# 信息检索 Elasticsearch Pt2

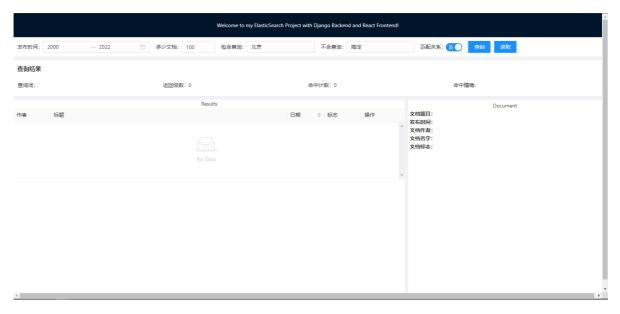
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#### **Abstract**

This homework is an extension of the previous Elasticsearch homework. Our goal add more functionality to our IR system by using more techniques that we had learned in the second half of the semester

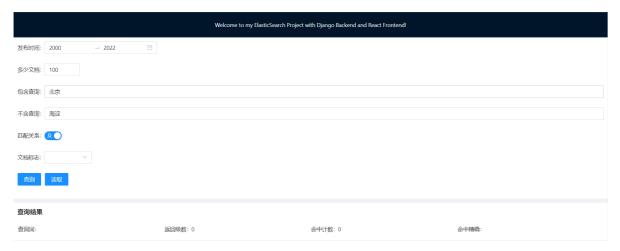
## **Background**

This is what the experiment initially looked like. It only had basic Elasticsearch functionality which is based on Boolean search. It had two search relationships. If the tab displays 及, then the query has an AND relationship. And the 或 describes an OR relationship. This is explained in the documentation



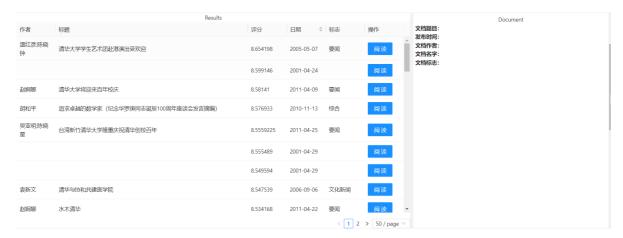
## **Implementation**

I slightly changed the format of the page, and added a couple new functionalities. The first small addition is adding functionality that searches documents by its column. It uses Elasticsearch to match the column sections in the index.



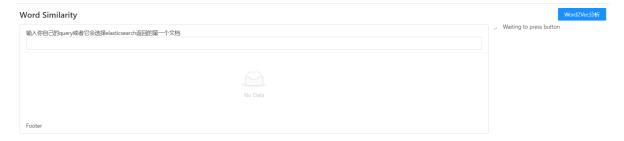


The document table is the same.

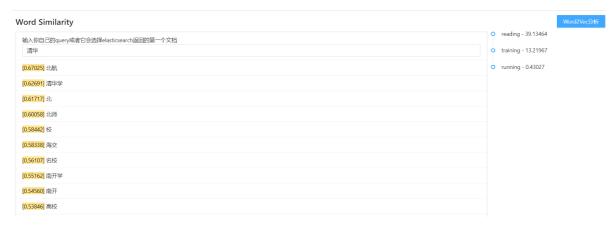


#### **Word2vec Word Similarity**

The following below are the three new functionality that I have added. The first is word similarity. It takes the documents returned by Elasticsearch and does word similarity on the documents.



It splits the request in three sections, and returns the time to read, train, and run.



The request on the frontend is as such.

```
this.setState(word sim list items: [], word_sim_pending: "Naiting to read", word_sim_loading: true ])
var result = this.state.documents.map(function(a) {return a.id})
var result = this.setstate({word_sim_reading_time: response.data.results, word_sim_list_items: temp, word_sim_pending: "Naiting to train"))
console.log(response.data);
)).then(response.data);
)).then(response.data);
)).then(response.data);
)).then(response.data);
)).then(running > {
    if (this.state.documents.length === 0) {
        this.setState({ word_sim_reading_time: "Naiting to press button",word_sim_loading: false, word_sim_list_items: []))
        message.error("没有国样声,语言语")
        return)
}

const data3 = {"task": "run", "query": this.state.word_sim_chosen_word === "" ? this.state.query_include: this.state.word_sim_chosen_word ]
        WordSimilartyRunning(data3).then(response>{
        const data3 = {"task": "run", "query": this.state.word_sim_chosen_word === "" ? this.state.query_include: this.state.word_sim_chosen_word ]
        WordSimilartyRunning(data3).then(response>>{
        const data3 = {"task": "run", "query": this.state.word_sim_chosen_word === "" ? this.state.query_include: this.state.word_sim_chosen_word ]
        WordSimilartyRunning(data3).then(response>>{
        const data3 = {"task": "run", "query": this.state.word_sim_chosen_word === "" ? this.state.query_include: this.state.word_sim_chosen_word ]
        if (response.data1);
        if (response.data1);
        if (response.data2);
        if (response.data3);
        if (response.data3);
        if (response.data3);
        if (response.data3);
        if (response.data4);
```

And the python backend is simply implements the functionality of word2vec. For example, the train function is as such. The implementations for the following are similar.

```
fef word_sim_train():
    """train corpus based on parameters"""
    start = time.time()
    lines = []
    with open("data.jsonl") as f:
        lines = f.read().splitlines()
        text_corpus = json.loads(lines[0])
    text_corpus = [text.split() for text in text_corpus]

params = {...
    }

# train model
    model = Word2Vec(sentences=text_corpus, **params)
    model.save(f"sg(params['sg'])_hs(params['hs'])_win(params['window'])_size(params['vector_size']).model")

end = time.time()
    spent_time = end - start
    return "%.5f"%spent time
```

### **Doc2vec Document Similarity**

I used Gensim's Doc2vec to implement document similarity. You can enter your own document or query, or it will use the first result returned by elasticsearch. In word2vec, you train to find word vectors and then run similarity queries between words. In doc2vec, you tag your text and you also get tag vectors. Then, after doc2vec training you can use the same vector arithmetic's to run similarity queries on author tags, which document are most similar to the one being queried.

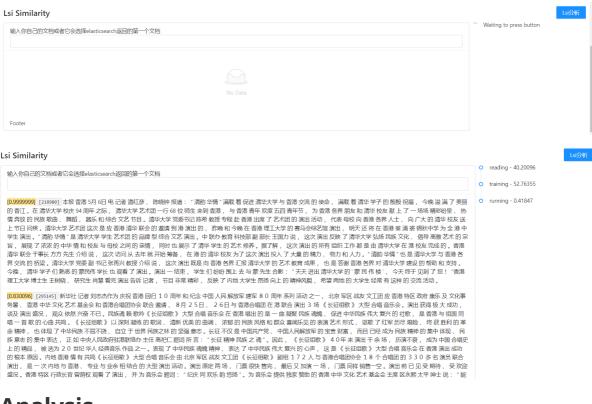


It returns the top 5 results



#### **Lsi Document Similarity**

Similar to document similarity, but still using LSI.



#### **Analysis**

We can see from the results that Doc2Vec and LSI to compare each method.

Using Elasticsearch, we queried the corpus and got back 10000 results



The result with the highest score is this Elasticsearch query is

| <u> 查询结果</u> |  |                |           |            |           |    |   |  |
|--------------|--|----------------|-----------|------------|-----------|----|---|--|
| 查询词: 北京      | 5但不包含海淀(及)                               | 返回级数: 10000    |           | 命中         | 计数: 10000 |    | 命中精确: gte   |  |
| Results      |  |                |           |            |           |    | Document  |  |
| 作者           | 标题                                       |                | 评分        | 日期 💠       | 标志        | 操作 | 文档题目: 《中国大博览》北京分册出版发行<br>发布时间: 2007-03-03   |  |
| 智文           | 《中国大博览》北京分册出版发行                          |                | 4.1907825 | 2007-03-03 | 国际要闻      | 阅读 | 文档作者: 智文<br>文档名字: deta11@record=2742&channelid=200703&searchword=&sortfield=  |  |
|              | 关于表彰2005年度区域经济五十强二三产业<br>资先进集体、文明富裕村等的决定 | 先进镇、二三产业先进村招商引 | 4.1759167 | 2006-03-01 | 公告        | 阅读 | 文档标志: 国际要闻<br>本报北京 3月 1日讯在北京 紧锣密鼓迎接 2008年 奥运会之际,21<br>世纪中国大型对外宣传画册——(中国大博览)北京分册正式出版发<br>传、中国大博览)北京分册为大8 开精装本,分上下两册,中英文<br>对照、共计46万字,2000余幅图片;由魅力北京、解煌北京、                    |  |
|              |  |                | 4.1672716 | 2002-12-07 |           | 阅读 |   |  |
|              |  |                | 4.1637135 | 2001-02-21 |           | 阅读 | 经贸北京、风采北京、旅游北京、投资北京、畅想北京、明珠北京、信息北京 9 部分组成,全方位、多角度反映 7 近年来普部北京 发展的 新成就、新风扇、新举措,充分展现了老北京的解维历史、新北京的 迷人魅力和未来北京的美好覆景。具有较强的 权威胜、实用性和收藏价值。中共中央政治周委员、北京市委书记刘膑为该分册作序,主编为北京市长王岐山。(管文) |  |
| 钟文           | 将真实的北京展示给世界(五环漫笔)                        |                | 4.1616807 | 2008-07-09 | 奥运特刊      | 阅读 |   |  |
| 阎晓明;王建<br>新  | 燕京啤酒成为北京奥运会赞助商(2008北京                    | 奥运之窗)          | 4.1604757 | 2005-08-11 | 体育        | 阅读 |   |  |

Then, to compare the methods, we can look at the results given. The algorithms and methods used for this extension are the same as the homework for 6 and 7, and the conclusions are pretty much the same. LSI is a count based model where similar terms have same counts for different documents. Then dimensions of this count matrix is reduced using SVD. For both the models similarity can be calculated using cosine similarity. Word2vec is a prediction based model, for example, the given the vector of a word predict the context word vectors (such as skipgram method). When utilizing a small window count, Doc2vec organizes results by terms that are 相似,while LSI organizes results by 相关. Training an LSI system takes much more time than Doc2vec on its basic window of 5, and with 5 epochs.

Compared to Doc2vec and LSI, Elasticsearch is much faster, and cheaper, and handles only pure and simple keyword searches. Thus, when handling simple keyword searches such as 清华 or 北京, Elasticsearch gives us a much better results when we search for documents with simple queries.

Thus, when handling larger document based similarity searches (larger queries), it is better to use Doc2Vec or LSI methods.

### **Improvements**

Based on this experiment, and throughout this class, it is easy to see how easy to hard it is to make a good IR system. There are a lot of things to consider. If I have more time to work on this experiment, I would like to have implemented more features, and tried more information retrieval methods, such as BERT, and do a deeper comparison between these methods and find a way to display the similarities and differences. I would also like to have improved the interface.

Thanks!