

# Information Retrieval and Web Search

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Credits for slides: Mooney

Retrieval Models

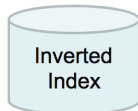
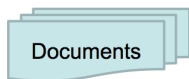
# Vector Space Model: Implementation Steps

- Step 1: Preprocessing
- Step 2: Indexing
- Step 3: Retrieval
- Step 4: Ranking

# Step 1: Preprocessing

- Implement the preprocessing functions:
  - For tokenization
  - For stop word removal
  - For stemming
- **Input:** Documents that are read one by one from the collection
- **Output:** Tokens to be added to the index
  - No punctuation, no stop-words, stemmed

## Step 1: Preprocessing (II)



case folding, tokenization, stopword  
removal, stemming  
~~semantics~~, ~~syntax~~, etc.

# Text as Sparse Vectors

- Vocabulary and therefore dimensionality of vectors can be very large,  $\approx 10^5$ .
- However, most documents and queries do not contain most words, so vectors are sparse (i.e. most entries are 0).
- Need efficient methods for storing and computing with sparse vectors.

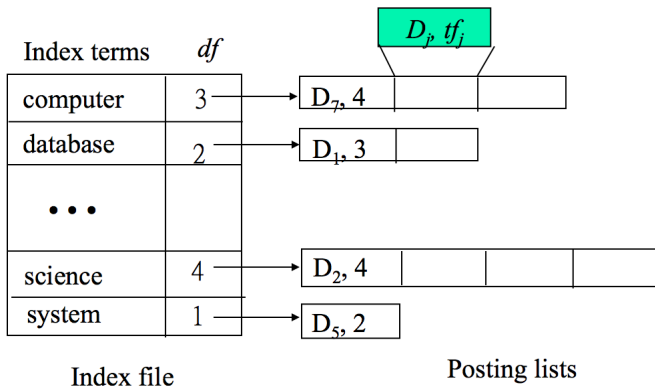
## Step 2: Indexing

- Build an inverted index, with an entry for each word in the vocabulary
- **Input:** Tokens obtained from the preprocessing module
- **Output:** An inverted index for fast access
- Many data structures are appropriate for fast access
  - We will use hashtables
    - Store tokens in hashtable, with token string as key and weight as value.
    - Table must fit in main memory.

## Step 2: Indexing (II)

- We need:
  - One entry for each word in the vocabulary
  - For each such entry:
    - Keep a list of all the documents where it appears together with the corresponding frequency  $\rightarrow$  TF
    - Keep the total number of documents in which the corresponding word appears  $\rightarrow$  IDF
- Constant time to find or update weight of a specific token.

# Inverted Index





## Inverted Index: TF-IDF

Doc1

one fish, two fish

Doc2

red fish, blue fish

Doc3

cat in the hat

Doc4

green eggs and ham



## Indexing - How many passes through the data?

- TF and IDF for each token can be computed in one pass
- Cosine similarity also requires document lengths
- Need a second pass to compute document vector lengths
  - Remember that the length of a document vector is the square-root of sum of the squares of the weights of its tokens.
  - Remember the weight of a token is:  $TF * IDF$
  - Therefore, must wait until IDF's are known (and therefore until all documents are indexed) before document lengths can be determined.
- Do a second pass over all documents: keep a list or hashtable with all document id's, and for each document determine its length.

# Time Complexity of Indexing

- Complexity of creating vector and indexing a document of  $n$  tokens is  $O(n)$ .
- So indexing  $m$  such documents is  $O(m \cdot n)$ .
- Computing token IDF's can be done during the same first pass
- Computing vector lengths is also  $O(m \cdot n)$ .
- Complete process is  $O(m \cdot n)$ , which is also the complexity of just reading in the corpus.

## Step 3: Retrieval

- **Input:** Query and Inverted Index (from Step 2)
- **Output:** Similarity values between query and documents
- Tokens that are not in both the query and the document have no effect on the cosine similarity.
  - Product of token weights is zero and does not contribute to the dot product.
- Usually the query is fairly short, and therefore its vector is *extremely* sparse.
- Use the inverted index (from Step 2) to find the limited set of documents that contain at least one of the query words.

# Processing the Query

- Incrementally compute cosine similarity of each indexed document as query words are processed one by one.
- To accumulate a total score for each retrieved document, store retrieved documents in a hashtable, where the document id is the key and the partial accumulated score is the value.

# Inverted Query Retrieval Efficiency

- Assume that, on average, a query word appears in  $B$  documents:



- Then retrieval time is  $O(|Q|B)$ , which is typically much better than naïve retrieval that examines all  $|D|$  documents,  $O(|V||D|)$ , because  $|Q| \ll |V|$  and  $B \ll |D|$ .

## Step 4: Ranking

- Sort the hashtable including the retrieved documents based on the value of cosine similarity
- Return the documents in descending order of their relevance
- **Input:** Similarity values between query and documents
- **Output:** Ranked list of documents in reversed order of their relevance

# Term Weights

- Weights applied to both document terms and query terms
- Direct impact on the final ranking
  - Direct impact on the results
  - Direct impact on the quality of IR system



# Next

- Evaluation of IR systems