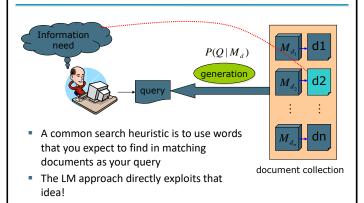
Information Retrieval & Social Web

CS 525/DS 595 Worcester Polytechnic Institute Department of Computer Science Instructor: Prof. Kyumin Lee

Previous Class...

Statistical Language Models

IR based on Language Model (LM)



Basic mixture model summary

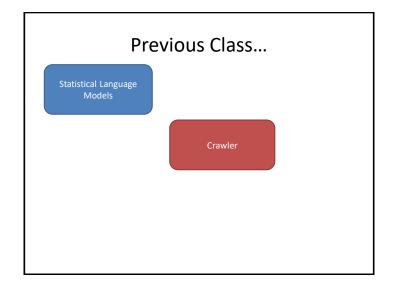
General formulation of the LM for IR

$$P(q|d) \propto \prod_{t \in q} ((1-\lambda)P(t|M_c) + \lambda P(t|M_d))$$
 general language model individual-document model

- The user has a document in mind, and generates the query from this document.
- The equation represents the probability that the document that the user had in mind was in fact this one.

Example

- Document collection (2 documents)
 - d₁: Xerox reports a profit but revenue is down
 - d₂: Lucent narrows quarter loss but revenue decreases further
- Model: MLE unigram from documents; $\lambda = \frac{1}{2}$
- Query: revenue down
 - P(Q|d₁) = $[(1/8 + 2/16)/2] \times [(1/8 + 1/16)/2]$ = $1/8 \times 3/32 = 3/256$
 - P(Q|d₂) = [(1/8 + 2/16)/2] x [(0 + 1/16)/2] = 1/8 x 1/32 = 1/256
- Ranking: $d_1 > d_2$



Previous Class... Statistical Language Models Crawler Web APIs

Available Web APIs

- Twitter: https://dev.twitter.com/
- Flickr: http://www.flickr.com/services/api/
- Google Maps: https://developers.google.com/maps/
- Facebook: http://developers.facebook.com/
- Foursquare: https://developer.foursquare.com/
- Yahoo Boss API: http://developer.yahoo.com/search/boss/
- Wikipedia API: http://www.mediawiki.org/wiki/API:Main page
- Youtube API: http://code.google.com/apis/youtube/overview.html
- Openstreetmap API: http://wiki.openstreetmap.org/wiki/API
- Halo API: https://developer.haloapi.com/
- List of APIs

https://www.reddit.com/r/webdev/comments/3wrswc/what_are_some_f un_apis_to_play_with/

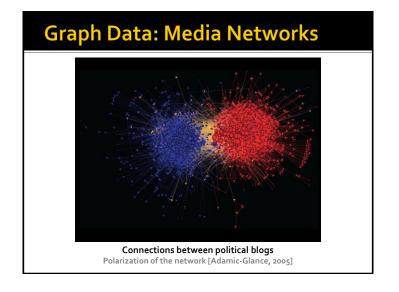
Static quality scores

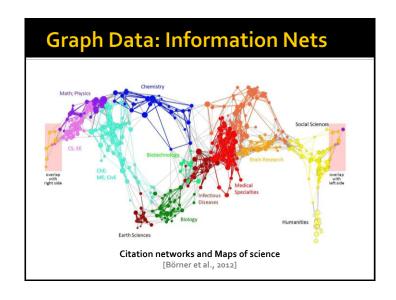
- We want top-ranking documents to be both relevant and authoritative
- *Relevance* is being modeled by cosine scores
- Authority is typically a query-independent property of a document
- Examples of authority signals
 - Wikipedia among websites
 - Articles in certain newspapers
 - A paper with many citations
 - Many bitly's or diggs
 - (Pagerank) ←

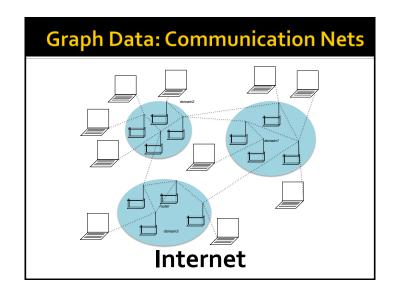
Today: Link Analysis

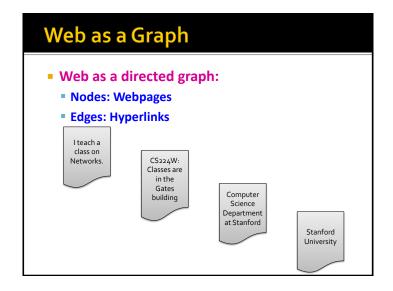
- Anchor text
- PageRank

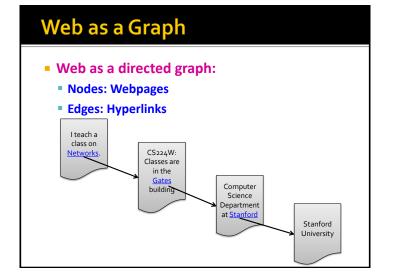
Facebook social graph 4-degrees of separation [Backstrom-Boldi-Rosa-Ugander-Vigna, 2011]

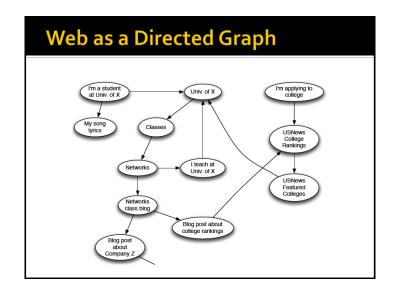








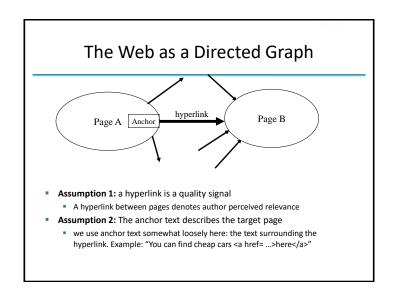




■ How to organize the Web? ■ First try: Human curated Web directories ■ Yahoo, DMOZ, LookSmart ■ Second try: Web Search ■ Information Retrieval investigates: Find relevant docs in a small and trusted set ■ Newspaper articles, Patents, etc. ■ But: Web is huge, full of untrusted documents,

random things, web spam, etc.

Anchor Text



[document text only] vs. [document text + anchor text]

- Searching on [document text + anchor text] is often more effective than searching on [document text only].
- Example: Query IBM
 - Matches IBM's copyright page
 - Matches many spam pages
 - Matches IBM wikipedia article
 - May not match IBM home page! (if IBM home page is mostly graphical)
- Searching on anchor text is better for the query IBM.
- Represent each page by all the anchor text pointing to it.
- In this representation, the page with the most occurrences of IBM is www.ibm.com.

Anchor text containing *IBM* pointing to www.ibm.com

www.slashdot.org: "New IBM optical chip"

www.stanford.edu:/"IBM faculty award recipients"

www.ibm.com

Indexing anchor text

- Thus: anchor text is often a better description of a page's content than the page itself
- Anchor text can be weighted more highly than document text (based on Assumptions 1 & 2)
- Indexing anchor text can have unexpected side effects -Google bombs.
- A Google bomb is a search with "bad" results due to maliciously manipulated anchor text
- Google introduced a new weighting function in January 2007 that fixed many Google bombs

Google bomb example





Web Search: Pre-History

Brief (non-technical) history of Web Search

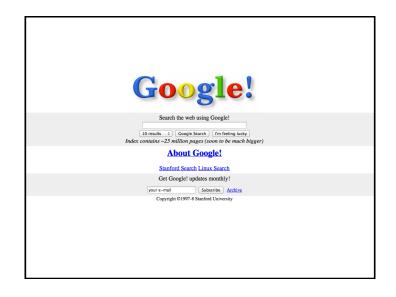
- Early keyword-based engines ca. 1995-1997
 - Altavista, Excite, Infoseek, Inktomi, Lycos,
- Paid placement ranking: Goto.com (morphed into Overture.com → Yahoo!)
 - Your search ranking depended on how much you paid
 - Auction for keywords: <u>casino</u> was expensive!

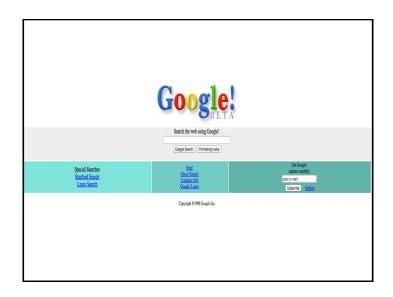


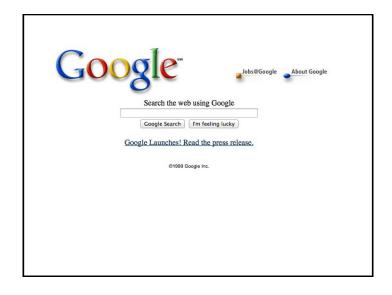






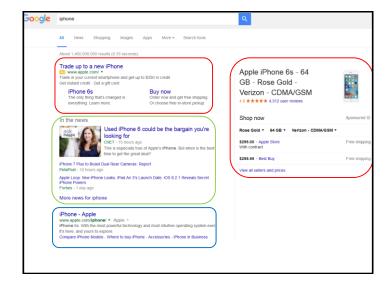


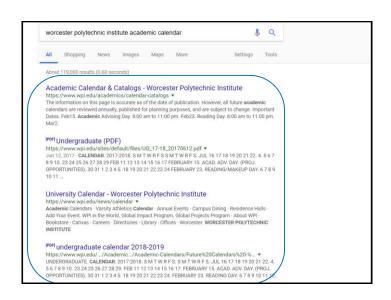


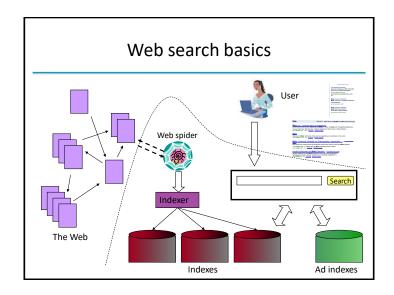


Brief (non-technical) history

- 1998+: Link-based ranking pioneered by Google
 - Blew away all early engines
 - Great user experience in search of a business model
 - Meanwhile Goto/Overture's annual revenues were nearing \$1 billion
- Result: Google added paid-placement "ads" to the side, independent of search results
 - Yahoo follows suit, acquiring Overture (for paid placement) and Inktomi (for search)
- 2005+: Google gains search share, dominating in Europe and very strong in North America
 - 2009: Yahoo! and Microsoft propose combined paid search offering







PageRank

Link-based ranking

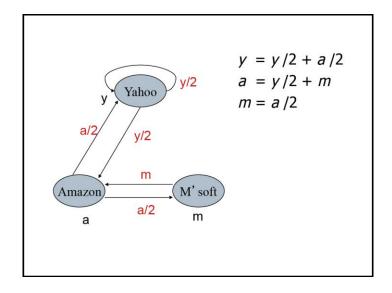
- Query processing with link-based ranking:
 - First retrieve all pages meeting the query (say venture capital)
 - Order these by their link popularity (= citation frequency, first generation)
 - . . . or by Pagerank (second generation)

- Simple link popularity (= number of inlinks of a page) is easy to spam.
- Why?



PageRank: Recursive formulation

- Each link's vote is proportional to the importance of its source page
- If page P with importance x has n outlines, each link gets x/n votes
- Page P's own importance is the sum of the vote on its inlinks

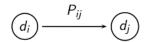


PageRank basics

- Imagine a web surfer doing a random walk on the web
 - 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 longterm visit rate - use this as the page's score.
- PageRank = steady state probability= long-term visit rate

Markov chains

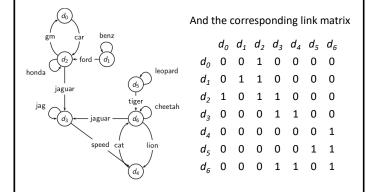
- A Markov chain consists of n states, plus an n×n transition probability matrix P.
- state = page
- At each step, we are on exactly one of the states.
- For $1 \le i, j \le n$, the matrix entry P_{ij} tells us the probability of j being the next state (page), given we are currently on page (state) i.



Markov chains

- Clearly, for all i, $\sum_{i=1}^{N} P_{ij} = 1$
- Markov chains are abstractions of random walks.

Example web graph



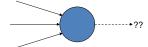
Transition probability matrix P

Long-term visit rate

- Recall: PageRank = long-term visit rate
- Long-term visit rate of page d is the probability that a web surfer is at page d at a given point in time.
- Next: what properties must hold of the web graph for the long-term visit rate to be well defined?

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.

Teleporting Matrix

• Recall: At a dead end, jump to a random web page

Formalization of "visit": Probability vectors

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

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

Result of teleporting

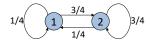
- With teleporting, we cannot get stuck in a dead end
- There is a long-term rate at which any page is visited (not obvious, will show this).
- How do we compute this visit rate?

Change in probability vector

- If the probability vector is $\mathbf{x} = (x_1, ... x_n)$ 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**.

Steady state example

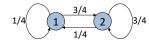
- The steady state looks like a vector of probabilities $\mathbf{a} = (a_1, ... a_n)$:
- a_i is the probability that we are in state i.



What is the steady state in this example?

Steady state example

- The steady state looks like a vector of probabilities $\mathbf{a} = (a_1, ... a_n)$:
- a_i is the probability that we are in state i.



For this example, $a_1=1/4$ and $a_2=3/4$.

How to compute the steady-state?

- Recall, regardless of where we start, we eventually reach the steady state **a**.
- Start with any distribution (say x=(10...0)).
- After one step, we're at xP;
- after two steps at \mathbf{xP}^2 , then \mathbf{xP}^3 and so on.
- "Eventually" means for "large" k, $\mathbf{x}\mathbf{P}^k = \mathbf{a}$.
- Algorithm: multiply x by increasing powers of P until the product looks stable.
- This is called the power method

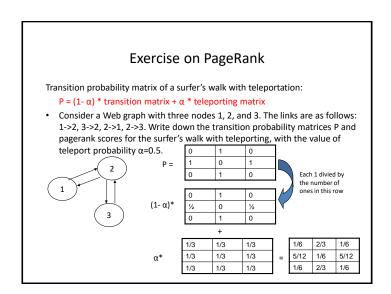
Power method: example

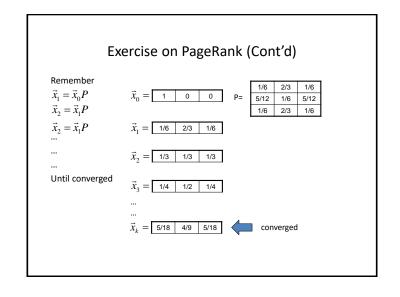
Two-node example: $\vec{x} = (0.5, 0.5), P = \begin{pmatrix} 0.25 & 0.75 \\ 0.25 & 0.75 \end{pmatrix}$

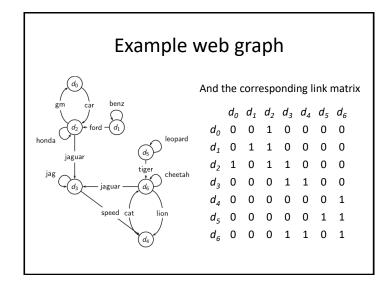
$$\vec{x}P = (0.25, 0.75) = \vec{x}_2$$

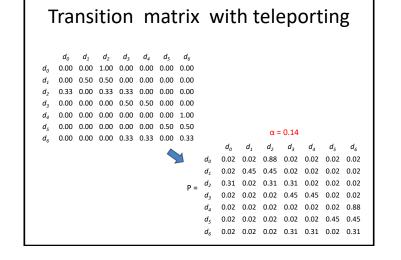
$$\vec{x}_2 P = (0.25, 0.75)$$

Convergence in one iteration!









Power method convergence

PageRank issues

- Real surfers are not random surfers Markov model is not a good model of surfing.
 - Issues: back button, short vs. long paths, bookmarks, directories – and search!
- Simple PageRank ranking (as described on previous slide) produces bad results for many pages.
 - Consider the query video service
 - The Yahoo home page (i) has a very high PageRank and (ii) contains both words.
 - If we rank all Boolean hits according to PageRank, then the Yahoo home page would be top-ranked.
 - Clearly not desirable
- In practice: rank according to weighted combination of many factors, including raw text match, anchor text match, PageRank and many other factors

Pagerank summary

- · Preprocessing:
 - Given graph of links, build matrix P.
 - From it compute **a**.
 - 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.
 - Order is query-independent.

How important is PageRank?

- Frequent claim: PageRank is the most important component of web ranking.
- The reality:
 - There are several components that are at least as important: e.g., anchor text, indexing, zone weighting, phrases ...
- Rumor has it that PageRank in his original form (as presented here) now has a negligible impact on ranking!
- However, variants of a page's PageRank are still an essential part of ranking.
- Addressing link spam is difficult and crucial.

