Indexing: Part IV

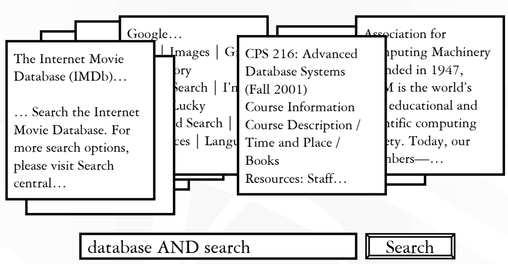
CPS 216

Advanced Database Systems

Announcements (February 17)

- Homework #2 due in two weeks
- Reading assignments for this and next week
  - "The" query processing survey by Graefe
  - Due next Wednesday
- Midterm and course project proposal in three weeks

Keyword search



What are the documents containing both "database" and "search"?

Keywords × documents

All documents

All keywords	Document 1	Document 2	Document 3	…	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

With compression, of course!

Inverted lists

- Store the matrix by rows
- For each keyword, store an inverted list
  - ⟨*keyword*, *doc-id-list*⟩
  - ⟨"database", {3, 7, 142, 857, …}⟩
  - ⟨"search", {3, 9, 192, 512, …}⟩
  - 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 lists

- 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

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; not useful in search
  - Example: a, of, the, it
- Combine words with common stems
  - They can be treated as the same for the purpose of search
  - Example: database, databases

Frequency and proximity

- Frequency
  - ⟨*keyword*, { ⟨*doc-id*, *number-of-occurrences*⟩,
    ⟨*doc-id*, *number-of-occurrences*⟩,
    … }⟩
- Proximity (and frequency)
  - ⟨*keyword*, { ⟨*doc-id*, ⟨*position-of-occurrence*$_1$,
    position-of-occurrence$_2$, …⟩,
    ⟨*doc-id*, ⟨*position-of-occurrnece*$_1$, …⟩⟩,
    … }⟩
  - When doing AND, check for positions that are near

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
hash("database") = 0110	doc_1 contains "database": 0110	"database"?
hash("dog") = 1100	doc_2 contains "dog": 1100	
hash("cat") = 0010	doc_3 contains "cat" and "dog": 1110	

☞ Some false positives; no false negatives

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 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!

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

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

- Vocabulary: $\{w_1, \ldots, w_n\}$
- IDF (Inverse Document Frequency): $\{f_1, \ldots, f_n\}$
  - $f_i = \log_2$ (total # of docs / # of docs containing w_i)
- TF (Term Frequency): $\{p_1, \ldots, p_n\}$
  - p_i = # of times w_i appears on p
- Significance of words on page p: $\{p_1 f_1, \ldots, p_n f_n\}$
- Textual similarity between two pages p and q is defined to be $\{p_1 f_1, \ldots, p_n f_n\} \cdot \{q_1 f_1, \ldots, q_n f_n\} = p_1 q_1 f_1^2 + \ldots + p_n q_n f_n^2$
  - q could be the query text

Why weight significance by IDF?

- 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

- 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

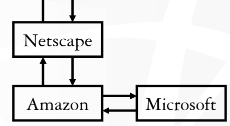
- A page with more backlinks is ranked higher
- Intuition: Each backlink is a "vote" for the page's importance
- Based on local link structure; still easy to spam
  - Create lots of pages that point to a particular page

Google's PageRank

- Main idea: Pages pointed to 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
  - $\text{PageRank}(p) = \Sigma_{q \in B(p)} (\text{PageRank}(q) / N(q))$
  - ☞ 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

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



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

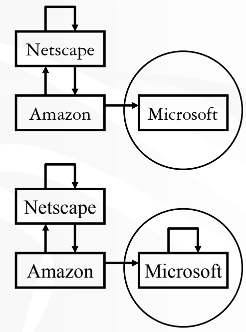
$$\begin{bmatrix} n \\ m \\ a \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 0.5 \\ 1.5 \end{bmatrix}, \begin{bmatrix} 1.25 \\ 0.75 \\ 1 \end{bmatrix}, \begin{bmatrix} 1.125 \\ 0.5 \\ 1.375 \end{bmatrix}, \begin{bmatrix} 1.25 \\ 0.6875 \\ 1.0625 \end{bmatrix}, \ldots,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

Random surfer model

- 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

- 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

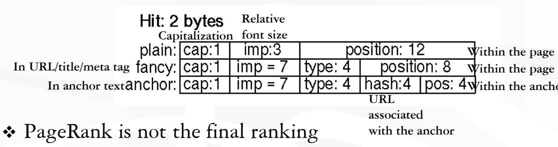


Practical PageRank

- d: decay factor
- PageRank(p) =
  $d \cdot \Sigma_{q \in B(p)} (\text{PageRank}(q) / N(q)) + (1 - d)$
- 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)

- Inverted lists in practice contain a lot of context information



- 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

Suffix arrays (*SODA*, 1990)

- Another index for searching text
- Conceptually, to construct a suffix array for string S
  - Enumerate all $|S|$ suffixes of S
  - Sort these suffixes in lexicographical order
- To search for occurrences of a substring
  - Do a binary search on the suffix array

Suffix array example

S = mississippi q = sip

Suffixes:	Sorted suffixes:	Suffix array:
mississippi	i	10
ississippi	ippi	7
ssissippi	issippi	4
sissippi	ississippi	1
issippi	mississippi	0
ssippi	⇨ pi	9
sippi	ppi	8
ippi	⇨ sippi	6
ppi	⇨ sissippi	3
pi	ssippi	5
i	ssissippi	2

No need to store the suffix strings; just store where they start

$O(|q| \cdot \log |S|)$

One improvement

❖ Remember how much of the query string has been matched

q = sisterhood

…

low: ⇨ sissipi… Matched 3 characters

…

middle: ⇨ sisterhood… Start checking from the 4th character

…

high: ⇨ sistering… Matched 6 characters

…

Another improvement

❖ Pre-compute the longest common prefix information between suffixes

- For all (*low*, *middle*) and (*middle*, *high*) pairs that can come up in a binary search

q = sisterhood $O(|q| + \log |S|)$

…

low: ⇨ sissipi… Matched 3 characters

…

middle: ⇨ sisterhood… Start checking from the 7th character

… Matched 6 characters (pre-computed)

high: ⇨ sistering… Matched 6 characters

…

Suffix arrays versus inverted lists

❖ Suffix arrays are more powerful because they index all substrings (not just words)

- No problem with long phase searches
- No problem if there is no word boundary
- No problem with a huge vocabulary of words

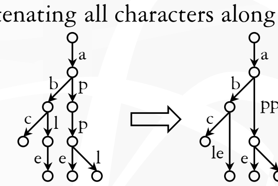
❖ Suffix arrays use more space than inverted lists?

- Check out compressed suffix arrays (*STOC* 2000)

Trie: a string index

❖ 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

Index all suffixes of a large string in a compact trie

☞ Can support the same queries as a suffix array

❖ 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

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 large string in a Patricia trie

❖ A String B-tree uses a Patricia trie to store and compare strings in B-tree nodes

Summary

- General tree-based string indexing tricks
  - Trie, Patricia trie, String B-tree
  - Good exercise: put them in a GiST! ☺
- Two general ways to index for substring queries
  - Index words: inverted lists, signature files
  - Index all suffixes: suffix array, suffix tree, Pat tree
- Web search and information retrieval go beyond substring queries
  - TF/IDF, PageRank, …