# **Project Report**

# Natural Language Processing (CSE 3201)

# By Team: console.log

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GitHub Link: <a href="https://github.com/Vatsal32/NLP\_Project\_Round\_1">https://github.com/Vatsal32/NLP\_Project\_Round\_1</a>
GitHub Link: <a href="https://github.com/Vatsal32/NLP\_Project\_Round\_2">https://github.com/Vatsal32/NLP\_Project\_Round\_2</a>

# **Data Description**

The book we have used is:

Software Engineering
Eight Edition By
Ian Sommerville

**Number Of pages**: 865

**Number of words**: 13,97,281

# Common processing for Part 1 and Part 2

Processing and plotting are done using libraries of Python programming language. We have used:

- NLTK library that is Natural Language Toolkit for text processing.
- Matplotlib, pyplot and wordcloud for data visualization.
- Spacy for NER Labelling.

### **Data Preparation**

#### **Text Pre-Processing Steps**

Text Pre-processing is the first step in the pipeline of Natural Language Processing (NLP). It brings the text into a form that is predictable and analysable for a machine learning algorithm.

The Pre-processing tasks performed in our code are:

- 1) Manually removed Contents, Glossary, Index, Authors, and References.
- 2) Removing the footer
  - a) Footer has 2 lines:
    - i) It denotes the end of page using 4 dots as '•• ••', we find it using regex and delete it

ii) 2nd has a date '4/4/06' mentioned in it, so we find it using regex and delete that line

$$T1 = re.sub ('.* 4/4/06 .*\n', '', T1)$$

#### 3) Removing the header

- a) Header is of three types
  - i) Left page header has the form '<Page No.> Chapter <Chapter No.> ■
     <Chapter Name>', we find and delete it using regex as,

$$T1 = re.sub('[0-9]+[]+Chapter.*\n', '', T1)$$

ii) Right page header has the form '<section No.> ■ <Section Name> <Page No.>', we use regex to remove it

T1 = re.sub('
$$[0-9]$$
+. $[0-9]$ +  $\blacksquare$ .\* $[0-9]$ + $n'$ , '', T1)

iii) 'Key Points' and 'Exercise' sections of the chapters on the right page have the form 'Chapter <Chapter No.> ■ <Key Points>|<Exercises> <Page No.>', we again use regex to remove it

T1 = re.sub('Chapter 
$$[0-9]+ \blacksquare .*[0-9]+\n', '', T1$$
)

#### 4) Removing Punctuations and Normalization:

- a) For punctuations and other irrelevant symbols, we create a string that contains all such elements. Then, we filter the original text by removing any elements that match anything in our created string.
- b) All the heading of sections and sub-sections in a chapter are of no use to us as they do not follow grammatical structure. They have the form '<section No.> <Section Name>' removed using regex as follows

$$T1 = re.sub(r'\d+(\.\d+)*\.\d+.*\n', '', T1)$$

c) Chapter titles can be removed as well. They are of the form

'<Chapter No.>\n<Chapter Name>\n', using regex as follows

$$T1 = re.sub('[0-9]+\n[a-zA-Z]+\n', '', T1)$$

d) When a word crosses the limit of characters possible in one line the rest is written on the next line denoted by a hyphen on the current line, in the form 'soft-\nware' we join these words by removing '-\n' using regex

$$T1 = re.sub(r'-\n\s*', '', T1)$$

e) For tables we first divide whole text according to the lines, then we divide each line into number of columns based on sentences divided by a group of spaces using regex as

f) Then for the lines with more than two columns are ignored as they make up a row in the table. Two columns because the book indentation makes start of each line as a group of spaces.

objectives the objectives of this chapter are to introduce software engineering and to provide a framework for understanding the rest of the book when you have read this chapter you will understand what software engineering is and why it is important know the answers to key questions that provide an introduction to software engineering understand some entire that is not to the provide an introduction to software engineering in the provided of the provided and t

Output for book: Final Text after Pre-Processing

#### **Tokenization**

For tokenizing the text, we use the word\_tokenize function of nltk library by passing our finalText into it. Tokenizers divide strings into lists of substrings.

```
[ ] #Tokenizing the text
     tokens = nltk.word_tokenize(finalText)
     ['objectives',
       'the',
      'objectives',
      'of',
'this',
       'chapter',
      'are',
'to',
      'introduce',
      'software',
       'engineering',
      'and',
      'provide',
'a',
       'framework',
       'for',
       'understanding',
       'the',
'rest',
       'of',
'the',
'book',
       'when',
      'you',
'have',
'read',
'this',
       'chapter',
      'you<sup>'</sup>,
'will',
       'understand',
       'what',
       'software',
       'engineering',
```

List of tokens

# Project Round 1

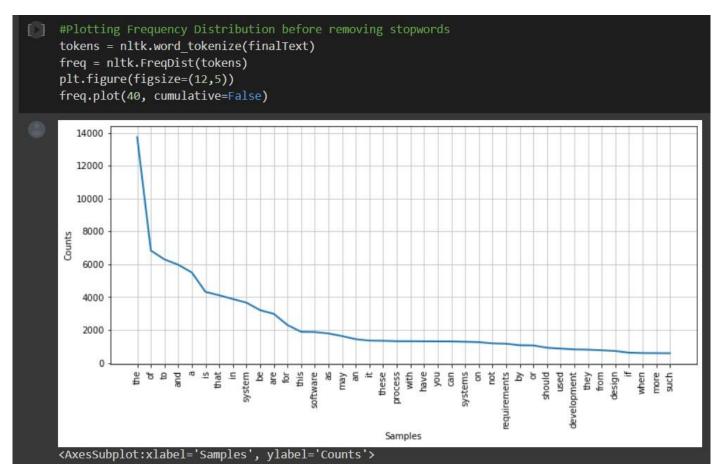
### **Problem Statement Round 1**

- 1. Download any Computer Science book (in PDF Format) that you had used in one of the course that you have studied till now at LNMIIT but that contains at least 200 pages in it.
- 2. Convert the book from PDF to text format (you can use online web-based tools for this). Using Python do the following:
- 3. Import the text, lets call it as T1 (book that you have downloaded)
- 4. Perform simple text pre-processing steps you may have to do the removal of running section / chapter names / remove the pictures / tables and so on. Explore the txt file you will understand.
- 5. Tokenise the text T1
- 6. Analyze the frequency distribution of tokens in T1.
- 7. Create a Word Cloud of T1 using the token that you have got
- 8. Remove the stop words from T1 and then again create a word cloud what's the difference it gives when you compare with word cloud got before the removal of stop words?
- 9. Evaluate the relationship between the word length and frequency for T1 what's your result?
- 10.Do PoS Tagging for T1 using anyone of the four tag sets studied in the class and get the distribution of various tags (preferably use Treebank tagset)

#### **Data Visualization**

#### **Before Removing Stop Words**

• The resulting list of tokens is analyzed by plotting its frequency distribution. We get the distribution by using the FreqDist function in nltk library.



Frequency Distribution of Tokens in finalText beforer removing stop words

- Without removing Stop Words, we create a Word Cloud using the wordcloud library and passing our text into its generate method. The word cloud generated is then plotted using matplotlib.
- In a word cloud, size of each word is proportional to its frequency or importance in the text.

```
#Creating a wordcloud before removing StopWords
wordcloud = Wordcloud(stopwords={}, background_color='black').generate(finalText)

#Plotting the wordcloud
plt.figure(figsize = (10,10), facecolor = 'black')
plt.mshow(wordcloud)
plt.axis("off")
plt.tight_layout(pad = 3)
plt.show()

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plt.mshow(w
```

Output for Word Cloud (with Stopwords)

#### Inference

- "The, of, to, and, a, is, that, in" are the largest words seen in the word cloud.
- And as inferred from the frequency distribution as well these stop words occupy an unnecessary high frequency count which is meaningless in the processing of the text.
- These hide the essence of the corpus.

#### **Removing Stop Words**

Stopwords refers to the extra common words used in natural language such as articles (the, an, a). In NLP and text mining applications, stop words are used to eliminate unimportant words, allowing applications to focus on the important words instead. So, we need to eliminate the Stop words.

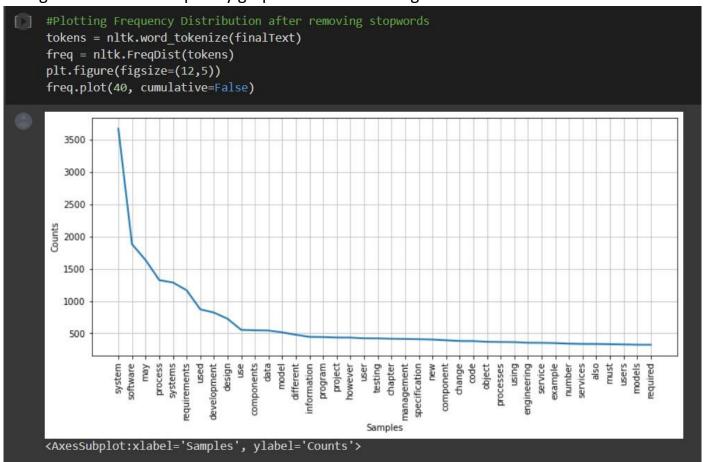
a. We include STOPWORDS and utilize it to create a set of english stop words.

We then filter our tokens by eliminating all the words that are common in the b. stopword set and our tokens.

```
stop_words = stopwords.words('english'))
filtered_tokens = [w for w in tokens if w not in stop_words]
tokens = filtered_tokens
finalText = " "
objectives objectives chapter introduce software engineering provide framework understanding rest book road chapter understand software engineering important know answers key questions provide introduction software engineering understand ethical professional issues important to fivers engineer, contents virtually countries depend complex computer sold the professional issues important to fivers engineer, contents virtually countries depend complex computer sold financial system therefore producing mixtualing software costseffectively essential functioning national international economics of them on quincering engineering discipline whose focus cost effective development highpulity software expresses software abstract intengible constrained enterials generally professional initiations proteoners believe to be a software engineering physical lams manufacturing processes was simplifies software engineering physical lams manufacturing processes was simplified to the proposed to the contract of the proposed to the complex proposed to software engineering first proposed took conference held discuss called software abstract is software engineering first proposed took counter applications feasible proposition resulting software resulted directly introduction new computer handware based integrated circuits power made hitherto unrealisable computer applications feasible proposition resulting software cost much predicted unreliable difficult maintain performed poorly software engineering widely used however publish software costs rising rapidly new technique large cost much predicted unreliable difficult animal performed poorly software engineering widely used however publish software engineering exhibition systems complexty approaches software increased complexty software specification systems complexty increased consumers and produce software unreliable delivered late budget think made tremendous progress since 1968 devel opment software engineering markedly improved software much better understanding activities involve
```

Final Text after removing Stopwords

We again create the frequency graphs of the remaining words.



Frequency Distribution of Tokens in finalText after removing stop words

 After cleaning the data of stopwords, we again create the word cloud using the wordcloud library

```
#Generating wordcloud after removing stopwords
wordcloud = Wordcloud(stopwords={}, background_color='black').generate(finalText)

plt.figure(figsize = (10,10), facecolor = 'black')
plt.imshow(wordcloud)
plt.axis("off")
plt.tight_layout(pad = 3)
plt.show()

#Generating wordcloud(stopwords={}, background_color='black').generate(finalText)

##Generating wordcloud(stopwords
```

Output for Word Cloud (without Stopwords)

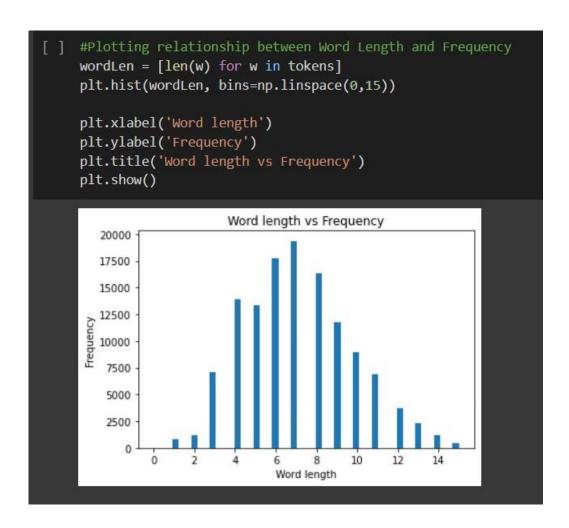
#### Inference

- The prominent words now are "system, software, process, requirements, used, development" etc instead of stop words.
- Frequency distribution also shows more subject specific words occupying higher frequencies.
- Now true essence of the text is delivered.

#### Relation Between the Word Length and Frequency

Here, we tend to analyse a relationship between the word length and how many words with such word length occurs.

- We first associate a bin for the bar graph using "numpy" library
- Then using len() function we calculate the length of each token
- Then we plot a graph for frequency of such word lengths using matplotlib.pyplot



#### Inference

- It is observed that most of the common words are of medium length between 4 and 10.
- As we go away from the peak, generally the count decreases.
- Distribution appears to be roughly normal

#### **PoS Tagging**

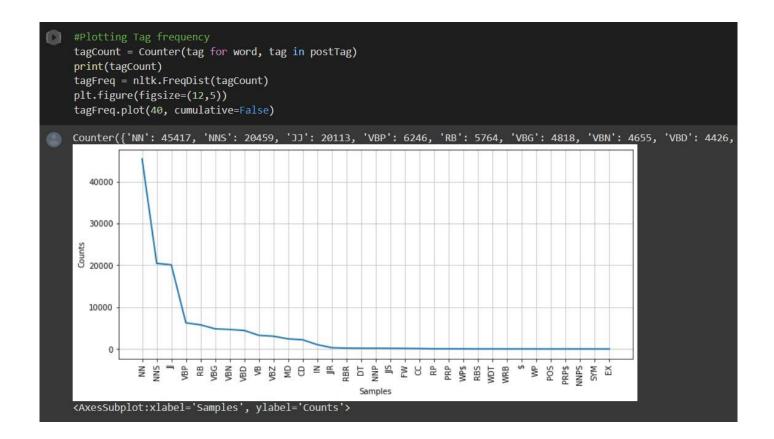
- Finally, after complete processing, now we assign appropriate Part-of-Speech Tags to the words.
- We utilize the pos\_tag feature of nltk library and pass our list of tokens into it to get the POS tagged list of tokens.
- The pos\_tag() function uses the Penn Treebank Tag Set , which has 36 tags to assign from to the words.
- A tuple consisting of the tokens and tags is returned.

```
#POS Tagging
postTag = nltk.pos tag(tokens)
postTag
[('objectives', 'NNS'),
  ('objectives', 'VBZ'),
 ('chapter', 'NN'),
 ('introduce', 'NN'),
('software', 'NN'),
  ('engineering', 'NN'),
   'provide', 'NN'),
'framework', 'NN'
  ('understanding', 'VBG'),
   'rest', 'JJ'),
'book', 'NN'),
 ('read', 'VBP'),
   'chapter', 'NN'),
   'understand', 'ŃŃ'),
'software', 'NN'),
   'engineering', 'NN'),
                     'JJ'),
   'important',
   'know', 'VBP'),
   'answers', 'NNS'),
   'key', 'JJ'),
'questions', 'NNS'),
'provide', 'VBP'),
   'introduction', 'NN'),
   'software', 'NN'),
 ('engineering', 'NN'),
('understand', 'JJ'),
   'ethical', 'JJ'),
  ('professional', 'NN'),
   'issues', 'NNS'),
   'important', 'JJ'
   'software', 'NN'),
   'engineers', 'NNS'),
  'contents', 'NNS'),
'virtually', 'RB'),
'countries', 'NNS'),
   'depend', 'VBP'),
```

Part-of-Speech Tags

### Distribution of Part-of-Speech Tags

- To analyse the obtained list, we plot the frequency of different tags.
- "Counter" library was used which calculates the frequency of each tag used for the final text.



#### Inference

- From the above plot we see NN is the most common tag out of all.
- Also, from the tuple of pos tags returned we see that same words are assigned many tags. For example, first 2 words 'objectives' is assigned 'NNS' and 'VBZ' respectively.
- There are a smaller number of ambiguous words (i.e., with multiple parts of speech tags) but they are being frequently used (as observed from frequency distribution and tuple of pos tags).

# Project Round 2

### **Problem Statement Round 2**

#### **First Part:**

- 1. Find the nouns and verbs in the book. Get the categories that these words fall under in the WordNet. Note that there are 25 categories and 16 categories for Nouns and Verbs respectively.
- 2. Get the frequency of each category for each noun and verb in their corresponding heirarchies and plot a histogram for the same.

#### **Second Part:**

1. Recognise all entities (Types given in Fig 22.1). For this you have to do two steps: (1) First recognise all the entity and then (2) recognise all entity types. Use performance measures to measure the performance of the method used - For evaluation you take a considerable amount of random passages from the book, do a manual labelling and then compare your result with it. Present the accuracy here and F1 score.

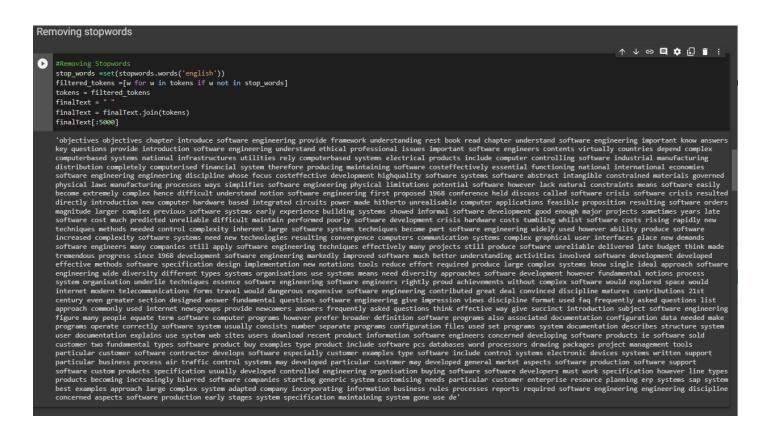
#### **Third Part:**

For extracting the relationship between the entities from the book - what are the
features necessary for this? Use the ideas given in the book and presented in the class
to augment the data of Entities and augment that data by extracting additional
features and build the table and present it.

#### **Removing Stop Words**

Stopwords refers to the extra common words used in natural language such as articles (the, an, a). In NLP and text mining applications, stop words are used to eliminate unimportant words, allowing applications to focus on the important words instead. So, we need to eliminate the Stop words.

- a. We include STOPWORDS and utilize it to create a set of english stop words.
- b. We then filter our tokens by eliminating all the words that are common in the stopword set and our tokens.



Final Text after removing Stopwords

#### **PoS Tagging**

- After processing, now we assign appropriate Part-of-Speech Tags to the words.
- We utilize the pos\_tag feature of nltk library and pass our list of tokens into it to get the POS tagged list of tokens.
- The pos\_tag() function uses the Penn Treebank Tag Set , which has 36 tags to assign from to the words.
- A tuple consisting of the tokens and tags is returned.

```
    Perform POS Tagging

     [ ] #POS Tagging
              postTag = nltk.pos_tag(tokens)
              postTag
              [('objectives', 'NNS'),
  ('objectives', 'VBZ'),
                ('chapter', 'NN'),
('introduce', 'NN'),
('software', 'NN'),
('engineering', 'NN'),
                ('provide', 'NN'),
('framework', 'NN'),
                 ('understanding', 'VBG'),
                ('rest', 'JJ'),
('book', 'NN'),
('read', 'VBP'),
                .
('chapter', 'NN'),
                ('understand', 'NN'),
('software', 'NN'),
                   'engineering', 'ŃŃ'),
'important', 'JJ'),
                ('know', 'VBP'),
                ('answers', 'NNS'),
                ('key', 'JJ'),
('questions', 'NNS'),
('provide', 'VBP'),
                 ('introduction', 'NN'),
                 ('software', 'NN'),
                ('engineering', 'NN'),
('understand', 'JJ'),
                (ˈethicalˈ, ˈj͡Jˈ),
                ('professional', 'NN'),
                ('issues', 'NNS'),
('important', 'JJ'),
('software', 'NN'),
('engineers', 'NNS'),
('contents', 'NNS'),
('virtually', 'RB'),
('countries', 'NNS'),
                ('depend', 'VBP'),
('complex', 'JJ'),
('computerbased', 'VBN'),
                ('systems', 'NNS'),
('national', 'JJ'),
```

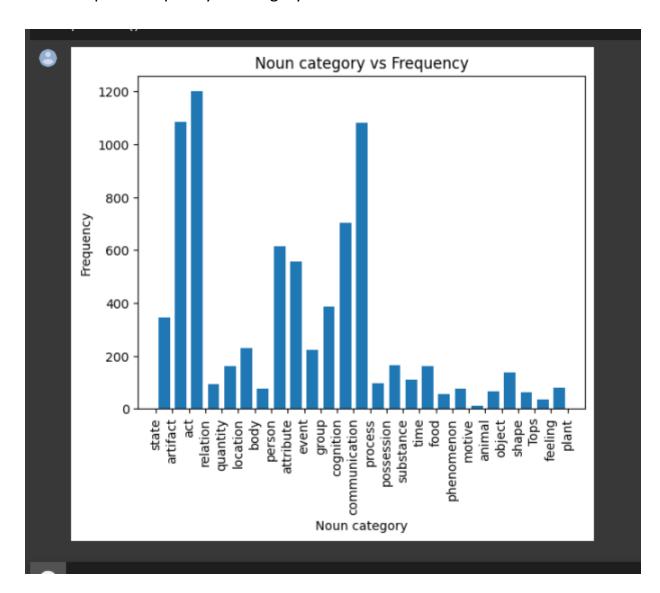
# **First Part**

#### Categorising Nouns and plotting their frequencies

- Separate the nouns from the text, out of all the assigned tags, check for the words having NN tag.
- Now iterate through all 25 categories of nouns using: for syn in wn.synsets(word[0], wn.NOUN):
- Record the frequency of each category by incrementing the count in a dictionary for every occurrence.

```
cat_freq = {}
f = []
for word in set(postTag):
  if (word[1] == 'NN'):
    for syn in wn.synsets(word[0], wn.NOUN):
      key = syn.lexname().split('.')[1]
      if (key in cat_freq):
        cat_freq[key] += 1
      else:
        cat_freq[key] = 1
      f.append(key)
      print(word[0], syn.lexname())
judgement noun.communication
judgement noun.cognition
judgement noun.cognition
judgement noun.cognition
judgement noun.attribute
judgement noun.act
judgement noun.act
pm noun.act
pm noun.substance
pm noun.person
pm noun.communication
computer noun.artifact
computer noun.person
convergence noun.event
convergence noun.cognition
convergence noun.cognition
convergence noun.act
knowing noun.cognition
initialisation noun.communication
session noun.communication
session noun.time
session noun.act
session noun.group
manipulation noun.act
manipulation noun.act
medication noun.artifact
medication noun.act
press noun.state
press noun.communication
```

- Now plot a histogram using matplotlib.pyplot
- X axis depicts Noun category.
- Y axis depicts Frequency of category.



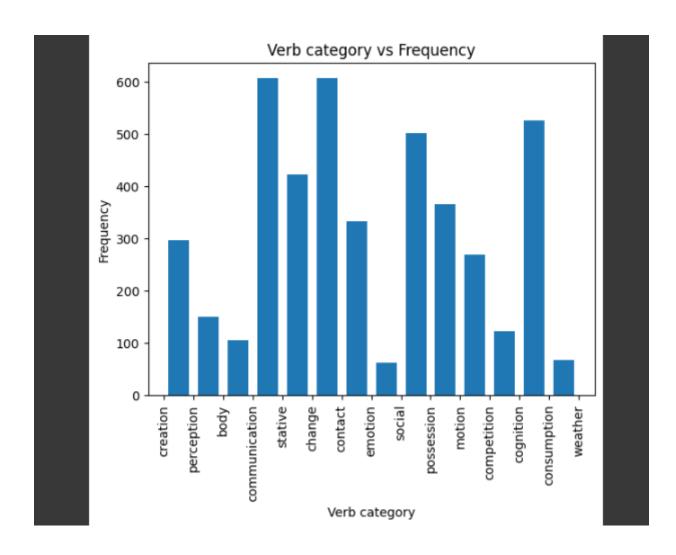
Frequency distribution graph for noun categories

# Categorising verbs and plotting their frequencies

- Separate the verbs from the text, out of all the assigned tags, check for the words having VB tag.
- Now iterate through all 25 categories of nouns using: for syn in wn.synsets(word[0], wn.VERB):
- Record the frequency of each category by incrementing the count in a dictionary for every occurrence.

```
cat_freq1 = {}
 f1 = []
 for word in set(postTag):
   if (word[1] == 'VB'):
     for syn in wn.synsets(word[0], wn.VERB):
       key = syn.lexname().split('.')[1]
       if (key in cat_freq1):
         cat_freq1[key] += 1
       else:
         cat_freq1[key] = 1
       f1.append(key)
       print(word[0], syn.lexname())
 cat1 = [x for (x, y) in cat_freq1.items()]
 plt.hist(f1, bins=cat1, rwidth=0.7)
 plt.xlabel('Word length')
 plt.xticks(rotation='vertical')
 plt.ylabel('Frequency')
 plt.title('Word length vs Frequency')
 plt.show()
 confused verb.cognition
 confused verb.cognition
 confused verb.emotion
 confused verb.creation
 confused verb.cognition
 read verb.cognition
 read verb.stative
 read verb.cognition
 read verb.cognition
 read verb.cognition
 read verb.cognition
 read verb.cognition
 read verb.communication
 read verb.creation
 read verb.cognition
 read verb.cognition
 secure verb.possession
 secure verb.contact
 secure verb.possession
 secure verb.communication
 secure verb.contact
 secure verb.contact
 signal verb.communication
 signal verb.communication
 reflected verb.perception
 reflected verb.cognition
 reflected verb.perception
 reflected verb.weather
 reflected verb.perception
 reflected verb.communication
 reflected verb.communication
 introduced verb.communication
 introduced verb.creation
 introduced verh change
```

- Now plot a histogram using matplotlib.pyplot
- X axis depicts Verb category.
- Y axis depicts Frequency of category.



Frequency distribution graph for Verb categories

# **Second Part**

#### **Manual NER Tagging**

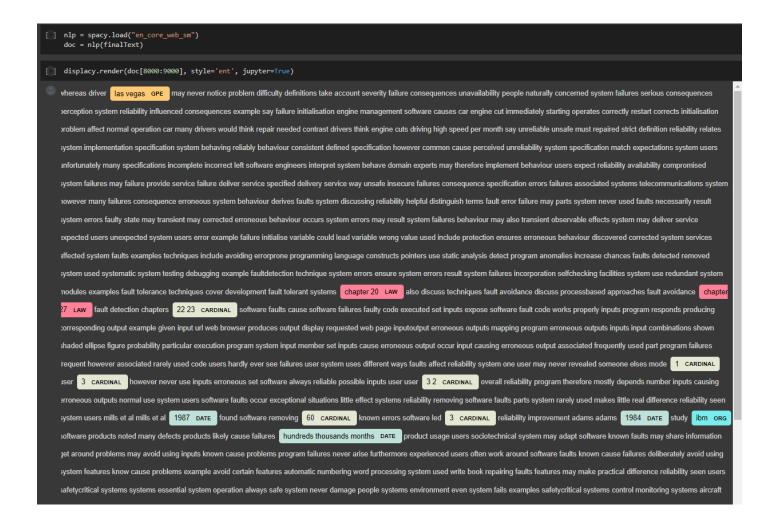
- Below is the screenshot for manual NER tagging for a 1000 words random passage from the book
- It can be found in the 'Manual NER.txt' file of the github repo.

sheross driver (las vogas)(PRF) any never notice problem difficulty definitions take account severity fallows consequences suncellability prople naturally concerned system fallows services correctly restrict corrects initialisation epidem affect normal operation can many drivers would think repair needed contrast drivers think engine cuts driving high speed per normal soperation can many drivers would think repair needed contrast drivers think engine cuts driving high speed per normal source control and the property of t

Manually assigned NER tags

#### **NER Tagging**

- Load the wordnet
  - o nlp = spacy.load("en\_core\_web\_sm")
- Initialize the text as a part of this wordnet
  - o doc = nlp(finalText)
- Display the NER labels as follows:
  - displacy.render(doc, style='ent', jupyter=True)
- Get the required NER labels for 8000th to 9000th word of the book (the random passage):
  - displacy.render(doc[8000:9000], style='ent', jupyter=True



#### Algorithm generated NER Tags

#### **NER Labelling Evaluation**

- Get the values for True Positive, True Negative, False Positive, and False Negative by a comparision with the manual NER
- Get the values for Recall, Precision, Accuracy and F1-Score:
  - o recall = TP / (TP + FN)
  - o precision = TP / (TP + FP)
  - $\circ$  accuracy = (TP + TN) / (TP + FN + FP + TN)
  - F1Score = 2 \* precision \* recall / (precision + recall)
- Display accuracy and F1Score

```
[ ] TP = 3
    FN = 2
    FP = 0
    TN = 995

accuracy = (TP + TN) / (TP + FN + FP + TN)
    precision = TP / (TP + FP)
    recall = TP / (TP + FN)
    F1Score = 2 * precision * recall / (precision + recall)
    accuracy, F1Score

(0.998, 0.74999999999999)
```

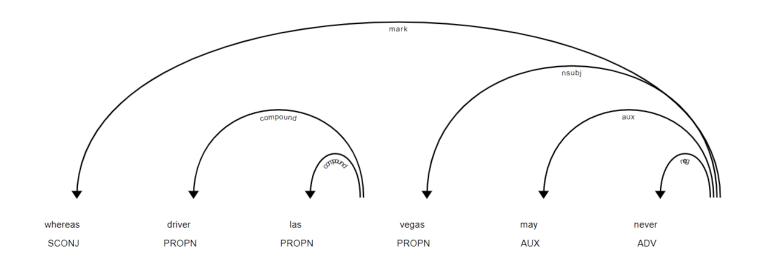
**Evaluation scores** 

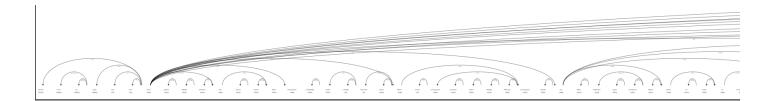
**Accuracy of Model: 99.8%** 

**F1 Score of Model:** 0.7499999

# **Third Part**

#### Relationship between entities





- Detailed entity relationship chart can be viewed through ipynb notebook.
- Snippets for rough idea are presented here.

GitHub Link: <a href="https://github.com/Vatsal32/NLP\_Project\_Round\_1">https://github.com/Vatsal32/NLP\_Project\_Round\_1</a>
GitHub Link: <a href="https://github.com/Vatsal32/NLP\_Project\_Round\_2">https://github.com/Vatsal32/NLP\_Project\_Round\_2</a>

# **Thank You**