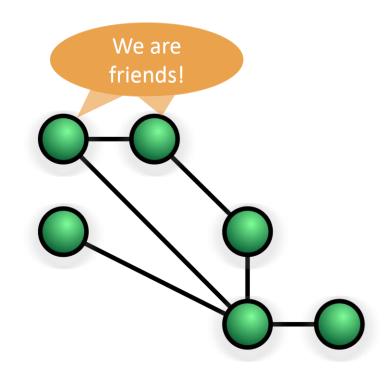
Network analysis

TOPICS OF DATA ENGINEERING

Networks appear everywhere

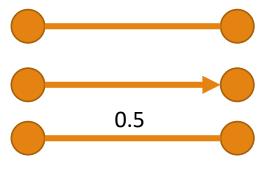
- Examples

 - Social networks
 - Friend networks
 - SNS
 - Chemical interactions in a human body



Nodes and edges

- ■Node (vertex)
 - A fundamental unit of a graph (network).
 - Represented as a dot
- Edge
 - Connects two nodes
- Each edge connects two nodes
 - Undirected edges
 - Directed edges
 - Weighted edges



Adjacency matrix

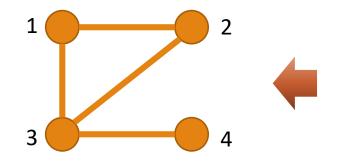
- is a representative data structure to describe a network structure.
- The elements are one or zero depending on connectivity.

$$A_{ij} = egin{cases} 1 & & & & & & \\ 1 & & & & & & \\ 0 & & & & & & \\ \end{pmatrix}$$

Examples of adjacency matrices

Undirected graph

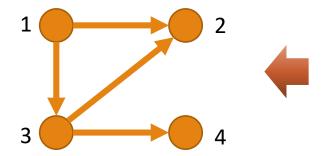
$$\begin{pmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix}$$

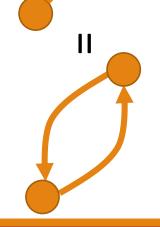


They are equivalent under

Directed graph

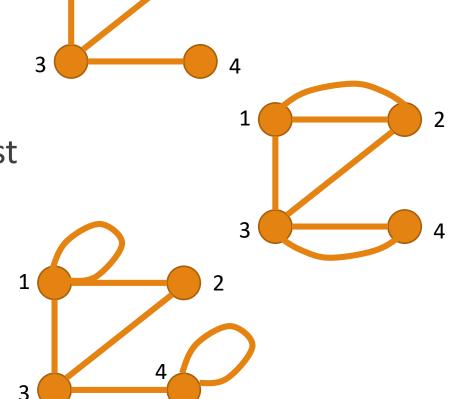
From
$$\begin{pmatrix} 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$





Types of graph structures

- Simple graph
 - No multiple edges
 - No self loop
- Multi graph
 - Multiple edges exist
 - No self loop
- Graph with loop
 - Self loops exist



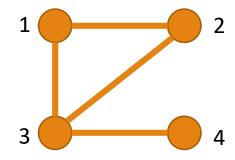
Hereafter, we focus only on a simple graph.

Degree

The number of edges from a node

$$k_1 = 2$$
 $k_2 = 2$ $k_3 = 3$ $k_4 = 1$

$$k_3 = 3$$
 $k_4 = 1$



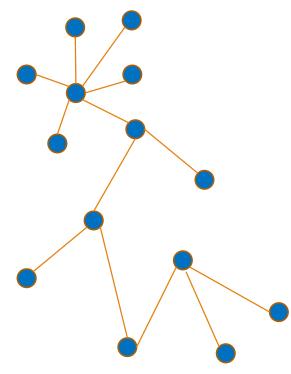
The sum of degrees are equal to twice the number of nodes M

$$\sum_{i} k_i = 2 + 2 + 3 + 1 = 8 = 2M$$

Centrality

Centrality

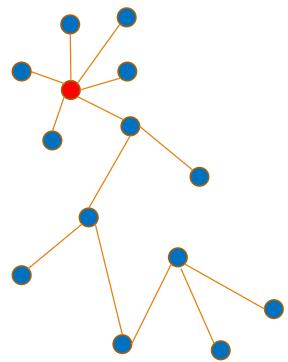
- Node characteristics to identify importance in a graph
- Many types
 - Degree centrality
 - Betweenness centrality
 - Eigenvector centrality
 - HITS
 - Page rank centrality



Degree centrality

- Based on the idea "the person who has the most friends is important".
- Definition

$${ullet} C_d(i) = k_i$$



Betweenness centrality

- Based on the idea "the person who can mediate between the most pair of friends is important".
- Definition

$$C_b(i) = \frac{\sum_{i,k} sp_{j,k}(i)}{n(n-1)/2}$$

where
$$sp_{j,k}(i) = \begin{cases} 1 & \text{if Node } i \text{ is on the shortest path between Node } j \text{ and Node } k. \\ 0 & \text{Otherwise} \end{cases}$$

$$n = \# \ of \ nodes$$

Eigenvector centrality

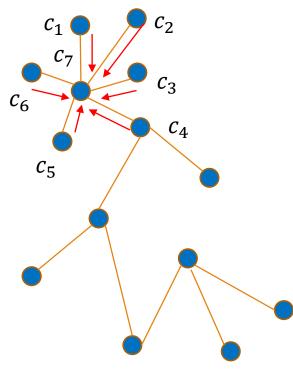
Based on the idea "if important persons think a friend is important, he/she is important". $c_1
ightharpoonup c_2$

Definition

$$c_i^{(n+1)} = \frac{1}{\lambda} \sum_j A_{ij} c_j^{(n)}$$

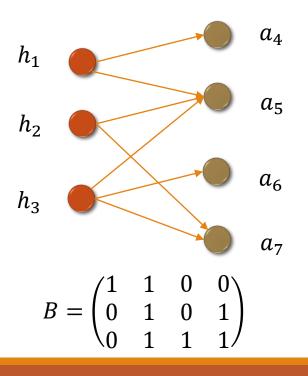
$$c^{(n+1)} = \frac{1}{\lambda} A c^{(n)}$$

•If
$$\lim_{n\to\infty} c^{(n)} = c$$
, $Ac = \lambda c$



HITS

- An extension of eigenvector centrality
- It assumes hubs and authorities



$$\boldsymbol{h}^{(n+1)} = \frac{1}{\lambda_1} B \boldsymbol{a}^{(n)}$$

$$\boldsymbol{a}^{(n+1)} = \frac{1}{\lambda_2} B^T \boldsymbol{h}^{(n)}$$

PageRank

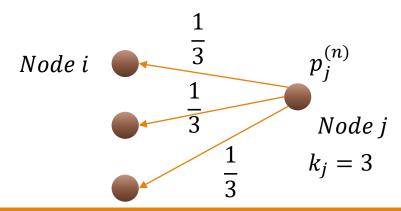
The Google algorithm of web page importance algorithm

n = # of nodes

The probability to see Node i

The probability after seeing Node j

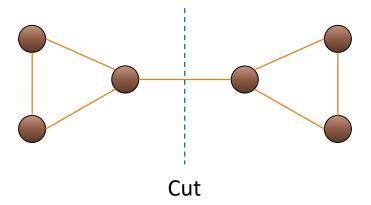
The probability to randomly see Node i



Network clustering

Cluster

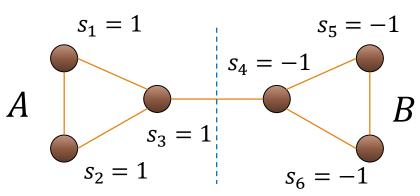
- A part of the network which is densely connected to each other
 - Cut the edges which connect clusters (MinCut)
 - Then, how should we define "densely connected" or "MinCut"?



Spectral clustering

Spectral clustering

- Separate a network into two clusters
 - easily extendable to more clusters
- Assign +1 or -1 as a cluster label to each node
- Two clusters should have a minimum bridge between them



Normalized cut - (1)

 $\overline{}$ cut(A, B): the number of edges bridging Cluster A and Cluster B

$$cut(A,B) = \sum_{i \in A} \sum_{j \in B} A_{ij}$$
$$= \frac{1}{2} \cdot \frac{1}{4} \sum_{i,j} A_{ij} (s_i - s_j)^2$$

Normalized cut - (2)

-vol(A): the number of edges connected to nodes in Cluster A

$$vol(A) = \sum_{i \in A} k_i = \frac{1}{2} \sum_{i} k_i (1 - s_i)$$
$$vol(B) = \sum_{i \in B} k_i = \frac{1}{2} \sum_{j} k_j (1 + s_j)$$

Normalized cut - (3)

-ncut(A, B): the ratio of the number of bridges to nodes in clusters

$$ncut(A, B) = \frac{cut(A, B)}{vol(A)} + \frac{cut(A, B)}{vol(B)}$$

$$= \underbrace{cut(A, B)}_{\text{Part 1}} \left(\frac{1}{vol(A)} + \frac{1}{vol(B)} \right)$$
Part 1

Part 2

$$\frac{2}{\sum_{i} k_{i} (1 - s_{i})} + \frac{2}{\sum_{j} k_{j} (1 + s_{j})} = 2\left(\frac{1}{2\sum_{i} k_{i} - \sum_{i} k_{i} (1 + s_{i})} + \frac{1}{\sum_{j} k_{j} (1 + s_{j})}\right)$$

$$= \frac{1}{\sum_{i} k_{i}} \left(\frac{1}{1 - \frac{\sum_{i} k_{i} (1 + s_{i})}{2\sum_{i} k_{i}}} + \frac{1}{\frac{\sum_{i} k_{i} (1 + s_{i})}{2\sum_{i} k_{i}}}\right)$$

$$= \frac{1}{\sum_{i} k_{i}} \left(\frac{1}{1 - r} + \frac{1}{r}\right)$$

$$= \frac{1}{\sum_{i} k_{i}} \frac{1}{r(1 - r)} = \frac{1}{\sum_{i} k_{i} \left(\frac{1 - r}{2} (1 + s_{i}) - \frac{r}{2} (1 - s_{i})\right)^{2}}$$

The detail of the calculation

$$\sum_{i} k_{i} \left(\frac{(1-r)(1+s_{i})-r(1-s_{i})}{2} \right)^{2}$$

$$= \frac{1}{4} \sum_{i} k_{i} (1-r)^{2} (1+s_{i})^{2} - \frac{2}{4} r (1-r) \sum_{i} k_{i} (1+s_{i}) (1-s_{i}) + \frac{r^{2}}{4} \sum_{i} k_{i} (1-s_{i})^{2}$$

$$= \frac{1}{2} (1-r)^{2} \sum_{i} k_{i} (1+s_{i}) + \frac{1}{2} r^{2} \sum_{i} k_{i} (1-s_{i})$$

$$= (1-r)^{2} \sum_{i} k_{i} r + r^{2} \sum_{i} k_{i} (1-r)$$

$$= \sum_{i} k_{i} r (1-r)$$

Part 1

$$\frac{1}{8} \sum_{i,j} A_{ij} (s_i^2 - 2s_i s_j + s_j^2) = \frac{1}{4} \sum_{i,j} (A_{ij} s_i^2 - A_{ij} s_i s_j)$$

$$= \frac{1}{4} \sum_{i,j} (k_i \delta_{ij} s_i s_j - A_{ij} s_i s_j)$$

$$= \frac{1}{4} \sum_{i,j} (k_i \delta_{ij} - A_{ij}) s_i s_j$$

$$= \frac{1}{2} \sum_{i,j} (k_i \delta_{ij} - A_{ij}) \frac{(1-r)(1+s_i) - r(1-s_i)}{2} \frac{(1-r)(1+s_j) - r(1-s_j)}{2}$$

The detail of the calculation

$$\begin{split} & \sum_{i,j} \left(k_i \delta_{ij} - A_{ij} \right) \frac{(1-r)(1+s_i) - r(1-s_i)}{2} \frac{(1-r)(1+s_j) - r(1-s_j)}{2} \\ &= \frac{1}{4} \sum_{i,j} \left(k_i \delta_{ij} - A_{ij} \right) ((1-r)^2 (1+s_i)(1+s_j) + r^2 (1-s_i)(1-s_j) - 2r(1-r)(1-s_i)(1+s_j)) \\ &= \frac{1}{2} \sum_{i,j} \left(k_i \delta_{ij} - A_{ij} \right) (r^2 s_i s_j + (1-r)^2 s_i s_j + 2r(1-r) s_i s_j) \\ &= \frac{1}{2} \sum_{i,j} \left(k_i \delta_{ij} - A_{ij} \right) (1-2r+2r^2+2r(1-r)) s_i s_j \\ &= \frac{1}{2} \sum_{i,j} \left(k_i \delta_{ij} - A_{ij} \right) s_i s_j \end{split}$$

Normalized cut - (3)

-ncut(A, B): the ratio of the number of bridges to nodes in clusters

where
$$y_i = \frac{2 \cdot ncut(A, B)}{\sum_{i,j} (k_i \delta_{ij} - A_{ij}) y_i y_j}$$

$$= \frac{\sum_{i,j} (k_i \delta_{ij} - A_{ij}) y_i y_j}{\sum_{i} k_i y_i^2}$$

$$= \frac{\mathbf{y}^T (D - A) \mathbf{y}}{\mathbf{y}^T D \mathbf{y}}$$

Relaxation of condition

- We want to find y that minimizes $\frac{y^T(D-A)y}{y^TDy}$
- Let elements in y take arbitrary real values
- Since there is a scaling symmetry, $y \rightarrow ay$ gives the same ncut value.
 - Take y so as to $y^T Dy = 1$
 - Then, the problem is to minimize $y^T(D-A)y$ under the condition $y^TDy=1$

Generalized eigenvalue problem

Applying Lagrange multiplier, we get

$$L = \mathbf{y}^{T}(D - A)\mathbf{y} - \lambda(\mathbf{y}^{T}D\mathbf{y} - 1)$$

$$\frac{1}{2}\frac{\partial L}{\partial \mathbf{y}} = (D - A)\mathbf{y} - \lambda D\mathbf{y} = 0$$

$$(D - A)\mathbf{y} = \lambda D\mathbf{y}$$

After solving the generalized eigenvalue problem ...

Apply K-means problem

Modularity maximization

Modularity Q

- $e_{aa} = \sum_{ij} \frac{A_{ij}}{2M} \delta(c_i, a) \delta(c_j, a)$
 - the probability to find edges connecting nodes inside Cluster a
- $a_{a} = \sum_{b} e_{ab} = \sum_{i} \frac{k_{i}}{2M} \delta(c_{i}, a)$
 - the probability of edges connecting to Cluster a
 - a_a^2 is a probability to find edges under the assumption that edges are randomly connected to nodes

$$Q = \sum_{a} (e_{aa} - a_a^2) = \frac{1}{2M} \sum_{ij} (A_{ij} - \frac{k_i k_j}{2M}) \delta(c_i, c_j)$$

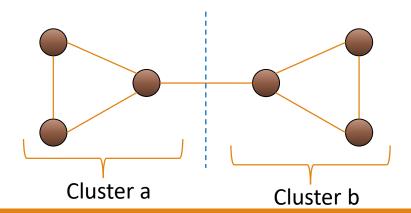
An example

The number of edges M = 7

$$e_{aa} = \frac{3}{7}$$
, $e_{ab} = \frac{1}{7}$, $e_{bb} = \frac{3}{7}$

$$\mathbf{a}_{a} = e_{aa} + e_{ab} = \frac{4}{7}, a_{a}^{2} = \frac{16}{49} = a_{b}^{2}$$

$$Q = e_{aa} - a_a^2 + e_{bb} - a_b^2 = 2\left(\frac{3}{7} - \frac{16}{49}\right) = \frac{10}{49}$$



Resolution limit

Modularity maximization tends to give larger clusters than expected.

