Query Operations

Relevance Feedback &
Query Expansion
Relevance Feedback

- After initial retrieval results are presented, allow the user to provide feedback on the relevance of one or more of the retrieved documents.
- Use this feedback information to reformulate the query.
- Produce new results based on reformulated query.
- Allows more interactive, multi-pass process.
Relevance Feedback Architecture

- **Query String**
- **Revised Query**
- **Query Reformulation**
- **Feedback**

**Document corpus**

**IR System**

**Ranked Documents**

**ReRanked Documents**

1. Doc1
2. Doc2
3. Doc3

1. Doc2
2. Doc4
3. Doc5

Query Reformulation

• Revise query to account for feedback:
  – Query Expansion: Add new terms to query from relevant documents.
  – Term Reweighting: Increase weight of terms in relevant documents and decrease weight of terms in irrelevant documents.

• Several algorithms for query reformulation.
Query Reformulation for VSR

- Change query vector using vector algebra.
- Add the vectors for the relevant documents to the query vector.
- Subtract the vectors for the irrelevant docs from the query vector.
- This both adds both positive and negatively weighted terms to the query as well as reweighting the initial terms.
Optimal Query

• Assume that the relevant set of documents $C_r$ are known.

• Then the best query that ranks all and only the relevant queries at the top is:

$$
\tilde{q}_{opt} = \frac{1}{|C_r|} \sum_{\forall \tilde{d}_j \in C_r} \tilde{d}_j - \frac{1}{N - |C_r|} \sum_{\forall \tilde{d}_j \not\in C_r} \tilde{d}_j
$$

Where $N$ is the total number of documents.
Standard Rochio Method

• Since all relevant documents unknown, just use the known relevant ($D_r$) and irrelevant ($D_n$) sets of documents and include the initial query $q$.

$$\tilde{q}_m = \alpha \tilde{q} + \frac{\beta}{|D_r|} \sum_{\forall \tilde{d}_j \in D_r} \tilde{d}_j - \frac{\gamma}{|D_n|} \sum_{\forall \tilde{d}_j \in D_n} \tilde{d}_j$$

- $\alpha$: Tunable weight for initial query.
- $\beta$: Tunable weight for relevant documents.
- $\gamma$: Tunable weight for irrelevant documents.
Ide Regular Method

• Since more feedback should perhaps increase the degree of reformulation, do not normalize for amount of feedback:

\[ \tilde{q}_m = \alpha \tilde{q} + \beta \sum_{\forall \tilde{d}_j \in D_r} \tilde{d}_j - \gamma \sum_{\forall \tilde{d}_j \in D_n} \tilde{d}_j \]

\(\alpha\): Tunable weight for initial query.
\(\beta\): Tunable weight for relevant documents.
\(\gamma\): Tunable weight for irrelevant documents.
Ide “Dec Hi” Method

• Bias towards rejecting just the highest ranked of the irrelevant documents:

\[ \tilde{q}_m = \alpha \tilde{q} + \beta \sum_{\forall \tilde{d}_j \in D_r} \tilde{d}_j - \gamma \max_{\text{non-relevant}} (\tilde{d}_j) \]

\( \alpha \): Tunable weight for initial query.
\( \beta \): Tunable weight for relevant documents.
\( \gamma \): Tunable weight for irrelevant document.
Comparison of Methods

• Overall, experimental results indicate no clear preference for any one of the specific methods.

• All methods generally improve retrieval performance (recall & precision) with feedback.

• Generally just let tunable constants equal 1.
Relevance Feedback in Java VSR

- Includes “Ide Regular” method.
- Invoke with “-feedback” option, use “r” command to reformulate and redo query.
- See sample feedback trace.
- Since stored frequencies are not normalized (since normalization does not effect cosine similarity), must first divide all vectors by their maximum term frequency.
Evaluating Relevance Feedback

• By construction, reformulated query will rank explicitly-marked relevant documents higher and explicitly-marked irrelevant documents lower.
• Method should not get credit for improvement on these documents, since it was told their relevance.
• In machine learning, this error is called “testing on the training data.”
• Evaluation should focus on generalizing to other un-rated documents.
Fair Evaluation of Relevance Feedback

• Remove from the corpus any documents for which feedback was provided.
• Measure recall/precision performance on the remaining *residual collection*.
• Compared to complete corpus, specific recall/precision numbers may decrease since relevant documents were removed.
• However, *relative* performance on the residual collection provides fair data on the effectiveness of relevance feedback.
Why is Feedback Not Widely Used

- Users sometimes reluctant to provide explicit feedback.
- Results in long queries that require more computation to retrieve, and search engines process lots of queries and allow little time for each one.
- Makes it harder to understand why a particular document was retrieved.
Pseudo Feedback

• Use relevance feedback methods without explicit user input.
• Just assume the top $m$ retrieved documents are relevant, and use them to reformulate the query.
• Allows for query expansion that includes terms that are correlated with the query terms.
Pseudo Feedback Architecture

Query String

Revised Query

Query Reformulation

Pseudo Feedback

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.
PseudoFeedback Results

• Found to improve performance on TREC competition ad-hoc retrieval task.
• Works even better if top documents must also satisfy additional boolean constraints in order to be used in feedback.
A thesaurus provides information on synonyms and semantically related words and phrases.

Example:

physician

   syn: | croaker, doc, doctor, MD, medical, mediciner, medico, | sawbones
   rel: medic, general practitioner, surgeon,
Thesaurus-based Query Expansion

• For each term, $t$, in a query, expand the query with synonyms and related words of $t$ from the thesaurus.
• May weight added terms less than original query terms.
• Generally increases recall.
• May significantly decrease precision, particularly with ambiguous terms.
  – “interest rate” $\rightarrow$ “interest rate fascinate evaluate”
WordNet

- A more detailed database of semantic relationships between English words.
- Developed by famous cognitive psychologist George Miller and a team at Princeton University.
- About 144,000 English words.
- Nouns, adjectives, verbs, and adverbs grouped into about 109,000 synonym sets called synsets.
WordNet Synset Relationships

• **Antonym**: front → back
• **Attribute**: benevolence → good (noun to adjective)
• **Pertainym**: alphabetical → alphabet (adjective to noun)
• **Similar**: unquestioning → absolute
• **Cause**: kill → die
• **Entailment**: breathe → inhale
• **Holonym**: chapter → text (part to whole)
• **Meronym**: computer → cpu (whole to part)
• **Hyponym**: plant → tree (specialization)
• **Hypernym**: apple → fruit (generalization)
WordNet Query Expansion

• Add synonyms in the same synset.
• Add hyponyms to add specialized terms.
• Add hypernyms to generalize a query.
• Add other related terms to expand query.
Statistical Thesaurus

- Existing human-developed thesauri are not easily available in all languages.
- Human thesauri are limited in the type and range of synonymy and semantic relations they represent.
- Semantically related terms can be discovered from statistical analysis of corpora.
Automatic Global Analysis

• Determine term similarity through a pre-computed statistical analysis of the complete corpus.
• Compute association matrices which quantify term correlations in terms of how frequently they co-occur.
• Expand queries with statistically most similar terms.
**Association Matrix**

<table>
<thead>
<tr>
<th></th>
<th>$w_1$</th>
<th>$w_2$</th>
<th>$w_3$</th>
<th>$\ldots$</th>
<th>$w_n$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$w_1$</td>
<td>$c_{11}$</td>
<td>$c_{12}$</td>
<td>$c_{13}$</td>
<td>$\ldots$</td>
<td>$c_{1n}$</td>
</tr>
<tr>
<td>$w_2$</td>
<td>$c_{21}$</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>$w_3$</td>
<td>$c_{31}$</td>
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<tr>
<td>$w_n$</td>
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<td></td>
<td></td>
<td>$c_{n1}$</td>
</tr>
</tbody>
</table>

$c_{ij}$: Correlation factor between term $i$ and term $j$

$$c_{ij} = \sum_{d_k \in D} f_{ik} \times f_{jk}$$

$f_{ik}$: Frequency of term $i$ in document $k$
Normalized Association Matrix

• Frequency based correlation factor favors more frequent terms.

• Normalize association scores:

\[ s_{ij} = \frac{c_{ij}}{c_{ii} + c_{jj} - c_{ij}} \]

• Normalized score is 1 if two terms have the same frequency in all documents.
Metric Correlation Matrix

• Association correlation does not account for the proximity of terms in documents, just co-occurrence frequencies within documents.

• Metric correlations account for term proximity.

\[ c_{ij} = \sum_{k_u \in V_i} \sum_{k_v \in V_j} \frac{1}{r(k_u, k_v)} \]

- **V_i**: Set of all occurrences of term i in any document.
- **r(k_u, k_v)**: Distance in words between word occurrences \( k_u \) and \( k_v \) (\( \infty \) if \( k_u \) and \( k_v \) are occurrences in different documents).
Normalized Metric Correlation Matrix

- Normalize scores to account for term frequencies:

\[ s_{ij} = \frac{c_{ij}}{|V_i| \times |V_j|} \]
Query Expansion with Correlation Matrix

• For each term $i$ in query, expand query with the $n$ terms, $j$, with the highest value of $c_{ij}$ ($s_{ij}$).

• This adds semantically related terms in the “neighborhood” of the query terms.
Problems with Global Analysis

• Term ambiguity may introduce irrelevant statistically correlated terms.
  – “Apple computer” → “Apple red fruit computer”

• Since terms are highly correlated anyway, expansion may not retrieve many additional documents.
Automatic Local Analysis

• At query time, dynamically determine similar terms based on analysis of top-ranked retrieved documents.

• Base correlation analysis on only the “local” set of retrieved documents for a specific query.

• Avoids ambiguity by determining similar (correlated) terms only within relevant documents.
  – “Apple computer” → “Apple computer Macbook laptop”
Global vs. Local Analysis

• Global analysis requires intensive term correlation computation only once at system development time.

• Local analysis requires intensive term correlation computation for every query at run time (although number of terms and documents is less than in global analysis).

• But local analysis gives better results.
Global Analysis Refinements

• Only expand query with terms that are similar to all terms in the query.

\[ sim(k_i, Q) = \sum_{k_j \in Q} c_{ij} \]

- “fruit” not added to “Apple computer” since it is far from “computer.”
- “fruit” added to “apple pie” since “fruit” close to both “apple” and “pie.”

• Use more sophisticated term weights (instead of just frequency) when computing term correlations.
Query Expansion Conclusions

• Expansion of queries with related terms can improve performance, particularly recall.
• However, must select similar terms very carefully to avoid problems, such as loss of precision.