Detect fake news using Spark NLP and deep learning models

Motivation (Abstract)

In the recent years of information transfer we have seen how major shortcomings in the field of technology have affected the lives of the people. The times of social media has catalyzed the process of propagating a lot of fake news from anti-social elements all across the world. We as a group want to solve this problem by applying the concepts of Machine Learning learnt in the class and get a result which enables us to solve the problem. We thought about this project by first interacting with many of our friends and peers which made us aware of the issue. One can also see how in the past as well as in the present there has been chaos which has also led to loss of human lives due to transfer of incorrect news in places. So all in all our group wants to contribute in ensuring peace and sanity by identifying which is fake and real news through the use of Machine Learning Concepts.

1. INTRODUCTION TO THE PROBLEM STATEMENT

Though, technology has been the reason for the recent positive developments in the human history it also has had its fair share of disadvantages too. One can see that there was a time when we had to search books for gathering information or maybe read newspapers for reading news but now people have both information and news in their pockets in the form of mobile phones. With regards to news which comes from various sectors in the form of social media, digital news etc. people tend to rely on certain things which are not true. This results in the propagation of information which is wrong. This is happening extensively nowadays due to bias with which journalists are reporting incidents due to their involvement of a particular political organization. Just recently we saw how there were riots in India due to circulation of news where a person belonging from a certain community was accused killing someone from the other communities. We have also observed how political parties instigate the public by using their IT cell networks to hide truth as well as polarize the voters. So all in all our problem statement is to analyze news that we get from social media and label them as fake or real. In this project we will get the data in form of paragraphs and would see which person has spoken the words from which political party. Depending on the sentiment analysis which would be handled by applying Natural Language Processing where we would be able to analyze the text and convert it into numeric data which would help us to apply our algorithms properly. Several machine learning models have already been applied to solve this problem. But of the people have tried to test the models on particular datasets thereby inducing dataset biases. So if a particular algorithm works on a specific type of dataset it may work poorly on the other. In our case we preprocess the data and train six different models which are logistic regression, Naïve Bayes, Decision Tree, Random Forrest, Neural Networks, Support Vector Machine and ADABoost Classifier. Here Naïve Bayes serves us the threshold level of accuracy and we accordingly work on the other models. The neural Networks was involved in the application of Deep Learning. It helps in the better learning of the data which enables us to give better accuracies then the models used earlier. While using Neural Networks we have used to algorithms which are used for better data visualization. The algorithms are respectively PCA and t-SNE which helps in reducing dimensionalities thereby helping in noise filtering and feature extraction. Now getting insights become easier for us hence enabling us to get proper results. The best part of the algorithms is that preserves the global data even after preserving the data. Feature extractions have been done which has enabled us to form 4 types where we consider the speaker and the party and then further divide it on the basis of the vectorization techniques like BOW(Bag of Words) and TF-IDF which involves converting the text into numeric vectors and the features that we have.

2. DATASET WITH PRE-PROCESSING TECHNIQUES

Here we have taken the data from the dataset for fact-checking and fake news detection in our paper. This data has evidence sentences which are straight extracted from report written by journalists in Politifact.

Dataset Information
Develop a Deep learning program to identify if an article might be fake news or not.

Attributes

- id: unique id for a news article
- title: the title of a news article
- author: author of the news article
- text: the text of the article; could be incomplete
- label: a label that marks the article as potentially unreliable
    - 1: unreliable
    - 0: reliable

3. Import Modules

- **pandas** - used to perform data manipulation and analysis
- **numpy** - used to perform a wide variety of mathematical operations on arrays

- **matplotlib** - used for data visualization and graphical plotting
- **seaborn** - built on top of matplotlib with similar functionalities
- **re** – used as a regular expression to find particular patterns and process it
- **nltk** – a natural language processing toolkit module
- **warnings** - to manipulate warnings details
- **%matplotlib inline** - to enable the inline plotting

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
import re
import nltk
import warnings
%matplotlib inline

warnings.filterwarnings('ignore')
```

4. **Loading the Dataset**

```
df = pd.read_csv('train.csv')
df.head()
```

	id	title	author	text	label
0	0	House Dem Aide: We Didn't Even See Comey's Let...	Darrell Lucus	House Dem Aide: We Didn't Even See Comey's Let...	1
1	1	FLYNN: Hillary Clinton, Big Woman on Campus - ...	Daniel J. Flynn	Ever get the feeling your life circles the rou...	0
2	2	Why the Truth Might Get You Fired	Consortiumnews.com	Why the Truth Might Get You Fired October 29, ...	1
3	3	15 Civilians Killed In Single US Airstrike Hav...	Jessica Purkiss	Videos 15 Civilians Killed In Single US Airstr...	1
4	4	Iranian woman jailed for fictional unpublished...	Howard Portnoy	Print \nAn Iranian woman has been sentenced to...	1

- We can see the top 5 samples from the data
- Important information is in the 'text' column and the label column so other columns are irrelevant for the process

Let us visualize the title and the text of the first article.

```
df['title'][0]
```

'House Dem Aide: We Didn’t Even See Comey’s Letter Until Jason Chaffetz Tweeted It'

```
df['text'][0]
```

'House Dem Aide: We Didn’t Even See Comey’s Letter Until Jason Chaffetz Tweeted It By Darrell Lucus on October 30, 2016 Subscribe Jason Chaffetz on the stump in American Fork, Utah (image courtesy Michael Jolley, available under a Creative Commons-BY license) \nWith apologies to Keith Olbermann, there is no doubt who the Worst Person in The World is this week–FBI Director James Comey. But according to a House Democratic aide, it looks like we also know who the second-worst person is as well. It turns out that when Comey sent his now-infamous letter announcing that the FBI was looking into emails that may be related to Hillary Clinton’s email server, the ranking Democrats on the relevant committees didn’t hear about it from Comey. They found out via a tweet from one of the Republican committee chairmen. \nAs we now know, Comey notified the Republican chairmen and Democratic ranking members of the House Intelligence, Judiciary, and Oversight committees that his agency was reviewing emails it had recently discovered in order to see if they contained classified information. Not long after this letter went out, Oversight Committee Chairman Jason Chaffetz set the political world ablaze with this tweet. FBI Dir just informed me, "The FBI has learned of the existence of emails that appear to be pertinent to the investigation." Case reopened \n— Jason Chaffetz (@jasoninthehouse) October 28, 2016 \nOf course, we now know that this was not the case . Comey was actually saying that it was reviewing the emails in light of “an unrelated case”–which we now know to be Anthony Weiner’s sexting with a teenager. But apparently such little things as facts didn’t matter to Chaffetz. The Utah Republican had already vowed to initiate a raft of investigations if Hillary wins–at least two years’ worth, and possibly an entire term’s worth of them. Apparently Chaffetz thought the FBI was already doing his work for him–resulting in a tweet that briefly roiled the nation before cooler heads realized it was a dud. \nBut according to a senior House Democratic aide, misreading that letter may have been the least of Chaffetz' sins. That aide told Shareblue that his boss and other Democrats didn't even know about Comey's letter at the time–and only found out when they checked Twitter. "Democratic Ranking Members on the relevant committees didn't receive Comey's letter until after the Republican Chairmen. In fact, the Democratic Ranking Members didn' receive it until after the Chairman of the Oversight and Government Reform Committee, Jason Chaffetz, tweeted it out and made it public." \nSo let's see if we've got this right. The FBI director tells Chaffetz and other GOP committee chairmen about a major development in a potentially politically explosive investigation, and neither Chaffetz nor his other colleagues had the courtesy to let their Democratic counterparts know about it. Instead, according to this aide, he made them find out about it on Twitter. \nThere has already been talk on Daily Kos that Comey himself provided advance notice of this letter to Chaffetz and other Republicans, giving them time to turn on the spin machine. That may make for good theater, but there is nothing so far that even suggests this is the case. After all, there is nothing so far that suggests that Comey was anything other than grossly incompetent and tone-deaf. \nWhat it does suggest, however, is that Chaffetz is acting in a way that makes Dan Burton and Darrell Issa look like models of responsibility and bipartisanship. He didn't even have the decency to notify ranking member Elijah Cummings about something this explosive. If that doesn't trample on basic standards of fairness, I don't know what does. \nGranted, it's not likely that Chaffetz will have to answer for this. He sits in a ridiculously Republican district anchored in Provo and Orem; it has a Cook Partisan Voting Index of R+25, and gave Mitt Romney a punishing 78 percent of the vote in 2012. Moreover, the Republican House leadership has given its full support to Chaffetz' planned fishing expedition. But that doesn't mean we can't turn the hot lights on him. After all, he is a textbook example of what the House has become under Republican control. And he is also the Second Worst Person in the World. About Darrell Lucus \nDarrell is a 30-something graduate of the University of North Carolina who considers himself a journalist of the old school. An attempt to turn him into a member of the religious right in college only succeeded in turning him into the religious right\'s worst nightmare--a charismatic Christian who is an unapologetic liberal. His desire to stand up for those who have been scared into silence only increased when he survived an abusive three-year marriage. You may know him on Daily Kos as Christian Dem in NC . Follow him on Twitter @DarrellLucus or connect with him on Facebook . Click here to buy Darrell a Mello Yello. Connect'

- Punctuations and escape characters are present in the text, they can be filtered to keep only meaningful information

Let us see the datatypes and no. of samples in the dataframe

```
df.info()
```

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 20800 entries, 0 to 20799

Data columns (total 5 columns):

```
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   id      20800 non-null  int64
 1   title   20242 non-null  object
 2   author  18843 non-null  object
 3   text    20761 non-null  object
 4   label   20800 non-null  int64
```

dtypes: int64(2), object(3)

memory usage: 812.6+ KB

- Total of 20800 articles in the dataset
- There are less data in the text meaning the remaining has null values.

5. Data Preprocessing

Now we filter the data for processing

```
# drop unnecessary columns
df = df.drop(columns=['id', 'title', 'author'], axis=1)
```

```
# drop null values
df = df.dropna(axis=0)
```

```
len(df)
```

20761

- Drops entire row if it has a NULL value

```
# remove special characters and punctuations
df['clean_news'] = df['text'].str.lower()
df['clean_news']
```

```
0        house dem aide: we didn’t even see comey’s let...
1        ever get the feeling your life circles the rou...
2        why the truth might get you fired october 29, ...
3        videos 15 civilians killed in single us airstr...
4        print \nan iranian woman has been sentenced to...
                               ...
20795    rapper t. i. unloaded on black celebrities who...
20796    when the green bay packers lost to the washing...
20797    the macy’s of today grew from the union of sev...
20798    nato, russia to hold parallel exercises in bal...
20799      david swanson is an author, activist, journa...
Name: clean_news, Length: 20761, dtype: object
```

- **str.lower()** - converts all characters to lower case

Now we proceed in removing the punctuations and special characters

```
df['clean_news'] = df['clean_news'].str.replace('[^A-Za-z0-9\s]', '')
df['clean_news'] = df['clean_news'].str.replace('\n', '')
df['clean_news'] = df['clean_news'].str.replace('\s+', ' ')
df['clean_news']
```

```
0        house dem aide we didnt even see comeys letter...
1        ever get the feeling your life circles the rou...
2        why the truth might get you fired october 29 2...
3        videos 15 civilians killed in single us airstr...
4        print an iranian woman has been sentenced to s...
                               ...
20795    rapper t i unloaded on black celebrities who m...
20796    when the green bay packers lost to the washing...
20797    the macys of today grew from the union of seve...
20798    nato russia to hold parallel exercises in balk...
20799      david swanson is an author activist journalis...
Name: clean_news, Length: 20761, dtype: object
```

- All special characters and punctuations are removed
- Escape characters are removed
- Extra spaces are removed

```
# remove stopwords
from nltk.corpus import stopwords
stop = stopwords.words('english')
df['clean_news'] = df['clean_news'].apply(lambda x: " ".join([word for word in x.split() if word not in stop]))
df.head()
```

	text	label	clean_news
0	House Dem Aide: We Didn't Even See Comey's Let...	1	house dem aide didnt even see comeys letter ja...
1	Ever get the feeling your life circles the rou...	0	ever get feeling life circles roundabout rathe...
2	Why the Truth Might Get You Fired October 29, ...	1	truth might get fired october 29 2016 tension ...
3	Videos 15 Civilians Killed In Single US Airstr...	1	videos 15 civilians killed single us airstrike...
4	Print \nAn Iranian woman has been sentenced to...	1	print iranian woman sentenced six years prison...

Preprocessed Dataset

- Stop words are meaningless information, removing them simplifies the text data for good feature extraction
- Stop words are removed from text by splitting the original text and comparing with the **STOPWORDS** list

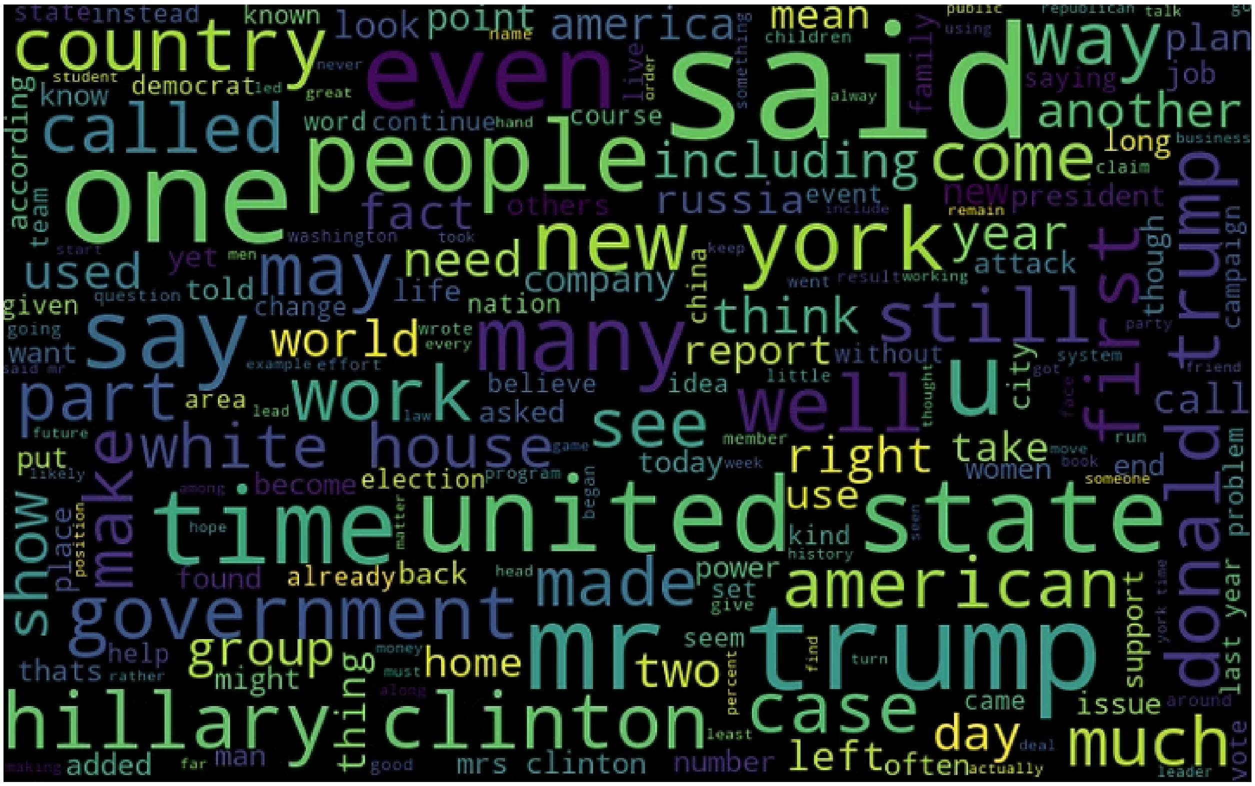
- Stop words are meaningless information, removing them simplifies the text data for good feature extraction
- Stop words are removed from text by splitting the original text and comparing with the STOPWORDS list

6. Exploratory Data Analysis

```
# visualize the frequent words
all_words = " ".join([sentence for sentence in df['clean_news']])

wordcloud = WordCloud(width=800, height=500, random_state=42, max_font_size=100).generate(all_words)

# plot the graph
plt.figure(figsize=(15, 9))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.show()
```



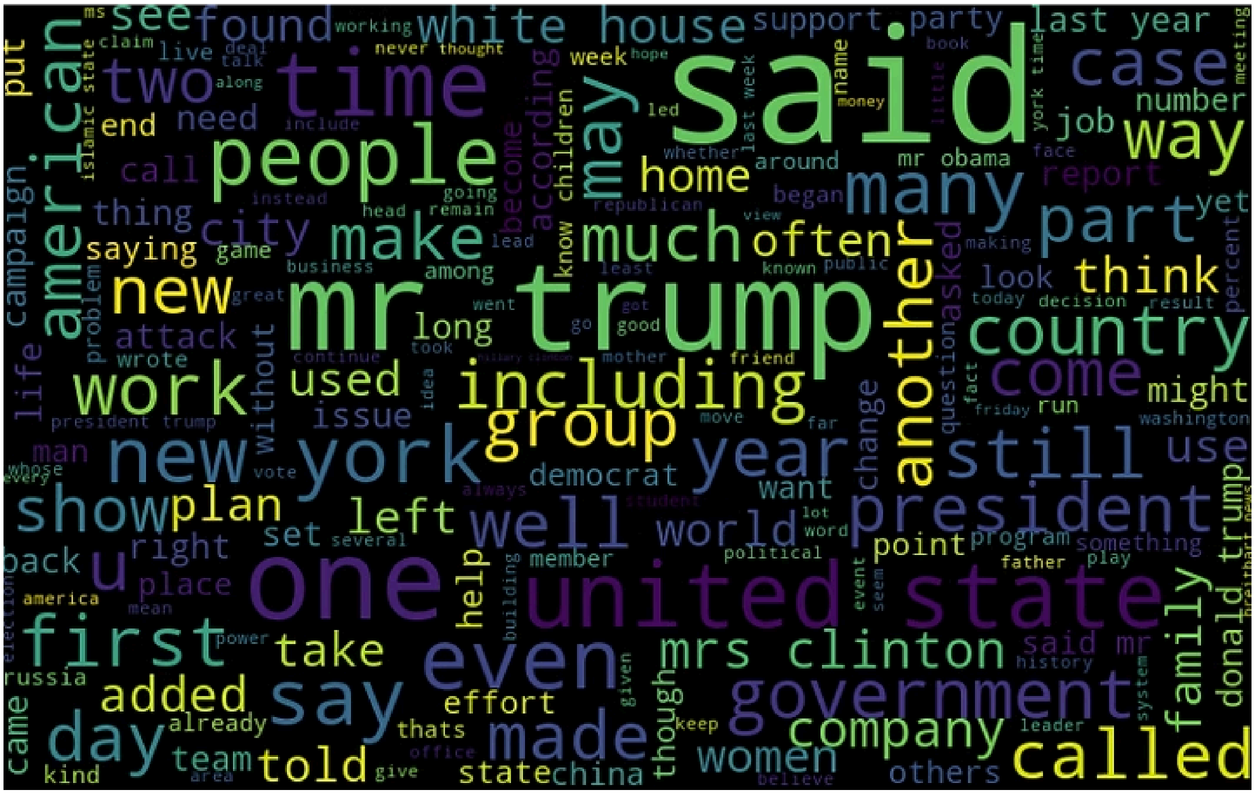
Word Cloud for Frequent Words

- Concatenation of all the sentences from **clean_news** column
- The most frequent words are larger and less frequent words are smaller
- Visualization of frequent words from genuine and fake news.

```
# visualize the frequent words for genuine news
all_words = " ".join([sentence for sentence in df['clean_news']
[df['label']==0]])

wordcloud = WordCloud(width=800, height=500, random_state=42,
max_font_size=100).generate(all_words)

# plot the graph
plt.figure(figsize=(15, 9))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.show()
```



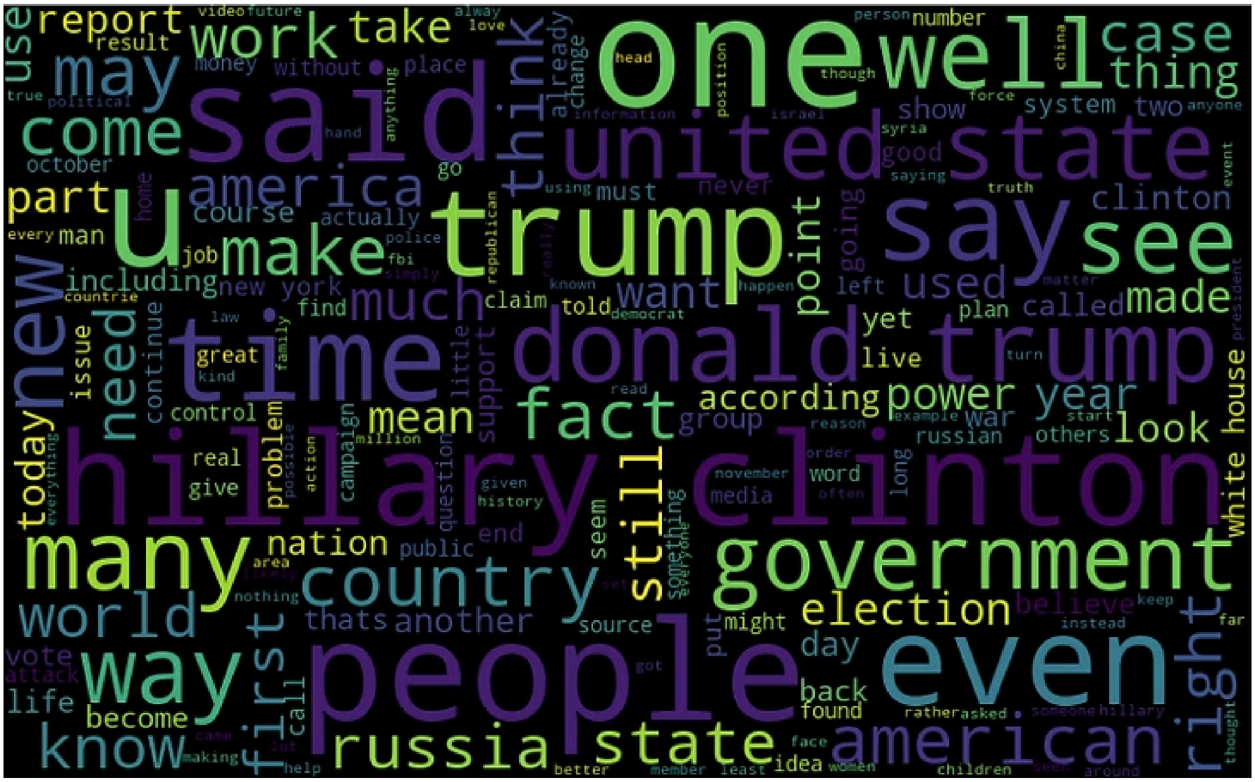
Word Cloud for Genuine News

- Concatenation of sentences of genuine news only
- Visualization of most frequent words of genuine news

```
# visualize the frequent words for fake news
all_words = " ".join([sentence for sentence in df['clean_news']
[df['label']==1]])

wordcloud = WordCloud(width=800, height=500, random_state=42,
max_font_size=100).generate(all_words)

# plot the graph
plt.figure(figsize=(15, 9))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.show()
```



Word Cloud for Fake News

- Concatenation of sentences of fake news only
- Visualization of most frequent words of fake news
- Compared with the plot of genuine news, there's a difference in the frequency of the words, including different words

7. **Create Word Embeddings**

```
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
```

- **Tokenizer** - used for loading the text and convert them into a token
- **pad_sequences -** used for equal distribution of words in sentences filling the remaining spaces with zeros

```
# tokenize text
tokenizer = Tokenizer()
tokenizer.fit_on_texts(df['clean_news'])
word_index = tokenizer.word_index
vocab_size = len(word_index)
vocab_size
```

199536

- Returns all unique words as tokens
- **vocab_size** returns the total number of unique words from the data

```
# padding data
sequences = tokenizer.texts_to_sequences(df['clean_news'])
padded_seq = pad_sequences(sequences, maxlen=500, padding='post',
truncating='post')
```

- Padding the data equalizes the length of all sentences
- For this project we determine the max length to 500 words for faster processing, normally you must find the max length of a sentence in the whole dataset

```
# create embedding index
embedding_index = {}
with open('glove.6B.100d.txt', encoding='utf-8') as f:
    for line in f:
        values = line.split()
        word = values[0]
        coefs = np.asarray(values[1:], dtype='float32')
        embedding_index[word] = coefs
```

- Must download the Glove embedding file for this process and place it in the same folder as the notebook
- Glove embedding dictionary contains vectors for words in 100 dimensions, mainly all words from the dictionary

You may download the Glove embedding file here

```python
# create embedding matrix
embedding_matrix = np.zeros((vocab_size+1, 100))
for word, i in word_index.items():
    embedding_vector = embedding_index.get(word)
    if embedding_vector is not None:
        embedding_matrix[i] = embedding_vector
```

```python
embedding_matrix[1]
```

```
array([-0.13128   , -0.45199999,  0.043399  , -0.99798   , -0.21053   ,
       -0.95867997, -0.24608999,  0.48413   ,  0.18178   ,  0.47499999,
       -0.22305   ,  0.30063999,  0.43496001, -0.36050001,  0.20245001,
       -0.52594   , -0.34707999,  0.0075873 , -1.04970002,  0.18673   ,
        0.57369   ,  0.43814   ,  0.098659  ,  0.38769999, -0.22579999,
        0.41911   ,  0.043602  , -0.73519999, -0.53583002,  0.19276001,
       -0.21961001,  0.42515001, -0.19081999,  0.47187001,  0.18826   ,
        0.13357   ,  0.41839001,  1.31379998,  0.35677999, -0.32172   ,
       -1.22570002, -0.26635   ,  0.36715999, -0.27586001, -0.53245997,
        0.16786   , -0.11253   , -0.99958998, -0.60706002, -0.89270997,
        0.65156001, -0.88783997,  0.049233  ,  0.67110997, -0.27553001,
       -2.40050006, -0.36989   ,  0.29135999,  1.34979999,  1.73529994,
        0.27000001,  0.021299  ,  0.14421999,  0.023784  ,  0.33643001,
       -0.35475999,  1.09210002,  1.48450005,  0.49430001,  0.15688001,
        0.34678999, -0.57221001,  0.12093   , -1.26160002,  1.05410004,
        0.064335  , -0.002732  ,  0.19038001, -1.76429999,  0.055068  ,
        1.47370005, -0.41782001, -0.57341999, -0.12129   , -1.31690001,
       -0.73882997,  0.17682   , -0.019991  , -0.49175999, -0.55247003,
        1.06229997, -0.62879002,  0.29098001,  0.13237999, -0.70414001,
        0.67128003, -0.085462  , -0.30526   , -0.045495  ,  0.56509   ])
```

- Vectors in the embedding matrix as float32 data type
- The 100 values represents a single word

8. **Input Split**

```
padded_seq[1]
```

```
array([   258,     28,   1557,     92,   4913,  27340,    415,   2246,
         2067,    377,    532,   1558,   5339,     29,     12,    796,
          179,    361,   1917,  17459,    829,  20147,   2990,   2626,
          640,    747,    252,   2025,   3113,  10995,    125,     39,
         2086,  78618,   3022,   3646,   3561,   3113,    835,    153,
         3458,     29,   9775,  51963,   3724,     18,    218,     20,
         3234,  20147,  10024,    625,     11,    481,   2494,   2417,
         8173,    442,    701,    613,    147,     14,  22280,    902,
          324,      8,    164,   3712,     60,  11541,    867,   2644,
           16,    864,   4422,    176,   5305,   2086,   4253,     40,
          257,    835,    192,     10,   2403,     10,   2086,   9775,
           58,   8372,  11246, 104297,  20952,   3713,  20953,  78619,
       104298,   5459,  31169,  25044,   7998,  19120,  65806,   4403,
          168,    261,  25045,   4403,    162,    355,    904,   1581,
          424,   1302,     20,    344,     37,   1963,    187,    394,
           59,   8107,   3658,  18529,    177,   1356,    745,   7401,
         2379,   7787,   1602,   2532,    152,     12,    458,  10153,
        11900,  17701,   8681,    128,    102,  22769,  10582,  10025,
        13518,   9418,    316,      7,    136,    626,    480,    370,
           95,  47538,   2439,  19434,   1139,   9775,   7163,   3591,
         8173,      4,    840,    169,    625,  14079,    414,     51,
          465,    177,      1,    446,   1139,    446,   1078,   1139,
           10,     39,    369,    182,    446,   1139,   8031,     51,
           51,   1557,  30058,   1703,    516,     16,   2633,  19772,
         1139,   8031,    957,  11901,    165,     60,    493,    957,
           16,    588,      6,  19772,  13107,  35329,   1635,   1688,
         3751,   2121,    254,     12,    104,  19772,   1099,    287,
         8032,  12768,   1159,  19121,     52,  14721,   8208,     22,
```

```
    6,     3, 20548,  3724,    69,  3241,    69,   292,
  893,  2020, 17201,    37,  1615,   250,   448,  2825,
14721,    12,   562,104299,   471,  7358,  1910,  2322,
 1438,  1502,  1212,   592,   448,   674,  1452,    22,
    6,  2420,  1387,   592,   197, 12000,   142,   192,
   42,    49,     6,   102, 14885,  1502,   230,   292,
  973,  1019,   137,   209,   627,   994, 17202,     8,
   15,     6,  4785,  3640,    29,    12,  9944,   907,
   86,  2648,  1521,   229,   176, 13108,  1376, 20147,
  481,    95,    11,   164,  2557,    12,  9203,    70,
  146,   604,  1732,  2688,   263, 25735, 41482,  4166,
   21, 20147, 13639,  4977,   118,    39,    43,  8681,
   86,   320,  2478,   447,  1049,   335,  1304,  1273,
  447,  1049,   247,   891,  1871,   335,   179,   361,
 1917,  4311,   361,    44,    41,  7472,   489,  1464,
   16,   335,  1453,   683,   737,  1032,   169,   934,
   30,  3341,   557,    11,   361,  5797,  7952, 20954,
 6089,   148, 51964,  7203,  1387,   637,   418,  1615,
   37,    53,     8,  1809, 47539, 11442,  3561,    53,
19773,   981, 12649,     0,     0,     0,     0,     0,
    0,     0,     0,     0,     0,     0,     0,     0,
    0,     0,     0,     0,     0,     0,     0,     0,
    0,     0,     0,     0,     0,     0,     0,     0,
    0,     0,     0,     0,     0,     0,     0,     0,
    0,     0,     0,     0,     0,     0,     0,     0,
    0,     0,     0,     0,     0,     0,     0,     0,
    0,     0,     0,     0,     0,     0,     0,     0,
    0,     0,     0,     0,     0,     0,     0,     0,
    0,     0,     0,     0,     0,     0,     0,     0,
    0,     0,     0,     0,     0,     0,     0,     0,
    0,     0,     0,     0,     0,     0,     0,     0,
```

```
0,    0,    0,    0,    0,    0,    0,    0,
0,    0,    0,    0,    0,    0,    0,    0,
0,    0,    0,    0,    0,    0,    0,    0,
      0,    0,    0,    0])
```

- Visualization of word index from the padded sequence
- Good example viewing a padded sentence, remaining spaces filled with zero to match the max length

Now we proceed in splitting the data for training

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(padded_seq,
df['label'], test_size=0.20, random_state=42, stratify=df['label'])
```

- 80% data split for training and remaining 20% for testing
- stratify will equally distribute the samples for train and test

9. Model Training

```
from keras.layers import LSTM, Dropout, Dense, Embedding
from keras import Sequential

# model = Sequential([
#     Embedding(vocab_size+1, 100, weights=[embedding_matrix],
trainable=False),
#     Dropout(0.2),
#     LSTM(128, return_sequences=True),
#     LSTM(128),
#     Dropout(0.2),
#     Dense(512),
#     Dropout(0.2),
#     Dense(256),
#     Dense(1, activation='sigmoid')
# ])

model = Sequential([
    Embedding(vocab_size+1, 100, weights=[embedding_matrix],
trainable=False),
    Dropout(0.2),
    LSTM(128),
    Dropout(0.2),
    Dense(256),
    Dense(1, activation='sigmoid')
])
```

- **Embedding** - maps the word index to the corresponding vector representation
- **LSTM** - process sequence of data
- **Dense** - single dimension linear layer
- Use **Dropout** if augmentation was not applied on the data to avoid over fitting
- **activation='sigmoid'** - used for binary classification

```python
model.compile(loss='binary_crossentropy', optimizer='adam',
metrics='accuracy')
model.summary()
```

Model: "sequential_2"

____

Layer (type) Output Shape Param #

===

embedding_2 (Embedding) (None, None, 100) 19953700

____

dropout_5 (Dropout) (None, None, 100) 0

____

lstm_3 (LSTM) (None, 128) 117248

____

dropout_6 (Dropout) (None, 128) 0

____

dense_5 (Dense) (None, 1) 129

===

Total params: 20,071,077

Trainable params: 117,377

Non-trainable params: 19,953,700

____

- **model.compile()** - compilation of the model
- **optimizer='adam'** - automatically adjust the learning rate for the model over the no. of epochs
- **loss='binary_crossentropy'** - loss function for binary outputs

```python
# train the model
history = model.fit(x_train, y_train, epochs=10, batch_size=256,
validation_data=(x_test, y_test))
```

Epoch 1/10
65/65 [==============================] - 42s 617ms/step - loss: 0.6541 - accuracy: 0.6098 - val_loss: 0.6522 - val_accuracy: 0.6152
Epoch 2/10
65/65 [==============================] - 39s 607ms/step - loss: 0.6436 - accuracy: 0.6241 - val_loss: 0.5878 - val_accuracy: 0.6769
Epoch 3/10
65/65 [==============================] - 40s 611ms/step - loss: 0.6057 - accuracy: 0.6688 - val_loss: 0.5908 - val_accuracy: 0.7144
Epoch 4/10
65/65 [==============================] - 40s 613ms/step - loss: 0.5693 - accuracy: 0.7239 - val_loss: 0.6280 - val_accuracy: 0.6326
Epoch 5/10
65/65 [==============================] - 40s 612ms/step - loss: 0.5990 - accuracy: 0.6699 - val_loss: 0.5887 - val_accuracy: 0.6959
Epoch 6/10

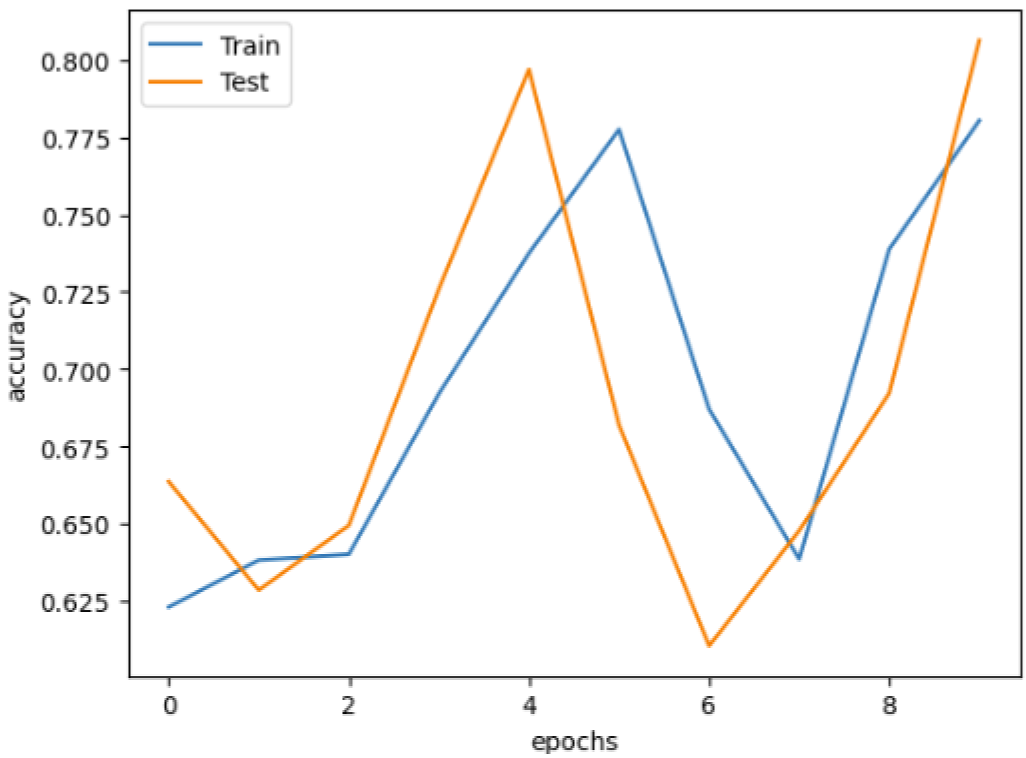
65/65 [==============================] - 40s 614ms/step - loss: 0.6060 - accuracy: 0.6593 - val_loss: 0.5807 - val_accuracy: 0.6766
Epoch 7/10
65/65 [==============================] - 40s 609ms/step - loss: 0.5546 - accuracy: 0.6906 - val_loss: 0.5704 - val_accuracy: 0.6641
Epoch 8/10
65/65 [==============================] - 39s 606ms/step - loss: 0.5517 - accuracy: 0.6973 - val_loss: 0.5553 - val_accuracy: 0.6689
Epoch 9/10
65/65 [==============================] - 33s 508ms/step - loss: 0.5400 - accuracy: 0.6855 - val_loss: 0.5281 - val_accuracy: 0.7226
Epoch 10/10
65/65 [==============================] - 40s 609ms/step - loss: 0.5244 - accuracy: 0.7236 - val_loss: 0.5442 - val_accuracy: 0.6988

- Set the no. of epochs and batch size according to the hardware specifications
- Training accuracy and validation accuracy increases each iteration
- Training loss and validation loss decreases each iteration
- The maximum validation accuracy is 72.26 and can be increased further if we increase the no. of epochs.

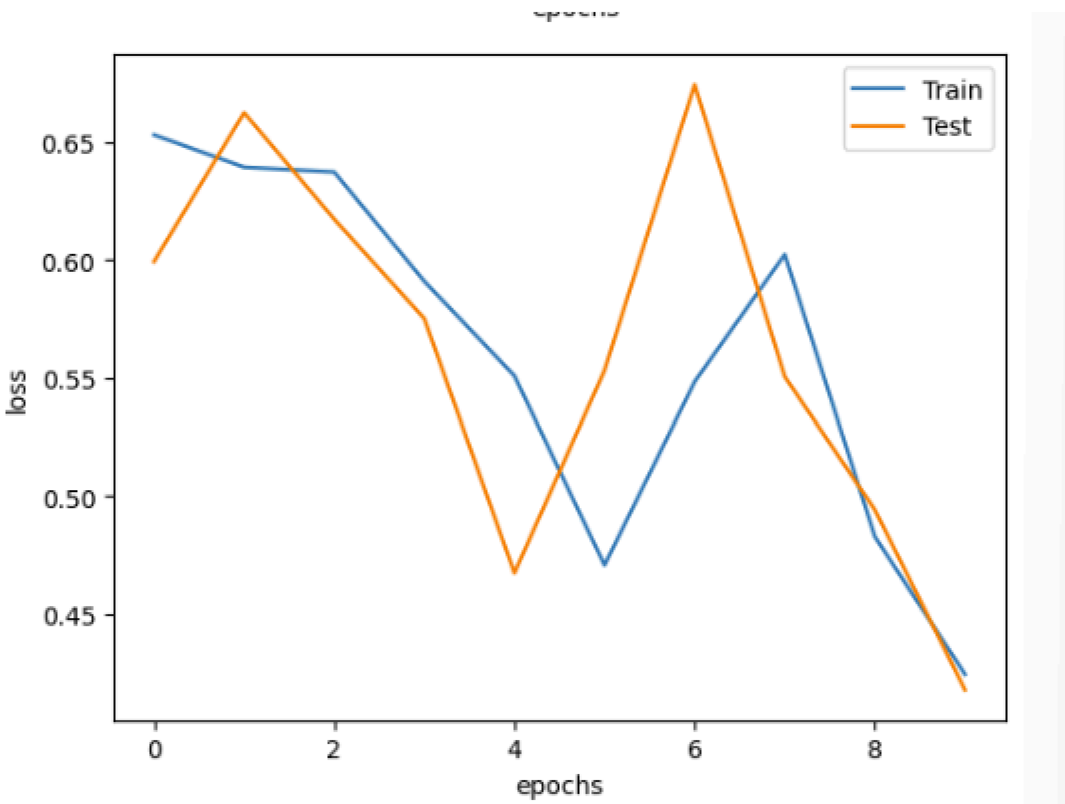
Now we visualize the results through a plot graph

```
# visualize the results
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.xlabel('epochs')
plt.ylabel('accuracy')
plt.legend(['Train', 'Test'])
plt.show()

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.xlabel('epochs')
plt.ylabel('loss')
plt.legend(['Train', 'Test'])
plt.show()
```



Train
Test
accuracy
0.800
0.775
0.750
0.725
0.700
0.675
0.650
0.625
0
2
4
6
8
epochs



Train
Test
loss
0.65
0.60
0.55
0.50
0.45
0
2
4
6
8
epochs

10. **Final Thoughts**

- Training the model by increasing the no. of epochs can give better and more accurate results.
- Processing large amount of data can take a lot of time and system resource.
- Basic deep learning model trained in a small neural network, adding new layers may improve the results.
- We can trained a LSTM model to predict the fake news and other models like GRU, Bi-LSTM, Transformers can be used to improve the performance of the model.

11.REFERENCES

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2. https://paperswithcode.com/paper/liar-liar-pants-on -fire-a-new-benchmark

3. https://arxiv.org/pdf/1705.00648.pdf%E2%80%8

4. https://www.overleaf.com/latex/templates/cvpr-20 22-author-kit/qbmjsdxryffn