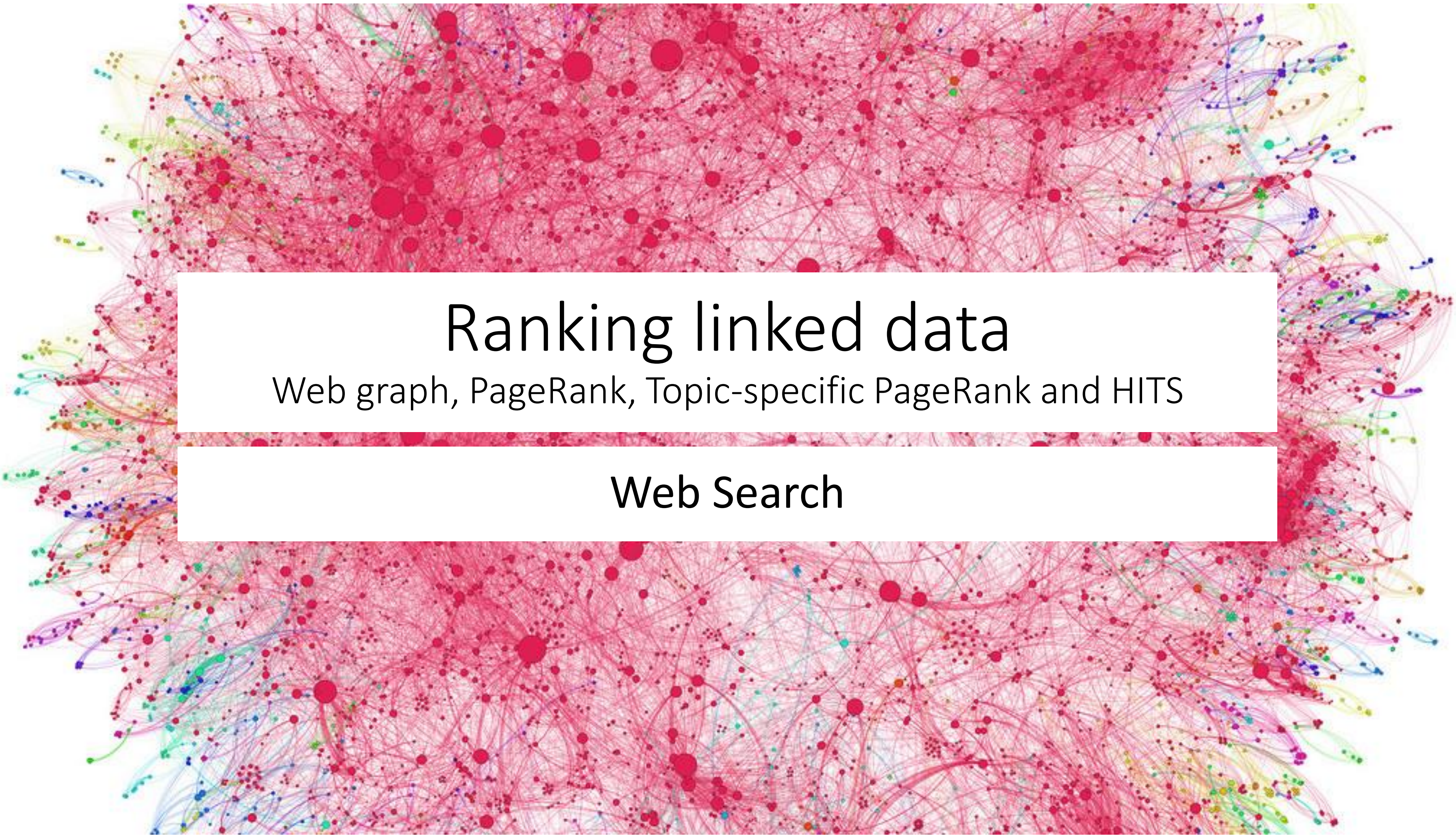
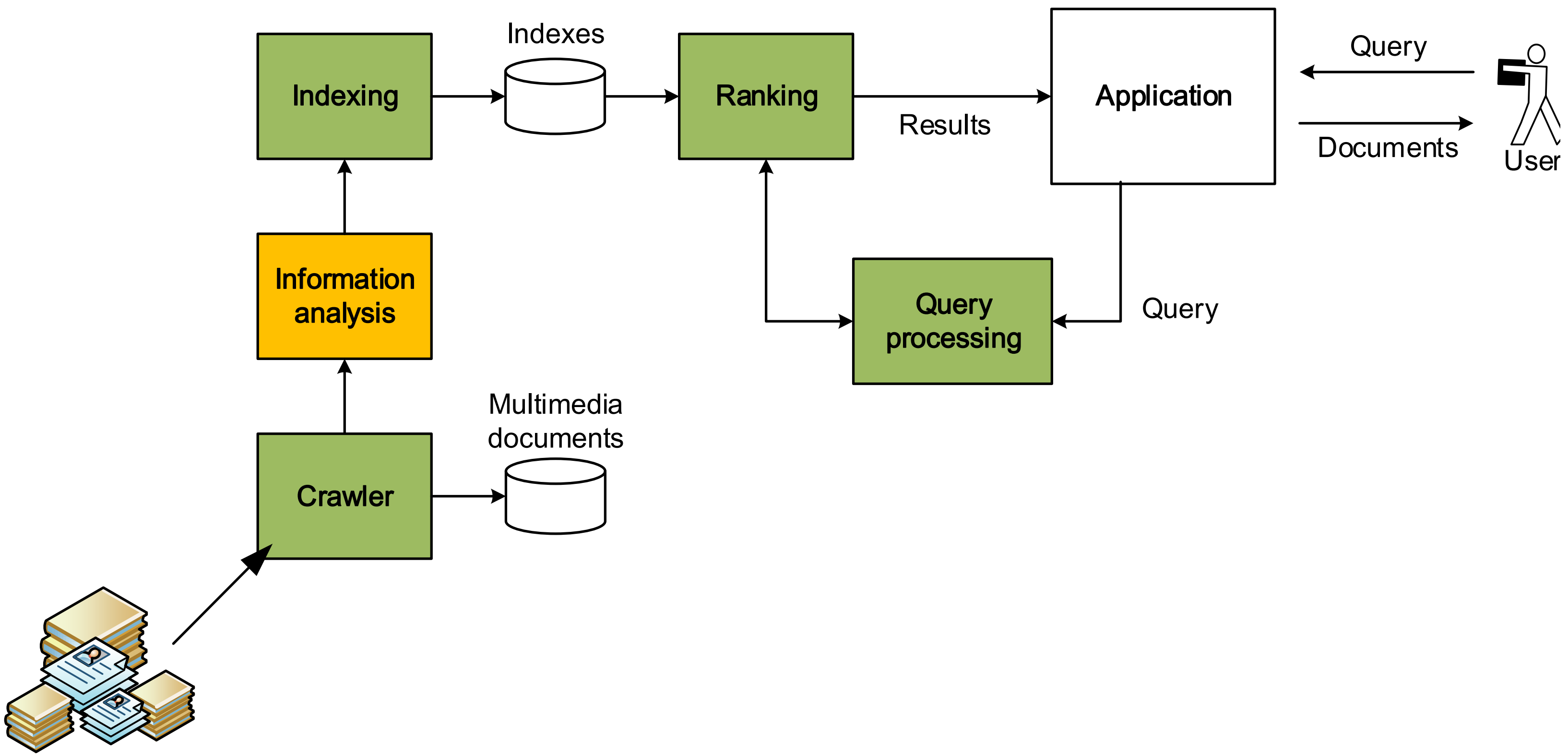


Ranking linked data

Web graph, PageRank, Topic-specific PageRank and HITS

Web Search

Overview



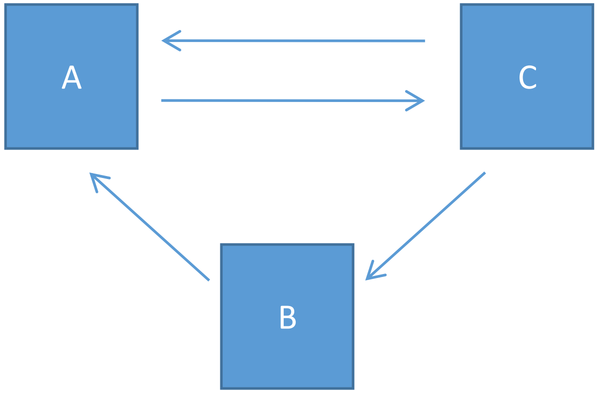
Indexing
Indexes
Ranking
Application
Query
Results
Documents
User
Information analysis
Query processing
Query
Multimedia documents
Crawler

Ranking linked data

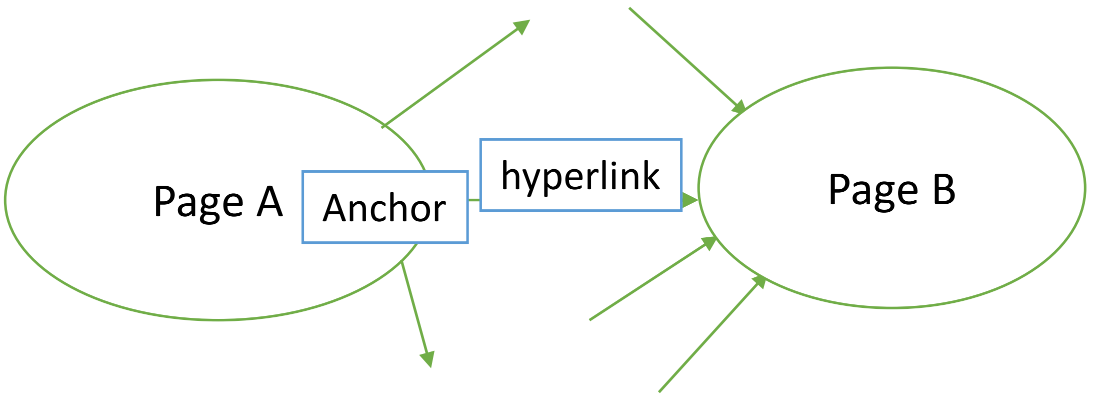
- Links are inserted by humans.

- **They are one of the most valuable judgments of a page's importance.**

- A link is inserted to denote an association. The anchor text describes the type of association.



The Web as a directed graph

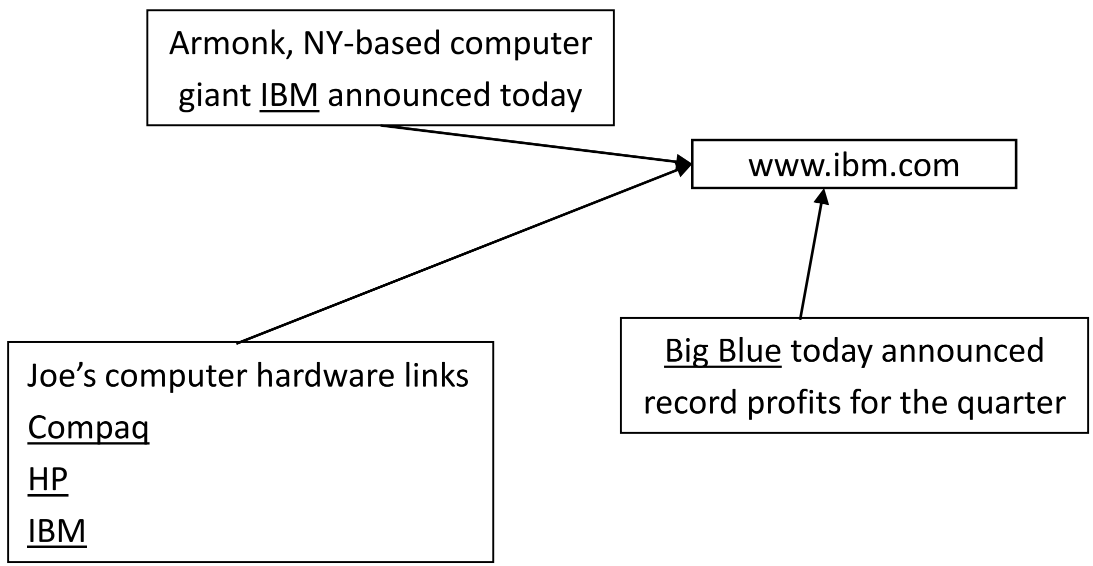


Assumption 1: A hyperlink between pages denotes author perceived relevance (quality signal)

Assumption 2: The anchor of the hyperlink describes the target page (textual context)

Anchor text

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



Indexing anchor text

- Can sometimes have unexpected side effects - *e.g., evil empire.*

- Can boost 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

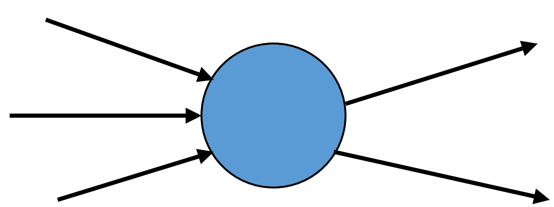
Citation analysis

- Citation frequency
- Co-citation coupling frequency
  - Co-citations with a given author measures “impact”
  - Co-citation analysis [Mcca90]
- Bibliographic coupling frequency
  - Articles that co-cite the same articles are related
- Citation indexing
  - Who is author cited by? [Garf72]
- PageRank preview: Pinsker and Narin ’60s

Incoming and outgoing links

- The popularity of a page is related to the number of incoming links
  - Positively popular
  - Negatively popular

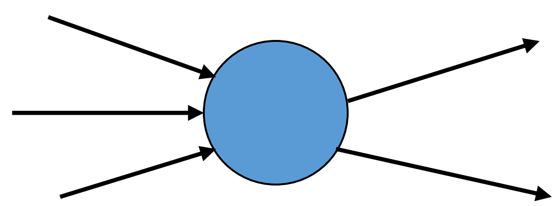
- The popularity of a page is related to the popularity of pages pointing to them



Query-independent ordering

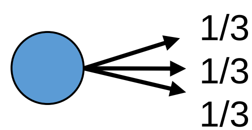
- First generation: using link counts as simple measures of popularity.

- Two basic suggestions:
  - Undirected popularity:
    - Each page gets a score = the number of in-links plus the number of out-links (3+2=5).
  - Directed popularity:
    - Score of a page = number of its in-links (3).



PageRank scoring

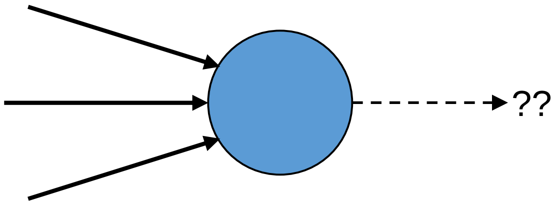
- Imagine a browser doing a random walk on web pages:
  - Start at a random page
  - At each step, go out of the current page along one of the links on that page, equiprobably



- "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.

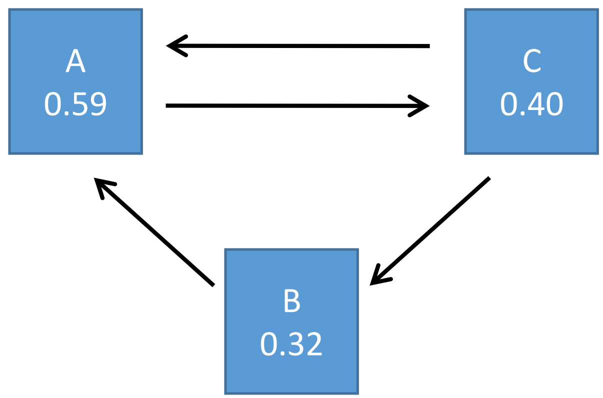


Teleporting

- 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 at which any page is visited.
  - How do we compute this visit rate?

The random surfer

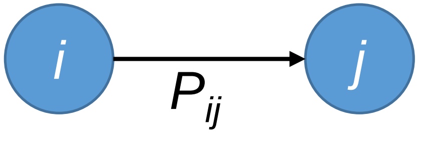
- The PageRank of a page is the probability that a given random “Web surfer” is currently visiting that page.



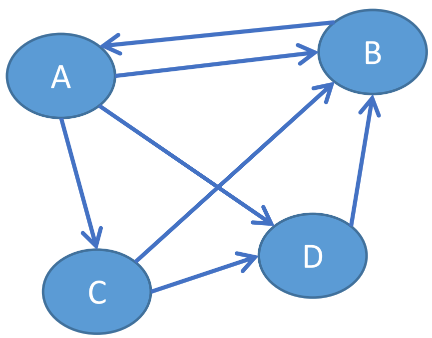
- This probability is related to the incoming links and to a certain degree of browsing randomness (e.g. reaching a page through a search engine).

Markov chains

- A Markov chain consists of n states, plus an $n \times n$ 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.



Transitions probability matrix

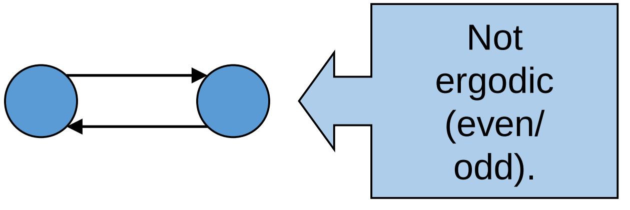


	A	B	C	D
A	0	1	1	1
B	1	0	0	0
C	0	1	0	1
D	0	1	0	0

	A	B	C	D
A	0	P_{ab}	P_{ac}	P_{ad}
B	P_{ba}	0	0	0
C	0	P_{cb}	0	P_{cd}
D	0	P_{db}	0	0

Ergodic Markov chains

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



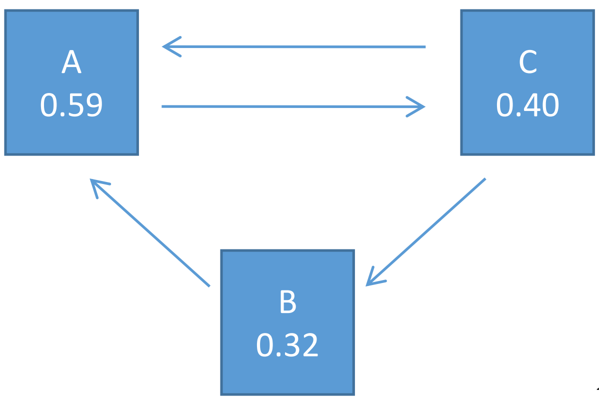
Ergodic Markov chains

- For any ergodic Markov chain, there is a unique long-term visit rate for each state.
  - Steady-state probability distribution.
- Over a long time-period, we visit each state in proportion to this rate.
- It doesn't matter where we start.

The PageRank of Web page ***i*** corresponds to the probability of being at page ***i*** after an infinite random walk across all pages (i.e., the stationary distribution).

PageRank

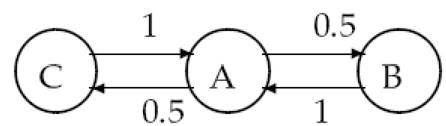
- The rank of a page is related to the number of incoming links of that page and the rank of the pages linking to it.



$$PR(A) = (1 - d) + d \cdot \left[\frac{PR(B)}{OL(B)} + \frac{PR(C)}{OL(C)}\right]$$

PageRank: formalization

- The RandomSurfer model assumes that the pages with more inlinks are visited more often

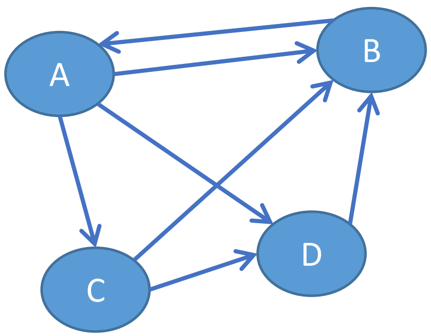


- The rank of a page is computed as:

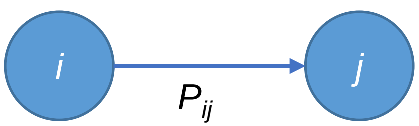
$$p_i = (1 - d) + d \sum_{j=1}^{N} (\frac{L_{ij}}{c_j}) p_j$$

where L_{ij} is the link matrix , c_j is the number of links of page and p_j is the PageRank of that page

Transitions probability matrix



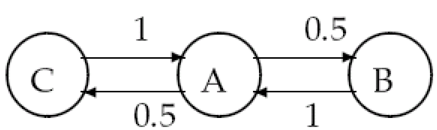
	A	B	C	D
A	0	1	1	1
B	1	0	0	0
C	0	0	1	1
D	0	1	0	0



	A	B	C	D
A	0	P_{ab}	P_{ac}	P_{ad}
B	P_{ba}	0	0	0
C	0	0	P_{cc}	P_{cd}
D	0	P_{db}	0	0

Example

- Consider three Web pages:



$$p_i = (1-d) + d\sum_{j=1}^{N}(\frac{L_{ij}}{c_j})p_j$$

- The transition matrix $\frac{L_{ij}}{c_j}$ is:

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

PageRank: issues and variants

- How realistic is the random surfer model?
  - What if we modeled the back button? [Fagi00]
  - Surfer behavior sharply skewed towards short paths [Hube98]
  - Search engines, bookmarks & directories make jumps non-random.

- Biased Surfer Models
  - Weight edge traversal probabilities based on match with topic/query (non-uniform edge selection)
  - Bias jumps to pages on topic (e.g., based on personal bookmarks & categories of interest)

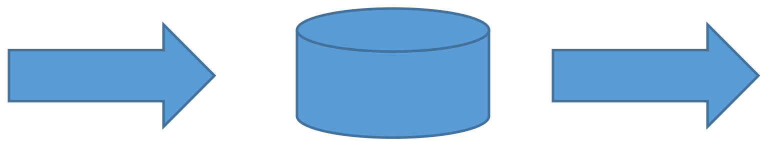
Topic Specific Pagerank [Have02]

- Conceptually, we use a random surfer who teleports, with ~10% probability, using the following rule:
  - Selects a category (say, one of the 16 top level categories) based on a query & user -specific distribution over the categories
  - Teleport to a page uniformly at random within the chosen category

- Sounds hard to implement: can't compute PageRank at query time!

Query topic classification

Query



Doc 1	Sports
Doc 2	Health
Doc 3	Sports
Doc 4	Sports
Doc 5	Sports

Query category = 90% sports + 10% health

Web page topic classifier

- Web pages have specific topics that can be detected by some classifier.

- Links are more likely between topics of the same topic.

- Links between pages of the same topic are more likely to be followed.

fastText https://fasttext.cc/docs/en/english-vectors.html

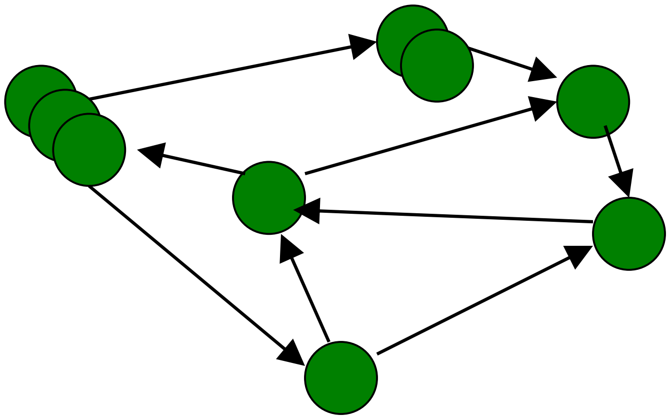
Topic Specific PageRank - Implementation

- **offline**: Compute pagerank distributions wrt individual categories
  - Query independent model as before
  - Each page has multiple pagerank scores – one for each category, with teleportation only to that category

- **online**: Distribution of weights over categories computed by query context classification
  - Generate a dynamic pagerank score for each page - weighted sum of category-specific pageranks

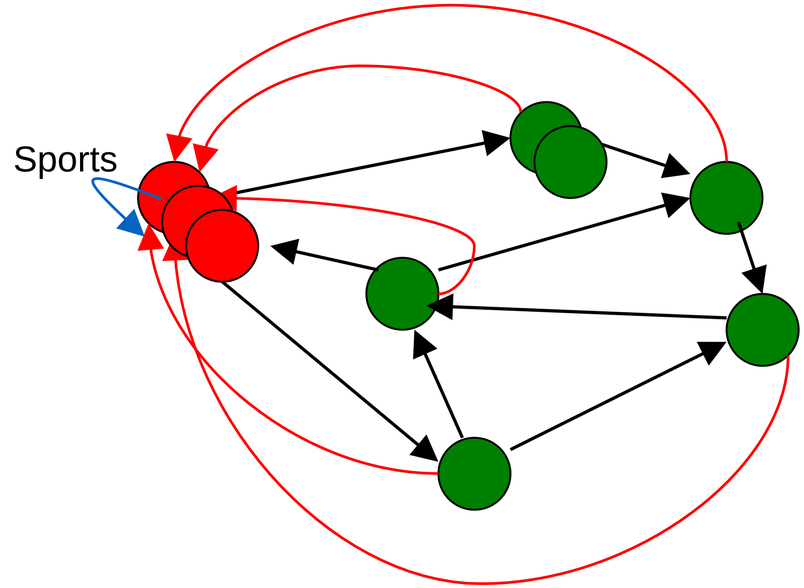
Example

- Consider a query on a given set of Web pages with the following graph:

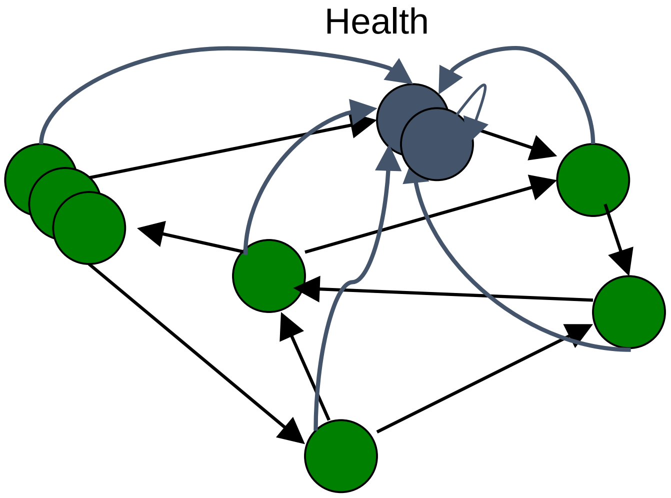


- The query has **90%** probability of being about **Sports**.
- The query has **10%** probability of being about **Health**.

Non-uniform Teleportation

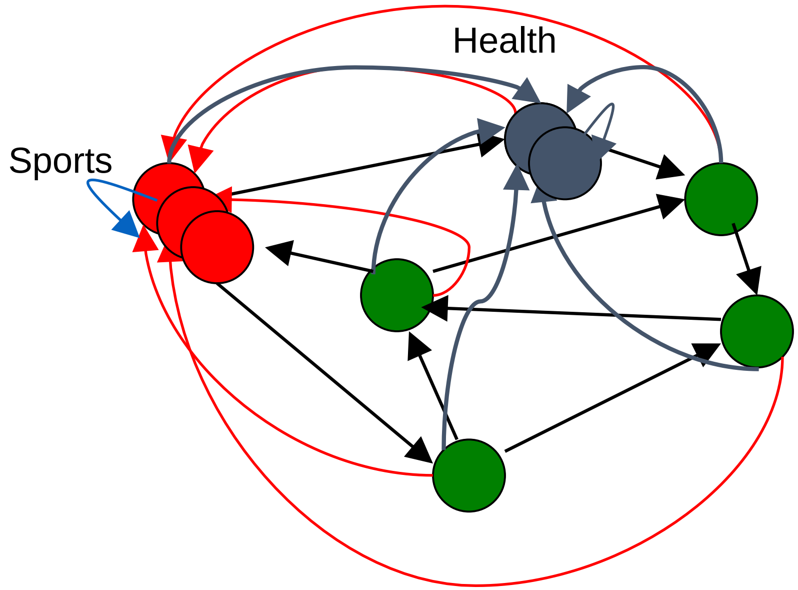


Sports teleportation



Health teleportation

Interpretation

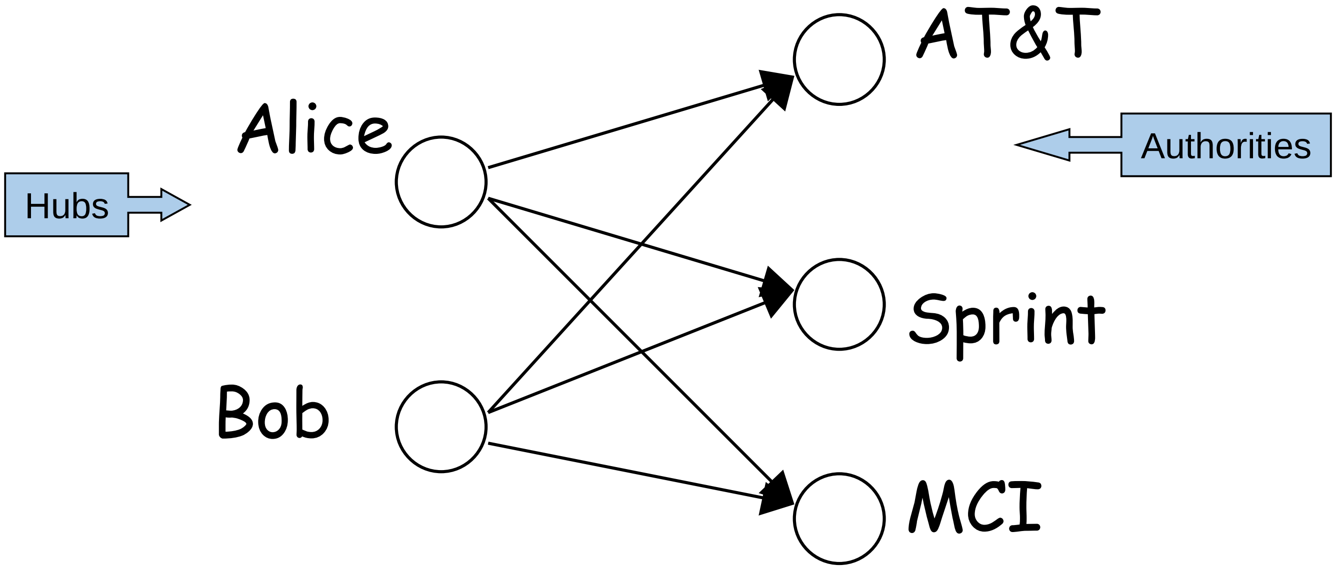


pr = (0.9 PR_{sports} + 0.1 PR_{health}) gives you:
90% sports teleportation, 10% health teleportation

Hyperlink-Induced Topic Search (HITS) - Klei98

- In response to a query, instead of an ordered list of pages each meeting the query, find <u>two</u> sets of inter-related pages:
  - *Hub pages* are good lists of links on a subject.
    - e.g., "Bob's list of cancer-related links."
  - *Authority pages* occur recurrently on good hubs for the subject.
- Best suited for "broad topic" queries rather than for page-finding queries.
- Gets at a broader slice of common *opinion*.

The hope



Long distance telephone companies

High-level scheme

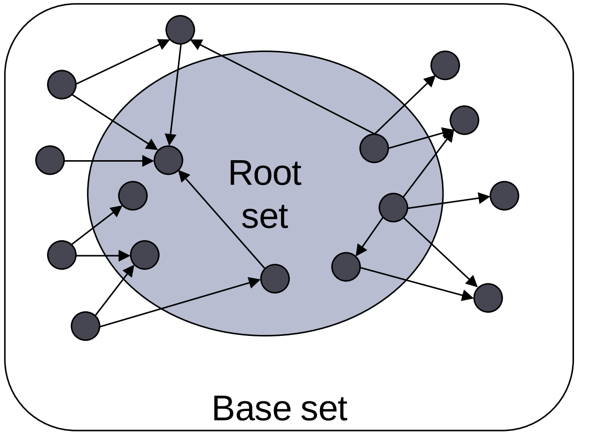
- Extract from the web a base set of pages that could be good hubs or authorities.
- From these, identify a small set of top hub and authority pages;
  - iterative algorithm.

Base set and root set

- Given text query (say *browser*), use a text index to get all pages containing *browser*.
  - Call this the root set of pages.

- Add in any page that either
  - points to a page in the root set, or
  - is pointed to by a page in the root set.

- Call this the base set.



Distilling hubs and authorities

- Compute, for each page x in the base set, a hub score h(x) and an authority score a(x).

- Initialize: for all x, $h(x) \leftarrow 1$; $a(x) \leftarrow 1$;

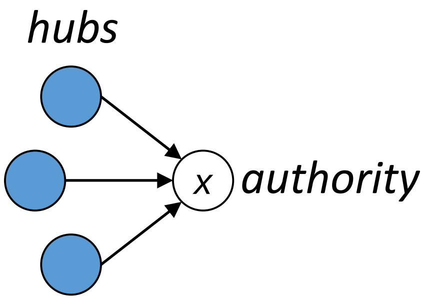
- Iteratively update all h(x), a(x);

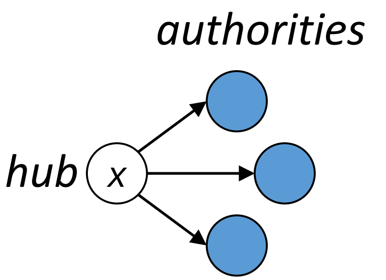
Key

- After iterations
  - output pages with highest h() scores as top hubs
  - highest a() scores as top authorities.

Iterative update

- Repeat the following updates, for all *x*:





$$a(x) \leftarrow \sum_{y \mapsto x} h(y) \qquad h(x) \leftarrow \sum_{x \mapsto y} a(y)$$

How many iterations?

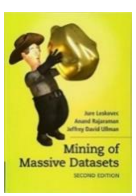
- Claim: relative values of scores will converge after a few iterations:
  - in fact, suitably scaled, h() and a() scores settle into a steady state!

- We only require the <u>relative orders</u> of the h() and a() scores - not their absolute values.

- In practice, ~5 iterations get you close to stability.

Summary

- Web graphs denote a relation of relevance between edges
- Introduced a new way of modeling the value of Web links.
- Key algorithms: PageRank, Topic Specific PageRank, HITS
- References:



Chapter 5 of Jure Leskovec, Anand Rajaraman, Jeff Ullman, “**Mining of Massive Datasets**”, Cambridge University Press, 2011.