twitter-sentiment-analysis

January 5, 2024

[49]:

```python
#Importing Necessary Libraries
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns

from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, f1_score
from imblearn.over_sampling import SMOTE

from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier

from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from wordcloud import WordCloud, STOPWORDS
import re
import warnings
warnings.filterwarnings('ignore')
```

1 Data Loading

[50]:

```python
train_df = pd.read_csv('/kaggle/input/twittersentimentdata/train.csv')
test_df = pd.read_csv('/kaggle/input/twittersentimentdata/test.csv')
```

[51]:

```python
train_df.shape
```

[51]:

```
(31962, 3)
```

[52]:

```python
train_df.duplicated().sum()
```

[52]:

```
0
```

[53]:

```
train_df.dtypes
```

[53]:

```
id          int64
label       int64
tweet      object
dtype: object
```

[54]:

```
train_df.isnull().sum()
```

[54]:

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

[55]:

```
test_df.isnull().sum()
```

[55]:

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

[56]:

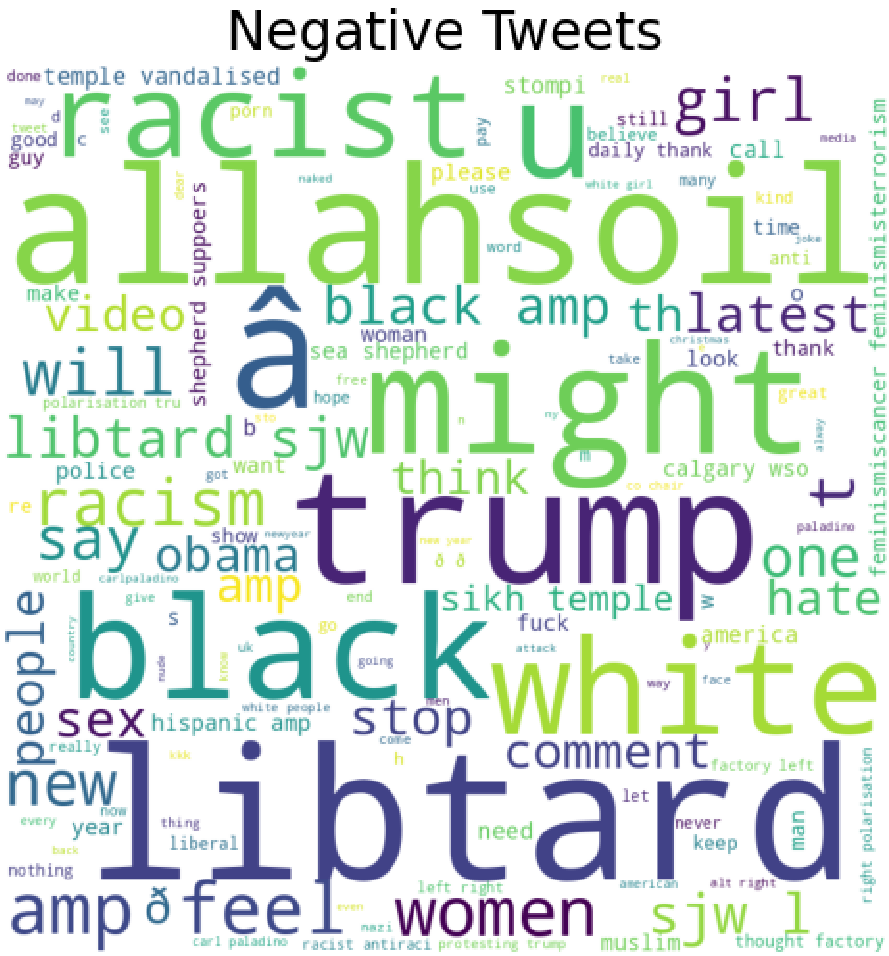
```
# Plotting Word Clouds
stopwords = set(STOPWORDS)
stopwords.add('user')

def plot_wordcloud(tweets, title):
    wordcloud = WordCloud(width=800, height=800, background_color='white',␣
 ↪stopwords=stopwords, min_font_size=10).generate(tweets)
    plt.figure(figsize=(14, 6), facecolor=None)
    plt.imshow(wordcloud)
    plt.axis("off")
    plt.title(title, fontdict={'fontsize': 20})
    plt.show()
```

[57]:

```
negative_tweets = train_df['tweet'][train_df['label'] == 1].to_string()
positive_tweets = train_df['tweet'][train_df['label'] == 0].to_string()

plot_wordcloud(negative_tweets, 'Negative Tweets')
plot_wordcloud(positive_tweets, 'Positive Tweets')
```


Negative Tweets
allahsoil
libtard
trump
might
black
white
racist
u
â
girl
will
black amp
latest
th
video
libtard sjw
racism
say
obama
one
hate
amp
think
people
new
sex
stop
comment
amp ð feel
women
sjw l
sikh temple
temple vandalised
stompi
porn
please
still
believe
daily thank
call
good
guy
done
shepherd suppoers
sea shepherd
woman
make
time
anti
kind
look
thank
police
want
calgary wso
polarisation tru
hope
great
feminismiscancer feminismisterrorism
right polarisation
show
world
america
fuck
hispanic amp
really
year
liberal
need
nothing
keep
never
man
let
factory left
muslim
thought factory
racist antiraci
protesting trump
carl paladino
left right
alt right
american
paladino
carlpaladino
newyear
new year
white people
white girl
christmas
media
joke
naked
use
word
many
take
free
real
pay
see
tweet
may
dear
sto
n
ny
m
alway
co chair
re
give
end
go
country
nude
know
uk
going
attack
men
way
face
come
kkk
h
now
every
thing
back
even
nazi
got
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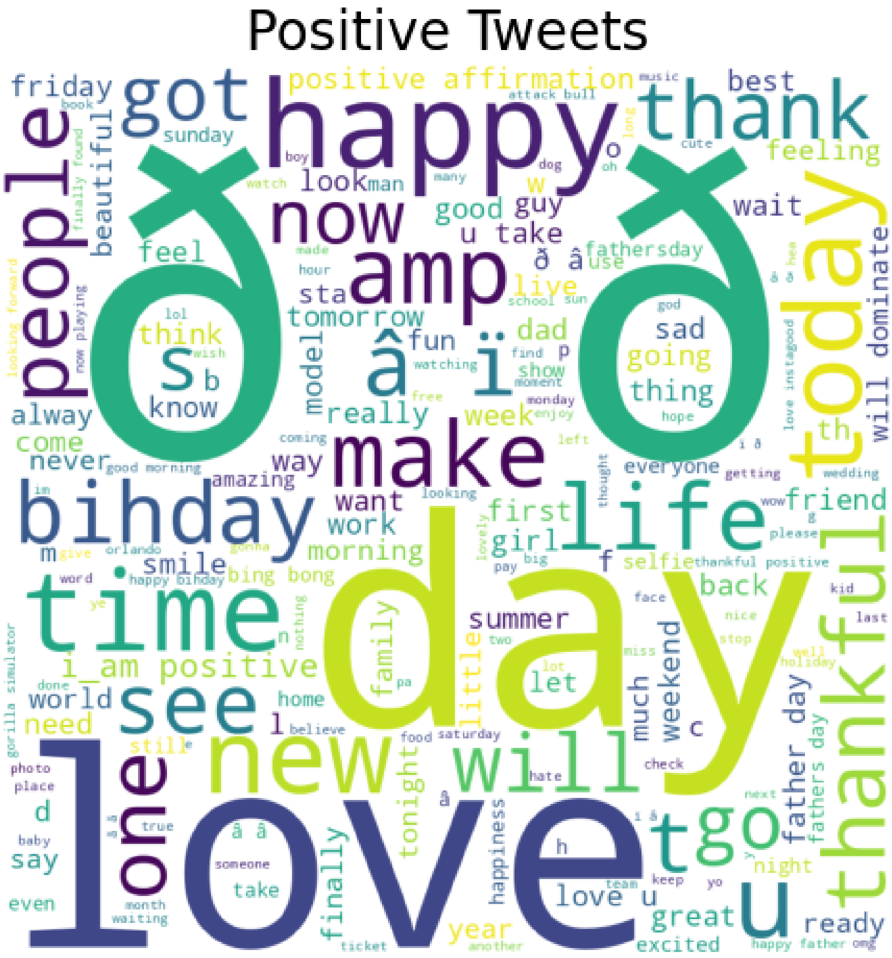


2 Feature Engineering

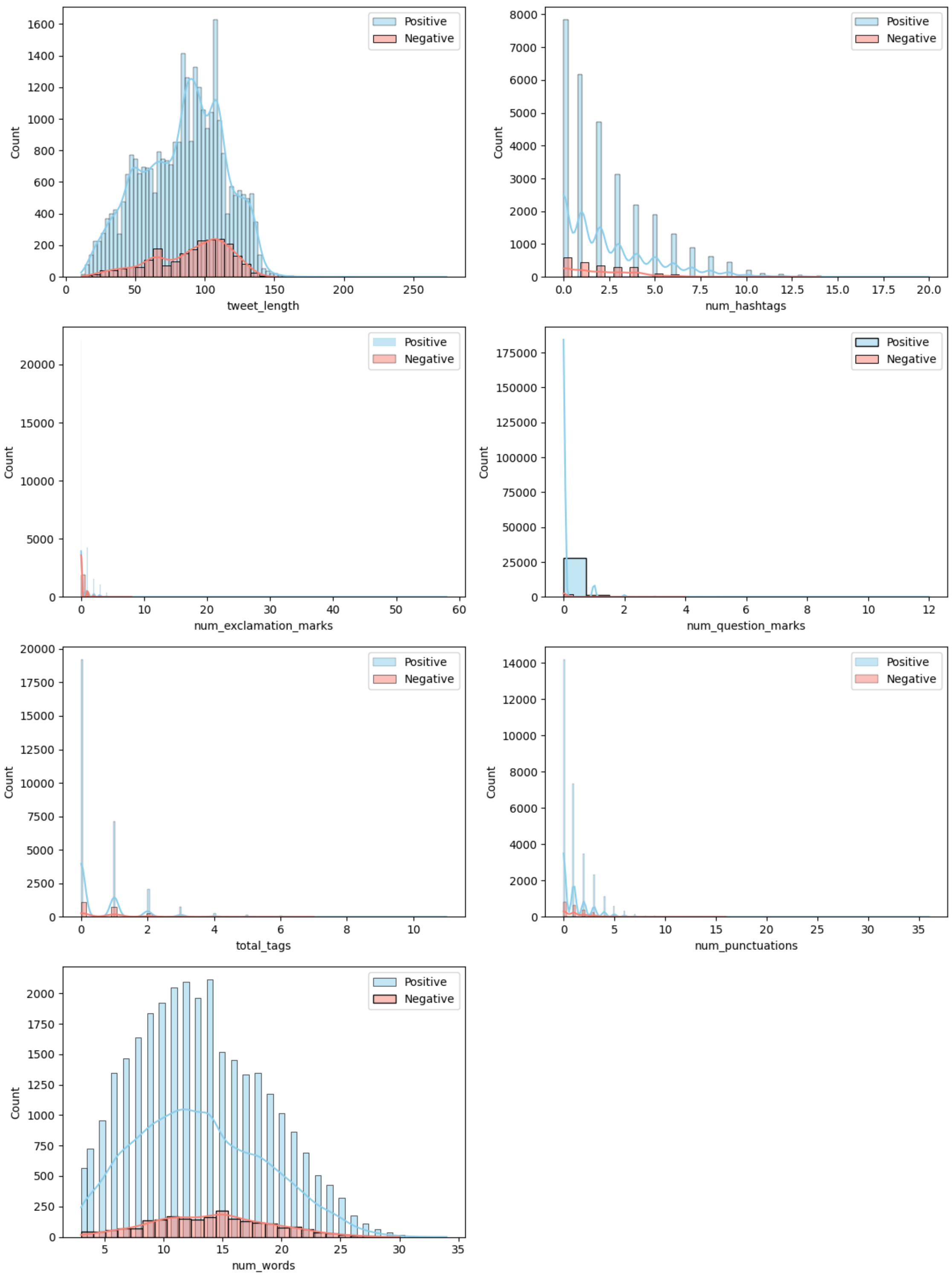
[58]:
```
# Feature Engineering
train_df_fe = train_df.copy()
train_df_fe['tweet_length'] = train_df_fe['tweet'].str.len()
train_df_fe['num_hashtags'] = train_df_fe['tweet'].str.count('#')
train_df_fe['num_exclamation_marks'] = train_df_fe['tweet'].str.count('!')
train_df_fe['num_question_marks'] = train_df_fe['tweet'].str.count('\?')
train_df_fe['total_tags'] = train_df_fe['tweet'].str.count('@')
train_df_fe['num_punctuations'] = train_df_fe['tweet'].str.count('[.,:;]')
train_df_fe['num_words'] = train_df_fe['tweet'].apply(lambda x: len(x.split()))
train_df_fe.head()
```

[58]:
```
   id  label                                              tweet  tweet_length  \
0   1      0   @user when a father is dysfunctional and is s…           102
1   2      0  @user @user thanks for #lyft credit i can't us…           122
```

```
2   3      0                                bihday your majesty            21
3   4      0  #model    i love u take with u all the time in …           86
4   5      0              factsguide: society now    #motivation            39

   num_hashtags  num_exclamation_marks  num_question_marks  total_tags  \
0             1                      0                   0           1
1             3                      0                   0           2
2             0                      0                   0           0
3             1                      3                   0           0
4             1                      0                   0           0

   num_punctuations  num_words
0                 1         18
1                 1         19
2                 0          3
3                 0         14
4                 1          4
```

[59]:

```
# Visualizing Relationship of Engineered Features with Sentiments
features = ['tweet_length', 'num_hashtags', 'num_exclamation_marks',␣
 ↪'num_question_marks', 'total_tags', 'num_punctuations', 'num_words']

# Check if train_df_fe has the expected columns
if set(features).issubset(train_df_fe.columns):
    plt.figure(figsize=(12, 16))
    colors = ['skyblue', 'salmon']

    for i, feature in enumerate(features, 1):
        plt.subplot(4, 2, i)
        sns.histplot(train_df_fe[train_df_fe.label == 0][feature],␣
 ↪label='Positive', kde=True, color=colors[0])
        sns.histplot(train_df_fe[train_df_fe.label == 1][feature],␣
 ↪label='Negative', kde=True, color=colors[1])
        plt.legend()

    plt.tight_layout()
    plt.show()
```


Positive
Negative
Count
tweet_length
0
200
400
600
800
1000
1200
1400
1600
0
50
100
150
200
250
num_hashtags
0
1000
2000
3000
4000
5000
6000
7000
8000
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
num_exclamation_marks
0
5000
10000
15000
20000
0
10
20
30
40
50
60
num_question_marks
0
25000
50000
75000
100000
125000
150000
175000
0
2
4
6
8
10
12
total_tags
0
2500
5000
7500
10000
12500
15000
17500
20000
0
2
4
6
8
10
num_punctuations
0
2000
4000
6000
8000
10000
12000
14000
0
5
10
15
20
25
30
35
num_words
0
250
500
750
1000
1250
1500
1750
2000
5
10
15
20
25
30
35

3 Data Preprocessing

[60]:

```
# Data Preprocessing
X = train_df.drop(columns=['label'])
y = train_df['label']
test = test_df
```

[61]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
  ↪random_state=42)
```

3.1 Text Normalization

[62]:

```
def tokenize_and_clean(text):
    lowered = text.lower()
    cleaned = re.sub('@user', '', lowered)
    tokens = word_tokenize(cleaned)
    filtered_tokens = [token for token in tokens if re.match(r'\w{1,}', token)]
    stemmer = PorterStemmer()
    stems = [stemmer.stem(token) for token in filtered_tokens]
    return stems
```

3.2 Vectorization

[63]:

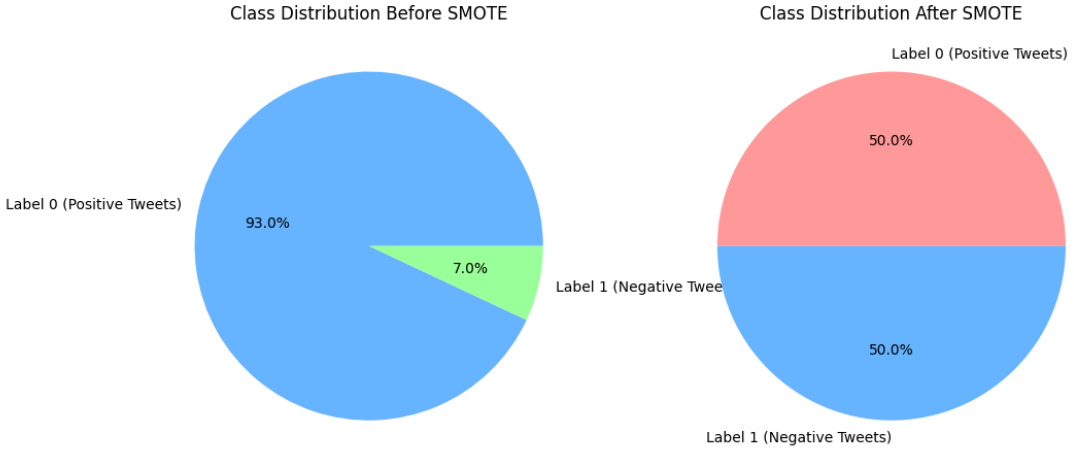
```
# TF-IDF Vectorization
tfidf_vectorizer = TfidfVectorizer(tokenizer=tokenize_and_clean,␣
  ↪stop_words='english')
X_train_tweets_tfidf = tfidf_vectorizer.fit_transform(X_train['tweet'])
X_test_tweets_tfidf = tfidf_vectorizer.transform(X_test['tweet'])
X_tweets_tfidf = tfidf_vectorizer.fit_transform(X['tweet'])
test_tweets_tfidf = tfidf_vectorizer.transform(test['tweet'])
```

3.3 SMOTE

[64]:

```
# Class Imbalance Check Before SMOTE
plt.figure(figsize=(12, 6))

# Colors for the pie charts
colors_before_smote = ['#66b3ff', '#99ff99']
colors_after_smote = ['#ff9999', '#66b3ff']

labels = ['Label 0 (Positive Tweets)', 'Label 1 (Negative Tweets)']

# Plotting before SMOTE
plt.subplot(1, 2, 1)
plt.pie(y_train.value_counts(), labels=labels, autopct='%0.1f%%',␣
  ↪colors=colors_before_smote)
```

```
plt.title('Class Distribution Before SMOTE')

# SMOTE to deal with the class imbalance
smote = SMOTE()
X_train_smote, y_train_smote = smote.fit_resample(X_train_tweets_tfidf, y_train.
  ↪values)

# Plotting after SMOTE
plt.subplot(1, 2, 2)
plt.pie(pd.value_counts(y_train_smote), labels=labels, autopct='%0.1f%%',␣
  ↪colors=colors_after_smote)
plt.title('Class Distribution After SMOTE')
plt.show()
```



4 ML Model

[65]:
```
# Functions to print scores
def training_scores(y_act, y_pred):
    acc = round(accuracy_score(y_act, y_pred), 3)
    f1 = round(f1_score(y_act, y_pred), 3)
    print(f'Training Scores: Accuracy={acc}, F1-Score={f1}')

def validation_scores(y_act, y_pred):
    acc = round(accuracy_score(y_act, y_pred), 3)
    f1 = round(f1_score(y_act, y_pred), 3)
    print(f'Validation Scores: Accuracy={acc}, F1-Score={f1}')
```

[66]:
```
# Machine Learning Modeling
def train_and_evaluate(model, X_train, y_train, X_test, y_test):
    model.fit(X_train, y_train)
    y_train_pred = model.predict(X_train)
    y_test_pred = model.predict(X_test)

    training_scores(y_train, y_train_pred)
    validation_scores(y_test, y_test_pred)
```

[67]:

```
# Logistic Regression
lr = LogisticRegression()
train_and_evaluate(lr, X_train_smote, y_train_smote, X_test_tweets_tfidf,␣
 ↪y_test)
```

```
Training Scores: Accuracy=0.974, F1-Score=0.975
Validation Scores: Accuracy=0.924, F1-Score=0.601
```

[68]:

```
# Naive Bayes Classifier
mnb = MultinomialNB()
train_and_evaluate(mnb, X_train_smote, y_train_smote, X_test_tweets_tfidf,␣
 ↪y_test)
```

```
Training Scores: Accuracy=0.966, F1-Score=0.967
Validation Scores: Accuracy=0.921, F1-Score=0.609
```

[69]:

```
# Random Forest Classifier
rf = RandomForestClassifier()
train_and_evaluate(rf, X_train_smote, y_train_smote, X_test_tweets_tfidf,␣
 ↪y_test)
```

```
Training Scores: Accuracy=1.0, F1-Score=1.0
Validation Scores: Accuracy=0.955, F1-Score=0.648
```

[70]:

```
# Extreme Gradient Boosting Classifier
xgb = XGBClassifier(objective='binary:logistic', eval_metric='logloss')
train_and_evaluate(xgb, X_train_smote, y_train_smote, X_test_tweets_tfidf,␣
 ↪y_test)
```

```
Training Scores: Accuracy=0.941, F1-Score=0.938
Validation Scores: Accuracy=0.942, F1-Score=0.597
```

5 Hyperparameter Tuning

[71]:

```
rf_tuned = RandomForestClassifier(criterion='entropy',
                                  max_samples=0.8,
                                  min_samples_split=10,
                                  random_state=0)
train_and_evaluate(rf_tuned, X_train_smote, y_train_smote, X_test_tweets_tfidf,␣
 ↪y_test)
```

```
Training Scores: Accuracy=0.999, F1-Score=0.999
Validation Scores: Accuracy=0.957, F1-Score=0.682
```

[72]:

```
xgb_tuned = XGBClassifier(objective='binary:logistic',
                          eval_metric='logloss',
                          learning_rate=0.8,
                          max_depth=20,
                          gamma=0.6,
                          reg_lambda=0.1,
                          reg_alpha=0.1)
train_and_evaluate(xgb_tuned, X_train_smote, y_train_smote,␣
 ↪X_test_tweets_tfidf, y_test)
```

```
Training Scores: Accuracy=0.998, F1-Score=0.998
Validation Scores: Accuracy=0.954, F1-Score=0.65
```

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