Web Searching & Indexing

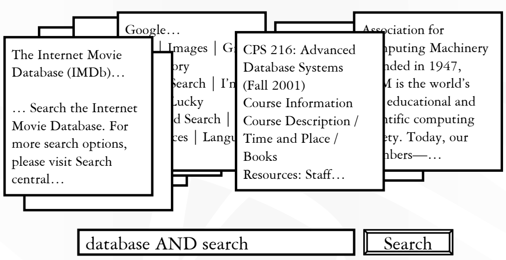
CPS 116

Introduction to Database Systems

Announcements (December 6)

- Homework #4 due on today (will be graded by this weekend)
- Course project demo
- Final exam on Tuesday, Dec. 13, 7-10pm
  - Again, open book, open notes
  - Focus on the second half of the course

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

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, 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

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

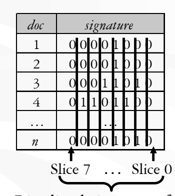
hash("database") = 0110 — doc_1 contains "database": 0110
hash("dog") = 1100 — doc_2 contains "dog": 1100
hash("cat") = 0010 — doc_3 contains "cat" and "dog": 1110

Does doc_3 contain "database"?

☞ 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



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): $[f_1, \ldots, f_n]$
  - $f_i = 1$ / the number of times w_i appears on the Web
- Significance of words on page p: $[p_1 f_1, \ldots, p_n f_n]$
  - p_i is the number of times w_i appears on p
- Textual similarity between two pages p and q is defined to be $[p_1 f_1, \ldots, p_n f_n] \cdot [q_1 f_1, \ldots, q_n f_n] = p_1 q_1 f_1^2 + \ldots + p_n q_n f_n^2$
  - 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

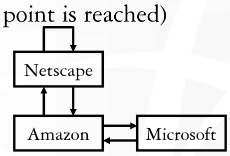
- Based on local link structure; still easy to spam
  - Create lots of pages that point to a particular page

Google's PageRank

- Main idea: Pages pointed 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)



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

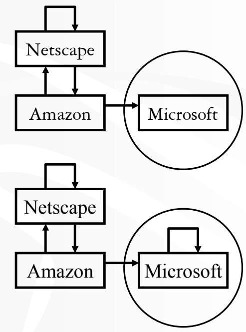
$$\begin{bmatrix} n \\ m \\ a \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 0.5 \\ 1.5 \end{bmatrix}, \begin{bmatrix} 1.25 \\ 0.75 \\ 1 \end{bmatrix}, \begin{bmatrix} 1.125 \\ 0.5 \\ 1.375 \end{bmatrix}, \begin{bmatrix} 1.25 \\ 0.6875 \\ 1.0625 \end{bmatrix}, \ldots,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

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

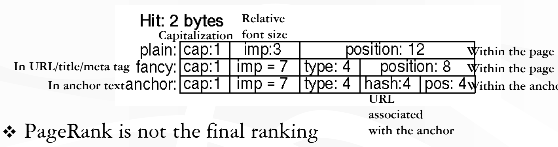


Practical PageRank

- d: decay factor
- PageRank(p) =
  $d \cdot \Sigma_{q \in B(p)}$ (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)

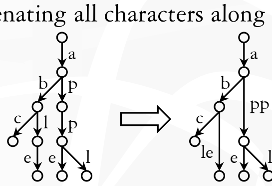
- Inverted lists in practice contain a lot of context information



- 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

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 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

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

- ❖ 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, …