# Depression Sentiment analysis with Embedding and LSTM

## **Import Dependince**

```
In [1]: import numpy as np
import pandas as pd
import nltk
import re
import string
from nltk.corpus import stopwords
nltk.download("stopwords")
stemmer = nltk.SnowballStemmer("english")
stopword=set(stopwords.words('english'))
from nltk.sentiment.vader import SentimentIntensityAnalyzer
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator
```

[nltk\_data] Downloading package stopwords to /Users/vikky/nltk\_dat
a...
[nltk data] Package stopwords is already up-to-date!

### **Data collection**

```
In [2]: #loading the dataset panda dataframe
data = pd.read_csv('depression_dataset_reddit_cleaned.csv')
```

In [3]: #check first five rows of the dataset
data.head()

### Out[3]:

	clean_text	is_depression
0	we understand that most people who reply immed	1
1	welcome to r depression s check in post a plac	1
2	anyone else instead of sleeping more when depr	1
3	i ve kind of stuffed around a lot in my life d	1
4	sleep is my greatest and most comforting escap	1

In [4]: #check last five rows of the dataset
data.tail()

### Out[4]:

	clean_text	is_depression
7726	is that snow	0
7727	moulin rouge mad me cry once again	0
7728	trying to shout but can t find people on the list	0
7729	ughh can t find my red sox hat got ta wear thi	0
7730	slept wonderfully finally tried swatching for	0

# In [5]: #check columns of the dataset data.columns

Out[5]: Index(['clean\_text', 'is\_depression'], dtype='object')

# In [6]: #check more infomation of the dataset data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7731 entries, 0 to 7730
Data columns (total 2 columns):

# Column Non-Null Count Dtype
--- --- 7731 non-null object
1 is\_depression 7731 non-null int64
dtypes: int64(1), object(1)
memory usage: 120.9+ KB

# In [7]: #check mathmatic realtionship of the dataset data.describe()

### Out[7]:

	is_depression
count	7731.000000
mean	0.495537
std	0.500012
min	0.000000
25%	0.000000
50%	0.000000
75%	1.000000
max	1.000000

```
In [8]: #check missing value of the dataset
data.isnull().sum()
```

Out[8]: clean\_text 0
is\_depression 0
dtype: int64

**EDA** 

```
In [9]: import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [10]: data['is_depression'].value_counts()
```

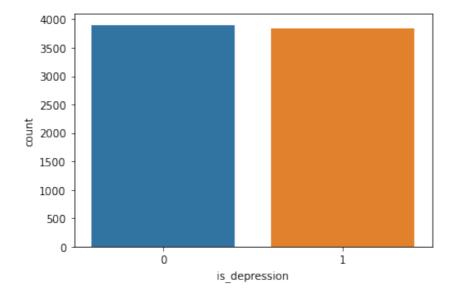
Out[10]: 0 3900 1 3831

Name: is\_depression, dtype: int64

```
In [11]: #count the valur is_depression dataset colums
sns.countplot(data['is_depression'])
```

/Users/vikky/opt/anaconda3/lib/python3.9/site-packages/seaborn/\_de corators.py:36: FutureWarning: Pass the following variable as a ke yword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation. warnings.warn(

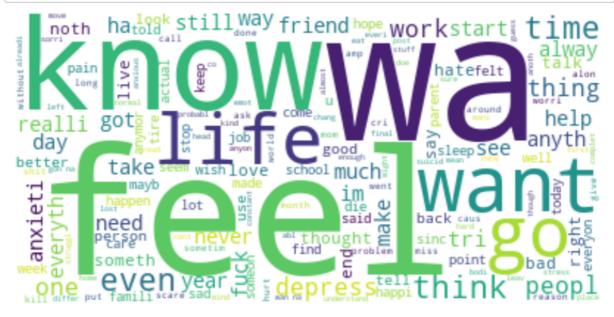
Out[11]: <AxesSubplot:xlabel='is\_depression', ylabel='count'>



```
In [12]: #cleaning the dataset
def clean(text):
    text = str(text).lower()
    text = re.sub('\[.*?\]', '', text)
    text = re.sub('https?://\S+|www\.\S+', '', text)
    text = re.sub('<.*?>+', '', text)
    text = re.sub('[%s]' % re.escape(string.punctuation), '', text)
    text = re.sub('\n', '', text)
    text = re.sub('\w*\d\w*', '', text)
    text = re.sub('\w*\d\w*', '', text)
    text = [word for word in text.split(' ') if word not in stopword text=" ".join(text)
    text = [stemmer.stem(word) for word in text.split(' ')]
    text=" ".join(text)
    return text
```

```
In [14]: # apply clean function for dataset colum clean_text
data["clean_text"] = data["clean_text"].apply(clean)
```

```
In [15]: #Now let's have a look at the kind of words people use in the is_de
    text = " ".join(i for i in data.clean_text)
    stopwords = set(STOPWORDS)
    wordcloud = WordCloud(stopwords=stopwords, background_color="white"
    plt.figure( figsize=(15,10))
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis("off")
    plt.show()
```



## Spliting the dataset

```
In [16]: \#spliting the dataset in x and y
         x = data["clean_text"]
         y = data["is_depression"]
In [17]: | #print x and y
         print(x)
         print(y)
                  understand peopl repli immedi op invit talk pr...
                  welcom r depress check post place take moment ...
         1
         2
                  anyon els instead sleep depress stay night avo...
         3
                  kind stuf around lot life delay inevit work jo...
         4
                  sleep greatest comfort escap whenev wake day l...
         7726
                                                                 snow
         7727
                                                 moulin roug mad cri
         7728
                                           tri shout find peopl list
         7729
                  ughh find red sox hat got ta wear creepi nick ...
         7730
                  slept wonder final tri swatch new project clas...
         Name: clean_text, Length: 7731, dtype: object
                  1
         1
                  1
         2
                  1
         3
                  1
         4
                  1
         7726
                  0
         7727
                  0
         7728
                  0
         7729
                  0
         7730
         Name: is_depression, Length: 7731, dtype: int64
```

## **Train-Test split**

```
In [18]: #spliting the dataset in X_train and Y_train
    from sklearn.model_selection import train_test_split
    X_train,X_test,Y_train,Y_test=train_test_split(x,y,test_size=0.2)
In [19]: #check shape X_train and Y_train
    print(X_train.shape,X_test.shape,Y_train.shape,Y_test.shape)
    (6184,) (1547,) (6184,) (1547,)
```

### **Text Vectorization**

```
In [20]: #using Text Vectorizatio
         round(sum([len(i.split()) for i in X_train])/len(X_train))
Out[20]: 34
In [21]: # import TextVectorization
         import tensorflow as tf
         from tensorflow.keras.layers import TextVectorization
In [22]: # spliting the dataset in text_vectorizer
         max_vocab_length = 10000
         max_length = 34
         text vectorizer = TextVectorization(max tokens=max vocab length,
                                              output mode="int",
                                              output_sequence_length=max_leng
In [23]: #check X_train after splitng Text_vectorizer
         text_vectorizer.adapt(X_train)
In [24]: #finf Words in vocab
         words_in_vocab = text_vectorizer.get_vocabulary()
         top_5_words = words_in_vocab[:5]
         bottom_5_words = words_in_vocab[-5:]
         print(f"Vocablary size: {len(words_in_vocab)}")
         print(f"Top 5 most common words: {top 5 words}")
         print(f"Bottom 5 least common words:: {bottom 5 words}")
         Vocablary size: 10000
         Top 5 most common words: ['', '[UNK]', 'feel', 'wa', 'like']
         Bottom 5 least common words:: ['inna', 'inlov', 'inlaw', 'inkart',
         'ink'l
```

## **Embedding Layer**

```
In [25]: #using Embedding layer
from tensorflow.keras import layers

embedding = layers.Embedding(input_dim=max_vocab_length, output_dim embeddings_initializer="uniform", input_length=max_length
)
```

```
In [26]: from tensorflow.keras import layers
       inputs = layers.Input(shape=(1,), dtype=tf.string)
       x = text vectorizer(inputs)
       x = embedding(x)
       x = layers.GlobalAveragePooling1D()(x)
       outputs = layers.Dense(1, activation="sigmoid")(x)
       model_1 = tf.keras.Model(inputs, outputs, name="model_1_dense")
In [27]: #model compile
       model_1.compile(loss='binary_crossentropy',optimizer='adam',metrics
In [28]: #train model
       history = model 1.fit(X train,Y train,validation data=(X test,Y tes
       Epoch 1/10
       194/194 [============== ] - 8s 27ms/step - loss: 0.
       4695 - accuracy: 0.8357 - val_loss: 0.3507 - val_accuracy: 0.8655
       Epoch 2/10
       194/194 [============= ] - 5s 25ms/step - loss: 0.
       2837 - accuracy: 0.8991 - val loss: 0.2763 - val accuracy: 0.8966
       Epoch 3/10
       194/194 [============ ] - 5s 25ms/step - loss: 0.
       2158 - accuracy: 0.9221 - val_loss: 0.2265 - val_accuracy: 0.9147
       Epoch 4/10
       1663 - accuracy: 0.9402 - val_loss: 0.1883 - val_accuracy: 0.9276
       Epoch 5/10
       194/194 [============= ] - 6s 31ms/step - loss: 0.
       1296 - accuracy: 0.9560 - val_loss: 0.1622 - val_accuracy: 0.9412
       Epoch 6/10
       194/194 [============= ] - 5s 27ms/step - loss: 0.
       1046 - accuracy: 0.9680 - val loss: 0.1458 - val accuracy: 0.9502
       Epoch 7/10
       0867 - accuracy: 0.9753 - val loss: 0.1340 - val accuracy: 0.9606
       Epoch 8/10
       0738 - accuracy: 0.9788 - val_loss: 0.1314 - val_accuracy: 0.9580
       Epoch 9/10
       194/194 [============ ] - 6s 28ms/step - loss: 0.
       0638 - accuracy: 0.9821 - val_loss: 0.1271 - val_accuracy: 0.9599
       Epoch 10/10
       194/194 [============= ] - 6s 29ms/step - loss: 0.
       0569 - accuracy: 0.9843 - val_loss: 0.1283 - val_accuracy: 0.9580
```

```
In [30]: history.history
Out[30]: {'loss': [0.46946293115615845,
            0.2837080955505371,
            0.21580171585083008,
            0.16626225411891937,
            0.12964126467704773,
            0.10459963977336884,
            0.08674520999193192,
            0.07382360845804214.
            0.06380867213010788.
           0.05686891824007034],
           'accuracy': [0.835705041885376,
            0.8990944623947144,
            0.9220569133758545,
            0.9401682019233704,
            0.9560155272483826.
            0.9679818749427795,
            0.9752587080001831,
            0.9788162708282471,
            0.9820504784584045,
            0.9843143820762634],
           'val loss': [0.3507160246372223,
            0.2762649357318878,
            0.2264728993177414,
            0.18832530081272125,
            0.16224391758441925,
            0.14581571519374847,
            0.13403543829917908.
            0.13141471147537231,
            0.12711641192436218,
            0.12834328413009644],
           'val_accuracy': [0.8655462265014648,
            0.8965740203857422,
            0.9146735668182373,
            0.9276018142700195.
            0.9411764740943909.
            0.9502262473106384,
            0.9605688452720642,
            0.9579831957817078,
            0.9599224328994751,
            0.9579831957817078]}
```

## **Classification Report for Model 1**

In [33]: from sklearn.metrics import confusion\_matrix
from sklearn.metrics import classification\_report
print(classification\_report(Y\_test,Y\_pred))

	precision	recall	f1-score	support
0 1	0.93 0.98	0.98 0.93	0.96 0.96	770 777
accuracy macro avg weighted avg	0.96 0.96	0.96 0.96	0.96 0.96 0.96	1547 1547 1547

### LSTM model

```
In [34]: #using Lstm model
    from tensorflow.keras import layers
    inputs = layers.Input(shape=(1,), dtype=tf.string)
    x = text_vectorizer(inputs)
    x = embedding(x)
    x = layers.LSTM(64, activation="tanh")(x)
    outputs = layers.Dense(1, activation="sigmoid")(x)
    model_2 = tf.keras.Model(inputs, outputs, name="model_2_lstm")
```

```
In [35]: #compile model
model_2.compile(loss='binary_crossentropy',optimizer='adam',metrics
```

### In [36]: #train model using lstm history = model\_2.fit(X\_train,Y\_train,validation\_data=(X\_test,Y\_tes Epoch 1/10 194/194 [============= ] - 17s 67ms/step - loss: 0 .1219 - accuracy: 0.9657 - val\_loss: 0.1875 - val\_accuracy: 0.9418 Epoch 2/10 .0443 - accuracy: 0.9880 - val\_loss: 0.1772 - val\_accuracy: 0.9463 Epoch 3/10 194/194 [============= ] - 13s 67ms/step - loss: 0 .0337 - accuracy: 0.9898 - val\_loss: 0.1912 - val\_accuracy: 0.9535 Epoch 4/10 .0386 - accuracy: 0.9905 - val\_loss: 0.1657 - val\_accuracy: 0.9489 Epoch 5/10 194/194 [============= ] - 12s 61ms/step - loss: 0 .0285 - accuracy: 0.9927 - val\_loss: 0.1657 - val\_accuracy: 0.9457 Epoch 6/10 194/194 [============= ] - 12s 60ms/step - loss: 0 .0175 - accuracy: 0.9958 - val\_loss: 0.2598 - val\_accuracy: 0.9438 Epoch 7/10 194/194 [============= ] - 12s 61ms/step - loss: 0 .0176 - accuracy: 0.9947 - val\_loss: 0.2520 - val\_accuracy: 0.9438 Epoch 8/10 194/194 [============= ] - 12s 61ms/step - loss: 0 .0223 - accuracy: 0.9930 - val loss: 0.2109 - val accuracy: 0.9483

Epoch 9/10

Epoch 10/10

```
In [37]: history.history
Out[37]: {'loss': [0.12194930762052536,
            0.04434535279870033.
            0.03370266035199165,
            0.03857898712158203,
            0.028453631326556206,
            0.01745663397014141,
            0.01756499893963337,
            0.022268325090408325.
            0.013344790786504745,
            0.0361902117729187],
           'accuracy': [0.9657179713249207,
            0.988033652305603,
            0.989812433719635,
            0.9904592633247375,
            0.9927231669425964.
            0.9957956075668335,
            0.994663655757904,
            0.9930465817451477,
            0.9962807297706604,
            0.9896507263183594],
           'val loss': [0.18753276765346527,
            0.17715151607990265,
            0.19118280708789825,
            0.16568949818611145,
            0.1657085120677948,
            0.2597535252571106,
            0.2520136535167694
            0.21087147295475006,
            0.3077019453048706,
            0.26683393120765686],
           'val_accuracy': [0.94182288646698,
           0.9463477730751038,
            0.953458309173584,
            0.9489334225654602.
            0.9457013607025146.
            0.9437621235847473,
            0.9437621235847473,
            0.9482870101928711,
            0.930187463760376,
            0.9392372369766235]}
```

### Classification Report for Model 2

In [39]: from sklearn.metrics import confusion\_matrix
from sklearn.metrics import classification\_report
print(classification\_report(Y\_test,Y\_pred))

	precision	recall	f1-score	support
0 1	0.95 0.93	0.93 0.95	0.94 0.94	770 777
accuracy macro avg weighted avg	0.94 0.94	0.94 0.94	0.94 0.94 0.94	1547 1547 1547

In []: