# Improving Recall In Text Retrieval Using Rank Fusion

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# Abstract

Rank-fusion, where the output of more than one retrieval system is fused into a final coalesced result set to be inspected by the user, is a classic approach used in information retrieval to improve system effectiveness. The key idea is to use different sources of information to find a set of documents that are most likely to be relevant. Combining query variations and fusing them has been shown to be a highly effective in improving effectiveness aggregate scores. However, it's unclear whether fusion is equitably improving the retrieval effectiveness across all topics compared to a single-shot baseline. In this work, we explore the use of rank fusion techniques to improve both recall and risk-reward pay-offs, and explore the tension between these two objectives. Through our experimental study, we show that combining rank-fusion, query variations, and system variations into the same fusion pool can dramatically increase the end-to-end effectiveness of recall-sensitive evaluation metrics and also provide the least risk out of all other fusion combinations studied.

# Publications Derived From This Thesis


[1] R. Benham and J. S. Culpepper 2017. Risk-reward Trade-offs in Rank Fusion. 2017. In: *Proc. ADCS*. Accepted 26 Oct 2017.

[2] R. Benham, L. Gallagher, J. Mackenzie, T. T. Damessie, R-C. Chen, F. Scholer, A. Moffat and J. S. Culpepper. RMIT at the TREC CORE Track. 2017. In: *Proc. TREC*. Submitted 25 Oct 2017.

[3] L. Gallagher, J. Mackenzie, R. Benham, R-C. Chen, F. Scholer and J. S. Culpepper. RMIT at the NTCIR-13 We Want Web Task. 2017. In: *Proc. NTCIR-13*.

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CHAPTER 1

# Introduction

We exist in a sea of exponential growth in the information we have at our fingertips. This information overload has strong implications on the society we live in, as digitizing resources becomes increasingly important. Information Retrieval (IR), which once belonged to the field of library sciences, has revolutionized the way humanity learns about the world in which we live. The most familiar IR use case for users is web search, where they express their information need as a keyword-based query and submit it to their favorite search engine, in order to receive a list of ranked websites— generally showing 10 results per page. Given the growing number of Internet users and the impact that web search has on daily life, it is unsurprising that most research efforts are focused on improving early precision— optimising systems to ensure the most relevant documents are densely populated at the head of the result list. However, there are also IR use cases in which the user requires all pertinent documents to resolve an information need. Examples of these situations are: finding all relevant documents for civil litigation, research papers for citations, or for policy-makers to make informed decisions. To resolve these kinds of information needs, we explore techniques in this thesis that aim to maximise recall in IR systems. It lays the foundations for future work aiming to apply multi-stage retrieval— a cascade of steps into which a pool of candidate documents are input into a learning-to-rank stage, to yield the high-precision result lists expected from a search engine.

Techniques that have been shown to improve the effectiveness of the retrieved result lists against other methods have been shown to exhibit a risk-reward payoff. Pseudo-relevance feedback and Markov random fields are prime examples of this phenomenon where most topics see strong improvement, however, a minority of topics are harmed. In general, IR researchers when evaluating their retrieval systems use an evaluation metric, observe whether the aggregate score across all topics is higher than the baseline, and finally conduct a paired t-test to check whether assertions can be made about a statistically significant difference. This aggregate-based approach to evaluating system improvement can hide or obscure the losses incurred relative to the baseline. In this thesis, we use recent risk-sensitive evaluation techniques to investigate whether different fusion approaches are not only improving effectiveness but if they are also reducing the risk of harming a baseline. Risk-sensitive evaluation is of great

interest to us because it is difficult to assert that you are improving recall if you are diminishing the effectiveness of some topics.

The body of work in this thesis can be viewed as an extension of the very recent SIGIR paper by Bailey et al. [3], which shows that incredible retrieval performance can be attained by rank fusing query variations together. Building on this result, the authors used "double fusion"— fusion of runs built by query variations over different systems, and found that retrieval effectiveness improved. This thesis contributes an offline query variation collection similar to UQV100 that can be used on the Robust04 and the new *New York Times* corpora. It also establishes that query fusion does exhibit a risk-reward payoff while improving recall and that double fusion reduces risk while maintaining or improving effectiveness across different metrics. Incidentally, we report discoveries about whether a "best" query exists across document collections of similar composition, and observe the spread of retrieval effectiveness of offline query variation collections for the first time.

## 1.1 Research Questions

### 1.1.1 Can Rank-fusion over Adhoc Runs Using Different Retrieval Models Increase Recall in the Fused Set?

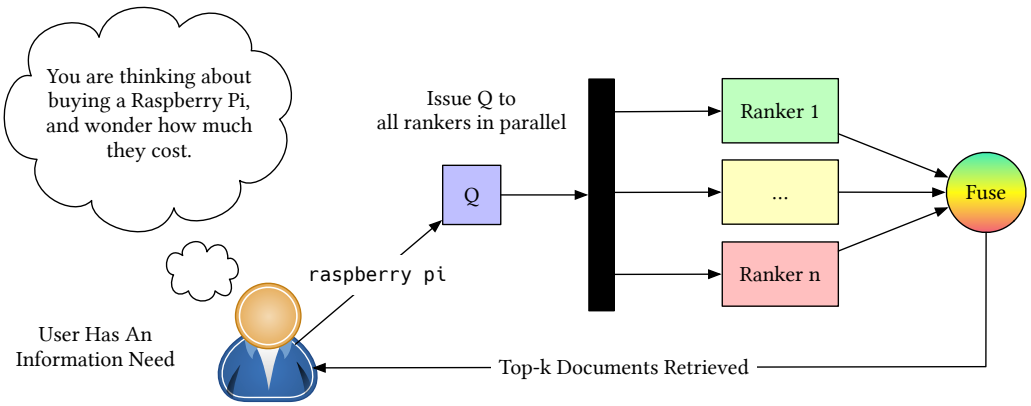



FIGURE 1.1. System fusion example.

We predict that it will, as it allows for a more diverse range of retrieval approaches to be applied towards a user's query. No one retrieval model performs the best in all situations for all topics— so it should follow that recall is improved by fusing system results together.

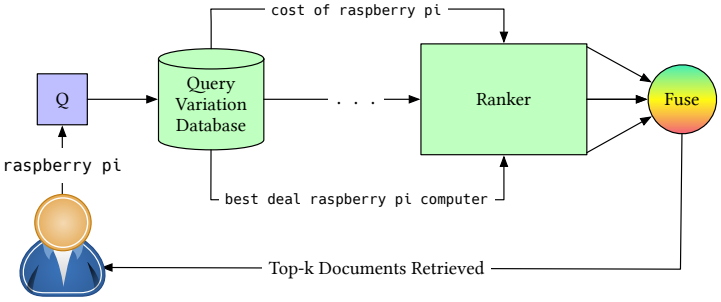



FIGURE 1.2. Query fusion example. Accept Q from user, select all query variants of Q, issue all variants to ranker, fuse all result lists into one.

### 1.1.2 Does Fusing Manual Query Variations over Fixed Systems Improve Recall?

Does issuing similar queries to the same system and fusing the results together improve recall? How does it compare to system fusion over a single query? We predict that it will be more effective than system fusion, as Bailey et al. [3] shown substantial improvement in retrieval effectiveness using query fusion. We explore how recall improves on the Robust04 document collection using our new query variation set, as the Robust04 collection has more extensive relevance judgments available.

### 1.1.3 Can Combining both System Configurations and Query Variations Improve Recall?

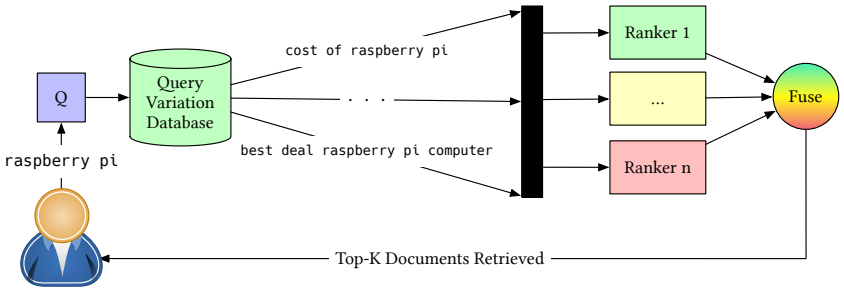



FIGURE 1.3. Double fusion fusion example. All query variations for Q are submitted in parallel to every ranker, where all combinations of query variant and ranker are fused.

Bailey et al. [3] describe further improvement in retrieval effectiveness by the use of double fusion. Using the same approach as we do for observing the recall of query fusion, we interpret the results compared to all of the above fusion techniques.

### 1.1.4 How Does the Risk-sensitivity of Each Fusion Scenario Compare?

Finally, we present our results in the context of risk-sensitive retrieval. Here we quantify and investigate which of the above fusion methods results in the greatest risk-reward payoff.

CHAPTER 2

# Background

## 2.1 Information Retrieval

Information Retrieval (IR) is a research area concerned with finding answers to questions from collections of unstructured data. Unstructured data can exist in many different forms— text, sound, images, and videos. Although these resources inherently contain structure, automatically extracting features of the datasets that are helpful for retrieval purposes require careful review of over 60 years of literature. Before the World-Wide Web allowed massive amounts of information to be accessible to anyone with an Internet connection, libraries were the most popular IR resource, where information needs were resolved by physically traversing books categorized by topic. Using classification systems, such as the Dewey Decimal Classification system, library users are able to reduce the search-space of a cataloged item. Eventually, the library user will converge on the most useful book by manually searching to resolve their information need. This system works when there is enough physical space to fit the library catalog, however in 2008 Google ran algorithms "over twenty petabytes of data per day" [24]. This suggests that a printed repository for online information would yield intractable search times, and an overwhelmingly large building would be required to store the documents. Sanderson and Croft [70] provide a more expansive discussion on the history of IR research, including the pre-computing development of electromechanical machines using microfilm as an index to search a library collection.

### 2.1.1 Indexing Text Collections

Indexing text collections are useful for allowing the efficient search of unstructured text. A brute force search over gigabytes of data would yield intractable wait times for a user issuing a query. Indexing is the process of performing this high effort scan across all documents once, to extract all terms in a document and store them in a data structure designed for fast lookup. Typically, the inverted index is the data structure of choice for most retrieval scenarios [82].

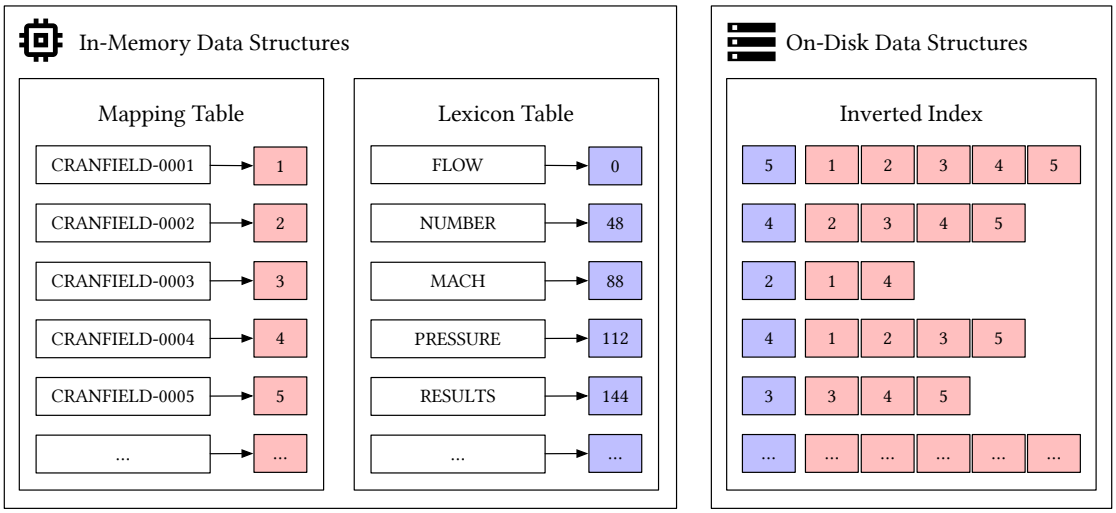



FIGURE 2.1. A simplified diagram of a hypothetical inverted index constructed over the Cranfield test collection.

The inverted index, also known as a postings list, associates terms in a collection with a list of document identifiers containing the term. It can also contain preprocessed statistics, such as the number of documents containing the term in the collection. This is generally a useful thing to do, as many retrieval models require these statistics in order to provide ranked result lists (discussed in Section 2.2). Term identifiers are registered in the *lexicon* (or vocabulary) table, which maps terms to their corresponding on-disk byte offset in the inverted index. When a document identifier is retrieved from the inverted index, its identifier needs to be resolved using the *mapping* table. Figure 2.1 describes the intimate relationship between these three components to enable the goal of efficient search on large volumes of text data.

At index construction time, it is highly beneficial to normalize terms in documents and queries to the same base form, to allow for better matching of query terms. This leads onto a discussion of text normalization in the next section.

### 2.1.2 Text Normalisation

One simple text normalization technique is known as casefolding, where all terms are made lowercase [47]. In English, all sentences start with a capital letter, and so casefolding accommodates search over these terms. Another simple technique that is often applied is punctuation removal [47]. As an indexer typically tokenizes English text by spaces, the inclusion of punctuation can be problematic as every sentence ends with a full-stop. Therefore, punctuation is removed to allow matching more terms with the query terms.

Another important technique that has been shown to improve retrieval effectiveness is stemming. Stemming trims endings of words to allow them to be normalized to their base form [38, 47]. Jivani [38] surveys the different kinds of stemming algorithms available. There are many kinds of stemmers, the simplest and most intuitive of which is the s-stemmer. An s-stemmer simply removes the "s" from the end of words, normalizing words from their plural form to their singular form. The Lovins stemmer by Lovins [44] is cited as the first stemming technique and has a lookup table with 294 endings, 29 conditions and 35 transformation rules [38, 81]. Porter [60] proposed the use of a Porter stemmer, of which its use is very popular [38]. Willett [81] describes the changes to Porter as compared to Lovins, detailing that the Porter stemmer only has 60 suffixes. Finally, and what is often used today, Krovetz [40] published the Krovetz stemmer inspired by the Porter stemmer, whereby after each step of the Porter process, the word is looked up in a dictionary (in their case they used the *Longman Dictionary of Contemporary English*), and if there's a match discontinue stemming. This helps for situations where the Porter stemmer would conflate `distributing` and `distributed`, with the stem `distribut` [40].

Stemmers are a subset of the body of work known as lemmatization, where lemmatization is concerned with reducing words to their normal form [57]. Stemmers are a context-insensitive approach, however, and only look at the words independently. Some lemmatization methods are context-sensitive and make use of natural language processing (NLP) algorithms to reduce words into a simpler form [57].

## 2.2 Retrieval Algorithms

### 2.2.1 Boolean Queries

The Boolean query retrieval method is the earliest IR model [47]. A Boolean query is formulated by using combinations of AND — the conjunction operator, OR — the disjunction operator and NOT — the negation operator. For example, if we were searching for `fixing UV skin damage`, we may be disinterested in documents containing the term `cosmetics`, as our goal is to heal the damage not conceal it. A Boolean query could be constructed as: `fixing AND UV AND skin AND damage NOT cosmetics`. Synonyms could be added as disjunctive clauses to the above query to improve recall, reducing the impact of the vocabulary mismatch problem [29]. This might result in an expanded query: `(fixing OR curing OR healing) AND (UV or ultraviolet) AND skin AND (damage OR sunburn OR cancer) NOT (cosmetics OR concealer)`, however, it is not the only query that could resolve the information need as different users supply a highly diverse range of queries to resolve an information need [51].

The Boolean model is not without its criticisms though. Cooper [20] describes the Boolean query model as suffering from an "inhospitable request formalism, frequent null output and output overload, and lack of provision for differing emphasis on different facets of the search". Null outputs are a common issue where too many conjunction operators are present in a query, and "output overload" is typically a result of reformulating the Boolean query to remove one of the original facets— "at a certain cost in time and frustration". Cleverdon [16] similarly criticizes the use of Boolean search at a time when "all major publicly available databases require Boolean searching," arguing the need for ranked output. The extended Boolean model proposed by Salton et al. [69] addresses some of these issues, by providing a ranked output of result lists and different weightings on facets of the search, where users could adjust which facets are most important. The term weighting formula is derived from the Vector Space model which we discuss in the next section. Pohl et al. [58] showed that the extended Boolean model can be used for improving the practicality of systematic biomedical reviews, as the ordered ranking allowed for determining an upfront fixed number of documents to assess. The extended Boolean model outperformed Boolean baselines, the `Ovid` online domain-specific search tool and the Okapi BM25 (explained in upcoming sections) retrieval model where free-text queries were submitted. However, given the usability problems associated with using Boolean queries, we are motivated to explore techniques that improve recall using free-text queries.

### 2.2.2 Vector Space Model

The Vector Space Model utilizes free-text queries instead of Boolean queries. As the name suggests, queries and documents represented in a vector form, where similarity measures are computed to produced a ranked document listing. Gerald Salton is typically referenced as the author of the first Vector Space Model paper [68], however Dubin [27] explains that this published paper does not discuss the Vector Space Model in the retrieval model form, and authors often cite a 1975 paper "A Vector Space Model for Information Retrieval" that was never published in any journal. During this time, Wong and Raghavan [83] discuss the formalities associated with whether queries and documents conform to a vector space, where finally a full description of the model is available in Salton's book [27, 66]. Salton and Buckley [67] explains the use of three important term weighting schemes— term frequency (TF), inverse document frequency (IDF) and length normalization, also known as inverse document length (IDL) to weight the importance of terms in a search. All three of these statistics are important components of the Vector Space Model, and much more retrieval methods to come in this section.

Term frequency refers to how frequently a term occurs in a document. Intuitively, a document that contains a query term more often than other documents is more likely to be able to resolve the user's

information need. Document frequency refers to the number of times a term occurs across other documents in the collection. Inverse document frequency reduces the impact of terms that are common across many documents, such as the word "the". Therefore rarer terms are more discriminative of the user's information need and weighted more highly than other more common terms. Finally, document length normalization can be applied to reduce the impact of larger documents dominating the document rankings. Larger documents have a greater chance of having a larger term frequency than shorter documents which can bias the search results. Thus, the average document length is computed over the collection at index construction time and inverse document length is computed for each document, where the metadata is stored in the mappings table for efficiently searching the collection.

The Vector Space Model is typically discussed in textbooks [47, 82] in the presence of the cosine similarity formula, and in the presence of term frequency (TF) and inverse document frequency (IDF) term weighting formulas. The cosine similarity formula for two n-dimensional vectors appears as:

$$cos\theta = \frac{X \cdot Y}{|X||Y|} = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} x_i^2} \sqrt{\sum_{i=1}^{n} y_i^2}} \tag{2.1}$$

Which can be written in terms of a query vector and a document vector:

$$\text{cosim}(Q, D) = \frac{Q \cdot D}{|Q||D|} = \frac{\sum_{t=1}^{n} w_{q,t} w_{d,t}}{\sqrt{\sum_{t=1}^{n} w_{q,t}^2} \sqrt{\sum_{t=1}^{n} w_{d,t}^2}} \tag{2.2}$$

In the above equation, $w_{q,t}$ represents a term weighting for the query terms, and $w_{d,t}$ similarly represents a weighting for the document containing the term. Frequently the usual example is to set $w_{q,t} = (1 + log_e(f_{d,t}))$ and $w_{d,t} = log_e(1 + \frac{N}{f_t})$; however, Zobel and Moffat [91] survey many similarity measures that can be applied in the Vector Space Model and apply many different term weighting approaches outside of the most commonly utilised TF $\times$ IDF approaches, finding that no one particular model consistently worked well across all queries in a query set.

### 2.2.3 Okapi BM25

The third TREC conference saw the debut of the Okapi group's BM25 algorithm [63], outperforming the aforementioned TF $\times$ IDF approaches in the vector space models. The Okapi BM25 algorithm is a probabilistic "bag-of-words" ranking model, meaning that the order for which the terms are presented are unimportant.

The BM25 function takes a query and a document, looks at all terms independent of each other and aggregates a sum for each term's score. The formula appears as follows:

$$\text{BM25}(Q, D) = \sum_{t \in Q} w_t \cdot \frac{(k_1 + 1) f_{d,t}}{B + f_{d,t}} \cdot \frac{(k_3 + 1) f_{q,t}}{k_3 + f_{q,t}} \tag{2.3}$$

Where $w_t$ is the Robertson-Sparck Jones weight— corresponding to the inverse document length component, and $k_1$ and $k_3$ are tuning constants. $B$ is defined as:

$$B = k_1 \cdot ((1 - b) + \frac{b \cdot L_d}{AL}) \tag{2.4}$$

$B$ is the length normalization component, where $b$ is a tuning constant that adjusts how much impact length normalization should have. $L_d$ represents the length of the document and $AL$ represents the average length of all documents. Both values can be represented in bytes, or the number of characters— however, they must be consistent and use the same measurement.

The Roberson Sparck-Jones weight [62] appears as follows:

$$w_t = log \frac{(r + 0.5)/(R - r + 0.5)}{(n - r + 0.5)/(N - n - R + r + 0.5)} \tag{2.5}$$

Where $N$ represents the number of documents in the corpus, $R$ represents the number of relevant documents for the query, $n$ represents the term frequency (number of documents with $t$— also known as $f_t$ in the modern nomenclature) and $r$ corresponds to the number of relevant documents containing $t$. The authors allow $R = r = 0$, as there is no relevance information. Thus, the above formula becomes:

(1) Reduction:

$$\begin{aligned} w_t = log \frac{(r + 0.5)/(R - r + 0.5)}{(n - r + 0.5)/(N - n - R + r + 0.5)} &= log \frac{0.5/0.5}{(n - 0.5)/(N - n + 0.5)} \\ &= log \frac{1}{\frac{n - 0.5}{N - n + 0.5}} \\ &= log \frac{N - n + 0.5}{n - 0.5} \end{aligned}$$

The BM25 algorithm is an effective baseline and tool used in certain circumstances today, where it is known as an efficient and quite effective retrieval technique.

### 2.2.4 Language Model

Ponte and Croft [59] introduce in seminal work a formal argument for the use of a language modeling retrieval model (LM) in information retrieval. A language model uses conditional probability to identify words in a sequence, depending on the presence of previous words or on collection-wide term statistics. A bigram language model appears as such:

$$P(s) = \prod_{i=1}^{l} P(t_i|t_{i-1}) \tag{2.6}$$

Where $s$ represents a sentence, and $l$ represents the length of the sentence.

A more general $n-$gram model appears as:

$$P(s) = \prod_{i=1}^{l} P(t_i|t_{i-(n-1)}, ..., t_{i-1}) \tag{2.7}$$

Where $n$ is selected depending on the application purposes. Hence, $n = 2$ for a bigram model, $n = 3$ for a trigram model, and so on. A unigram model ($n = 1$) is also possible, where only $P(t_i)$ is considered—i.e. the probability of the term occuring in the document.

The process of smoothing the language model function is of vital importance, as it allows for tuning the maximum-likelihood estimator to improve retrieval performance [86]. The smoothing method also ensures that unseen words are not assigned a value of zero. Zhai and Lafferty [86] survey different LM smoothing options, and find that some smoothing methods work better for long queries than keyword queries, and vice versa. The authors also find that parameter selection with these models is of high importance, relating to term selection formula for traditional retrieval methods.

The LM method has also been applied in topic segmentation domains, that allow for partitioning sections of text into topical categorization [6].

### 2.2.5 Markov Random Fields

Metzler and Croft [49] introduce the use of Markov random fields to be used in conjunction with the aforementioned language model framework. It enables searching over single terms, phrase queries, bigrams and unordered windows of arbitrary sizes in the same framework. Generally, window sizes of 8 are considered.

For the query `catalonia independence movement`, the sequential dependency model (SDM) Indri query language code is represented as:

```
#weight(
  α #combine(catalonia independence movement)
  β1 #combine(#1(independence movement) #1(catalonia independence))
  β2 #combine(#uw8(independence movement) #uw8(catalonia independence))
)
```

The $\alpha$ parameter adjusts the weighting of searching over the original query and $\beta$ adjusts the weightings for the different SDM components of phrase search and unordered window search. Similarly, the full dependency model (FDM) is represented as:

```
#weight(
  α #combine(catalonia independence movement)
  β1 #combine(
    #1(independence movement)  #1(catalonia independence)
    #1(catalonia independence movement)
  )
  β2 #combine(#uw8(independence movement) #uw8(catalonia movement)
    #uw8(catalonia independence)
    #uw12(catalonia independence movement)
  )
)
```

Observe that the full dependency model considers more than just the adjacent terms— where a phrase search of the whole query is issued and `catalonia movement` is considered in an unordered window. This can improve the recall of documents related to the query, as a sentence containing `catalonia movement` is likely to be relevant to the information need.

Using the SDM model over different fields has also been shown to be effective. Some document collections contain metadata, such as page titles or link-text, which can be utilized to improve retrieval effectiveness. For the query `high court australia` over the sequential dependency model using fields, the Indri fields-based query language representation appears as follows:

```
#weight(
  α1 #combine(high.title court.title australia.title)
```

```
    α2 #combine(high.inlink court.inlink australia.inlink)
    α3 #combine(high.body court.body australia.body)
    β1 #combine(#1(high.body court.body)
       #1(court.body australia.body))
    β2 #combine(#uw8(high.body court.body)
       #uw8(court.body australia.body))
)
```

Both of the components `high court` and `court australia` are observed as phrase queries using the sequential dependency model, observing title text, link text, and body text— and are also searched for in unordered window sizes of eight terms. A drawback to modeling term dependencies is the expensive computation involved as the number of combinations of terms increase in a query. Bendersky and Croft [9] show through the use of Markov random fields that shorter queries can be more effective than verbose queries, by using machine learning techniques to discover and extract key concepts.

## 2.3 Evaluation

IR test collections, sometimes described as offline evaluation in modern nomenclature, have a long history dating back to the Cranfield Experiments in the 1960s— describing the need for topics, relevance assessments and document collections in order to evaluate IR systems [17]. Hofmann et al. [35] provide a rich discussion on online evaluation methods— where systems are constantly being evaluated based on signals from users in real-time, where the reader is directed for further information about the topic.

### 2.3.1 Information Needs

An information need is a description of what a user is attempting to find an answer to, through the use of an IR system. An information need is typically synonymous with "user request" or topics [33]. Topics to undergo evaluation purposes for test collections must be selected with an intuition that the collection will be able to resolve that information need somehow. Topics are different from queries, in that queries are the data structure that is sent to the system to resolve the information need, whereas a topic describes the information need in different facets. For example, the Robust04 track in TREC for each topic was supplied a title, a description and a narrative with relevance criteria.

The highly influential paper by Broder [12] describes the tendency for information needs to fall under three distinct categories, and suggests that search engines should be able to resolve all of them:

```
301 0 FBIS3-10082 1
301 0 FBIS3-10169 0
301 0 FBIS3-10243 1
301 0 FBIS3-10319 0
301 0 FBIS3-10397 1
...
```

FIGURE 2.2. The beginning of the Robust04 qrels file. A qrels file contains in order: the topic id, feedback iteration (almost never used), document id and relevance score.

- Informational— Information present on one or more pages.
- Navigational— Reaching a particular website.
- Transactional— Need is resolved by using a website to obtain something else, e.g. shopping, media downloads.

It is important to categorize these queries differently for evaluation purposes. For example, the best result for a navigational query will be at the top of a list and all other documents will be irrelevant. The evaluation metric applied should be reflective of the end-users goals.

### 2.3.2 Relevance Assessments

Voorhees [74] provides an excellent overview of the evaluation philosophy used at TREC, CLEF and the NTCIR conferences. Perhaps most importantly, it describes the compromises the IR community has made in order to balance the expenses (both in time and money) incurred to evaluate ranked document lists. The most useful and informative source of relevance is a user who has issued a query and is attempting to resolve their information need. However, exhaustively assessing the relevance of all documents in a collection is intractable in the order of 100MB. Therefore, a typical relevance assessment process on a document collection follows this process:

- A set of topics representative of the corpus' contents is formed.
- There is a call for participation from many research groups to submit their best top-$k$ list of documents.
- All runs for each topic are unioned to a pooling depth $d$.
- One relevance assessor for each topic performs relevance assessments of the pooled documents.
- A set of relevance assessments, often referred to as a "qrels" file is formed (shown in Figure 2.2), allowing reusable evaluation of systems.

Voorhees [73] details an important experiment where the disagreement between different relevance assessors is observed, and despite the disagreement, relative system comparisons remained consistent

and conclusive (e.g. System A is better than B over X measure). This paper validates the use of a single assessor when building test collections, acknowledging aspects of how variable and dynamic notions of relevance can be [71]. Further work has been conducted recently to gauge the quality of relevance assessments of crowdsourced workers by observing inter-assessor agreements, to attempt to make relevance assessments cheaper and similar in quality to the TREC NIST assessed judgments [22].

### 2.3.3 Document Collections

Voorhees [74] shows throughout the history of TREC experimentation, that the size of document collections matters— where a technique that works well on small corpora might not necessarily work well on larger corpora.

**Newswire**. Newswire document collections led the TREC framework to the success it has enjoyed. Harman [33] details the list of text collections used in the first eight TREC experiments, and explains how they were procured. Table 2.1 provides a brief summary of each of these collections to illustrate their size and composition. Of note, is the differences between the Federal Register and Department of Energy document collections, compared to the LA Times collections. These anomalous collections were intentionally added to the TREC-7 and TREC-8 ad hoc tasks as "noise" sources rather than likely sources of relevant documents. Harman [34] explains which disks/datasets were used for each TREC ad hoc retrieval experiment.

**Web Data**. Harman [34] also details the history of the inclusion of very large datasets in TREC. David Hawking formed a large newswire collection to explore the efficiency effectiveness effects in larger collections. The first collection was called VLC1 (very large collection), consisting of 20GB of data in TREC-6. The second large text collection VLC2 built for TREC-7 is 100GB and contains a combination of newswire and web data. However, it was deemed an incomplete test collection due to the shallow judgement pool sizes of 20 documents instead of 100 [34]. The 2GB WT2g collection was formed in TREC-8, built using a representative sample of the VLC2 collection and shared the same TREC-8 topics as the ad hoc newswire test collection. The TREC 2009 Web Track was the first track to use the ClueWeb09 collection [15], consisting of over a billion web pages in 10 languages [1]. TREC 2013 saw the inclusion of the ClueWeb12 corpus [18], succeeding the ClueWeb09 corpus. The ClueWeb12 corpus has 733,019,372 pages, however they are all in English [2].

[1] The ClueWeb09 Dataset `https://lemurproject.org/clueweb09/`
[2] The ClueWeb12 Dataset `https://lemurproject.org/clueweb12/`

TABLE 2.1. A brief description of TREC test collections used in the first eight TRECs.

| Disk | Year Published | Size | Collections |
|---|---|---|---|
| 1 | 1992 | 1207MB | Wall Street Journal 1987–1989 (WSJ)<br>Associated Press, 1989<br>Computer Selects articles, Ziff-Davis (ZIFF)<br>Federal Register, 1989 (FR)<br>Abstracts of US Department of Energy publications (DOE) |
| 2 | 1992 | 863MB | WSJ: 1990–1992<br>Associated Press, 1988<br>ZIFF<br>FR: 1988 |
| 3 | 1993 | 1112MB | San Jose Mercury News, 1991 (SJM)<br>Associated Press, 1990<br>ZIFF<br>U.S. patents, 1993 |
| 4 | 1996 | 1194MB | Financial Times, 1991–1994 (FT)<br>Federal Register, 1994 (FR94)<br>Congressional Record, 1993 (CR) |
| 5 | 1997 | 945MB | Foreign Broadcast Information Service (FBIS)<br>LA Times, 1989–1990 |
| 6 | 1997 | 965MB | Foreign Broadcast Information Service (FBIS)<br>LA Times, 1994 |

### 2.3.4 Precision and Recall

Precision and Recall are two simple evaluation measures that demonstrate the retrieval effectiveness of an unordered set. Precision is a measure of how precisely a ranker extracts relevant documents towards resolving the user's query, and is calculated as:

$$\text{Precision} = \frac{\text{number of retrieved relevant documents}}{\text{total number of documents retrieved}} \tag{2.8}$$

Recall is a measure of how well the ranker is able to extract all relevant documents related to the user's query, calculated as:

$$\text{Recall} = \frac{\text{number of retrieved relevant documents}}{\text{total number of relevant documents in corpus}} \tag{2.9}$$

There is an innate tension between these two measures. If a ranker returned the entire corpus recall would be maximised, but precision would be very low. Alternatively, if a ranker retrieved only one relevant document, precision would be maximised but the recall would be low (assuming the corpus

has more than one relevant document). In an ideal scenario, retrieval systems would only return all relevant documents— thus maximising recall and precision.

Observing the quantitative value of recall in large text collections is problematic, due to the intractability of exhaustively assessing the relevance of all documents in large collections. Zobel et al. [92] state that "Measurement of recall is neither feasible nor meaningful in web search," where they argue that there is no link between user experience and recall as it is not possible for the user to know how many relevant documents there are in a collection anyhow. The authors instead take the position that utility-based evaluation measures observing precision are the only useful measure for large text collections. We accept this assessment of the situation and the inability to properly measure recall quantitatively. However, this does not diminish the value and importance of improving recall aspirationally. Although the user doesn't know if the recall is high, a user will become more persistent and be trusting of a system that retrieves many relevant documents if that is their goal, while also maintaining a high level of precision. Cognizant of these issues, improvement of recall remains an area of high impact, in the 2016 and 2017 TREC high-recall tracks [31, 65], and seven years of running the TREC Legal track [3].

### 2.3.5 Text REtrieval Conference

The Text REtrieval Conference (TREC) is a venue that started in 1992 funded by the National Institute of Standards and Technology (NIST) to foster industry collaboration with researchers in improving IR effectiveness. Prior to this conference, there was little consistency in the evaluation metrics that researchers evaluated their systems with, making knowledge transfer difficult and IR improvements hard to substantiate. The TIPSTER corpus to be released for IR experimentation in TREC was approximately a hundred times larger than test collections available in the public domain [77].

Voorhees and Harman [77] states that the four main goals of TREC are to:

- Encourage research in text retrieval based on large test collections
- Increase communication among industry, academia and government by creating an open forum for the exchange of research ideas
- Speed the transfer of technology from research labs into commercial products by demonstrating substantial improvements in retrieval technologies on real-world problems
- Increase the availability of appropriate evaluation techniques for use by industry and academia, including the development of new evaluation techniques more applicable to current systems

[3] A federated list of all TREC Legal Tracks and their result papers `https://trec-legal.umiacs.umd.edu/`

The proceedings of TREC have greatly benefited the IR research area by providing many large text collections and doubling retrieval effectiveness in the first eight years of running [78]. The TREC conference proved the viability of pooled relevance judgments over large-text collections, allowing tractable measurement of improvement [90].

### 2.3.6 Metrics

Imagine that you have issued a query to a retrieval system, where there are relevance judgments available over the collection. A relevance assessor has judged documents with a pooling depth of 100 documents (the same as the Robust04 collection [46]), indicating there could be some small uncertainty in the metrics. Unjudged documents are the source of the uncertainly, and evaluation metrics pessimistically assume they are irrelevant. Suppose that the relevance assessors found only 12 relevant documents for this topic– where if a result list contained all of these items it would have achieved "total recall".

TABLE 2.2. A hypothetical retrieval output (or run), considering the judgments of a relevance assessor.

| Rank | Relevance Judgement |
|---|---|
| 1 | Irrelevant (0) |
| 2 | Highly Relevant (2) |
| 3 | Unjudged (?) |
| 4 | Relevant (1) |
| 5 | Highly Relevant (2) |
| 6 | Irrelevant (0) |
| 7 | Irrelevant (0) |
| 8 | Irrelevant (0) |
| 9 | Relevant (1) |
| 10 | Irrelevant (0) |

There are many different contexts for which this result list can be evaluated. Lu et al. [46] differentiate the two main archetypes: *recall-based*– where the measure is volatile with respect to the depth of the judgement pool as it measures with respect to the "best" score possible, and *utility-based* where the stress is on how the user will perceive the quality of the system by observing the density of highly relevant documents at the head of the result list.

**Precision@*k***. Precision@*k* or simply *P@k* is a utility-based metric with a history of use before TREC [13]. *P@k* is calculated as the ratio of the number of relevant documents returned compared to the cutoff *k*. For the above list, $P@5 = \frac{3}{5} = 0.6$, and $P@10 = \frac{4}{10} = 0.4$.

**Average Precision**. Average Precision (AP) is an evaluation measure with a long history of usage on Newswire data in TREC. It can be computed as:

$$\text{AP} = \sum_{i=1}^{k} \frac{P@i}{R} \tag{2.10}$$

Where $P@i$ represents the precision at each incremental step as the result list is traversed, and $R$ represents the number of relevant documents in this collection.

(1) AP@10:

$$\begin{aligned}\text{AP} = \sum_{i=1}^{k} \frac{P@i}{R} &= \frac{\frac{0}{1} + \frac{1}{2} + \frac{1}{3} + \frac{2}{4} + \frac{3}{5} + \frac{3}{6} + \frac{3}{7} + \frac{3}{8} + \frac{4}{9} + \frac{4}{10}}{12} \\ &= \frac{0 + 0.5 + 0.333 + 0.5 + 0.6 + 0.5 + 0.429 + 0.375 + 0.444 + 0.4}{12} \\ &= \frac{4.081}{12} \\ &= 0.340\end{aligned}$$

**Mean Average Precision**. Also known as MAP, can be calculated by taking the mean of all AP scores over all topics, to get the mean effectiveness of the system.

**Cumulative Gain**.

The cumulative gain metric sums the relevance scores as the result list is traversed, and is computed by the recursive function [37]:

$$\text{CG}(i) = \begin{cases} \text{G[1], if i=1} \\ \text{CG[i-1]+G[i], otherwise} \end{cases}$$

Therefore for the above result list, the vector appears as:

$$\langle 0, 2, 2, 3, 5, 5, 5, 5, 6, 6 \rangle \tag{2.11}$$

Where $CG(10) = 6$ as it is the 10th index of the vector. Although CG is insensitive to the knowledge of recall, there are problems with defining this metric as utility-based. If a highly relevant document occurs deeper in the list at a point where a user is more unlikely to see it, the calculation can result in

the same or better score. Discounted cumulative gain helps to resolve this issue, by discounting the gain incurred from relevant documents seen deeper in the list.

**Discounted Cumulative Gain**.

Discounted Cumulative Gain (DCG) is a utility-based metric computed by the formula [37]:

$$\text{DCG}(i) = \begin{cases} \text{CG[1], if i<b} \\ \text{CG[i-1]+}\frac{G[i]}{\log_b i}\text{, otherwise} \end{cases}$$

Where the base of the logarithm $b$ is typically set to 2. Therefore, the above result list becomes:

$$\langle 0.000, 2.000, 1.261, 1.500, 2.153, 1.934, 1.781, 1.667, 1.893, 1.806 \rangle \tag{2.12}$$

Where $DCG(10) = 1.806$. CG and DCG both report significantly different scores across different topics depending on the graded assessments, making system-wide evaluation difficult. Normalized Discounted Cumulative Gain addresses this issue.

**Normalized Discounted Cumulative Gain**.

Järvelin and Kekäläinen [37] presented the Normalized Discounted Cumulative Gain (NDCG) measure, which forms a ratio of the discounted cumulative gain to the ideal discounted cumulative gain.

To form the ideal discounted cumulative gain, the relevant documents are organized from largest gain to least. As we mentioned previously, there are 12 relevant documents for this query. For this hypothetical scenario, we set the eight unseen documents to a relevance assessment of *Relevant (1)*. As such, this evaluation metric becomes a recall-based metric as knowledge of recall is required to calculate the result.

An ideal gain vector could appear as:

$$\langle 2, 2, 1, 1, 1, 1, 1, 1, 1, 1 \rangle \tag{2.13}$$

Note that we do not produce a vector of size 12, as this would reduce the upper bound of the NDCG score to a number less than 1.

The cumulative gain would then appear as:

$$\langle 2, 4, 5, 6, 7, 8, 9, 10, 11, 12 \rangle \tag{2.14}$$

Further, the Discounted Cumulative Gain is calculation is:

$$\langle 2.000, 4.000, 3.155, 3.000, 3.015, 3.095, 3.206, 3.333, 3.470, 3.612 \rangle \tag{2.15}$$

Finally, the NDCG can be computed as:

$$\frac{\langle 0.000, 2.000, 1.261, 1.500, 2.153, 1.934, 1.781, 1.667, 1.893, 1.806 \rangle}{\langle 2.000, 4.000, 3.155, 3.000, 3.015, 3.095, 3.206, 3.333, 3.470, 3.612 \rangle} \tag{2.16}$$

$$\langle 0.000, 0.500, 0.400, 0.500, 0.714, 0.625, 0.556, 0.5000.545, 0.500 \rangle \tag{2.17}$$

Where NDCG@10 is equal to 0.500. As the NDCG value is normalized as a function of the best achievable score, it can therefore be averaged across different topics in the collection and yield an interpretable result.

**Rank-Biased Precision**.

Moffat and Zobel [50] published Rank-Biased Precision (RBP) to build an evaluation metric that better matched the behavior of a user utilizing a retrieval system. The metric is utility-based, where a user's behavior is modeled by the persistence $p$ value. It is calculated as:

$$\text{RBP}(p) = (1 - p) \sum_{i=1}^{d} r_i p^{i-1} \tag{2.18}$$

As the RBP measure uses a geometric probability distribution to discount the impact of relevant documents deeper in the list, the expected viewing depth for any $p$ value can be computed with the formula:

$$\text{Expected Value} = \frac{1}{1 - p} \tag{2.19}$$

Using the formula above, $p = 0.9$ would give an expected viewing depth of 10 documents in the ranked list. Calculating the value would appear as:

(1) RBP ($p = 0.9$):

$$\begin{aligned}\text{RBP}(0.9) = (1-0.9)\sum_{i=1}^{d} r_i 0.9^{i-1} &= 0.1[0 + (2\cdot 0.9) + (0) + (1\cdot 0.9^3) + (2\cdot 0.9^4) + 0 + 0 + 0 + (1\cdot 0.9^8) + 0] \\ &= 0.1[(2\cdot 0.9) + (1\cdot 0.9^3) + (2\cdot 0.9^4) + (1\cdot 0.9^8)] \\ &= 0.1[(1.8) + (0.729) + (1.3122) + (0.430)] \\ &= 0.1\cdot 4.271 \\ &= 0.427\end{aligned}$$

An RBP score is incomplete without mentioning the degree of uncertainty in the score, known as the residual. As our ranked list contained a unjudged document, we compute the residual score as:

$$\text{Residual} = 0.9^{10} + (1-0.9)(0.9^{3-1}) = 0.430 \tag{2.20}$$

As the residual value is greater than the retrieved score for $p = 0.9$ for the result set above, it is considered an untrustworthy score. RBP is therefore very useful in pooled evaluation scenarios to verify whether conclusions can be drawn from experiments. Although not shown in our chapters for brevity, we evaluate RBP alongside other evaluation metrics to observe the residual as a sanctity check.

**Reciprocal Rank**.

Reciprocal Rank is typically used for evaluating navigational queries [72].

$$\text{RR}(d) = \frac{1}{r(d)} \tag{2.21}$$

Mean Reciprocal Rank (MRR) is computed in a similar spirit to MAP, where the average is taken across all queries.

**Expected Reciprocal Rank**.

Chapelle et al. [14] presented the Expected Reciprocal Rank (ERR) measure, as a shallow evaluation metric that correlates well with click-data on search engines. The measure is inspired by RBP, however, it uses a reciprocal distribution instead of geometric.

$$\text{ERR}(d,k) = \sum_{r=1}^{n} \frac{1}{r(d)} P(\text{user stops at k}) \tag{2.22}$$

The probability function used to calculate ERR is defined as:

$$P(\text{user stops at k}) = \prod_{i=1}^{k-1}(1 - R_i)R_k \tag{2.23}$$

Where $R_i$ represents the probability of being satisfied at the $i$th document, correlating with the probability of a click.

### 2.3.7 Risk-Sensitive Retrieval

The canonical risk-sensitive evaluation measure is URisk for risk-sensitive retrieval, which was used for risk-sensitive evaluation in the TREC Web tracks in 2013-14 [18, 19]. URisk takes the sum of the wins minus the sum of losses, where a $\alpha$ value linearly scales the size of the losses to entertain different scenarios, e.g. $\alpha = 1$ the losses will be increased twofold, $\alpha = 5$, sixfold, etc. However, a drawback of the URisk model is that the scores it returns may obfuscate the risk, and it is not clear how to interpret them. URisk scores are simple to compute:

$$\text{URisk}_\alpha = \frac{1}{|Q|}\left[\sum \text{Win} - (1+\alpha)\cdot\sum \text{Loss}\right] \tag{2.24}$$

URisk is a tool that can be used for descriptive risk-analysis. In conjunction with this method of communicating risk, Dinçer et al. [26] recently proposed a new risk-sensitive retrieval evaluation measure called TRisk, that generalizes the URisk measure to allow for inferential risk analysis. This works by transforming URisk scores for a selected $\alpha$ value to follow a Student t-distribution. Any given TRisk score is then provided as a function of the URisk score and the sample error, where values reported above 2 represent no risk (with statistical significance) compared to a baseline, and conversely, a value below $-2$ indicates a statistically significant risk. In more recent work, Dinçer et al. [25] have proposed several other risk-sensitive measures such as ZRisk, which allows multiple systems to be compared simultaneously, and GeoRisk which is similar in spirit to GMAP [61] in that it attempts to reward improvements on hard topics more than easy ones. However, neither of these are *inferential*, and so we limit our exploration to TRisk.

## 2.4 Query Variations

Noreault et al. [55] had the incidental discovery when evaluating different systems, that when different users created queries to resolve the same information need, the amount of overlapping documents

for each user's result sets were very low. In his study, it was only 9%, and when only relevant documents are considered it was 22%. Belkin et al. [7] exploit this in an exploration of combining Boolean queries together to improve retrieval effectiveness. Ten skilled searchers provided a Boolean query variation, where their queries were combined in five different groups and executed against the retrieval system. The paper found that in general combining more queries together improves retrieval effectiveness. Bailey et al. [2] recently provides a collection of free-text queries, pooling a diverse range of query variations from 263 individuals over 100 topics.

### 2.4.1 Query Logs

A decade before the release of the UQV100 dataset by Bailey et al. [2], the AOL query logs were controversially released by Pass et al. [56]. The queries were collected from the AOL website, a conduit for Google search, between the dates of 01 March, 2006 and 31 May, 2006— consisting of 10,154,742 unique query variations from 657,426 unique users. Data that was originally only available to researchers working in industry was now publicly available. Having access to the AOL query logs has been of great benefit for session detection methods in query logs, enabling capture and analysis of query reformulations for example [30].

However, a significant problem with the AOL query logs is that they also supply unique user identifiers that allow grouping queries by user. Thelma Arnold, a 62-year-old widow's identity was exposed from the logs, with personal queries such as `numb fingers`, `60 single men` and `dog that urinates on everything` exposed to the public domain [5]. Although Gayo-Avello [30] is aware of how contentious use of the AOL logs is, Gayo-Avello [30] claims that "The main conclusion one can achieves from such consultations is that any research not aiming the identification of actual people could be judged as ethically acceptable." Hafner [32] ran an article in the New York Times entitled "Researchers yearn to use AOL logs, but they hesitate", where Professor Kleinberg from Cornell states "The number of things it reveals about individual people seems much too much. In general, you don't want to do research on tainted data." Bar-Ilan [4] published a paper regarding the troubled state of affairs for using the AOL query log data with the opinion "Their hesitation is understandable, even though I am confident that these researchers would not be looking for embarrassing personal data, and only use the logs for pure research purposes."

Despite the privacy concerns, it is difficult to suggest that use of the AOL query logs is all bad. Westerlund et al. [80] use the logs to understand the information seeking behaviors of vulnerable suicidal Internet users. From a utilitarian perspective, this may lead to a greater good where suicides are avoided by diverting searchers to help services. Zimmer [88] reviews the privacy concerns of Google using their

own search log data internally to improve their search engine, claiming the use of the data is akin to engaging in a Faustian bargain: *Faust, in the legend, traded his soul to the devil in exchange for knowledge. To "strike a Faustian bargain" is to be willing to sacrifice anything to satisfy a limitless desire for knowledge or power*. Zimmer [89] published an article about Facebook researchers publishing data about its users in a dataset, where Facebook took the position that the data was already public and therefore unproblematic to use. There's a similar duality between this mindset and using the AOL query logs, where just because it's there and it's available, it doesn't mean it's yours to use. The UQV100 collection and approaches similar to it are not encumbered by the ethical problems listed above, as participants are able to opt-in and privacy safeguards can be established in the experimental design.

## 2.5 Query Expansion

### 2.5.1 Rocchio-Relevance Feedback

Rocchio [64] presented a human-in-the-loop relevance feedback approach called Rocchio-Relevance Feedback (also known as explicit, or manual relevance feedback). It works by interactively selecting documents throughout the search process to shift the user's original query towards the intended relevant documents, by adding terms to the original query.

$$Q' = \alpha Q + \frac{\beta}{|R|} \sum_{D_d \in R} D_d - \frac{\gamma}{|\overline{R}|} \sum_{D_d \in \overline{R}} D_d \tag{2.25}$$

$\alpha$, $\beta$ and $\gamma$ weight different components of the computation, where $\alpha$ controls how much weight is given to the original query, $\beta$ weights the impact of relevantly marked instances, and $\gamma$ weights how strongly irrelevant instances are avoided.

### 2.5.2 Pseudo-Relevance Feedback

Pseudo-relevance feedback is also sometimes referred to as automatic query expansion. As shown in Figure 2.3, a user issues a query $Q$ to a system, where it adds expansion terms to the original $Q$ forming $Q'$, where the results are then returned to the user. It is denoted at "pseudo" relevance, as the top $R$ documents are assumed to be relevant sources of information to retrieve the top $T$ expansion terms to be included in $Q'$. Billerbeck and Zobel [11] explain that using fixed $R$ and $T$ parameters are questionable across experiments with different collections, as they are highly sensitive to the document collection.

Lavrenko and Croft [41] introduced the first use of language models over pseudo-relevance feedback, known as a relevance-based language model. There are four different RM variants, however, in practice

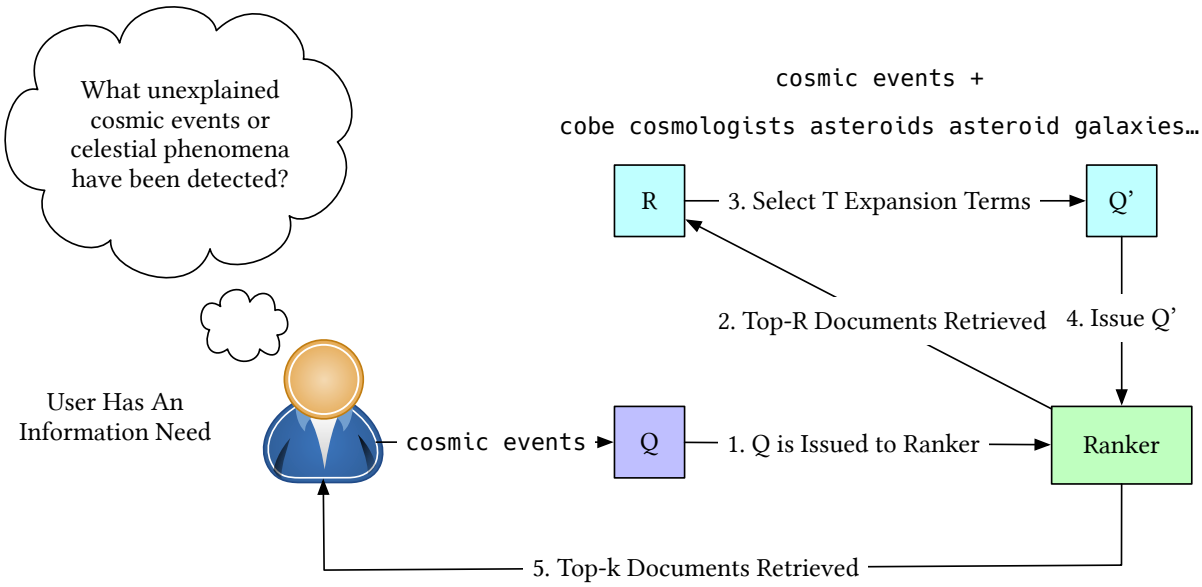



FIGURE 2.3. A high-level overview of pseudo-relevance feedback.

RM3 is the most popular. For brevity and for understanding the underlying assumptions made in each step, the reader is referred to a presentation given at UMass on the subject matter [4]. RM3 extends on RM1 to reweight the original query terms higher than the expansion terms, e.g. the user's original query is weighted 60% more than the expansion terms. This can be helpful in reducing the problem of "query drift" exhibited by pseudo-relevance feedback. For example, if the query `cosmic events` elicited many highly ranked documents about aliens, it may drift the intended query away from the user's intention.

## 2.6 Unsupervised Rank Fusion

### 2.6.1 Rank Fusion Origins

Rank fusion is a technique used to more effectively resolve a user's information need, by combining knowledge from the output of more than one system [28] or query variation [8]. Rank fusion can be applied in a supervised machine learning or unsupervised scenario. In this work, we focus strictly on the discussion of unsupervised rank fusion methods. Fox and Shaw [28] published seminal work on unsupervised rank fusion, describing six methods belonging to the "Comb" family. The retrieval scores of five different IR systems were merged, with an observed improvement in the precision and recall of the result sets. Of this family of algorithms, the most effective methods of combining evidence

[4] UMass Query Expansion and Pseudo-relevance Feedback Lecture 11: `https://people.cs.umass.edu/~jpjiang/cs646/11_qm.pdf`

from the different systems used were CombSUM and CombMNZ. CombSUM, shown in Equation 2.26, simply aggregates the retrieval score for each document and presents the highest scoring results sorted in descending order. $d$ in the equations below represents a single document and $D$ refers to the universe of documents to undergo fusion.

$$\text{CombSUMScore}(d, D) = \sum_{d \in D} Score(d) \tag{2.26}$$

CombMNZ shown in Equation 2.27, is similar to CombSUM's aggregation of retrieval score across different lists, however, this score is further multiplied by the number of times the document has appeared in all lists. Note that bars in Equation 2.27, and all other equations in this section refer to the cardinality of the set.

$$\text{CombMNZScore}(d, D) = |d \in D| \cdot combSUMScore(d, D) \tag{2.27}$$

Ng and Kantor [54] performed a regression analysis to determine if improved performance by utilizing CombSUM could be predicted observing output dissimilarity between lists and a pairwise measure of the performance between systems [53], with a success rate of 70% over the test set. Wu and McClean [84] improved on this work, primarily by observing the number of overlapping documents present in each list as a feature to accurately predict improved performance using CombSUM and CombMNZ with over 90% accuracy.

Rank fusion algorithms can broadly be classified into two categories [36]. Score-based rank fusion algorithms such as CombSUM and CombMNZ depend on information learned from the retrieval score column in a result list. Rank-based fusion algorithms simply rely on the order of documents in each observed result list. In a rank-based scenario, voting algorithms used for establishing democratically elected candidates have been abstracted to re-rank documents. The Borda count method developed to determine the winner of elections in 1784 has been used with success in an IR context (analogous to Borda-fuse) [23, 85]. A Borda count over a set of lists, observes the rank of each candidate, and sums the difference in rank position from the total number of candidates in each list. Finally, each candidate is presented to the user in descending order of this calculation. Condorcet voting was developed a year later in response to the Borda count method, offering an alternative method of preferential voting that biases candidates ranking highly across all lists [85]. It was Condorcet's view that the candidate with the highest pairwise ranking among all votes (the "Condorcet winner") would reflect the view of society's best candidate. To generalize Condorcet voting to a rank-fusion scenario, an ordered result list can be formed by iteratively finding and removing the "Condorcet winner" and appending it to the tail

of the final result list to be supplied to the user. Unfortunately, fusion using Condorcet's voting scheme is computationally expensive, with the best performing implementation having a time complexity of $O(nklog_2n)$, where $n$ represents the number of lists, and $k$ represents the number of documents [52].

### 2.6.2 Recent Developments

Cormack et al. [21] found that fusion by summing and sorting the reciprocal rank, for a document over each list, outperforms Condorcet fusion in effectiveness; naming the method Reciprocal Rank Fusion (RRF). Equation 2.28 describes the scoring formula, where $k = 60$ is a constant known to produce effective results under the test collections evaluated against, and $r(d)$ in this equation, and all further equations in this section represents the rank position of the document.

$$\text{RRFScore}(d, D, k) = \sum_{d \in D} \frac{1}{k + r(d)} \tag{2.28}$$

This unsupervised fusion method has been regarded as a strong baseline in recent work against a supervised rank-fusion method [42]. RRF has been extended by Maurao et al. [48], where the authors increased the growth rate of the denominator in the reciprocal rank summation to behave quadratically; named Inverse Square Rank (ISR, Equation 2.29).

$$\text{ISRScore}(d, D) = |d \in D| \cdot \sum_{d \in D} \frac{1}{r(d)^2} \tag{2.29}$$

That is, the weighting of observed ranked documents now follows a hyperbola with a faster growth rate. The authors experimented with multiplying the summation by the logarithm of the document frequency in a method similar to CombMNZ, naming the method logISR (Equation 2.30).

$$\text{logISRScore}(d, D) = log(|d \in D|) \cdot \sum_{d \in D} \frac{1}{r(d)^2} \tag{2.30}$$

The conclusion reached in this experimentation is that ISR appears to outperform RRF in the ImageCLEF medical case retrieval collection, however, RRF outperforms ISR on the ImageCLEF medical image retrieval collection.

Bailey et al. [3] draw inspiration from the Borda-fuse method, altering the approach to aggressively discount documents ranked deeper in runs by means of a user-model, named Rank Biased Centroid (RBC, Equation 2.31).

$$\text{RBCScore}(d, D, \phi) = \sum_{d \in D} (1 - \phi)\phi^{r(d)-1} \tag{2.31}$$

This geometric distribution based model is also utilized in the rank-biased precision (RBP) evaluation metric proposed by Moffat and Zobel [50]. This is a powerful feature of the fusion algorithm, as the gain function can be tuned to reflect the intrinsic distribution of relevant documents over the document collection, retrieval function, query quality and type, and judgement pool depth. The authors show that RBC produces results that are competitive with CombMNZ and Borda count, using the UQV100 test collection on the ClueWeb12-B corpus [2], and that strong results can be achieved using query fusion.

CHAPTER 3

# TREC CORE 2017 User Query Variations

The Text REtrieval Conference (TREC) annually provides a set of research areas named "tracks" which can differ annually, where each track is a competition to perform a specified IR task in the most effective manner. Last year, TREC celebrated 25 years of encouraging research in IR over large text collections. The "Common CORE" [1] track made its debut this year and has the goal of attracting a diverse pool of high-quality IR search result lists— discussed as "runs" from hereon, to investigate new methods for creating IR test collections. This is often referred to as an *ad hoc* retrieval task [78]. For large text collections, exhaustively judging all documents against a set of queries in a collection is infeasible [39]. TREC makes use of pooled relevance evaluation on large text collections, where a subset of the top-$k$ documents from each submitted run are unioned to a *pooling depth* $d$, and judged on a graded relevance scale. These judgements and test collections can be used thereafter for evaluating new retrieval systems as evidence of improved retrieval effectiveness [1].

Participation in CORE is of interest to our goal of improving recall in text retrieval using rank fusion— where we attempted to develop a recall-oriented approach that exploits user query variations and rank fusion. We venture that the ability to retrieve a large number of relevant documents that other systems fail to find is indicative of a high-recall system. As the TREC conference typically attracts runs of a high effectiveness caliber from research groups worldwide (as was the case for the Robust04 track [76]), we assert that this is an opportune track to test our approach. The previous TREC newswire ad hoc task was the "Robust" 2004 track, where the emphasis was on improving the effectiveness of poorly performing topics in previous tracks. The Robust collection has been one of the most popularly studied corpora to assert effectiveness claims in a decade of IR research [1]. The TREC CORE 2017 track reuses the same topic set as Robust04, for the development of relevance judgements over a new *New York Times* corpus— composed of newswire articles published between January 1, 1987 and June 19, 2007 [2]. To our knowledge, there has never been a call for participation in an ad hoc retrieval task that has existing relevance judgements available on another corpus of similar textual composition. This allows for the

[1] TREC 2017 CORE Track: `http://trec-core.github.io/2017/`

[2] The New York Times Annotated Corpus `https://catalog.ldc.upenn.edu/ldc2008t19`

first time, evaluation of a transfer learning approach from another collection's relevance assessments in the presence of a new collection with a similar composition.

A byproduct of this research is the ability to compare query variation phenomena across corpora in a consistent and reproducible manner. The UQV100 test collection contains one hundred single-faceted topics with over five thousand unique query variations [2], however with the limitation they can only be used on ClueWeb12B. The new query variation collection produced for participation in the CORE track, while smaller in scope than the UQV100 collection, enables comparisons of query variations to be made across different document representations and editorial quality. Observing the relative effectiveness across ClueWeb12-B and Robust04, one composed of websites and another composed of journalistic content, is of interest to the overall goal of the thesis, as it demonstrates how transferable our approach is to different corpora, and the rank fusion mechanisms based on those query variations.

**Research Goals**. In order to achieve these goals, we focus on the related research questions:

**Sub-Research Question (S-RQ1):** *Can tuned parameterized query fusion be used to improve the number of unique relevant documents found relative to other participants?*

**Sub-Research Question (S-RQ2):** *Do query variations that are good in one collection also perform well in another collection?*

**Sub-Research Question (S-RQ3):** *Are the score ranges caused by user query variations consistent across different test collections?*

In the first section, we described the user study conducted to collect query variations for use in this work. In the second section we discuss our submissions with more detail, and place our query variations into context with the existing UQV100 test collection. Finally, we list the results of each of our submitted runs using the NIST assessed fifty queries. As of writing, croudsourced relevance assessments of two hundred topics remains unreleased, reducing the depth of our exploration.

## 3.1 User Study

In order to collect query variations that could be used in many experimental settings, such as query fusion and query rewriting over three distinct document collections, a tool to collect variations was developed. All authors of the published workshop paper Benham et al. [10] contributed up to ten queries that they thought would be useful to resolve an information need expressed in the 250 topics to undergo relevance evaluation. They were the only participants in this user study. The information

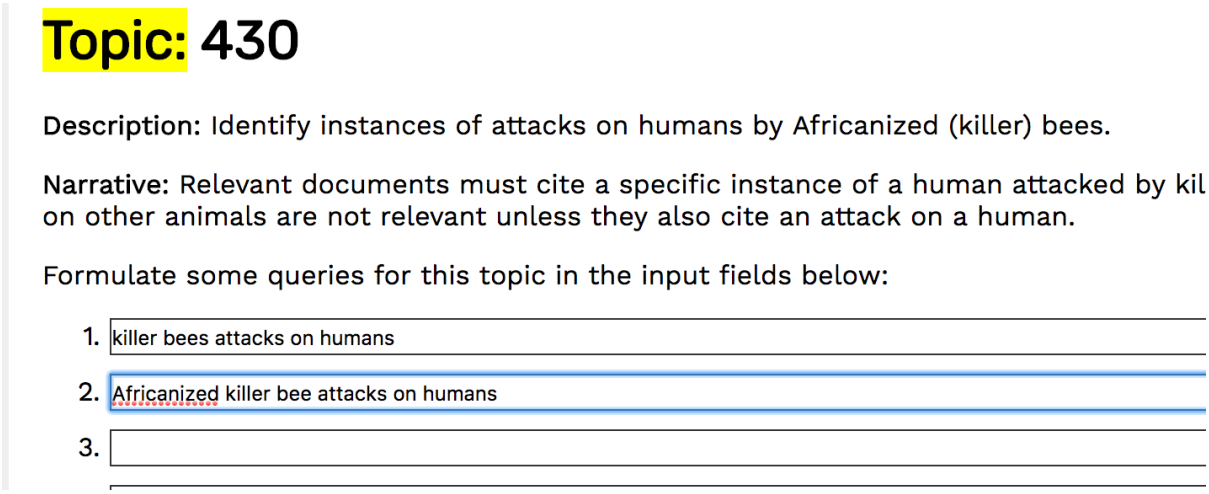



FIGURE 3.1. The query variation submission interface.

need descriptions to form the queries from are taken from the modernised Robust04 topic narratives and descriptions supplied by the track organisers. Participants were not presented the title of the topic when formulating queries alongside the narrative and description supplied in the topic set, to avoid biasing their queries. The query capture interface was password-protected to protect the integrity of the query variants collected. Figure 3.1 shows a screenshot describing the form for filling out query variations for one of the 250 topics.

No query transformations were applied on the raw queries collected using this tool, where the onus was on the user to supply the best query that they thought would resolve the information need. Indeed, many Internet browsers offer spelling correction and underline words in text fields that are found to be misspelled. We capture the raw queries, allowing query normalisation to be applied for future experiments where appropriate. Although text fields were presented to the user in an ordinal numbered list, this was not used to indicate a preference for users best query, but rather the first query that came to mind for the topic. We used ordering effects to bias the collection of query variations to supply more queries to the 50 NIST assessed topics, while ensuring that all other topics received acceptable coverage. The distinction between these two sets were made with the use of a heading, to differentiate the two sets. For all topics, a minimum of eight query variations per topic were captured.

One limitation of formulating query variations in this study, is that the title queries for the topics under study are available online on the TREC website, whereby some participants knew what the title query was for some topics through exposure in other works. Participants were also given the option to export all query variations dynamically; given access to a file containing the fields `TRECTopic`, `UQVId`, `User` and `RawQuery` enabling the potential for responses to become biased by other authors. We permitted the use of this feature to allow for experimentation with query variations while they were being pooled

TABLE 3.1. Number of query variations submitted by each author.

| | Queries Submitted |
|---|---|
| Participant 1 | 1261 |
| Participant 2 | 367 |
| Participant 3 | 342 |
| Participant 4 | 341 |
| Participant 5 | 270 |
| Participant 6 | 238 |
| Participant 7 | 175 |
| Participant 8 | 158 |

as a living document, and monitoring of how many variants were collected throughout the experiment. Despite these limitations on the sanctity of the query variations collected, all participants made a best effort to write queries based on the description and narratives that were presented on the form.

In Table 3.1, we see that there is a bias in the number of query variations collected per user— where Participant 1 has contributed more than a third of the query variations in the collection. As the authors of the query variations were assigned an id number in the metadata, a more representative sample of query variations on a per-user basis can be formed where appropriate in future studies.

In this section we described the user study the eight authors of this paper participated in to pool query variations. In the next section, we evaluate the effectiveness of our new collection in the context of existing query variation collections; motivating our submission approach.

## 3.2 Approach

To use Indri [3] 5.11 to index the collection and form our runs, we convert the NYT corpus from XML to SGML by parsing the fields using Nokogiri— a libxml2 wrapper. Table 3.2 displays an abridged description of each run, where we elucidate how they were constructed in this section. An automatic run is formed by an IR system where there is no human involvement when retrieving ranked documents, outside of issuing the topics supplied by NIST to the system. Manual runs are all other types of runs. As we submit two runs derived from query variations in the query construction stage, they are marked manual as to allow them to be treated differently.

TABLE 3.2. A brief description of the RMIT runs.

| Run | Type | Description |
|---|---|---|
| RMITRBCUQVT5M1 | Manual | Combines the top five runs per topic based on Robust04. Okapi and SDM+QE was executed over all variations, and the Robust04 collection used to determine the five best. |
| RMITUQVBestM2 | Manual | The best query variation per topic (FDM+QE), as determined by outcomes on the Robust04 collection. |
| RMITFDMQEA1 | Automatic | FDM + RM3 query expansion using only the title queries supplied by the track organisers. |

**Oracle-based Manual Query Rewriting**. Firstly, in order to illustrate the power of using a better query to satisfy an information need, we observe the effectiveness of individual queries on a per-topic basis using the AP measure on the Robust04 collection (computed using the standard `trec_eval` utility) [4], and the NDCG@10 (computed using `gdeval`) [5] measure on the UQV100 test collection. The *New York Times* collection could not be utilised, as no judgements existed at the time of submission for this collection. Instead, we use the Robust04 collection as there are relevance assessments available for the same topics. Documents are formed with similar editorial quality to those in the NYT corpus, allowing inference to be made about the spread of retrieval effectiveness using different queries. To analyse this volatility in query effectiveness, we use our newly created query variation set and contrast with the existing UQV100 set on the separate ClueWeb12B collection. On the ClueWeb12B collection, no such editorial quality control exists, as is the nature and design of the World Wide Web. This gives us an additional contrast to see if the same volatility holds across collections, to answer our ancillary research question **S-RQ3**. As another point of comparison, we show how the spread of retrieval effectiveness varies with respect to the title query published with the Robust04 set, and the most frequently submitted query variation in the UQV100 set.

[3] Indri Homepage: `https://www.lemurproject.org/indri/`
[4] `http://trec.nist.gov/trec_eval/`
[5] `http://trec.nist.gov/data/web/10/gdeval.pl`

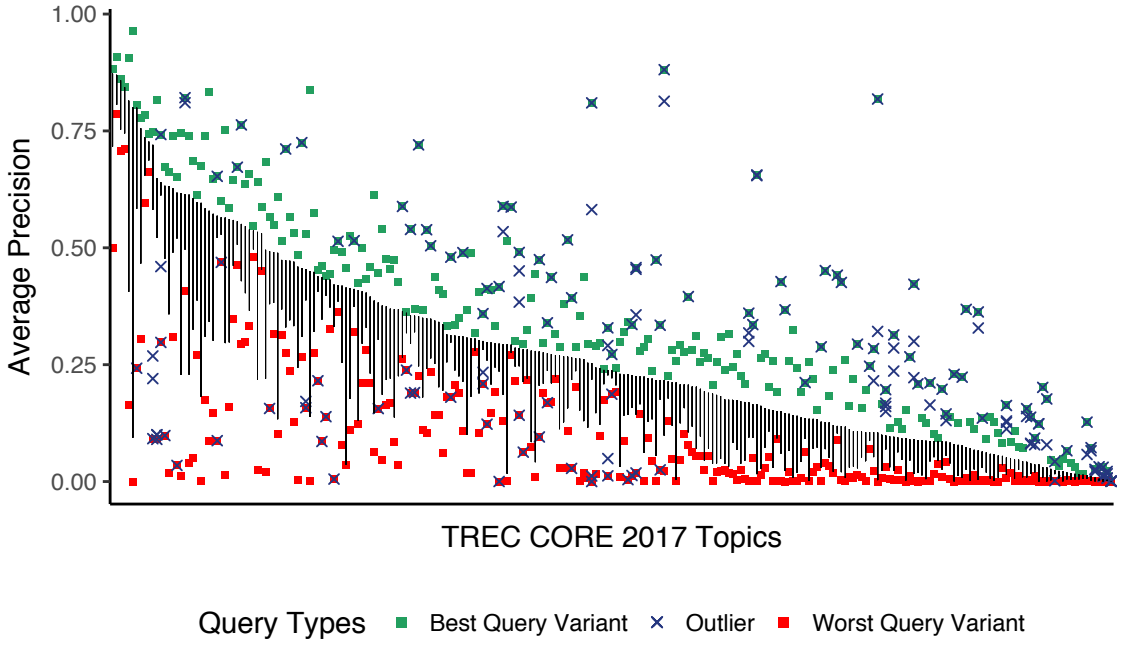



FIGURE 3.2. Average precision score distributions for all 249 topics in the author-generated CORE query variations on Robust04 Corpus. Lines represent IQR, topics are sorted from greatest 75th percentile to lowest.

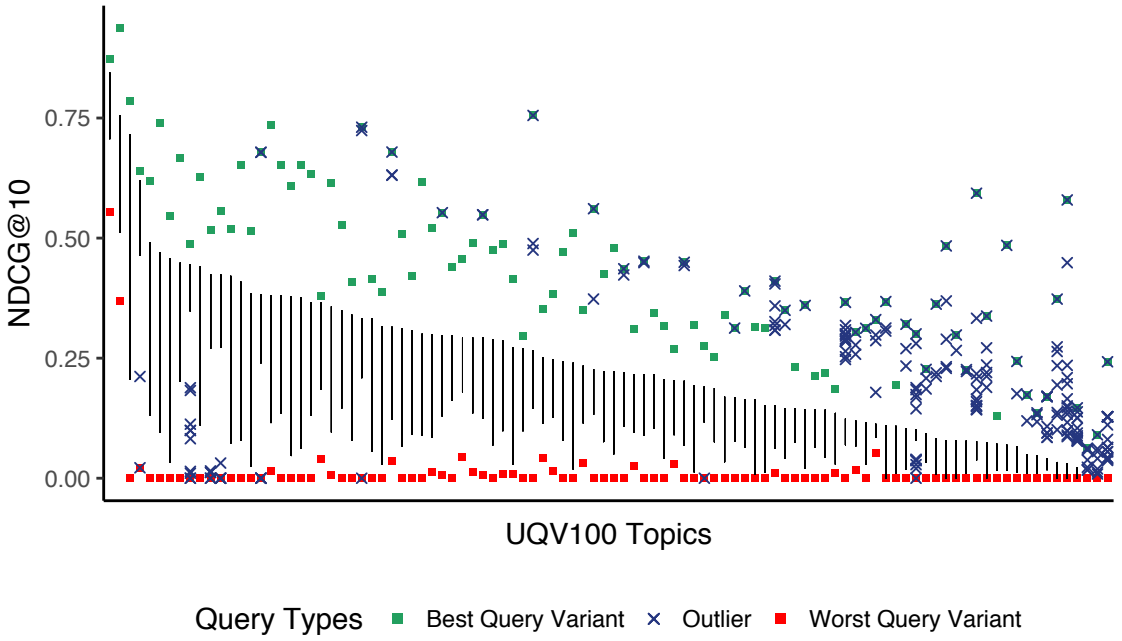



FIGURE 3.3. NDCG@10 score distributions for all 100 topics in UQV100 judgement set and the ClueWeb12B Corpus. Lines represent IQR, topics are sorted from greatest 75th percentile to lowest.

Figure 3.2 shows the variance of the Okapi BM25 per-topic AP effectiveness, sorted from greatest effectiveness in the 75th percentile to least, juxtaposed with the best and worst performing query variant in our new query variation collection. The spread of effectiveness for the query variations is stark. The UQV100 test collection has a similar extreme spread of per-topic effectiveness, per query variation submitted. Figure 3.3 shows a contrasting view of the per-topic NDCG@10 effectiveness for the most popularly submitted query variations in the UQV100 test collection on ClueWeb12B. On the tail ends of both distributions, outliers outperforming the interquartile range are surprisingly common. On the opposite side of the distribution on the highly effective topics, many of the best performing topics have outliers exhibiting severely diminished effectiveness. In both cases however, outliers exist more frequently in improving retrieval effectiveness rather than damaging it. Pleasantly surprisingly across both collections— the best query variations are generally more distant from the interquartile range than the worst query variations. From this graph, we answer **S-RQ3** as we have shown that the spread of retrieval effectiveness is similar in nature across different query variation collections and corpora.

**Title Only**. To compare the effectiveness of using the best query variations per topic on the Robust04 collection using FDM+QE, as a baseline we submitted an automatic run that only used the supplied TREC titles. Figure 3.4 shows a comparison of the monotonically decreasing AP score per topic of the title-only automatic run, compared against the best score achieved by a single query variation in the set of CORE variations we compiled. In most cases, the best query variation is more effective than the TREC title query counterpart— however there is a sizable number of cases where the TREC title query is performing more effectively. As we are already submitting an automatic run with the TREC title queries as a baseline and it is assumed that many other participants will, we take the best query variation without including the set of original TREC queries despite knowledge that some are performing better than the best query variation. We did this in an attempt to find more uniquely relevant documents through diversifying our queries. Figure 3.4 therefore compares our submitted best query variation run RMITUQVBESTM2, against RMITFDMQEA1— where the system has remained fixed and all that has changed in the queries issued.

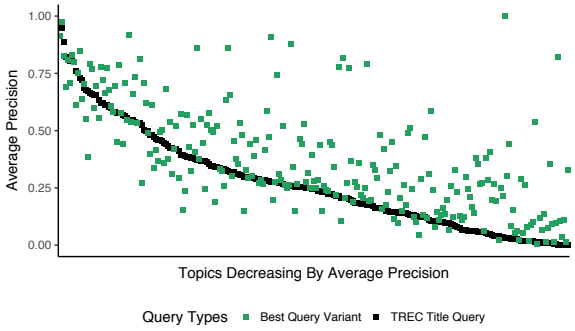



FIGURE 3.4. A comparison of FDM+QE runs using AP on the Robust04 title-only queries from most effective to least, and the best per-topic AP query of the TREC CORE query variants, according to the Robust04 collection.

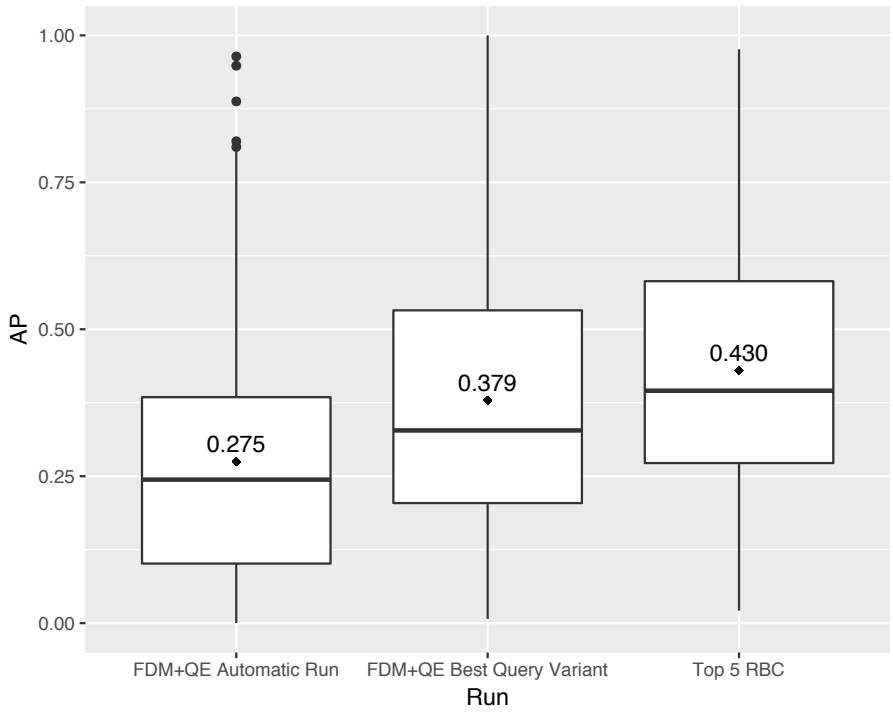



FIGURE 3.5. A comparison of effectiveness by AP, for all runs to be submitted on the Robust04 collection.

**Query Fusion**. Fusing query variations has been shown to improve retrieval effectiveness [3]. By introducing more diversity into the final coalesced run, our hypothesis is that it also increases the chances of finding more uniquely relevant documents. Experimentation on Robust04 found that fusing the top five most effective AP scoring query variation runs for each topic using the RBC fusion method resulted in an extremely high AP score of 0.430. For each query fusion performed, the persistence parameter $\phi$ was swept to find the optimal value using the Robust04 relevance assessments. This process was conducted over two distinct retrieval systems, BM25 and SDM+QE. Finally, the best per-topic fused run is selected with only BM25 runs or SDM+QE runs. In other words, a top-five fused run at the topic level consisted of a single retrieval system only. The parameters and retrieval system used were logged for this run, to be reran over the new *New York Times* document collection. This forms the run RMITRBCUQVT5M1.

Figure 3.5 shows the retrieval effectiveness of all runs on the Robust04 collection. We observe that our query variation approaches should in theory be significantly more effective than the title query run, when the same retrieval techniques are applied on the *New York Times* corpus. Note that these numbers should be interpreted with caution, as our runs are tuned with knowledge derived from the relevance assessments. The approach shows fantastic performance on the Robust collection, and we wish to observe if this can be transferred over to a new collection of similar composition.

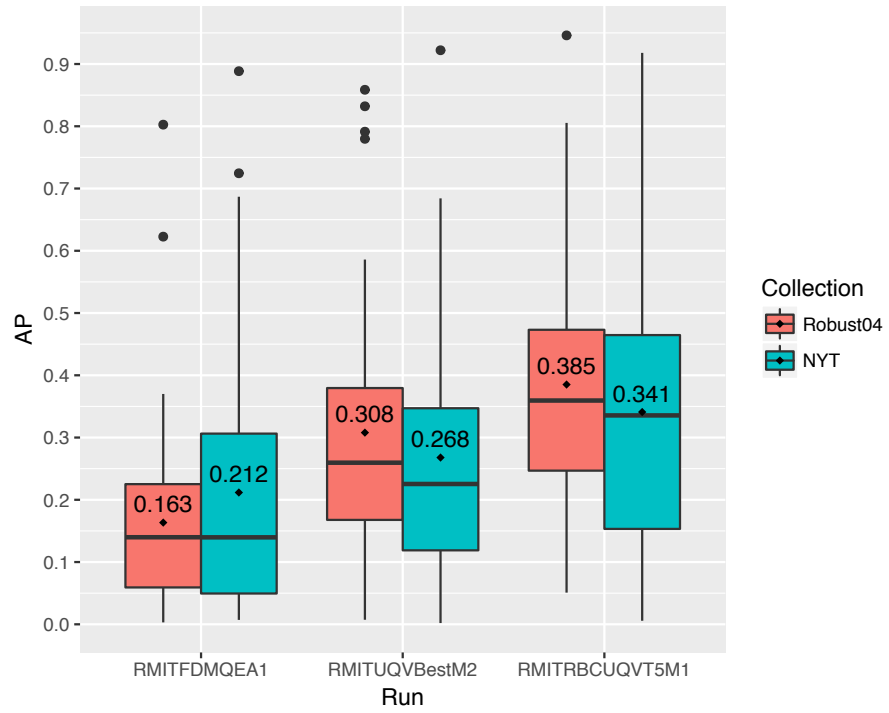



FIGURE 3.6. A comparison of effectiveness by AP, for all runs on the 50 NIST assessed topics. Our Robust04 oracle run is listed on the left— restricted to the 50 topics assessed by NIST assessors, for a like-for-like comparison with the NIST assessed plot on the right.

## 3.3 Results

The CORE track organisers published the relevance assessments formed by NIST for their fifty topics deliverable. We restrict our analysis of our results to the NIST sample as the crowd-sourcing relevance judgements are not yet released.

All of our runs met the effectiveness requirements formed by the track organisers to contribute to the pool of relevance assessments. Figure 3.6 shows a box-plot to observe how our knowledge transfer approach worked— note that the distribution of scores on Robust is different to Figure 3.5 as only the NIST topics are compared here. This plot helps answer **S-RQ2**, where we find that the "best" UQV found for each topic over AP on the Robust04 collection outperforms the TREC title run. However, when the same approach of selecting the best query variation was employed over the new judgement set, only 12 of the 50 topics had the same "best" query as Robust. Where the best query variations were selected over the judgement set for failure analysis, an AP score of 0.346 is achieved, outperforming our fusion run. This seems to suggest that there is no "best" query, and that the best query is coupled to the collection.

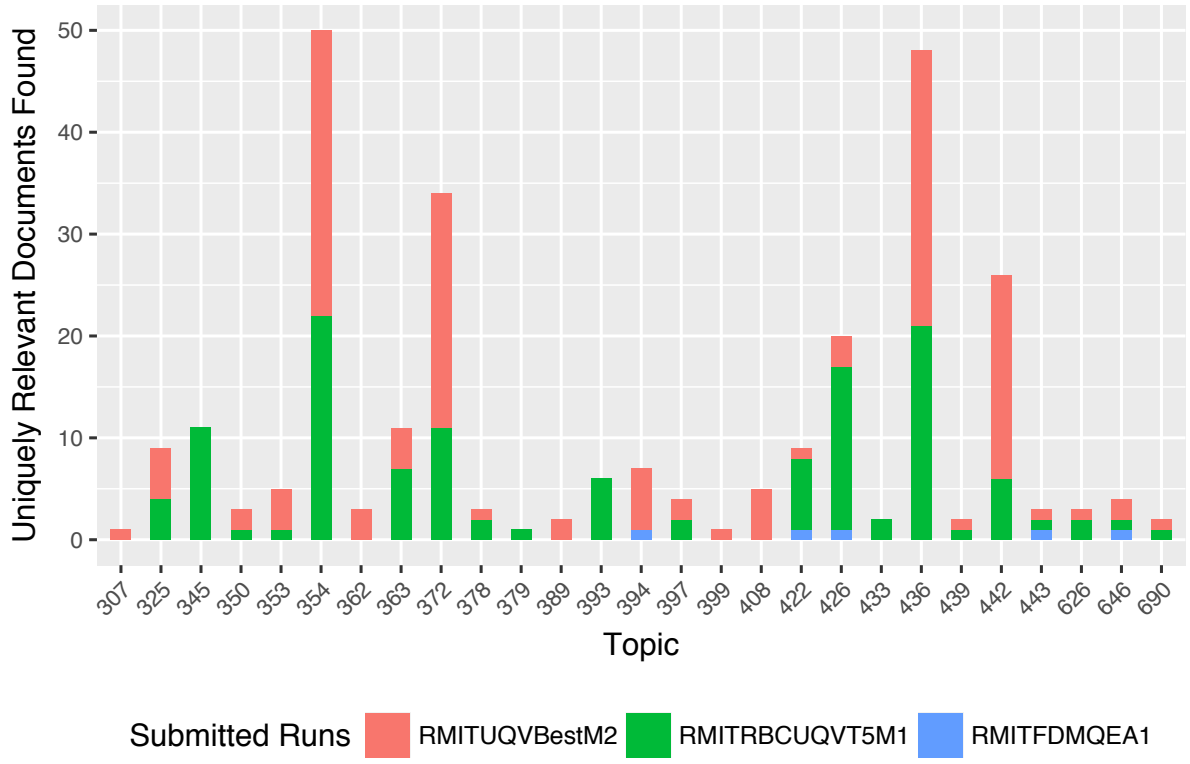



FIGURE 3.7. The distribution of uniquely relevant documents found across all NIST assessed topics.

Although we do not get the same performance as fusion, both manual runs exhibit scores with acceptable effectiveness and contributed 229 uniquely relevant documents no other system found. Out of all fifteen submissions, our approach placed fourth, over the 50 topic NIST sample. The most uniquely relevant document count came from the `Sabir` submission, with a count of 694 from automatic runs. Our submission was the only contribution to the pool that resulted retrieving 3 uniquely relevant documents across both our automatic run and manual runs. The number of uniquely contributed documents for each submitted run is RMITFDMQEA1: 5, RMITRBCUQVT5M1: 126 and RMITUQVBESTM2: 144. Surprisingly, the RMITUQVBESTM2 run extracts more unique relevant documents than our fusion run. Of note, the number of uniques for RMITUQVBESTM2 and RMITRBCUQVT5M1 sum to 270, indicating that 41 uniquely relevant documents overlapped between both retrieval approaches. This is unsurprising, as the top 5 submission contained the top queries used in RMITUQVBESTM2. Figure 3.7 shows the per-topic breakdown of topics that we successfully retrieved uniquely relevant documents for over each of our runs. We observe a relatively even distribution of uniquely contributed runs between the RMITUQVBESTM2 and RMITRBCUQVT5M1 approaches, where both runs appear to be complementary. We

TABLE 3.3. The per-topic effectiveness of our runs when placed into context with other submissions over different categories. The Median column represents how many topics we achieve better or equal scores than the median value across all participants. As we merge the best scores across manual and automatic runs for Auto ⋃ Manual, the median value across this set is unknown as other participant's runs are not publicly available.

| | AP | | | NDCG | | | P@10 | | |
|---|---|---|---|---|---|---|---|---|---|
| Run | Best | ⇑ Median | Worst | Best | ⇑ Median | Worst | Best | ⇑ Median | Worst |
| Automatic Runs | | | | | | | | | |
| RMITFDMQEA1 | 0 | 21 | 0 | 0 | 17 | 0 | 4 | 32 | 4 |
| Manual Runs | | | | | | | | | |
| RMITRBCUQVT5M1 | 6 | 20 | 1 | 10 | 21 | 3 | 14 | 36 | 2 |
| RMITUQVBestM2 | 1 | 12 | 14 | 0 | 12 | 12 | 9 | 32 | 8 |
| All Runs, Best of Auto ⋃ Manual | | | | | | | | | |
| RMITFDMQEA1 | 0 | — | 0 | 0 | — | 0 | 4 | — | 4 |
| RMITRBCUQVT5M1 | 2 | — | 0 | 2 | — | 0 | 12 | — | 1 |
| RMITUQVBestM2 | 0 | — | 0 | 0 | — | 0 | 9 | — | 2 |

therefore positively answer **S-RQ1** as it can yield competitive results compared to other participants, however they were not the best over the top 100 – even in the case of our single query run.

Alongside knowledge of the number of uniquely relevant documents retrieved for each research group, a per-topic breakdown of the best, median and worst scores were supplied to each group for the evaluation metrics AP, NDCG and P@10. These figures were provided for relative comparison between automatic submissions and manual submissions. Table 3.3 shows how our automatic run performed relative to others in the same category at a per-topic level. We find that no topics in our automatic run achieved the best or worst AP or NDCG scores relative to others. We achieve the best P@10 value on four topics— 336, 394, 416 and 614. Notwithstanding, we also achieve the worst scores on four topics— 325, 356, 367 and 445. Note that when we describe best or worst here, other groups may have achieved these figures too, and is more likely with P@10 than AP or NDCG by nature of its design. Less than half of our topics surpassed the median scores on AP and NDCG, indicating that our automatic run was relatively weak compared to other submissions providing high-utility results.

Table 3.3 also shows the per-topic breakdown of how our two manual runs performed relative to other manual runs. Our query fusion oracle run achieved the best results out of all three runs, where 6 topics performed the best out of all manual submissions for AP: 372, 379, 404, 419, 422 and 443. We also achieved the best NDCG score for ten topics: 341, 353, 379, 404, 416, 419, 443, 614, 620 and 677. However for AP we achieve the worst performance on topic 690, and for NDCG 626, 646 and 690. As an example, topic 404 occurs in both of these lists, with the title query "Ireland, peace talks"— where the goal is

to extract documents that discuss "How often were the peace talks in Ireland delayed or disrupted as a result of acts of violence?". The most effective query fusion configuration found on the Robust04 set, were the query variations (in order): "ireland peace talk delay violence bombing", "ireland peace talks disruption roken off violence attack threat fighter IRA republican army british ulster", "peace talks delayed Ireland violence", "Ireland peace talk delay disrupt violence" and "North Ireland peace process delayed violence". All of these query variations were fused using RBC $\phi = 0.99$, where it was found that BM25 gave more effective results than SDM+QE for this query on the Robust04 collection. Our best query variation run RMITUQVBestM2 achieved the best AP score for topic 435 "curbing population growth", with the query "population growth control".

Finally, in Table 3.3, we merge the best and worst scores across automatic and manual submissions to see how we compared globally against all participants. RMITRBCUQVT5M1 achieves the best AP scores on a per-topic level for topics 372; "Native American casino" with AP score 0.691 and 379; "mainstreaming" with score 0.374. The median scores for both of these queries were 0.423 and 0.199 respectively. For NDCG, 379 reappears with the NDCG score of 0.781 where the median is 0.549, and 416; "Three Gorges Project" appears with the NDCG score 0.912 where the median is 0.855.

## 3.4 Conclusion

All three of our runs met the track organisers quality criteria for inclusion into the judgement pool. RMITRBCUQVT5M1 was our most effective run for AP achieving an AP score of 0.341, however RMITUQVBestM2 attracted more unique and relevant documents than the former to cutoff 100. We were met with some fierce competition in the track, where we were outperformed in uniquely contributed documents by the Sabir run produced by Chris Buckley, and two submissions from the University of Waterloo— placing us fourth out of fifteen participants in this respect. Our automatic run did not appear to perform well compared to other automatic submissions, however we did not anticipate it to do so as it was used as a baseline for comparison with our manual query fusion approaches. Query fusion was able to produce a highly effective result list with a sub-par retrieval model in comparison to other participants. This confirms previous observations that query fusion is an highly effective technique in maximising recall, and we look to pursue further experimentation with it in future work using stronger systems— indeed learning from the notebook papers submitted from other participants. We are pleased with our results and very much look forward to reading about the approaches other participants utilised, and to participate in future ad hoc retrieval tracks.

CHAPTER 4

# Risk-Reward Trade-offs in Rank Fusion

Unsupervised rank fusion, the process of combining knowledge from many Information Retrieval outputs into one coalesced set, is a classic approach used in Information Retrieval to improve the utility of results displayed to users. This can be accomplished by combining the outputs from multiple systems [28] or multiple expressions of a single information need (query variation) [8]. The generation of this set can be varied by the fusion method(s) utilized, systems used, the topics used, or all of the above. These techniques have been a mainstay in IR research, but have fallen out of favour in recent years as search engines move to more complex Learning-to-Rank (LtR) Models. However, as search engines become more reliant on stage-wise retrieval, combining rank fusion and LtR models in interesting new ways is likely to reap additional improvements in overall system performance.

In the previous chapter, we observed the effectiveness score ranges caused by user query variations, and how query fusion can be used to improve retrieval effectiveness. In this chapter, we revisit rank fusion in the context of risk-sensitive evaluation. *Risk* occurs when a new system under-performs when compared to a simpler baseline model for a given query. Users are very sensitive to significant failures in a search session, which can even result in a user mistrusting a system and even stop using it [75]. This issue is often ignored in IR evaluation exercises as measuring system performance using aggregate scores does not penalise a new system for significant failures on a topic. Many IR techniques have been shown to exhibit a risk-reward trade-off, such as query expansion and FDM.

In this chapter we explore the central aim of improving recall in text retrieval using rank fusion. We start by interpreting and understanding the risks associated with using rank fusion to improve retrieval effectiveness, and then proceed to investigate methods of minimising risk and maximising effectiveness, by combining systems and queries together in a fusion. We focus on two related research questions to achieve these goals:

**Sub-Research Question (S-RQ1):** *How susceptible are system-based and query-based rank fusion methods to query performance degradation?*

**Sub-Research Question (S-RQ2):** *How can system-based and query-based fusion methods be combined to achieve the best risk-reward trade-offs?*

## 4.1 Background and Related Work

For the convenience of the reader, we supply a summary of each rank fusion algorithm in the table below. For a more complete discussion on rank fusion, refer to Section 2.6. Similarly, for an overview of risk-sensitive retrieval please refer to Section 2.3.7.

TABLE 4.1. A survey of rank fusion methods implemented and observed in our study.

| Name | Author | Function | Description |
|---|---|---|---|
| **CombSUM** | Fox and Shaw [28] | $\sum_{d \in D} S(d)$ | Score-based— Adds the retrieval scores of documents contained in more than one list and rearranges the order |
| **CombMNZ** | Fox and Shaw [28] | $\lvert d \in D \rvert \cdot \sum_{d \in D} S(d)$ | Score-based— Adds the retrieval scores of documents contained in more than one list, and multiplies their sum by the number of lists each document occurs in. |
| **Borda** | de Borda [23] | $\frac{n - r(d) + 1}{n}$ | Rank-based— Voting algorithm that sums the difference in rank position from the total number of document candidates in each list. |
| **RRF** | Cormack et al. [21] | $\sum_{d \in D} \frac{1}{k + r(d)}$ | Rank-based— discounts the weight of documents occuring deep in retrieved lists using a reciprocal distribution. $k$ is typically set to 60. |
| **ISR** | Maurao et al. [48] | $\lvert d \in D \rvert \cdot \sum_{d \in D} \frac{1}{r(d)^2}$ | Rank-based— inspired by RRF, discounts documents occuring deep more severely. |
| **logISR** | Maurao et al. [48] | $\log(\lvert d \in D \rvert) \cdot \sum_{d \in D} \frac{1}{r(d)^2}$ | See above. |
| **RBC** | Bailey et al. [3] | $\sum_{d \in D} (1 - \phi)\phi^{r(d)-1}$ | Rank-based— discounts the weights of documents following a geometric distribution, inspired by the RBP evaluation metric. [50] |

## 4.2 Experimental Setup

All runs are produced using Indri 5.11 with Krovetz stemming. For evaluation, `trec_eval` is used to compute AP, and `gdeval` was used to compute NDCG@10. Throughout the paper, † represents significance with $p < 0.05$, and ‡ represents significance with $p < 0.001$ when using a two-tailed paired $t$-test.

**Document Collections**. In our study, we observe the impact of fusion over two popular TREC collections, Robust04 and ClueWeb12B. As our query variation collections are restricted to a range of topics, our selection of corpora must have a relevance assessment set for these queries in order to evaluate our approach. The Robust04 collection [78] was shown to be the most popular test collection utilized in 2009, in a survey of a decade of Information Retrieval publications [1]. ClueWeb12 is the most recent web collection to be studied in the TREC Web tracks of 2013-14 [18, 19]. Table 4.2 details summary statistics of each of the corpora utilized.

TABLE 4.2. Summary statistics of the document collections studied.

| **Corpus** | No. Docs | Unique Terms | Total Terms |
|---|---|---|---|
| **ClueWeb12B** | 52,343,021 | 165,309,501 | 39,888,793,330 |
| **Robust04** | 528,155 | 664,603 | 253,367,449 |

**System Configurations**. For both document collections our reference baseline for risk-reward analysis is BM25. The intuition for this selection is derived from its capacity to effectively retrieve documents across many document collections, independent of their makeup. We expand on this reasoning with an exploration of the inherent risks "more effective" retrieval models (having a larger mean effectiveness score), can bring to a BM25 baseline. For brevity in our study, we only focus on methods that show an improvement in effectiveness and risk-sensitivity. We were unable to parameterize pseudo-relevance feedback for ClueWeb12B in a way that enabled it to behave in a risk-sensitive manner, but this is almost certainly an interesting area of future exploration [87]. For web queries, we use a field-based sequential dependency model, SDM+Fields, which we have found to work well in practice. The query terms are searched for in titles, anchor text and in the body of documents. Information on how the SDM+Fields model works is available in Section 2.2.5. We used the values $\alpha = (0.2, 0.05, 0.75)$ and $\beta = (0.1, 0.2)$ for SDM+Fields in our study.

For the Robust04 document collection, we use pseudo-relevance feedback with the following parameterization: an assumption that the top 10 documents will contain relevant terms to add to the query ($R_d = 10$), adding 50 terms to the original query ($R_t = 50$) and weighting these additional terms at 60% of the weighting of the original query ($R_w = 0.6$). We also use a full-dependency model (FDM), both with and without pseudo-relevance feedback. This combination represents a strong baseline on the original title-queries for Robust04.

**Query Variation Collections**. The query variation collections we use in query fusion scenarios are from the UQV100 test collection [2], for experimentation over the ClueWeb12B document collection. A new

query variation collection was created for the TREC CORE 2017 track, and was also utilized for cross-examination of query fusion methods on the Robust04 collection. The collection of the TREC CORE 2017 queries was undertaken with the goal of appropriating the methodology used to form the UQV100 test collection, to enable this purpose. Table 4.3 lists summary statistics of each of these collections. As the UQV100 collection has a considerable number of duplicate queries, when filtering for duplicates there are 5,764 queries remaining. The TREC CORE 2017 set has considerably fewer duplicates, due to fewer users in the study. No duplicate filtering was performed on this set as a result. After spelling normalization using the Bing API, removal of query variations with 15 or more terms, the true count of query variations utilized in the UQV100 set is 5,243, and 3,001 from the TREC CORE 2017 set.

TABLE 4.3. Summary statistics of the query variation collections studied.

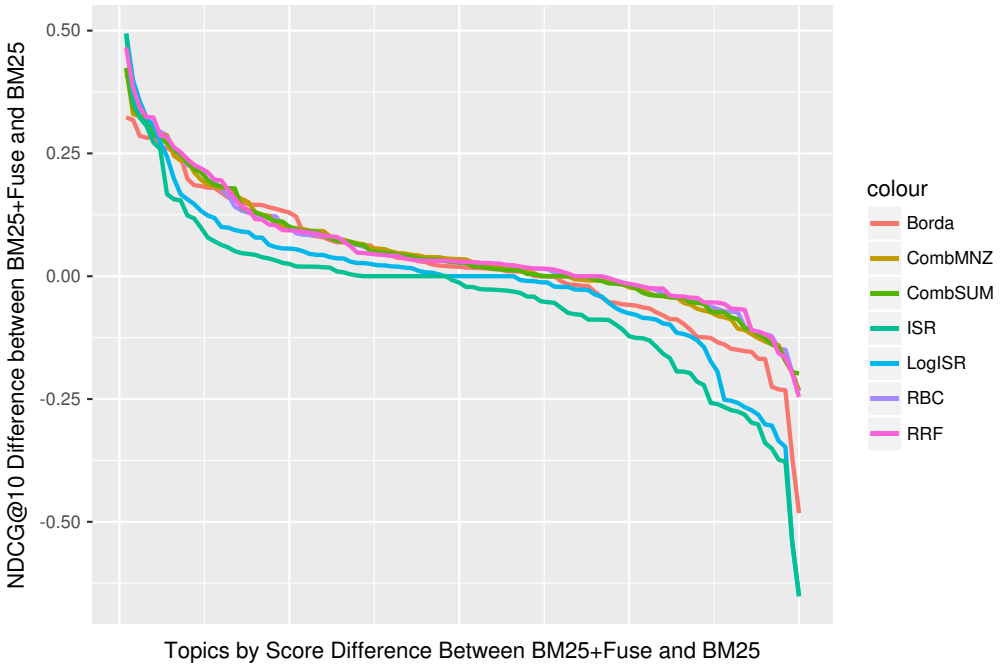
| **Collection** | Topics | Submissions | Users |
|---|---|---|---|
| **TREC CORE 2017** | 250 | 3,152 | 8 |
| **UQV100** | 100 | 10,835 | 263 |

The UQV100 test collection's topics were derived from the 100 topics that were used in the TREC Web tracks in 2013-14. Additional details on the collection can be found in the original collection description [2]. Note that the Robust04 document collection contains topics with a single facet. Along with the title queries, an unambiguous back-story is supplied for each topic, detailing in advance what assessors will mark as a relevant document. When evaluating the retrieval effectiveness of the Robust04 queries we use the AP evaluation measure, consistent with that which was used in the original Robust04 track.

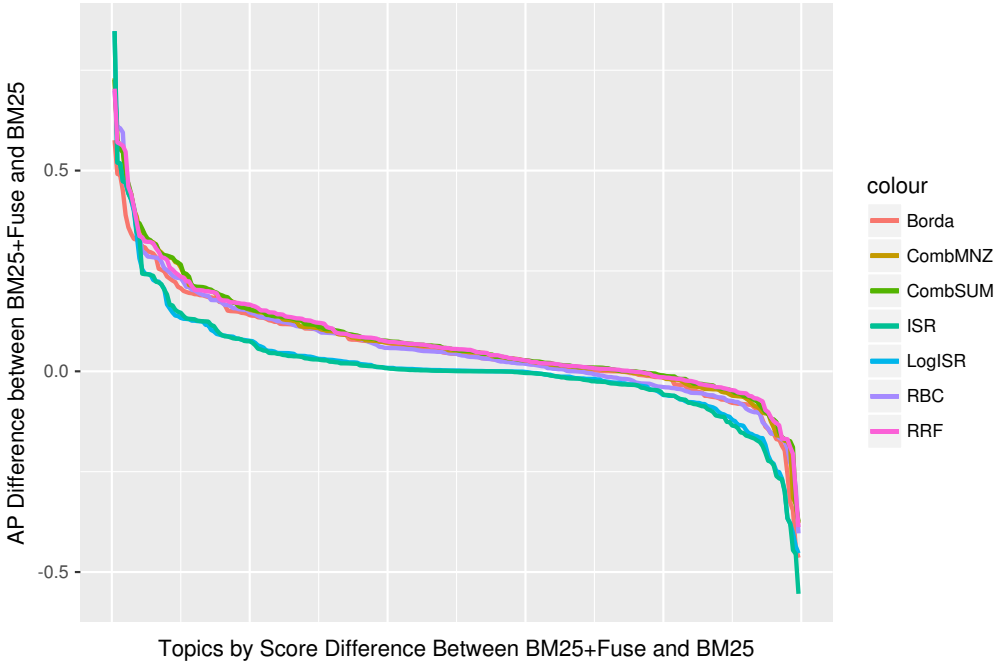
**Rank Fusion**. We do not engage in any parameter tuning in our study, and only utilize parameters that were explicitly mentioned in their respective papers. For the RRF method, we fix the constant $k = 60$ for all experimental analysis. All RBC fusion results are observed within the scope of those mentioned in the original paper: $\phi = (0.90, 0.95, 0.98, 0.99)$. Other values of $\phi$ were tested, but the results are consistent with the ones presented in the following sections. A fusion depth of 3,000 was used, but all runs were scored to depth 1,000.

## 4.3 Fusion Performance Degradation

In the recently published work of Bailey et al. [3], query variations were used with the newly proposed RBC rank fusion method to fuse the result lists for each query. The authors evaluated their approach in the presence of the recall-oriented metrics AP and NDCG, and the utility-based evaluation metrics RBP and INST. Query variation fusion showed a significant improvement in retrieval effectiveness in




(A) NDCG@10 difference for all fusion methods on BM25+Fuse with ClueWeb12B, compared against the most frequently submitted query variation per topic ($v = 1$) in the UQV100 test collection on BM25.




(B) AP difference for all fusion methods on BM25+Fuse with Robust04, compared against Robust Title Queries on BM25.

FIGURE 4.1. Effectiveness difference in "user query variation" fusion using the fusion methods described in Table 4.1.

TABLE 4.4. Effectiveness comparisons for all fusion methods for both collections using BM25 with all query variations. Wins and Losses are computed when the score is 10% greater or less than the BM25 baseline on the original title-only topic run.

| System | Robust04 | | | ClueWeb12B | | |
|---|---|---|---|---|---|---|
| | AP | Wins | Losses | NDCG@10 | Wins | Losses |
| Borda | 0.311 ‡ | 148 | 49 | 0.235 | 55 | 32 |
| CombMNZ | 0.327 ‡ | 149 | 44 | 0.258 ‡ | 55 | 24 |
| CombSUM | 0.331 ‡ | 153 | 38 | 0.258 ‡ | 52 | 24 |
| ISR | 0.264 | 92 | 78 | 0.165 † | 29 | 50 |
| logISR | 0.267 | 99 | 75 | 0.199 | 41 | 38 |
| RRF | 0.331 ‡ | 156 | 39 | 0.263 ‡ | 59 | 21 |
| RBC,$\phi = 0.90$ | 0.306 ‡ | 140 | 67 | 0.250 † | 55 | 21 |
| RBC,$\phi = 0.95$ | 0.314 ‡ | 144 | 64 | 0.257 ‡ | 52 | 20 |
| RBC,$\phi = 0.98$ | 0.323 ‡ | 151 | 45 | 0.260 ‡ | 52 | 21 |
| RBC,$\phi = 0.99$ | 0.326 ‡ | 153 | 44 | 0.260 ‡ | 60 | 24 |

all of the tested configurations for all of the evaluation metrics. The authors also observed the "consistency" of query variations, where consistency was defined as how consistently different query variants returned the same documents, relative to each other using Rank-Biased Overlap [79]. Inspired by the encouraging retrieval effectiveness exhibited over query fusion in their work, we extend the exploration to risk-reward trade-offs in both system fusion and query fusion.

In Figure 4.1, the effectiveness profiles of a query fusion for all variants where runs are formed using BM25 is shown. Despite significant improvements in overall effectiveness, fusion is still susceptible to performance degradation in both newswire and web data, where $\approx 70\%$ of queries show improvement over a BM25 baseline, but the remaining $\approx 30\%$ are worse. This is a well-known problem in query expansion [11] and even sequential dependency models [45], but is generally ignored. From Figure 4.1a and 4.1b, we see that most rank fusion methods are behaving with a similar profile — with the exception of ISR and logISR which performs less effectively than all others, and Borda does not appear to be operating with the same risk-sensitivity as CombMNZ, CombSUM, RBC $\phi = 0.99$ and RRF on the ClueWeb12B collection.

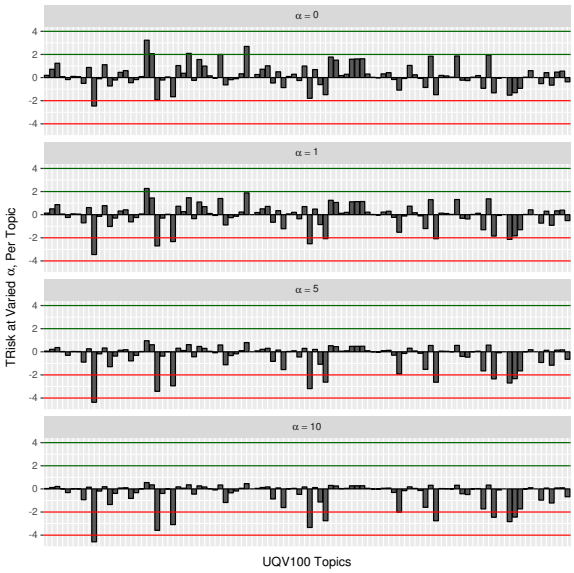
Table 4.4 lists the overall retrieval effectiveness for each of these methods, where RRF is shown to be marginally more effective than other methods surveyed in their current parameterized form. All of the methods outperform a single query baseline, but incur risk. That is, a reasonable number of queries in both collections are at least 10% worse than the baseline. When wins and losses are counted as deviations 10% more or less than the per-topic baseline score, we observe that RRF incurs fewer losses than any other surveyed method for BM25 query fusion. In theory, RBC is a more general method that RRF, but RRF performs very well when using untuned parameters. Our overarching goal in this work is to maintain these effectiveness gains, but at the same time minimising the likelihood of losses.

TABLE 4.5. Risk-reward comparisons for all fusion methods for both collections using BM25 with all query variations. Significant TRisk scores are marked in bold.

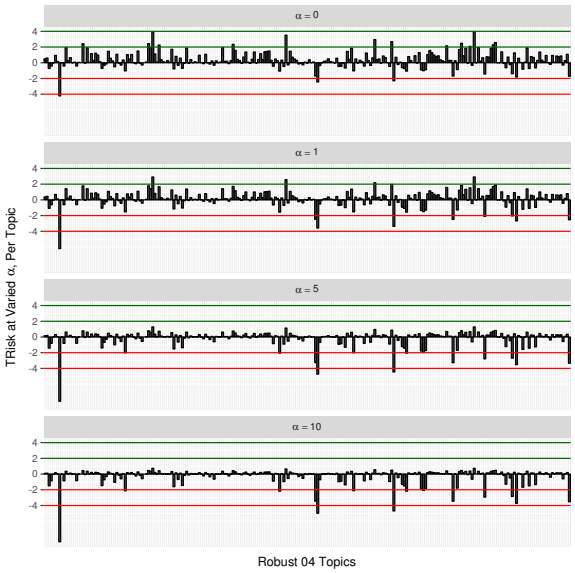
| System | $\alpha = 0$ | | | $\alpha = 1$ | | | $\alpha = 5$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | $U_{Risk}$ | $T_{Risk}$ | $p$-value | $U_{Risk}$ | $T_{Risk}$ | $p$-value | $U_{Risk}$ | $T_{Risk}$ | $p$-value |
| Robust04 | | | | | | | | | |
| Borda | 0.057 | **6.788** | $< 0.001$ | 0.035 | **3.054** | 0.003 | -0.054 | **-2.060** | 0.040 |
| CombMNZ | 0.073 | **8.142** | $< 0.001$ | 0.055 | **4.980** | $< 0.001$ | -0.016 | -0.712 | 0.477 |
| CombSUM | 0.077 | **8.772** | $< 0.001$ | 0.062 | **5.801** | $< 0.001$ | 0.000 | 0.006 | 0.995 |
| ISR | 0.010 | 1.094 | 0.275 | -0.028 | **-2.046** | 0.042 | -0.180 | **-5.408** | $< 0.001$ |
| logISR | 0.013 | 1.407 | 0.161 | -0.023 | -1.765 | 0.079 | -0.165 | **-5.294** | $< 0.001$ |
| RRF | 0.077 | **8.817** | $< 0.001$ | 0.062 | **5.833** | $< 0.001$ | 0.001 | 0.023 | 0.982 |
| RBC $\phi = 0.90$ | 0.052 | **5.729** | $< 0.001$ | 0.026 | **2.179** | 0.030 | -0.080 | **-3.220** | 0.001 |
| RBC $\phi = 0.95$ | 0.060 | **6.724** | $< 0.001$ | 0.038 | **3.334** | 0.001 | -0.053 | **-2.308** | 0.022 |
| RBC $\phi = 0.98$ | 0.069 | **7.662** | $< 0.001$ | 0.050 | **4.513** | $< 0.001$ | -0.026 | -1.217 | 0.225 |
| RBC $\phi = 0.99$ | 0.072 | **8.104** | $< 0.001$ | 0.054 | **4.950** | $< 0.001$ | -0.018 | -0.851 | 0.396 |
| ClueWeb12B | | | | | | | | | |
| Borda | 0.023 | 1.625 | 0.107 | -0.019 | -0.912 | 0.364 | -0.189 | **-3.583** | 0.001 |
| CombMNZ | 0.046 | **3.792** | $< 0.001$ | 0.022 | 1.391 | 0.167 | -0.074 | **-2.229** | 0.028 |
| CombSUM | 0.046 | **3.867** | $< 0.001$ | 0.024 | 1.551 | 0.124 | -0.066 | **-2.091** | 0.039 |
| ISR | -0.046 | **-2.698** | 0.008 | -0.128 | **-4.432** | $< 0.001$ | -0.457 | **-5.773** | $< 0.001$ |
| logISR | -0.012 | -0.725 | 0.470 | -0.074 | **-2.661** | 0.009 | -0.319 | **-4.314** | $< 0.001$ |
| RRF | 0.051 | **4.156** | $< 0.001$ | 0.031 | 1.987 | 0.050 | -0.050 | -1.573 | 0.119 |
| RBC $\phi = 0.90$ | 0.037 | **3.414** | 0.001 | 0.018 | 1.165 | 0.247 | -0.068 | **-2.079** | 0.040 |
| RBC $\phi = 0.95$ | 0.045 | **3.988** | $< 0.001$ | 0.027 | 1.914 | 0.057 | -0.045 | -1.552 | 0.124 |
| RBC $\phi = 0.98$ | 0.049 | **4.063** | $< 0.001$ | 0.030 | 1.994 | 0.049 | -0.047 | -1.590 | 0.115 |
| RBC $\phi = 0.99$ | 0.049 | **4.081** | $< 0.001$ | 0.028 | 1.812 | 0.073 | -0.057 | -1.810 | 0.073 |

Table 4.5 provides another angle for the observation of query fusion risk-reward payoff using the TRisk evaluation metric. Where $\alpha = 0$, this represents an ordinary pairwise two-tailed t-test. We observe that in all cases across all collections, except for logISR and ISR, that the fusion methods are significantly improving the baseline, where t-values above 2 indicate no significant risk of harm. When the impact of losses is penalized twofold on Robust04 ($\alpha = 1$), the same positive result applies. For ClueWeb12B, however, no query fusion methods are able to pass a t-test. When $\alpha = 5$, the only certainty for most rank fusion methods is that the baseline score will be significantly harmed. The RRF rank fusion method exhibits the greatest risk-sensitivity in almost all situations across both document collections, with the exception of $\alpha = (1, 5)$ on ClueWeb12B where RBC $\phi = (0.98, 0.95)$ is marginally better.

Despite achieving commendable evaluation scores over different retrieval metrics, there are effectiveness risks to a sizable minority of topics where a simple BM25 single query run would have been more effective. In order to understand whether these risks are endemic to query fusion, or are latent in retrieval methods more generally, we first compare the risks with choosing one retrieval model over another, issuing a single query. When a single query BM25 run is formed using the most frequently




(A) SDM+Fields vs. BM25 on ClueWeb12B using the most frequently submitted query variation per topic ($v = 1$) in the UQV100 test collection.




(B) BM25+QE vs. BM25 on Robust04 using the Robust title-query.

FIGURE 4.2. Rolling the dice: Although the aggregate scores can show improved effectiveness, significantly harming the baseline is possible for a subset of topics when only using a single system.

| Topic ID | ⇑ / ⇓ | Title Query |
|---|---|---|
| 210 | ⇓ | `golf gps` |
| 220 | ⇑ | `nba records` |
| 221 | ⇑ | `electoral college 2008 results` |
| 228 | ⇑ | `hawaiian volcano observatories` |
| 239 | ⇑ | `frank lloyd wright biography` |

(A) ClueWeb12B

| Topic ID | ⇑ / ⇓ | Title Query |
|---|---|---|
| 308 | ⇓ | `implant dentistry` |
| 352 | ⇑ | `british chunnel impact` |
| 430 | ⇓ | `killer bee attacks` |
| 616 | ⇓ | `volkswagen mexico` |
| 654 | ⇑ | `same-sex schools` |

(B) Robust04

TABLE 4.6. List of topics Figure 4.2 is able to statistically significantly change the risk where TRisk $\alpha = 0$. An up arrow indicates no significant risk to the baseline, conversely a down arrow indicates risk of harming the baseline.

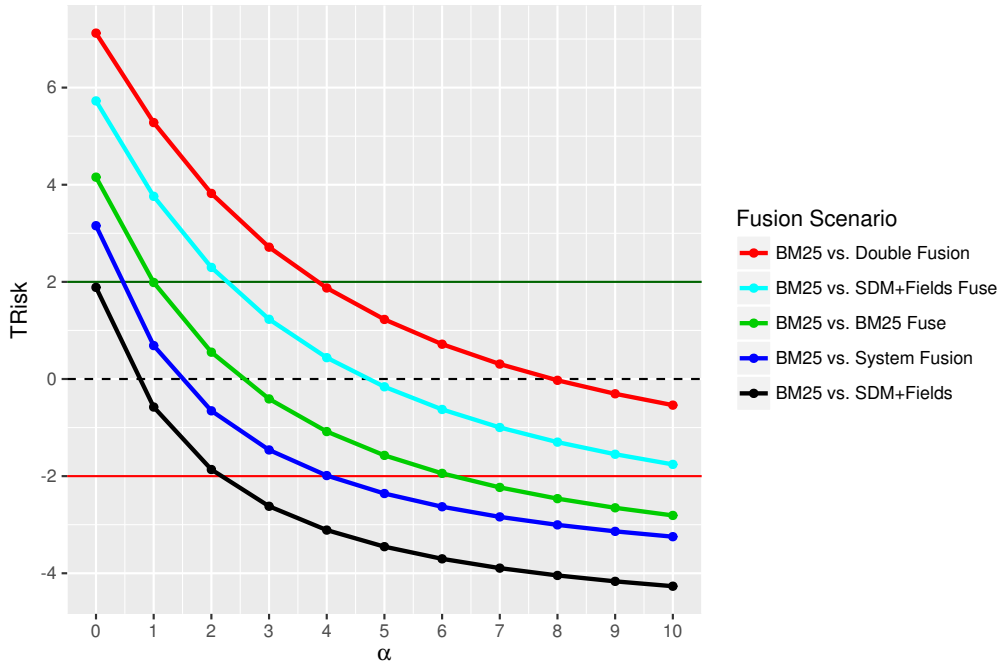
submitted query variant in the UQV100 test collection on the ClueWeb12B corpus, the NDCG@10 aggregate score is 0.212. When issuing the same query to a more effective sequential dependency model weighted for terms occurring in different fields in a web document, the NDCG@10 aggregate across all topics is 0.233. Despite the improved score, it is not significant (p-value = 0.06). However, although a global inference could not be made, a small subset of topics are shown in Figure 4.2 that demonstrate no chance of damaging the baseline effectiveness, or significantly damaging the baseline score.

Figure 4.2a shows the TRisk per-topic profile for SDM+Fields compared against BM25 on the ClueWeb12B corpus. When $\alpha = 0$, topics 220, 221, 228 and 239 all show no harm to the baseline, conversely, topic 210

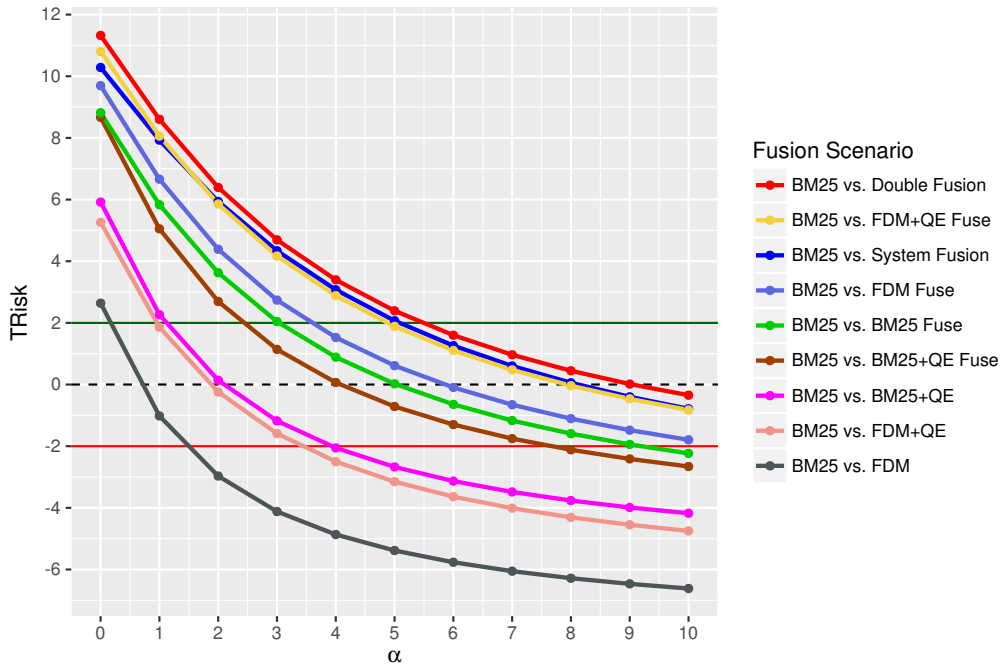
has significant TRisk. As the $\alpha$ value increases, only topic 220 is shown to operate with risk-sensitivity compared to the baseline, while more topics experience statistically significant loss. Figure 4.2b, shows a similar story for pseudo-relevance feedback on BM25 using Robust04. While many topics show no chance of harm, the most significant of which; topics 352 and 654 — topics 308, 430 and 616 harm the baseline BM25 effectiveness over a 95% confidence interval. Table 4.6a shows the raw query submitted to the system for the above topics, and their statistically significant help or harm indicated by the arrows. As the impact of losses is scaled twofold, many topics are still showing significant improvement over the baseline — a testament to the strength of pseudo-relevance feedback when no query drift has a occurred, and previously observed by Zighelnic and Kurland [87]. But for every topic still showing no harm, the amount of topics showing significant harm has doubled. This situation illustrates the need to diversify the retrieval methods employed in a system if it is to behave with risk-sensitivity, as one retrieval model's weaknesses is another model's strength [43].

In order to show this, we used RRF to fuse all system variations together, where each system's effectiveness with per-topic wins and losses is documented in the top-half of Table 4.7 and 4.8. When fusing all Robust04 system variations, an AP score of 0.286‡ is achieved, where 142 topics are improved and 21 are worsened with respect to the baseline. By observing the wins and losses columns in Table 4.7 showing system variations, and Table 4.4 showing BM25 query fusion, we observe that 21 losses is significantly less than other methods, despite the aggregate score in the fused run being lower than BM25+QE alone. The second-smallest number of losses is incurred with query fusion, in all, totalling 39 topics. Over ClueWeb12B, we fused only SDM+Fields and BM25 together. The fused result has an NDCG@10 score of 0.235†, with 55 wins and 32 losses. This is a marginally better aggregate score than SDM+Fields, however now 10 additional topics are achieving better scores with no relative loss. BM25 query fusion outperforms system fusion in both aggregate score, and risk-sensitivity; where RRF is able to achieve an NDCG@10 score of 0.263‡ with 21 losses.

There are two important observations to be gleaned in this section. We show that query fusion exhibits a risk-reward trade-off when compared to a single query, and that rank fusion can improve the risk-reward payoff — compared to independent retrieval systems and in Robust04's case, query fusion. In the next section, we observe the risk-reward payoff of query fusion when undertaken in the presence of multiple systems. Further, we explore whether *double fusion* of system and query variations is additive, and try to determine if it changes the balance of risk and reward.




(A) All query variants vs. BM25 on ClueWeb12B using the most frequently submitted query variation per topic ($v = 1$) in the UQV100 test collection as the benchmark.




(B) All query variants vs. BM25 on Robust04 using the original Robust title-queries as the benchmark.

FIGURE 4.3. The TRisk risk-reward profiles for all fusion technique combinations used in this study. All runs were fused using RRF.

TABLE 4.7. Effectiveness comparisons for all retrieval models on Robust04 using BM25 as a baseline. Wins and Losses are computed when the score is 10% greater or less than the BM25 baseline on the original title-only topic run.

| System | AP | Wins | Losses |
|---|---|---|---|
| BM25 | 0.254 | - | - |
| BM25+QE | 0.292 ‡ | 130 | 62 |
| FDM | 0.264 † | 86 | 66 |
| FDM+QE | 0.275 ‡ | 102 | 46 |
| BM25+Fuse | 0.331 ‡ | 156 | 39 |
| BM25+QE+Fuse | 0.340 ‡ | 166 | 41 |
| FDM+Fuse | 0.336 ‡ | 171 | 34 |
| FDM+QE+Fuse | 0.349 ‡ | 174 | 32 |

TABLE 4.8. Effectiveness comparisons for all retrieval models on ClueWeb12B using BM25 as a baseline. Wins and Losses are computed when the score is 10% greater or less than the BM25 baseline on the original title-only topic run.

| System | NDCG@10 | Wins | Losses |
|---|---|---|---|
| BM25 | 0.212 | - | - |
| SDM+Fields | 0.233 | 45 | 32 |
| BM25+Fuse | 0.263 ‡ | 59 | 21 |
| SDM+Fields+Fuse | 0.294 ‡ | 65 | 18 |

## 4.4 Reducing Query Fusion Risk with Retrieval Models

In the previous section, we showed that query variation fusion over BM25 exhibits a risk-reward trade-off, when juxtaposed against its initial query variant BM25 counterpart. In this section, we take methods known to improve the retrieval effectiveness, and apply them to query variant runs.

Observe in the bottom-half of Table 4.7 and 4.8, the properties of query fusion runs formed using RRF over different retrieval systems. Table 4.7 shows query fusion on the Robust04 corpus using the TREC CORE 2017 query variants. A significant boost in retrieval effectiveness in query fusion is shown to be possible by using more effective systems. FDM+QE+Fuse is the best performing query fusion run. Surprisingly, in a title-only situation the aggregate score for BM25 with pseudo-relevance feedback was greater than FDM with query expansion. However, in a query fusion scenario, FDM with pseudo-relevance feedback is more effective than BM25+QE. The reasoning behind this unclear — one hypothesis could be that FDM is able to perform significantly better with more terms, and query variations tend to be more verbose than the original title queries. We leave the analysis of this phenomena to future work. Also of interest in Table 4.7 are the wins and losses columns. As the query fusion method becomes more effective, there are fewer losses and more wins — rather than a case where there are

more ties or a change only on one side of the risk-reward trade-off. Indeed, this observation is reflected in Table 4.8, albeit on a small sample. Drawing our attention back to the previous section where we performed a system fusion over Robust04, the system fused run incurred a loss over 32 queries when compared to a BM25 title run. Here, we see that FDM+QE+Fuse is able to incur the same number of losses, but with a significantly greater AP effectiveness of 0.349‡.

**Double Fusion**. Double fusion is the process of taking query variation runs generated by multiple systems, and performing a single rank fusion over them all to retrieve a result set with improved precision and recall. In a double fusion over the Robust04 query/system combinations, an AP score of 0.354‡ is achieved with 183 wins and 25 losses using RRF. Similarly for ClueWeb12B, an NDCG@10 score of 0.300‡ is attained, with 71 wins and 10 losses. Figure 4.3 displays the risk-reward profile of double fusion, in the context of all system configurations discussed in this paper — where all fusion methods are generated using RRF. For ClueWeb12B in Figure 4.3a, double fusion is a clear winner when evaluated using the TRisk measure. Remarkably, when $\alpha = 3$, that is the impact of losses is quadrupled, the double fusion method is improving a BM25 baseline with statistical significance on a Student t-test. In contrast, quadrupling the losses incurred on a SDM+Fields run would result in significant harm to the baseline. In Figure 4.3b, the risk-reward payoff of double fusion follows a similar curve to the most effective risk-reward trade-off previously discovered over system fusion. Here we show that even with an $\alpha = 5$, Robust04 double fusion is still able to show a strongly positive risk-reward trade-off relative to the baseline.

## 4.5 Failure Analysis

In Table 4.5 observe that RRF exhibits greater risk-sensitivity than CombSUM on the Robust04 collection over the TRisk measure. However, the effectiveness aggregate score in Table 4.4 indicates that both of these fusion methods have equal effectiveness. To get a more granular idea of measurement in the risk-reward measure, we reduce the threshold of the win-tie-loss calculation from 10% to a fixed, very small value of $\Delta 0.025$, to capture tie information. Table 4.9 captures these finer details. We observe that although CombSUM appears to win on one more topic in the absolute wins count, it experiences significantly more summative loss across all topics. This therefore provides evidence of correctness of the TRisk implementation.

It is worth noting that our double fusion run on the Robust04 collection has an AP effectiveness comparable to the best known run on this collection – `pircRB04td2`. Our system is statistically significantly better than this run for P@10 (0.550 vs 0.541). To explore whether reducing the amount of query variations fused helps improve the retrieval performance, we make use of the UQV100 corpus and

TABLE 4.9. Wins, ties and losses for each fused system over TREC Core 2017 variation runs built with BM25 on the Robust04 corpus, when compared against BM25 Robust title queries, using AP@1000. Scores are tied for AP@1000 $\Delta \pm 0.025$, and ignored in the $\sum Win$ and $\sum Loss$ columns.

| | $AP_{1000}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Fusion Method | Score | Win | Tie | Loss | $\frac{Win}{Loss}$ | $\sum Win$ | $\sum Loss$ | $\frac{\sum Win}{\sum Loss}$ |
| Borda | 0.311 | 144 | 59 | 46 | 3.130 | 49.932 | 12.132 | 4.116 |
| CombMNZ | 0.327 | 151 | 55 | 43 | 3.512 | 54.307 | 13.343 | 4.070 |
| CombSUM | 0.331 | 152 | 57 | 40 | 3.800 | 54.573 | 12.783 | 4.269 |
| ISR | 0.264 | 78 | 97 | 74 | 1.054 | 26.605 | 17.321 | 1.536 |
| logISR | 0.267 | 83 | 95 | 71 | 1.169 | 27.528 | 16.975 | 1.622 |
| RRF | 0.331 | 151 | 59 | 39 | 3.872 | 54.667 | 11.839 | 4.618 |
| RBC $\phi = 0.90$ | 0.250 | 47 | 31 | 22 | 2.136 | 13.304 | 6.484 | 2.052 |
| RBC $\phi = 0.95$ | 0.257 | 43 | 38 | 19 | 2.263 | 13.509 | 5.259 | 2.569 |
| RBC $\phi = 0.98$ | 0.260 | 46 | 34 | 20 | 2.300 | 14.153 | 6.534 | 2.166 |
| RBC $\phi = 0.99$ | 0.260 | 53 | 25 | 22 | 2.409 | 14.986 | 6.590 | 2.274 |

Common Baseline: 0.254

ClueWeb12B as we can bias the inclusion of query variations by their duplicate counts. The TREC CORE variants do not have enough duplicate variants in order to explore this thoroughly, limiting our investigation. As shown in Figure 4.4, across most $\alpha$ values fusing all query variations gives the most risk-sensitivity compared to a BM25 baseline. A detailed analysis of the effectiveness for each number of query variations fused is available in Appendix A.1.

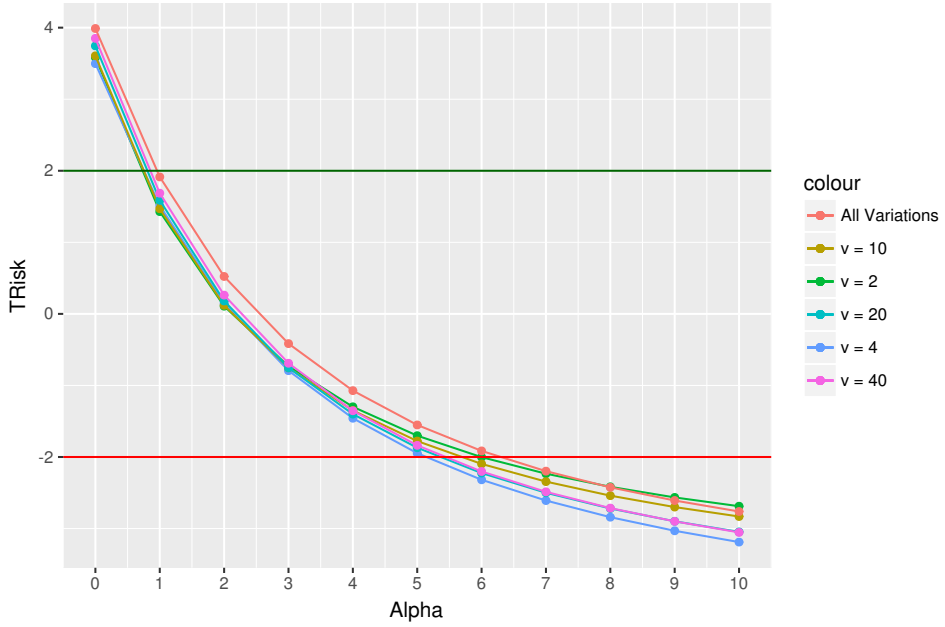
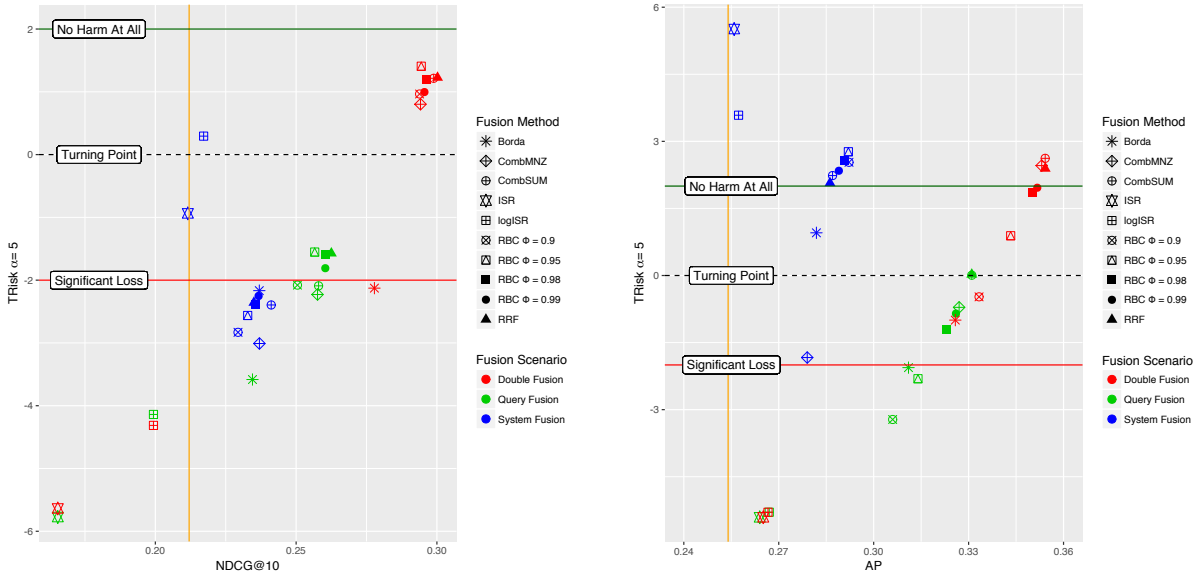



FIGURE 4.4. Risk-reward payoff when fusing queries by number of duplicates using RRF, the UQV100 test collection on the ClueWeb12B corpus.




(A) ClueWeb12-B (B) Robust04

FIGURE 4.5. Effectiveness vs. Risk-Reward payoff over all fusion methods for all fusion scenarios. Yellow line indicates the baseline effectiveness score to be improved.

## 4.6 Conclusion

To summarize our findings, Figure 4.5 displays all fusion methods over the main fusion scenarios investigated: fusion over system variations, query fusion using BM25, and double fusion. Figure 4.5a shows that both query fusion and system fusion exhibit a similar degradation in performance, however Figure 4.5b shows that system fusion can exhibit a similar risk-reward profile with that of double fusion. We show that both system fusion and query fusion are both susceptible to query performance degradation, as TRisk scores in Figure 4.5a are below zero. However, we find in Figure 4.5b that perhaps system fusion is less volatile than query fusion at harming the risk-reward payoff — tentatively answering **S-RQ1**. Figure 4.5 also shows that system-based and query-based rank fusion methods are able to achieve the best risk-reward trade-off using double fusion out of all methods studied, where the top-right-most cluster of rank fusion methods is shown in both effectiveness vs. TRisk graphs across Robust04 and ClueWeb12B — answering **S-RQ2**.

CHAPTER 5

# Conclusions and Future Work

## 5.1 Increasing Recall with Fusion

We coalesce the results of observing fusion over different retrieval models, query variants on the same system, and "double fusion" over both— finding that in all cases recall is improved. We measure the improvement of recall through the strong participation of our TREC fusion run against our automatic baseline without fusion— showing a marked improvement in the number of uniquely relevant documents extracted. Another source of evidence is the significantly higher AP measures of the fused runs against our single-shot "best" title queries submitted to the TREC track, where AP has been shown to be a recall-sensitive evaluation measure. From our results, system fusion offered the least improvement, where query fusion markedly improves recall and double fusion performs best overall.

## 5.2 Risk-sensitivity Of Each Fusion Scenario

Our results show that double fusion exhibits the most risk-sensitivity. For ClueWeb12B, when the impact of losses is increased fourfold on double fusion it still passes a paired t-test indicating the harm is statistically insignificant. When compared to a system fusion without any query fusion, there's a statistically significant chance of harm. A similar result is exhibited on the Robust04 collection. This result provides confident use of double fusion, as prior to having conducted this research it was unclear if it was making some topics perform very well at the expense of many others.

## 5.3 Future Work

In future work, we aim to apply query fusion and double fusion to a candidate generation stage in a Multi-stage retrieval system— and answer the question should fusion occur before a learning-to-rank stage, or after? However, many questions remain unanswered from our approach. In the CORE submission, we were able to find a method for selecting the top 5 query variations using the relevance assessments, however, this is impractical in a real system. Using post-retrieval features like Clarity may

enable us to more robustly understand how many queries we should be fusing rather than selecting a top 5 or naively fusing all queries, and under which per-topic conditions should we do so.

An anonymous reviewer of Chapter 4 questions the applicability of double fusion, stating that a single and better query could potentially be built using the query variation set without using rank fusion. This is an excellent recommendation for exploration of future work, alongside understanding the efficiency considerations involved in issuing queries to multiple systems vs. a large one-shot query. Indeed, for the full-dependency retrieval model when the number of keywords in a query is greater than 15 in our experience, it becomes an intractable search. An efficiency-effectiveness exploration in this domain would, therefore, be of significant benefit in justifying the use of query fusion, and double fusion by extension.

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APPENDIX A

# Appendix

TABLE A.1. Analysis of varying the number of query variations fused, biasing the fusion by the most amount of duplicate queries submitted to least using RBC. Wins, ties and losses for each fused system over UQV100 variation runs built with BM25 on the ClueWeb12B corpus, when compared against a BM25 single query variation with the most duplicates, using NDCG@10. Scores are tied for NDCG@10 $\Delta \pm 0.025$, and ignored in the $\sum Win$ and $\sum Loss$ columns.

| NDCG@10 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Fusion Method | Score | Win | Tie | Loss | $\frac{Win}{Loss}$ | $\sum Win$ | $\sum Loss$ | $\frac{\sum Win}{\sum Loss}$ |
| RBC $\phi = 0.90$ | 0.228 | 35 | 47 | 18 | 1.944 | 10.007 | 4.029 | 2.484 |
| RBC $\phi = 0.95$ | 0.233 | 40 | 42 | 18 | 2.222 | 10.916 | 3.923 | 2.783 |
| RBC $\phi = 0.98$ | 0.239 | 43 | 41 | 16 | 2.688 | 11.629 | 3.433 | 3.388 |
| RBC $\phi = 0.99$ | 0.244 | 44 | 40 | 16 | 2.750 | 12.496 | 3.529 | 3.541 |

(A) $v = 2$

| NDCG@10 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Fusion Method | Score | Win | Tie | Loss | $\frac{Win}{Loss}$ | $\sum Win$ | $\sum Loss$ | $\frac{\sum Win}{\sum Loss}$ |
| RBC $\phi = 0.90$ | 0.231 | 37 | 42 | 21 | 1.762 | 10.307 | 6.269 | 1.644 |
| RBC $\phi = 0.95$ | 0.236 | 38 | 39 | 23 | 1.652 | 9.685 | 6.554 | 1.478 |
| RBC $\phi = 0.98$ | 0.238 | 38 | 40 | 22 | 1.727 | 10.778 | 7.446 | 1.447 |
| RBC $\phi = 0.99$ | 0.246 | 43 | 36 | 21 | 2.048 | 11.890 | 6.945 | 1.712 |

(B) $v = 4$

| NDCG@10 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Fusion Method | Score | Win | Tie | Loss | $\frac{Win}{Loss}$ | $\sum Win$ | $\sum Loss$ | $\frac{\sum Win}{\sum Loss}$ |
| RBC $\phi = 0.90$ | 0.241 | 43 | 36 | 21 | 2.048 | 11.370 | 5.680 | 2.002 |
| RBC $\phi = 0.95$ | 0.250 | 48 | 31 | 21 | 2.286 | 14.181 | 5.836 | 2.430 |
| RBC $\phi = 0.98$ | 0.255 | 48 | 34 | 18 | 2.667 | 13.777 | 5.883 | 2.342 |
| RBC $\phi = 0.99$ | 0.253 | 51 | 29 | 20 | 2.550 | 14.806 | 5.899 | 2.510 |

(C) $v = 10$

| NDCG@10 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Fusion Method | Score | Win | Tie | Loss | $\frac{Win}{Loss}$ | $\sum Win$ | $\sum Loss$ | $\frac{\sum Win}{\sum Loss}$ |
| RBC $\phi = 0.90$ | 0.250 | 45 | 31 | 24 | 1.875 | 12.658 | 6.847 | 1.849 |
| RBC $\phi = 0.95$ | 0.252 | 45 | 33 | 22 | 2.045 | 12.941 | 7.104 | 1.822 |
| RBC $\phi = 0.98$ | 0.260 | 47 | 31 | 22 | 2.136 | 13.713 | 7.031 | 1.950 |
| RBC $\phi = 0.99$ | 0.264 | 55 | 23 | 22 | 2.500 | 16.187 | 5.862 | 2.762 |

(D) $v = 20$

| NDCG@10 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Fusion Method | Score | Win | Tie | Loss | $\frac{Win}{Loss}$ | $\sum Win$ | $\sum Loss$ | $\frac{\sum Win}{\sum Loss}$ |
| RBC $\phi = 0.90$ | 0.248 | 47 | 31 | 22 | 2.136 | 13.376 | 6.143 | 2.177 |
| RBC $\phi = 0.95$ | 0.254 | 46 | 33 | 21 | 2.190 | 14.054 | 5.707 | 2.462 |
| RBC $\phi = 0.98$ | 0.259 | 48 | 31 | 21 | 2.286 | 14.340 | 6.738 | 2.128 |
| RBC $\phi = 0.99$ | 0.258 | 54 | 23 | 23 | 2.348 | 15.433 | 6.752 | 2.286 |

(E) $v = 40$