In [1]: pwd

Out[1]: 'C:\\Users\\MANAY'

In [2]: import re

#regular expression: provide regular matching operations; RegEx is a sequence of characters that forms a search pattern.

In [3]: import pandas as pd

#data manipulation and analysis tool using its powerful data structures import numpy as np

#general purpose array-processing package, it provide high performance multidim ensional array object and tools working on it.

import matplotlib.pyplot as plt

import seaborn as sns

#it will bw used in making statistical graphics

import string

#strings in Python are arrays of bytes representing unicode characters

import nltk

#for working with human language data processing

import warnings

#This is the base class of all warning category classes. It handles waring. Pr ogram doesn't terminate when warning is encountered

warnings.filterwarnings("ignore", category=DeprecationWarning)

#ignoring disapproval warnings

%matplotlib inline

In [4]: train = pd.read\_csv('train\_E6oV3lV.csv')
 test = pd.read\_csv('test\_tweets\_anuFYb8.csv')

In [5]: | train.head()

Out[5]:

	i	id	label	tweet
	) _	1	0	@user when a father is dysfunctional and is s
	1 2	2	0	@user @user thanks for #lyft credit i can't us
[	2 3	3	0	bihday your majesty
[	3 4	4	0	#model i love u take with u all the time in
	1 5	5	0	factsguide: society now #motivation

In [6]: #label is the target variable

#tweet contains the tweets that we will clean and preprocess

```
In [7]: # 1.we will try to get rid of the punctuations, numbers and special characters.
# 2.small words are of no use as they do not add much value e.g. your, all, th
e, and. we will try to remove them.
# 3.executed the above steps, we can split every tweet into individual words o
r tokens.
# which is an essential step in any NLP task.
# 4. We will reduce loves, loving, lovable etc in the data to "love".
# Then we can reduce the total number of unique words in our data without losi
ng a significant amount of information.
```

# **Removing Twitter Handle**

```
In [8]: combi = train.append(test, ignore_index=True)
#append train and test to remove @user at a time, just reducing the task
```

C:\Users\MANAY\Anaconda3\lib\site-packages\pandas\core\frame.py:6201: FutureW arning: Sorting because non-concatenation axis is not aligned. A future versi on

of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=True'.

To retain the current behavior and silence the warning, pass sort=False sort=sort)

In [9]: combi.head()

Out[9]:

	id	label	tweet
0	1	0.0	@user when a father is dysfunctional and is s
1	2	0.0	@user @user thanks for #lyft credit i can't us
2	3	0.0	bihday your majesty
3	4	0.0	#model i love u take with u all the time in
4	5	0.0	factsguide: society now #motivation

```
In [10]: def remove_pattern(input_txt, pattern):
    r=re.findall(pattern, input_txt)
    for i in r:
        input_txt= re.sub(i,'',input_txt)
    return input_txt
```

# remove tweetter handles (@user)

```
In [12]: combi['tidy_tweet'] = np.vectorize(remove_pattern)(combi['tweet'], "@[\w]*")
#
```

# Remove punctuations, numbers, punctuations

```
In [13]: # remove special characters, numbers, punctuations
    combi['tidy_tweet'] = combi['tidy_tweet'].str.replace("[^a-zA-Z#]", " ")
```

In [14]: combi.head()

Out[14]:

	id	label	tweet	tidy_tweet
0	1	0.0	@user when a father is dysfunctional and is s	when a father is dysfunctional and is so sel
1	2	0.0	@user @user thanks for #lyft credit i can't us	thanks for #lyft credit i can t use cause th
2	3	0.0	bihday your majesty	bihday your majesty
3	4	0.0	#model i love u take with u all the time in	#model i love u take with u all the time in
4	5	0.0	factsguide: society now #motivation	factsguide society now #motivation

## Removing short words

```
In [15]: combi['tidy_tweet'] = combi['tidy_tweet'].apply(lambda x: ' '.join([w for w in x.split() if len(w)>3]))
```

In [16]: combi.head()

Out[16]:

	id	label	tweet	tidy_tweet
0	1	0.0	@user when a father is dysfunctional and is s	when father dysfunctional selfish drags kids i
1	2	0.0	@user @user thanks for #lyft credit i can't us	thanks #lyft credit cause they offer wheelchai
2	3	0.0	bihday your majesty	bihday your majesty
3	4	0.0	#model i love u take with u all the time in	#model love take with time
4	5	0.0	factsguide: society now #motivation	factsguide society #motivation

#### **Tokenization**

### **Stemming**

```
#Stemming is a rule based process of stripping the suffixes ("ing","ly","e
In [19]:
         s", "s" etc) from a word
         from nltk.stem.porter import *
         stemmer = PorterStemmer()
         tokenized tweet = tokenized tweet.apply(lambda x: [stemmer.stem(i) for i in x
         1)
              #stemming.
In [20]:
        tokenized_tweet.head()
              [when, father, dysfunct, selfish, drag, kid, i...
Out[20]: 0
         1
              [thank, #lyft, credit, caus, they, offer, whee...
         2
                                         [bihday, your, majesti]
         3
                                [#model, love, take, with, time]
                                    [factsguid, societi, #motiv]
         Name: tidy_tweet, dtype: object
In [21]: for i in range(len(tokenized tweet)):
             tokenized_tweet[i]=' '.join(tokenized_tweet[i])
         combi['tidy_tweet']=tokenized_tweet
```

In [22]: combi.head()

Out[22]:

	id	label	tweet	tidy_tweet
0	1	0.0	@user when a father is dysfunctional and is s	when father dysfunct selfish drag kid into dys
1	2	0.0	@user @user thanks for #lyft credit i can't us	thank #lyft credit caus they offer wheelchair
2	3	0.0	bihday your majesty	bihday your majesti
3	4	0.0	#model i love u take with u all the time in	#model love take with time
4	5	0.0	factsguide: society now #motivation	factsguid societi #motiv

# Story Generation and Visualization from tweets

# Understanding the common words used in the tweets: WordCloud

```
In [23]: all_words=' '.join([text for text in combi['tidy_tweet']])
In [24]: from wordcloud import WordCloud
In [25]: wordcloud=WordCloud(width=800, height=500, random state=21, max font size=110).
         generate(all words)
```

```
In [26]: plt.figure(figsize=(10,7))
   plt.imshow(wordcloud, interpolation="bilinear")
   plt.axis('off')
   plt.show()
```

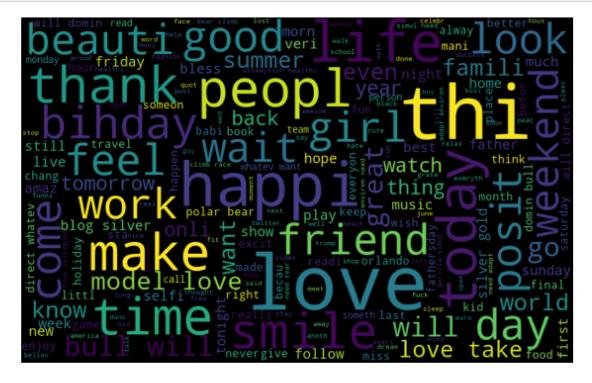
```
work back good year trump bull will everyon always bear trump bull will everyon book bampa tather bless mani show travel readi befor summer home even book bampa tather bless mani show travel readi befor summer home even book bampa tather bless mani show travel readi befor summer home even work thing model love en love the back great trump bull will everyon to read to be summer home even bank book bampa tather bless mani show travel readi befor summer home even en love the back great always to health school we exclude the book bampa tather bless mani show travel readi befor summer home even en love the book bampa tather bless mani show travel readi befor summer home even en love the befor en love the befor summer home even en love the befor summer home even en love the befor en love the before the before the before the before the before the be
```

#### Words in non racist/sexist tweets

```
In [27]: normal_words=''.join([text for text in combi['tidy_tweet'][combi['label'] == 0
]])
```

In [28]: wordcloud=WordCloud(width=800, height=500, random\_state=21, max\_font\_size=110).
generate(normal\_words)

```
In [29]: plt.figure(figsize=(10,7))
    plt.imshow(wordcloud, interpolation="bilinear")
    plt.axis('off')
    plt.show()
```



#### **Racist/Sexist Tweets**

```
In [32]: plt.figure(figsize=(10,7))
    plt.imshow(wordcloud, interpolation="bilinear")
    plt.axis('off')
    plt.show()
```

```
black feel manipulation of the politic think girl good word broken is rae!

Solve must be politic think girl good with the politic t
```

## Understanding the impact of Hashtags on tweets sentiment

#extracting hashtag from racist/sexist tweets

#### **#HASHTAG**

```
In [33]: #function to collect hashtags
    def hashtag_extract(x):
        hashtags=[]
        for i in x:
            ht=re.findall(r"#(\w+)",i)
            hashtags.append(ht)

        return hashtags

In [34]: #extracting hashtag from non racist/sexist tweets
    HT_regular = hashtag_extract(combi['tidy_tweet'][combi['label']==0])
```

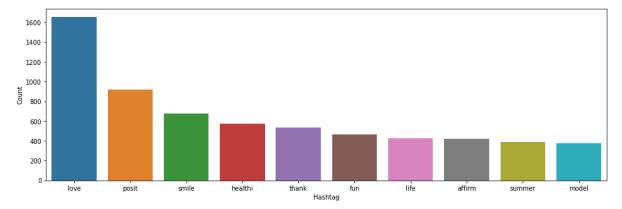
HT\_negative = hashtag\_extract(combi['tidy\_tweet'][combi['label']==1])

#unnesting list

HT\_regular = sum(HT\_regular,[])
HT negative = sum(HT negative,[])

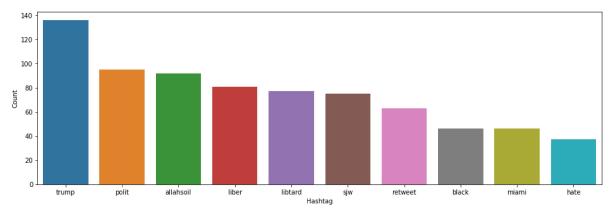
#### Non-Racist/Sexist Tweets

```
In [35]: a=nltk.FreqDist(HT_regular)
d=pd.DataFrame({
    'Hashtag':list(a.keys()),
    'Count' : list(a.values())
})
#selecting top 10 most frequent hashtag
d= d.nlargest(columns="Count", n=10)
plt.figure(figsize=(16,5))
ax=sns.barplot(data=d,x='Hashtag', y='Count')
ax.set(ylabel = 'Count')
plt.show()
```



#### Racist/Sexist tweets

```
In [36]: b = nltk.FreqDist(HT_negative)
e = pd.DataFrame({
    'Hashtag': list(b.keys()),
    'Count': list(b.values())
})
# selecting top 10 most frequent hashtags
e = e.nlargest(columns="Count", n = 10)
plt.figure(figsize=(16,5))
ax = sns.barplot(data=e, x= "Hashtag", y = "Count")
ax.set(ylabel = 'Count')
plt.show()
```



# **Extracting Features from Clean Tweets**

Using assorted techniques - Bag-of-words & TF-IDF

## **Building model using Bag-of-Words features**

```
In [37]: from sklearn.feature_extraction.text import CountVectorizer
bow_vectorizer = CountVectorizer(max_df=0.90, min_df=2, max_features=1000, sto
p_words='english')
# bag-of-words feature matrix
bow = bow_vectorizer.fit_transform(combi['tidy_tweet'])
```

```
In [38]:
         from sklearn.linear model import LogisticRegression
         from sklearn.model selection import train test split
         from sklearn.metrics import f1_score
         train bow = bow[:31962,:]
         test_bow = bow[31962:,:]
         # splitting data into training and validation set
         xtrain_bow, xvalid_bow, ytrain, yvalid = train_test_split(train_bow, train['la
         bel'], random_state=42, test_size=0.3)
         lreg = LogisticRegression()
         lreg.fit(xtrain_bow, ytrain) # training the model
         prediction = lreg.predict proba(xvalid bow) # predicting on the validation set
         prediction_int = prediction[:,1] >= 0.3 # if prediction is greater than or equ
         al to 0.3 than 1 else 0
         prediction_int = prediction_int.astype(np.int)
         f1_score(yvalid, prediction_int) # calculating f1 score
```

Out[38]: 0.5307820299500832

```
In [39]: test_pred = lreg.predict_proba(test_bow)
    test_pred_int = test_pred[:,1] >= 0.3
    test_pred_int = test_pred_int.astype(np.int)
    test['label'] = test_pred_int
    submission = test[['id','label']]
    submission.to_csv('sub_lreg_bow.csv', index=False) # writing data to a CSV file
```

## **Building Model using TF-IDF features**

Out[41]: 0.5446507515473032