

SC435
Introduction to Complex Networks-3

Centrality

- Many networks are heterogeneous \Rightarrow wide variability in the properties and role of their elements.
- **Importance** of a **node** or a **link** in the network is measured by its position with respect to others.

Degree Centrality

- degree of a node (number of nearest neighbors)

$$C_D(i) = k_i = \sum_j A_{ij}$$

- normalized degree centrality

$$C_D^* = \frac{1}{n-1} C_D(i)$$

does not contain any information about the structure of the graph

Centrality

Closeness centrality

Measures how close an actor is to all other actors in the network.

- Mean geodesic distance from i to j

$$l_i = \frac{1}{n} \sum_j d_{ij} = \frac{1}{n-1} \sum_{j(\neq i)} d_{ij}$$

l_i gives a low value for more central vertices and high value for less central vertices.

- Closeness Centrality

$$C_C(i) = \frac{1}{\sum_j d_{ij}}$$

- Normalized closeness centrality

$$C_C^*(i) = \frac{1}{l_i} = \frac{n-1}{\sum_{j(\neq i)} d_{ij}}$$

Actors in the center can quickly interact with others (minimal number of steps to reach others)

Value's dynamic range is relatively close \Rightarrow fluctuates as network changes.

Betweenness centrality

Many phenomena taking place in networks are based on diffusion process, example disease spread, information spread in social networks, transport etc \Rightarrow node is more central if it is more often involved in these processes.

- Betweenness centrality measures the extent to which a vertex lies on the shortest paths between vertices.
- Betweenness Centrality

$$C_B(i) = \sum_{s,t} \frac{\sigma_{st}(i)}{\sigma_{st}}$$

- Normalized Betweenness centrality

$$C_B^* = \frac{2}{(n-1)(n-2)} C_B(i)$$

Eigenvector centrality

- Degree centrality assumes all neighbors are equal \Rightarrow only the number of neighbors matter.
- In many cases importance of the node depends on the importance of its neighbors.
- How can we construct a centrality based on this idea?

Eigenvector centrality (Bonacich (1987))

- Assume initially that everyone has a score $x_i = 1$ we update its centrality using the sum/scores of their neighbors

$$x'_i = \sum_j A_{ij} x_j \Rightarrow \boxed{\mathbf{x}' = A\mathbf{x}}$$

- After t steps we have a vector of centralities $\mathbf{x}(t)$ given by

$$\mathbf{x}(t) = A^t \mathbf{x}(0)$$

- Expressing $\mathbf{x}(0)$ as a linear combination of the eigenvalues of A , we have $\mathbf{x}(0) = \sum_i c_i \mathbf{v}_i$

$$\mathbf{x}(t) = A^t \sum_i c_i \mathbf{v}_i = \lambda_1^t \sum_i \left(\frac{\lambda_i}{\lambda_1} \right)^t c_i \mathbf{v}_i$$

- $\mathbf{x}(t)$ converges to a limit given by the eigenvector corresponding to the maximum eigenvalue.

$$\lim_{t \rightarrow \infty} \mathbf{x}(t) \rightarrow c_1 \mathbf{v}_1 \lambda_1^t \quad \boxed{A\mathbf{v} = \lambda \mathbf{v}}$$

Eigenvector centrality

- Eigenvector centrality can be large either because (either/or or both)
 - a vertex has many neighbors
 - it has important neighbors
- Eigenvector centrality of all vertices are non-negative.
- Directed graphs:
 - Two sets of eigenvectors, since A is asymmetric.
 - in-degree (a vertex is important if it is referred to by others)

$$x_i = \frac{1}{\kappa_i} \sum_j A_{ij} x_j$$

Centrality

Katz centrality

- Problems with eigenvector centrality
 - Only vertices that are in a strongly connected component of two or more vertices, or the out-component of such a component can have non-zero eigenvector centrality.
 - Acyclic directed graph
- **Solution:** Add a constant (importance) to each vertex

$$x_i = \alpha \sum_j A_{ij} x_j + \beta$$

- **Katz Centrality:** With $\beta = 1$

$$\mathbf{x} = (I - \alpha A)^{-1} \mathbf{1} = \sum_n \alpha^n A^n$$

Centrality

Page Rank

- One problem with eigenvector centrality is that a page gets a high centrality since it has a in-degree from a high centrality page.
- The fix is to divide the centrality contribution of a vertex by its out-degree.
- Page rank centrality

$$x_i = \alpha \sum_j A_{ij} \frac{x_j}{k_j^{out}}$$

- Matrix Notation:

$$\mathbf{x} = \alpha \mathbf{A} \mathbf{D}^{-1} \mathbf{x} + \beta \mathbf{1}$$

- If there are any vertex with out-degree 0 then the first term becomes indeterminate \Rightarrow artificially set k_j^{out} to 1.

The random walk (surfer) view

- Page rank can be thought of as a model of user behavior.
- Assume a random surfer (walker), who starts at a page and moves along the directed path by choosing links at random.
- Once in a while the user gets bored and starts on another random page.
- The steady state distribution, probability that the random surfer visits a page is its page rank score.
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$$P(v_i) = \frac{1-d}{N} + d \sum_{j \in \mathcal{N}(i)} \frac{P(v_j)}{k_j^{out}}$$

Hubs and Authority

- **Authority:** Nodes that contain useful information on a topic of interest.
- **Hubs:** Nodes that point to authorities or tell us where the best authority can be found (points the search engine in the right direction).
- **HITS:** Hyperlink induced text search assigns two different centralities to any vertex
 - Authority centrality x_i
 - Hub centrality y_i

HITS (Jon Kleinberg (Cornell))

- The authority centrality of vertex i is proportional to the sum of the hub centralities of the vertices that point to it.
- Hub centrality of a vertex is proportional to the sum of the authority centrality of the vertices that it points to.
- Authority centrality

$$x_i = \alpha_i \sum_j A_{ij} y_j$$

$$\mathbf{x} = \alpha \mathbf{A} \mathbf{y}$$

- Hub Centrality

$$y_i = \beta \sum_j A_{ji} x_j$$

$$\mathbf{y} = \beta \mathbf{A}^T \mathbf{x}$$

Centrality

HITS

- The authority and hub centralities are the eigenvectors of AA^T and $A^T A$ with the same leading eigenvalue

$$AA^T \mathbf{x} = \lambda \mathbf{x}$$

$$A^T A \mathbf{y} = \lambda \mathbf{y}$$

- All the eigenvalues are the same for AA^T and $A^T A$.
- $AA^T \Rightarrow$ Bibliography coupling
- $A^T A \Rightarrow$ Cocitation coupling
- λ is the dominant eigenvalue (Perron-Frobenius Theorem)
- vertices not cited by any can have zero authority centrality but still have non zero hub centrality.

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