

# PageRank

Introduction to Network Science

Carlos Castillo

Topic 10

# Sources

- Networks, Crowds, and Markets Ch 14
- Fei Li's lecture on PageRank
- Evimaria Terzi's lecture on link analysis.
- C. Castillo: Link-based ranking slides 2016

# Backrub!

Part of a research project that started in 1995 ...



Search The Web (type only necessary words):

10 results

clustering on

Search

Current Repository Size: ~25 million pages (searchable index slightly smaller)

## [Research Papers about Google and the WebBase](#)

## Credits

Current Development: [Sergey Brin](#) and [Larry Page](#)

Design and Implementation Assistance: [Scott Hassan](#) and [Alan Sterenberg](#)

Faculty Guidance: [Hector Garcia-Molina](#), [Rajeev Motwani](#), [Jeffrey D. Ullman](#), and [Terry Winograd](#)

Equipment Donations: [IBM](#), [Intel](#), and [Sun](#)

Software: [GNU](#), [Linux](#), and [Python](#)

Collaborating Groups in the [Computer Science Department](#) at [Stanford University](#): [The Digital Libraries Project](#), [The Project on People Computers and Design](#), [The Database Group](#), [The MIDAS Data Mining Group](#), and [The Theory Division](#)

Outside Collaborators: [Interval Research Corporation](#) and the [IBM Almaden Research Center](#)

Technical Assistance: [The Computer Science Department's Computer Facilities Group](#), [Stanford's Distributed Computing](#) and [Intra-Networking Systems Group](#)

Note: Google is research in progress and there are only a few of us so expect some downtimes and malfunctions. This system used to be called Backrub.

New! Wonder what your search runs on? Here are some [pictures and stats](#) for the Google Hardware.

1. This new index contains only a very limited number of international pages because we do not want to congest busy international links.
2. When no documents match your query, the system will return 20000 random web pages.
3. For improved speed, try to avoid common words unless they are necessary, and use as few search terms as possible.

Before emailing a question please read the [FAQ](#). Thanks! We can be reached at [google@google.stanford.edu](mailto:google@google.stanford.edu) and we appreciate your comments.

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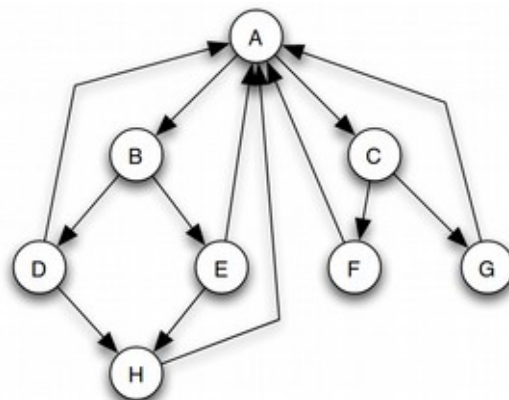
A multi-line list sourced from MailList.org

# PageRank

- *The pagerank citation algorithm: bringing order to the web by L Page, S Brin, R Motwani, T Winograd - 7th World Wide Web Conference, 1998 [[link](#)].*
- A very good starting point, but not the end of web ranking!
  - Today, it's unlikely to be a top feature

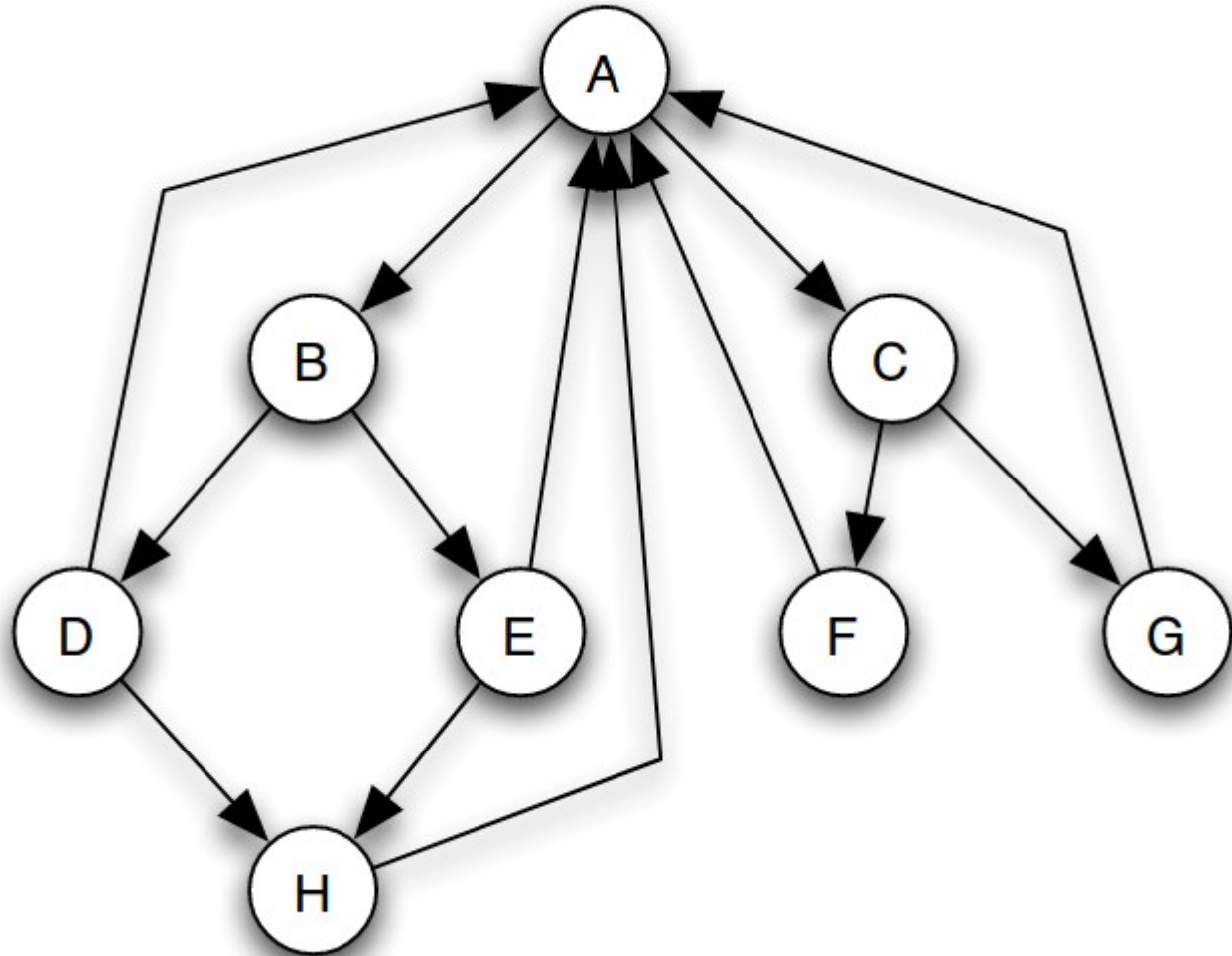
# (Simplified) PageRank

- All nodes start with score  $1/N$
- Repeat  $t$  times:
  - Divide equally and “send” its score to out-links
  - Add received scores

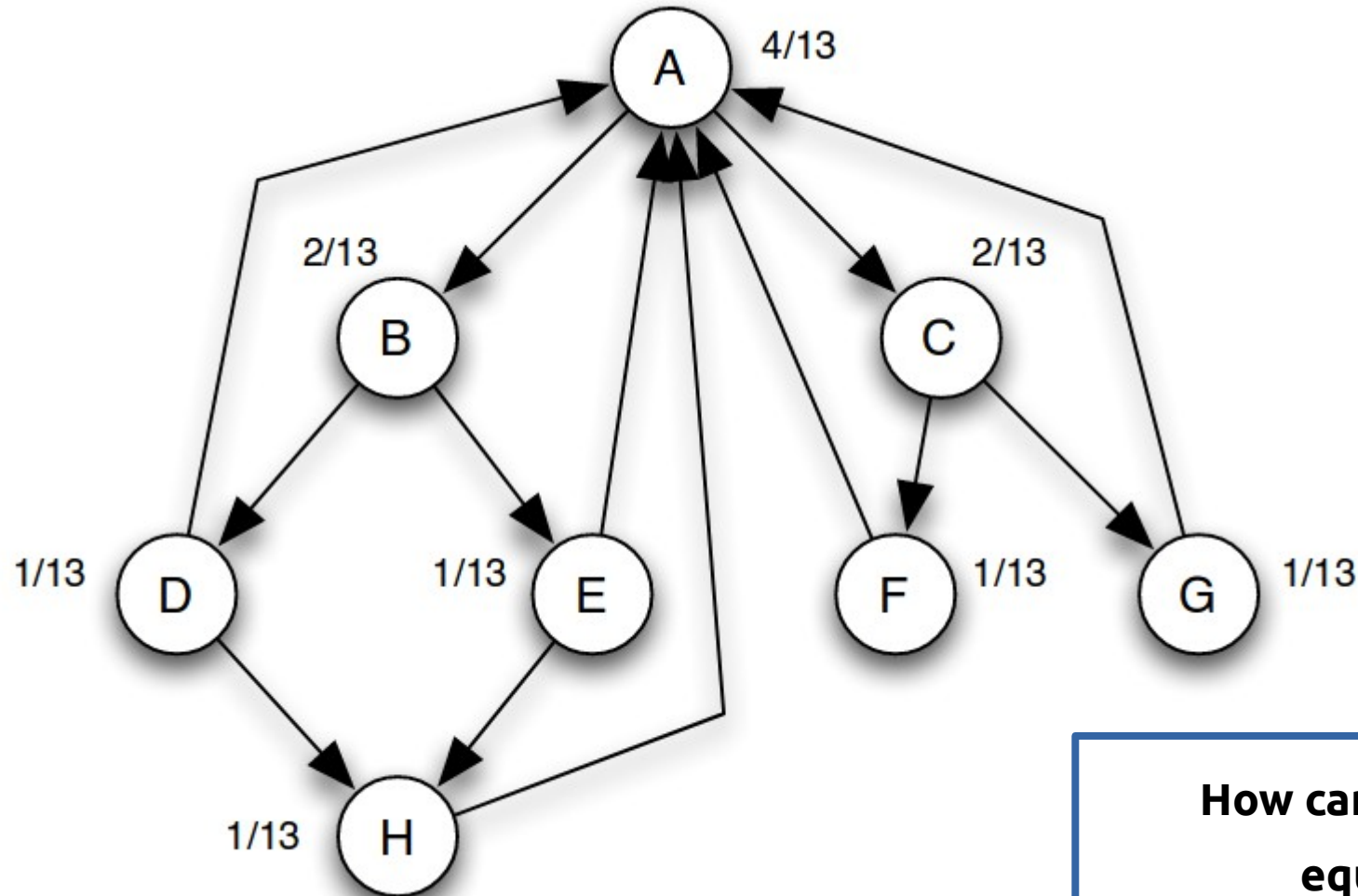


## Execute simplified PageRank:

- All nodes start with score  $1/N$
- Repeat  $t$  times:
  - Divide equally and “send” its score to out-links
  - Add received scores
- Keep intermediate values in a table
- Try to arrive to equilibrium values



# Equilibrium values



**How can you prove these are  
equilibrium values?**



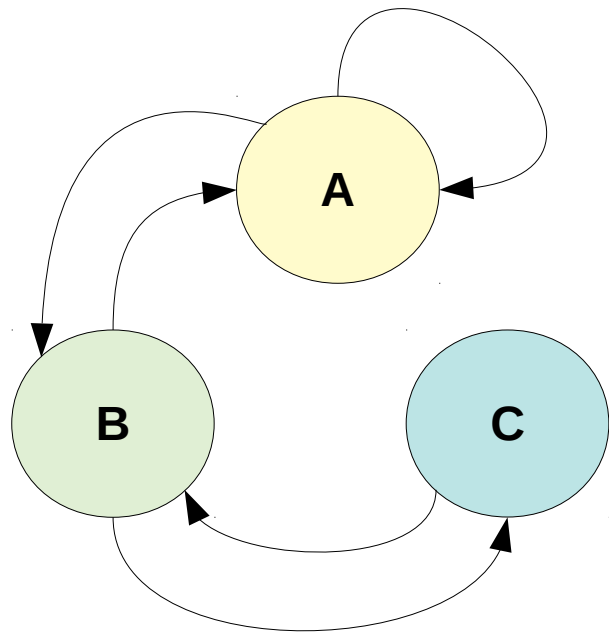
# (Simplified) PageRank

$$P_i = c \sum_{j \rightarrow i} \frac{P_j}{k_j^{\text{out}}}$$

- $k_j^{\text{out}}$  is the number of out-links of page  $j$
- $c$  is a normalization factor to ensure

$$\|P\|_{L1} = |P_1 + \dots + P_N| = 1$$

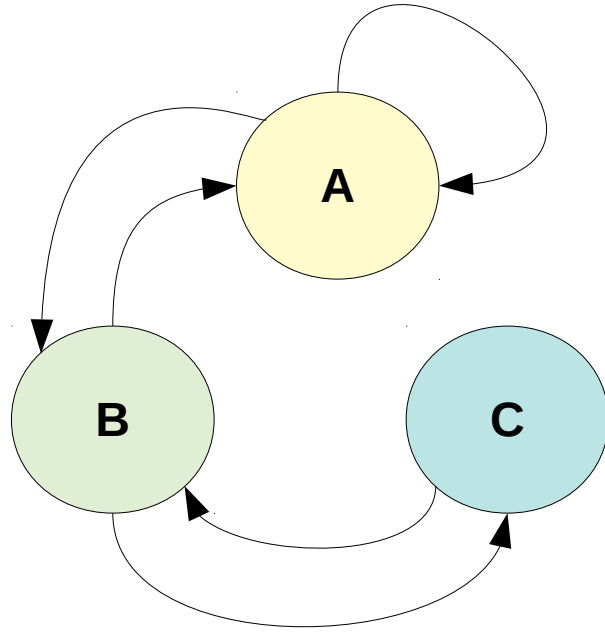
# Running simplified PageRank on a graph



$$M = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \quad \text{Adjacency matrix}$$

$$\hat{M} = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 1/2 \\ 0 & 1 & 0 \end{bmatrix} \quad \text{Row-stochastic adjacency matrix}$$

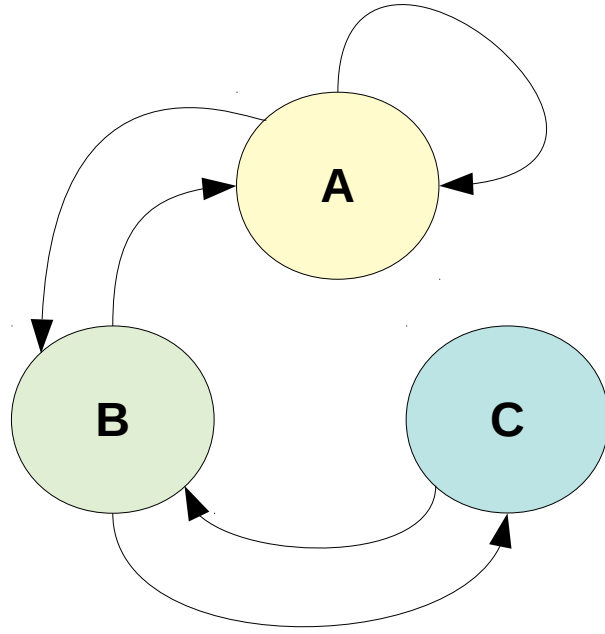
# Another example of Simplified PageRank



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

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

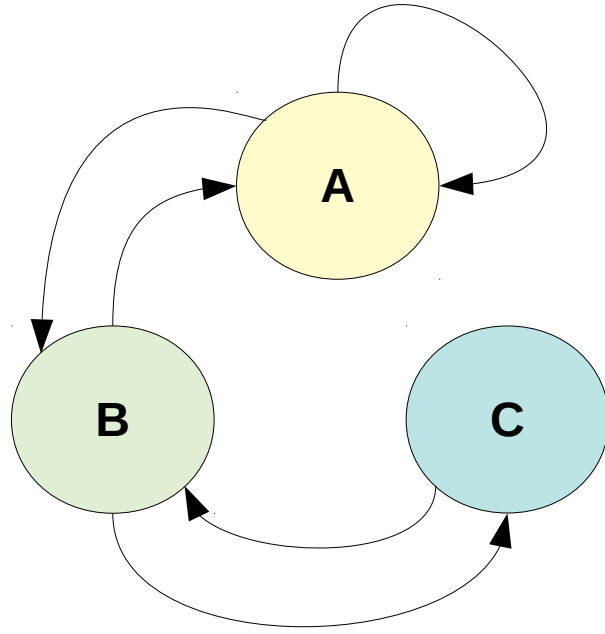
# Another example of Simplified PageRank



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

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

# Another example of Simplified PageRank



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

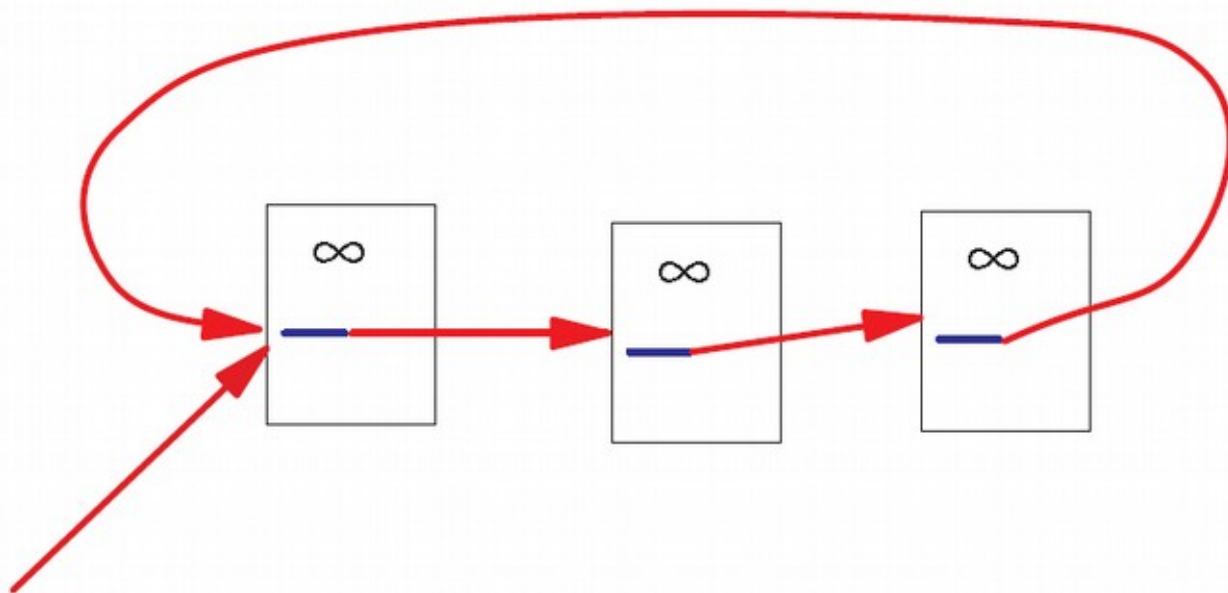
$$\begin{bmatrix} 3/8 \\ 11/24 \\ 1/6 \end{bmatrix} \begin{bmatrix} 5/12 \\ 17/48 \\ 11/48 \end{bmatrix} \dots$$

$$\boxed{\begin{bmatrix} 2/5 \\ 2/5 \\ 1/5 \end{bmatrix}}$$

Final score

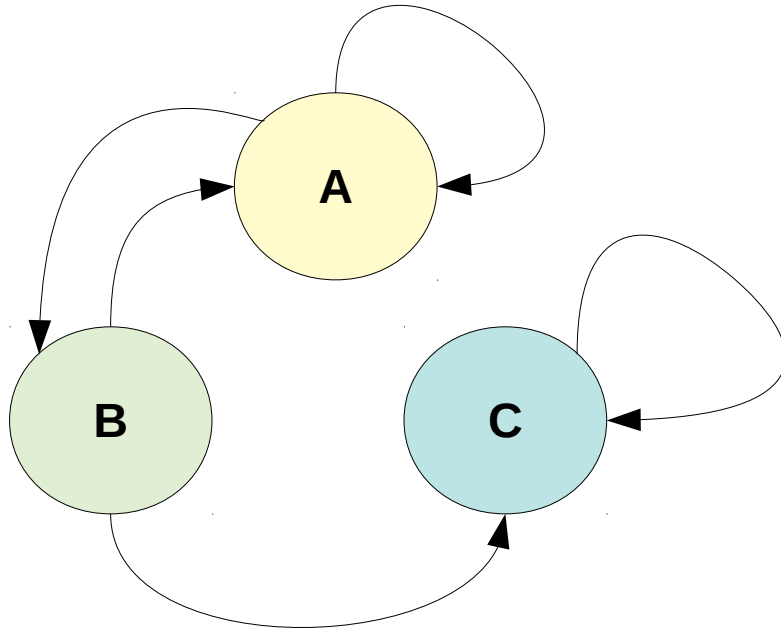
# A Problem with Simplified PageRank

A loop:



During each iteration, the loop accumulates score but never distributes score to other pages!

# Example of the problem ...

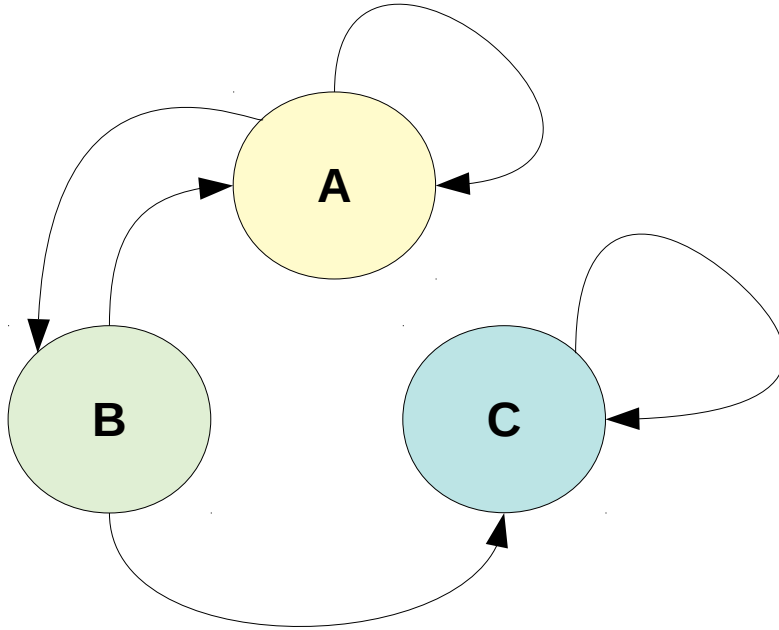


$$\hat{M}^T = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 0 \\ 0 & 1/2 & 1 \end{bmatrix}^*$$

First iteration of calculation:

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

# Example of the problem ...



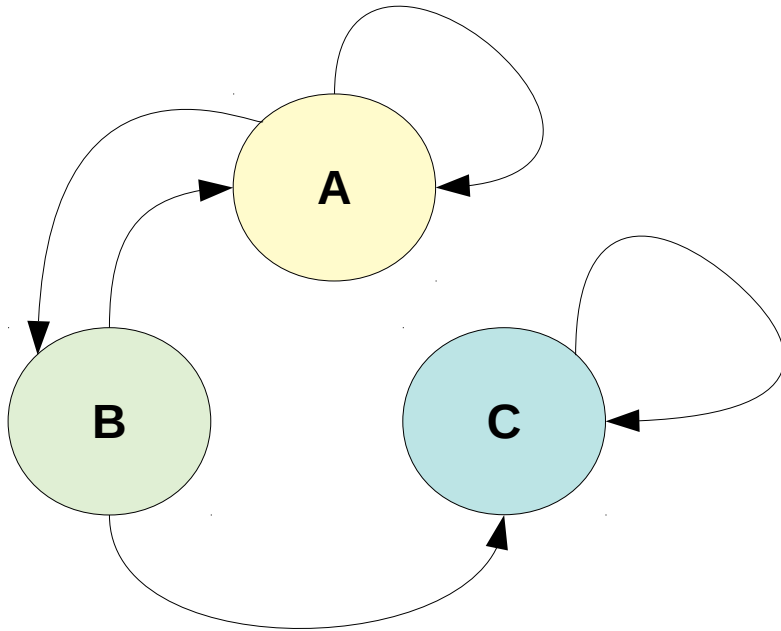
$$\hat{M}^T = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 0 \\ 0 & 1/2 & 1 \end{bmatrix}^*$$

Second iteration:

$$\begin{bmatrix} 1/4 \\ 1/6 \\ 7/12 \end{bmatrix} = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 0 \\ 0 & 1/2 & 1 \end{bmatrix} \begin{bmatrix} 1/3 \\ 1/6 \\ 1/2 \end{bmatrix}^*$$



# Example of the problem ...



$$\hat{M}^T = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 0 \\ 0 & 1/2 & 1 \end{bmatrix}^*$$

$$\begin{bmatrix} 5/24 \\ 1/8 \\ 2/3 \end{bmatrix}$$

$$\begin{bmatrix} 1/6 \\ 5/48 \\ 35/48 \end{bmatrix}$$

....

$$\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

The winner  
takes all!

# What are we computing?

$$p^t = Ap^{t-1}$$

after convergence :  $p = Ap$

A is the transposed row-stochastic adjacency matrix

What is p?

How do you call this method to compute p?

# What are we computing?

$$p^t = Ap^{t-1}$$

after convergence :  $p = Ap$

- This will converge if A is:
  - Stochastic (each row adds up to one)
  - Irreducible (represents a strongly connected graph)
  - Aperiodic (does not represent a bipartite graph)

# Markov Chain

- Discrete process over a set of **states**
- Next state computed from **current state** only (no memory of older states)
  - Higher-order Markov chains can be defined
- Stationary distribution of Markov chain is a probability distribution such that  $p = Ap$
- Intuitively,  $p$  represents “the average time spent” at each node if the process continues forever

# Random Walks in Graphs

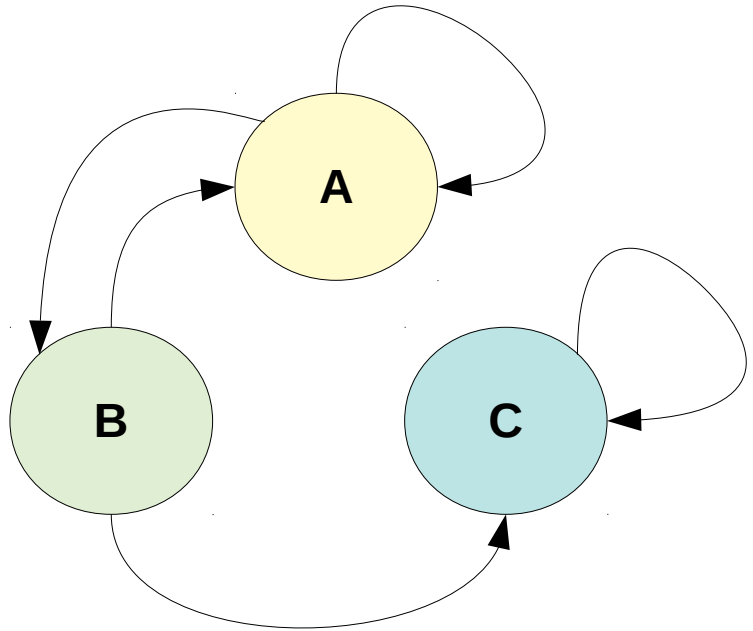
- Random Surfer Model
  - The simplified model: the standing probability distribution of a random walk on the graph of the web. simply keeps clicking successive links at random
- Modified Random Surfer
  - The modified model: the “random surfer” simply keeps clicking successive links at random, but periodically “gets bored” and jumps to a random page based on a distribution  $R$  (e.g., uniform)
  - This guarantees **irreducibility**
  - Pages without out-links (dangling nodes) are a row of zeros, can be replaced by  $R$ , or by a row of  $1/N$

# PageRank

$$P_i = \alpha \sum_{j \rightarrow i} \frac{P_j}{k_j^{\text{out}}} + (1 - \alpha)R(i)$$

$R(i)$ : web pages that “users” jump to when they “get bored”;  
Uniform preferences  $\Rightarrow R(i) = 1/N$

# An example of PageRank $\alpha = 0.8$



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

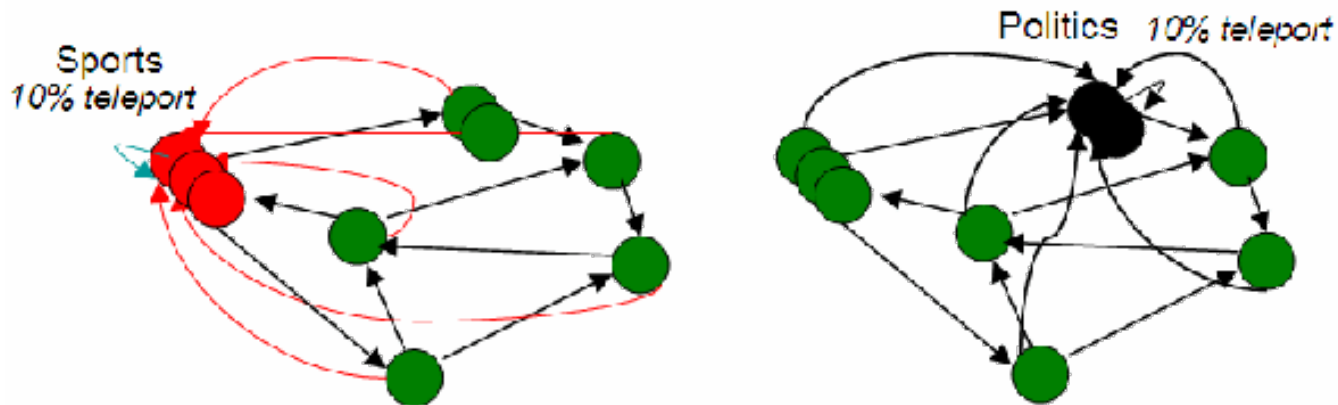
$$\alpha \hat{M}^T + (1 - \alpha)R = 0.8 \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 0 \\ 0 & 1/2 & 1 \end{bmatrix} + 0.2 \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \end{bmatrix}$$

$$\begin{bmatrix} 0.333 \\ 0.333 \\ 0.333 \end{bmatrix} \quad \begin{bmatrix} 0.333 \\ 0.200 \\ 0.467 \end{bmatrix} \quad \begin{bmatrix} 0.280 \\ 0.200 \\ 0.520 \end{bmatrix} \quad \begin{bmatrix} 0.259 \\ 0.179 \\ 0.563 \end{bmatrix} \quad \dots \quad \boxed{\begin{bmatrix} 7/33 \\ 5/33 \\ 21/33 \end{bmatrix}}$$

Was:  $\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$

# Variant: personalized PageRank

- Modify  $R(i)$  according to users' tastes (e.g. user interested in sports vs politics)





# PageRank and internal linking

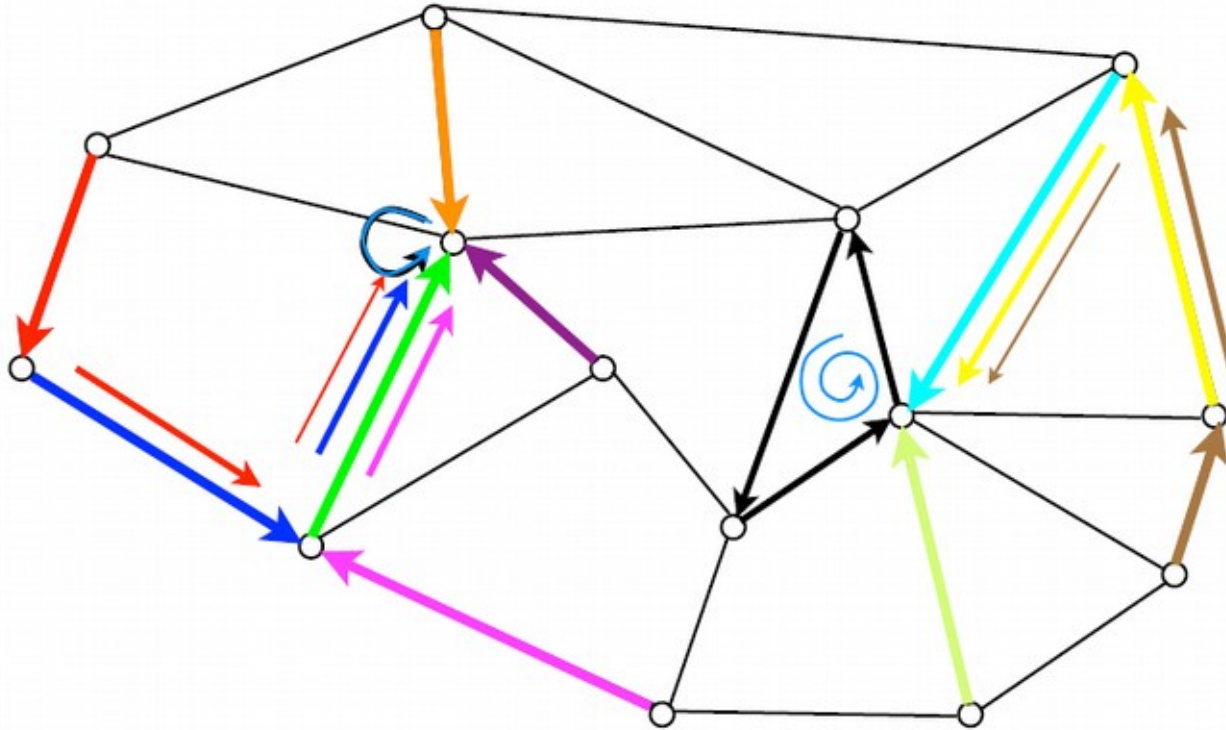
- A website has a maximum amount of Page Rank that is distributed between its pages by internal links [depends on internal links]
- The maximum amount of Page Rank in a site increases as the number of pages in the site increases.
- By linking poorly, it is possible to fail to reach the site's maximum Page Rank, but it is not possible to exceed it.

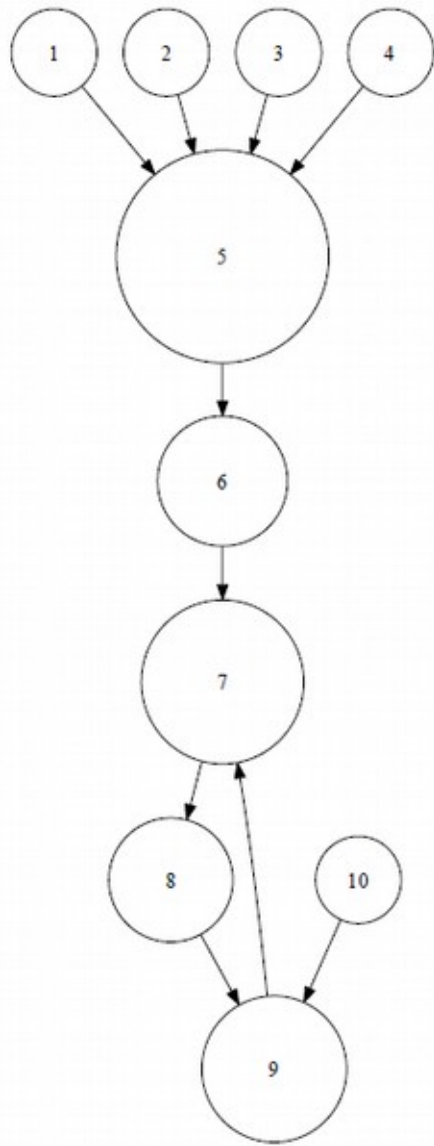
# Liquid democracy

# PageRank as a form of actual voting (liquid democracy)

- If  $\alpha = 1$ , we can implement liquid democracy
  - In liquid democracy, people chose to either vote or to delegate their vote to somebody else
- If  $\alpha < 1$ , we have a sort of “viscous” democracy where delegation is not total

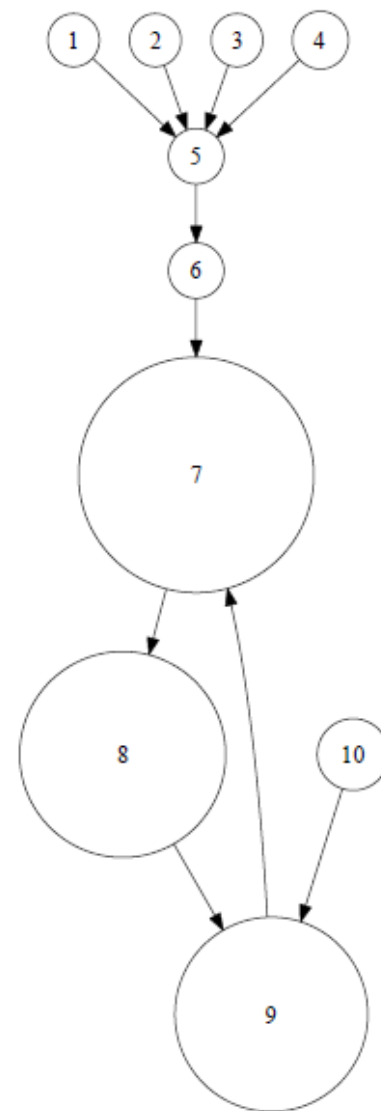
# PageRank as a form of liquid democracy





These two graphs  
have different alpha  
(0.2 and 0.9)

Which one is  
which?



# PageRank Implementation

- Suppose there are  $n$  pages and  $m$  links
- Trivial implementation of PageRank requires  $O(M+N)$  memory
- **Streaming** implementation requires  $O(N)$  memory ... *how?*
  - Streaming: graph is never held on memory