#### **COEN 169**

# **PageRank**

Yi Fang

Department of Computer Engineering

Santa Clara University

#### **Administrative Stuff**

- Midterm exam is on May 5 (Thursday). Sample questions are posted on Camino. You can bring one cheat sheet and a calculator.
- Office hours: Friday 1-2pm; Tuesday 2-3pm
- Additional office hours for the midterm: Wednesday 4-5pm.

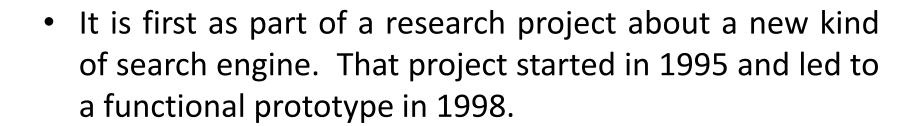
#### Motivation and Introduction

- What is PageRank?
  - A method for rating the importance of web pages objectively and mechanically using the link structure of the web.
- Why is Page Importance important?
  - New challenges for information retrieval on the World Wide Web.
  - Huge number of web pages: 150 million by 1998
     1000 billion by 2008
  - Diversity of web pages: different topics, different quality, etc.

# The History of PageRank

PageRank was developed by Larry Page (hence the name

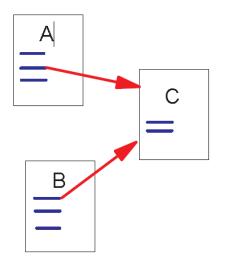
Page-Rank) and Sergey Brin.



Shortly after, Page and Brin founded Google.

## Link Structure of the Web

150 million web pages (in 1998) → 1.7 billion links



In-links and Out-links:

- A and B are C's in-links
- ➤ C is A and B's out-link

Intuitively, a webpage is important if it has a lot of in-links.

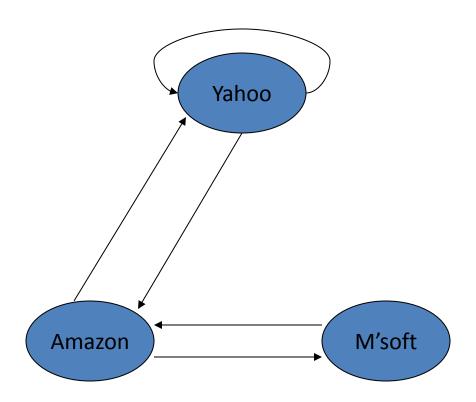
What if a webpage has only one link coming from www.yahoo.com?

### Intuition

• Solve the recursive statement:

"a page is important if many important pages exclusively link to it."

# Example



# Example

Solving equations:

$$PR(y) = PR(y)* 1/2 + PR(a)*1/2+PR(m)*0$$
  
 $PR(a) = PR(y)*1/2 + PR(a)*0+PR(m)*1$   
 $PR(m) = PR(y)*0+PR(a)*1/2+PR(m)*0$ 

```
PR(y)
           1/3
                                               2/5
                 1/3
                        5/12
                                3/8
PR(a) =
          1/3
                 1/2 1/3
                                               2/5
                                11/24
PR(m)
           1/3
                 1/6
                        1/4
                                1/6
                                               1/5
```

Converge!

# **Matrix Representation**

• 
$$v = \begin{bmatrix} PR(y) \\ PR(a) \\ PR(m) \end{bmatrix}$$
,  $M = \begin{bmatrix} 0.5 & 0.5 & 0 \\ 0.5 & 0 & 1 \\ 0 & 0.5 & 0 \end{bmatrix}$ 

• 
$$v_{t+1} = Mv_t$$

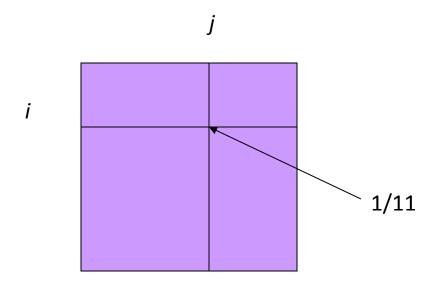
### Stochastic Matrix of the Web

Page i corresponds to row and column I

- M [i,j] = 1/n if page j links to n pages, including page i; 0 if j does not link to i.
  - M [i,j] is the probability we'll next be at page i if we are now at page j.

# Example

Suppose page *j* links to 11 pages, including *i* 

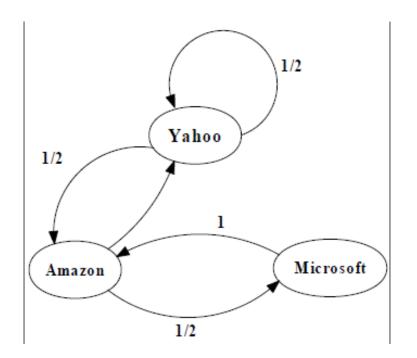


# Power Method for PageRank

#### The iterative method to calculate PageRank

- Pick an initial guess  $v_0$  ( $v_0$  is a vector)
- $v_1 = Mv_0$
- $v_2 = Mv_1 = M^2v_0$
- $v_3 = Mv_2 = M^3v_0$
- •
- Compute  $v_n$  until it converges (e.g.,  $||v_n v_{n-1}|| < \varepsilon$  where  $\varepsilon$  is a small value)

# An example of PageRank



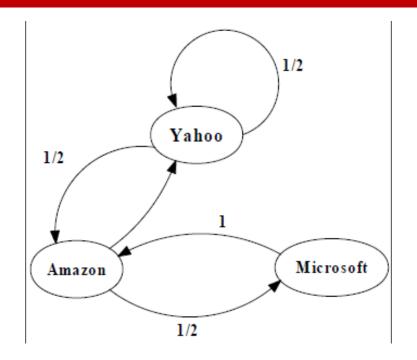
$$M = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 1 \\ 0 & 1/2 & 0 \end{bmatrix}$$

$$\begin{bmatrix} yahoo \\ Amazon \\ Microsoft \end{bmatrix} = \begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix}$$

$$\begin{bmatrix} 1/3 \\ 1/2 \\ 1/6 \end{bmatrix} = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 1 \\ 0 & 1/2 & 0 \end{bmatrix} \begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix}$$

PageRank Calculation: first iteration

## An example of PageRank



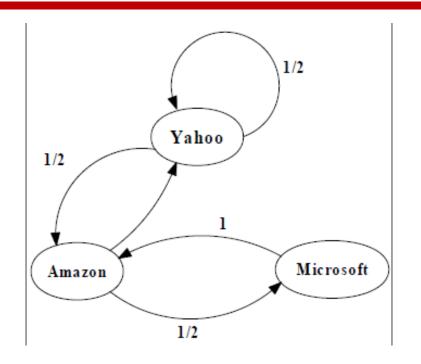
$$M = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 1 \\ 0 & 1/2 & 0 \end{bmatrix}$$

$$\begin{bmatrix} yahoo \\ Amazon \\ Microsoft \end{bmatrix} = \begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix}$$

$$\begin{bmatrix} 5/12 \\ 1/3 \\ 1/4 \end{bmatrix} = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 1 \\ 0 & 1/2 & 0 \end{bmatrix} \begin{bmatrix} 1/3 \\ 1/2 \\ 1/6 \end{bmatrix}$$

PageRank Calculation: second iteration

# An example of PageRank



$$M = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 1 \\ 0 & 1/2 & 0 \end{bmatrix}$$

$$\begin{bmatrix} yahoo \\ Amazon \\ Microsoft \end{bmatrix} = \begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix}$$

$$\begin{bmatrix} 3/8 \\ 11/24 \\ 1/6 \end{bmatrix} \begin{bmatrix} 5/12 \\ 17/48 \\ 11/48 \end{bmatrix} \dots \begin{bmatrix} 2/5 \\ 2/5 \\ 1/5 \end{bmatrix}$$

Convergence after some iterations

# PageRank

PageRank essentially solves the following eigenvector problem:

Find v to satisfy

$$v = Mv$$

Eigenvalue is equal to 1

The \$25,000,000,000 dollar eigenvector



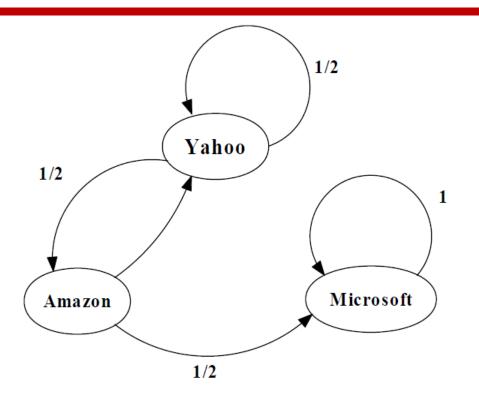
#### Random Walks on the Web

- Imagine a web surfer doing a random walk on the web
  - Start at a random page
  - At each step, go out of the current page along one of the links on that page, with equal probability (the transition probability from page j to i is  $M_{ij}$ )

#### Random Walks on the Web

- After many random walks, the visit rate is the page's PageRank.
- Intuition: pages are important in proportion to how often a random walker would visit them

# An example of the Problem



$$M = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 0 \\ 0 & 1/2 & 1 \end{bmatrix}$$

$$\begin{bmatrix} yahoo \\ Amazon \\ Microsoft \end{bmatrix} = \begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix}$$

$$\begin{bmatrix} 5/24 \\ 1/8 \\ 2/3 \end{bmatrix} \begin{bmatrix} 1/6 \\ 5/48 \\ 35/48 \end{bmatrix} \dots \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

# Google Solution to Traps: Teleporting

- At a dead end, jump to a random web page.
- At any non-dead end, with probability 20%, jump to a random web page.
  - With remaining probability (80%), go out on a random link.
  - -20% a parameter.

# Result of teleporting

- Now cannot get stuck locally.
- There is a long-term rate at which any page is visited
- How do we compute this visit rate?

# Example: Previous with 20% Tax

• Equations  $\mathbf{v} = 0.8(M \mathbf{v}) + 0.2*1/3$ :

$$y = 0.8(y/2 + a/2) + 0.2*1/3$$

$$a = 0.8(y/2) + 0.2*1/3$$

$$m = 0.8(a/2 + m) + 0.2*1/3$$

```
      Y
      1/3
      1.00/3
      0.84/3
      0.776/3
      7/33

      a =
      1/3
      0.60/3
      0.60/3
      0.536/3
      5/33

      m
      1/3
      1.40/3
      1.56/3
      1.688/3
      21/33
```

# Modified Version of PageRank

$$PR(p_i) = \frac{1 - d}{N} + d \sum_{p_j \in M(p_i)} \frac{PR(p_j)}{L(p_j)}$$

## Power Method for PageRank with teleporting

- Pick an initial guess  $v_0$  ( $v_0$  is a vector)
- $v_1 = dMv_0 + \frac{1-d}{N}I$  (I is a vector with all ones)
- $v_2 = dMv_1 + \frac{1-d}{N}I$  (d is teleporting parameter with typical value 0.8)
- $v_3 = dMv_2 + \frac{1-d}{N}I$
- •
- Compute  $v_n$  until it converges (e.g.,  $||v_n v_{n-1}|| < \varepsilon$  where  $\varepsilon$  is a small value)

# Random Walks in Graphs

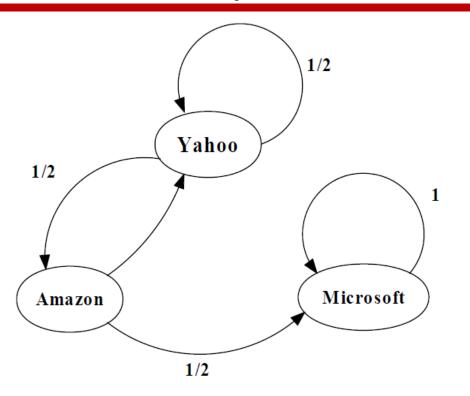
#### The Random Walk Model

 The simplified model: the standing probability distribution of a random walk on the graph of the web. Simply keeps clicking successive links at random

#### The Modified Model

 The modified model: the "random surfer" simply keeps clicking successive links at random, but periodically "gets bored" and jumps to a random page based on teleporting

# An example of Modified PageRank



$$M = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 0 \\ 0 & 1/2 & 1 \end{bmatrix}$$

$$\begin{bmatrix} yahoo \\ Amazon \\ Microsoft \end{bmatrix} = \begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix}$$

$$C_1 = 0.8$$
  $C_2 = 0.2$ 

$$\begin{bmatrix} 0.333 \\ 0.333 \\ 0.333 \end{bmatrix} \begin{bmatrix} 0.333 \\ 0.200 \\ 0.333 \end{bmatrix} \begin{bmatrix} 0.280 \\ 0.200 \\ 0.520 \end{bmatrix} \begin{bmatrix} 0.259 \\ 0.179 \\ 0.563 \end{bmatrix} \dots \begin{bmatrix} 7/33 \\ 5/33 \\ 21/33 \end{bmatrix}$$

# Matlab Implementation

#### PageRank MATLAB/Octave implementation

```
% Parameter M adjacency matrix where M i, j represents the link from 'j' to 'i', such that for all 'j' sum(i, M i, j) = 1
% Parameter d damping factor
% Parameter v quadratic error quadratic error for v
% Return v, a vector of ranks such that v i is the i-th rank from [0, 1]
function [v] = rank(M, d, v quadratic error)
N = size(M, 2); % N is equal to half the size of M
v = rand(N, 1);
v = v . / norm(v, 2);
last v = ones(N, 1) * inf;
M \text{ hat} = (d .* M) + (((1 - d) / N) .* ones(N, N));
while(norm(v - last v, 2) > v quadratic error)
        v = \overline{M} hat * v;
        v = v./ norm(v, 2);
end
endfunction
```

Example of code calling the rank function defined above:

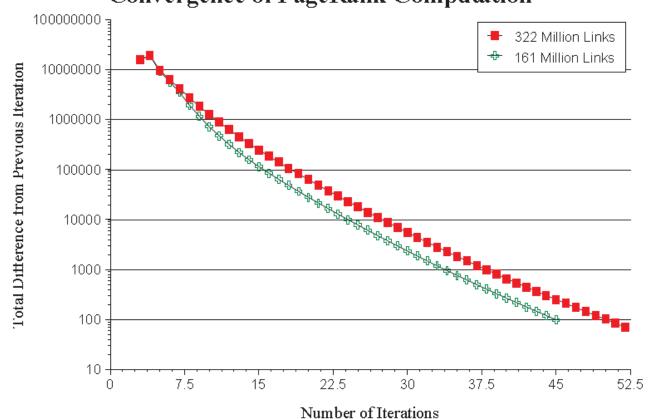
```
M = [0 0 0 0 1; 0.5 0 0 0 0; 0.5 0 0 0 0; 0 1 0.5 0 0; 0 0 0.5 1 0];
rank(M, 0.80, 0.001)
```

This example takes 13 iterations to converge.

# Convergence Property

- PR (322 Million Links): 52 iterations
- PR (161 Million Links): 45 iterations
- Scaling factor is roughly linear in *logn*

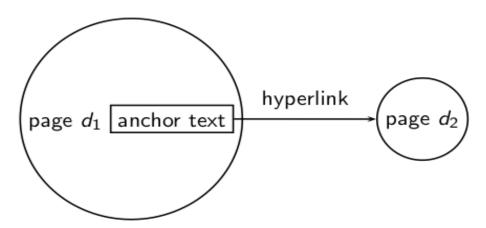
#### Convergence of PageRank Computation



#### Questions

- How to find the important persons on Twitter?
- How to find the important persons on Facebook?
- How to find the important persons on Yahoo Answers?

## The web as a directed graph

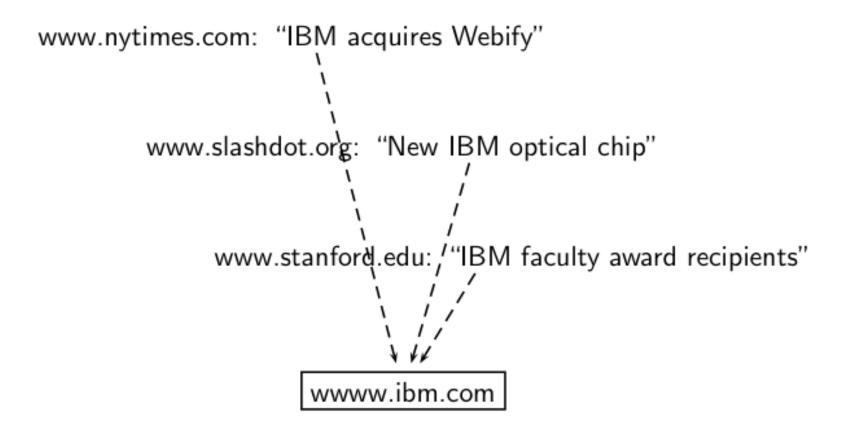


- A hyperlink is a quality signal.
  - The hyperlink  $d_1 \rightarrow d_2$  indicates that  $d_1$ 's author deems  $d_2$  high-quality and relevant.
- The anchor text describes the content of  $d_2$ .
  - We use anchor text somewhat loosely here for: the text surrounding the hyperlink.
  - Example: "You can find cheap cars <a href =http://...>here </a >. "
  - Anchor text: "You can find cheap here"

#### [text of $d_2$ ] only vs. [text of $d_2$ ] + [anchor text $\rightarrow d_2$ ]

- Searching on [text of  $d_2$ ] + [anchor text  $\rightarrow d_2$ ] is often more effective than searching on [text of  $d_2$ ] only.
- Example: Query Bing
  - Matches Bing's Legal page
  - Matches many spam pages
  - Matches Bing's wikipedia article
  - May not match Bing home page!
  - ... if Bing home page is mostly graphics
- Searching on [anchor text  $\rightarrow d_2$ ] is better for the query *Bing*.
  - In this representation, the page with most occurrences of Bing is www.bing.com

#### Anchor text containing IBM pointing to www.ibm.com

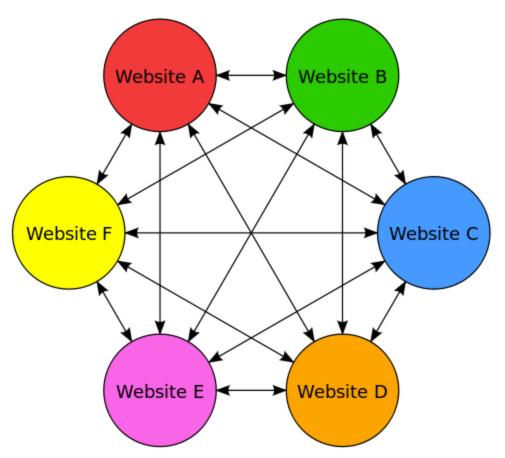


#### **Exercise: Assumptions**

- Assumption 1: A link on the web is a quality signal the author of the link thinks that the linked-to page is highquality.
- Assumption 2: The anchor text describes the content of the linked-to page.
- Is assumption 1 true in general?
- Is assumption 2 true in general?

#### Link Farm

A form of spamming trying to increasing the PageRank of member pages



### Google bombs

 A Google bomb is a search with "bad" results due to maliciously manipulated anchor text.

 Google introduced a new weighting function in January 2007 that fixed many Google bombs.

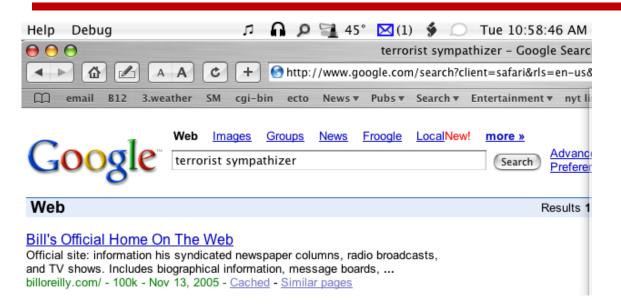
### Google bombs

Coordinated link creation by those who dislike

George W. Bush



### More Google bombs



#### murder

About 212,000,000 results (0.17 seconds)

#### ► Murder - Wikipedia, the free encyclopedia ☆ 🥄

Murder is the unlawful killing of another human being with "malice aforethought", an generally this state of mind distinguishes murder from other forms of ...

Murder (United States law) - Murder in English law - Murder (Canadian law)
en.wikipedia.org/wiki/Murder - Cached - Similar

#### Abortion - Wikipedia, the free encyclopedia chick

Generally, the former position argues that a human fetus is a human being ... United States - Methods of abortion - Abortion by country - Abortion law en.wikipedia.org/wiki/Abortion - Cached - Similar

♣ Show more results from wikipedia.org

### Origins of PageRank: Citation analysis

Citation analysis: analysis of citations in the scientific literature

 PageRank was invented in the context of citation analysis by Pinsker and Narin in the 1960s

Weighted citation frequency

### Question

 How to measure the similarities between webpages just based on the link structure?

Measure the similarity of two pages by the overlap of other pages linking to them

Google's "find pages like this" or "Similar" feature

### Origins of PageRank: Summary

- We can use the same formal representation for
  - hyperlinks on the web
  - citations in the scientific literature
  - social networks

• • •