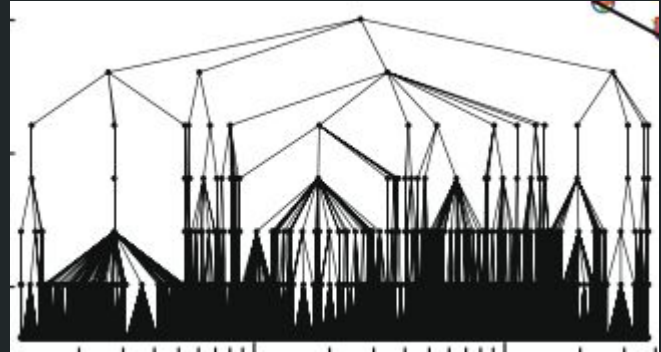


Modeling data with and without networks

Data course CRI 2020
Marc Santolini
Liubov Tupikina
Class 5

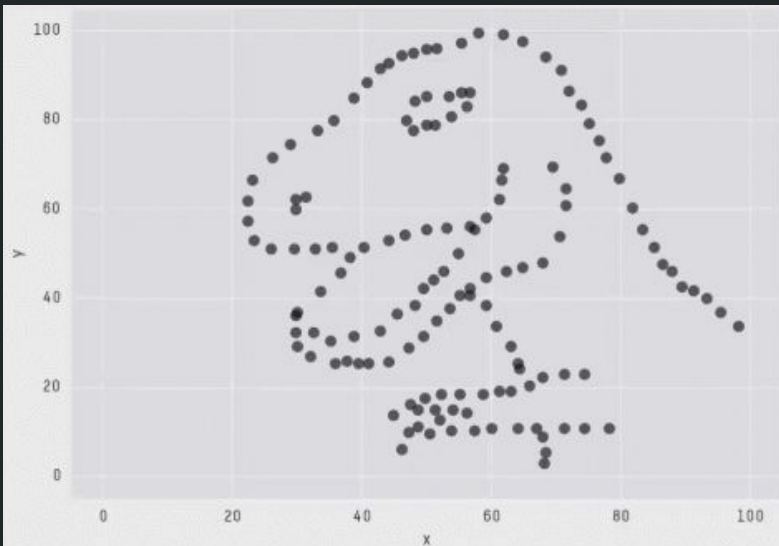


Outline of the day

1. Organisation of the week
2. Projects overview
3. Class 5 lecture
4. Notebooks
5. Take home messages round table

Resources of the day

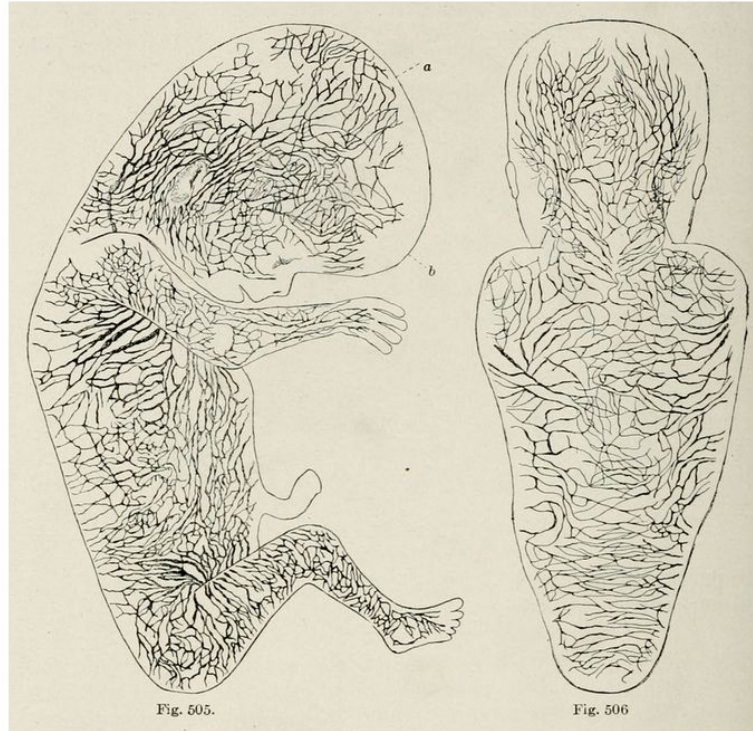
1. Network collection <https://snap.stanford.edu/data>
2. Networkx library
<https://networkx.org/documentation/networkx-1.9/examples>



X Mean: 54.2659224
Y Mean: 47.8313999
X SD : 16.7649829
Y SD : 26.9342120
Corr. : -0.0642526

Modeling data

Class 2 reminder



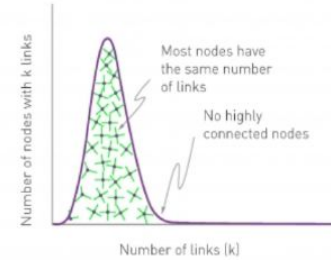
Distension of the lymphatic vessels in the human foetus, from Franz Kriebel, *Manual of human embryology*, 1910

Class 2 reminder

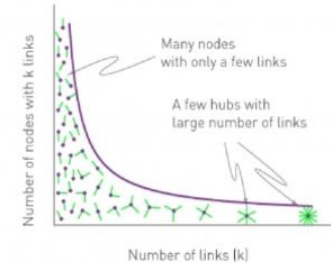
Distribution of degrees
Distribution of other measures



a. POISSON



c. POWER LAW



Class 2 reminder

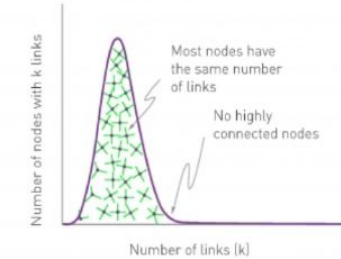
Small exercise

<https://snap.stanford.edu/data>

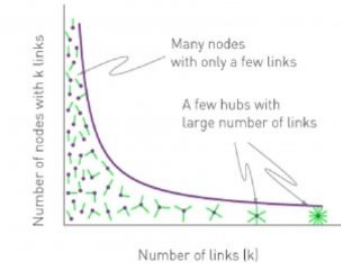
Choose a network and show
the degree distribution



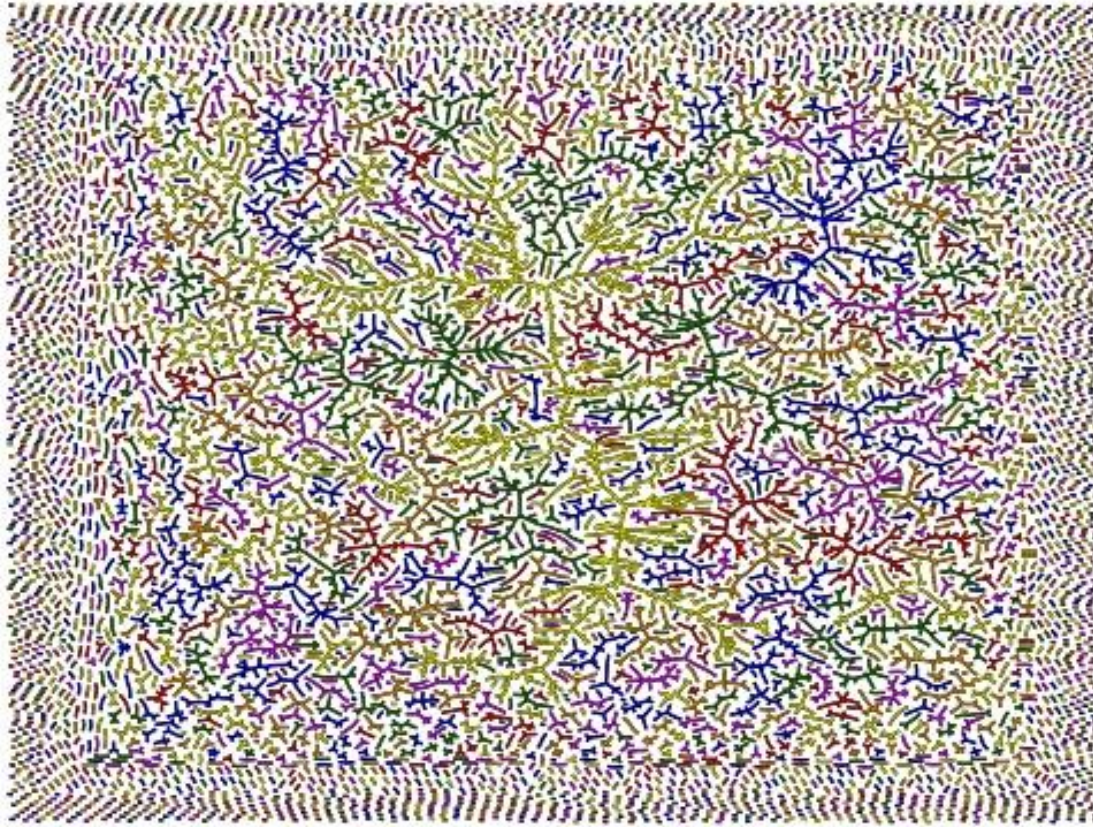
a. POISSON



c. POWER LAW



How random are real networks?



Modeling with networks

1. Random network models
2. Models of networks in time and space
3. Models of processes on networks

Modeling without networks

1. Random walks models
2. Skewed data models (epidemics spreading example)

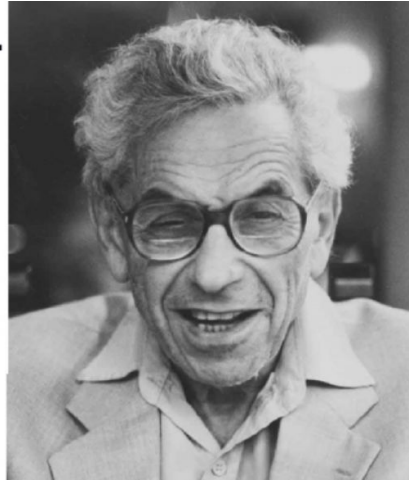
Modeling with networks: random network models

1. Erdos Renyi
2. Barabasi Albert
3. Random geometric graph

Main resource

<http://networksciencebook.com/chapter/3>

a.



b.



Modeling with networks:

Erdos-Renyi random network models

Algorithm:

1. Choose any two nodes
2. Toss a coin
3. Draw a link if coin is up



Modeling with networks:

Erdos-Renyi random network models

Algorithm:

1. Choose any two nodes
2. Toss a coin (is it always fair?)
3. Draw a link if coin is up



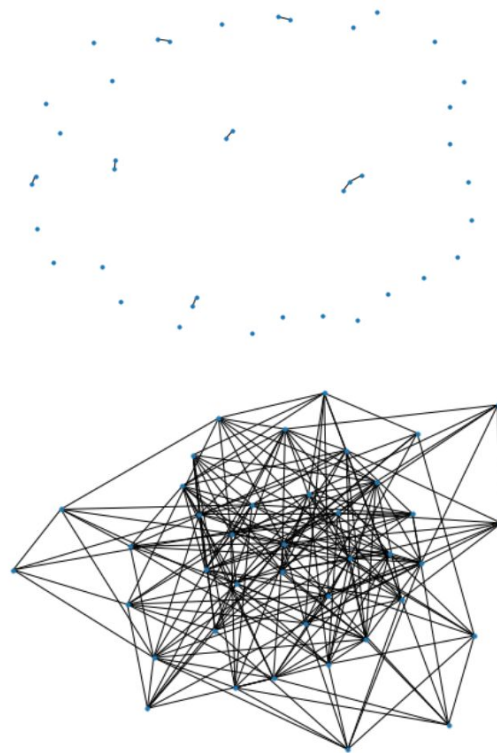
Modeling with networks:

Erdos-Renyi random network model

Algorithm:

1. Choose any two nodes from N nodes
2. Toss a coin (with probability p)
3. Draw a link if coin is up

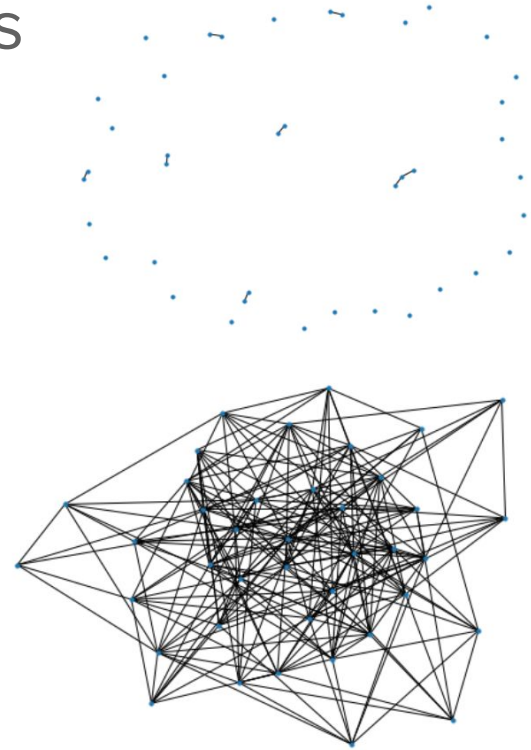
Phase-transition threshold $1/\langle k \rangle$:
below which the network becomes fragmented,
while above which a giant connected component
of order N exists.



Modeling with networks:

Erdos-Renyi random network models

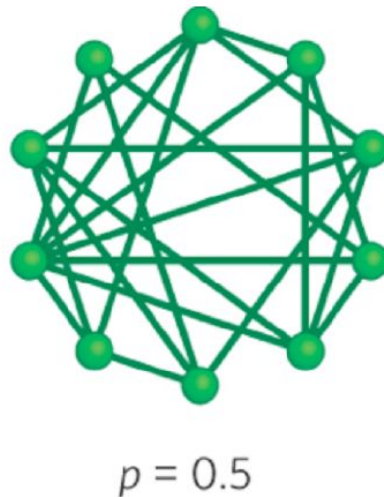
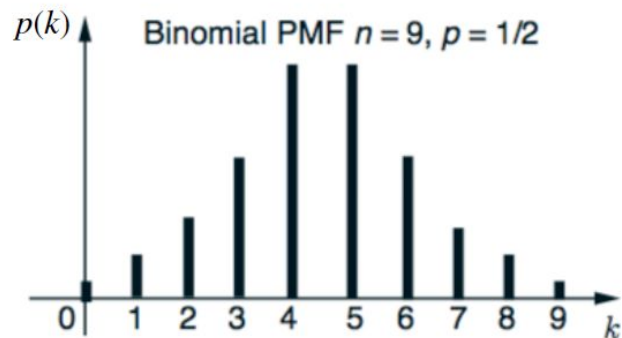
Which degree distribution do you expect?



Modeling with networks:

Erdos-Renyi random network models

Which degree distribution do you expect?



Modeling with networks:

Barabasi-Albert random network models

How could we replicate social interactions?

www.wired.com



Modeling with networks:

Barabasi-Albert random network models

Algorithm:

1. Choose core of m connected nodes
2. Grow with preferential attachment

to previous core nodes:

Probability to connect is proportional
to the number of links that the
existing nodes

Reference:

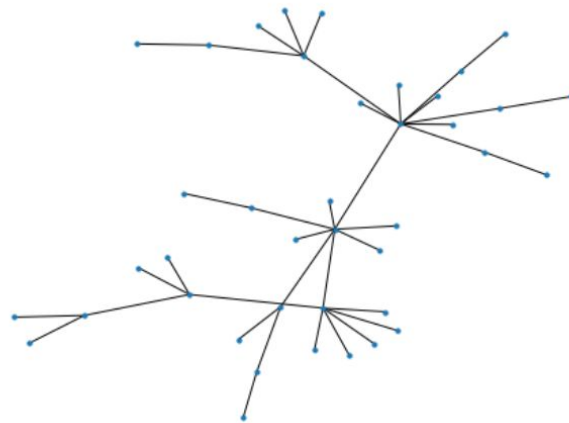
[Albert, Réka](#); [Barabási, Albert-László](#) (2002). ["Statistical mechanics of complex networks"](#) (PDF)

Modeling with networks:

Barabasi-Albert random network models

Algorithm:

1. Choose core of m connected nodes
2. Grow with preferential attachment to previous core nodes:
Probability to connect is proportional to the number of links that the existing nodes



Reference:

[Albert, Réka; Barabási, Albert-László \(2002\). "Statistical mechanics of complex networks" \(PDF\)](#)

Modeling with networks:

Barabasi-Albert random network

Algorithm:

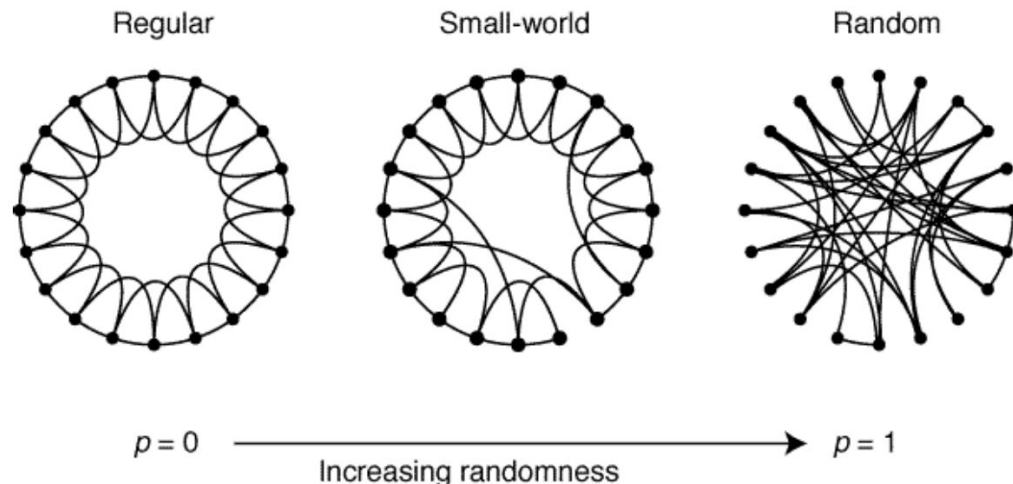
1. Choose core of connected nodes
2. Grow with preferential attachment
To previous core nodes



Modeling with networks:

Watts-Strogatz random network

But does it replicate any random network?



Modeling with networks:

Watts-Strogatz random network

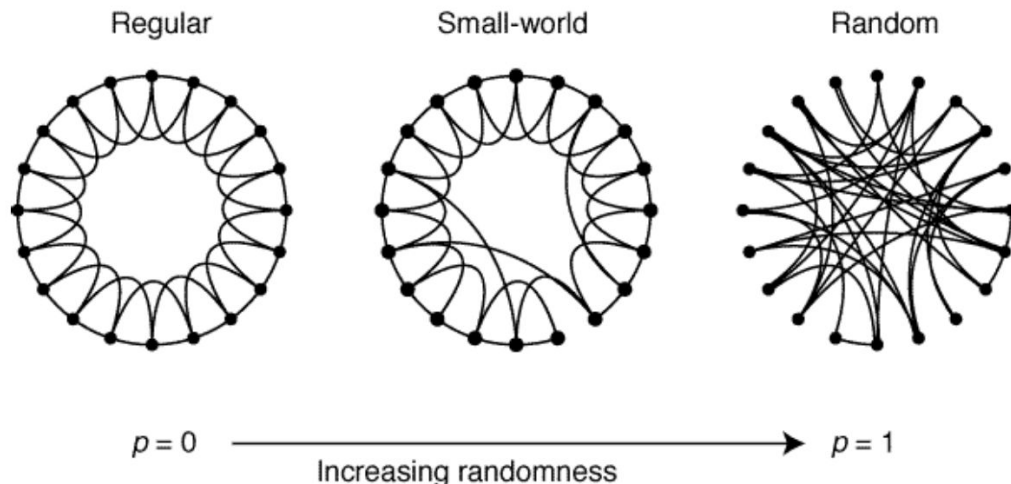
Algorithm:

1. Start from a regular k-circle-network
2. Rewire links from a regular circle

References:

[Watts, D. J.; Strogatz, S. H. \(1998\).](#)

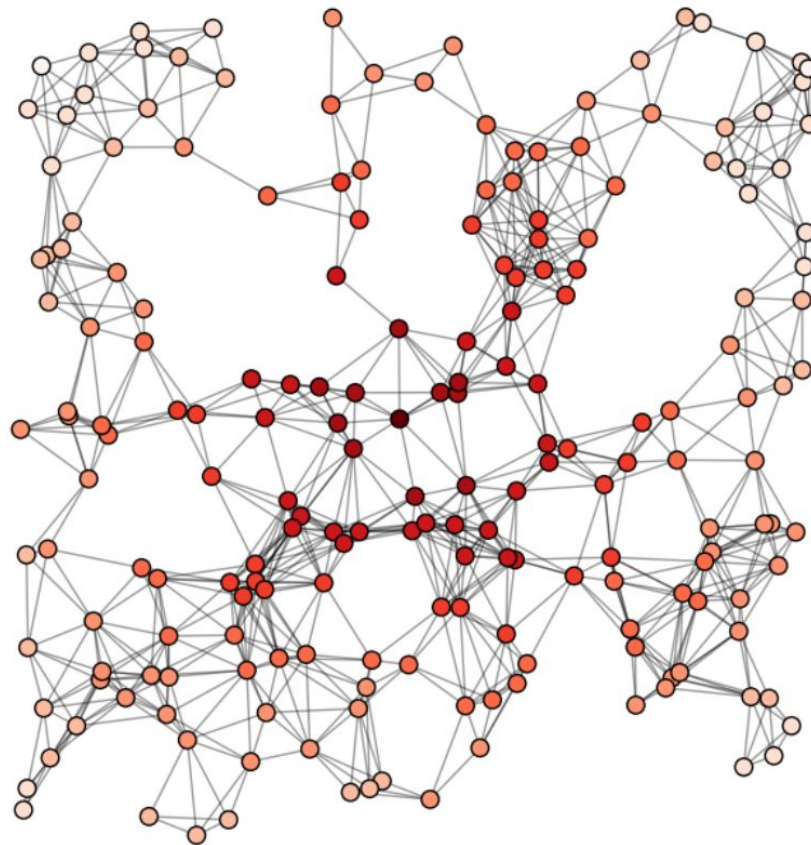
["Collective dynamics of 'small-world' networks"](#) (PDF).



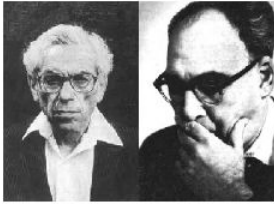
Modeling with networks: Geometric random network

Algorithm:

1. Choose any two nodes within R (radius)
2. Toss a coin
3. Draw a link if coin is up and nodes are close enough



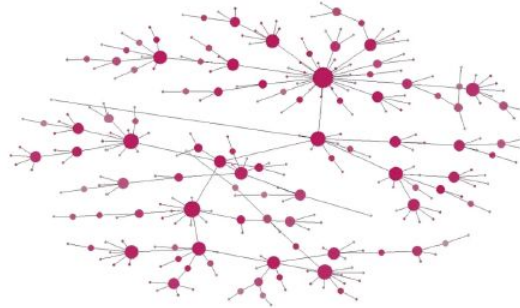
Take-home messages



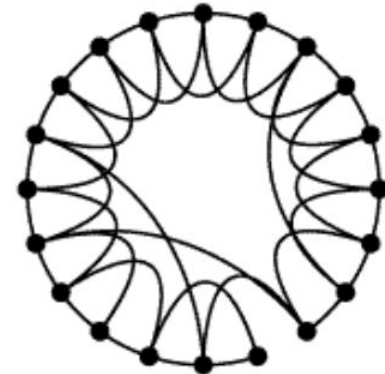
Erdős-Rényi
networks



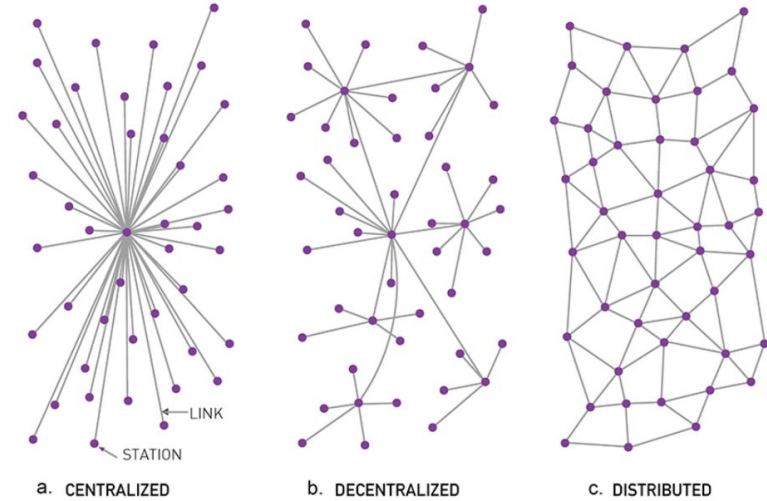
Barabási-Albert
networks



Watts-Strogatz
networks



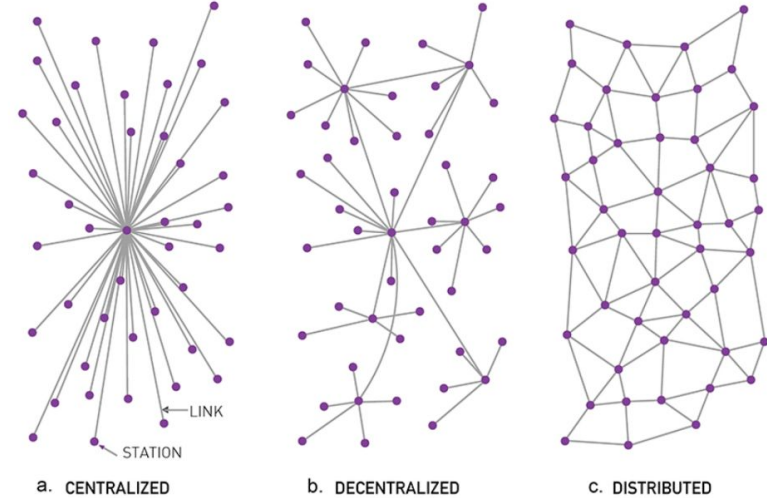
How to generate robust random network?



How to generate robust random network?

Ideas:

- Remove links from network
- Detect changes globally and locally
- Define measures for characterisation of network robustness

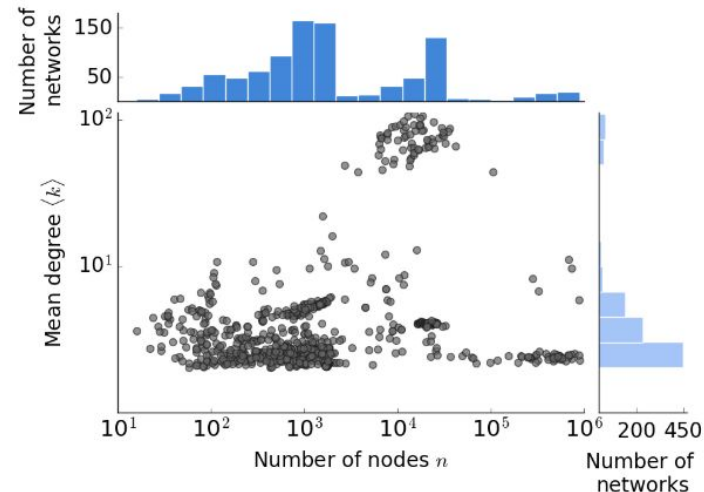


How do random networks help?

Main ideas:

- Not to model the exact network, but the global properties
- To grasp average characteristics

A. Broido et al. on scale-free networks



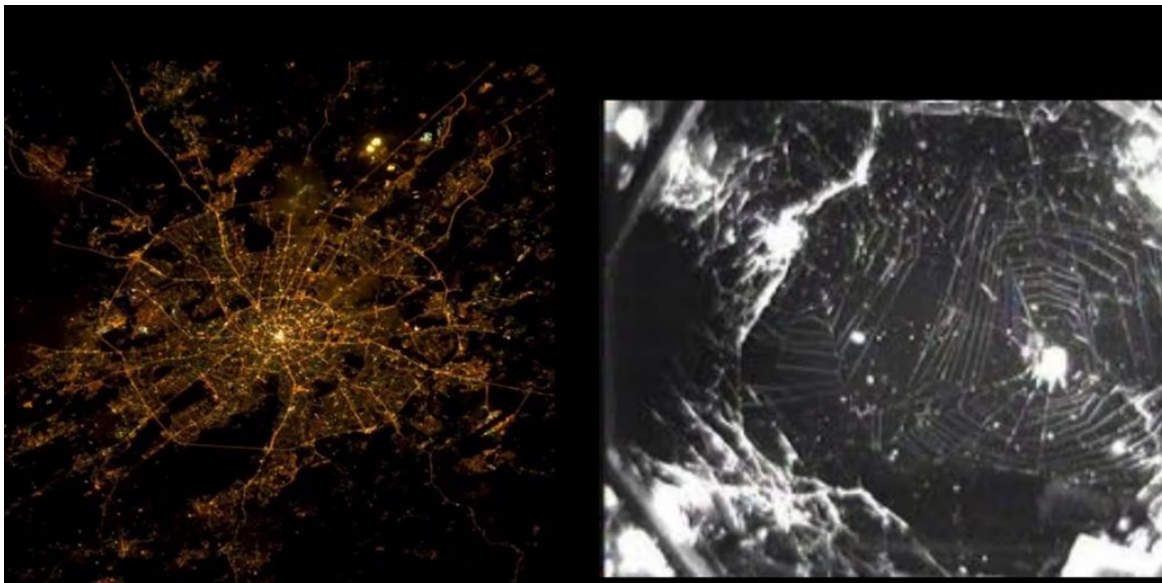
How do random networks help?

Main ideas:

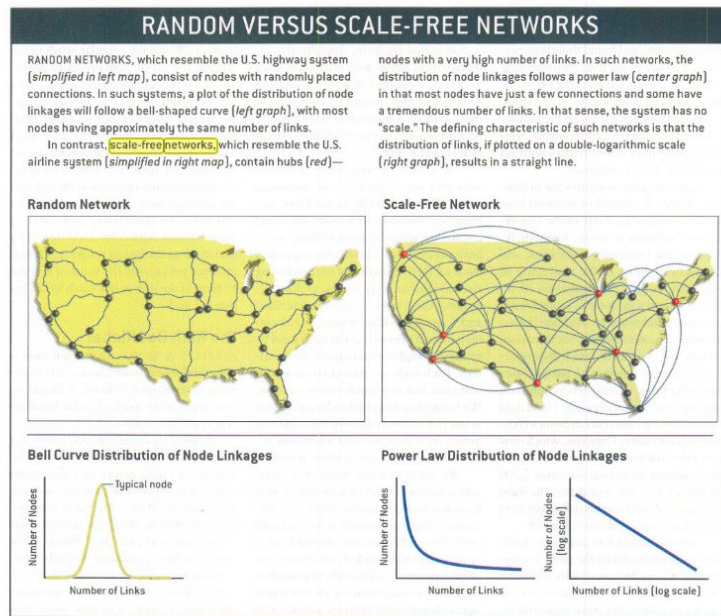
- Not to model the exact network, but the global properties
- To grasp average characteristics

Look for analogies:

Web - Web



How do random networks help?



Specifically, a power law does not have a peak, as a bell curve does, but is instead described by a continuously decreasing function. When plotted on a double-logarithmic scale, a power law is a straight line [see illustration above]. In contrast to the democratic distribution of links seen in random networks, power laws describe

Scale-Free Networks Abound

OVER THE PAST several years, researchers have uncovered scale-free structures in a stunning range of systems. When we studied the World Wide Web, we looked at the *virtual* network of Web pages connected to one another by hyperlinks. In contrast, Michalis Faloutsos

some social networks are scale-free. A collaboration between scientists from Boston University and Stockholm University, for instance, has shown that a network of sexual relationships among people in Sweden followed a power law: although most individuals had only a few sexual partners during their lifetime, a few (the

Pushing Networks to the Limit

PERSPECTIVE

Revisiting the Foundations of Network Analysis

Carter T. Butts

Network analysis has emerged as a powerful way of studying phenomena as diverse as interpersonal interaction, connections among neurons, and the structure of the Internet. Appropriate use of network analysis depends, however, on choosing the right network representation for the problem at hand.

The past decade has seen a dramatic surge of interest in the study of networks, with much of it in fields outside the “traditional” areas of mathematics, computer science, and the social sciences (1, 2). By providing a formal mechanism for representation, measurement, and modeling of relational structure, the use of network analytic methods in these new domains (including

the reductive nature of graphical structure that has facilitated its rich mathematical development (3) and associated scientific applications (4, 5).

Extensions and relaxations of this basic framework designed to accommodate more complex situations are many and varied. We may avoid the assumption of dichotomous relationships by allowing edges to carry different weights [such as

to make. The biologist’s method of defining potential feeding sites will greatly influence the structure of the interaction network.

The basic problem is the definition of the class of distinct entities on which one’s relation of interest will be defined. The mere act of positing such a class, of course, smuggles in the tacit assumption that such a class can be defined (and moreover, that it is scientifically useful to do so). The choice of individual humans as nodes in studies of friendship (11) or kinship (12) networks and the use of individual publications in citation studies (13) are examples in which this assumption is well-justified. On the other hand, studies of interactions between aggregates such as groups (14), households (15), or organizations may encounter problems due to the fluidity of the interacting units and the fact that subunits of a larger unit may themselves interact with others both within and without the “parent.”

As in the biological example, collapsing all potentially interacting elements into a single unit

Pushing Networks to the Limit

PERSPECTIVE

Revisiting the Future of Network Analysis

Carter T. Butts

Network analysis has emerged as a powerful tool for studying interpersonal interaction, connections among groups, and systems. Appropriate use of network analysis depends on the representation for the problem at hand.

The past decade has seen a dramatic surge of interest in the study of networks, with much of it in fields outside the “traditional” areas of mathematics, computer science, and the social sciences (1, 2). By providing a formal mechanism for representation, measurement, and modeling of relational structure, the use of network analytic methods in these new domains (including

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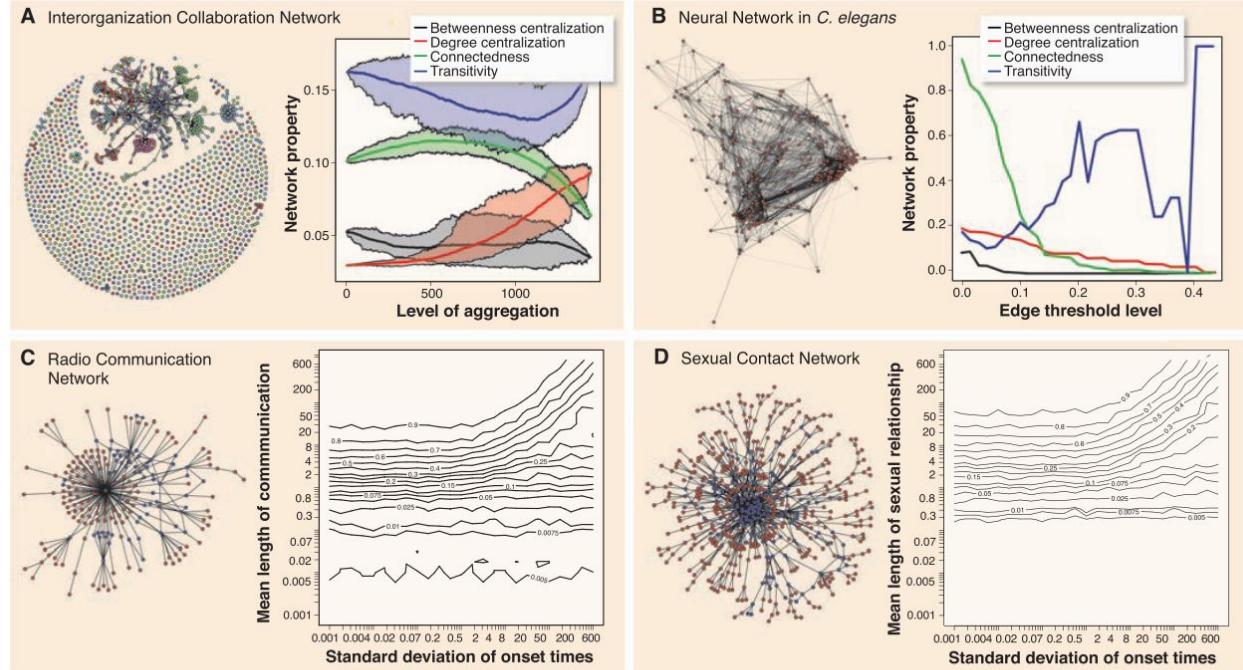


Fig. 1. Effects of changing definitions of “node” and “edge.” (A) Network of interorganizational collaboration in the first 13 days of the Hurricane Katrina response (39) illustrates potential consequences of node aggregation; edges

different structural properties (right). (C) and (D) show the effects of edge timing, depicted as contour plots (right), in systems in which the edges are not static; each line represents the fraction of the population reached by the diffusion process.

How to generate random network?

1. Random network models
2. Models of networks in time and space
3. **Models of processes on networks and beyond**

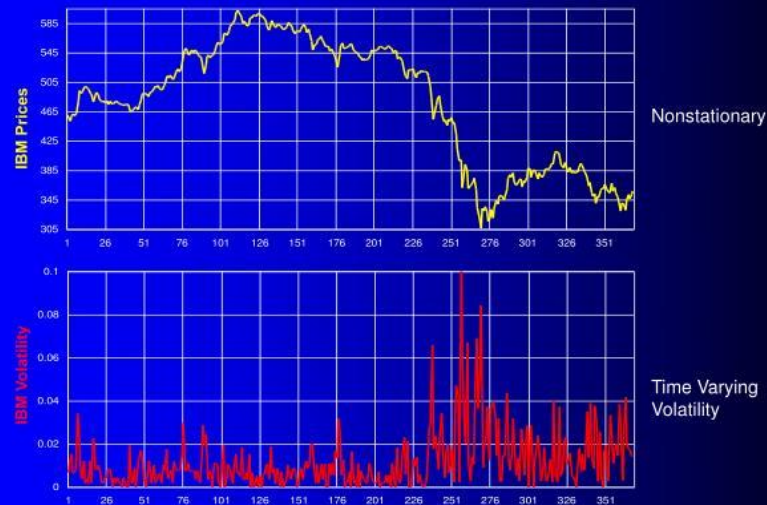
Random walks models

Main ideas:

- Not to model the exact time-series, but the global properties
- To grasp average characteristics

Klafter et al. on “First steps in random walks”

Financial Time Series Data Characteristics



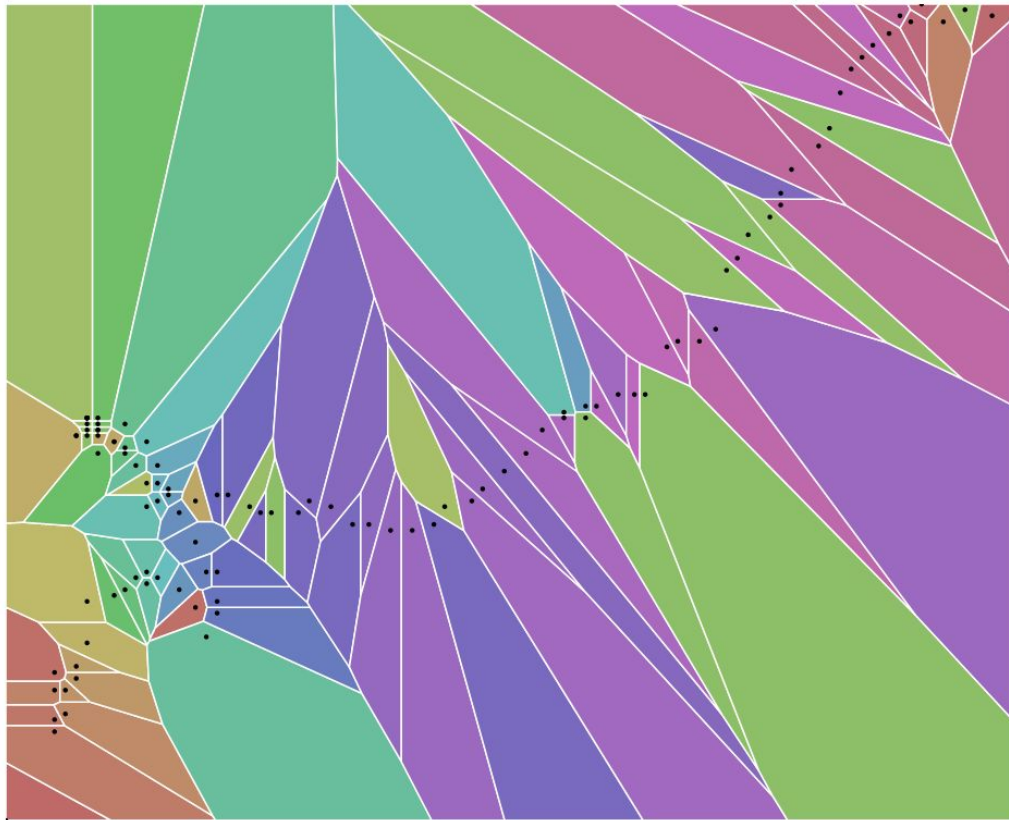
Random walks models

Main ideas:

- Not to model the exact time-series, but the global properties
- To grasp average characteristics

Klafter et al. on “First steps in random walks”
Data walking visualisations

https://github.com/Liyubov/DATA_WALKING



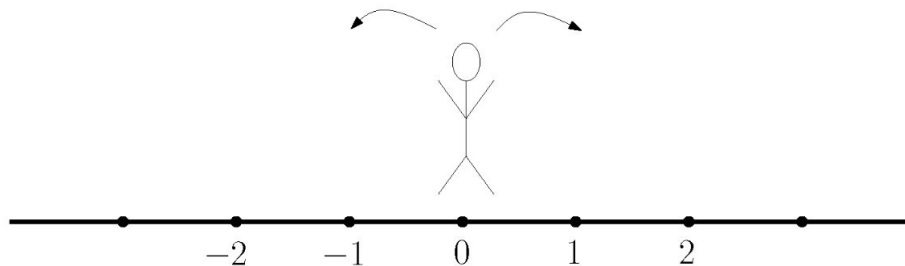
Can simple random walk model help?

Main ideas:

- Not to model the exact process but the global properties
- To grasp average characteristics

For more processes modeling go to

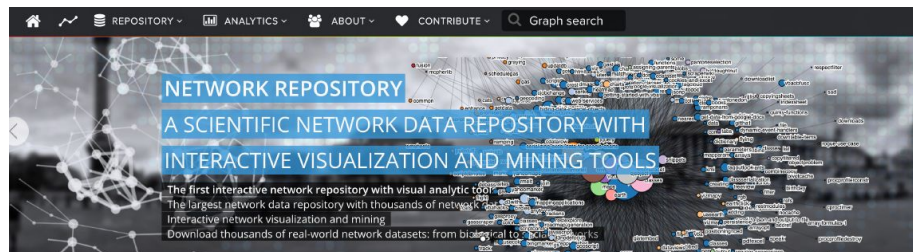
<https://github.com/Liyubov/heterogeneous-dynamics-on-networks>



Network resources

<http://networkrepository.com/networks.php>

<http://networksciencebook.com/chapter/3#advanced-b>




Network Repository. An Interactive *Scientific* Network Data Repository.

THE FIRST SCIENTIFIC NETWORK DATA REPOSITORY WITH INTERACTIVE VISUAL ANALYTICS.

NEW **GraphVis: interactive visual graph mining and machine learning**

The first interactive data and network data repository with real-time visual analytics. Network repository is not only the first interactive repository, but also the *largest network repository* with thousands of donations in 30+ domains (from biological to social network data). This large comprehensive collection of network graph data is useful for making significant research findings as well as benchmark network data sets for a wide variety of applications and domains (e.g., network science, bioinformatics, machine learning, data mining, physics, and social science) and includes relational, attributed, heterogeneous, streaming, spatial, and time series network data as well as non-relational machine learning data. All graph data sets are easily downloaded into a standard consistent format. We also have built a multi-level interactive graph analytics engine that allows users to visualize the structure of the network data as well as macro-level graph data statistics as well as important micro-level network properties of the nodes and edges.

Check out **GraphVis**: the interactive visual network mining and machine learning tool.

 GET NETWORK DATA

 COMPARE GRAPH DATA

 VISUALIZE NETWORKS

Network resources

<http://networkrepository.com/networks.php>

<http://networksciencebook.com/chapter/3#advanced-b>

Spatial Networks

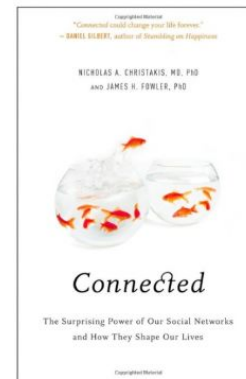
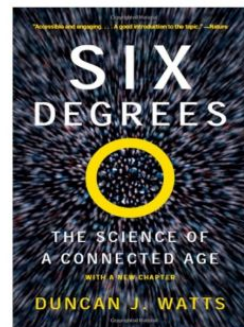
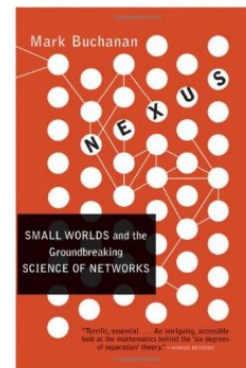
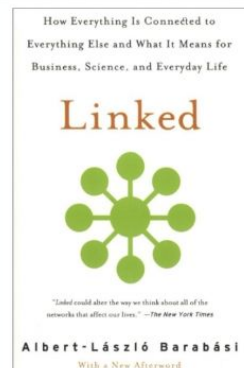
Marc Barthélemy*

*Institut de Physique Théorique, CEA, IPhT CNRS, URA 2306 F-91191 Gif-sur-Yvette France and
Centre d'Analyse et de Mathématique Sociales (CAMS, UMR 8557 CNRS-EHESS)
Ecole des Hautes Etudes en Sciences Sociales, 54 bd. Raspail, F-75270 Paris Cedex 06, France.*

Complex systems are very often organized under the form of networks where nodes and edges are embedded in space. Transportation and mobility networks, Internet, mobile phone networks, power grids, social and contact networks, neural networks, are all examples where space is relevant and where topology alone does not contain all the information. Characterizing and understanding the structure and the evolution of spatial networks is thus crucial for many different fields ranging from urbanism to epidemiology. An important consequence of space on networks is that there is a cost associated to the length of edges which in turn has dramatic effects on the topological structure of these networks. We will expose thoroughly the current state of our understanding of how the spatial constraints affect the structure and properties of these networks. We will review the most recent empirical observations and the most important models of spatial networks. We will also discuss various processes which take place on these spatial networks, such as phase transitions, random walks, synchronization, navigation, resilience, and disease spread.

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Jupyter notebooks:

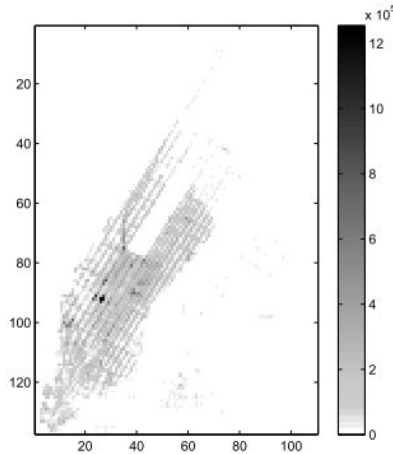
1.Random graphs

2.Spatial network modeling

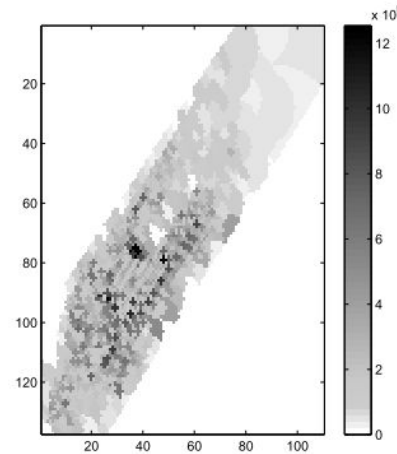
Models of transport (jupyter notebook with Chakresh on taxi moves)



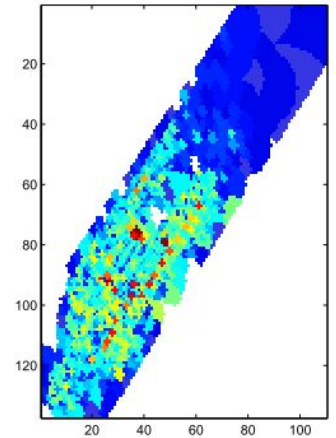
(a)



(b)



(c)



(d)

Jupyter notebooks and resources

<https://classroom.google.com/u/0/w/MjA3ODcyNzc4NDYy/t/all>