# ARSEN KUZMIN

### **OVERVIEW**

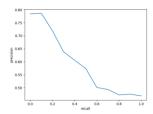
I evaluated local and global methods on cranfield dataset. I evaluated by finding top 30 relevant documents.

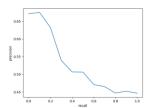
### **BASE MODEL**

Base search engine without any query expansion

### Results:

Name of method	Cosine ranking		OKAPI ranking	
	NDSG	Mean average	NDSG	Mean average
		precision		precision
Base	0.457	0.482	0.5376	0.5774





- 1) Base okapi ranking
- 2) Base cos ranking

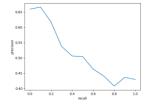
### **GLOBAL METHODS**

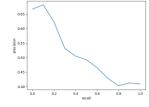
For query expansion I implemented 2 methods:

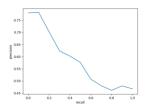
- 1) Method that uses word2vec model to expand query. Word2Vec is one of technique to learn word embedding using neural network. Word2Vec allow to represent word as a vector so we can define similarity between words. Using similarity, we can find the most similar word for a given word I used library genism to learn word2vec model. For each word in query I found the most similar using word2vec and expanded with it query. I trained word2vec model on Quora dataset.
- 2) Method that uses WordNet large lexical database of English. Using WordNet, I expanded query by adding one synonym of each word of query.

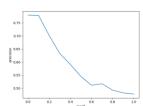
# Results:

Name of method	Cosine ranking		OKAPI ranking	
	NDSG	Mean average	NDSG	Mean average
		precision		precision
WordNet	0.4592	0.4781	0.5309	0.5636
Word2Vec	0.4522	0.4889	0.5307	0.5557









- 1) Word2Vec cosine ranking
- 2) WordNet cosine ranking
- 3) Word2Vec OKAPI ranking
- 4) WordNet OKAPI scoring

# LOCAL METHODS

For local query expansion I implemented 2 methods:

 Rocchio algorithm for relevance feedback. Rocchio algorithm is used to compute new vector with maximum similarity with relevant documents and minimum similarity with nonrelevant documents.

$$\vec{q}_m = \alpha \vec{q}_0 + \beta \frac{1}{|D_r|} \sum_{\vec{d}_j \in D_r} \vec{d}_j - \gamma \frac{1}{|D_{nr}|} \sum_{\vec{d}_j \in D_{nr}} \vec{d}_j$$

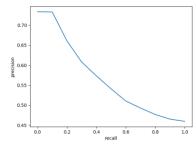
I used a=1 b=0.75 y=0.15

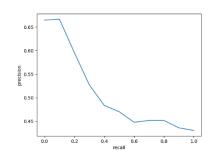
2) Rocchio algorithm for pseudo relevance feedback. In pseudo relevance feedback we assume that the top k ranked documents are relevant, and finally to do Rocchio relevance feedback. I used k = 10

### Results:

(There is no meaning to use local methods since OKAP consider only presence of term)

Name of method	Cosine ranking	
	NDSG	Mean average precision
Rocchio algorithm for relevance feedback	0.6529	0.8039
Rocchio algorithm for pseudo relevance feedback.	0.4401	0.4341





- 1) Rocchio algorithm for relevance feedback
- 2) Rocchio algorithm for pseudo relevance feedback

# Comparison

Rocchio algorithm for relevance feedback algorithm shows much better results than base

Rocchio algorithm for pseudo relevance feedback performs slightly worth than base

### **DOCUMENT SUMMARIZATION**

I used 3 approaches to get summary of document:

- 1) I extracted 2 first and 2 last sentences of document. In many cases these sentences contain most of information
- 2) Top n documents that have highest sum of term frequencies of query.
- 3) Text rank. In text rank we find similarities between sentence vectors are then calculated and stored in a matrix. Then similarity matrix is then converted into a graph, with sentences as vertices and similarity scores as edges, for sentence rank calculation. Finally, a certain number of top-ranked sentences form the final summary

I evaluated these approaches by choosing 2 random texts from this <u>dataset</u>. And used rouge 1 metric. Following result was produced. In second algorithm text I used: 'museum' as query for first text and 'architecture' for second text.

```
In first and last sentences

Real pummary (then Peant's Household State treasure-houses such as the Louve or the Not improve the stories of the individual. Exhibitions should become ever more intinate and local

To record Communication is limited our one homes.

In the future of manema is limited our one homes.

In the future of manema is limited our one homes.

In the future of manema is limited our one homes.

The principle is, in fact, simply.

The principle is in fact, in
```

### For the first text

- 1<sup>st</sup> approach works quite well. 3<sup>rd</sup> sentence match with the real summary.
- 2<sup>nd</sup> approach performs works better than first one because 2<sup>nd</sup> sentence match better.
- $3^{rd}$  approach is the best from these  $1^{st}$  and  $3^{rd}$  sentences display real summary.

## For the second

- 1<sup>st</sup> approach shows good results since 2<sup>nd</sup> and 3<sup>rd</sup> sentences describe main concept of the article
- 2<sup>nd</sup> approach performs not well on this text. Quite hard to understand main concept.
- 3<sup>rd</sup> performs not well too since Modernism has not mentioned

References:
Text rank:
https://www.analyticsvidhya.com/blog/2018/11/introduction-text-summarization-textrank-python/
Word2Vec:
https://radimrehurek.com/gensim/models/word2vec.html
Rogue score

https://github.com/bdusell/rougescore/blob/master/rougescore/rougescore.py

# **README:**

In order to launch code following libraries should be installed:

genism 3.7.2

networkx 2.3

nltk 3.4

matplotlib 3.0.3

smart-open 1.8.1

scipy 1.2.1

numpy 1.16.2

### Word2Vec

In order to use word2vec you can download ready model from <u>link</u> or train by yourself by downloading quora dataset: <u>link</u> and changing path\_to\_dataset variable in word2vec\_expansion.py file.

## Evaluation

Change PATH\_TO\_DATA variable in main.py to path where cranfield dataset located.

#### Part1

To reproduce results of part1 run main.py

# Part2

To reproduce results of part1 run doc\_summary\_evaluation.py

If you want to plot results change variable in evaluation.py file eleven\_points\_interpolated\_avg function plot=True.