# Report

# **Approach**

I have extended my own pre-processor from the previous assignment where I used BeautifulSoup to parse the HTML documents and removed the punctuation by using RegexpTokenizer method from NLTK package. I used python because of the availability of various package which helps me manipulate my Data frames with an ease.

The stop words and the words that appear only once in the entire corpus were removed from the file before calculating TF-IDF values.

# **TERM WEIGHTHING CALCULATION:**

After preprocessing, each output file contained the tokens and the word frequency associated with each token in a csv format.

#### TF:

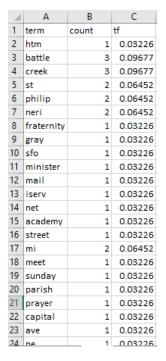
I have calculated term frequency based on the traditional formula which states:

TF (w, d) = Number of occurrences of w in document d / Number of words in the document d Here,

- $w \rightarrow$  The tokens(terms)
- d → document(file) which has set of tokens

For ease of processing, I have stored the output of each file after removal of stop words in csv format.

Using the csv format, I can calculate TF of each word based on the count column and the sum of count column (i.e.: length of document) by performing operations on Data Frames using pandas.



 $df['tf'] = df['count']. div(df['count']. sum ()) \rightarrow (In the code)$ 

#### IDF:

Inverse document frequency is calculated based on:

#### $IDF(w) = log_e$ ((Total number of documents) / (Number of documents containing the word w))

For calculating IDF, I have created a dictionary which stores key as the word and value as the number of documents containing the word. Iterating over the dictionary, IDF is calculated based on the above formula and stored in the below dictionary. I have used Counter () to store dictionary keys and values.

# idf[term]= math.log(float(N) / term\_freq) → (In the code)

Where N  $\rightarrow$  Total number of documents (503)

Term freq → the number of documents containing a word

# TF-IDF:

Overall formula is:

TF-IDF = TF \* IDF

I have stored the results of TF-IDF in another dictionary and then wrote the term weights of each word in an output file for each input file.

# **Usage Guidelines:**

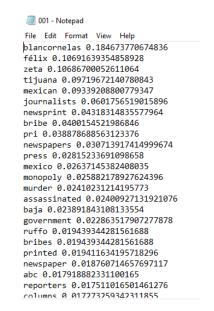
Input: python <file\_name> <input\_dir> <output\_dir>

2020-03-11 19:38:16.981583 input directory is: C:\Users\Vrindavan\Downloads\Krithika\_Verma\_HW1\files
putput directory is: C:\Users\Vrindavan\Downloads\Krithika\_Verma\_HW1\tokenized

#### **Output:**

- 1) Directory containing output files of the tokenized words for each input file. (\*\tokenized)
- 2) A file of all tokens and frequencies sorted by token (alpha.txt)
- 3) A file all tokens and frequencies sorted by frequency (freq.txt)
- 4) A directory containing tokens after removal of stop words and TF values of each word (\*\stop)
- 5) A directory containing output files of tokens and term weights (\*\TF\_IDF)

# Input File (001.html), Output File (001.txt)



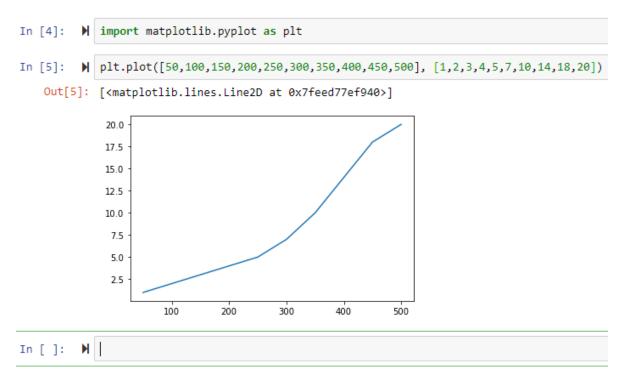




002.txt

#### **Runtime Analysis:**

Number of Input Documents	Time Takes (in seconds)
50	1
100	2
150	3
200	4
250	5
300	7
350	10
400	14
450	18
50	20



#### **Effect of stop words:**

In previous assignment, the number of tokens present after tokenization in file 1 (001.txt) was 1308 and after removal of stop words, the tokens have reduced to 401

Similarly, in file 2 (002.txt) the number of tokens were 1809 and the current generated file has 647 tokens.

Same effect was seen in all other files. Hence the effect of removing stop words was clear.

Attaching the following folders and files for your reference:

- 1) Tokenized folder containing tokens
- 2) Alpha file containing tokens and frequencies sorted alphabetically
- 3) Freq file containing tokens and frequencies sorted by frequency
- 4) Tokens without stop words folder (includes TF values as well)
- 5) TF\_IDF (term weights) folder containing the term and its weight output file for each input file