PROJECT REPORT ON TF-IDF Query Retrieval on Shakespeare's Corpus

A Project Work Submitted in Partial Fulfilment of the requirements for

The Course

ALGORITHMS FOR INTELLIGENCE WEB AND INFORMATION RETRIEVAL

By

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1. Introduction

Term Frequency is defined as the ratio of the number of times the "Term" appeared in a document to the total number of Terms in the document.

Inverse Document Frequency is the ratio of Total Number of Documents to the Number of Documents Containing the Term.

The product of the Term Frequency and Inverse Document Frequency is TF-IDF. This method is widely used for Information Retrieval and Text Mining. Computer can understand data in the form of numerical values , so for this reason we vectorize all of the text so the computer can understand better. By vectorizing the documents we can perform various numerical operations like ranking , clustering and so on. This is the same thing. This is the same thing that happens when you perform a Google search. The web pages are called Documents and the search text is called Query. When you search with a query, google will find the relevance of the query with all of the documents, ranks them in the order of relevance and shows you the top k documents.

2. Overview of the Project

The data that we are using is Shakespeare's Poems Corpus in a folder called **Stories** . The folder contains 23 Shakespeare's Poems in .txt format . Each document has different names. There is also an **index.html** file which contains the name and the location where all these poems are stored which can be used for efficient query retrieval.

The project is not only limited to Shakespeare's Corpus , it can also be applied to any corpus that is in text (i.e. .txt) format.

3. Algorithm and Pseudocode

As mentioned in the title we will be using TF-IDF as well as Cosine similarities to rank documents. In order to rank the documents according to their TF-IDF / Cosine similarities we have to first convert the input string to a set of Tokens viz called as Tokenization.

For this , we follow the below steps :

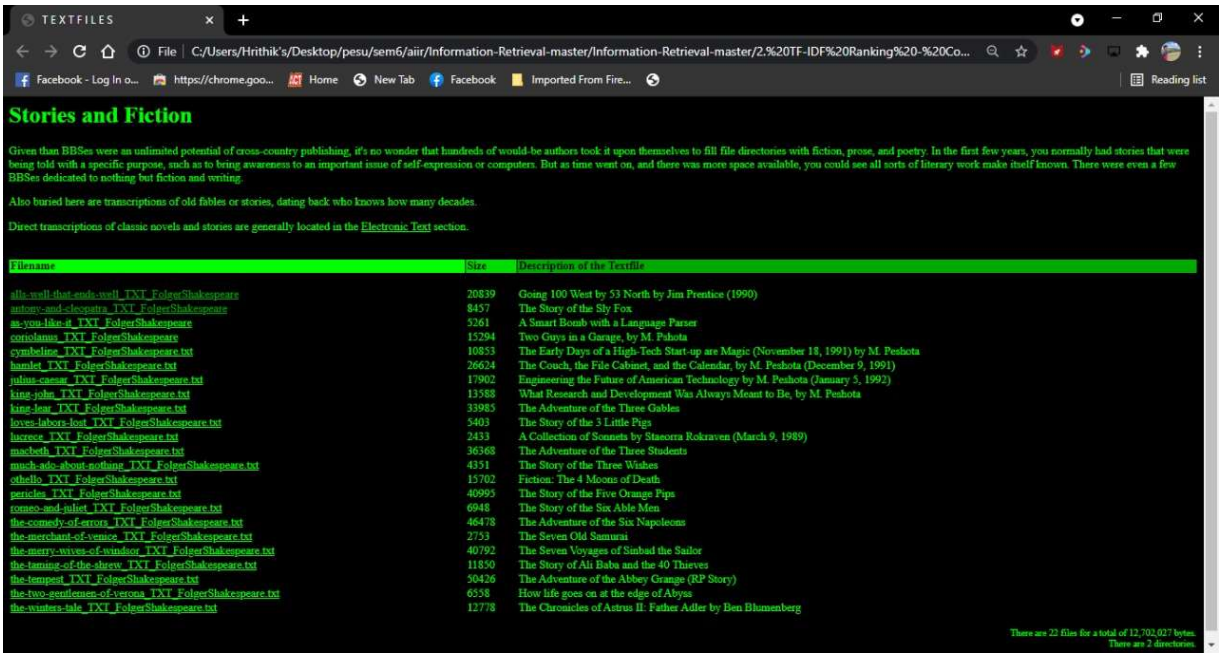
- We convert all words into lower case.
- Stop word removal using **ntlk** library.
- Punctuation removal.
- Elimination of Single Characters.
- Conversion of Numbers to Alphabets (For ex. $100 is converted to hundred dollars).
- Lemmatisation.
- And the most important part of pre-processing , Stemming.

Finally , after doing all this we calculate :

- TF-IDF = Term-Frequency *Inverse Document Frequency
- Cosine Similarity = Dot Product of vector a and vector b.

Since TF-IDF is a way to measure the importance of tokens in text and Cosine Similarity is used to compare the similarity of the query words with those present in other documents , we use Cosine Similarity as our final ranking parameter.

The **index.html** file:



The libraries that we need :

Imports

In [2]:
```
# !unzip stories
```

In [3]:
```
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer
from collections import Counter
from num2words import num2words

import nltk
import os
import string
import numpy as np
import copy
import pandas as pd
import pickle
import re
import math

# %load_ext autotime
```

Pre-processing :

Step 1 :Extracting Data:

All the corpus is stored in the **stories** zip folder in .txt format . First we need to extract them

Extracting Data

```
In [25]: processed_text = []
         processed_title = []

         for i in dataset[:N]:
             file = open(i[0], 'r', encoding="utf8", errors='ignore')
             text = file.read().strip()
             file.close()

             processed_text.append(word_tokenize(str(preprocess(text))))
             processed_title.append(word_tokenize(str(preprocess(i[1]))))

In [ ]:
```

Step 2 : Collecting File Names and Titles :

Next , we create an empty list called **dataset** which contains the titles of all the .txt files in the stories folder.

Collecting the file names and titles

```
In [7]: dataset = []

        c = False

        for i in folders:
            file = open(i+"/index.html", 'r')
            text = file.read().strip()
            file.close()

            file_name = re.findall('><A HREF="(.*)">', text)
            file_title = re.findall('<BR><TD> (.*)\n', text)

            if c == False:
                file_name = file_name[2:]
                c = True

            print(len(file_name), len(file_title))

            for j in range(len(file_name)):
                dataset.append((str(i) +"/"+ str(file_name[j]), file_title[j]))

        21 23
```

Step 3 : Converting Strings to Numbers

Vectorising tf-idf

In [47]:
```
D = np.zeros((N, total_vocab_size))
for i in tf_idf:
    try:
        ind = total_vocab.index(i[1])
        D[i[0]][ind] = tf_idf[i]
    except:
        pass
```

In [48]:
```
def gen_vector(tokens):

    Q = np.zeros((len(total_vocab)))

    counter = Counter(tokens)
    words_count = len(tokens)

    query_weights = {}

    for token in np.unique(tokens):

        tf = counter[token]/words_count
        df = doc_freq(token)
        idf = math.log((N+1)/(df+1))

        try:
            ind = total_vocab.index(token)
            Q[ind] = tf*idf
        except:
            pass
    return Q
```

Step 4 : Calculating Document Frequency

Document frequency is defined as the ratio of the Number of Documents containing the Term to the Total number of Documents.

Calculating DF for all words

In [26]:
```
DF = {}

for i in range(N):
    tokens = processed_text[i]
    for w in tokens:
        try:
            DF[w].add(i)
        except:
            DF[w] = {i}

    tokens = processed_title[i]
    for w in tokens:
        try:
            DF[w].add(i)
        except:
            DF[w] = {i}
for i in DF:
    DF[i] = len(DF[i])
```

Step 5 : Calculate TF-IDF of the body.

We calculate the TF-IDF value to the body of the document , ignoring the Terms in the Title.

Calculating TF-IDF for body, we will consider this as the actual tf-idf as we will add the title weight to this.

In [33]:
```
doc = 0

tf_idf = {}

for i in range(N):

    tokens = processed_text[i]

    counter = Counter(tokens + processed_title[i])
    words_count = len(tokens + processed_title[i])

    for token in np.unique(tokens):

        tf = counter[token]/words_count
        df = doc_freq(token)
        idf = np.log((N+1)/(df+1))

        tf_idf[doc, token] = tf*idf

    doc += 1
```

Step 6 : Calculate TF-IDF of the Title.

We calculate the TF-IDF value of the Title , ignoring the Terms present in the Body of the document.

Calculating TF-IDF for Title

In [35]:
```
doc = 0

tf_idf_title = {}

for i in range(N):

    tokens = processed_title[i]
    counter = Counter(tokens + processed_text[i])
    words_count = len(tokens + processed_text[i])

    for token in np.unique(tokens):

        tf = counter[token]/words_count
        df = doc_freq(token)
        idf = np.log((N+1)/(df+1)) #numerator is added 1 to avoid negative values

        tf_idf_title[doc, token] = tf*idf

    doc += 1
```

Step 7 : Calculating TF-IDF Matching Score

We multiply the weight alpha to the body and 1-alpha to the title and find the Matching Score.

TF-IDF Matching Score Ranking

In [42]:
```
def matching_score(k, query):
    preprocessed_query = preprocess(query)
    tokens = word_tokenize(str(preprocessed_query))

    print("Matching Score")
    print("\nQuery:", query)
    print("")
    print(tokens)

    query_weights = {}

    for key in tf_idf:

        if key[1] in tokens:
            try:
                query_weights[key[0]] += tf_idf[key]
            except:
                query_weights[key[0]] = tf_idf[key]

    query_weights = sorted(query_weights.items(), key=lambda x: x[1], reverse=True)
    print("")
    l = []
    for i in query_weights[:10]:
        l.append(i[0])

    print(l)
matching_score(10, "But I have a son, sir, by order of law,some year elder than this ")
```

Step 8 : Calculating Cosine Similarity

We find cosine similarity using dot product

In [49]:
```
def cosine_similarity(k, query):
    print("Cosine Similarity")
    preprocessed_query = preprocess(query)
    tokens = word_tokenize(str(preprocessed_query))

    print("\nQuery:", query)
    print("")
    print(tokens)

    d_cosines = []

    query_vector = gen_vector(tokens)

    for d in D:
        d_cosines.append(cosine_sim(query_vector, d))

    out = np.array(d_cosines).argsort()[-k:][::-1]

    print("")

    print(out)

#     for i in out:
#         print(i, dataset[i][0])

Q = cosine_similarity(10, "But I have a son, sir, by order of law,some year elder than this")
```

Using the above 2 similarity methods we rank the documents.

4. Results and Discussions

The output rankings for the following queries are :

Query 1 – “Why , Enobarbus , When Anthony found Julius Caesar dead , He cried almost to roaring ; and he wept . When at Philippi he found Brutus slain ”

```
Matching Score

Query: Why, Enobarbus, When Anthony found Julius Caesar dead, He cried almost to roaring; and he wept. When at Philippi he foun
d Brutus slain

['enobarbu', 'anthoni', 'found', 'juliu', 'caesar', 'dead', 'cri', 'almost', 'roar', 'wept', 'philippi', 'found', 'brutu', 'sla
in']

[4, 1, 2, 8, 13, 3, 10, 9, 19, 7]
```

```
Cosine Similarity

Query: Why, Enobarbus, When Anthony found Julius Caesar dead, He cried almost to roaring; and he wept. When at Philippi he foun
d Brutus slain

['enobarbu', 'anthoni', 'found', 'juliu', 'caesar', 'dead', 'cri', 'almost', 'roar', 'wept', 'philippi', 'found', 'brutu', 'sla
in']

[ 4  1  8  2 13  3  7 10 20 15]
```

Hence , seeing the above rankings we can say that Document 4 is highly ranked.

Query 2 – “I did enact Julius Caesar . I was killed i’ the capitol ; Brutus killed me”

```
Matching Score

Query: I did enact julius Caesar.I was killed i' the capitol; Brutus killed me

['enact', 'juliu', 'caesar', 'kill', 'capitol', 'brutu', 'kill']

[4, 1, 2, 8, 3, 15, 18, 9, 0, 7]
```

```
Cosine Similarity

Query: I did enact julius Caesar.I was killed i' the capitol; Brutus killed me

['enact', 'juliu', 'caesar', 'kill', 'capitol', 'brutu', 'kill']

[ 4  1  8  2  3 15 18  7  9 16]
```

Hence , seeing the above rankings we can say that Document 4 is highly ranked.

Query 3 – “But I have a son , sir , by order of law , some year older than this”

```
Matching Score
Query: But I have a son, sir, by order of law,some year elder than this
['son', 'sir', 'order', 'lawsom', 'year', 'elder']
[16, 17, 14, 7, 20, 0, 19, 12, 6, 2]
```

```
Cosine Similarity
Query: But I have a son, sir, by order of law,some year elder than this
['son', 'sir', 'order', 'lawsom', 'year', 'elder']
[ 5 17 16 20 12  7  2  4  0  6]
```

Hence , seeing the above rankings we can say that Document 17 is highly ranked.

5. Conclusion and Future Scope

As a part od our 6th semester AIW&IR project we have created a TF-IDF Query Retriever on Shakespeare’s’ Corpus.

There is still room for improvement in our Project , for example our Project is only limited to Corpus which is in .txt format , we can expand our project to include more document types and use more complex algorithms to retrieve queries.

6. References & Sources

We referred the following websites to learn more about how to improve our project:

- www.geeksforgeeks.com
- www.wikipedia.com
- www.stackoverflow.com
- https://cs.stanford.edu