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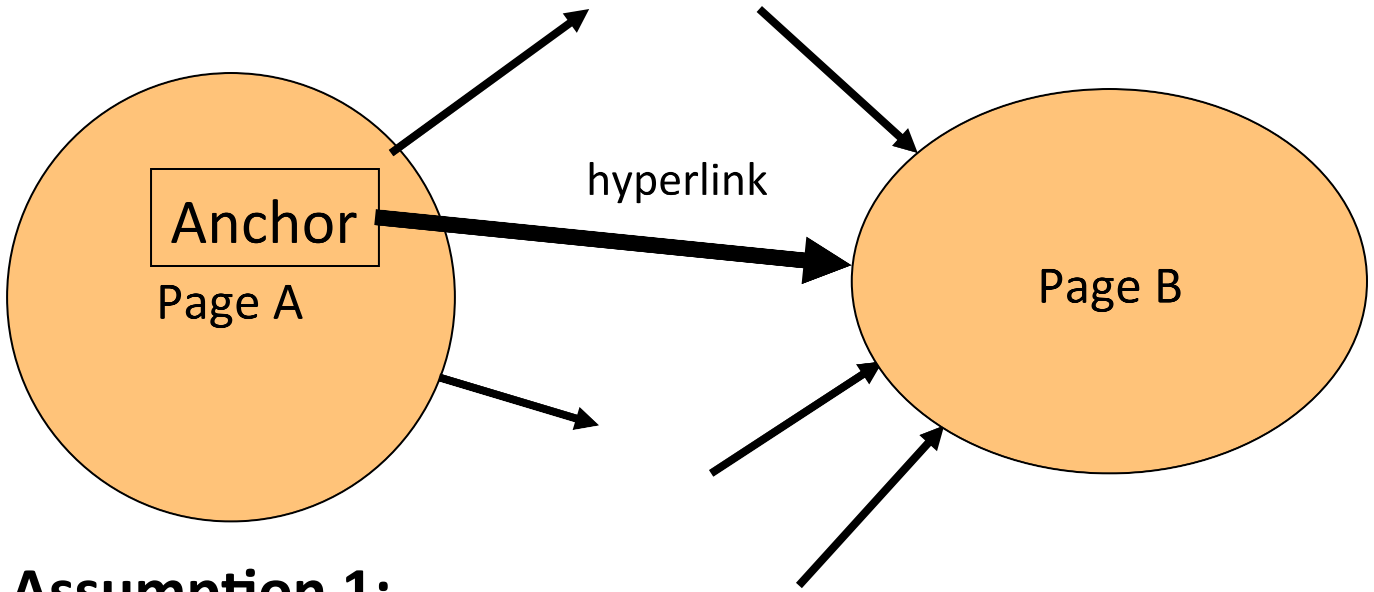
# Networks and Link Analysis

## Web Anchor Text

# The Web as a Directed Graph




**Assumption 1:**

A hyperlink between pages denotes author perceived relevance (quality signal)

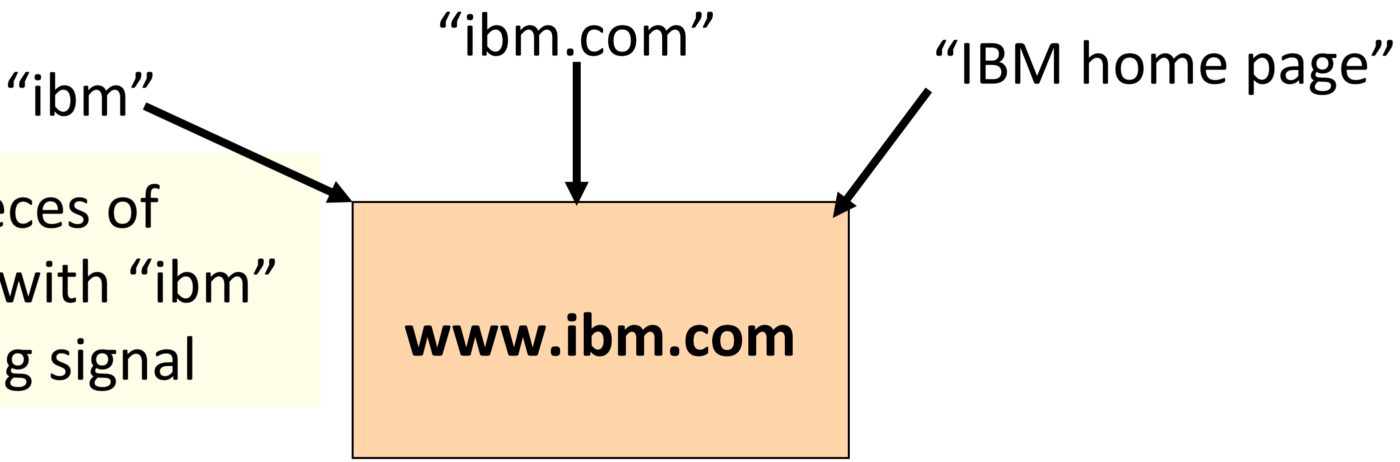
**Assumption 2:**

The anchor of the hyperlink describes the target page (textual context)

# Anchor Text

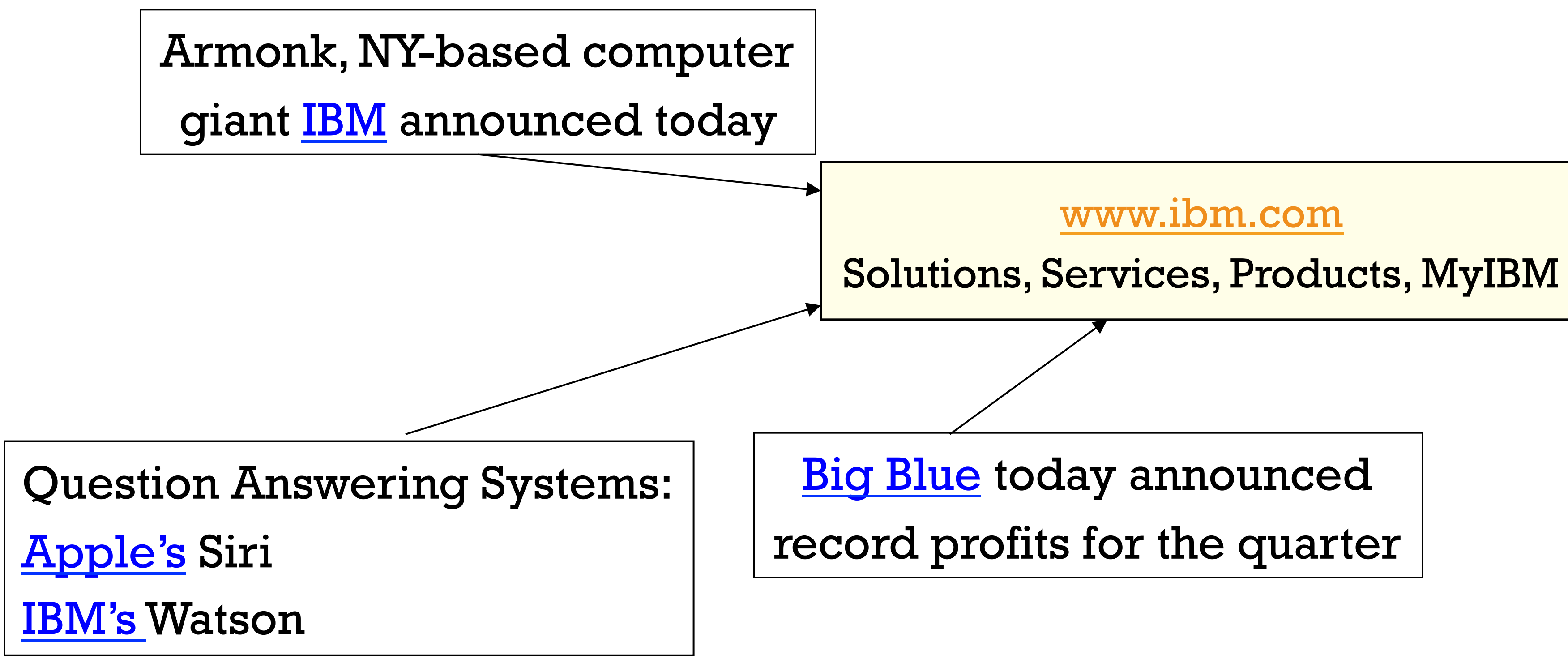
- For ***ibm*** how to distinguish between:
  - IBM's home page (mostly graphical)
  - IBM's copyright page (high term frequency for "ibm")
  - Rival's spam page (arbitrarily high term frequency)

A million pieces of anchor text with "ibm" send a strong signal



# Indexing anchor text

When indexing a document *D*, include anchor text from links pointing to *D*.



# Indexing anchor text

- Can sometimes have unexpected side effects –
  - Google bombing
- Can score anchor text with weight depending on the authority of the anchor page's website
  - E.g., if we were to assume that content from cnn.com or yahoo.com is authoritative, then trust the anchor text from them

# Many NLP Applications of Anchor Text

- Finding synonyms
  - Federal Reserve: “Fed”, “U.S. Federal Reserve Board", “U.S. Federal Reserve System”, “Federal Reserve Bank”
- Finding translations of named entities
- Providing constituent boundaries for parsers


# Networks and Link Analysis

## Web Anchor Text


# Networks and Link Analysis

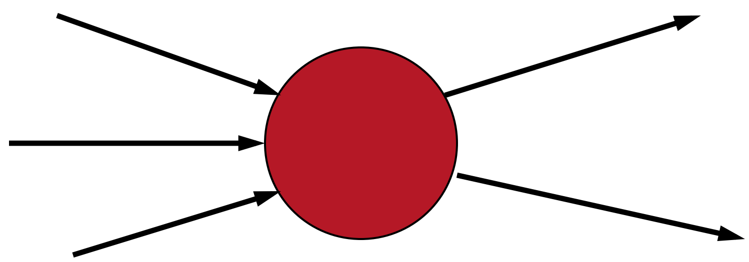
## PageRank: Overview and Markov Chains

# Combining link structure with text

- A good search result looks at more than just query-document text overlap
- One factor: page **popularity**.
  - Pages that are pointed to by lots of other pages are popular.
  - We can use link counts as a measure of static goodness,
  - Combine link counts with the text match score

# Using link structure to measure page importance

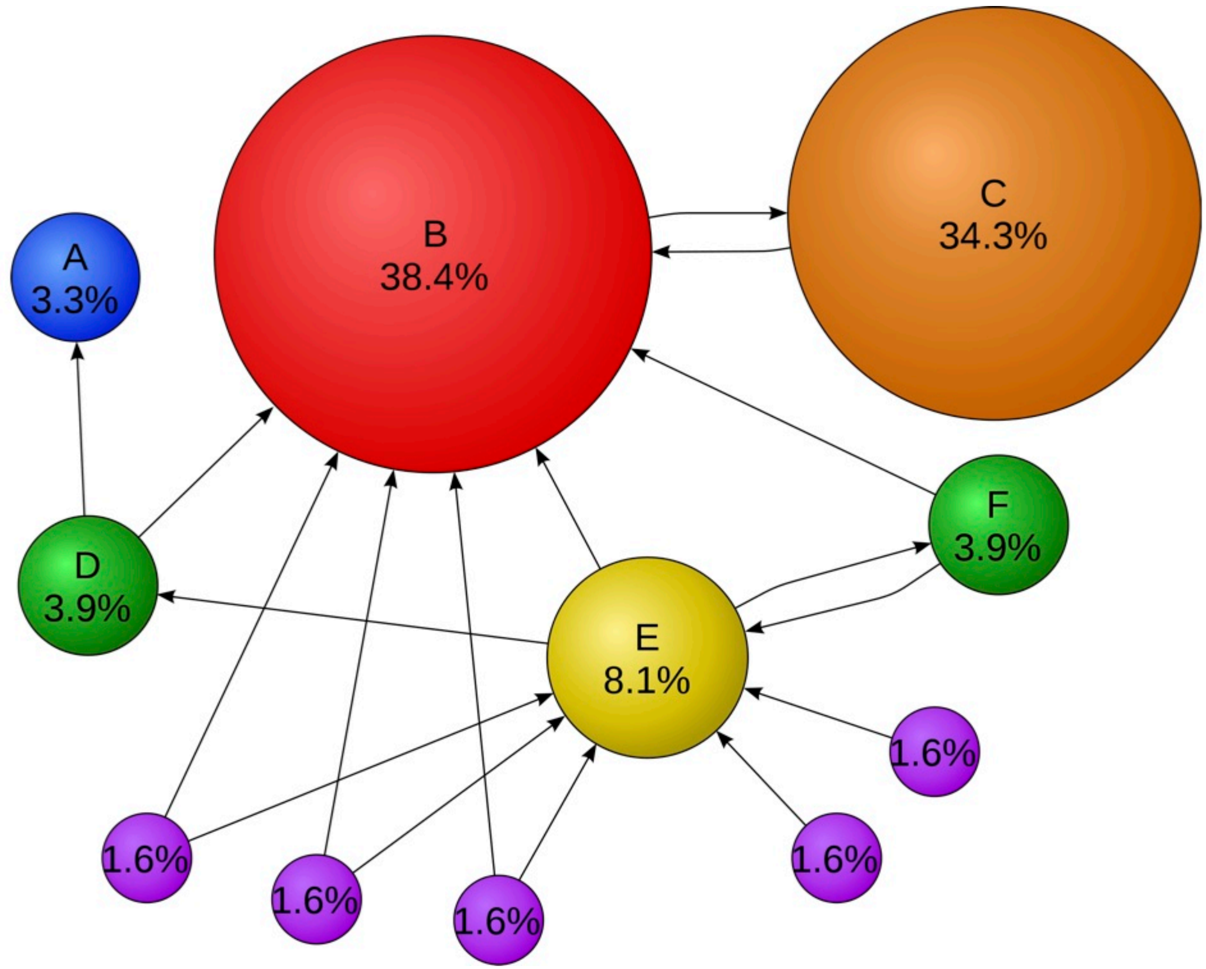
- Simplest: use link counts as popularity measure
  - **Undirected popularity**:
    - Page score= **degree**: the number of in-links plus the number of out-links (3+2=5).
  - **Directed popularity**:
    - Page score = number of in-links (3).



# Spamming simple popularity

- Simple popularity heuristics can be spammed to give your page a high score, whether it's:
  - the number of in-links plus the number of out-links
  - number of in-links

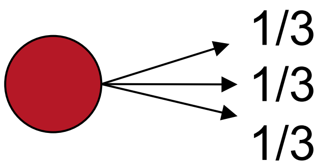
# Intuition of PageRank




C has higher PageRank than E, even though E has more inlinks

# PageRank scoring

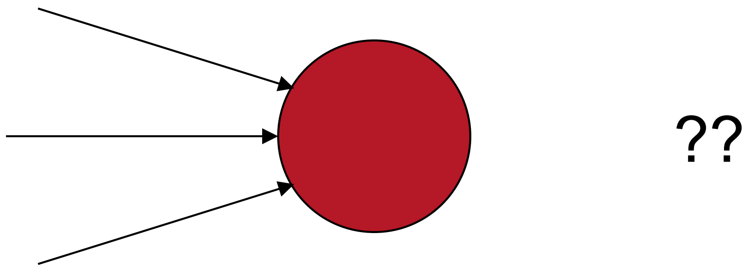
- Imagine a browser doing a random walk on web pages:




  - Start at a random page
  - At each step, go out of the current page along one of the links on that page, equiprobably
- “In the steady state” each page has a long-term visit rate - use this as the page’s score.

# Not quite enough

- The web is full of dead-ends.
  - Random walk can get stuck in dead-ends.
  - Makes no sense to talk about long-term visit rates.



# Teleporting

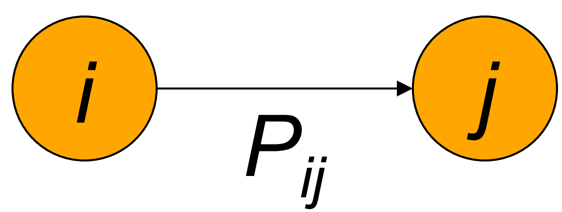
- At a dead end, jump to a random web page.
- At any non-dead end, with probability 10%, jump to a random web page.
  - With remaining probability (90%), go out on a random link.
  - 10% - a parameter.

# Result of teleporting

- Now cannot get stuck locally.
- There is a long-term rate, the Pagerank, at which any page is visited

# Markov chains

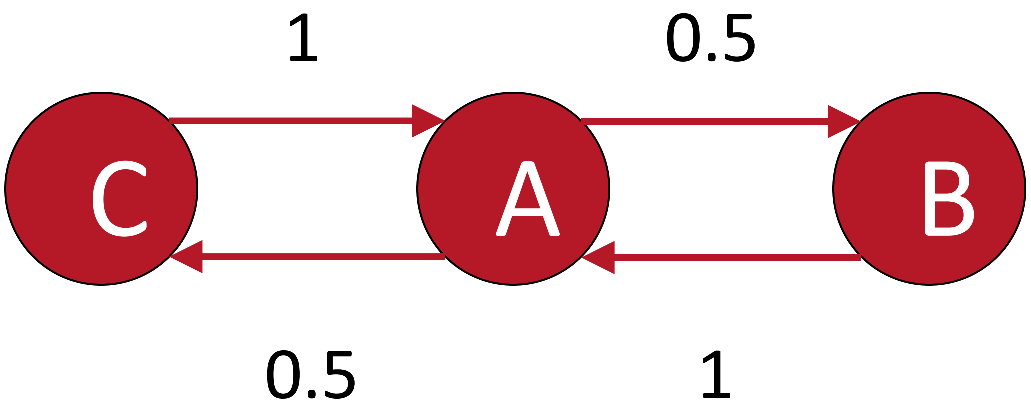
- A Markov chain:
  - *N* states,
  - *An N*×*N* transition probability matrix **P**.
- At each step, we are in exactly one of the states.
- For $1 \leq i,j \leq n$, the matrix entry $P_{ij}$ tells us the probability of *j* being the next state, given we are currently in state *i*.




- For all i,

$$\sum_{j=1}^{n} P_{ij} = 1.$$

# Markov chains




- Transition probability matrix P

$$P = \begin{pmatrix} 0 & 0.5 & 0.5 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}$$

# Random Surfers and Markov chains

- Markov chains are abstractions of random walks.
- Each state
  - represents one web page
- Each transition probability
  - represents the probability of moving from one page to another
- We can derive the transition probability P from the adjacency matrix A of the web graph.

# Teleporting, more formally

- If a node has no out-links, the random surfer teleports:
  - the transition probability to each node in the N-node graph is 1/N
- If a node has K>0 outgoing links:
  - with probability $0 < \alpha < 1$ the surfer teleports to a random node
    - probability is $\alpha/N$
  - with probability $1- \alpha$ the surfer takes a normal random walk
    - probability is $(1- \alpha)/K$

# Deriving transition probability matrix P from adjacency matrix A

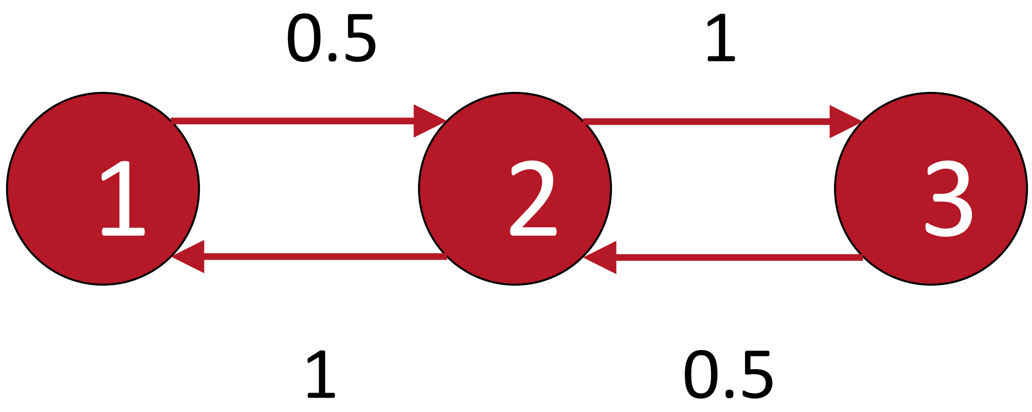
- A is the adjacency matrix of the web graph
  - $A_{ij}$ is 1 if there is a hyperlink from page *i* to page *j*

- If a row of A has no 1's, then replace each element by 1/N.

For all other rows proceed as follows.

- Divide each 1 in A by the number of 1's in its row. Thus, if there is a row with three 1's, then each of them is replaced by 1/3
- Multiply the resulting matrix by $(1-\alpha)$
- Add $\alpha/N$ to every entry of the resulting matrix, to obtain P.

# Computing P with teleportation




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

P[1,*] = (1-α) (0 1 0) + α (1/N 1/N 1/N)

P[1,*] = 0.5 (0 1 0) + 0.5(1/3 1/3 1/3)

$$P_{\alpha=0} = \begin{pmatrix} 0 & 1 & 0 \\ 0.5 & 0 & 0.5 \\ 0 & 1 & 0 \end{pmatrix}$$

$$P_{\alpha=0.5} = \begin{pmatrix} 1/6 & 2/3 & 1/6 \\ 5/12 & 1/6 & 5/12 \\ 1/6 & 2/3 & 1/6 \end{pmatrix}$$


# Networks and Link Analysis

## PageRank: Overview and Markov Chains


# Networks and Link Analysis

## PageRank: Computation

# Computing PageRank: The probability of being in a state

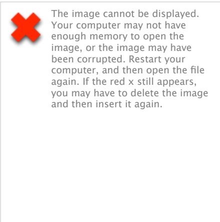
- A probability (row) vector $\mathbf{x} = (x_1, \ldots x_n)$ tells us where the walk is at any point.
- E.g., $(\underset{1}{0}00\ldots\underset{i}{1}\ldots00\underset{n}{0})$ means we're in state *i*.

More generally, the vector $\mathbf{x} = (x_1, \ldots x_n)$ means the walk is in state *i* with probability $x_i$.

$$\sum_{i=1}^{n} x_i = 1$$

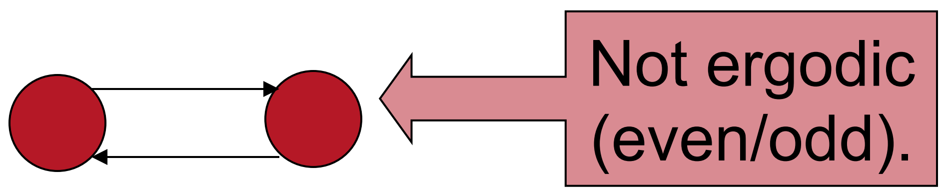
# Computing PageRank: Change in probability vector

- If the probability vector is $\mathbf{x} = (x_1, \ldots x_n)$ at this step, what is it at the next step?
- Recall that row *i* of transition matrix P tells us where we go next from state *i*.
- So from **x**, our next state is distributed as **xP**.



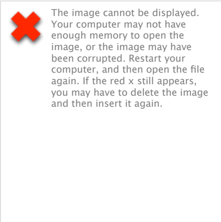

# Ergodic Markov chains

- A Markov chain is ergodic if
  - you have a path from any state to any other
  - For any start state, after a finite transient time $T_0$, the probability of being in any state at a fixed time $T>T_0$ is nonzero.



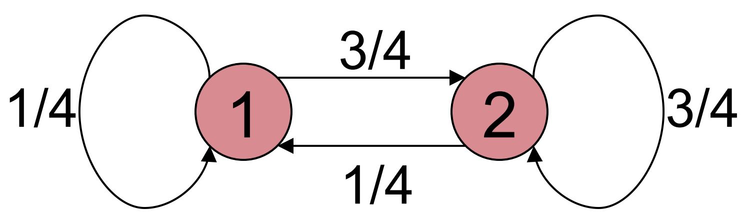
# Ergodic Markov chains

- For any ergodic Markov chain, there is a unique long-term visit rate for each state.
  - A steady-state probability distribution $\boldsymbol{\pi} = (\boldsymbol{\pi}_1, \ldots \boldsymbol{\pi}_n)$.
  - Over a long time-period, we visit each state in proportion to this rate.
  - Thus $\boldsymbol{\pi}_i$ is the PageRank of state $i$.
- It doesn't matter where we start.

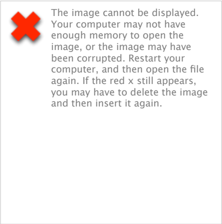



# Steady state example

- The steady state looks like a vector of probabilities $\boldsymbol{\pi} = (\boldsymbol{\pi}_1, \ldots \boldsymbol{\pi}_n)$:
  - $\boldsymbol{\pi}_i$ is the probability that we are in state *i*.

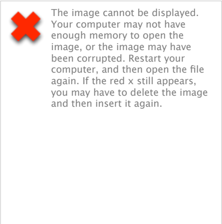



For this example, $\boldsymbol{\pi}_1 = 1/4$ and $\boldsymbol{\pi}_2 = 3/4$.



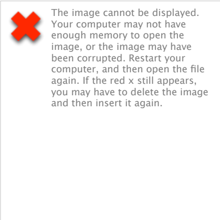

# How do we compute this vector?

- Let $\boldsymbol{\pi} = (\boldsymbol{\pi}_1, \ldots \boldsymbol{\pi}_n)$ denote the row vector of steady-state probabilities
- If our current position is described by $\boldsymbol{\pi}$, then the next step is distributed as $\boldsymbol{\pi}$**P**.
- But $\boldsymbol{\pi}$ is the steady state, so $\boldsymbol{\pi}$=$\boldsymbol{\pi}$**P**.
- Solving this matrix equation gives us $\boldsymbol{\pi}$.
  - So $\boldsymbol{\pi}$ is the (left) eigenvector for **P**.
  - (Corresponds to the "principal" eigenvector of **P** with the largest eigenvalue.)
  - Transition probability matrices always have largest eigenvalue 1.




# The power iteration method of computing $\pi$

- Recall, regardless of where we start, we eventually reach the steady state $\boldsymbol{\pi}$.
- Start with any distribution (say $\mathbf{x}=(10\ldots0)$).
- After one step, we're at $\mathbf{xP}$;
- after two steps at $\mathbf{xP}^2$ , then $\mathbf{xP}^3$ and so on.
- "Eventually" means for "large" $k$, $\mathbf{xP}^k = \boldsymbol{\pi}$.
- Algorithm: multiply $\mathbf{x}$ by increasing powers of $\mathbf{P}$ until the product looks stable.




# Example of power iteration

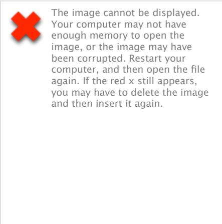
$$P_{\alpha=0.5} = \begin{pmatrix} 1/6 & 2/3 & 1/6 \\ 5/12 & 1/6 & 5/12 \\ 1/6 & 2/3 & 1/6 \end{pmatrix}$$

- Let's say surfer starts in state 1:

$$\vec{x}_0 = \begin{pmatrix} 1 & 0 & 0 \end{pmatrix}$$

$$\vec{x}_1 = \vec{x}_0 P = \begin{pmatrix} 1/6 & 2/3 & 1/6 \end{pmatrix}$$

$$\vec{x}_2 = \vec{x}_1 P = \begin{pmatrix} 1/6 & 2/3 & 1/6 \end{pmatrix} \begin{pmatrix} 1/6 & 2/3 & 1/6 \\ 5/12 & 1/6 & 5/12 \\ 1/6 & 2/3 & 1/6 \end{pmatrix} = \begin{pmatrix} 1/3 & 1/3 & 1/3 \end{pmatrix}$$




# Power iteration example (continued)

| | | | |
|---|---|---|---|
| $\vec{x}_0$ | 1 | 0 | 0 |
| $\vec{x}_1$ | 1/6 | 2/3 | 1/6 |
| $\vec{x}_2$ | 1/3 | 1/3 | 1/3 |
| $\vec{x}_3$ | 1/4 | 1/2 | 1/4 |
| $\vec{x}_4$ | 7/24 | 5/12 | 7/24 |
| … | … | … | … |
| $\vec{x} = \vec{\pi}$ | 5/18 | 4/9 | 5/18 |

Node 1 PageRank

Node 2 PageRank

Node 3 PageRank

# PageRank summary

- Preprocessing:
  - Given graph of links, build matrix **P**.
  - From it compute the PageRank vector $\boldsymbol{\pi}$.
  - The PageRank of page i, $\boldsymbol{\pi}_i$ is between 0 and 1
- Query processing:
  - Retrieve pages meeting query.
  - Rank them by their PageRank.
  - Order is query-*independent*.


# Networks and Link Analysis

## PageRank: Computation

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