COEN 169

Relevance Feedback

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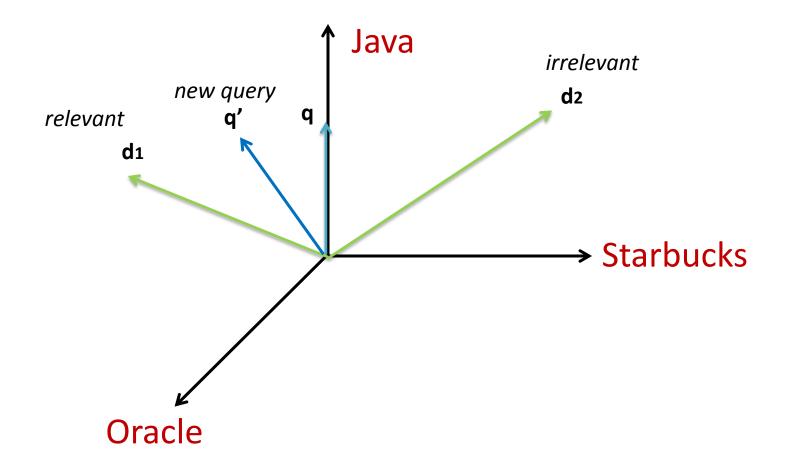
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Query representation

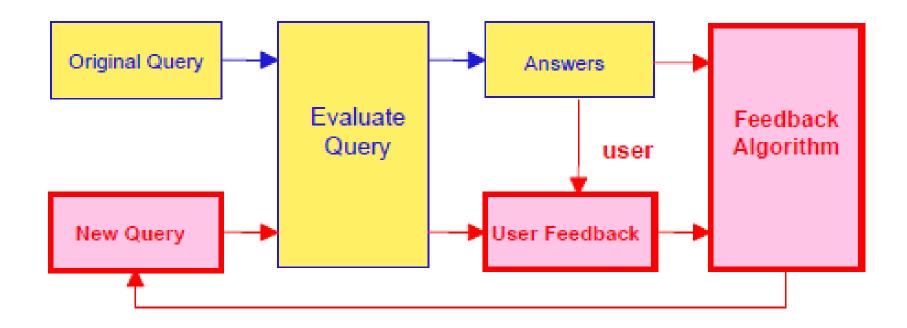
- Improving results
 - For high recall. E.g., searching for aircraft doesn't match with plane; nor car with automobile
- Options for improving results...
 - Local methods
 - Relevance feedback
 - Pseudo relevance feedback
 - Global methods
 - Query expansion
 - Thesauri
 - Automatic thesaurus generation

Query representation



Relevance feedback

- Relevance feedback: user feedback on relevance of docs in initial set of results
 - User issues a (short, simple) query
 - The user marks some results as relevant or nonrelevant.
 - The system computes a better representation of the information need based on feedback.
 - Relevance feedback can go through one or more iterations.
- Idea: it may be difficult to formulate a good query when you don't know the collection well, so iterate



Example: image search

Querylmage

Euclidean distance

32-D HSV histograms









B45981.jpg d=0.000000

B42162.jpg d=0.163017

B10952.jpg d=0.188954

B45976.jpg d=0.189377

502900.jpg d=0.196651











503000.jpg d=0.197358 554600.jpg d=0.203710

B45986.jpg d=0.204831

B47348.jpg d=0.206816

B35333.jpg d=0.209186

This is the initial query, for which 2 object are assessed as relevant by the user

Precision = 0.3 (including the query image)

Example: image search



These are the results of the "refined" (new) query
 Precision = 0.8

Example: document search

- Initial query: New space satellite applications
 - + 1. 0.539, 08/13/91, NASA Hasn't Scrapped Imaging Spectrometer
 - + 2. 0.533, 07/09/91, NASA Scratches Environment Gear From Satellite Plan
 - 3. 0.528, 04/04/90, Science Panel Backs NASA Satellite Plan, But Urges Launches of Smaller Probes
 - 4. 0.526, 09/09/91, A NASA Satellite Project Accomplishes Incredible Feat: Staying Within Budget
 - 5. 0.525, 07/24/90, Scientist Who Exposed Global Warming Proposes Satellites for Climate Research
 - 6. 0.524, 08/22/90, Report Provides Support for the Critics Of Using Big Satellites to Study Climate
 - 7. 0.516, 04/13/87, Arianespace Receives Satellite Launch Pact From Telesat Canada
 - + 8. 0.509, 12/02/87, Telecommunications Tale of Two Companies
- User then marks relevant documents with "+".

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Expanded query after relevance feedback

- 2.074 new
- 30.816 satellite
- 5.991 nasa
- 4.196 launch
- 3.516 instrument
- 3.004 bundespost
- 2.790 rocket
- 2.003 broadcast
- 0.836 oil

- 15.106 space
- 5.660 application
- 5.196 eos
- 3.972 aster
- 3.446 arianespace
- 2.806 ss
- 2.053 scientist
- 1.172 earth
- 0.646 measure

Sec. 9.1.1

Results for expanded query

- 2 1. 0.513, 07/09/91, NASA Scratches Environment Gear From Satellite Plan
- 1 2. 0.500, 08/13/91, NASA Hasn't Scrapped Imaging Spectrometer
 - 3. 0.493, 08/07/89, When the Pentagon Launches a Secret Satellite, Space Sleuths Do Some Spy Work of Their Own
 - 4. 0.493, 07/31/89, NASA Uses 'Warm' Superconductors For Fast Circuit
- 8 5. 0.492, 12/02/87, Telecommunications Tale of Two Companies
 - 6. 0.491, 07/09/91, Soviets May Adapt Parts of SS-20 Missile For Commercial Use
 - 7. 0.490, 07/12/88, Gaping Gap: Pentagon Lags in Race To Match the Soviets In Rocket Launchers
 - 8. 0.490, 06/14/90, Rescue of Satellite By Space Agency To Cost \$90 Million

Query point movement

The idea is simply to move the query point so as to get closer to relevant objects



Rocchio Algorithm

- The first formulation of the query point movement (QPM) strategy dates back to 70's, when it was proposed by J.J. Rocchio
- The <u>centroid</u> is the center of mass of a set of points
- Remember that we represent documents as points in a high-dimensional space
- Definition: Centroid

$$\vec{\mu}(C) = \frac{1}{|C|} \sum_{d \in C} \vec{d}$$

where C is a set of documents.

Rocchio 1971 Algorithm (SMART)

Used in practice:

$$\vec{q}_{m} = \alpha \vec{q}_{0} + \beta \frac{1}{|D_{r}|} \sum_{\vec{d}_{j} \in D_{r}} \vec{d}_{j} - \gamma \frac{1}{|D_{nr}|} \sum_{\vec{d}_{j} \in D_{nr}} \vec{d}_{j}$$

- D_r = set of known relevant doc vectors
- D_{nr} = set of <u>known</u> irrelevant doc vectors
- q_m = modified query vector; q_0 = original query vector
- α, β, γ : weights (hand-chosen or set empirically)
- New query moves toward relevant documents and away from irrelevant documents

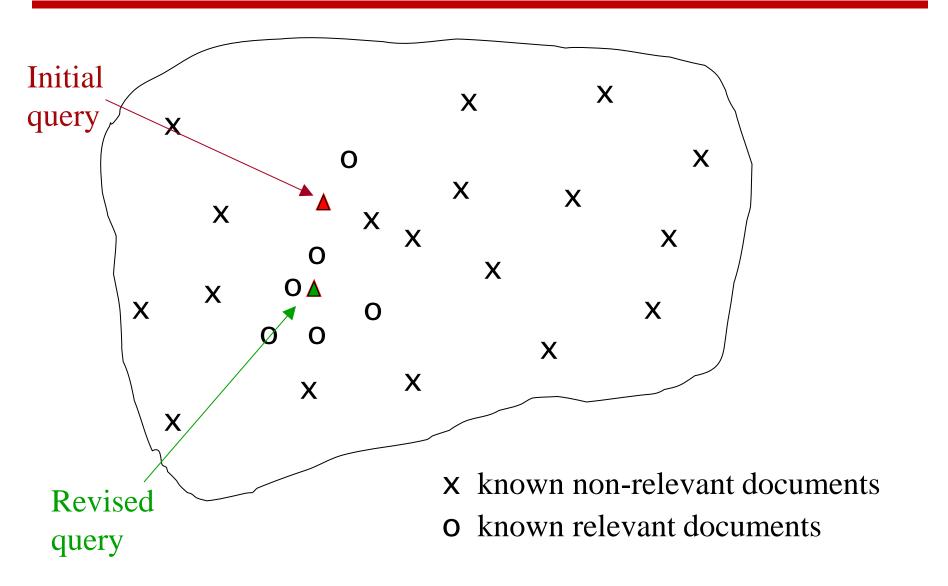
Sec. 9.1.1

Subtleties to note

- Tradeoff α vs. β/γ : If we have a lot of judged documents, we want a higher β/γ .
- In general, $\alpha = 1$, $\beta = 0.75$, $\gamma = 0.25$
- Some weights in query vector can go negative
 - Negative term weights are ignored (set to 0)

Sec. 9.1.1

Relevance feedback on initial query



Relevance Feedback in vector spaces

- We can modify the query based on relevance feedback and apply standard vector space model.
- Use only the docs that were marked.
- Relevance feedback can improve recall and precision
- Relevance feedback is most useful for increasing recall in situations where recall is important
 - Users can be expected to review results and to take time to iterate

Sec. 9.1.1

Positive vs Negative Feedback

- Positive feedback is more valuable than negative feedback (so, set $\gamma < \beta$; e.g. $\gamma = 0.25$, $\beta = 0.75$).
- Many systems only allow positive feedback $(\gamma=0)$.

Relevance Feedback: Assumptions

- Assumption 1: User has reasonable knowledge for initial query.
- Assumption 2: Relevance prototypes are "wellbehaved".
 - Term distribution in relevant documents will be similar
 - Term distribution in non-relevant documents will be different from those in relevant documents
 - All relevant documents are tightly clustered
 - Similarities between relevant and irrelevant documents are small

Violation of Assumption 2

Relevant (or irrelevant) documents show multimodal behaviors

Relevance Feedback: Problems

- Long queries are inefficient for typical IR engine.
 - Long response times for user.
 - High cost for retrieval system.
 - Partial solution:
 - Only reweight certain prominent terms
 - Perhaps top 20 by term frequency
- Users are often reluctant to provide explicit feedback

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Rule-of-thumb

- Empirically, one round of relevance feedback is often very useful. Two rounds is sometimes marginally useful.
- Having at least 5 judged documents is recommended

Relevance Feedback on the Web

- Most Web search engines do not provide the relevance feedback feature because it is hard to explain to average user:
 - Google
 - Bing
 - Yahoo
- Google's SearchWiki was released in 2008 and discontinued in 2010
- allowed logged-in users to annotate and re-order search results

Google's SearchWiki



Excite Relevance Feedback

 Excite initially had true relevance feedback, but abandoned it due to lack of use

Spink et al. 2000

- Only about 4% of query sessions from a user used relevance feedback option
 - Expressed as "More like this" link next to each result
- Relevance feedback improved results about 2/3 of the time

Pseudo relevance feedback

- Pseudo-relevance feedback automates the "manual" part of true relevance feedback.
- Pseudo-relevance algorithm:
 - Retrieve a ranked list of hits for the user's query
 - Assume that the top k documents are relevant.
 - Do relevance feedback (e.g., Rocchio)
- Works very well on average
- But can go horribly wrong for some queries.
- Several iterations can cause query drift.

Sec. 9.2.2

Query Suggestion

- In relevance feedback, users give additional input (relevant/non-relevant) on documents, which is used to reweight terms in the documents
- In query suggestion, users give additional input (good/bad search term) on words or phrases

Query assist



Would you expect such a feature to increase the query volume at a search engine?

How do we augment the user query?

- Thesaurus
 - E.g. MedLine: physician, syn: doc, doctor, MD, medico
 - Can be query rather than just synonyms
- Global Analysis: (static; of all documents in collection)
 - Automatically derived thesaurus
 - (co-occurrence statistics)
 - Refinements based on query log mining
 - Common on the web
- Local Analysis: (dynamic)
 - Analysis of documents in result set

Thesaurus-based query expansion

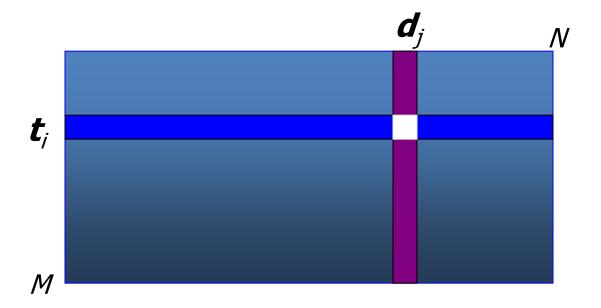
- For each term, t, in a query, expand the query with synonyms and related words of t from the thesaurus
 - feline \rightarrow feline cat
- May weight added terms less than original query terms.
- Generally increases recall
- Widely used in many science/engineering fields
- May significantly decrease precision, particularly with ambiguous terms.
 - "interest rate" → "interest rate fascinate evaluate"
- There is a high cost of manually producing a thesaurus
 - And for updating it for scientific changes

Automatic Thesaurus Generation

- Attempt to generate a thesaurus automatically by analyzing the collection of documents
- Fundamental notion: similarity between two words
- Definition 1: Two words are similar if they co-occur frequently in a document or paragraph.
- Definition 2: Two words are similar if they occur in a given grammatical relation with the same words.
- You can harvest, peel, eat, or prepare apples and pears, so apples and pears must be similar.
- Co-occurrence based is more robust, grammatical relations are more accurate.

Co-occurrence Thesaurus

- Simplest way to compute one is based on term-term similarities in $C = AA^T$ where A is term-document matrix.
- $w_{i,j} = \text{(normalized)}$ weight for (t_i, \mathbf{d}_j)



What does *C* contain if *A* is a term-doc binary (0/1) matrix?

For each t_i, pick terms with high values in C

Sec. 9.2.3

Automatic Thesaurus Generation Example

word	ten nearest neighbors
absolutely	absurd whatsoever totally exactly nothing
bottomed	dip copper drops topped slide trimmed slig
captivating	shimmer stunningly superbly plucky witty:
doghouse	dog porch crawling beside downstairs gazed
Makeup	repellent lotion glossy sunscreen Skin gel p
mediating	reconciliation negotiate cease conciliation p
keeping	hoping bring wiping could some would othe
lithographs	drawings Picasso Dali sculptures Gauguin I
pathogens	toxins bacteria organisms bacterial parasit ϵ
senses	grasp psyche truly clumsy naive innate awl

Automatic Thesaurus Generation Discussion

- Quality of associations is usually a problem.
- Term ambiguity may introduce irrelevant statistically correlated terms.
 - "Apple computer" → "Apple red fruit computer"
- Problems:
 - False positives: Words deemed similar that are not
 - False negatives: Words deemed dissimilar that are similar
- Since terms are highly correlated anyway, expansion may not retrieve many additional documents.

Indirect relevance feedback

- On the web, indirect/implicit relevance feedback is abundantly available
- implicit relevance feedback:
- which documents they do and do not select for viewing
 - the duration of time spent viewing a document
 - page browsing or scrolling actions, etc.
- Not necessarily user or query specific
 - This is the general area of clickstream mining
- Today handled as part of machine-learned ranking