Introduction to

Information Retrieval

CS276
Information Retrieval and Web Search
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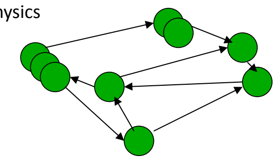
Lecture 18: Link analysis

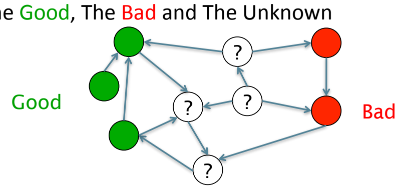
Today's lecture – hypertext and links

- We look beyond the *content* of documents
  - We begin to look at the hyperlinks between them
- Address questions like
  - Do the links represent a conferral of authority to some pages? Is this useful for ranking?
  - How likely is it that a page pointed to by the CERN home page is about high energy physics
- Big application areas
  - The Web
  - Email
  - Social networks



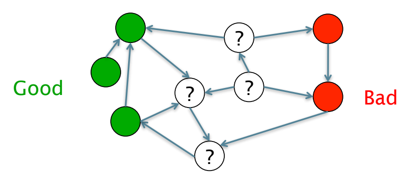
Links are everywhere

- Powerful sources of authenticity and authority
  - Mail spam – which email accounts are spammers?
  - Host quality – which hosts are "bad"?
  - Phone call logs
- The Good, The Bad and The Unknown



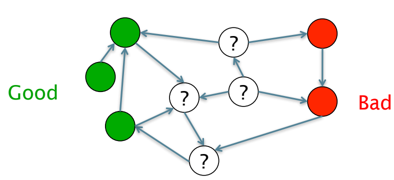
Simple iterative logic

- The Good, The Bad and The Unknown
  - Good nodes won't point to Bad nodes
  - All other combinations plausible



Simple iterative logic

- Good nodes won't point to Bad nodes
  - If you point to a Bad node, you're Bad
  - If a Good node points to you, you're Good



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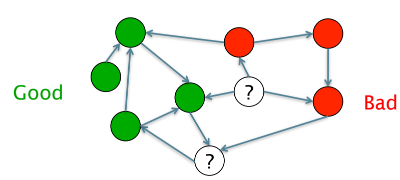

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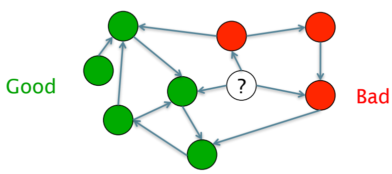


Sometimes need probabilistic analogs – e.g., mail spam

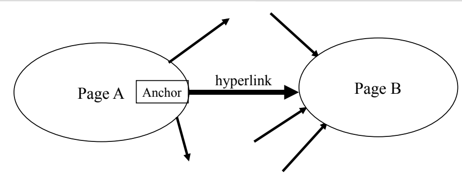
Many other examples of link analysis

- Social networks are a rich source of grouping behavior
- E.g., Shoppers' affinity – Goel+Goldstein 2010
  - Consumers whose friends spend a lot, spend a lot themselves
- http://www.cs.cornell.edu/home/kleinber/networks-book/

Our primary interest in this course

- Analogs of most IR functionality based purely on text
  - Scoring and ranking
  - Link-based clustering – topical structure from links
  - Links as features in classification – documents that link to one another are likely to be on the same subject
- Crawling
  - Based on the links seen, where do we crawl next?

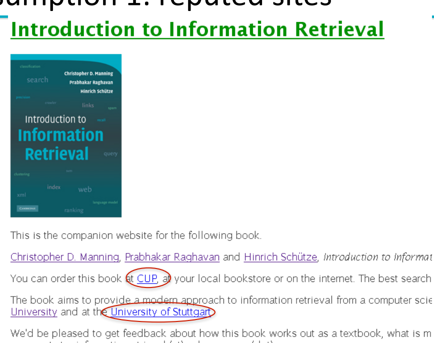
The Web as a Directed Graph



Assumption 1: A hyperlink between pages denotes a conferral of authority (quality signal)

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

Assumption 1: reputed sites


Introduction to Information Retrieval

Christopher D. Manning
Prabhakar Raghavan
Hinrich Schütze
Introduction to Information Retrieval

This is the companion website for the following book.

Christopher D. Manning, Prabhakar Raghavan and Hinrich Schütze, *Introduction to Informat*

You can order this book at CUP, at your local bookstore or on the internet. The best search

The book aims to provide a modern approach to information retrieval from a computer scie
University and at the University of Stuttgart

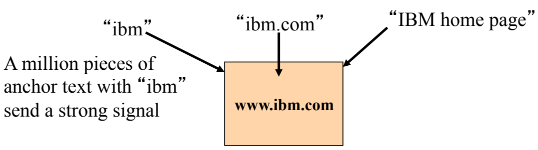
We'd be pleased to get feedback about how this book works out as a textbook, what is m
comments to: informationretrieval (at) yahoogroups (dot) com

Assumption 2: annotation of target

Anchor Text

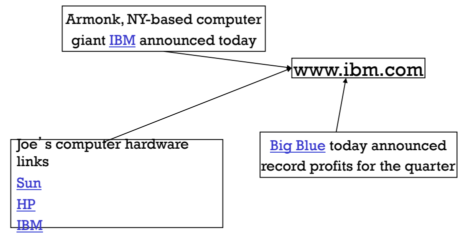
WWW Worm - McBryan [Mcbr94]

- 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 (with some weight) anchor text from links pointing to *D*.



Indexing anchor text

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

Anchor Text

- Other applications
  - Weighting/filtering links in the graph
  - Generating page descriptions from anchor text

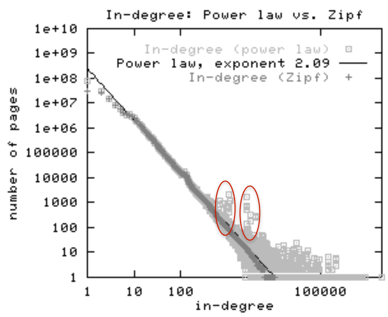
Citation Analysis

- Citation frequency
- Bibliographic coupling frequency
  - Articles that co-cite the same articles are related
- Citation indexing
  - Who is this author cited by? (Garfield 1972)
- Pagerank preview: Pinsker and Narin '60s

The web isn't scholarly citation

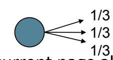
- Millions of participants, each with self interests
- Spamming is widespread
- Once search engines began to use links for ranking (roughly 1998), link spam grew
  - You can join a group of websites that heavily link to one another

In-links to pages – unusual patterns ☺



Pagerank scoring

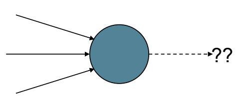
- Imagine a browser doing a random walk on web pages:
  - Start at a random page
  - At each step, go out of the current page along one of the links on that page, equiprobably



- "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

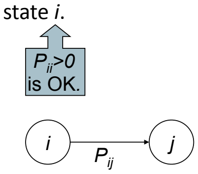
- At a dead end, jump to a random web page.
- At any non-dead end, with probability 10%, jump to a random web page.
  - With remaining probability (90%), go out on a random link.
  - 10% - a parameter.

Result of teleporting

- Now cannot get stuck locally.
- There is a long-term rate at which any page is visited (not obvious, will show this).
- How do we compute this visit rate?

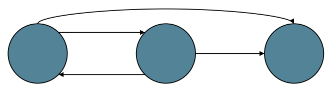
Markov chains

- 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 $1 \le i,j \le n$, the matrix entry P_{ij} tells us the probability of *j* being the next state, given we are currently in state *i*.



Markov chains

- Clearly, for all *i*, $\sum_{j=1}^{n} P_{ij} = 1.$
- Markov chains are abstractions of random walks.
- *Exercise*: represent the teleporting random walk from 3 slides ago as a Markov chain, for this case:



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.

Probability vectors

- A probability (row) vector **x** = $(x_1, \ldots x_n)$ tells us where the walk is at any point.
- E.g., (000…1…000) means we're in state *i*.
  1 i n

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

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

Change in probability vector

- If the probability vector is **x** = $(x_1, \ldots x_n)$ at this step, what is it at the next step?
- Recall that row *i* of the transition prob. Matrix **P** tells us where we go next from state *i*.
- So from **x**, our next state is distributed as **xP**
  - The one after that is $\mathbf{xP}^2$, then $\mathbf{xP}^3$, etc.
  - (Where) Does the converge?

How do we compute this vector?

- Let **a** = $(a_1, \ldots a_n)$ denote the row vector of steady-state probabilities.
- If our current position is described by **a**, then the next step is distributed as **aP**.
- But **a** is the steady state, so **a**=**aP**.
- Solving this matrix equation gives us **a**.
  - So **a** 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.

Pagerank summary

- Preprocessing:
  - Given graph of links, build matrix **P**.
  - From it compute **a** – left eigenvector of **P**.
  - The entry a_i is a number between 0 and 1: the pagerank of page *i*.
- Query processing:
  - 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
  - Many sophisticated features are used
  - Some address specific query classes
  - Machine learned ranking (Lecture 19) heavily used
- Pagerank still very useful for things like crawl policy

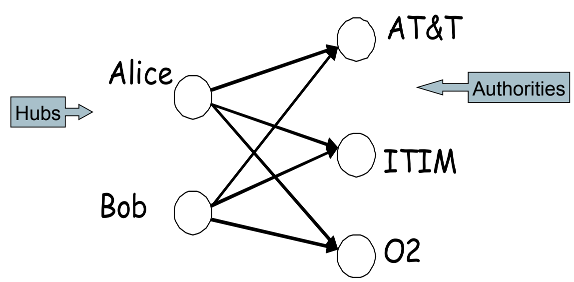
Hyperlink-Induced Topic Search (HITS)

- 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*.

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



Mobile telecom companies

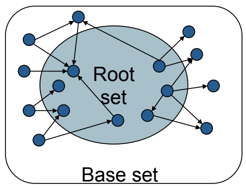
High-level scheme

- Extract from the web a <u>base set</u> 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 <u>root set</u> 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 <u>base set</u>.

Visualization



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

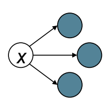
Distilling hubs and authorities

- 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)*←*1; a(x)* ←*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.

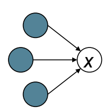
Iterative update

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

Japan Elementary Schools

Hubs

- schools
- LINK Page-13
- “ú–{,ÌŠw’Z
- ’a‰„¬Šw’Zƒz[ƒƒy[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[ƒƒy[ƒW
- UNIVERSITY
- ‰J—³¬Šw’Z DRAGON97-TOP
- Â‰ª¬Šw’Z,T”N,P ‘gƒz[ƒƒy[ƒW
- ¶µ°é¼ÂÁ© ¥á¥Ë¥å¡¼ ¥á¥Ë¥å¡¼

Authorities

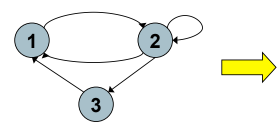
- The American School in Japan
- The Link Page
- ‰ª’ès—§ˆä“c¬Šw’Zƒz[ƒƒy[ƒW
- Kids' Space
- ˆÀés—§ˆÀé¼•”¬Šw’Z
- ‹{é‹³ˆç ‘åŠw•’ ‘®¬Šw’Z
- KEIMEI GAKUEN Home Page (Japanese)
- Shiranuma Home Page
- fuzoku-es.fukui-u.ac.jp
- welcome to Miasa E&J school
- _“ÞìŒ§E‰¡•ls—§’ †ì¼¬Šw’Z,Ìƒy
- http://www...p/~m_maru/index.html
- 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 after base set assembled
  - iterative scoring is query-independent.
- Iterative computation after text index retrieval - significant overhead.

Proof of convergence

- *n*×*n* adjacency matrix **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**=**Aa**.
- **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

Connectivity servers

Connectivity Server

- Support for fast queries on the web graph
  - Which URLs point to a given URL?
  - Which URLs does a given URL point to?

Stores mappings in memory from
    - URL to outlinks, URL to inlinks
- Applications
  - Crawl control
  - Web graph analysis
    - Connectivity, crawl optimization
  - Link analysis

Boldi and Vigna 2004

- http://www2004.org/proceedings/docs/1p595.pdf
- Webgraph – set of algorithms and a java implementation
- Fundamental goal – maintain node adjacency lists in memory
  - For this, compressing the adjacency lists is the critical component

Adjacency lists

- The set of neighbors of a node
- Assume each URL represented by an integer
- E.g., for a 4 billion page web, need 32 bits per node
- Naively, this demands 64 bits to represent each hyperlink

Adjaceny list compression

- Properties exploited in compression:
  - Similarity (between lists)
  - Locality (many links from a page go to "nearby" pages)
  - Use gap encodings in sorted lists
  - Distribution of gap values

Storage

- Boldi/Vigna get down to an average of ~3 bits/link
  - (URL to URL edge)
- How?

Why is this remarkable?

Main ideas of Boldi/Vigna

- Consider lexicographically ordered list of all URLs, e.g.,
  - www.stanford.edu/alchemy
  - www.stanford.edu/biology
  - www.stanford.edu/biology/plant
  - www.stanford.edu/biology/plant/copyright
  - www.stanford.edu/biology/plant/people
  - www.stanford.edu/chemistry

Boldi/Vigna

- Each of these URLs has an adjacency list
- Main idea: due to templates, the adjacency list of a node is similar to one of the 7 preceding URLs in the lexicographic ordering
- Express adjacency list in terms of one of these
- E.g., consider these adjacency lists
  - 1, 2, 4, 8, 16, 32, 64
  - 1, 4, 9, 16, 25, 36, 49, 64
  - 1, 2, 3, 5, 8, 13, 21, 34, 55, 89, 144
  - 1, 4, 8, 16, 25, 36, 49, 64

Why 7?

Encode as (-2), remove 9, add 8

Gap encodings

- Given a sorted list of integers x, y, z, …, represent by x, y-x, z-y, …
- Compress each integer using a code
  - γ code - Number of bits = $1 + 2 \lfloor \lg x \rfloor$
  - δ code: …
  - Information theoretic bound: $1 + \lfloor \lg x \rfloor$ bits
  - ζ code: Works well for integers from a power law Boldi Vigna DCC 2004

Main advantages of BV

- Depends only on locality in a canonical ordering
  - Lexicographic ordering works well for the web
- Adjacency queries can be answered very efficiently
  - To fetch out-neighbors, trace back the chain of prototypes
  - This chain is typically short in practice (since similarity is mostly intra-host)
  - Can also explicitly limit the length of the chain during encoding
- Easy to implement one-pass algorithm

Resources

- IIR Chap 21
- http://www2004.org/proceedings/docs/1p309.pdf
- http://www2004.org/proceedings/docs/1p595.pdf
- http://www2003.org/cdrom/papers/refereed/p270/kamvar-270-xhtml/index.html
- http://www2003.org/cdrom/papers/refereed/p641/xhtml/p641-mccurley.html
- The WebGraph framework I: Compression techniques (Boldi et al. 2004)