NLP Course Work CW-1

Individual Submission

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For this project we are asked to work on three components of the chatbot 1) Intent Classification 2) Named Entity Recognition 3) Dialogue flow manager

Intent Classifiaction

intent classifiaction is used for defining what is the reason for the sentance at a higher level , In terms of a chat bot this is used to understand what the user is trying to express and what he might be expecting as the outcome.

Some example sentances and their possible intent are
Hi , How are you doing -- > Greeting
Hello --> Greeting
Bye , Thanks --> Good bye
Can i know the price od Pixel 6 --> Price_info

For this task i will be using a Data set called as ATIS which is very commonly used for intent classifiaction training (https://www.kaggle.com/datasets/hassanamin/atis-airlinetravelinformationsystem)

In [1]:
```
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
import numpy as np
```

In [2]:
```
train_data = pd.read_csv('Data/atis_intents_train.csv', names=['target', 'text'])
test_data=pd.read_csv('Data/atis_intents_test.csv', names=['target', 'text'])
```

EDA of Intent Data set

Perfroming Exploratory Data Analysis on the ATIS data set

In [3]:
```
print('Length of Training Data Set is ',train_data.shape[0])
print('Length of Testing Data Set is ',test_data.shape[0])
```

```
Length of Training Data Set is  4834
Length of Testing Data Set is  800
```

There are 4834 records for Training and 800 for testing

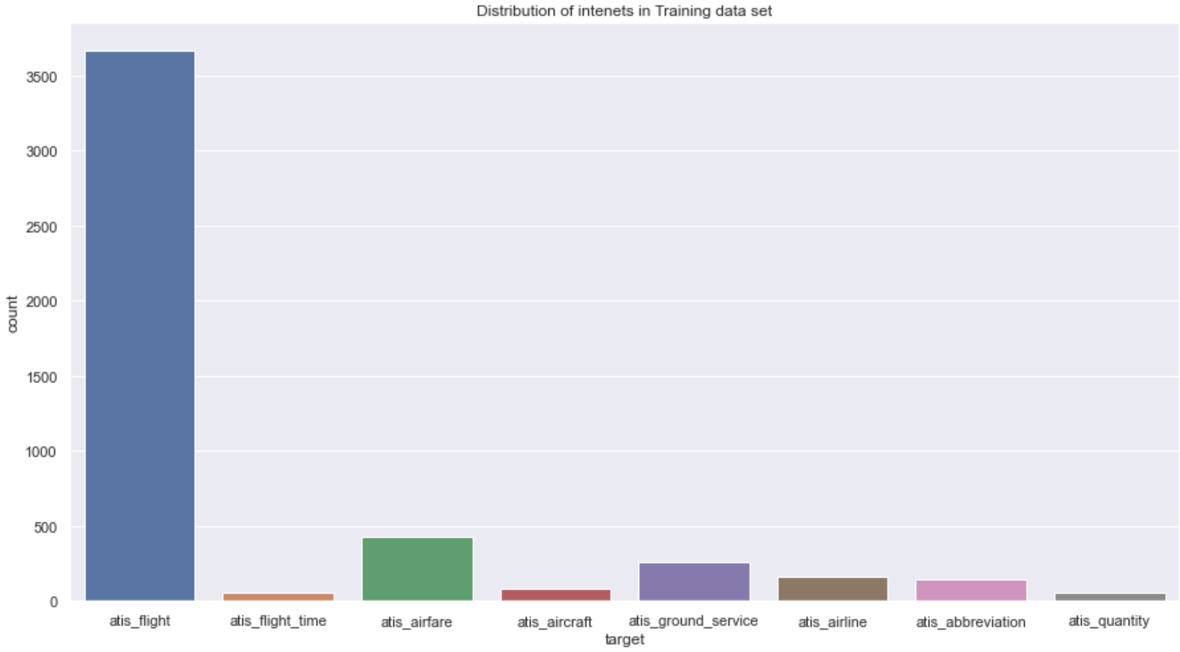
In [4]:
```
print('Unique Intents in Training Data set',train_data['target'].nunique())
print('Unique Intents in Testing Data set',test_data['target'].nunique())
```

```
Unique Intents in Training Data set 8
Unique Intents in Testing Data set 8
```

In [5]:
```
import matplotlib.pyplot as plt
```

```
plt.rcParams["figure.figsize"] = (15,8)
import seaborn as sns
sns.set_theme(style="darkgrid")
print(train_data['target'].value_counts())
ax = sns.countplot(x="target", data=train_data).set(title='Distribution of intenet
```

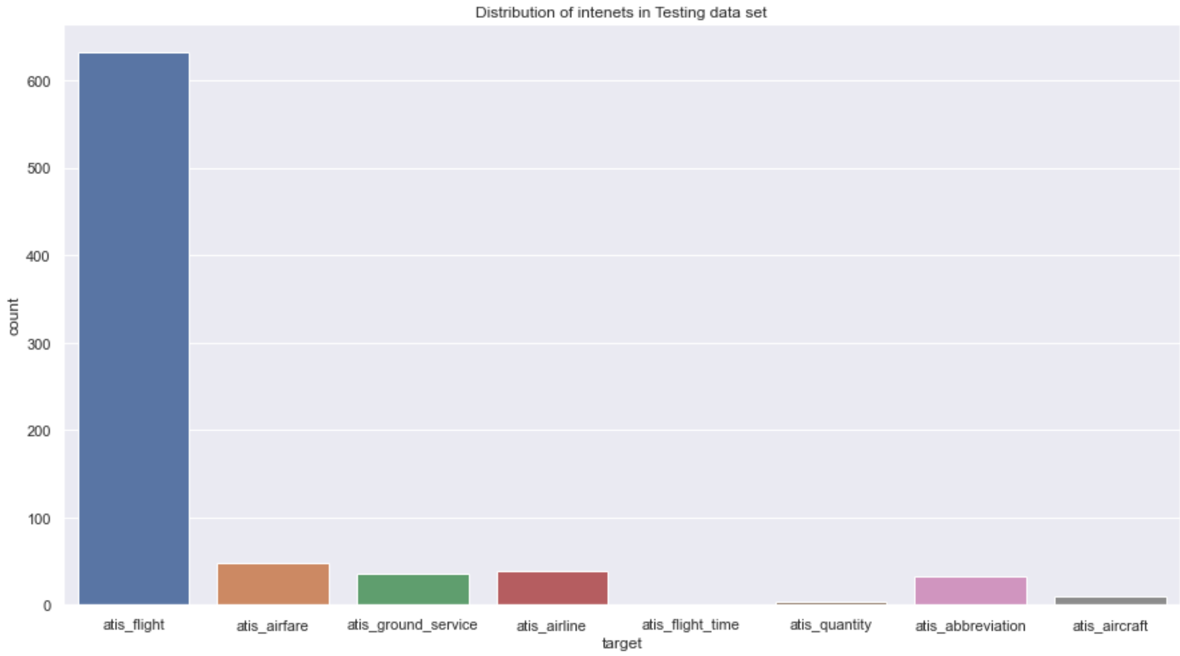
```
atis_flight             3666
atis_airfare             423
atis_ground_service      255
atis_airline             157
atis_abbreviation        147
atis_aircraft             81
atis_flight_time          54
atis_quantity             51
Name: target, dtype: int64
```



Here we can observe the spread of different intetns in the Training , We can see atis_flight has the most representation

In [6]:
```
print(test_data['target'].value_counts())
ax = sns.countplot(x="target", data=test_data).set(title='Distribution of intenets
```

```
atis_flight             632
atis_airfare             48
atis_airline             38
atis_ground_service      36
atis_abbreviation        33
atis_aircraft             9
atis_quantity             3
atis_flight_time          1
Name: target, dtype: int64
```



In testing Data set as well there is same level of the representation

I want to check the average length of sentances for each Intent

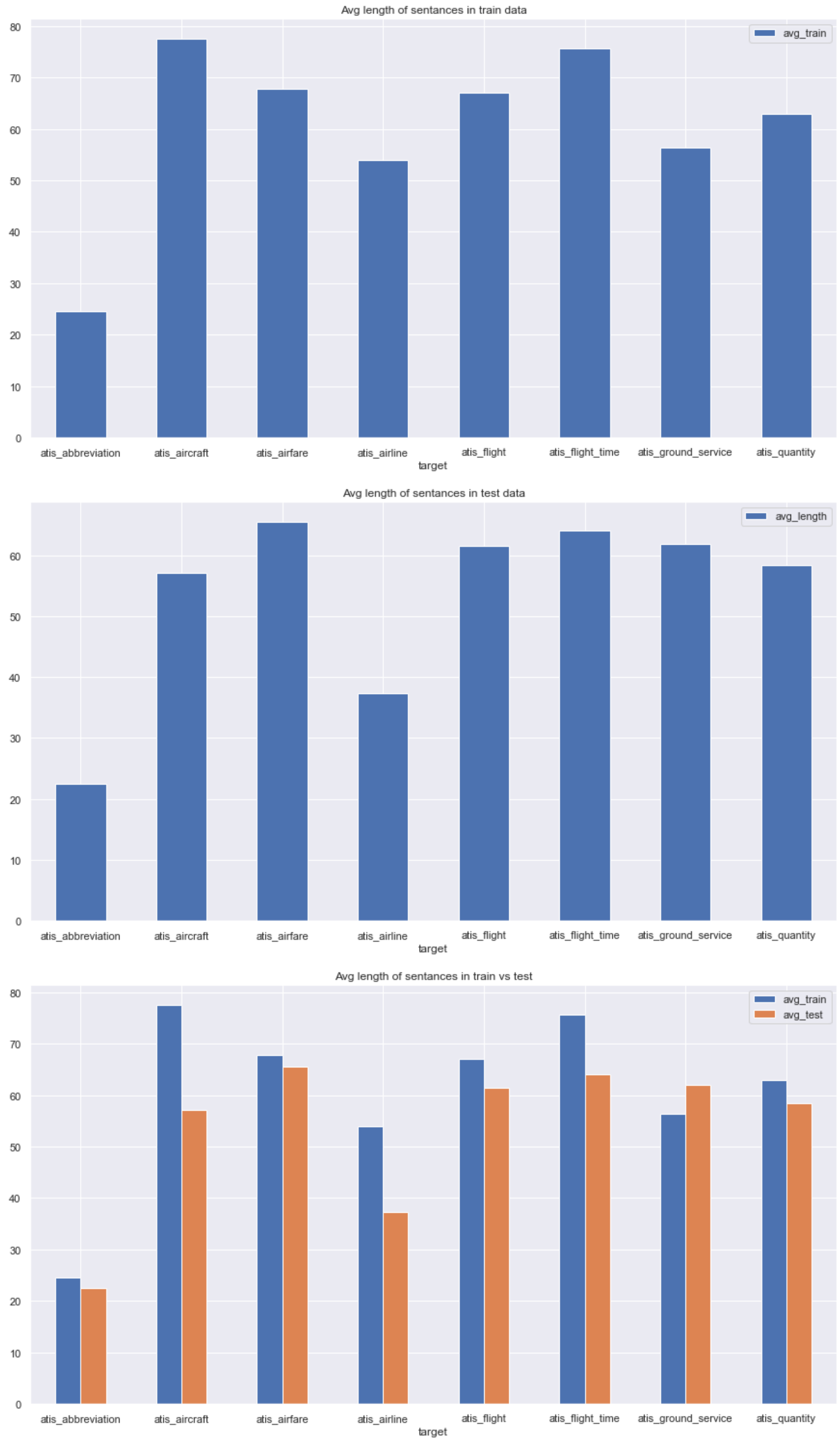
In [7]:

```
#Returns a df with each intent and avg length
def avg_length(df2):
    cols = df2['target'].unique()
    cols.sort()
    avg=[]
    for j in cols :
        df = df2.loc[df2['target'] == j]
        df['name_length']  = df['text'].str.len()
        avg.append(df['name_length'].sum()/df['name_length'].count())
    avg_listt = list(zip(cols,avg))
    return pd.DataFrame(avg_listt,columns=['target', 'avg_length'])
```

In [8]:

```
avg_train = avg_length(train_data)
avg_test = avg_length(test_data)
dff = avg_train
dff.rename({'avg_length':"avg_train"},axis=1,inplace = True)
dff['avg_test']=avg_test['avg_length']
print(dff)
ax = avg_train.plot.bar(x=0, y=1, rot=0).set(title='Avg length of sentances in trai
ax = avg_test.plot.bar(x=0, y=1, rot=0).set(title='Avg length of sentances in test
ax = dff.plot.bar(x=0,rot=0).set(title='Avg length of sentances in train vs test')
```

```
                 target  avg_train   avg_test
0     atis_abbreviation  24.544218  22.545455
1         atis_aircraft  77.506173  57.111111
2          atis_airfare  67.723404  65.479167
3          atis_airline  54.025478  37.342105
4           atis_flight  66.983906  61.493671
5      atis_flight_time  75.555556  64.000000
6   atis_ground_service  56.419608  61.888889
7         atis_quantity  63.000000  58.333333
```



Here we can see the average length is very similar for both Data sets

Data Preprocessing

For Data Preprocessing we need to convert the words in vectors . For this i am using DictVectorizer which creates numpy array of the sentances

In [10]:
```
data = pd.read_csv('Data/atis_intents_train.csv', encoding = "ISO-8859-1",names=['
data_test = pd.read_csv('Data/atis_intents_test.csv', encoding = "ISO-8859-1",name
data=data.append(data_test)
y = data['target']
```

In [11]:
```
from sklearn.feature_extraction import DictVectorizer
v = DictVectorizer(sparse=False)#vectorising the data
X= data.drop('target', axis=1)# dropping the tag data
X= v.fit_transform(X.to_dict('records'))
```

In [12]:
```
classes = np.unique(y)
classes = classes.tolist()
new_classes = classes.copy()
#new_classes.pop()
```

In [13]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.30, random_
```

Perceptron

I am using perceptron and using Partial fit to train the perceptron to fit for each different Intent.

In [14]:
```
from sklearn.linear_model import Perceptron
perceptron = Perceptron(verbose=10,n_jobs=-1,n_iter_no_change=10)
perceptron.partial_fit(X_train, y_train, classes) #Fitting data to each different 
```

```
-- Epoch 1-- Epoch 1-- Epoch 1
-- Epoch 1

-- Epoch 1-- Epoch 1-- Epoch 1

-- Epoch 1


Norm: 16.34, NNZs: 210, Bias: -1.000000, T: 3943, Avg. loss: 0.024093
Total training time: 0.11 seconds.
Norm: 10.82, NNZs: 108, Bias: -1.000000, T: 3943, Avg. loss: 0.013188
Total training time: 0.10 seconds.
Norm: 16.46, NNZs: 253, Bias: -1.000000, T: 3943, Avg. loss: 0.031195
Total training time: 0.11 seconds.
Norm: 8.66, NNZs: 75, Bias: -1.000000, T: 3943, Avg. loss: 0.009384
Total training time: 0.09 seconds.
Norm: 20.42, NNZs: 405, Bias: -1.000000, T: 3943, Avg. loss: 0.050723
Total training time: 0.11 seconds.
Norm: 8.31, NNZs: 66, Bias: -1.000000, T: 3943, Avg. loss: 0.008116
Total training time: 0.11 seconds.
Norm: 25.94, NNZs: 643, Bias: -1.000000, T: 3943, Avg. loss: 0.080142
Total training time: 0.13 seconds.
Norm: 41.92, NNZs: 1646, Bias: 1.000000, T: 3943, Avg. loss: 0.203906
Total training time: 0.14 seconds.
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done   2 out of   8 | elapsed:    0.0s remaining:    0.3s
[Parallel(n_jobs=-1)]: Done   3 out of   8 | elapsed:    0.0s remaining:    0.1s
[Parallel(n_jobs=-1)]: Done   4 out of   8 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=-1)]: Done   5 out of   8 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=-1)]: Done   6 out of   8 | elapsed:    0.1s remaining:    0.0s
[Parallel(n_jobs=-1)]: Done   8 out of   8 | elapsed:    0.1s remaining:    0.0s
[Parallel(n_jobs=-1)]: Done   8 out of   8 | elapsed:    0.1s finished
```

Out[14]:
```
Perceptron(n_iter_no_change=10, n_jobs=-1, verbose=10)
```

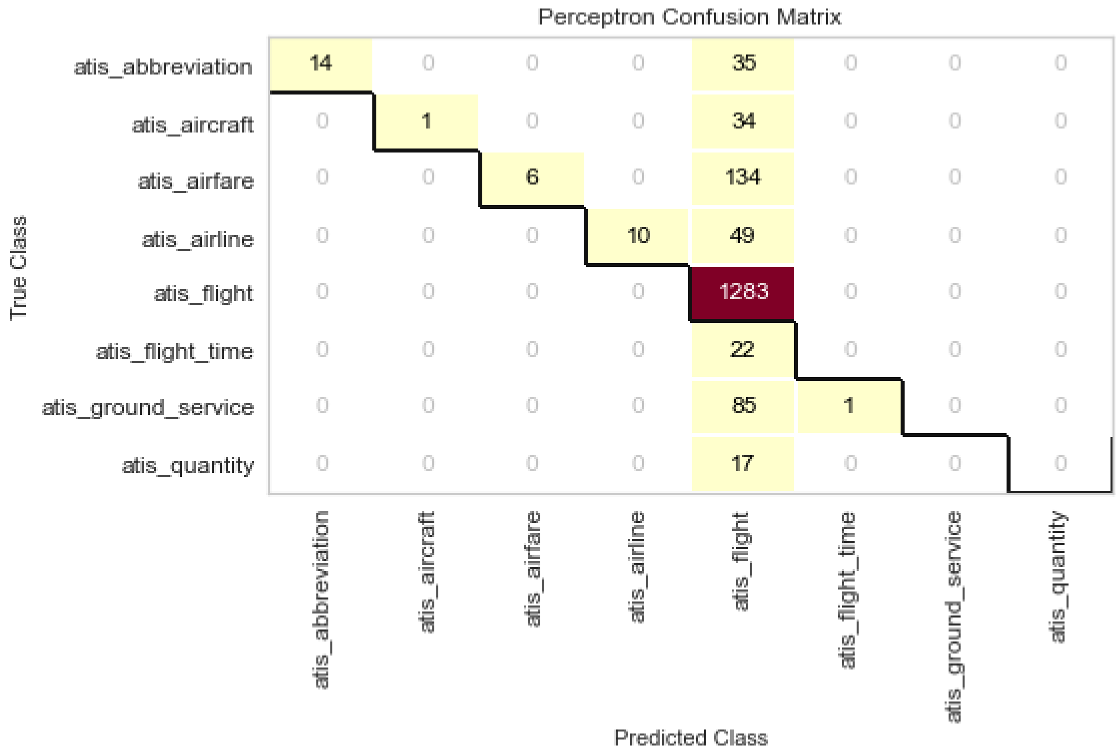
In [15]:
```python
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.linear_model import PassiveAggressiveClassifier
import sklearn.metrics
from yellowbrick.classifier import ConfusionMatrix
classification_per = classification_report(y_pred=perceptron.predict(X_train), y_tr
per_acc_Train =accuracy_score(y_true=y_train, y_pred=perceptron.predict(X_train))
per_acc_Test =accuracy_score(y_true=y_test, y_pred=perceptron.predict(X_test))
print(classification_per)
print('Accuracy Score on Train data:', per_acc_Train)
print('Accuracy Score on Test data:', per_acc_Test)
cm_per= ConfusionMatrix(perceptron, classes=classes)
cm_per.score(X_test, y_test)
cm_per.show()
```

```
                     precision    recall  f1-score   support

  atis_abbreviation       1.00      0.98      0.99       131
      atis_aircraft       1.00      0.89      0.94        55
       atis_airfare       1.00      0.92      0.96       331
       atis_airline       1.00      0.96      0.98       136
        atis_flight       0.91      1.00      0.95      3015
   atis_flight_time       1.00      0.06      0.11        33
atis_ground_service       1.00      0.04      0.08       205
      atis_quantity       0.00      0.00      0.00        37

           accuracy                           0.92      3943
          macro avg       0.86      0.61      0.63      3943
       weighted avg       0.92      0.92      0.89      3943

Accuracy Score on Train data: 0.9223941161552117
Accuracy Score on Test data: 0.7776463630987581
```



Out[15]:

```
<AxesSubplot:title={'center':'Perceptron Confusion Matrix'}, xlabel='Predicted Cla
ss', ylabel='True Class'>
```

As we can see here perceptron performed very good by giving us the accuracy as 92% on Train ans only 77% on Test. I want to try several other models as well for Intent

Linear classifiers with SGD training

In [16]:

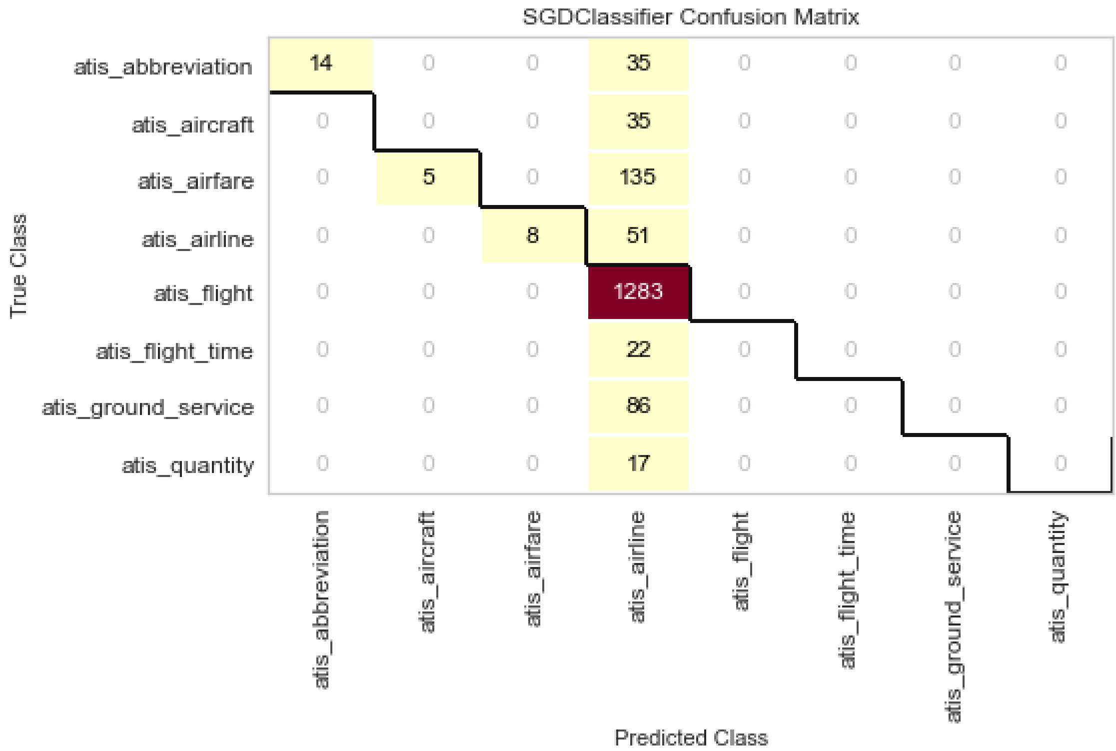
```python
from sklearn.linear_model import SGDClassifier
sgd_classifier = SGDClassifier()
sgd_classifier.partial_fit(X_train, y_train, classes)
classification_sgd = classification_report(y_pred=sgd_classifier.predict(X_test), y
print(classification_sgd)
sgd_acc_train=accuracy_score(y_true=y_train, y_pred=sgd_classifier.predict(X_train
sgd_acc_test= accuracy_score(y_true=y_test, y_pred=sgd_classifier.predict(X_test))
print('Accuracy Score on Train data:',sgd_acc_train )
print('Accuracy Score on Test data:', sgd_acc_test)
cm_sgd = ConfusionMatrix(sgd_classifier, classes=classes)
cm_sgd.score(X_test, y_test)
cm_sgd.show()
```

```
                     precision    recall  f1-score   support

  atis_abbreviation       1.00      0.29      0.44        49
      atis_aircraft       0.00      0.00      0.00        35
       atis_airfare       1.00      0.04      0.07       140
       atis_airline       1.00      0.14      0.24        59
        atis_flight       0.77      1.00      0.87      1283
   atis_flight_time       0.00      0.00      0.00        22
atis_ground_service       0.00      0.00      0.00        86
      atis_quantity       0.00      0.00      0.00        17

           accuracy                           0.77      1691
          macro avg       0.47      0.18      0.20      1691
       weighted avg       0.73      0.77      0.69      1691

Accuracy Score on Train data: 0.8879026122241948
Accuracy Score on Test data: 0.7746895328208161
```



Out[16]:

```
<AxesSubplot:title={'center':'SGDClassifier Confusion Matrix'}, xlabel='Predicted Class', ylabel='True Class'>
```

SGD classigfier is a classification model and it has performed very good in Train data but was not able to do good in Test data.

Classic models like Perceptron and SGD classifier are not well suited for this kind of tasks. Neural network based models such as LSTM and RNN will run good . I will use LSTM for next part of the question

Named Entity Recognition

Named Entity Recognition can be done in several different ways , I mainly want to explore how a prebuilt model like Spacy or NLTK works and how they may differ from trainig our own machine learning model like Perceptron, Multi layer Perceptron , CNN and several other works.

The main objective for me is to figure out the best approach and also find and explore different models and data sets.

Named Entity can be defined as the word which has significant value . One way describe it is it's "Noun" in a sentance . It can be name of a person , Name of a city , Date , Organization name, Amount and much more.

Some of the most common Named Entities are

Entity Type	Description	Example
PERSON	Name of a person (Usually recognized as first name and last name	Kowshik Kesavarapu
NORP	Nationalities or Religious/Political Groups	India , UK
FAC	Facility Name	IFH , CERN

Entity Type	Description	Example
ORG	Organization Name	WHO
GPE	Geopolitical Entity	UN
LOC	location	Guildford
PRODUCT	Product Name	Google Pixel
EVENT	Event Name	Google I/O
WORK OF ART	Work of art	Picaso
LAW	A law that has been published	US Act XXXX
LANGUAGE	Language Name	Telugu , English
DATE	Date , I dosen't have to be exact date terms like yesterday are also comes under this	21/04/2002 , Tuesday
TIME	Time , It also usually considers terms like Afternoon , Evening	2:00PM . Tonight
PERCENT	Percentage	100
MONEY	Money	$100
QUANTITY	Measurements of weight or distance	10 Kms
CARDINAL	A number, similar to quantity but not a measurement	25 Books (here 25 is Cardinal)
ORDINAL	A number, but signifying a relative position such as “first” or “second	First prize

I want to observe how Prebuilt Models like Spacy , NLP and Text Api works when compared to Classic models like Perceptron , SVM and Advanced Neural network like LSTM

Pre built Models Used are

```
1. Spacy (https://spacy.io/)
2. NLTK (https://www.nltk.org/book/ch07.html)
3. The Text API (https://www.thetextapi.com/)
```

Classic Machine Learning Models

```
1.Perceptron
2.SGD classifier
3.Naive Bayes
4.Passive Agressive Classifier
```

Advanced neural network

```
1. Bi-Directional LSTM
```

I will Try the Pre built models using a simple example statemt ""World Health Organisation announced today that it is spending $100 Million dollars to help with corona virus vacccination is African Countries""

This sentance has 4 Named Entities 1) World Health Organisation - Organization 2) African - NORP 3) $100 Million - Money 4) Today - Date

NER Using Spacy

In [17]:
```
ex = "World Health Organisation announced today that it is spending $100 Million do
```

In [18]:
```
import spacy
from collections import Counter
import en_core_web_sm
nlp = en_core_web_sm.load()
```

In [19]:
```
def spacy_ner(sent):
    doc = nlp(sent)

    for ent in doc.ents:
        print(ent.text, ent.label_)
```

In [20]:
```
spacy_ner(ex)
```

```
World Health Organisation ORG
today DATE
$100 Million dollars MONEY
African NORP
```

This particular method is very intuitive and relatively easy to implement , We dont need to worry about Tokenization or any other pre processing , This works relatively well. It was able to find all the Named Entities.

Spacy is particulary designed to work very efficiently and also swiftly. It was trained using tranformers and has support for 66+ languages. The latest build of spacey has accuravy if 89.8% accuracy for NER.

Reference - https://spacy.io/

NER using NLTK

For NLTK we need tokenize and also tag POS using the pos_tag in nltk

These tags are genrated using Penn Treebank Project.

The full forms of these tags are

Number	Tag	Description
1.	CC	Coordinating conjunction
2.	CD	Cardinal number
3.	DT	Determiner
4.	EX	Existential *there*
5.	FW	Foreign word
6.	IN	Preposition or subordinating conjunction

7.	JJ	Adjective
8.	JJR	Adjective, comparative
9.	JJS	Adjective, superlative
10.	LS	List item marker
11.	MD	Modal
12.	NN	Noun, singular or mass
13.	NNS	Noun, plural
14.	NNP	Proper noun, singular
15.	NNPS	Proper noun, plural
16.	PDT	Predeterminer
17.	POS	Possessive ending
18.	PRP	Personal pronoun
19.	PRP$	Possessive pronoun
20.	RB	Adverb
21.	RBR	Adverb, comparative
22.	RBS	Adverb, superlative
23.	RP	Particle
24.	SYM	Symbol
25.	TO	*to*
26.	UH	Interjection
27.	VB	Verb, base form
28.	VBD	Verb, past tense
29.	VBG	Verb, gerund or present participle
30.	VBN	Verb, past participle
31.	VBP	Verb, non-3rd person singular present
32.	VBZ	Verb, 3rd person singular present
33.	WDT	Wh-determiner
34.	WP	Wh-pronoun
35.	WP$	Possessive wh-pronoun
36.	WRB	Wh-adverb

"Reference - https://www.ling.upenn.edu/courses/Fall_2003/ling001/penn_treebank_pos.html"

Once the sentance is Tokenized we can perform NER , I wrote a simple function to do all this when passed with the sentance

We can perfoem NER and here we can see that

Here we can see the sentance splitted and POS tagged

In [21]:
```
import nltk
tokenized = nltk.word_tokenize(ex)#Tokenizing
pos_tagged = nltk.pos_tag(tokenized)#Tagging POS
print(pos_tagged)
```

```
[('World', 'NNP'), ('Health', 'NNP'), ('Organisation', 'NNP'), ('announced', 'VB
D'), ('today', 'NN'), ('that', 'IN'), ('it', 'PRP'), ('is', 'VBZ'), ('spending',
'VBG'), ('$', '$'), ('100', 'CD'), ('Million', 'NNP'), ('dollars', 'NNS'), ('to',
'TO'), ('help', 'VB'), ('with', 'IN'), ('corona', 'JJ'), ('virus', 'NN'), ('vaccci
nation', 'NN'), ('is', 'VBZ'), ('African', 'JJ'), ('Countries', 'NNS')]
```

In [22]:
```
def ner_nltk(sent):
    tokenized = nltk.word_tokenize(sent)#Tokenizing
    pos_tagged = nltk.pos_tag(tokenized)#Tagging POS
    chunks = nltk.ne_chunk(pos_tagged)#Performing NER
    for chunk in chunks:
        if hasattr(chunk, 'label'):
            print(chunk)
```

In [23]:
```
ner_nltk(ex)
```

```
(GPE African/JJ)
```

Here we can see that the NLTK havent performed well and was only able to find One entities. Although this seems to be not at all scientific way to compare from my research i found that Spacy often performs well than NLTK as it was trained on much larger data set.

Now there is also a another way of getting the NER this is by using The Text API which is a Text analysis model.

NER using Text API

In [24]:
```
import requests
import json
def text_api(text):

        headers = {
            "Content-Type": "application/json",
            "apikey": '6d8398eb-dd38-4e39-b28f-8ce00ff9c4d3'
        }
        body = {
            "text": text
        }
        url = "https://app.thetextapi.com/text/ner"

        response = requests.post(url, headers=headers, json=body)
        ner = json.loads(response.text)["ner"]
        print(ner)
```

In [25]:
```
text_api(ex)
```

```
[['ORG', 'World Health Organisation'], ['DATE', 'today'], ['MONEY', '$100 Million
dollars'], ['ORG', 'African Countries']]
```

This is another way and for this example it performed relatively well and found all the Named entities

Now that we covered three different relatively straight forward ways to do NER , Now i am going to experiment with building my own model by training using the dataset found on kaggle, Which contains the data of several thousand sentances along with their POS and NER tags.

Exploring the Data Set

Data set is from Kaggle (https://www.kaggle.com/datasets/abhinavwalia95/entity-annotated-corpus) , It consists of sentances and Parts of Search and their named entitiesa

In [26]:
```
data = pd.read_csv('Data/data.csv', encoding = "ISO-8859-1")
data = data[:100000]
data.head()
```

Out[26]:

	Sentence #	Word	POS	Tag
0	Sentence: 1	Thousands	NNS	O
1	NaN	of	IN	O
2	NaN	demonstrators	NNS	O
3	NaN	have	VBP	O
4	NaN	marched	VBN	O

This data set needs a little cleaning so i am just using ffill to fill the nan with previous found data.

In [27]:
```
data = data.fillna(method='ffill')
```

In [28]:
```
data[20:30]
```

Out[28]:

	Sentence #	Word	POS	Tag
20	Sentence: 1	from	IN	O
21	Sentence: 1	that	DT	O
22	Sentence: 1	country	NN	O
23	Sentence: 1	.	.	O
24	Sentence: 2	Families	NNS	O
25	Sentence: 2	of	IN	O
26	Sentence: 2	soldiers	NNS	O
27	Sentence: 2	killed	VBN	O
28	Sentence: 2	in	IN	O
29	Sentence: 2	the	DT	O

Here we can observe how the data is distributed . Now i will try to do some exploration of the data

EDA

In [29]:
```
data['Sentence #'].nunique(), data.Word.nunique(), data.Tag.nunique()
```

Out[29]:
```
(4544, 10922, 17)
```

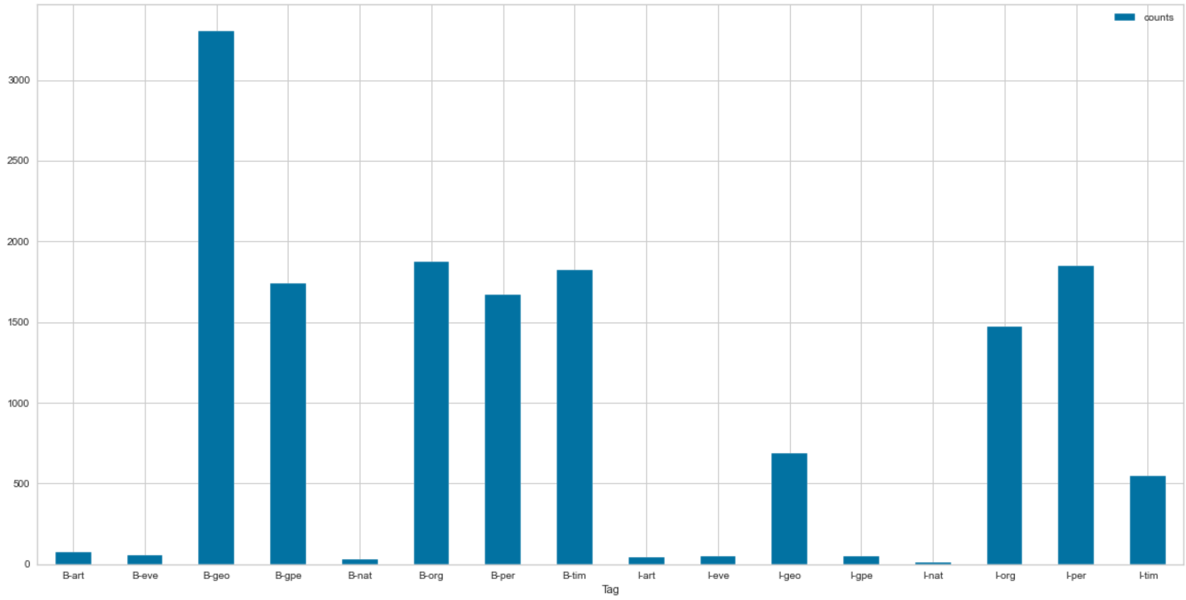
Here we can see we have 4544 sentances , 10922 words and 17 tags , Lets see what the tags are

In [30]:
```
Ner_Tag = data.groupby('Tag').size().reset_index(name='counts')
print(Ner_Tag)
```

```
      Tag  counts
0   B-art      75
1   B-eve      53
2   B-geo    3303
3   B-gpe    1740
4   B-nat      30
5   B-org    1876
6   B-per    1668
7   B-tim    1823
8   I-art      43
9   I-eve      47
10  I-geo     690
11  I-gpe      51
12  I-nat      11
13  I-org    1470
14  I-per    1846
15  I-tim     549
16      O   84725
```

This data set is not certainly a good data set as there is a possibility of overfitting and underfitting of the data as all the classes are not represented equally.So i will be carefull while building the models.

In [31]:
```
tags1=Ner_Tag[:-1] # removing "O" -other
plt.rcParams["figure.figsize"] = (20,10)
ax = tags1.plot.bar(x='Tag', y='counts', rot=0)
```

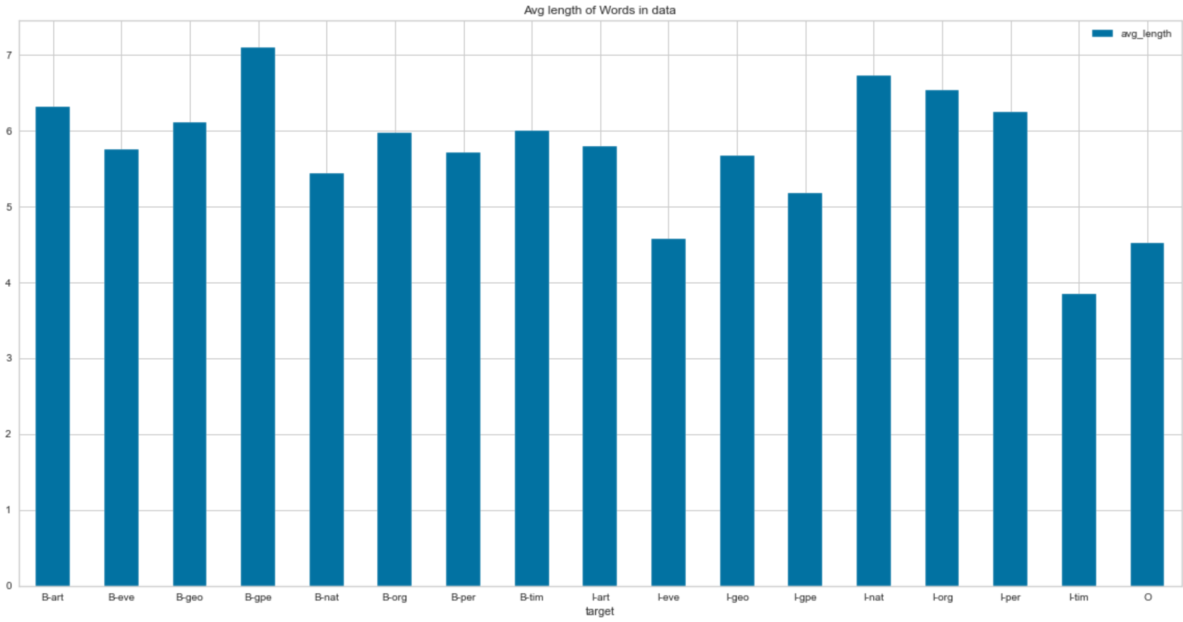


Let's see how is the avg length among the words for each TAG

In [32]:
```
#Returns a df with each NER tag and avg length
def avg_length(df2):
    cols = df2['Tag'].unique()
    cols.sort()
    avg=[]
    for j in cols :
        df = df2.loc[df2['Tag'] == j]
        df['name_length']  = df['Word'].str.len()
        avg.append(df['name_length'].sum()/df['name_length'].count())
    avg_listt = list(zip(cols,avg))
    return pd.DataFrame(avg_listt,columns=['target', 'avg_length'])
```

In [33]:
```
dataaaa=avg_length(data)
print(dataaaa)
ax = dataaaa.plot.bar(x=0, y=1, rot=0).set(title='Avg length of Words in data')
```

```
   target  avg_length
0   B-art    6.320000
1   B-eve    5.754717
2   B-geo    6.107175
3   B-gpe    7.096552
4   B-nat    5.433333
5   B-org    5.967484
6   B-per    5.714628
7   B-tim    5.996160
8   I-art    5.790698
9   I-eve    4.574468
10  I-geo    5.666667
11  I-gpe    5.176471
12  I-nat    6.727273
13  I-org    6.538095
14  I-per    6.252438
15  I-tim    3.848816
16      O    4.524627
```



In [34]:
```
Pos_Tag = data.groupby('POS').size().reset_index(name='counts')
Pos_Tag=Pos_Tag.sort_values(by=['counts'],ascending=False)
Pos_Tag=Pos_Tag.reset_index(drop=True)
print(Pos_Tag)
```

	POS	counts
0	NN	13975
1	NNP	12526
2	IN	11658
3	DT	9470
4	JJ	7365
5	NNS	7298
6	.	4533
7	VBD	3686
8	VBN	3067
9	,	3061
10	VBZ	2428
11	CC	2276
12	VB	2276
13	CD	2259
14	TO	2174
15	RB	1991
16	VBG	1826
17	VBP	1533
18	PRP	1289
19	POS	1042
20	PRP$	810
21	MD	658
22	``	372
23	WDT	352
24	JJR	309
25	JJS	290
26	NNPS	239
27	RP	232
28	WP	232
29	WRB	225
30	RBR	103
31	$	86
32	:	73
33	LRB	72
34	RRB	72
35	EX	60
36	;	32
37	RBS	24
38	PDT	17
39	WP$	8
40	UH	1

Here we can distibution of different Parts of Speech

Model Building

In [35]:
```
from sklearn.feature_extraction import DictVectorizer
from sklearn.feature_extraction.text import HashingVectorizer
from sklearn.linear_model import Perceptron
from sklearn.model_selection import train_test_split
from sklearn.linear_model import SGDClassifier
from sklearn.linear_model import PassiveAggressiveClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.linear_model import PassiveAggressiveClassifier
import sklearn.metrics
from yellowbrick.classifier import ConfusionMatrix
from sklearn.svm import LinearSVC
```

```
import warnings
warnings.filterwarnings('ignore')
plt.rcParams["figure.figsize"] = (10,8)
```

In [36]:
```
data = pd.read_csv('Data/data.csv', encoding = "ISO-8859-1")
data = data.fillna(method='ffill')
data = data[:100000]#Using only a part of dataset as using more is creating Memory
y = data.Tag.values
```

In [37]:
```
np.unique(y)
```

Out[37]:
```
array(['B-art', 'B-eve', 'B-geo', 'B-gpe', 'B-nat', 'B-org', 'B-per',
       'B-tim', 'I-art', 'I-eve', 'I-geo', 'I-gpe', 'I-nat', 'I-org',
       'I-per', 'I-tim', 'O'], dtype=object)
```

In [38]:
```
v = DictVectorizer(sparse=False)#vectorising the data
X= data.drop('Tag', axis=1)# dropping the tag data
X = v.fit_transform(X.to_dict('records'))
```

In [39]:
```
classes = np.unique(y)
classes = classes.tolist()
new_classes = classes.copy()
new_classes.pop()
```

Out[39]:
```
'O'
```

In [40]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.33, random_
```

Perceptron

In [41]:
```
perceptron = Perceptron(verbose=10,n_jobs=-1,n_iter_no_change=10)
perceptron.partial_fit(X_train, y_train, classes) #Fitting data to each different 
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 8 concurrent workers.
-- Epoch 1-- Epoch 1

-- Epoch 1
-- Epoch 1-- Epoch 1
-- Epoch 1-- Epoch 1


-- Epoch 1
Norm: 11.53, NNZs: 113, Bias: -3.000000, T: 67000, Avg. loss: 0.001060
Total training time: 3.45 seconds.
-- Epoch 1
Norm: 48.83, NNZs: 1578, Bias: -4.000000, T: 67000, Avg. loss: 0.022328
Total training time: 3.48 seconds.
-- Epoch 1
Norm: 68.07, NNZs: 2642, Bias: -4.000000, T: 67000, Avg. loss: 0.041776
Total training time: 3.58 seconds.
-- Epoch 1
Norm: 56.87, NNZs: 2044, Bias: -4.000000, T: 67000, Avg. loss: 0.034970
Total training time: 3.55 seconds.
-- Epoch 1
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    3.9s
[Parallel(n_jobs=-1)]: Done   4 out of  17 | elapsed:    4.0s remaining:   13.1s
```

```
Norm: 8.43, NNZs: 57, Bias: -3.000000, T: 67000, Avg. loss: 0.000567
Total training time: 3.71 seconds.
-- Epoch 1
Norm: 13.42, NNZs: 162, Bias: -4.000000, T: 67000, Avg. loss: 0.001642
Total training time: 3.78 seconds.
-- Epoch 1
[Parallel(n_jobs=-1)]: Done   6 out of  17 | elapsed:    4.2s remaining:    7.8s
Norm: 49.90, NNZs: 1337, Bias: -4.000000, T: 67000, Avg. loss: 0.015328
Total training time: 3.90 seconds.
-- Epoch 1
Norm: 44.41, NNZs: 1127, Bias: -4.000000, T: 67000, Avg. loss: 0.017164
Total training time: 3.93 seconds.
-- Epoch 1
[Parallel(n_jobs=-1)]: Done   8 out of  17 | elapsed:    4.4s remaining:    4.9s
Norm: 10.44, NNZs: 106, Bias: -3.000000, T: 67000, Avg. loss: 0.001060
Total training time: 2.12 seconds.
-- Epoch 1
Norm: 11.45, NNZs: 96, Bias: -3.000000, T: 67000, Avg. loss: 0.000776
Total training time: 2.12 seconds.
Norm: 11.00, NNZs: 102, Bias: -3.000000, T: 67000, Avg. loss: 0.001209
Total training time: 2.10 seconds.
Norm: 35.13, NNZs: 803, Bias: -4.000000, T: 67000, Avg. loss: 0.011149
Total training time: 2.16 seconds.
[Parallel(n_jobs=-1)]: Done  10 out of  17 | elapsed:    6.0s remaining:    4.2s
[Parallel(n_jobs=-1)]: Done  12 out of  17 | elapsed:    6.1s remaining:    2.5s
Norm: 6.24, NNZs: 31, Bias: -3.000000, T: 67000, Avg. loss: 0.000209
Total training time: 2.39 seconds.
Norm: 53.57, NNZs: 1703, Bias: -4.000000, T: 67000, Avg. loss: 0.026224
Total training time: 2.32 seconds.
Norm: 30.53, NNZs: 672, Bias: -4.000000, T: 67000, Avg. loss: 0.012030
Total training time: 2.21 seconds.
Norm: 60.35, NNZs: 2091, Bias: -6.000000, T: 67000, Avg. loss: 0.026940
Total training time: 2.29 seconds.
[Parallel(n_jobs=-1)]: Done  14 out of  17 | elapsed:    6.5s remaining:    1.3s
Norm: 73.89, NNZs: 2851, Bias: 4.000000, T: 67000, Avg. loss: 0.048866
Total training time: 1.39 seconds.
[Parallel(n_jobs=-1)]: Done  17 out of  17 | elapsed:    7.3s finished
```

Out[41]:
```
Perceptron(n_iter_no_change=10, n_jobs=-1, verbose=10)
```

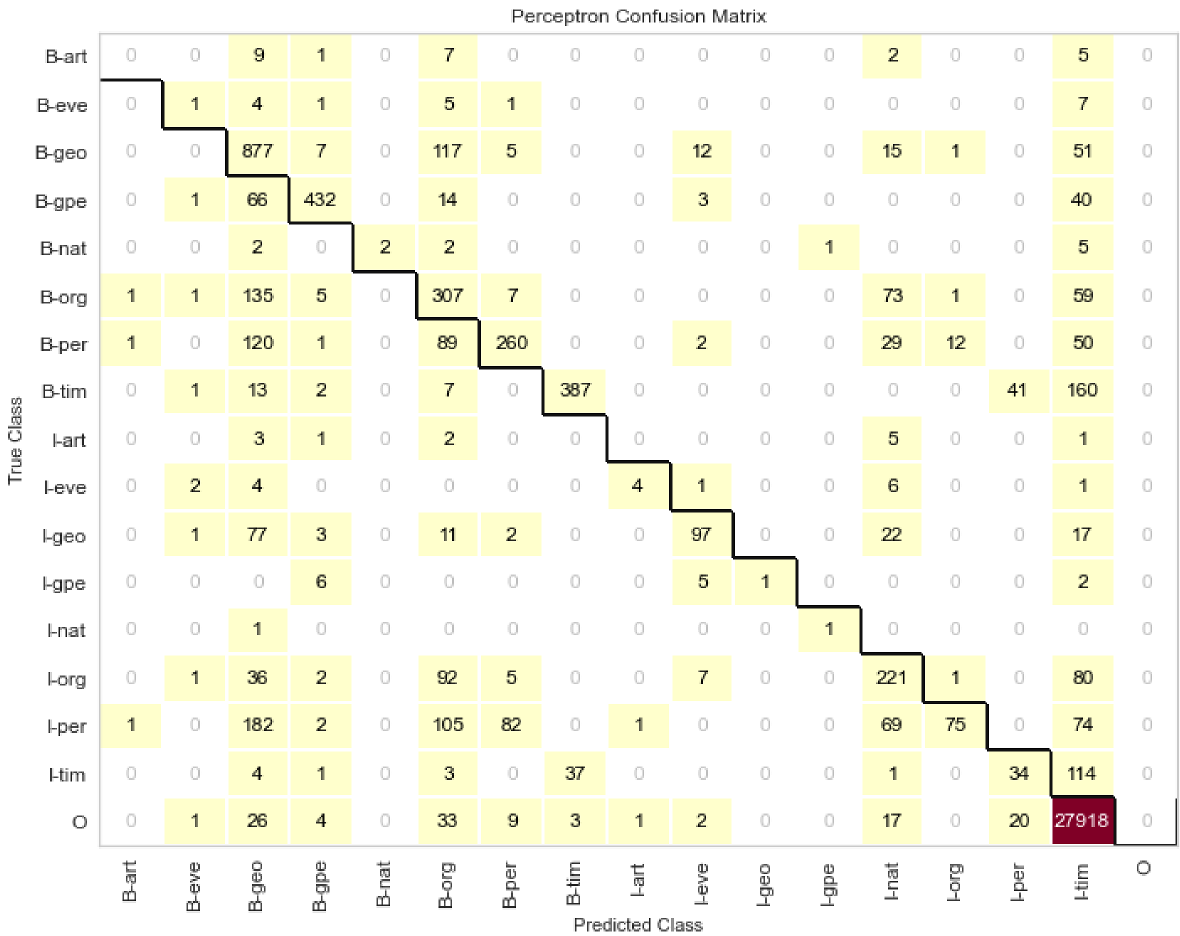
In [42]:
```python
classification_per = classification_report(y_pred=perceptron.predict(X_test), y_tru
per_acc_Train =accuracy_score(y_true=y_train, y_pred=perceptron.predict(X_train))
per_acc_Test =accuracy_score(y_true=y_test, y_pred=perceptron.predict(X_test))
print(classification_per)
print('Accuracy Score on Train data:', per_acc_Train)
print('Accuracy Score on Test data:', per_acc_Test)
cm_per= ConfusionMatrix(perceptron, classes=classes)
cm_per.score(X_test, y_test)
cm_per.show()
```

```
              precision    recall  f1-score   support

       B-art       0.00      0.00      0.00        24
       B-eve       0.11      0.05      0.07        19
       B-geo       0.56      0.81      0.66      1085
       B-gpe       0.92      0.78      0.84       556
       B-nat       1.00      0.17      0.29        12
       B-org       0.39      0.52      0.44       589
       B-per       0.70      0.46      0.56       564
       B-tim       0.91      0.63      0.75       611
       I-art       0.00      0.00      0.00        12
       I-eve       0.67      0.22      0.33        18
       I-geo       0.75      0.42      0.54       230
       I-gpe       1.00      0.07      0.13        14
       I-nat       0.50      0.50      0.50         2
       I-org       0.48      0.50      0.49       445
       I-per       0.83      0.13      0.22       591
       I-tim       0.36      0.18      0.24       194
           O       0.98      1.00      0.99     28034

    accuracy                           0.93     33000
   macro avg       0.60      0.38      0.41     33000
weighted avg       0.93      0.93      0.92     33000

Accuracy Score on Train data: 0.9525671641791045
Accuracy Score on Test data: 0.9277878787878788
```



Out[42]: <AxesSubplot:title={'center':'Perceptron Confusion Matrix'}, xlabel='Predicted Class', ylabel='True Class'>

Linear classifiers with SGD training

In [43]:
```
sgd_classifier = SGDClassifier()
sgd_classifier.partial_fit(X_train, y_train, classes)
```

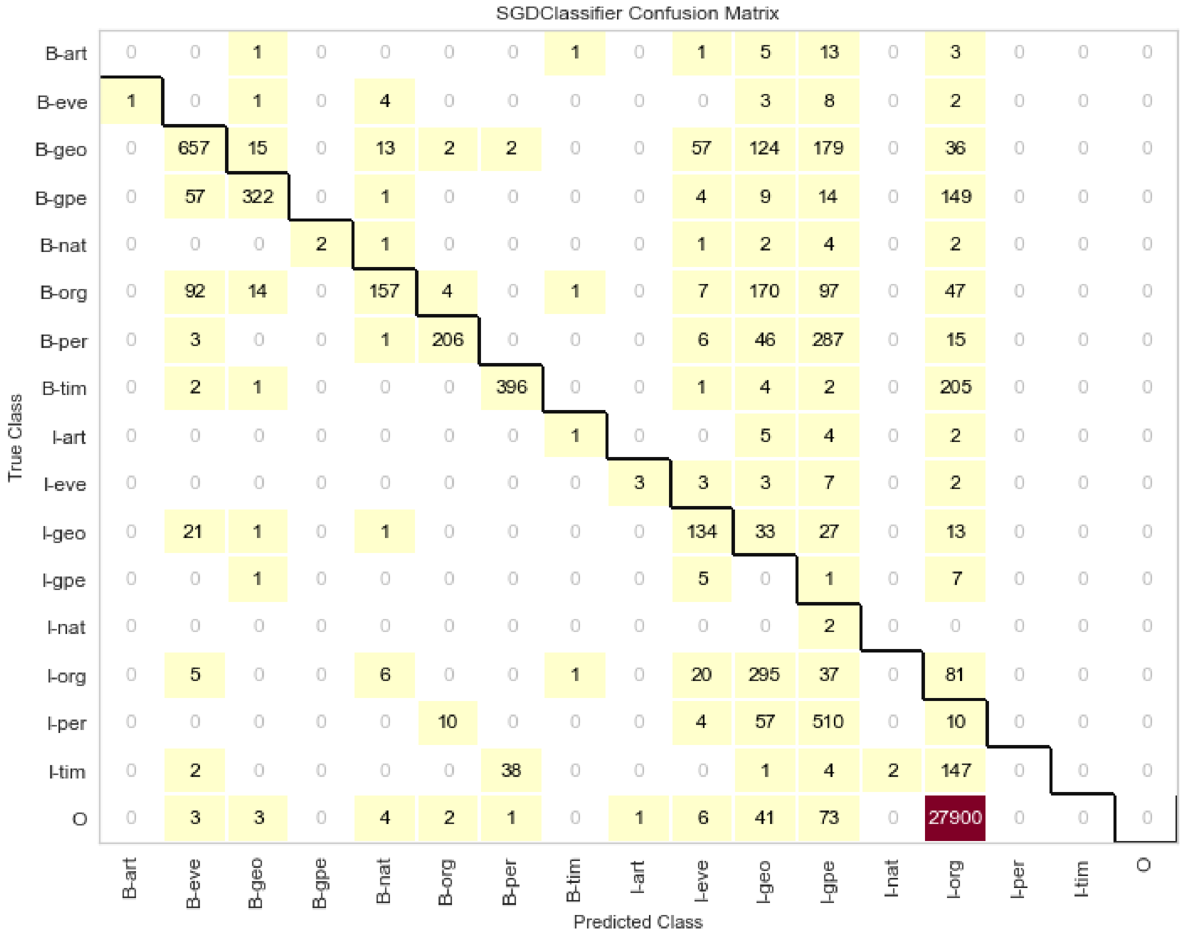
```
classification_sgd = classification_report(y_pred=sgd_classifier.predict(X_test), y
print(classification_sgd)
sgd_acc_train=accuracy_score(y_true=y_train, y_pred=sgd_classifier.predict(X_train
sgd_acc_test= accuracy_score(y_true=y_test, y_pred=sgd_classifier.predict(X_test))
print('Accuracy Score on Train data:',sgd_acc_train )
print('Accuracy Score on Test data:', sgd_acc_test)
cm_sgd = ConfusionMatrix(sgd_classifier, classes=classes)
cm_sgd.score(X_test, y_test)
cm_sgd.show()
```

```
              precision    recall  f1-score   support

       B-art       0.00      0.00      0.00        24
       B-eve       1.00      0.05      0.10        19
       B-geo       0.78      0.61      0.68      1085
       B-gpe       0.90      0.58      0.70       556
       B-nat       1.00      0.17      0.29        12
       B-org       0.84      0.27      0.40       589
       B-per       0.92      0.37      0.52       564
       B-tim       0.91      0.65      0.76       611
       I-art       0.25      0.08      0.12        12
       I-eve       0.75      0.17      0.27        18
       I-geo       0.54      0.58      0.56       230
       I-gpe       0.00      0.00      0.00        14
       I-nat       0.00      0.00      0.00         2
       I-org       0.37      0.66      0.47       445
       I-per       0.40      0.86      0.55       591
       I-tim       1.00      0.01      0.02       194
           O       0.97      1.00      0.98     28034

    accuracy                           0.93     33000
   macro avg       0.62      0.36      0.38     33000
weighted avg       0.94      0.93      0.92     33000

Accuracy Score on Train data: 0.9376417910447761
Accuracy Score on Test data: 0.9268484848484848
```



Out[43]:
```
<AxesSubplot:title={'center':'SGDClassifier Confusion Matrix'}, xlabel='Predicted Class', ylabel='True Class'>
```

Naive Bayes classifier for multinomial models

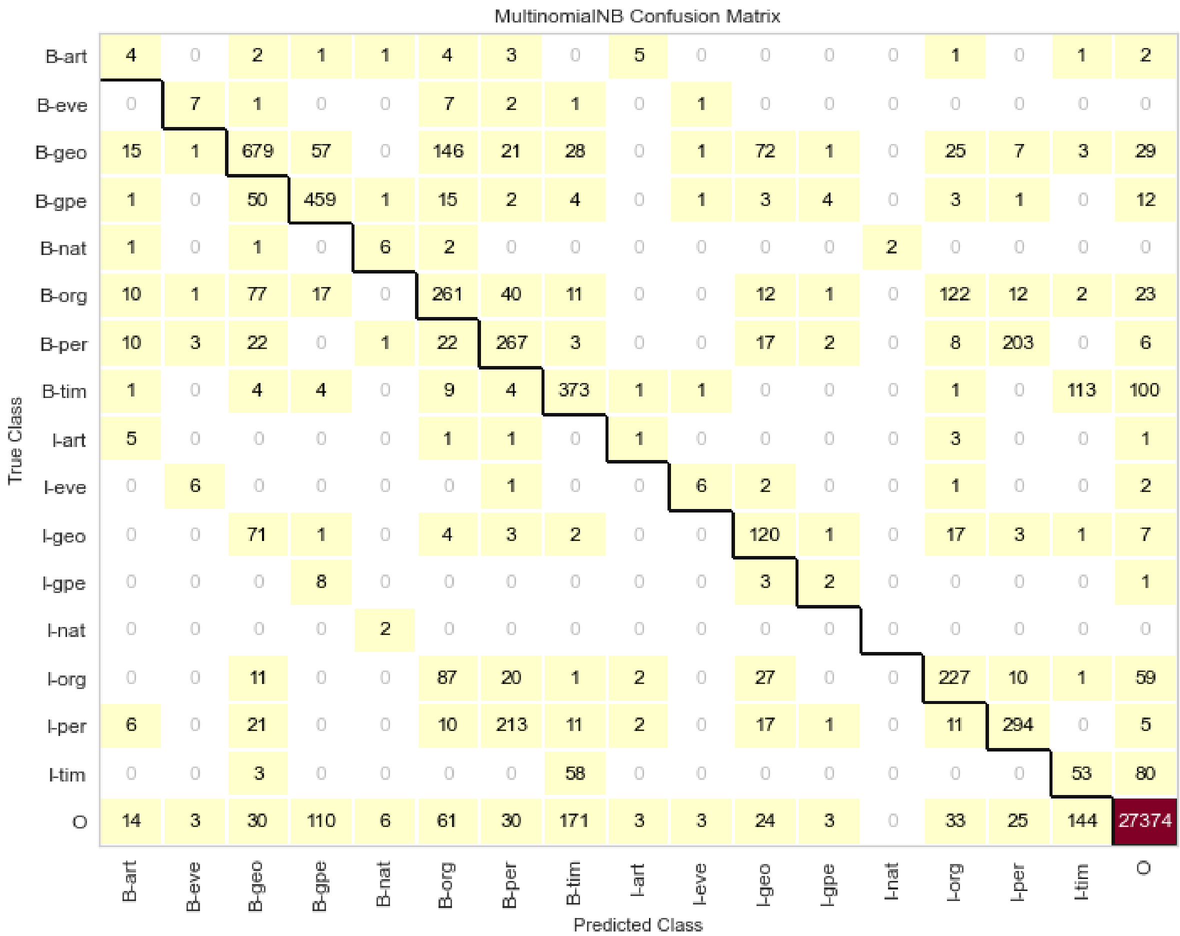
In [44]:
```
naive_bayes = MultinomialNB(alpha=0.01)
naive_bayes.partial_fit(X_train, y_train, classes)
classification_naive_bayes = classification_report(y_pred=naive_bayes.predict(X_te
print(classification_naive_bayes)
nb_acc_train =accuracy_score(y_true=y_train, y_pred=naive_bayes.predict(X_train))
nb_acc_test = accuracy_score(y_true=y_test, y_pred=naive_bayes.predict(X_test))
print('Accuracy Score on Train data:',nb_acc_train )
print('Accuracy Score on Test data:', nb_acc_test)
cm_nb = ConfusionMatrix(naive_bayes, classes=classes)
cm_nb.score(X_test, y_test)
cm_nb.show()
```

```
              precision    recall  f1-score   support

       B-art       0.06      0.17      0.09        24
       B-eve       0.33      0.37      0.35        19
       B-geo       0.70      0.63      0.66      1085
       B-gpe       0.70      0.83      0.76       556
       B-nat       0.35      0.50      0.41        12
       B-org       0.41      0.44      0.43       589
       B-per       0.44      0.47      0.46       564
       B-tim       0.56      0.61      0.59       611
       I-art       0.07      0.08      0.08        12
       I-eve       0.46      0.33      0.39        18
       I-geo       0.40      0.52      0.46       230
       I-gpe       0.13      0.14      0.14        14
       I-nat       0.00      0.00      0.00         2
       I-org       0.50      0.51      0.51       445
       I-per       0.53      0.50      0.51       591
       I-tim       0.17      0.27      0.21       194
           O       0.99      0.98      0.98     28034

    accuracy                           0.91     33000
   macro avg       0.40      0.43      0.41     33000
weighted avg       0.92      0.91      0.92     33000

Accuracy Score on Train data: 0.9763582089552238
Accuracy Score on Test data: 0.9131212121212121
```



Out[44]: <AxesSubplot:title={'center':'MultinomialNB Confusion Matrix'}, xlabel='Predicted Class', ylabel='True Class'>

Using Passive Aggressive Classifier

In [45]:

```
paclass = PassiveAggressiveClassifier(max_iter=1000, random_state=0,n_jobs=-1)
paclass.partial_fit(X_train, y_train, classes)
```

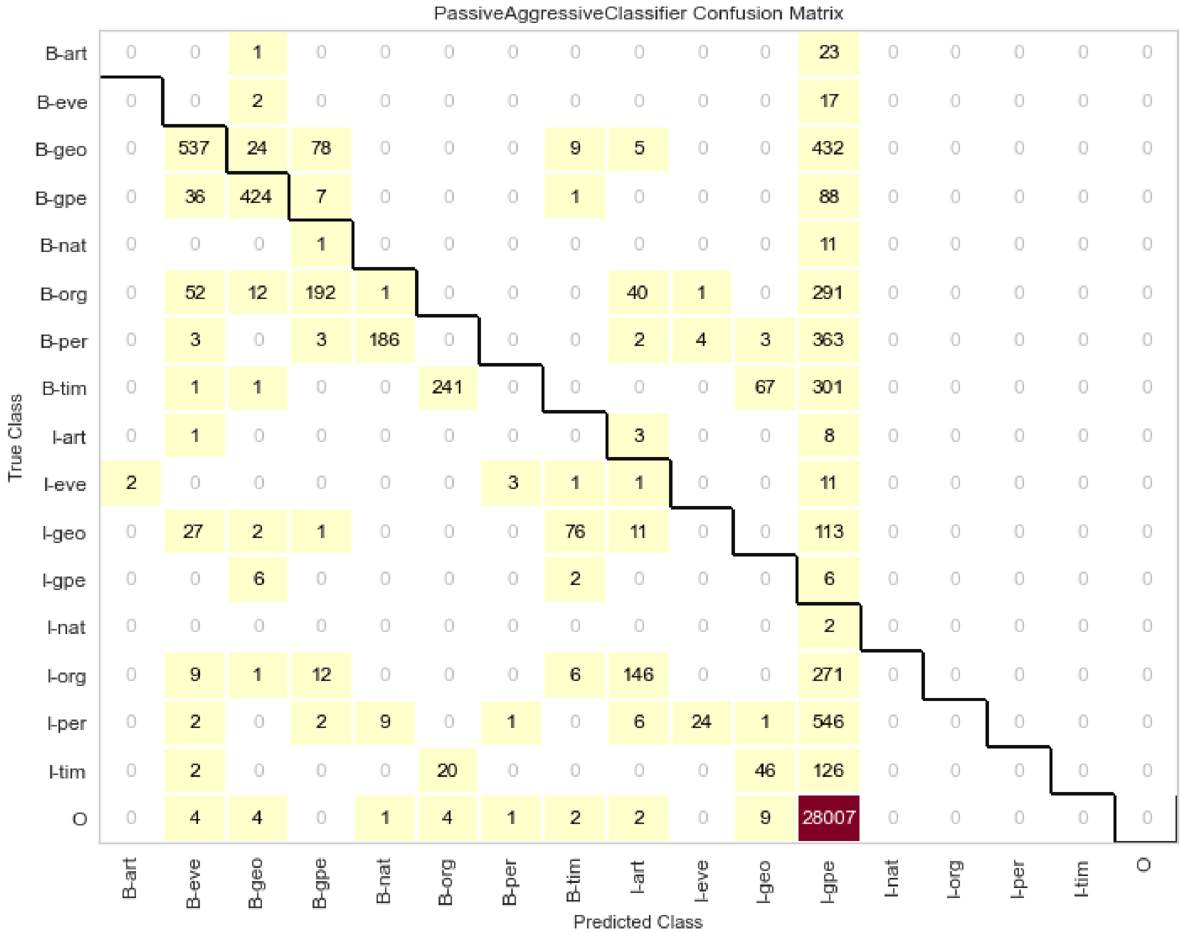
```
classification_paclass = classification_report(y_pred=paclass.predict(X_test), y_tı
print(classification_paclass)
paclass_acc_train =accuracy_score(y_true=y_train, y_pred=paclass.predict(X_train))
paclass_acc_test = accuracy_score(y_true=y_test, y_pred=paclass.predict(X_test))
print('Accuracy Score on Train data:',paclass_acc_train )
print('Accuracy Score on Test data:', paclass_acc_test)
paclass = ConfusionMatrix(paclass, classes=classes)
paclass.score(X_test, y_test)
paclass.show()
```

```
              precision    recall  f1-score   support

       B-art       0.00      0.00      0.00        24
       B-eve       0.00      0.00      0.00        19
       B-geo       0.80      0.49      0.61      1085
       B-gpe       0.89      0.76      0.82       556
       B-nat       0.00      0.00      0.00        12
       B-org       0.65      0.33      0.43       589
       B-per       0.94      0.33      0.49       564
       B-tim       0.91      0.39      0.55       611
       I-art       0.00      0.00      0.00        12
       I-eve       0.60      0.17      0.26        18
       I-geo       0.78      0.33      0.46       230
       I-gpe       0.00      0.00      0.00        14
       I-nat       0.00      0.00      0.00         2
       I-org       0.68      0.33      0.44       445
       I-per       0.83      0.04      0.08       591
       I-tim       0.37      0.24      0.29       194
           O       0.91      1.00      0.96     28034

    accuracy                           0.91     33000
   macro avg       0.49      0.26      0.32     33000
weighted avg       0.89      0.91      0.88     33000

Accuracy Score on Train data: 0.9214776119402985
Accuracy Score on Test data: 0.9055151515151515
```



Out[45]:
```
<AxesSubplot:title={'center':'PassiveAggressiveClassifier Confusion Matrix'}, xlab
el='Predicted Class', ylabel='True Class'>
```

Using Bidirectional LSTM

In [46]:
```python
import tensorflow as tf
import matplotlib.pyplot as plt
```

In [47]:
```python
data = pd.read_csv('Data\data.csv', encoding='latin1')
data = data.fillna(method='ffill')
data.head(10)
```

Out[47]:

	Sentence #	Word	POS	Tag
0	Sentence: 1	Thousands	NNS	O
1	Sentence: 1	of	IN	O
2	Sentence: 1	demonstrators	NNS	O
3	Sentence: 1	have	VBP	O
4	Sentence: 1	marched	VBN	O
5	Sentence: 1	through	IN	O
6	Sentence: 1	London	NNP	B-geo
7	Sentence: 1	to	TO	O
8	Sentence: 1	protest	VB	O
9	Sentence: 1	the	DT	O

Retrieve sentences and corresponding tags

In [48]:
```
#This function will group and bind all the sentences
class Sentence_Getter(object):
    def __init__(self, df):
        self.n_sent = 1
        self.df = df
        agg_func = lambda s: [(w, p, t) for w, p, t in zip(s['Word'].values.tolist
                                                           s['POS'].values.tolist()
                                                           s['Tag'].values.tolist()
        self.grouped = self.df.groupby('Sentence #').apply(agg_func)
        self.sentences = [s for s in self.grouped]
```

In [49]:
```
decouple = Sentence_Getter(data)
sentences = decouple.sentences
```

In [50]:
```
sentences[0]
```

Out[50]:
```
[('Thousands', 'NNS', 'O'),
 ('of', 'IN', 'O'),
 ('demonstrators', 'NNS', 'O'),
 ('have', 'VBP', 'O'),
 ('marched', 'VBN', 'O'),
 ('through', 'IN', 'O'),
 ('London', 'NNP', 'B-geo'),
 ('to', 'TO', 'O'),
 ('protest', 'VB', 'O'),
 ('the', 'DT', 'O'),
 ('war', 'NN', 'O'),
 ('in', 'IN', 'O'),
 ('Iraq', 'NNP', 'B-geo'),
 ('and', 'CC', 'O'),
 ('demand', 'VB', 'O'),
 ('the', 'DT', 'O'),
 ('withdrawal', 'NN', 'O'),
 ('of', 'IN', 'O'),
 ('British', 'JJ', 'B-gpe'),
 ('troops', 'NNS', 'O'),
 ('from', 'IN', 'O'),
 ('that', 'DT', 'O'),
 ('country', 'NN', 'O'),
 ('.', '.', 'O')]
```

Define mappings between sentences and tags

In [51]:
```
words = list(set(data['Word'].values))
words.append('ENDPAD')
num_words = len(words)
tags = list(set(data['Tag'].values))
num_tags = len(tags)
word2idx = {w: i+1 for i, w in enumerate(words)}
tag2idx = {t: i for i, t in enumerate(tags)}
```

Padding input sentences and creating train/test split

In [52]:
```
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.utils import to_categorical

maximum_len = 50
X = [[word2idx[w[0]] for w in s] for s in sentences]
```

```
X = pad_sequences(maxlen = maximum_len, sequences = X, padding='post', value=num_wo

y = [[tag2idx[w[2]] for w in s] for s in sentences]
y = pad_sequences(maxlen = maximum_len, sequences = y, padding = 'post', value = ta
y = [to_categorical(i, num_classes=num_tags) for i in y]
```

In [53]:
```
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.1, random_sta
```

Build and compile a Bidirectional LSTM model

In [54]:
```
from tensorflow.keras import Model, Input
from tensorflow.keras.layers import LSTM, Embedding, Dense
from tensorflow.keras.layers import TimeDistributed, SpatialDropout1D, Bidirectiona
```

In [55]:
```
input_word = Input(shape=(maximum_len, ))
model = Embedding(input_dim = num_words, output_dim = maximum_len, input_length = m
model = SpatialDropout1D(0.1)(model)
model = Bidirectional(LSTM(units=100, return_sequences=True, recurrent_dropout=0.1
out = TimeDistributed(Dense(num_tags, activation='softmax'))(model)
model = Model(input_word, out)
model.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 input_1 (InputLayer)        [(None, 50)]              0         
                                                                 
 embedding (Embedding)       (None, 50, 50)            1758950   
                                                                 
 spatial_dropout1d (SpatialD  (None, 50, 50)           0         
 ropout1D)                                                       
                                                                 
 bidirectional (Bidirectiona  (None, 50, 200)          120800    
 l)                                                              
                                                                 
 time_distributed (TimeDistr  (None, 50, 17)           3417      
 ibuted)                                                         
                                                                 
=================================================================
Total params: 1,883,167
Trainable params: 1,883,167
Non-trainable params: 0
_________________________________________________________________
```

In [56]:
```
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy
```

Train the model

In [57]:
```
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping
from livelossplot.tf_keras import PlotLossesCallback
```

In [58]:
```
early_stopping = EarlyStopping(monitor='val_accuracy', patience=1, verbose=0, mode=
callbacks = [PlotLossesCallback(), early_stopping]

history = model.fit(
    x_train, np.array(y_train),
    validation_split=0.2,
    batch_size = 64,
    epochs = 5,
```

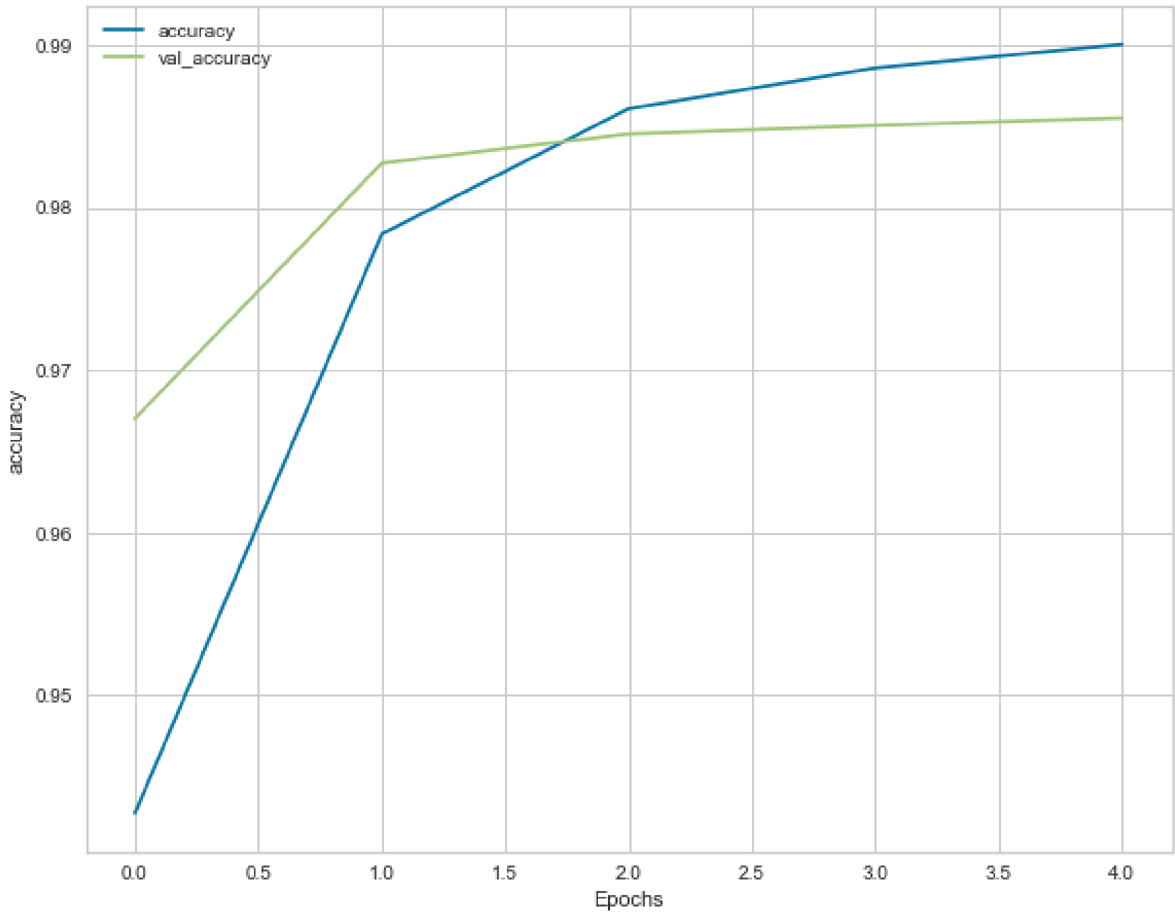
```
    verbose = 1,
)
```

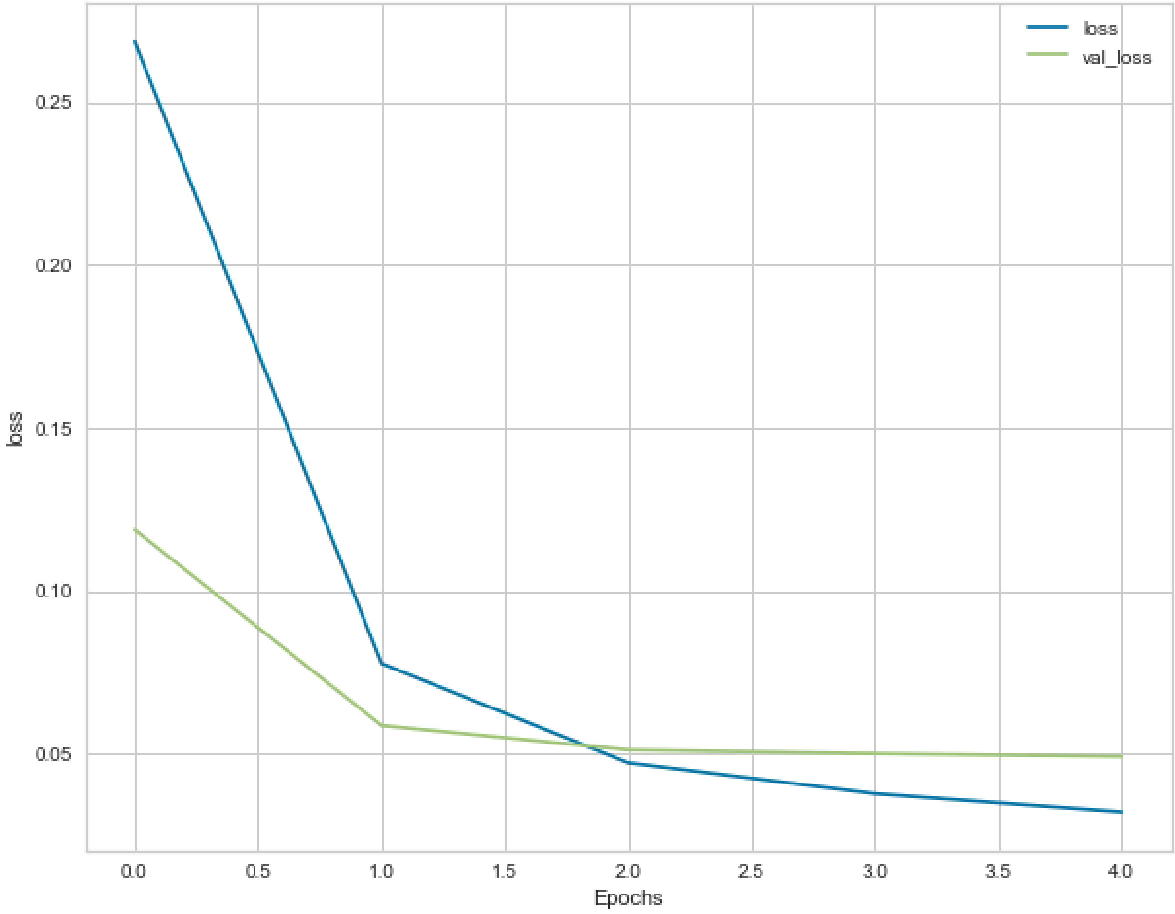
```
Epoch 1/5
540/540 [==============================] - 74s 120ms/step - loss: 0.2684 - accurac
y: 0.9428 - val_loss: 0.1188 - val_accuracy: 0.9670
Epoch 2/5
540/540 [==============================] - 60s 111ms/step - loss: 0.0778 - accurac
y: 0.9784 - val_loss: 0.0588 - val_accuracy: 0.9827
Epoch 3/5
540/540 [==============================] - 60s 111ms/step - loss: 0.0473 - accurac
y: 0.9861 - val_loss: 0.0513 - val_accuracy: 0.9845
Epoch 4/5
540/540 [==============================] - 60s 111ms/step - loss: 0.0379 - accurac
y: 0.9886 - val_loss: 0.0501 - val_accuracy: 0.9851
Epoch 5/5
540/540 [==============================] - 63s 117ms/step - loss: 0.0323 - accurac
y: 0.9900 - val_loss: 0.0493 - val_accuracy: 0.9855
```

In [59]:

```
def plot_graphs(history, string):
    plt.plot(history.history[string])
    plt.plot(history.history['val_'+string])
    plt.xlabel("Epochs")
    plt.ylabel(string)
    plt.legend([string, 'val_'+string])
    plt.show()

plot_graphs(history, "accuracy")
plot_graphs(history, "loss");
```





Here we can see the model is able to get to accuracy of more than 98.5 % which is very good

In [60]:
```
lstm_acc=model.evaluate(x_test, np.array(y_test))
lstm_acc=lstm_acc[1]
print (lstm_acc)
```

```
150/150 [==============================] - 3s 22ms/step - loss: 0.0510 - accuracy:
0.9851
0.9851251244544983
```

In [61]:
```
print('Accuracy of Perceptron :', round(per_acc_Test*100))
print('Accuracy of SGD :', round(sgd_acc_test*100))
print('Accuracy of Naive Bayes :', round(nb_acc_test*100))
print('Accuracy of Passive-Aggressive :', round(paclass_acc_test*100))
print ("Accuracy of LSTM: " , round(lstm_acc*100))
```

```
Accuracy of Perceptron : 93
Accuracy of SGD : 93
Accuracy of Naive Bayes : 91
Accuracy of Passive-Aggressive : 91
Accuracy of LSTM:  99
```

Changing Test- Train Split

In [62]:
```
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_st
```

In [63]:
```
early_stopping = EarlyStopping(monitor='val_accuracy', patience=1, verbose=0, mode=
callbacks = [PlotLossesCallback(), early_stopping]

history = model.fit(
    x_train, np.array(y_train),
```

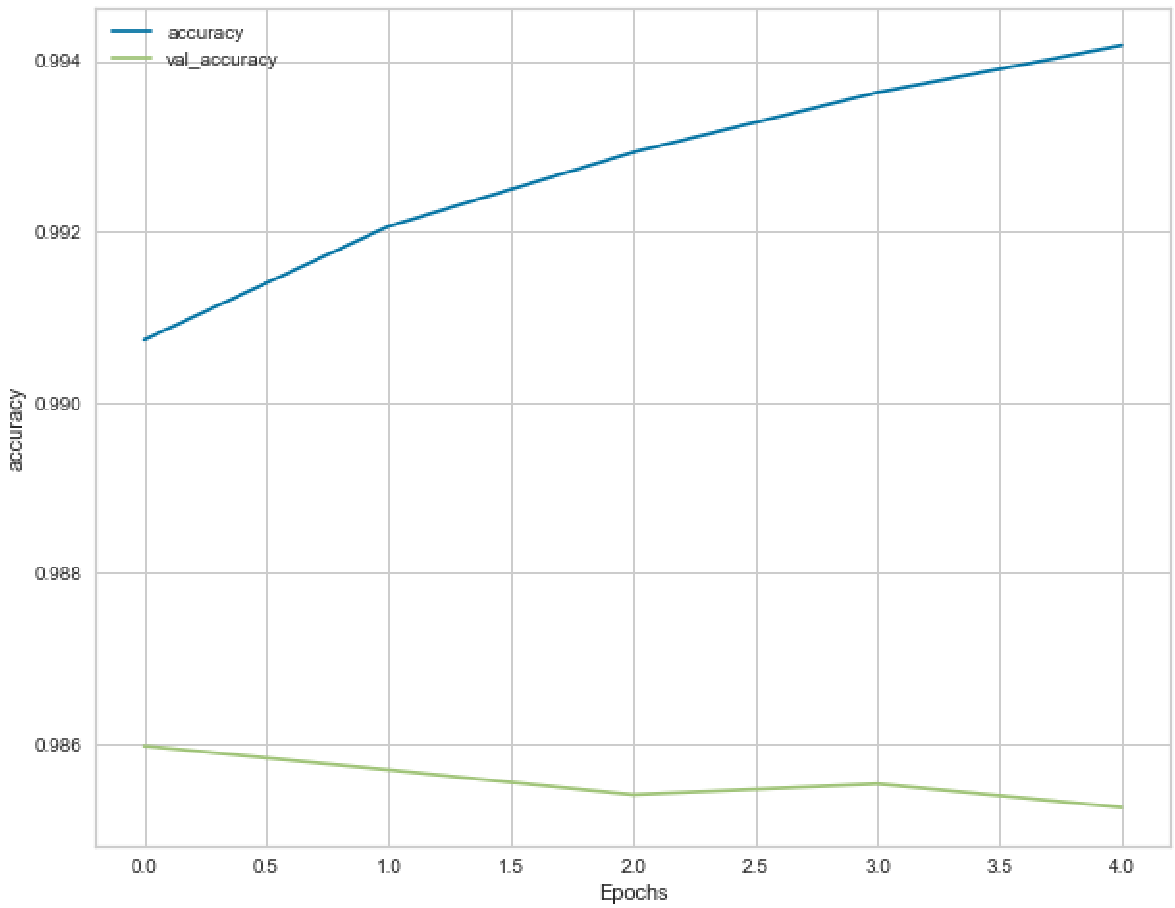
```
    validation_split=0.2,
    batch_size = 64,
    epochs = 5,
    verbose = 1,
)
```

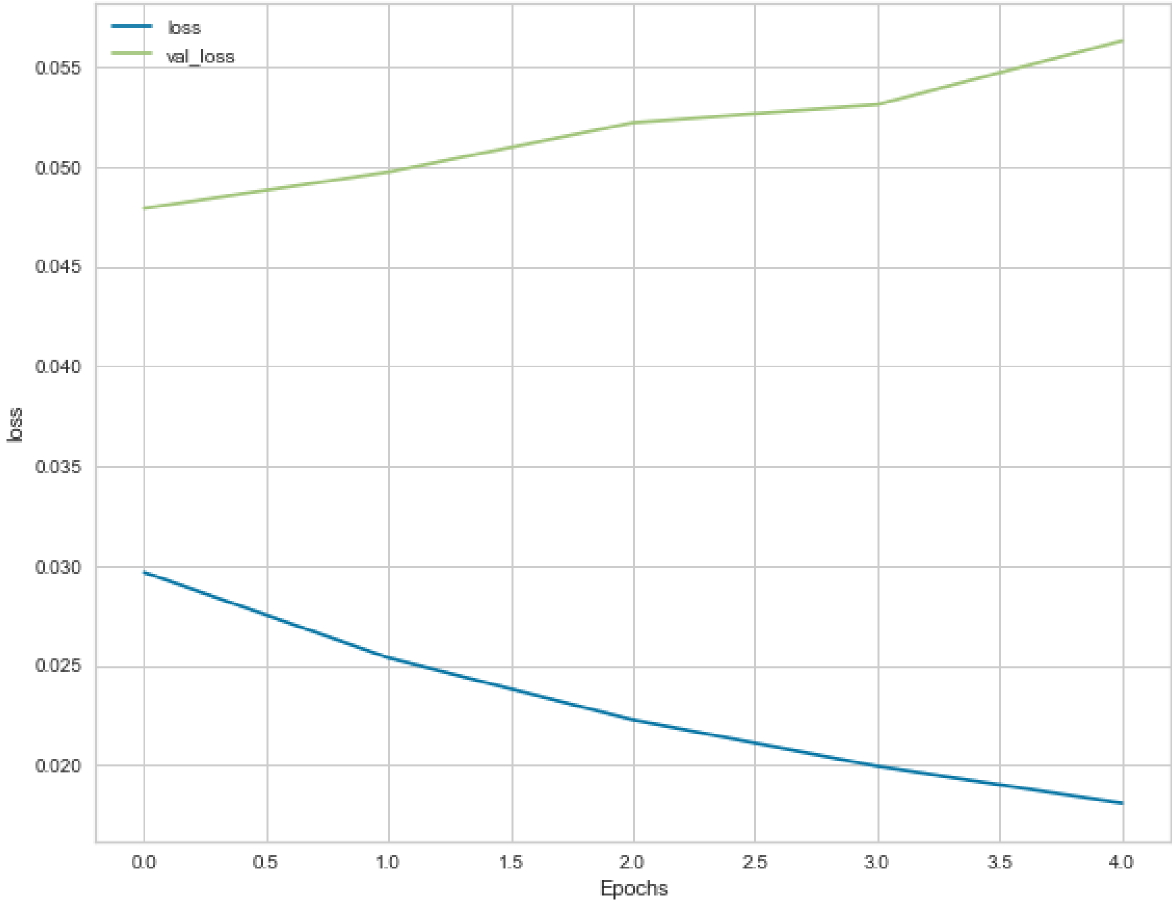
```
Epoch 1/5
420/420 [==============================] - 51s 121ms/step - loss: 0.0297 - accurac
y: 0.9907 - val_loss: 0.0479 - val_accuracy: 0.9860
Epoch 2/5
420/420 [==============================] - 51s 121ms/step - loss: 0.0254 - accurac
y: 0.9921 - val_loss: 0.0497 - val_accuracy: 0.9857
Epoch 3/5
420/420 [==============================] - 51s 121ms/step - loss: 0.0223 - accurac
y: 0.9929 - val_loss: 0.0522 - val_accuracy: 0.9854
Epoch 4/5
420/420 [==============================] - 51s 121ms/step - loss: 0.0199 - accurac
y: 0.9936 - val_loss: 0.0531 - val_accuracy: 0.9855
Epoch 5/5
420/420 [==============================] - 51s 121ms/step - loss: 0.0181 - accurac
y: 0.9942 - val_loss: 0.0563 - val_accuracy: 0.9853
```

In [64]:

```
def plot_graphs(history, string):
    plt.plot(history.history[string])
    plt.plot(history.history['val_'+string])
    plt.xlabel("Epochs")
    plt.ylabel(string)
    plt.legend([string, 'val_'+string])
    plt.show()

plot_graphs(history, "accuracy")
plot_graphs(history, "loss");
```





In [65]:
```
lstm_acc=model.evaluate(x_test, np.array(y_test))
lstm_acc=lstm_acc[1]
print(lstm_acc*100)
```

```
450/450 [==============================] - 7s 15ms/step - loss: 0.0423 - accuracy:
0.9883
98.83416891098022
```

Here i tried to change the Test Train split and was only able to get 0.5% increase in accuracy . Although these gains are small when the accuarcy is in high 90's these small increases are very diffuclt so its a good increse in accuracy

Comparing Different Models

Making a Sentance from the Data set

In [66]:
```
def make_sentance (sent) :  # Takes a array of words and returns a setance so can l
    length = len(sent)
    for i in range(length) :
        if i == 0 :
            final = sent[i]
        else :
            final = final +" "+ sent[i]
    return final + " ."
```

Making a function that compares LSTM with Spacy NER and TEXT-API

In [67]:
```
def expermnt (count,nltk_flag,text_flag):
    for z in range(count):
            print("-"*15,z+1,"-"*15)
            i = np.random.randint(0, x_test.shape[0]) # Getting a random sentance i
```

```
            p = model.predict(np.array([x_test[i]])) #Predicting using LSTM
            p = np.argmax(p, axis=-1) # Conberting from vectoers to tag
            random_sent = []
            r_sent = ''
            y_true = np.argmax(np.array(y_test), axis=-1)[i]
            print ("Using LSTM")
            print('-'*30)
            print('{:15}{:5}\t {}'.format('Word', 'True', 'Pred'))
            print('-'*30)
            for w, true, pred in zip(x_test[i], y_true, p[0]):
                if (words[w-1] == '.'):
                    break
                else :
                    print('{:15}{}\t{}'.format(words[w-1], tags[true], tags[pred]))
                    random_sent.append(words[w-1])
            r_sent = make_sentance(random_sent)
            print('-'*30)
            print ("Using Spacy")
            print('-'*30)
            spacy_ner(r_sent)
            if (nltk_flag ==1 ) :
                print('-'*30)
                print(" Using NLTK\n")
                print('-'*30)
                ner_nltk(r_sent)
            if (text_flag ==1 ) :
                print('-'*30)
                print("Using text\n")
                text_api(r_sent)
                print('-'*30)
```

In [68]:
```
expermnt(5,1,1)
```

```
--------------- 1 ---------------
Using LSTM
------------------------------
Word           True      Pred
------------------------------
It             O         O
will           O         O
produce        O         O
plutonium      O         O
once           O         O
it             O         O
is             O         O
completed      O         O
------------------------------
Using Spacy
------------------------------
------------------------------
 Using NLTK

------------------------------
------------------------------
Using text

[]
------------------------------
--------------- 2 ---------------
Using LSTM
------------------------------
Word           True      Pred
------------------------------
Five           O         O
Philippine     B-org     B-org
legislators    O         O
accused        O         O
of             O         O
plotting       O         O
a              O         O
coup           O         O
against        O         O
the            O         O
president      O         O
have           O         O
emerged        O         O
from           O         O
the            O         O
Congress       B-org     B-org
building       O         O
where          O         O
they           O         O
took           O         O
refuge         O         O
more           O         O
than           O         O
two            B-tim     O
months         O         O
ago            O         O
------------------------------
Using Spacy
------------------------------
Five CARDINAL
Philippine NORP
Congress ORG
more than two months ago DATE
------------------------------
```

```
 Using NLTK

------------------------------
(ORGANIZATION Congress/NNP)
------------------------------
Using text

[['ORG', 'Congress'], ['DATE', 'more than two months ago']]
------------------------------
--------------- 3 ---------------
Using LSTM
------------------------------
Word           True      Pred
------------------------------
In             O        O
1997           B-tim    B-tim
,              O        O
the            O        O
IMF            B-org    B-org
suspended      O        O
Kenya          B-geo    B-org
's             O        O
Enhanced       B-org    B-org
Structural     I-org    I-org
Adjustment     I-org    I-org
Program        I-org    I-org
due            O        O
to             O        O
the            O        O
government     O        O
's             O        O
failure        O        O
to             O        O
maintain       O        O
reforms        O        O
and            O        O
curb           O        O
corruption     O        O
------------------------------
Using Spacy
------------------------------
1997 DATE
IMF ORG
Kenya GPE
Enhanced Structural Adjustment Program ORG
------------------------------
 Using NLTK

------------------------------
(ORGANIZATION IMF/NNP)
(PERSON Kenya/NNP)
(ORGANIZATION Enhanced/NNP Structural/NNP Adjustment/NNP)
------------------------------
Using text

[['DATE', '1997'], ['ORG', 'IMF'], ['ORG', 'Enhanced Structural Adjustment Progra
m']]
------------------------------
--------------- 4 ---------------
Using LSTM
------------------------------
Word           True      Pred
------------------------------
Another        O        O
```

```
former         O       O
president      O       O
,              O       O
Leslie         B-per   B-per
Manigat        I-per   I-per
,              O       O
is             O       O
second         O       O
with           O       O
12             O       O
percent        O       O
------------------------------
Using Spacy
------------------------------
Leslie Manigat PERSON
second ORDINAL
12 percent PERCENT
------------------------------
 Using NLTK

------------------------------
(PERSON Leslie/NNP Manigat/NNP)
------------------------------
Using text

[['PERSON', 'Leslie Manigat']]
------------------------------
--------------- 5 ---------------
Using LSTM
------------------------------
Word           True     Pred
------------------------------
The            O       O
Institute      B-org   B-org
for            I-org   I-org
Science        I-org   I-org
and            I-org   I-org
International  I-org   I-org
Security       I-org   I-org
reports        O       O
that           O       O
satellite      O       O
photos         O       O
show           O       O
a              O       O
possible       O       O
construction   O       O
site           O       O
for            O       O
a              O       O
larger         O       O
nuclear        O       O
reactor        O       O
near           O       O
the            O       O
small          O       O
one            O       O
in             O       O
the            O       B-geo
Khushab        B-geo   B-geo
district       O       O
of             O       O
Punjab         B-geo   B-geo
province       O       O
```

```
-----------------------------
Using Spacy
-----------------------------
The Institute for Science and International Security ORG
Khushab PERSON
-----------------------------
 Using NLTK

-----------------------------
(ORGANIZATION Institute/NNP)
(ORGANIZATION Science/NNP)
(ORGANIZATION International/NNP)
(ORGANIZATION Khushab/NNP)
(GPE Punjab/NNP)
-----------------------------
Using text

[['ORG', 'The Institute for Science and International Security']]
-----------------------------
```

Dialogue Flow Manager

For Dialogue Flow manager I will be doing a simple heurustic , Which based on the Intent and NER will try to guess the next response.

I did this as part of the Group Course work and will explain how it works in detail

note - The required code to train and save is submitted as additional file in supporting Documents

Here i have two functions

ner_function - Here spacy is used to create a prebuilt model that identifies tags such as RESTAURANT_NAME , RESTAURANT_TYPE , CAMPUS_NAME , TIME

intent_function - Here a cnn model is used to create a model that predicts intents like "info_timings" , "info_location" , "info_type" , "greetings" , "goodbye"

In [70]:
```
class ner_function():
    def load_ner():#Loads the model
        import spacy
        from spacy.tokens import DocBin
        from tqdm import tqdm
        global nlp_ner
        nlp_ner = spacy.load("Models/model-best")
    def get_ner(sent,tag):
        flag =0
        doc = nlp_ner(sent)
        for ent in doc.ents:
            if ent.label_ == tag:
                return (ent.text)
                flag =1
        if flag == 0:
            return("NO_ENTITY_FOUND")
```

In [76]:
```
class intent_function():
    from keras.preprocessing.sequence import pad_sequences
    def load_intent():#Loads the model
```

```
        import pickle
        import numpy as np
        from keras.models import load_model
        from keras.preprocessing.sequence import pad_sequences
        global model
        model=load_model('Models/models/intents.h5')
        with open('Models/utils/classes.pkl', 'rb') as file:
            global classes
            classes=pickle.load(file)
        with open('Models/utils/tokenizer.pkl', 'rb') as file:
            global tokenizer
            tokenizer=pickle.load(file)
        with open('Models/utils/label_encoder.pkl', 'rb') as file:
            global label_encoder
            label_encoder=pickle.load(file)
    def get_intent(senttt):
        from keras.preprocessing.sequence import pad_sequences
        import numpy as np
        class IntentClassifier:
            from keras.preprocessing.sequence import pad_sequences
            def __init__(self, classes, model, tokenizer, label_encoder):
                self.classes=classes
                self.classifier=model
                self.tokenizer=tokenizer
                self.label_encoder=label_encoder
            def predict_intent(self, text):
                from keras.preprocessing.sequence import pad_sequences
                self.text=[text]
                self.test_keras=self.tokenizer.texts_to_sequences(self.text)
                self.test_keras_sequence=pad_sequences(self.test_keras, maxlen=8, 
                self.pred=self.classifier.predict(self.test_keras_sequence)
                return label_encoder.inverse_transform(np.argmax(self.pred, 1))[0]
        nlu=IntentClassifier(classes, model, tokenizer, label_encoder)
        return(nlu.predict_intent(senttt))
```

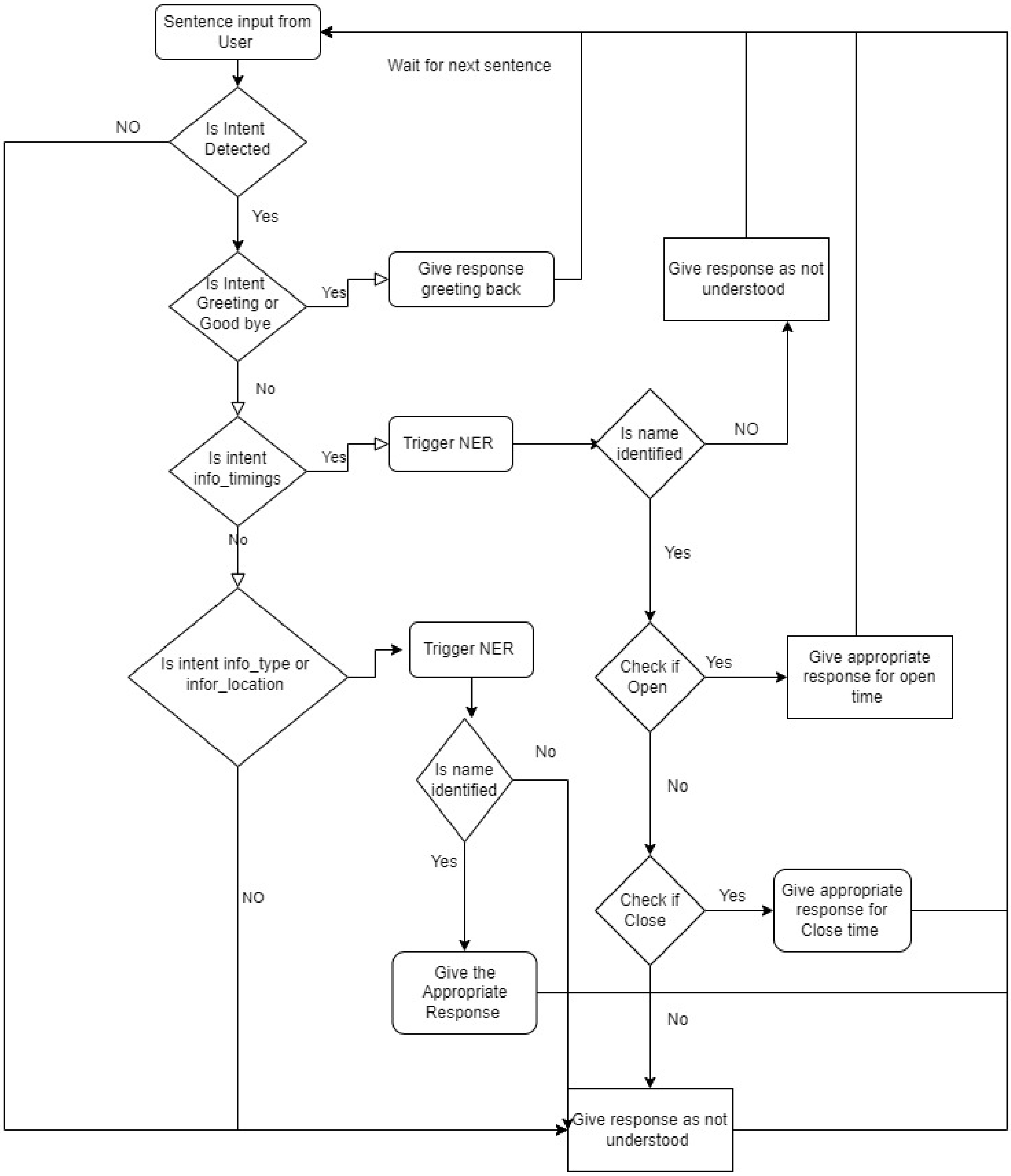
In [73]:

```
def get_info(rest_name,info_needed):
    import ast
    file = open("Data\dictionary.txt", "r")
    contents = file.read()
    dictionary = ast.literal_eval(contents)
    if rest_name in dictionary.keys():#handling for key error
        information = dictionary[rest_name][info_needed]
        return information
    else :
        return  'no_info_found'
```

The above function will get the info like opening times and closing types from the dictionary

This is the main Dialogue flow manager .

The flow can be explained using a flow chart



In [74]:
```
def get_response(intent_detected,sentence):
    import random
    resp_greet =['Hello', 'Heya','Hi','Hi! How are you doing?','Hey!how are you do
    resp_goobye =['Bye Bye!', 'Goodbye','See you!','Bye, it was nice talking to you
    resp_timings =['time','timeess']
    resp_type=['typeeee','typessss']
    resp_locc =['locccc','location']
    sorry = "Sorry i dont understand the question i will prepare well next time"
    if intent_detected == 'greeting':
        return (random.choice(resp_greet))
    elif intent_detected == 'goodbye':
        return (random.choice(resp_goobye))
    elif intent_detected == 'info_timings':
        namess = ner_function.get_ner(sentence,'RESTAURANT_NAME')
        if namess == "NO_ENTITY_FOUND" :
            return (sorry)
        elif 'open' in sentence:
            info_needed = get_info(namess,'info_open')
            if info_needed == 'no_info_found':
                return (sorry)
            else :
                ress = namess + ' opening timings are ' + info_needed
```

```
                return (ress)
        elif 'close' in sentence:
            info_needed = get_info(namess,'info_close')
            if info_needed == 'no_info_found':
                return (sorry)
            else :
                ress = namess + ' Closing timings are ' + info_needed
                return (ress)
    elif intent_detected == 'info_type':
        namess = ner_function.get_ner(sentence,'RESTAURANT_NAME')
        if namess == "NO_ENTITY_FOUND":
            return (sorry)
        else :
            info_needed = get_info(namess,'type')
            if info_needed == 'no_info_found':
                return (sorry)
            else :
                ress = namess + ' is  ' + info_needed
                return (ress)
    elif intent_detected == 'info_location':
        namess = ner_function.get_ner(sentence,'RESTAURANT_NAME')
        if namess == "NO_ENTITY_FOUND":
            return (sorry)
        else :
            info_needed = get_info(namess,'location')
            if info_needed == 'no_info_found':
                return (sorry)
            else :
                ress = namess + ' is located  ' + info_needed
                return (ress)
```

In [78]:

```
bot_name ='infomania'
intent_function.load_intent() #loading the model
ner_function.load_ner() #loading model
print("Hi i am INFORMIA and i will help you find information about restuarants in U
print("Disclaimer :: ---- I am still learning and will get better over time please
print("Let's chat! (type 'quit' to exit)")
bot_name ='infomania'
sent_list=[]
resp_list=[]
intent_list =[]
curr_log=[]
while True:
    # sentence = "do you use credit cards?"
    sentence = input("You: ")
    curr_log.append(('You :' + sentence))
    sent_list.append(sentence)
    if sentence == "quit":
        break

    else:
        intent_detected = intent_function.get_intent(sentence)
        intent_list.append(intent_detected)
        response = get_response(intent_detected,sentence)
        resp_list.append(response)
        print(f"{bot_name}:",response )
        curr_log.append(('infomania :' + response))
```

```
Hi i am INFORMIA and i will help you find information about restuarants in Univert
sity of surrey
Disclaimer :: ---- I am still learning and will get better over time please dont b
e MAD AT ME
Let's chat! (type 'quit' to exit)
```

```
infomania: hillside opening timings are 11:00

infomania: starbucks is located  stag hill

infomania: Heya

infomania: pizzaman Closing timings are 21:45
```

Here we can see the Dialogue flow manager is performing relatively well , This can be further increased by training the intent and NER models to be more efficient and functionality can also be incresed in future by adding more intent classes and NER classes

note - The training and storing of the models and their code is added in the supporting files

Final Explanation and Answering the question

The experiments i have conducted and their outcomes are as follows

Experiment 1 - I tried to understand how different models perform for NER . I have used Prebuilt models like SPACY . NLTK and Text API and classic models like Perceptron , SVM , Passive Agresive Classifier and Naive Bayes and finally LSTM

```
From These i understood that NLTK is very basic and it performs
well for genralised data but fails in specaliased use cases

Text API is a model which is very new and being pursued by small
team and they are adding more and more functionalties

Spacy is by far more advanced and powerful as it allows to train
with custom tags and also provides a base line empty english model
on which we can train our custom models .
and support of pipelines makes it very powerful and also makes it
easy to upgrade the model with new data

Classic alogorithms like Perceptron , SVM , Passive Agressive
Classifier and Naive Bayes are relatively accurtate but they do
require lot of training and they dont have the advantages provided
by Spacy

Bi directional LSTM is very accuarate and also gives very accurate
results but it also wont be able to identify words that it havent
seen before.

After all the experimentation and research i can say for NER Spacy
is very useful powerful and also very versatile.
```

Experiment 2 - For this i have tried changing the Test train split for LSTM

```
I was able to get the accruacy up by 0.5% using 70-30 split. I
have also tried changing the split for classic models but they
havent produced any significant change.
```

I tried using different ways of data pre processing and use the same type of preprocessing for LSTM and classic models but it was not able to achieve this

In order to undertand how different models perform i created a function to experiment and see how they work (expermnt) to compare them

As for Questions

a. “Can the chatbot components you experimented with fulfil their purpose?”

```
Yes all the Components were able to give good results
```

b. “What is good enough accuracy?”

```
In Real life situation NER and intent should be identified at very
high consistancy. So good enough accuracy would be more than 99% .
But this can only be achieved when we have lot of base data and
also good understanding of all sitiation
```

c. If any of the models did not perform well, what is needed to improve?

```
While testing with data sets like ATIS and NER data set the models
performed very well , but when i start building a model to handel
a specific task i understood that more data there is better
results there will be
This is realisation after working in Dialogue flow management and
also during group part of the CW
```

d. If any of the models performed really well, could you make it more efficient and sacrifice some quality?

```
Spacy is one model that has lot of potential in future i would
like to try more using Spacy and pipelines
```

Failed Experimentaiton

In [ ]:
```
r=0
j=0
for i in Ner_list:
    axs = plt.subplots(5,5)
    df1 = data.loc[data['Tag'] == i]
    df2 = df1.groupby('POS').size().reset_index(name='counts')
    df2=df2.sort_values(by=['counts'],ascending=False)
    df2=df2.reset_index(drop=True)
    df3=df2[1:6]
    #print(df3)
    axs[r,j] = df3.plot.bar(x='POS',y='counts',rot=0).set(title=str(('Ner Tag ')+i
    j =j+1
    if j >4:
        r =r +1
        j =0
```

In [ ]:
```
pos = Pos_Tag[1:11]
```

In [ ]:
```
pos_list=pos['POS'].unique()
pos_list
```

In [ ]:
```
def pos_count(df,pos):

    tags=df['Tag'].unique()
    cols.sort()
    POS=[]
    TAG=[]
    count=[]
    count_listt=[]
    for j in tags :
        df1 = df.loc[df['Tag'] == j]
        for i in pos:
                    df2 = df1.loc[df1['POS'] == i]
                    POS.append(i)
                    TAG.append(j)
                    count.append(len(df2))
    count_listt = list(zip(TAG,POS,count))
    return pd.DataFrame(count_listt,columns=['POS', 'TAG','Count'])
```

In [ ]:
```
countttt=pos_count(data,pos_list)
```

In [ ]:
```
countttt
```

In [ ]:
```
wide = countttt.pivot("POS", "TAG", "Count")
print(wide)
ax = wide.plot.bar(rot=0).set(title='Avg length of Words in data')
```

Here we can see

In [ ]:
```

```