**A0172868M-A0171426J-A0168355W-A0164816Y**

**QUERY REFINEMENT AND EXPANSION**

We experimented with different types of query refinement techniques. They are mostly implemented in QueryExpansion.py. In the final submission, we decided not to use most of these techniques, and preserve only the removal of boolean operators and phrasal markers, as well as WordNet query expansion.

## Relaxing boolean and phrasal queries

The first stage of query expansion, as explained above, involves relaxing the restrictions placed on the query from phrases and boolean operators. Since the terms in the user queries may not be the exact terms desired, we need to relax the AND portion of the query, so that even if the term given is not correct, the results for other parts of the query can still be returned. To achieve a baseline tf-idf framework, all boolean operators and phrase markers were stripped from the query string.

Every query can one of the following four types:

1. +phrase, + boolean: e.g. "fertility treatment" AND damages  
2. +phrase, -boolean: e.g. "fertility treatment" damages  
3. -phrase, +boolean: e.g. fertility AND treatment AND damages  
4. -phrase, -boolean: e.g. fertility treatment damages (basic free text query without phrases or boolean operator)

For an original query string with both phrases and the "AND" boolean operator, query expansion can allow us to relax these restrictions in order to produce the other 3 combinations. When the original query either does not have phrases or the boolean operator, it can still be relaxed to the free text query. For a maximally complex query of type 1 (including boolean operator and phrases), the orders of search between these four types of queries can be permuted and experimented with to determine the importance of preserving the additional information of phrases and boolean operators.

For 3. We note that the set of documents containing the phrase “fertility treatment” is a subset of the set of documents containing (fertility AND treatment).

## WordNet/Thesaurus Query Expansion

The NLTK WordNet was used as a thesaurus to implement query expansion. In particular, the synonyms of the terms were found using the synset feature of WordNet. We decided to use WordNet expansion particularly because the sample query 1 (quiet phone call) for which relevant documents are available strongly suggested that “silent telephone call” was what should have been searched for instead. Thus, it was important to retrieve synonyms for the original query terms.

Additionally, we also experimented with using hypernyms and hyponyms to return related words, however, because too many of such words were returned, we decided to stick with synonyms. The additional synonyms retrieved were appended onto the free text version of the original query to create a longer free text query. Due to time constraints we were unable to implement a potential improvement, which involves ensuring for a boolean query that the synonyms were intersected. For example, a query 'quiet AND phone call' could be expanded to '(quiet OR silent) AND (phone call OR telephone call)'.

## Relevance Feedback and Rocchio Algorithm

For relevance feedback based on the Rocchio Algorithm, our system makes use of the top 1000 returned documents from the basic search which are assumed to be relevant, on top of the list of documents identified as relevant in the original query file. The document IDs are then used to retrieve precomputed and stored document vectors in the document properties file, which are then combined to give the centroid vector of the relevant documents. This is done such that there is no need to traverse the postings file to build the document vector for each relevant document, which would be extremely expensive. We incorporated this requirement into our indexing phase, using properties\_helper.py and vectors.txt.

An additional optimisation involves storing the vectors as sparse vectors using a dictionary mapping terms to the tf values. This is necessary since the vectors would include many 0 terms if the dimension of the vector was the size of the entire dictionary. Furthermore, even after computing the centroid vector, there will still remain many non-zero dimensions in the centroid. In order to improve on efficiency, there is a need to remove some of the non-zero terms. To do this, each component was multiplied with idf in order to reduce the value of more common and hence less useful terms. The top 50 terms (excluding stopwords and punctuations) were chosen for the final centroid vector, as 1. Too many terms may slow down the query and 2. Useless dimensions that would not contribute much to the query can be removed.

The new centroid vector can then be added to the original query vector to derive a new query vector used for VSM retrieval. For simplicity, the original query vector is made to be a free text query such that boolean operators are removed and phrases are converted to single word terms. Furthermore, since we lack training data, it was not possible to tune the weights given to the original query vector and the centroid vector. Hence, equal weight was given to both vectors. The additional documents found from relevance feedback are appended after the already returned documents.

# **Experimental Results**

We use notations to denote the order we executed the query refinement techniques.

1. POSITIVE LIST
2. +PHRASE, + BOOLEAN ("fertility treatment" AND damages)
3. +PHRASE, - BOOLEAN ("fertility treatment" damages)
4. -PHRASE, -BOOLEAN (fertility treatment damages, baseline)
5. +WORDNET, -BOOLEAN
6. ROCCHIO ALGORITHM
7. -PHRASE, +BOOLEAN (fertility AND treatment AND damages)

### QUERY RETRIEVAL

To understand our performance against the different query types, we retrieved the query strings from the competition framework:

|  |  |
| --- | --- |
| q1 | quiet AND "phone call" |
| q2 | prostitute AND "forced sex" AND payment |
| q3 | pretend to be officer |
| q4 | "fertility treatment" AND damages |
| q5 | publish hurt son |
| q6 | "good grades" AND exchange AND scandal |

### APPROACHING BASELINE

We first implemented a baseline system disregarding any query refinement (-phrase, -boolean), so ("fertility treatment" AND damages) becomes (fertility treatment damages).

|  |  |  |
| --- | --- | --- |
|  | BASELINE | OURS (JSON) |
| Q1 Average F2 | 0.0108595077894779 | 0.0108201093105916 |
| Q2 Average F2 | 0.362745098039216 | 0.362745098039216 |
| Q3 Average F2 | 0.0113111117361595 | 0.0112925624835047 |
| Q4 Average F2 | 0.496296296296296 | 0.496296296296296 |
| Q5 Average F2 | 0.104510939130271 | 0.103200491131526 |
| Q6 Average F2 | 0.3 | 0.30050505050505 |
| Mean Average F2 | 0.214287158831903 | 0.214143267961031 |

As expected, we were close to the baseline tf-idf model. However, we were still slightly below and we hypothesised that the baseline model appended the title to the content before processing, so we did that as well.

### INITIAL TEST

We did an initial test of the techniques above:

1. positive list 2. +boolean, +phrase 3. -boolean, -phrase 4. +phrase -boolean 5. Wordnet expansion 6. Rocchio expansion

|  |  |
| --- | --- |
| Q1 Average F2: 0.0318471337579618 | +193% |
| Q2 Average F2: 0.276839007986549 | -24% |
| Q3 Average F2: 0.00854730742939909 | -24% |
| Q4 Average F2: 0.516624579124579 | +4% |
| Q5 Average F2: 0.103200491131526 | -1% |
| Q6 Average F2: 0.172659817351598 | -42% |
| Mean Average F2: 0.184953056130269 | -14% |

This performed worse than the baseline tf-idf. There was only improvement to two of the queries, over the baseline results.

We realised that we may have been too hasty in our assumption of subsets in the permutation of boolean and phrasal saerch earlier. Logically, it is true that 1 < 2 < 3 < 4 for the permutations listed below. However, users do not distinguish between these four types of queries.

1. +PHRASE, + BOOLEAN ("fertility treatment" AND damages)
2. +PHRASE, - BOOLEAN ("fertility treatment" damages)
3. -PHRASE, +BOOLEAN (fertility AND treatment AND damages)
4. -PHRASE, -BOOLEAN (fertility treatment damages, baseline)

A user issuing the query expect these four queries to return the same set of relevant documents, because of the semantic interpretation of the document content. As such, in our final implementation, we kept close to the baseline tf-idf and only used type 4 queries, stripping all information on AND and phrasal markers.

## VOCABULARY MISMATCH

Given what we have, we do feel that it is important to address the anomalous state of knowledge (ASK) or vocabulary mismatch problem. The above methods to permute different forms of queries will only return documents that have at least a partial vocabulary match. To overcome the vocabulary mismatch, WordNet and Rocchio feedback can be used.

WordNet can directly address the ASK problem, while Rocchio feedback relies on the returned documents containing related terms. We experiment with these two methods below.

### IMMEDIATE WORDNET EXPANSION

We analysed the submissions made by other teams, as well as the given positive list. Interestingly, we found that the positive list for “quiet phone call” did not contain the exact terms. Rather, “telephone call” was in the document.

This led us to the revelation that it may be better to do a wordnet expansion first. To better isolate our results, we attempted to only do the wordnet expansion. That is, we only return the results from the wordnet expansion (not including positive list or the hard conjunctions). We did this because an accurate wordnet expansion should still retrieve the positive list results. By right, the wordnet expansion should also return the results of the original query (we append the original query string to the wordnet expansion).

Unfortunately, we received very bad results on this experiment. WordNet expansion is still used in the final submission, but the additional results are appended only after the first round of search with expansion. This is done in order to deal with cases where very few documents are returned due to the incorrect search terms being used in the query.

|  |  |
| --- | --- |
| Q1 Average F2: 0.00198346589850713 | -82% |
| Q2 Average F2: 0.00152853996309595 | -100% |
| Q3 Average F2: 0.00109824660167018 | -90% |
| Q4 Average F2: 0.00148902389641845 | -100% |
| Q5 Average F2: 0.00166292668856411 | -98% |
| Q6 Average F2: 0.000682437441147597 | -100% |
| Mean Average F2: 0.00140744008156724 | -99% |

### IMMEDIATE ROCCHIO FEEDBACK

Given the same concerns as earlier (that is, the returned documents in the positive list do not contain the exact query terms) we try another way to return the documents, using Rocchio feedback. In theory, Rocchio feedback will find the documents containing “quiet phone call”. It is possible that these documents also synonymously use “telephone call” in some instances, so we will get “telephone call” in our centroid. This was done by first retrieving relevant documents using a regular VSM approach, and then using that to retrieve documents using the Rocchio algorithm. The original relevant documents were then discarded.

|  |  |
| --- | --- |
| Q1 Average F2: 0.00198346589850713 | -82% |
| Q2 Average F2: 0.00152853996309595 | -100% |
| Q3 Average F2: 0.00111074417157611\*\* | -90% |
| Q4 Average F2: 0.00148902389641845 | -100% |
| Q5 Average F2: 0.00166292668856411 | -98% |
| Q6 Average F2: 0.000682437441147597 | -100% |
| Mean Average F2: 0.00140952300988489 | -99% |

The results were poor, although this could simply due to the original query being diluted by many other terms. Interestingly, we see the results being very familiar to when we did wordnet expansion. We suspect that we were returning almost the entire corpus, so our precision is very very low.

Legal documents are very verbose, so one technique we implemented was to remove stopword terms in the Rocchio query returned. This way, the number of documents returned by Rocchio is limited. Another way we stem the number of documents is to only collect Rocchio feedback from the top k documents. We let k = 1000, which is about 5% of the corpus.

We continued our analysis by learning from our classmates. We saw some groups implement part-of-speech (pos) tagging, but we omit these because our current problem is that we are returning too many documents, causing precision to be very low. Pos tagging is similar to implementing a co-occurrence thesaurus, which we did not implement.

### WORDNET VS ROCCHIO FEEDBACK

From our analysis of the positive list and other groups’ run logs, we find WordNet to be crucial because of the vocabulary mismatch issue. WordNet directly expands the query vocabulary.

On the other hand, Rocchio is unstable because it picks related words given relevant documents. Unfortunately, many legal documents use common terms like “pleading guilty” “charged with” “compensation”, and these terms have no direct relation to the cases at hand. Rocchio algorithm may be returning all these query terms in the result. Furthermore, given two relevant documents with entirely different vocabulary (for instance, the cases were from different countries), Rocchio cannot retrieve one document given the other. It is more likely to return two documents from the same country because they use similar non-case-specific terminology.

Nevertheless, recall is very important in this assignment. Most queries seem to only have 6-10 relevant documents, and F2 measure places more importance on the recall. It is then important to make sure that enough documents are returned. We set a threshold k, such that if fewer than k documents are returned by the wordnet expansion, we will run the Rocchio feedback to get more results.

# **Conclusion**

We implemented a lot of query refinement techniques but due to limited information on the nature of the corpus, it was difficult to finetune the way we implement query refinement. Nevertheless, we have understood more about the nuances of the different techniques through this assignment.