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# Learning Term Weights for Ad-hoc Retrieval

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## ABSTRACT

Most Information Retrieval models compute the relevance score of a document for a given query by summing term weights specific to a document or a query. Heuristic approaches, like TF-IDF, or probabilistic models, like BM25, are used to specify how a term weight is computed. In this paper, we propose to leverage learning-to-rank principles to learn how to compute a term weight for a given document based on the term occurrence pattern.

## 1. INTRODUCTION

Ad-hoc Information Retrieval aims at ranking documents according to their relevance to a query. Many different models exist, such as BM25 [18] and language models [24]. The core of most IR model is the term weighting formula, that assigns a weight to each term of each document according to its importance – how likely the document is relevant if such a term appears in a query? Such term weighting functions are crucial, even for state of the art learning-to-rank approaches [12] – the fact that such approaches systematically use one or more IR models as term weight-based features outlines their importance.

Term weighting functions have been, from the very beginning of research on IR models, a focus of many works. Attempts to improve the weighting scheme include developing different models of the IR process [24, 1], estimating more reliably some of its components [25], or, and this is the focus of this paper, learning the term weighting function [23]. As the latter leverages the same source of information as learning-to-rank models, learning the term weight function has a great potential, provided enough training data, and expressiveness power for the function.

The approach we propose is inspired by recent work in representation learning [2] whose main idea is to process directly raw data rather than computing features. In Information Retrieval, this corresponds to designing a model that would take as input words, outputting a score for a given document. This approach has been followed by some

recent works like [16], using recurrent neural networks, and [10], using convolutional neural networks. Those works aim at embedding documents in a low-dimensional space, and are thus comparable to latent space approaches like LSA [8], sharing their properties [9] of increasing recall at the expense of precision. This has been confirmed in tasks like question-answering, where a query referring to a named entity should be answered by documents containing it. In that case, approaches based on dimensionality reduction do not perform well, even if trained in a supervised way [20]. Another drawback of such approaches is that they need great quantities of data to set the different parameters of these models, since rare terms will tend to have their representation badly estimated. As rare terms might be good indicators of document relevance, we believe this is a problem.

The main proposal of this paper is that a representation of a term be the positions it occurs in in the documents of the collection and in the document for which we want to compute the term weight. We can then compare terms based on their *patterns of occurrences* to determine what their term weight should be. The advantages of doing so, compared to actual neural network based approaches, is that (1) less training data is needed since two terms might share a common occurrence pattern while being semantically not related; (2) inverted indices can still be used, allowing fast retrieval. Finally, compared to standard IR weighting schemes, no prior hypothesis on the functional form of the term weighting function is made.

Using term occurrence pattern would help to distinguish the cases of – the list is not exhaustive:

1. Terms occurring regularly, whatever the document, would likely be unimportant words.
2. Terms occurring most of the time at the same position (e.g. “Introduction” for scientific papers) could be important when occurring at other places.
3. Terms occurring throughout a document would be more important than those occurring only in one part.

In this paper, we present preliminary work that we have undertaken in this direction, using a representation based on a clustering of the term occurrence patterns. In the following, we first present related work (Section 2), before introducing our approach (Sections 3 and 4), giving some preliminary experimental results (Section 5), and concluding (Section 6).

## 2. RELATED WORK

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Related work can be divided in two parts: (1) some works have tried to learn various parts of the term weighting model – ranging from hyperparameters to full term weighting functions; (2) more recently, some approaches have tried to compute the relevance score of a document for a given query, using neural networks. We describe those two lines of research in turn.

Taylor et al. [23] proposed to learn the BM25 parameters ( $k_1$  and  $b$ ) using a pairwise RankNet loss function, and have shown that this led to the best results achievable given appropriate training. Schuth et al. [19] extended this approach by leveraging user clicks rather than relevance assessments.

Rather than relying on a pre-established term weighting function whose hyperparameters are learned, it can be interesting to learn the term weighting function directly. This has been explored by using genetic algorithms to evolve term weighting functions (represented as trees) [7], using terminals like term frequency and document frequency, and non-terminals (functions) like sum, product and logarithm. Closer to our work, Svore et al. [22] proposed to use a multi-layer neural network to learn directly the term weight given features like term frequency and document frequency. In this work, we go further, and instead of using pre-defined features, we propose to estimate the term weight directly from the occurrences of a given term in the document and its context (the document collection).

This approach goes in the same direction as deep neural architectures that have had a great success in the field of image processing [2], one of the working hypothesis is to train a neural network to predict a value given the raw representation of an object. In the field of natural language processing and information access, this usually means that terms are used as the input. Most models rely on low-dimensional representation of words, such as those obtained by word2vec [14], where each word is associated to one vector in a low-dimensional latent space.

Huang et al. [10] proposed to use a convolutional neural network. Instead of starting from word embeddings, they did use letter tri-grams (so as to have a small size vocabulary), i.e. each document is represented by the count of the tri-grams occurring in it. The output is a fixed size representation vector that is used to compute the relevance to a query. Shen et al. [21] extended their work by first computing the representation of word tri-grams, before using a *pooling layer* (maximum over each dimension of the representation space) to represent the full document. Finally, [16] used a recurrent neural network (RNN), the representation of a document or a query being the state of the RNN at the end of the processed sequence. Compared to our work, these approach need a great quantity of training data, and we believe they are not suited for many IR tasks dealing with precise named entities. In the context of question-answering, [20] proposed to learn whether a sentence is an answer to a given query using a convolutional neural network, but had to introduce a set of query-document features to improve their results, such as the word overlap count.

In parallel, Zheng and Callan [26] proposed a *somehow* term-independent representation of query terms to define the *query* weight of each term. The central idea of their work is to represent each term of the query as the difference between the term vector and the mean of the vectors representing the terms of the query thus capturing the semantic

difference between the term and the query. Our research is direction is orthogonal, since we are interested by the document weight and not the query one, but the idea of finding a term-independent representation inspired our present work.

### 3. PROBLEM FORMULATION

We start by exposing briefly the overall learning-to-rank optimization scheme. The relevance score of a document for a given query is given as a weighted sum, over terms present in the query, of their importance  $w(t, d)$ , that is

$$s_\theta(q, d) = \sum_{t \in q} f_\theta(t, q) w_\theta(t, d) \quad (1)$$

where  $f_\theta(t, q)$  denotes the importance of the term(s)  $t$  in the query  $q$  (we suppose in this paper that it is a constant equal to 1) and  $w_\theta(t, d)$  is the computed term weight. Both depend on the model parameters  $\theta$ .

To learn the parameters  $\theta$ , many different optimization functions could be used. We choose the RankNet pairwise criterion [3] because it is simple and was shown to perform well on a variety of test collections. It supposes that the probability that a document  $a$  is ranked before the document  $b$  given a query  $q$  is given by

$$\sigma(s_\theta(q, a) - s_\theta(q, b))$$

where  $\sigma(x)$  is the sigmoid function  $1/(1 + \exp(-x))$ . The cross-entropy cost function is then used to optimize the parameters  $\theta$  of the model. In our case, this gives

$$\mathbb{E} \left( \sigma \left( \sum_{t \in q} w_\theta(t, a) - w_\theta(t, b) \right) \right)$$

where the expectation is over all triplets  $(q, a, b)$  such that  $a$  is more relevant than  $b$  – for binary relevance like in our experiments, this corresponds to the cases where  $a$  is relevant and  $b$  is not. We further suppose that  $w_\theta(t, d) = 0$  if the term  $t$  does not appear in the document  $d$  – this is a common hypothesis made by all term weighting schemes.

We now turn to the problem of computing  $w_\theta(t, a)$ . The general model is presented in Figure 1, where the weight of a term is computed by considering two sources of information, the document (left) and the collection (right). We would like to be able to compute a term-document representation  $x_{td} \in \mathbb{R}^n$  that *captures* the pattern of occurrence of term  $t$  in document  $d$ , and of a term-collection representation  $x_{tc} \in \mathbb{R}^p$  that *captures* the pattern of occurrence of term  $t$  in collection  $c$ . Given these two pieces of information, a term weight can be computed through the function  $w_\theta$ .

### 4. PROPOSED MODEL

While we could learn directly the term weight given the term occurrence pattern in the document and the collection, we choose to decompose the problem in two parts: (1) computing a faithful representation of the document/collection term occurrence pattern and (2) computing the term weight. End-to-end learning is a longer term objective, but we first need to find the most promising options. While other choices are possible and will be explored, we describe next a first and simple instance of this model, using K-Means for (1) and neural networks for (2).

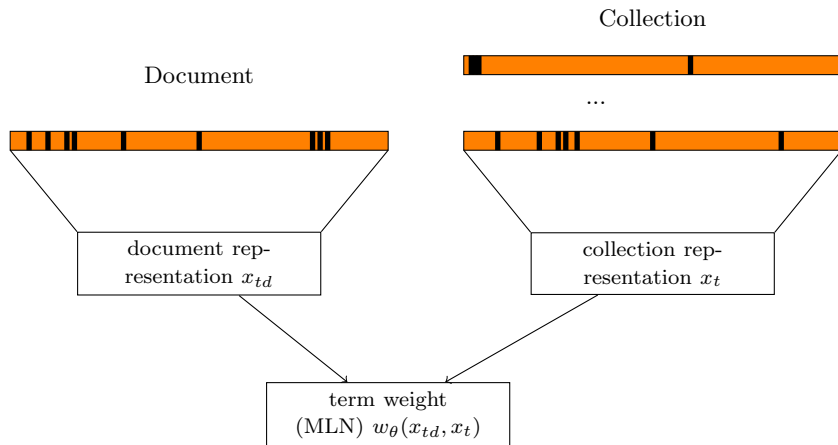


Figure 1: General model for computing the weight of term  $t$  in document  $d$ . The term occurrences are marked with a black bar, and are used to compute for a single term (left) the representation of a document (right) the representation of the collection. Both representations can then be used to compute the final term weight.

#### 4.1 Document and collection representation with K-means

In this preliminary work, we experimented with a simple method where we used  $k$ -means to compute the term document and collection representations. We followed a standard approach for representing object with  $k$ -means [6]: we first clustered patterns of occurrences of all the terms into  $k$  clusters; then, each document is represented by a vector in  $\mathbb{R}^k$  where each component is the distance of the corresponding centroid to the document representation. We now describe more in details the methodology.

The initial document representation is a probability distribution over the positions in a document, i.e. the probability of a term  $t$  occurring at a given position  $p$  in document  $d$  is given by:

$$P(p|d) = \frac{1}{\#d} \delta_{pd}$$

where  $\#d$  is the number of term occurrences in documents (i.e. its length),  $\delta_{pd}$  is the Dirac function that is 1 when the term appears at position  $p$ . The position  $p$  can be *normalized* or not: if normalized,  $p$  ranges from 0 to 1, otherwise from 0 to the length of the document. The interest of normalizing is that documents of different lengths can be directly compared, and more meaningful clusters be found.

To compute the distance between two document distributions, we use the quadratic Wasserstein metric  $W_2$  [17] which amounts at computing the minimum “move of probability mass” (squared distance  $\times$  probability mass) so that one (continuous) distribution can be transformed in another – it is related to the Earth Mover Distance (EMD) — using the square of the distance rather than the distance itself, and has interesting computational properties for  $k$ -means. This distance seems also more adapted than a  $L_2$  distance (in the vector space defined by quantized positions) since it takes into account the proximity of one position to another.

Unfortunately, for computational reasons, we had to represent the distribution by vectors of fixed size (we used a dimension  $D = 100$  in the experiments), i.e. a document is represented as a vector  $p_d \in \mathbb{R}^D$ . The distribution probabil-

ity can then be defined from the vector  $p_d$  as:

$$\tilde{P}(p|d) = \frac{1}{d} \# \{j | p_{dj} = p\}$$

which is an approximation of the original probability – the  $p_{dj}$  were computed so as to minimized the  $W_2$  distance between  $\tilde{P}$  and  $P$ . If the  $p_{dj}$  are increasing (i.e.  $p_{dj} \geq p_{d_j'}$ , if  $j \geq j'$ ), the  $L_2$ -norm can be used directly to compute the  $W_2$  distance between two distributions while the mean can be used to compute the centroid [17].

The representation  $x_{td}$  of a term for a document is then given by its distance to the corresponding centroid, that is the  $i$ th component of the vector representing the term  $t$  in document  $d$  is given by:

$$x_{tdi} = W_2(p_d, c_i)$$

where  $c_i$  is the  $i$ th cluster.

For the term-collection representation  $x_t$ , we chose to either compute the mean of the document vectors for the corresponding terms, or to compute the sum. The interest of the latter is that the sum captures somehow the number of occurrences of a term in the document collection. Formally,

$$x_t^{(sum)} = \sum_{d/t \in d} x_{td}$$

and

$$x_t^{(mean)} = \frac{1}{\# \{d/t \in d\}} \sum_{d/t \in d} x_{td}$$

#### 4.2 Term weighting

Knowing  $x_t$  and  $x_{td}$ , we then used a multi-layer network to compute the score of a term given its document and collection representation. Each layer was composed by a linear transformation followed by an activation function – we choose the ReLU activation [15], which was shown in many cases to facilitate learning. Each layer corresponds to the function

$$y = \max(0, Ax + b)$$

where  $x$  is the input,  $y$  the output,  $A/b$  the parameters, and the maximum is component-wise. The first layer had  $2k$  inputs, corresponding to the size of the vectors  $x_t$  and  $x_{td}$ . The last layer has one output, which corresponds to the term weight. In this work, we only experimented with one hidden layer (of size 50).

## 5. PRELIMINARY EXPERIMENTS

*Test collections.* We used the TREC 1 to 8 collections. We split the dataset in two parts (TREC 1-4, TREC 5-8), and use one part to train the models (TREC 1-4, resp. TREC 5-8), and the other (TREC 5-8, resp. TREC 1-4) to evaluate its performance using mean average precision (MAP). Experiments were conducted using the *title* field of the TREC topics (except for TREC-4 where only long versions are available, and were thus used).

*Models.* In this preliminary set of experiments, we compared three models – it would be useful to compare the results to neural networks approaches trained on the same dataset to get a full picture of the method potential, but in this preliminary work we were more interested in bringing our model up to the standard IR models:

1. BM25 with hyperparameters set to their default values, i.e  $k_1 = 1.2$  and  $b = 0.75$
2. BM25 whose hyperparameters  $k_1$  and  $b$  were learnt, following the work described in [23]. The weighting function is

$$w(t, d) = \frac{tf(t, d) \cdot (k_1 + 1)}{tf(t, d) + k_1 \left(1 - b + b \cdot \frac{l_d}{l}\right)} \times \log \frac{N - df(t) + 0.5}{df(t) + 0.5}$$

where  $k_1$  that controls the bustiness of words (how likely a term occur again) and  $b$  that controls the verbosity of documents (are the documents mono or multi-topical?). We left out the parameter  $k_3$  of our study since it is not useful when query terms occur only once (in queries).

3. K-Means + MLN as described in Sections 4.1 (K-Means) and 4.2. We experimented with the following parameters:
  - (a) Dimension of the document and collection representations was varied, taking the values  $K = 10, 50, 100$  and  $200$ .
  - (b) The position was normalized or not (i.e. divided or not by the length of the document).
  - (c) The MLP hidden layer was composed of 50 units

Both models were trained with the ADAM optimizer that takes into account second order information [11], with  $\epsilon$  set to respectively  $1e-4$  (BM25) and  $1e-8$  (our model), and other hyperparameters set to their default values. They were found to decrease the training cost in our preliminary experiments. We used 1000 iterations for learning, where during each iterations we computed the loss with respect to a sample of 50 000 triples (query, document  $a$  and  $b$ ).

We report the results in Table 1. As the behavior of the different systems was stable over these collections, we average the MAP over TREC-1 and TREC-8. Experimental

results confirm the fact that learning the BM25 parameters using a learning-to-rank cost function is effective [23]. When comparing the performance of BM25 to our proposed model, the results were disappointing, but we can formulate the following observations:

1. We observed that in some cases the learning process did not converge, so actual results might be higher than presented;
2. Normalized length seem to provide better results than non-normalized when the dimension is low (10-100) and then the performance is matched when  $k = 200$ . This is consistent with the fact that when positions are not normalized, more clusters are necessary to distinguish different patterns of occurrence in documents of varying lengths. Experiments will be run with higher dimensions to explore whether this trend holds;
3. Increasing the representation dimension seems to improve results for all models but the normalized/sum one – we have no clear explanation for this observation;
4. There is no clear effect of using a sum or a mean for the document collection representation, but looking at the learned parameters will help in determining the usefulness of each part of the representation.

We also looked at the clusters. In the case of not normalized positions, the discovered clusters were mostly positions within the document (i.e. the distribution corresponds to a single Dirac function); this shows that there was not pattern discovered with such an approach. Normalized positions led to better clusters as shown in Figure 2. In this case, we have 5 clusters corresponding to specific positions in a document which are evenly spaced. We have then 5 different clusters, corresponding for example to terms occurring throughout the document, or at the beginning and the end. Even in this case, the information captured might not reflect the true diversity of word occurrences – a better way to compute document and collection term representations could be necessary.

## 6. CONCLUSION AND FUTURE WORK

In this paper, we proposed to learn the term weight directly from the occurrences of terms in documents. This has the potential to capture patterns of occurrences that are linked with the importance of a term in a document and a collection. Once learned – and provided the model is improved, indexing a full collection could be performed with a low penalty compared to other weighting schemes like e.g. BM25.

Preliminary results have shown that there is still an important gap between standard IR models and this type of approach. We believe that this is due to several reasons, the first one being the poor representation as computed by k-means with the Wasserstein distance. Besides increasing the model expressiveness (dimension, size and number of hidden layers in the MLP), we believe that this is due to the fact that (1) we did use rough approximations (for position distribution), and (2) the Wasserstein distance is not really adapted to the IR setting. For instance, it does not properly model the *burstiness* of a term [4] that seems to be an

BM25	BM25+	Not Normalized		Normalized		$k$
		Mean	Sum	Mean	Sum	
0.18	0.19	0.03	0.03	0.10	0.11	10
		0.06	0.07	0.10	0.10	50
		0.07	0.09	0.11	0.09	100
		0.10	0.09	0.11	0.09	200

Table 1: Results for all models – averaged over all TRECs

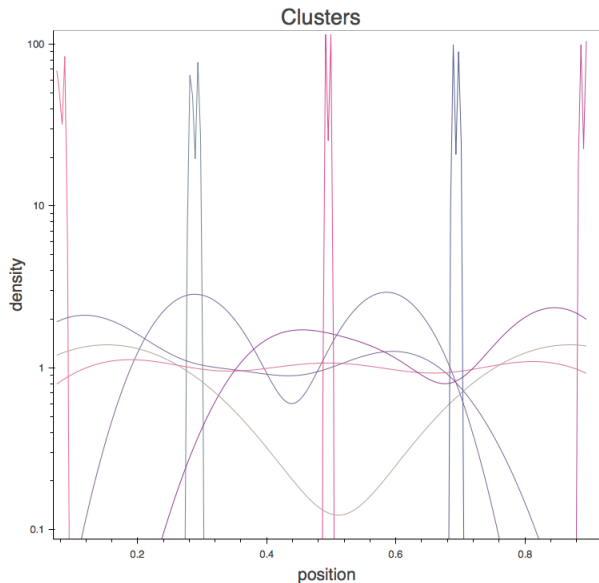


Figure 2: Discovered clusters ( $k = 10$ , normalized length)

important property of word occurrences. We are working on a recurrent neural network model that would maximize the probability of observing a series of positions in a document:

$$P(p_1|x_{td}) \dots P(p_n|p_1, \dots, p_{n-1}, x_{td}) P(x_{td}|x_d)$$

where the probability  $P(x_{td}|x_d)$  would model the distribution probability of the positions of a term/document representation knowing the term/collection representation. Both vectors  $x_t$  and  $x_{td}$  would be learned, and the various models could be compared on their likelihood before using one for term weight prediction.

To further strengthen the model, we could furthermore try to integrate constraints formulated in [5] to regularize or constrain the functional form of the computation of a term weight. Semantic proximity between terms could be used to increase the accuracy of the term weighting function. This could be achieved by encoding not only the position of a term, but the positions of related terms.

Finally, we believe that this approach could be extended in several interesting ways: (1) by computing term weights for frequent bi or tri-grams, in order to capture concepts like “information retrieval”; (2) by computing the full RSV of a document given the pattern of occurrence of the different query terms. In the latter case, we could capture the fact that some query terms occur close to each other – extending approaches like e.g. positional language models [13].

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