Report

Assignment - 2

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Question 1 - [40 Points] Scoring and Term-Weighting

Assumptions:

There are no duplicate files present in the dataset.
The document indexing starts from 0.

PreProcessing Steps:

Normalization : All the text is converted into lower case format.

Tokenization : The text is split into smaller units using nltk library.

StopWord Removal : All the stop words from the English language list from the nltk library are removed from the list.

Punctuation removal: All the special symbols are removed including the numbers 0-9.

Whitespace removal : All the white spaces are removed if any are present.

Lemmatization : It stems from the word but makes sure that the word does not lose its meaning.

Preprocessing returns a list of all the clean words.

PART A : Jaccard Coefficient [20 points]

Methodology:

- For every document, create a token list that contains the preprocessed terms in that particular document. Create a dataframe with the document name, preprocessed terms and the length as columns.
- Jaccard coefficient is calculated by the following formulae Jaccard Coefficient = Intersection of (doc,query) / Union of (doc,query). Therefore preprocess the query and get the token list for the query.
- Find the ***intersection*** and the ***union*** of the query with each document term list.

- Apply the formula for jaccard and store it.
- Sort from largest to smallest according to the jaccard values and return the first 5.

```python
def relevance(query):
    import joblib
    # print("Jaccard_coeff")
    query_token_list = preProcess(query)

    doc_df_preprocessed = joblib.load('doc_df_preprocessed.joblib')
                                (variable) doc_df_preprocessed: Any

    doc_df_preprocessed['union'] = doc_df_preprocessed.apply(lambda row:list(set(row['doc_token']) | set(query_token_list)),axis=1 )
    doc_df_preprocessed['intersection'] = doc_df_preprocessed.apply(lambda row:list(set(row['doc_token']) & set(query_token_list)),axis=1 )
    doc_df_preprocessed['jaccard_coeff'] = doc_df_preprocessed.apply(lambda row:len(row['intersection'])/len(row['union']),axis=1 )
    # doc_df_preprocessed.set_index('doc_name')
    return doc_df_preprocessed


""" Find the relevance with the query using the dataframe"""
doc_df_preprocessed = relevance('jokes rules attends received')

""" Top 5 """
top5 = doc_df_preprocessed.nlargest(5, ['jaccard_coeff'])
print('top5 relevant docs--->\n',top5[['jaccard_coeff']])
```

```
top5 relevant docs--->
               jaccard_coeff
doc_name
languag.jok         0.015873
temphell.jok        0.015152
calif.hum           0.014706
gaiahuma            0.012821
hedgehog.txt        0.012579
```

PART B : TF-IDF Matrix [20 points]

Methodology:

- Find the unique words in the dataset and store it as corpus words.
- Create a dataframe with corpus words as index and document name as the columns.
- Iterate over each (word,document) pair in the dataframe and count the frequency of that word in that particular document with the help of document token list.
- For different weighting scheme, fill the matrix differently\
    - Binary: if the word is in the document's token list fill (word,document) =1 else 0.
    - Raw count: fill (word,document) with the count of words in the document's token list.
    - Term Frequency: fill (word,document) with count(word in the document)/ total words in document.
    - Log normalization : fill (word,document) with log(1+frequency of term in the document)
    - Double normalization : fill (word,document) with 0.5+0.5*(term frequency in document d / max(term frequency in document d)
- Find the IDF values by dividing the total number of documents by the number of documents containing a term t.

- Multiply the idf & tf values and then sort the documents according to the values. Display top 5.

```
scores,results =TF_IDF('polio genovese chest')
scores
```

	Top1	Top2	Top3	Top4	Top5
Binary	1.000000	1.000000	1.000000	1.000000	1.000000
Raw count	6.000000	6.000000	5.000000	4.000000	4.000000
Term frequency	0.006969	0.004926	0.004630	0.004053	0.003911
Log normalization	1.945910	1.945910	1.791759	1.609438	1.609438
Double normalization	0.515544	0.510363	0.507576	0.505848	0.505181

```
results
```

	Top1	Top2	Top3	Top4	Top5
Binary	gameshow.txt	facedeth.txt	insults1.txt	cucumber.jok	barney.txt
Raw count	practica.txt	quest.hum	facedeth.txt	luzerzo2.hum	prac3.jok
Term frequency	ghostfun.hum	age.txt	back1.txt	luzerzo2.hum	t_zone.jok
Log normalization	practica.txt	quest.hum	facedeth.txt	luzerzo2.hum	prac3.jok
Double normalization	quest.hum	prac3.jok	t_zone.jok	practica.txt	back1.txt

Question 2 - [25 points] Ranked-Information Retrieval and Evaluation

Methodology:

- Filter the dataset such that it contains only the rows for qid:4
- Make a dataframe using the filtered dataset with column relevance score.
- Sort the dataframe by the relevance score in the descending order and save it.
- Count the frequency of relevance 0,1,2 and 3.
- To find the total number of files, multiply the fact(count_0)*fact(count_1)*fact(count_2)*fact(count_3).
- To find the DCG, iterate over the dataframe and apply the formula

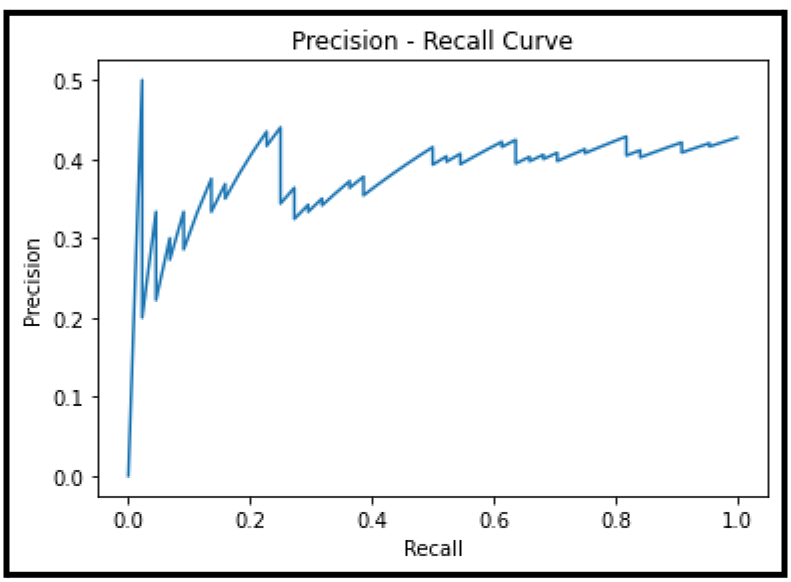
$$\mathrm{DCG_p} = \sum_{i=1}^{p} \frac{rel_i}{\log_2(i+1)} = rel_1 + \sum_{i=2}^{p} \frac{rel_i}{\log_2(i+1)}$$

  as we move down the rows.
- Sort the dataframe in descending order of the relevance score and apply the same formula to get IDCG.
- Get nDCG = DCG/IDCG

```
"""MaxDCG"""
maxDCG = DCG(final_data,len(final_data))

"""nDCG for 50 values"""
trueDCG50 = DCG(final_data,51)
idealDCG50 = DCG(ideal_data,51)

"""nDCG for whole dataset"""
trueDCG = DCG(final_data,len(final_data))
idealDCG = DCG(ideal_data,len(ideal_data))

nDCG50 = trueDCG50/idealDCG50
nDCG = trueDCG/idealDCG

print("Max DCG is: {}".format(maxDCG))
print("nDCG at 50: {}".format(nDCG50))
print("nDCG whole Dataset: {}".format(nDCG))
```

```
Max DCG is: 12.550247459532576
nDCG at 50: 0.41082175342157357
nDCG whole Dataset: 0.6976332021320715
```

- For the precision and recall curve, calculate the precision as the number of relevant documents/ total number of documents retrieved as we iterate through the dataframe.
- Recall is calculated by the number of relevant retrieved documents divided by the number of total relevant documents.
- Append both the values in their respective lists while iterating.
- Plot the curve.



Question 3 - [35 points] Naive Bayes Classifier

Dataset: 20_newsgroups.zip

Dataset is downloaded and loaded into the notebook and documents belonging only [comp.graphics, sci.med, talk.politics.misc, rec.sport.hockey, sci.space] are selected for text classifier.

PreProcessing Steps:

- Normalization : All the text is converted into lower case format.
- Tokenization : The text is split into smaller units using nltk library.
- StopWord Removal : All the stop words from the English language list from the nltk library are removed from the list.
- Punctuation removal: All the special symbols are removed including the numbers 0-9.
- Whitespace removal : All the white spaces are removed if any are present.
- Lemmatization : It stems from the word but makes sure that the word does not lose its meaning.

Preprocessing returns a list of all the clean words for each document.

Test and train DataSplit:

Split is done using train_test_split of sklearn.model_selection

- The data is split into 80:20 train -test ratio
- The data is split into 70:30 train -test ratio
- The data is split into 50:50 train -test ratio

TF-ICF calculation:

TF-ICF score for a given term belonging to a class can be calculated as follows:

- Term Frequency (TF): Number of occurrences of a term in all documents of a particular class
- Class Frequency (CF): Number of classes in which that term occurs
- Inverse-Class Frequency (ICF): log(N / CF), where N represents the number of classes

Based on the Tf-icf value , words with top k value are selected for further analysis.

Here , K= 10

Top k Features from each 5 classes are :

{'capolitics', 'hallam', 'nsmca', 'simtel', 'shuttle', 'sciastro', 'auroraalaskaedu', 'abortion', 'sinus', 'hammerl', 'scorer', 'fbi', 'health', 'geb', 'optilinkcom', 'quicktime', 'alchemychemutorontoca', 'vertex', 'photoshop', 'playoff', 'pixel', 'altsciplanetary', 'orbit', 'recsporthockey', 'allergy', 'altpoliticsclinton', 'billboard', 'kinsey', 'altsex', 'talkreligionmisc', 'baalke', 'kilometer', 'pov', 'ramseycslaurentianca', 'lyme', 'sky', 'sabre', 'chi', 'altbinariespicturesd', 'gilmour', 'cramer', 'altconspiracy', 'kelvinjplnasagov', 'antibiotic', 'astronaut', 'venus', 'lunar', 'zootorontoedu', 'bitmap', 'batf', 'tiff', 'talkabortion', 'ahl', 'candida', 'talkpoliticsmisc', 'pittuucp', 'noring', 'compmultimedia', 'texture', 'misclegal', 'scispaceshuttle', 'oiler', 'compgraphics', 'yeast', 'hockey', 'bruin', 'lilley', 'scoring', 'socmen', 'jpeg', 'scimed', 'altactivism', 'msg', 'hiv', 'phill', 'compgraphicsanimation', 'stl', 'rind', 'topazucscedu', 'siggraph', 'maynard', 'spacecraft', 'pluto', 'altfanrushlimbaugh', 'infection', 'optilink', 'xv', 'dcx', 'gif', 'nfotis', 'higgins', 'raster', 'mccall', 'image', 'scienergy', 'canuck', 'vga', 'vitamin', 'det', 'goalie', 'nyi', 'comet', 'stephanopoulos', 'espn', 'recfoodcooking', 'hicnet', 'altsciphysicsnewtheories', 'coach', 'scianthropology', 'nhl', 'clayton', 'jfif', 'polygon', 'prb', 'pit', 'dyer', 'dscomsadesyde', 'patient', 'altpoliticslibertarian', 'cspittedu', 'scispace', 'altgraphicspixutils', 'migraine', 'puck'}

Naive Bayes algorithm :

Multinomial naive bayes are implemented from scratch.
The model is trained on train data and accuracy is found on the different test datas.

- **80:20 split**

  Accuracy 0.995

  Classification matrix

	precision	**recall**	**f1-score**	**support**
0	0.98	0.99	0.99	196
1	1.00	1.00	1.00	205
2	1.00	0.99	1.00	206
3	0.99	0.99	0.99	199
4	1.00	1.00	1.00	194
accuracy			0.99	1000
macro avg	0.99	1.00	0.99	1000
weighted avg	1.00	0.99	1.00	1000

Confusion Matrix

```
[[195   0   0   1   0]
 [  0 205   0   0   0]
 [  1   0 204   1   0]
 [  2   0   0 197   0]
 [  0   0   0   0 194]]
```

- **70:30 split**

Accuracy 0.994

Classification matrix

	precision	recall	f1-score	support
0	0.99	0.99	0.99	297
1	1.00	1.00	1.00	284
2	1.00	0.99	0.99	324
3	0.99	0.99	0.99	296
4	1.00	1.00	1.00	299
accuracy			0.99	1500
macro avg	0.99	0.99	0.99	1500
weighted avg	0.99	0.99	0.99	1500

Confusion Matrix

```
[[294   0   1   2   0]
 [  0 284   0   0   0]
 [  2   0 321   1   0]
 [  2   0   0 294   0]
 [  0   1   0   0 298]]
```

- **50:50 split**

Accuracy 0.9948

Classification matrix

precision recall f1-score support

0	0.99	0.99	0.99	487
1	1.00	1.00	1.00	511
2	0.99	1.00	0.99	507
3	0.99	0.99	0.99	495
4	1.00	1.00	1.00	500
accuracy			0.99	2500
macro avg	0.99	0.99	0.99	2500
weighted avg	0.99	0.99	0.99	2500

Confusion Matrix

```
[[481   0   5   1   0]
 [  0 511   0   0   0]
 [  1   0 505   1   0]
 [  3   0   0 492   0]
 [  0   1   0   1 498]]
```

Analysis:
There is no significant change in the accuracy of the three splits.
Also from the confusion matrix , it can be seen that the mostly all values are on diagonal, that represents that the classification is 99% correct for all the three cases.