RAMAIAH
Institute of Technology

Department of

Computer Science and Engineering

Information Retrieval

CSE645

Assignment-1

20-marks lab component

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Exercise 1: Implementation of Pre-processing of a Text Document.

Aim: Given a set of documents, implement the preprocessing procedures and store the resulting file.

Steps to execute:

Step 1: read the document and store it in a string

Step 2: convert to lower case and remove all the digits , non-ascii characters , whitespaces

Step 3: tokenize the string and remove all the stop words present in that language

Step 4: use stemming on the resultant tokenized words and stem the words to its root form

Step 5: store the processed words in a text file.

Code (python3 / jupyter notebook) / input / output:

```
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem import WordNetLemmatizer
from nltk.tokenize import word_tokenize
from nltk import ne_chunk
from nltk import pos_tag
import re
import string
import os
from sys import getsizeof
import unicodedata
```

```
def preprocess(data):
    data = data.lower()
    data = re.sub(r'\d+','',data)
    data = re.sub(r'\n',' ',data)
    data = re.sub(r'[^A-Za-z]+',' ',data)
    data = data.translate(str.maketrans('','', string.punctuation))
    data = data.strip()

    stop_words = set(stopwords.words('english'))
    tokens = word_tokenize(data)
    result = [i for i in tokens if  i not in stop_words]
    result = [unicodedata.normalize('NFKD', i).encode('ascii', 'ignore').decode('utf-8', 'ignore') for i in result]

    stemmer= PorterStemmer()
    new_result = [stemmer.stem(i) for i in result]
    new_result = [i for i in new_result if  i not in stop_words]


    return new_result
```

```
path = os.getcwd() + "\\Inverted Index"

preprocessed_text = []
size_info = {}

for filename in os.listdir(path):
    if filename.split(".")[-1] == "txt" :
        with open(path + "//" + filename,"r") as file:
```

```
        with open(path + "//" + filename,"r") as file:
            data = file.read()
        result = preprocess(data)
        preprocessed_text = preprocessed_text + result
        size_info[filename] = [getsizeof(data),getsizeof(result)]
```

```
for i in size_info:
    print("size of document before processing: ",size_info[i][0]," bytes",",  size of document after processing: ",size_info[i][1]," bytes")
```

```
size of document before processing:  55164  bytes ,  size of document after processing:  43032  bytes
size of document before processing:  18566  bytes ,  size of document after processing:  14672  bytes
size of document before processing:  72948  bytes ,  size of document after processing:  54560  bytes
size of document before processing:  55626  bytes ,  size of document after processing:  43032  bytes
size of document before processing:  23717  bytes ,  size of document after processing:  16552  bytes
size of document before processing:  16691  bytes ,  size of document after processing:  13000  bytes
size of document before processing:  11438  bytes ,  size of document after processing:  7976  bytes
size of document before processing:  19853  bytes ,  size of document after processing:  14672  bytes
size of document before processing:  41433  bytes ,  size of document after processing:  30112  bytes
size of document before processing:  63478  bytes ,  size of document after processing:  43032  bytes
```

```
preprocessed_text = list(set(preprocessed_text))
preprocessed_text.sort()

with open(os.path.join(os.getcwd(),"preprocessed_text.txt"),"w") as wf:
    wf.write(" ".join(preprocessed_text))
```

Inference / Conclusion:

Every document has certain format / styles / content that is irrelevant when someone is searching for the document, preprocessing the document by removing stopwords, numbers, and stemming each word makes it easier to compress the content of the document for easier searching and ranking.

Exercise 2: Implementation of Inverted Index: Construction and Searching

Aim: To construct an inverted index to access word count of all the words in a particular document from the processed text

Steps to execute:

Step 1: pre-process the set of documents and store the processed words in a text .

Step 2: store each processed document separately using a data structure (dictionary) .

Step 3: for each word in the processed text file get the count of that word in every document and store it in an easily accessible data structure (hash table / DataFrame in python) .

Step 4: take some word as a query input and get its count details by using the word as the hashed value to access it .

Step 5: Store the resultant inverted index in csv format.

Code (python 3 / jupyter notebook) / input / output:

```python
import os
import re
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.tokenize import word_tokenize
import unicodedata,string
import pandas as pd
```

```python
path = os.getcwd() + "\\preprocessed_text.txt"

with open(path,"r") as file:
    preprocessed_text = file.read().split()
```

```python
def preprocess(data):
    # convert to lower case and remove numbers , punctuations , whitespaces

    data = data.lower()
    data = re.sub(r'\d+','',data)
    data = re.sub(r'\n',' ',data)
    data = re.sub(r'[^A-Za-z]+',' ',data)
    data = data.translate(str.maketrans('','', string.punctuation))
    data = data.strip()


    stop_words = set(stopwords.words('english'))
    tokens = word_tokenize(data)
    result = [i for i in tokens if  i not in stop_words]
    result = [unicodedata.normalize('NFKD', i).encode('ascii', 'ignore').decode('utf-8', 'ignore') for i in result]

    stemmer= PorterStemmer()
    new_result = [stemmer.stem(i) for i in result]
    new_result = [i for i in new_result if  i not in stop_words]


    return new_result
```

```python
def get_index(word,documents):
    index = {}

    for i in documents.keys():
        count = documents[i].count(word)
        index[i] = count

    return index
```

```python
path = os.getcwd() + "\\Inverted Index"

documents = {}

for filename in os.listdir(path):
    if filename.split(".")[-1] == "txt" :
        with open(path + "//" + filename,"r") as file:
            data = file.read()
        result = preprocess(data)
        documents[filename] = result
```

```python
inverted_index = {}

for i in preprocessed_text:
    inverted_index[i] = get_index(i,documents)
```

```python
dataframe = pd.DataFrame(inverted_index).T
dataframe
```

	T1.txt	T10.txt	T2.txt	T3.txt	T4.txt	T5.txt	T6.txt	T7.txt	T8.txt	T9.txt
abandon	1	0	0	0	0	0	0	0	2	0
abbrevi	0	0	1	0	0	0	0	0	0	0
abdomen	0	0	1	0	0	0	0	0	0	0
abdomin	0	0	1	0	0	0	0	0	0	0
aberdeen	0	0	0	0	0	0	0	0	0	1
...	...	...	...	...	...	...	...	...	...	...
zo	0	0	0	1	0	0	0	0	0	0
zone	0	0	2	0	0	0	0	0	0	0
zoolog	0	0	0	0	0	0	0	0	0	5
zoologist	0	0	2	0	0	0	0	0	0	0
zoophyt	0	0	0	3	0	0	0	0	0	1

```
word = input("enter word :")

if word in dataframe.index:
    print("\n",dataframe.loc[word])
```

```
enter word : human

 T1.txt     1
T10.txt    0
T2.txt     6
T3.txt     3
T4.txt     3
T5.txt     1
T6.txt     0
T7.txt     1
T8.txt     0
T9.txt     8
Name: human, dtype: int64
```

```
dataframe.to_csv("inverted_index.csv")
```

Inference/ Conclusion:

Inverted indexing is the procedure in which the frequency of occurrence of each word in the document is stored. Preprocessing of documents is required before storing the inverted index to store relevant content.

Exercise 3: Implementation of vector Space model

A. Rank 10 documents for a given query.

B. Computing Similarity between any two documents.

Aim: To implement a vector Space model and for a given query rank 10 documents and also compute similarity between any two documents using and similarity method.

Steps to execute:

Step 1: pre-process the set of documents and store the processed words in a text

Step 2: construct an inverted index for all the words in the pre-processed text file as mentioned in 2nd exercise.

Step 3: for the inverted index find the tf-idf scores as follows :

Step 3.1: normalise the data w.r.t document (columns)

Step 3.2: get count of number of documents containing a word w and also get count of number of documents as N.

Step 3.3: get tf-idf score of a word by using formula log10(N/count[w])

Step 4: prompt the user to enter a query word/words and pre-process those words.

Step 5: get the tf-idf scores for the pre-processed words and store it in a dictionary

Step 6: to get the rank of the query words follow the steps:

Step 6.1: calculate the distance of the query vector using square root of sum of squares and store in it variable 'dist1'

Step 6.2: calculate the vector product by multiplying the query and each document vector and store it in 'vec_product'

Step 6.3: for each document find the distance 'dist2' using same method and get the similarity between query vector and document vector as (vec_product / dist1 * dist2)

Step 7: sort and display the rank of the query w.r.t the documents

Step 8: repeat same steps for document similarity but instead of query vector compare each document vector with rest and store the result

Step 9: display the confusion matrix obtained from comparison.

Code (python 3 / jupyter notebook) / input / output:

```
import pandas as pd
import os
import re
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.tokenize import word_tokenize
import unicodedata,string
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
data = pd.read_csv("inverted_index.csv")
data.index = data['Unnamed: 0']
data = data.drop(['Unnamed: 0'],axis=1)
data.index = data.index.rename("words")
data
```

	T1.txt	T10.txt	T2.txt	T3.txt	T4.txt	T5.txt	T6.txt	T7.txt	T8.txt	T9.txt
words										
abandon	1	0	0	0	0	0	0	0	2	0
abbrevi	0	0	1	0	0	0	0	0	0	0
abdomen	0	0	1	0	0	0	0	0	0	0
abdomin	0	0	1	0	0	0	0	0	0	0
aberdeen	0	0	0	0	0	0	0	0	0	1
...	...	...	...	...	...	...	...	...	...	...
zo	0	0	0	1	0	0	0	0	0	0
zone	0	0	2	0	0	0	0	0	0	0
zoolog	0	0	0	0	0	0	0	0	0	5
zoologist	0	0	2	0	0	0	0	0	0	0
zoophyt	0	0	0	3	0	0	0	0	0	1

```python
def preprocess(data):
    # convert to lower case and remove numbers , punctuations , whitespaces

    data = data.lower()
    data = r e.sub(r'\d+','',data)
    data = re.sub(r'\n',' ',data)
    data = re.sub(r'[^A-Za-z]+',' ',data)
    data = data.translate(str.maketrans('','', string.punctuation))
    data = data.strip()


    # tokenization

    # 1. stop words removal

    stop_words = set(stopwords.words('english'))
    tokens = word_tokenize(data)
    result = [i for i in tokens if  i not in stop_words]
    result = [unicodedata.normalize('NFKD', i).encode('ascii', 'ignore').decode('utf-8', 'ignore') for i in result]

    # 2. stemming

    stemmer= PorterStemmer()
    new_result = [stemmer.stem(i) for i in result]
    new_result = [i for i in new_result if  i not in stop_words]


    return new_result
```

```python
def tf_idf(data):
    #normalise
    data = data.apply(lambda x : x/np.max(x),axis=0)

    #idf
    idf_score = {}
    count = data.astype('bool').sum(axis=1)
    N = data.shape[1]

    for word in data.index:
            idf_score[word] = np.log10(N/count[word])

    #tf-idf
    data = data.multiply(idf_score,axis=0)

    return data,idf_score
```

```python
def get_tf_idf_query(query_words,idf_score):
    query = [0 for i in range(data.shape[0])]
    query = pd.DataFrame(query,index = data.index ,columns=['query'])

    for i in query_words:
        if i in query.index:
            query.loc[i] = query_words.count(i)

    query = query.apply(lambda x : x/np.max(x),axis=0)
    query = query.multiply(idf_score,axis=0)

    return query
```

```python
tf_idf_data , idf_score = tf_idf(data)
tf_idf_data
```

	T1.txt	T10.txt	T2.txt	T3.txt	T4.txt	T5.txt	T6.txt	T7.txt	T8.txt	T9.txt
words										
abandon	0.006853	0.0	0.000000	0.000000	0.0	0.0	0.0	0.0	0.015707	0.000000
abbrevi	0.000000	0.0	0.012658	0.000000	0.0	0.0	0.0	0.0	0.000000	0.000000
abdomen	0.000000	0.0	0.012658	0.000000	0.0	0.0	0.0	0.0	0.000000	0.000000
abdomin	0.000000	0.0	0.012658	0.000000	0.0	0.0	0.0	0.0	0.000000	0.000000
aberdeen	0.000000	0.0	0.000000	0.000000	0.0	0.0	0.0	0.0	0.000000	0.010989
...	...	...	...	...	...	...	...	...	...	...
zo	0.000000	0.0	0.000000	0.011765	0.0	0.0	0.0	0.0	0.000000	0.000000
zone	0.000000	0.0	0.025316	0.000000	0.0	0.0	0.0	0.0	0.000000	0.000000
zoolog	0.000000	0.0	0.000000	0.000000	0.0	0.0	0.0	0.0	0.000000	0.054945
zoologist	0.000000	0.0	0.025316	0.000000	0.0	0.0	0.0	0.0	0.000000	0.000000
zoophyt	0.000000	0.0	0.000000	0.024670	0.0	0.0	0.0	0.0	0.000000	0.007681

4431 rows × 10 columns

```python
def get_rank(tf_idf_data , tf_idf_query):
    dist1 = np.sqrt(tf_idf_query.apply(np.square).sum()).values[0]
    query_docs = {}
    query_docs["query"] = {}

    if(dist1==0):
        return None

    for column in tf_idf_data:
        num = 0
        sum_of_squares = 0

        sum_of_squares = tf_idf_data[column].apply(np.square).sum()
        vec_product = tf_idf_data[column].multiply(tf_idf_query.values.reshape(tf_idf_query.shape[0])).sum()

        dist2 = np.sqrt(sum_of_squares)
        cosine_similarity = vec_product / (dist1 * dist2)
        query_docs["query"][column] = cosine_similarity

    return query_docs
```

```python
query  = input('enter query : ')
pquery = preprocess(query)
print(pquery)
```

```
enter query :  intelligence
['intellig']
```

```python
tf_idf_query = get_tf_idf_query(pquery , idf_score)
```

```python
rank = get_rank(tf_idf_data , tf_idf_query)

if(rank):
    rank = pd.DataFrame(rank).sort_values(by = "query" , ascending=False)
else:
    print('no query match found in any document')
```

```python
rank.T
```

	T10.txt	T2.txt	T9.txt	T6.txt	T3.txt	T4.txt	T1.txt	T5.txt	T7.txt	T8.txt
query	0.128587	0.041869	0.028533	0.026315	0.01682	0.006898	0.0	0.0	0.0	0.0

```python
for i in pquery:
    if i in data.index:
        print((data.loc[i]).sort_values(),"\n")
```

```
T1.txt      0
T5.txt      0
T7.txt      0
T8.txt      0
T4.txt      1
T6.txt      2
T3.txt      5
T9.txt      7
T2.txt     17
T10.txt    20
Name: intellig, dtype: int64
```

```python
def doc_similarity(tf_idf_docs):
    res = {}

    for col in tf_idf_docs:
        dist1 = np.sqrt(tf_idf_docs[col].apply(np.square).sum())
        res[col] = {}

        for column in tf_idf_docs:
            vec_product = 0
            sum_of_squares = 0

            sum_of_squares = tf_idf_docs[column].apply(np.square).sum()
            vec_product = tf_idf_docs[column].multiply(tf_idf_docs[col]).sum()

            dist2= np.sqrt(sum_of_squares)

            cosine_similarity = vec_product / (dist1 * dist2)
            res[col][column] = cosine_similarity

    return pd.DataFrame(res)
```

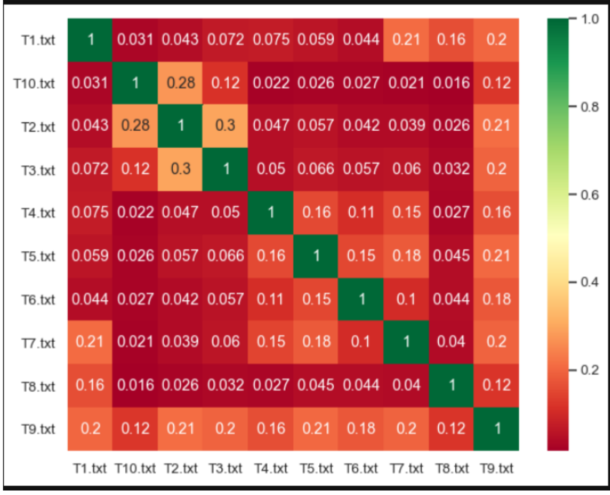
```python
sns.set()

mat = doc_similarity(tf_idf_data)
features = mat.index
```

```python
sns.set()

mat = doc_similarity(tf_idf_data)
features = mat.index

plt.figure(figsize=(8,6),dpi=90)
g = sns.heatmap(mat[features],annot=True,cmap="RdYlGn")
plt.show()
```



Inference/Conclusion:

Vector Space model is a clever method to find and rank the documents based on a query and compare the similarity between two documents. It treats each document as a vector of tf-idf weights and when a cosine product is applied it gives a similarity in the range of 0 to 1.

Exercise 4: Implementation of probabilistic Model.

Rank 10 documents for a given query.

Aim: Implement probabilistic model on a given set of 10 documents and Rank the documents for a given query.

Steps to execute:

Step 1: Preprocess the documents and obtain the inverted index for the files.

Step 2: Input the query from the user.

Step 3: Preprocess the query to obtain appropriate tokens to implement probabilistic model.

Step 4: Send the preprocessed query and the inverted index file into get_conditional_probability function to obtain a probability matrix.

Step5: Arrange the probabilities from the matrix obtained in descending order to get the Documents ranked from most relevant to least relevant.

Code (python 3):

```
import nltk
import re
from nltk.tokenize import RegexpTokenizer
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
import pandas as pd

xfiles = ['T1.txt', 'T2.txt', 'T3.txt', 'T4.txt', 'T5.txt', 'T6.txt',
'T7.txt', 'T8.txt', 'T9.txt', 'T10.txt']


# Tokenizing the text, return token list


def preprocess(sentence):
    sentence = sentence.lower()
    tokenizer = RegexpTokenizer(r'\w+')
    tokens = tokenizer.tokenize(sentence)
    return nltk.word_tokenize(" ".join(tokens))


# Stopwords removal, return list
def stop_words_remove(tokens):
    stop = stopwords.words('english')
    new_tokens = [i for i in tokens if i not in stop]
    return new_tokens

def remove_numbers(words):
    """Replace all interger occurrences in list of tokenized words with
textual representation"""
    new_words = []
    for word in words:
        new_word = re.sub(r'\d+','',word)
        if new_word != '':
            new_words.append(new_word)
    return new_words
```

```python
# Stemming of tokens, return list
def stem_tokens(new_tokens):
    ps = PorterStemmer()
    stemmed = []
    for i in new_tokens:
        stemmed.append(ps.stem(i))
    return stemmed


inv_file = r'Inverted.csv'


def get_relevance(n, nw):
    return (n - nw + 0.5) / (nw + 0.5)


def get_probability_matrix(n, df, toks):
    prob_matrix = {}

    for i in toks:
        nw = df.loc[i, 'Occurences'].count(')')

        prob_matrix[i] = [nw, get_relevance(n, nw)]
    return prob_matrix


def get_query_tokens(query):
    tokens = preprocess(query.lower())
    tokens = remove_numbers(tokens)
    tokens = stop_words_remove(tokens)
    tokens = stem_tokens(tokens)
    return tokens


def get_conditional_probability(qtok, inv_file):
    prob_matrix = {}

    df = pd.read_csv(inv_file)
    toks = list(df['Tokens'])

    df.set_index('Tokens', inplace=True)

    word_matrix = get_probability_matrix(len(xfiles), df, toks)

    # print(word_matrix)
    for i in xfiles:
        flag = False
        val = 1
        prob_matrix[i] = 0

        for j in qtok:
            if j in toks:
                if i in df.loc[j, 'Occurences']:
                    flag = True
                    val *= word_matrix[j][1]
        prob_matrix[i] = val if flag else 0

    return prob_matrix
```

```
print("Program 4: \n\tProbablistic Model Implementation")

# print("Query : ")

# kldsjflksajdk = get_query_tokens(input())
print("Enter your query here :", end=" ")
out1=get_query_tokens(input())
print(out1)
rel_docs = get_conditional_probability(out1, inv_file)

rel_docs = {k: "{0:.5f}".format(v) for k, v in sorted(rel_docs.items(),
key=lambda item: item[1], reverse=True)}

# print(vect)
print("The documents in the order of relevance to the query are as follows:
")
print(pd.DataFrame(rel_docs.items(), columns=['File', 'Relevance']))
```

input/output:

Program 4:

Probabilistic Model Implementation

Enter your query here: Sunshine ten

The documents in the order of relevance to the query are as follows:

	File	Relevance
0	T7.txt	3.40000
1	T6.txt	1.00000
2	T1.txt	0.29412
3	T2.txt	0.29412
4	T3.txt	0.29412
5	T4.txt	0.29412
6	T5.txt	0.29412
7	T9.txt	0.29412
8	T10.txt	0.29412
9	T8.txt	0.00000

Process finished with exit code 0

Inference/Conclusion:

Probabilistic model is used in a corpus where the set of relevant documents for a query is predetermined and appropriate formula is applied to find the most relevant document for a given query.

Exercise 5: Implementation of various evaluation measures.

a) Calculate recall and precision values for all relevant documents and draw precision vs recall curve. Also calculate R-precision.
b) Compare performance of two IR algorithms for the same query q.
c) Calculate harmonic mean and E-measure (All three cases b=1, b>1, b<1)

Aim: To build a program that executes above tasks sequentially.

Steps to execute (a):

Step 1: Assume a set of relevant documents and a set of retrieved documents for a query q.

Step 2: Calculate the recall and precision value for each document in the retrieved set.

Step 3: Plot a curve with recall in x-axis and precision in y-axis using calculated values.

Step 4: Calculate the R-precision value which is equal to total documents in the retrieved set that belong to the relevant set divided by the total number of documents in the relevant set.

Steps to execute (b):

Step 1: Assume 5 queries were made with each query having it's own set of relevant documents and the list of documents retrieved by the algorithm A and algorithm B.

Step 2: Calculate the R-precision value for each algorithm for each query.

Step 3: Subtract the R-precision value of algorithm B from algorithm A and store the value in an array X.

Step 4: Plot the array X into a histogram with x-axis being the query number and y-axis being R-precision A/B.

Step 5: If the sum of elements in array X is positive print algorithm A is better else print algorithm B is better.

Steps to execute (c):

Step 1: Assume a query for which relevant documents set and a list of Retrieved documents for an algorithm is available.

Step 2: Calculate the recall and precision for each document in the relevant set found in the retrieved list.

Step 3: Calculate the harmonic mean, E-precision for b value equal to 1 , 0.2 and 2 respectively and save the output in the form of a table.

Code (python 3):

```python
import matplotlib.pyplot as plt
# matplotlib.use("gtk")
import pandas as pd
```

```python
"""
5.a : Recall Precision graph for the following relevant documents and
documents retrieved

Rq= {d3,d5, d9,d25,d39,d44,d56,d71,d89,d94,d105,d119,d124,d136, d144}
Aq ={d123,d84,d56,d6,d8,d9,d511,d129,d187,d25,d38,d48,d250,d113 ,
d44,d99,d95,d214,d136,d39,d128,d71,d14,d5}

"""
# Relevant documents set
# rq = [3,5,9,25,39,44,56,71,89,123]
rq = [3, 5, 9, 25, 39, 44, 56, 71, 89, 94, 105, 119, 124, 136, 144]

# Answer set

aq = [123, 84, 56, 6, 8, 9, 511, 129, 187, 25, 38, 48, 250, 113, 44, 99,
95, 214, 136, 39, 128, 71, 14, 5]
# aq = [123,84,56,6,8,9,511,129,187,25,38,48,250,113,3]

# Recall list initialization
recall = []

# Precision list initialization
precision = []

rlen = len(rq)
alen = len(aq)

recallCount = 0

# to keep track of the retrieved documents
retrievedDocumentCount = 0
# pc = 0

rr = 0
pr = 0

for i in aq:
    retrievedDocumentCount += 1
    if i in rq:
        recallCount += 1
        rr = recallCount / rlen

    pr = recallCount / retrievedDocumentCount

    # print(rr,pp,recall_count,precision_count)
    recall.append(rr * 100)
    precision.append(pr * 100)

print("\n\nThe R-precision value is :", rr)
dashline = "\n\n---------------------------------------------------"
print(dashline)

plt.plot(recall, precision, color='orange')
plt.title('Recall Precision curve')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.xlim(0, 115)
plt.ylim(0, 115)
plt.show()
```

```python
# 5.b: r-precision comparison for to different algorithms for 5 different
queries

algo_a = []
algo_b = []


def r_precision(a, b, r):
    c1 = 0
    c2 = 0
    for i in a:
        if i in r:
            c1 += 1
    for i in b:
        if i in r:
            c2 += 1

    algo_a.append(c1 / len(a))
    algo_b.append(c2 / len(b))


# list of the 5 queries, relevant documents, documents retrieved by
algorithm a and b respectively
rel1 = [3, 5, 9, 25, 39, 44, 56, 71, 89, 123]
algoA1 = [123, 84, 56, 6, 8, 9, 511, 129, 187, 25, 38, 48, 250, 113, 3]
algoB1 = [12, 39, 13, 123, 8, 9, 19, 89, 87, 25, 70, 71, 29, 44, 3]

rel2 = [3, 20, 5, 68, 51, 21, 27, 64, 6, 93]
algoA2 = [3, 13, 5, 68, 51, 67, 32, 64, 45, 6, 94, 95, 93]
algoB2 = [20, 30, 7, 78, 21, 27, 14, 15, 16, 6, 54, 4, 6]

rel3 = [38, 65, 73, 88, 93, 74, 36, 4, 28, 30]
algoA3 = [66, 88, 45, 43, 23, 12, 188, 200, 34, 4]
algoB3 = [56, 73, 65, 3, 2, 99, 146, 93, 76, 74, 4]

rel4 = [85, 95, 25, 64, 52, 12, 43, 18, 6, 66]
algoA4 = [52, 62, 64, 77, 12, 45, 18, 43, 6]
algoB4 = [95, 85, 25, 77, 123, 3213, 78, 18, 6]

rel5 = [9, 76, 78, 31, 7, 47, 30, 8, 43, 51]
algoA5 = [76, 75, 31, 7, 30, 44, 56, 50, 94, 223]
algoB5 = [78, 9, 48, 47, 4, 31, 43, 56, 55, 99, 123, 222]


r_precision(algoA1, algoB1, rel1)
r_precision(algoA2, algoB2, rel2)
r_precision(algoA3, algoB3, rel3)
r_precision(algoA4, algoB4, rel4)
r_precision(algoA5, algoB5, rel5)

print('\n\n')
print('algorithm a is better' if sum(algo_a) > sum(algo_b) else 'algorithms
b is better')
print(dashline)

# algo_a = [0.3,0.6,0.3,0.5,1,0.78,0.24]
# algo_b = [0.1,0.3,0.6,0.4,0,0.7,0.01]

x = map(lambda a, b: a - b, algo_a, algo_b)
x = list(x)
```

```python
fig = plt.figure(figsize=(10, 10))
langs = [i for i in range(1, len(x) + 1)]

plt.xlabel("Query Number")
plt.ylabel("R Precision A/B")
plt.title("Precision Histogram")

plt.bar(langs, list(x), color='purple', width=0.5)

plt.show()

# 5.c : Harmonic Mean and E-Measure

Rq = ['d3', 'd5', 'd9', 'd25', 'd39', 'd44', 'd56', 'd71', 'd89', 'd123']
A1 = ['d123', 'd84', 'd56', 'd6', 'd8', 'd9', 'd511', 'd129', 'd187',
'd25', 'd38', 'd48', 'd250', 'd113', 'd3']


def calhme(Rq, Aq):
    rel_doc_count = 0
    rn = len(Rq)
    recall, precision, harmonic_mean, em1, em2, em0 = {}, {}, {}, {}, {},
{}

    for i in range(len(Aq)):
        if Aq[i] in Rq:
            rel_doc_count += 1
            recall[Aq[i]] = (round(rel_doc_count / rn, 2))
            precision[Aq[i]] = (round(rel_doc_count / (i + 1), 2))
            harmonic_mean[Aq[i]] = round(2 / ((1 / recall[Aq[i]]) + (1 /
precision[Aq[i]])), 2)
            em0[Aq[i]] = round(1 - harmonic_mean[Aq[i]], 2)
            # Set b=2 for E-Measure
            b = 2
            em1[Aq[i]] = round(1 - ((1 + (b ** 2)) / (((b ** 2) /
recall[Aq[i]]) + (1 / precision[Aq[i]]))), 2)

            b = 0.2
            em2[Aq[i]] = round(1 - ((1 + (b ** 2)) / (((b ** 2) /
recall[Aq[i]]) + (1 / precision[Aq[i]]))), 2)

        else:
            pass


    return pd.DataFrame({'Recall': pd.Series(recall), 'Precision':
pd.Series(precision), 'Harmonic mean': pd.Series(harmonic_mean),
                         'E-Measure (b=1)': pd.Series(em0), 'E-Measure
(b>1)': pd.Series(em1),
                         'E-Measure (b<1)': pd.Series(em2)})


# Harmonic Mean and E-Measure
resultDataframe = calhme(Rq, A1)
print()
print()
print(resultDataframe)
# resultDataframe.to_csv('5(c).csv')
```

Input/output:

a) Console output:

The R-precision value is : 0.5333333333333333

----

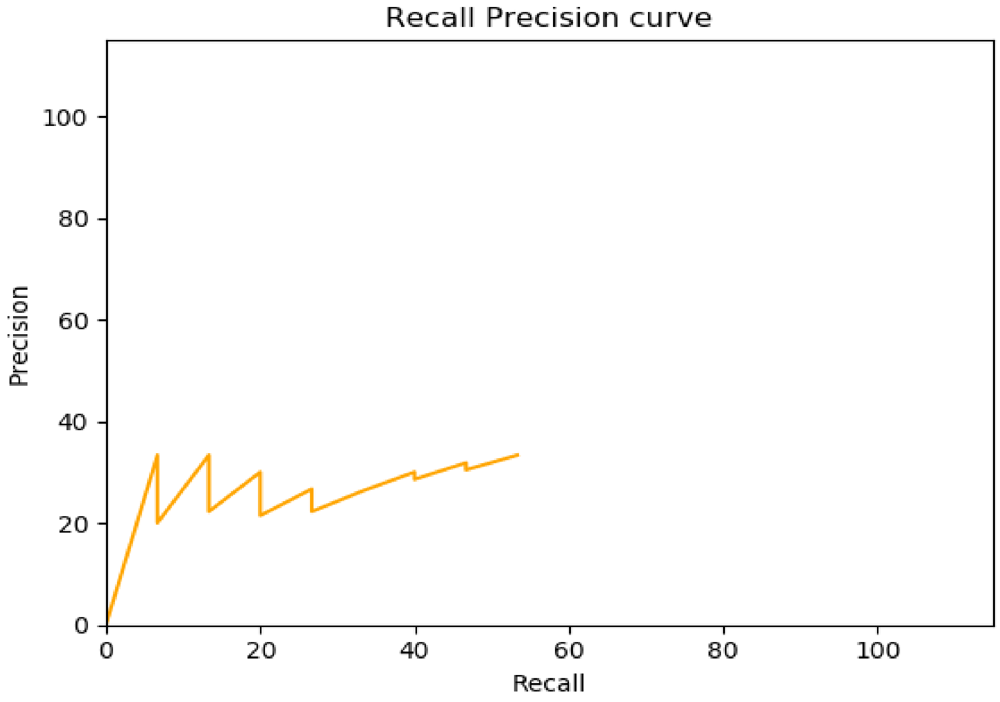
algorithms b is better

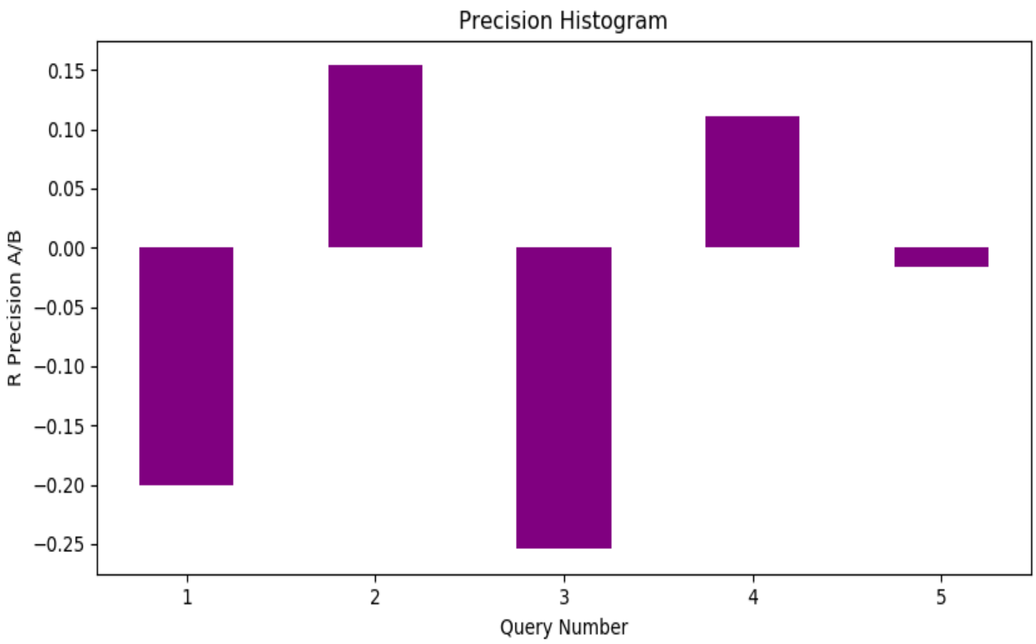
	Recall	Precision	...	E-Measure (b>1)	E-Measure (b<1)
d123	0.1	1.00	...	0.88	0.26
d56	0.2	0.67	...	0.77	0.39
d9	0.3	0.50	...	0.67	0.51
d25	0.4	0.40	...	0.60	0.60
d3	0.5	0.33	...	0.55	0.67

[5 rows x 6 columns]

Process finished with exit code 0

Graph output:





Saved table:

	Recall	Precision	Harmonic mean	E-Measure (b=1)	E-Measure (b>1)	E-Measure (b<1)
d123	0.1	1	0.18	0.82	0.88	0.26
d56	0.2	0.67	0.31	0.69	0.77	0.39
d9	0.3	0.5	0.37	0.63	0.67	0.51
d25	0.4	0.4	0.4	0.6	0.6	0.6
d3	0.5	0.33	0.4	0.6	0.55	0.67

Inference/Conclusion:

Precision and Recall are one of the measures to determine if the algorithm used to obtain relevant documents is good or not. R-precision can be used to compare the algorithms, Harmonic mean and E-Measures are more refined measures to determine how good an algorithm is.