NPFL103 Information Retrieval: Assignment 1

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1 Introduction

This report examines using the vector-space model for information retrieval on sets of documents in both English and Czech. I explore different ways to create an inverted index for both languages, examining which techniques work best for the two different languages, and further go on to examine different techniques for improving results, including modifying weightings of terms and documents, and different approaches towards document length normalization. The results for a baseline system (run-0) and an improved system (run-1) are shown and discussed.

2 Preprocessing and Index Construction

To create the inverted index, I first processed the documents by creating intermediate files consisting of (term, docID) pairs for every term in every document, as well as equivalent (docID, [terms]) pairs, consisting of document id and the list of terms in the document. The terms were extracted from the xml structure. From the Czech documents, I kept terms that were tagged with Geography, Title, Heading, and Text. From the English documents, I kept terms that were tagged with PH, KH, HD, DH, SE, DL, LD, TE, CP, DC, CR, DP, and SM.

For the baseline system these terms were left in their word forms. In the improved version, I removed stopwords (using a list of stopwords from the `spacy` and `spacy_udpipe` python packages for English and Czech respectively), performed case-folding and experimented with both lemmatization and stemming of queries and documents. Lemmatization used the `spacy` and `spacy_udpipe` packages for the respective languages, while for English stemming the `nltk` package was used with the `PorterStemmer`. `nltk` does not have Czech stemming capabilities, so the documents and queries were stemmed with this Czech Stemmer implementation based on the SnowballStemmer. Experimentation results for the various preprocessing methods are discussed in Section 5.1.

With the processed documents, I use the single-pass in-memory indexing (SPIMI) algorithm to create an inverted index for each file. These files are then merged together to create the final inverted index, and this is saved on disk.

3 Query Processing and Retrieval

With the list of topics, I created a dictionary of `topic_num:[terms]` for all topics, where the terms are the tokenized and processed terms from the title of each topic, preprocessed in the same way as the document terms for each experiment. For the baseline model, I then proceed to compute the cosine similarity between the query terms and documents for each topic, using the `FastCosineScore` algorithm from Manning et al. [1, p. 125]. A heap is then used to retrieve the top 1000 documents for the query, which is sorted by score and saved for evaluation.

4 Baseline Results

With the constrained baseline results as specified in the assignment brief, my system achieved a mean average precision (MAP) score of 0.0597 on the Czech training topics, and a P_{10} score of 0.0840. The averaged 11-point precision/recall graph is shown in Fig. 1.

For the English documents, the baseline MAP score was 0.0445, with a P_{10} score of 0.0840. The averaged 11-point precision/recall graph is shown in Fig. 2.

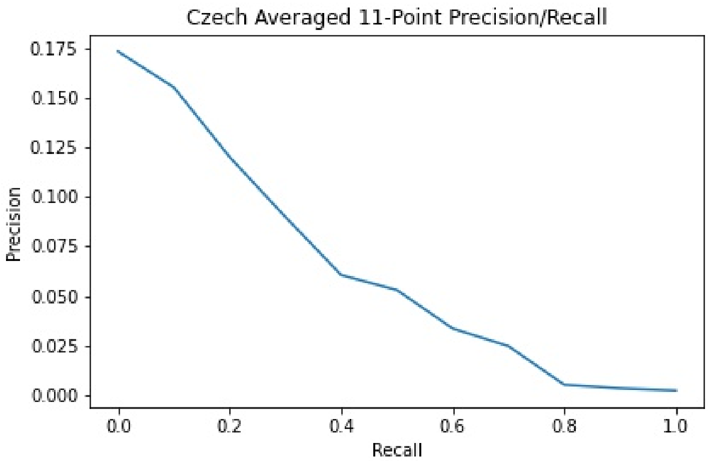


Figure 1: Averaged 11-point Precision/Recall for Czech training data on run-0

5 Experiments

5.1 Preprocessing Methods for Indexing

I experimented with stopwords, lemmatization and stemming. In every case, I also converted all words to lower case. The results are shown in Table 1.

For English documents, preprocessing with stopwords lists and stemming produced the best results, both for MAP and P_{10}, while using stopwords lists and lemmas produced the best results for Czech documents.

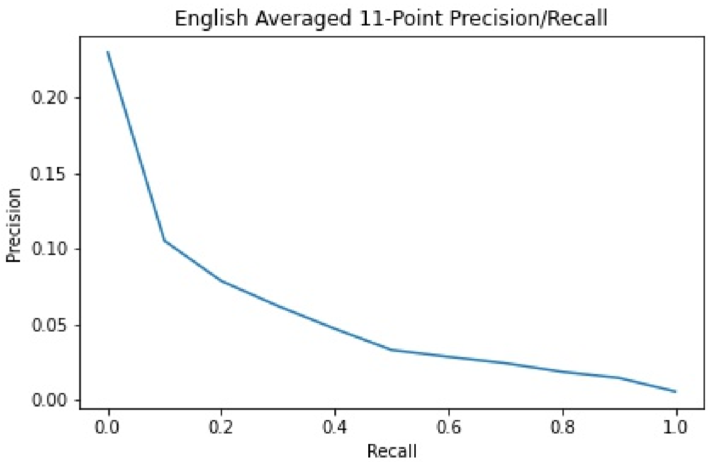


Figure 2: Averaged 11-point Precision/Recall for English training data on run-0

Table 1: Mean average precision (MAP) and P_{10} precision of the first 10 documents training performance with different preprocessing techniques.
wf: word forms, sw: stopwords, l: lemmatization, s: stemming

Language		wf	sw	sw+l	sw+s
English	MAP	0.0445	0.1244	0.0834	**0.1751**
	P_{10}	0.084	0.172	0.136	0.252
Czech	MAP	0.0597	0.0770	**0.1553**	0.0672
	P_{10}	0.084	0.100	0.148	0.060

5.2 Term/Document Frequency Weighting

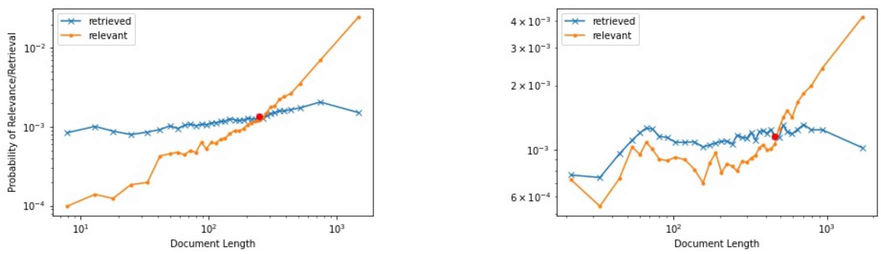
I experimented with different term frequency and document frequency weighting scores. From Table 2 it can be seen that for both languages there is significant performance improvement on the training data with natural term frequency weighting, and either inverse document frequency or probabilistic idf for both English and Czech documents, with prob idf marginally better than standard idf in both cases. Using a different term weighting than just term frequency (logarithm or augmented) produced significantly weaker results.

Table 2: Mean average precision (MAP) and P_{10} precision of the first 10 documents training performance with different tf-idf weightings.
SMART notation tags are applied to both query and document in all cases.

Language		nnc	ntc	npc	ltc	apc
English	MAP	0.1751	0.2244	**0.2248**	0.1320	0.0469
	P_{10}	0.252	0.328	0.328	0.172	0.092
Czech	MAP	0.1553	0.1933	**0.1947**	0.0879	0.0922
	P_{10}	0.148	0.224	0.228	0.096	0.100

5.3 Pivoted document length normalization

I experimented with using pivoted document length normalization instead of cosine similarity. The pivot value was selected following the process described in Singhal et al. [2]. Fig. 3 shows document lengths for retrieval and relevance with respect to their probabilities. With the crossover point p at document length l_p, the pivot value was determined as the mean of the cosine normalization values for documents of length l_p. For Czech, this was 24.6788, and for English this was 40.7795.



(a) Czech (b) English

Figure 3: Document lengths for retrieval using cosine normalization compared to relevance. The orange lines show the document lengths of relevant documents with respect to the probability of relevance, while the blue lines show the same for retrieved documents. The red circle indicates the crossover point in document length.

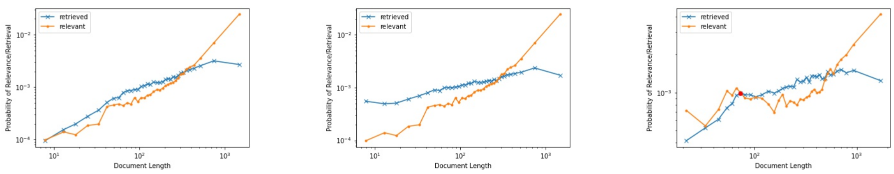
Table 3 shows MAP scores for different values of the scaling factor a. The

P_{10} value for English with a scaling factor of 0.85 was 0.352. The P_{10} value for Czech with a scaling factor of 0.9 was 0.232.

Table 3: MAP training performance of pivoted document length normalization with different values of scaling factor a

	0.6	0.7	0.8	0.85	0.9	0.95	cosine
English	0.2428	0.2442	0.2446	**0.2453**	0.2450	0.2423	0.2248
Czech	0.1830	0.1869	0.1932	0.1938	**0.2053**	0.2010	0.1947

Fig. 4 shows how the lengths of the retrieved documents was affected by pivoted document length normalization, with a closer correlation to relevance for both Czech and English compared to retrieval using cosine normalization. But while the close line for English, particularly for small to medium length documents corresponded with the best MAP score on the training data, the value of the scaling factor $a = 0.6$ which produced very similar document lengths for retrieval and relevance for the Czech documents performed worse than $a = 0.9$, with a MAP of 0.1830 compared to 0.2053.



(a) Czech, $a = 0.6$ (b) Czech, $a = 0.9$ (c) English, $a = 0.85$

Figure 4: Document lengths for retrieval using pivoted document length normalization compared to relevance.

6 Run-1 Results

The best Czech system achieved a mean average precision score of 0.2053, with a P_{10} score of 0.232. This was obtained by preprocessing the documents and queries by filtering stopwords and lower-casing and lemmatizing words. Natural term weighting and probabilistic idf document weighting achieved the best performance in my experiments, so this was used, and pivoted document length normalization was also used with a scaling factor of 0.9. The precision/recall graph for the Czech training topics is shown in Fig. 5.

The best system for English achieved a mean average precision score of 0.2453, and a P_{10} score of 0.352. The parameters for achieving this were that the documents were preprocessed by filtering stopwords, lower-casing, and stemming every word. Further, natural term weighting and probabilistic idf document weighting was used, and pivoted document length normalization was also used with a scaling factor of 0.85. The precision/recall graph is shown in Fig. 6.

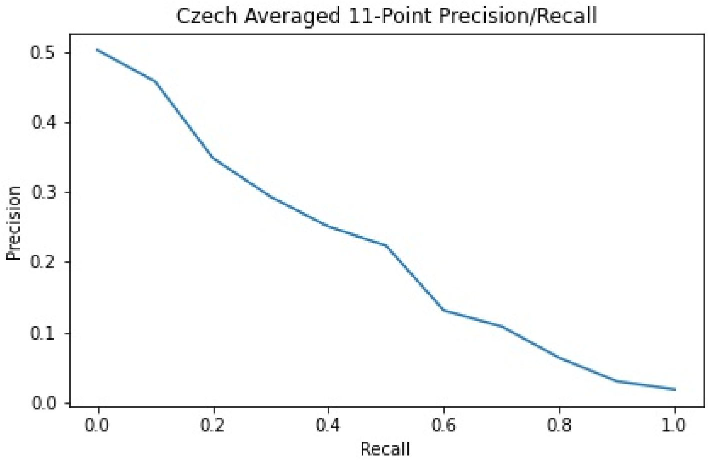


Figure 5: Averaged 11-point Precision/Recall for Czech training data on run-1

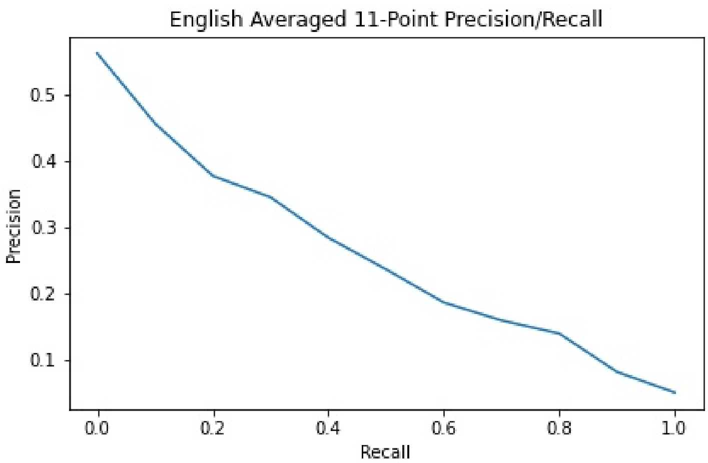


Figure 6: Averaged 11-point Precision/Recall for English training data on run-1

7 Conclusion

There was a significant performance increase from the baseline system to the improved system (run-1). The largest performance increase for both languages came from better preprocessing techniques, with the best improvement for English yielding a +393% MAP performance increase, while for Czech there was a +260% increase.

Better document weighting also led to substantial improvements, with probabilistic inverse document frequency seen to be the best performing technique for both languages on the training topics. Further, improving document length normalization by using a pivot led to small improvements in both languages, although for Czech it was not the case that the most precise mapping of relevance and retrieval led to the highest performance increase.

The overall performance increase from the baseline system to the improved system for English was +551% MAP, +419% P_{10}. For Czech the performance increase was +343% MAP, +276% P_{10}.

Generally the approach for Czech and English was similar, although it differed in some key areas. For Czech, lemmatization was found to work better, whereas stemming worked much better for English. A possible reason for this is due to the morphological richness of Czech compared to English, which means that stemming maybe misses some inflections of Czech that it wouldn't for English. It is also possible that the stemmer for Czech was missing some rules, or that it was overly aggressive and lost a lot of precision on certain terms where precise terms were stemmed and the effective meaning of the term was altered. Also, the best scaling factor for pivoted document length normalization was slightly different for Czech compared to English, although this was marginal.

References

[1] Christopher D. Manning, Prabhakar Raghavan, and Hinrich Schütze. *Introduction to Information Retrieval.* Cambridge University Press, 2008.

[2] Amit Singhal, Chris Buckley, and Mandar Mitra. "Pivoted document length normalization". In: *Proc. SIGIR* (1996).

A Set Up and Running Experiments

Make sure all requirements are installed:

```
pip install -r requirements.txt
python -c "import spacy_udpipe; spacy_udpipe.download('cs')"
python -m spacy download en_core_web_sm
```

To run experiments run the following commands, replacing `train` with `test` where appropriate to obtain results for the test topics. The program must be run from the parent directory of the documents.

```
python run.py -q topics-train_en.xml -d documents_en.lst -r run-0_en
    -o run-0_train_en.res

python run.py -q topics-train_cs.xml -d documents_cs.lst -r run-0_cs
    -o run-0_train_cs.res

python run.py -q topics-train_en.xml -d documents_en.lst -r run-1_en
    -o run-1_train_en.res --stopwords --lowercase --stemming
    --df-weighting prob_idf --pivoted 0.85

python run.py -q topics-train_cs.xml -d documents_cs.lst -r run-1_cs
    -o run-1_train_cs.res --stopwords --lowercase --lemmas
    --df-weighting prob_idf --pivoted 0.9
```

The program will create an inverted index or load a saved one based on the value of the -r parameter. That is, if the same run parameter has been called before, there will be a saved index which does not need to be recreated, and the queries can be run directly on that. Otherwise, it will construct a new one before running the queries.