A simple search engine for keywords in Arxiv dataset

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1 Problem

Given a keyword (e.g., "linear regression" or "deep learning"), design a system that will find sentences (from the abstracts of papers in the dataset) whose "subjects" contain the keyword. Return the list of sentences with their subjects highlighted.

Input

- A list of papers w including the fields such as title, authors, abstract,...
- A keywords x, assumed to have no typos.

Output

- A list of sentences (from the abstracts) whose "subjects" contain the keyword.
- Highlight subjects that including the keyword.

2 System architecture

I design my search engine as follows:

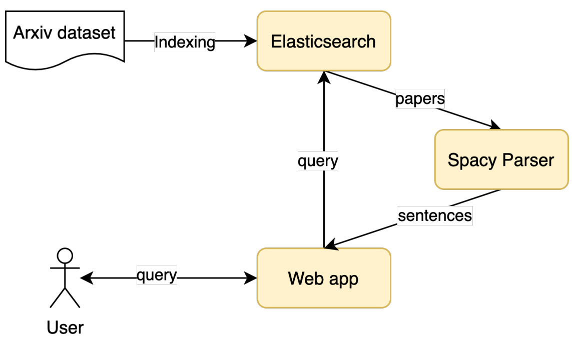

Figure 1: Search engine architecture.

2.1 Full-text search

The input is first queried in the database and return a set of potential paper in which their abstract contains the input keywords. This phase requires a full-text search engine that can perform fast query in the database including 1.7 million papers with more than 11 million sentences.

I use Elasticsearch for this purpose. The most advantage of Elasticsearch compared to Whoosh is the speed. A speed test of some full text search engines shows that Elasticsearch can perform a query in a database with 1 million records in 9ms, compared to 2s in the same database of Whoose.

I use *match_phrase* query to exact search the input keyword in database. In order to handle the different morphology of words, I add a custom analyzer using Porter stem for both indexed data and input query before the matching phase.

```
{
    'from': _from,
    'size': _size,
    'query': {
        'match_phrase': {
            field: {
                "query": phrase,
                "analyzer": "english_exact"
            }
        }
    }
}
```

2.2 Parser

A set of paper's abstracts obtained from Elasticsearch is later parsed into dependency tree by SpaCy framework. To detect subjects in the sentences, I use a set of noun chunks in the sentences and check if their dependency on the action is *nominal subject (nsubj)* or *passive nominal subject (nsubjpass)*.

I remove the commoner morphological and inflexional endings from both noun chunks and the input keyword. Due to the default *Lemmatizer* of SpaCy transforming words depends on their context. It leads to the same word may have different variations. An independent *PosterStemmer* in *nltk* framework is used instead.

I also provide two options for just considering noun chunks or both noun chunks and their modifiers as the subject of a sentence. However, both options have their own drawback. For example, in the sentence:

The formal definition of the data structure is presented along with the proper justification from real world scenarios. insight.

There are two recognized noun chunks including "formal definition" (act as nominal subject of the verb "presented") and "data structure" (act as object of a preposition "of"). If we only use noun chunk as the subject, it will miss the keyword "data structure". Therefore, considering both noun chunk and its all modifiers (its subtree in the dependency tree) may be more accurate in this case. However, considering the following sentence:

The expected number of point-line comparisons performed by this data structure, when the queries are distributed according to D*, is* $H + O(H^{2/3} + 1)$.

The nominal subject is the "expected number", and its all modifiers is "The expected number of point-line comparisons performed by this data structure, when the queries are distributed according to D". Then this clause is highlighted as the subject of the sentence. That seems to be redundant.

2.3 Web app

I build a simple Flask web app to encapsulate this search engine. It has some features as described in Figure 2

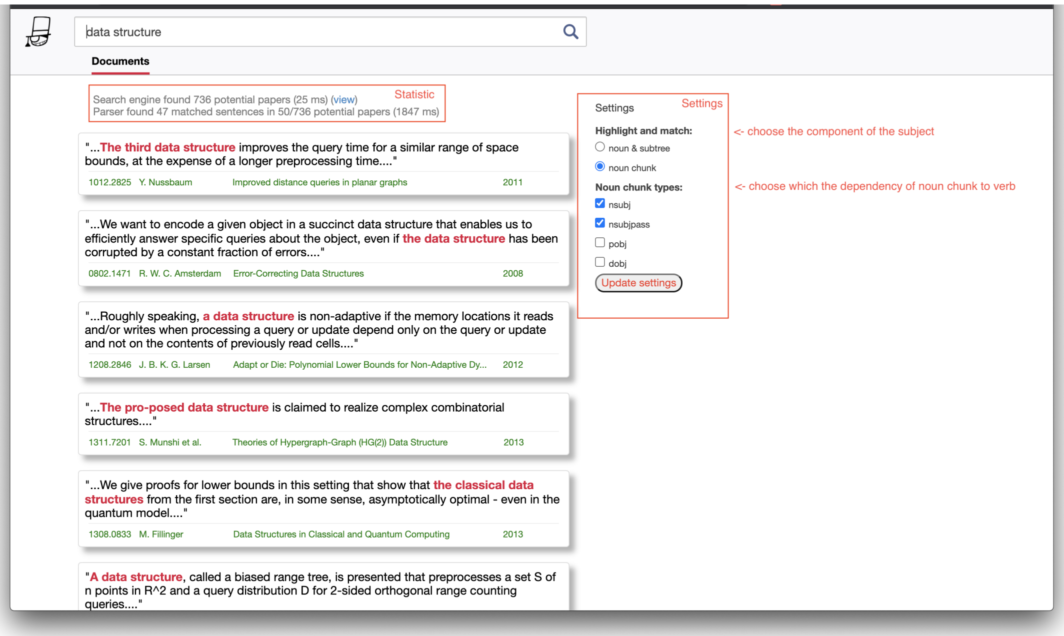

Figure 2: Demo

3 Conclusion

In this project, I have successfully built a search engine for Arxiv dataset. It can search for different morphology of the keyword. However, it still has some drawbacks:

- The index and query process of Elasticsearch is fast. However, Spacy Parser is the bottleneck of this process. Elasticsearch takes around 10ms for a query and this number of Parser is about 2s for only each batch of 50 papers. I plan to store the list of subjects in the abstract of each paper in the database. It will reduce the time for the following queries.
- As mentioned in Section 2.2, both approach of finding subjects are not accurate as I expected. I aim to exclude the redundant modifiers of noun chunks by only considering some *typed dependencies* [1] as a part of the subject.

References

[1] Marie-Catherine De Marneffe and Christopher D Manning. Stanford typed dependencies manual. Technical report, Technical report, Stanford University, 2008.