Social Network Analysis: Theory, Visualization, and Modeling

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Outline

An interdisciplinary enterprise

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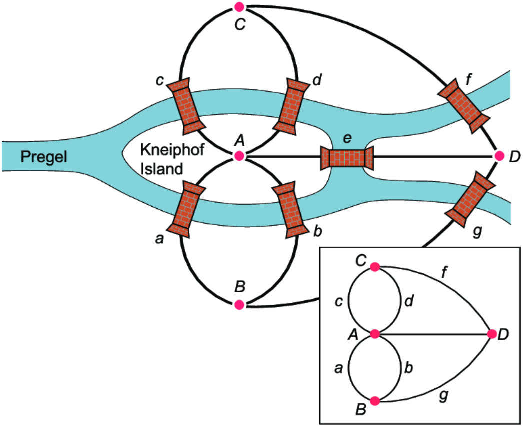
- An increasingly number of **economists** also start to investigate the impacts of relational structure on economic activities (e.g., Jackson and Zenou, 2015)
- However, the recent increased visibility of network analysis is owed mainly to **statistical physicists** (e.g., Barabási and Albert, 1999).

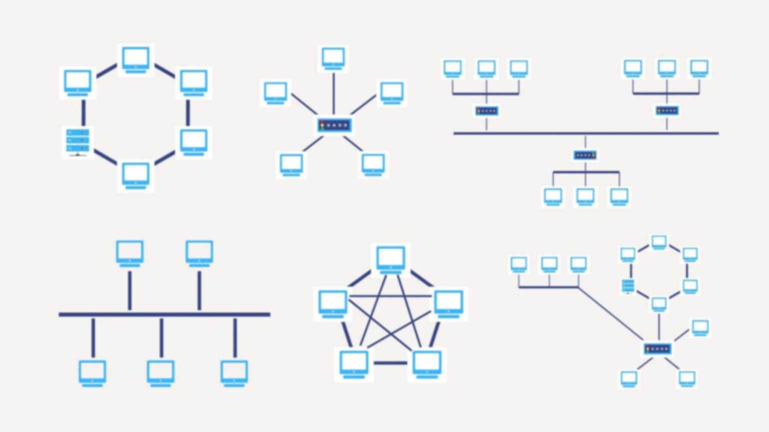
Euler and seven bridges of Königsberg

- Problem: Can we devise a walk through the city that would cross each of those bridges once and only once?
- A **negative** resolution was provided by Euler in 1736.



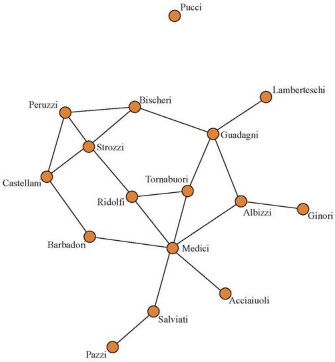
Network typology and Internet

- Computer scientists and the development of Internet



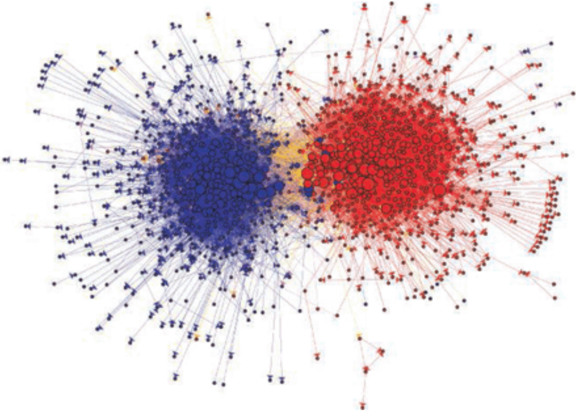
From 2-player games to multi-player games

- Strategies in a networked setting (e.g., Jackson, 2010)
  - e.g., 15th Century Florentine marriage networks (Padgett and McLean, 2006)



Computational social science

- Stronger computational capacity and bigger data (e.g., Lazer et al., 2009)



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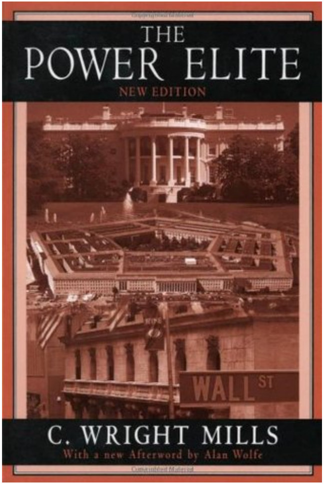
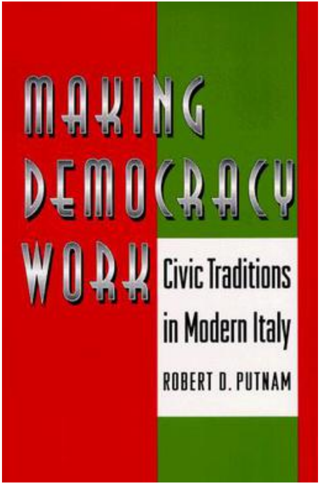
Network theory in PoliSci





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  - Power and influence do not derive solely from agents' **attributes**; they can be results of agents' **positions** in a network. (Levels of analysis)
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- The nature of networks leads to **dependence between actors** and also to **dependence between network ties**.

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- The ideas of embeddedness and interdependence are attractive, but how to study **complex networks**?
- From **local dynamics** to **global patterns**
  - social network theories focus on local dynamics and how they generate complex global networks

From local competition to global evolution

From local rational persons to global equilibrium

Outline

Rating restaurants

- You are landed in a foreign city, and you have no travel guides or access to the Internet.
- You are not desperately hungry.

A heuristic shortcut

Scale-free network (Barabási and Albert, 1999)

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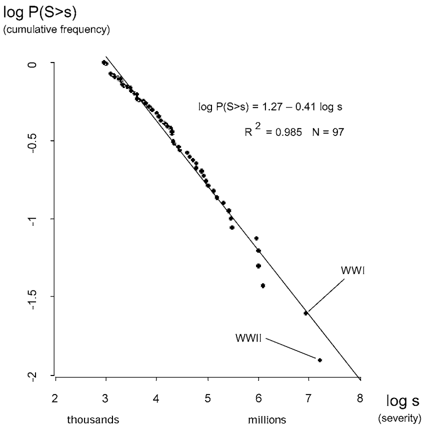
- Result: A hub-and-spoke network and it is scale free.
- Evidence:
  - WWW, Facebook, metropolitan cities, ...
  - Cederman (2003): Sizes of war
  - Baumgartner, Box-Steffensmeier and Campbell (2018): Executions in US

Cederman (2003)

FIGURE 1. Cumulative Frequency Distribution of Severity of Interstate Wars, 1820–1997



Source: COW data.

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- Simulation 1: Matthew effects, "the rich get richer and the poor get poorer"
- Simulation 2: Talent vs luck

Outline

Hunting flats

Strong ties, weak ties, and a small world

- My story: Richard told me that Neil had a mortgage friend good at handling cases like mine.
- Two kinds ties
  - type 1: me <–> Richard, Richard <–> Neil, me <–> Neil
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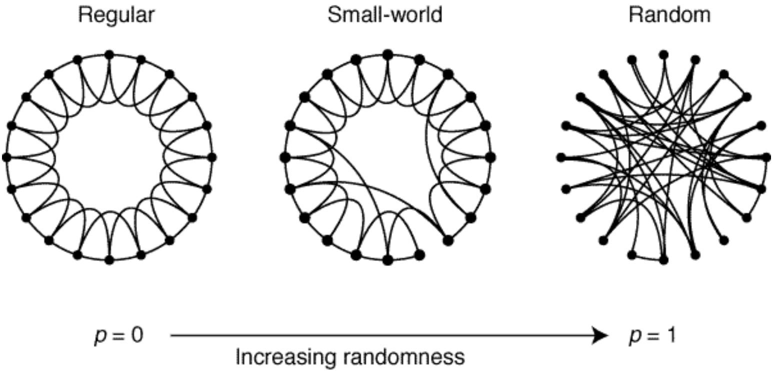
  - While strong ties bond, weak ties bridge.
- Watts and Strogatz (1998) formalize the idea (also see "Six Degrees of Separation")
  - the network is numerically large
  - the network is sparse
  - the network is decentralized
  - the network is highly clustered

A small-world network



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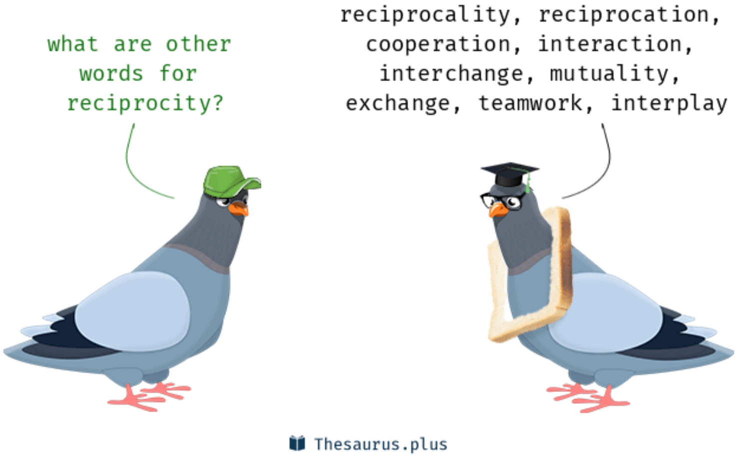
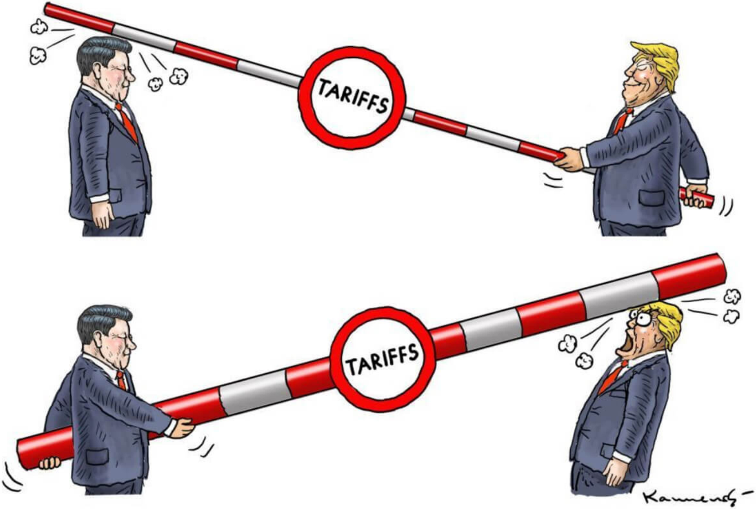
How to (un)make friends



How to (un)make friends: Axelrod (1984)



Confucius and reciprocity

Analects 15.24 *Zigong asked: "Is there a single teaching that can be practiced to the end of one's life?" Confucius replied: "It is reciprocity! What you don't desire for yourself, do not desire for others."*

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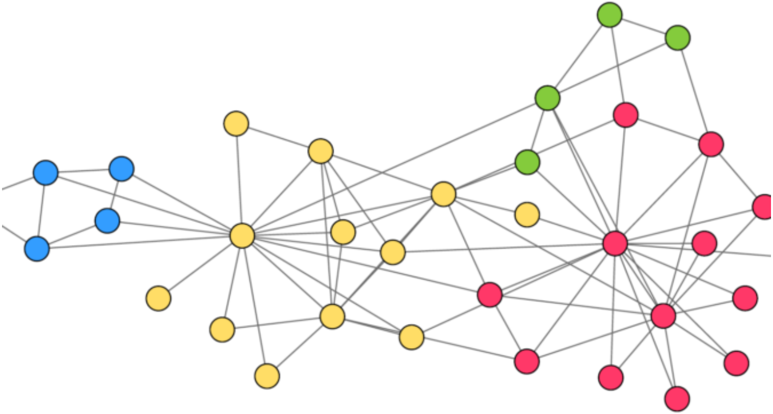
- **Reciprocation of directed ties** is a basic feature of social networks.
- **Homophily** denotes the tendency of similar actors to relate to each other.
- There are many other important types of dependencies.

Bringing back agent attributes: McPherson, Smith-Lovin and Cook (2001)



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How to model network structures

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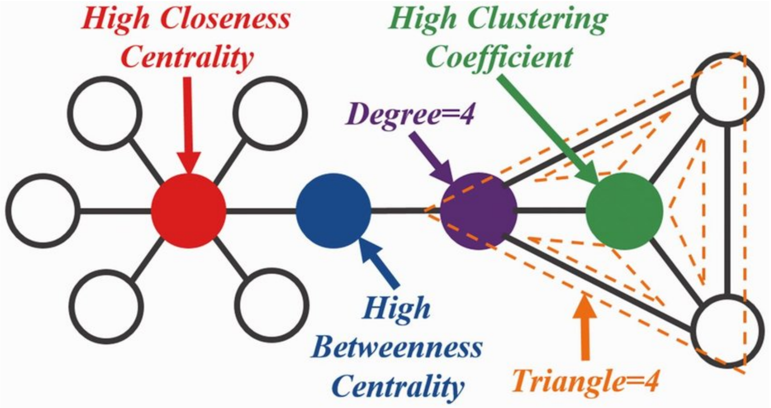
- Controlling for certain aspects of network dependencies while not explicitly modeling them (e.g., the quadratic assignment procedure, QAP)
- Modeling network structure

Centrality measures



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Some common models

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- Latent space models
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- **Exponential random graph models (ERGMs)**

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- Conditioning on the other random variables, two random variables are **independent** unless they are tied.
- A stochastic graph, $X = (X_{ij})$, is a Markov graph if, for each set of four distinct nodes $\{i, j, h, k\}$, the random ties X_{ij} and X_{hk} are conditionally independent, given all the other random variables in X.

ERGMs

- A generalized Markov graph model incorporates any kind of dependence between tie variable (Cranmer and Desmarais, 2010),

$$\Pr(\mathrm{Y} = \mathrm{y}) = \frac{1}{\kappa} \exp\left\{\sum_{A} \eta_A g_A(\mathrm{y})\right\} \tag{1}$$

where,

1. the summation is over all configuration types A; different sets of configuration types represent different models;
2. η_A is the parameter corresponding to configuration of type A;
3. $g_A(\mathrm{y})$ is the *network statistic* corresponding to configuration A (for homogeneous Markov graph models, this is the number of configurations of type A observed in the network: for example, the number of triangles); and
4. κ is a normalizing quantity to ensure that (1) is a proper probability distribution.

Problems

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- The Markov model is not a reasonable representation for most empirically observed social networks when $N > 30$.
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- The complexity of dependencies in networks is so great that modeling large networks in a way that passes the high requirements of a good statistical fit seems intrinsically difficult to achieve (Snijders et al., 2006).

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- Temporal ERGMs (TERGMs)
- Stochastic agent-oriented models (SAOMs)

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