CS276B

Text Retrieval and Mining
Winter 2005

Lecture 11

This lecture

- Wrap up pagerank
- Anchor text
- HITS
- Behavioral ranking

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 say 10% probability, using the following rule:
  - Selects a category (say, one of the 16 top level ODP 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!

Topic Specific Pagerank [Have02]

- Implementation
  - **offline**:Compute pagerank distributions wrt to *individual* categories

    Query independent model as before

    Each page has multiple pagerank scores – one for each ODP category, with teleportation only to that category
  - **online**: Distribution of weights over categories computed by query context classification

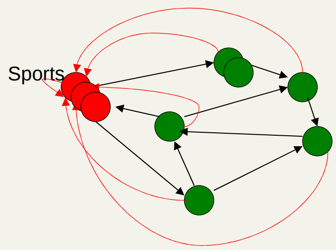
    Generate a dynamic pagerank score for each page – weighted sum of category-specific pageranks

Influencing PageRank (“Personalization”)

- Input:
  - Web graph W
  - influence vector **v**

    v : (page $\rightarrow$ degree of influence)
- Output:
  - Rank vector **r**: (page $\rightarrow$ page importance wrt **v**)
- **r** = PR(W, **v**)

Non-uniform Teleportation



Teleport with 10% probability to a Sports page

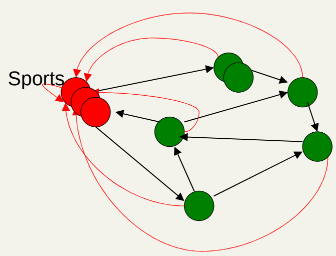
Interpretation of Composite Score

- For a set of personalization vectors $\{v_j\}$

$$\sum_j [w_j \cdot PR(W, v_j)] = PR(W, \sum_j [w_j \cdot v_j])$$

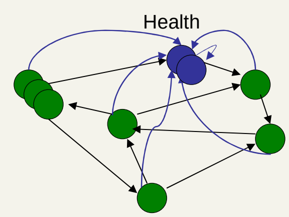
- Weighted sum of rank vectors itself forms a valid rank vector, because PR() is linear wrt v_j

Interpretation



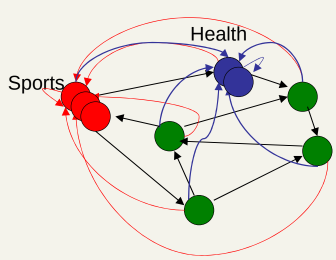
10% Sports teleportation

Interpretation



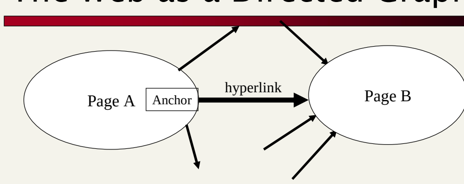
10% Health teleportation

Interpretation



pr = (0.9 PR_{sports} + 0.1 PR_{health}) gives you:
9% sports teleportation, 1% health teleportation

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)

Assumptions Tested

- A link is an endorsement (quality signal)
  - Except when *affiliated*
  - Can we recognize *affiliated links*? [Davi00]
    - 1536 links manually labeled
    - 59 binary features (e.g., on-domain, meta tag overlap, common outlinks)
    - C4.5 decision tree, 10 fold cross validation showed 98.7% accuracy
      - Additional surrounding text has lower probability but can be useful

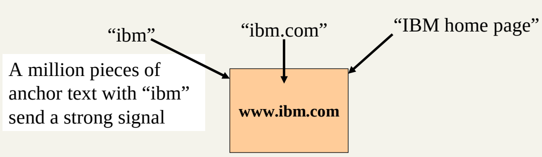
Assumptions tested

- Anchors describe the target
  - Topical Locality [Davi00b]
    - ~200K pages (query results + their outlinks)
    - Computed "page to page" similarity (TFIDF measure)
      - Link-to-Same-Domain > Cocited > Link-to-Different-Domain
    - Computed "anchor to page" similarity
      - Mean anchor len = 2.69
      - 0.6 mean probability of an anchor term in target page

Anchor Text

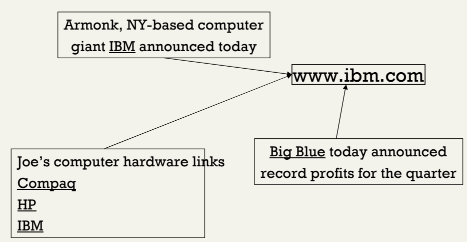
WWW Worm – McBryan [Mcbr94]

- For [ibm] how to distinguish between:
  - IBM's home page (mostly graphical)
  - IBM's copyright page (high term freq. for 'ibm')
  - Rival's spam page (arbitrarily high term freq.)



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 - *e.g., evil empire*.
- Can index anchor text with less weight.

Anchor Text

- Other applications
  - Weighting/filtering links in the graph
    - HITS [Chak98], Hilltop [Bhar01]
  - Generating page descriptions from anchor text [Amit98, Amit00]

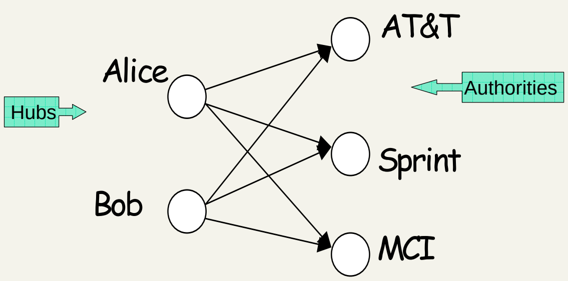
Hyperlink-Induced Topic Search (HITS) - Klei98

- 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.
- Best suited for "broad topic" queries rather than for page-finding queries.
- Gets at a broader slice of common *opinion*.

Hubs and Authorities

- Thus, a good hub page for a topic *points* to many authoritative pages for that topic.
- 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



Long distance telephone companies

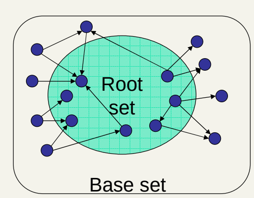
High-level scheme

- 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

- 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



Assembling the base set [Klei98]

- Root set typically 200-1000 nodes.
- Base set may have up to 5000 nodes.
- How do you find the base set nodes?
  - Follow out-links by parsing root set pages.
  - Get in-links (and out-links) from a *connectivity server*.
  - (Actually, suffices to text-index strings of the form ***href="URL"*** to get in-links to *URL*.)

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 $h(x)$, $a(x)$;

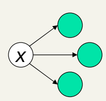
Key

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

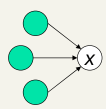
Iterative update

- Repeat the following updates, for all x:

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



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



Scaling

- To prevent the $h()$ and $a()$ values from getting too big, can scale down after each iteration.
- Scaling factor doesn't really matter:
  - 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!
  - proof of this comes later.
- We only require the relative orders of the $h()$ and $a()$ scores - not their absolute values.
- In practice, ~5 iterations 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

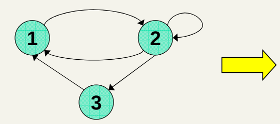
- The American School in Japan
- The Link Page
- ‰ª è s—§ˆä“c ¬Šw Zƒz [ƒ ƒy [ƒW
- Kids' Space
- ˆÀ é s—§ˆÀ é ¼•” ¬Šw Z
- ‹{ é‹³ˆç‘åŠw• ‘® ¬Šw Z
- KEIMEI GAKUEN Home Page (Japanese)
- Shiranuma Home Page
- fuzoku-es.fukui-u.ac.jp
- welcome to Miasa E&J school
- _“Þ ìŒ§ E‰¡•l s—§’† ì ¼ ¬Šw Z,Ìƒy
- http://www...p/~m_maru/index.html
- 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.
- Use *only* link analysis <u>after</u> base set assembled
  - iterative scoring is query-independent.
- Iterative computation <u>after</u> text index retrieval - significant overhead.

Proof of convergence

- $n \times n$ <u>adjacency matrix</u> **A**:
  - each of the n pages in the base set has a row and column in the matrix.
  - Entry $A_{ij} = 1$ if page i links to page j, else = 0.



	1	2	3
1	0	1	0
2	1	1	1
3	1	0	0

Hub/authority vectors

- View the hub scores *h()* and the authority scores *a()* as vectors with *n* components.
- Recall the iterative updates

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

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

Rewrite in matrix form

- **h**=A**a**.
- **a**=A^t**h**.

Recall A^t is the transpose of A.

Substituting, **h**=**AA^{t}h** and **a**=**A^{t}Aa**.

Thus, **h** is an eigenvector of **AA^t** and **a** is an eigenvector of **A^{t}A**.

Further, our algorithm is a particular, known algorithm for computing eigenvectors: the *power iteration* method.

Guaranteed to converge.

Issues

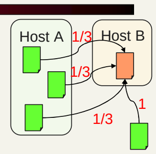
- Topic Drift
  - Off-topic pages can cause off-topic "authorities" to be returned
    - E.g., the neighborhood graph can be about a "super topic"
- Mutually Reinforcing Affiliates
  - Affiliated pages/sites can boost each others' scores
    - Linkage between affiliated pages is not a useful signal

Solutions

- ARC [Chak98] and Clever [Chak98b]
  - Distance-2 neighborhood graph
  - Tackling affiliated linkage
    - IP prefix (E.g., 208.47.*.*) rather than hosts to identify "same author" pages
  - Tackling topic drift
    - Weight edges by match between query and extended anchor text
    - Distribute hub score <u>non-uniformly</u> to outlinks
      Intuition: Regions of the hub page with links to good authorities get more of the hub score
    (For follow-up based on *Document Object Model* see [Chak01])

Solutions (contd)

- Topic Distillation [Bhar98]
  - Tackling affiliated linkage
    - Normalize weights of edges from/to a single host
  - Tackling topic drift
    - Query expansion.
    - "Topic vector" computed from docs in the initial ranking.
    - Match with topic vector used to weight edges and remove off-topic nodes
- Evaluation
  - 28 broad queries. Pooled results, blind ratings of results by 3 reviewers per query
  - Average precision @ 10
    - Topic Distillaton = 0.66, HITS = 0.46



Hilltop
[Bhar01]

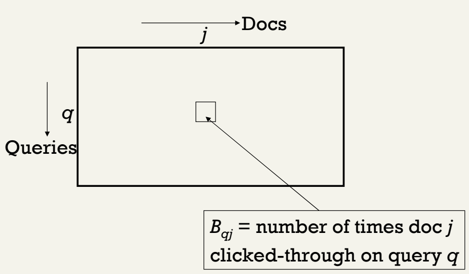
- *Preprocessing:* Special index of "expert" hubs
  - Select a subset of the web (~ 5%)
  - High out-degree to non-affiliated pages on a theme
- At query time compute:
  - Expert score (Hub score)
    - Based on text match between query and expert hub
  - Authority score
    - Based on scores of non-affiliated experts pointing to the given page
    - Also based on match between query and extended anchor-text (includes enclosing headings + title)
  - Return top ranked pages by authority score

Behavior-based ranking

Behavior-based ranking

- For each query *Q*, keep track of which docs in the results are clicked on
- On subsequent requests for *Q*, re-order docs in results based on click-throughs
- First due to DirectHit →AskJeeves
- Relevance assessment based on
  - Behavior/usage
  - vs. content

Query-doc popularity matrix B



When query q issued again, order docs by B_{qj} values.

Issues to consider

- Weighing/combining text- and click-based scores.
- What identifies a query?
  - Ferrari Mondial
  - Ferrari   Mondial
  - Ferrari mondial
  - ferrari mondial
  - "Ferrari Mondial"
- Can use heuristics, but search parsing slowed.

Vector space implementation

- Maintain a term-doc popularity matrix **C**
  - as opposed to query-doc popularity
  - initialized to all zeros
- Each column represents a doc *j*
  - If doc *j* clicked on for query **q**, update $C_j \leftarrow C_j + \varepsilon$ **q** (here **q** is viewed as a vector).
- On a query **q'**, compute its cosine proximity to C_j for all *j*.
- Combine this with the regular text score.

Issues

- Normalization of C_j after updating
- Assumption of query compositionality
  - "white house" document popularity derived from "white" and "house"
- Updating - live or batch?

Basic Assumption

- Relevance can be directly measured by number of click throughs
- Valid?

Validity of Basic Assumption

- Click through to docs that turn out to be non-relevant: what does a click mean?
- Self-perpetuating ranking
- Spam
- All votes count the same

Variants

- Time spent viewing page
  - Difficult session management
  - Inconclusive modeling so far
- Does user back out of page?
- Does user stop searching?
- Does user transact?