##REAL OR FAKE JOB POSTING PREDICTION This dataset contains 18K job descriptions out of which about 800 are fake. The data consists of both textual information and meta-information about the jobs.

The objective is to create a classification model that uses text data features and meta-features and predict which job description are fraudulent or real.

Link for the dataset: https://www.kaggle.com/shivamb/real-or-fake-fake-jobposting-prediction

```
#importing necessary libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from tensorflow.keras.layers import Embedding
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.preprocessing.text import one_hot
from tensorflow.keras.layers import LSTM
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Bidirectional
from tensorflow.keras.layers import Dropout
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, f1_score, recall_score,
precision_score, classification_report, accuracy_score
import nltk
import re
from nltk.corpus import stopwords

#load the dataset
df1=pd.read_csv("/content/drive/MyDrive/fakejob.csv")

df1.head()

   job_id                                            title
location  \
0       1                                 Marketing Intern    US, NY, New
York
1       2  Customer Service - Cloud Video Production      NZ, ,
Auckland
2       3    Commissioning Machinery Assistant (CMA)       US, IA,
Wever
3       4          Account Executive - Washington DC  US, DC,
Washington
4       5                        Bill Review Manager  US, FL, Fort
Worth

  department salary_range
company_profile  \
0  Marketing          NaN  We're Food52, and we've created a
```

```
groundbreaki...
1    Success          NaN  90 Seconds, the worlds Cloud Video
Production ...
2        NaN          NaN  Valor Services provides Workforce Solutions
th...
3      Sales          NaN  Our passion for improving quality of life
thro...
4        NaN          NaN  SpotSource Solutions LLC is a Global Human
Cap...

                                         description  \
0  Food52, a fast-growing, James Beard Award-winn...
1  Organised - Focused - Vibrant - Awesome!Do you...
2  Our client, located in Houston, is actively se...
3  THE COMPANY: ESRI – Environmental Systems Rese...
4  JOB TITLE: Itemization Review ManagerLOCATION:...

                                        requirements  \
0  Experience with content management systems a m...
1  What we expect from you:Your key responsibilit...
2  Implement pre-commissioning and commissioning ...
3  EDUCATION: Bachelor’s or Master’s in GIS, busi...
4  QUALIFICATIONS:RN license in the State of Texa...

                                            benefits  telecommuting  \
0                                                NaN              0
1  What you will get from usThrough being part of...              0
2                                                NaN              0
3  Our culture is anything but corporate—we have ...              0
4                              Full Benefits Offered              0

   has_company_logo  has_questions employment_type required_experience
\
0                 1              0           Other          Internship

1                 1              0       Full-time      Not Applicable

2                 1              0             NaN                 NaN

3                 1              0       Full-time    Mid-Senior level

4                 1              1       Full-time    Mid-Senior level


  required_education                   industry           function
\
0                NaN                        NaN          Marketing

1                NaN  Marketing and Advertising   Customer Service
```

```
2                 NaN                        NaN                     NaN

3  Bachelor's Degree          Computer Software                   Sales

4  Bachelor's Degree     Hospital & Health Care  Health Care Provider


   fraudulent
0           0
1           0
2           0
3           0
4           0
```

```
df1.shape
```

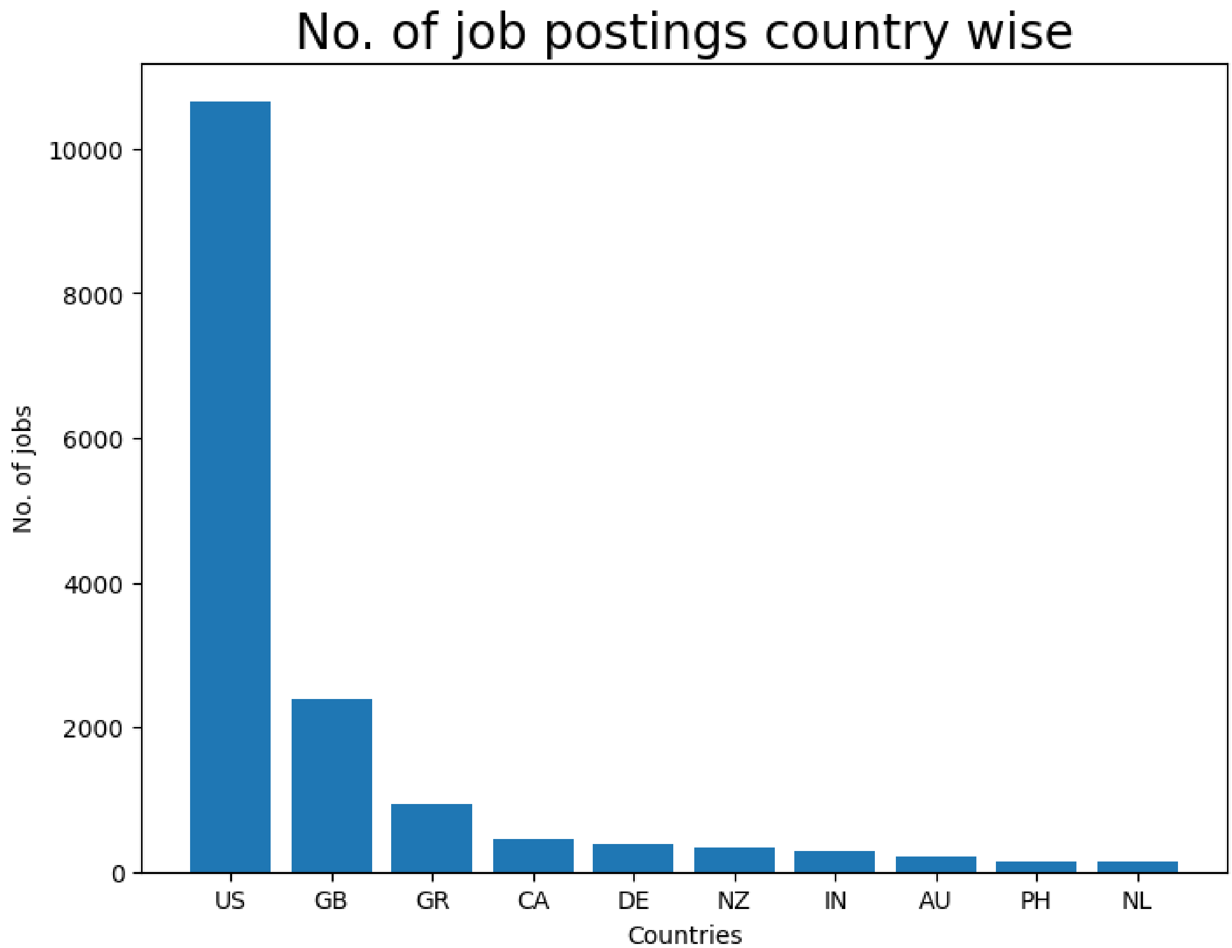
```
(17880, 18)
```

```
df1.columns
```

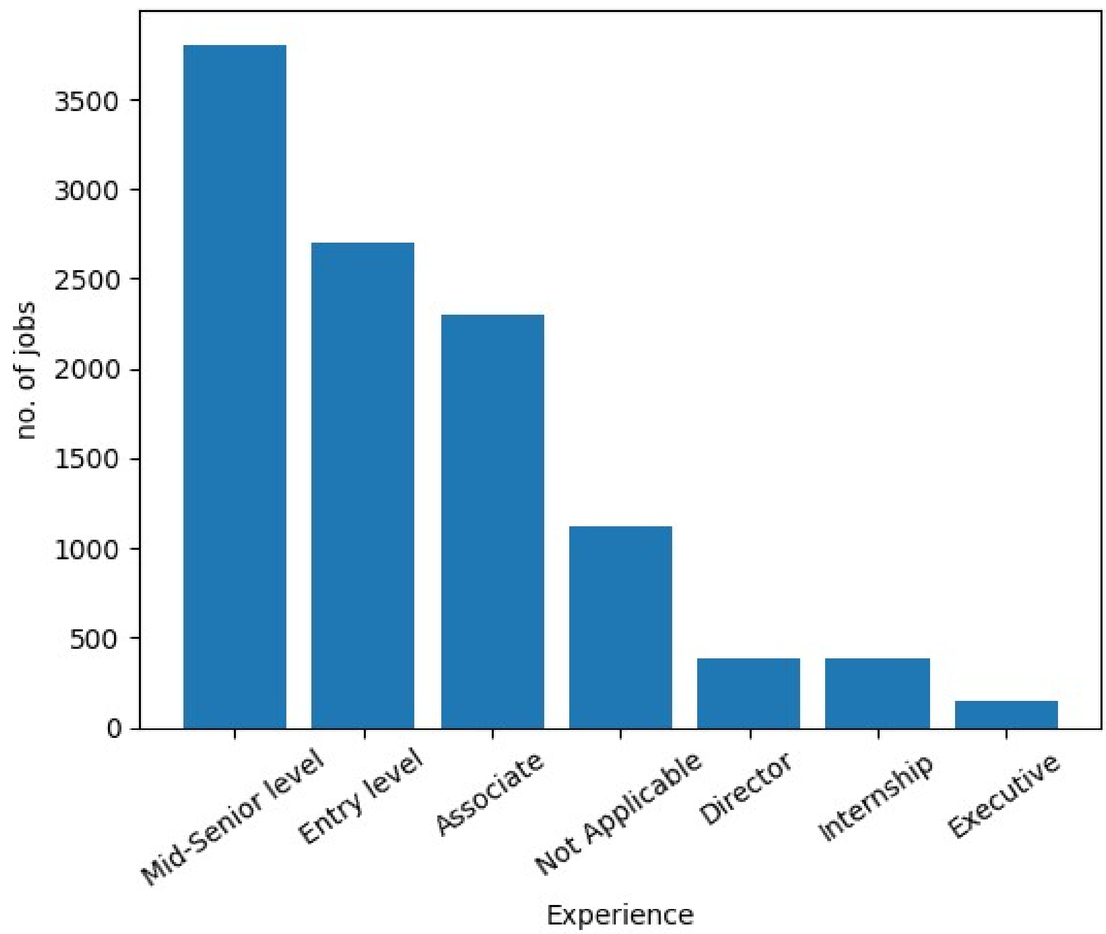
```
Index(['job_id', 'title', 'location', 'department', 'salary_range',
       'company_profile', 'description', 'requirements', 'benefits',
       'telecommuting', 'has_company_logo', 'has_questions',
'employment_type',
       'required_experience', 'required_education', 'industry',
'function',
       'fraudulent'],
      dtype='object')
```

```
# Removing NAN values and useless columns
columns=['job_id', 'telecommuting', 'has_company_logo',
'has_questions', 'salary_range', 'employment_type']
for col in columns:
    del df1[col]

df1.fillna(' ', inplace=True)

#checking which country posts most number of jobs
def split(location):
    l = location.split(',')
    return l[0]

df1['country'] = df1.location.apply(split)

country = dict(df1.country.value_counts()[:11])
del country[' ']
plt.figure(figsize=(8,6))
plt.title('No. of job postings country wise', size=20)
plt.bar(country.keys(), country.values())
plt.ylabel('No. of jobs', size=10)
plt.xlabel('Countries', size=10)
```

```
Text(0.5, 0, 'Countries')
```




```
# checking about which type of experience is required in most number of jobs
experience = dict(df1.required_experience.value_counts())
del experience[' ']
plt.bar(experience.keys(), experience.values())
plt.xlabel('Experience', size=10)
plt.ylabel('no. of jobs', size=10)
plt.xticks(rotation=35)
plt.show()
```




```
# Which industry have the maximum number of fake job postings?
# Group the data by the 'industry' column and count the occurrences of
'fake' values
df_vc = df1[df1['fraudulent'] == 1].groupby('industry')
['industry'].count()
# Sort the industry counts in descending order
sorted_industry_counts = df_vc.sort_values(ascending=False)
# Print the industries and their fake job posting counts in descending
order
for industry, count in sorted_industry_counts.items():
    print(f"Industry: {industry}, Fake Job Postings Count: {count}")

Industry:  , Fake Job Postings Count: 275
Industry: Oil & Energy, Fake Job Postings Count: 109
Industry: Accounting, Fake Job Postings Count: 57
Industry: Hospital & Health Care, Fake Job Postings Count: 51
Industry: Marketing and Advertising, Fake Job Postings Count: 45
Industry: Financial Services, Fake Job Postings Count: 35
Industry: Information Technology and Services, Fake Job Postings
Count: 32
Industry: Telecommunications, Fake Job Postings Count: 26
```

```
Industry: Consumer Services, Fake Job Postings Count: 24
Industry: Real Estate, Fake Job Postings Count: 24
Industry: Leisure, Travel & Tourism, Fake Job Postings Count: 21
Industry: Health, Wellness and Fitness, Fake Job Postings Count: 15
Industry: Hospitality, Fake Job Postings Count: 14
Industry: Computer Networking, Fake Job Postings Count: 12
Industry: Staffing and Recruiting, Fake Job Postings Count: 8
Industry: Management Consulting, Fake Job Postings Count: 6
Industry: Human Resources, Fake Job Postings Count: 6
Industry: Insurance, Fake Job Postings Count: 6
Industry: Computer Software, Fake Job Postings Count: 5
Industry: Retail, Fake Job Postings Count: 5
Industry: Automotive, Fake Job Postings Count: 5
Industry: Computer & Network Security, Fake Job Postings Count: 5
Industry: Entertainment, Fake Job Postings Count: 5
Industry: Electrical/Electronic Manufacturing, Fake Job Postings
Count: 4
Industry: Mechanical or Industrial Engineering, Fake Job Postings
Count: 4
Industry: Design, Fake Job Postings Count: 4
Industry: Biotechnology, Fake Job Postings Count: 4
Industry: Media Production, Fake Job Postings Count: 3
Industry: Environmental Services, Fake Job Postings Count: 3
Industry: Business Supplies and Equipment, Fake Job Postings Count: 3
Industry: Computer Hardware, Fake Job Postings Count: 3
Industry: Construction, Fake Job Postings Count: 3
Industry: Banking, Fake Job Postings Count: 3
Industry: Transportation/Trucking/Railroad, Fake Job Postings Count: 3
Industry: Animation, Fake Job Postings Count: 2
Industry: Market Research, Fake Job Postings Count: 2
Industry: Logistics and Supply Chain, Fake Job Postings Count: 2
Industry: Apparel & Fashion, Fake Job Postings Count: 2
Industry: Information Services, Fake Job Postings Count: 2
Industry: Facilities Services, Fake Job Postings Count: 2
Industry: Executive Office, Fake Job Postings Count: 2
Industry: E-Learning, Fake Job Postings Count: 2
Industry: Defense & Space, Fake Job Postings Count: 2
Industry: Utilities, Fake Job Postings Count: 1
Industry: Security and Investigations, Fake Job Postings Count: 1
Industry: Outsourcing/Offshoring, Fake Job Postings Count: 1
Industry: Airlines/Aviation, Fake Job Postings Count: 1
Industry: Ranching, Fake Job Postings Count: 1
Industry: Public Safety, Fake Job Postings Count: 1
Industry: Warehousing, Fake Job Postings Count: 1
Industry: Civil Engineering, Fake Job Postings Count: 1
Industry: Online Media, Fake Job Postings Count: 1
Industry: Military, Fake Job Postings Count: 1
Industry: Medical Practice, Fake Job Postings Count: 1
Industry: Medical Devices, Fake Job Postings Count: 1
```

```
Industry: Investment Management, Fake Job Postings Count: 1
Industry: Broadcast Media, Fake Job Postings Count: 1
Industry: Building Materials, Fake Job Postings Count: 1
Industry: Food Production, Fake Job Postings Count: 1
Industry: Cosmetics, Fake Job Postings Count: 1
Industry: Civic & Social Organization, Fake Job Postings Count: 1
Industry: Consumer Goods, Fake Job Postings Count: 1
Industry: Wholesale, Fake Job Postings Count: 1
```

```
#selecting only important columns as there are many columns in the dataset
df=df1[['description','requirements','fraudulent']]
df.head()
```

```
                                         description  \
0  Food52, a fast-growing, James Beard Award-winn...
1  Organised - Focused - Vibrant - Awesome!Do you...
2  Our client, located in Houston, is actively se...
3  THE COMPANY: ESRI – Environmental Systems Rese...
4  JOB TITLE: Itemization Review ManagerLOCATION:...

                                        requirements  fraudulent
0  Experience with content management systems a m...           0
1  What we expect from you:Your key responsibilit...           0
2  Implement pre-commissioning and commissioning ...           0
3  EDUCATION: Bachelor’s or Master’s in GIS, busi...           0
4  QUALIFICATIONS:RN license in the State of Texa...           0
```

```
#checking for the total number of null values in the dataset
df.isna().sum()
```

```
description     0
requirements    0
fraudulent      0
dtype: int64
```

```
#dropping null values from the dataset
df=df.dropna()
```

```
df.shape
```

```
(17880, 3)
```

```
from wordcloud import WordCloud
```

```
fraud=" ".join(df[df["fraudulent"]==1]["description"])
fraud
```

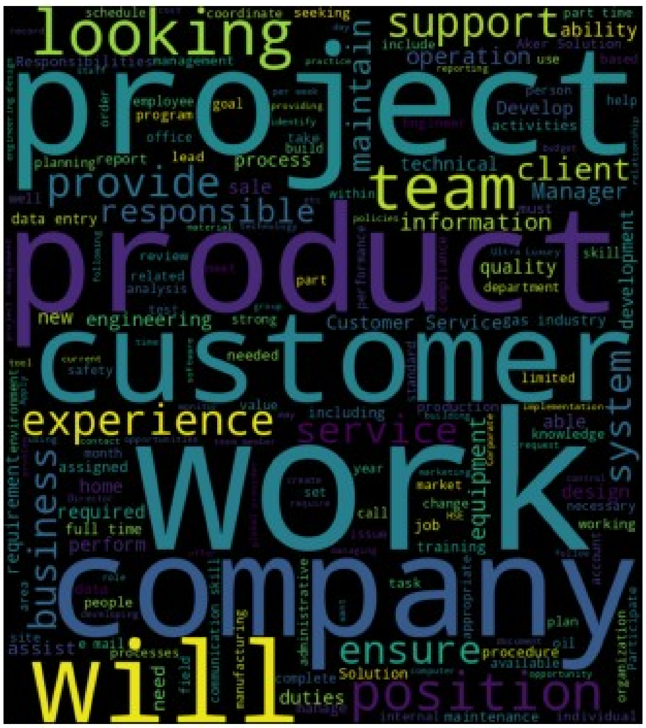
{"type":"string"}

```
real=" ".join(df[df["fraudulent"]==0]["description"])
real
```

{"type":"string"}

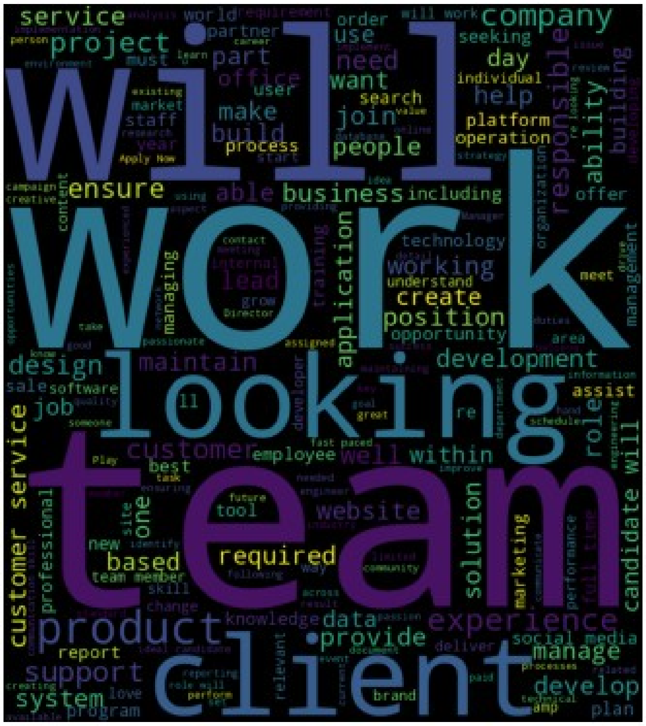
```
wc=WordCloud(width=800,height=900,background_color="black",min_font_size=12)
wc.generate(fraud)
plt.imshow(wc)
plt.axis("off")
```

```
(-0.5, 799.5, 899.5, -0.5)
```




```
wc=WordCloud(width=800,height=900,background_color="black",min_font_size=12)
wc.generate(real)
plt.imshow(wc)
plt.axis("off")
```

```
(-0.5, 799.5, 899.5, -0.5)
```



```
#splitting dataset into x (independent variables) and y (dependent variable)
x=df.iloc[:,:-1]    #to select all rows and all columns except the last one
y=df.iloc[:,-1]     #to select last column which is target column

voc_size=5000
#limiting vocabulary size to the top 5000 most frequently occurring words in your text corpus.
#Words outside this vocabulary would either be ignored or replaced with a special token.

#copying content of x to new variable 'message' to ensure that changes made to 'message' do not affect the original DataFrame x.
message = x.copy()
message.head()
```

```
                                         description  \
0  Food52, a fast-growing, James Beard Award-winn...
1  Organised - Focused - Vibrant - Awesome!Do you...
2  Our client, located in Houston, is actively se...
3  THE COMPANY: ESRI – Environmental Systems Rese...
4  JOB TITLE: Itemization Review ManagerLOCATION:...

                                        requirements
0  Experience with content management systems a m...
1  What we expect from you:Your key responsibilit...
```

```
2  Implement pre-commissioning and commissioning ...
3  EDUCATION: Bachelor’s or Master’s in GIS, busi...
4  QUALIFICATIONS:RN license in the State of Texa...
```

```python
message['description'][1]
```

```
{"type":"string"}
```

```python
message.reset_index(inplace=True)
#The reset_index() method helps to reset the index back to the default integer index,
#and the inplace=True argument ensures that the modification is done on the DataFrame itself, without creating a new DataFrame.
```

```python
nltk.download('stopwords')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

```
True
```

```python
#Stemming is a process of reducing words to their root form, which can help to normalize the text and reduce word variations
from nltk.stem.porter import PorterStemmer
ps = PorterStemmer()  #Creating an instance of the PorterStemmer class, which will be used for stemming words.
corpus = [] # Creating an empty list named corpus where preprocessed text will be stored.
for i in range(0, len(message)):
#Removing all characters that are not letters (using a regular expression) and replacing them with spaces.
#This step effectively removes any special characters, digits, or punctuation from the text.
    review = re.sub('[^a-zA-Z]', ' ', message['description'][i])
    review = review.lower()   # Converting the entire text to lowercase. This step helps in standardizing the text and avoiding case sensitivity
    review = review.split()   #Splitting the text into a list of words
#Applying stemming using the PorterStemmer on each word in the list while also removing any words that are in the NLTK English stopwords list
    review = [ps.stem(word) for word in review if not word in stopwords.words('english')]
    review = ' '.join(review)   #Joining the stemmed words back together into a single string.
    corpus.append(review)     #Adding the preprocessed and stemmed text to the corpus list.
```

```python
corpus[1] #content of the corpus list after the preprocessing steps
#processed text of the second entry in the corpus list
```

{"type":"string"}

```
onehot_repr=[one_hot(words,voc_size)for words in corpus]
#A one-hot representation is a binary vector where each word in the
vocabulary is represented by a unique index position,
# and only the index corresponding to the current word is set to 1,
while all others are set to 0
onehot_repr[1]
#output appears to be a list of integers, where each integer
represents the index of a word in the vocabulary so it won't be in
binary
```

```
[2955,
 3313,
 2137,
 1375,
 2521,
 4738,
 981,
 3636,
 4261,
 3057,
 2069,
 96,
 3456,
 4982,
 1237,
 2354,
 113,
 1263,
 4109,
 3715,
 2559,
 276,
 871,
 823,
 981,
 854,
 1598,
 551,
 968,
 4176,
 4063,
 959,
 2681,
 169,
 3970,
 823,
 2340,
 4738,
```

```
981,
665,
4677,
3865,
1026,
1231,
2438,
3456,
3456,
1668,
3783,
871,
2438,
3456,
1420,
2479,
1460,
823,
272,
1575,
3104,
4461,
3341,
3763,
3833,
4728,
2990,
472,
4112,
3708,
1923,
1401,
851,
4105,
3865,
292,
3873,
891,
4838,
4001,
2209,
2848,
2509,
4918,
1923,
3865,
2509,
1595,
2287,
```

```
169,
276,
871,
823,
981,
3783,
1514,
4975,
2433,
1274,
4272,
1794,
147,
1416,
2204,
2204,
1794,
2888,
4983,
2287,
169,
276,
871,
823,
981,
4572,
4461,
1771,
1301,
2335,
3908,
3757,
871,
3028,
2398,
2718,
2038,
169,
3448,
2849,
3456,
1263,
276,
3203,
2398,
2287,
3489,
3866,
4513,
```

```
4989,
4760,
299,
1575,
1963,
871,
823,
130,
3456,
39,
1580,
871,
2438,
368,
3757,
320,
292,
4620,
2489,
871,
1918,
2030,
1761,
823,
1668,
4728,
2030,
3152,
871,
2438,
1668,
2844,
4050,
1119,
1471,
230,
1794,
2287,
2718,
2056,
871,
2030,
3833,
4461,
4139,
169,
4795,
4139,
3437,
```

```
 1633,
 4761,
 4667,
 2241,
 1940,
 2985,
 4335,
 4002,
 1863,
 2318,
 4566,
 2985,
 1940,
 1974,
 2509,
 180,
 3320,
 3124,
 640,
 4790,
 981]
```

```python
#Embedding Representation ((onehot_repr) into padded sequences of
fixed length (sent_length))
sent_length=40
embedded_docs=pad_sequences(onehot_repr,padding='pre',maxlen=sent_leng
th)
#padding='pre' specifies that the padding should be added at the
beginning of each sequence (so the zeros are added to the left).
print(embedded_docs)
```

```
[[4391 3028 3456 ...  619 3501 3398]
 [1668 2844 4050 ...  640 4790  981]
 [   0    0    0 ... 1032 4020 1112]
 ...
 [2184 3340 3068 ... 2161  756 4331]
 [1654 3783 1353 ... 4577  891 2438]
 [  37 3193 3637 ... 1344 2902 4756]]
```

```python
embedded_docs[1]
```

```
array([1668, 2844, 4050, 1119, 1471,  230, 1794, 2287, 2718, 2056,
871,
       2030, 3833, 4461, 4139,  169, 4795, 4139, 3437, 1633, 4761,
4667,
       2241, 1940, 2985, 4335, 4002, 1863, 2318, 4566, 2985, 1940,
1974,
       2509,  180, 3320, 3124,  640, 4790,  981], dtype=int32)
```

```
## Creating model
embedding_vector_features=50
model1=Sequential()
model1.add(Embedding(voc_size,embedding_vector_features,input_length=s
ent_length))
model1.add(Bidirectional(LSTM(100))) ##Just add bidirectional, except
it would just behave as normal LSTM Model
model1.add(Dropout(0.3))
model1.add(Dense(1,activation='sigmoid'))
model1.compile(loss='binary_crossentropy',optimizer='adam',metrics=['a
ccuracy'])
#print(model1.summary())
```

```
len(embedded_docs),y.shape
```

```
(17880, (17880,))
```

```
#converting data into NumPy arrays
xfinal=np.array(embedded_docs)
yfinal=np.array(y)
```

```
xfinal[1]
```

```
array([1668, 2844, 4050, 1119, 1471,  230, 1794, 2287, 2718, 2056,
871,
       2030, 3833, 4461, 4139,  169, 4795, 4139, 3437, 1633, 4761,
4667,
       2241, 1940, 2985, 4335, 4002, 1863, 2318, 4566, 2985, 1940,
1974,
       2509,  180, 3320, 3124,  640, 4790,  981], dtype=int32)
```

```
#spliting data into training and testing sets
xtrain, xtest, ytrain, ytest = train_test_split(xfinal, yfinal,
test_size=0.25, random_state=32)
```

```
#training data
model1.fit(xtrain,ytrain,validation_data=(xtest,ytest),epochs=12,batch
_size=64)
```

```
Epoch 1/12
210/210 [==============================] - 35s 144ms/step - loss:
0.1888 - accuracy: 0.9551 - val_loss: 0.1334 - val_accuracy: 0.9644
Epoch 2/12
210/210 [==============================] - 29s 139ms/step - loss:
0.0934 - accuracy: 0.9725 - val_loss: 0.1225 - val_accuracy: 0.9705
Epoch 3/12
210/210 [==============================] - 29s 136ms/step - loss:
0.0591 - accuracy: 0.9823 - val_loss: 0.1034 - val_accuracy: 0.9734
Epoch 4/12
210/210 [==============================] - 29s 138ms/step - loss:
0.0383 - accuracy: 0.9878 - val_loss: 0.1222 - val_accuracy: 0.9747
```

```
Epoch 5/12
210/210 [==============================] - 29s 138ms/step - loss: 
0.0213 - accuracy: 0.9931 - val_loss: 0.1333 - val_accuracy: 0.9767
Epoch 6/12
210/210 [==============================] - 29s 139ms/step - loss: 
0.0115 - accuracy: 0.9966 - val_loss: 0.1460 - val_accuracy: 0.9736
Epoch 7/12
210/210 [==============================] - 29s 139ms/step - loss: 
0.0087 - accuracy: 0.9977 - val_loss: 0.2058 - val_accuracy: 0.9749
Epoch 8/12
210/210 [==============================] - 29s 139ms/step - loss: 
0.0051 - accuracy: 0.9989 - val_loss: 0.1829 - val_accuracy: 0.9707
Epoch 9/12
210/210 [==============================] - 29s 138ms/step - loss: 
0.0056 - accuracy: 0.9984 - val_loss: 0.1652 - val_accuracy: 0.9640
Epoch 10/12
210/210 [==============================] - 32s 151ms/step - loss: 
0.0045 - accuracy: 0.9990 - val_loss: 0.2310 - val_accuracy: 0.9671
Epoch 11/12
210/210 [==============================] - 30s 143ms/step - loss: 
0.0058 - accuracy: 0.9983 - val_loss: 0.2255 - val_accuracy: 0.9738
Epoch 12/12
210/210 [==============================] - 29s 136ms/step - loss: 
0.0031 - accuracy: 0.9993 - val_loss: 0.2418 - val_accuracy: 0.9727

<keras.callbacks.History at 0x7f71d863b820>

#evaluate the model
model1.evaluate(xtest, ytest)

140/140 [==============================] - 2s 17ms/step - loss: 0.2418 
- accuracy: 0.9727

[0.24182961881160736, 0.9727069139480591]

#make prediction on testing data using trained model
y_pred=model1.predict(xtest)

140/140 [==============================] - 3s 16ms/step

#the threshold of 0.5 is commonly used to decide between the two 
classes.
#For each value, if threshold is greater than or equal to 0.5, it 
assigns 1; otherwise, it assigns 0. This creates a list of binary 
predictions.
preds_y = [1 if x >=0.5 else 0 for x in y_pred] #providing threshold 
value
print("Accuracy  {:.3} %".format(accuracy_score(ytest, preds_y)*100))
print("Recall Score  {:.3} %".format(recall_score(ytest, 
preds_y)*100))
print("Precision Score  {:.3} %".format(precision_score(ytest,
```

```
preds_y)*100))
print("F1 Score  {:.3} %".format(f1_score(ytest, preds_y)*100))
```

```
Accuracy  97.3 %
Recall Score  61.9 %
Precision Score  78.9 %
F1 Score  69.3 %
```

```
print(classification_report(ytest, preds_y))
```

```
              precision    recall  f1-score   support

           0       0.98      0.99      0.99      4247
           1       0.79      0.62      0.69       223

    accuracy                           0.97      4470
   macro avg       0.88      0.81      0.84      4470
weighted avg       0.97      0.97      0.97      4470
```

Prediction on Unknown job descrition

```
unknown_text = "About the CompanyThis is anÂ amazing job opportunity
with one of the most robust companies in the EnergyÂ Industry!
Opportunities for advancement are extensive as theÂ company is
currently growing and looking for outstanding employees to grow with
it. Strong compensation and benefits packages areÂ available for
qualified candidates who want to join the largest player in the
BakkenÂ Shale and leader in the Oklahoma Shale plays. Contact us today
for an opportunity to join one of the Industryâ€™s leaders in the
mission to achieve American energyÂ independence!Please note: This job
will require relocation to Oklahoma City, OK.SummaryAssist in
preparing completions, testing, and workover procedures. Maintain
project management control over equipment installation, well
completion, and workovers.Essential Job FunctionsMonitor completion
operations, costs, and profitability.Design and implementÂ completion
and well workover plans and procedures.Generate and review AFEs for
capital expenditures.Review expenditures for properties within a
specified area.AnalyzeÂ well problems and direct actions to be
taken.Work well in a fast paced environment.Solve minor problems with
little supervision.Consult with Completion Manager on higher risk and
more complex problems and projects.Track costs and operational
efficiency on a daily basis and report trends.Perform post completion
appraisal and provide recommendations for performance improvement.Work
with Completion Foremen to ensure safe and efficient
operations.Support asset teams as requested.Assure compliance with
governmental requirements and company policies.Provide training and
resources to accomplish production goals."
```

```
unknown_text2="collecting and entering data in databases and maintaining accurate records of valuable company information"

unknown_text3="Collaborating with finance and sales professionals to maintain accounts receivable. Compiling and process information such as prices, discounts, shipping rates etc. Ensuring customers are billed correctly for services offered."

unknown_text4="Jaco Oil and Refined Resources have partnered up in an effort to streamline the hiring process and provide a more efficient and effective recruitng model.Â  Our focus is to help develop and achieve your career goals while makeing a solid geographical, cultural and professional fiit when leveraging your career into your new and exciting professional venture!Please direct all communications to the HR Department within Refined Resources (#URL_80d75e0d07ca8b108539318a0443bfe5d1ff472afa0c4540b77079c5d5f31eee#)Â #EMAIL_0b13a2cfd4718ce252c09b2353d692a73bd32552e922c5db6cad5fb7e9a2c6c3#Darren Lawson | VP of Recruiting |Â #EMAIL_395225df8eed70288fc67310349d63d49d5f2ca6bc14dbb5dcbf9296069ad88c#Â |#PHONE_70128aad0c118273b0c2198a08d528591b932924e165b6a8d1272a6f9e2763d1#"

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

tokenizer = Tokenizer(num_words=10000, oov_token='<OOV>')
tokenizer.fit_on_texts(unknown_text)
max_sequence_length = 100

# Preprocess the unknown text
unknown_sequence = tokenizer.texts_to_sequences([unknown_text])
unknown_padded = pad_sequences(unknown_sequence, maxlen=max_sequence_length, padding='post')

# Make prediction
prediction = model1.predict(unknown_padded)
```

```
1/1 [==============================] - 0s 33ms/step
```

```
# Interpret the prediction
if prediction >= 0.5:
    prediction_label = "Fake"
else:
    prediction_label = "Real"

print(f"The job description is predicted as: {prediction_label} (Score: {prediction[0][0]:.4f})")
```

```
The job description is predicted as: Fake (Score: 0.9998)
```