



Fake News Detection using NLP

PHASE IV PROJECT SUBMISSION

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Problem Statement:

Begin building the fake news detection model by loading and preprocessing the dataset. Load the fake news dataset and preprocess the textual data.

Data Cleaning:



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Begin building the fake news detection model by loading and preprocessing the dataset. Load the fake news dataset and preprocess the textual data.

Data Cleaning:



Data cleaning is a process of removing inconsistencies in the dataset and incorrect values. It also involves handling missing values either by removing them or assigning them average values. It helps to improve the efficiency of the model.

In the first step, we will only remove the unnecessary data points from the dataset which does not help in improving the model performance.

Initially we import the necessary packages for our data cleaning process and also in the future purposes,

```
[ ] import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import nltk
import re
from wordcloud import WordCloud
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Embedding, LSTM, Conv1D, MaxPool1D
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score
import numpy as np
import pandas as pd
```

we use these packages in various stages of our cleaning process and also in the future in which we need to build models.

Here, we read the .csv files of true and fake news and then explore

We use these packages in various stages of our cleaning process and also in the future in which we need to build models.

Here, we read the .csv files of true and fake news and then explore the count values of their subjects

```
import os
for dirname, _, filenames in os.walk('/content/drive/MyDrive/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

/content/drive/MyDrive/input/True.csv
/content/drive/MyDrive/input/Fake.csv
```

```
[ ] fake_news = pd.read_csv('/content/drive/MyDrive/input/Fake.csv')
fake_news.head()
```

	title	text	subject	date
0	Donald Trump Sends Out Embarrassing New Year'...	Donald Trump just couldn't wish all Americans ...	News	December 31, 2017
1	Drunk Bragging Trump Staffer Started Russian ...	House Intelligence Committee Chairman Devin Nu...	News	December 31, 2017
2	Sheriff David Clarke Becomes An Internet Joke...	On Friday, it was revealed that former Milwauk...	News	December 30, 2017
3	Trump Is So Obsessed He Even Has Obama's Name...	On Christmas day, Donald Trump announced that ...	News	December 29, 2017
4	Pope Francis Just Called Out Donald Trump Dur...	Pope Francis used his annual Christmas Day mes...	News	December 25, 2017

```
[ ] fake_news.columns
```

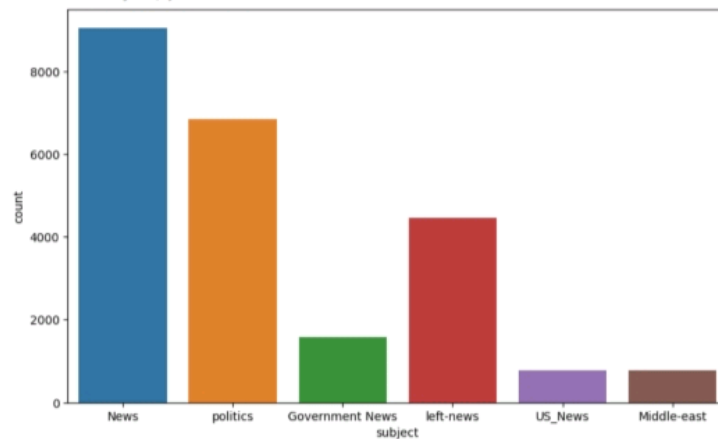
```
Index(['title', 'text', 'subject', 'date'], dtype='object')
```

```
[ ] fake_news['subject'].value_counts()
```

```
News          9050
politics      6841
left-news     4459
Government News 1570
US_News       783
Middle-east   778
Name: subject, dtype: int64
```

```
plt.figure(figsize=(10,6))
sns.countplot(x='subject',data=fake_news)
```

```
<Axes: xlabel='subject', ylabel='count'>
```



Here, we have used wordcloud to see that which word has mostly used for the fake news. By seeing that we can make a conclusion that which topic (about a person, event or anything) is mostly contains fake news. We also do the same for true news.

Word Cloud for Fake News:

```
wordcloud = WordCloud(width=1000, height=1000).generate(text)
fig = plt.figure(figsize=(10,10))
```

Word Cloud for Fake News:

[illegible]

Word cloud for True News:

	title	text	subject	date
0	As U.S. budget fight looms, Republicans flip t...	WASHINGTON (Reuters) - The head of a conserv...	politicsNews	December 31, 2018
1	U.S. military to accept transgender recruits o...	WASHINGTON (Reuters) - Transgender people will...	politicsNews	December 29, 2018
2	Senior U.S. Republican senator: 'Let Mr. Mueller...	WASHINGTON (Reuters) - The special counsel inv...	politicsNews	December 31, 2018
3	FBI Russia probe helped by Australian diplomat...	WASHINGTON (Reuters) - Trump campaign adviser ...	politicsNews	December 30, 2018
4	Trump wants Postal Service to charge 'much mor...	SEATTLE/WASHINGTON (Reuters) - President Donald...	politicsNews	December 29, 2018

[illegible]

	title	text	subject	date
5953	Peru and Colombia vow to stand with Mexico aft...	LIMA (Reuters) - Peru and Colombia vowed to st...	politicsNews	January 27, 2016
15390	North Korean embassy official in focus at Kim ...	KUALA LUMPUR (Reuters) - Three men wanted for ...	worldnews	November 8, 2011
6088	Trump's exit from Pacific trade deal opens doo...	BERLIN (Reuters) - Germany would take advantag...	politicsNews	January 23, 2016
8915	Albanian low backs Clinton with bronze bust	SARANDE, Albania (Reuters) - Whatever the outc...	politicsNews	June 30, 2016
12319	House Republicans to take up disaster funding ...	WASHINGTON (Reuters) - U.S. House of Represent...	politicsNews	October 11, 2015

```
[ ] unknown_publishers = []
    for index, row in enumerate(real_news.text.values):
        try:
            record = row.split(' - ', maxsplit=1)
            record[1]
```

6088	Trump's exit from Pacific trade deal opens doo...	BERLIN (Reuters) - Germany would take advantag...	politicsNews	January 23, 2017
8915	Albanian town backs Clinton with bronze bust	SARANDE, Albania (Reuters) - Whatever the outc...	politicsNews	June 30, 2016
1319	House Republicans to take up disaster funding ...	WASHINGTON (Reuters) - U.S. House of Represent...	politicsNews	October 11, 2017

Let's create a list of news lists in `real_news.csv` with unknown publishers by using the following code snippets

```
[ ] unknown_publishers = []
for index, row in enumerate(real_news.text.values):
    try:
        record = row.split(' - ', maxsplit=1)
        record[1]

        assert(len(record[0])<260)
    except:
        unknown_publishers.append(index)
```

```
[ ] len(unknown_publishers)
```

```
35
```

```
real_news.iloc[unknown_publishers].text
```

```
2922 The following statements were posted to the ve...
3488 The White House on Wednesday disclosed a group...
3782 The following statements were posted to the ve...
4358 Neil Gorsuch, President Donald Trump's appoint...
4465 WASHINGTON The clock began running out this we...
5290 The following statements were posted to the ve...
5379 The following statements were posted to the ve...
5412 The following statements were posted to the ve...
5504 The following statements were posted to the ve...
5538 The following statements were posted to the ve...
5588 The following statements were posted to the ve...
5593 The following statements were posted to the ve...
5761 The following bullet points are from the U.S. ...
5784 Federal appeals court judge Neil Gorsuch, the ...
6026 The following bullet points are from the U.S. ...
6184 The following bullet points are from the U.S. ...
6660 Republican members of Congress are complaining...
6823 Over the course of the U.S. presidential campa...
7922 After going through a week reminiscent of Napo...
8194 The following timeline charts the origin and s...
8195 Global health officials are racing to better u...
8247 U.S. President Barack Obama visited a street m...
8465 ALGONAC, MICH.-Parker Fox drifted out of the D...
8481 Global health officials are racing to better u...
8482 The following timeline charts the origin and s...
8505 Global health officials are racing to better u...
8506 The following timeline charts the origin and s...
8771 In a speech weighted with America's complicate...
8970
9008 The following timeline charts the origin and s...
9009 Global health officials are racing to better u...
9307 It's the near future, and North Korea's regime...
9618 GOP leaders have unleashed a stunning level of...
9737 Caitlyn Jenner posted a video on Wednesday (Ap...
10479 The Democratic and Republican nominees for the...
Name: text, dtype: object
```

```
publisher = []
tmp_text = []

for index, row in enumerate(real_news.text.values):
    if index in unknown_publishers:
        tmp_text.append(row)
        publisher.append('Unknown')

    else:
        record = row.split(' - ', maxsplit=1)
        publisher.append(record[0].strip())
        tmp_text.append(record[1].strip())
```

```
[ ] real_news['publisher'] = publisher
real_news['text'] = tmp_text
```

```
[ ] real_news.head()
```

```
[ ] real_news.head()
```

	title	text	subject	date	publisher
0	As U.S. budget fight looms, Republicans flip l...	The head of a conservative Republican faction ...	politicsNews	December 31, 2017	WASHINGTON (Reuters)
1	U.S. military to accept transgender recruits o...	Transgender people will be allowed for the fir...	politicsNews	December 29, 2017	WASHINGTON (Reuters)
2	Senior U.S. Republican senator: 'Let Mr. Muel...	The special counsel investigation of links bet...	politicsNews	December 31, 2017	WASHINGTON (Reuters)
3	FBI Russia probe helped by Australian diplomat...	Trump campaign adviser George Papadopoulos tol...	politicsNews	December 30, 2017	WASHINGTON (Reuters)
4	Trump wants Postal Service to change 'touch mor...	President Donald Trump called on the U.S. Post...	politicsNews	December 29, 2017	SEATTLE/WASHINGTON (Reuters)

```
[ ] real_news.shape
(21417, 5)
```


	test	class
0	as u.s. budget fight looms, republicans flip f...	f
1	u.s. military to accept transgender recruits o...	f
2	senior u.s. republican senator 'let me museli...	f
3	for russia probe helped by australian diplom...	f
4	trump wants postal service to charge 'much mor...	f

[illegible]

```
from google.colab import drive
drive.mount('/content/drive')

# Drive already mounted at /content/drive, to attempt to forcibly remount, call drive.mount('/content/drive', force_remount=True).

In [ ]: import gensim

In [ ]: y = data['class'].values

In [ ]: X = [x.split() for d in data['text'].tolist()]

In [ ]: type(X)
Out[ ]: list

In [ ]: type(X[0])
Out[ ]: list

In [ ]: print(X[0])

['the', 'we', 'budget', 'fight', 'issue', 'repulsion', 'file', 'their', 'visual', 'script', 'the', 'best', 'of', 'a', 'conservative', 'repulsion', 'faction', 'is', 'the', 'a', 'congress', 'who', 'total', 'this', 'month', 'for', 'a', 'h']

In [ ]:

In [ ]: DDM = 300
vobv_model = gensim.models.word2vec(sentences=X, vector_size=DDM, window =10, min_count=1)

In [ ]: vobv_model.save('india')

array([[1.717186 , 0.09900073, -0.54519834, 2.873536 , 1.1529748 ,
-0.612415 , -0.462369 , 1.1535874 , -1.3637966 , 1.7516707 ,
2.5935231 , 1.0115959 , -1.7413545 , 2.1367418 , 0.30687247,
2.0040805 , 0.7798712 , 1.5431712 , -2.6378732 , -2.512189 ,
1.1308114 , 1.6377032 , 1.4371284 , -2.7276765 , 0.8462333 ,
-0.50685384, 0.9316704 , -0.17280449, -1.396307 , -0.29016781,
1.5676288 , -0.66227571, -0.49168876 , 1.5287828 , 0.3889559 ,
4.206401 , -1.0358044 , 0.12552945 , 2.3705717 , 2.274364 ,
-0.06561634, -2.254771 , 2.0662938 , -0.8159753 , -2.254789 ,
-0.25137071, 1.6215089 , 0.84563375 , -2.134084 , -0.4018005 ,
-0.20788828, 1.3558859 , 3.4065708 , 0.53475 , 0.001231458 ,
2.2241623 , 1.7851181 , 0.507703 , 0.2085184 , -1.2646186 ,
0.9508465 , 1.2744708 , -2.876682 , -0.3734416 , 1.1651148 ,
2.8682878 , 0.0116589 , 0.1842725 , 2.6508075 , 0.01186266 ,
-0.8666595 , -3.034646 , 1.9152772 , 1.1891268 , 2.0976603 ,
0.19012403, -0.4842304 , 0.2136272 , 0.36068046 , -1.2318734 ,
-0.0441185 , 1.193174 , 0.26039815 , -0.28398276 , 1.721177 ,
-1.0592842 , 0.02164 , 0.74604486 , -1.7531212 , 1.2779034 ,
1.557519 , 2.2837704 , -0.4710132 , 1.6767781 , 2.008745 ,
0.7605516 , 0.39826797 , -2.181018 , -1.1530005 , 1.040491 ,
0.7596123])
```

```
[ ] w2v_model.wv.most_similar('india')

[('pakistan', 0.7414124011993408),
 ('malaysia', 0.6891000412231465)]
```

```
-0.9446105, 1.195174 , -0.2603855, -0.28388276, 1.791177 ,  
-1.8392262 , 0.61264 , 0.75691486, -1.751122 , 1.2778814 ,  
1.557519 , 2.2037704 , -0.470112 , 1.8767181 , 0.088740 ,  
0.7605155 , 0.29026797, -2.281819 , -1.1538865 , 1.948919 ],  
dtype=float32)
```

```
[ ] w2v_model.wv.most_similar('india')  
  
[('pakistan', 0.7614124811991488),  
 ('malaysia', 0.6891809412231443),  
 ('china', 0.6626362208515097),  
 ('australia', 0.645016759967804),  
 ('beljings', 0.6376861227851581),  
 ('norway', 0.627438543279568),  
 ('japan', 0.611946702803479),  
 ('controichina', 0.6118749244689941),  
 ('indian', 0.6049248827568425),  
 ('indias', 0.5988717079162998)]
```

```
[ ] w2v_model.wv.most_similar('china')  
  
[('beijing', 0.864797617677387),  
 ('taiwan', 0.8080918181272583),  
 ('chinas', 0.7648462680974384),  
 ('pyongyang', 0.6972812679748535),  
 ('chinese', 0.6958182481275635),  
 ('india', 0.6626362208515097),  
 ('japan', 0.6597905131874884),  
 ('beljings', 0.6444934818945676),  
 ('si', 0.6359792947769165),  
 ('waterway', 0.616282881862439)]
```

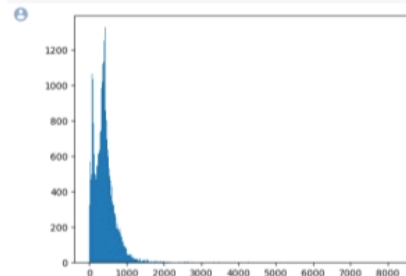
```
[ ] w2v_model.wv.most_similar('usa')  
  
[('acculloughthis', 0.5617169141769489),  
 ('wirecom', 0.5184991955757141),  
 ('nlintgell', 0.518539718211088),  
 ('pacharyil', 0.4913540482521057),  
 ('pictuttrcomsfedoll', 0.4856384228185167),  
 ('orgs', 0.4728092980188955),  
 ('pictuttrcomskut79511', 0.4677456821388899),  
 ('biz', 0.4658149182796478),  
 ('flopped', 0.4636186680182133),  
 ('gospel', 0.4619819846343994)]
```

```
[ ] w2v_model.wv.most_similar('gandhi')  
  
[('rahul', 0.7098805038542175),  
 ('75yearold', 0.6625688801841736),  
 ('cristina', 0.658746899472046),  
 ('cume', 0.6513821184371948),  
 ('tounes', 0.64185592258824),  
 ('sobotka', 0.6337286171581483),  
 ('grillo', 0.6289781638876679),  
 ('inyellat', 0.6274651944778442),  
 ('mediashy', 0.6266793012619019),  
 ('pastrana', 0.6204155683517456)]
```

```
[ ] tokenizer = Tokenizer()  
tokenizer.fit_on_texts(X)
```

```
[ ] X = tokenizer.texts_to_sequences(X)
```

```
[ ] plt.hist([len(x) for x in X], bins=700)  
plt.show()
```



```
[ ] nos = np.array([len(x) for x in X])  
len(nos[nos>1000])
```

1588

```
[ ] maxlen = 1000  
X = pad_sequences(X, maxlen=maxlen)
```

```
[ ] len(X[101])
```

1000

```
[ ] vocab_size = len(tokenizer.word_index)+1  
vocab = tokenizer.word_index
```

```
[ ] def get_weight_matrix(model):  
    weight_matrix = np.zeros((vocab_size, DDH))  
    for word, i in vocab.items():  
        weight_matrix[i] = model.wv[word]  
    return weight_matrix
```

```
[ ] embedding_vectors = get_weight_matrix(w2v_model)
```

```
[ ] embedding_vectors.shape  
  
(211818, 100)
```

```
[ ] model = Sequential()  
model.add(Embedding(vocab_size, output_dim=DDH, weights = [embedding_vectors], input_length=maxlen, trainable = False))  
model.add(LSTM(units=128))  
model.add(Dense(1, activation='sigmoid'))  
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['acc'])
```

```
[ ] model.summary()
```

```
Model: "sequential"  
Layer (type) Output Shape Param #  
-----  
embedding (Embedding) (None, 1000, 100) 21185000  
lstm (LSTM) (None, 128) 117248  
dense (Dense) (None, 1) 129  
-----  
Total params: 23302377 (88.59 MB)  
Trainable params: 117377 (458.59 KB)  
Non-trainable params: 23185000 (88.44 MB)
```

```
[ ] model = Sequential()
model.add(Embedding(vocab_size, output_dim=EMBEDDING_DIM, weights=[embedding_vectors], input_length=maxlen, trainable = False))
model.add(LSTM(units=128))
model.add(Dense(1, activation='sigmoid'))
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['acc'])
```

```
[ ] model.summary()

Model: "sequential"
Layer (type) Output Shape Param #
-----
embedding (Embedding) (None, 1000, 100) 21185000
lstm (LSTM) (None, 128) 117248
dense (Dense) (None, 1) 129
-----
Total params: 21302277 (88.89 MB)
Trainable params: 117377 (468.08 KB)
Non-trainable params: 21185000 (88.44 MB)
```

```
[ ] X_train, X_test, y_train, y_test = train_test_split(X, y)
```

```
[ ] model.fit(X_train, y_train, validation_split=0.2, epochs=1)

842/842 [=====] - 42s 40ms/step - loss: 0.1594 - acc: 0.9393 - val_loss: 0.8484 - val_acc: 0.9841
keras.src.callbacks.history at 0x7af6234f5e0
```

```
[ ] y_pred = (model.predict(X_test) >= 0.5).astype(int)

351/351 [=====] - 8s 23ms/step
```

```
[ ] accuracy_score(y_test, y_pred)

0.9824488880614254
```

```
[ ] print(f"accuracy_score : {accuracy_score(y_test, y_pred).round(4)*100}%")

accuracy_score : 98.24488880614254%
```

```
[ ] print(classification_report(y_test, y_pred))

              precision    recall  f1-score   support

     0       0.99      0.98      0.98       5966
     1       0.97      0.99      0.98       5259

 accuracy          0.98      0.98      0.98      11225
 macro avg         0.98      0.98      0.98      11225
 weighted avg      0.98      0.98      0.98      11225
```

```
[ ] x = ['this is a news']
import tensorflow as tf

[ ] x = tokenizer.texts_to_sequences(x)
x = pad_sequences(x, maxlen=maxlen)

[ ] (model.predict(x))

1/1 [=====] - 0s 31ms/step
array([[0.00372225]], dtype=float32)

[ ] if (model.predict(x) >= 0.5).astype(int) == 0:
    print("the input 'x' is fake news")
else:
    print("the input 'x' is real news")

1/1 [=====] - 0s 30ms/step
the input 'x' is fake news

[ ] model.predict(x)

1/1 [=====] - 0s 51ms/step
array([[0.00372225]], dtype=float32)
```

```
[ ] i = ["The heart and neurological disorders have seen an uptick as a result of the post-COVID condition which reportedly began since the second wave of the virus, according to health experts. Speaking to NLI on Saturday, Dr Debi Prasad Sinha said that the incidence of COVID patients developing clot forms, and clots in the brain or in the heart. But that pattern we see only during the second wave. However, Dr Nitish Kulkarni, Professor, Department of Cardiology, AIIMS, Delhi said that the study about the role of COVID in precipitating acute cardiac problems after recovery is still ongoing. "All flu like illnesses have always been associated with the expert explained that it can happen that some persons may experience persistent aches and pains, fatigue and palpitations during the recovery phase like after any viral illness.""]

x = tokenizer.texts_to_sequences(x)
x = pad_sequences(x, maxlen=maxlen)

print(model.predict(x))

if (model.predict(x) >= 0.5).astype(int) == 0:
    print("the input 'x' is fake news")
else:
    print("the input 'x' is real news")

1/1 [=====] - 0s 68ms/step
[[0.00359804]]
1/1 [=====] - 0s 47ms/step
the input 'x' is real news
```

Conclusion:

In conclusion, utilizing Natural Language Processing (NLP) techniques for fake news detection has proven to be a significant advancement in combating misinformation. The model demonstrates the potential of machine learning in identifying deceptive content, contributing to the ongoing efforts to maintain the integrity of information online. By leveraging NLP algorithms, the accuracy and efficiency of fake news detection have been greatly enhanced, empowering users to make informed decisions and fostering a more reliable digital information ecosystem. As we move forward, continued research and development in this field will play a pivotal role in ensuring the authenticity and trustworthiness of online content, thereby promoting a healthier and more informed society.



THANK YOU!

