Project: Help Twitter Combat Hate Speech Using NLP and Machine Learning

by SHAKTINATH SAINI

In [70]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

In [ ]:

```
####################################################################
''' 1. Load the tweets file using read_csv function from Pandas package. '''
####################################################################
```

In [4]:

```
data=pd.read_csv('TwitterHate.csv', encoding="utf-8")
data.head(3)
```

Out[4]:

	id	label	tweet
0	1	0	@user when a father is dysfunctional and is s...
1	2	0	@user @user thanks for #lyft credit i can't us...
2	3	0	bihday your majesty

In [5]:

```
data.shape
```

Out[5]:

```
(31962, 3)
```

In [6]:

```
data.isnull().sum()
```

Out[6]:

```
id       0
label    0
tweet    0
dtype: int64
```

In [7]:

```
#####################################################################
''' 2. Get the tweets into a list for easy text cleanup and manipulation. '''
#####################################################################
```

In [7]:

```
data=data[['tweet','label']]
```

In [8]:

```
data.shape
```

Out[8]:

```
(31962, 2)
```

In [9]:

```
data.isnull().sum()
```

Out[9]:

```
tweet    0
label    0
dtype: int64
```

In [10]:

```
data.head(3)
```

Out[10]:

	tweet	label
0	@user when a father is dysfunctional and is s...	0
1	@user @user thanks for #lyft credit i can't us...	0
2	bihday your majesty	0

In [ ]:

```
#####################################################################
"""
3. To cleanup:
        1. Normalize the casing.
        2. Using regular expressions, remove user handles. These begin with '@’.
        3. Using regular expressions, remove URLs.
        4. Using TweetTokenizer from NLTK, tokenize the tweets into individual terms.
        5. Remove stop words.
        6. Remove redundant terms like ‘amp’, ‘rt’, etc.
        7. Remove ‘#’ symbols from the tweet while retaining the term.
"""
#####################################################################
```

In [12]:

```
import nltk
nltk.download('stopwords')
from nltk.corpus import stopwords
stop_words=set(stopwords.words('english'))
```

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

In [13]:

```
from nltk.tokenize import TweetTokenizer
```

In [15]:

```
def preprocess_tweet_text(tweet):
 # Normalize the casing.
 tweet.lower()

 tweet = re.sub('[^A-Za-z0-9]+', ' ', tweet)

 # Remove user @ references and '#' from tweet
 tweet = re.sub(r'\@\w+|\#','', tweet)

 # Remove urls
 tweet = re.sub(r"http\S+|www\S+|https\S+", '', tweet, flags=re.MULTILINE)

 # Remove punctuations
 tweet = tweet.translate(str.maketrans('', '', string.punctuation))

 #Using TweetTokenizer from NLTK, tokenize the tweets into individual terms.
 tk = TweetTokenizer()
 tweet_tokens = tk.tokenize(tweet)

 # Remove stopwords
 filtered_words = [w for w in tweet_tokens if not w in stop_words]

 # Remove redundant terms like ‘amp’, ‘rt’, etc.
 filtered_words_final = [w for w in filtered_words if not w in ('amp', 'rt')]

 return " ".join(filtered_words_final)
```

In [17]:

```
import re
```

In [19]:

```
import string
```

In [20]:

```
data.tweet = data['tweet'].apply(preprocess_tweet_text)
```

In [21]:

```
data.head(3)
```

Out[21]:

	tweet	label
0	user father dysfunctional selfish drags kids d...	0
1	user user thanks lyft credit use cause offer w...	0
2	bihday majesty	0

In [22]:

```
###################################################################
''' 4. Extra cleanup by removing terms with a length of 1.'''
###################################################################
```

In [23]:

```
data['length']= data['tweet'].apply(len)
data.head(3)
```

Out[23]:

	tweet	label	length
0	user father dysfunctional selfish drags kids d...	0	60
1	user user thanks lyft credit use cause offer w...	0	87
2	bihday majesty	0	14

In [24]:

```
data.shape
```

Out[24]:

```
(31962, 3)
```

In [25]:

```
len(data[data['length'] == 0])
```

Out[25]:

```
11
```

In [26]:

```
len(data[data['length'] == 1])
```

Out[26]:

```
2
```

In [27]:

```
len(data[data['length']>1])
```

Out[27]:

```
31949
```

In [28]:

```
data[data['length'] == 0]
```

Out[28]:

	tweet	label	length
3351		0	0
7222		0	0
10461		0	0
13038		0	0
15434		0	0
16250		0	0
20261		0	0
22709		0	0
25629		1	0
29803		1	0
31781		0	0

In [29]:

```
data = data[data['length']>1]
```

In [30]:

```
data.shape
```

Out[30]:

```
(31949, 3)
```

In [31]:

```
data.head(3)
```

Out[31]:

	tweet	label	length
0	user father dysfunctional selfish drags kids d...	0	60
1	user user thanks lyft credit use cause offer w...	0	87
2	bihday majesty	0	14

In [ ]:

```
####################################################################
"""
5. Check out the top terms in the tweets:

      1. First, get all the tokenized terms into one large list.
      2. Use the counter and find the 10 most common terms.
"""
####################################################################
```

In [32]:

```
def token_text(text):
 # tokenize the text into a list of words
 tokens = nltk.tokenize.word_tokenize(text)
 return tokens
```

In [34]:

```
import nltk
nltk.download('punkt')
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
```

Out[34]:

```
True
```

In [35]:

```
# Final list with tokenized words
tokenized_large = []
# Iterating over each string in data
for x in data['tweet']:
 # Calling preprocess text function
 token = token_text(x)
 tokenized_large.append(token)
flattened_tokeninized_final = [i for j in tokenized_large for i in j]
```

In [36]:

```
type(flattened_tokeninized_final)
```

Out[36]:

```
list
```

In [37]:

```
# Use the counter and find the 10 most common terms.
from collections import Counter
most_common_words= [word for word, word_count in Counter(flattened_tokeninized_final).most_
print(most_common_words)
```

```
['user', 'love', 'day', 'happy', 'u', 'life', 'time', 'like', 'today', 'ne
w']
```

In [ ]:

```
######################################################################
"""
6. Data formatting for predictive modeling:

      1. Join the tokens back to form strings. This will be required for the vectorizers.
      2. Assign x and y.
      3. Perform train_test_split using sklearn.
"""
######################################################################
```

In [38]:

```
data.head()
```

Out[38]:

	tweet	label	length
0	user father dysfunctional selfish drags kids d...	0	60
1	user user thanks lyft credit use cause offer w...	0	87
2	bihday majesty	0	14
3	model love u take u time ur	0	27
4	factsguide society motivation	0	29

In [39]:

```
data.shape
```

Out[39]:

```
(31949, 3)
```

In [40]:

```
X = data['tweet']
Y = data['label']
```

In [41]:

```
# Splitting data into train and test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, Y ,test_size=0.20, random_state=10)
```

In [ ]:

```
######################################################################
"""
7. We’ll use TF-IDF values for the terms as a feature to get into a vector space model.

      1. Import TF-IDF vectorizer from sklearn.
      2. Instantiate with a maximum of 5000 terms in your vocabulary.
      3. Fit and apply on the train set.
      4. Apply on the test set.
"""
######################################################################
```

In [43]:

```
 # 1. Import TF-IDF vectorizer from sklearn.
from sklearn.feature_extraction.text import TfidfVectorizer
```

In [44]:

```
# 2. Instantiate with a maximum of 5000 terms in your vocabulary.
tfidf_vect = TfidfVectorizer(max_features =5000)
```

In [45]:

```
# 3. Fit and apply on the train set.
X_train_tfidf = tfidf_vect.fit_transform(X_train)
```

In [46]:

```
# 4. Apply on the test set.
X_test_tfidf = tfidf_vect.transform(X_test)
```

In [ ]:

```
####################################################################
"""
8. Model building: Ordinary Logistic Regression

      1. Instantiate Logistic Regression from sklearn with default parameters.
      2. Fit into the train data.
      3. Make predictions for the train and the test set.
"""
####################################################################
```

In [47]:

```
# Logistic Regression
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
```

In [48]:

```
lr.fit(X_train_tfidf, y_train)
```

Out[48]:

```
LogisticRegression()
```

In [49]:

```
# Make predictions for the train and the test set.
predictions_train = lr.predict(X_train_tfidf)
predictions_test = lr.predict(X_test_tfidf)
```

In [ ]:

```
#####################################################################
"""
9. Model evaluation: Accuracy, recall, and f_1 score.

      1. Report the accuracy on the train set.
      2. Report the recall on the train set: decent, high, or low.
      3. Get the f1 score on the train set.
"""
#####################################################################
```

In [51]:

```
from sklearn.metrics import classification_report, recall_score, accuracy_score, f1_score
```

In [52]:

```
print(classification_report(y_test, predictions_test))
```

```
              precision    recall  f1-score   support

           0       0.96      1.00      0.98      5965
           1       0.93      0.35      0.51       425

    accuracy                           0.95      6390
   macro avg       0.94      0.67      0.74      6390
weighted avg       0.95      0.95      0.95      6390
```

In [53]:

```
print("Recall : ", recall_score(y_test, predictions_test))
```

```
Recall :  0.34823529411764703
```

In [54]:

```
### Recall is 34%. ie Sensitivity or true positive rate is 34%, which is very low.
```

In [55]:

```
print("f1_score : ",f1_score(y_test, predictions_test))
```

```
f1_score :  0.5068493150684932
```

In [56]:

```
print(accuracy_score(y_test, predictions_test))
```

```
0.9549295774647887
```

In [ ]:

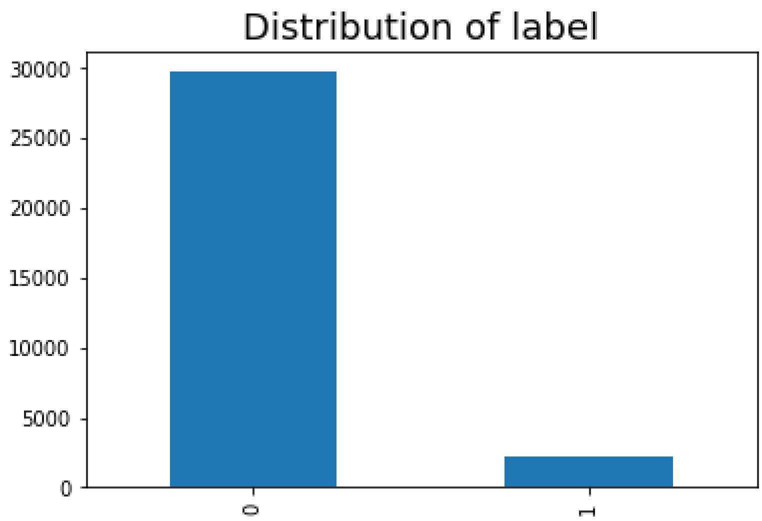
```
##########################################################################
"""
10. Looks like you need to adjust the class imbalance, as the model seems to focus on the 0

      1. Adjust the appropriate class in the LogisticRegression model.

"""
##########################################################################
```

In [57]:

```
data['label'].value_counts().plot(kind='bar')
plt.title("Distribution of label", size=18)
```

Out[57]:

```
Text(0.5, 1.0, 'Distribution of label')
```



In [58]:

```
# distribution
data['label'].value_counts()/data.shape[0]
```

Out[58]:

```
0    0.929888
1    0.070112
Name: label, dtype: float64
```

In [59]:

```
# define class weights
w = {0:1, 1:92} # lable distribution % is 1:0==7:92
lr_2 = LogisticRegression(random_state=11, class_weight=w)
```

In [ ]:

```
#####################################################################
"""
11. Train again with the adjustment and evaluate.

      1. Train the model on the train set.
      2. Evaluate the predictions on the train set: accuracy, recall, and f_1 score.

"""
#####################################################################
```

In [71]:

```
lr_2.fit(X_train_tfidf, y_train)
```

Out[71]:

```
LogisticRegression(class_weight={0: 1, 1: 92}, random_state=11)
```

In [61]:

```
predictions_2 = lr_2.predict(X_test_tfidf)
```

In [62]:

```
print("Accuracy : ", accuracy_score(y_test, predictions_2))
print(" Recall : ", recall_score(y_test, predictions_2))
print("f1_score : ", f1_score(y_test, predictions_2))
```

```
Accuracy :  0.8539906103286385
 Recall :  0.8870588235294118
f1_score :  0.4469472436277415
```

In [ ]:

```
#####################################################################
"""
12. Regularization and Hyperparameter tuning:

      1. Import GridSearch and StratifiedKFold because of class imbalance.
      2. Provide the parameter grid to choose for ‘C’ and ‘penalty’ parameters.
      3. Use a balanced class weight while instantiating the logistic regression.
"""
#####################################################################
```

In [64]:

```
from sklearn.model_selection import GridSearchCV, StratifiedKFold
```

In [65]:

```
C_val = np.arange(0.5, 20.0, 0.5)
penalty_val = ["l1", "l2"]
```

In [66]:

```
hyperparam_grid = {"penalty": penalty_val, "C": C_val }
```

In [67]:

```
lr_3 = LogisticRegression(random_state=11, class_weight=w)
```

In [ ]:

```
#####################################################################
"""
13. Find the parameters with the best recall in cross validation.

      1. Choose ‘recall’ as the metric for scoring.
      2. Choose stratified 4 fold cross validation scheme.
      3. Fit into the train set.
"""
#####################################################################
```

In [68]:

```
grid = GridSearchCV(lr_3, hyperparam_grid, scoring="recall", cv=4)
```

In [72]:

```
grid.fit(X_train_tfidf, y_train)
```

Out[72]:

```
GridSearchCV(cv=4,
             estimator=LogisticRegression(class_weight={0: 1, 1: 92},
                                          random_state=11),
             param_grid={'C': array([ 0.5,  1. ,  1.5,  2. ,  2.5,  3. ,  3.
5,  4. ,  4.5,  5. ,  5.5,
        6. ,  6.5,  7. ,  7.5,  8. ,  8.5,  9. ,  9.5, 10. , 10.5, 11. ,
       11.5, 12. , 12.5, 13. , 13.5, 14. , 14.5, 15. , 15.5, 16. , 16.5,
       17. , 17.5, 18. , 18.5, 19. , 19.5]),
                         'penalty': ['l1', 'l2']},
             scoring='recall')
```

In [ ]:

```
#####################################################################
''' 14. What are the best parameters? '''
#####################################################################
```

In [73]:

```
print(f'Best recall: {grid.best_score_} with param: {grid.best_params_}')
```

```
Best recall: 0.9019215995176552 with param: {'C': 0.5, 'penalty': 'l2'}
```

In [ ]:

```
###################################################################
"""
15. Predict and evaluate using the best estimator.

      1. Use the best estimator from the grid search to make predictions on the test set.
      2. What is the recall on the test set for the toxic comments?
      3. What is the f_1 score?

"""
###################################################################
```

In [74]:

```
lr_4 = LogisticRegression(random_state=11, class_weight=w, C=0.5, penalty='l2')
lr_4.fit(X_train_tfidf, y_train)
```

Out[74]:

```
LogisticRegression(C=0.5, class_weight={0: 1, 1: 92}, random_state=11)
```

In [75]:

```
predictions = lr_4.predict(X_test_tfidf)
```

In [76]:

```
print("Accuracy : ", accuracy_score(y_test, predictions))
print(" Recall : ", recall_score(y_test, predictions))
print("f1_score : ", f1_score(y_test, predictions))
```

```
Accuracy :  0.8195618153364632
 Recall :  0.9129411764705883
f1_score :  0.4022809745982374
```

In [1]:

```
###################################################################
'''                            End                            '''
###################################################################
```

Out[1]:

```
'                            End                            '
```