Information Retrieval and Web Search Engines

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Information Retrieval (IR)

- Originally, used for document management systems
- Popular now due to web search engines
- IR has some similarities with traditional databases
  - very large data sets
  - use of indexes for fast access
- but IR has many differences from traditional databases
  - unstructured data (text documents)
  - keyword search queries
    - eg, “windows and (glass or door) and not Microsoft”
  - read mostly -- but addition of new documents occasionally (off-line)
  - requires relevance ranking to retrieve the top-k results
  - imprecise semantics

Inverted File

- Also known as *inverted index*
- Maps words into document locations (URLs)
  - from each word, you get the set of documents that contain this word
- Relational schema

Document (id, URL)	key is id
Word (term, docID)	key is the combination of term/docID

- ... but IR systems do not use a RDBMS
  - they may use a B+tree or a hash index without a table
  - the index delivers the list of documents containing the word sorted by docID
- Keyword queries
  - the result of each query term is a list of documents sorted by docID

query1 and query2:	list intersection (merging)
query1 or query2:	list union
query1 and not query2:	list subtraction

Keyword Queries in SQL

- Single-table selects plus UNION, INTERSECT, and EXCEPT

“windows and (glass or door) and not Microsoft”

-->

```
((select docID from Word where term=“windows”)
intersect
(select docID from Word where term=“glass” or term=“door”))
except
(select docID from Word where term=“Microsoft”)
```

- Never done this way in IR!
  - they use special-purpose, optimized search engines
- Needs also relevance ranking
  - requires statistics
    - how often a term appears in a document?
    - how rare the term is among all documents?
  - not easy to calculate using RDBMS

Better Schema

- Need to include
  - number of documents containing the term
  - the term position in document (for checking term proximity)
    - Document (id, URL)
    - Word (termID, term, count)
    - Posting (termID, position, docID)
- Integrity constraint: for each term (tid,term,cnt) in Word
  - cnt = count(select distinct docID from Posting where termID=tid)
- Keyword query: "computer and science"

```
select distinct p1.docID
from Word w1, Posting p1, Word w2, Posting p2
where w1.term="computer" and w2.term="science"
and w1.termID=p1.termID and w2.termID=p2.termID
and p1.docID=p2.docID
order by abs(p1.position-p2.position)
```


The Vector Space Model

- A model for estimating relevance ranking and document similarities
- Documents and queries are represented as vectors of floats
  - vector elements correspond to indexed terms (words)
  - vector values are term weights
  - highly sparse vector, usually implemented by inverted lists
- *Stop words* are considered irrelevant and are eliminated
  - e.g., certain words such as "the", "a", and HTML tags such as <p>
- Terms are usually *stems*
  - *stemming*: use language language-specific rules to convert words to their basic forms
  - e.g., "toys", "toying", are converted to "toy"

Example

- Document vectors can indicate frequency of terms in document

	computer	science	engineering
D1	2		3
D2		1	1
D3	1	4	2
D4		2	

- A query vector indicates the weight (ie, the importance) you give to a search term

	computer	science	engineering
Query	1		2

- If documents and the query are represented as points in a multidimensional space (one dimension per term), then relevance ranking is space proximity
  - the best match is the document closest to the query in the multidimensional space

TFxIDF Weights

- For a given document i and a term k we have:
  - the *term frequency* tf_{ik} of term k in document i
  - the *inverse document frequency* idf_k of term k, given by

$$idf_k = \log(N/n_k)$$

  - where N is the total number of documents and n_k is the number of documents that contain the term k
- The *weight* is $w_{ik} = tf_{ik} * idf_k$
- Normalization: force w_{ik} to be between 0 and 1
  - that way, weights resemble probabilities

$$w_{ik}' = w_{ik} / \sqrt{\sum_{j=1} w_{ij}^2}$$

- Relevance of a query Q to a document D_i:

$$sim(Q,D_i) = \sum_{k=1} q_k * w_{ik}$$

Example

tf_{ik}	computer	science	engineering
D1	2		3
D2		1	1
D3	1	4	2
D4		2	

	computer	science	engineering
idf_k	log(4/2) = 0.3	log(4/3) = 0.12	log(4/3) = 0.12

	computer	science	engineering
Query	1		2

w_{ik}	computer	science	engineering
D1	0.6		0.36
D2		0.12	0.12
D3	0.3	0.48	0.24
D4		0.24	

$sim(Q,D_i)$	
D1	0.6+2*0.36 = 1.32
D2	2*0.12 = 0.24
D3	0.3+2*0.24 = 0.78
D4	0

so document D1 is the best match

Document Similarity

Pairwise document similarity

$$sim(D_i,D_j) = \Sigma_{k=1} w_{ik} * w_{jk}$$

Normalization: divide by $\sqrt{\Sigma_{k=1} w_{ik}^2}$ and by $\sqrt{\Sigma_{k=1} w_{jk}^2}$

Text clustering

- finds overall similarities among groups of documents

How to expand the search?

- thesaurus expansion
- relevance feedback

Web Search Engines

These are IR systems for web-accessible HTML pages

Inverse indexes are populated by web-crawlers off-line

1) new index entries are created from the HTML documents
2) then, the new entries are sorted
3) finally, the results are merged with the existing index and a new index is created

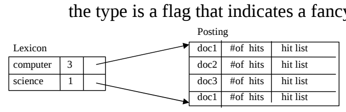
Relevance ranking goes beyond TFxIDF

- page popularity
  - gives higher score to frequently visited web pages
- based on the importance of other pages that refer to this page
  - if a page is referred to by an “important” page, then it is also “important”
  - Google's PageRank

Google

The Indexer converts each crawled HTML document into a collection of “hits” and puts them into “barrels”

- each barrel contains postings for a range of words
- each barrel has one Lexicon with entries (word,wordID,docs,offset)
  - docs is the number of documents containing the word
  - offset points to the first entry in the Posting (the first hit)
  - the Lexicon is always in memory
- a hit is (wordID,position,font,type). It is 2 bytes.
  - wordID is a reference to a word in the “lexicon”
  - position is the position of the word in the document
  - font indicates whether the word is inside , , etc
  - the type is a flag that indicates a fancy hit (word in title, URL, etc) or not



PageRank

- Assumption: if the pages pointing to a page are important, then the latter page is also important
- Let A1, A2, ..., An be the pages that point to the page A. Then the PageRank of A is
  - PR(A) = (1-d) + d*(PR(A1)/C(A1) + ... + PR(An)/C(An))

  where C(Ai) is the number of outgoing links from Ai
- The PR vector is the principal eigenvector of the link matrix of the web
  - can be computed as the fixpoint of the above equation
  - in practice, it is computed incrementally
- Google computes the relevance of a page for a given search by first computing an TFxIDF relevance and then adjusting it by taking into account the PR of the top-ranked pages