CS3245

Information Retrieval

Lecture 12: Web Search







Last Time

Chapter 11

- Probabilistic Approach to Retrieval / Basic Probability Theory
- 2. Probability Ranking Principle
- 3. OKAPI BM25

Chapter 12

1. Language Models for IR





Today

Chapter 19

- Web search big picture
- Search Advertising
- Duplicate Detection

Chapter 20

Crawling

Chapter 21

- Anchor Text
- PageRank

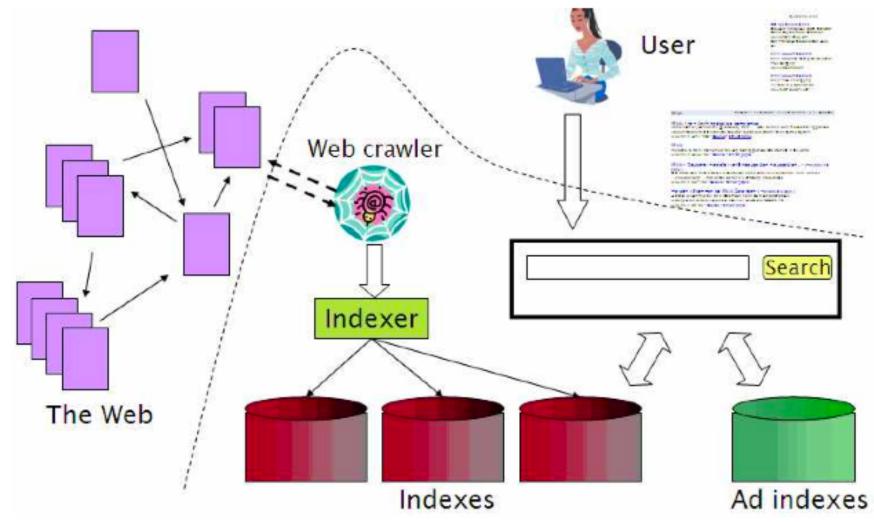


IR on the web vs. IR in general

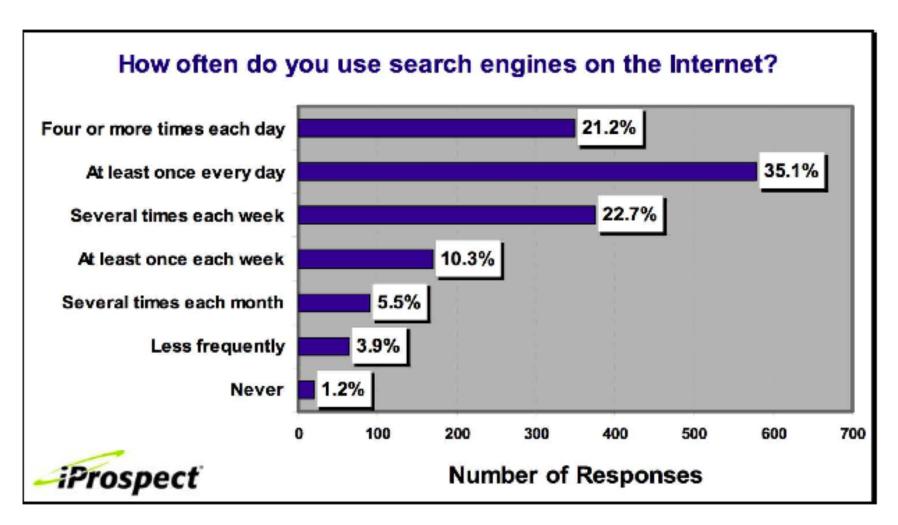
- On the web, search is not just a nice feature.
 - Search is a key enabler of the web: financing, content creation, interest aggregation, etc.
 - → look at search ads
- The web is a chaotic und uncoordinated collection.
 - → lots of duplicates need to detect duplicates
- No control / restrictions on who can author content.
 - → lots of spam need to detect spam
- The web is very large. \rightarrow need to know how big it is.



Web search overview



Search is the top activity on the web



Without search engines, the web wouldn't work





- Without search, content is hard to find.
- → Without search, there is no incentive to create content.
 - Why publish something if nobody will read it?
 - Why publish something if I don't get ad revenue from it?
- Somebody needs to pay for the web.
 - Servers, web infrastructure, content creation
 - A large part today is paid by search ads: Search pays for the web.



Interest aggregation

- Unique feature of the web: A small number of geographically dispersed people with similar interests can find each other.
 - Elementary school kids with hemophilia
 - People interested in translating R5R5 Scheme into relatively portable C (open source project)
 - Search engines are a key enabler for interest aggregation.
- The Long Tail







1st Generation of Search Ads: Goto (1996)





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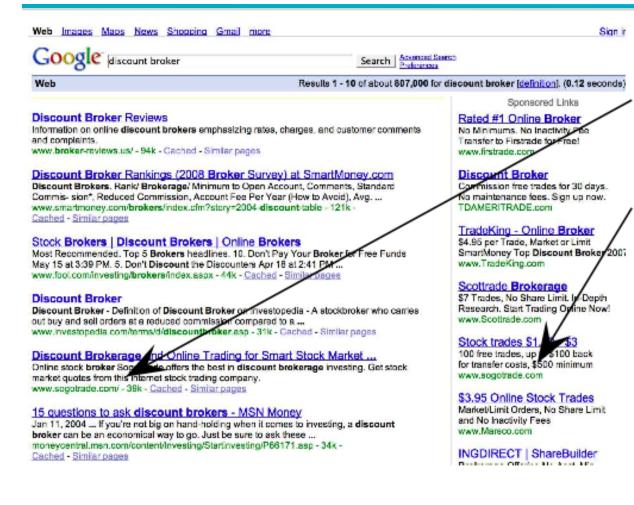




- Buddy Blake bid the maximum (\$0.38) for this search.
- He paid \$0.38 to Goto every time somebody clicked on the link.
- Pages were simply ranked according to bid revenue maximization for Goto.
- No separation of ads/docs. Only one result list!
- Upfront and honest. No relevance ranking, . . .
 - . . . but Goto did not pretend there was any.

2nd generation of search ads: Google (2000)





SogoTrade appears in search results.

SogoTrade appears in ads.

Do search engines rank advertisers higher than non-advertisers?

All major search engines claim "no".

Do ads influence editorial content?

- Similar problem at newspapers / TV channels
- A newspaper is reluctant to publish harsh criticism of its major advertisers.
- The line often gets blurred at newspapers / on TV.
- No known case of this happening with search engines yet?
- Leads to the job of white and black hat search engine optimization (organic) and search engine marketing (paid).





How are ads ranked?

- Advertisers bid for keywords sale by auction.
- Open system: Anybody can participate and bid on keywords.
- Advertisers are only charged when somebody clicks on your ad (i.e., CPC)

How does the auction determine an ad's rank and the price paid for the ad?

- Basis is a second price auction, but with twists
- For the bottom line, this is perhaps the most important research area for search engines – computational advertising.
 - Squeezing an additional fraction of a cent from each ad means billions of additional revenue for the search engine.



How are ads ranked?

- First cut: according to bid price a la Goto
 - Bad idea: open to abuse!
 - Example: query [does my husband cheat?] → ad for divorce lawyer
 - We don't want to show nonrelevant ads.

Instead: rank based on bid price and relevance

- Key measure of ad relevance: clickthrough rate
 - clickthrough rate = CTR = clicks per impressions
- Result: A nonrelevant ad will be ranked low.
 - Even if this decreases search engine revenue short-term
 - Hope: Overall acceptance of the system and overall revenue is maximized if users get useful information.
- Other ranking factors: location, time of day, quality and loading speed of landing page
- The main ranking factor: the query



Google's second price auction

advertiser	bid	CTR	ad rank	rank	paid
A	\$4.00	0.01	0.04	4	(minimum)
В	\$3.00	0.03	0.09	2	\$2.68
C	\$2.00	0.06	0.12	1	\$1.51
D	\$1.00	0.08	0.08	3	\$0.51

- bid: maximum bid for a click by advertiser
- CTR: click-through rate: when an ad is displayed, what percentage of time do users click on it? CTR is a measure of relevance.
- ad rank: bid × CTR: this trades off (i) how much money the advertiser is willing to pay against (ii) how relevant the ad is
- rank: rank in auction
- paid: second price auction price paid by advertiser



Google's second price auction

	advertiser	bid	CTR	ad rank	rank	paid
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	C	\$2.00	0.06	0.12	1	\$1.51
	D	\$1.00	0.08	0.08	3	\$0.51

- Second price auction: The advertiser pays the minimum amount necessary to maintain their position in the auction (plus 1 cent).
- price₁ × CTR₁ = bid₂ × CTR₂ (this will result in rank₁=rank₂)
- price₁ = bid₂ × CTR₂ / CTR₁
- $p_1 = bid_2 \times CTR_2/CTR_1 = 3.00 \times 0.03/0.06 = 1.50$
- $p_2 = bid_3 \times CTR_3/CTR_2 = 1.00 \times 0.08/0.03 = 2.67$
- $p_3 = bid_4 \times CTR_4/CTR_3 = 4.00 \times 0.01/0.08 = 0.50$





Keywords with high bids

According to http://www.cwire.org/highest-paying-search-terms/

mesothelioma treatment options \$69.1 \$65.9 personal injury lawyer michigan \$62.6 student loans consolidation \$61.4 car accident attorney los angeles \$59.4 online car insurance quotes \$59.4 arizona dui lawyer \$46.4 asbestos cancer \$40.1 home equity line of credit \$39.8 life insurance quotes \$39.2 refinancing \$38.7 equity line of credit \$38.0 lasik eye surgery new york city \$37.0 2nd mortgage \$35.9 free car insurance quote



Search ads: A win-win-win?

- The search engine company gets revenue every time somebody clicks on an ad.
- The user only clicks on an ad if they are interested in the ad.
 - Search engines punish misleading and nonrelevant ads.
 - As a result, users are often satisfied with what they find after clicking on an ad.
- The advertiser finds new customers in a costeffective way.

Not a win-win-win: Keyword arbitrage





- Buy a keyword on Google
- Then redirect traffic to a third party that is paying much more than you are paying Google.
 - E.g., redirect to a page full of ads
- This rarely makes sense for the user.
- (Ad) spammers keep inventing new tricks.
- The search engines need time to catch up with them.
- Adversarial Information Retrieval

Not a win-win-win: Violation of trademarks





- Example: geico
- During part of 2005: The search term "geico" on Google was bought by competitors.
- Geico lost this case in the United States.
- Louis Vuitton lost a similar case in Europe.
- See http://google.com/tm complaint.html
- It's potentially misleading to users to trigger an ad off of a trademark if the user can't buy the product on the site.









Duplicate detection

- The web is full of duplicated content.
- More so than many other collections
- Exact duplicates
 - Easy to detect; use hash/fingerprint (e.g., MD5)
- Near-duplicates
 - More common on the web, difficult to eliminate
- For the user, it's annoying to get a search result with near-identical documents.
- Marginal relevance is zero: even a highly relevant document becomes nonrelevant if it appears below a (near-)duplicate.



Near-duplicates: Example





Detecting near-duplicates

- Compute similarity with an edit-distance measure
- We want "syntactic" (as opposed to semantic) similarity.
 - True semantic similarity (similarity in content) is too difficult to compute.
- We do not consider documents near-duplicates if they have the same content, but express it with different words.
- Use similarity threshold θ to make the call "is/isn't a near-duplicate".
- E.g., two documents are near-duplicates if similarity
- \bullet > θ = 80%.



Recall: Jaccard coefficient

- A commonly used measure of overlap of two sets
- Let A and B be two sets
- Jaccard coefficient:

$$JACCARD(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

$$(A \neq \emptyset \text{ or } B \neq \emptyset)$$

- JACCARD(A,A) = 1
- JACCARD(A,B) = 0 if A \cap B = 0
- A and B don't have to be the same size.
- Always assigns a number between 0 and 1.

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Jaccard coefficient: Example

- Three documents:
- d₁: "Jack London traveled to Oakland"
- d_2 : "Jack London traveled to the city of Oakland"
- d₃: "Jack traveled from Oakland to London"
- Based on shingles of size 2 (2-grams or bigrams), what are the Jaccard coefficients J(d1, d2) and J(d1, d3)?
- $J(d_1, d_2) = 3/8 = 0.375$
- $J(d_1, d_3) = 0$
- Note: very sensitive to dissimilarity



A document as set of shingles

- A shingle is simply a word n-gram.
- Shingles are used as features to measure syntactic similarity of documents.
- For example, for n = 3, "a rose is a rose is a rose" would be represented as this set of shingles:
 - { a-rose-is, rose-is-a, is-a-rose }
- We define the similarity of two documents as the Jaccard coefficient of their shingle sets.





Fingerprinting

- We can map shingles to a large integer space $[1..2^m]$ (e.g., m = 64) by fingerprinting.
- We use s_k to refer to the shingle's fingerprint in $1..2^m$.
- This doesn't directly help us we are just converting strings to large integers
- But it will help us compute an approximation to the actual Jaccard coefficient quickly

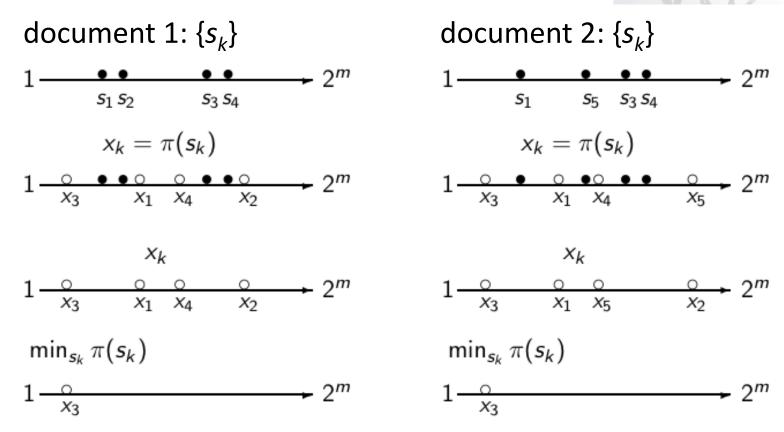


Documents as sketches

- The number of shingles per document is large, difficult to exhaustively compare
- To make it fast, we use a sketch, a subset of the shingles of a document.
- The size of a sketch is, say, n = 200 and is defined by a set of permutations $\pi_1 \dots \pi_{200}$.
- Each π_i is a random permutation on $1..2^m$
- The sketch of d is defined as:
 - $< \min_{s \in d} \pi_1(s), \min_{s \in d} \pi_2(s), \dots, \min_{s \in d} \pi_{200}(s) >$ (a vector of 200 numbers).

Deriving a sketch element: a permutation of the original hashes

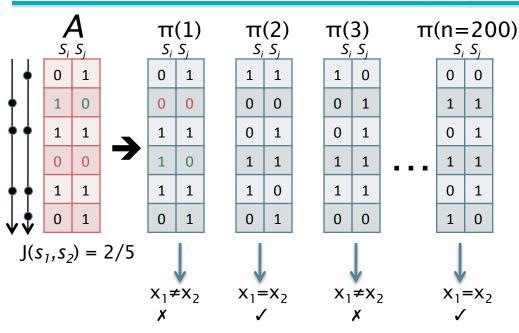




We use $\min_{s \in d_1} \pi(s) = \min_{s \in d_2} \pi(s)$ as a test for: are d_1 and d_2 near-duplicates? In this case: permutation π says: $d_1 \approx d_2$

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Proof that $J(S(d_1), s(d_2)) \cong P(x_1^{\pi} = x_2^{\pi})$



We view a matrix A:

- 1 column per set of hashes
- Element $A_{i,j} = 1$ if element i in set S_i is present
- Permutation $\pi(n)$ is a random reordering of the rows in A
- \mathcal{X}_{i}^{T} is the first non-zero entry in $\pi(i)$, i.e., first shingle present
- Let $C_{00} = \#$ of rows in A where both entries are 0, define C_{11} , C_{10} , C_{01} likewise.
- $J(s_i, s_j)$ is then equivalent to $C_{11} / C_{10} + C_{01} + C_{11}$
- $P(x_{i1}=x_{i2})$ then is equivalent to $C_{11} / C_{10} + C_{01} + C_{11}$



Estimating Jaccard

- Thus, the proportion of successful permutations is the Jaccard coefficient.
 - Permutation π is successful iff $\min_{s \in d_1} \pi(s) = \min_{s \in d_2} \pi(s)$
- Picking a permutation at random and outputting 1 (successful) or 0 (unsuccessful) is a Bernoulli trial.
- Estimator of probability of success: proportion of successes in n Bernoulli trials. (n = 200)
- Our sketch is based on a random selection of permutations.
- Thus, to compute Jaccard, count the number k of successful permutations for $< d_1, d_2 >$ and divide by n = 200.
- k/n = k/200 estimates $J(d_1, d_2)$



Shingling: Summary

- Input: N documents
- Choose n-gram size for shingling, e.g., n = 5
- Pick 200 random permutations, represented as hash functions
- Compute N sketches: 200 × N matrix shown on previous slide, one row per permutation, one column per document
- Compute $\frac{N \cdot (N-1)}{2}$ pairwise similarities
- Transitive closure of documents with similarity $> \theta$
- Index only one document from each equivalence class







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What any crawler should do

- Be capable of distributed operation
- Be scalable: need to be able to increase crawl rate by adding more machines
- Fetch pages of higher quality first
- Continuous operation: get fresh version of already crawled pages



How hard can crawling be?

- Web search engines must crawl their documents.
- Getting the content of the documents is easier for many other IR systems.
 - E.g., indexing all files on your hard disk: just do a recursive descent on your file system
- Ok: for web IR, getting the content of the documents takes longer . . .
- . . . because of latency.
- But is that really a design/systems challenge?



Basic crawler operation

- Initialize queue with URLs of known seed pages
- Repeat
 - Take URL from queue
 - Fetch and parse page
 - Extract URLs from page
 - Add URLs to queue
- Fundamental assumption: The web is well linked.



What's wrong with this crawler?

```
urlqueue := (some carefully selected set of
  seed urls)
while urlqueue is not empty:
myurl := urlqueue.getlastanddelete()
mypage := myurl.fetch()
fetchedurls.add(myurl)
newurls := mypage.extracturls()
for myurl in newurls:
if myurl not in fetchedurls and not in
 urlqueue:
urlqueue.add(myurl)
addtoinvertedindex(mypage)
```

What's wrong with the simple crawler





- Scale: we need to distribute.
- We can't index everything: we need to subselect. How?
- Duplicates: need to integrate duplicate detection
- Spam and spider traps: need to integrate spam detection
- Politeness: we need to be "nice" and space out all requests for a site over a longer period (hours, days)
- Freshness: we need to recrawl periodically.
 - Because of the size of the web, we can do frequent recrawls only for a small subset.
 - Again, subselection problem or prioritization

Magnitude of the crawling problem





- To fetch 20,000,000,000 pages in one month . . .
 - . . . we need to fetch almost 8000 pages per second!
- Actually: many more since many of the pages we attempt to crawl will be duplicates, unfetchable, spam etc.



What a crawler must do

Be polite

- Don't hit a site too often
- Only crawl pages you are allowed to crawl: robots.txt

Be robust

 Be immune to spider traps, duplicates, very large pages, very large websites, dynamic pages etc



Robots.txt

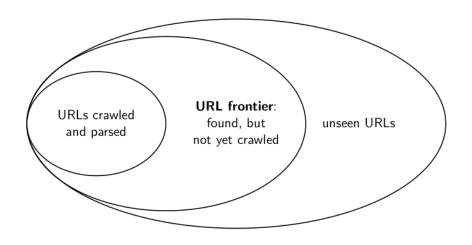
- Protocol for giving crawlers ("robots") limited access to a website, originally from 1994
- Example:

```
User-agent: *
    Disallow: /yoursite/temp/
User-agent: searchengine
    Disallow: /
```

Important: cache the robots.txt file of each site we are crawling



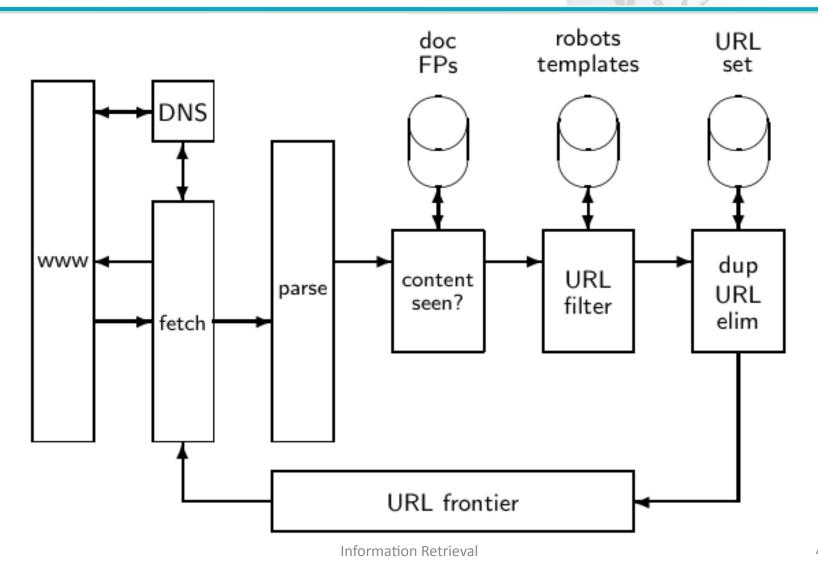
URL Frontier



- The URL frontier is the data structure that holds and manages URLs we've seen, but that have not been crawled yet.
- Can include multiple pages from the same host
- Must avoid trying to fetch them all at the same time
- Must keep all crawling threads busy

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Basic Crawling Architecture





URL normalization

- Some URLs extracted from a document are relative URLs.
- E.g., at http://mit.edu, we may have aboutsite.html
 - This is the same as: http://mit.edu/aboutsite.html
- During parsing, we must normalize (expand) all relative URLs.



Content seen

- For each page fetched: check if the content is already in the index
- Check this using document fingerprints or shingles
- Skip documents whose content has already been indexed

 Still need to consider Freshness: Crawl some pages (e.g., news sites) more often than others



Distributing the crawler

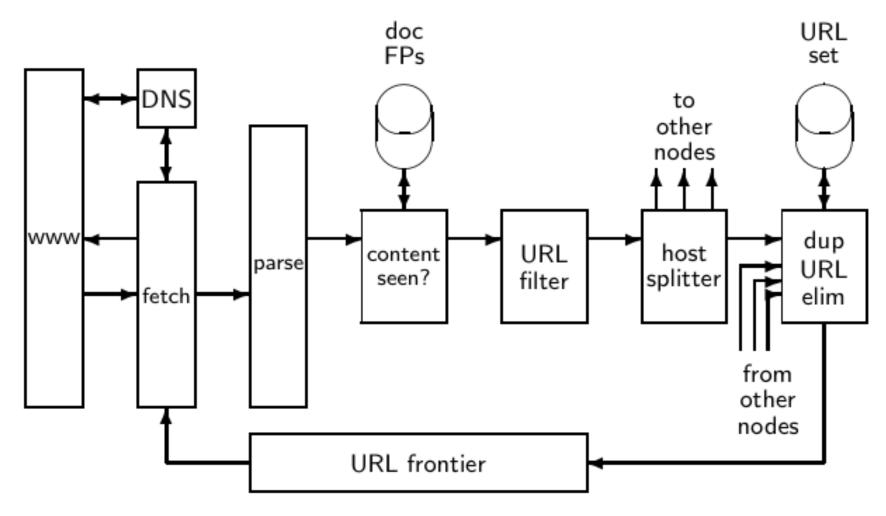
- Run multiple crawl threads, potentially at different nodes
 - Usually geographically distributed nodes
- Partition hosts being crawled into nodes



Distributed crawling architecture







A Crawler Issue: Spider traps





- Malicious server that generates an infinite sequence of linked pages
- Sophisticated spider traps generate pages that are not easily identified as dynamic.

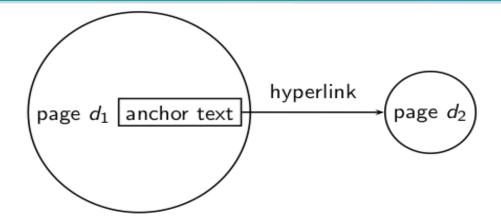








The web as a directed graph



- Assumption 1: A hyperlink is a quality signal.
 - The hyperlink $d_1 \rightarrow d_2$ indicates that d_1 's author deems d_2 high-quality and relevant.
- Assumption 2: The anchor text describes the content of d_2 .
 - We use anchor text somewhat loosely here for: the text surrounding the hyperlink.
 - Example: "You can find cheap cars here. "
 - Anchor text: "You can find cheap cars here"

[text of d_2] only vs. [text of d_2] + [anchor text $\rightarrow d_2$]



- Searching on [text of d_2] + [anchor text $\rightarrow d_2$] is often more effective than searching on [text of d_2] 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 graphics
- Searching on [anchor text $\rightarrow d_2$] is better for the query *IBM*.
 - In this representation, the page with most occurences of IBM is www.ibm.com

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



```
www.nytimes.com: "IBM acquires Webify"
        www.slashdot.org: "New IBM optical chip"
              www.stanford.edu: / "IBM faculty award recipients"
                     wwww.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 Assumption 1&2)



Assumptions underlying PageRank

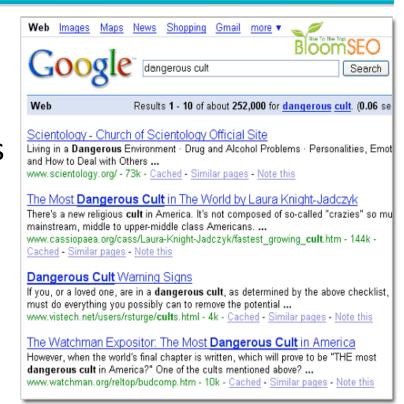
- Assumption 1: A link on the web is a quality signal the author of the link thinks that the linked-to page is highquality.
- Assumption 2: The anchor text describes the content of the linked-to page.
- Is Assumption 1 true in general?
- Is Assumption 2 true in general?





Google bombs

- Is a search with "bad" results due to maliciously manipulated anchor text.
- Still some remnants: [dangerous cult] on Google, Bing, Yahoo
 - Coordinated link creation by those who dislike the Church of Scientology
- Google introduced a new weighting function in January 2007
 - that fixed many Google bombs.
- Defused Google bombs: [who is a failure?], [evil empire]





Free Photoshop PSD file download Resolution 1280x1024 p: www.psdgraphics.com





Origins of PageRank: Citation analysis (1)





- Citation analysis: analysis of citations in the scientific literature.
- Example citation: "Miller (2001) has shown that physical activity alters the metabolism of estrogens."
- We can view "Miller (2001)" as a hyperlink linking two scientific articles.
- One application of these "hyperlinks" in the scientific literature:
 - Measure the similarity of two articles by the overlap of other articles citing them.
 - This is called cocitation similarity.
 - Cocitation similarity on the web: Google's "find pages like this" or "Similar" feature.



Citation analysis (2)

- Another application: Citation frequency can be used to measure the impact of an article.
 - Simplest measure: Each article gets one vote not very accurate.
- On the web: citation frequency = inlink count
 - A high inlink count does not necessarily mean high quality ...
 - ... mainly because of link spam.
- Better measure: weighted citation frequency or citation rank
 - An article's vote is weighted according to its citation impact.
 - Circular? No: can be formalized in a well-defined way



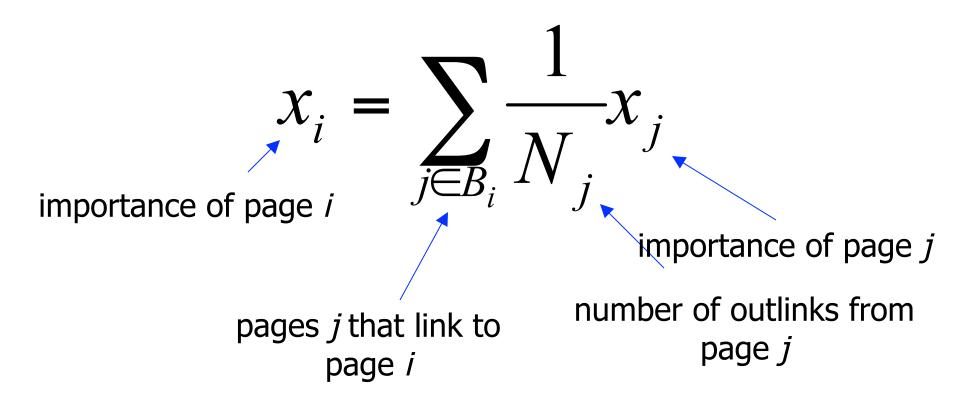
Citation analysis (3)

- Better measure: weighted citation frequency or citation rank, invented in the context of citation analysis by Pinsker and Narin in the 1960s.
- This is basically PageRank.
- We can use the same formal representation for
 - citations in the scientific literature
 - hyperlinks on the web
- Appropriately weighted citation frequency is an excellent measure of quality ...
 - ... both for web pages and for scientific publications.



Definition of PageRank

 The importance of a page is given by the importance of the pages that link to it.





Pagerank scoring

- Imagine a browser doing a random walk on web pages:
 - Start at a random page
 - At each step, follow one of the n links on that page, each with 1/n probability
- Do this repeatedly. Use the "long-term visit rate" as the page's score
- This is a global score for the page, based on the topology of the network.
- Think of it as g(d) from Chapter 7

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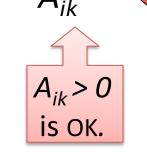


Markov chains

A Markov chain consists of n states, plus an $n \times n$ transition probability matrix A.

- At each step, we are in exactly one of the states.
- For $1 \le i,k \le n$, the matrix entry A_{ik} tells us the probability of k being the next state, given we are currently in state i.

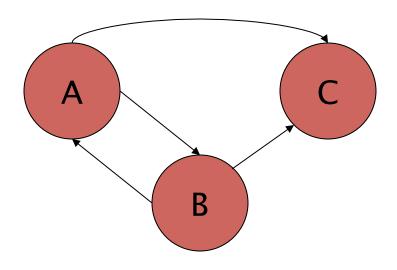
Memorylessness property: The next state depends only at the current state (first order Markov Chain)





Markov chains

- Clearly, for all i, $\sum_{k=1}^{n} A_{ik} = 1$.
- Markov chains are abstractions of random walks



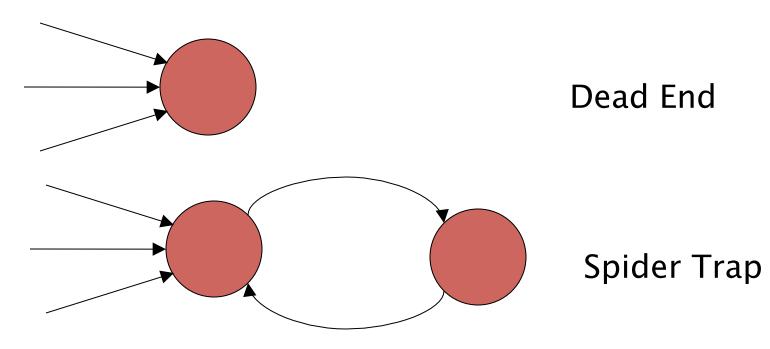
Try this: Calculate the matrix A_{ik} using 1/n possibility

A_{ik:}
A
B
C
B
C



Not quite enough

- The web is full of dead ends.
 - What sites have dead ends?
 - Our random walk can get stuck.



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Teleporting

- At each step, with probability 10%, teleport to a random web page
- With remaining probability (90%), follow a random link on the page
 - If a dead-end, stay put in this case

Follow!

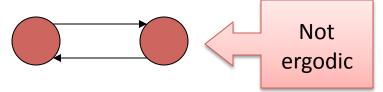
$$\overrightarrow{rank} = (1 - a)\overrightarrow{A} \times \overrightarrow{rank} + \alpha \left[\frac{1}{N}\right] N \times 1$$

Teleport!



Ergodic Markov chains

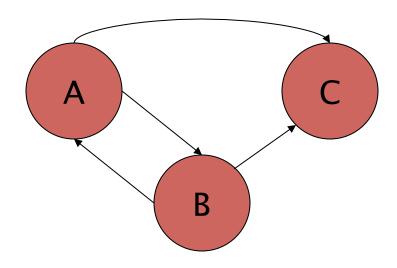
- A Markov chain is ergodic if
 - you have a path from any state to any other
 - you can be in any state at every time step, with non-zero probability



- With teleportation, our Markov chain is ergodic
- Theorem: With an ergodic Markov chain, there is a stable long term visit rate.



Markov chains (2nd Try)



Try this: Calculate the matrix A_{ik} using a 10% chance of teleportation

A_{ik:}
A
B
C



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.
 i n

More generally, the vector $x = (x_1, ..., x_n)$ 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 $\mathbf{x} = (x_1, ... x_n)$ at this step, what is it at the next step?
- Recall that row i of the transition prob. Matrix A tells us where we go next from state i.
- So from x, our next state is distributed as xA.



Pagerank algorithm

- 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 xA
 - After two steps at xA^2 , then xA^3 and so on.
 - "Eventually" means for "large" k, xA^k = a
- Algorithm: multiply x by increasing powers of A until the product looks stable



Steady State

- For any ergodic Markov chain, there is a unique longterm visit rate for each state
 - Over a long period, we'll visit each state in proportion to this rate
 - It doesn't matter where we start



Eigenvector formulation

The flow equations can be written

$$r = Ar$$

- So the rank vector is an eigenvector of the adjacency matrix
 - In fact, it's the first or principal eigenvector, with corresponding eigenvalue 1





Pagerank summary

- Pre-processing:
 - Given graph of links, build matrix A
 - From it compute a
 - The pagerank a_i is a scaled number between 0 and 1
- Query processing:
 - Retrieve pages meeting query
 - Rank them by their pagerank
 - Order is query-independent





PageRank issues

- Real surfers are not random surfers.
 - Examples of nonrandom surfing: back button, short vs. long paths, bookmarks, directories – and search!
 - → Markov model is not a good model of surfing.
 - But it's good enough as a model for our purposes.
- 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 video and service.
 - If we rank all Boolean hits according to PageRank, then the Yahoo home page would be top-ranked.
 - Clearly not desireble.



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, phrases, proximity, tiered indexes ...
 - 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.
 - Adressing link spam is difficult and crucial.





Summary

- Chapters 19, 20 and 21 of IIR
- Resources
 - Paper on Mercator crawler by Heydon et al.
 - Robot exclusion standard
 - American Mathematical Society article on PageRank (popular science style)
 - Google's official description of PageRank: "PageRank reflects our view of the importance of web pages by considering more than 500 million variables and 2 billion terms. Pages that believe are important pages receive a higher PageRank and are more likely to appear at the top of the search results"