Informatics 225
Computer Science 221

Information Retrieval

Lecture 24

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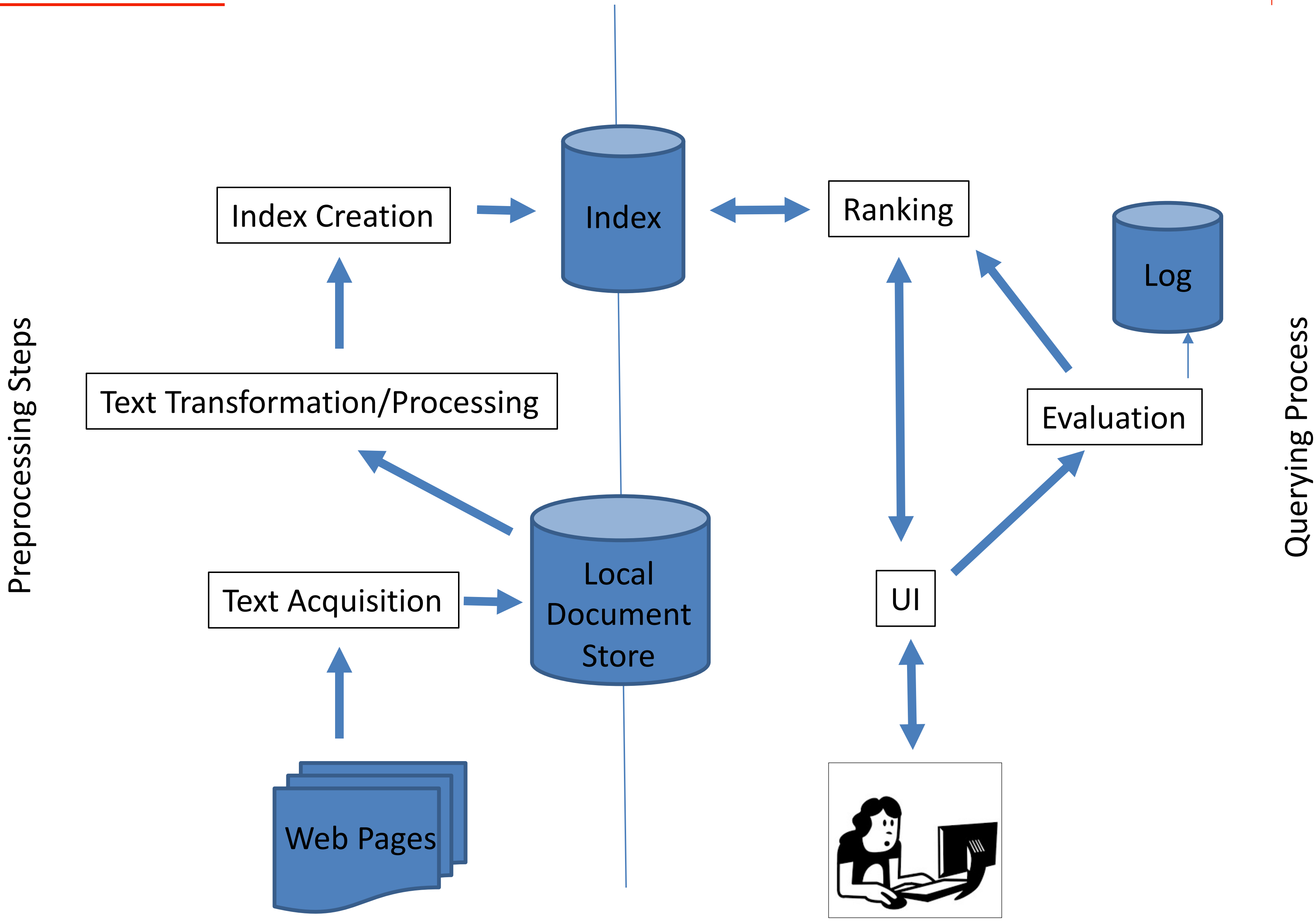
Architecture



Link Analysis

Information Retrieval

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HUBS AND AUTHORITIES

Hyperlink-Induced Topic Search (HITS)

- In response to a query, instead of an ordered list of pages each meeting the query, find two 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.

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- Best suited for “broad topic” queries rather than for page-finding queries.

- Gets at a broader slice of common *opinion*.

Hubs and Authorities

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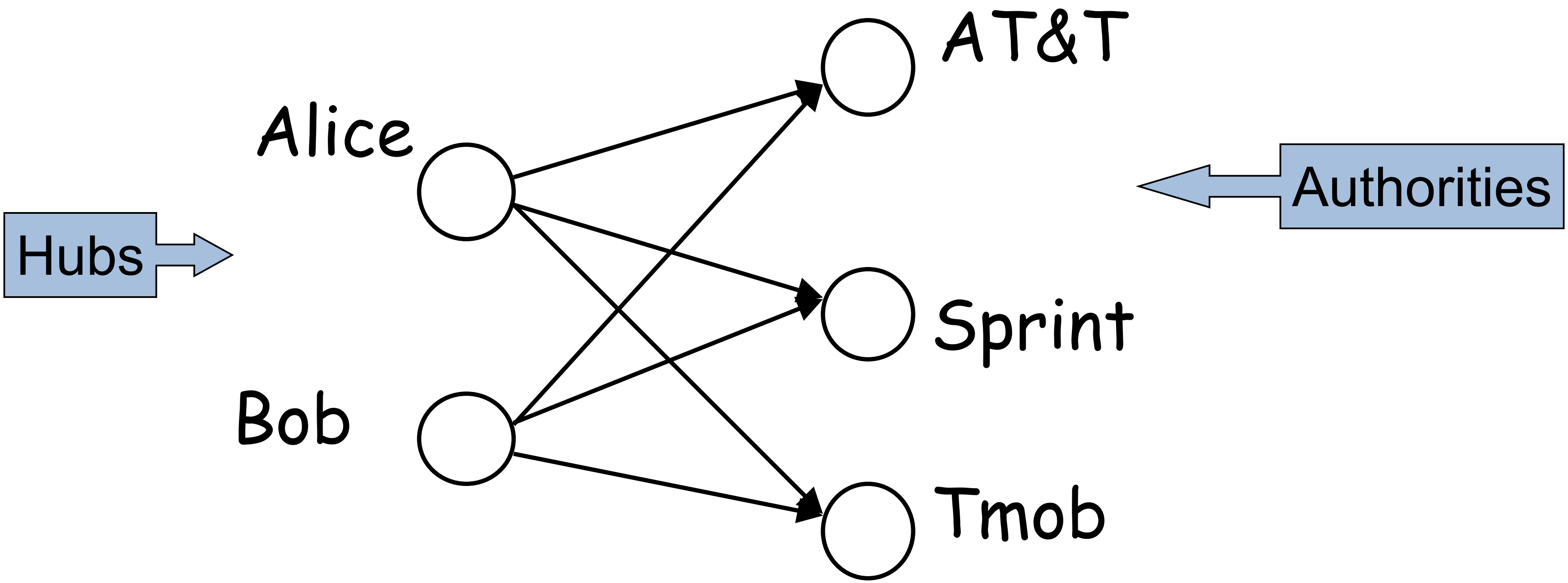
- A good authority page for a topic is *pointed* to by many good hubs for that topic.
- Circular definition - will turn this into an iterative computation.

The hope



Mobile telecom 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.

Creating the Base set

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

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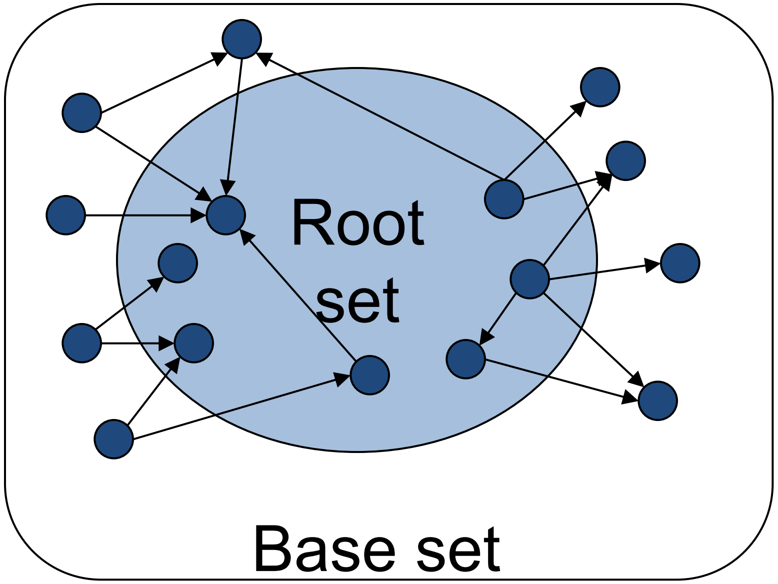
- Given text query (say ***browser***), use a text index to get all pages containing ***browser.***
  - Call this the root set of pages.
- Add in any page that either
  - points to a page in the root set, or
  - is pointed to by a page in the root set.
- Call this the base set.

Visualization



Get in-links (and out-links) from a ***connectivity server***

Connectivity Server

- Support for fast queries on the web graph
  - Which URLs point to a given URL?
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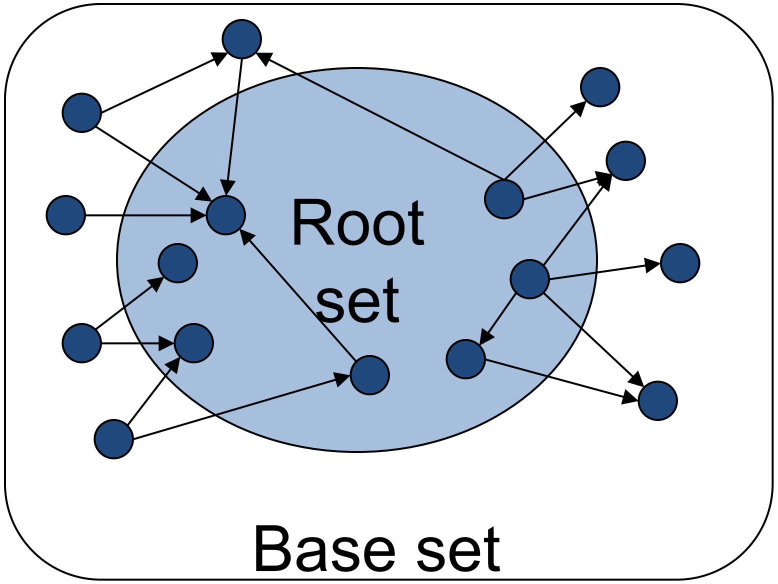
- Applications
  - Crawl control
  - Web graph analysis
    - *Connectivity, crawl optimization*
  - Link analysis (HITS, PageRank, …)

Visualization



Get in-links (and out-links) from a ***connectivity server***

Distilling hubs and authorities

- Compute, for each page *x* in the base set:
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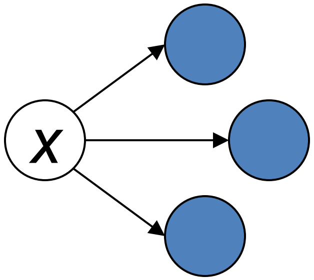
- Initialize: for all *x*, $h(x) \leftarrow 1$; $a(x) \leftarrow 1$;
- Iteratively update all *h(x), a(x)*;
- After a few iterations (or convergence)
  - output pages with highest *h()* scores as top hubs
  - highest *a()* scores as top authorities.

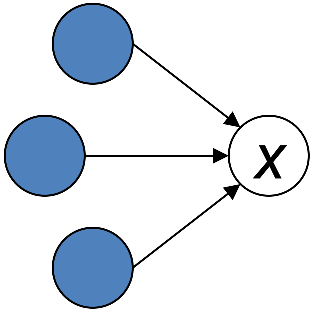
Iterative update

- Repeat the following updates of the **hub score h(x)** and the **authority score a(x)**, for all *x*:

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



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



Scaling

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- *Scaling factor doesn't really matter (as long as you are consistent):*
  - *we only care about the relative values of the scores.*

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!
  - *You can demonstrate this…*
- In practice, ~5 iterations is enough to get you close to stability.

Japan Elementary Schools

Hubs

- schools
- LINK Page-13
- “ú–{,ÌŠw□Z
- □a‰„□¬Šw□Zƒz□[ƒ□ƒy□[ƒW
- 100 Schools Home Pages (English)
- K-12 from Japan 10/...rnet and Education)
- http://www...iglobe.ne.jp/~IKESAN
- ,l,f,j□¬Šw□Z,U”N,P‘g•¨Œê
- □ÒŠ—’¬—§□ÒŠ—“Œ□¬Šw□Z
- Koulutus ja oppilaitokset
- TOYODA HOMEPAGE
- Education
- Cay's Homepage(Japanese)
- –y“ì□¬Šw□Z,Ìƒz□[ƒ□ƒy□[ƒW
- UNIVERSITY
- ‰J—³□¬Šw□Z DRAGON97-TOP
- □Â‰ª□¬Šw□Z,T”N,P‘gƒz□[ƒ□ƒy□[ƒW
- ¶µ°é¼ÂÁ© ¥á¥Ë¥å¡¼ ¥á¥Ë¥å¡¼

Authorities

- The American School in Japan
- The Link Page
- ‰ª□è□s—§ˆä“c□¬Šw□Zƒz□[ƒ□ƒy□[ƒW
- Kids' Space
- ˆÀ□é□s—§ˆÀ□é□¼•”□¬Šw□Z
- ‹{□é‹³ˆç‘åŠw•□‘®□¬Šw□Z
- KEIMEI GAKUEN Home Page (Japanese)
- Shiranuma Home Page
- fuzoku-es.fukui-u.ac.jp
- welcome to Miasa E&J school
- □_“Þ□ìŒ§□E‰¡•l□s—§’†□ì□¼□¬Šw□Z,Ìƒy
- http://www...p/~m_maru/index.html
- fukui haruyama-es HomePage
- Torisu primary school
- goo
- Yakumo Elementary,Hokkaido,Japan
- FUZOKU Home Page
- Kamishibun Elementary School...

Things to note

- Pulled together good pages **regardless of language of page content.**

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- Pulled together good pages **regardless of language of page content.**

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- Iterative computation <u>after</u> text index retrieval - significant overhead (but not at query-time!)

Hyper-link Induced Topic Search Issues

- Topic Drift
  - Off-topic pages can cause off-topic “authorities” to be returned
    - E.g., the neighborhood graph can be about a “super topic”

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- Topic Drift
  - Off-topic pages can cause off-topic “authorities” to be returned
    - E.g., the neighborhood graph can be about a “super topic”
- Mutually Reinforcing Affiliates
  - Affiliated pages/sites can boost each others’ scores
    - *Linkage between affiliated pages is not a useful signal, so avoid considering them in the analysis*

Overview!

- Compute, for each page *x* in the base set:
  - a **hub score** ***h(x)***
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- Initialize: for all *x*,
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- Iteratively update all
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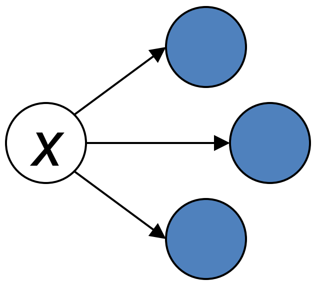

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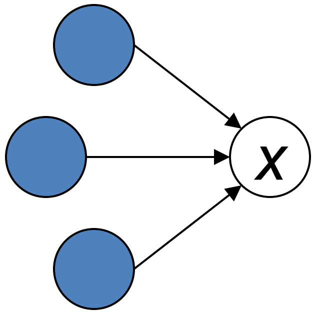


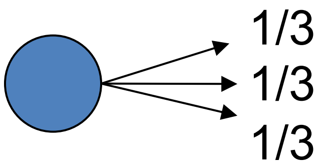
To prevent the *h()* and *a()* values from getting too big, can scale down after each iteration.

Scaling factor doesn’t really matter : only relative values are important

PAGE RANK

Pagerank scoring

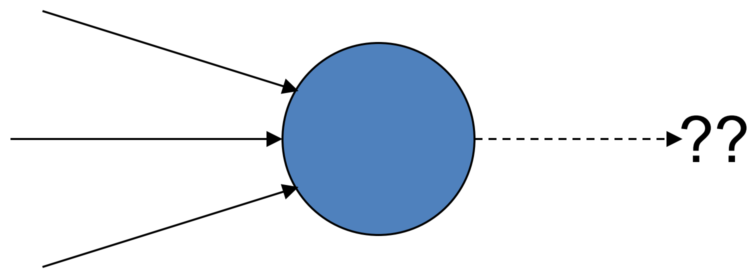
- Imagine a browser doing a random walk on web pages:
  - Start at a random page
  - At each step, go out of the current page along one of the links on that page, equiprobably



- "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.

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PageRank

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- *See the original Google and PageRank papers in Canvas*

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- There is a long-term rate at which any page is visited (not obvious).
  - **The idea of page rank is that pages that are visited more by this random walker are more important**
- **How do we compute this visit rate?**

Computing PageRank

1. **Algebraic calculation (given in Google paper)**

2. Markov chain model

PageRank -- Algebraic

$$p_i = \boxed{\text{matemagic}}\; p_j$$

PageRank -- Algebraic

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

PageRank -- Algebraic

PageRank of page i $$p_i = (1-d) + d\sum_{j=1}^{N}\left(\frac{L_{ij}}{c_j}\right)p_j$$ PageRank of page j

PageRank -- Algebraic

Liij = 1 if page j points to i, and zero otherwise

PageRank of page i

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

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$$\boxed{c_j = \sum_{i=1}^{N} L_{ij}}$$

How many pages are leaving page j

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damping factor d

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PageRank of page j

$$\boxed{c_j = \sum_{i=1}^{N} L_{ij}}$$

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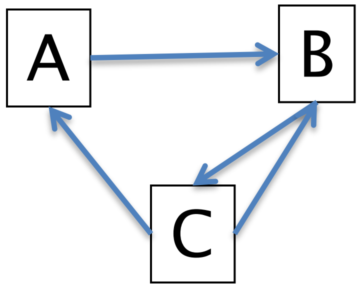
PageRank -- Algebraic

$$PR(A) = (1\text{-}d) + d \sum (PR(Ti)/C(Ti))$$

$$PR(A) = (1\text{-}d) + d\ (PR(T1)/C(T1) + \ldots + PR(Tn)/C(Tn))$$

Where
A is a page
d is a damping/teleport factor (usually 0.85)
T1...Tn are pages that link to A
PR(Ti) is the PageRank of Ti
C(Ti) is the number of outgoing links from Ti

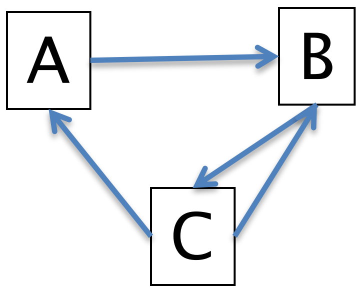
Example



PR(A) = 0.15 + 0.85 * PR(C)/2
PR(B) = 0.15 + 0.85 * (PR(A)/1 + PR(C)/2)
PR(C) = 0.15 + 0.85 * (PR(B)/1)

How do we start?!?
Guess: PR(p) = 1 for starters
Then, iterate

Example – Iterations



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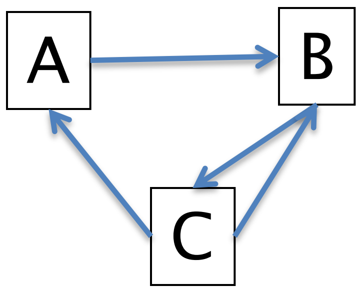
Iter 1 $\left\{ \begin{array}{l} PR(A) = 0.15+0.85 * 1/2 = 0.575 \\ PR(B) = 0.15+0.85 * (1+1/2) = 1.425 \\ PR(C) = 0.15+0.85 * 1 = 1 \end{array} \right.$

Example – Iterations



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PR(C) = 0.15+0.85 * 1 = 1

Iter 2
PR(A) = 0.15+0.85 * 1/2 = 0.575
PR(B) = 0.15+0.85 * (0.575+1/2) = 1.06375
PR(C) = 0.15+0.85 * 1.425 = 1.36125

...

Example -- Iterations

- Algorithm converges after N iterations
- Once converged, normalized probability distribution (average PageRank for all pages) will be 1
- You can gain some visual intuition : http://ed.ilogues.com/projects/2015/03/22/pagerank-visualization

Pagerank summary

- Preprocessing:
  - Given graph of links, build a (sparse) matrix of the links.
  - From it compute **page rank**
- One possibility to add PR in query processing (at query time):
  - Retrieve pages meeting query.
  - Rank them by their pagerank.
  - But this rank order is query-*independent* …

The reality

- Pagerank is used in google and other engines, but is hardly the full story of ranking
  - **It is just one among many criteria used in relevance scoring**
  - Many additional sophisticated features are used
  - Some address specific query classes
  - Machine learned ranking is used each time more

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- **Given a query, a real-life search engine will compute a composite score for each web page that combines hundreds of features** (cosine similarity, term proximity, PageRank, HITS, etc.)

- Pagerank *alone* is still very useful for things like crawl policy

PageRank – Algebraic in matrix notation

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

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$$\mathbf{p} = (1-d)\mathbf{e} + d \cdot \mathbf{L}\mathbf{D}_c^{-1}\mathbf{p}$$

Vector of N ones

Diagonal matrix with diagonal elements c_j

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If we adopt a normalization factor
such that the average pagerank is 1

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$$\begin{aligned}\mathbf{p} &= \left[(1-d)\mathbf{e}\mathbf{e}^T/N + d\mathbf{L}\mathbf{D}_c^{-1}\right]\mathbf{p} \\ &= \mathbf{A}\mathbf{p}\end{aligned}$$

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$$\mathbf{p}_k \leftarrow \mathbf{A}\mathbf{p}_{k-1}; \quad \mathbf{p}_k \leftarrow N\frac{\mathbf{p}_k}{\mathbf{e}^T\mathbf{p}_k}.$$