Retrieval Strategies and Vector Space Model Implementation Details

Retrieval Strategies

- Manual Systems
  - Boolean, Fuzzy Set, Inference Networks
- Automatic Systems
  - Vector Space Model
  - Latent Semantic Indexing
- Adaptive
  - Probabilistic, Genetic Algorithms , Neural Networks

Manual Systems

- Boolean Retrieval
- Extended Boolean Retrieval
- Fuzzy Set Retrieval
- Vector Space Model

Manual

- For many years, most commercial systems were only Boolean.
- Most old library systems and Lexis/Nexis have a long history of Boolean retrieval.
- Users who are experts at a complex query language can find what they are looking for.
- Ex: (t1 AND t2) OR (t3 AND t3) WITHIN 2 Sentences of (t4 AND t5) NOT (t9 OR t10).

Boolean Retrieval

- *Expression*:=
  - term
  - (*expr*)
  - NOT *expr*
  - *expr* AND *expr*
  - *expr* OR *expr*
- (cost OR price) AND paper AND NOT article

Extended (Weighted) Boolean Retrieval

- Ranking by term frequency (Sony Search Engine)
  - x AND y: $tf_x \times tf_y$
  - x OR y: $tf_x + tf_y$
  - NOT x: 0 if $tf_x > 0$, 1 if $tf_x = 0$
- User may assign term weights
  - cost and +paper

Summary of Boolean Retrieval

- Pro
  - Can use very restrictive search
  - Makes experienced users happy
- Con
  - Complex query language, confusing to end users

Retrieval Strategies

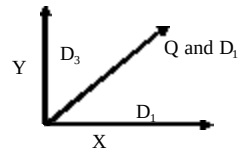
- Given a query of *t* terms, find a measure of relevance between the documents and the query. Rank documents based on this measure.
- Most commonly used strategy is the vector space model (proposed by Salton in 1975)

Vector Space Model

- Documents are mapped into term vector space.
- Each dimension represents tf-idf for one term.
- Queries are treated like documents.
- Documents are ranked by closeness to the query. Closeness is determined by a similarity score calculation.

VSM Example

- Consider a two term vocabulary, D and I
  Query: A I
  D_1 - A I
  D_2 - A
  D_3 - I



Cosine Measure

- If X and Y are two *n*-dimensional vectors $<x_i>$ and $<y_i>$, the angle θ between them satisfies:
  - $X\ Y = |X|\ |Y| \cos \theta$
  - $\cos \theta = X\ Y / (|X||Y|)$

Similarity Measures

- Inner Product
  - $SC(Q, D_i) = (D_i)(Q)$
- Cosine
  - $SC(Q, D_i) = (D_i)(Q) / (|D_i||Q|)$
- Dice
  - $SC(Q, D_i) = 2(D_i)(Q) / (D^2)\ (Q^2)$
- Jaccard
  - $SC(Q, D_i) = (D_iQ) / ((D_i)^2 + Q^2 - |D_i||Q|)$

VSM Similarity Measure

- Similarity is computed as the Euclidean distance from the query to each document:
- $SC(Q, D_2) = (Q\ D_2) / |Q|\ |D_2|$

  $Q = <1,1>$

  $D_2 = <1,0>$

  $Q\ D_1 = (1)(1)+(1)(0) = 1$

  $|Q| = (1^2 + 1^2)^{1/2} = 2^{1/2} = 1.414$

  $|D_2| = (1^2 + 0^2)^{1/2} = 1$

  $SC(Q, D_2) = (1.414)(1) / (1.414)(1) = 1.0$

Vector Example

- Q: "gold silver truck"
- D_1: "Shipment of gold delivered in a fire"
- D_2: "Delivery of silver arrived in a silver truck"
- D3: "Shipment of gold arrived in a truck"
- Number of documents a term appears in is called the *document frequency*.
  - Document Frequency of the *j*th term (df_j)
- Inverse Document Frequency (idf) = $\log_{10}(n / df_j)$

Id	Term	df	idf
1	a	3	0
2	arrived	2	0.176
3	damaged	1	0.477
4	delivery	1	0.477
5	fire	1	0.477
6	gold	1	0.176
7	in	3	0
8	of	3	0
9	silver	1	0.477
10	shipment	2	0.176
11	truck	2	0.176

Incorporating Term Frequency

- Term Frequency is the number of times a term *i* appears in document *j* (tf_{ij})

doc	t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8	t_9	t_{10}	t_{11}
D_1	0	0	.477	0	.477	.176	0	0	0	.176	0
D_2	0	.176	0	.477	0	0	0	0	.954	0	.176
D_3	0	.176	0	0	0	.176	0	0	0	.176	.176
Q	0	0	0	0	0	.176	0	0	.477	0	.176

- $SC(Q, D_1) = (0)(0) + (0)(0) + (0)(0.477) + (0)(0) + (0)(0.477) + (0.176)(0.176) + (0)(0) + (0)(0)$
- This SC uses the inner product.

Algorithm for Vector Space (dot product)

Assume: t.idf gives the idf of any term *t*
q.tf gives the tf of any query term

Begin
  Score[] ← 0
  For each term *t* in Query Q
    Obtain posting list *l*
    For each entry *p* in *l*
      Score[p.docid] = Score[p.docid] + (p.tf * t.idf)(q.tf * t.idf)

Final Stage

- Now we have a SCORE array that is unsorted.
- Sort the score array and display top *x* results.

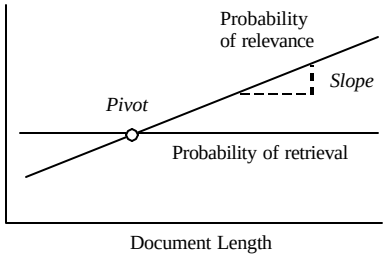
Weights for Term Components

- Classic thing to do is use tf x idf
- Incorporate idf in the query and the document, one or the other or neither.
- Scale the *idf* with a log or even a double log.
- Augment the weight with some constant (e.g.; w = (w)(0.5))

Incorporating Document Length

- Inner Product
  - Longer documents will score very high because they have more chances to match query words
- Cosine
  - Longer documents are somewhat penalized because the weight of the document |D| may be very high.
- Singhal found that longer documents tend to be more relevant than shorter ones so he proposed an adjusted *document weight.*

Document Length Normalization



Summary: Vector Space Model

- Pros
  - Fairly cheap to compute
  - Yields decent effectiveness
  - Very popular -- SMART is most commonly used academic prototype
- Cons
  - No theoretical foundation
  - Weights in the vectors are very arbitrary
  - Assumes term independence