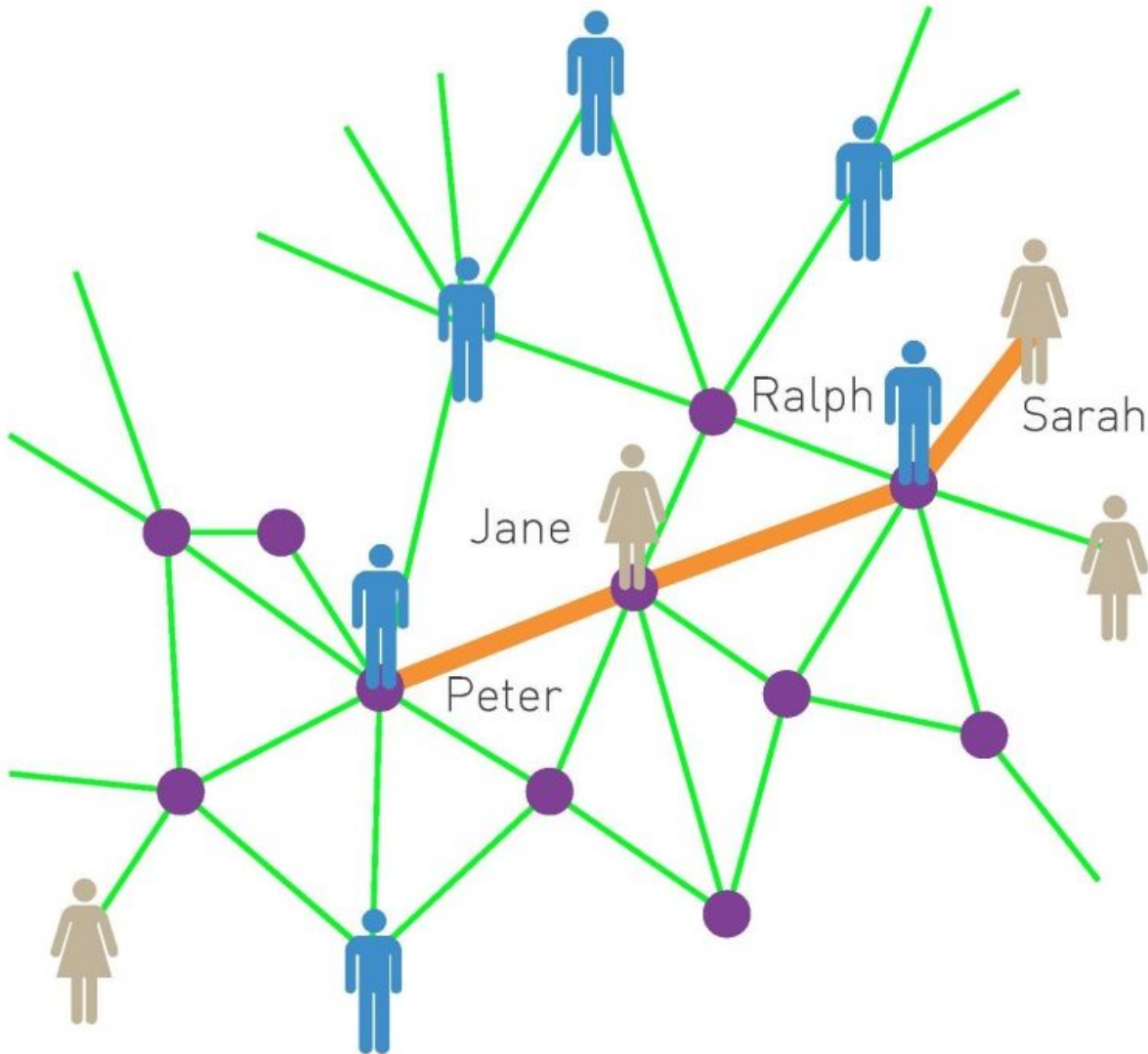
Typical questions:

- What are the most influential nodes?
- What are the shortest paths between nodes?
- Is the network assortative? (i.e. most connected nodes are friends with other influential nodes, and the less connected nodes have links with other of the same kind - degree correlation)
- What is the degree distribution? (Poisson, Power Law, ...)
- Is the network bipartite?
- Is the network connected?
- Are your friends also friends with each other? (Clustering Coefficient, triadic closure)
- Which network model resembles a certain network? (Erdős-Rényi, Small-world, Scale-free)

Network topology and models

Network topology - Small-world

Six Degree of Separation



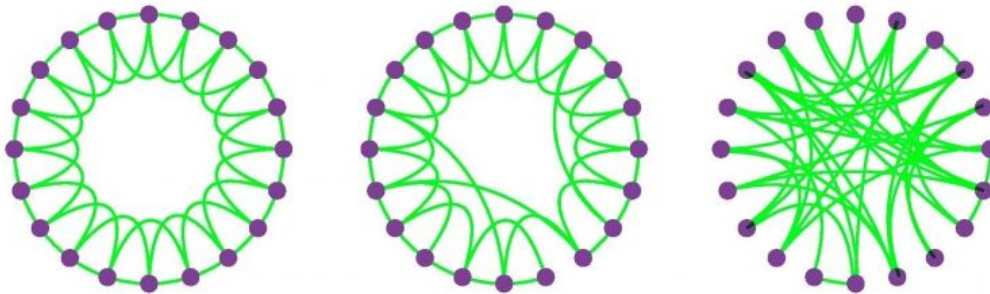
(MILGRAM, 1967)

Network models - Small-world

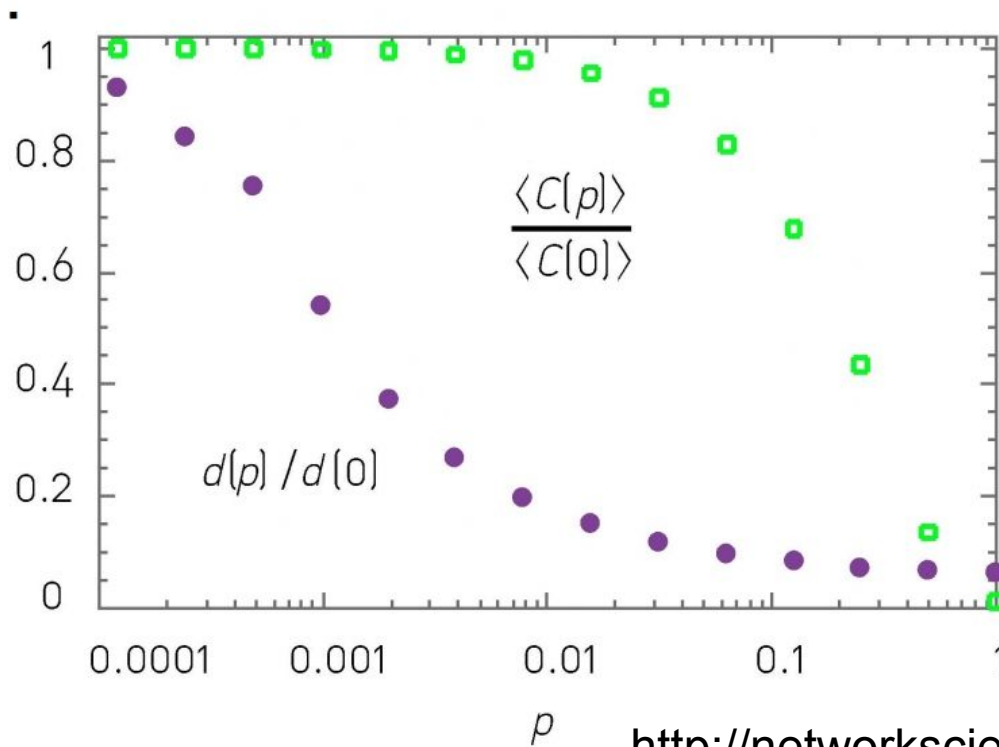
REGULAR

SMALL-WORLD

RANDOM



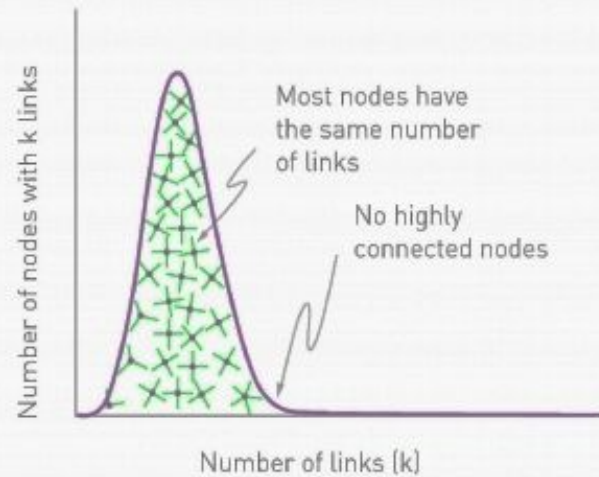
$p = 0$ \longrightarrow $p = 1$
Increasing randomness



(WATTS and STROGATZ, 1998)

Network topology - Scale-free

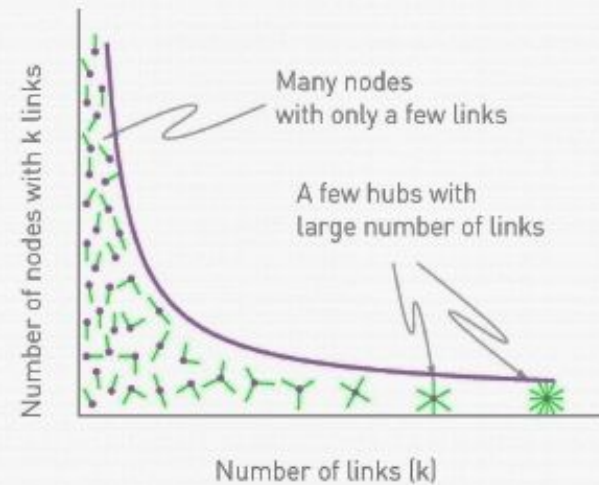
a. POISSON



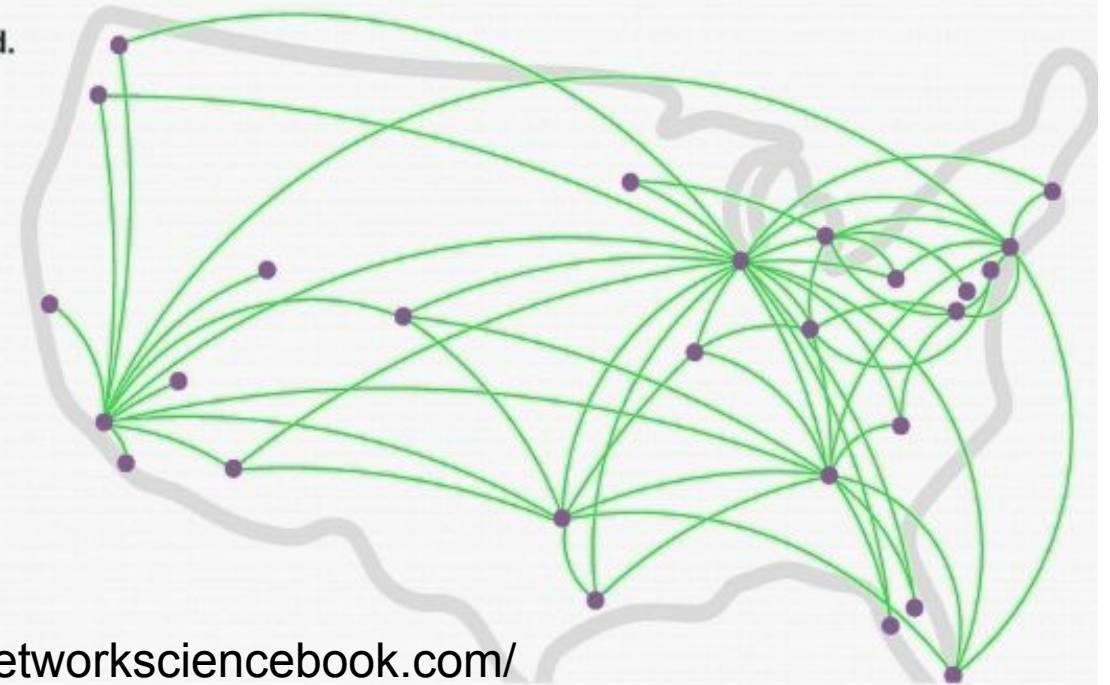
b.



c. POWER LAW

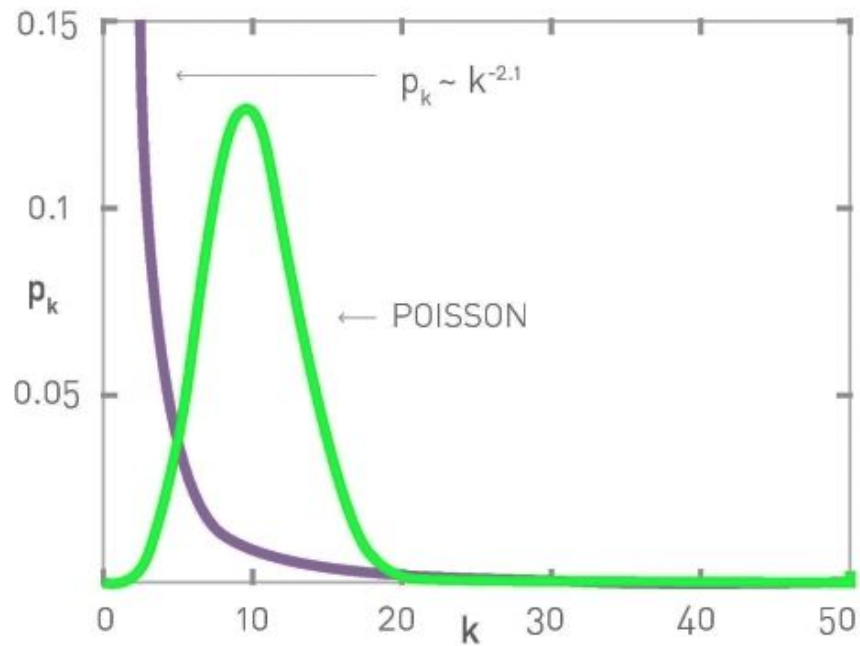


d.

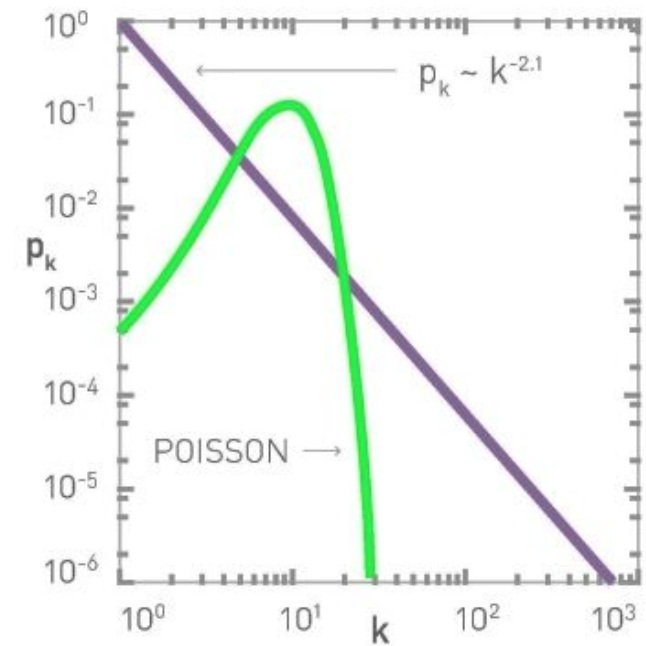


Network topology - Scale-free

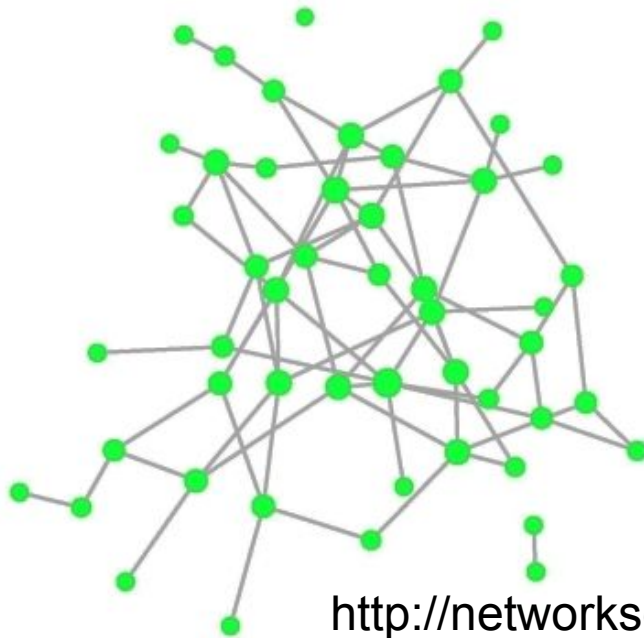
a.



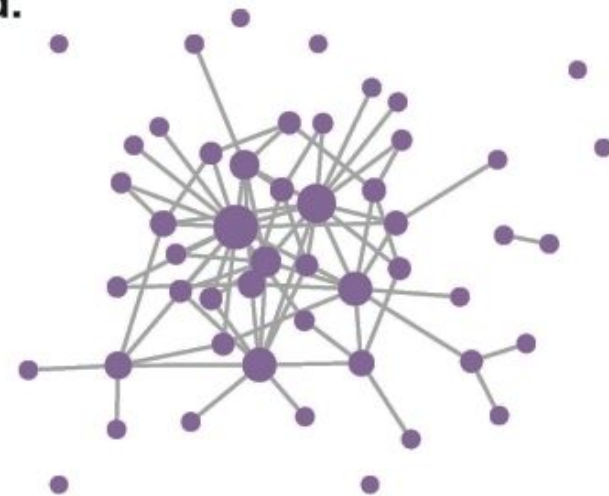
b.



c.



d.



Barabási-Albert Model

- Growth: at each time step we add a new node with m links that connect to m nodes added earlier.
- Preferential Attachment (rich-gets-richer phenomenon)

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

Video: <http://networksciencebook.com/images/ch-05/video-5-2.webm>

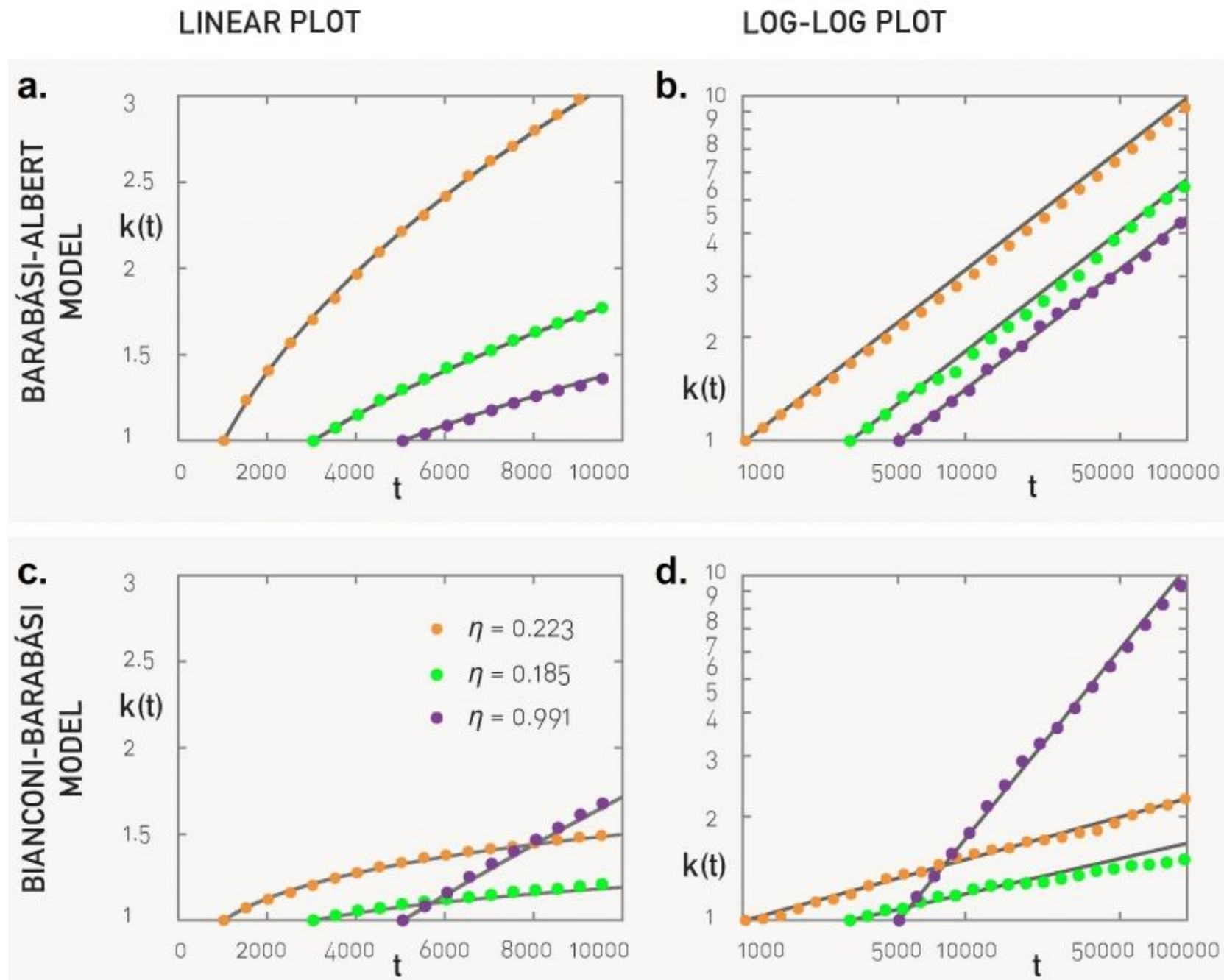
Bianconi-Barabási Model

- Growth: at each time step we add a new node with m links and fitness η_j , where η_j is a random number chosen from a fitness distribution $\rho(\eta)$. The fitness of a node does not change.
- Preferential Attachment considers fitness as well

$$\Pi(k_i) = \frac{\eta_i k_i}{\sum_j \eta_j k_j}$$

Video: <http://networksciencebook.com/images/ch-06/video-6-1.webm>

Network models - Scale-free



Network models - Summary

Model Class	Examples	Characteristics
Static Models	Erdos-Rényi Watts-Strogatz	<ul style="list-style-type: none">• N fixed• p_k exponentially bounded• Static, time independent topologies
Generative Models	Configuration Model Hidden Parameter Model	<ul style="list-style-type: none">• Arbitrary pre-defined p_k• Static, time independent topologies
Evolving Network Models	Barabási-Albert Model Bianconi-Barabási Model Initial Attractiveness Model Internal Links Model Node Deletion Model Accelerated Growth Model Aging Model	<ul style="list-style-type: none">• p_k is determined by the processes that contribute to the network's evolution.• Time-varying network topologies

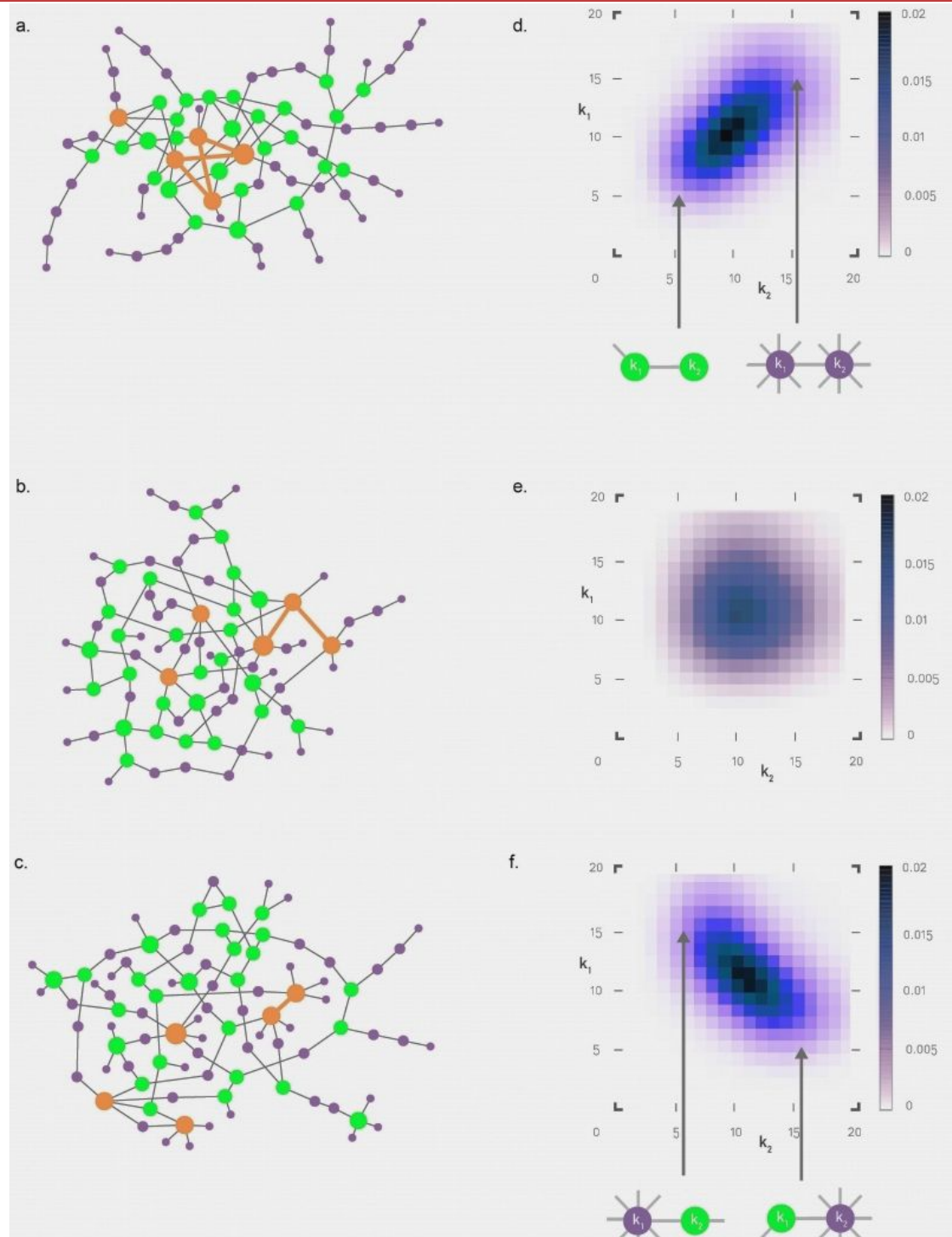
Assortativity and homophily

Degree correlations

What is the true chance that a celebrity marries another celebrity?



Degree correlations



Assortative Network

Neutral Network

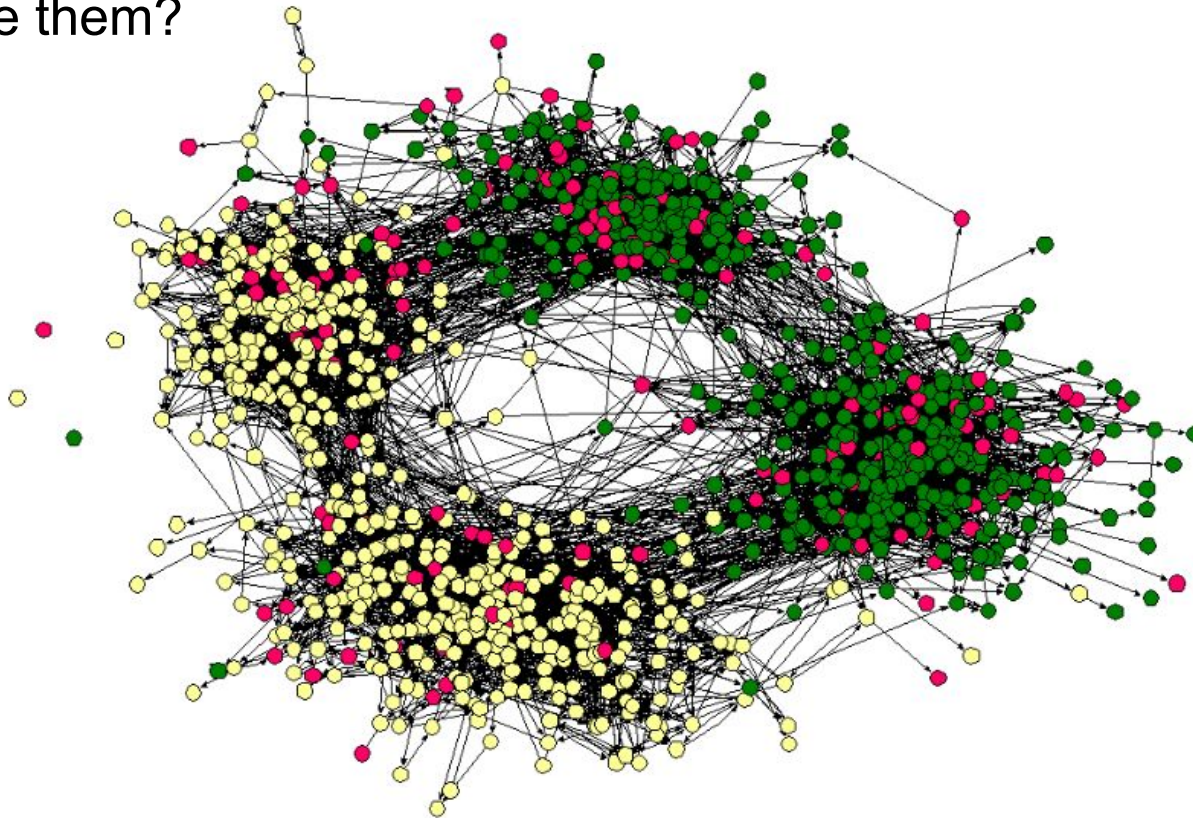
Disassortative Network

Homophily

Based on ideas such as:

- “Similarity begets friendship” (Plato)
- People “love those who are like themselves” (Aristotle)
- “birds of a feather flock together” (probably William Turner, 1545)

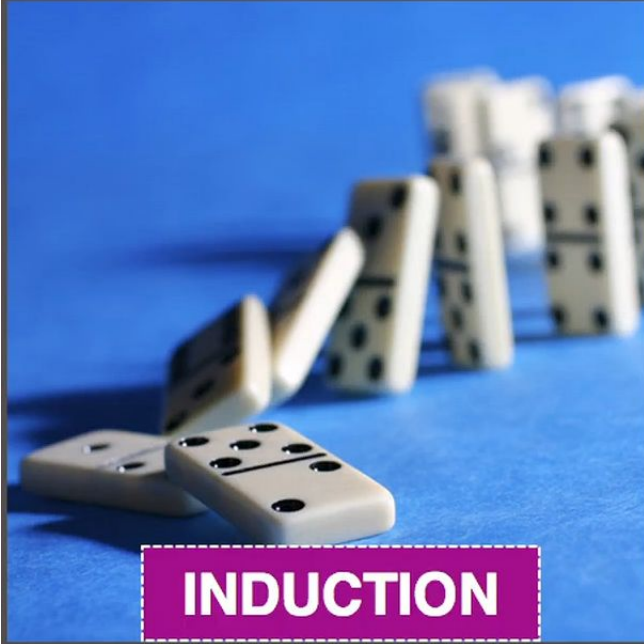
Selection and social influence: Have the people in the network adapted their behaviors to become more like their friends, or have they sought out people who were already like them?



Two divisions in the network are apparent: one based on race (with students of different races drawn as differently colored circles), and the other based on friendships in the middle and high schools respectively (EASLEY and KLEINBERG, 2010)

Homophily

Causes of Similarity and Clustering

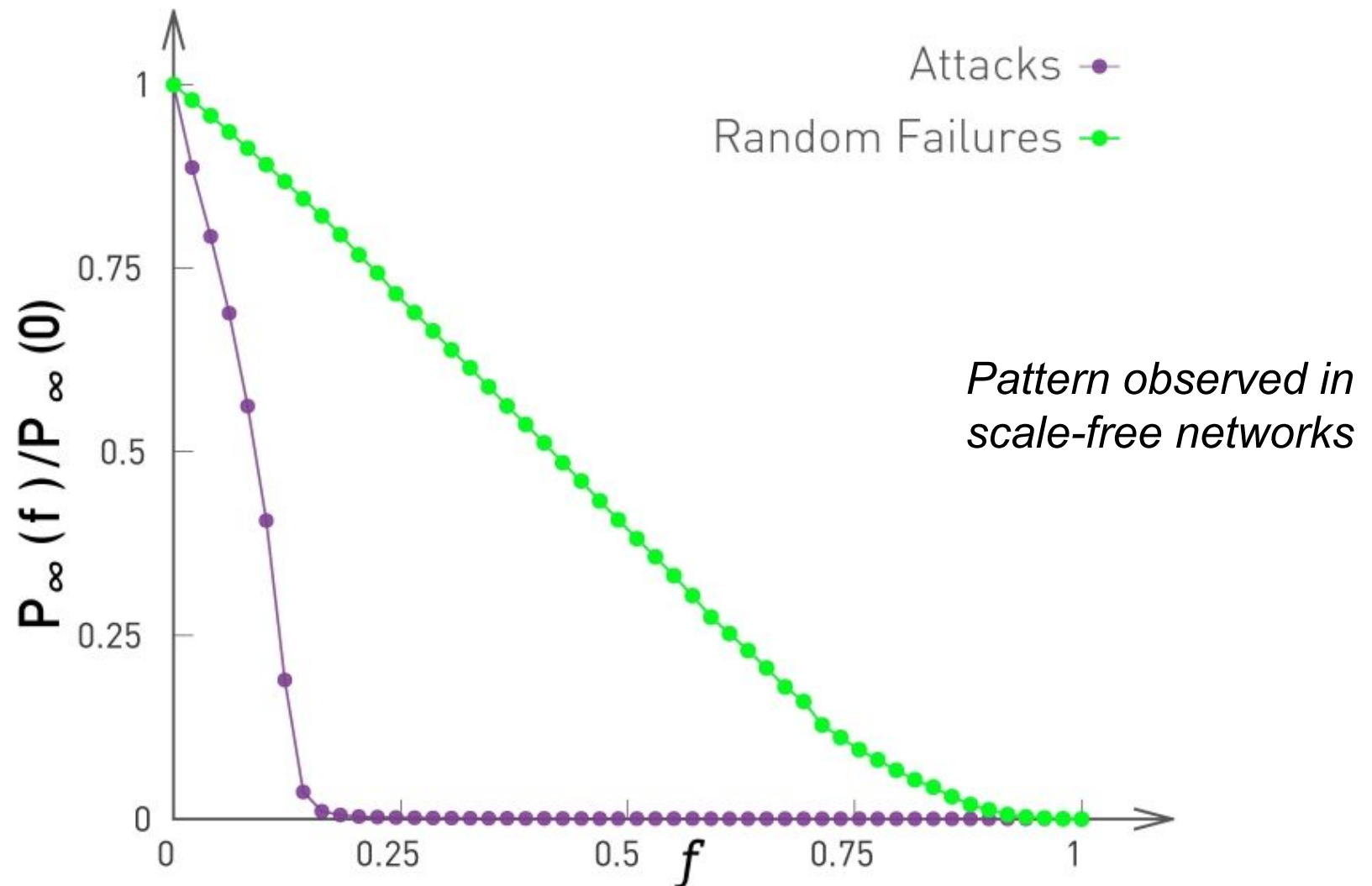


Robustness

Robustness

How may one efficiently fragment a network?

Video: <http://networksciencebook.com/images/ch-08/video-8-2.webm>



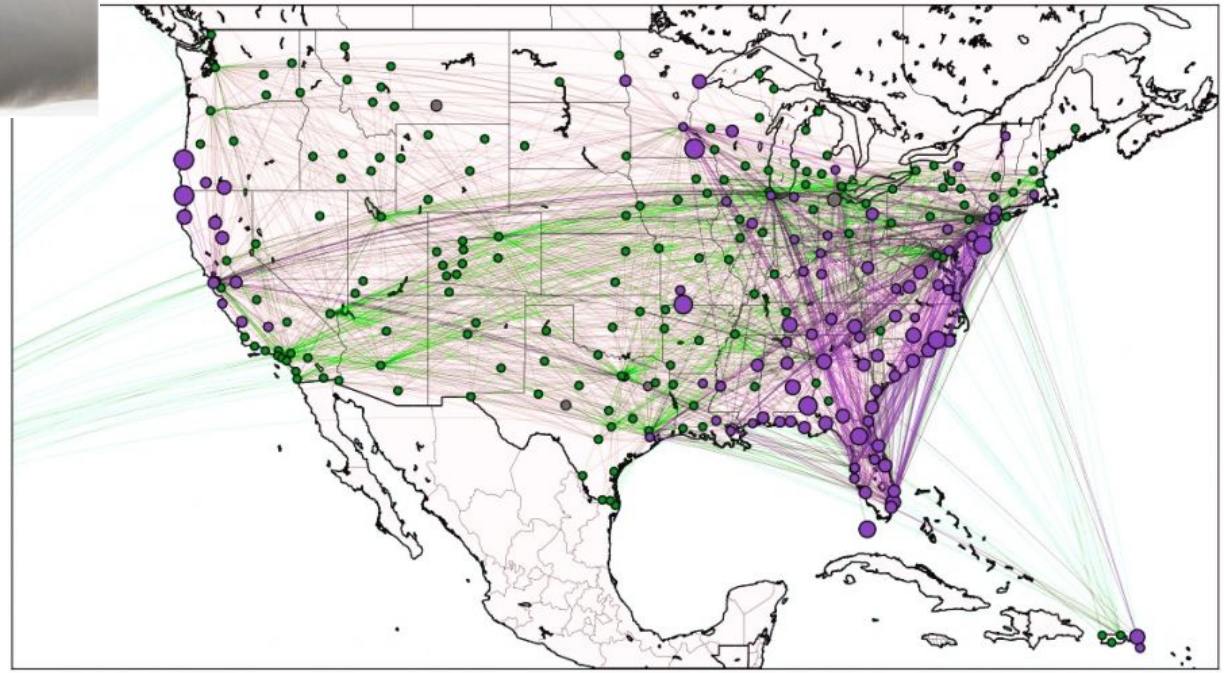
Fonte: <http://networksciencebook.com/chapter/8#robustness>

Robustness

Network	Random Failures (Real Network)	Random Failures (Randomized Network)	Attack (Real Network)
Internet	0.92	0.84	0.16
WWW	0.88	0.85	0.12
Power Grid	0.61	0.63	0.20
Mobile Phone Calls	0.78	0.68	0.20
Email	0.92	0.69	0.04
Science Collaboration	0.92	0.88	0.27
Actor Network	0.98	0.99	0.55
Citation Network	0.96	0.95	0.76
E. Coli Metabolism	0.96	0.90	0.49
Protein Interactions	0.88	0.66	0.06

Robustness

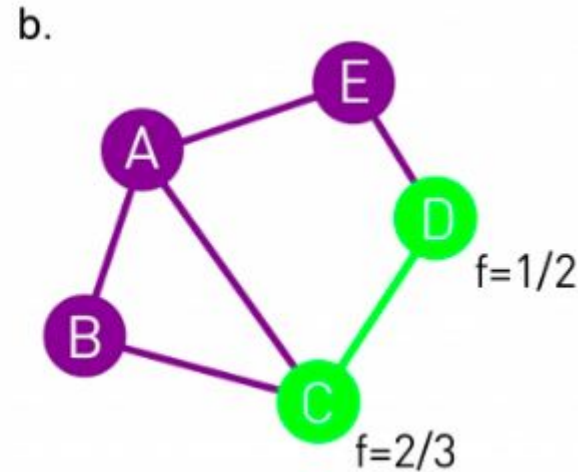
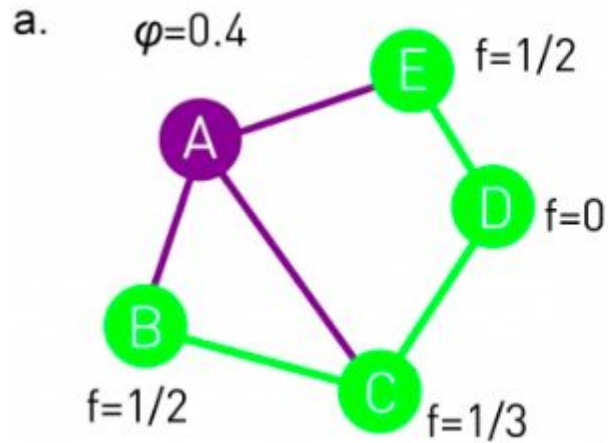
Cascading Failures



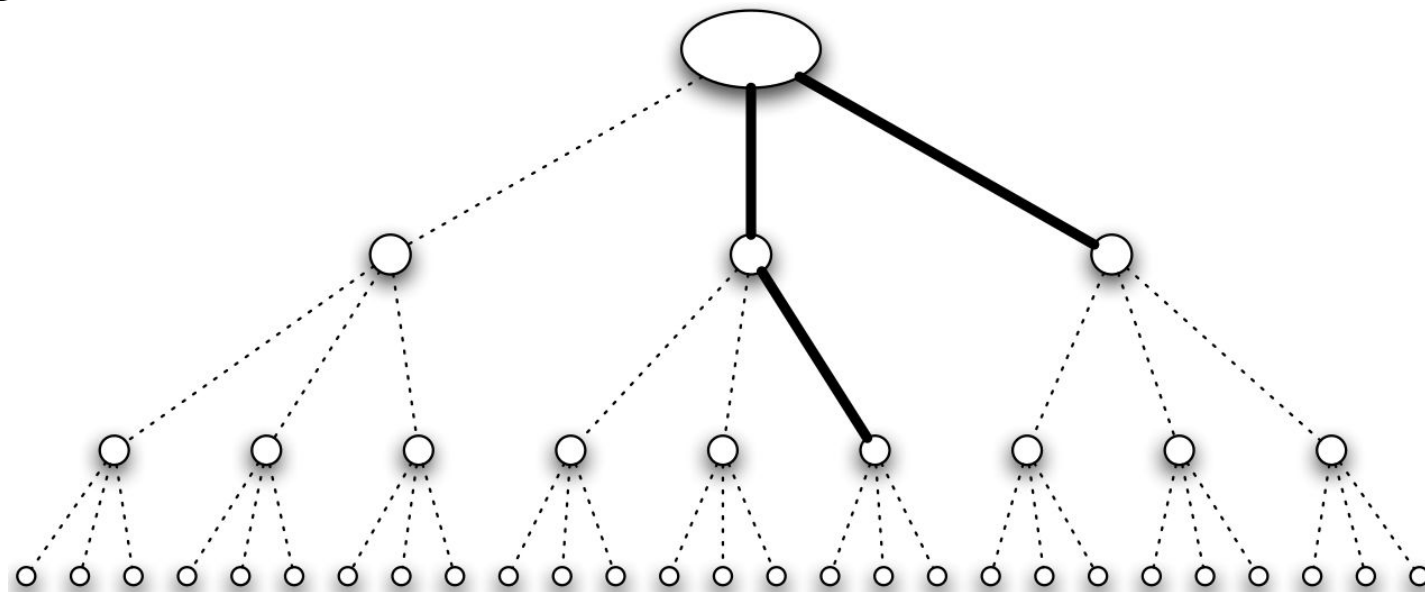
Robustness

Failure Propagation Model

<http://networksciencebook.com/>



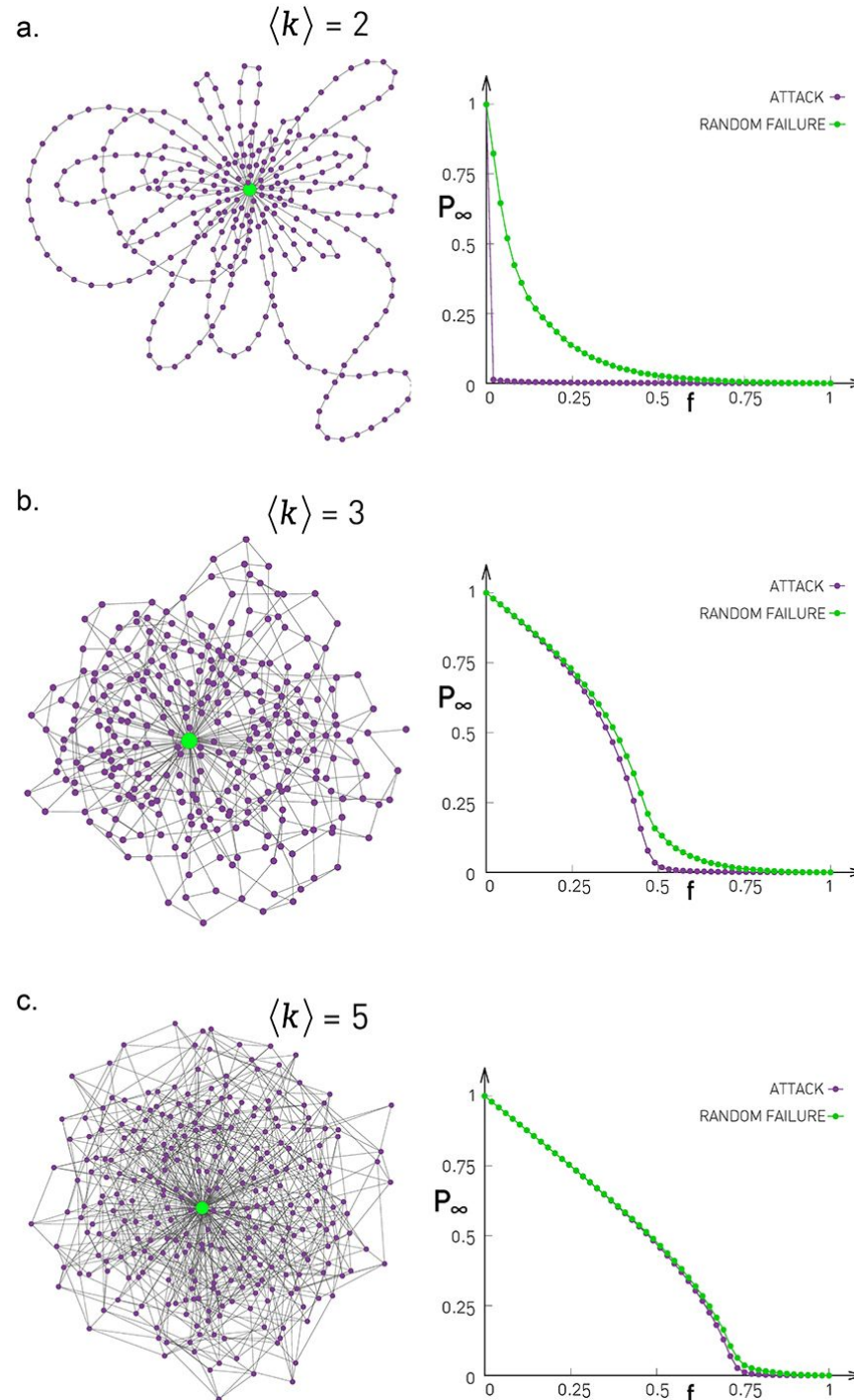
Branching Model



(EASLEY and KLEINBERG, 2010)

Robustness

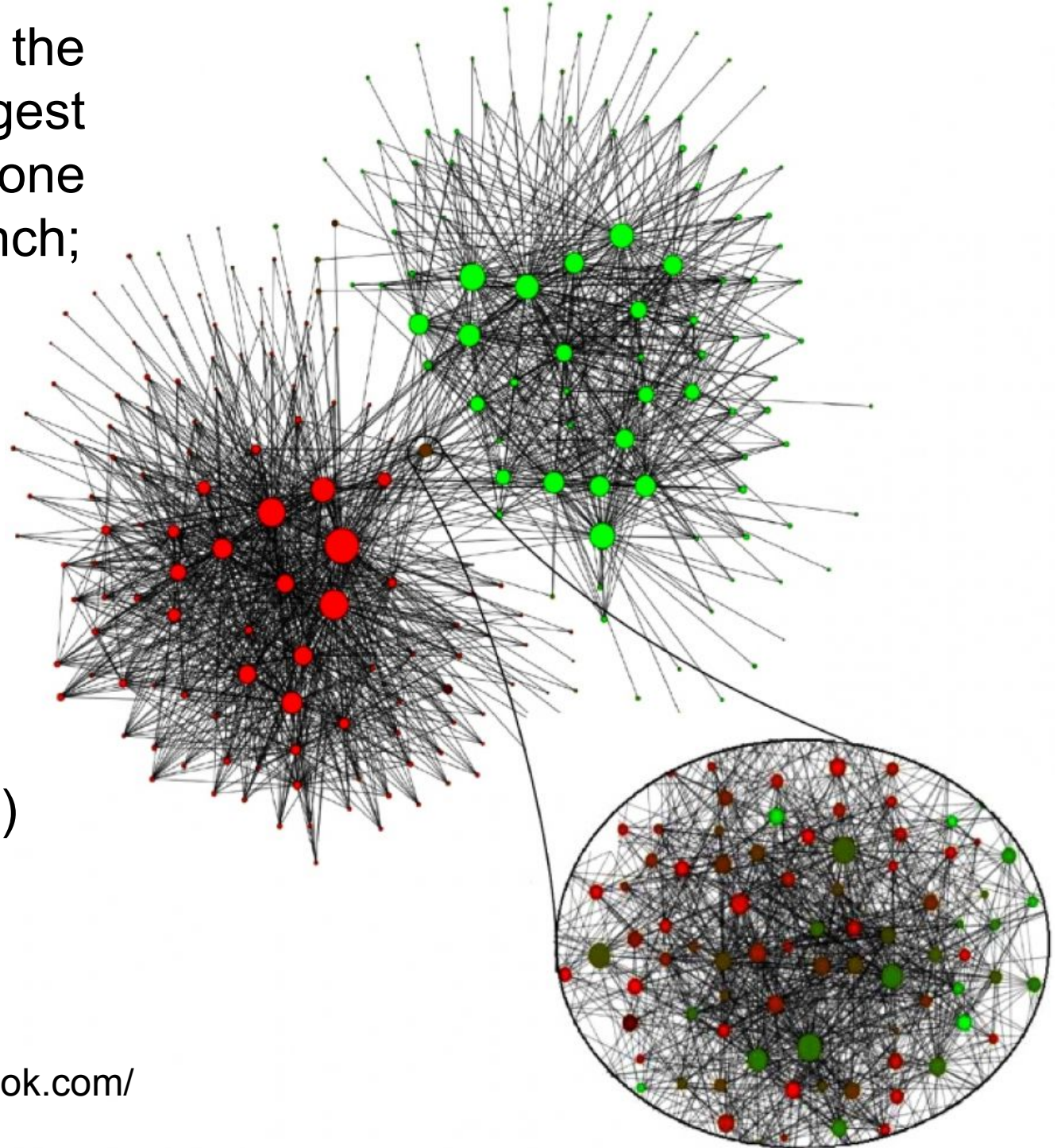
Building robustness



Communities

Communities

Call pattern of the consumers of the largest Belgian mobile phone company. Red: french; Green: Dutch.

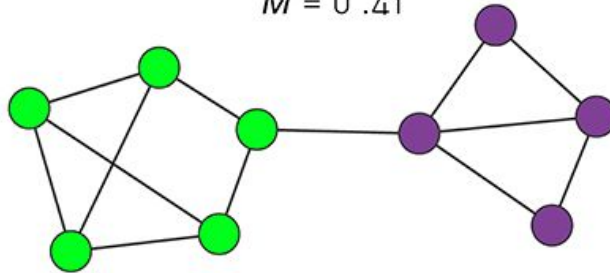


(FORTUNATO, 2010)

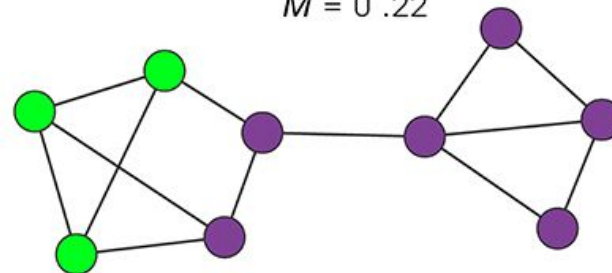
Communities

- Graph partitioning vs Community detection
- Agglomerative Procedures: the Ravasz Algorithm
- Divisive Procedures: the Girvan-Newman Algorithm
- Modularity: When the number of links between pairs of nodes is higher than the “expected”, the modularity increases, showing possible true communities.

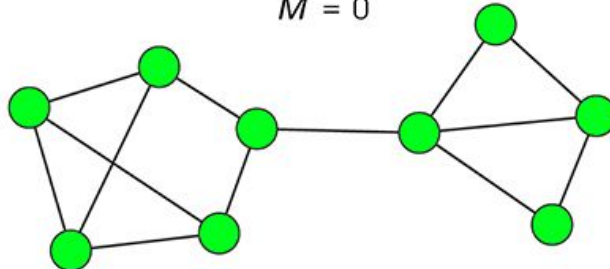
a. OPTIMAL PARTITION
 $M = 0.41$



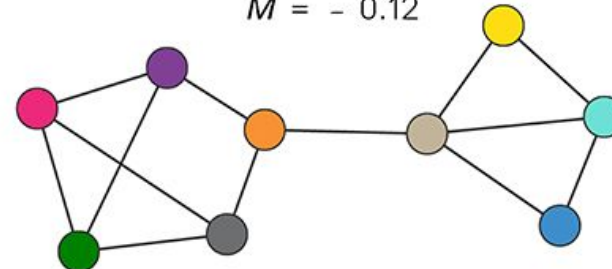
b. SUBOPTIMAL PARTITION
 $M = 0.22$



c. SINGLE COMMUNITY
 $M = 0$



d. NEGATIVE MODULARITY
 $M = -0.12$



Communities

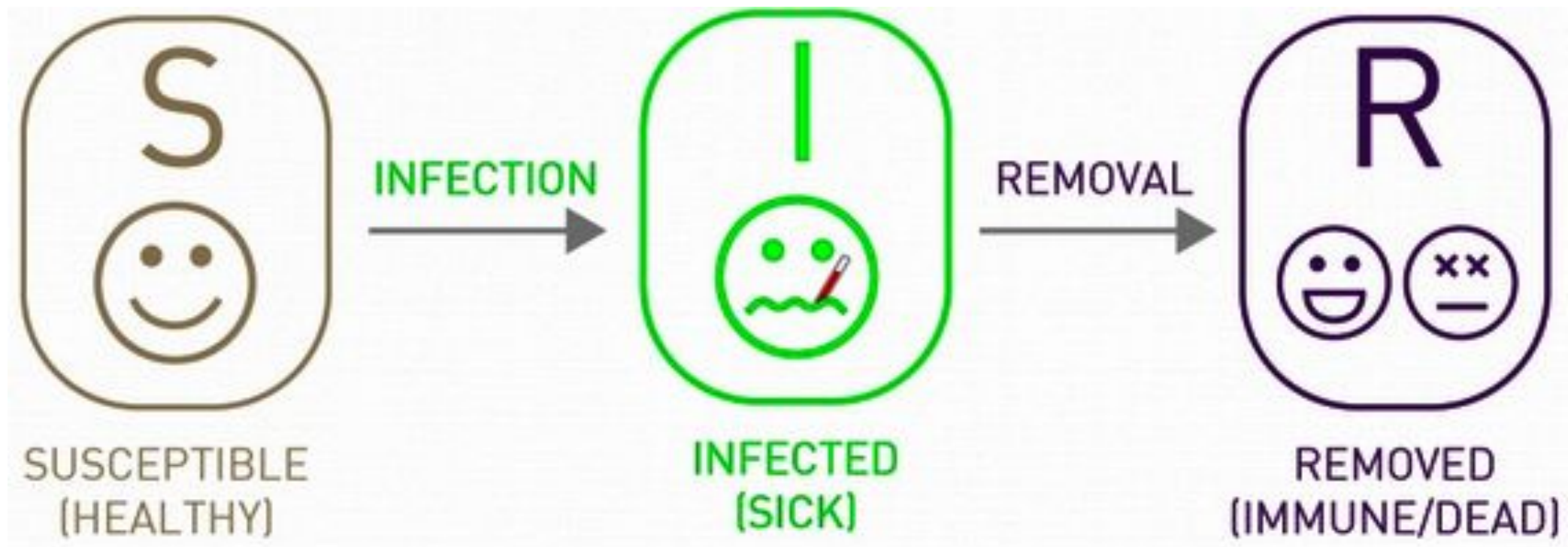
Name	Nature	Comp.
Ravasz	Hierarchical Agglomerative	$O(N^2)$
Girvan-Newman	Hierarchical Divisive	$O(N^2)$
Greedy Modularity	Modularity Optimization	$O(N^2)$
Greedy Modularity (Optimized)	Modularity Optimization	$O(N \log^2 N)$
Louvain	Modularity Optimization	$O(L)$
Infomap	Flow Optimization	$O(N \log N)$
Clique Percolation (CFinder)	Overlapping Communities	$\text{Exp}(N)$
Link Clustering	Hierarchical Agglomerative; Overlapping Communities	$O(N^2)$

Spreading Phenomena

Spreading Phenomena

Phenomena	Agent	Network
Venereal Disease	Pathogens	Sexual Network
Rumor Spreading	Information, Memes	Communication Network
Diffusion of Innovations	Ideas, Knowledge	Communication Network
Computer Viruses	Malwares, Digital viruses	Internet
Mobile Phone Virus	Mobile Viruses	Social Network/Proximity Network
Bedbugs	Parasitic Insects	Hotel - Traveler Network
Malaria	Plasmodium	Mosquito - Human network

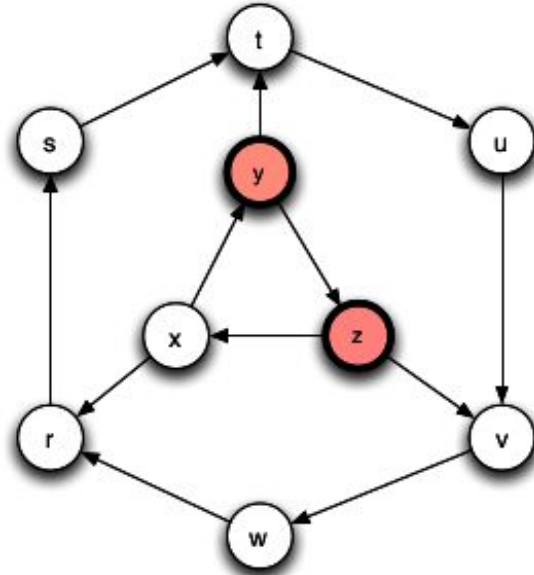
Spreading Phenomena



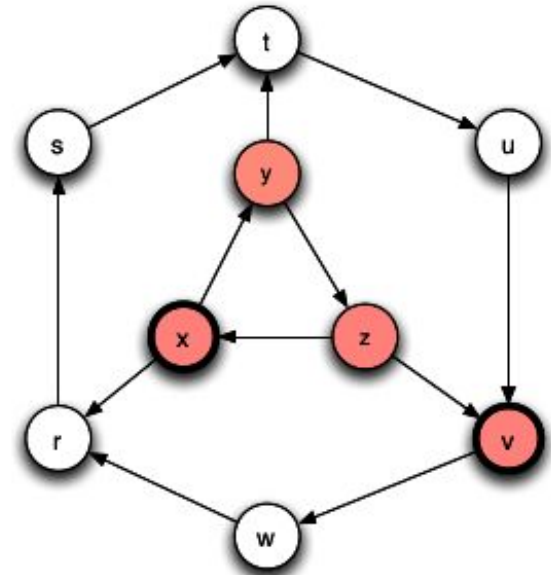
Spreading Phenomena

Simulation:
y and z initially
infected

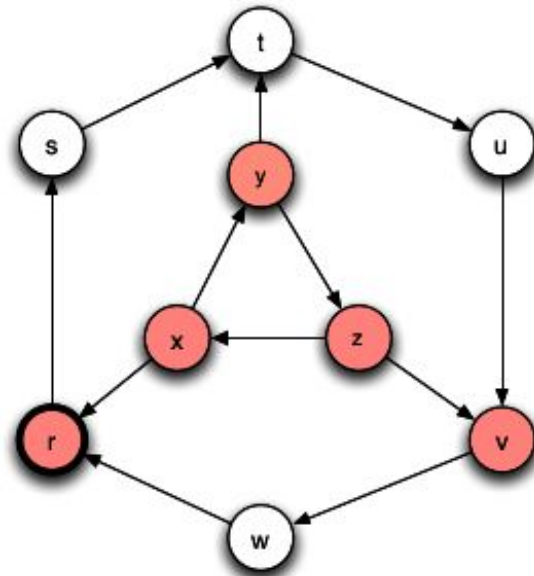
(EASLEY and
KLEINBERG,
2010)



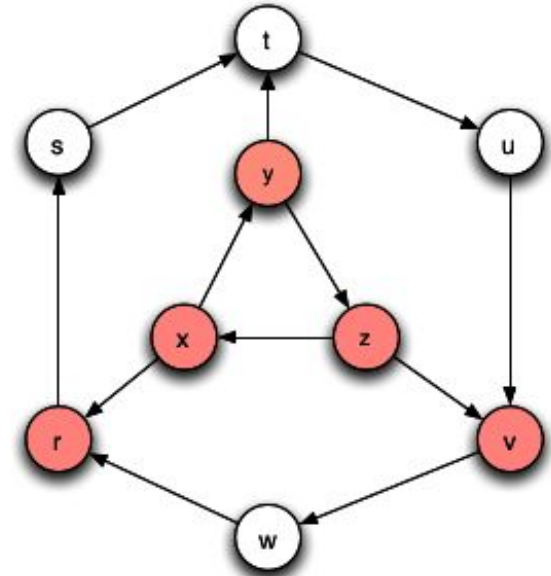
(a)



(b)



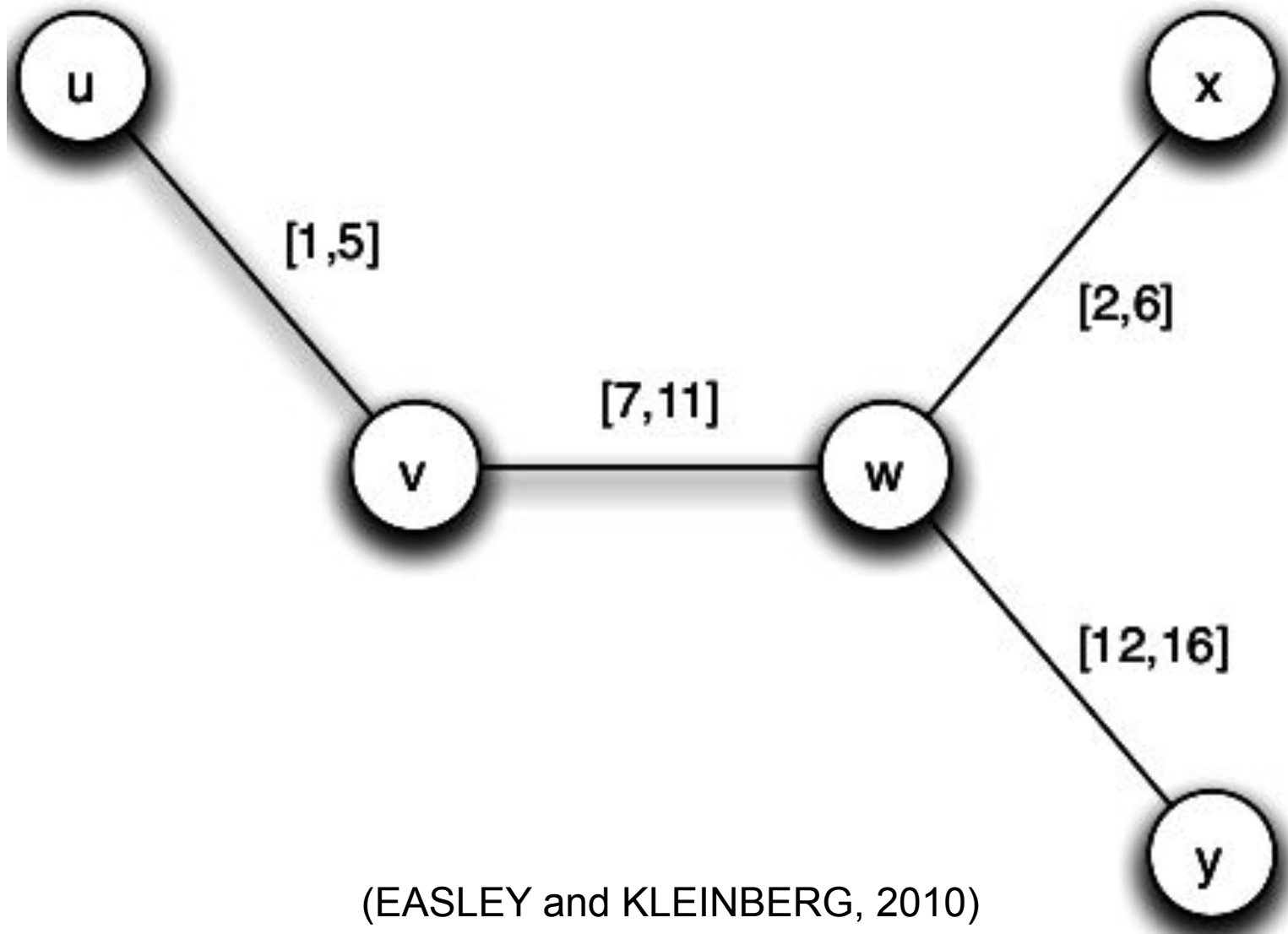
(c)



(d)

Spreading Phenomena

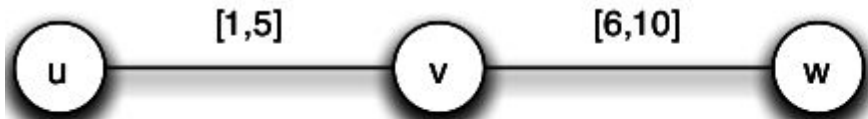
Transient contact networks



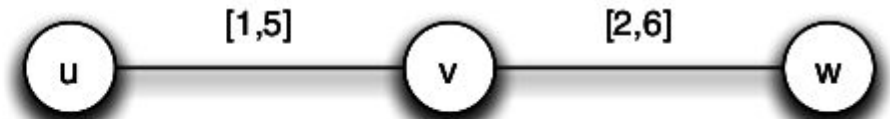
(EASLEY and KLEINBERG, 2010)

Spreading Phenomena

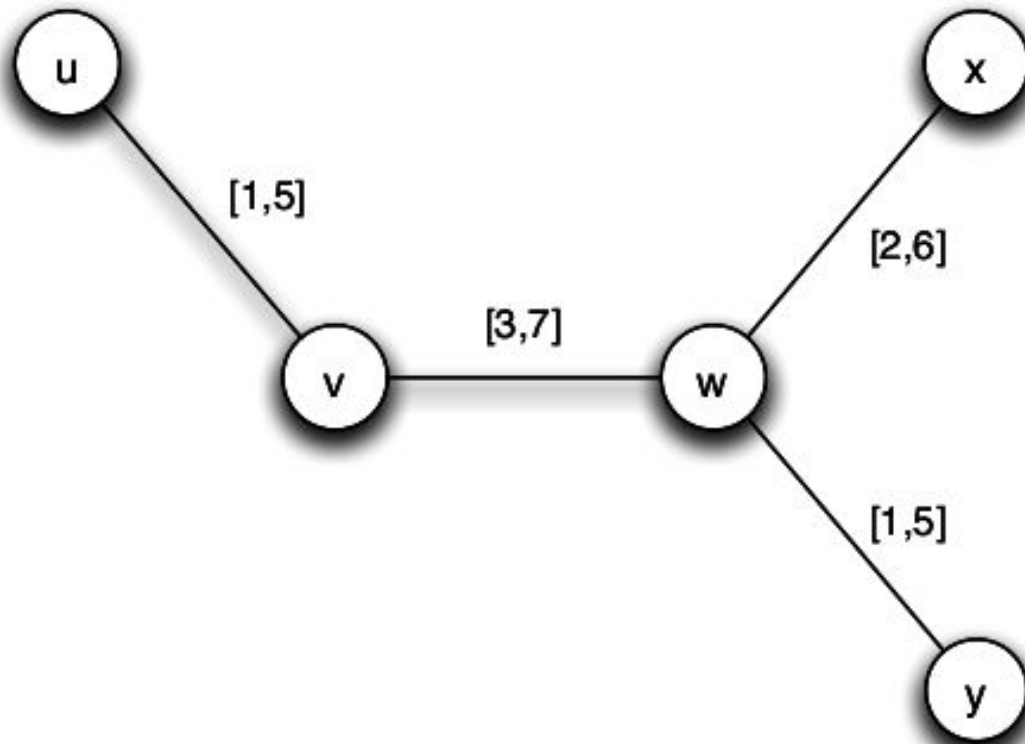
Concurrency:



(a) *v's two partnerships happen serially*



(b) *v's two partnership's happen concurrently*

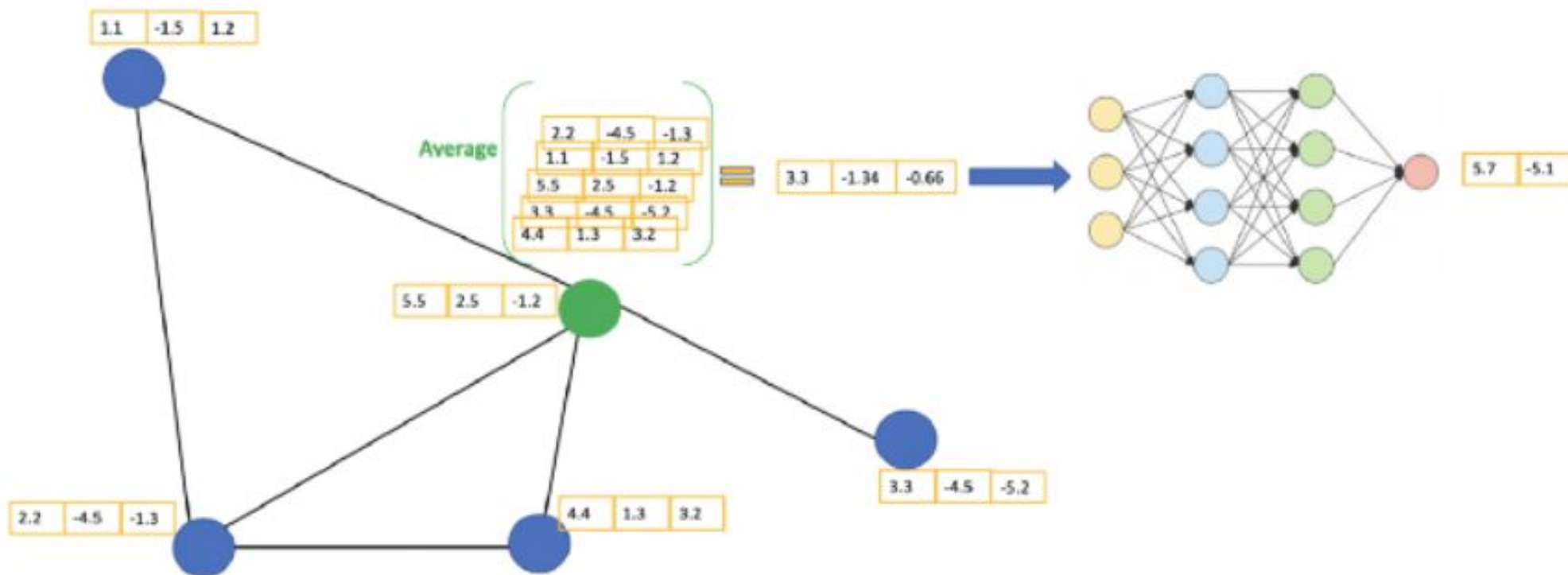


Small concurrency
addition implies big
propagation addition.

Network Science + Machine Learning

GNN

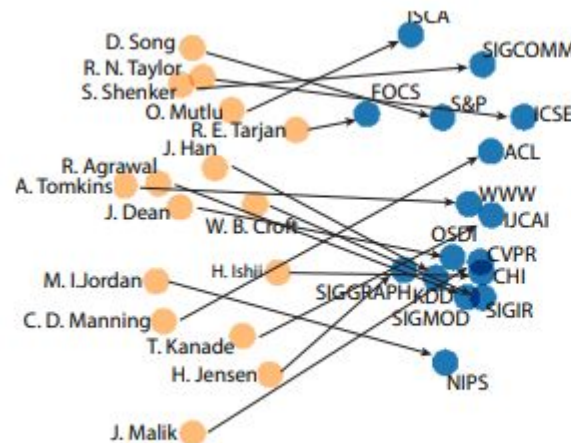
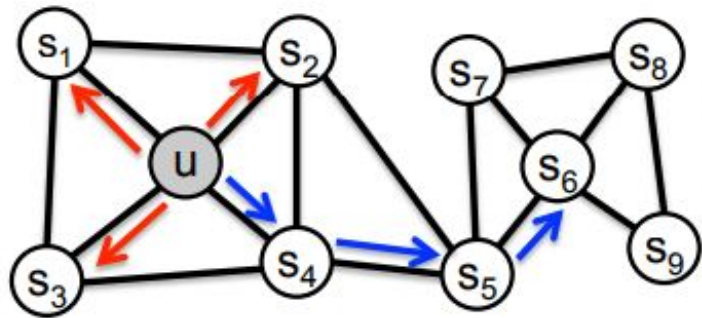
- Basics of Graph Neural Networks:
<https://www.graphneuralnets.com/p/basics-of-gnns/?src=yt%29>
- GCN: <https://www.topbots.com/graph-convolutional-networks/>



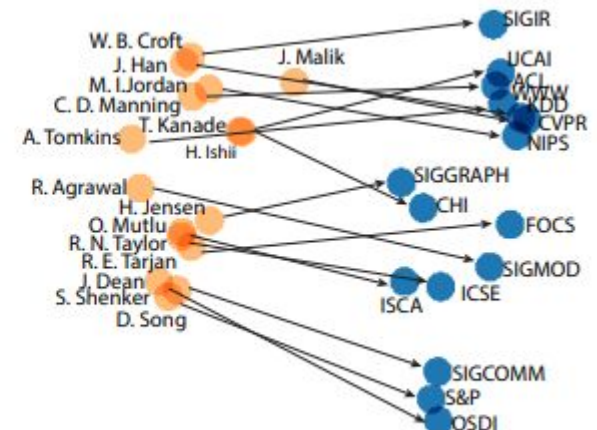
Network Science + Machine Learning

Embeddings:

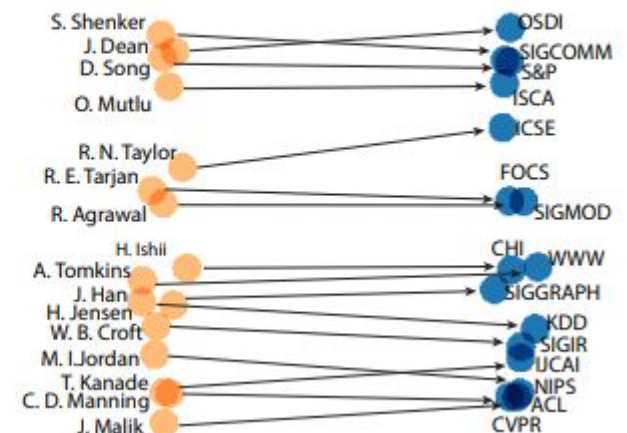
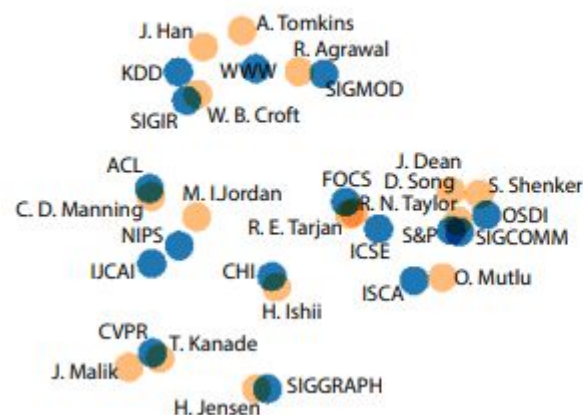
- node2vec (<https://dl.acm.org/doi/10.1145/2939672.2939754>)
- metapath2vec (<https://dl.acm.org/doi/10.1145/3097983.3098036>)



(a) DeepWalk / node2vec



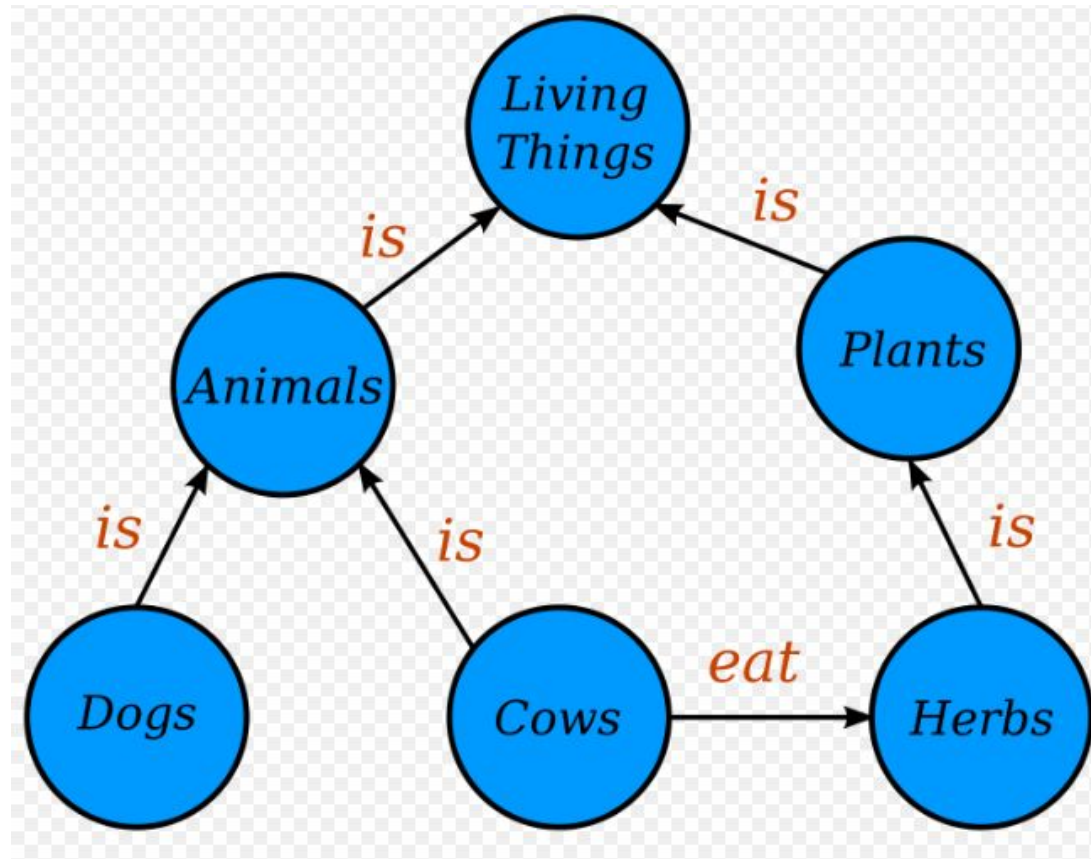
(b) PTE



Network Science + Machine Learning

Knowledge Graphs:

- Natural Language Processing + Graphs
(<https://doi.org/10.1016/j.eswa.2019.112948>)
- GraphRAG
(<https://www.microsoft.com/en-us/research/project/graphrag/>)



Conclusions

- Complex networks are everywhere
 - sociology, engineering, math, physics, computer science, biology, ...
- Highly interdisciplinary

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<http://networksciencebook.com/>

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Questions?