

Web Searching & Indexing

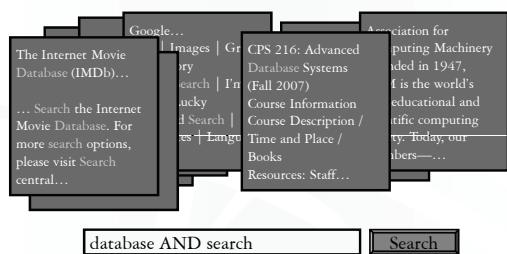
CPS 116

Introduction to Database Systems

Announcements (November 29)²

- ❖ Homework #4 due today
- ❖ Course project demo Dec. 7-14
 - Each project gets a 30-minute slot with me and Yi
 - Watch for an email this weekend scheduling demo slots
- ❖ Final exam on Saturday, Dec. 15, 7-10pm
 - Again, open book, open notes
 - Focus on the second half of the course

Keyword search³



What are the documents containing both “database” and “search”?

Keywords × documents⁴

All keywords	All documents	Document 1	Document 2	Document 3	Document ...	Document n
“a”	1	1	1	...	1	
“cat”	1	1	0	...	0	
“database”	0	0	1	...	0	
“dog”	0	1	0	...	1	
“search”	0	0	1	...	0	
...

1 means keyword appears in the document;
0 means otherwise

- ❖ Inverted lists: store the matrix by rows
- ❖ Signature files: store the matrix by columns

Inverted lists⁵

- ❖ Store the matrix by rows
- ❖ For each keyword, store an inverted list
 - $\langle \text{keyword}, \text{doc-id-list} \rangle$
 - $\langle \text{“database”}, \{3, 7, 142, 857, \dots\} \rangle$
 - $\langle \text{“search”}, \{3, 9, 192, 512, \dots\} \rangle$
 - It helps to sort doc-id-list (why?)
- ❖ Vocabulary index on keywords
 - B⁺-tree or hash-based
- ❖ How large is an inverted list index?

Using inverted lists⁶

- ❖ Documents containing “database”
 - Use the vocabulary index to find the inverted list for “database”
 - Return documents in the inverted list
- ❖ Documents containing “database” AND “search”
 - Return documents in the intersection of the two inverted lists
- ❖ OR? NOT?
 - Union and difference, respectively

7 What are “all” the keywords?

- ❖ All sequences of letters (up to a given length)?
 - ... that actually appear in documents!
- ❖ All words in English?
- ❖ Plus all phrases?
 - Alternative: approximate phrase search by proximity
- ❖ Minus all stop words
 - They appear in nearly every document, e.g., a, of, the, it
 - Not useful in search
- ❖ Combine words with common stems
 - Example: database, databases
 - They can be treated as the same for the purpose of search

8 Frequency and proximity

- ❖ Frequency
 - $\langle \text{keyword}, \{ \langle \text{doc-id}, \text{number-of-occurrences} \rangle, \langle \text{doc-id}, \text{number-of-occurrences} \rangle, \dots \} \rangle$
- ❖ Proximity (and frequency)
 - $\langle \text{keyword}, \{ \langle \text{doc-id}, \langle \text{position-of-occurrence}_1, \text{position-of-occurrence}_2, \dots \rangle, \langle \text{doc-id}, \langle \text{position-of-occurrence}_1, \dots \rangle \rangle, \dots \} \rangle$
 - When doing AND, check for positions that are near

9 Signature files

- ❖ Store the matrix by columns and compress them
 - ❖ For each document, store a w -bit signature
 - ❖ Each word is hashed into a w -bit value, with only $s < w$ bits turned on
 - ❖ Signature is computed by taking the bit-wise OR of the hash values of all words on the document
- Does doc_3 contain
 $\text{hash}(\text{"database"}) = 0110$ doc_1 contains “database”: 0110 “database”?
 $\text{hash}(\text{"dog"}) = 1100$ doc_2 contains “dog”: 1100
 $\text{hash}(\text{"cat"}) = 0010$ doc_3 contains “cat” and “dog”: 1110
- ❖ Some false positives; no false negatives

10 Bit-sliced signature files

- ❖ Motivation
 - To check if a document contains a word, we only need to check the bits that are set in the word’s hash value
 - So why bother retrieving all w bits of the signature?
 - ❖ Instead of storing n signature files, store w bit slices
 - ❖ Only check the slices that correspond to the set bits in the word’s hash value
 - ❖ Start from the sparse slices
- | doc | Signature |
|--------------|--------------------|
| 1 | 0 0 0 0 1 0 0 0 |
| 2 | 0 0 0 0 0 1 0 0 0 |
| 3 | 0 0 0 1 1 0 1 0 |
| 4 | 0 1 1 0 1 1 0 0 |
| ... | ... |
| N | 0 0 0 0 1 0 1 0 |
- Slice 7 ... Slice 0
- Bit-sliced signature files
- Starting to look like an inverted list again!

11 Inverted lists versus signatures

- ❖ Inverted lists better for most purposes (*TODS*, 1998)
- ❖ Problems of signature files
 - False positives
 - Hard to use because s , w , and the hash function need tuning to work well
 - Long documents will likely have mostly 1’s in signatures
 - Common words will create mostly 1’s for their slices
 - Difficult to extend with features such as frequency, proximity
- ❖ Saving grace of signature files
 - Sizes are tunable
 - Good for lots of search terms
 - Good for computing similarity of documents

12 Ranking result pages

- ❖ A single search may return many pages
 - A user will not look at all result pages
 - Complete result may be unnecessary
 - Result pages need to be ranked
- ❖ Possible ranking criteria
 - Based on content
 - Number of occurrences of the search terms
 - Similarity to the query text
 - Based on link structure
 - Backlink count
 - PageRank
 - And more...

Textual similarity

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- ❖ Vocabulary: $\{w_1, \dots, w_n\}$
- ❖ IDF (Inverse Document Frequency): $\{f_1, \dots, f_n\}$
 - $f_i = 1 / \text{the number of times } w_i \text{ appears on the Web}$
- ❖ Significance of words on page p : $\{p_1 f_1, \dots, p_n f_n\}$
 - p_i is the number of times w_i appears on p
- ❖ Textual similarity between two pages p and q is defined to be $\{p_1 f_1, \dots, p_n f_n\} \cdot \{q_1 f_1, \dots, q_n f_n\} = p_1 q_1 f_1^2 + \dots + p_n q_n f_n^2$
 - q could be the query text

Why weight significance by IDF?

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- ❖ Without IDF weighting, the similarity measure would be dominated by the stop words
- ❖ “the” occurs frequently on the Web, so its occurrence on a particular page should be considered less significant
- ❖ “engine” occurs infrequently on the Web, so its occurrence on a particular page should be considered more significant

Problems with content-based ranking

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- ❖ Many pages containing search terms may be of poor quality or irrelevant
 - Example: a page with just a line “search engine”
- ❖ Many high-quality or relevant pages do not even contain the search terms
 - Example: Google homepage
- ❖ Page containing more occurrences of the search terms are ranked higher; spamming is easy
 - Example: a page with line “search engine” repeated many times

Backlink

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- ❖ A page with more backlinks is ranked higher
- ❖ Intuition: Each backlink is a “vote” for the page’s importance
- ❖ Based on local link structure; still easy to spam
 - Create lots of pages that point to a particular page

Google’s PageRank

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- ❖ Main idea: Pages pointed by high-ranking pages are ranked higher
 - Definition is recursive by design
 - Based on global link structure; hard to spam
- ❖ Naïve PageRank
 - $N(p)$: number of outgoing links from page p
 - $B(p)$: set of pages that point to p
 - $\text{PageRank}(p) = \sum_{q \in B(p)} (\text{PageRank}(q) / N(q))$
 - Each page p gets a boost of its importance from each page that points to p
 - Each page q evenly distributes its importance to all pages that q points to

Calculating naïve PageRank

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- ❖ Initially, set all PageRank’s to 1; then evaluate $\text{PageRank}(p) \leftarrow \sum_{q \in B(p)} (\text{PageRank}(q) / N(q))$ repeatedly until the values converge (i.e. a fixed point is reached)

$$\begin{bmatrix} n \\ m \\ a \end{bmatrix} = \begin{bmatrix} 0.5 & 0 & 0.5 \\ 0 & 0 & 0.5 \\ 0.5 & 1 & 0 \end{bmatrix} \begin{bmatrix} n \\ m \\ a \end{bmatrix}$$

$$\begin{bmatrix} n \\ m \\ a \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 0.5 \\ 1.5 \end{bmatrix}, \begin{bmatrix} 1.25 \\ 0.75 \\ 1.375 \end{bmatrix}, \begin{bmatrix} 1.125 \\ 0.5 \\ 1.0625 \end{bmatrix}, \begin{bmatrix} 1.25 \\ 0.6875 \\ 1.2 \end{bmatrix}, \dots, \begin{bmatrix} 1.2 \\ 0.6 \\ 1.2 \end{bmatrix}$$

Random surfer model

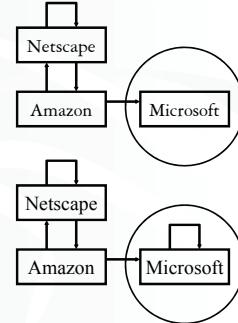
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- ❖ A random surfer
 - Starts with a random page
 - Randomly selects a link on the page to visit next
 - Never uses the “back” button
- ❖ PageRank(p) measures the probability that a random surfer visits page p

Problems with the naïve PageRank

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- ❖ Dead end: a page with no outgoing links
 - A dead end causes all importance to “leak” eventually out of the Web
- ❖ Spider trap: a group of pages with no links out of the group
 - A spider trap will eventually accumulate all importance of the Web



Practical PageRank

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- ❖ d : decay factor
- ❖ PageRank(p) =

$$d \cdot \sum_{q \in B(p)} (\text{PageRank}(q) / N(q)) + (1 - d)$$
- ❖ Intuition in the random surfer model
 - A surfer occasionally gets bored and jump to a random page on the Web instead of following a random link on the current page

Google (1998)

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- ❖ Inverted lists in practice contain a lot of context information

Hit: 2 bytes		Relative Capitalization		font size	
plain:	cap:1	imp:3		position: 12	Within the page
In URL/title/meta tag	fancy:	cap:1	imp = 7	type: 4	position: 8
In anchor text	anchor:	cap:1	imp = 7	type: 4	hash:4 pos: 4 Within the anchor URL associated with the anchor
- ❖ PageRank is not the final ranking
 - Type-weight: depends on the type of the occurrence
 - For example, large font weights more than small font
 - Count-weight: depends on the number of occurrences
 - Increases linearly first but then tapers off
 - For multiple search terms, nearby occurrences are matched together and a proximity measure is computed
 - Closer proximity weights more

Trie: a string index

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- ❖ A tree with edges labeled by characters
- ❖ A node represents the string obtained by concatenating all characters along the path from the root

What's the max fan-out?
- ❖ Compact trie: replace a path without branches by a single edge labeled by a string

Suffix tree

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- Index all suffixes of a large string in a compact trie
- ❖ Can support arbitrary substring matching
- ❖ Internal nodes have fan-out ≥ 2 (except the root)
- ❖ No two edges out of the same node can share the same first character

To get linear space

- ❖ Instead of inlining the string labels, store pointers to them in the original string
- ❖ Bad for external memory

Patricia trie, Pat tree, String B-tree

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- A Patricia trie is just like a compact trie, but
- ❖ Instead of labeling each edge by a string, only label by the first character and the string length
 - ❖ Leaves point to strings
 - ❖ Faster search (especially for external memory) because of inlining of the first character
 - ❖ But must validate answer at leaves for skipped characters
 - ❖ A Pat tree indexes all suffixes of a string in a Patricia trie
 - ❖ A String B-tree uses a Patricia trie to store and compare strings in B-tree nodes

Summary

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- ❖ General tree-based string indexing tricks
 - Trie, Patricia trie, String B-tree
- ❖ Two general ways to index for substring queries
 - Index words: inverted lists, signature files
 - Index all suffixes: suffix tree, Pat tree, suffix array (not covered)
- ❖ Web search and information retrieval go beyond substring queries
 - IDF, PageRank, ...