Graph Theory and Social Networks - part 3

EE599: Social Network Systems

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Overview

- Continuation of graph theory for social networks
 - Typical social network properties
 - Graph measures to quantify
 - Examples

References

- Easley & Kleinberg, Ch 3
 - Focus on relationship to social nets with little math
- Jackson, Ch 2-3
 - Social network focus with more formal math

Motivation



Figure 3.11: The contrast between densely-knit groups and boundary-spanning links is reflected in the different positions of nodes A and B in the underyling social network. Easley & Kleinberg

- Not all nodes and edges are "equal"
 - A vs. B

Motivation

Our discussion thus far suggests a general view of social networks in terms of tightly-knit groups and the weak ties that link them. The analysis has focused primarily on the roles that different kinds of edges of a network play in this structure — with a few edges spanning different groups while most are surrounded by dense patterns of connections. Easley & Kleinberg.pg. 64

- Our goal
 - Motivate this from a few social rules simple, yet reasonable
 - Define qualitative terms and quantitative measures to capture these properties

Overview

- Triadic Closure & Cluster Coefficients
 - Our friends usually become friends
- Strong & Weak Ties
 - Most people get jobs from acquaintances rather than close friends
- Centrality and Prestige Measures
 - Some people (or connections) are more critical than others
 - Next time

Related Concepts & Terminology



Figure 3.11: The contrast between densely-knit groups and boundary-spanning links is reflected in the different positions of nodes A and B in the underyling social network.

Easley & Kleinberg

Social Capital?

- Embeddedness of edge connecting A and B
 - number of common neighbors of A,B
 - A, B connected by embedded edge implies high degree of trust
- Structural Holes are filled by nodes with access to local brides
 - amplifies creativity
 - serves as a gatekeeper of information flow across suborganizations
 - Can create power struggles and trust issues



(a) A sample network



(b) Tightly-knit regions and their nested structure

Figure 3.14: In many networks, there are tightly-knit regions that are intuitively apparent, and they can even display a *nested* structure, with smaller regions nesting inside larger ones.

- How to identify tightly knight regions in a social network from the graph structure?
 - Assume we have a method of identifying the most "central" edges
 - Remove these edges to break the graph into components
 - Repeat this process on the components as they arise
 - Girvan-Newman Algorithm

Easley & Kleinberg



Figure 3.16: The steps of the Girvan-Newman method on the network from Figure 3.14(a).



Figure 3.12: A co-authorship network of physicists and applied mathematicians working on networks [322]. Within this professional community, more tightly-knit subgroups are evident from the network structure. Easley & Kleinberg



Figure 3.15: A network can display tightly-knit regions even when there are no bridges or local bridges along which to separate it.

Easley & Kleinberg



Figure 3.17: The steps of the Girvan-Newman method on the network from Figure 3.15. Easley & Kleinberg

Centrality Measures

- How to measure the "centrality" of a given node or edge?
 - Obvious in some cases (e.g., star graph)
- Many measures have been proposed for measuring the importance, centrality, or prestige of a node based only on the network topology

- Degree Centrality:
- Closeness Centrality:

$$\frac{1}{d_{\text{ave}(i)}} = (N-1) \left[\sum_{j \neq i} d(i,j) \right]^{-1}$$

 k_{i}

 $\overline{N-1}$

- Decay Centrality:
 - delta~0: ~degree centrality
 - delta~l:~size of largest component containing i

$$\sum_{j \neq i} \delta^{d(i,j)}, \quad \delta \in (0,1]$$

- Betweenness Centrality:
 - Fraction of shortest paths in the network that pass through node i

$$B(i) = \sum_{(j,k), i \notin \{j,k\}} \frac{P_i(j,k)}{P(j,k)} = \frac{\text{number of shortest paths between j \& k, passing through i}}{\text{number of shortest paths between j \& k}}$$

Often normalized by:
$$\left(egin{array}{c} N-1 \\ 2 \end{array}
ight)$$
 (number of pairs excluding node i)

- Eigen Centrality:
 - Based on the idea that importance is determined by how many important friends you have

$$\lambda p_i = \sum_{j=1}^N a_{ij} p_j$$
$$\mathbf{Ap} = \lambda \mathbf{p}$$

 Vector of node centralities is the eigenvector of the adjacency matrix with largest eigenvalue

• Katz Prestige:

normalize impact of friendships by node degree

$$p_i = \sum_{j=1}^n a_{ij} \frac{p_j}{k_j} = \sum_{j=1}^n \frac{a_{ij}}{k_j} p_j = \sum_{j=1}^n h_{ij} p_j$$
d on
ity
$$\mathbf{p} = \mathbf{H}\mathbf{p}$$

Google's page-rank is based on an eigen centrality measure

> Vector of node centralities is the eigenvector of a weighted adjacency matrix with eigenvalue I (exists by stationary theorem of Markov Chains)

Centrality Example



FIGURE 2.13 A central node with low degree centrality.

TABLE 2.1Centrality comparisons for Figure 2.13

	Measure of centrality	Nodes 1, 2, 6, and 7	Nodes 3 and 5	Node 4
	Degree (and Katz prestige P^K)	.33	.50	.33
	Closeness	.40	.55	.60
	Decay centrality ($\delta = .5$)	1.5	2.0	2.0
	Decay centrality ($\delta = .75$)	3.1	3.7	3.8
	Decay centrality ($\delta = .25$)	.59	.84	.75
	Betweenness	.0	.53	.60
	Eigenvector centrality	.47	.63	.54
	Katz prestige-2 P^{K2} , $a = 1/3$	3.1	4.3	3.5
	Bonacich centrality $b = 1/3, a = 1$	9.4	13.0	11.0
	Bonacich centrality $b = 1/4, a = 1$	4.9	6.8	5.4

Computing Betweenness (edge)



Easley & Kleinberg



Figure 3.16: The steps of the Girvan-Newman method on the network from Figure 3.14(a).

Computing Betweenness (edge)



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Figure 3.17: The steps of the Girvan-Newman method on the network from Figure 3.15. Easley & Kleinberg