Fundamental Characteristics of Networks Models of Random Graphs Network Application Diagnostics B2M32DSA

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Outline

1 Fundamental Characteristics of Networks

- Complex Network Properties
- Topology statistics

2 Models Random Networks

- Overview
- ER Model
- SW Model
- SF Model

3 Rich Club

- Case Study
- Rich Club Identification



The Network Perspective [Weh13]

Mainstream Social Science

- Society is a set of independent individuals.
- Individuals are the unit of analysis, treated as bundles of attributes.

Complex Network Analysis (CNA)

- Relations (dyads, triads) are the unit of analysis.
- Actions of actors are interdependent.
- Static: Structure is (first of all) thought to be a stable pattern.
- **Dynamic**: Choices/actions result in structures, but structures shapes decisions and actions, i.e. processes take place on networks.



Complex Network Properties

Networks Focused on Relations [Weh13]

RELATIONS MATTER!

Contrasted with both an *atomistic* perspective or a *whole-group* perspective

Social Network Analysis (SNA)

- Humanities and social science
- Activities and structures tied with people
 - Shopping basket analysis, targeted advertising
 - Enterprise processes analysis(people cooperation, good distribution)

Complex Network Analysis (CNA)

- Uses the same method as SNA
- Applied to all domains of human acting
- Biology, military, computer network, citations, telecommunication

Network Properties [Weh13]

- A graph ${\mathcal G}$ can be represented as sets or with matrices.
- \bullet Properties of vertices ${\cal P}$ and lines ${\cal W}$ can be measured in different scales:
 - numerical (mapped to real numbers),
 - ordinal (categorical value with an order), and
 - nominal (categorical value with no natural ordering).
- The size of a network/graph is expressed by two numbers:
 - number of vertices $N=|\mathcal{V}|$
 - number of lines $M = |\mathcal{L}|$.



How to Analyze Complex Networks [Erc15]

- Determination of what properties to search for.
- Which nodes of the complex networks are more important than others.
- Which groups of nodes are more closely related to each other.
- To see if some subgraph pattern is repeating itself significantly
 - an indication of a fundamental network functionality



Typical Characteristics of Complex Networks [Erc15, Weh13]

• Local (node) view

• Degree Heterogeneity

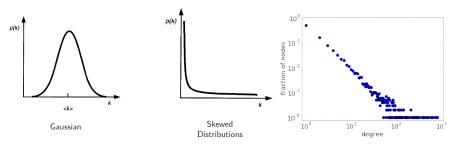
- Actors differ in the number of ties they maintain.
- Centrality measures help to identify prominent actors.
- Presumption is that nodes or edges that are (in some sense) in the middle of a network are important for the network's function.

• Bridges and Small Worlds

- New information arrives over weak ties (Granovetter) or bridges (Burt).
- Bridges tend to be short cuts in the networks,
- ... are responsible for short average path lengths.
- Global (community, structure, network) view
 - Networks often have dense subgraphs.
 - Community detection helps to find them.
 - Clusters
 - Modularity
 - Based on a different null models.

Degree Heterogeneity [Weh13]

- Not all nodes show the same activity (degree) in networks.
- Some nodes show an astounding activity.
- Degree is most of all a question of tie formation cost.
 - Preferential attachment
 - Fitness model



Vertex Degree Statistics [Erc15]

Theorem 1 (Theorem 4.1 [Erc15], p.64)

For any graph G(V, E), the sum of the degrees of vertices is twice the number of its edges, stated formally as follows:

$$\sum_{v \in V} k(v) = 2M \tag{1}$$

where k(v) is the degree of vertex x.

• The average degree of a graph

$$\bar{k} = \langle k \rangle = \frac{1}{N} \sum_{v \in V} k(v) = \frac{2M}{N}$$
⁽²⁾

Degree Variability [Erc15]

• The degree variance $\sigma(G)$ of a graph G(E, V)

$$\sigma(G) = \frac{1}{N-1} \sum_{v \in V} (k(v) - \bar{k})^2$$
(3)

• The mean of absolute distance between node degrees and the average degress of a graph G

$$\tau(G) = \frac{1}{N} \sum_{v \in V} |k(v) - \bar{k}| \tag{4}$$

Graph Density [Die05, Weh13, Erc15]

- The density ρ of a graph is the proportion of present lines to the maximum possible number of lines.
- A **complete graph** is a graph with maximum density.
- There are $\binom{N}{2} = N(N-1)/2$ possible lines (unordered pairs).
- The graph (edge) density for undirected simple graphs

$$\rho_G = \frac{2|E|}{|V||V|-1} = \frac{2M}{N(N-1)} = \frac{\bar{k}}{(N-1)}$$
(5)

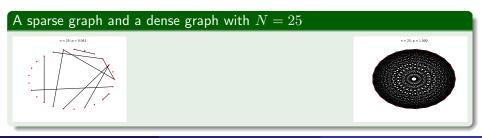
- for large networks where $N>>1\text{, }\rho=\bar{k}/N$
- The graph (edge) density for directed simple graphs

$$\rho_{\vec{G}} = \frac{|E|}{|V||V|-1)} = \frac{M}{N(N-1)}$$

(6)

Graph Sparsity [Die05, Erc15]

- The network is called dense
 - if ρ does not change significantly as $N \rightarrow \infty$ [Erc15], p. 65
 - the number of edges is about quadratic in their number of vertices, i.e. $|E|\approx |V|^2$ [Die05], p. 163
- The network is called sparse
 - if $\rho \rightarrow 0$ as $N \rightarrow \infty$ [Erc15], p. 65
 - the number of edges is about linear in their number of vertices, i.e. $|E| \approx \alpha |V|$ [Die05], p. 164 or $|E| \rightarrow \text{const.}$ as $N \rightarrow \infty$ [New10]
- A dramatic impact on processing of graphs.



Degree Sequence [Erc15]

- The **degree sequence** of a graph G is the listing of the degrees of its vertices, usually in descending order.
- In regular graphs each vertex has the same degree.





Degree Distribution [Erc15]

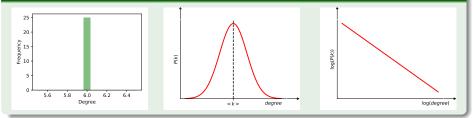
Definition 1 (Definition 3 [Erc15], p.65)

The degree distribution P(k) of degree k in a graph G is given as the fraction of vertices with the same degree to the total number of vertices as below.

$$P(k) = \frac{n_k}{N} \tag{7}$$

where n_k is the number of vertices with degree k.

Degree distributions of regular, random, small-world graphs



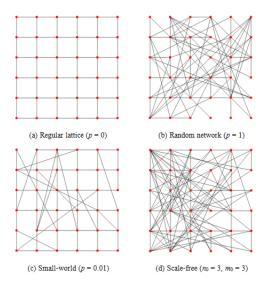
Random Graphs

- Basic idea
 - $\bullet\,$ Edges are added at random between a fixed number N of vertices
 - Each instance is a snapshot at a particular time of a stochastic process, starting with unconnected vertices and for every time unit adding a new edge
- Four basic models of complex networks
 - Regular lattices (meshes) and trees
 - Erdös-Renyi Random Graphs (ER)
 - A disconnected set of nodes that are paired with a uniform probability.
 - Watts-Strogatz Models ^[WS98] (WS, SW)
 - Small-world networks
 - Connections between the nodes in a regular graph were rewired with a certain probability
 - Barabási-Albert Model ^[BAJ99] (BA, SF)
 - Scale-free networks characterized by a highly heterogeneous degree distribution, which follows a "power-law"

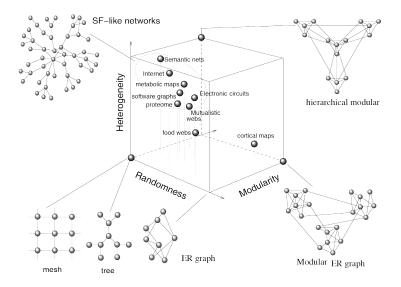
P

$$(k) \sim k^{-\gamma}$$

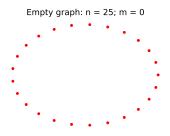
Complex Network Models [GDZ⁺15]



Zoo of Complex Networks [SV04]



Basic Topologies of Graphs I

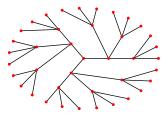


Path graph: n = 25; m = 24



Star graph: n = 26; m = 25

Tree graph: n = 40; m = 39

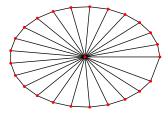


Basic Topologies of Graphs II

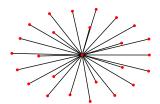
Cycle graph: n = 25; m = 25



Wheel graph: n = 25; m = 48



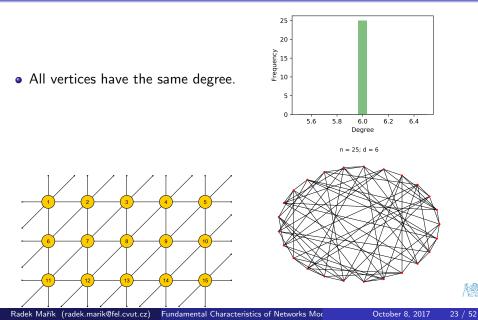
Star graph: n = 26; m = 25



Complete graph: n = 25; m = 48



Regular Graph [Erc15]



Models Random Networks

ER Model

The Erdös and Renyi Model



(1913 - 1996)



Alfréd Rényi (1921 - 1970)



Classical Random Graph (ER-model) [New10, Erc15]

- Proposed by Erdös and Renyi
- Let G(V, E) be a simple graph with n vertices and m edges
- The propability to have an edge between any pair of nodes is distributed uniformly at random.

$$p = \frac{2M}{N(N-1)}$$

- The degree distribution of ER-model is binomial
 - A given vertex is connected with independent probability p to each of the N-1 other vertices.
 - The probability of being connected to a particular k other vertices and not to any of the others $p^k(1-p)^{N-1-k}.$
 - There are $\binom{N-1}{k}$ way to choose those k other vertices.
 - The total probability of being connected to exactly \boldsymbol{k} others is

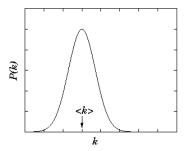
$$p_k = p(k) = {\binom{N-1}{k}} p^k (1-p)^{N-1-k}$$

Models Random Networks ER Model

ER-model Properties [New10, Erc15, EA15]

- It does not represent many real complex networks.
- It exhibits
 - homogeneous degree distribution.
 - a small diameter

• Approaching Poisson distribution as $N \to \infty$ $P(k) \sim e^{-\langle k \rangle} \frac{\langle k \rangle^k}{k!}$





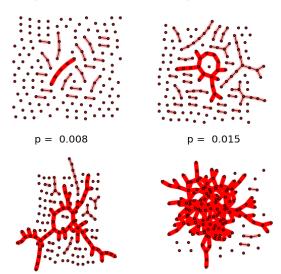
Models Random Networks

ER Model

ER-model. Giant Component [HSSO8, New10]

p = 0.003

p = 0.006



Six Degree of Separation - Milgram Experiment 1967

- Random people from Nebraska were to send a letter (via intermediaries) to a stock broker in Boston.
- Could only send to someone with whom they were on a first-name basis.
- Among the letters that found the target, the average number of links was **six**.

six degree of separation [Erc15]



Stanley Milgram (1933 - 1984)



SW Model

The Watts-Strogatz Model



Duncan J. Watts (born 1971)

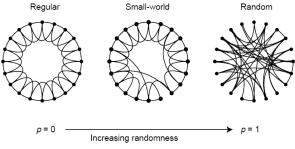


Steven Strogatz (born 1959)



Models Random Networks SW Model

The Watts-Strogatz Small World Model



- A simple model for interpolating between regular and random networks
- Randomness controlled by a single tuning parameters

The Model

- Take a regular clustered network
- Rewire the endpoint of each link to a random node with probability p

Small World Model - Properties [Erc15, EA15]

The Watts-Strogatz Model [WS98]

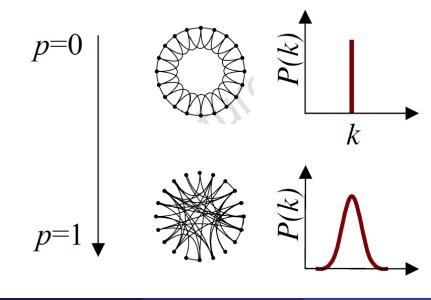
- Starting from the circulant network with *n* nodes connected to *k* neighbors.
- The diameter of the network increases with the logarithms of the network order:

$$d \approx \log N$$
 as $N \to \infty$

- A high local clustering
 - The starting is a ring topology which each node is connected to its closest k/2 left neighbors and k/2 right neighbors

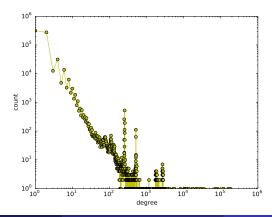
Models Random Networks SW Model

Small World Model - Degree Distributions [Erc15, EA15]



Real-world Networks with Fat-tail Distributions [Erc15, EA15]

- Many networks in the real-world have a fat-tailed degree distribution.
- Many real-life complex networks dynamically grow and change by adding and removing nodes and edges.
- Free-scale IP2IP network



Models Random Networks SF Model

The Barabási and Albert Model



Albert-László Barabási (born 1967)



Réka Albert (born 1972)



Models Random Networks SF Model

Scale-Free (BA) Network [BAJ99, Erc15, EA15]

Node Degree Distribution

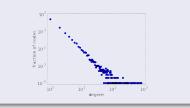
- a heavy-tailed distribution
- follows a power law (asymptotically)

$$P(k) \sim k^{-\gamma}$$

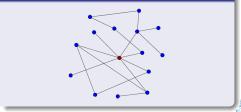
Assumptions:

- Preferential attachment
- Fitness model

Degree Distribution



Small network hub



Barabási-Albert Model [BAJ99, Erc15, EA15]

The outline of the model:

- Begin with a small number, m_0 , of nodes.
- At each step, add a new node v to the network, and connect it to $m \leq m_0$ of the existing nodes $u \in V$ with probability

$$p_{uv} = \frac{k_u}{\sum_{w \in V} k_w}$$

Algorithm 1 BA_Generator

1: Input: G(V, E), V_{new} ... new vertices to joined to G2: $m_0 \leftarrow |E|$ 3: for all $v \in V_{new}$ do 4: $V \leftarrow V \cup \{v\}$ 5: for m = 0; $m \le m_0$; m + + do 6: attach v to $u \in V$ with probability $P_{uv} = k_u / \sum_{w \in V} k_w$ 7: end for 8: end for

Scale-Free (BA) Network - Properties [BAJ99, Erc15, EA15]

• Scale-free property, c is a constant

$$p(k) = Ak^{-\gamma}$$

$$p(ck) = A(ck)^{-\gamma} = c^{-\gamma}p(k)$$

• The intercept and the slope is preserved on a logarithmic scale

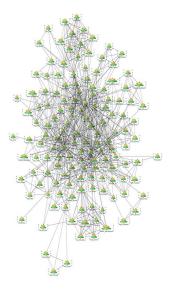
$$\ln p(k) = -\gamma \ln k + \ln A$$

$$\ln p(ck) = -\gamma \ln(ck) + \ln A = -\gamma \ln(k) + \ln A - \gamma \ln(c)$$

- Degree distribution follows power law, with the exhibition of very few high degree nodes and many low degree nodes. $P(k)\sim k^{-3}$
- The average clustering coefficient of these networks is low due to the large number of low-degree nodes. $C\sim N^{-0.75}$
- The average diameter is low due to the clustering of nodes around the high-degree nodes. $\ell \sim \frac{\ln N}{\ln \ln N}$

Rich Club Case Study

Example - Collaboration of People on Projects



N.

- the presence of non trivial correlations in network connectivity pattern.
- Assortative mixing, or assortativity, or homophily in SNA (CZ asortativní párování) (i.e., "love of the same") is the tendency of agents to associate and bond with similar others.
 - as in the proverb "birds of a feather flock together"
- **Disassortative mixing** is a bias in favor of connections between dissimilar nodes.
- Degree correlations ... assortativity regarding to node degree.
- Assortativity coefficient: vertex is labeled with a scalar value or an enumerative/categorical value (e.g., shape, color) ^[New02, New03a].



- **Rich-club phenomenon**: Hubs (nodes of high degree) tend to connect to other hubs (rich tends to connect to other rich)
- **Rich-club coefficient** ... the fraction between the *actual* and the potential number of edges among $V_{>k}$.

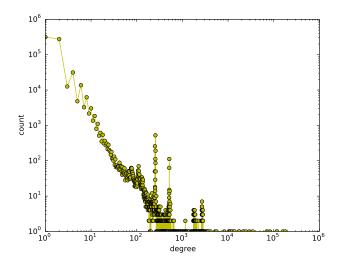
$$\Phi(k) = \frac{2E_{>k}}{N_{>k}(N_{>k}-1)}$$

where

- $V_{>k}$ is the set of vertices with degree larger than k,
- $N_{>k}$ is the number of such vertices, and
- $E_{>k}$ is the number of edges among such vertices.

Rich Club Rich Club Identification

Real-world Networks with Fat-tail Distributions





- Complex networks basic characteristics
- Topological forms
- Random Network Models
 - Classical Erdos-Renyi model
 - Small world model
 - Scale-free model
- Rich club detection



Competencies

- Describe the network perspective approach to problem solutions.
- What are the typical characteristics of complex networks?
- Describe the meaning of degree hetergeneity.
- Define graph density and sparsity.
- Define graph degree distribution and show some its typical examples.
- List the four basic models of complex networks and their characteristics.
- List basic graph topologies.
- Describe Erdos-Renyi graph model.
- Describe Watts-Strogatz graph model.
- Describe Barabasi-Albert graph model and its scale-free property.
- What is the meaning of "the rich-club phenomenon".

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