GL Applied Data Science Program

Network Analysis

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Overview

Overview of this week / module:

- Data collection and visualization for exploratory data analysis
- Network analysis
- Unsupervised learning clustering

Overview of this lecture:

- Examples of networks and representing networks
- Summary statistics of a network
- Centrality measures finding important nodes in a network This file is meant for personal use by jacesca@gmail.com only.

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Network

A **network** (or **graph**) G is a collection of **nodes** (or **vertices**) V connected by **links** (or **edges**) E. The network is denoted by G = (V, E).

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Network research:

- In recent years network research witnessed a big change:
 - From study of a single graph on 10-100 nodes to the statistical properties of large networks on millions of nodes
 - Characterize the structure of networks
 - Identify important nodes / edges in a network
 - Identify missing links in a network

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Examples of networks

Network	Vertex	Edge
World Wide Web	web page	hyperlink
Internet	computer	network protocol interaction
power grid	generating station / substation	transmission line
friendship network	person	friendship
gene regulatory network	gene	regulatory effect
neural network	neuron	synapse
transportation	airport	direct flight
Netflix	person / movie	rating

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Different kinds of networks

- simple network: undirected network with at most one edge between any pair of vertices and no self-loops
 - e.g. Internet, power grid, telephone network
- multigraph: self-loops and multiple links between vertices possible
 - e.g. neural network, road network
- directed network: $i \rightarrow j$ does not imply $j \rightarrow i$
 - e.g. World Wide Web, food web, citation network
- weighted network: with edge weights or vertex attributes
 - e.g. transportation networks
- bipartite network: edges between but not within classes
 - e.g. recommender systems such as Netflix
- hypergraph: generalized 'edges' for interaction between > 2 nodes
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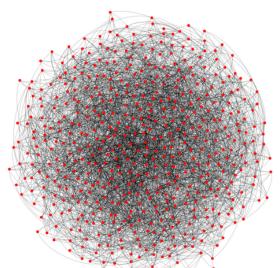
 Share e.g. protein-protein interaction network full is light for level action.

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Large networks look like hairballs



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Representation of a network

Two common representations of a network G = (V, E):

- adjacency list
 - undirected graph 1-2-3: $E = \{\{1,2\},\{2,3\}\}$
 - directed graph $1 \to 2 \leftarrow 3$: $E = \{(1,2), (3,2)\}$
- adjacency matrix of size $n \times n$ (where n = |V|) with

$$A_{ij} = \begin{cases} 1 & \text{if } (i,j) \in E \\ 0 & \text{otherwise} \end{cases}$$

 \bullet For weighted graph, A_{ij} can be non-binary

How does the adjacency matrix of an undirected graph look like? How to count their file is mean for personal user by accessed graph commonly or k?

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Representation of a network

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Quantitative measures of networks

Some quantitative measures of networks to describe structural patterns of a network and to compare networks:

- connected components
- degree distribution
- diameter and average path length
- homophily or assortative mixing

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Connected Components

Connected component: set of nodes that are reachable from one another

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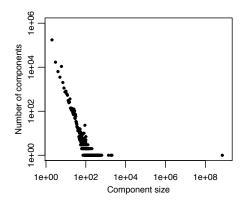
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Connected Components

Connected component: set of nodes that are reachable from one another

Many networks consist of one large component and many small ones



Component risize distribution in the 2011 Facebook network on a log-log scale, Most vertices (99.91%) are in the largest component legal action

Degree distribution of the Internet

Degree of a node: number of edges connected to a node

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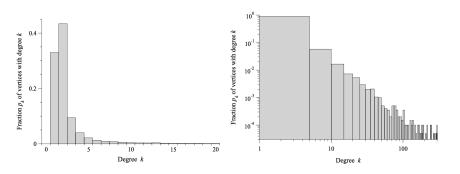
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Degree distribution of the Internet

Degree of a node: number of edges connected to a node

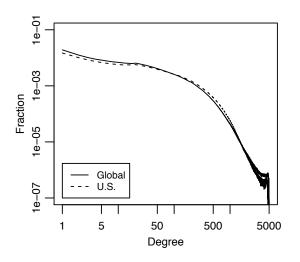
 Many networks show a power-law degree distribution (i.e., distribution that is linear in log-log plot)



Figures from Chapter 8 in "Networks: An Introduction" by M.E.J. Thewfile is (2020) for personal use by jacesca@gmail.com only.

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Degree distribution of Facebook network



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Diameter of a graph

- Let d_{ii} denote the length of the geodesic path (or shortest path) between node i and j
- The diameter of a network is the largest distance between any two nodes in the network:

$$\operatorname{diameter} = \max_{i,j \in V} d_{ij}$$

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- If network is not connected, one often computes the diameter in the largest component.
- Algorithms for finding shortest paths: breadth-first search for unweighted graph, Dijkstra's algorithm for weighted graphs

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Small-world and 6 degrees of separation

- Concept of 6 degrees of separation was made famous by sociologist Stanley Milgram and his study "The Small World Problem" (1967)
- In his experiment participants from a particular town were asked to get a letter to a particular person in a different town by passing it from acquaintance to acquaintance.
- 18 out of 96 letters made it in an average of 5.9 steps, suggesting that the diameter of the social network in the US is 6
- Any reasons why we should take the conclusion of 6 degrees of separation with a grain of salt?

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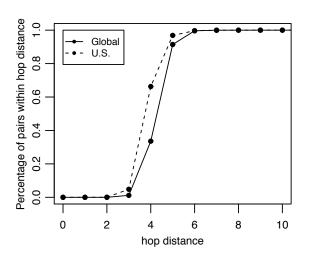
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Diameter of Facebook (2011)



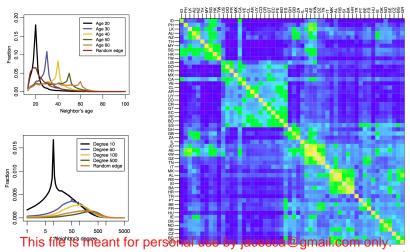
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Homophily

Homophily (or assortative mixing): tendency of people to associate with others that are similar



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Centrality measure: A measure that captures importance of a node's position in the network; there are many different centrality measures:

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Centrality measure: A measure that captures importance of a node's position in the network; there are many different centrality measures:

degree centrality

- Simple and intuitive: individuals with more connections have more influence and more access to information.
- Does not capture "cascade of effects": importance better captured by having connections to important nodes

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eigenvector centrality

- score that is proportional to the sum of the score of all neighbors is captured by largest eigenvector of adjacency matrix
- builds the foundation for Google's PageRank algorithm

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closeness centrality

• tracks how close a node is to any other node

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tracks how close a node is to any other node

betweenness centrality
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measures the extent to which a node lies on paths between Caroline Uhler (MIT) 17 / 25

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Which centrality measure to use

Choice of centrality measure depends on application!

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Which centrality measure to use

Choice of centrality measure depends on application!

In a friendship network:

- high degree centrality: most popular person
- high eigenvector centrality: most popular person that is friends with popular people
- high closeness centrality: person that could best inform the group
- high betweenness centrality: person whose removal could best break the network apart

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- ullet Data based on 11 wiretap warrants from 1994-1996 ightarrow 11 periods
- Mandate of CAVIAR project: Seize drugs, arrests only in period 11
- 11 seizures total with monetary losses for traffickers of \$32 mio
 - phase 4: 1 seizure \$ 2.5mio, 300kg of marijuana
 - phase 6: 3 seizures \$ 1.3mio, 2 x 15kg of marijuana, 1 x 2 kg of cocaine
 - phase 7: 1 seizure \$ 3.5mio, 401kg of marijuana
 - phase 8: 1 seizure \$ 0.4mio, 9kg of cocaine
 - ullet phase 9: 2 seizures \$ 4.3mio, 2kg of cocaine + 1 x 500kg marijuana
 - phase 10: 1 seizure \$ 18.7mio, 2200kg of marijuana
 - ullet phase 11: 2 seizures \$ 1.3mio, 12kg of cocaine + 11kg of cocaine

Unique opportunity to study changes in the structure of a criminal network in uphed his file is meant fee personal use by jacesca@gmail.com only.

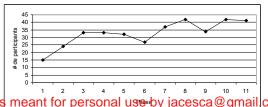
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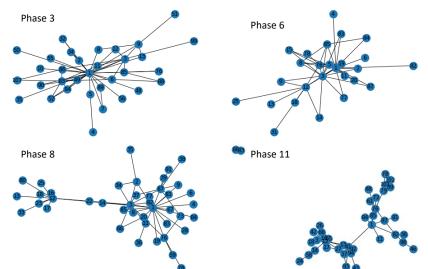
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- network consists of 110 (numbered) players: 1-82 are traffickers, 83-110 are non-traffickers (financial investors, accountants, owners of various importation businesses, etc.)
- initially, investigation targeted Daniel Serero, alleged mastermind of drug network in downtown Montreal
- initially marijuana was imported to Canada from Morocco
- after first seizure in phase 4, traffickers reoriented to cocaine import from Colombia, transiting through the United States



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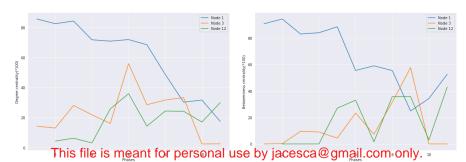


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Role of the different actors:

- Daniel Serero (node 1): mastermind of the network
- Pierre Perlini (node 3): principal lieutenant of Serero (executes his instructions)
- Ernesto Morales (node 12): principal organizer of the cocaine import, intermediary between the Colombians and the Serero organization



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Optional: Additional thoughts - Criminal networks

- Given a social network and *k* criminal suspects, how to determine other suspects?
- Same question is extremely important in biology: given certain genes that are known to cause a certain disease, determine other candidate genes (e.g. based on protein-protein interaction network for determining autism genes: http://dx.doi.org/10.1101/057828)
- How do we identify nodes that are "between" a given set of seed nodes?

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Optional: Steiner trees

Determine a small subnetwork that contains the given suspects / genes and connects these nodes

Steiner tree:

- shortest subnetwork that contains a given set of nodes
- NP-complete problem
- there exist polynomial time approximations
- ⇒ use collection of approximate Steiner trees for further analysis: autism interactome / criminal interactome
 - For genomics applications, see:
 - http://fraenkel-nsf.csbi.mit.edu/steinernet/tutorial.html
- ⇒ compute nodes with high betweenness centrality in interactome to This file is meant for personal use by jacesca@gmail.com only. obtain candidate genes / suspects Sharing or publishing the contents in part or full is liable for legal action.

References

- Chapters 1 10 (but mostly chapters 6 8) in
 M. E. J. Newman. Networks: An Introduction. 2010.
- For an analysis of the Facebook network:
 - J. Ugander, B. Karrer, L. Backstrom and C. Marlow. *The Anatomy of the Facebook Social Graph.* 2011.
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 - C. Morselli. Inside Criminal Networks (Springer, New York). Chapter 6: Law-enforcement disruption of a drug-importation network. 2009.

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