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A Study on Ranking Fusion Approaches for the Retrieval of Medical Publications

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Dedicated to all the people that I care about.

Abstract

In this work we wanted to compare and analyze a variety of approaches in the task of Medical Publications Retrieval. We used state-of-the-art models and weighting schemes with different types of preprocessing as well as applying query expansion (QE) and relevance feedback (RF) in order to see how much the results improve. We also tested three different Fusion approaches to see if the merged runs perform better than the single models. We found that query expansion and relevance feedback greatly improve the performance while by fusing the runs of different models the gain is not significant. We also conducted statistical analysis of the runs and found that by applying QE+RF, the performance of the system does not depend much on which type of preprocessing is used but on which weighting scheme is applied.

Sommario

In questo lavoro abbiamo comparato e analizzato una varietà di approcci nel *task* di reperimento di pubblicazioni medicali. Abbiamo usato modelli e schemi di pesatura allo stato dell'arte con diversi tipi di pre elaborazione così come applicando query expansion (QE) e relevance feedback (RF) per vedere quanto è il beneficio di applicare questi approcci. Abbiamo anche testato tre metodi diversi di fusione per vedere se le *run* così ottenute hanno prestazioni superiori alle *run* ottenute da un singolo modello. Abbiamo scoperto che query expansion e relevance feedback migliorano sensibilmente le prestazioni mentre il guadagno ottenuto dalla fusione di modelli diversi non è significativo. Abbiamo anche condotto analisi statistiche sulle *run* e abbiamo trovato che applicando QE+RF, le prestazioni del sistema non dipende dal tipo di pre elaborazione usata ma risulta strettamente legata a quale schema di pesatura viene applicato.

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1 Introduction

Information Retrieval (IR) is research area that has seen a massive growth in interest together with the growth of the internet: since the number of sites and documents began to increase, there was, and there still is, a need to be able to search for information on the web. Google, one of the largest and most famous tech company worldwide, has shown how important this field is.

However, IR is not a new field of research, in fact it existed almost since the dawn of the computers. The term was coined by Mooers in the 1950s:

> Information retrieval is the name of the process or method whereby a prospective user of information is able to convert his need for information into an actual list of citations to documents in storage containing information useful to him [1].

The field of IR draws its origins from the libraries. When a new book or article was to be added to a library, a librarian would have to compile, manually, a card and store it. On the card was written typically title of the document, author, year of publication and the location in the library. Some libraries wrote also some key-words on the cards about the document to aid the user or the librarian in judging if the document was relevant or not to the area of interest.

This method works reasonable well on small collections but as library collections increased it soon became clear that more sophisticated methods were necessary.

With the explosion of the computers and the World Wide Web, the catalogues had to be converted in digital form, providing faster access to the collection. The retrieval was, however, still done by means of *data retrieval* rather than *information retrieval* which means that searches were done based on information *about* the documents and not on the *content* of the books.

To be able to search based on the content, it was necessary to develop a method for computers to be able to store information about the text of every document in the collection and then to retrieve the IDs of the books and articles relevant to the query of the user.

Following the growth in performance of the computers and the development of ways to store data and retrieve it from memory, like databases, the field of IR acquired increasingly importance in the computer science world, which culminated with the explosion of the *world wide web*.

IR systems can nowadays store *hundreds* of billions of documents, which not necessarily are composed only by text, but also by images, audios, videos etc and are able to retrieve *millions* of relevant results to a query in fractions of seconds [2].

The typical IR system allows the user to compose a *query* which is normally formed by one or more words that somehow describe the information need. The words of the query are then used to classify every document in the collection either by relevant/non-relevant or by assigning to each a score that should represent the likelihood of the document to be relevant for the query.

One of the first systems represented the query in a Boolean way, which means that the words of the query were combined by Boolean operators like *AND*, *OR* or *NOT*. Many IR systems use still today this system of specifying which terms should be present or not in the documents retrieved, one example is *PUBMED* * which is an online search tool for biomedical literature. Most common search engines today, however, allow users to express queries my means of *phrases*, just think of how you search on Google.

Usually, an IR system output is composed by a list of of documents from the collection, ranked by their score to the query. The goal of every IR model is to retrieve as many relevant documents as possible, while retrieving as few non-relevant documents as possible.

Over the years, numerous approaches to IR have been proposed and developed. Some share some similarities, some are completely different from each other. They can be different on how they represent a document, on which algorithm they apply to rank the results, on which steps and in what order to apply the preprocessing of the collection and so on [3].

*https://www.ncbi.nlm.nih.gov/pubmed

1.1 Research questions

The goal of the work is to find what is the best approach when dealing with the retrieval of medical documents. This brings to the three research questions that this work tries to answer:

1. **RQ1**: is there a single model that stands out in terms of performance?
2. **RQ2**: does the use of query expansion and relevance feedback improve the results?
3. **RQ3**: is there a fusion method that does better retrieval than using a single model?

With **RQ1** we wanted to explore the possibility that a model could do better than the others with different setups, as explained later in section 3.2.1. Since query expansion and relevance feedback usually give an increase of the performance of a IR system, we wanted to test if this was the case also in our task, thus with **RQ2** we wanted to verify this assumption. Finally, given the reasons of data fusion that we explain in section 2.5, with **RQ3** we compared the single model runs with different kinds of fusions to see if there is actually a gain in doing them.

1.2 Thesis overview

The thesis is organized as follows: in chapter 2 we explain how each of the models and fusions used in the thesis work and how they are able to rank the documents. We also introduce the measures used to compare the *runs* in the thesis and how to compute them; chapter 3 presents the experiments and the experimental setting used to study the research questions; in chapter 4 and 5 we first present the results then we analyze them answering the research questions; finally in chapter 6 we wrap up all the work done and give our final remarks.

2

Background

In this chapter we describe the models used in this manuscript, how they work, how they use the query to rank the documents in the collection.

Traditionally, one way to find out if a document may be relevant with respect to a certain query is to count how many times the words that compose the query appear in the document. Intuitively, if a document deals with a certain topic, then is very likely that the word which describes the argument is present more than once.

To make an example, let us assume that we are interested in the following query: 'tropical fish'. Then, a document to be relevant to this query, should at least contain once these two words otherwise it's very unlikely that it could be relevant.

This approach, proposed by Luhn [4], is very simple, yet very powerful. Many models exploit this property, incorporating the *term frequency* in their formula that computes the scores of the documents.

Term frequency alone, however, could not be sufficient. If a document is composed by more than a few paragraphs, then some words will have a very high count without telling much about the topic of the document. These words are, for example, prepositions that do not distinguish a document from another, since both will contain a high frequency of the same words. At the other side of the spectrum, words that are present just once in the document might not be very useful as well, since they may be spelling errors or words that do not possess enough *resolving power*.

The *resolving power* of a word was defined by Luhn [4] and is the ability of a word to identify and distinguish a document from another.

Consequently, in the case of IR systems, may be useful to do some preprocessing of the documents during the indexing of the collection. Queries should also go through the same processing.

There exist two main approaches to remove the words that do not possess enough resolving power from a document. The first one is through statistical analysis. Since the most and the least repeated words are not likely to hold discriminative power, it is sufficient to establish a low and high frequency of cutoff: words that appear more or less than the cutoffs are removed from the document. This approach works well since the cutoffs can be tuned based on the collection, however it is not easy to find the best values and may be necessary to go through a long process of tuning. A second approach is by using a word list, which takes the name of *stop-list* of the most frequent words and then use it to remove those words from the documents of the collection [5]. This approach is faster since it does not require any tuning and works well in practice, it's the approach that has been used in the thesis.

One of the problems of the approach seen so far is that it counts words twice only if they are *exact* matches. So if a word appears in it's singular and plural forms they are counted as two different words. This is just an example that highlights the fact that a natural language can be very expressive and thus the same concept can be communicated in many ways with different words that usually share a common *root* from which they derive.

With this observation in mind, Lovin [6] developed the first algorithmic *stemmer* which is a program able to bring a word to its root and thus increasing the probability of repeated words.

The most famous and used stemmer, however, is the one developed by Porter [7] in 1980 and is the one used in this thesis during the phase of *stemming* of the documents.

2.1 TF-IDF weighting

TF-IDF is a statistic used as weighting scheme in order to produce the score by which to order the documents of a collection given a query.

This score can be computed in different ways, the simplest one being *summing* all the *TF-IDF* of the terms that compose the query.

This statistic is composed by two parts, one being the *term frequency* which has been dis-

cussed in the previous section and the *inverse document frequency* or *idf* for short.

IDF it's based on the concept that words that occur in all of the documents in a collection do not possess much resolving power, thus their weight should be inferior with respect to the weight of a word that appears only in one document and not in the others.

In order to obtain the final TF-IDF value, it is sufficient to multiply the two terms together. However, there have been proposed many ways to calculate the values of the two statistics. In this thesis it has been used the default weighting computed by *Terrier* (see section 3.2), which uses the normalized term frequency and the idf proposed by Robertson and Jones [8].

The term-frequency of a term is computed as:

$$TF = \frac{k_1 * tf}{tf + k_1 \left(1 - b + b * \frac{doclength}{avgdoclength}\right)} \tag{2.1}$$

where $b = 0.75$ and $k_1 = 1.2$ are two free parameters.

The inverse document frequency is obtain by:

$$IDF = \log\left(\frac{\#docs}{docfrequency + 1}\right) \tag{2.2}$$

where $\#docs$ is the total number of documents present in the collection and $docfrequency$ is the frequency of the term in the collection.

Given a query, the score for each term is given by the following formula.

$$score = keyfrequency * TF * IDF \tag{2.3}$$

where $keyfrequency$ is the frequency of the term in the query.

2.2 IR models

2.2.1 BM25

The *BM25* [8] weighting scheme is a *bag-of-words* retrieval function that ranks the documents in the collection based on the query terms that appear in each document, it can be seen as an evolution of the simpler TF-IDF scheme presented in section 2.1.

Given a query Q composed by the query terms $q_1, q_1, ..., q_n$ and a document D from a collection, the score of D is calculated as:

$$score(D,Q) = \sum_{i=1}^{n} IDF(q_i) \frac{f(q_i,D)(k_1+1)}{f(q_i,D) + k_1 \left(1 - b + b * \frac{|D|}{avgdl}\right)} \tag{2.4}$$

where:

- $f(q_i, D$ is the *frequency* of the term q_i in the document D
- $|D|$ is the *length* of the document in terms of number of words that compose $|D|$
- $avgdl$ is the average length of a document in the collection
- k_1 and b are two free parameters with $k_1 \in [1.2, 2.0]$ and $b = 0.75$. *Terrier* uses $k_1 = 1.2$
- $IDF(q_i)$ is the *inverse document frequency* of the term q_i

The IDF is here computed as $IDF(q_i) = \log\left(\frac{N - n(q_i) + 0.5}{n(q_i) + 0.5}\right)$ where: N is the number of documents in the collection, while $n(q_i)$ is the number of documents that contain at least once the term q_i.

2.2.2 DirichletLM

The *DirichletLM* is a weighting scheme applied to a *language model* [9]. To be more precise, *Dirichlet* is a smoothing technique applied to the maximum likelihood estimator of a language model [10]. A language model (LM) is a probability distribution over a set of words, it assigns a probability to each word in a document.

In IR, the basic idea is to estimate a LM for each document D in the collection C and then rank the documents based on the *probability* that the LM of a document has produced the query Q.

The use of a *maximum likelihood* (ML) estimator brings some problems, namely the fact that this estimator tends to underestimate the probability of *unseen* words, those that are not present in the document. To overcome this, there have been proposed many *smoothing* techniques that try to assign a non-zero probability to unseen words.

For this model, we assume that a query Q is been produced by a probabilistic model based on a document D. So, given a query $Q = q_1, q_2, ..., q_n$ and a document $D = d_1, d_2, ..., d_m$ we want to estimate the probability $p(D|Q)$ which is the probability that the document has generated the query.

Applying the Bayes formula and ditching the constant term, we can write that

$$p(D|Q) \propto p(Q|D)p(D) \tag{2.5}$$

where $p(Q|D)$ is the query likelihood given D while $p(D)$ is the prior probability that a document is relevant to a query and is assumed uniform, therefore it does not affect the ranking and can be ditched.

Finally, we obtain that $p(D|Q) \propto p(Q|D)$. Since we are interested in a *unigram* LM, the ML estimate is:

$$p(Q|D) = \prod_i (q_i|D) \tag{2.6}$$

Smoothing methods use two distributions: one for the *seen* words, p_s and one for the *unseen* ones, called p_u thus, the log-likelihood can be written as:

$$\log p(Q|D) = \sum_i \log p(q_i|D) = \sum_{i:f(q_i,D)>0} \log \frac{p_s(q_i|D)}{p_u(q_i|D)} + \sum_i p_u(q_i|D) \tag{2.7}$$

The probability of the unseen words is usually assumed to be proportional to the frequency of the word in the collection:

$$p_u(q_i|D) = \alpha_D p(q_i|\mathcal{C}) \tag{2.8}$$

where α_D is a constant that depends on the document.

With this final derivation, we can write the final formula of the ML estimator:

$$\log p(Q|D) = \sum_{i:f(q_i,D)>0} \log \frac{p_s(q_i|D)}{\alpha_D p_u(q_i|\mathcal{C})} + n \log \alpha_D + \sum_i \log p(q_i|\mathcal{C}) \tag{2.9}$$

The formula is composed by three terms. The last one does not depend on the document so can be ignored since it does not affect the final ranking of the documents. The second term can be interpreted as the normalization of the length of the document since it is the product of $n = |Q|$ and α_D, intuitively if a document is longer it is less likely that there are unseen words therefore the constant should be smaller, it needs *less* smoothing than a shorter document. The first term is proportional to the frequency of the term in the document,

similar to the TF seen in section 2.1. The term at the denominator instead, is proportional to the document frequency of the word in the collection so it is similar to the IDF.

To sum up, we want to estimate the probability $p(w|D)$, the maximum likelihood estimator leads to:

$$p_{ML}(w|D) = \frac{c(w, D)}{\sum_w c(w, D)} \tag{2.10}$$

where $c(w, D)$ is the count of word w in the document D. This estimate suffers from underestimate the probabilities of unseen words, thus we apply smoothing to the estimator.

Since a Language Model is a multinomial distribution, the conjugate prior for Bayesian analysis is the Dirichlet distribution, thus the final model is given by:

$$P(w|d) = \frac{c(w, d) + \mu P(w|\mathcal{C})}{\sum_w c(w, d) + \mu} \tag{2.11}$$

where μ is a free parameter.

2.2.3 PL2

The models seen so far have always some parameters that ideally should be tuned for every collection and can have a notable influence, in terms of performance, even if they changed slightly. The goal of the PL2 weighting scheme, is to have a model that does not have any tunable parameter [11].

PL2 is then a model without parameters which derives from a weighting scheme that measures the *divergence from randomness* of the actual term from the one obtained by a random process. This model belongs to a family of models which differ one from the other by the types of normalization used when computing the score.

Models based on measuring the divergence from randomness do not consider the relevance of a document with respect to a query as a core concept, instead, they rank documents computing the gain in retrieving a document that contains a term from the query.

The fundamental formula of these models is the following:

$$w = (1 - P_2)(-\log_2 P_1) = -\log_2 P_1^{1-P_2} \tag{2.12}$$

We also define the *informative content* of a word in a document as:

$$Inf_1 = -\log_2 P_1 \tag{2.13}$$

with P_1 being the probability that a term has tf occurrences in the document by *chance*, based on the model of randomness adopted. P_2 is obtained by observing only the subset of documents of the collection that contain the the term t. This subset is called *elite set*. P_2 represents the probability that t is present in a document with respect to its elite set and is correlated to the risk $1 - P_2$ of accepting a word as a good descriptor when a document is compared to the elite set. If this probability is low, which means that the frequency of the term is low in the document with respect to the elite set, then the gain in terms of informative content brought by that term is high and viceversa.

To be able to actually computing this probabilities and weights, we start by assuming that F is the total number of *tokens* of an observed word t in a collection $\mathcal{C}$ of N documents. Furthermore, let's assume that the tokens of a *non-specialty* word are distributed on the N documents following the binomial distribution. Non-specialty words are those words which do not possess much discriminative power since they are present in most documents of the collection, think about terms like *the*. Given this assumptions, the probability of having tf occurrences in a document is given by:

$$P_1(tf) = P_1 = B(N, F, tf) = \binom{F}{tf} p^{tf} q^{F-tf} \tag{2.14}$$

where $p = \frac{1}{N}$ and $q = \frac{N-1}{N}$. Words with a high P_1 are the non-specialty words, while those who have a low P_1 are less distributed among the documents and thus is very unlikely that a random process has generated those words distribution.

To sum up, the probability P_1 is obtained by an ideal process called *model of randomness*, the lower this probability the lower the chance that the tf of the term relative to P_1 is generated randomly by the process and thus is very unlikely to obtain that word by accident.

P_2 is the conditional probability of success of obtaining an additional token of a certain word in a document based on statistics of the elite set. This probability is used as a way to measure the gain of information that a word has in terms of informative content.

The differences between these models are given by the models used to approximate the binomial process and the type of normalization applied. The letters in PL2 mean that has been used the Poisson process to approximate P_1 and the Laplace law of succession to compute P_2, while the 2 means that it has been applied the *second normalization* to tf.

Assuming that the tokens of a non-specialty word should distribute on the N documents of the collection following the binomial law, we obtain the equation 2.14, therefore the expected relative frequency in the collection is given by $\lambda = \frac{F}{N}$, thus we can write:

$$Inf_1(tf) = -\log_2 \left(\binom{F}{tf} p^{tf} q^{F-tf} \right) \tag{2.15}$$

In order to be able to compute this value, we approximate the binomial process with a Poisson process, assuming p small and that it decreases to 0 when N increases while $\lambda = pF$ remains constant. An approximation is given by:

$$\begin{aligned} Inf_1(tf) &= -\log B(N, F, tf) \\ &\sim -\log_2 \frac{e^{-\lambda}\lambda^{tf}}{tf!} \\ &\sim -tf \log_2 \lambda + \lambda \log_2 e + \log_2(tf!) \\ &\sim tf \log_2 \left(\frac{tf}{\lambda}\right) + \left(\lambda + \frac{1}{12tf} - tf\right) \log_2 e + 0.5 \log_2(2\pi tf) \end{aligned} \tag{2.16}$$

Moving to the L part of the model, let's assume that $P_2(tf)$ is relative only to the elite set of the word and that is obtained from the conditional probability $P(tf + 1|tf, D)$ of having an additional occurrence of the word t given the document D. Using the Laplace law of succession, P_2 can be seen as the probability of having tf occurrences given the fact that we have seen $tf - 1$ occurrences, thus:

$$P_2 = \frac{tf}{tf + 1} \tag{2.17}$$

From this equation directly derives:

$$w(t, D) = \frac{1}{tf + 1} \cdot Inf_1(tf) \tag{2.18}$$

In a collection of documents, the tf of a word depends also on the *length* of the document analyzed, thus for collections with documents with different lengths, is necessary to introduce a *normalization* of the tf. This operation takes the name of *second normalization* and can be computed as:

$$tf_n = tf \log_2 \left(1 + \frac{avgdl}{|D|}\right) \tag{2.19}$$

where $avgdl$ is the average document length in the collection, while $|D|$ is the length of the document analyzed.

2.2.4 Word2Vec

Word2Vec (from now on w2v) is a group of models that are used to produce term *embeddings* and has been proposed by Mikolov [12]. An embedding is a representation of an item, in this case of a word, in a new space such that the properties of the item are respected. In other words, a w2v model tries to create a vector representation of a word in a *distributed* fashion. In input the model takes the collection of documents and in output it gives the vector representation of each word contained in the collection. Since the model computes the embedding of a word by considering the words surrounding it, words that have similar semantic meaning are close one to another in the vector space.

Mikolov [12] proposed two architectures for this model: Continuos-bag-of-words and Skip-gram. The first tries to predict a word that would fit best given a set of words while the second does the opposite: it tries to predict words that could be in the surrounding of a given word. Both models are shallow, two-layer neural networks, the scheme of the architectures can be seen in figure 2.1 below.

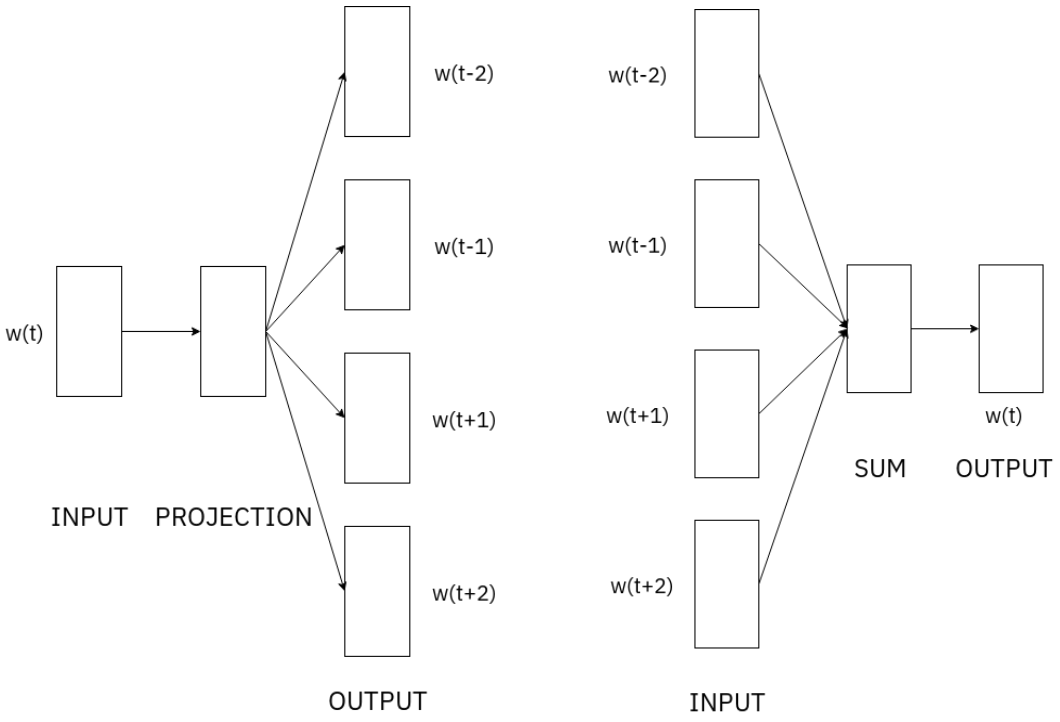
In this theses was used the skip-gram model so next we will concentrate only on this architecture. The training goal is to find embeddings of words that are useful to predict the surrounding words of the actual term. So, given a sequence of $w_1, w_2, ..., w_T$ training words from a training set W, the objective of the network is to maximize the average log probability

$$\frac{1}{T} \sum_{t=1}^{T} \sum_{-c \leq j \leq c \,:\, j \neq 0} \log p(w_{t+j}|w_t) \tag{2.20}$$

where c is the size of the training window and T is the total number of words in W.

Using a large training window, the accuracy of the embeddings improves at the expenses of training time since the number of examples also increases. The usual skip-gram formulation uses a soft-max definition for the probability $p(w_{t+j}|w_t)$:

$$p(w_O|w_I) = \frac{\exp(v'^{\intercal}_{w_O} v_{w_I})}{\sum_{w=1}^{|W|} (v'^{\intercal}_{w} v_{w_I})} \tag{2.21}$$



(a) Skip-gram architecture.

(b) Continuos bag of words architecture.

Figure 2.1: The two architectures for w2v.

where v_w is the *input* representation of the word while v'_w is the *output* representation. This definition is however impractical since it has a high cost of computing.

There exist many approaches to approximate this probability such as hierarchical soft-max, negative sampling, sub-sampling of recurring words [13]. Hierarchical soft-max uses a binary tree representation of the output layer, having a number of leaves equal to the number of words in the vocabulary ($|W|$) and having every internal node representing the relative probability of its child nodes. With this approach the model has only to evaluate $\log_2(|W|)$ nodes. The sub-sampling of frequent words has another approach, every time the model looks at a word $w_i \in W_T$, that word has a certain probability to be ignored equal to $p(w_i) = 1 - \sqrt{\frac{t}{f(w_i)}}$ where t is a threshold and $f(w_i)$ is the frequency of the word.

The approach used in this work is the negative sampling (NEG). This approximation is the simplification of the Noise Contrastive Estimation (NCE), proposed Gutmann and Hyvarinen [14] which states that a good model should be able to differentiate noise data from useful data by means of logistic regression. The NEG objective is then the following:

$$\log \sigma(v'^{\intercal}_{w_O} v_{w_I}) + \sum_{j=1}^{k} \mathbb{E}_{w_i \sim P_n(w)}[\log \sigma(-v'^{\intercal}_{w_j} v_{w_I})] \tag{2.22}$$

where $\sigma(x) = \frac{1}{1+e^{-x}}$, $P_n(w)$ is the noise distribution and k are the samples drawn as *negative* samples for the model. Using this formula to replace every $\log(p(w_O|w_I))$ in the skip-gram objective we get an approximation of the objective. The distribution $P_n(w)$ is a free parameter, usually the unigram distribution taken to the power of $3/4$ is used.

Until now, we have seen how the embeddings are learned by the model, finally we can move on and see how we can use this embeddings to do information retrieval.

At this point we only have vector representations of words, so what about documents? One possibility is to learn representations of entire phrases/paragraphs/documents by an unsupervised algorithm that tries to predict words in a document [15].

Another possibility is simply to *sum* the vectors of the words that form a document and then take the resulting vector as the vector which represents the document. So, given a document D composed by $d_1, d_2, ..., d_m$ words, given the vector representations of these words $v_1, v_2, ..., v_m$, the vector of the document can be computed as:

$$v(D) = \sum_{j=1}^{m} v_j \tag{2.23}$$

Taking the *average* of all the word vectors that form the document is also a possibility. We will call this approach from now on *w2v-avg* and is one of the models considered in the thesis.

To take into account also statistics as *TF-IDF* discussed previously. This means that every vector that composes a document is weighted by its TF-IDF score and then summed to compose the representation of the document. This approach makes use of *self information* since it uses statistics based on the document and the collection and we will call this model *w2v-si*. The representation of the document is:

$$v(D) = \sum_{j=1}^{m} w(v_j) v_j \tag{2.24}$$

where the weight is the TF-IDF score of the word.

To be able to rank the documents for a query, first the query needs to be projected into the vector space. To do that is sufficient to follow the same scheme as for the document vector: the vector is obtained by averaging the word embeddings that compose the query.

The score of a document can then be computed by taking the *cosine* similarity between the query and document vector. So, given the query vector q and the document vector d, the score of the document with respect to the query is computed as:

$$score(q, d) = \frac{q \cdot d}{|q||d|} = \frac{\sum_{i=1}^{n} q_i d_i}{\sqrt{\sum_{i=1}^{n} q_i^2}\sqrt{\sum_{i=1}^{n} d_i^2}} \tag{2.25}$$

where n is the dimension of the vectors.

2.3 Query expansion

So far we assumed implicitly that the query is formulated *correctly* in the sense that the user *knows* exactly what he is searching for. This assumption however is a bit unrealistic. Usually, queries are formulated in *natural* language which has a high degree of *expressiveness*: one can express the same concept using different words. Another problem could be the fact that user usually search for very short queries, sometimes formed only by one term, which makes it very difficult for a system to understand what is the information need needed. These are obviously important problems for an IR model since different formulations of the same information need can lead to great differences in performance even with the same IR model.

Query expansion (QE) is a set of techniques that reformulate the query to improve performance of a IR system [16]. The techniques used can be:

- finding synonyms for words and search also for the synonyms
- finding semantic related words
- finding all the morphological forms of words by stemming the words in the query
- fixing any spelling errors found in the formulation of the query and using the corrected query to search the collection
- re-weighting the terms of the query in the model

Query expansion can be used on top of the preprocessing discussed previously to try to improve further the performance of the system.

2.4 Relevance feedback

The models presented in the previous sections implicitly make use only of information available *before* actually running the query. These approaches assume that we do not have any *user* feedback of the query done by the user. The idea of relevance feedback is to take the results obtained by running a query, gather user feedback and from this new information, perform a new query which should lead to a better set of results.

There are three types of relevance feedback: explicit, implicit and blind or pseudo feedback.

Explicit feedback means that the results of a query are *explicitly* marked as relevant or not relevant by an *assessor*. The grade of relevance can be binary, relevant/not-relevant or multi-graded. Graded relevance rates the documents based on a scale of numbers, letters or descriptions of relevance (for example not relevant, somewhat relevant, relevant, very relevant).

Implicit feedback does not require any explicit judgement from the user, instead it infers the grade of relevance by observing which documents are viewed most and for longer for similar queries. This implicit feedback can be measured and then used as a feedback for the system to try to improve the search results.

Blind feedback does not require any user interaction and also does not track user actions, instead it retrieves a set of documents using the standard procedure and then it assumes that the top-k documents in the list are relevant, since it is where they are more likely to appear. With this information, the model does relevance feedback as if it was provided by the user.

Relevance information can be used by analyzing the relevant documents content to adjust the weights of the words in the original query or by expanding the query with new terms. For example, a simple approach that uses the blind feedback is the following:

1. perform the retrieval of the query normally
2. assume that the top-k documents retrieved are relevant
3. select top-k_1 terms from the documents using some score, like TF-IDF
4. do query expansion by adding these terms to the initial query
5. return the list of documents found with the expanded query

Relevance feedback (RF) is, however, often implemented using the Rocchio algorithm [17]. The algorithm includes in the search results an arbitrary number of relevant and non

relevant documents in order to improve the *recall* of the system. The number of such relevant or not documents are controlled by three variables, a, b, c in the following formula:

$$\overrightarrow{Q_m} = (a \cdot \overrightarrow{Q_0}) + \left(b \cdot \frac{1}{|D_R|} \cdot \sum_{\overrightarrow{D_j} \in D_R} \overrightarrow{D_j} \right) - \left(c \cdot \frac{1}{|D_{NR}|} \cdot \sum_{\overrightarrow{D_k} \in D_{NR}} \overrightarrow{D_k} \right) \tag{2.26}$$

where $\overrightarrow{Q_m}$ is the modified vector representation of the query, D_R is the set of relevant documents considered, D_{NR} is the set of non-relevant documents and a is the parameter that selects how near the new vector should be from the original query, while b and c are responsible for how much $\overrightarrow{Q_m}$ will be close to the set of relevant or non-relevant documents.

2.5 Fusions

Ranking fusion is a method used to combine different ranking list into one. The idea behind this approach can be drawn from the fact that some IR models are better in specific queries than others, thus the sets of retrieved documents of two different models can be very different, therefore by fusing together the two runs, the overall recall is very likely to increase. Another observation that can be made is the fact that, if a document is retrieved by two or more different IR models, the probability that the document is relevant is very high. Indeed, it has been shown that by combining different lists of retrieved documents improves the accuracy of the final system [18].

In the following sections, three different kinds of fusions are analyzed and considered in this work.

2.5.1 Comb methods

Among the first methods to combining evidence from multiple models are the ones developed by Belkin et al. [19]. These approaches are very simple and can obtain very good performances. In the original paper, the authors proposed six different methods to fuse the data together, in this section we will see only the first three.

The setup is the following: we have n lists of retrieved documents by n different models, each list contains m retrieved documents for each query. Each list of retrieved documents contains also the score that the model assigned to each document for the given query.

So, given a query q, the most simple way of combining the lists is by using the *CombSUM* method.

The score of a document in the final list is simply obtained by *summing* all the scores of the document for each model:

$$score_{CombSUM}(d) = \sum_{m \in D_m} score(d) \tag{2.27}$$

where D_m are all the models used and d is the actual document.

Another method, called *CombANZ* is to take the score of CombSUM and divide it by the number of models for which the document appeared in the top-1000 for the given query:

$$score_{CombANZ}(d) = \frac{1}{\sum_{m \in D_m:\, d \in top_m(1000)} (1)} \sum_{m \in D_m} score(d) \tag{2.28}$$

where $top_m(1000)$ represents the top-1000 documents retrieved by model m.

CombMNZ multiplies the sum of the scores by the number of models for which the document appears in the top-1000:

$$score_{CombMNZ}(d) = \sum_{m \in D_m:\, d \in top_m(1000)} 1 \cdot \sum_{m \in D_m} score(d) \tag{2.29}$$

We used CombSUM later in the thesis, thus we will concentrate on this approach from now on.

The score computed in equation 2.27 works well if the scores of the models use similar values, however, if the values of the scores are very different that would mean that the final score would be biased towards the system which has higher score. In order to prevent this, the score is normalized before being summed.

There exist many kinds of normalizations, although we used the *min-max* one, we will see also the *sum* normalization and *zero mean unit variance* normalization.

The simplest of the three normalizations is min-max. With this approach the score of a document is rescaled between 0 and 1: the minimum score is re-scaled to take the value of 0 while the maximum score will take value 1. normalized score for every document d is thus computed as:

$$score_{minmax}(d) = \frac{s_L(d) - min_{d' \in L} s_L(d')}{max_{d' \in L} s_L(d') - min_{d' \in L} s_L(d')} \tag{2.30}$$

where $s_L(d)$ is the non-normalized score of the current document, L is the list with the documents and $max_{d' \in L} s_L(d')$ and $min_{d' \in L} s_L(d')$ are respectively the maximum and minimum score of a document in the list L.

A second possible normalization is to impose that the *sum* of all the scores to be equal to 1 while the minimum value should be 0. This approach is called sum normalization and the normalized score for each document d in the list L can be computed as:

$$score_{sumnorm}(d) = \frac{s_L(d) - min_{d' \in L} s_L(d')}{\sum_{d' \in L}(s_L(d') - min_{d'' \in L} s_L(d''))} \tag{2.31}$$

Another possible normalization is to impose the *mean* of the scores to be 0 whit variance equal to 1. The score in this case is calculated as:

$$score_{norm}(d) = \frac{s_L(d) - \mu}{\sigma} \tag{2.32}$$

where $\mu = \frac{1}{|L|} \sum_{d' \in L} s_L(d')$ and $\sigma = \sqrt{\frac{1}{|L|} \sum_{d' \in L}(s_L(d') - \mu)^2}$, with $|L|$ being the length of the list of documents.

All these normalizations can be used with all the rules of combining that we've seen before. We used the CombSUM with *min-max* normalization as it yielded better performance than the other rules and normalizations for the task of the this work.

2.5.2 Reciprocal ranking fusion

The fusion methods seen in the previous section used the scores of the documents assign to them by tha various models, this lead to the need to introduce some sort of normalization of the scores. Reciprocal ranking fusion (RR), introduced by Cormack [20], does not look to the scores of the documents but takes into account only the *positions* occupied by a document in the various lists to be merged by assigning a score to a document by summing the *reciprocal* of the position occupied by the document d in the set of rankings R, with each object of this set being a permutation on $1, ..., |D|$, where $|D|$ is the total number of documents in the lists.

The score for RR is then computed as:

$$score_{RR}(d) = \sum_{r \in R} \frac{1}{k + r(d)} \tag{2.33}$$

where $k = 60$ is a constant that was used by the author and that we have not changed.

2.5.3 Probfuse

Probfuse is a supervised probabilistic data fusion method that ranks the documents based on the probability that they are relevant for a query [21].

The fusion is composed by two phases: a training phase and the fusion phase. The method takes into account the performance of every system to be fused, assigning a higher or lower probability to the documents retrieved by that model.

More precisely, the *training* phase takes in input the results retrieved by the different IR systems for the same set of queries Q. The list of the retrieved documents is then divided into x segments and for each segment it is computed the probability that a document in the segment has to be relevant. This probability is then averaged on the total of the queries available for the training.

Therefore, in a training set of $|Q|$ queries, the probability that a document d retrieved in the k-th segment is relevant, being part of the list of retrieved documents of the model m is computed as:

$$P(d_k|m) = \frac{1}{|Q|} \cdot \sum_{q=1}^{|Q|} \frac{|R_{k,q}|}{|k|} \tag{2.34}$$

where $|R_{k,q}|$ is the number of relevant documents in the k-th segment for the query q and $|k|$ is the total number of documents retrieved in the k-th segment.

To compute this probability, non-judged documents are assumed to be non-relevant. The authors proposed also a variation of this probability by only looking at judged documents in a segment. In this case, the probability is be computed as:

$$P(d_k|m) = \frac{1}{|Q|} \sum_{q=1}^{|Q|} \frac{|R_{k,q}|}{|R_{k,q}| + |N_{k,q}|} \tag{2.35}$$

where $|N_{k,q}|$ is the total number of documents that are judged to be non-relevant in the k-th segment for the query q.

With the all the sets of probabilities computed for each input system, a fused set is built by computing a score $score(d)$ for each document for a given query q:

$$score_{probfuse}(d) = \sum_{m=1}^{M} \frac{P(d_k|m)}{k} \tag{2.36}$$

where M is the number of systems to fuse, k is the segment in which the document d appears

for the model m and $P(d_k|m)$ is the probability computed in equation 2.34 or 2.35 and k is the segment that d appears in. If a document is not retrieved by all of the models, its probability for the systems that did not return it is assumed to be 0.

Probfuse has x as a free parameter. We used $x = 20$ in our experiments later in the thesis.

2.6 Evaluation Measures

In IR, there are many ways to measure the performance of a system and compare the effectiveness of different models and approaches. In this section, we will present the three main measures used in this work to assess the performance of the different experiments.

2.6.1 Precision

Precision (P) is one of the simplest measures available. It measures the ability of a system to *avoid* retrieving non relevant documents. More precisely, given a list L of documents retrieved by a model for a given query, the precision is computed as:

$$P = \frac{|Rel_L|}{|L|} \tag{2.37}$$

where Rel_L is the set of the *relevant* documents in the list L, $|L|$ is the total number documents retrieved.

This measure is a good indicator on how good a system is but it looks only at the system in its entirety. To better understand how the system performs, it is possible to compute the precision at different thresholds, in order to see how the precision of the system evolves scrolling down through the results.

In order to do so, it is sufficient to extract a subset $L_{cutoff} \in L$ which is composed only by the documents which position in the list are within a *cutoff* threshold. Doing so it is possible to compute the precision at different cutoffs. The notation becomes then P_k which denotes the precision of the system in the first k documents. Precision at document cutoff k is computed as:

$$P\_k = \frac{1}{k} \sum_{i=1}^{k} r_i \tag{2.38}$$

where $r_i \in 0, 1$ is the relevance judgement of the i-th document in the list L.

2.6.2 Recall

Another widely used measure is Recall (R), it measures the proportion of relevant documents retrieved by the system. So, given a list L of retrieved documents for a given query q and the list R of all relevant documents for q, the recall of the system is computed as:

$$Recall = \frac{|Rel_L|}{|RB|} \tag{2.39}$$

where Rel_L is the set of the *relevant* documents in the list L, and $|RB|$ is the total number of relevant documents for the query q.

As in the case of Precision above, Recall is usually computed at a *cutoff*. In this later case the notation will change slightly, becoming for example R_k for the Recall of the first k documents in the list L.

Recall at document cutoff k is computed as:

$$Recall\_k = \frac{1}{|RB|} \sum_{j=1}^{n} r_j \tag{2.40}$$

where $r_j \in 0, 1$ is the relevance judgement for the j-th document in the list L.

2.6.3 Normalized discounted cumulative gain

Recall and Precision, although widely used, have an important flaw in their formulation: they threat non-graded and multi-graded relevant judgements *indistinctly*. This can bring to a somewhat distorted vision of the results: if a system retrieves less relevant documents than another system but the retrieved documents are all *very relevant* to the query then it is arguably a better system than the other, yet with only Precision and Recall, the second system would be favored. Another problem is the fact that very relevant documents retrieved *later* in the list, do not hold the same value to the user as the relevant documents retrieved in the first positions.

To tackle these problems, Järvelin and Kekäläinen [22] proposed a novel type of measurement: *cumulative gain*. The cumulative gain is computed as the sum of the *gain* that a system obtains by having retrieved a document. More precisely, given a list of results L, denoting L_i as the document in the i-th position of the list we can build a *gain* vector G which represents the relevance judgements of the documents of the list L. Given all of above, the *cumulative gain* (CG) is defined recursively by the following:

$$CG[i] = \begin{cases} G[1], & \text{if } i = 1 \\ CG[i-1] + G[i], & \text{otherwise} \end{cases} \tag{2.41}$$

where $CG[i]$ denotes the cumulative gain at position i in the list.

The CG tackles the first problem, but does not take into account the fact that relevant documents retrieved early are more important than relevant documents retrieved later. This can be justified by the fact that a user is unlikely to scroll trough *all* of the results, due to lack of time, effort and cumulated information from documents already seen early in the list.

Thus, a *discounting* factor has been introduced to progressively reduce the gain of a relevant document as its rank in the list increases. This discounting, however, should not be very steep to allow for user persistance to also be taken into account.

The proposed discounting function is the *logarithmic* function: by dividing the gain G by the logarithm of the rank of a document, the gain decreases with the increase of relevant documents ranks but it does not decrease too steeply. The discounted cumulative gain is computed then by:

$$DCG[i] = \begin{cases} CG[i] & \text{if } i < b \\ DCG[i-1] + \frac{G[i]}{\log_b i} & \text{if } i \geq b \end{cases} \tag{2.42}$$

where b is the base of the logarithm and i the rank of the document. Note how the documents that are retrieved in the first b positions are not discounted: this makes sense since the higher the base, the lower the discount. By changing the base of the logarithm, it is possible to model the behavior of a user: the higher the base, the more the user is *patient* and looks at more documents and viceversa.

The DCG computed in equation 2.42 is an absolute measure: it is not relative to any ideal measure which makes it difficult to compare two different systems by their DCG. We thus introduce of a normalization of the measure: every element of the DCG vector is divided by the relative ideal DCG counterpart, $iDCG$, which is built by ordering the documents in decreasingly order of relevance. The elements of the resulting vector, called $NDCG$, will take value in $[0, 1]$ where 1 means that the system has ideal performance. Thus, given the DCG and $iDCG$ vectors, the $NDCG$ is computed, for every k by:

$$NDCG(k) = \frac{DCG(k)}{iDCG(k)} \tag{2.43}$$

3
Experimental setup

In this section, we describe the setting of our experiments for the comparison of the different models. In Section 3.1, we describe the experimental collection used; then, in Section 3.2 the Terrier software that implements the IR models studied in this work; finally, each experiment, also known as run in the IR community, is described in Section 3.3.

3.1 Datasets

In order to conduct our experiments we used the topics of the different tasks of the CLEF e-Health tracks (link: http://clef-ehealth.org/). We chose Task1 (T1) of the 2018 and 2019 tracks and the Task2 (T2) of the 2017, 2018 and 2019 tracks.

- T1 uses as dataset all the articles present on PUBMED (title + abstract);
- T2's tracks are constructed upon the results of a boolean search on PUBMED for each topic.

Thus we differentiated between T1 and T2 by constructing different datasets. First, we merged the topics of the two T1 tracks, then we downloaded all the articles on PUBMED Medline, which can be done in different ways [*], and we used this dataset for the topics.

For T2, since every track used different datasets, we downloaded only the documents which appeared as results of the boolean search done by CLEF for each track. In order to

[*] https://www.ncbi.nlm.nih.gov/home/download/

do so, we used the *Biopython* [23] python library with a custom script that extracts all the *PMID*s from the files provided by the tracks and then proceeds to download and save them to plain text files. We executed the retrieval separately for the three tracks and then merged them into one final result. This has been possible since the topics were different for each track so no overlapping of results happened.

Finally, table 3.1 shows a summary of the datasets used with respectively the total number of topics.

Task	Tracks	Dataset	# topics
Task1	2018 and 2019	All articles of PUBMED	60
Task2	2017 and 2018 and 2019	Result of boolean search on PUBMED	90

Table 3.1: Summary of the datasets used.

All the topics, qrels and list of PMIDs of the various tracks, can be found at the following link: https://github.com/CLEF-TAR/tar.

3.2 Terrier

Terrier is an open source IR platform, written in Java, that implements state of the art indexing and retrieval functionalities. It is developed by the University of Glasgow [24] and it implements many IR models [†]. Terrier allows indexing and retrieval of a collection of documents and it is also fully compatible with the *TREC* requirements. It also allows for *query expansion* and *relevance feedback* to be used with the models to improve the performance of the systems.

In this work we used Terrier with the BM25, DirichletLM, PL2 and TF-IDF weighting schemes as well for the runs with query expansion and relevance feedback. For BM25, *Terrier* multiplies the score computed in equation 2.4 by $\frac{(k_3+1)f(q_i,Q)}{k_3+f(q_i,Q)}$, where $k_3 = 8$ and $f(q_i, Q)$ is the frequency of the term q_i in the query Q. Thus, the score computed by Terrier for the BM25 weighting scheme is:

$$score(D,Q) = \sum_{i=1}^{n} IDF(q_i) \frac{f(q_i,D)(k_1+1)}{f(q_i,D) + k_1\left(1 - b + b * \frac{|D|}{avgdl}\right)} \frac{(k_3+1)f(q_i,Q)}{k_3 + f(q_i,Q)} \quad (3.1)$$

For DirichletLM, in Terrier, the score of a term $q_i \in Q$ is given by:

[†] http://terrier.org/download/

$$score(q_i, D) = \log\left(1 + \frac{TF}{\mu \frac{f(q_i, \mathcal{C})}{\#oftokens}}\right) + \log\left(\frac{\mu}{|D| + \mu}\right) \tag{3.2}$$

where parameter $\mu = 2500$.

Finally, for the PL2 model, putting all the equations presented in Section 2.2.3, in Terrier the PL2 score is computed as:

$$s = \frac{kf}{1 + tf_n} \cdot \left(tf_n \log_2\left(\frac{1}{tf}\right) + \frac{tf}{\ln 2} + \frac{\log_2(2\pi tf_n)}{2} + tf_n\left(\log_2(tf_n) - \frac{1}{\ln 2}\right)\right) \tag{3.3}$$

where kf is the frequency of the term in the query, tf_n is the normalized tf computed in equation 2.19 and tf is the non normalized term frequency of the word.

For the runs with QE+RF, Terrier uses the Bo1 algorithm, proposed by Amati [25]. The model operation is similar to the simple one described for the pseudo relevance above, of which this algorithm is a variant: the algorithm extracts the most informative terms from the top-k documents retrieved as expanded query terms. These terms are then weighted using a particular *divergence from randomness* term weighting scheme. The one used in this work is Bo1 which stands for Bose-Einstein 1 and is parameter free.

The algorithm assigns a weight to each term based on a measure of *informativeness* $w(t)$ of the term t. This value is given by:

$$w(t) = tf \cdot \log_2\left(\frac{1 + P_n}{P_n}\right) + \log_2(1 + P_n) \tag{3.4}$$

where tf is the frequency of the terms in the pseudo relevant set of documents selected and P_n is given by $\frac{F}{N}$ which are the same parameters as those discussed in section 2.2.3, F is the term frequency of t in the collection while N is the number of documents in the collection. Amati suggests to use the first three documents as relevant set from which to take the top-10 most informative terms, in this work we followed the advice and leaved the default parameters for the QE+RF.

3.2.1 Setup

The setup used for Terrier is the following. We first wrote one property file [‡] for each model, for each different *index* used and for each Task. Then we created all the different indexes that we wanted to test, and run the retrieval for the different topics. Of course, since T2 uses different datasets, we executed the retrieval for each track and then merged the results into one result file, for a total of 90 topics. For T1 instead, we first merged the all the topics, obtaining 60 different topics, and subsequently run the retrieval with Terrier.

In figure 3.1 we show a graph with all the steps done in order to evaluate the various index/models combinations with Terrier.

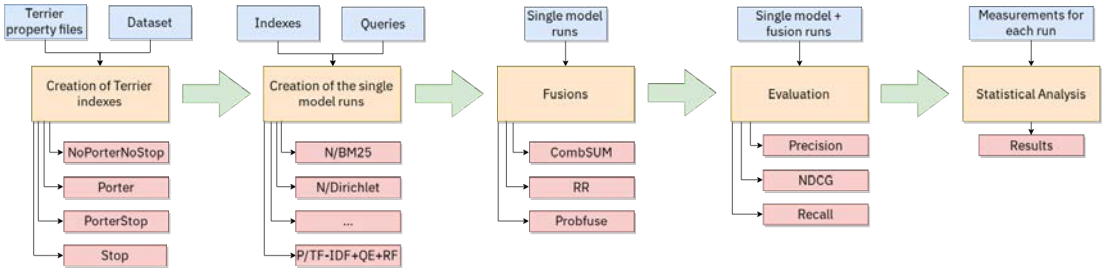


Figure 3.1: Graph showing the pipeline steps done in order to prepare the indexes and do the runs.

To fuse the topics and the results, we used the *trectools* [26] python library. For convenience, we also wrote a bash script that takes in input the directory of the Terrier properties files and then is able to create the index and execute the retrieval with or without query expansion and relevance feedback.

We did not adjust any of the tuning parameters available for the various models since we preferred to see how the default worked. As parameters for query expansion and relevance feedback, we also left the Terrier defaults, which means that were used th first 3 documents as relevant, from which were taken the 10 most influent words to expand the query.

For the word2vec runs, we used pre-trained vectors [27] with 200 dimensions trained on the full PUBMED article set of titles and abstracts [§].

We wrote a python script that created the average or the self-information representation of all the documents in the collection, see section 2.2.4 for more details on these representations, using the same pre-processing as the one used before the training of the word embeddings.

[‡] see configuration of Terrier here: http://terrier.org/docs/v5.1/configure_general.html

[§] The vectors can be downloaded at the following link: https://github.com/RaRe-Technologies/gensim-data/issues/28, see also https://ia802807.us.archive.org/21/items/pubmed2018_w2v_200D.tar/README.txt for the details about the collection and preprocessing

With the representations of all documents, we created a script that computes the similarity between a given topic and all the documents in the collection, compiling a ranked list of scores and document ids which then is stored on disk as the result list. We created the representations of the documents for each different dataset. The queries underwent the same pre-processing as the documents creating firstly a vector representation of the topics and then computing the cosine similarity between query and document.

In figure 3.2 there is a graphical representations of the procedure described above. It is similar to the Terrier runs.

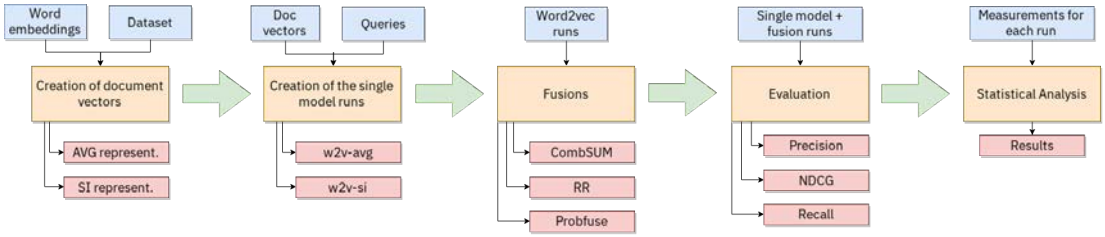


Figure 3.2: Graph showing the pipeline steps done in order to do the word2vec runs.

Finally, in order to do the fusions, we also used the trectools [26] which provide all the Comb fusions and the Reciprocal Ranking (RR) fusion, with default parameter $k = 60$. However, we implemented the min-max normalization, see equation 2.30, for Comb since it was not developed in the library.

We wrote a simple script that reads two or more result files of different runs and then merges them by means of CombSUM-norm or RR into a single file, which can then be saved locally on the disk.

Regarding Probfuse, we implemented all the algorithm from scratch in python. Since CLEF e-Health tracks come together with some test and train topics, we used the training topics for the train part of the fusion and then executed the fusion on the results of the test topics, which are the ones used in T1 and T2.

We chose to ignore the documents without a relevance judgement and used $x = 20$, which means that we had a total of 20 segments each containing 50 documents.

All the software and property files used in this work is available at the following git repo: `https://gitlab.com/chaosphere/master-thesis`.

3.3 Runs

To be able to answer to **RQ1**, we constructed four different types of indexes:

1. **NoPorterNoStop** (N): in this index we did not applied any type of preprocessing
2. **Porter** (P): an index built applying the Porter Stemmer to the documents
3. **PorterStop** (P+S): an index built applying th Porter Stemmer and using a Stop-list for the removal of the words with less resolving power
4. **Stop** (S): an index built only by using a Stop-list, removing the words with less resolving power

For each of these indexes, we used the TF-IDF weighting scheme, PL2, Dirichlet_LM and BM25 models. Thus, each index yields four different results list, one for each weighting scheme/model. In addition, we also wanted to test this models against word2vec, consequently we also did the retrieval of the same topics using the w2v model.

RQ	Runs	Total per task
RQ1	BM25, Dirichlet, PL2, TF-IDF, w2v-avg, w2v-si	18
RQ2	QE+RF of BM25, Dirichlet, PL2, TF-IDF	16
RQ3	RQ1, RQ2, N, P, P+S, S	18

Table 3.2: Summary of all the runs.

Since **RQ2** is about query expansion and relevance feedback, and since Terrier allows the usage of QE+RF simply by passing a further parameter, we used exactly the same indexes also to answer to **RQ2**.

To see if doing the fusion of the results of different IR systems improves the overall performance, **RQ3**, we decided to fuse all the following runs, using all the three fusion methods presented:

1. **Per index**: we fused all the runs using the same index, so for example we fused all the runs of the **N** index together
2. **Per model**: we fused all the runs of the *same* IR model, for example all the runs of the PL2 model using the different indexes

Since we worked with two different tasks, we created the runs for both T1 as well as T2. The final count of runs and their composition is summed in table 3.2, per task.

4 Results

In this chapter we analyze the results of the different runs per task. In Section 4.1, we analyze the simplest runs produces with Terrier; in Section 4.2 and Section 4.3 we describe the results using QE + RF and word2vec, respectively.

All the runs have been evaluated using the *trec_eval* software, developed by the US National Institute of Standards and Technology (NIST) [*].

In the next sections we reported a subset of all the plots, which can be found in Appendix A.

4.1 Terrier runs baseline

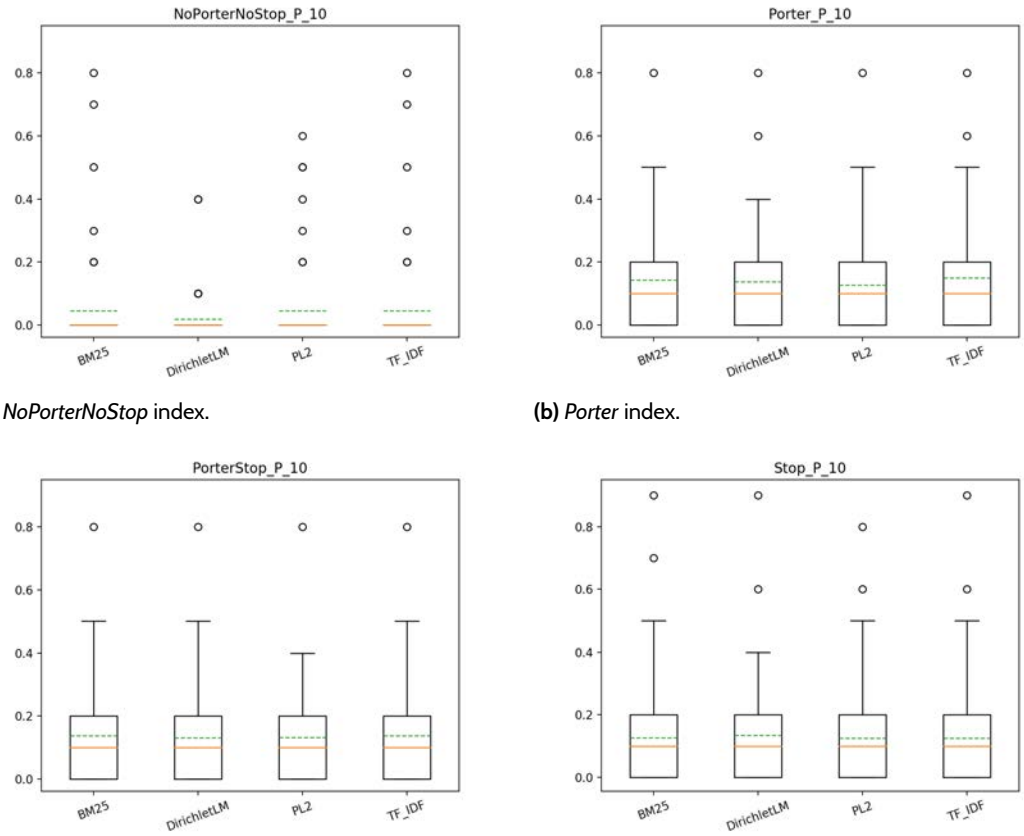
4.1.1 Task1

Starting with Task1 (T1), we first investigate if there is a model that has an appreciable better performance than the others across the different indexes used. In figure 4.1 are presented the Box Plots of the different models with the different indexes.

From the plots, it is clear that there there is little difference between the models with the same index and as it can be seen in figure 4.2, there is a significant advantage in using some form of preprocessing, regardless of what *type* it is.

This result can be observed constantly across different measurements, which means that it

[*] https://trec.nist.gov/trec_eval/



(a) *NoPorterNoStop* index.

(b) *Porter* index.

(c) *PorterStop* index.

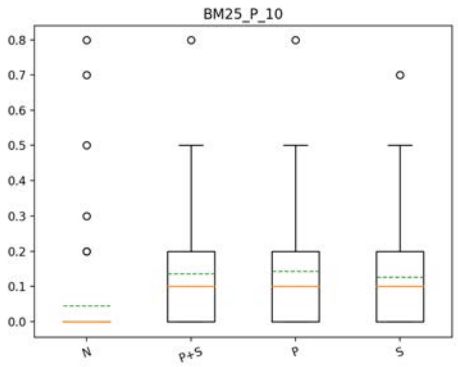
(d) *Stop* index.

Figure 4.1: T1: Box Plots for P@10 of the different models for each index.

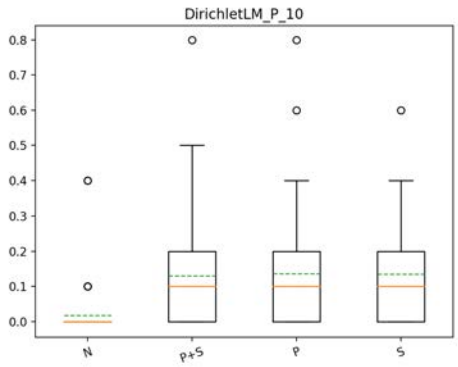
is not only one type of performance which benefits from using a stemmer or a stop-list, but instead the overall performance of the system increases.

In table 4.1 we report the various measures of *NDCG* and *Recall@R* which is the *Recall* computed at document cutoff equal to R that is the total number of documents judged relevant by the assessors for a certain topic. We also highlighted the best value for each measure.

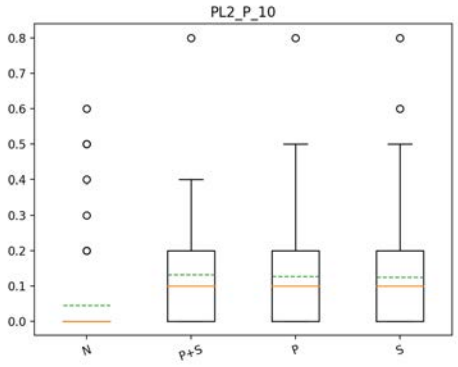
From the scores obtained by the systems, it follows that the combination of Porter Stemmer with Dirichlet weighting, although not significant better than the other models, has a better NDCG score *later* in the result list, while Porter Stemmer with TF-IDF weighting does well in the first part of the results. This behavior is true also for Precision: the score of P@10 and P@100 is higher for Porter/TF-IDF, 0.15 vs 0.1367 and 0.1048 vs 0.1025 respectively, while the overall precision being slightly better for Porter/DirichletLM, 0.0365 vs 0.0361.



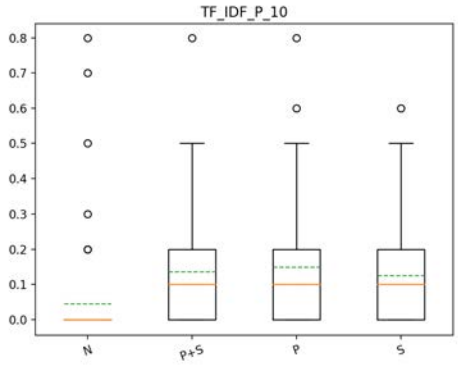
(a) Precision for BM25 with different indexes.



(b) Precision for DirichletLM with different indexes.



(c) Precision for PL2 with different indexes.



(d) Precision for TF-IDF with different indexes.

Figure 4.2: T1: Box Plots for P@10 of the different indexes for each model.

In conclusion of this first part, for T1, our findings show that the use of a type of preprocessing increases significantly the overall performance of a systems, regardless of the model used. Furthermore, it seems that the best scores are obtained by models using the Porter index, specifically with TF-IDF weighting scheme even if there is no clear winner.

4.1.2 Task2

Task2 (T2) are results obtained on a dataset of documents after an initial boolean search on PUBMED (see the Section 3.1 for more information). Like in the previous section, we start by comparing the results of the systems with the same index, then we compare the models using different indexes.

Coherently with the findings for T1, we can see in figure 4.3 that even for T2 there is no systems that stands out from the others. However, we can observe that the *NoPorterNoStop*

Index/Model	NDCG@10	NDCG@100	NDCG@1000	R@R
NoPorterNoStop/BM25	0.0443	0.0389	0.082	0.0244
NoPorterNoStop/Dirichlet	0.0167	0.0238	0.065	0.0169
NoPorterNoStop/PL2	0.0454	0.0387	0.0782	0.0243
NoPorterNoStop/TF_IDF	0.0448	0.0393	0.0821	0.0248
Porter/BM25	0.1346	0.1538	0.2549	0.1045
Porter/Dirichlet	0.1276	0.1652	**0.2749**	**0.1088**
Porter/PL2	0.1257	0.1495	0.2462	0.0985
Porter/TF_IDF	**0.1451**	**0.1682**	0.2692	0.1077
PorterStop/BM25	0.1316	0.1559	0.2597	0.1004
PorterStop/Dirichlet	0.1217	0.1612	0.2662	0.1003
PorterStop/PL2	0.1297	0.1461	0.2426	0.0928
PorterStop/TF_IDF	0.1306	0.1551	0.258	0.1001
Stop/BM25	0.1186	0.1458	0.2374	0.0911
Stop/Dirichlet	0.1243	0.1538	0.2496	0.1017
Stop/PL2	0.1209	0.1396	0.2238	0.0851
Stop/TF_IDF	0.1172	0.1464	0.237	0.0911

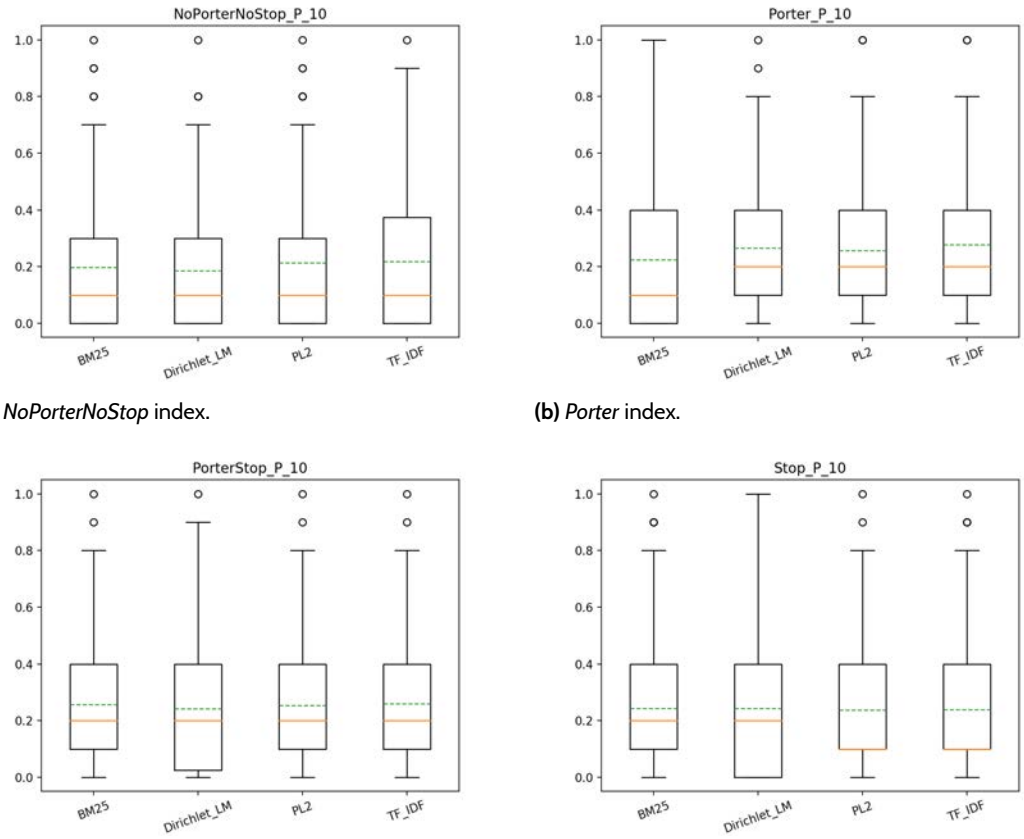
Table 4.1: NDCG at various cut offs and Recall@R for the different models for T1.

index produces better results than for T1, probably thanks to the pre-boolean search which restricted the document collection as a whole.

Similarly to T1, also for T2 there is little different between models using the same type of index, however, when comparing the same models with different indexes things change.

In figure 4.4 we can see that some indexes benefit more a models than others, this is evident for each model. Let's take BM25 as an example. From the graphic it is clear that *PorterStop* and *Stop* indexes yield the best scores when compared to the other two indexes. This is true in general for each model, there is always at least one index that achieves significant better score than the rest. It also can be seen that the index *NoPorterNoStop*, although achieving noticeable better scores for T2 than for T1, it remains inferior to the others.

Another interesting observation that can be made is that not always the combination of Porter Stemmer and a Stop-list achieves better performance than just using the Porter Stemmer or the Stop-list alone. Nevertheless, overall it seems that with the combination of the two yields more constant scores regardless of the model in use, as it can be see from figure 4.3 by comparing the variation of the mean scores of the models using the *PorterStop* index and the others.



(a) *NoPorterNoStop* index.

(b) *Porter* index.

(c) *PorterStop* index.

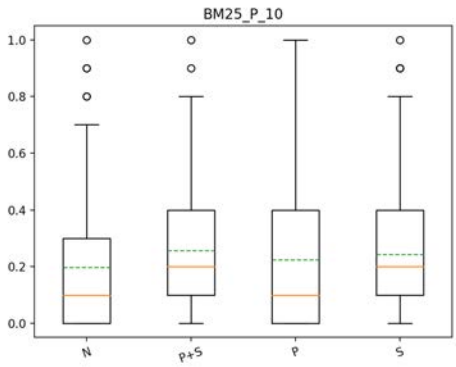
(d) *Stop* index.

Figure 4.3: T2: Box Plots for P@10 of the different models for each index.

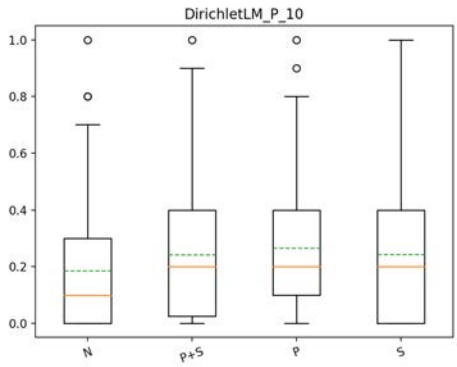
To sum up, for T2 the models behavior is similar to the one for T1. The use of preprocessing increases noticeably the scores of the systems but this time, although essential, improves *less* the performance of a system. The fact that the dataset is significantly smaller helps in this regard since the probability that a document is seen and thus judged by an assessor is higher. More considerations on this will be made in the next chapter.

Coherently with T1, also for T2 there seems to be a combination of index/model that is obtains constantly better scores than the rest of the combinations, as it can be seen in table 4.2. The TF-IDF weighting scheme with the *Porter* index holds the best overall scores in terms of NDCG, at all the different cutoffs, as well as for Recall@R and Precision.

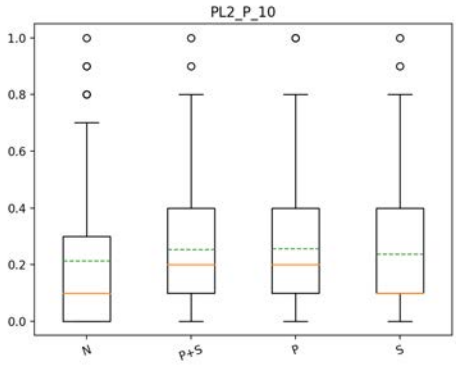
This is the same combination as the best one for T1, which indicates that it could be the index/model that we search for in **RQ1**. We will analyze better the performance of this model in the next chapter, as well as keep this combination in mind when we will see the results of



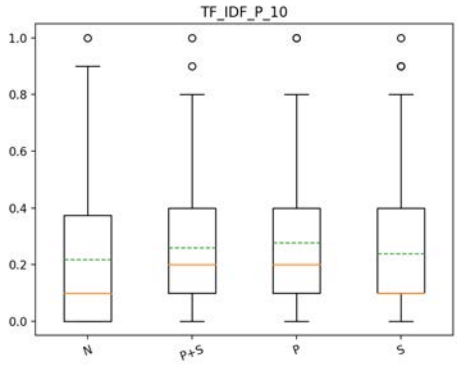
(a) Precision for BM25 with different indexes.



(b) Precision for DirichletLM with different indexes.



(c) Precision for PL2 with different indexes.



(d) Precision for TF-IDF with different indexes.

Figure 4.4: T2: Box Plots for P@10 of the different indexes for each model.

the systems with the usage of query expansion and relevance feedback in the next section.

Differently from T1, in T2 there is some much more difference between models using the same index. Looking at the plots in figure 4.3 and the at the table 4.2 there is a more obvious preference of some models towards some specific types of indexes.

This is obvious in the case of the *Porter* index, where the BM25 model has a median score fo Precision@10 noticeably lower than the other models. This phenomenon can be observed also for the *Stop* index: the difference between the BM25 and Dirichlet median score with respect to the PL2 and TF-IDF score is evident. Interestingly for this index, this fact is not reflected for the various mean scores, which are very similar.

The last observation can be extended also for the other indexes: in general the mean scores are more similar one from another than the median scores.

Index/Model	NDCG@10	NDCG@100	NDCG@1000	R@R
NoPorterNoStop/BM25	0.1861	0.2406	0.3737	0.166
NoPorterNoStop/Dirichlet	0.1786	0.2526	0.3878	0.1707
NoPorterNoStop/PL2	0.2052	0.2525	0.3929	0.1803
NoPorterNoStop/TF_IDF	0.2075	0.2665	0.4031	0.1835
Porter/BM25	0.2162	0.2654	0.4127	0.1814
Porter/Dirichlet	0.2662	0.3165	0.459	0.2067
Porter/PL2	0.2565	0.2969	0.4464	0.2041
Porter/TF_IDF	**0.2761**	**0.3202**	**0.4716**	**0.2156**
PorterStop/BM25	0.26	0.3144	0.4682	0.2062
PorterStop/Dirichlet	0.2438	0.3032	0.4456	0.1959
PorterStop/PL2	0.2584	0.3058	0.4608	0.2037
PorterStop/TF_IDF	0.2618	0.3148	0.4683	0.2072
Stop/BM25	0.2396	0.2967	0.4501	0.2004
Stop/Dirichlet	0.2363	0.2977	0.4373	0.1981
Stop/PL2	0.2387	0.2933	0.4455	0.196
Stop/TF_IDF	0.2391	0.2987	0.451	0.2015

Table 4.2: NDCG at various cut offs and Recall@R for the different models for T2.

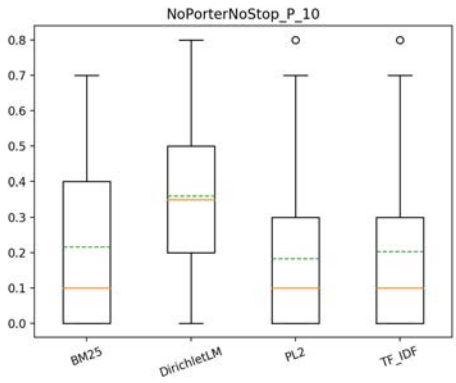
4.2 Terrier runs with Query Expansion and Relevance Feedback

4.2.1 Taski

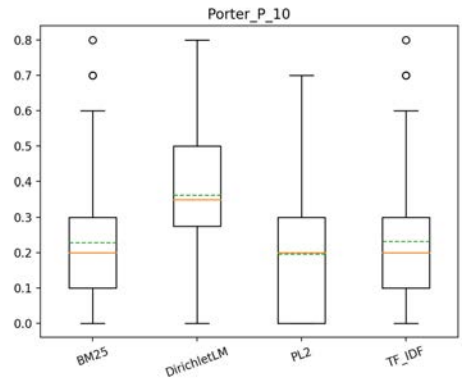
In figure 4.5 we reported the results of the different models for each index considered. From the results, it emerges that by doing QE+RF the performance of *all* of the models increased significantly. Even the performance of some models using the *NoPorterNoStop* index are very high and comparable to the rest of the indexes, which suggests the fact that QE+RF efficacy is *index independent*.

This fact can also be observed by looking at figure 4.6, from which is evident how much better the models using the *NoPorterNoStop* index do with respect to the performance of the runs *without* QE+RF. For the DirichletLM weighting scheme, the scores obtained are very similar for each index, strengthening the aforementioned idea that doing QE+RF is index independent.

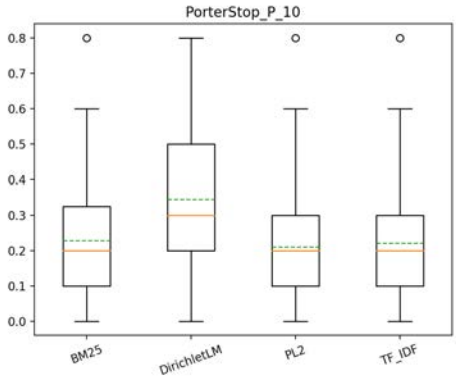
Another thing that can be observed, is that within the same index, some models benefit *a lot* more than the others from QE+RF. For instance, the DirichletLM weighting scheme, outperforms every other model for *each* index considered, thus suggesting that this model



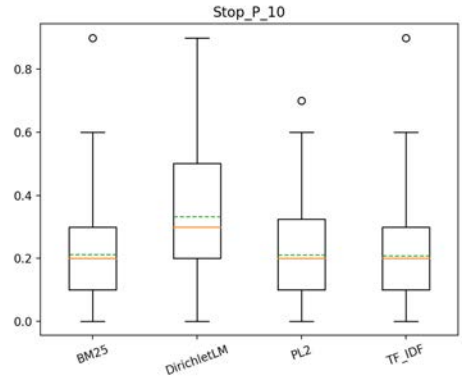
(a) *NoPorterNoStop* index.



(b) *Porter* index.



(c) *PorterStop* index.



(d) *Stop* index.

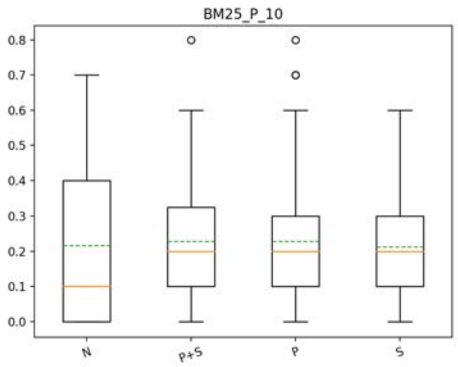
Figure 4.5: T1: Box Plots for P@10 of the different models for each index, with QE and RF.

benefits heavily from this type of postprocessing.

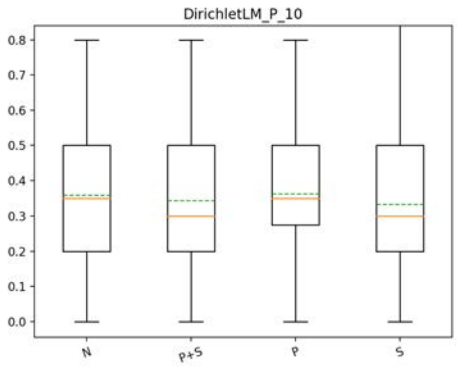
Index	P@10	P@100	P@1000
NoPorterNoStop	0.36	0.1782	0.0557
Porter	**0.3633**	0.1842	**0.0558**
PorterStop	0.345	0.1773	0.0549
Stop	0.3333	**0.1853**	0.0553

Table 4.3: DirichletLM+QE+RF for T1: P@10, P@100 and P@1000.

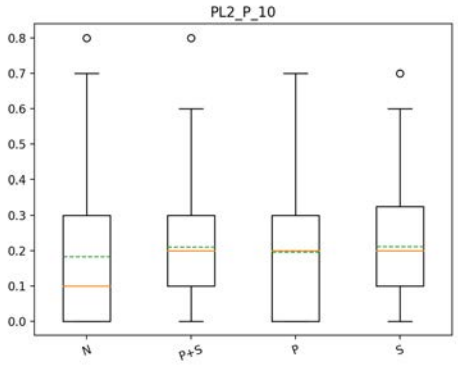
In table 4.4 we summed up, as usual, the results of the different models for each index. From the table we can see that our previous observation made on the *NoPorterNoStop* index for P@10 is true also for the measures of NDCG and R@R: the scores obtained by the various models are very similar no matter the index used.



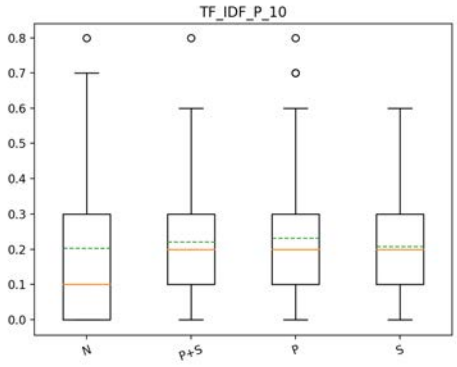
(a) Precision for BM25 with different indexes.



(b) Precision for DirichletLM with different indexes.



(c) Precision for PL2 with different indexes.



(d) Precision for TF-IDF with different indexes.

Figure 4.6: T1: Box Plots for P@10 of the different indexes for each model, with QE+RF.

Furthermore, not doing preprocessing is, for some models, the best approach and for the DirichletLM weighting scheme is the best approach in terms of NDCG and R@R. Looking also at the Precision values, however, the *NoPorterNoStop* index is not the best choice. This can be seen from table 4.3: although the scores are very similar, NoPorterNoStop is never the best index to use. It is interesting to notice how the performance, in terms of Precision, is worse around the cutoff of 100 to then recover to the end of the list.

The best combination of index/model for T1 with query expansion and relevance feedback seems to be Porter/DirichletLM and NoPorterNoStop/DirichletLM. In terms of Precision, is better to choose the first one, while in terms of NDCG and R@R the better choice is the second one.

Index/Model	NDCG@10	NDCG@100	NDCG@1000	R@R
NoPorterNoStop/BM25	0.2313	0.227	0.3382	0.1471
NoPorterNoStop/Dirichlet	**0.3792**	0.339	**0.4687**	0.2332
NoPorterNoStop/PL2	0.1987	0.2003	0.3101	0.1282
NoPorterNoStop/TF_IDF	0.2162	0.2182	0.3297	0.1385
Porter/BM25	0.2417	0.2603	0.3872	0.1728
Porter/Dirichlet	0.3778	**0.3397**	0.4684	0.2329
Porter/PL2	0.2114	0.2433	0.372	0.1549
Porter/TF_IDF	0.2404	0.2576	0.3855	0.1624
PorterStop/BM25	0.2397	0.2484	0.3763	0.1584
PorterStop/Dirichlet	0.3498	0.3256	0.4558	0.2252
PorterStop/PL2	0.2237	0.2337	0.3609	0.1485
PorterStop/TF_IDF	0.233	0.2453	0.3736	0.1571
Stop/BM25	0.2201	0.239	0.3619	0.1586
Stop/Dirichlet	0.3436	0.3273	0.4551	**0.2372**
Stop/PL2	0.2112	0.2234	0.3443	0.1503
Stop/TF_IDF	0.2139	0.2354	0.3575	0.1573

Table 4.4: T1: NDCG at various cut offs and Recall@R for the different models with QE+RF.

4.2.2 Task2

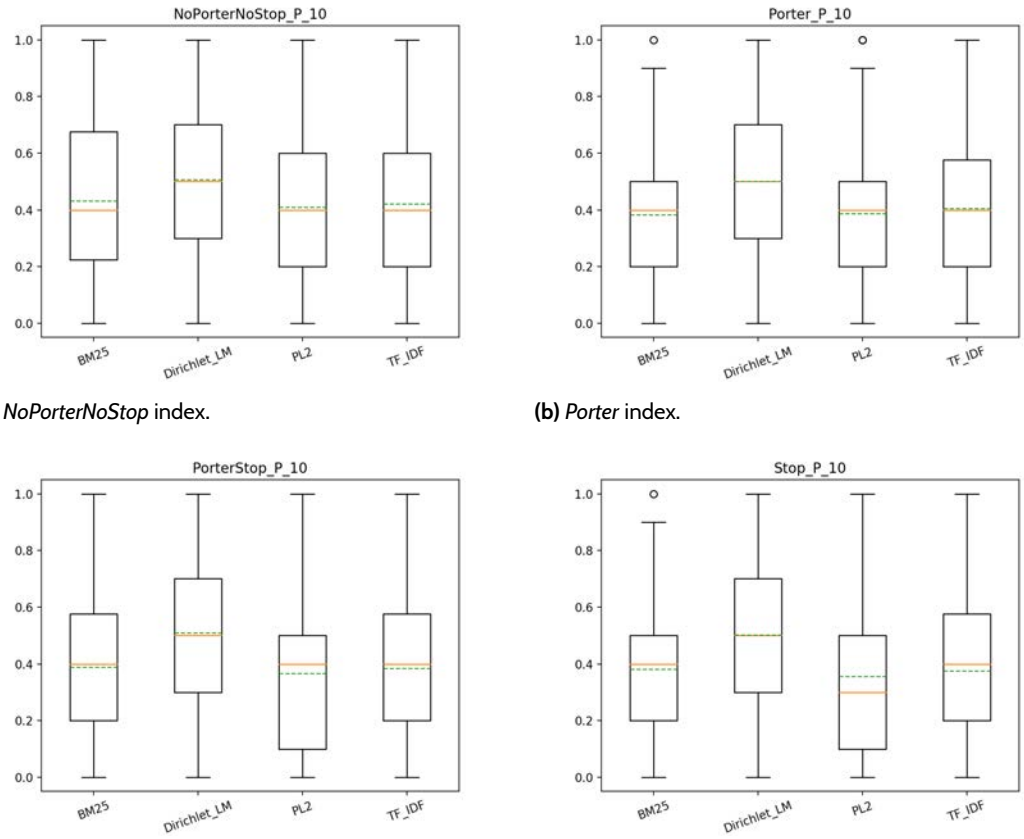
In figure 4.7 we reported the Box Plots of the runs done for T2 with query expansion and relevance feedback. Similarly to T1, the *NoPorterNoStop* index is not the worst choice, on the contrary the scores are very good for each model that uses this index.

Index	P@10	P@100	P@1000
NoPorterNoStop	0.5056	**0.2412**	**0.0602**
Porter	0.5	**0.2412**	0.0601
PorterStop	**0.5089**	0.2337	0.0593
Stop	0.5011	0.2351	0.0599

Table 4.5: DirichletLM+QE+RF for T2: P@10, P@100 and P@1000.

This can also be seen in figure 4.8, where it emerges that it does not matter too much which type of index is used, the performance of a model is similar, in general, regardless of the index.

As in the section above, the model that achieves the best scores is DirichletLM. This is different from the runs without QE and RF where the best weighting scheme was TF-IDF. We suppose that this is due to the fact that QE+RF brings much more performance to Dirich-



(a) *NoPorterNoStop* index.

(b) *Porter* index.

(c) *PorterStop* index.

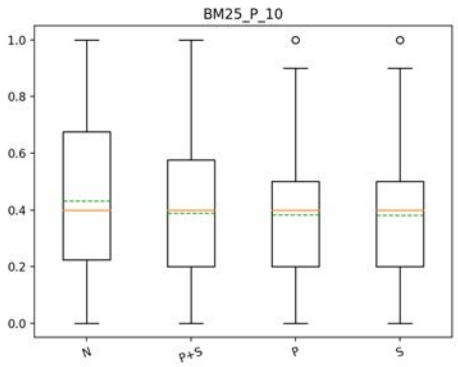
(d) *Stop* index.

Figure 4.7: T2: Box Plots for P@10 of the different models for each index, with QE and RF.

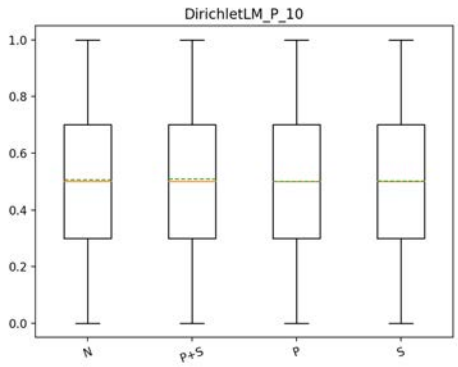
letLM than to TF-IDF, especially for T1. For T2 this fact is less evident, but it is still evident from the box plots in figure 4.7.

In table 4.6 we reported the NDCG and R@R measurements for the runs. Like for the runs for T1, the best combination of index/model result to be NoPorterNoStop/Dirichlet and Porter/Dirichlet, with the DirichletLM obtaining significant higher scores than the rest of the models tested.

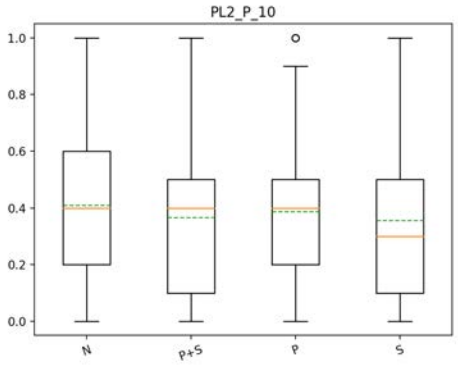
Table 4.5 shows the Precision scores of the runs. We can see that, although the best index for P@10 is *PorterStop*, it suffers a decrease in performance and loses ground to *NoPorterNoStop* and *Porter* indexes. Combining the scores of NDCG, Precision and Recall@R, we can safely say that the best index/model combinations are NoPorterNoStop/Dirichlet and Porter/Dirichlet. In chapter 5 we analyze and compare the two runs to see if there is some difference between the two or not.



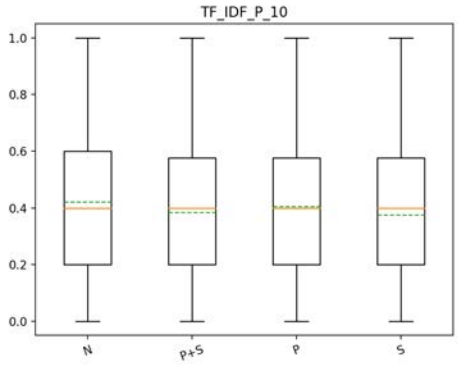
(a) Precision for BM25 with different indexes.



(b) Precision for DirichletLM with different indexes.



(c) Precision for PL2 with different indexes.



(d) Precision for TF-IDF with different indexes.

Figure 4.8: T2: Box Plots for P@10 of the different indexes for each model, with QE+RF.

To summarize this first part of the results, we can draw some conclusions. The preprocessing of the collection seems more necessary if query expansion and relevance feedback is not used. It does not matter too much what type of preprocessing is done, but the best scores are achieved by models which use the *Porter* and *PorterStop* indexes.

Comparing the runs done with and without query expansion and relevance feedback, we can see that QE+RF do improve significantly every model performance, regardless of the index used. However this comes at the cost of a noticeable higher query time, which increases with the dimension of the document collection.

The combination of preprocessing and QE+RF is not necessary a better approach than just doing plain QE+RF, this is a somewhat surprising finding. We have no conclusive explanation on this phenomenon and more work it is probability needed to understand why this fact happens.

Index/Model	NDCG@10	NDCG@100	NDCG@1000	R@R
NoPorterNoStop/BM25	0.4449	0.474	0.6113	0.3321
NoPorterNoStop/Dirichlet	**0.5231**	0.5359	0.6644	0.3857
NoPorterNoStop/PL2	0.42	0.4581	0.6019	0.3239
NoPorterNoStop/TF_IDF	0.4325	0.4681	0.6092	0.3175
Porter/BM25	0.3966	0.434	0.5815	0.3007
Porter/Dirichlet	0.5213	**0.5367**	**0.6648**	**0.3877**
Porter/PL2	0.3939	0.4398	0.5878	0.3097
Porter/TF_IDF	0.4182	0.4557	0.603	0.3125
PorterStop/BM25	0.4045	0.4484	0.5981	0.3066
PorterStop/Dirichlet	0.52	0.5231	0.6525	0.3741
PorterStop/PL2	0.3801	0.4356	0.5864	0.3013
PorterStop/TF_IDF	0.3958	0.443	0.5931	0.3017
Stop/BM25	0.3868	0.4329	0.5829	0.3046
Stop/Dirichlet	0.5149	0.5231	0.6544	0.3691
Stop/PL2	0.3616	0.4225	0.574	0.2955
Stop/TF_IDF	0.3776	0.4272	0.5781	0.2985

Table 4.6: T2: NDCG at various cut offs and Recall@R for the different models with QE+RF.

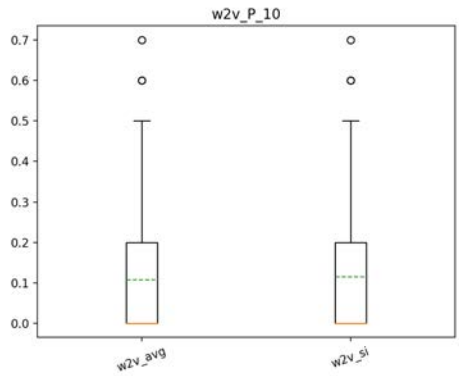
There is no clear better model, neither for T1 nor for T2. If we look at the performance of models in section 4.1, those without QE+RF, then the best weighting scheme is the classic TF-IDF. However, when we look at the scores obtained by the runs in this section, then the better scheme is Dirichlet. Since QE+RF improves performance, the Dirichlet model is the one that *overall* achieves the higher scores.

Remembering the **RQ2** which stated:

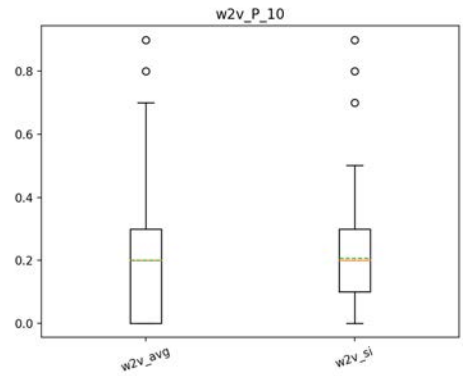
> **RQ2**: does the use of query expansion and relevance feedback improve the results?

We can answer by saying that QE+RF improve significantly the results, regardless of the model/combination used to retrieve the documents. We can observe this fact by comparing the scores of the runs with and without QE+RF, looking at the plots in figures 4.1 and 4.5 for T1 and 4.3 and 4.7 for T2.

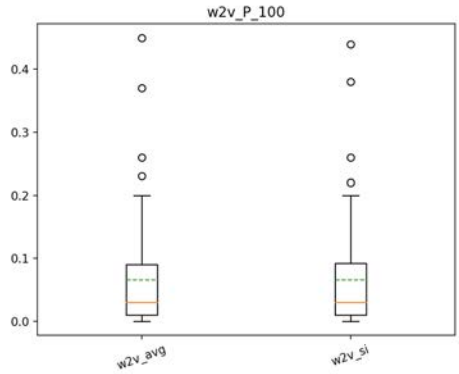
In order to answer **RQ1** we need to also see the results of the *word2vec* runs and then to analyze the best models to see if there is a clear winner.



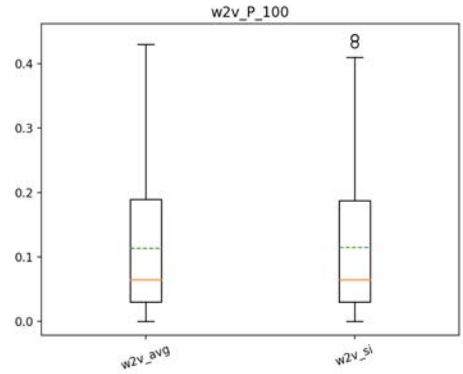
(a) T1: P**@**10 for w2v_avg and w2v_si.



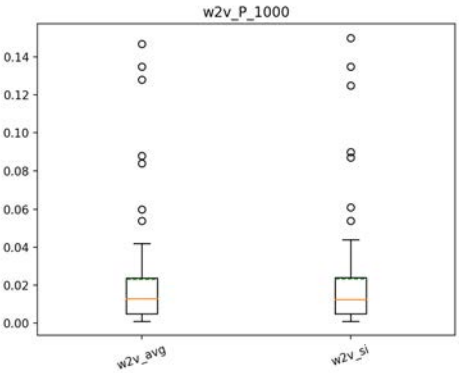
(b) T2: P**@**10 for w2v_avg and w2v_si.



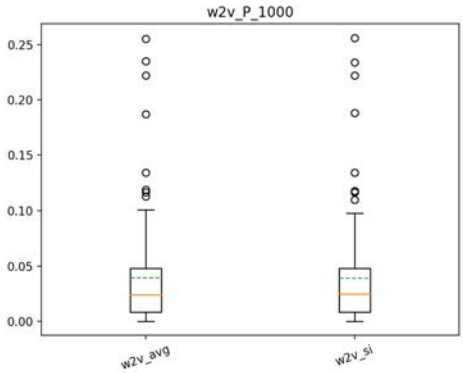
(c) T1: P**@**100 for w2v_avg and w2v_si.



(d) T2: P**@**100 for w2v_avg and w2v_si.



(e) T1: P**@**1000 for w2v_avg and w2v_si.



(f) T2: P**@**1000 for w2v_avg and w2v_si.

Figure 4.9: Precision: Box Plots of the w2v runs.

4.3 Word2vec runs

The plots for the word2vec runs are reported in figure 4.9. For this runs no pre-process has been done, it has been used only a *bioclean* [†] cleaning function before the training process

[†]Bioasq challenge: http://www.bioasq.org/

and the same function has also been applied to the queries.

Comparing the two runs to each other, it results that *w2v_si* achieves better performance than the plain *w2v_avg*, although the difference is not very marked.

As for the Terrier runs, the runs for T2 achieve better scores than the runs of T1, suggesting that a first round of boolean search can improve the performance of a model.

From the plots we can observe that the performance of the w2v runs are not very good. In fact they are comparable to the *NoPorterNoStop* runs for Terrier without QE+RF since no pre-processing has been done nor has been applied query expansion and relevance feedback.

Index/Model	NDCG@10	NDCG@100	NDCG@1000	R@R
w2v_avg	0.1144	0.1109	0.1692	0.0689
w2v_si	0.1185	0.1123	0.1708	0.0688
NoPorterNoStop/BM25	0.0443	0.0389	0.082	0.0244
NoPorterNoStop/Dirichlet	0.0167	0.0238	0.065	0.0169
NoPorterNoStop/PL2	0.0454	0.0387	0.0782	0.0243
NoPorterNoStop/TF_IDF	0.0448	0.0393	0.0821	0.0248

Table 4.7: T1: scores of NDCG and R@R of w2v runs and Terrier with *NoPorterNoStop* index.

Index/Model	NDCG@10	NDCG@100	NDCG@1000	R@R
w2v_avg	0.2065	0.2228	0.3523	0.1328
w2v_si	0.2104	0.2238	0.3539	0.1347
NoPorterNoStop/BM25	0.1861	0.2406	0.3737	0.166
NoPorterNoStop/Dirichlet	0.1786	0.2526	0.3878	0.1707
NoPorterNoStop/PL2	0.2052	0.2525	0.3929	0.1803
NoPorterNoStop/TF_IDF	0.2075	0.2665	0.4031	0.1835

Table 4.8: T2: scores of NDCG and R@R of w2v runs and Terrier with *NoPorterNoStop* index.

With respect to this observation, in table 4.7 and 4.8, we reported the scores of NDCG and Recall@R of the w2v runs and for the runs which use the *NoPorterNoStop* index.

From the table we can say that for T1, the w2v runs achieve scores comparable to the ones obtained by the Terrier runs in table 4.1 and 4.2. For T2, w2v does not obtain the same boost in performance as the Terrier runs and as a result, it achieves worst performance.

Given the improvement that the models achieved with the usage of QE+RF, it would be interesting to see if the same would apply also for w2v. Also, to better compare the models, would be necessary to do some preprocessing of the embeddings, which we did not do since we used pre-trained vectors.

To sum up, the w2v runs achieve significant better scores than models which used the *NoPorterNoStop* index for T1. For T2, however, w2v does not keep up with the improvement that happens for the Terrier runs, achieving worst scores. Since no run w2v+QE+RF has been done, it means that the w2v results are not comparable with the runs of Terrier+QE+RF which dominates completely the performance.

4.4 Fusions

In this section, we present the results of the three types of fusions that we have performed in these experiments. We then compare briefly this results with the single models from sections 4.1 and 4.2 before analyzing and answering to the two remaining research questions in the next chapter, chapter 5.

In figure 4.10 we represented the box plots of the various fusions approaches with the P@10 measure for T1. As it can be seen, there is not much difference between CombSUM and RR methods, while Probfuse achieves poorer performance. As found before, fusions of the runs with query expansion and relevance feedback have noticeable higher scores than the runs without as it is expected.

For T2, we can see in figure 4.11 that Probfuse is able to obtain comparable scores to the other two fusion methods. Of course, starting from systems which have better scores, the fusion of the runs with QE+RF achieve higher performance than the fusions of the systems without, getting even double the precision.

In table 4.9 and 4.10 we reported the scores for NDCG and Recall@R of the fusions for T1. As we observed for P@10, also for this measures Probfuse does not achieve great results, especially for the runs without query expansion and relevance feedback.

The best fusion approach is not alway the same: it depends on the index used by the models that are merged together, for instance for the *Porter* index, RR seems to be the better choice, while for the *Stop* index the better choice is CombSUM. An interesting thing to notice is the fact that RR is able to obtain a higher NDCG@1000 score in 6 out of 8 index/fusion comparison done for T1.

In table 4.11 and 4.12 we reported also the scores for the fusions of T2. From the table we can see that the observation made before still hold, Probfuse is the fusion approach with the poorer scores, while RR and CombSUM are pretty equivalent.

Unlike the results for T1, the best fusion approach for T2 seems to be CombSUM since it achieves generally better performance than RR in the majority of the Index/Fusion combi-

Index/Fusion	NDCG@10	NDCG@100	NDCG@1000	R@R
N/CombSUM	0.0474	0.0439	0.0836	0.0246
N/ProbFUSE	0.0269	0.0378	0.0778	0.0249
N/RR	0.0453	0.0405	0.0794	0.0241
P/CombSUM	0.1438	**0.1715**	0.2718	0.1095
P/ProbFUSE	0.0552	0.1498	0.2569	0.1013
P/RR	**0.1538**	0.1701	**0.2726**	**0.1096**
P+S/CombSUM	0.1383	0.1628	0.2671	0.105
P+S/ProbFUSE	0.0543	0.1441	0.2499	0.0932
P+S/RR	0.1447	0.1635	0.2649	0.1029
S/CombSUM	0.1198	0.1551	0.242	0.0973
S/ProbFUSE	0.0634	0.1427	0.2368	0.0875
S/RR	0.1264	0.1529	0.2437	0.0973

Table 4.9: T1: NDCG and Recall@R for the fusion runs.

Index/Fusion	NDCG@10	NDCG@100	NDCG@1000	R@R
N/CombSUM	0.2861	0.2756	0.3749	0.1813
N/ProbFUSE	0.1995	0.2476	0.3918	0.1702
N/RR	0.2796	0.2588	0.3984	0.1672
P/CombSUM	**0.3084**	**0.3154**	0.4278	**0.2101**
P/ProbFUSE	0.1798	0.269	0.4107	0.1912
P/RR	0.2952	0.2964	**0.4341**	0.1942
P+S/CombSUM	0.2889	0.2963	0.4135	0.1963
P+S/ProbFUSE	0.1758	0.2499	0.3975	0.1788
P+S/RR	0.2878	0.2801	0.4224	0.1822
S/CombSUM	0.2824	0.2842	0.3956	0.1915
S/ProbFUSE	0.1874	0.248	0.3898	0.1751
S/RR	0.2661	0.2684	0.4039	0.186

Table 4.10: T1: NDCG and Recall@R for the fusion runs with QE+RF.

nation that we analyzed. The difference between the two is not too big. In the next chapter we conduct an ANOVA test for the fusions to see if there is a statistical difference between the two fusions or not.

To sum up the findings for the fusion runs, we can say that CombSUM and RR are the ones that achieve better scores. They are very much equal in terms of performance of the merged list.

Comparing the best runs from tables 4.12 and 4.6 we can see that there is no fusion approach that is better than the single rank runs. This could be caused by the less performing

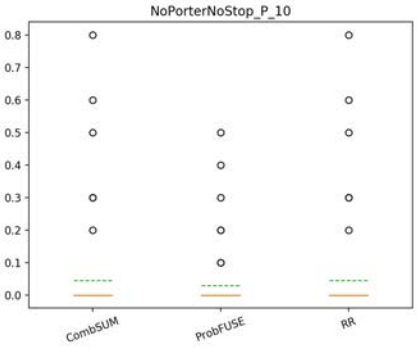
Index/Fusion	NDCG@10	NDCG@100	NDCG@1000	R@R
N/CombSUM	0.2061	0.2652	0.4028	0.1852
N/ProbFUSE	0.1546	0.2446	0.3844	0.1621
N/RR	0.2117	0.2673	0.4044	0.1815
P/CombSUM	**0.2746**	**0.3189**	0.4694	0.213
P/ProbFUSE	0.1831	0.2873	0.4377	0.1913
P/RR	0.2752	0.3158	0.4667	0.2132
P+S/CombSUM	0.2642	0.3175	**0.47**	0.2064
P+S/ProbFUSE	0.172	0.281	0.4353	0.1789
P+S/RR	0.2612	0.3152	0.4688	0.2063
S/CombSUM	0.242	0.2993	0.4516	0.2018
S/ProbFUSE	0.1674	0.2791	0.4293	0.1765
S/RR	0.246	0.3007	0.4505	**0.219**

Table 4.11: T2: NDCG and Recall@R for the fusion runs.

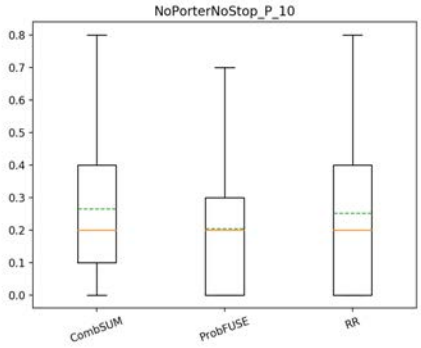
Index/Fusion	NDCG@10	NDCG@100	NDCG@1000	R@R
N/CombSUM	**0.4867**	**0.5098**	0.6407	**0.3664**
N/ProbFUSE	0.3264	0.4451	0.5814	0.2982
N/RR	0.4708	0.4992	0.6392	0.3512
P/CombSUM	0.4837	0.5056	**0.6417**	0.3574
P/ProbFUSE	0.3378	0.4413	0.5821	0.2899
P/RR	0.4628	0.4881	0.6332	0.3492
P+S/CombSUM	0.4531	0.4852	0.6236	0.3442
P+S/ProbFUSE	0.3139	0.4281	0.571	0.2868
P+S/RR	0.4353	0.4737	0.6211	0.3346
S/CombSUM	0.4462	0.4738	0.6103	0.339
S/ProbFUSE	0.323	0.4266	0.5691	0.2797
S/RR	0.4311	0.461	0.6103	0.319

Table 4.12: T2: NDCG and Recall@R for the fusion runs with QE+RF.

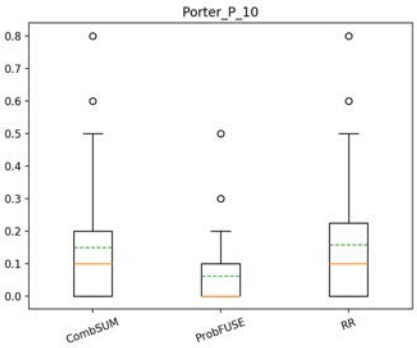
systems that probably lower the scores. In the next chapter we fuse the best runs from each index/model and then compare the merged run with the best single model from T2+QE+RF to see if the fusions are still worse than the single rank run.



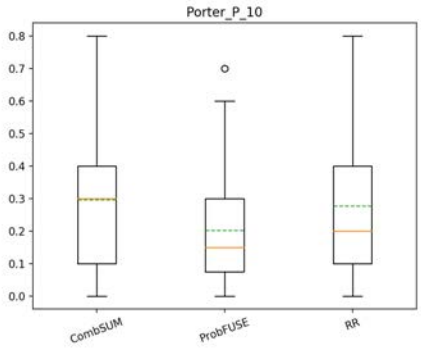
(a) NoPorterNoStop fusions of the runs.



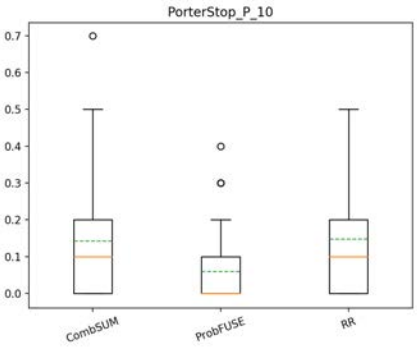
(b) NoPorterNoStop+QR+RF fusions of the runs.



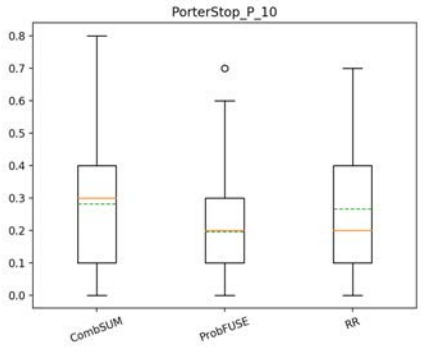
(c) Porter fusions of the runs.



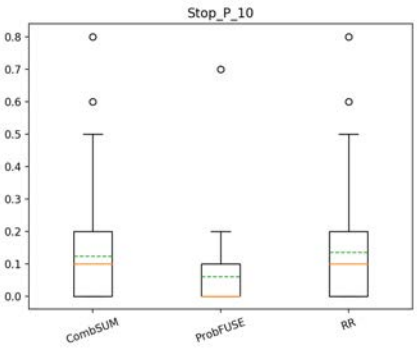
(d) Porter+QE+RF fusions of the runs.



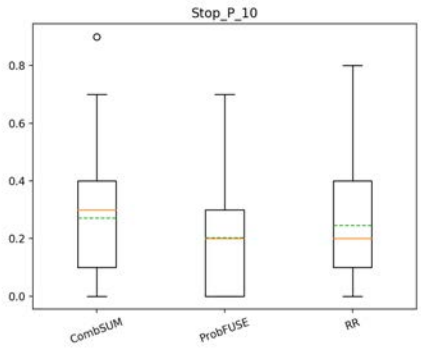
(e) PorterStop fusions of the runs.



(f) PorterStop+QE+RF fusions of the runs.

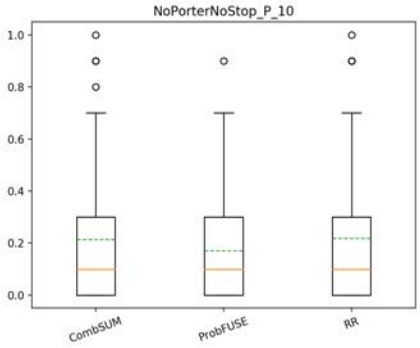


(g) Stop fusions of the runs.

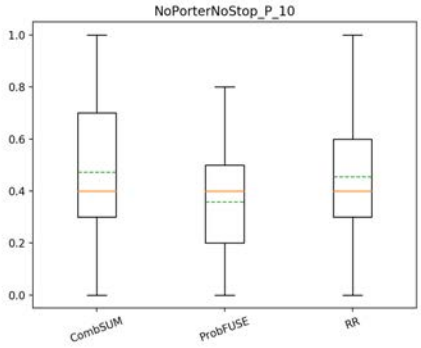


(h) Stop+QE+RF fusions of the runs.

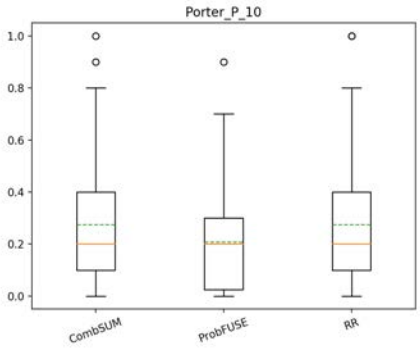
Figure 4.10: T1: Box Plots of P@10 of the fusion methods.



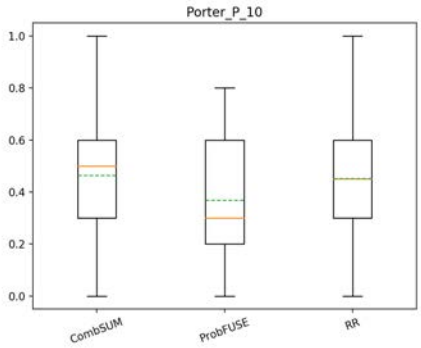
(a) NoPorterNoStop fusions of the runs.



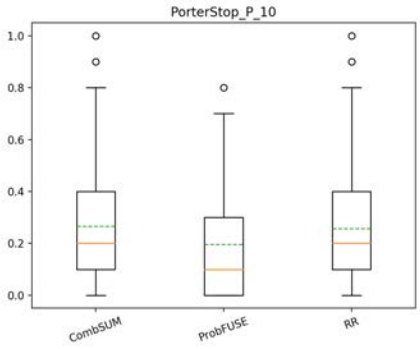
(b) NoPorterNoStop+QR+RF fusions of the runs.



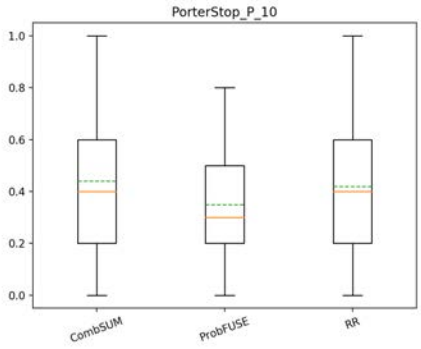
(c) Porter fusions of the runs.



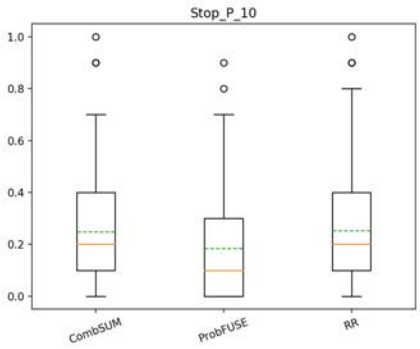
(d) Porter+QE+RF fusions of the runs.



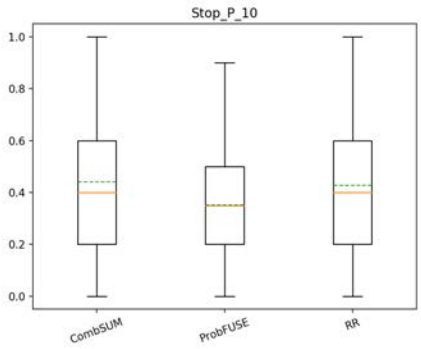
(e) PorterStop fusions of the runs.



(f) PorterStop+QE+RF fusions of the runs.



(g) Stop fusions of the runs.



(h) Stop+QE+RF fusions of the runs.

Figure 4.11: T2: Box Plots of P@10 of the fusion methods.

5

Statistical analysis of the results

In chapter 4 we presented the results of the single model runs as well as the fusions. We compared the runs in terms of pure score performance, looking only at the *mean* of the measures for the whole system while plotting the scores of each topic just in terms of P@10.

5.1 Measures

Before diving into the analysis, first we introduce two measures used in order to see if a system is actually better than another. The first one is very simple, one way to tell if a model is better than another is to simply *count* the number of topics for which model 1 has a higher score than model 2. Intuitively, if a model 1 outscores model 2 in many topics, then is very likely that model 1 is a better system than model 2.

However, this way of comparing two systems is not very precise, and sometimes could lead in choosing the poorer system. As an example, let's suppose that we have 30 topics and two models to compare m_1 and m_2. Suppose that we are interested in which is the better system in terms of P@10 and suppose that m_1 has *slightly* better scores than m_2 in 25 out of the 30 topics, while in the remaining 5 topics m_2 outscores m_1 by a great margin. In this case, the intuition says that we should choose m_2 since it obtains almost the same performance as m_1 in the majority of the topics while being significantly better in the rest. By simply counting the number of times that a system is better than the other, however, we would choose m_1 over m_2.

In order to avoid this scenario, we use a *mean* that takes into account the observation made and tries to tilt the favor toward m_2 in the previous example.

So, given the set containing all the topics Q, the score of each topic $q \in Q$ for each of the model to be compared, then, for each system i, we compute the *mean difference per topic* as:

$$mdpt_{m_i} = \frac{1}{|Q|}\left(\sum_{q \in Q} score_{m_i}(q) - \sum_{j=2}^{|M|}\sum_{q \in Q} score_{m_j}(q)\right) \tag{5.1}$$

where $|M|$ is the total number of systems to compare and $m_1, m_2, ..., m_{|M|} \in M$, with M being the set of the models. In the following analysis we always compare two systems to each other so $|M| = 2$.

The $mdpt$ score we just introduced, represents the *mean score* that we loose or gain by choosing m_1 over m_2 per topic. The smaller this mean is, the smaller is the difference in performance between the systems analyzed.

5.2 Best overall run

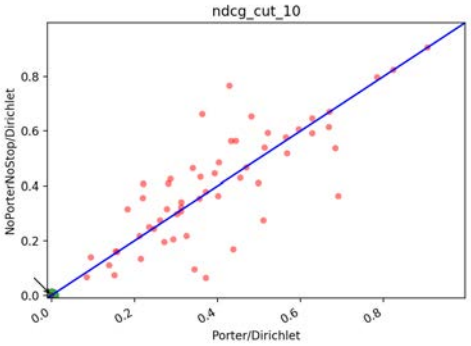
In chapter 4 we found out that the best results are achieved when QE+RF are used, thus we analyze the best runs for T1 and T2 with query expansion and relevance feedback in order to find which run is the best overall across the different scores we used. All this is done in order to be able to answer **RQ1**, which stated:

> **RQ1**: is there a single model that stands out in terms of performance?

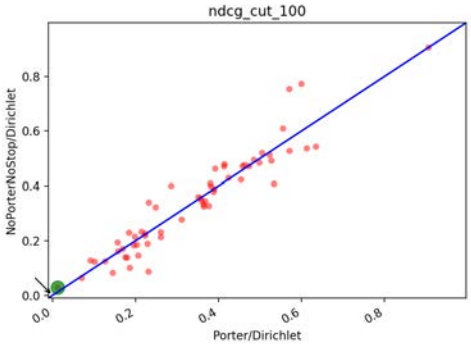
Starting with T1, looking at the tables and plots in section 4.2.1, we can see that there are two combinations of index/model that candidate themselves as the best overall run: *NoPorter-NoStop/DirichletLM* (N/D) and *Porter/DirichletLM* (P/D).

In figure 5.1 we report the scatter plots of the two runs for Precision and NDCG measures. Looking at the plots we cannot say if one system is better than the other. Interestingly, as the cutoff threshold of the Precision increases, the two runs become increasingly *similar* and the points accumulate on the bisector line, which means that the scores obtained by the runs are the same.

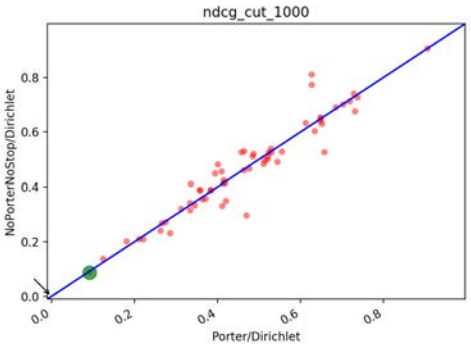
In table 5.1 we reported the $mdpt$ of *Porter/Dirichlet* vs *NoPorterNoStop/Dirichlet* and the respective count of the total number of topics for which one system has a better score than the other. It results that the better run of the two is *Porter/DirichletLM* since the



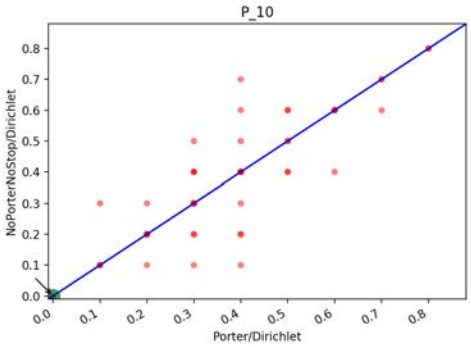
(a) NDCG@10.



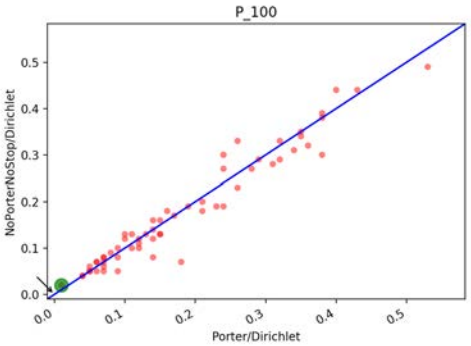
(b) NDCG@100.



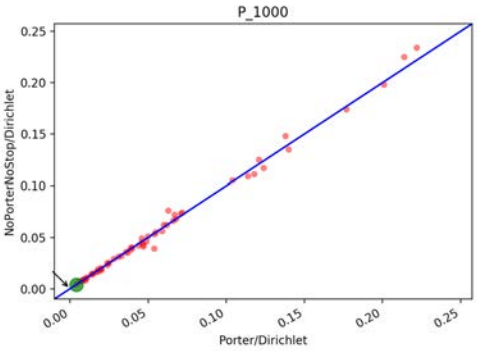
(c) NDCG@1000.



(d) Precision@10.



(e) Precision@100.



(f) Precision@1000.

Figure 5.1: T1: Scatter Plots for Porter/Dirichlet vs NoPorterNoStop/Dirichlet with QE+RF.

count of the topics is often higher for it, furthermore, the *mdpt* is almost always positive, which means that on average P/D achieves always a better overall mean score than N/D.

Measure	*mdpt*	# of outscored topics P/D vs N/D
P@10	0.003	12 vs 11
P@100	0.006	26 vs 21
P@1000	0	23 vs 17
NDCG@10	-0.001	24 vs 29
NDCG@100	0.001	32 vs 27
NDCG@1000	0	32 vs 27

Table 5.1: T1: *mdpt* of P/D vs N/D and count of the number of topics in which P/D is better than N/D and viceversa.

Thus, the best system for T1 results to be *Porter/DirichletLM*+QE+RF, although the difference in performance is very limited.

Let's move on to T2 to examine the also the runs done to see which is the best system for this task. Looking at table 4.5 and 4.6 we choose *Porter/DirichletLM* and *NoPorter-NoStop/Dirichlet* as candidates for the best system since they are the ones that achieve better scores also for T2.

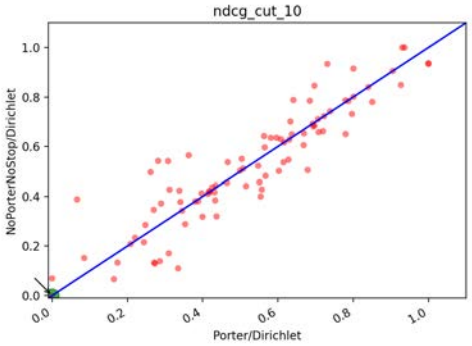
In figure 5.2 we can see the scatter plots of the two runs one against the other. No system looks obviously better than the other and as before we can see that with higher cutoff values the systems tend to equate: this is particularly evident from the plots of P@100 and P@1000.

Measure	*mdpt*	# of outscored topics P/D vs N/D
P@10	-0.006	21 vs 22
P@100	0	26 vs 21
P@1000	0	13 vs 19
NDCG@10	-0.002	42 vs 39
NDCG@100	0.001	50 vs 38
NDCG@1000	0	53 vs 36

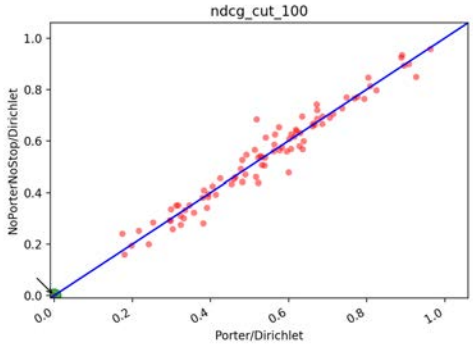
Table 5.2: T2: *mdpt* of P/D vs N/D and count of the number of topics in which P/D is better than N/D and viceversa.

From table 5.2 it results that the best combination of index/model is N/D. The difference between the two runs is limited, thus we cannot conclude in a clear way which one of them is best: for T1 it seems that P/D is better, while for T2 is N/D.

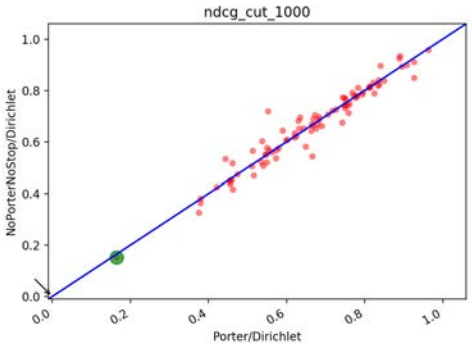
Given the findings above, we can answer to **RQ1** and say that for the medical retrieval task the best single system that can be used is to use the DirichletLM with the Porter and NoPorterNoStop index and using query expansion and relevance feedback. These systems achieves the best scores in terms of NDCG, Precision and Recall@R both for T1 and for T2.



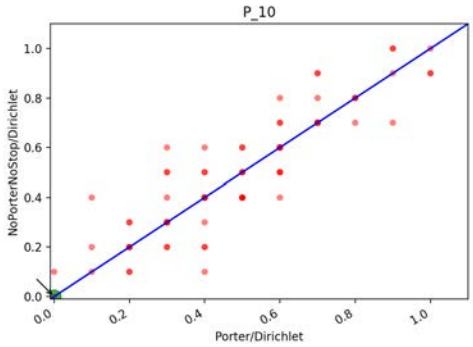
(a) NDCG@10.



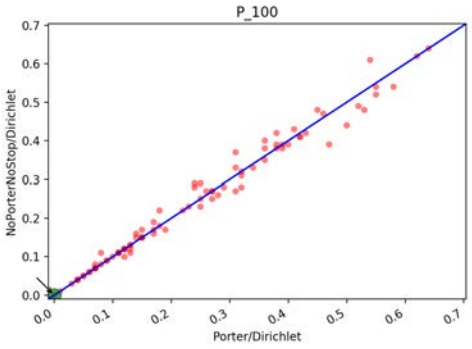
(b) NDCG@100.



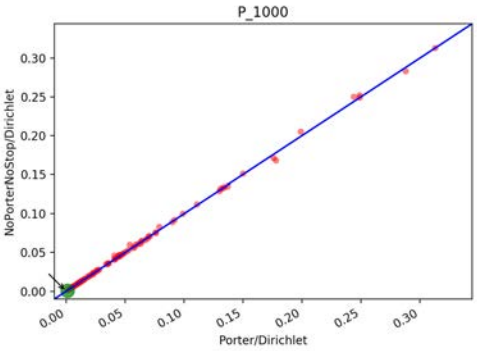
(c) NDCG@1000.



(d) Precision@10.



(e) Precision@100.



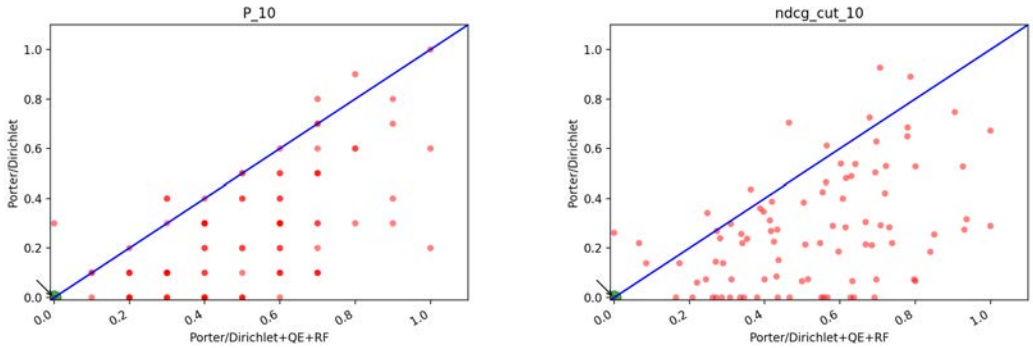
(f) Precision@1000.

Figure 5.2: T2: Scatter Plots for Porter/Dirichlet vs NoPorterNoStop/Dirichlet with QE+RF.

5.3 Gain of using QE+RF

In chapter 4 we stated that the runs with QE+RF achieve far better performance than the *normal* runs. In order to better demonstrate this fact, we now compare 4 runs: Porter/Dirichlet

with QE+RF vs Porter/Dirichlet and NoPorterNoStop/BM25 with QE+RF vs NoPorter-NoStop/BM25. In order to shorten the names, from now on we will call the runs respectively P/D+QE+RF, P/D, N/B+QE+RF and N/B. We will use the runs for T2 as example.



(a) P@10. **(b)** NDCG@10.

Figure 5.3: Scatter plots of Porter/Dirichlet with QE+RF vs the same run without QE+RF.

Starting with the DirichletLM runs, we can clearly see in figure 5.3 that the run with QE+RF has the upper hand. We reported only the plots for P@10 and NDCG@10 but the plots for the different cutoffs look very similar and they can be found in appendix B.

For completeness we also reported the measures from section 5.1 in table 5.3.

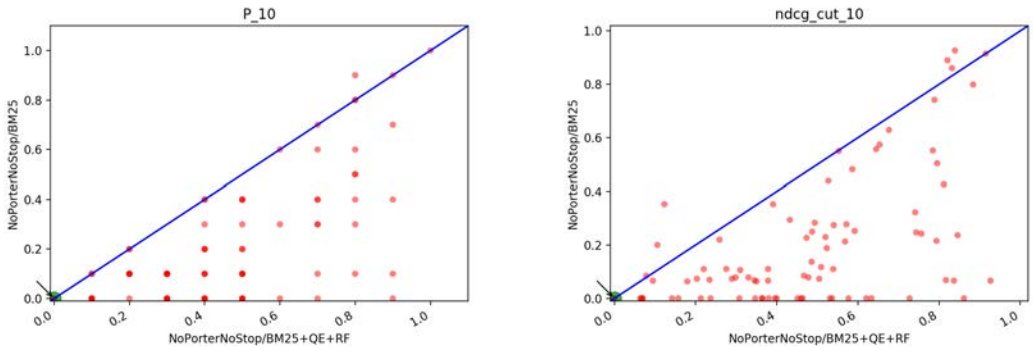
Measure	*mdpt*	# of outscored topics P/D+QE+RF vs P/D
P@10	0.234	73 vs 5
P@100	0.087	74 vs 3
P@1000	0.14	66 vs 3
NDCG@10	0.255	79 vs 10
NDCG@100	0.22	81 vs 8
NDCG@1000	0.206	84 vs 6

Table 5.3: Dirichlet+QE+RF run vs Dirichlet without QE+RF scores.

To demonstrate that this is not due to the index used or due to the model chosen, we show the same plots also for N/B+QE+RF and N/B.

In figure 5.4 we reported the scatter plots for P@10 and NDCG@10 for the two runs, while in table 5.4 we reported the numerical analysis of the two runs.

From the plots and table in this section we showed once more how much the use of query expansion and relevance feedback improves the performance of a system. We showed two



(a) P@10. **(b)** NDCG@10.

Figure 5.4: Scatter plots of NoPorterNoStop/BM25 with QE+RF vs the same run without QE+RF.

Measure	*mdpt*	# of outscored topics N/B+QE+RF vs N/B
P@10	0.236	70 vs 1
P@100	0.095	80 vs 2
P@1000	0.21	69 vs 1
NDCG@10	0.259	76 vs 6
NDCG@100	0.233	85 vs 4
NDCG@1000	0.238	86 vs 3

Table 5.4: BM25+QE+RF run vs BM25 without QE+RF scores.

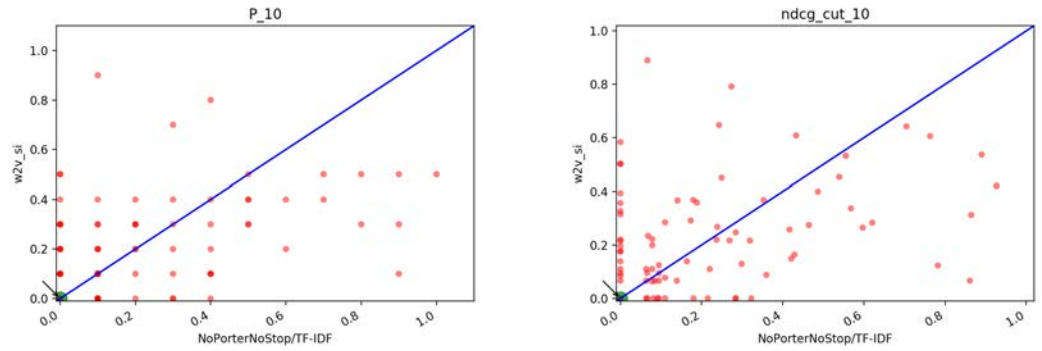
comparisons between the same index/model combination with and without QE+RF to demonstrate the advantage gained and we used two different combinations in order to prove that the gain is index independent.

5.4 NoPorterNoStop vs Word2Vec

In the previous chapter we found out that the word2vec runs were somewhat similar to the runs done with the NoPorterNoStop index since they don't use any preprocessing. In this section we would like to compare the performance of the two systems by seeing how the best run for each system contrast with the other.

We chose to compare the runs only for T2 and since the best one is TF-IDF for NoPorterNoStop and w2v-si for word2vec we put one against the other in the plots in figure 5.5.

From the plots we can see that the runs are similar, with many topics for which one model obtains a Precision or NDCG score equal to 0 while the other a score different than 0 and



(a) P@10. **(b)** NDCG@10.

Figure 5.5: Scatter plots of NoPorterNoStop/TF-IDF vs w2v-si.

sometimes even as high as 0.5 or 0.6.

Analyzing which topics are more difficult for one or the other system, we found that 3 of the most difficult topics for the w2v runs, that is the topics for which w2v obtained 0 as score for P@1000 and NDCG@100 where topics CD010860, CD012009 and CD011420. Looking at the queries we can see that there are a lot of words that are composed by two words, like *Mini-Cog*, *post-pancreatic* and *HIV-positive* which means that probably they are *out of vocabulary* words and this could be the cause of the poor scores.

On the other hand, 3 of the most difficult topics for the N/TF-IDF run were CD012179, CD012165 and CD012281. One thing that the topics share is the occurrence of the words *non-invasive* and the sequence *diagnosis of endometriosis* which probably are not put well in relation with the other words of the query and thus not being able to be specific enough in order to retrieve any relevant document.

Furthermore, it is also possible that these systems retrieve some relevant documents not seen by the assessors and thus assumed non-relevant by *trec_eval* during the evaluation of the runs.

The poor scores of the word2vec runs can be explained by the fact that no type of preprocessing has been used for them. Looking at the most difficult topics for the model we can see that the major problem are the OOV words. With a preprocessing that reduces the probability of a word to be OOV it's very likely that the performance of the model would be comparable to the ones that create the index in a similar manner.

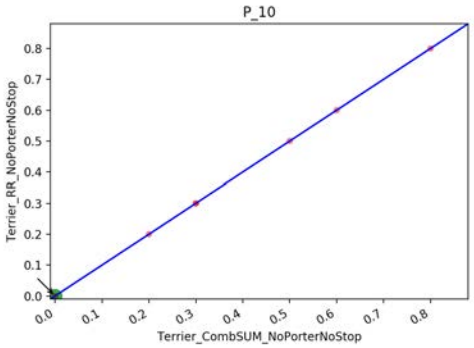
In order to do that, however, it's necessary to learn the embeddings of the preprocessed

words and thus we would need to re-learn all the vector representations of the words. Since we used a pre-trained collection of vectors, we haven't done that.

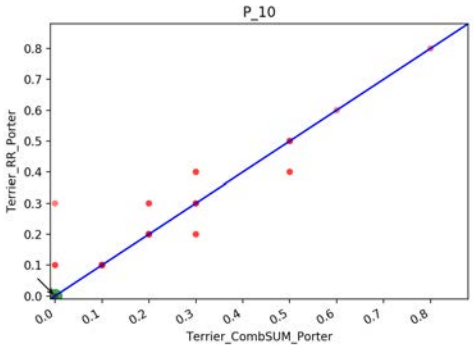
The use of query expansion and relevance feedback has proved to greatly increase the performance of a model regardless of the index used, thus is legitimate to think that it would also improve greatly the scores of the w2v runs.

5.4.1 Best overall fusion

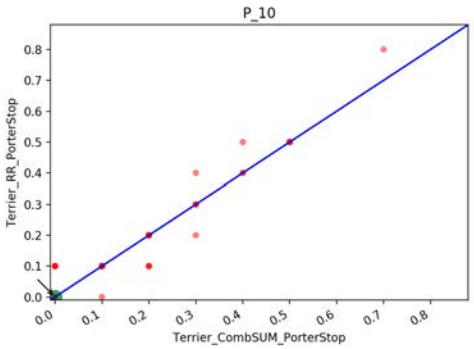
In this section we search the best fusion method for our tasks. We compare CombSUM with RR to see which one is the better approach. We decided to ignore Probfuse since in our tests it achieved noticeable poorer scores than the other two fusion approaches.



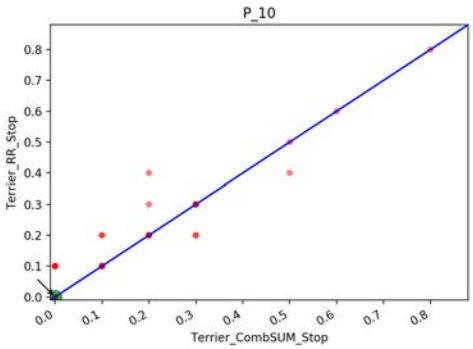
(a) CombSUM vs RR fusion of the Terrier runs using NoPorterNoStop index.



(b) CombSUM vs RR fusion of the Terrier runs using Porter index.



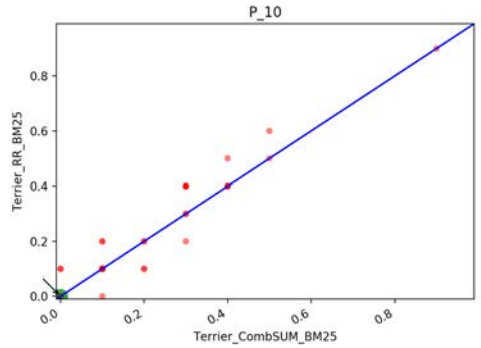
(c) CombSUM vs RR fusion of the Terrier runs using PorterStop index.



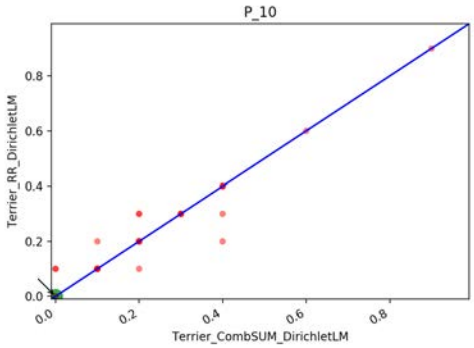
(d) CombSUM vs RR fusion of the Terrier runs using Stop index.

Figure 5.6: T1: scatter plots of P@10 of the fusion of all the models using the same index.

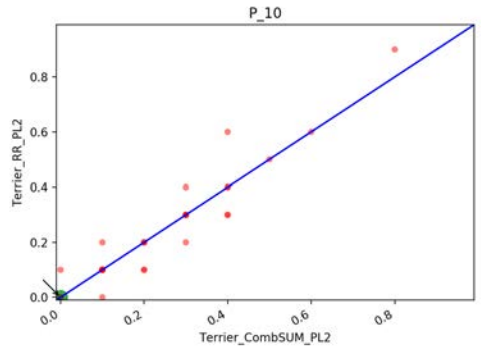
In figure 5.6 we reported the scatter plots for P@10 of CombSUM and RR runs. We fused together all the models using the same index, so every fusion combines BM25, DirichletLM, PL2 and TF-IDF. The rest of the plots can be found in the appendix B.



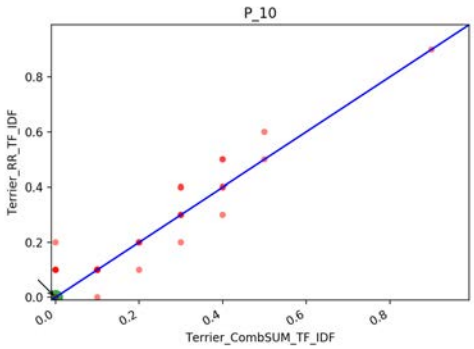
(a) CombSUM vs RR fusion of the Terrier runs with BM25 weighting scheme.



(b) CombSUM vs RR fusion of the Terrier runs with DirichletLM weighting scheme.



(c) CombSUM vs RR fusion of the Terrier runs with PL2 weighting scheme.



(d) CombSUM vs RR fusion of the Terrier runs with TF-IDF weighting scheme.

Figure 5.7: T1: scatter plots of P@10 of the fusion of the models with different indexes.

In figure 5.7 we reported, the scatter plots of the fusions done between the models using different indexes. For example we fused all the runs done with the TF-IDF weighting scheme, we fused together: NoPorterNoStop/TF-IDF, Porter/TF-IDF, PorterStop/TF-IDF and Stop/TF-IDF.

From the plots we have no way to say which fusion approach is the best one. Thus, we reported the measures of *mdpt* and the count of outscored topics in table 5.5.

The table contains the scores of *mdpt* and the counts of the number of topics for which

Fused Runs	Measure	P@10	P@100	P	NDCG@10	NDCG
NoPorterNoStop	*mdpt*	0	0.002	0.001	0.002	0.004
	# outscore	0 vs 0	8 vs 4	10 v 3	3 vs 2	26 vs 4
Porter	*mdpt*	-0.008	0.003	0	-0.01	-0.001
	# outscore	4 vs 7	17 vs 4	14 vs 15	12 vs 20	30 vs 29
PorterStop	*mdpt*	-0.005	0	0	-0.006	0.002
	# outscore	5 vs 8	11 vs 10	17 vs 12	12 vs 23	32 vs 26
Stop	*mdpt*	-0.012	0.002	0	-0.007	-0.002
	# outscore	3 vs 9	13 vs 3	17 vs 16	5 vs 23	26 vs 31
BM25	*mdpt*	-0.01	-0.03	0.02	-0.007	0.008
	# outscore	4 vs 10	7 vs 19	25 vs 11	12 vs 16	42 vs 18
DirichletLM	*mdpt*	-0.002	-0.005	-0.001	-0.004	-0.009
	# outscore	3 vs 5	13 vs 20	16 vs 19	11 vs 11	35 vs 24
PL2	*mdpt*	0	-0.004	0.001	-0.002	0.001
	# outscore	6 vs 5	5 vs 20	27 vs 13	20 vs 27	37 vs 23
TF-IDF	*mdpt*	-0.012	-0.004	0.002	-0.009	0.004
	# outscore	4 vs 10	4 vs 22	27 vs 9	15 vs 15	41 vs 19

Table 5.5: T1: scores to find the best fusion, CombSUM vs RR.

CombSUM outscores RR and viceversa of the runs in the plots. We added also the NDCG measure in this case.

Looking at the table is clear that the majority of the entries are negative which means that RR is the best fusion approach for this runs. The difference between the two is always within 1% which probably means that they are not statistically different, we analyze this fact in section 5.5.2.

The goal of this section was to find if there is a fusion approach that works best for the medical retrieval task. We found that CombSUM (with min-max normalization) and RR achieve almost the same scores.

Having to choose between the two, however, we choose RR since it is simpler than CombSUM to implement and gives slightly higher scores early on in the ranked list of documents returned, as it can be seen in table 5.5.

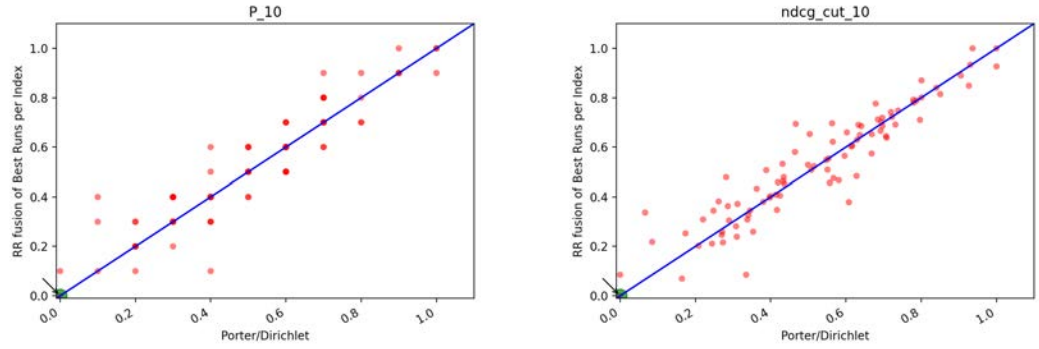
In the next section we search for the best combination of runs to fuse in order to obtain the highest possible scores. Given what we said above, we will look only to RR as fusion method. We will try to fuse the best runs of each index, the best runs of each model and the best runs with comparable scores in the hope of finding the best runs to fuse. Then, we will

compare the best fusion of runs to the best single model run to see what is the absolute best approach.

5.4.2 Best overall fusion vs best single run

In the first part of this section, we analyze the RR fusion of the best runs for index compared to the best single run. Since we are interested to find the overall optimum approach, we will fuse the runs with higher scores, which are Terrier+QE+RF, both for T1 and T2. This in order to find better evidence of the goodness or badness of the fusion.

Starting with the best run for each index, we fused all the runs with QE+RF done with the DirichletLM model. We then compared this fusion with the best single model found in section 5.2, which is Porter/DirichletLM.



(a) P@10. **(b)** NDCG@10.

Figure 5.8: T2: scatter plots of P@10 and NDCG@10 of Porter/DirichletLM vs RR fusion of best runs per index with QE+RF.

In figure 5.8 we reported the scatter plots for P@10 and NDCG@10 of the comparison of the two plots. Since the best model per index is the DirichletLM model, we fused together all the 4 runs done.

Looking at the tables 5.6 and 5.7 we can see that for both tasks there is not much difference between the two runs. For T1, the single run has the upper hand, while for T2 it's the fusion that achieves better scores. A negative number for $mdpt$ means that the RR run has better *mean* score per topic than the single model run.

Overall we do not have a clear answer to the question if the fusion works better than the single run. When it does, the gain is not that much and since we have to consider that the

Measure	*mdpt*	# outscore
P@10	0.012	14 vs 11
P@100	-0.004	20 vs 20
P@1000	-0.001	14 vs 21
NDCG@10	0.009	31 vs 19
NDCG@100	-0.006	28 vs 31
NDCG@1000	-0.008	24 vs 35

Table 5.6: T1: Porter/DirichletLM+QE+RF run vs RR fusion of DirichletLM+QE+RF model with the 4 indexes.

Measure	*mdpt*	# outscore
P@10	-0.012	18 vs 26
P@100	-0.001	21 vs 26
P@1000	0	10 vs 20
NDCG@10	-0.007	36 vs 41
NDCG@100	-0.002	40 vs 48
NDCG@1000	-0.001	41 vs 48

Table 5.7: T2: Porter/DirichletLM+QE+RF run vs RR fusion of DirichletLM+QE+RF model with the 4 indexes.

RR run needs to fuse 4 runs in order to get a slightly better performance the single model run is the best choice.

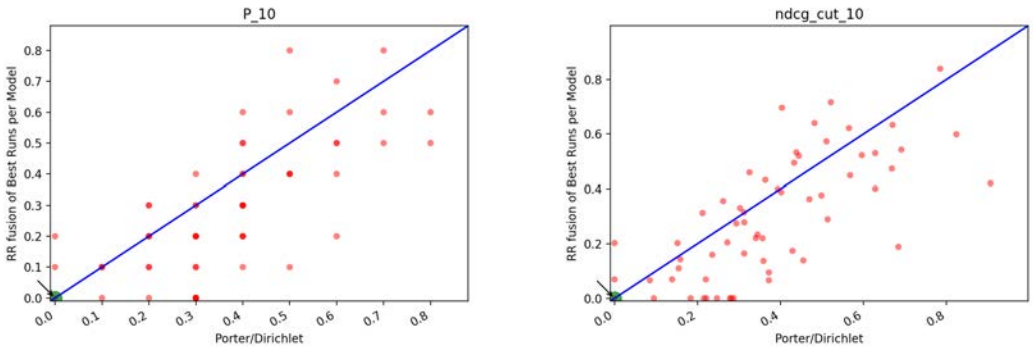
Since the best model for each index proved to be Dirichlet, we now fuse the index/model combination that achieved the higher scores for each model. Looking at the results in section 4.2. for T1 we fused all the runs that used the Porter index, while for T2 the runs that used the NoPorterNoStop index. We decided to do the RR fusion of the NoPorterNoStop/DirichletLM even if it is not the overall best run because all the other models achieved their best scores using this index and the difference between the two runs are not very high, as already observed in section 5.2.

We choose to do this fusion since in the previous case we merged always the same *model* regardless of the index, thus we want to see if by increasing the diversity of the models helps the merged run to obtain better scores or not.

In figure 5.9 and 5.10 we reported the scatter plots of the comparison between the best run and the RR fusion of Porter for T1 and NoPorterNoStop for T2.

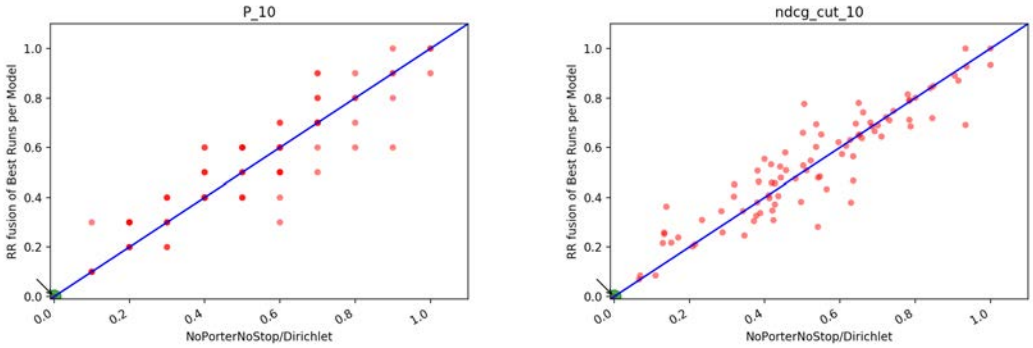
In tables 5.8 and 5.9 we can see that in this case the RR fusion run never manages to prevail above the best run. Thus, our hypothesis that fusing different models may help the overall accuracy is disproven.

So far we have not been able to find a merged run that outscores the best single run. We



(a) P@10. **(b)** NDCG@10.

Figure 5.9: T1: scatter plots of P@10 and NDCG@10 of Porter/DirichletLM vs RR fusion of best runs per index with QE+RF.



(a) P@10. **(b)** NDCG@10.

Figure 5.10: T2: scatter plots of P@10 and NDCG@10 of NoPorterNoStop/DirichletLM vs RR fusion of best runs per model with QE+RF.

now try one last time to find it by fusing together only the runs that have the best absolute performance.

Like before, we chose the runs to be merged by looking at the tables and plots in section 4.2. Given all the results found in this chapter and the plots and tables, we now compare the fusion of N/D and P/D against the single run P/D. We do this comparison for T1 and T2 with the use of QE+RF to see if by fusing the top two single runs together is possible to obtain a list of documents which is more relevant than the best single run.

Starting with T1, in figure 5.11 and tables 5.10 and 5.11 we reported the scatter plots of P@10

Measure	*mdpt*	# outscore
P@10	0.087	37 vs 12
P@100	0.013	34 vs 22
P@1000	0	26 vs 26
NDCG@10	0.083	40 vs 19
NDCG@100	0.043	45 vs 15
NDCG@1000	0.034	37 vs 23

Table 5.8: T1: Porter/DirichletLM+QE+RF run vs RR fusion of models using Porter Index.

Measure	*mdpt*	# outscore
P@10	0.046	44 vs 21
P@100	0.008	39 vs 25
P@1000	-0.001	20 vs 32
NDCG@10	0.051	54 vs 33
NDCG@100	0.037	54 vs 34
NDCG@1000	0.026	47 vs 42

Table 5.9: T2: Porter/DirichletLM+QE+RF run vs RR fusion of models using NoPorterNoStop index.

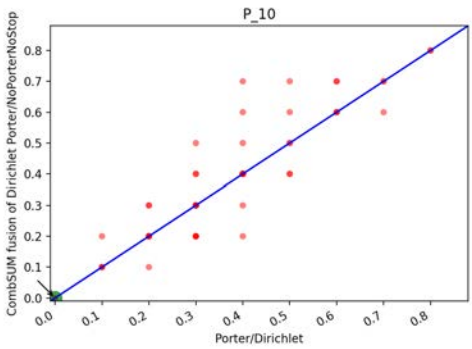
Measure	*mdpt*	# outscore
P@10	-0.012	10 vs 13
P@100	0.001	19 vs 16
P@1000	0	15 vs 10
NDCG@10	-0.011	24 vs 25
NDCG@100	-0.004	29 vs 28
NDCG@1000	-0.003	25 vs 34

Table 5.10: T1: Comparison of the best run vs the CombSUM fusion of the two best runs.

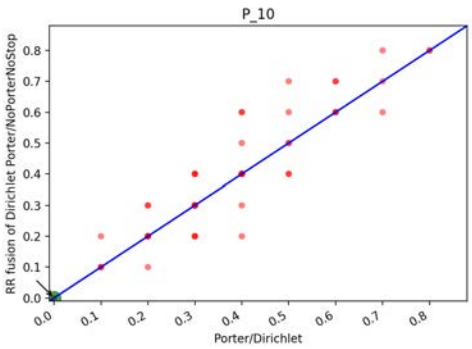
Measure	*mdpt*	# outscore
P@10	-0.012	9 vs 14
P@100	0.001	20 vs 18
P@1000	0	16 vs 14
NDCG@10	-0.016	18 vs 30
NDCG@100	-0.006	27 vs 32
NDCG@1000	-0.005	27 vs 31

Table 5.11: T1: Comparison of the best run vs the RR fusion of the two best runs.

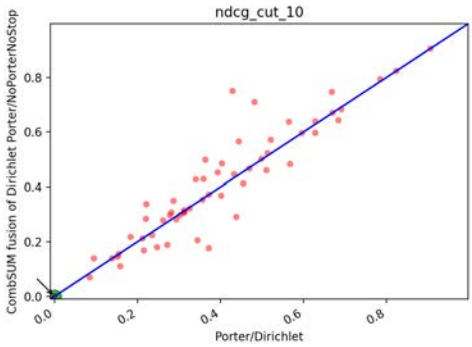
and NDCG@10 of the comparison of the runs. From the scores in the table, observing that a negative *mdpt* means that the fusions are better, it emerges that the fusions achieve a better mean score per topic early in the ranked list of documents, while as we move to the end of



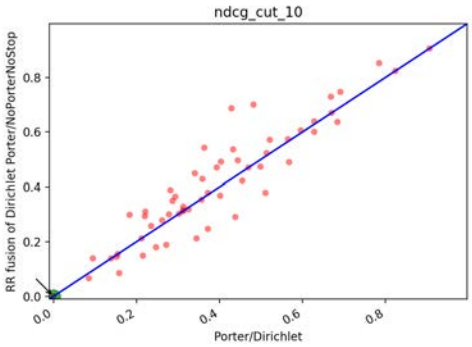
(a) P@10 for Porter/Dirichlet vs CombSUM.



(b) P@10 for Porter/Dirichlet vs RR.



(c) NDCG@10 for Porter/Dirichlet vs CombSUM.



(d) NDCG@10 for Porter/Dirichlet vs RR.

Figure 5.11: T1: Scatter plots of the best run vs the fusion of the two best runs.

the results the difference goes down.

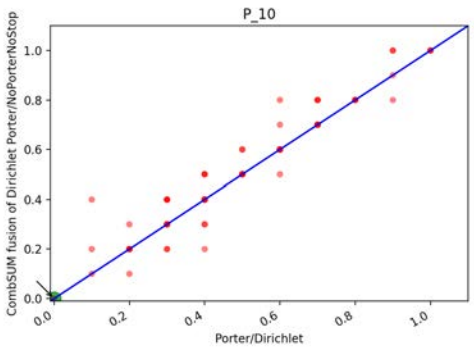
The gain of a fusion is, however, relatively low being around 1.2% for P@10 and 1.6% for NDCG@10.

Moving to T2, we reported the same plots and tables as for T1 in figure 5.12 and tables 5.12 and 5.13.

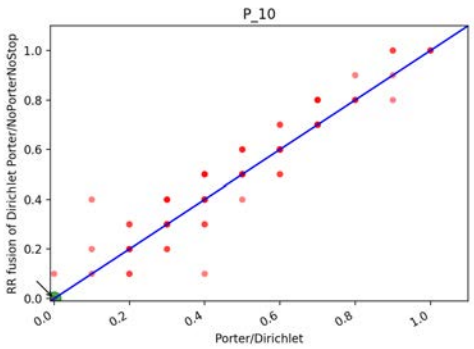
From the values in the table we can say that, also in this case, the gaining of the fusions is relatively small, around 1.6% maximum, being higher early on and decreasing with the increase of the cutoff.

For T2, however, the fusions are never beaten by the single run, at most they tie, which implies that for T2 the fusion is a better approach than for T1.

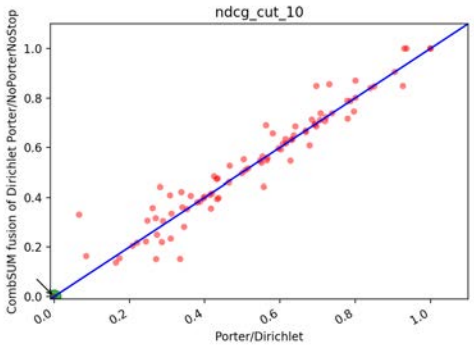
In neither case the fusion has been proved to be a clear better approach, furthermore, given



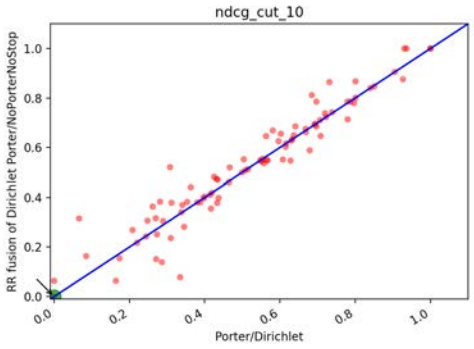
(a) P@10 for Porter/Dirichlet vs CombSUM.



(b) P@10 for Porter/Dirichlet vs RR.



(c) NDCG@10 for Porter/Dirichlet vs CombSUM.



(d) NDCG@10 for Porter/Dirichlet vs RR.

Figure 5.12: T2: Scatter plots of the best run vs the fusion of the two best runs.

all the results found in this section, we can say that the fusion increases the retrieved list of documents by less than 2% in terms of Precision and NDCG which for us is not sufficient to say that it should be the preferred approach.

Thus, we can answer **RQ3**:

> **RQ3**: is there a fusion method that does better retrieval than using a single model?

From our findings, the answer to this question is no. We motivate this answer by arguing that for an improvement of around one point percentage is not sufficient to justify the increased time complexity of having two or more models to retrieve and then merge them into one single run.

Measure	$mdpt$	# outscore
P@10	-0.014	8 vs 19
P@100	-0.001	16 vs 26
P@1000	0	7 vs 8
NDCG@10	-0.009	34 vs 35
NDCG@100	-0.001	48 vs 40
NDCG@1000	-0.002	45 vs 42

Table 5.12: T2: Comparison of the best run vs the CombSUM fusion of the two best runs.

Measure	$mdpt$	# outscore
P@10	-0.016	11 vs 25
P@100	-0.001	15 vs 25
P@1000	0	10 vs 13
NDCG@10	-0.009	35 vs 39
NDCG@100	-0.004	41 vs 45
NDCG@1000	-0.004	46 vs 42

Table 5.13: T2: Comparison of the best run vs the RR fusion of the two best runs.

5.5 Statistical analysis

From the results found in the previous sections we found that many runs achieved very similar performance, with little difference between the scores. For this reason, we now test the statistical difference between the different indexes and between RR fusion and CombSUM.

5.5.1 Statistical difference between different indexes

The first tests we want to conduct is to see if there is a statistical difference between using different indexes. We first look at T1.

Model	F test	p-value	Model	F test	p-value
BM25	4.321	0.0055	N	0.592	0.6211
BM25+QE+RF	0.055	0.9829	N+QE+RF	7.927	$4.65 \cdot 10^{-5}$
Dirichlet	9.343	$7.35 \cdot 10^{-6}$	P	0.198	0.8979
Dirichlet+QE+RF	0.278	0.8413	P+QE+RF	8.864	$1.37 \cdot 10^{-5}$
PL2	4.083	0.0075	P+S	0.026	0.9943
PL2+QE+RF	0.283	0.838	P+S+QE+RF	6.461	0.0003
TF-IDF	4.584	0.0039	S	0.046	0.9868
TF-IDF+QE+RF	0.244	0.8658	S+QE+RF	5.786	0.0008

Table 5.14: T1: ANOVA test results for the different models and indexes for P@10.

In table 5.14 we reported the results of the ANOVA test conducted on the various runs. We analyzed all the runs done using the same model, thus with a different index, and then all the runs done using the same index, thus with a different model. We tested the runs both with and without QE+RF.

Our findings are very interesting. From the values in the table, it results that without the use of query expansion and relevance feedback, the runs done with the same model but with a different index are statistically different one from another. When we apply QE+RF, however, the statistical difference disappears, this means that the usage of a different type of preprocessing creates different runs while when using QE+RF it does not matter which type of preprocessing is done, the resulting runs are all statistically equivalent.

On the other hand, for the runs done with the same index but with a different model things are the opposite: if we don't use QE+RF then it does not matter which weighting scheme we choose to rank the document collection, they are statistically equivalent while if we do use it, then the runs become different. This means that our hypothesis which stated that QE+RF benefits models in different ways was correct and that this was indeed the case. Therefore some weighting schemes get a more significant gain in terms of Precision (and also other measures) than others and this reflect into the fact that the resulting runs are more diverse.

To further confirm the findings above, we also run the ANOVA test for T2. In table 5.15 we reported the F score and p-value for the runs.

Model	F test	p-value	Model	F test	p-value
BM25	1.015	0.386	N	0.352	0.7876
BM25+QE+RF	0.743	0.527	N+QE+RF	2.404	0.0672
Dirichlet	1.938	0.1231	P	0.781	0.5051
Dirichlet+QE+RF	0.027	0.9939	P+QE+RF	4.066	0.0073
PL2	0.563	0.6398	P+S	0.094	0.9633
PL2+QE+RF	0.712	0.5452	P+S+QE+RF	5.64	0.0009
TF-IDF	0.933	0.4247	S	0.014	0.9977
TF-IDF+QE+RF	0.566	0.6379	S+QE+RF	5.664	0.0008

Table 5.15: T2: ANOVA test results for the different models and indexes for P@10.

Unlike T1, for T2 there is less evidence that runs without QE+RF with different indexes are statistically different since the p-value is always above $\alpha = 0.05$. Like T1, however, the usage of QE+RF uniforms the runs and makes them statistically equivalent. This means that

by doing first a boolean search, which type of preprocessing is done to the collection does not matter as much as the model chosen to actually rank the documents.

When we look at the test done for different models using the same index we find the same thing as for T1: without QE+RF the weighting scheme used to rank the documents does not determine the performance of the run as much as the type of preprocessing applied. Things, however, are reversed when applying QE+RF: in this case, also for T2, which model is used determines the goodness of the final results since it favors more some schemes than the others.

To sum up, in this section we argued that the use of QE+RF evens the runs done with the same model while it statistically differentiates runs done with the same index but with the same index. Also, if the collection is pre-filtered by a boolean search, then the type of preprocessing applied to the list of documents does not influence the performance of a run as much as the choice of the model which scores the documents.

We run the ANOVA test for P@10, in appendix C we reported other ANOVA tests done for different measures.

5.5.2 Statistical difference between CombSUM and RR

We now want to test if there is a statistical difference between applying CombSUM and Reciprocal Ranking fusions. Since in the previous section we found that runs done with QE+RF with different models are statistically different, we test if it is different to fuse them with CombSUM or RR.

Model	F test	p-value
NoPorterNoStop+QE+RF	0.09	0.76
Porter+QE+RF	0.26	0.61
PorterStop+S+QE+RF	0.17	0.68
Stop+QE+RF	0.47	0.49

Table 5.16: T1: ANOVA test results for the indexes for P@10.

Model	F test	p-value
NoPorterNoStop+QE+RF	0.24	0.62
Porter+QE+RF	0.11	0.74
PorterStop+S+QE+RF	0.31	0.58
Stop+QE+RF	0.11	0.74

Table 5.17: T2: ANOVA test results for indexes for P@10.

In table 5.16 and 5.17 we reported the scores of the ANOVA test for the runs with QE+RF

for T1 and T2, comparing the fusion of the models using the same index.

From the results we can see that there is no statistical difference between using CombSUM or RR as fusion approach, neither for T1 nor for T2, despite starting from statistically different models.

We hereby reported only the test for P@10 as, like we have already seen in chapter 4, higher the cutoff less the difference between the runs. The appendix C contains the remaining scores of the different measures.

6

Conclusions and future work

In this work we focused on the task of Retrieval of Medical Publications, using the CLEF e-Health tracks as our tasks. In chapter 2 we presented the different models and different types of preprocessing chosen to test which the system achieves better performance.

We then took a look to the usage of query expansion and relevance feedback in order to further improve the scores obtained by the runs and finally, we tried three different fusion approaches to see if by merging different runs into on single run, the performance improves further. We presented all the setup in chapter 3.

After reporting the experimental results in chapter 4, we analyzed them in chapter 5.

In section 1.1 we posed the following research questions:

1. **RQ1**: is there a single model that stands out in terms of performance?
2. **RQ2**: does the use of query expansion and relevance feedback improve the results?
3. **RQ3**: is there a fusion method that does better retrieval than using a single model?

For **RQ1**, we found out that the model that achieves better overall scores is **DirichletLM** with QE+RF. This model, regardless of the preprocessing applied to the collection, is the one that stands out in terms of performance. We also found that the best combinations of index/model are DirichletLM with *NoPorterNoStop* and *Porter* indexes, although we did not find statistical difference between the four runs with the different indexes.

The answer to **RQ2** is a certain yes, QE+RF improves greatly *all* of the models tested by us. A model with QE+RF sometimes even doubles the scores obtained for a particular measure.

Looking at the fusion approaches, we discovered that the usage of a fusion approach improves *slightly* the scores of the final run when compared to the best single model run. This improvement is higher in the first part of the document list and decreases as we look to the end of the list. Thus the answer to **RQ3** is that yes, there are fusion approaches that retrieve more relevant documents than the single runs, however this improvement is relatively small and it needs to be studied if the increased complexity is justified by the gain in performance.

For the word2vec runs we did not apply any type of preprocessing nor QE+RF and as a matter of fact, this runs did not achieve great scores. We did not apply any preprocessing due to the fact that we used pre-trained embeddings while the best approach would be to use the same preprocessing as the other runs and then compare them.

6.1 Future work

The immediate extension of this work could be to test the queries for *query difficulty* and to see if there are some topics more difficult for some systems than others. If this should be the case, then it would be interesting to build a system that recognizes the difficulty of the query to then execute the query with the system that has a higher probability of retrieving more relevant documents. This system could be a single model run or a fusion of more runs.

To further improve this system, it would be interesting to see if it is possible to *tune* it in order to maximize one particular score that could benefit most to the user, for example, if a user is interested in finding *all* the relevant documents in a collection, then it would be better to use the model or fusion that maximizes the *Recall*.

In this work we only had access to Title and Abstract of the publications, thus it would be interesting to compare the results found in this work with the same runs but done on the dataset of the *complete* articles and not just the abstracts.

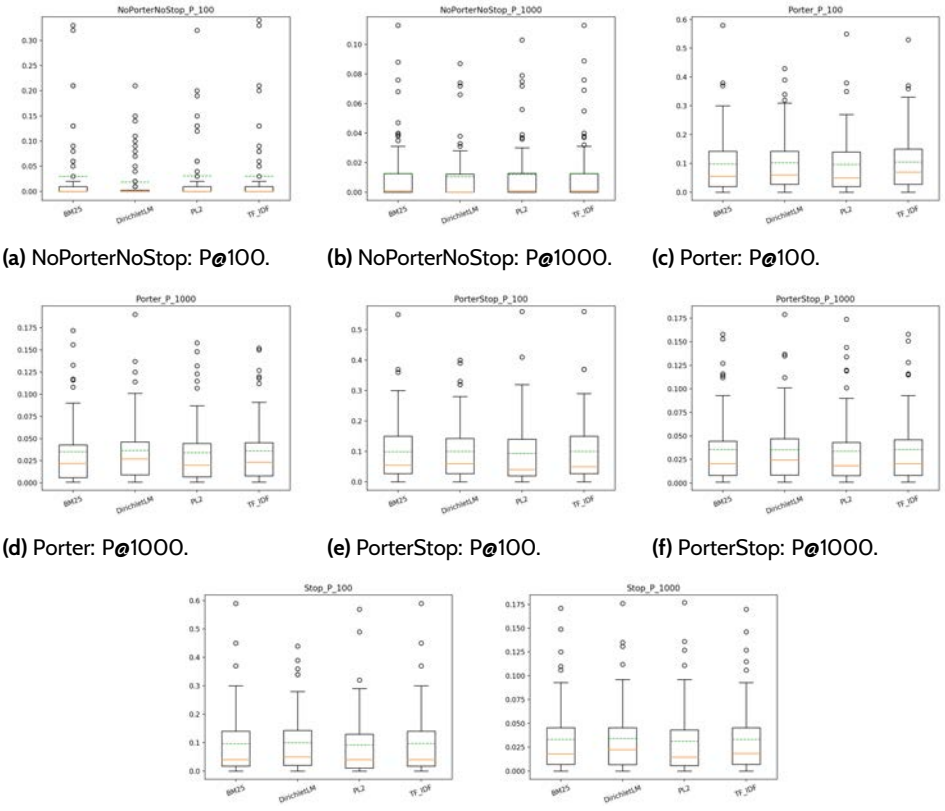
In our experiments, Probfuse did not obtain good results when compared to CombSUM and RR. By increasing or decreasing the number of runs to fuse as well as tuning the x parameter of the fusion it should be possible to achieve better results.

To maximize the performance of all the systems used in this work, tuning the various parameters of the models would be the necessary thing to do in order to develop a complete system which makes use of the findings in this work.

A

Box Plots and tables

A.1

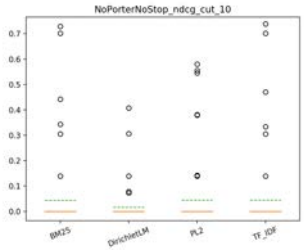


(a) NoPorterNoStop: P@100. **(b)** NoPorterNoStop: P@1000. **(c)** Porter: P@100.

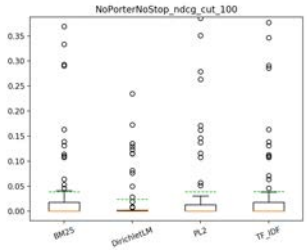
(d) Porter: P@1000. **(e)** PorterStop: P@100. **(f)** PorterStop: P@1000.

(g) Stop: P@100. **(h)** Stop: P@1000.

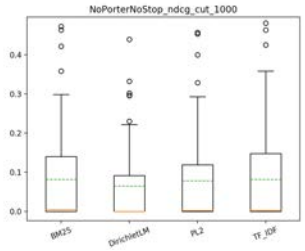
Figure A.1: T1: Box Plots for P@100 and P@1000 comparison per Index.



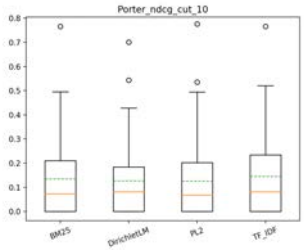
(a) NoPorterNoStop: NDCG**@**10.



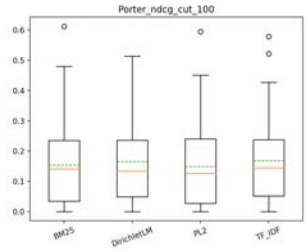
(b) NoPorterNoStop: NDCG**@**100.



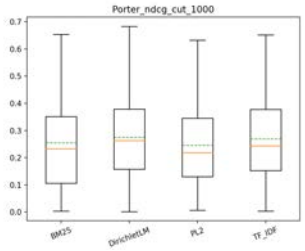
(c) NoPorterNoStop: NDCG**@**1000.



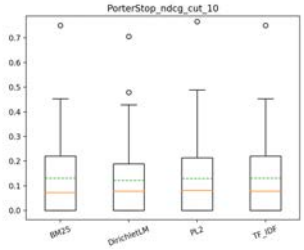
(d) Porter: NDCG**@**10.



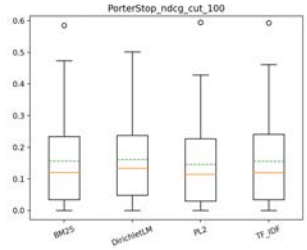
(e) Porter: NDCG**@**100.



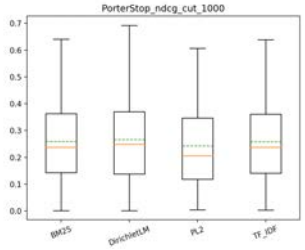
(f) Porter: NDCG**@**1000.



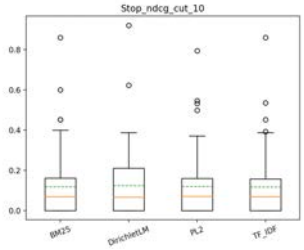
(g) PorterStop: NDCG**@**10.



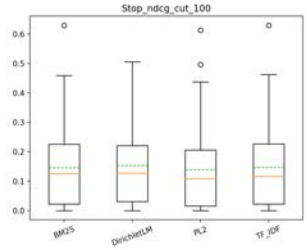
(h) PorterStop: NDCG**@**100.



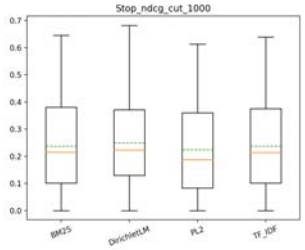
(i) PorterStop: NDCG**@**1000.



(j) Stop: NDCG**@**10.

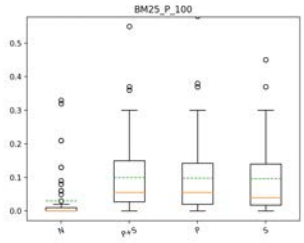


(k) Stop: NDCG**@**100.

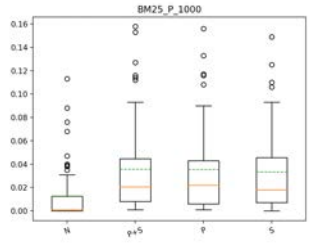


(l) Stop: NDCG**@**1000.

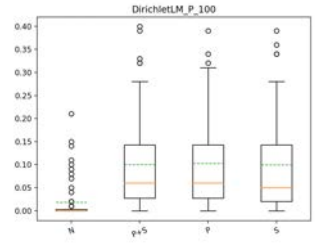
Figure A.2: T1: Box Plots for NDCG of the different models for each index.



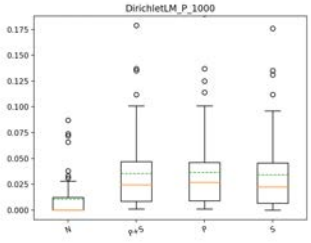
(a) BM25: BoxPlots for P**@**100.



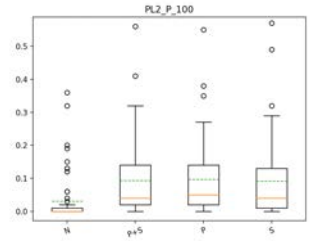
(b) BM25: BoxPlots for P**@**1000.



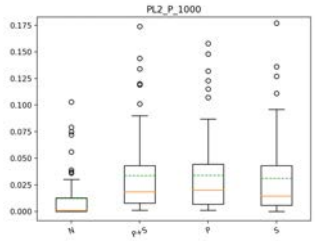
(c) DirichletLM: BoxPlots for P**@**100.



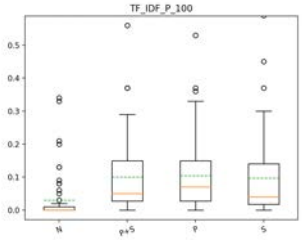
(d) DirichletLM: BoxPlots for P**@**1000.



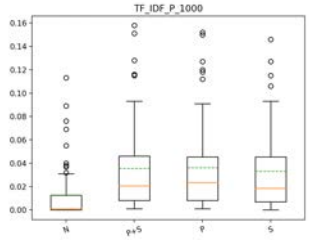
(e) PL2: BoxPlots for P**@**100.



(f) PL2: BoxPlots for P**@**1000.

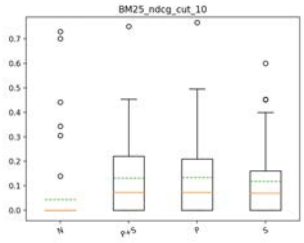


(g) TF-IDF: BoxPlots for P**@**100.

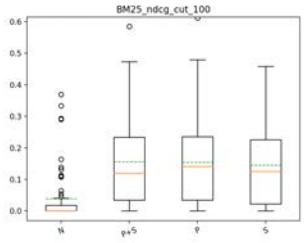


(h) TF-IDF: BoxPlots for P**@**1000.

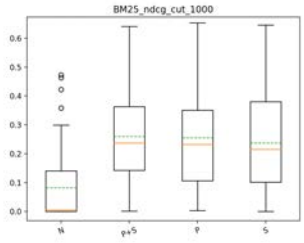
Figure A.3: Box plots of P**@**100 and P**@**1000 for every model.



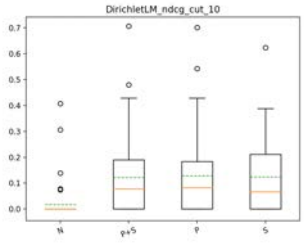
(a) BM25: NDCG**@**10.



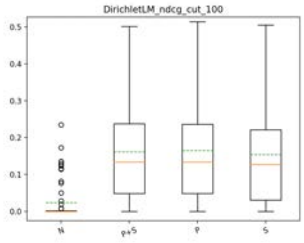
(b) BM25: NDCG**@**100.



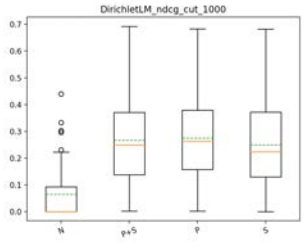
(c) BM25: NDCG**@**1000.



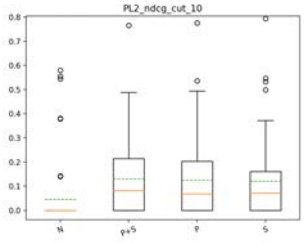
(d) DirichletLM: NDCG**@**10.



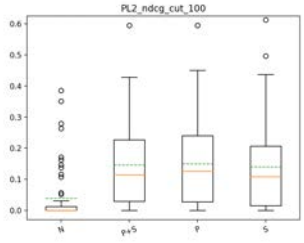
(e) DirichletLM: NDCG**@**100.



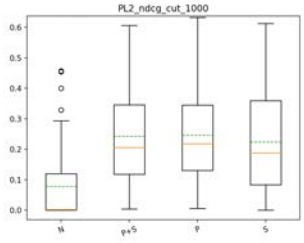
(f) DirichletLM: NDCG**@**1000.



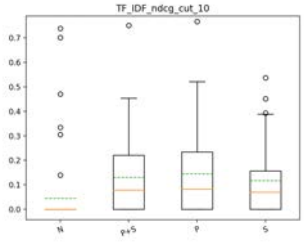
(g) PL2: NDCG**@**10.



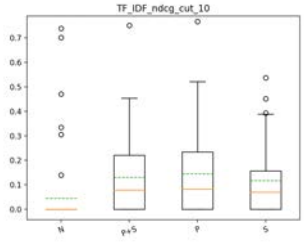
(h) PL2: NDCG**@**100.



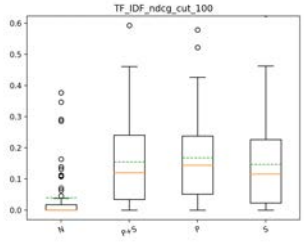
(i) PL2: NDCG**@**1000.



(j) TF-IDF: NDCG**@**10.



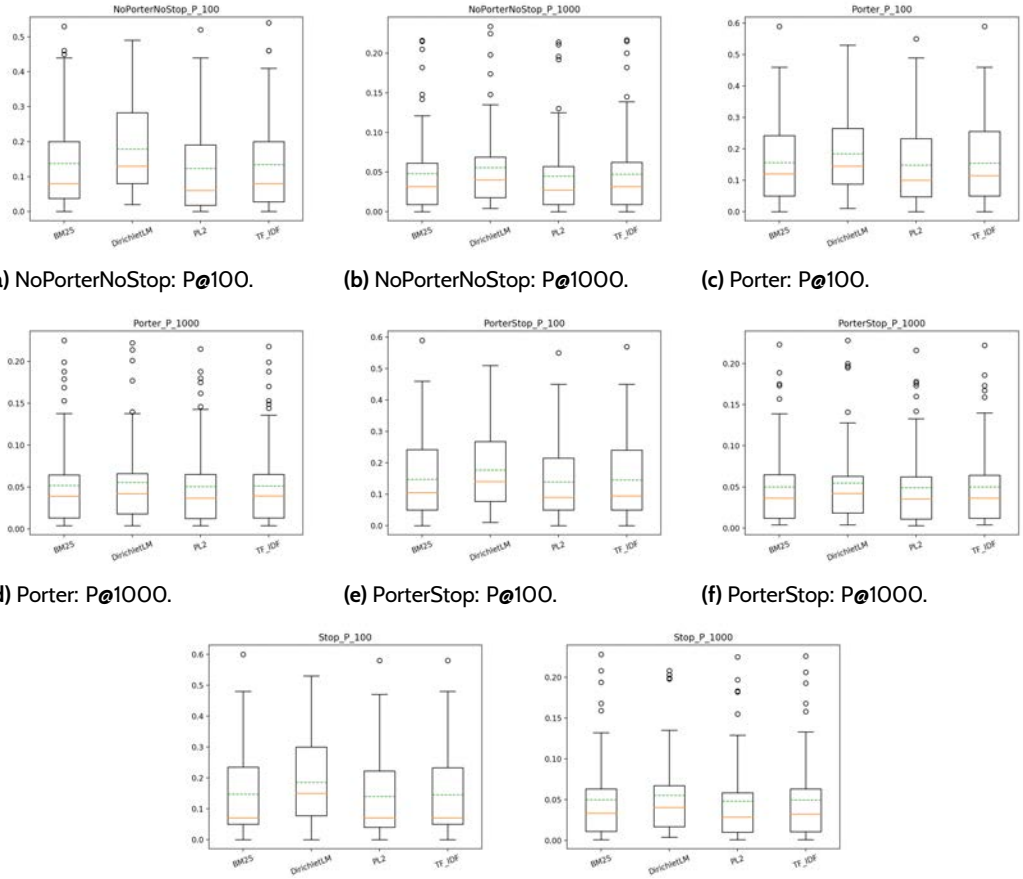
(k) TF-IDF: NDCG**@**100.



(l) TF-IDF: NDCG**@**100.

Figure A.4: T1: Box Plots for NDCG of the different indexes for each model.

A.1.1 Taski+QE+RF

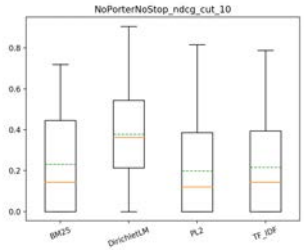


(a) NoPorterNoStop: P**@**100. **(b)** NoPorterNoStop: P**@**1000. **(c)** Porter: P**@**100.

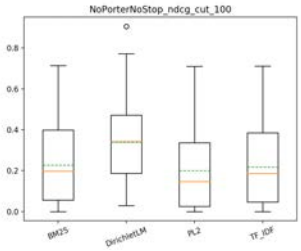
(d) Porter: P**@**1000. **(e)** PorterStop: P**@**100. **(f)** PorterStop: P**@**1000.

(g) Stop: P**@**100. **(h)** Stop: P**@**1000.

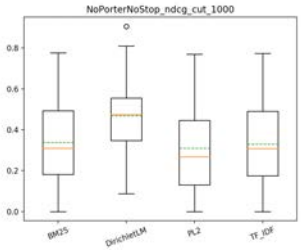
Figure A.5: T1: Box Plots for P**@**100 and P**@**1000 comparison per Index.



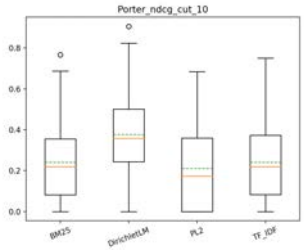
(a) NoPorterNoStop: NDCG**@**10.



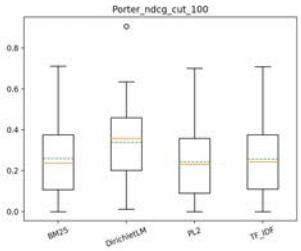
(b) NoPorterNoStop: NDCG**@**100.



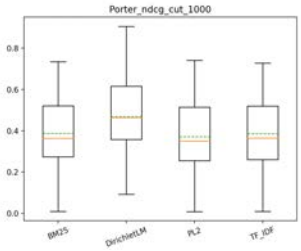
(c) NoPorterNoStop: NDCG**@**1000.



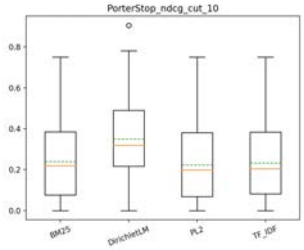
(d) Porter: NDCG**@**10.



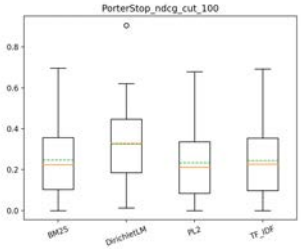
(e) Porter: NDCG**@**100.



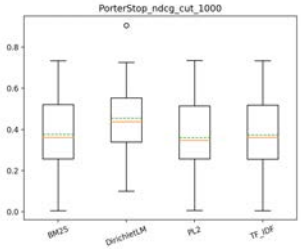
(f) Porter: NDCG**@**1000.



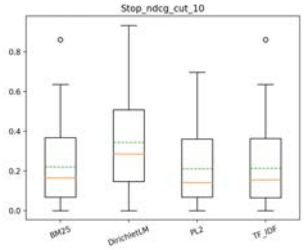
(g) PorterStop: NDCG**@**10.



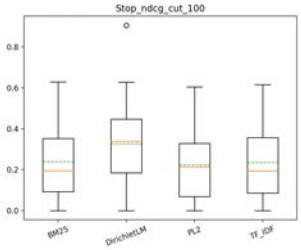
(h) PorterStop: NDCG**@**100.



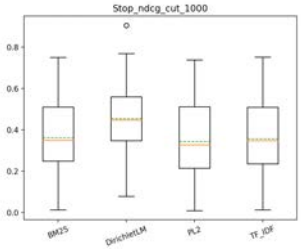
(i) PorterStop: NDCG**@**1000.



(j) Stop: NDCG**@**10.

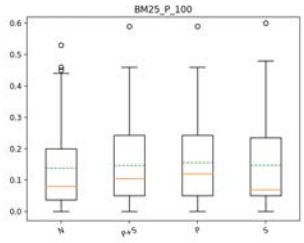


(k) Stop: NDCG**@**100.

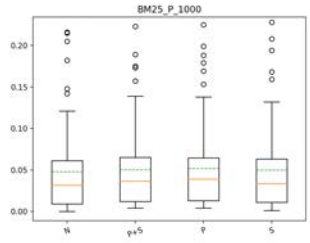


(l) Stop: NDCG**@**1000.

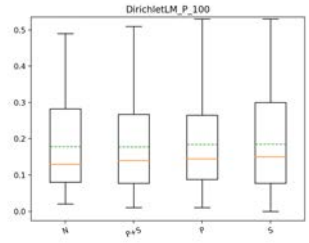
Figure A.6: T1: Box Plots for NDCG of the different models for each index.



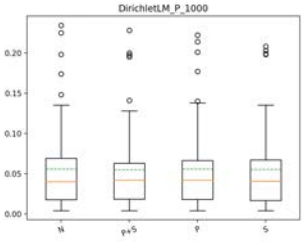
(a) BM25: BoxPlots for P**@**100.



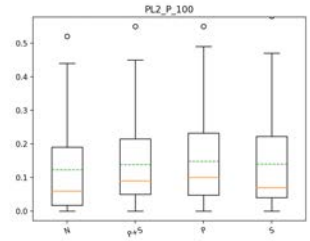
(b) BM25: BoxPlots for P**@**1000.



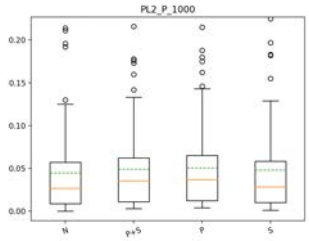
(c) DirichletLM: BoxPlots for P**@**100.



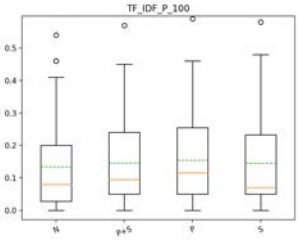
(d) DirichletLM: BoxPlots for P**@**1000.



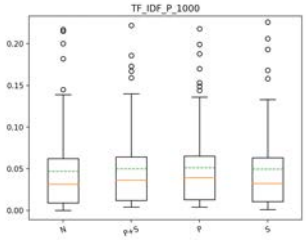
(e) PL2: BoxPlots for P**@**100.



(f) PL2: BoxPlots for P**@**1000.

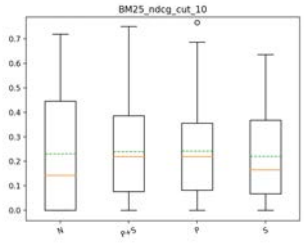


(g) TF-IDF: BoxPlots for P**@**100.

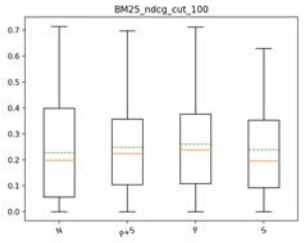


(h) TF-IDF: BoxPlots for P**@**1000.

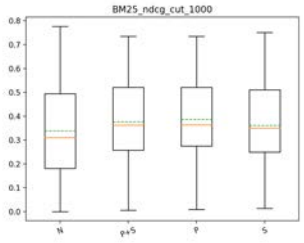
Figure A.7: Box plots of P**@**100 and P**@**1000 for every model.



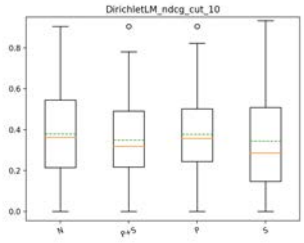
(a) BM25: NDCG**@**10.



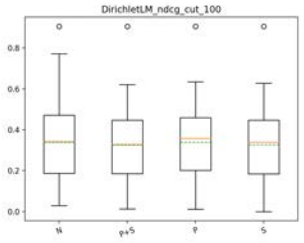
(b) BM25: NDCG**@**100.



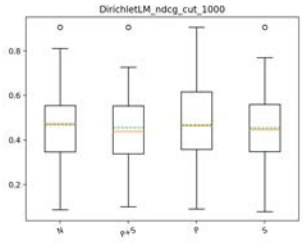
(c) BM25: NDCG**@**1000.



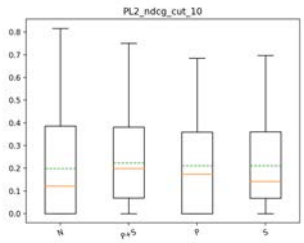
(d) DirichletLM: NDCG**@**10.



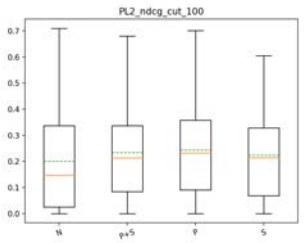
(e) DirichletLM: NDCG**@**100.



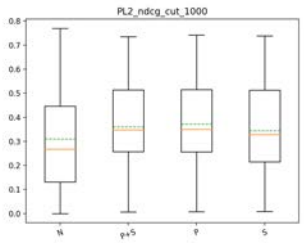
(f) DirichletLM: NDCG**@**1000.



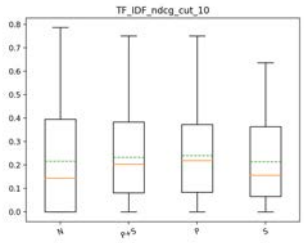
(g) PL2: NDCG**@**10.



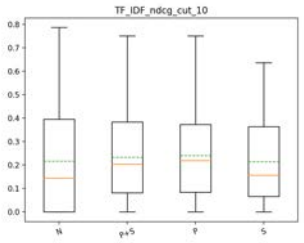
(h) PL2: NDCG**@**100.



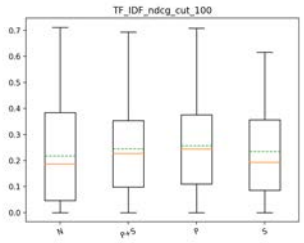
(i) PL2: NDCG**@**1000.



(j) TF-IDF: NDCG**@**10.



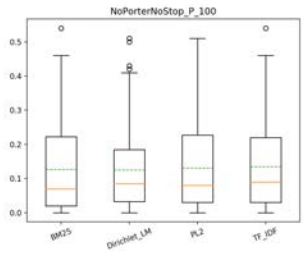
(k) TF-IDF: NDCG**@**100.



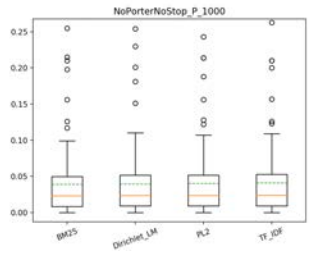
(l) TF-IDF: NDCG**@**100.

Figure A.8: T1: Box Plots for NDCG of the different indexes for each model.

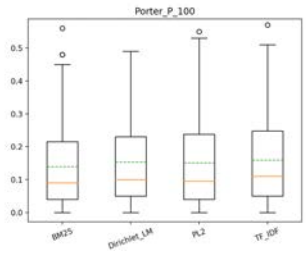
A.2 Task2



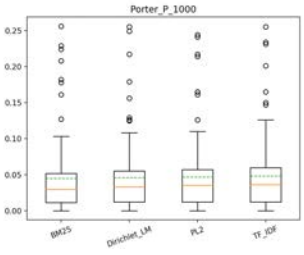
(a) NoPorterNoStop: P@100.



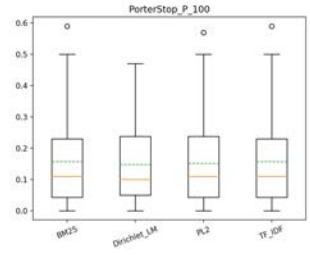
(b) NoPorterNoStop: P@1000.



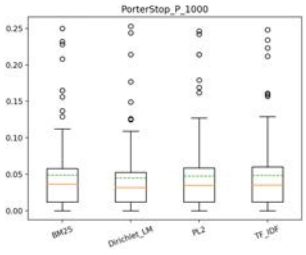
(c) Porter: P@100.



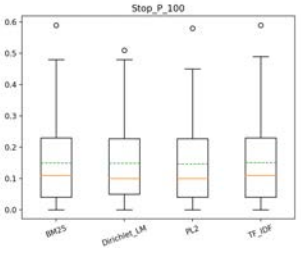
(d) Porter: P@1000.



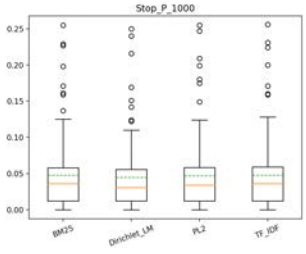
(e) PorterStop: P@100.



(f) PorterStop: P@1000.

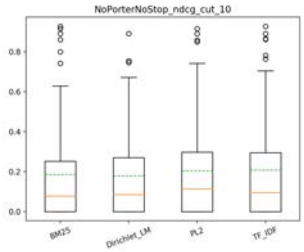


(g) Stop: P@100.

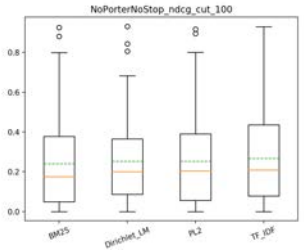


(h) Stop: P@1000.

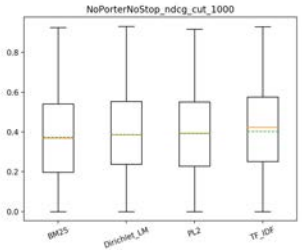
Figure A.9: T2: Box Plots for P@100 and P@1000 comparison per Index.



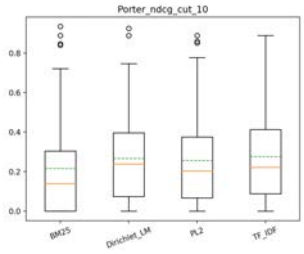
(a) NoPorterNoStop: NDCG**@**10.



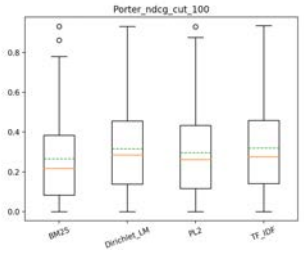
(b) NoPorterNoStop: NDCG**@**100.



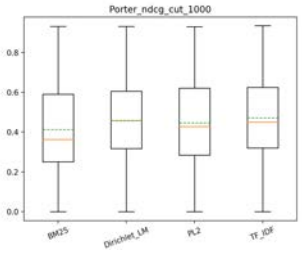
(c) NoPorterNoStop: NDCG**@**1000.



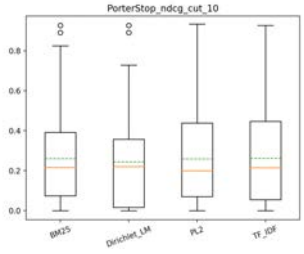
(d) Porter: NDCG**@**10.



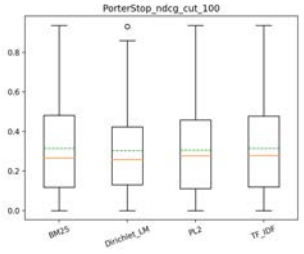
(e) Porter: NDCG**@**100.



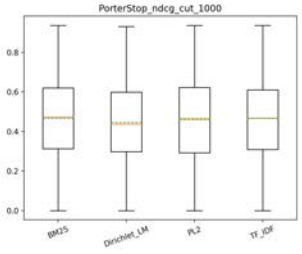
(f) Porter: NDCG**@**1000.



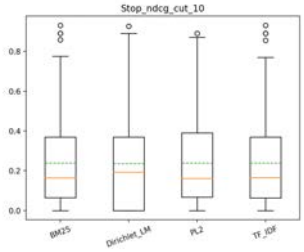
(g) PorterStop: NDCG**@**10.



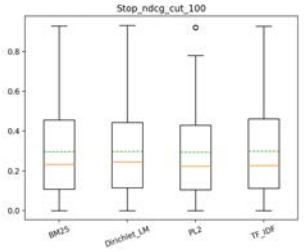
(h) PorterStop: NDCG**@**100.



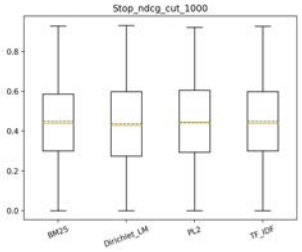
(i) PorterStop: NDCG**@**1000.



(j) Stop: NDCG**@**10.

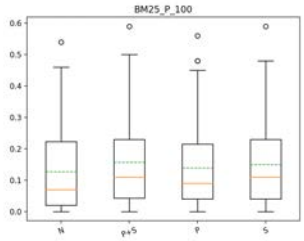


(k) Stop: NDCG**@**100.

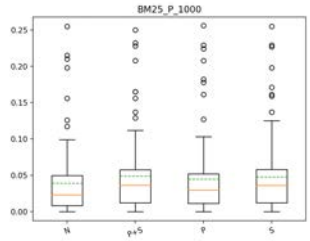


(l) Stop: NDCG**@**1000.

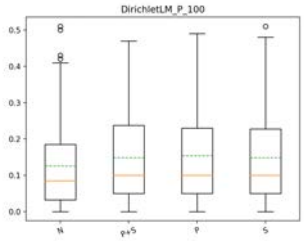
Figure A.10: T2: Box Plots for NDCG of the different models for each index.



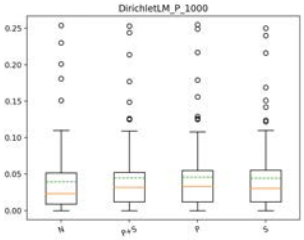
(a) BM25: BoxPlots for P**@**100.



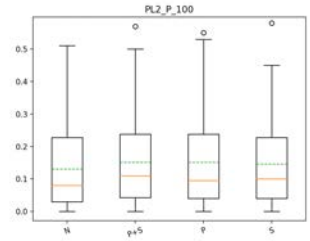
(b) BM25: BoxPlots for P**@**1000.



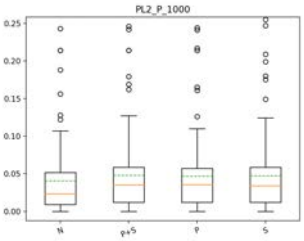
(c) DirichletLM: BoxPlots for P**@**100.



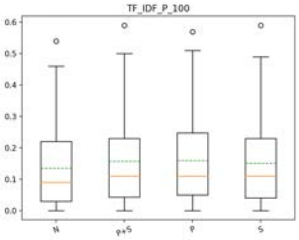
(d) DirichletLM: BoxPlots for P**@**1000.



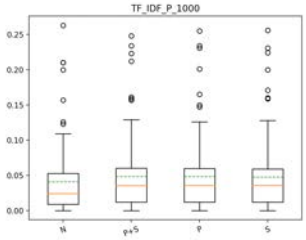
(e) PL2: BoxPlots for P**@**100.



(f) PL2: BoxPlots for P**@**1000.

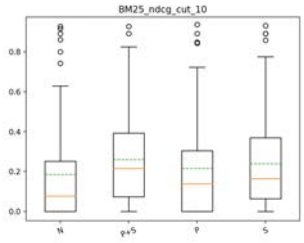


(g) TF-IDF: BoxPlots for P**@**100.

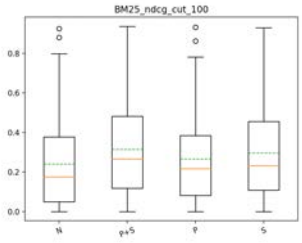


(h) TF-IDF: BoxPlots for P**@**1000.

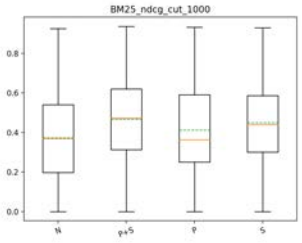
Figure A.11: Box plots of P**@**100 and P**@**1000 for every model.



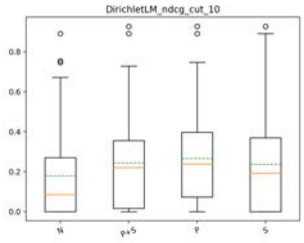
(a) BM25: NDCG**@**10.



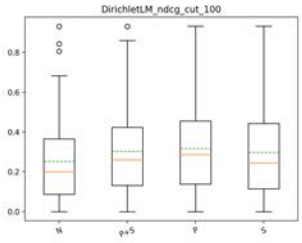
(b) BM25: NDCG**@**100.



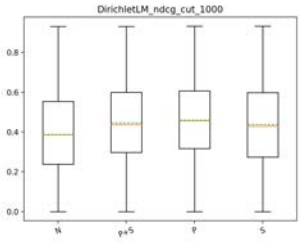
(c) BM25: NDCG**@**1000.



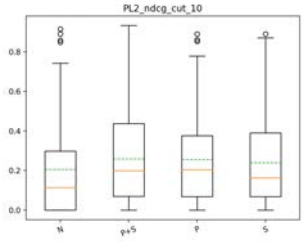
(d) DirichletLM: NDCG**@**10.



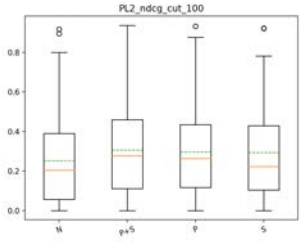
(e) DirichletLM: NDCG**@**100.



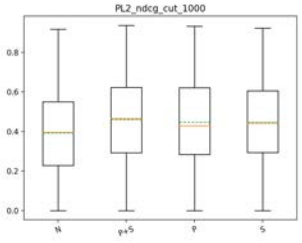
(f) DirichletLM: NDCG**@**1000.



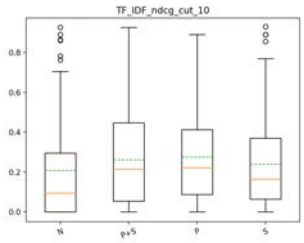
(g) PL2: NDCG**@**10.



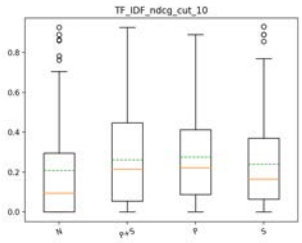
(h) PL2: NDCG**@**100.



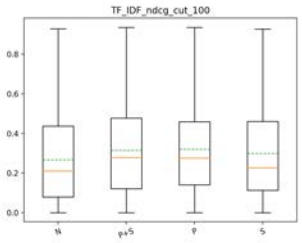
(i) PL2: NDCG**@**1000.



(j) TF-IDF: NDCG**@**10.



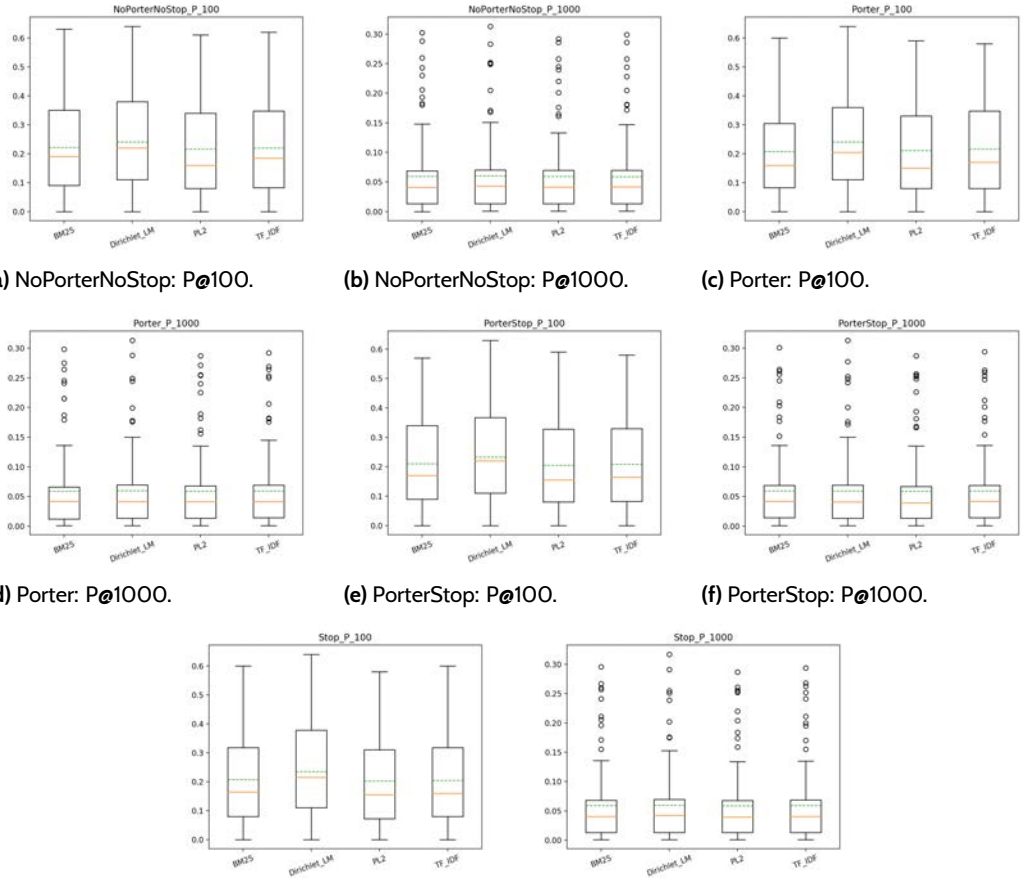
(k) TF-IDF: NDCG**@**100.



(l) TF-IDF: NDCG**@**100.

Figure A.12: T2: Box Plots for NDCG of the different indexes for each model.

A.2.1 Task2+QE+RF

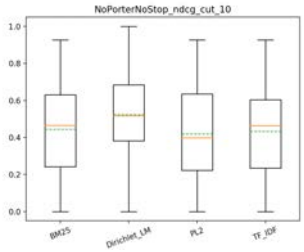


(a) NoPorterNoStop: P@100. **(b)** NoPorterNoStop: P@1000. **(c)** Porter: P@100.

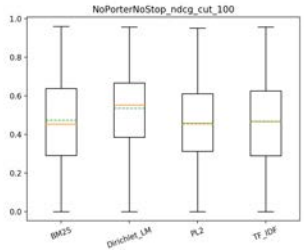
(d) Porter: P@1000. **(e)** PorterStop: P@100. **(f)** PorterStop: P@1000.

(g) Stop: P@100. **(h)** Stop: P@1000.

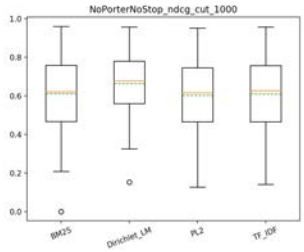
Figure A.13: T2: Box Plots for P@100 and P@1000 comparison per Index.



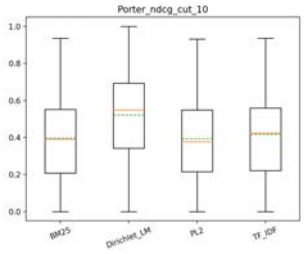
(a) NoPorterNoStop: NDCG**@**10.



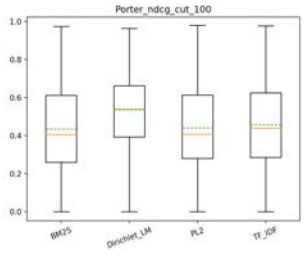
(b) NoPorterNoStop: NDCG**@**100.



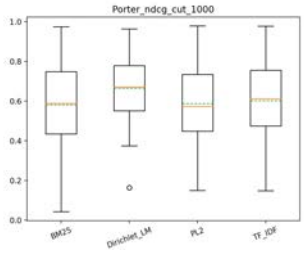
(c) NoPorterNoStop: NDCG**@**1000.



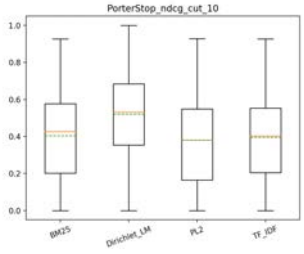
(d) Porter: NDCG**@**10.



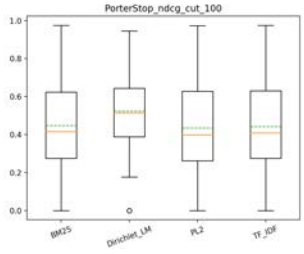
(e) Porter: NDCG**@**100.



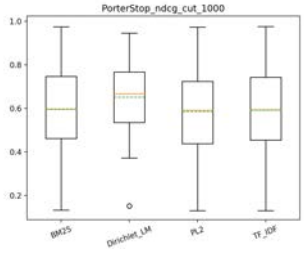
(f) Porter: NDCG**@**1000.



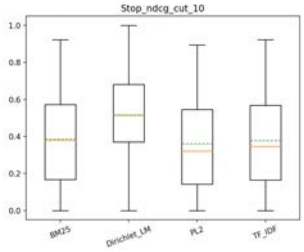
(g) PorterStop: NDCG**@**10.



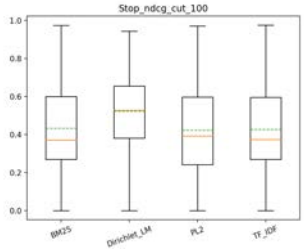
(h) PorterStop: NDCG**@**100.



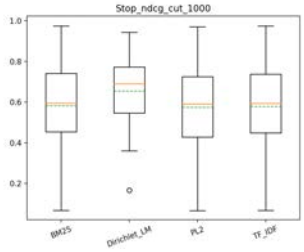
(i) PorterStop: NDCG**@**1000.



(j) Stop: NDCG**@**10.

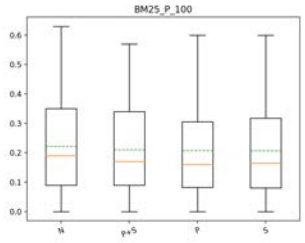


(k) Stop: NDCG**@**100.

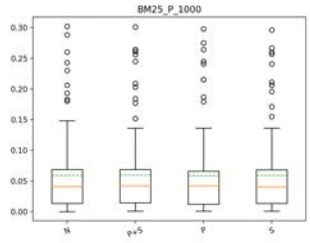


(l) Stop: NDCG**@**1000.

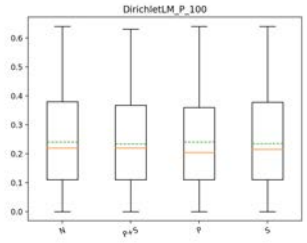
Figure A.14: T2: Box Plots for NDCG of the different models for each index.



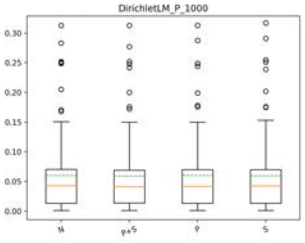
(a) BM25: BoxPlots for P**@**100.



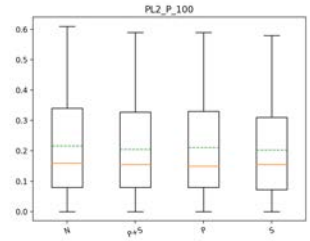
(b) BM25: BoxPlots for P**@**1000.



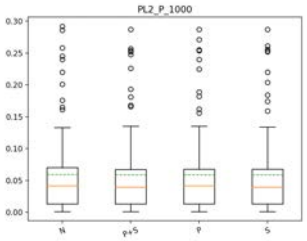
(c) DirichletLM: BoxPlots for P**@**100.



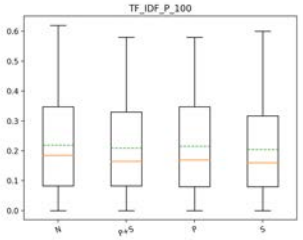
(d) DirichletLM: BoxPlots for P**@**1000.



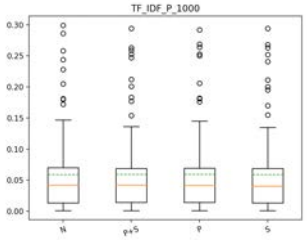
(e) PL2: BoxPlots for P**@**100.



(f) PL2: BoxPlots for P**@**1000.

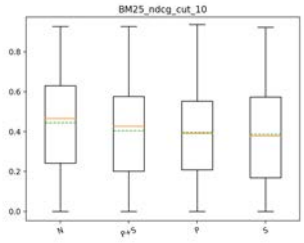


(g) TF-IDF: BoxPlots for P**@**100.

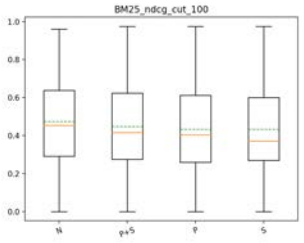


(h) TF-IDF: BoxPlots for P**@**1000.

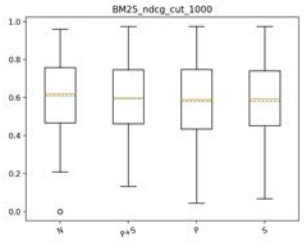
Figure A.15: Box plots of P**@**100 and P**@**1000 for every model.



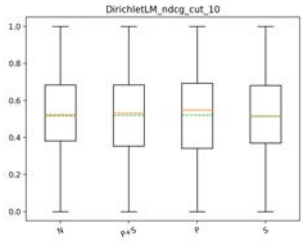
(a) BM25: NDCG**@**10.



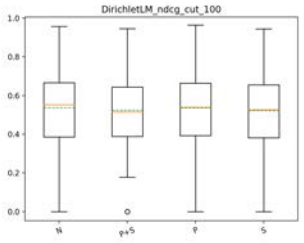
(b) BM25: NDCG**@**100.



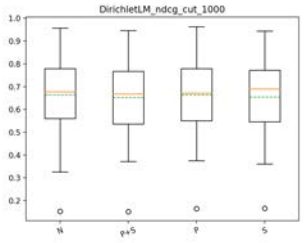
(c) BM25: NDCG**@**1000.



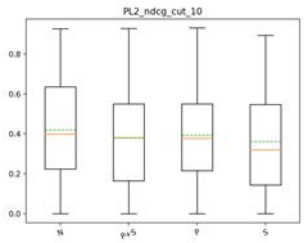
(d) DirichletLM: NDCG**@**10.



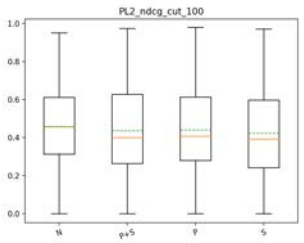
(e) DirichletLM: NDCG**@**100.



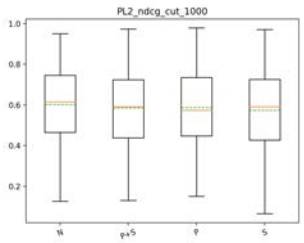
(f) DirichletLM: NDCG**@**1000.



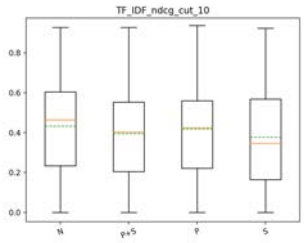
(g) PL2: NDCG**@**10.



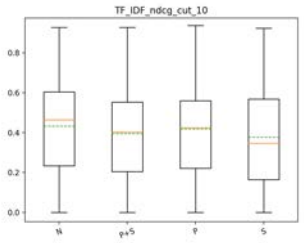
(h) PL2: NDCG**@**100.



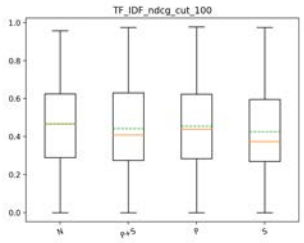
(i) PL2: NDCG**@**1000.



(j) TF-IDF: NDCG**@**10.



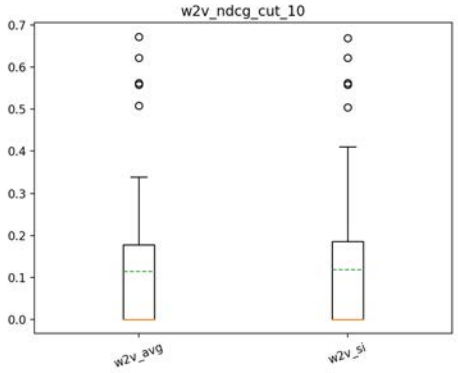
(k) TF-IDF: NDCG**@**100.



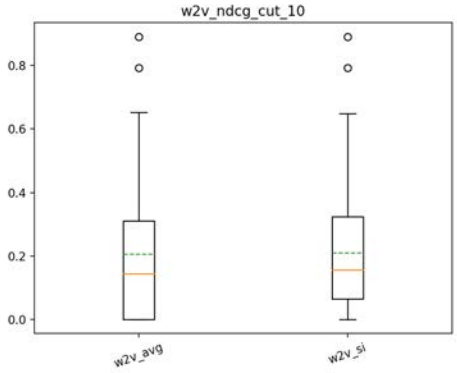
(l) TF-IDF: NDCG**@**100.

Figure A.16: T2: Box Plots for NDCG of the different indexes for each model.

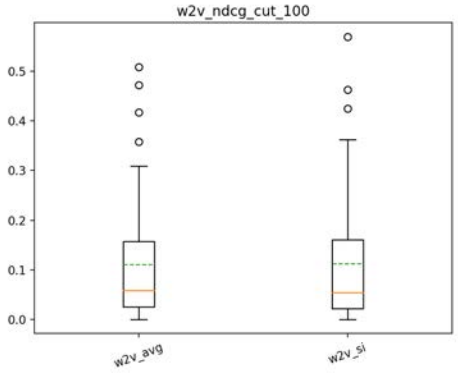
A.2.2 Word2Vec



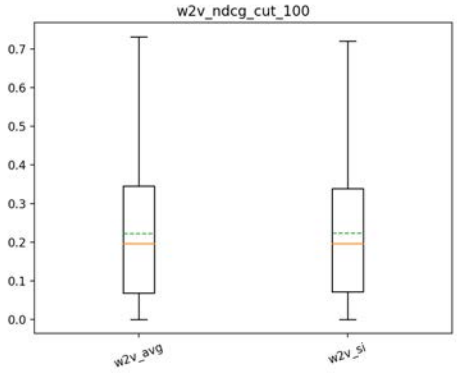
(a) T1: NDCG@10 for w2v_avg and w2v_si.



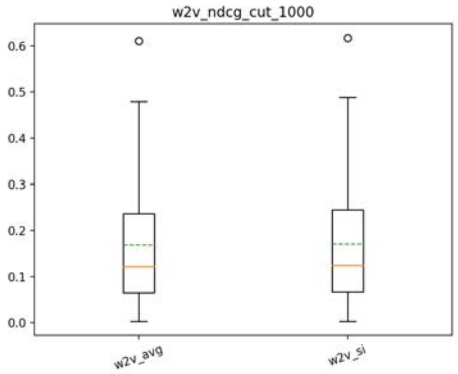
(b) T2: NDCG@10 for w2v_avg and w2v_si.



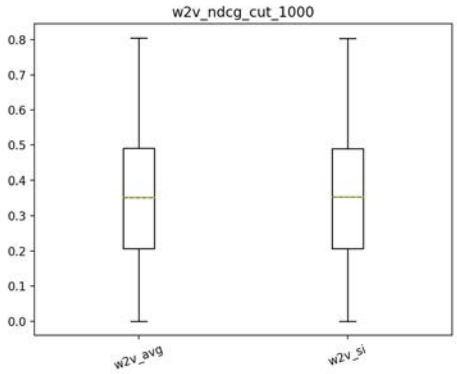
(c) T1: NDCG@100 for w2v_avg and w2v_si.



(d) T2: NDCG@100 for w2v_avg and w2v_si.



(e) T1: NDCG@1000 for w2v_avg and w2v_si.

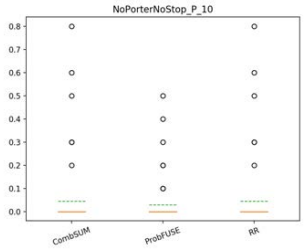


(f) T2: NDCG@1000 for w2v_avg and w2v_si.

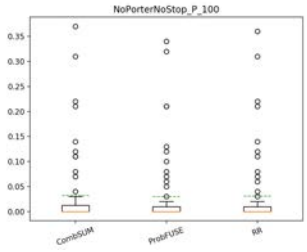
Figure A.17: NDCG: Box Plots of the w2v runs.

A.3 Fusions

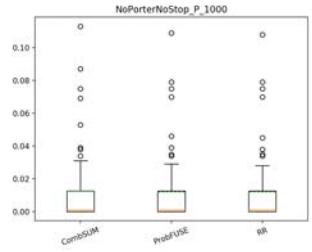
A.3.1 Taski



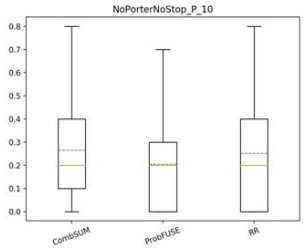
(a) NoPorterNoStop: BoxPlots for P**@**10.



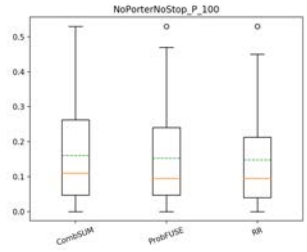
(b) NoPorterNoStop: BoxPlots for P**@**100.



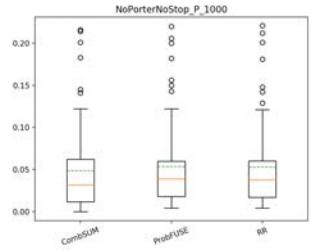
(c) NoPorterNoStop: BoxPlots for P**@**1000.



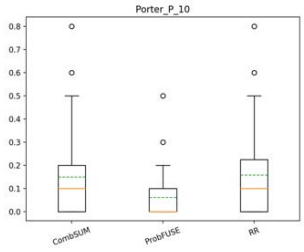
(d) NoPorterNoStop+QE+RF: BoxPlots for P**@**10.



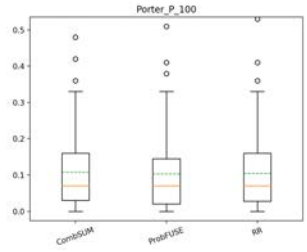
(e) NoPorterNoStop+QE+RF: BoxPlots for P**@**100.



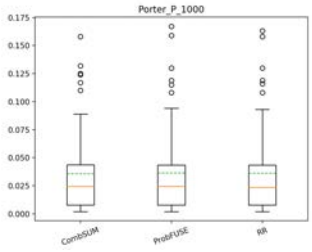
(f) NoPorterNoStop+QE+RF: BoxPlots for P**@**1000.



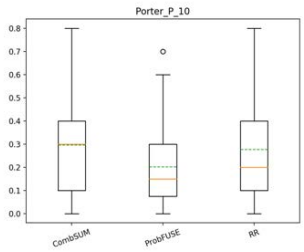
(g) Porter: BoxPlots for P**@**10.



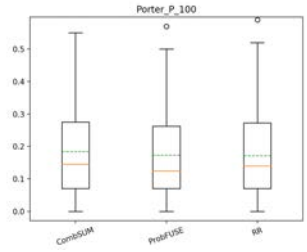
(h) Porter: BoxPlots for P**@**100.



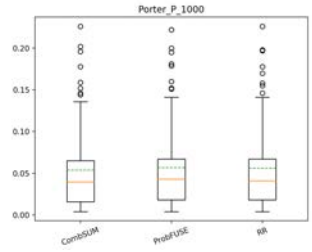
(i) Porter: BoxPlots for P**@**1000.



(j) Porter+QE+RF: BoxPlots for P**@**10.

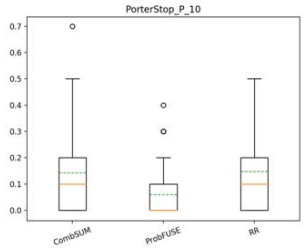


(k) Porter+QE+RF: BoxPlots for P**@**100.

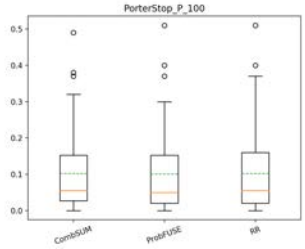


(l) Porter+QE+RF: BoxPlots for P**@**1000.

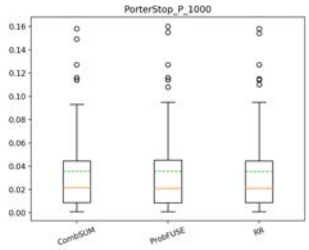
Figure A.18: Box plots for Precision of the fusions of the models using NoPorterNoStop and Porter indexes.



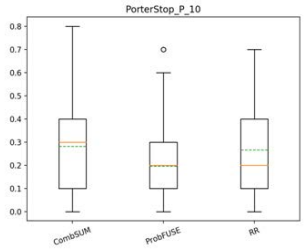
(a) PorterStop: BoxPlots for P**@**10.



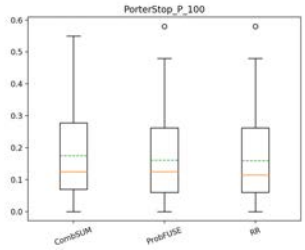
(b) NoPorterNoStop: BoxPlots for P**@**100.



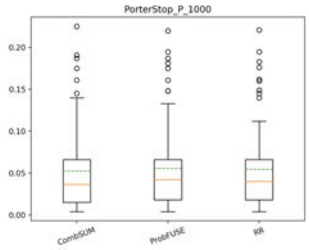
(c) PorterStop: BoxPlots for P**@**1000.



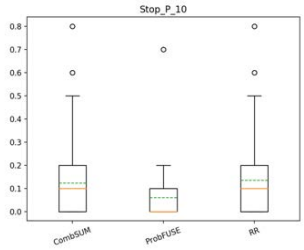
(d) PorterStop+QE+RF: BoxPlots for P**@**10.



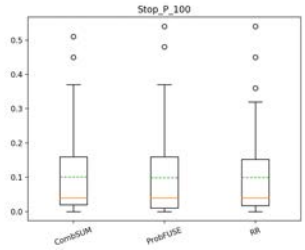
(e) PorterStop+QE+RF: BoxPlots for P**@**100.



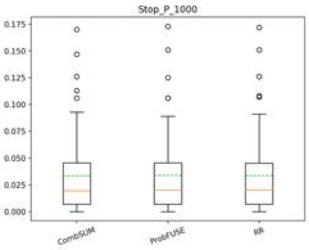
(f) PorterStop+QE+RF: BoxPlots for P**@**1000.



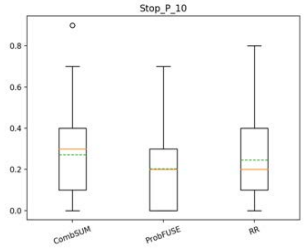
(g) Stop: BoxPlots for P**@**10.



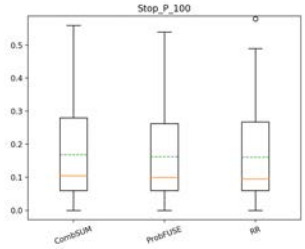
(h) Stop: BoxPlots for P**@**100.



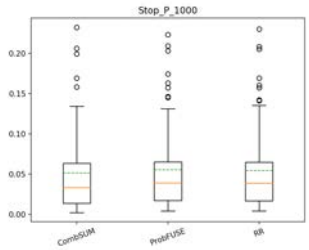
(i) Stop: BoxPlots for P**@**1000.



(j) Stop+QE+RF: BoxPlots for P**@**10.

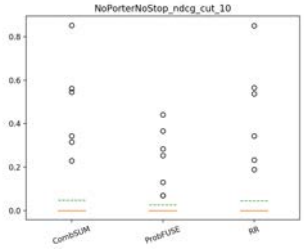


(k) Stop+QE+RF: BoxPlots for P**@**100.

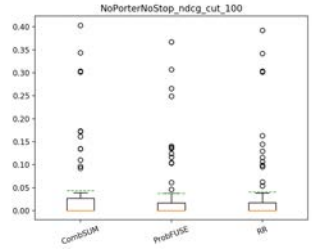


(l) Stop+QE+RF: BoxPlots for P**@**1000.

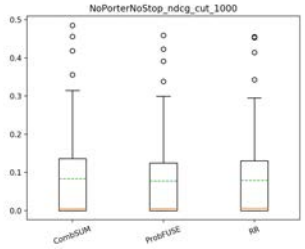
Figure A.19: Box plots for Precision of the fusions of the models using PorterStop and Stop indexes.



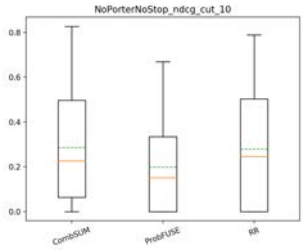
(a) NoPorterNoStop: BoxPlots for NDCG@10.



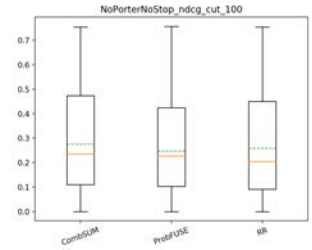
(b) NoPorterNoStop: BoxPlots for NDCG@100.



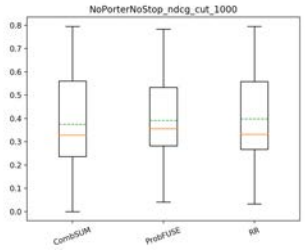
(c) NoPorterNoStop: BoxPlots for NDCG@1000.



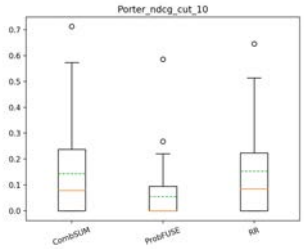
(d) NoPorterNoStop+QE+RF: BoxPlots for NDCG@10.



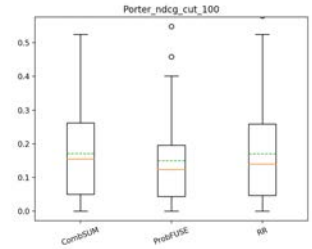
(e) NoPorterNoStop+QE+RF: BoxPlots for NDCG@100.



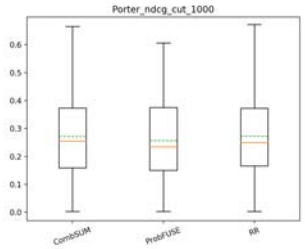
(f) NoPorterNoStop+QE+RF: BoxPlots for NDCG@1000.



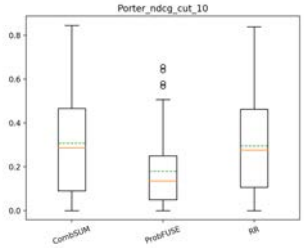
(g) Porter: BoxPlots for NDCG@10.



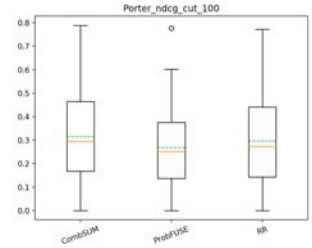
(h) Porter: BoxPlots for NDCG@100.



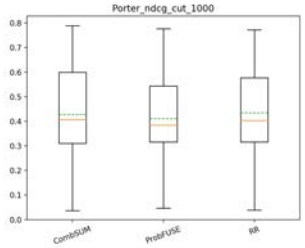
(i) Porter: BoxPlots for NDCG@1000.



(j) Porter+QE+RF: BoxPlots for NDCG@10.

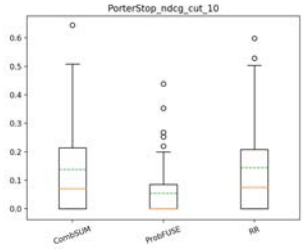


(k) Porter+QE+RF: BoxPlots for NDCG@100.

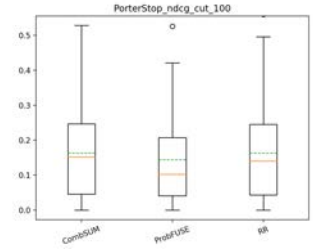


(l) Porter+QE+RF: BoxPlots for NDCG@1000.

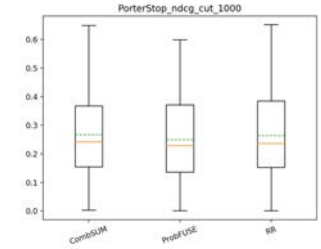
Figure A.20: Box plots for NDCG of the fusions of the models using NoPorterNoStop and Porter indexes.



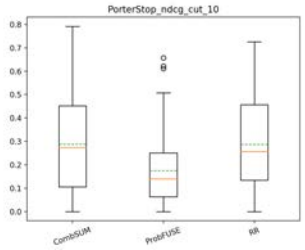
(a) PorterStop: BoxPlots for NDCG**@**10.



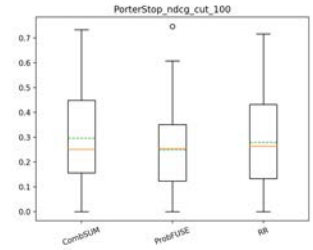
(b) NoPorterNoStop: BoxPlots for NDCG**@**100.



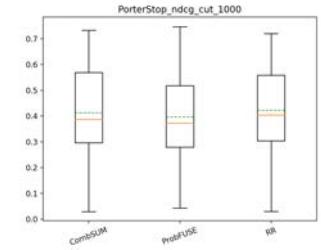
(c) PorterStop: BoxPlots for NDCG**@**1000.



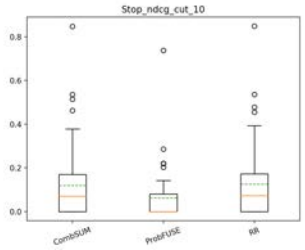
(d) PorterStop+QE+RF: BoxPlots for NDCG**@**10.



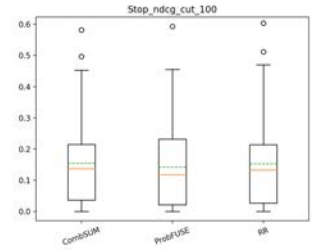
(e) PorterStop+QE+RF: BoxPlots for NDCG**@**100.



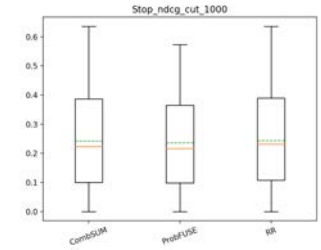
(f) PorterStop+QE+RF: BoxPlots for NDCG**@**1000.



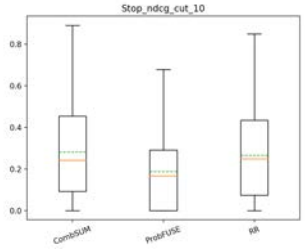
(g) Stop: BoxPlots for NDCG**@**10.



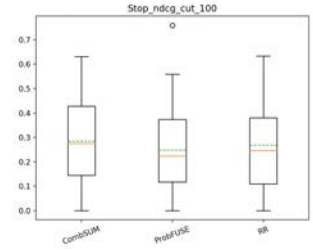
(h) Stop: BoxPlots for NDCG**@**100.



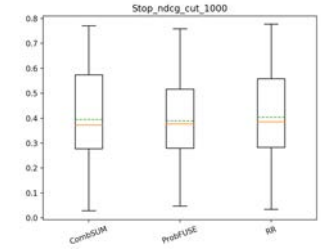
(i) Stop: BoxPlots for NDCG**@**1000.



(j) Stop+QE+RF: BoxPlots for NDCG**@**10.



(k) Stop+QE+RF: BoxPlots for NDCG**@**100.

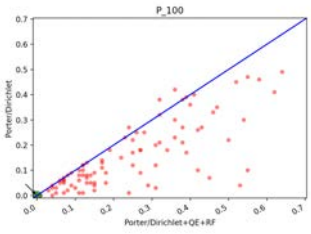


(l) Stop+QE+RF: BoxPlots for NDCG**@**1000.

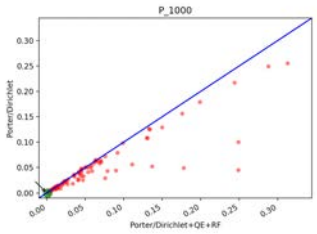
Figure A.21: Box plots for NDCG of the fusions of the models using PorterStop and Stop indexes.

B

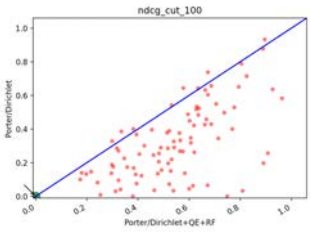
Scatter Plots



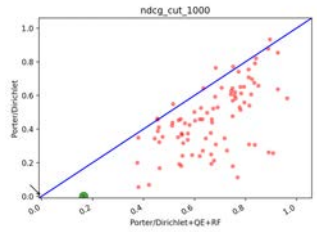
(a) P/D+QE+RF vs P/D: P@100.



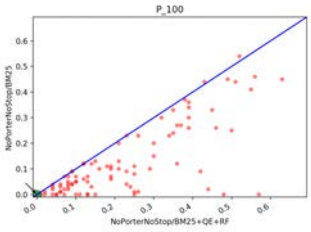
(b) P/D+QE+RF vs P/D: P@1000.



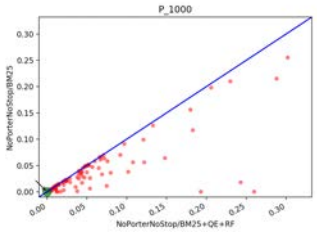
(c) P/D+QE+RF vs P/D: NDCG@100.



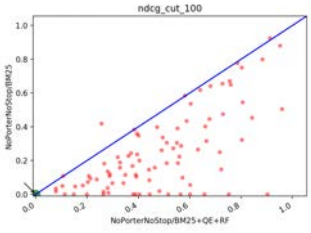
(d) P/D+QE+RF vs P/D: NDCG@1000.



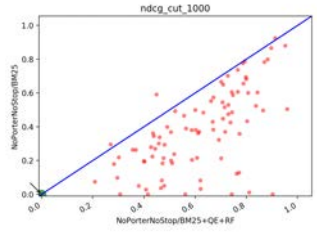
(e) N/BM25+QE+RF vs N/BM25: P@100.



(f) N/BM25+QE+RF vs N/BM25: P@1000.

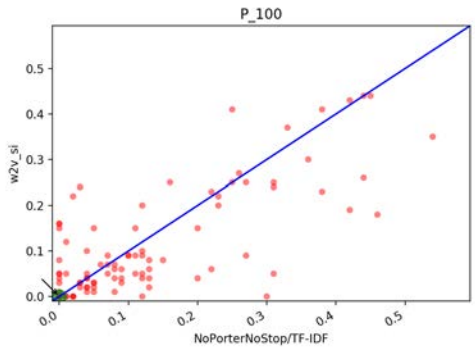


(g) N/BM25+QE+RF vs N/BM25: NDCG@100.

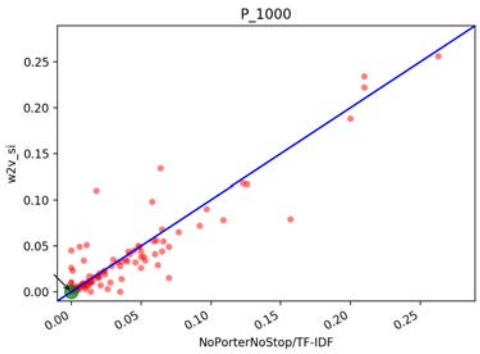


(h) N/BM25+QE+RF vs N/BM25: NDCG@1000.

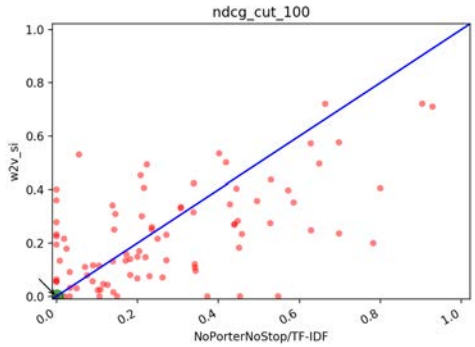
Figure B.1: T2: Scatter Plots of P@100, P@1000, NDCG@100 and NDCG@1000 that show the gain with QE+RF.



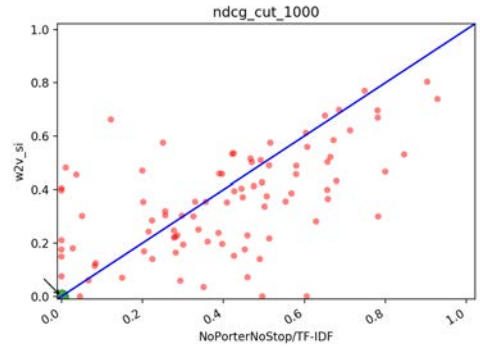
(a) N/TF-IDF vs w2v-si: P@100.



(b) N/TF-IDF vs w2v-si: P@1000.

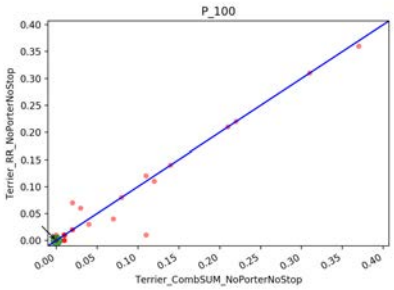


(c) N/TF-IDF vs w2v-si: NDCG@100.

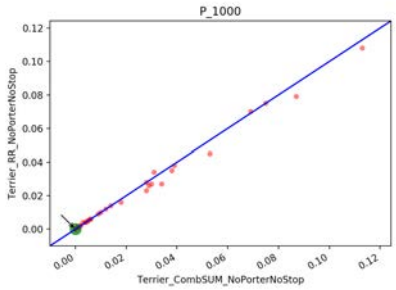


(d) N/TF-IDF vs w2v-si: NDCG@1000.

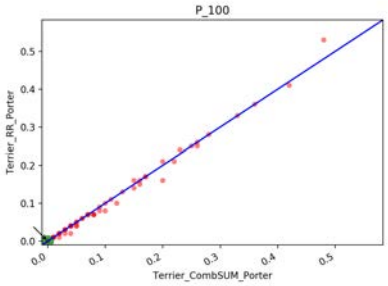
Figure B.2: T2: Scatter Plots of P@100, P@1000, NDCG@100 and NDCG@1000 of N/TF-IDF vs w2v-si.



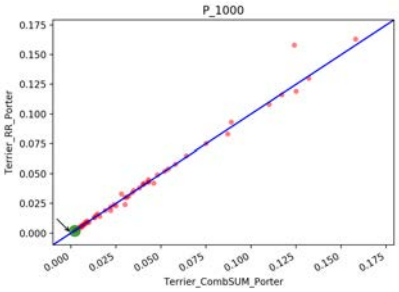
(a) CombSUM vs RR NoPorterNoStop: P@100.



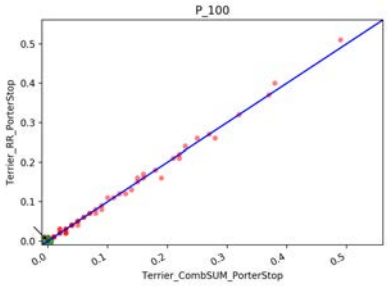
(b) CombSUM vs RR NoPorterNoStop: P@1000.



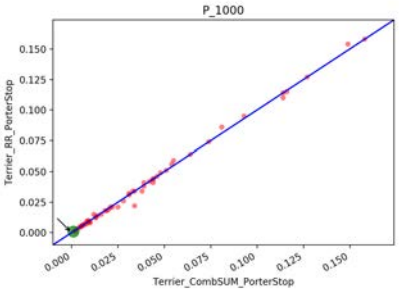
(c) CombSUM vs RR Porter: P@100.



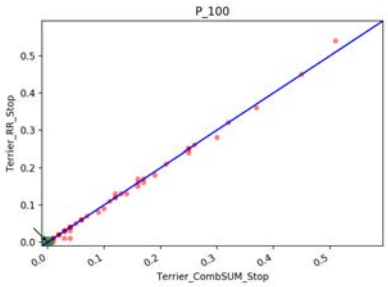
(d) CombSUM vs RR Porter: P@1000.



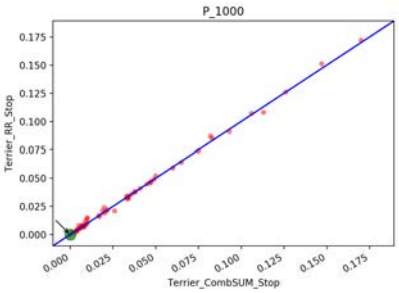
(e) CombSUM vs RR PorterStop: P@100.



(f) CombSUM vs RR PorterStop: P@1000.

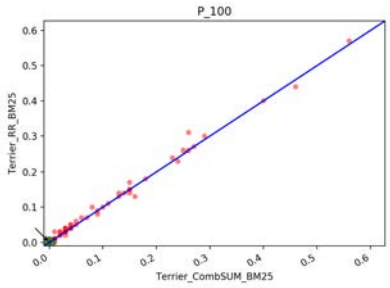


(g) CombSUM vs RR Stop: P@100.

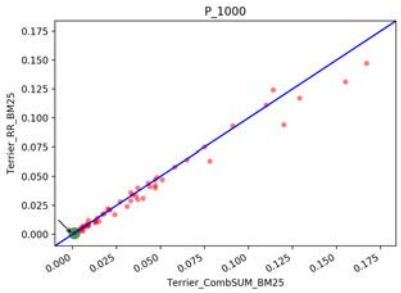


(h) CombSUM vs RR Stop: P@1000.

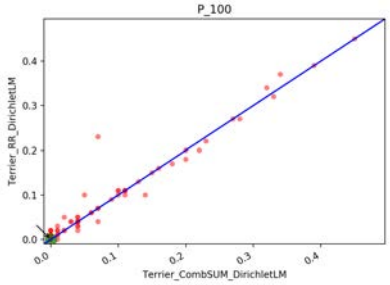
Figure B.3: T1: Scatter Plots of P@100, P@1000 of the fusions of the models using same index.



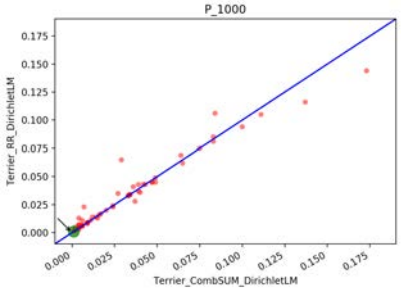
(a) CombSUM vs RR BM25: P@100.



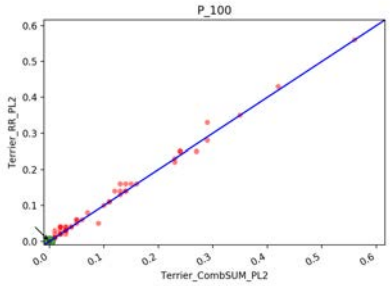
(b) CombSUM vs RR BM25: P@1000.



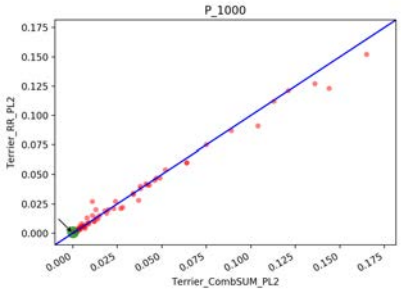
(c) CombSUM vs RR DirichletLM: P@100.



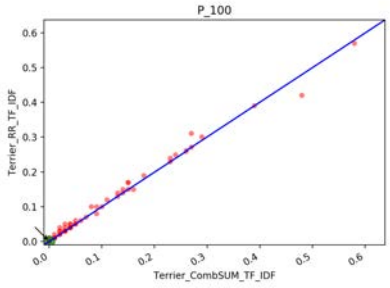
(d) CombSUM vs RR DirichletLM: P@1000.



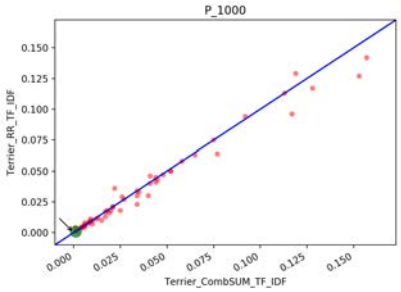
(e) CombSUM vs RR PL2: P@100.



(f) CombSUM vs RR PL2: P@1000.

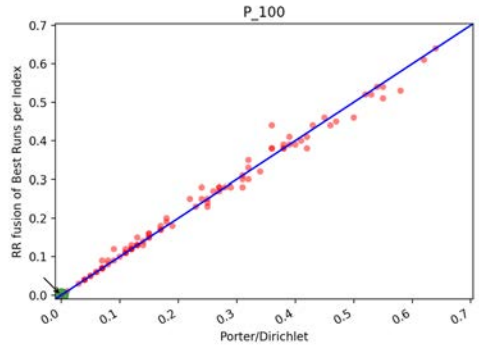


(g) CombSUM vs RR TF-IDF: P@100.

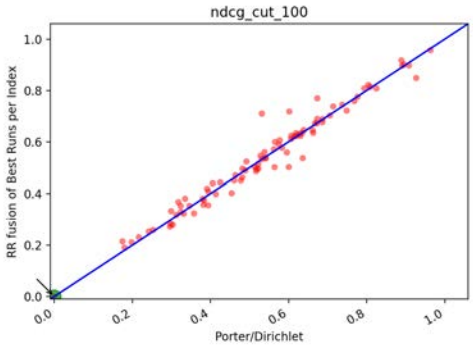


(h) CombSUM vs RR TF-IDF: P@1000.

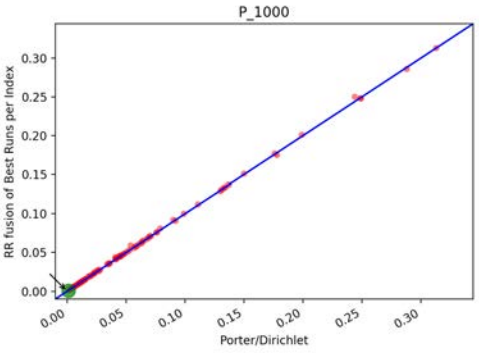
Figure B.4: T1: Scatter Plots of P@100, P@1000 of the fusions of the indexes using same model.



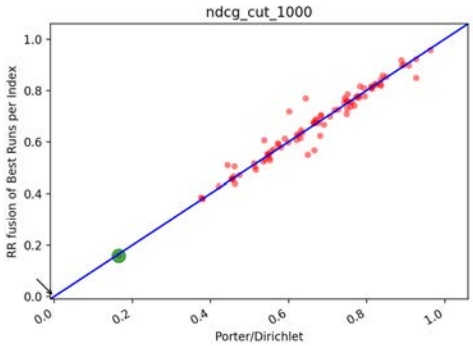
(a) P**@**100.



(b) NDCG**@**100.

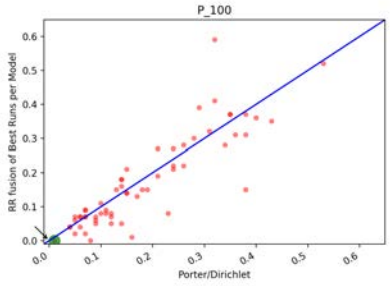


(c) P**@**1000.

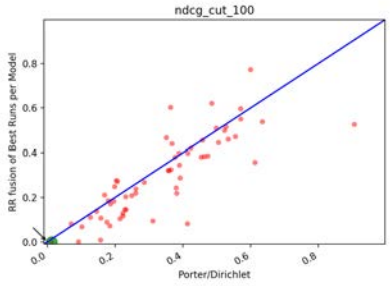


(d) NDCG**@**1000.

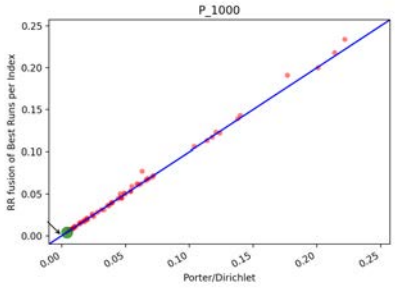
Figure B.5: T2: scatter plots of P**@**100, P**@**1000, NDCG**@**100 and NDCG**@**10000 of Porter/DirichletLM vs RR fusion of best runs per index with QE+RF.



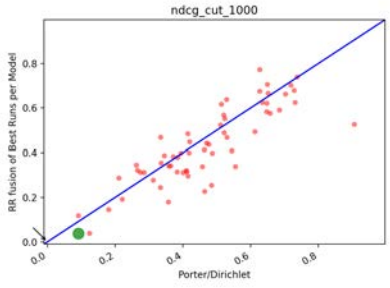
(a) T1: P**@**100.



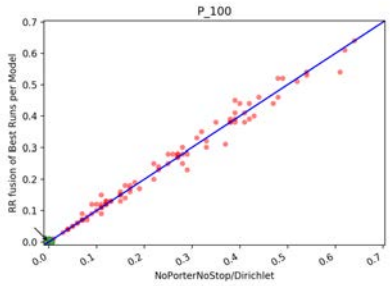
(b) T1: NDCG**@**100.



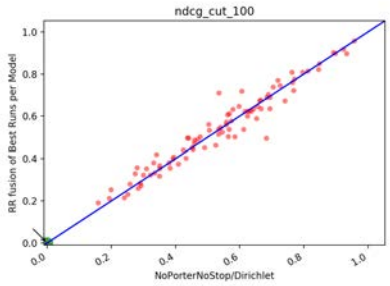
(c) T1: P**@**1000.



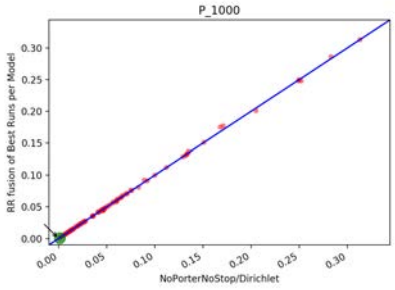
(d) T1: NDCG**@**1000.



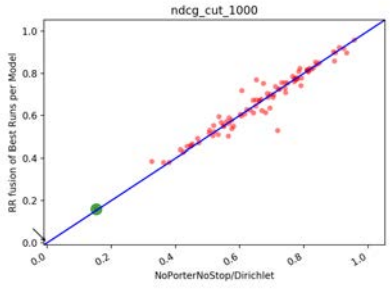
(e) T2: P**@**100.



(f) T2: NDCG**@**100.

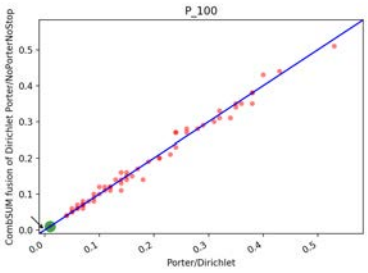


(g) T2: P**@**1000.

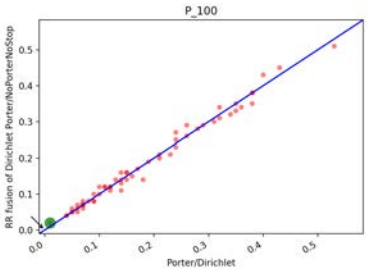


(h) T2: NDCG**@**1000.

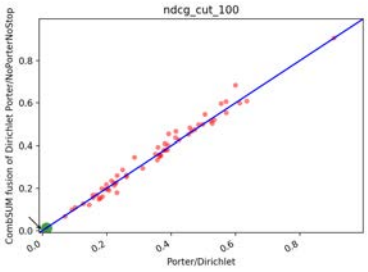
Figure B.6: T1 and T2: scatter plots of P**@**100, P**@**1000, NDCG**@**100 and NDCG**@**10000 of P/D for T1 and N/D for T2 vs RR fusion of best runs per model with QE+RF.



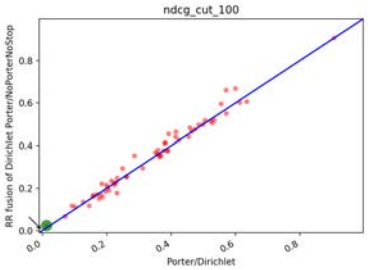
(a) P**@**100 for Porter/Dirichlet vs CombSUM.



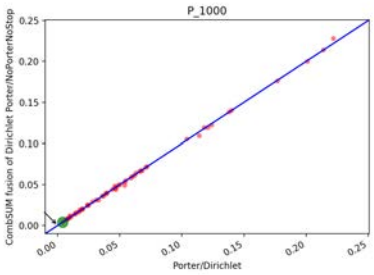
(b) P**@**100 for Porter/Dirichlet vs RR.



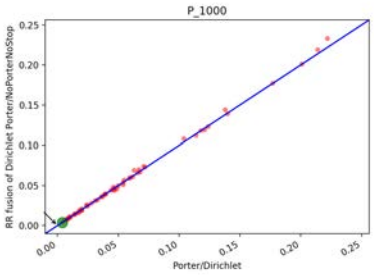
(c) NDCG**@**100 for Porter/Dirichlet vs CombSUM.



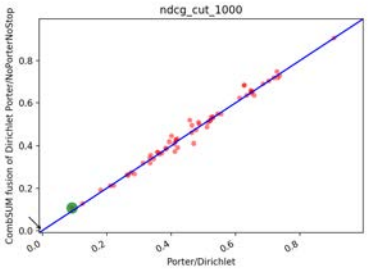
(d) NDCG**@**100 for Porter/Dirichlet vs RR.



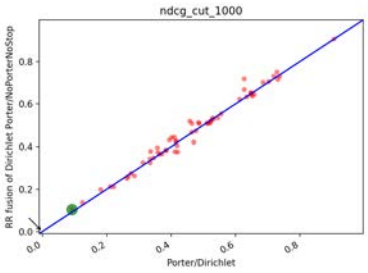
(e) P**@**1000 for Porter/Dirichlet vs CombSUM.



(f) P**@**1000 for Porter/Dirichlet vs RR.

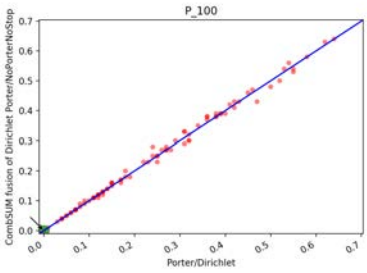


(g) NDCG**@**1000 for Porter/Dirichlet vs CombSUM.

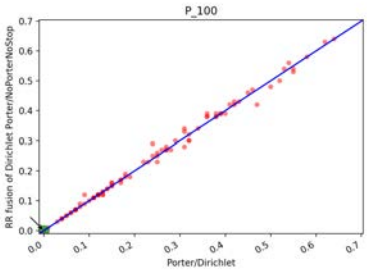


(h) NDCG**@**1000 for Porter/Dirichlet vs RR.

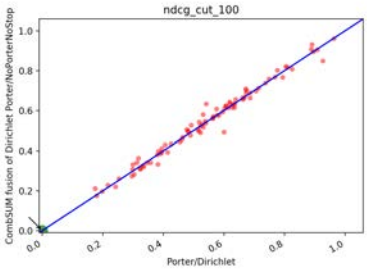
Figure B.7: T1: Scatter plots of the best run vs the fusion of the two best runs.



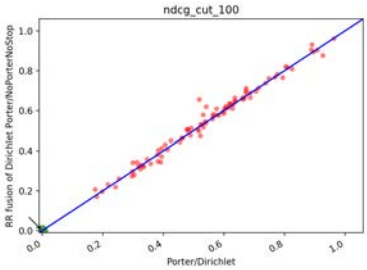
(a) P**@**100 for Porter/Dirichlet vs CombSUM.



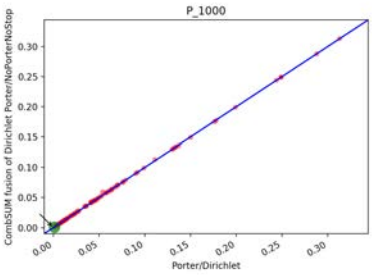
(b) P**@**100 for Porter/Dirichlet vs RR.



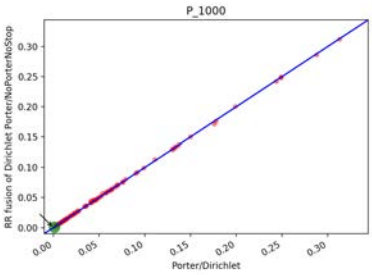
(c) NDCG**@**100 for Porter/Dirichlet vs CombSUM.



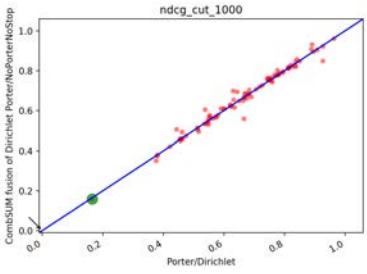
(d) NDCG**@**100 for Porter/Dirichlet vs RR.



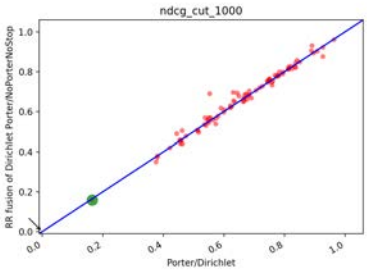
(e) P**@**1000 for Porter/Dirichlet vs CombSUM.



(f) P**@**1000 for Porter/Dirichlet vs RR.



(g) NDCG**@**1000 for Porter/Dirichlet vs CombSUM.



(h) NDCG**@**1000 for Porter/Dirichlet vs RR.

Figure B.8: T2: Scatter plots of the best run vs the fusion of the two best runs.

C

Statistical analysis of the runs

Measure		N+QE+RF		P+QE+RF		P+S+QE+RF		S+QE+RF	
		T1	T2	T1	T2	T1	T2	T1	T2
NDCG@10	F test	0.02	0.19	0.1	0.34	0.001	0.24	0.17	0.16
	p value	0.89	0.66	0.75	0.56	0.98	0.63	0.68	0.69
NDCG@100	F test	0.2	0.11	0.33	0.3	0.26	0.13	0.24	0.15
	p value	0.65	0.74	0.57	0.58	0.61	0.72	0.62	0.7
NDCG@1000	F test	0.41	0.003	0.04	0.12	0.08	0.01	0.07	0
	p value	0.53	0.95	0.85	0.73	0.78	0.92	0.8	0.999
Recall@R	F test	0.3	0.3	0.45	0.09	0.42	0.13	0.05	0.5
	p value	0.59	0.58	0.51	0.76	0.52	0.72	0.82	0.48
P@100	F test	0.24	0.014	0.25	0.03	0.39	0.03	0.09	0.03
	p value	0.63	0.91	0.62	0.87	0.53	0.87	0.77	0.86
P@1000	F test	0.17	0.016	0.05	0.01	0.04	0.01	0.08	0.02
	p value	0.68	0.9	0.83	0.93	0.84	0.92	0.77	0.89

Table C.1: ANOVA tests for different measures of the comparisons between RR and CombSUM for T1 and T2.

Model	NDCG@10		NDCG@100		NDCG@1000		Recall@R		P@100		P@1000	
	F test	p-value	F test	p-value	F test	p-value	F test	p-value	F test	p-value	F test	p-value
BM25	4.1	0.0073	11.09	$7.7 \cdot 10^{-7}$	17.02	$4.8 \cdot 10^{-10}$	9.8	$4 \cdot 10^{-6}$	6.18	0.0005	5.7	0.0009
BM25+QE+RF	0.13	0.94	0.39	0.76	0.75	0.53	0.41	0.75	0.18	0.91	0.06	0.98
Dirichlet	8.8	$1.5 \cdot 10^{-5}$	17.9	$1.8 \cdot 10^{-10}$	26	$1.3 \cdot 10^{-14}$	14.7	$8.3 \cdot 10^{-9}$	11.4	$5.4 \cdot 10^{-7}$	7.9	$4.7 \cdot 10^{-5}$
Dirichlet+QE+RF	0.42	0.74	0.11	0.96	0.12	0.95	0.11	0.96	0.07	0.98	0.003	0.99
PL2	3.8	0.01	9.9	$3.6 \cdot 10^{-6}$	15	$6 \cdot 10^{-9}$	8.8	$1.4 \cdot 10^{-5}$	5.4	0.001	5.3	0.001
PL2+QE+RF	0.15	0.93	0.68	0.57	1.2	0.31	0.52	0.67	0.38	0.77	0.13	0.94
TF-IDF	4.4	0.005	12.1	$2.1 \cdot 10^{-7}$	18	$1.4 \cdot 10^{-10}$	10	$2.8 \cdot 10^{-6}$	6.7	0.0002	5.9	0.0006
TF-IDF+QE+RF	0.23	0.87	0.54	0.65	0.97	0.41	0.4	0.75	0.22	0.88	0.07	0.98
NoPorterNoStop	0.68	0.56	0.54	0.66	0.27	0.85	0.28	0.84	0.47	0.71	0.12	0.95
N+QE+RF	7.5	$8.4 \cdot 10^{-5}$	6.6	0.0002	7.5	$7.7 \cdot 10^{-5}$	7.5	$7.7 \cdot 10^{-5}$	1.9	0.13	0.44	0.72
Porter	0.17	0.92	0.24	0.87	0.37	0.77	0.12	0.95	0.07	0.98	0.05	0.99
P+QE+RF	8.5	$2.1 \cdot 10^{-5}$	3.95	0.009	3.7	0.012	5	0.0023	0.92	0.43	0.11	0.96
PorterStop	0.05	0.99	0.12	0.95	0.22	0.88	0.09	0.97	0.05	0.99	0.03	0.99
P+S+QE+RF	5.3	0.0014	3.7	0.0127	3.5	0.016	5.4	0.0013	1.1	0.3428	0.15	0.93
Stop	0.02	0.99	0.095	0.96	0.23	0.88	0.297	0.83	0.047	0.99	0.058	0.98
S+QE+RF	5.7	0.0008	4.6	0.0038	4.6	0.0036	6.7	0.0002	1.4	0.2475	0.2	0.89

Table C.2: T1: ANOVA tests for different measures of the comparisons between models and indexes.

Model	NDCG@10		NDCG@100		NDCG@1000		Recall@R		P@100		P@1000	
	F test	p-value	F test	p-value	F test	p-value	F test	p-value	F test	p-value	F test	p-value
BM25	1.54	0.2036	1.78	0.1503	3.24	0.0223	0.94	0.4379	0.78	0.5082	0.64	0.5924
BM25+QE+RF	0.86	0.46	0.6	0.62	0.48	0.7	0.47	0.7	0.17	0.92	0.002	0.999
Dirichlet	2.44	0.0645	1.42	0.2381	1.97	0.1175	0.72	0.5388	0.83	0.4761	0.3	0.8243
Dirichlet+QE+RF	0.02	0.99	0.14	0.94	0.16	0.92	0.31	0.82	0.06	0.98	0.004	0.999
PL2	0.9	0.4406	0.95	0.4164	1.66	0.1756	0.34	0.7975	0.45	0.7171	0.39	0.7585
PL2+QE+RF	0.81	0.49	0.35	0.79	0.32	0.81	0.36	0.78	0.14	0.94	0.001	0.9999
TF-IDF	1.34	0.2625	0.99	0.3998	1.95	0.1206	0.5	0.6819	0.56	0.6403	0.42	0.7427
TF-IDF+QE+RF	0.8	0.5	0.52	0.67	0.48	0.7	0.19	0.9	0.16	0.93	0	0.9999
NoPorterNoStop	0.32	0.8109	0.19	0.91	0.24	0.8673	0.18	0.9071	0.09	0.9644	0.04	0.99
N+QE+RF	2.92	0.03	2.26	0.08	2.29	0.08	2.63	0.05	0.44	0.73	0.004	0.999
Porter	1.07	0.36	1.11	0.34	1.3	0.27	0.6	0.62	0.32	0.81	0.08	0.97
P+QE+RF	5.17	0.0016	4	0.0079	3.9	0.0095	4.3	0.0054	0.81	0.4889	0.006	0.999
PorterStop	0.1	0.96	0.06	0.98	0.24	0.87	0.07	0.97	0.08	0.97	0.1	0.96
P+S+QE+RF	5.96	0.0006	2.98	0.0315	2.68	0.0471	3.31	0.02	0.63	0.5994	0.001	0.9999
Stop	0.003	0.999	0.009	0.998	0.08	0.97	0.02	0.997	0.02	0.997	0.07	0.97
S+QE+RF	7.28	$9.4 \cdot 10^{-5}$	4.04	0.0077	3.88	0.0095	3.06	0.0283	0.85	0.47	0.004	0.999

Table C.3: T2: ANOVA tests for different measures of the comparisons between models and indexes.

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