15-853:Algorithms in the Virtual World

Indexing and Searching II

Indexing and Searching Outline

Introduction: model, query types
Inverted Indices: Compression, Lexicon, Merging
Vector Models:
- Selecting weights
- Cosine measure
- Relevance feedback

Latent Semantic Indexing:
Link Analysis: PageRank (Google), HITS
Duplicate Removal:

Vector Space Model

Model each document as a vector in *n* dimensional space: (.1, 0, 0, .9, .5, …, 0)

Aardvark (.1), Ant (.9), Zebra (0)

Query can also be modeled as a vector.
Uses:
- Ranked keyword search
- Relevance feedback
- Semantic indexing
- Clustering

Selecting Weights

$f_{d,t}$ = number of times t appears in document d
$w_{d,t}$ = weight of t in d

Accounting for frequency within a document
$w_{d,t} = f_{d,t}$ frequency
$w_{d,t} = \log(1 + f_{d,t})$ log frequency

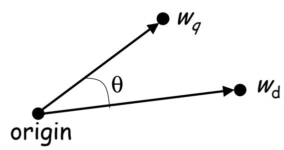
Accounting for information content of a term
$w_t = \log(1/p) = \log(N/f_t)$
giving: $w_{d,t} = \log(N/f_t)\log(1 + f_{d,t})$

Similarity between vectors

Dot product: $w_q \cdot w_d$
Inverse Euclidean distance: $1/||w_q - w_d||$

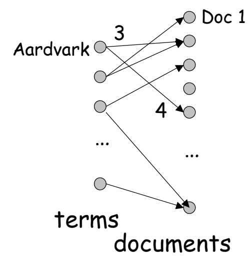
Problem: they weight longer documents more heavily.

Cosine metric: $\dfrac{w_q \cdot w_d}{\|w_q\| \cdot \|w_d\|}$



Based on $X \cdot Y = ||X||\ ||Y|| \cos\theta$

Frequencies and Inverted Lists



Each inverted list:

$\langle t; w_t; [(d_{t,1}, f_{d_{t,1},t}), (d_{t,2}, f_{d_{t,1},t}), \ldots, (d_{t,m}, f_{d_{t,m},t})] \rangle$

<aardvark;.1;[(2,3),(5,4)]>

Frequency counts can typically be compressed at least as well as distances. (2 bits/pointer in TREC).

Queries (cosine measure)

Algorithm: **Query**(Q)
  A = ∅ (Accumulators for documents)
  For each term $t \in Q$
    $\langle t; w_t; P_t \rangle$ = Search lexicon for t
    P_t = uncompress(P_t)
    for each $(d, f_{d,t})$ in P_t
      if $a_d \in A$
        $a_d = a_d + w_t \log(f_{d,t})$
      else
        $a_d = w_t \log(f_{d,t})$
        $A = A + \{a_d\}$
  For each $a_d \in A$
    $a_d = a_d/|d|$
  Select k documents from A with largest a_d

Relevance Feedback

Consider a sequence of queries $Q_1, Q_2, \ldots, Q_m$ in which R_i, I_i are the relevant and irrelevant documents returned by query *i* (typically marked by the user)

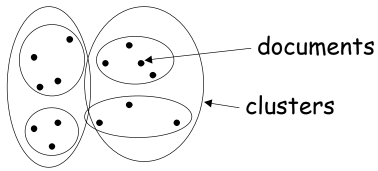
We can generate each query from previous queries:
$Q_{i+1} = \pi\, Q_0 + \omega\, Q_i + \alpha \sum_{d \in R_i} D_d + \beta \sum_{d \in I_i} D_d$

What is the efficiency problem with these queries?

Clustering

Goals:

1. Speed up searches for complicated queries
2. Find documents which are similar



There are many techniques for clustering, as well as many other applications of clustering.

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Vector Models: Weights, cosine distance
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- Singular Valued Decompositions
- Applications to indexing and searching

Link Analysis: PageRank (Google), HITS
Duplicate Removal: