NLP Course Work

Individual Submission

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Group - 1

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
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

NER Using Spacy

Considering an example to try different Methods

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

In [1]:
```
ex = 'World Health Organisation announced today that it is spending $100 Million dol
```

In [2]:
```
from spacy import displacy
from collections import Counter
import en_core_web_sm
nlp = en_core_web_sm.load()
```

```
2022-04-28 20:47:13.751214: W tensorflow/stream_executor/platform/default/dso_loade
r.cc:64] Could not load dynamic library 'libcudart.so.11.0'; dlerror: libcudart.so.1
1.0: cannot open shared object file: No such file or directory
2022-04-28 20:47:13.751248: I tensorflow/stream_executor/cuda/cudart_stub.cc:29] Ign
ore above cudart dlerror if you do not have a GPU set up on your machine.
```

In [3]:
```
def spacy_ner(sent):
    doc = nlp(sent)

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

In [4]:
```
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.

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 [5]:
```
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', 'VBD'),
('today', 'NN'), ('that', 'IN'), ('it', 'PRP'), ('is', 'VBZ'), ('spending', 'VBG'),
('$', '$'), ('100', 'CD'), ('Million', 'NNP'), ('dollars', 'NNS'), ('to', 'TO'), ('h
elp', 'VB'), ('with', 'IN'), ('corona', 'JJ'), ('virus', 'NN'), ('vacccination', 'N
N'), ('is', 'VBZ'), ('African', 'JJ'), ('Countries', 'NNS')]
```

In [6]:
```
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 [7]:
```
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 [8]:
```
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 [9]:
```
text_api(ex)
```

```
[['ORG', 'World Health Organisation'], ['DATE', 'today'], ['MONEY', '$100 Million do
llars'], ['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 [10]:

```
import pandas as pd #Importing pandas and numpy
import numpy as np
```

In [11]:

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

Out[11]:

	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 [12]:

```
data = data.fillna(method='ffill')
```

In [13]:

```
data[20:30]
```

Out[13]:

	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

In [14]:
```
data['Sentence #'].nunique(), data.Word.nunique(), data.Tag.nunique()
```

Out[14]:
```
(4544, 10922, 17)
```

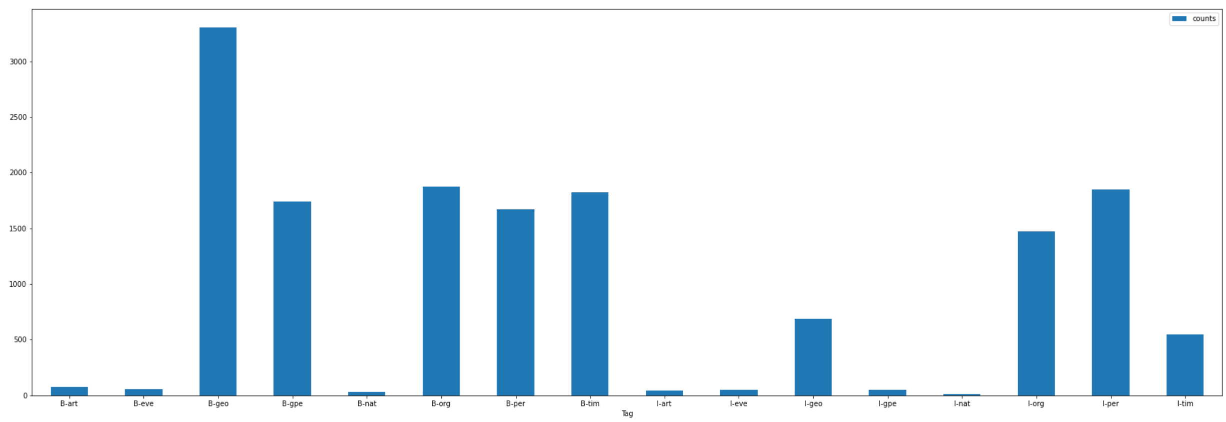
Here we can see we have 4544 sentances , 10922 words and 17 tags , Lets see what the tags are

In [15]:
```
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 [16]:
```
tags1=Ner_Tag[:-1] # removing "O" -other
import matplotlib.pyplot as plt
plt.rcParams["figure.figsize"] = (30,10)
ax = tags1.plot.bar(x='Tag', y='counts', rot=0)
```



Building the model

In [17]:
```
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
import warnings
warnings.filterwarnings('ignore')
```

In [18]:

```
data = pd.read_csv('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 e
y = data.Tag.values
```

In [19]:

```
v = DictVectorizer(sparse=False)
X= data.drop('Tag', axis=1)
X = v.fit_transform(X.to_dict('records'))
```

In [20]:

```
classes = np.unique(y)
classes = classes.tolist()
new_classes = classes.copy()
new_classes.pop()
```

Out[20]:

```
'O'
```

In [21]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.33, random_s
```

Perceptron

In [22]:

```
perceptron = Perceptron(verbose=10,max_iter=5)
perceptron.partial_fit(X_train, y_train, classes) #Fitting data to each different cl
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
-- Epoch 1
Norm: 13.42, NNZs: 162, Bias: -4.000000, T: 67000, Avg. loss: 0.001642
Total training time: 1.62 seconds.
-- Epoch 1
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    1.6s remaining:    0.0s
Norm: 11.53, NNZs: 113, Bias: -3.000000, T: 67000, Avg. loss: 0.001060
Total training time: 1.61 seconds.
-- Epoch 1
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    3.2s remaining:    0.0s
Norm: 68.07, NNZs: 2642, Bias: -4.000000, T: 67000, Avg. loss: 0.041776
Total training time: 1.68 seconds.
-- Epoch 1
[Parallel(n_jobs=1)]: Done   3 out of   3 | elapsed:    4.9s remaining:    0.0s
Norm: 49.90, NNZs: 1337, Bias: -4.000000, T: 67000, Avg. loss: 0.015328
Total training time: 1.64 seconds.
-- Epoch 1
[Parallel(n_jobs=1)]: Done   4 out of   4 | elapsed:    6.6s remaining:    0.0s
Norm: 8.43, NNZs: 57, Bias: -3.000000, T: 67000, Avg. loss: 0.000567
Total training time: 1.79 seconds.
-- Epoch 1
[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:    8.4s remaining:    0.0s
Norm: 56.87, NNZs: 2044, Bias: -4.000000, T: 67000, Avg. loss: 0.034970
```

```
Total training time: 1.67 seconds.
-- Epoch 1
[Parallel(n_jobs=1)]: Done   6 out of   6 | elapsed:   10.0s remaining:    0.0s
Norm: 48.83, NNZs: 1578, Bias: -4.000000, T: 67000, Avg. loss: 0.022328
Total training time: 1.65 seconds.
-- Epoch 1
[Parallel(n_jobs=1)]: Done   7 out of   7 | elapsed:   11.7s remaining:    0.0s
Norm: 44.41, NNZs: 1127, Bias: -4.000000, T: 67000, Avg. loss: 0.017164
Total training time: 1.62 seconds.
-- Epoch 1
[Parallel(n_jobs=1)]: Done   8 out of   8 | elapsed:   13.3s remaining:    0.0s
Norm: 10.44, NNZs: 106, Bias: -3.000000, T: 67000, Avg. loss: 0.001060
Total training time: 1.62 seconds.
-- Epoch 1
[Parallel(n_jobs=1)]: Done   9 out of   9 | elapsed:   14.9s remaining:    0.0s
Norm: 11.45, NNZs: 96, Bias: -3.000000, T: 67000, Avg. loss: 0.000776
Total training time: 1.61 seconds.
-- Epoch 1
Norm: 35.13, NNZs: 803, Bias: -4.000000, T: 67000, Avg. loss: 0.011149
Total training time: 1.62 seconds.
-- Epoch 1
Norm: 11.00, NNZs: 102, Bias: -3.000000, T: 67000, Avg. loss: 0.001209
Total training time: 1.63 seconds.
-- Epoch 1
Norm: 6.24, NNZs: 31, Bias: -3.000000, T: 67000, Avg. loss: 0.000209
Total training time: 1.62 seconds.
-- Epoch 1
Norm: 53.57, NNZs: 1703, Bias: -4.000000, T: 67000, Avg. loss: 0.026224
Total training time: 1.64 seconds.
-- Epoch 1
Norm: 60.35, NNZs: 2091, Bias: -6.000000, T: 67000, Avg. loss: 0.026940
Total training time: 1.65 seconds.
-- Epoch 1
Norm: 30.53, NNZs: 672, Bias: -4.000000, T: 67000, Avg. loss: 0.012030
Total training time: 1.62 seconds.
-- Epoch 1
Norm: 73.89, NNZs: 2851, Bias: 4.000000, T: 67000, Avg. loss: 0.048866
Total training time: 1.68 seconds.
[Parallel(n_jobs=1)]: Done  17 out of  17 | elapsed:   28.0s finished
```

Out[22]:

```
Perceptron(max_iter=5, verbose=10)
```

In [23]:

```python
classification_per = classification_report(y_pred=perceptron.predict(X_test), y_true
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)
```

```
              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

   micro avg       0.61      0.54      0.58      4966
   macro avg       0.57      0.34      0.38      4966
weighted avg       0.66      0.54      0.55      4966

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

Linear classifiers with SGD training

In [24]:

```
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)
```

```
              precision    recall  f1-score   support

       B-art       0.60      0.12      0.21        24
       B-eve       0.00      0.00      0.00        19
       B-geo       0.65      0.82      0.73      1085
       B-gpe       0.90      0.62      0.73       556
       B-nat       0.00      0.00      0.00        12
       B-org       0.68      0.38      0.48       589
       B-per       0.70      0.46      0.55       564
       B-tim       0.92      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       0.66      0.55      0.60       230
       I-gpe       1.00      0.14      0.25        14
       I-nat       0.00      0.00      0.00         2
       I-org       0.79      0.36      0.50       445
       I-per       0.44      0.82      0.57       591
       I-tim       0.31      0.02      0.04       194

   micro avg       0.66      0.58      0.62      4966
   macro avg       0.52      0.32      0.36      4966
weighted avg       0.69      0.58      0.60      4966

Accuracy Score on Train data: 0.9501194029850746
Accuracy Score on Test data: 0.9331212121212121
```

Naive Bayes classifier for multinomial models

In [25]:

```
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_test
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)
```

```
              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

   micro avg       0.52      0.56      0.54      4966
   macro avg       0.36      0.40      0.38      4966
weighted avg       0.54      0.56      0.54      4966

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

Using Bidirectional LSTM

In [26]:

```
import tensorflow as tf
import matplotlib.pyplot as plt
```

In [27]:

```
data = pd.read_csv('data.csv', encoding='latin1')
data = data.fillna(method='ffill')
data.head(10)
```

Out[27]:

	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 [28]:

```
#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 [29]:

```
decouple = Sentence_Getter(data)
sentences = decouple.sentences
```

In [30]:

```
sentences[0]
```

Out[30]:

```
[('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 [31]:

```
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 [32]:

```
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_wor

y = [[tag2idx[w[2]] for w in s] for s in sentences]
```

```
y = pad_sequences(maxlen = maximum_len, sequences = y, padding = 'post', value = tag
y = [to_categorical(i, num_classes=num_tags) for i in y]
```

In [33]:
```
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.1, random_stat
```

Build and compile a Bidirectional LSTM model

In [34]:
```
from tensorflow.keras import Model, Input
from tensorflow.keras.layers import LSTM, Embedding, Dense
from tensorflow.keras.layers import TimeDistributed, SpatialDropout1D, Bidirectional
```

In [35]:
```
input_word = Input(shape=(maximum_len, ))
model = Embedding(input_dim = num_words, output_dim = maximum_len, input_length = ma
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()
```

```
2022-04-28 20:49:00.105091: W tensorflow/stream_executor/platform/default/dso_loade
r.cc:64] Could not load dynamic library 'libcuda.so.1'; dlerror: libcuda.so.1: canno
t open shared object file: No such file or directory
2022-04-28 20:49:00.105128: W tensorflow/stream_executor/cuda/cuda_driver.cc:269] fa
iled call to cuInit: UNKNOWN ERROR (303)
2022-04-28 20:49:00.105155: I tensorflow/stream_executor/cuda/cuda_diagnostics.cc:15
6] kernel driver does not appear to be running on this host (default): /proc/driver/
nvidia/version does not exist
2022-04-28 20:49:00.105402: I tensorflow/core/platform/cpu_feature_guard.cc:151] Thi
s TensorFlow binary is optimized with oneAPI Deep Neural Network Library (oneDNN) to
use the following CPU instructions in performance-critical operations:  AVX2 AVX512F
FMA
To enable them in other operations, rebuild TensorFlow with the appropriate compiler
flags.
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 [36]:
```
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'
```

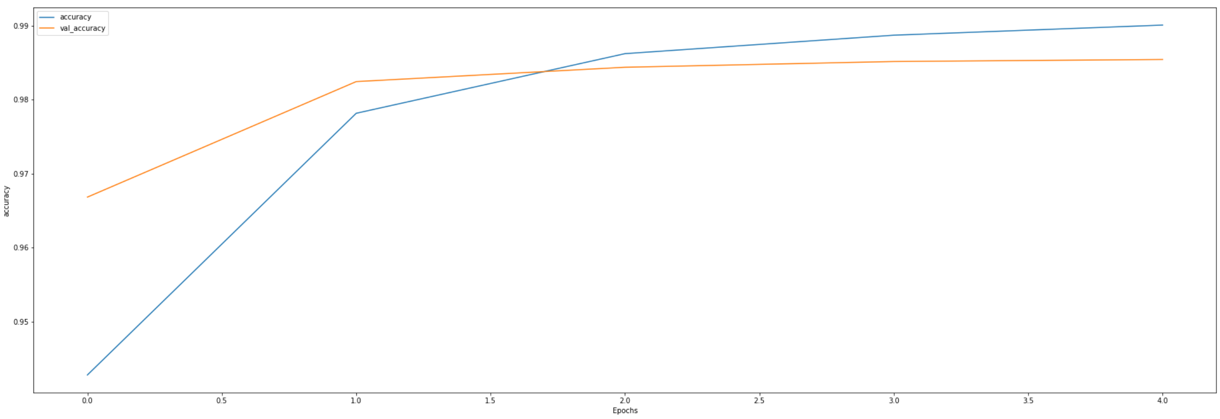
Train the model

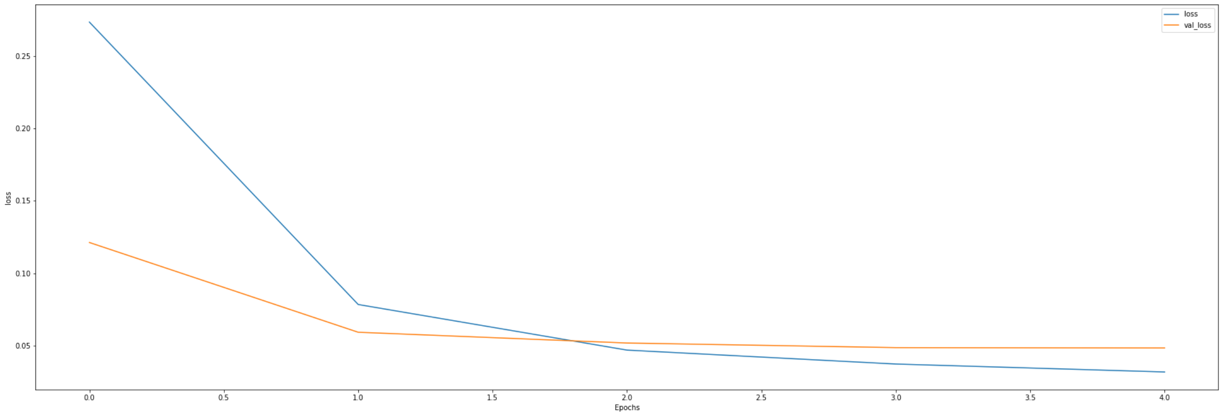
In [37]:
```
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping
from livelossplot.tf_keras import PlotLossesCallback
```

In [38]:
```
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 [==============================] - 70s 122ms/step - loss: 0.2733 - accuracy:
0.9428 - val_loss: 0.1213 - val_accuracy: 0.9668
Epoch 2/5
540/540 [==============================] - 65s 121ms/step - loss: 0.0786 - accuracy:
0.9781 - val_loss: 0.0594 - val_accuracy: 0.9824
Epoch 3/5
540/540 [==============================] - 65s 121ms/step - loss: 0.0471 - accuracy:
0.9862 - val_loss: 0.0520 - val_accuracy: 0.9844
Epoch 4/5
540/540 [==============================] - 66s 121ms/step - loss: 0.0375 - accuracy:
0.9887 - val_loss: 0.0488 - val_accuracy: 0.9851
Epoch 5/5
540/540 [==============================] - 65s 121ms/step - loss: 0.0320 - accuracy:
0.9901 - val_loss: 0.0486 - val_accuracy: 0.9854
```

In [39]:
```
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 [ ]:

```
model.evaluate(x_test, np.array(y_test))
lstm_acc=np.array(y_test)
```

```
150/150 [==============================] - 2s 16ms/step - loss: 0.0520 - accuracy:
0.9851
```

So we have used 3 Straight forward ways to predict the NER

```
1 - SPACY
2 - NLTK
3 - TEXT API
```

Then we have used 4 different models to train

```
1 - Perceptron
2 - SGD
3 - Naive Bayes
4 - LSTM
```

Now we have a data on accuracy on how the trained models performed lets see how all the 4 models performed

In [41]:

```
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 LSTM: " , round(lstm_acc*100))
```

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

Here we can see LSTM performed very well compared to the others , And yes this may be due to the fact lstm is trained with much larger data compared to other three but in my experimentation even when trained with much lesser data lstm performed well.

Now i want to see how LSTM performs compared to the best pre built model (in my opinion) SPACY and other methods as well lets see how they perform when compared to each other

In [42]:

```
def make_sentance (sent) :  # Takes a array of words and returns a setance so can be
```

```
    length = len(sent)
    for i in range(length) :
        if i == 0 :
            final = sent[i]
        else :
            final = final +" "+ sent[i]
    return final + " ."
```

In [43]:

```
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 nu
            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 [44]:

```
expermnt(2,1,1)
```

```
--------------- 1 ---------------
Using LSTM
------------------------------
Word           True      Pred
------------------------------
Afghan         B-gpe    B-gpe
officials      O        O
say            O        O
a              O        O
roadside       O        O
bomb           O        O
killed         O        O
six            O        O
civilians      O        O
and            O        O
wounded        O        O
```

```
nine           O        O
others         O        O
Sunday         B-tim    B-tim
in             O        O
southern       O        B-geo
Kandahar       B-geo    I-geo
province       O        O
------------------------------
Using Spacy
------------------------------
Afghan NORP
six CARDINAL
nine CARDINAL
Sunday DATE
Kandahar GPE
------------------------------
 Using NLTK

------------------------------
(GPE Afghan/NNP)
------------------------------
Using text

[['DATE', 'Sunday']]
------------------------------
--------------- 2 ---------------
Using LSTM
------------------------------
Word           True      Pred
------------------------------
Officials      O        O
are            O        O
taking         O        O
precautions    O        O
in             O        O
the            O        O
wake           O        O
of             O        O
the            O        O
destruction    O        O
caused         O        O
by             O        O
Hurricane      O        O
Katrina        O        O
------------------------------
Using Spacy
------------------------------
Hurricane Katrina EVENT
------------------------------
 Using NLTK

------------------------------
(PERSON Hurricane/NNP Katrina/NNP)
------------------------------
Using text

[['EVENT', 'Hurricane Katrina']]
------------------------------
```

After running the above experiment several times i am confident to say that Spacy one of the best way to do the NER as it was fast and often produces almost same or better results than the LSTM. LSTM does have its benifits like it was able to find the begin of the entity and end of the entity but spacy usually gives all the words as one entity which is convinient.

In conclusion i would say if the model is trained with large amount of data i performs very well but i would prefer using SPACY as it was way easier to implement .

References -

1 - Dipanjan Sarkar. "Text Analytics with Python" Text Book

2 - Kaggle Data set https://www.kaggle.com/datasets/abhinavwalia95/entity-annotated-corpus

3 - NER - https://towardsdatascience.com/named-entity-recognition-ner-meeting-industrys-requirement-by-applying-state-of-the-art-deep-698d2b3b4ede?gi=9de7da42bd43

4 - NER using LSTM - https://www.depends-on-the-definition.com/lstm-with-char-embeddings-for-ner/