COSI132 Final Project

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Topic TREC #815: Jason Rezaian released from Iran

Github Repo

Presentation Slides

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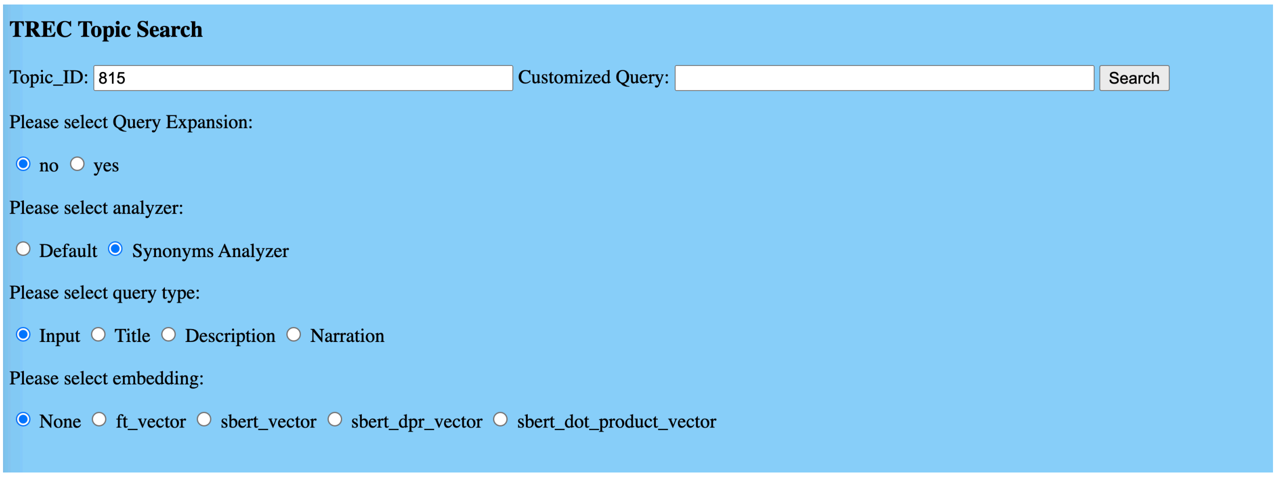
Project Intro:



Intro

- Our project topic: *#815: Jason Rezaian released from Iran*
- Description: Find documents that discuss Washington Post journalist Jason Rezaian release from Iranian prison.
- Narrative: Relevant documents include those that mention that Washington Post journalist Jason Rezaian had served in an Iranian prison and was released, as well as those that describe efforts from the Washington Post and others to have him released.

We first adopted the metric from HW5 to generate a baseline score on our topics. The baseline socre are shown as below:

Search Type	title	description	narration
BM25 Default	0.5233/0.2	0.4353/0.15	0.6389/0.25
BM25 + Custom	0.5222/0.2	0.5074/0.15	0.4577/0.25
fasttext	0.4716/0.2	0.5319/0.15	0.4120/0.25
sbert	0.6275/0.2	0.8779/0.15	0.6125/0.25

To identify the detailed results, we wrote some python script to identify all the false negative and false positive results.

False Negative: not retrieved, relevant

False Positive: retrieved, irrelevant

```
To improve FP and FN results:
  1.  FP: The documents contains more keywords,  but not highly related to the description retrieved.
    (Trial of Post reporter detained in Iran may be nearing end) Mentions about trails, but about serving and releasing from the prision.
    ( State Department urges Iran to release Washington Post correspondent) mentions the actions from US government, but also not including the effort to release the reporter neigher him serving in prison.

  2.  FN: Some documents that are highly related, not but containing the keywords are not selected.
    ( State Department urges Iran to release Washington Post correspondent) This document is about the effort from US Government, but the word “urges”, “free” is not mentioned in description, thus not selected.

We suspect the reason is that Bert is not as effective as expected. Also there are some terms in FN documents, such as “urges”, “to free” are not considered as relative terms, The possible solution is to apply some synonymous in the analyzer. Also fine tune bert with highly relevant documents would probably improve the effectiveness of Bert.
```

Based on the properties of FP/FN results, we further developed 4 techniques aiming to improve our retrieval results.

1. Apply a synonyms analyzer to generate a new index.
2. Apply Query Expansion
3. Select different pre-trained bert models
4. Fine tune on sbert model from HW5 (msmarcos-distilbert-base-v3) The detailed implementation will be discussed in later sections.

How to run

```
conda activate cosi132a
# load servers
# load fasttext embeddings that are trained on wiki news. Each embedding has
300 dimensions
python -m embedding_service.server --embedding fasttext  --model pa5_data/wiki-
news-300d-1M-subword.vec

# load sentence BERT embeddings that are trained on msmarco. Each embedding has
768 dimensions
python -m embedding_service.server --embedding sbert  --model msmarco-
distilbert-base-v3

# load sentence BERT embeddings that are trained on msmarco-roberta-base-ance-
fristp
python -m embedding_service.server --embedding sbert_dpr  --model msmarco-
roberta-base-ance-fristp

# load sentence BERT embeddings that are trained on facebook-dpr-ctx_encoder-
multiset-base
python -m embedding_service.server --embedding sbert_dot_product  --model
facebook-dpr-ctx_encoder-multiset-base

# load our own fine tuned model
python -m embedding_service.server --embedding sbert_fine_tune --model
sbert_fine_tune

python count.py --index_name wapo_docs_50k --topic_id 815 --query_type
narration --vector_name sbert_vector --top_k 20

# Run synonyms analyzer
# Build new index
# add synonym list in synonym.txt
cp ./es_service/synonym.txt $ELASTICSEARCH/elasticsearch-
7.10.2/config/analysis/
python load_es_index.py --index_name wapo_docs_50k_synonyms --wapo_path
pa5_data/subset_wapo_50k_sbert_ft_filtered.jl
#  Run evaluation based on new index
python count.py --index_name wapo_docs_50k_synonyms --topic_id 815 --query_type
description --vector_name sbert_vector --top_k 20 -u

# script
sh evaluation.sh

# Search webapp
python web.py --run
```

Dependencies

- elasticsearch_dsl
- elasticsearch
- sentence-transformers
- pytorch
- flask
- numpy
- zmq
- transformers

Pre-Trained Models

After trying the default fasttext and sBert models, we decide to check some other pre-trianed models.

- msmarco-distilbert-base-v3

The default sbert model uses cosine-similarity.

- msmarco-roberta-base-ance-fristp

It is a model uses dot-product instead of cosine-similarity. Models tuned for cosine-similarity will prefer the retrieval of short documents, while models tuned for dot-product will prefer the retrieval of longer documents.

- facebook-dpr-ctx_encoder-single-nq-base

It is a model based on Dense Passage Retrieval, which can outperform the traditional sparse retrieval component in open-domain question answering.

- stsb-mpnet-base-v2

It is a model measures the semantic similarity of two texts.

Results Table

NDCG@20 scores for different models:

Pre0trained Model	title	description	narration
msmarco-distilbert-base-v3 (Default)	0.6275	0.8779	0.6125
msmarco-roberta-base-ance-fristp (Dot-product)	0.4364	0.3826	0.8100
facebook-dpr-ctx_encoder-single-nq-base (Dense Passage Retrieval)	0.8031	0.7382	0.4790
stsb-mpnet-base-v2 (Semantic Textual Similarity)	0.4245	0.4190	0.5164

According to the results, the dot-product model performs better when narration is used as query type, and the DPR model performs better with title as query type, the STS model does not perform well in all 3 query types, therefore it will not be used in the following experiments.

Synonyms Analyzer

- One problem for our baseline score is that the False Negative Rate is relatively high. There are 20 level-2 docs in total, but 19 of them are in FN of top_20 retrieved documents

Approach

- One of our solution is to apply an synonyms analyzer. And use that analyzer to generate a new index. Our new search is then performed on the new index.

The synonyms analyzer maps the unretrieved terms in the FN results list. For example, "release" is synonyms of "effort， urges to free, released, nearing end", other parties is synonyms of "Washington Post, Jeff Bezos, National Press Club, U.N. human rights experts". We generated a new index called *wapo_docs_50k_synonyms* to test out the effect.

To run the new analyzer, first generate a new index with customized analyzer. Then run evaluation metrics on the new index.

Results Table

The metrics for synonyms analyzer are listed below:

Search Parameters	title	description	narration
BM25 + default analyzer	0.5233/0.2	0.43530/0.15	0.6389/0.25
BM25 + with synonyms	0.5026/0.3	0.6348/0.25	0.5871/0.3
fasttext + default analyzer	0.4716/0.2	0.5319/0.15	0.4120/0.25
fasttext + with synonyms	0.463/0.3	0.632/0.25	0.633/0.3
sbert + default analyzer	0.6275/0.2	0.8779/0.15	0.6125/0.25
sbert + with synonyms	0.645/0.3	0.779/0.25	0.831/0.3

Based on the results, the NDCG score increased a little on description and narrtives, and remains in the same range for title. We concluded that this method has some improvements on our retrieval system.

Potential problems:

One problem with the synonyms analyzer is that it requires the prior knowledge about description and narratives for each topic. Since we are manually adding synonyms mappings to the analyzer, we can hardly find a way to generalize the technique to some topics automatically.

To solve the problem, we looked into the method of query expansion in later experiments.

Query Expansion

Queries

Possible Methods:

- customize the query
- query expansion
- devide and combine query vectors
- Remove redundant words in narrations and descriptions
- Extract meaningful words, embedding them, Use IDF to filter synonyms

```
Example: “Do college graduates have higher income? Do high-school graduates have higher unemployment?” -> [[college, graduates, high, income], [high-school, graduates, high, unemployment]]
```

As it is analyzed in our baseline searches, the tier-2 relevant document is rarely retrieved by all methods. Based on the content of the tier-2 documents, one observation is that these document contains the exact information we need, but present using other expressions. Thus, query expansion is to broadens the query by introducing additional tokens or phrases. In our project, we use the automatic query expansion model, so that this mechanism can be applied to any queries under any topic.

Wordnet Synonyms Expansion

Query is expanded based on the synonyms of each term. Basically add the synonyms to the near position of each term.

Different threshold is experimented for the query. Threshold x means for each term there will be at most x synonyms added.

Example: Jason Rezaian released from Iran

Threshold 2: Jason let_go_of let_go release Iran Islamic_Republic_of_Iran Persia

Threshold 3: Jason let_go_of let_go release relinquish Iran Islamic_Republic_of_Iran Persia

Result

Threshold 3:

(ndcg@20score/precision)

Query Type	Title	Narration	Description
bm25	0.523/0.2	0.435/0.15	0.64/0.25
bm25 + qe(query expansion)	0.787/0.4	0.59/0.15	0.613/0.25
bm25 + synonyms_analyzer + qe	0.584/0.3	0.59/0.2	0.444/0.15
sbert	0.627/0.2	0.878/0.15	0.612/0.25
sbert + qe	0.784/0.4	0.342/0.15	0.428/0.25
sbert + synonyms_analyzer + qe	0.803/0.3	0.375/0.2	0.364/0.15

Threshold 5:

(ndcg@20score/precision)

Query Type	Title	Narration	Description
bm25	0.523/0.2	0.435/0.15	0.64/0.25
bm25 + qe(query expansion)	0.659/0.3	0.468/0.15	0.613/0.25
bm25 + synonyms_analyzer + qe	0.577/0.3	0.367/0.15	0.624/0.3
sbert	0.627/0.2	0.878/0.15	0.612/0.25
sbert + qe	0.578/0.3	0.365/0.15	0.405/0.25
sbert + synonyms_analyzer + qe	0.84/0.3	0.458/0.15	0.454/0.3

The result shows that Query Expansion with Wordnet can improve the precision as well as ndcg score for some combination of query type and search type. Combined with the synonyms analyzer we found a relatively optimized pair:

(`sbert + synonyms_analyzer + query_expansion` , `title`),

Threshold

As is described above, query expansion thresholds can affect the search result quite significantly. Thus, further experiments is carried out on testing different thresholds on (`sbert + synonyms_analyzer + query_expansion` , `title`)

Query Expansion Threshold	NCDG@20	Precision
3	0.803	0.3
5	0.84	0.3
10	0.924	0.25
15	0.749	0.2
20	0.799	0.15

The result shows that the threshold ten has the highest NCDG score but with some penalty on precision. Therefore, we choose **threshold 5** in the final setting.

Based on the characteristics of the False Negative docs' content, we can append more synonyms to `synonyms.txt`.

(`sbert + synonyms_analyzer + query_expansion` , `title`) is improve to (0.844, 0.4)

Bert model selection

ndcg@20score/precision for different pre-trained sbert models

Query Type	Title	Description	Narration
sbert_dot_product	0.803/0.20	0.738/0.15	0.479/0.25
sbert_dot_product + qe	0.505/0.30	0.420/0.25	0.308/0.15
sbert_dot_product + synonyms_analyzer + qe	0.899/0.40	0.463/0.35	0.390/0.15
sbert_dpr	0.436/0.20	0.383/0.15	0.810/0.25
sbert_dpr + qe(query expansion)	0.569/0.30	0.629/0.25	0.579/0.15
sbert_dpr + synonyms_analyzer + qe	0.641/0.40	0.674/0.35	0.395/0.15

It is obvious that query expansion and synonyms analyzer had improved the accuracy.

Embeddings

- Rank directly with Bert embeddings (no BM25)
- creating customized document vectors e.g. doc2vec
  - Removing words before training (tf-idf)
  - Training only on relevant documents vs whole corpus
  - Ranking from vectors directly

Fine tune on Bert

Intro

- Besides selecting different pre-trained models, we also experimented some fine tune method to the default sbert model (msmarcos-distilbert-base-v3) from HW5.
- Due to the limitation of computational power in our local machine, we choose to use Google Colab to deploy our code for training the bert model. We used the Hugging Face library to access some pre-trained bert models, including the one from HW5.
- Please refer to the code in Jupyter Notebook here.

Method

- Preprocessing
  1. First we extracted all documents that are labeled with our topic, including all documents woth annotation "815-0, 815-1, 815-2" in *get_relevant.py*.
  2. We uploaded the formated csv file to my personal google drive here in order to later use it in Google Colab.
- Setup for training
  1. Setup GPU and Hugging Face library
  2. Load data from uploaded csv file, which contains the labels (0 as irrelevant, 1 as relevant score of 1 or 2), and content and customized content.
  3. Adopt the default model from HW5, which is the msmarcos-distiled-bert-base-v3.
  4. In order to train the model based on our documents, we converted the model output into a two-class classification model. Documents with relative score of 1 or 2 are labels as positive, and documents with relative scores of 0 is labeled as 0.
  5. Tokenize the content using bert tokenizer, and convert the list of terms into a vector of integer. We also padded the vector with a [CLS] label for class, and a [SEP] label for ending symbol. Finally each content string is converted into a tensor vector of integers for training.
  6. Split the training data and test data into ratio of 9:1.
  7. Setup hyperparameters for training loop. We used the following hyperparameters
     - batch size 8
     - Epoch number 4
     - Learning rate 0.05
     - Adam optimizer
  8. Save the model to google drive, and apply the model to ES.

Problems

- When converting the content into vectors, the default config in bert limited the maximum vector length to 512. However, most of content string is longer than 512 tokens. Thus, we truncated the vectors to fit in the length. We are not sure if the truncation will affect informative level of the vector.
- Due to the limitation of memory in Google Colab, we have to reduce the batch size to a small number. We are not able to test if a larger batch size would give us better training results.
- We cannot find a simple approach to directly train the model just for embedding. Thus we converted the base distilled bert model into a classification model.

- After we saved the model, we had problem incorporate it with the current embedding server. Thus we cannot test the actual result in our evaluation metrics.

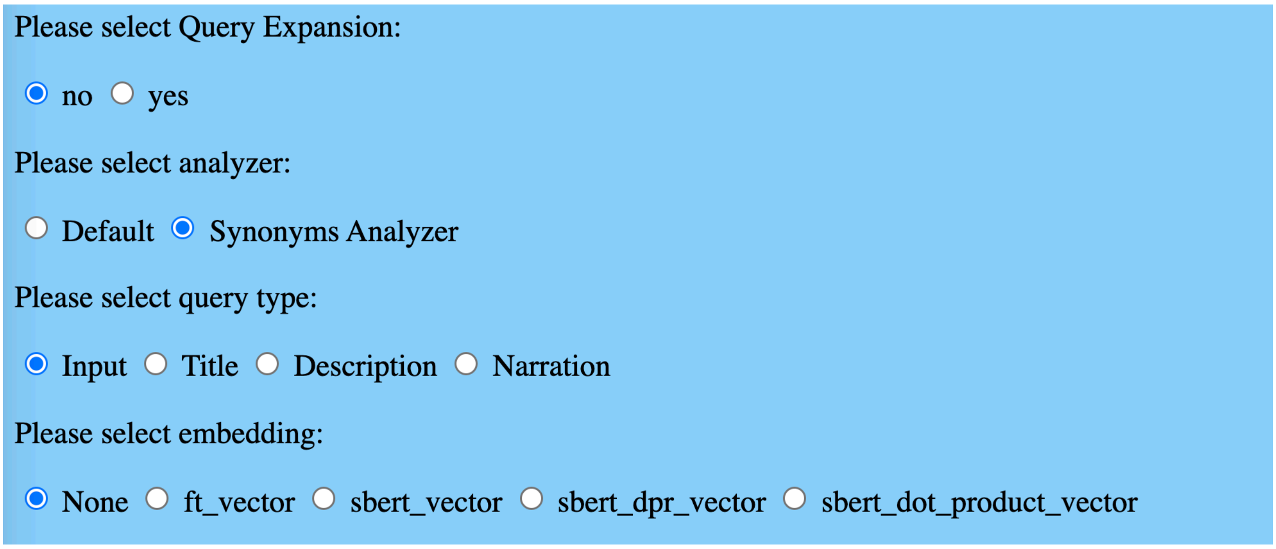
User Interface

This Flask App is aiming for providing the IR researcher with a friendly interface to observe the result of their searching strategies.

Input Text

- Topic_ID: topic id is the target id of the topic, it is neccessary for evaluation and query generate based on query type. e.g. title of topic 815
- Customized Query: when query type is selected as 'input', user can input their own query strings. If the topic title, description or narration is used as query, this box can be left blank.

Options



This search options are based on the experiments we made:

- WordNet Query Expansion
- Synonyms Analyzer
- Query type
- Embedding type

Search Results

The default behavior of this search engine is returning the top 20 results to the user.

- The **false positive** and **false negative** documents is listed for further improvement.
- The strategy is evaluated by **NCDG@20** and **precision** score, which is also shown at the top of the results list.
- Strategy summary and query string used for search are displayed to user.

- Relevance tag is shown for optimization
- Header

Search Result:

False Positive False Negative

Text representation: Query_expansion: yes, Analyzer: synonyms_analyzer, Query_type: title, Embedding_type: sbert_vector

Query: Jason let_go_of let_go release relinquish free liberate Iran Islamic_Republic_of_Iran Persia

NCDG@20: 0.844

Precision: 0.4

Total hit: 20

- False Positive Page

TREC Topic Search

False Positive List:

Total: 12

1. (Relevance: 815-0) The ordeal of Post reporter Jason Rezaian

   On July 22, 2014, Iranian authorities crashed into the Tehran home of Washington Post Iran correspondent Jason Rezaian and arrested him and his...
2. (Relevance: 815-0) Iran frees wife of Post's Tehran correspondent, but he remains in custody

   An Iranian journalist detained in Iran since July along with her husband, The Washington Post's bureau chief in Tehran, has been released from...
3. (Relevance: 815-0) The Post's Jason Rezaian held nearly 444 days, the duration of Iran hostage crisis

   Friday, October 9 marks the 444th day of Washington Post reporter Jason Rezaian's unlawful imprisonment in Iran. Rezaian, a private citizen and...
4. (Relevance: 815-0) Journalists and family of Jason Rezaian denounce guilty verdict

   The family of Washington Post reporter Jason Rezaian, convicted in an Iranian court over the weekend of charges that included espionage, decried...
5. (Relevance: 815-0) Detained Post reporter Jason Rezaian's family responds to Iran nuclear deal

   As Iran, the United States and other world powers announced the parameters of a nuclear deal, the family of detained Washington Post Tehran bureau...
6. (Relevance: 815-0) Post Publisher Frederick J. Ryan, Jr. issues statement on Jason Rezaian's 500th day in prison

   Statement from Frederick J. Ryan, Jr., publisher of The Washington Post, on Jason Rezaian's 500th day in prison: What should not have been a...
7. (Relevance: 815-0) Sketchbook: The Post's Jason Rezaian marks a year behind the bars of injustice

- Result list

Total hit: 20

1. (Score: 2.5735, Relevance: 815-1) This just in: The Post's Jason Rezaian is finally being freed [+Illustrations]

   [This post has been updated.] LAST NIGHT, my thoughts turned to Jason Rezaian, and how a wise friend who long ago served in the Iranian army once...
2. (Score: 2.5460, Relevance: 815-1) Muhammad Ali urges Iran to free jailed Post reporter Jason Rezaian

   American boxing legend Muhammad Ali has called on Iranian officials to release Jason Rezaian, The Washington Post correspondent who has been...
3. (Score: 2.5455, Relevance: 815-0) The ordeal of Post reporter Jason Rezaian

   On July 22, 2014, Iranian authorities crashed into the Tehran home of Washington Post Iran correspondent Jason Rezaian and arrested him and his...
4. (Score: 2.5419, Relevance: 815-0) Iran frees wife of Post's Tehran correspondent, but he remains in custody

   An Iranian journalist detained in Iran since July along with her husband, The Washington Post's bureau chief in Tehran, has been released from...
5. (Score: 2.5212, Relevance: 815-1) Family of jailed Washington Post journalist, held for 100 days, asks Iran to free him

   The family of a Washington Post reporter held without charge in Iran for more than three months called Wednesday on the authorities in Tehran to...
6. (Score: 2.5145, Relevance: 815-0) The Post's Jason Rezaian held nearly 444 days, the duration of Iran hostage crisis

   Friday, October 9 marks the 444th day of Washington Post reporter Jason Rezaian's unlawful imprisonment in Iran. Rezaian, a private citizen and...

Summary

- In summary, we used four approaches to improve our results.

1. Synonyms analyzer

2. Query Expansion
3. Different pre-trained model
4. Fine tune Distilled Bert

- We combined the first three techniques, and we witnessed improvements in both NDCG scores and precision values.
- In fine tune bert, we were expecting some improvement since we trained the model particularly on documents labeled with our topic. However, we failed to incorporate the saved model into the embedding server. We would like to work this particular problem and and the fine tune model work in further works.

Contribution

Shi Qiu: synonyms analyzer, train fine tuned bert, Incorporate embedding server

Tongkai Zhang: Query Expansion, Merge into ES webapp, User Interface

Bowei Sun: Pre-trained models, load servers