

PES UNIVERSITY

(Established under Karnataka Act No. 16 of 2013) 100 Ft. Road, BSK III Stage, Bengaluru – 560 085 DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING SESSION: AUG-DEC 2020

Course Title: Algorithms for Information Retrieval Course code: UE17CS412					
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ASSIGNMENT REPORT

Problem Statement

Search Engine based on a Vector-Space Model and a comparative evaluation alongside ElasticSearch Engine.

Description

Our 4 stage comparative study includes:

- 1. Pre-processing:
 - We use the famed NLTK module to implement the following pre-processing techniques

Tokenization

It is the transformation of a bunch of meaningful data into a string of abstract characters that can be mapped to, later on.

- 1. This helps in bringing in the abstraction of **term-id** which can later be used **not only** for more efficient querying **but also**
- 2. Correction measures such as edit distance measurement for the sake of error correction.

Lemmatization

The process of reducing a term to its "root" word Ex: standardise -> standard

Another option could have been stemming, where the same outcome is done using certain rules such as "remove -ish" etc. but sometimes, especially when there are a lot of proper nouns involved, it may lead to semantic loss.

Ex: "fetish" -> "fet"

We prefer lemmatization over stemming here since stemming may lead to loss of meaningful queries, owing to journalism usually dealing with tons of "people, places and things!"

We use NLTK's built-in **WordNet lemmatizer** that is sufficiently large and tailored to the English language

• Case Folding

Since case (lower or upper) does not make differ semantically for searching, we "fold" all root query words to a single type (here, all lower case)

2. B-tree implementation:

We use OOBTRee to build tree-based dictionaries and posting lists that are mapped to each entry

- We use a unique <term-frequency, doc-id> structure to index the inverted indices
- This structure can be put to use to find similarity measures later on

3. <Op>Closest word:

We used edit distance(Levenshtein distance) to obtain the closest word in the vocabulary.

It makes use of Dynamic Programming, a paradigm that invests in **overlapping subproblems** with repeatable measurements/ operations that build on each other.

$$\operatorname{lev}(a,b) = \begin{cases} |a| & \text{if } |b| = 0, \\ |b| & \text{if } |a| = 0, \\ \operatorname{lev}(\operatorname{tail}(a), \operatorname{tail}(b)) & \text{if } a[0] = b[0] \\ 1 + \min \begin{cases} \operatorname{lev}(\operatorname{tail}(a), b) \\ \operatorname{lev}(a, \operatorname{tail}(b)) & \text{otherwise.} \\ \operatorname{lev}(\operatorname{tail}(a), \operatorname{tail}(b)) \end{cases}$$

4. Ranking process

After applying similar pre-processing measures to the query as well, we begin the 4 stage ranking process

- Create a Term frequency vector
 Refer to the term frequency using the "files" OOBTree and keep track of each query term's tf score.
- Created a inverse frequency vector Refer to the posting lists and use a tf-idf matrix to similarly obtain idf scores.
- Create a tf-idf vector Using the "document-at-a-time" strategy, we obtain tf-idf score vector by multiplication.
- Finally cosine similarity for retrieving top k results

We look at a simple Euclidean distance to calculate similarity between document vectors and the query vector, but this leads to some blatant dissimilarities. Since the document tf-idf vectors exist in the same dimensions of the query tf-idf vectors, a simple dot product helps obtain a vector-based similarity measure for the same.

Now, a normalised dot-product of these vectors is equivalent to a cosine similarity (since cosine theta decreases with theta, and the closer the query to the document, the lower the angle, and hence larger the cosine measure)

$$similarity(A,B) = \frac{A \cdot B}{\|A\| \times \|B\|} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \times \sqrt{\sum_{i=1}^{n} B_i^2}}$$

This gives a convenient metric between [0,1] that can be ranked for all documents and returned by orders of top-k i.e. top-10, top-20 etc.

Code Snippets

```
| Second | S
```

```
search.py
                                                                                                                                                                                                                                                                                                                     *air.py
    dd=dict()
dd[ind]=ll
t[k]=dd
                                                                                                          else:
                                                                                                                          #ps.stem(row[j])
if(row[j] in tf[f[:-4]][ind]):
    tf[f[:-4]][ind][row[j]]=tf[f[:-4]][ind][row[j]]+1
                                                                                                                           else:
                                                                                                                          ll=list()
ll.append(pos)
                                                                                                                                                           pos=pos+1
t[row[j]][ind]=ll
                                                                                                                           else:
                                                                                                                                           ll=list()
ll.append(pos)
pos=pos+1
dd=dict()
dd[ind]=ll
                                                          afile = open(r"./"+f[:-4]+".pkl", 'wb')
pickle.dump(t, afile)
afile.close()
                                                                                                                                           t[row[j]]=dd
   103 afile = open(r' | 104 pickle.dump(t, afile.close()) |
105 end=time.time() |
107 df["N"]=N |
108 afile = open(r' , ''+"tf"+" , pkl", 'wb') |
109 pickle.dump(tf, afile) |
110 afile.close() |
111 afile = open(r' , ''+"df"+" , pkl", 'wb') |
112 pickle.dump(df, afile) |
113 afile.close() |
114 |
115 |
116 file2 = open(r' df.pkl", 'rb') |
117 new d = pickle.load(file2) |
118 file2.close() |
     103
   118 Tite2.ctose()
119
120 file1 = open(r"df.pkt", 'rb')
121 df = ptickle.load(file1)
122 file1.close()
123 file2 = open(Tf.pkt", 'rb')
124 tf = ptickle.load(file2)
125 file2.close()
                                                                                                                                                                                                                                                                                                                                Python ▼ Tab Width: 8 ▼ Ln 32, Col 10 ▼ INS
 search.pv
                                                                                                                                                                                                                                                                                                                     *air.py
                                                                                          dp[i][j] = 1 + min(dp[i][j-1],dp[i-1][j],dp[i-1][j-1])
Interpretable (query)

161

162 query=[i.lower() for i in query]

163 """for i,q in enumerate(query):

164 query[i]=oditDistDP(q)""

165 ql=[query.count(i)/len(query) for i in query]

166 for i in range(len(ql)):

167 if(query[i] in df):

168 ql[i]=ql[i]*math.log(df["N"]/df[query[i]])

169 else:

170 ql[i]=0

171 a=0

172 for i in ql:

173 a=a+i*i

174 a=pow(a,0.5)
Python ▼ Tab Width: 8 ▼ Ln 32, Col 10 ▼ INS
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Output Screenshots

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Ambiganbi-impries-SSSP-/AIR 97thm3 afr.py
-class 'ltar' 477
-class
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THE POWER OF THE POWER SEARCH TERMINAL HELP

MILE TYPE YOUR QUEY

BATER YOUR YEAR AND ALL A

tions to commit to a deal with climate change. brian: wow, joe biden says he doesn't want help from

doc: FOXNEWS.201304.csv row: 37 URL: https://archive.org/details/FOXNEWSM_20130407_030000_The_Journal_Editorial_Report#start/1115/end/1150 MatchDateTime : 4/7/2013 3:18:50 Station
FOXNEWS show: The Journal Editorial Report IAShowID: FOXNEWSM_20130407_030000 The_Journal_Editorial_Report IAPreviewThumb: https://archive.org/download/FOXNEWSM_20130407_030000 The_Journal_Editorial_Report/FOXNEWSM_20130407_030000 The_Journal_Editorial_Report/FOXNEWSM_20130407_03000 The_Journal_Editorial_Report/FOXNEWSM_20130407_03000 The_Journal_Editorial_Report_FOXNEWSM_20130407_030000 The_Journal_Editorial_Report_FOXNEWSM_20130407_03000 The_Journal_Editorial_Report_FOXNEWSM_20130407_03000 The_Journal_Editorial_Report_FOXNEWSM_20130407_03000 The_Journal_Editorial_Repor

doc: CNN_201207.csv row: 53
Ashbardo: CNN_201207.csv row: 53
Ashbardo: CNN_201207.csv row: 53
Ashbardo: CNN_201207.csv row: 54
Ashbardo: CNN_20120702.1300000 CNN_Newsroon Aproved with high style or gradual of the property of the property

time taken: 3.037285804748535

Interpretation of efficiency

Matches in the query	Time taken by custom search engine	Time taken by elastic search engine	Number of matches in top k	NAL score
greenhouse gas and global warming	3.6258	0.0109 s	12/18	1.13
barack obama	3.03728	0.0110 s	29/39	2.47
carbon dioxide	3.10845	0.0571 s	19/40	1.58

We observe that F scores are in the ranges of [0.09, 0.15] This is insufficient as a comparative measure

Custom Metric:

We notice that as word count increases, the proportion of top-ks decreases, since ElasticSearch has complex context-based implementations, hence we penalise the lower word error more.

Normalised average log-depreciation top-k comparison (NAL score):

NAL = n(Custom U Es) / log (N)

, where N is the number of terms in query

It is also observed that the performance of professional IR systems is substantially higher for proper nouns (of the same length) which further leads us to believe they use complex cotext0based algorithms.

This leads to an idea of finding global reference index of a specific term and incorporating it into our measure as well (G-NAL score)

Learning Outcome

- Appreciating the nuances of a complex search engine
- Implementing tf.idf scoring, vector space ranking from scratch helps keep track of various data structures involved and their interconnectedness.
- Observed the importance of metrics and how specific measures can be used to seed insights from and tell stories about IR systems.

Name and Signature of the Faculty