Link Analysis

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Recap: formula for Rocchio feedback

- Standard operation in vector space

Parameters

Modified query

$$\vec{q}_m = \alpha\vec{q} + \frac{\beta}{|D_r|}\sum_{\forall \vec{d}_i \in D_r} \vec{d}_i - \frac{\gamma}{|D_n|}\sum_{\forall \vec{d}_j \in D_n} \vec{d}_j$$

Original query

Rel docs

Non-rel docs

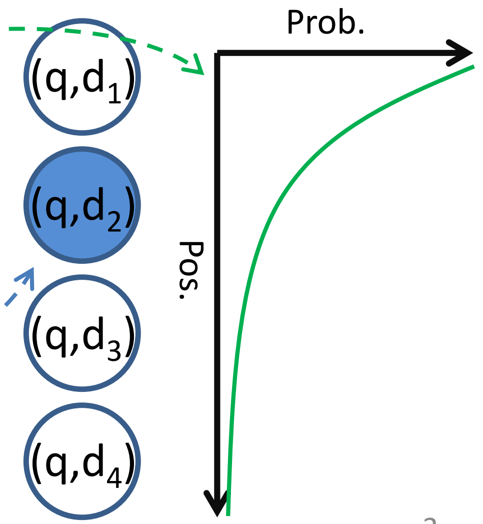
Recap: click models

- Decompose relevance-driven clicks from position-driven clicks
  - Examine: user reads the displayed result
  - Click: user clicks on the displayed result
  - Atomic unit: (query, doc)

$$P(C=1|d,i) = \sum_{e\in\{0,1\}} P(C=1|d,i,E=e)P(E=e|d,i)$$

$$= \underbrace{P(C=1|d,E=1)}_{\text{Click probability}}\underbrace{P(E=1|i)}_{\text{Examine probability}}$$

Relevance quality



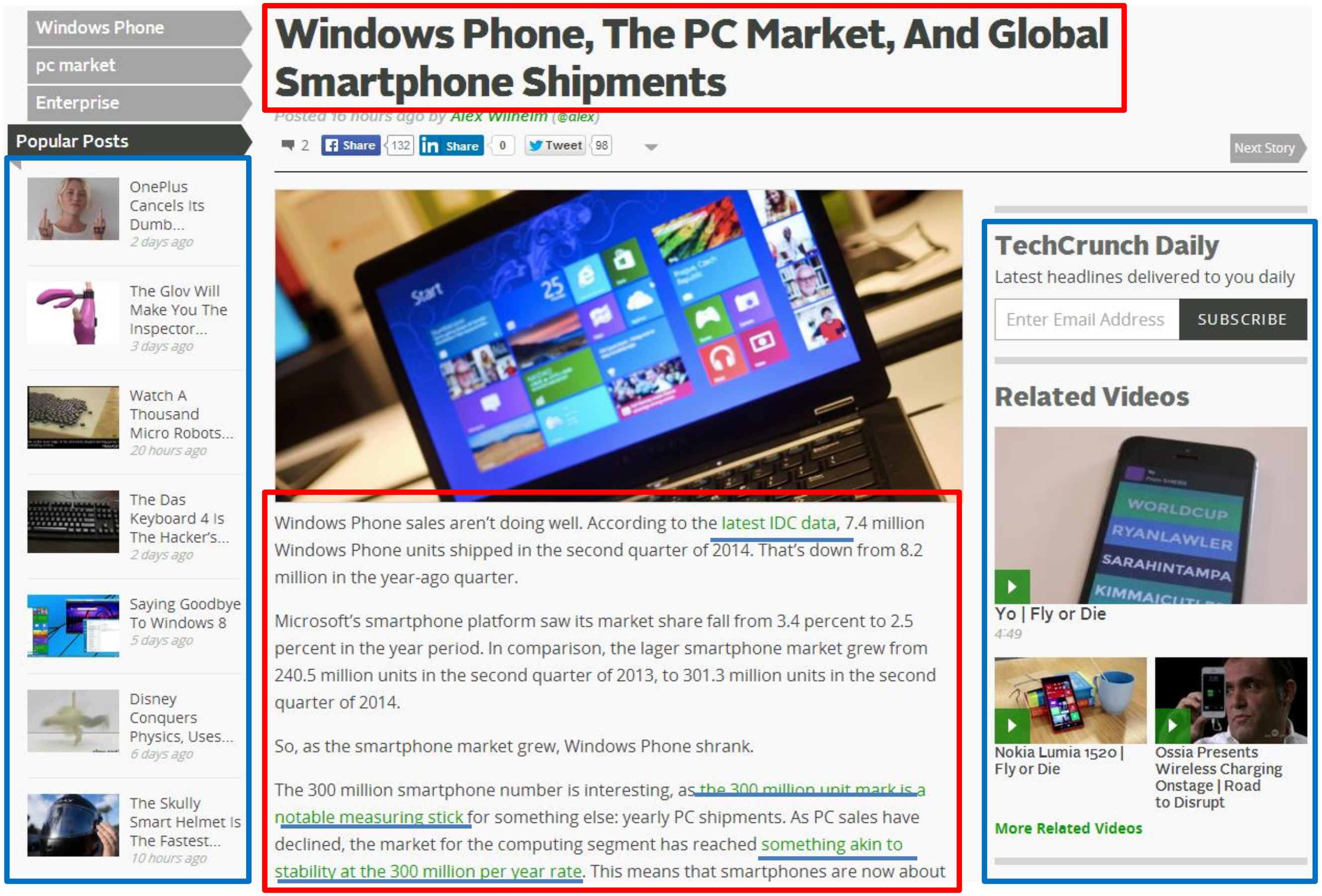
Structured v.s. unstructured data

- Our claim before
  - IR v.s. DB = unstructured data v.s. structured data
- As a result, we have assumed
  - Document = a sequence of words
  - Query = a short document
  - Corpus = a set of documents

However, this assumption is not accurate…

A typical web document has

Title



Windows Phone

pc market

Enterprise

Popular Posts

OnePlus Cancels Its Dumb... *2 days ago*

The Glov Will Make You The Inspector... *3 days ago*

Watch A Thousand Micro Robots... *20 hours ago*

The Das Keyboard 4 Is The Hacker's... *2 days ago*

Saying Goodbye To Windows 8 *5 days ago*

Disney Conquers Physics, Uses... *6 days ago*

The Skully Smart Helmet Is The Fastest... *10 hours ago*

Windows Phone, The PC Market, And Global Smartphone Shipments

Posted 16 hours ago by Alex Wilhelm (@alex)

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Next Story

Windows Phone sales aren't doing well. According to the latest IDC data, 7.4 million Windows Phone units shipped in the second quarter of 2014. That's down from 8.2 million in the year-ago quarter.

Microsoft's smartphone platform saw its market share fall from 3.4 percent to 2.5 percent in the year period. In comparison, the lager smartphone market grew from 240.5 million units in the second quarter of 2013, to 301.3 million units in the second quarter of 2014.

So, as the smartphone market grew, Windows Phone shrank.

The 300 million smartphone number is interesting, as the 300 million unit mark is a notable measuring stick for something else: yearly PC shipments. As PC sales have declined, the market for the computing segment has reached something akin to stability at the 300 million per year rate. This means that smartphones are now about

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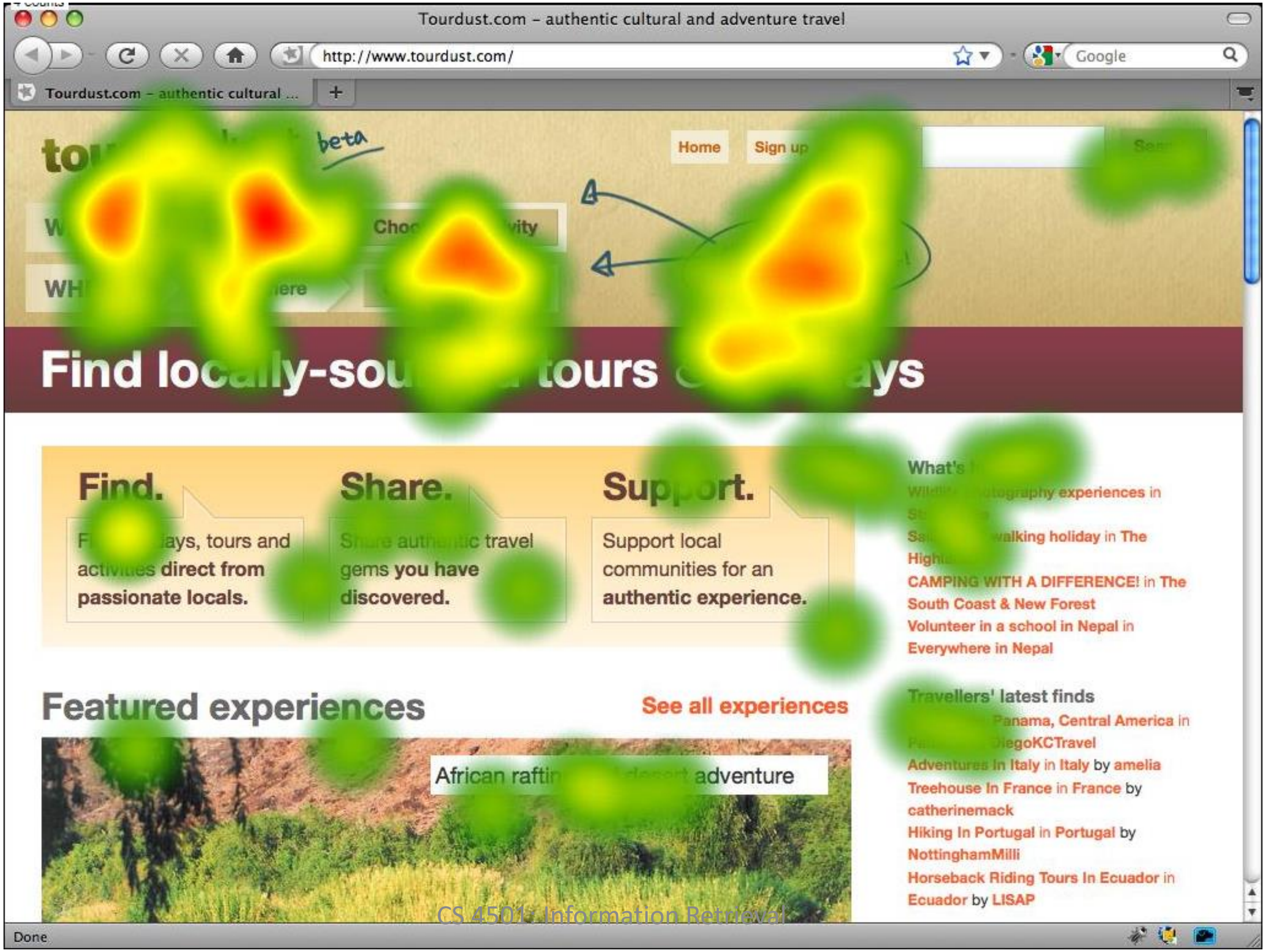
Anchor

Body

How does a human perceive a document's structure



Tourdust.com – authentic cultural and adventure travel
http://www.tourdust.com/
Google
Tourdust.com – authentic cultural ...
beta
Home
Sign up
Done

Find locally-sou... tours ... ays

Find.

F... ays, tours and activities direct from passionate locals.

Share.

Share authentic travel gems you have discovered.

Support.

Support local communities for an authentic experience.

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Wildlife photography experiences in ...

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CAMPING WITH A DIFFERENCE! in The South Coast & New Forest

Volunteer in a school in Nepal in Everywhere in Nepal

Travellers' latest finds

...anama, Central America in ...

...iegoKCTravel

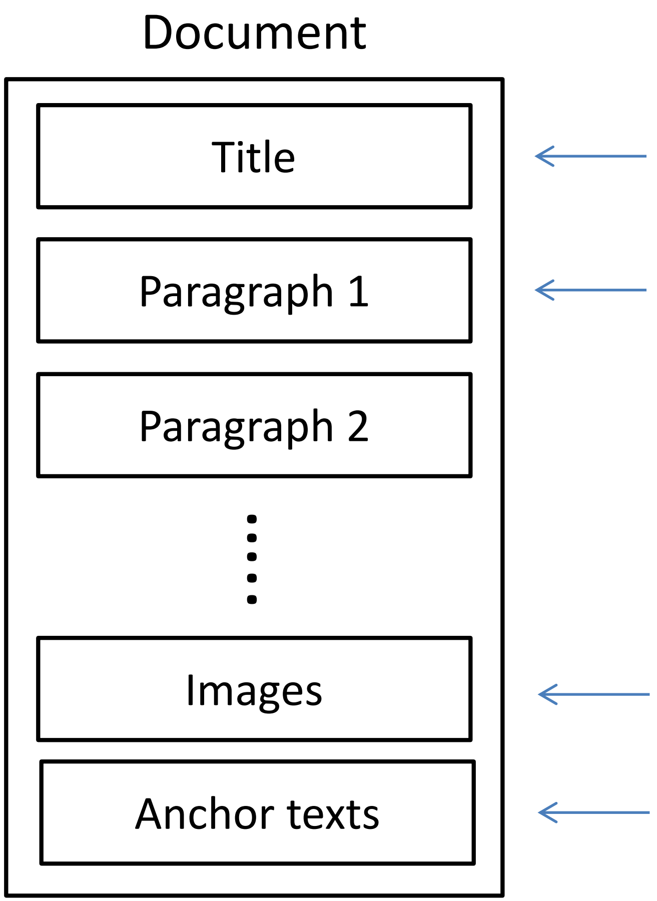
Adventures In Italy in Italy by amelia

Treehouse In France in France by catherinemack

Hiking In Portugal in Portugal by NottinghamMilli

Horseback Riding Tours In Ecuador in Ecuador by LISAP

Intra-document structures



Document

Title

Paragraph 1

Paragraph 2

Images

Anchor texts

Concise summary of the document

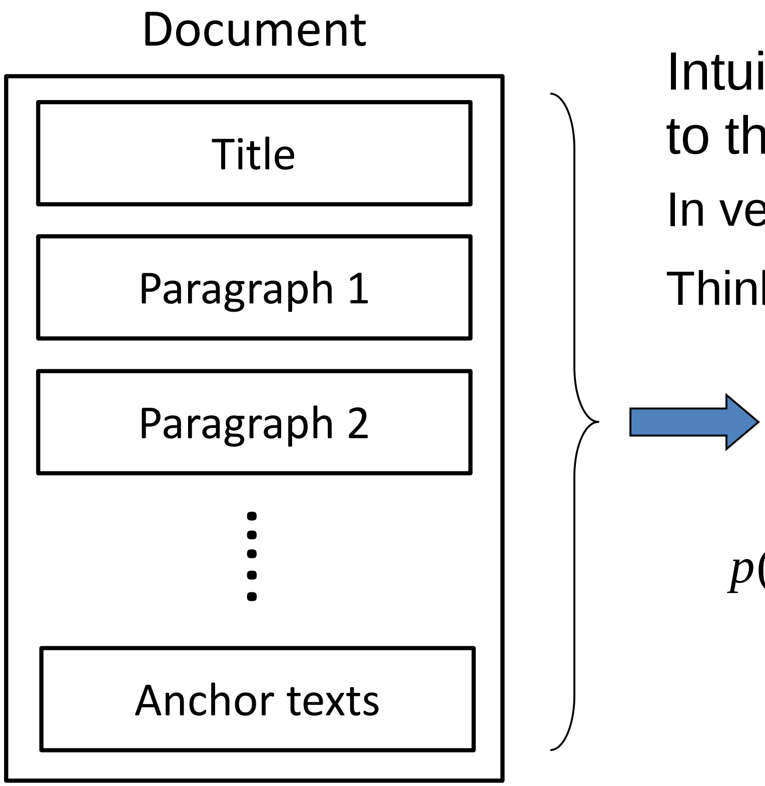
Likely to be an abstract of the document

They might contribute differently for a document's relevance!

Visual description of the document

References to other documents

Exploring intra-document structures for retrieval



Intuitively, we want to give different weights to the parts to reflect their importance

In vector space model? Weighted TF

Think about query-likelihood model…

Select D_j and generate a query word using D_j

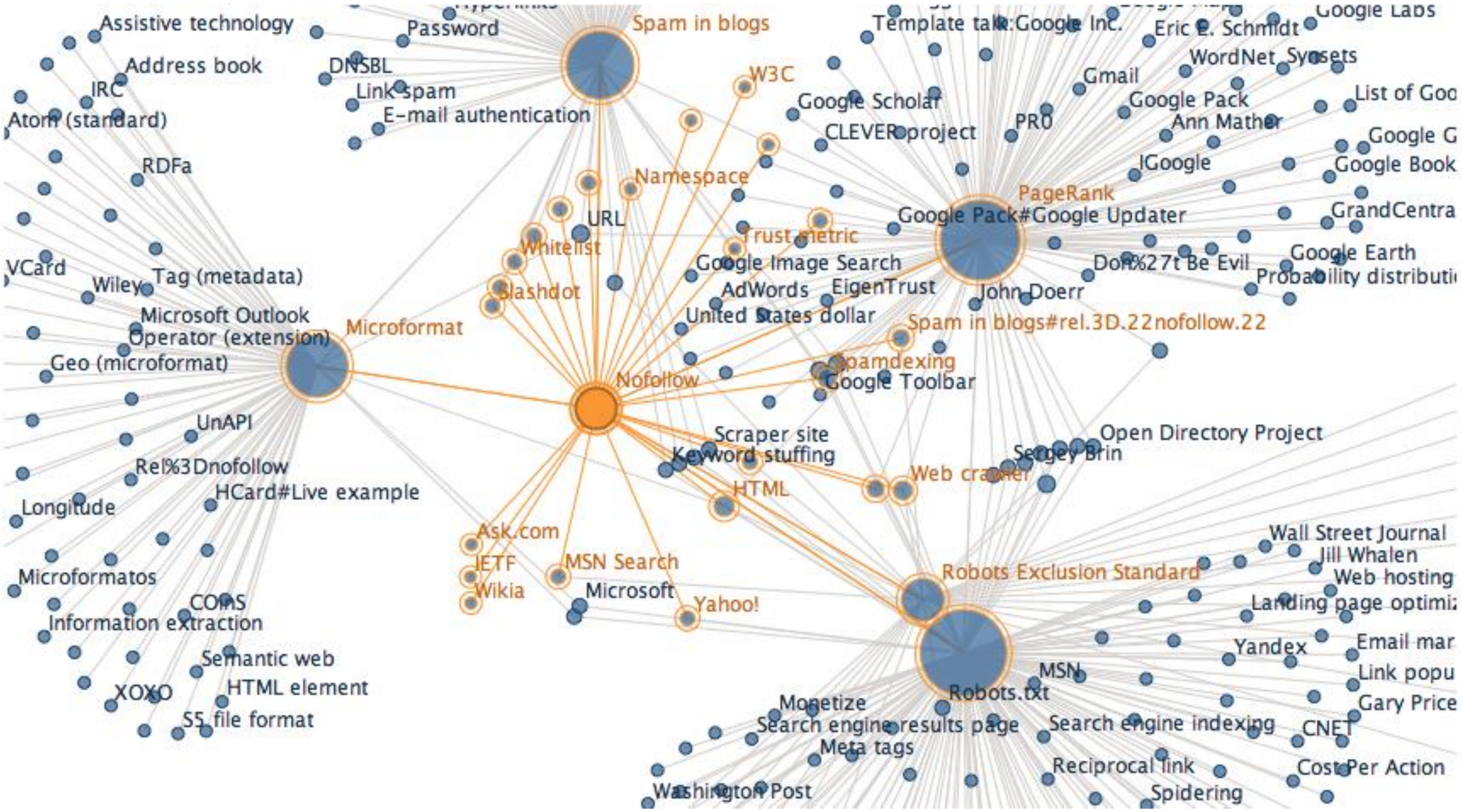
$$p(Q|D,R) = \prod_{i=1}^{n} p(w_i|D,R)$$

$$= \prod_{i=1}^{n} \sum_{j=1}^{k} \underline{s(D_j|D,R)}\, p(w_i|D_j,R)$$

"part selection" prob. Serves as weight for D_j
Can be estimated by EM or manually set

Inter-document structure

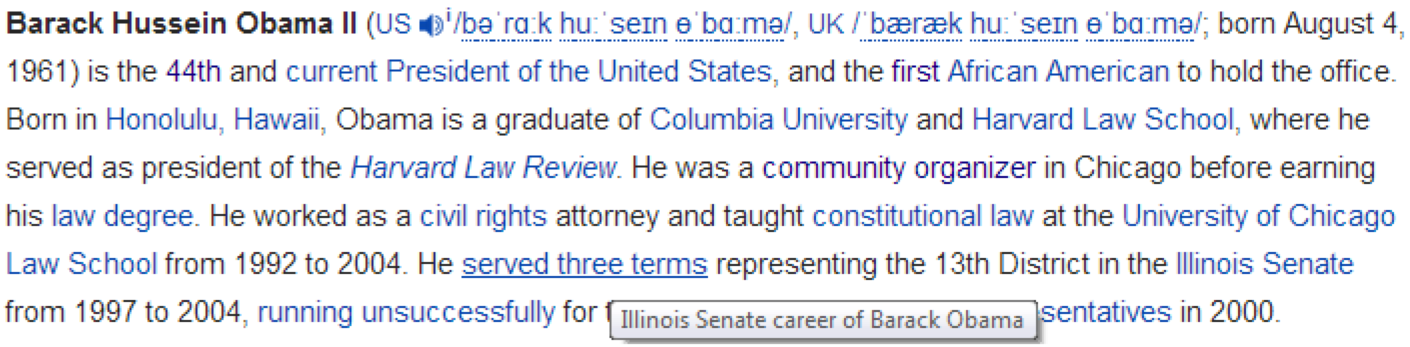
- Documents are no longer independent



Source: https://wiki.digitalmethods.net/Dmi/WikipediaAnalysis

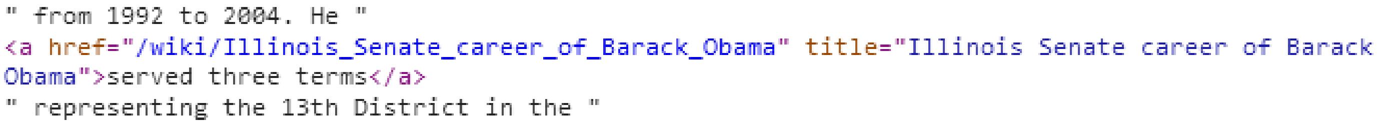
What do the links tell us?

- Anchor
  - Rendered form



Barack Hussein Obama II (US 🔊i/bəˈrɑːk huːˈseɪn ɵˈbɑːmə/, UK /ˈbæræk huːˈseɪn ɵˈbɑːmə/; born August 4, 1961) is the 44th and current President of the United States, and the first African American to hold the office. Born in Honolulu, Hawaii, Obama is a graduate of Columbia University and Harvard Law School, where he served as president of the *Harvard Law Review*. He was a community organizer in Chicago before earning his law degree. He worked as a civil rights attorney and taught constitutional law at the University of Chicago Law School from 1992 to 2004. He served three terms representing the 13th District in the Illinois Senate from 1997 to 2004, running unsuccessfully for t Illinois Senate career of Barack Obama sentatives in 2000.

  - Original form



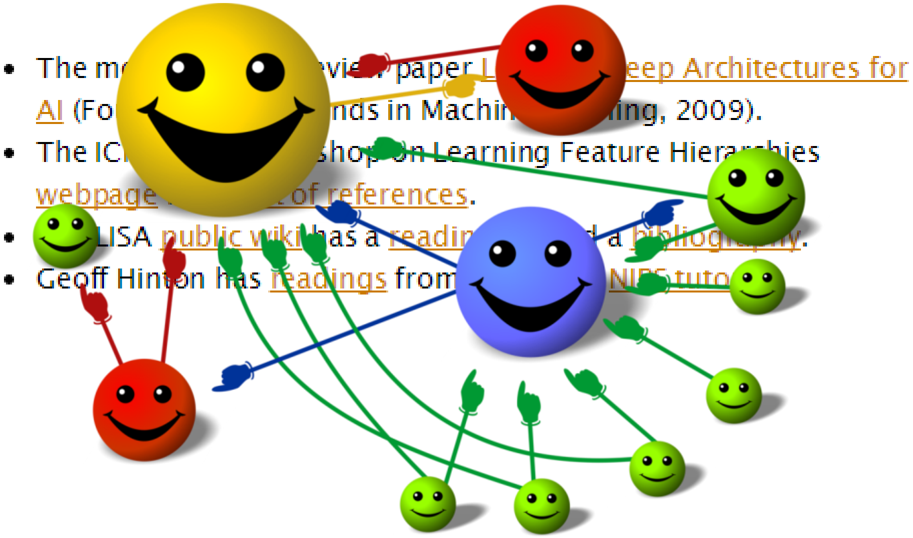
```
" from 1992 to 2004. He "
<a href="/wiki/Illinois_Senate_career_of_Barack_Obama" title="Illinois Senate career of Barack
Obama">served three terms</a>
" representing the 13th District in the "
```

What do the links tell us?

- Anchor text
  - How others describe the page
    - E.g., “big blue” is a nick name of IBM, but never found on IBM’s official web site
  - A good source for query expansion, or can be directly put into index

What do the links tell us?

- Linkage relation
  - Endorsement from others – utility of the page



The m… paper … eep Architectures for
AI (Fo… nds in Machi… ing, 2009).
The IC… shop on Learning Feature Hierarchies
webpage … of references.
LISA public wiki has a readin… a bibliography.
Geoff Hinton has readings from … NIPS tuto…

"PageRank-hi-res". Licensed under Creative Commons Attribution-Share Alike 2.5 via Wikimedia Commons - http://commons.wikimedia.org/wiki/File:PageRank-hi-res.png#mediaviewer/File:PageRank-hi-res.png

Analogy to citation network

- Authors cite others' work because
  - A conferral of authority
    - They appreciate the intellectual value in that paper
  - There is certain relationship between the papers
- Bibliometrics
  - A citation is a vote for the usefulness of that paper
  - Citation count indicates the quality of the paper
    - E.g., # of in-links

Situation becomes more complicated in the web environment

- Adding a hyperlink costs almost nothing
  - Taken advantage by web spammers
    - Large volume of machine-generated pages to artificially increase “in-links” of the target page
    - Fake or invisible links
- We should not only consider the count of in-links, but the quality of each in-link
  - PageRank
  - HITS

Link structure analysis

- Describes the characteristic of network structure
- Reflect the utility of web documents in a general sense
- An important factor when ranking documents
  - For learning-to-rank
  - For focused crawling

Recall how we do internet browsing

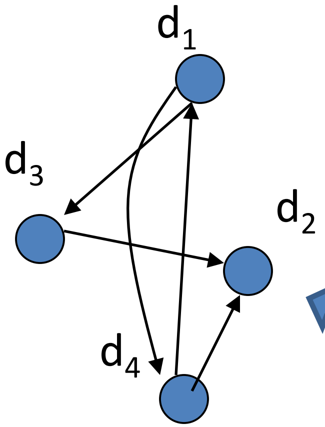
1. Mike types a URL address in his Chrome's URL bar;
2. He browses the content of the page, and follows the link he is interested in;
3. When he feels the current page is not interesting or there is no link to follow, he types another URL and starts browsing from there;
4. He repeats 2 and 3 until he is tired or satisfied with this browsing activity

PageRank

- A random surfing model of internet
  1. A surfer begins at a random page on the web and starts random walk on the graph
  2. On current page, the surfer uniformly follows an out-link to the next page
  3. When there is no out-link, the surfer uniformly jumps to a page from the whole page
  4. Keep doing Step 2 and 3 forever

PageRank

- A measure of web page popularity
  - Probability of a random surfer who arrives at this web page
  - Only depends on the linkage structure of web pages



Transition matrix

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

$$p_t(d) = \alpha M^T p_{t-1}(d) + \frac{(1-\alpha)}{N} p_{t-1}(d)$$

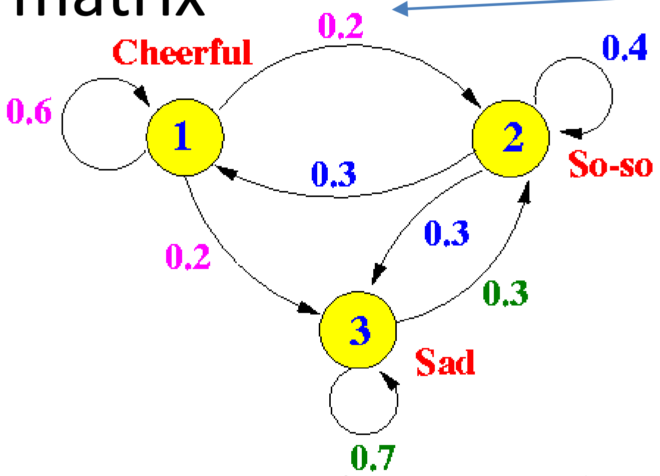
α: probability of random jump

N: # of pages

Random walk

Theoretic model of PageRank

- Markov chains
  - A discrete-time stochastic process
    - It occurs in a series of time-steps in each of which a random choice is made
  - Can be described by a directed graph or a transition matrix



P(So-so|Cheerful)=0.2

$$M = \begin{pmatrix} 0.6 & 0.2 & 0.2 \\ 0.3 & 0.4 & 0.3 \\ 0 & 0.3 & 0.7 \end{pmatrix}$$

A first-order Markov chain for emotion

Markov chains

- Markov property

  Idea of random surfing

  - $P(X_{n+1}|X_1, \dots, X_n) = P(X_{n+1}|X_n)$
    - Memoryless (first-order)
- Transition matrix
  - A stochastic matrix
    - $\forall i, \sum_j M_{ij} = 1$

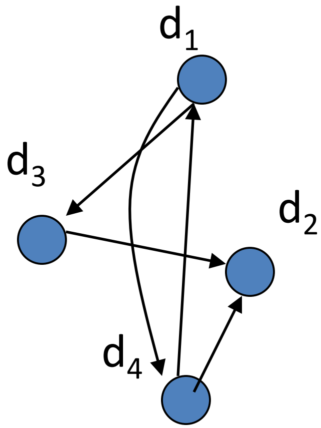
$$M = \begin{pmatrix} 0.6 & 0.2 & 0.2 \\ 0.3 & 0.4 & 0.3 \\ 0 & 0.3 & 0.7 \end{pmatrix}$$

  - Key property
    - It has a principal left eigenvector corresponding to its largest eigenvalue, which is one

Mathematical interpretation of PageRank score

Theoretic model of PageRank

- Transition matrix of a Markov chain for PageRank



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

1. Enable random jump on dead end

$$A' = \begin{pmatrix} 0 & 0 & 1 & 1 \\ 0.25 & 0.25 & 0.25 & 0.25 \\ 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \end{pmatrix}$$

2. Normalization

$$A'' = \begin{pmatrix} 0 & 0 & 0.5 & 0.5 \\ 0.25 & 0.25 & 0.25 & 0.25 \\ 0 & 1 & 0 & 0 \\ 0.5 & 0.5 & 0 & 0 \end{pmatrix}$$

3. Enable random jump on all nodes

$\alpha = 0.5$

$$M = \begin{pmatrix} 0.125 & 0.125 & 0.375 & 0.375 \\ 0.25 & 0.25 & 0.25 & 0.25 \\ 0.125 & 0.625 & 0.125 & 0.125 \\ 0.375 & 0.375 & 0.125 & 0.125 \end{pmatrix}$$

Steps to derive transition matrix for PageRank

1. If a row of *A* has no 1's, replace each element by 1/N.
2. Divide each 1 in *A* by the number of 1's in its row.
3. Multiply the resulting matrix by $1 - \alpha$.
4. Add α/N to every entry of the resulting matrix, to obtain *M*.

A: adjacent matrix of network structure;
α: dumping factor

PageRank computation becomes

- $p_t(d) = M^T p_{t-1}(d)$
  - Assuming $p_0(d) = \left[\frac{1}{N}, \dots, \frac{1}{N}\right]$
  - Iterative computation (forever?)
    - $p_t(d) = M^T p_{t-1}(d) = \cdots = (M^T)^t p_0(d)$
  - Intuition: after enough rounds of random walk, each dimension of $p_t(d)$ indicates the frequency of a random surfer visiting document d
  - Question: will this frequency converges to certain fixed, steady-state quantity?

Stationary distribution of a Markov chain

- For a given Markov chain with transition matrix M, its stationary distribution of π is

$$\left.\begin{aligned} &\forall i \in S, \pi_i \geq 0 \\ &\sum_{i \in S} \pi_i = 1 \end{aligned}\right\} \text{A probability vector}$$

$$\pi = M^T \pi \longrightarrow \text{Random walk does not affect its distribution}$$

  - Necessary condition
    - Irreducible: a state is reachable from any other state
    - Aperiodic: states cannot be partitioned such that transitions happened periodically among the partitions

Markov chain for PageRank

- Random jump operation makes PageRank satisfy the necessary conditions
  1. Random jump makes every node is reachable for the other nodes
  2. Random jump breaks potential loop in a sub-network
- What does PageRank score really converge to?

Stationary distribution of PageRank

- For any irreducible and aperiodic Markov chain, there is a unique steady-state probability vector π, such that if $c(i,t)$ is the number of visits to state i after t steps, then

$$\lim_{t\rightarrow\infty}\frac{c(i,t)}{t}=\pi_i$$

  - PageRank score converges to the expected visit frequency of each node

Computation of PageRank

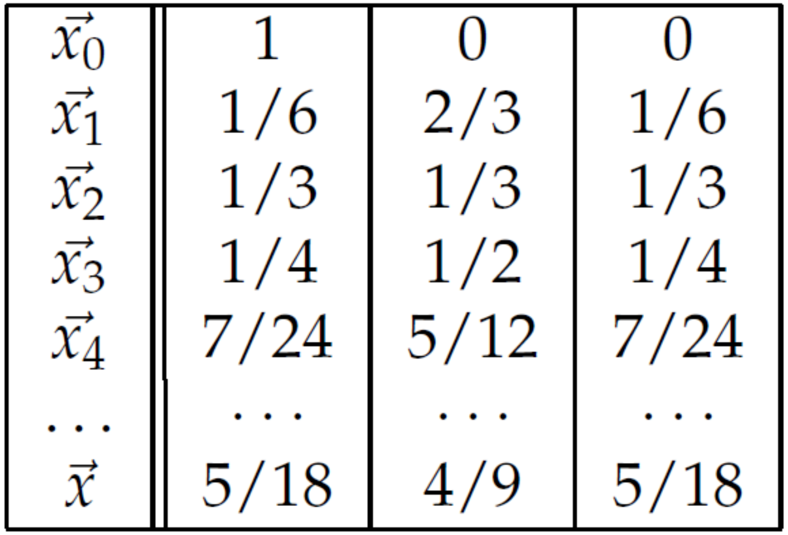
- Power iteration
  - $p_t(d) = M^T p_{t-1}(d) = \cdots = (M^T)^t p_0(d)$
    - Normalize $p_t(d)$ in each iteration
    - Convergence rate is determined by the second eigenvalue
  - Random walk becomes series of matrix production
  - Alternative interpretation of PageRank score
    - Principal left eigenvector corresponding to its largest eigenvalue, which is one

$$M^T \times \pi = 1 \times \pi$$

Computation of PageRank

- An example from Manning’s text book

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



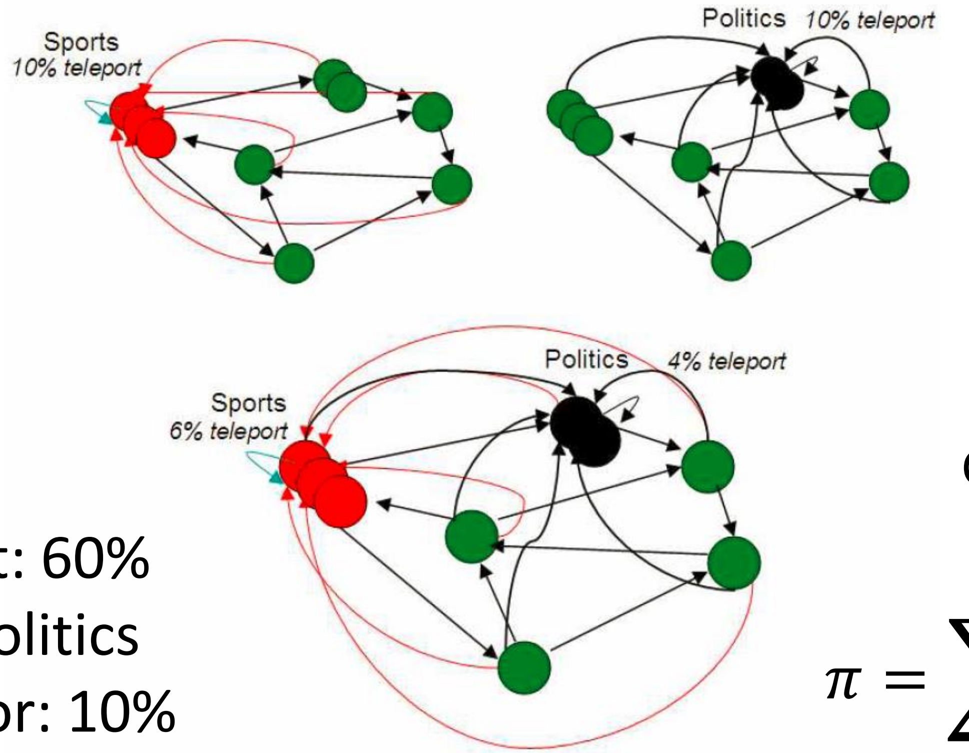
$\vec{x}_0$	1	0	0
$\vec{x}_1$	1/6	2/3	1/6
$\vec{x}_2$	1/3	1/3	1/3
$\vec{x}_3$	1/4	1/2	1/4
$\vec{x}_4$	7/24	5/12	7/24
…	…	…	…
$\vec{x}$	5/18	4/9	5/18

Variants of PageRank

- Topic-specific PageRank
  - Control the random jump to topic-specific nodes
    - E.g., surfer interests in Sports will only randomly jump to Sports-related website when they have no out-links to follow
  - $p_t(d) = [\alpha M^T + (1-\alpha)\vec{e}p^T(d)]p_{t-1}(d)$
    - $p^T(d) > 0$ iff d belongs to the topic of interest
    - $\vec{e}$ is a column vector of ones

Variants of PageRank

- Topic-specific PageRank
  - A user's interest is a mixture of topics



User's interest: 60% Sports, 40% politics
Damping factor: 10%

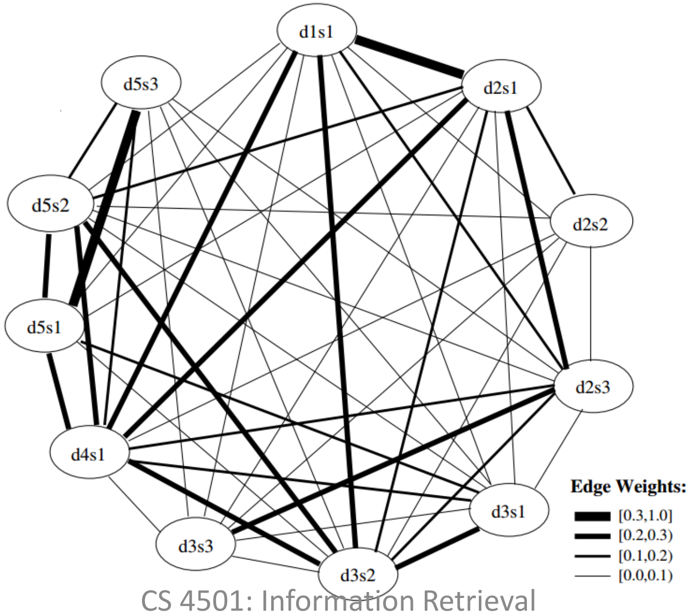
Compute it off-line

$$\pi = \sum_k p(T_k|user)\,\boxed{\pi_{T_k}}$$

Manning, "Introduction to Information Retrieval", Chapter 21, Figure 21.5

Variants of PageRank

- LexRank
  - *A sentence is important if it is similar to other important sentences*
  - PageRank on sentence similarity graph

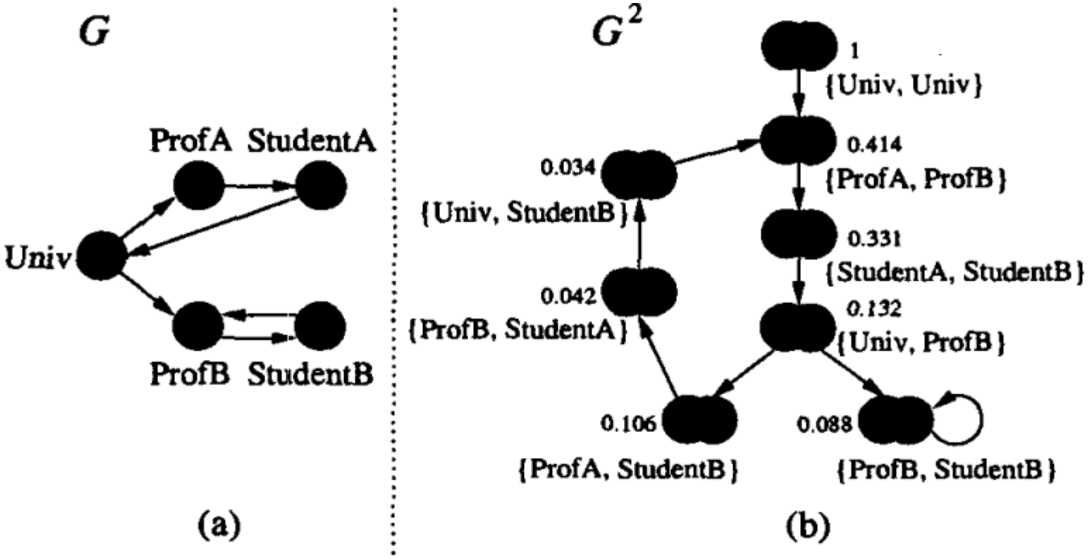


Centrality-based sentence salience ranking for document summarization

Erkan & Radev, JAIR’04

Variants of PageRank

- SimRank
  - *Two objects are similar if they are referenced by similar objects*
  - PageRank on bipartite graph of object relations

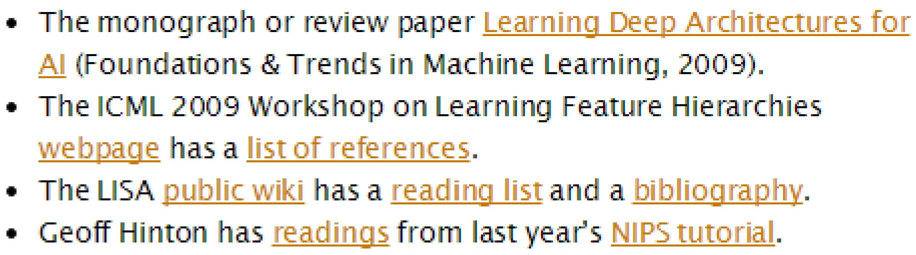


Measure similarity between objects via their connecting relation

Glen & Widom, KDD'02

HITS algorithm

- Two types of web pages for a broad-topic query
  - Authorities – trustful source of information
    - UVa-> University of Virginia official site
  - Hubs – hand-crafted list of links to authority pages for a specific topic
    - Deep learning -> deep learning reading list

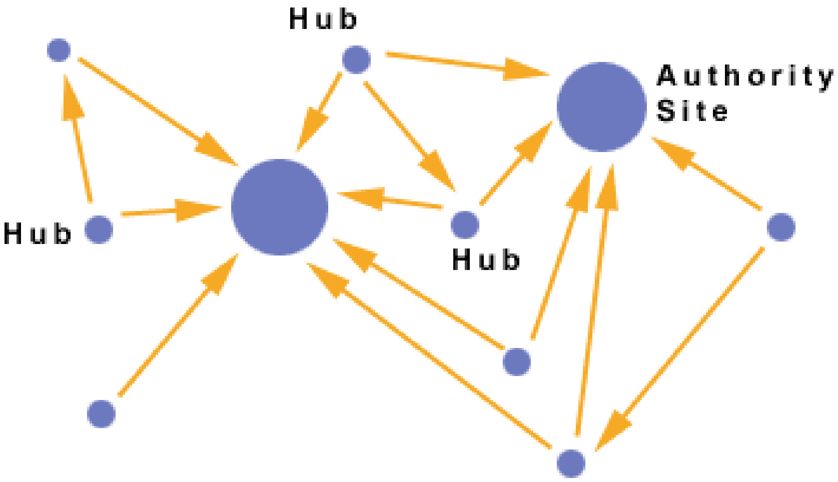


- The monograph or review paper Learning Deep Architectures for AI (Foundations & Trends in Machine Learning, 2009).
- The ICML 2009 Workshop on Learning Feature Hierarchies webpage has a list of references.
- The LISA public wiki has a reading list and a bibliography.
- Geoff Hinton has readings from last year's NIPS tutorial.

HITS algorithm

HITS=Hyperlink-Induced Topic Search

- Intuition
  - Using hub pages to discover authority pages
- Assumpt
  - A good … many good authori
  - A good … inted to by many g … score
- Recursive … ve algorithm



Computation of HITS scores

- Two scores for a web page for a given query
  - Authority score: $a(d)$
  - Hub score: $h(d)$

$v \to d$ means there is a link from v to d

$$\begin{tikzcd} a(d) \leftarrow \sum_{v \to d} h(v) \arrow[d, bend left] \\ h(d) \leftarrow \sum_{d \to v} a(v) \arrow[u, bend left] \end{tikzcd}$$

With proper normalization (L_2-norm)

Important HITS scores are query-dependent!

Computation of HITS scores

- In matrix form
  - $\vec{a} \leftarrow A^T \vec{h}$ and $\vec{h} \leftarrow A\vec{a}$
  - That is $\vec{a} \leftarrow A^T A\vec{a}$ and $\vec{h} \leftarrow AA^T \vec{h}$
  - Another eigen-system

$$\vec{a} = \frac{1}{\lambda_a} A^T A \vec{a}$$

$$\vec{h} = \frac{1}{\lambda_h} A A^T \vec{h}$$

Power iteration is applicable here as well

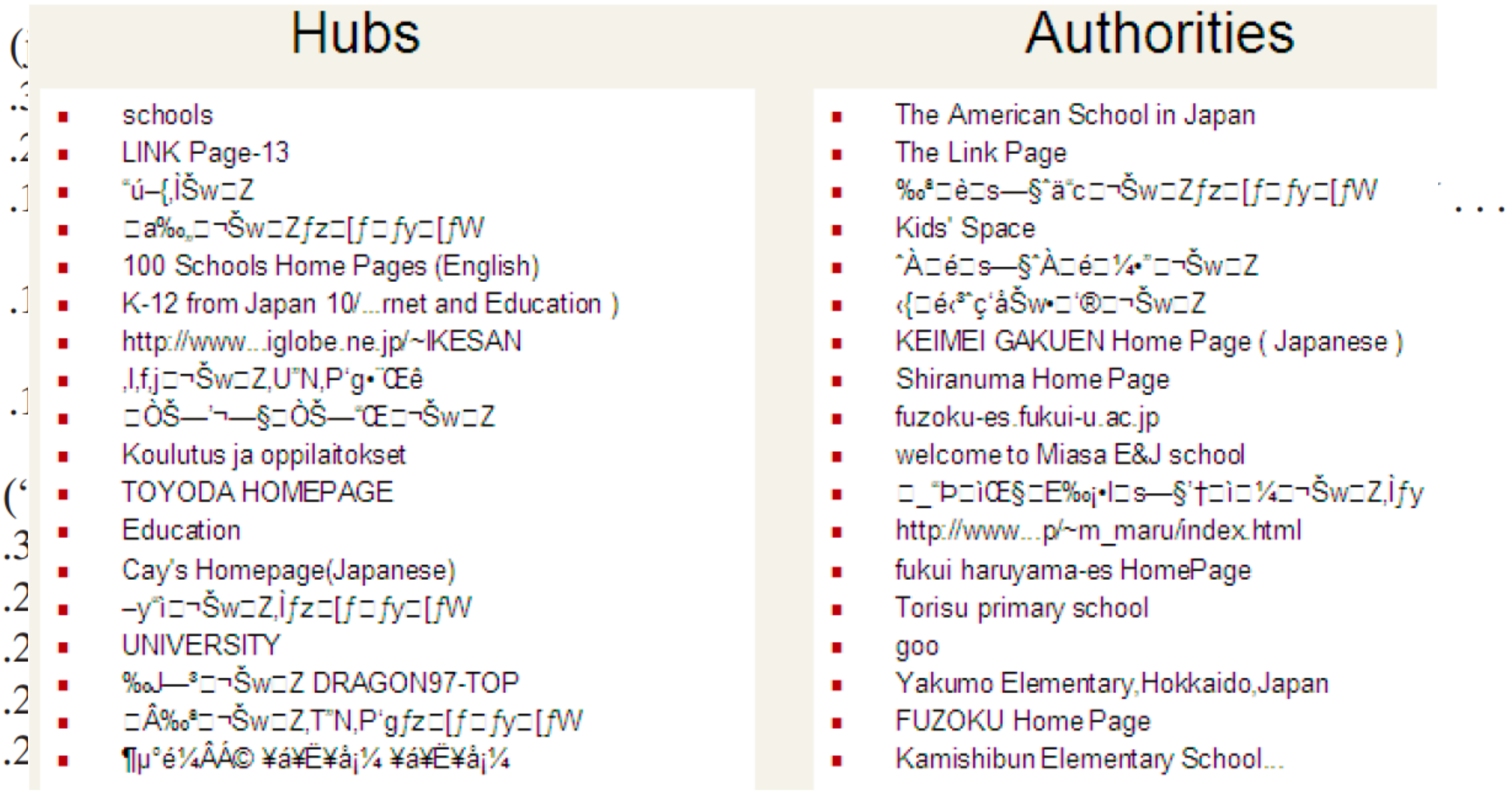
Constructing the adjacent matrix

- Only consider a subset of the Web
  1. For a given query, retrieve all the documents containing the query (or top *K* documents in a ranked list) – root set
  2. Expand the root set by adding pages either linking to a page in the root set, or being linked to by a page in the root set – base set
  3. Build adjacent matrix of pages in the base set

Constructing the adjacent matrix

- Reasons behind the construction steps
  - Reduce the computation cost
  - A good authority page may not contain the query text
  - The expansion of root set might introduce good hubs and authorities into the sub-network

Sample results



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...

Kleinberg, JACM'99

Manning, “Introduction to Information Retrieval”, Chapter 21, Figure 21.6

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