



The Whoosh search engine provides three different ranking functions: *BM25*, *TF-IDF* (i.e. cosine similarity) and *Frequency*<sup>1</sup>.

The following example code shows how to perform a query using the TF-IDF scoring function and obtain the corresponding textual similarity score:

```
from whoosh.index import open_dir
from whoosh.qparser import *
ix = open_dir("indexdir")
with ix.searcher(weighting=scoring.TF_IDF()) as searcher:
    query = QueryParser("content", ix.schema, group=OrGroup).parse(u"a query")
    results = searcher.search(query, limit=100)
    for i,r in enumerate(results):
        print r, results.score(i)
```

A similar procedure can be applied for the remaining ranking functions.

The goal of this exercise is to create a method for scoring the documents that combines the results from these three functions.

## 1

Using the Whoosh search engine with the document collection of the previous labs (files `pri_cfc.txt` and `pri_queries.txt`), implement a script that performs searches and returns the results ordered by a *linear combination* of the three textual similarities presented above.

The rank combination formula should be:

$$\text{score}(q, d) = \alpha_1 \text{bm25}(q, d) + \alpha_2 \cos(q, d) + \alpha_3 \text{freq}(q, d)$$

where  $d$  is the document,  $q$  is the query, `bm25` is the score obtained using the BM25 ranking function, `cos` is the score obtained using the TF-IDF ranking function, and `freq` is the score obtained using the Frequency ranking function.

Experiment with different values for weights  $\alpha_1$ ,  $\alpha_2$ , and  $\alpha_3$  and try to find an improvement in Mean Average Precision (MAP) over the results achieved with each individual ranking function used in isolation.

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<sup>1</sup><https://whoosh.readthedocs.io/en/latest/api/scoring.html>

## 2

The goal now is to try a more sophisticated approach for combining the ranking functions used in the previous exercise. To this effect we will use a *pointwise Learning to Rank* (L2R) approach.

Our approach consists in training a Logistic Regression classifier<sup>2</sup> on the set of queries available in `pri_queries.txt`. More specifically, you should:

(a) Create a dataset for training and testing your L2R approach:

- Use 50% of the queries for training and 50% for testing (you can vary these percentages if you wish);
- With the training queries, build the *training dataset*. This dataset should contain, for each (*query*  $q$ , *document*  $d$ ) pair, a set of classification instances with the format:

$$\text{bm25}(q, d), \cos(q, d), \text{freq}(q, d), r$$

where  $r = 1$  if document  $d$  is relevant for query  $q$  and  $r = 0$  otherwise. You can store this data on a *numpy* array;

- Use the same number of relevant and non-relevant documents for each query.

(b) Use the training dataset to learn a Logistic Regression classifier:

- The three ranking scores will be your classification features and  $r$  will be the target class.

(c) Execute the queries on the testing set, using the Logistic Regression classifier as your ranking function. Measure Precision, Recall, and  $F_1$  scores for the classifier, and measure the Mean Average Precision (MAP) for the produced ranking.

- To do this, first perform regular searches, using a each ranking function in isolation;
- The score of each ranking function will be the classification features and the classifier will return 1 if the document is relevant or 0 if otherwise;
- To order the resulting documents, you should use the *probability of the document being relevant*. This can be obtained through the `predict_proba` method of the `LogisticRegression` class.

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<sup>2</sup>[https://scikit-learn.org/stable/modules/generated/sklearn.linear\\_model.LogisticRegression.html](https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html)

### 3 Pen and Paper Exercise

Consider the problem of ranking search results with a learning-based method, leveraging the perceptron ranking algorithm introduced in the classes. Consider also a training dataset in which there are two user queries, each with three candidate documents that should be presented to the user. Each document-query pair is represented as a feature vector  $x$ , together with a relevance judgement  $y$  in a 3-point scale (i.e.,  $y \in 1, 2, 3, 4$ ):

- Query 1 and document 1 :  $x = \langle 0.50, 0.00, 0.25, 0.75 \rangle, y = 2$
  - Query 1 and document 2 :  $x = \langle 0.25, 0.00, 0.00, 0.25 \rangle, y = 1$
  - Query 1 and document 3 :  $x = \langle 0.75, 0.25, 0.25, 1.00 \rangle, y = 4$
  - Query 2 and document 1 :  $x = \langle 0.50, 0.00, 0.25, 1.00 \rangle, y = 3$
  - Query 2 and document 2 :  $x = \langle 0.25, 0.00, 0.00, 0.50 \rangle, y = 1$
  - Query 2 and document 3 :  $x = \langle 0.25, 0.00, 0.25, 0.50 \rangle, y = 2$
- (a) Simulate the execution of the training procedure for the perceptron ranking algorithm, considering one epoch over the training data. Consider an initial all-zeroes weight vector, and consider also an initial value of one for each of the 3 thresholds associated to the possible values for the relevance estimates.
- (b) Consider a new user query, for which there are two candidate documents. Each of the document-query pairs is represented by a feature vector  $x$  as follows:
- Query 3 and document 1 :  $x = \langle 0.50, 0.00, 0.25, 0.25 \rangle$
  - Query 3 and document 2 :  $x = \langle 0.50, 0.25, 0.50, 0.75 \rangle$

Using the trained perceptron from the previous exercise, estimate which of the documents should be ranked higher.