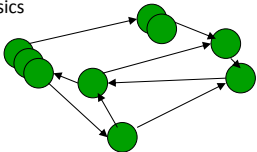


Introduction to
Information Retrieval

CS276
 Information Retrieval and Web Search
 Chris Manning, Pandu Nayak
 and Prabhakar Raghavan
 Link analysis

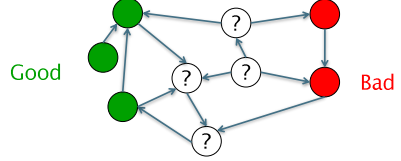
Today's lecture – hypertext and links

- 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

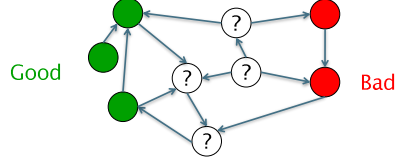
- Powerful sources of authenticity and authority
 - Mail spam – which email accounts are spammers?
 - Host quality – which hosts are “bad”?
 - Phone call logs
- The **Good**, The **Bad** and The Unknown



3

Example 1: **Good/Bad/Unknown**

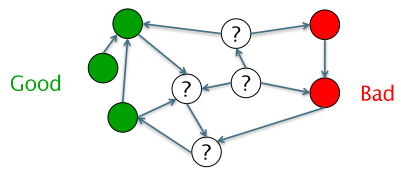
- The **Good**, The **Bad** and The Unknown
 - **Good** nodes won't point to **Bad** nodes
 - All other combinations plausible



4

Simple iterative logic

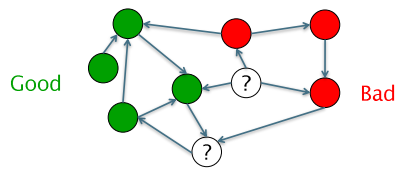
- **Good** nodes won't point to **Bad** nodes
 - If you point to a **Bad** node, you're **Bad**
 - If a **Good** node points to you, you're **Good**



5

Simple iterative logic

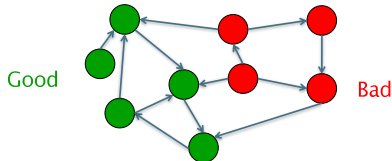
- **Good** nodes won't point to **Bad** nodes
 - If you point to a **Bad** node, you're **Bad**
 - If a **Good** node points to you, you're **Good**



6

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



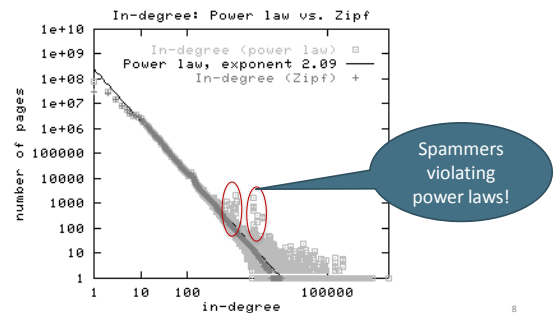
Sometimes need probabilistic analogs – e.g., mail spam

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/>

Example 2:

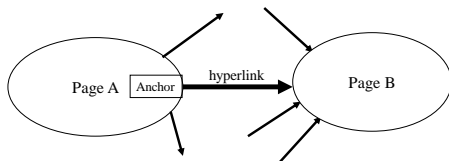
In-links to pages – unusual patterns ☺



Our primary interest in this course

- Link analysis for most IR functionality thus far 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

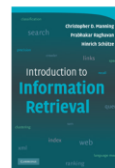


Hypothesis 1: A hyperlink between pages denotes a conferral of authority (quality signal)

Hypothesis 2: The text in the anchor of the hyperlink on page A describes the target page B

Assumption 1: reputed sites

Introduction to Information Retrieval



This is the companion website for the following book.

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

You can order this book [at CUP](#), your local bookstore or on the internet. The best search

The book aims to provide a modern approach to information retrieval from a computer science 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 missing, comments to: informationretrieval@yahoogroups.com

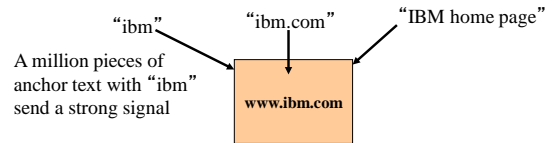
Assumption 2: annotation of target



Anchor Text

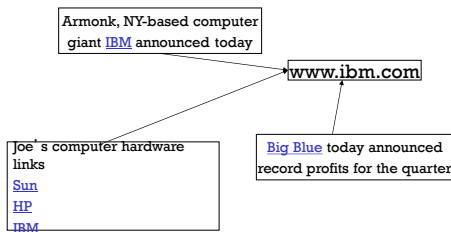
WWW Worm - McBryan [Mcb94]

- 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

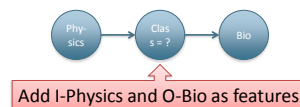
- Can sometimes have unexpected side effects - e.g., **evil empire**.
- Can score anchor text with weight depending on the authority of the anchor page's website
 - E.g., if we were to assume that content from cnn.com or yahoo.com is authoritative, then trust (more) the anchor text from them
 - Increase the weight of off-site anchors (non-nepotistic scoring)

Anchor Text

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

Web document classification

- Suppose we know the classes of some web pages
- How do we use these as features for learning the classes of neighboring pages?
- Basic approach – use known class labels together with in- or out-link info



(Important) Aside: Connectivity servers

Getting at all that link information.
Inexpensively.

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
- Boldi/Vigna get down to an average of ~3 bits/link
 - Further work achieves 2 bits/link

Adjacency 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

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 Why 7?
 - Main idea: due to templates, the adjacency list of a node is similar to one of the Z 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
- Encode as (-2), remove 9, add 8

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

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: Pinski and Narin ' 60s
 - Asked: which journals are authoritative?

Gap encodings


- Given a sorted list of integers x, y, z, \dots , represent by $x, y-x, z-y, \dots$
- 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

Back to link analysis

The web isn't scholarly citation

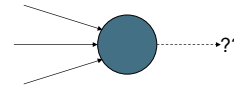
- Millions of participants, each with self interests
- Spamming is widespread
- Once search engines began to use links for ranking (roughly 1998), link spam grew
 - You can join a *link farm* – a group of websites that heavily link to one another

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 long run” 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

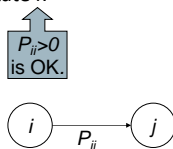
- At a dead end, jump to a random web page.
- At any non-dead end, with probability 10%, jump to a random web page.
 - With remaining probability (90%), go out on a random link.
 - 10% - a parameter.

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?

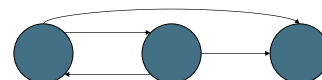
Markov chains

- A Markov chain consists of n states, plus an $n \times n$ transition probability matrix \mathbf{P} .
- At each step, we are in 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 .



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.

Change in probability vector

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

Pagerank summary

- Preprocessing:
 - Given graph of links, build matrix \mathbf{P} .
 - From it compute \mathbf{a} – left eigenvector of \mathbf{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* ...

Probability vectors

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

$$\begin{matrix} & 1 & & i & & n \\ & & & & & \end{matrix}$$

More generally, the vector $\mathbf{x} = (x_1, \dots, x_n)$ means the walk is in state i with probability x_i .

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

How do we compute this vector?

- Let $\mathbf{a} = (a_1, \dots, a_n)$ denote the row vector of steady-state probabilities.
- If our current position is described by \mathbf{a} , then the next step is distributed as \mathbf{aP} .
- But \mathbf{a} is the steady state, so $\mathbf{a} = \mathbf{aP}$.
- Solving this matrix equation gives us \mathbf{a} .
 - So \mathbf{a} is the (left) eigenvector for \mathbf{P} .
 - (Corresponds to the "principal" eigenvector of \mathbf{P} with the largest eigenvalue.)
 - Transition probability matrices always have largest eigenvalue 1.

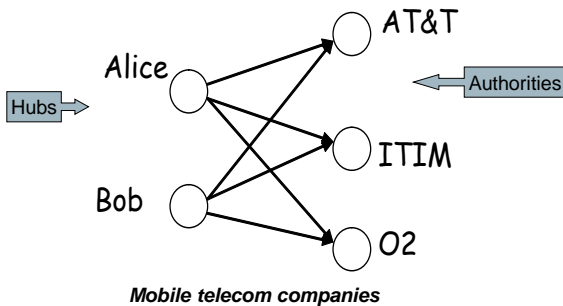
The reality

- Pagerank is used in web search engines, but is hardly the full story of ranking
 - Many sophisticated features are used
 - Some address specific query classes
 - Machine learned ranking 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 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*.

The hope



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.

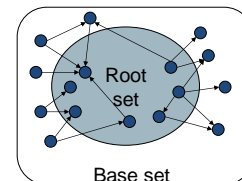
Hubs and Authorities

- 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.

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.

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 , $h(x) \leftarrow 1$; $a(x) \leftarrow 1$;
- 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.

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.

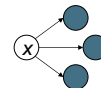
Japan Elementary Schools

Hubs	Authorities
<ul style="list-style-type: none"> schools LINK Page-13 u-1jSwZ afu-~SwZfjffjfw 100 Schools Home Pages (English) K-12 from Japan 101.net and Education) http://www...iglobe.ne.jp/~KESAN .11j~SwZU'N'P'g'~CE8 OS-~ ~ § OS-~ ~ CE~SwZ Kouikusha ja oppilatokset TOYODA HOMEPAGE Education Cay's Homepage(Japanese) -y'~SwZfjffjfw UNIVERSITY %J-~SwZ DRAGON87-TOP Å~SwZ,T'N'P' 'fjffjfw ¶ 6%ÅÅ@ %8VE%8% %8VE%8% 	<ul style="list-style-type: none"> The American School in Japan The Link Page %*#§ \$ % "c~SwZfjffjfw Kids' Space *A&- \$ Adit'~SwZ (6'g'~SwZ@~SwZ KEIMEI GAKUEN Home Page (Japanese) Shiranuma Home Page fuzoku-es.fukui-u.ac.jp welcome to Miasa E&J school *DUCE \$ E%y%— \$ '111r~SwZjfy http://www...pl~m_maru/index.html fukui haruyama-es HomePage Torisu primary school gao Yakumo Elementary/Hakkaido,Japan FLUZOKU Home Page Kamishibun Elementary School...

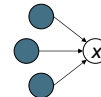
Iterative update

- Repeat the following updates, for all x :

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



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



How many iterations?

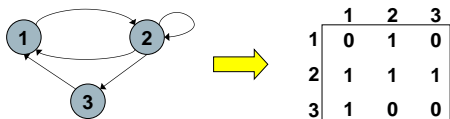
- Claim: relative values of scores will converge after a few iterations:
 - in fact, suitably scaled, $h()$ and $a()$ scores settle into a steady state!
 - proof of this comes later.
- In practice, ~5 iterations get you close to stability.**

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.

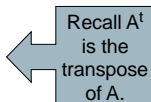
Proof of convergence

- $n \times n$ 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.



Rewrite in matrix form

- $\mathbf{h} = \mathbf{A}\mathbf{a}$.
- $\mathbf{a} = \mathbf{A}^t \mathbf{h}$.



Substituting, $\mathbf{h} = \mathbf{A}\mathbf{A}^t \mathbf{h}$ and $\mathbf{a} = \mathbf{A}^t \mathbf{A} \mathbf{a}$.

Thus, \mathbf{h} is an eigenvector of $\mathbf{A}\mathbf{A}^t$ and \mathbf{a} is an eigenvector of $\mathbf{A}^t \mathbf{A}$.

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

Guaranteed to converge.

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 \(Boldi et al. 2004\)](#)

Hub/authority vectors

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

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

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

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