Vector Space Scoring

Introduction to Information Retrieval
INF 141/ CS 121

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Content adapted from Hinrich Schütze
http://www.informationretrieval.org

Spamming indices

- This was invented before spam
- Consider:
  - Indexing a sensible passive document collection
  - vs.
  - Indexing an active document collection, where people, companies, bots are shaping documents to maximize scores
- Vector space scoring may not be as useful in this context.

Interaction: vectors and phrases

- Scoring phrases doesn't naturally fit into the vector space world:
  - How do we get beyond the "bag of words"?
  - "dark roast" and "pot roast"
  - There is no information on "dark roast" as a phrase in our indices.
- Biword index can treat some phrases as terms
  - postings for phrases
  - document wide statistics for phrases

Interaction: vectors and phrases

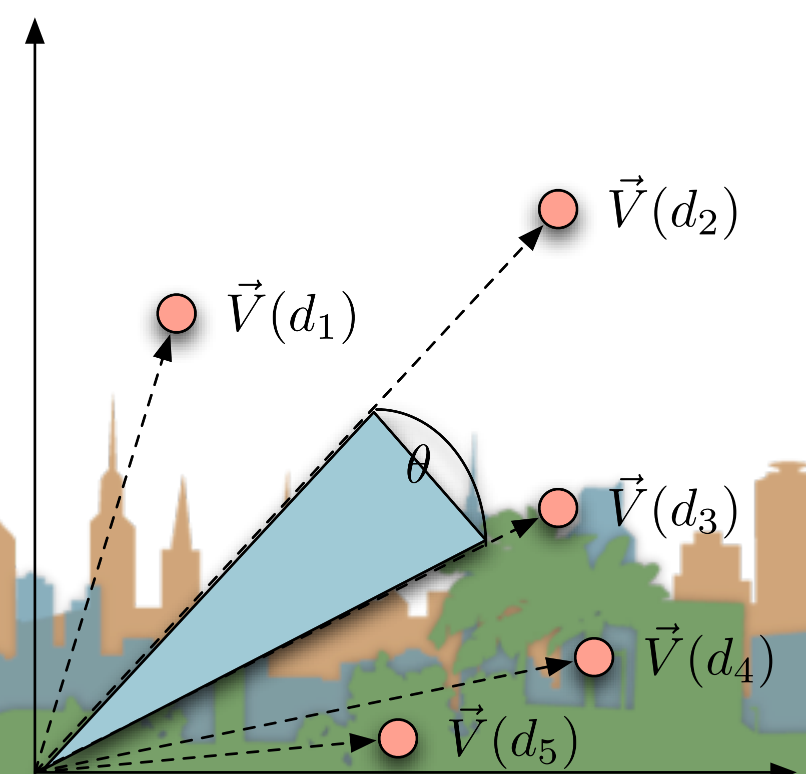
- Theoretical problem:
  - Axes of our term space are now correlated
    - There is a lot of shared information in “light roast” and “dark roast” rows of our index
- End-user problem:
  - A user doesn’t know which phrases are indexed and can’t effectively discriminate results.

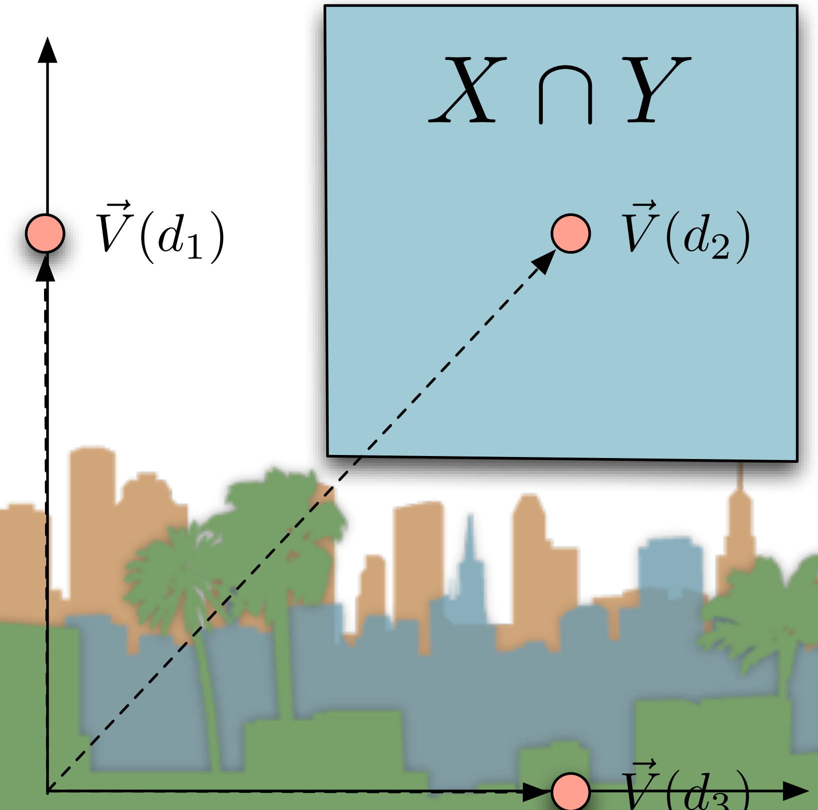
Multiple queries for phrases and vectors

- Query: “rising interest rates”
- Iterative refinement:
  - Run the phrase query vector with 3 words as a term.
  - If not enough results, run 2-phrase queries and fold into results: “rising interest” “interest rates”
  - If still not enough results run query with three words as separate terms.

Vectors and Boolean queries

- Ranked queries and Boolean queries don't work very well together
  - In term space
    - ranked queries select based on sector containment - cosine similarity
    - boolean queries select based on rectangle unions and intersections





Vectors and wild cards

- How could we work with the query, “quick* print*” ?
  - Can we view this as a bag of words?
  - What about expanding each wild-card into the matching set of dictionary terms?
- Danger: Unlike the boolean case, we now have tfs and idfs to deal with
- Overall, not a great idea

Vectors and other operators

- Vector space queries are good for no-syntax, bag-of-words queries
  - Nice mathematical formalism
  - Clear metaphor for similar document queries
  - Doesn't work well with Boolean, wild-card or positional query operators
  - But ...

Query language vs. Scoring

- Interfaces to the rescue
  - Free text queries are often separated from operator query language
  - Default is free text query
  - Advanced query operators are available in “advanced query” section of interface
  - Or embedded in free text query with special syntax
    - aka -term -”terma termb”

Alternatives to tf-idf

- Sublinear tf scaling
  - 20 occurrences of "mole" does not indicate 20 times the relevance
  - This motivated the WTF score.

$$
\begin{array}{lll}
\multicolumn{3}{l}{\mathrm{WTF}(t, d)} \\
1 & \textbf{if } tf_{t,d} = 0 & \\
2 & \quad \textbf{then } return(0) & \\
3 & \quad \textbf{else } \; return(1 + log(tf_{t,d})) &
\end{array}
$$

  - There are other variants for reducing the impact of repeated terms

TF Normalization

- Normalize tf weights by maximum tf in that document

$$ntf_{t,d} = \alpha + (1 - \alpha)\frac{tf_{t,d}}{tf_{max}(d)}$$

  - alpha is a smoothing term from (0 - 1.0) ~0.4 in practice
  - This addresses a length bias.
  - Take one document, repeat it, WTF goes up
    - this score reduces that impact

TF Normalization

- Normalize tf weights by maximum tf in that document

$$ntf_{t,d} = \alpha + (1-\alpha)\frac{tf_{t,d}}{tf_{max}(d)}$$

  - a change in the stop word list can change weights drastically - hard to tune
  - still based on bag of words model
    - one outlier word, repeated many times might throw off the algorithmic understanding of the content

Laundry List

Term Frequency		*Document Frequency*		*Normalization*	
$(n)atural$	$tf_{t,d}$	$(n)o$	1	$(n)one$	1
$(l)ogarithm$	$1 + log(tf_{t,d})$	$(t)idf$	$log\frac{\lvert corpus\rvert}{df_t}$	$(c)osine$	$\frac{1}{\sqrt{w_1{}^2+w_2{}^2+...+w_m{}^2}}$
$(a)ugmented$	$\alpha + (1-\alpha)\frac{tf_{t,d}}{tf_{max}(d)}$	$(p)robidf$	$max\{0, log(\frac{\lvert corpus\rvert - dft}{df_t})$	$(u)pivoted$	$1/u$
$(b)oolean$	$tf_{t,d} > 0?1:0$			$(b)yte$	$1/CharLength^{\alpha}, \alpha < 1$
$(L)ogaverage$	$\frac{1+log(tf_{t,d})}{1+log(ave_{t\in d}(tf_{t,d}))}$				

- SMART system of describing your IR vector algorithm
    - ddd.qqq (ddd = document weighting) (qqq = query weighting)
    - first is term weighting, second is document, then normalization
    - lnc.ltc is what?

Efficient Cosine Ranking

- Find the k docs in the corpus “nearest” to the query
    - the k largest query-doc cosines
- Efficient ranking means:
    - Computing a single cosine efficiently
    - Computing the k largest cosine values efficiently
        - Can we do this without computing all n cosines?
            - n = number of documents in corpus

Efficient Cosine Ranking

- Computing a single cosine
  - Use inverted index
  - At query time use an array of accumulators Aj to accumulate component-wise sum (incremental dot-product)
  - Accumulate scores as postings lists are being processed (numerator of similarity score)

$$A_j = \sum_t (w_{q,t} w_{d,t})$$

Efficient Cosine Ranking

- For the web
  - an array of accumulators in memory is infeasible
  - so only create accumulators for docs that occur in postings list
    - dynamically create accumulators
  - put the tf_d scores in the postings lists themselves
  - limit docs to non-zero cosines on rare words
    - or non-zero cosines on all words
    - reduces number of accumulators

Efficient Cosine Ranking

$\textsc{CosineScore}(q)$

$\quad \textsc{Initialize}(Scores[d \in D])$

$\quad \textsc{Initialize}(Magnitude[d \in D])$

$\quad \textbf{for } each\ term(t \in q)$

$\qquad \textbf{do } p \leftarrow \textsc{FetchPostingsList}(t)$

$\qquad\quad df_t \leftarrow \textsc{GetCorpusWideStats}(p)$

$\qquad\quad \alpha_{t,q} \leftarrow \textsc{WeightInQuery}(t, q, df_t)$

$\qquad\quad \textbf{for } each\ \{d, tf_{t,d}\} \in p$

$\qquad\qquad \textbf{do } Scores[d] += \alpha_{t,q} \cdot \textsc{WeightInDocument}(t, q, df_t)$

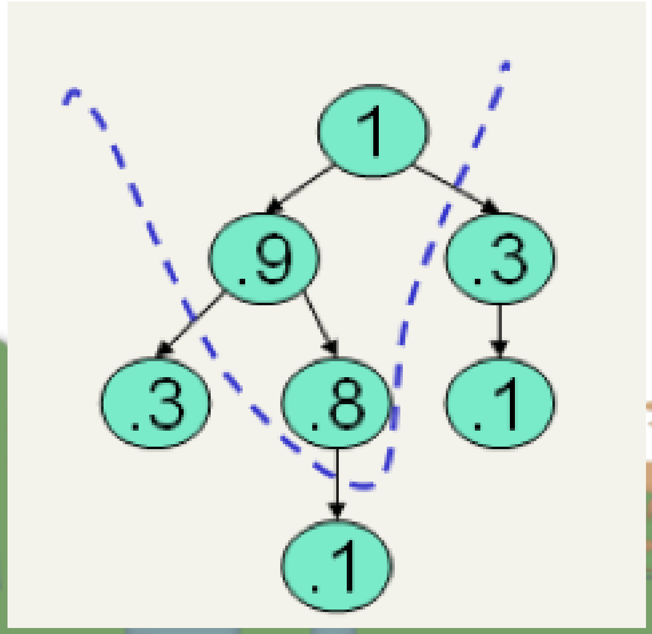
$\quad \textbf{for } d \in Scores$

$\qquad \textbf{do } \textsc{Normalize}(Scores[d], Magnitude[d])$

$\quad \textbf{return } top\ K \in Scores$

Use heap for selecting the top K Scores

- Binary tree in which each node’s value > the values of children
- Takes 2N operations to construct
  - then each of k “winners” read off in 2logn steps
  - For n =1M, k=100 this is about 10% of the cost of sorting
- Java “TreeMap” for example



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