PageRank

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Review of BoW

- 1. Build the vocabulary/dictionary from the given dataset
  - Get all the unique words in the given dataset
  - Each word in the vocabulary has an index

It was the best of times,
it was the worst of times,
it was the age of wisdom,
it was the age of foolishness,

The given dataset.
(Each sentence is a sample)

Get unique words

- "it"
- "was"
- "the"
- "best"
- "of"
- "times"
- "worst"
- "age"
- "wisdom"
- "foolishness"

Vocabulary/dictionary
(unique words in the given dataset)

Review of BoW

- 2. Represent each sentence/paragraph/article with the vocabulary
  - Use a vector whose dimensionality equals to the size of the vocabulary
  - If the word appears, add 1 to the corresponding element in the vector

- “it”
- “was”
- “the”
- “best”
- “of”
- “times”
- “worst”
- “age”
- “wisdom”
- “foolishness”

```
"it was the worst of times" = [1, 1, 1, 0, 1, 1, 1, 0, 0, 0]
"it was the age of wisdom" = [1, 1, 1, 0, 1, 0, 0, 1, 1, 0]
"it was the age of foolishness" = [1, 1, 1, 0, 1, 0, 0, 1, 0, 1]
```

Review of BoW

- Term Frequency-Inverse Document Frequency (TF-IDF)
  - Reflect how important a word is to a document in a collection

- Definition

$$TF(t,d) = \frac{\#t \text{ in document } d}{\#words \text{ in document } d} \qquad IDF(t) = \log \frac{\#documents}{\#documents \text{ containing } t}$$

$$TF\_IDF = TF(t,d) \times IDF(t)$$

Review of NMF

$$\min \| X - FG^T \|_F^2$$

$$s.t.\ F \geq 0, G \geq 0$$

- Columns of F are the underlying basis vectors

$$F = [f_1, f_2, \ldots, f_k]$$

- Rows of G give the weights associated with each basis vector.

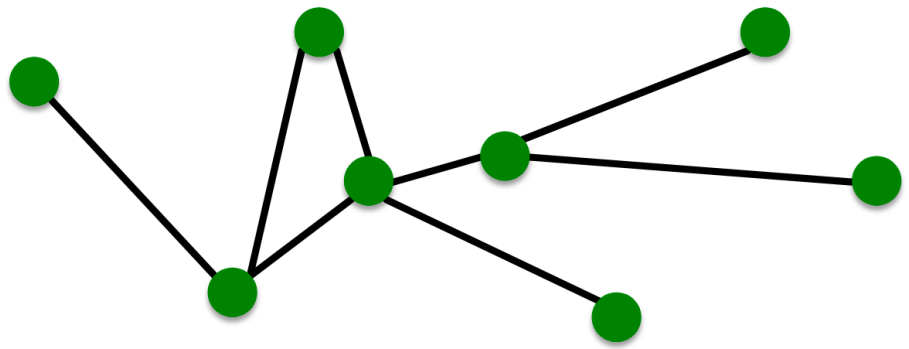
$$[\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_n] = [\mathbf{f}_1, \mathbf{f}_2, \cdots, \mathbf{f}_k] \begin{bmatrix} g_{11} & g_{21} & \cdots & g_{n1} \\ g_{12} & g_{22} & \cdots & g_{n2} \\ \vdots & \vdots & \vdots & \vdots \\ g_{1k} & g_{2k} & \cdots & g_{nk} \end{bmatrix}$$

$$\mathbf{x}_i = \mathbf{f}_1 g_{i1} + \mathbf{f}_2 g_{i2} + \cdots + \mathbf{f}_k g_{ik}$$

only additive combinations!!!

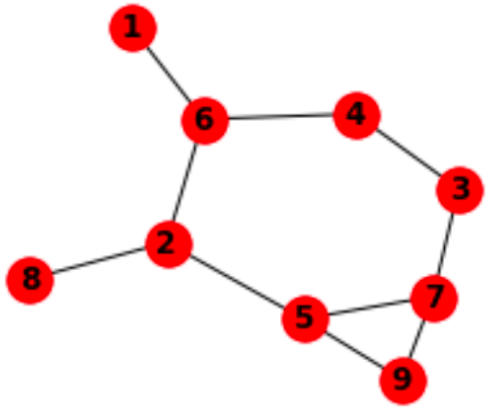
Graph Terminology

- Components of a Graph
  - Nodes/vertices
  - Edges/links
  - Graph/Network

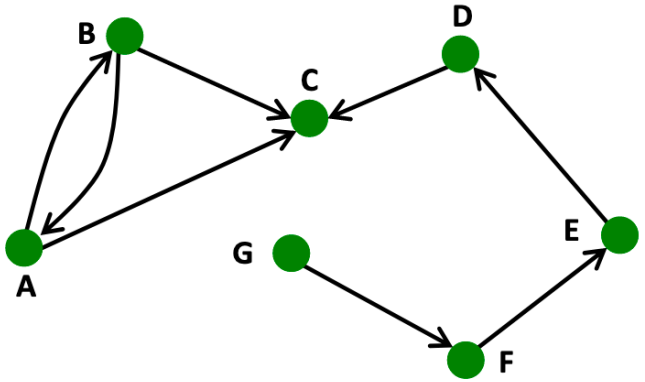


Graph Terminology

- Types of Graphs
  - Undirected Graph: links are undirected
    - Friendship on Facebook
  - Directed Graph: links are directed
    - Following on Twitter



Undirected graph

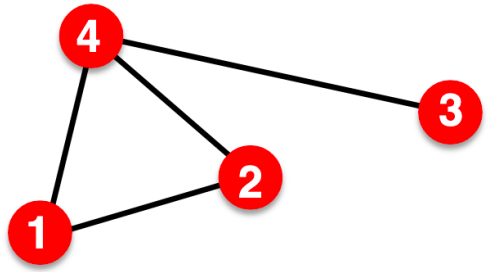


Directed graph

Graph Terminology

- Adjacency matrix

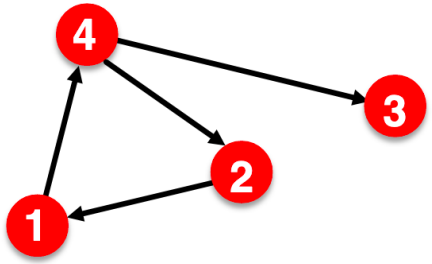
Undirected



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

$$A_{ij} = A_{ji}$$
$$A_{ii} = 0$$

Directed

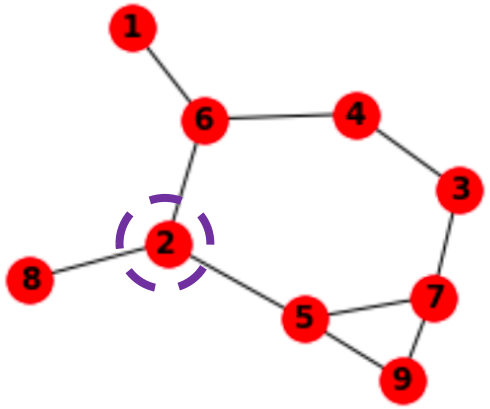


$$A = \begin{pmatrix} 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \end{pmatrix}$$

$$A_{ij} \neq A_{ji}$$
$$A_{ii} = 0$$

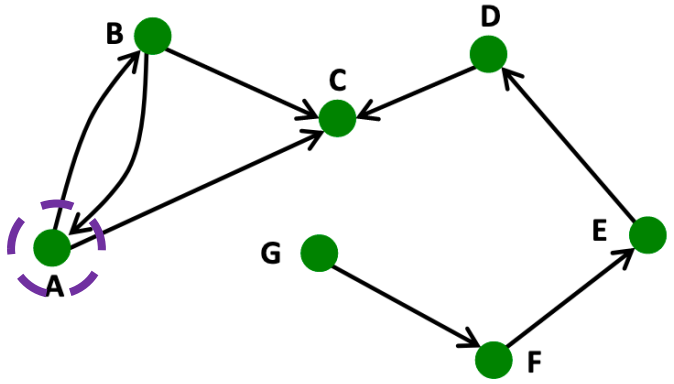
Graph Terminology

- Node degrees of undirected graph
  - The number of edges adjacent to a node



Node 2: d = 3

- Node degrees of directed graph
  - In-degree: the number of head ends adjacent to a node
  - Out-degree: the number of tail ends adjacent to a node

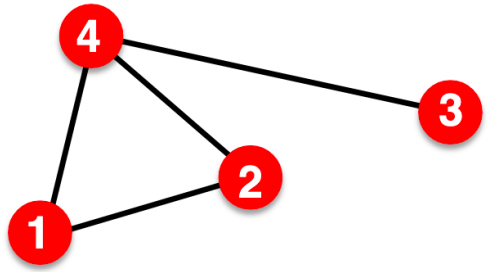


Node A: $d_{in}=1$, $d_{out}=2$

Graph Terminology

- Node degrees

Undirected

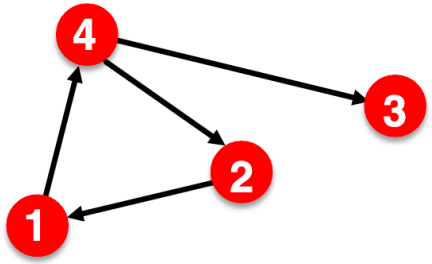


$$A = \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix}$$

Node 2: 1+0+0+1=2

$$A_{ij} = A_{ji}$$
$$A_{ii} = 0$$

Directed



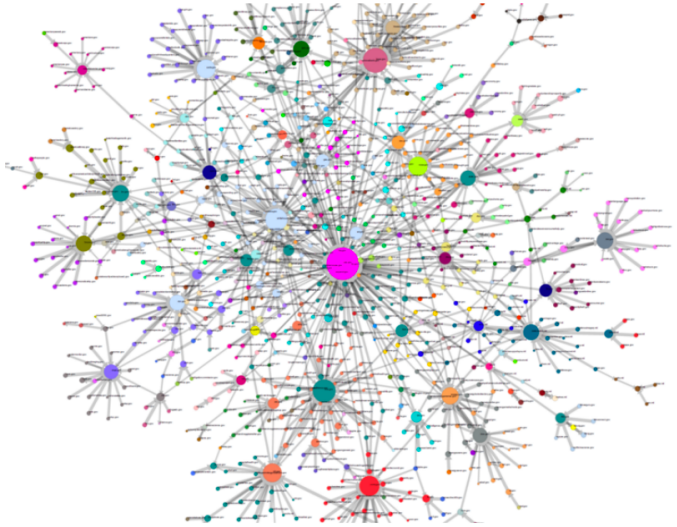
$$A = \begin{pmatrix} 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \end{pmatrix}$$

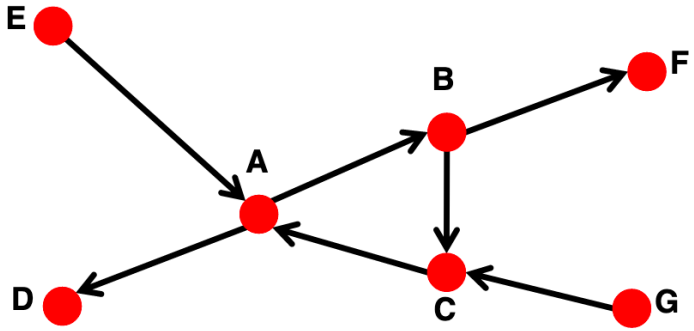
Node 4:
Indegree (column sum): 1+0+0+0=1
Outdegree (row sum): 0+1+1+0=2

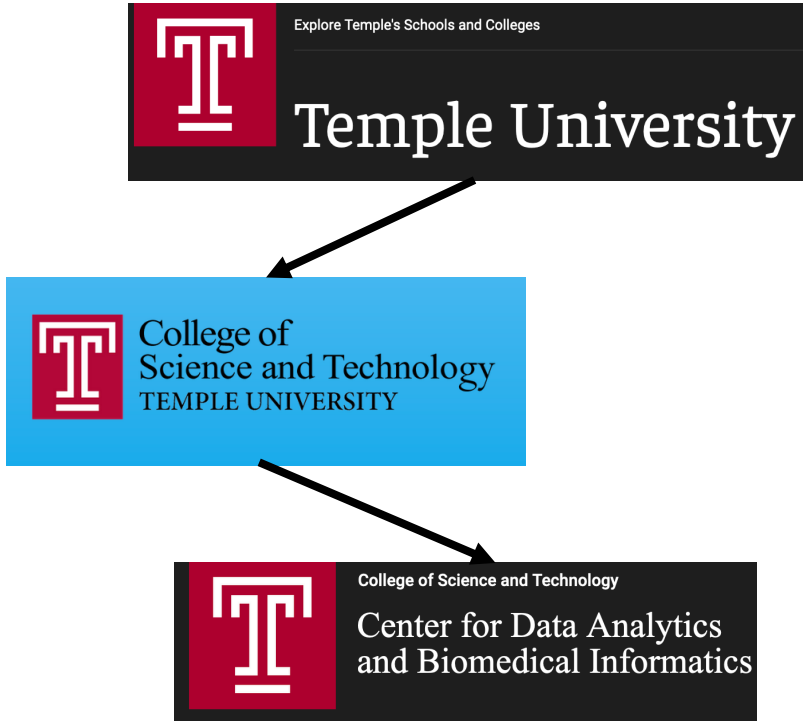
$$A_{ij} \neq A_{ji}$$
$$A_{ii} = 0$$

PageRank

- The web is a graph
  - Nodes: web pages
  - Edges: hyperlinks

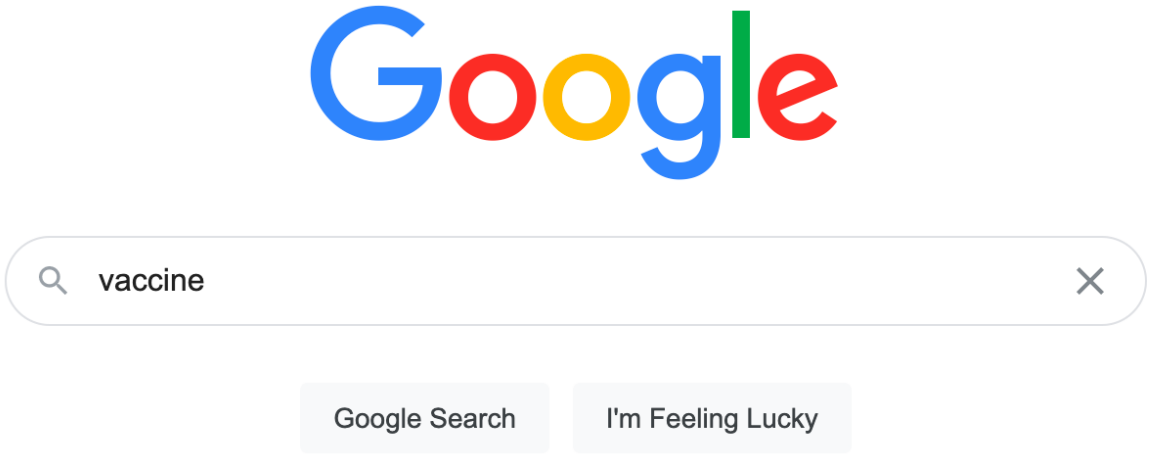






PageRank

- All web pages are not equally “important”
  - Some webpages should be assigned more priority than others, for being more important
  - Which node (webpage) is important?



scdhec.gov › covid19 › covid-19-vaccine-appointments

COVID-19 Vaccine Appointments | SCDHEC

Make an appointment with a **vaccine** provider to guarantee you'll receive your shot. If you're receiving the Pfizer-BioNTech or Moderna **vaccines**, you need to make ...

COVID-19 Vaccine Provider · Understanding the Vaccination... · Herd Immunity

www.cdc.gov › vaccines

Vaccines and Immunizations | CDC

Vaccine Communications. Past Announcements · Newsletters · Immunization MMWRs. email_03Get Email Updates. To receive email updates about this page, ...

COVID-19 Vaccination · Immunization Schedules · The Basics · Adults

www.cdc.gov › coronavirus › 2019-ncov › vaccines

When You've Been Fully Vaccinated | CDC

6 days ago — Recommendations on what activities people can do after they have been fully **vaccinated**, including how to gather safely with **vaccinated** and ...

vaccinefinder.org

VaccineFinder - Find COVID-19 vaccine locations near you

VaccineFinder helps you find clinics, pharmacies, and other locations that offer COVID-19 **vaccines** in the United States. In some states, information may be ...

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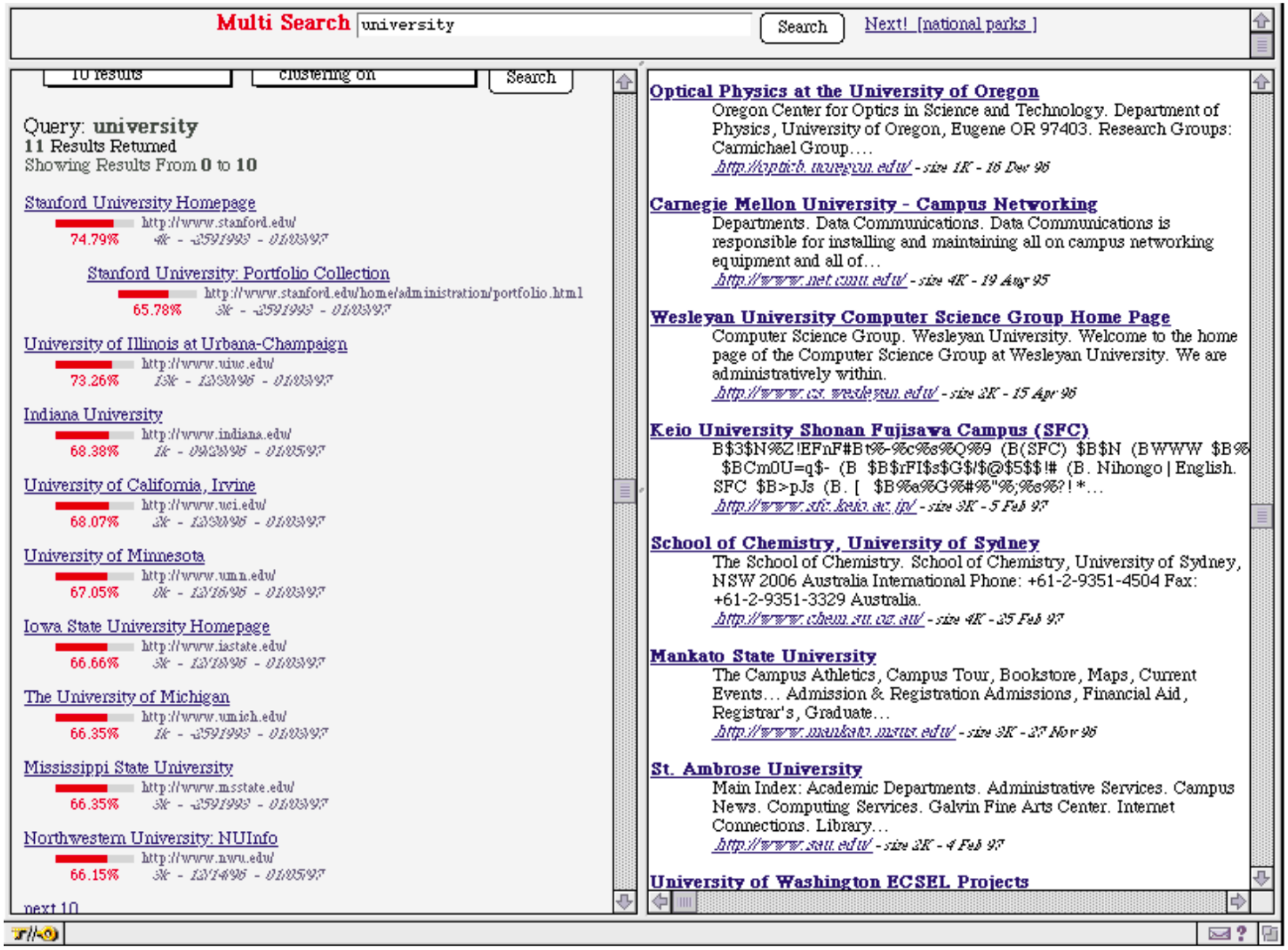
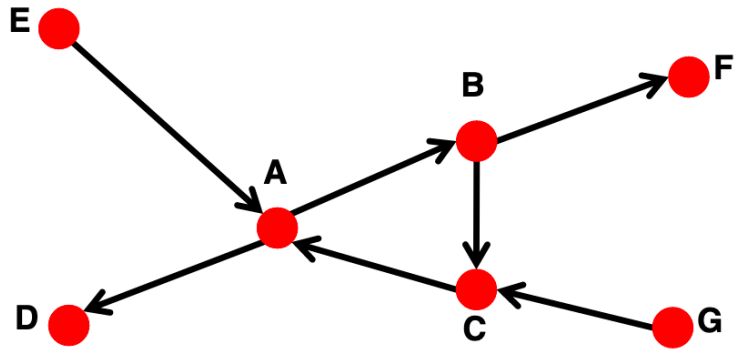


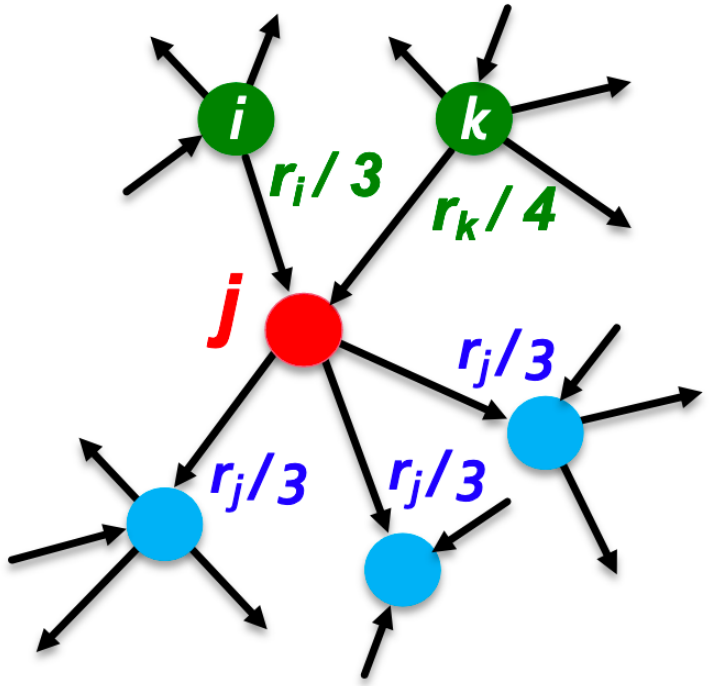
PageRank

- Compute the importance of nodes in a graph
  - Idea: Links as votes
  - Page is more important if it has more links
- Use in-links as votes
  - How to use votes to compute the importance score???
  - Q: E and C may be different. C may be more important.
  - How to differentiate their importance when they vote for A?



PageRank

- A vote from an important page is worth more:
  - Each link's vote is proportional to the **importance** of its source page
  - If page ***i*** with importance r_i has d_i out-links, each link gets r_i / d_i votes
  - Page ***j***'s own importance r_j is the sum of the votes on its in-links



$$r_j = r_i/3 + r_k/4$$

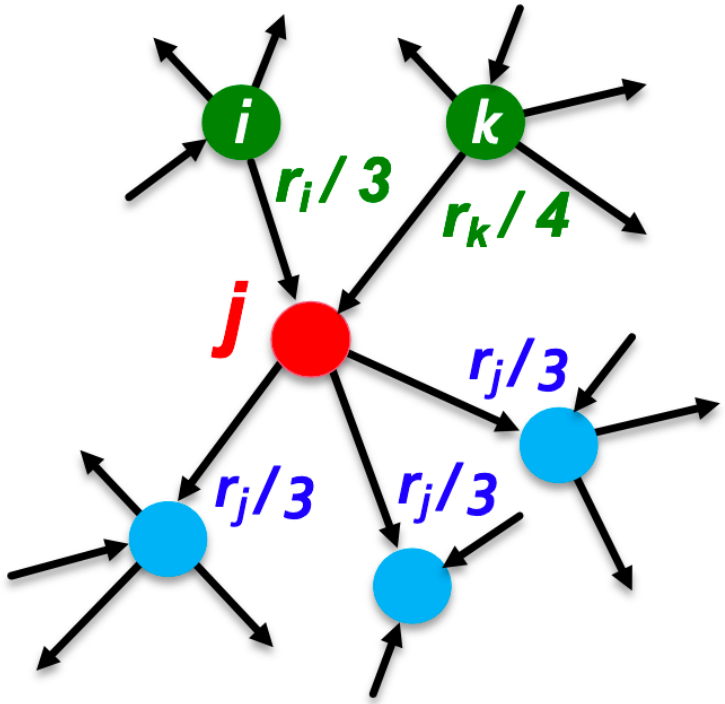
PageRank

- Formally, the importance score of each node is

$$r_j = \sum_{i \to j} \frac{r_i}{d_i}$$

d_i … out-degree of node i

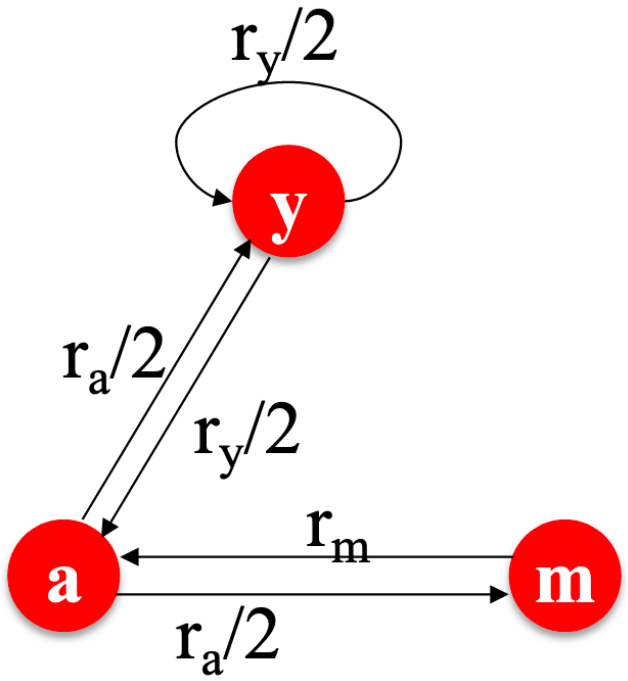
A page is important if it is pointed by other important pages



$r_j = r_i/3 + r_k/4$

PageRank

- Example



$$r_j = \sum_{i \to j} \frac{r_i}{d_i}$$

d_i … out-degree of node i

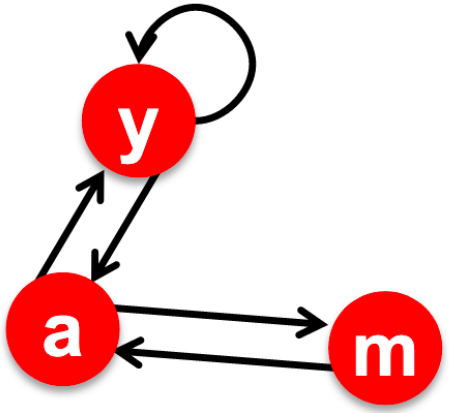
$r_y = r_y/2 + r_a/2$

$r_a = r_y/2 + r_m$

$r_m = r_a/2$

PageRank

- Matrix Form



Graph

Out-degree 2, 2, 1

	y	a	m
y	1	1	0
a	1	0	1
m	0	1	0

Adjacency matrix

	r_y	r_a	r_m
r_y	½	½	0
r_a	½	0	1
r_m	0	½	0

Transition matrix M

$$r_j = \sum_{i \to j} \frac{r_i}{d_i}$$

d_i … out-degree of node i

$r_y = r_y/2 + r_a/2$

$r_a = r_y/2 + r_m$

$r_m = r_a/2$

$$\begin{bmatrix} r_y \\ r_a \\ r_m \end{bmatrix} = \begin{bmatrix} ½ & ½ & 0 \\ ½ & 0 & 1 \\ 0 & ½ & 0 \end{bmatrix} \begin{bmatrix} r_y \\ r_a \\ r_m \end{bmatrix}$$

r M r

PageRank

- Property of the transition matrix M
  - Column sum is 1

- Property of the rank vector r
  - r_i is the importance score of page i

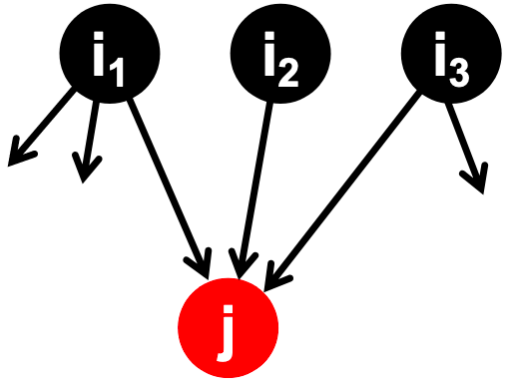
$$\sum_i r_i = 1$$

$$\begin{bmatrix} r_y \\ r_a \\ r_m \end{bmatrix} = \begin{bmatrix} ½ & ½ & 0 \\ ½ & 0 & 1 \\ 0 & ½ & 0 \end{bmatrix} \begin{bmatrix} r_y \\ r_a \\ r_m \end{bmatrix}$$

$$\boldsymbol{r} \qquad \boldsymbol{M} \qquad \boldsymbol{r}$$

PageRank

- Interpretation
  - At time t, the user is on page i
  - At time t+1, the user follows an out-link from i uniformly at random
  - Ends up on some page j linked from i



$$r_j = \sum_{i \to j} \frac{r_i}{d_{out}(i)}$$

$$\begin{bmatrix} r_y \\ r_a \\ r_m \end{bmatrix} = \begin{bmatrix} ½ & ½ & 0 \\ ½ & 0 & 1 \\ 0 & ½ & 0 \end{bmatrix} \begin{bmatrix} r_y \\ r_a \\ r_m \end{bmatrix}$$

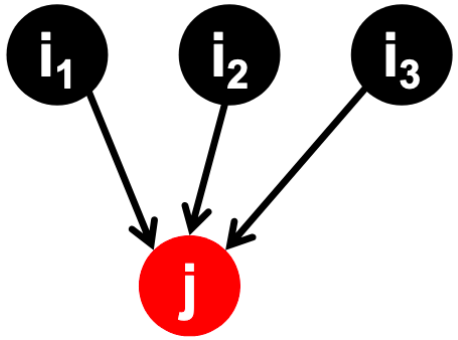
$\boldsymbol{r}$ $\quad$ $\boldsymbol{M}$ $\quad$ $\boldsymbol{r}$

PageRank

- Interpretation (continue):
  - Define $\boldsymbol{p}(\boldsymbol{t})$ is a probability distribution over pages
  - At time t+1, we have

$$\boldsymbol{p}(\boldsymbol{t}+\boldsymbol{1}) = \boldsymbol{M} \cdot \boldsymbol{p}(\boldsymbol{t})$$

Random walk

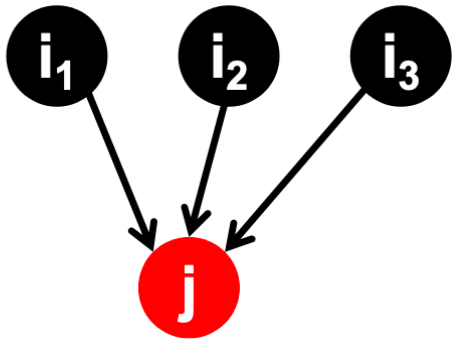


PageRank

- Solution of the importance score r:

$\boldsymbol{p(t)}$ is **stationary distribution** of a random walk

$$\boldsymbol{p(t+1) = M \cdot p(t)}$$



Random walk

Stationary distribution

$$\boldsymbol{r = M \cdot r}$$

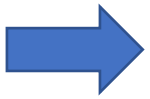
r is the stationary distribution of the random walk
r is the eigenvector of the transition matrix M (with eigenvalue 1)

PageRank

- Solution of the importance score r:
  - Compute the eigenvector of the transition matrix M with eigenvalue 1
  - Use power iteration to compute the eigenvector efficiently

- Assign each node an initial page rank
- Repeat until convergence ($\sum_i |r_i^{t+1} - r_i^t| < \epsilon$)
  - Calculate the page rank of each node

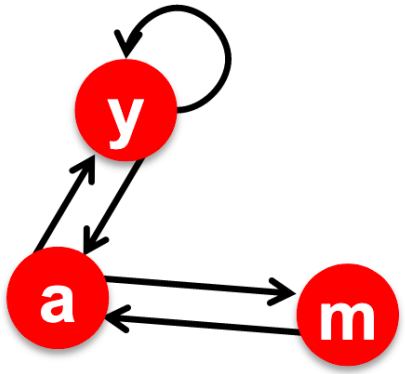
$$r_j^{(t+1)} = \sum_{i \to j} \frac{r_i^{(t)}}{d_i}$$



- Initialize: $\boldsymbol{r}^0 = [1/N, \ldots., 1/N]^T$
- Iterate: $\boldsymbol{r}^{(t+1)} = \boldsymbol{M} \cdot \boldsymbol{r}^t$
- Stop when $|\boldsymbol{r}^{(t+1)} - \boldsymbol{r}^t|_1 < \varepsilon$

PageRank

- Example



	y	a	m
y	½	½	0
a	½	0	1
m	0	½	0

$$\begin{bmatrix} r_y \\ r_a \\ r_m \end{bmatrix} = \begin{bmatrix} ½ & ½ & 0 \\ ½ & 0 & 1 \\ 0 & ½ & 0 \end{bmatrix} \begin{bmatrix} r_y \\ r_a \\ r_m \end{bmatrix}$$

$$r = M r$$

$$\begin{bmatrix} r_y \\ r_a \\ r_m \end{bmatrix} = \begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix} \begin{bmatrix} 1/3 \\ 3/6 \\ 1/6 \end{bmatrix} \begin{bmatrix} 5/12 \\ 1/3 \\ 3/12 \end{bmatrix} \begin{bmatrix} 9/24 \\ 11/24 \\ 1/6 \end{bmatrix} \ldots \begin{bmatrix} 6/15 \\ 6/15 \\ 3/15 \end{bmatrix}$$

Iteration 0, 1, 2, …