1. Importing libraries

```
import pandas as pd
from sklearn.linear_model import LogisticRegression
import tensorflow as tf
import matplotlib.pyplot as plt
import numpy as np
import nltk
nltk.download('stopwords')
from nltk.corpus import stopwords
from nltk.stem import SnowballStemmer
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
from sklearn import tree
from collections import Counter
import seaborn as sns
import re
from sklearn.neighbors import KNeighborsClassifier
import itertools
from keras.optimizers import Adam
from keras.callbacks import ReduceLROnPlateau
from keras.layers import Conv1D, Bidirectional, LSTM, Dense, Input,
Dropout, SpatialDropout1D
from tensorflow.keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
from gensim.scripts.glove2word2vec import glove2word2vec
from gensim.models import KeyedVectors
from keras.callbacks import ModelCheckpoint
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\adria\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

2. Accessing csv file with tweets

```
df = pd.read_csv('tweets.csv',encoding='latin-1')
df.head()
```

```
   0  1467810369  Mon Apr 06 22:19:45 PDT 2009  NO_QUERY
_TheSpecialOne_  \
0  0  1467810672  Mon Apr 06 22:19:49 PDT 2009  NO_QUERY
```

```
scotthamilton
1  0  1467810917  Mon Apr 06 22:19:53 PDT 2009  NO_QUERY
mattycus
2  0  1467811184  Mon Apr 06 22:19:57 PDT 2009  NO_QUERY
ElleCTF
3  0  1467811193  Mon Apr 06 22:19:57 PDT 2009  NO_QUERY
Karoli
4  0  1467811372  Mon Apr 06 22:20:00 PDT 2009  NO_QUERY
joy_wolf

  @switchfoot http://twitpic.com/2y1zl - Awww, that's a bummer.  You
shoulda got David Carr of Third Day to do it. ;D
0  is upset that he can't update his Facebook by ...

1  @Kenichan I dived many times for the ball. Man...

2    my whole body feels itchy and like its on fire

3  @nationwideclass no, it's not behaving at all....

4                      @Kwesidei not the whole crew
```

3.1 Data pre-preprocessing

```
df.columns = ['sentiment', 'id', 'date', 'query', 'user_id', 'text']
df = df.drop(['id', 'date', 'query', 'user_id'], axis=1)
df.loc[df['sentiment'] == 4, 'sentiment'] = 1
df.head()
```

```
   sentiment                                                  text
0          0  is upset that he can't update his Facebook by ...
1          0  @Kenichan I dived many times for the ball. Man...
2          0    my whole body feels itchy and like its on fire
3          0  @nationwideclass no, it's not behaving at all....
4          0                      @Kwesidei not the whole crew
```

3.2 Data preprocessing - Natural language processing (stopwords removal and stemming)

```
stop_words = stopwords.words('english')
stemmer = SnowballStemmer('english')

def preprocess(text):
    text = re.sub("@\S+|https?:\S+|http?:\S|\w*\d\w*|[^A-Za-z0-9]+|
www?:\S", ' ', str(text).lower())
    text = text.strip()
```

```
    tokens = []
    for word in text.split():
        if word not in stop_words:
            if stemmer.stem(word) != word: #checks whether stemming is
possible
                tokens.append(stemmer.stem(word))
            else:
                tokens.append(word)
    return " ".join(tokens)
```

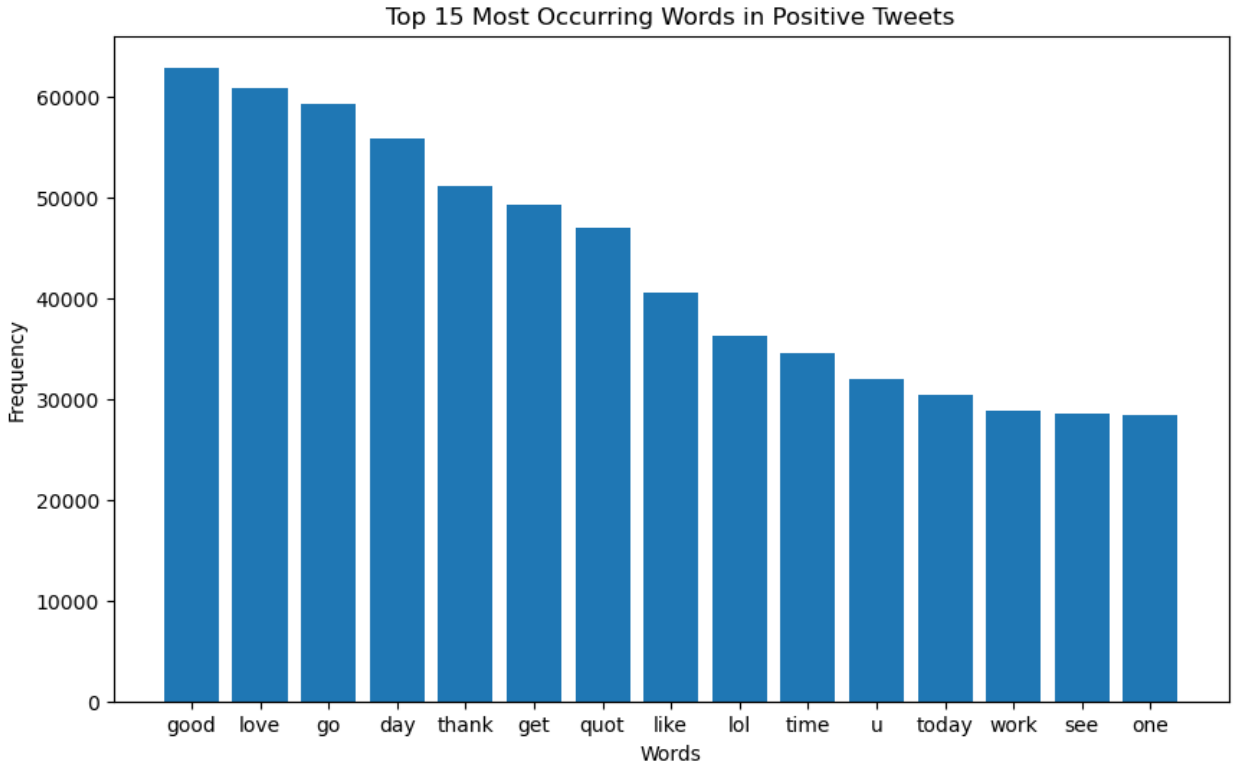
```
<>:2: SyntaxWarning: invalid escape sequence '\S'
<>:2: SyntaxWarning: invalid escape sequence '\S'
C:\Users\adria\AppData\Local\Temp\ipykernel_6980\4052145036.py:2:
SyntaxWarning: invalid escape sequence '\S'
  text = re.sub("@\S+|https?:\S+|http?:\S|\w*\d\w*|[^A-Za-z0-9]+|
www?:\S", ' ', str(text).lower())
```

```
df.text = df.text.apply(lambda x: preprocess(x))
df.head()
#df.text = df.text.apply(preprocess)
```

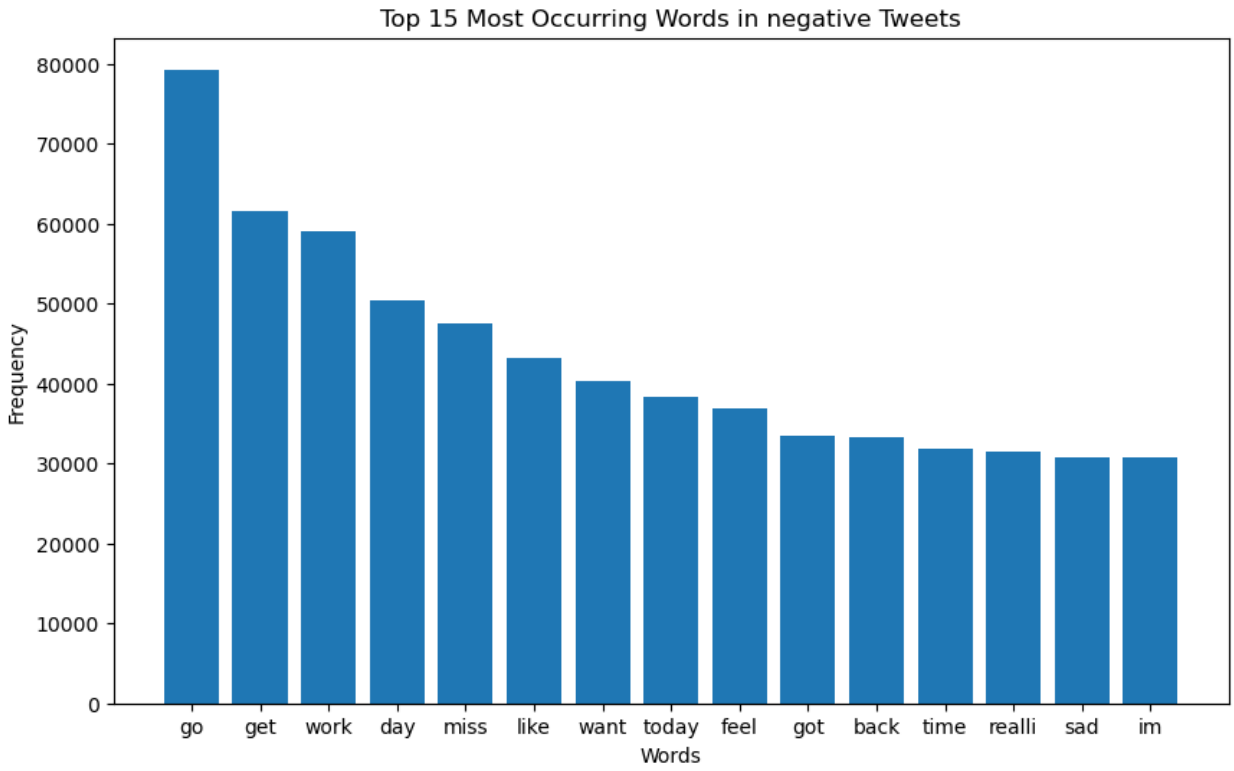
```
   sentiment                                                  text
0          0  upset updat facebook text might cri result sch...
1          0       dive mani time ball manag save rest go bound
2          0                    whole bodi feel itchi like fire
3          0                                  behav mad see
4          0                                     whole crew
```

4. Most often occuring words

```
positive_tweets = df[df.sentiment == 1]
negative_tweets = df[df.sentiment == 0]

pos_words = " ".join(positive_tweets.text)
pos_words = pos_words.split()

pos_words_freq = Counter(pos_words)

most_occur = pos_words_freq.most_common(15)
words, frequencies = zip(*most_occur)
plt.figure(figsize=(10, 6))
plt.bar(words, frequencies)
plt.xlabel('Words')
plt.ylabel('Frequency')
plt.title('Top 15 Most Occurring Words in Positive Tweets')

Text(0.5, 1.0, 'Top 15 Most Occurring Words in Positive Tweets')
```




```
neg_words = " ".join(negative_tweets.text)
neg_words = neg_words.split()

neg_words_freq = Counter(neg_words)
most_occur2 = neg_words_freq.most_common(15)
words2, frequencies2 = zip(*most_occur2)
plt.figure(figsize=(10, 6))
plt.bar(words2, frequencies2)
plt.xlabel('Words')
plt.ylabel('Frequency')
plt.title('Top 15 Most Occurring Words in negative Tweets')

Text(0.5, 1.0, 'Top 15 Most Occurring Words in negative Tweets')
```



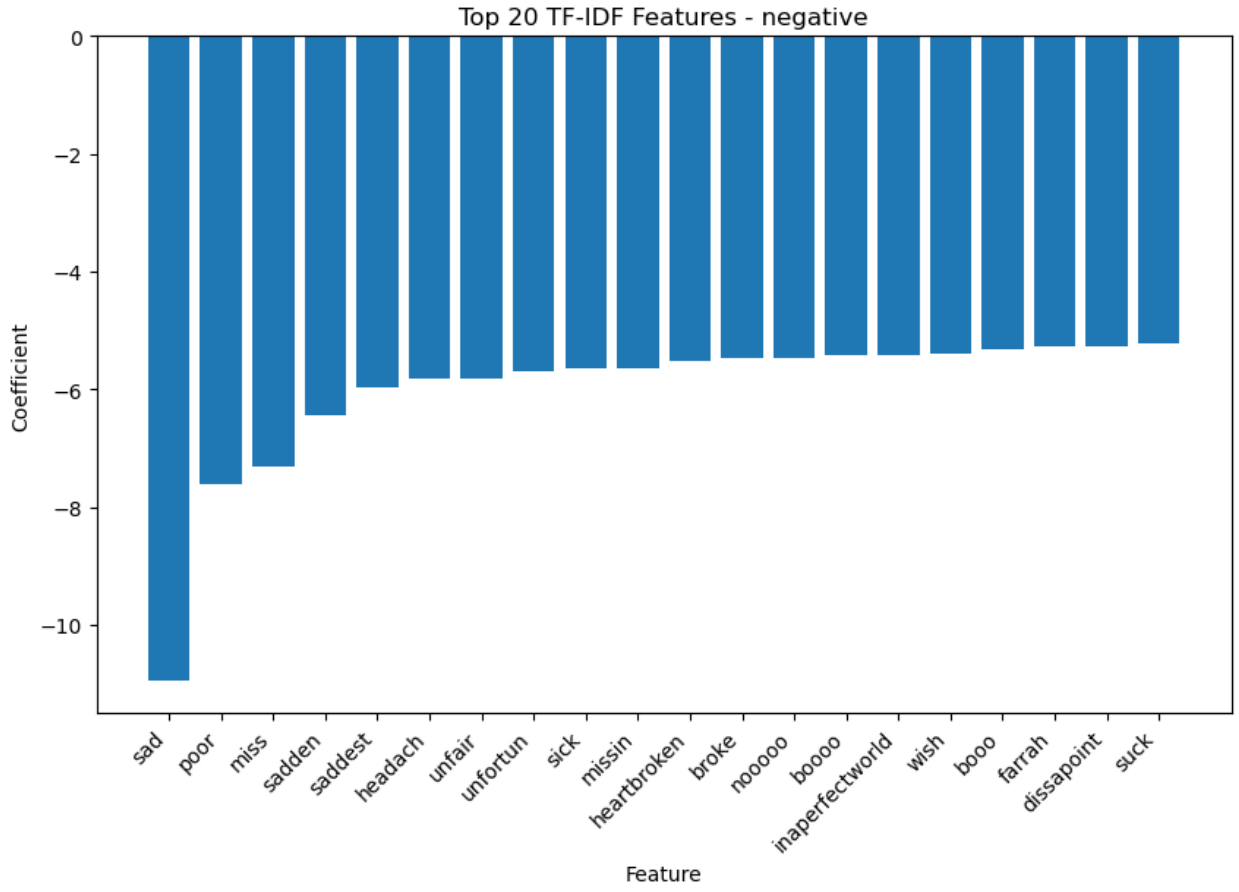
5. Logistic regression and naive bayes model creation + checking which words have the biggest "power" according to tfidf

```
tfidf_vectorizer = TfidfVectorizer(max_features=1000000000)
X = tfidf_vectorizer.fit_transform(df['text'])

y = df['sentiment']

# plitting into test and train set (default)
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=9)

#Logistic regression default model
model = LogisticRegression(max_iter=10000000)
model.fit(X_train, y_train)


LogisticRegression(max_iter=10000000)

#Naive Bayes default model
model2 = MultinomialNB()
model2.fit(X_train, y_train)
```

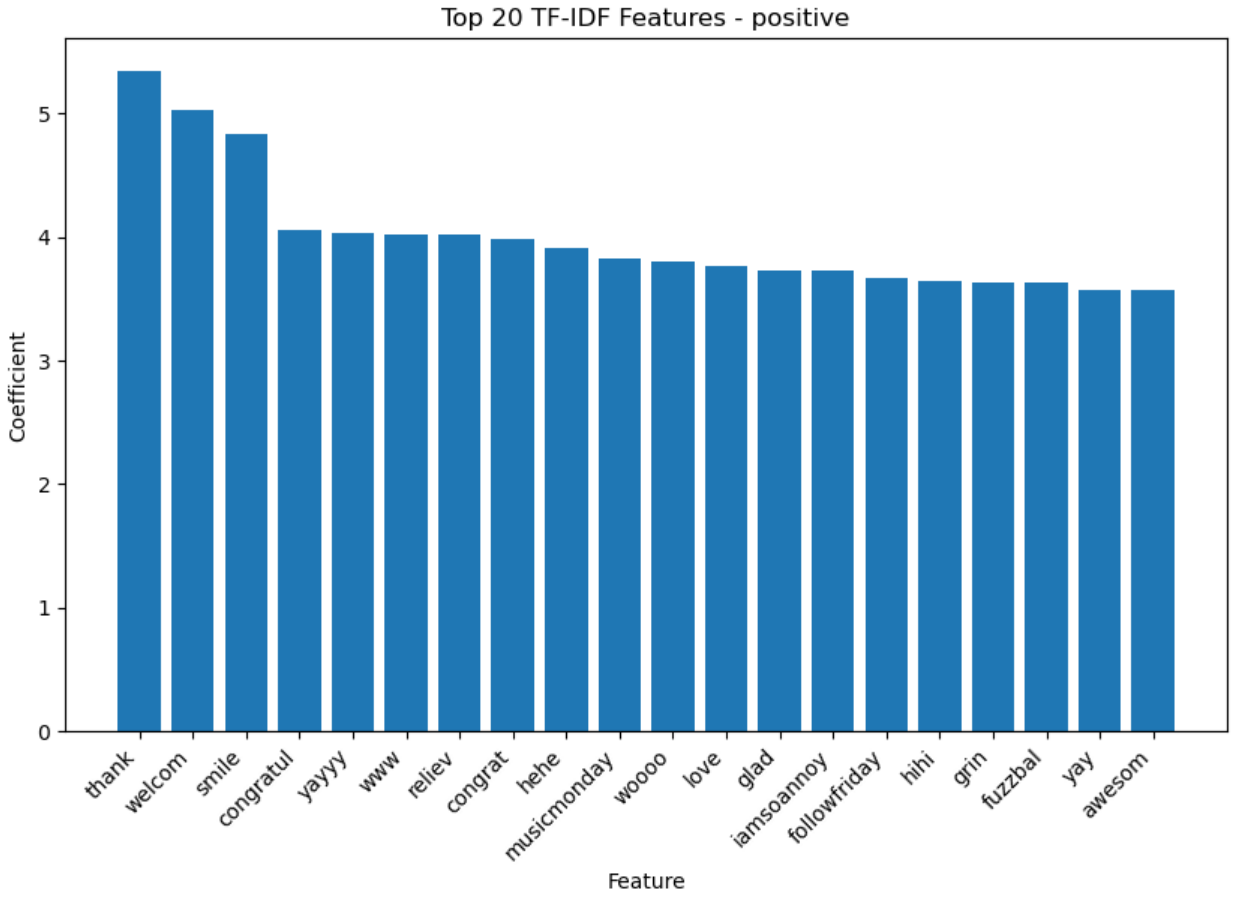
```
MultinomialNB()
```

5.1 Which words make tweets positive/negative

```
feature_names = np.array(tfidf_vectorizer.get_feature_names_out())
coefficients = model.coef_.flatten()

#Create a df to display feature importance
feature_importance_df = pd.DataFrame({'Feature': feature_names,
'Coefficient': coefficients})
feature_importance_df =
feature_importance_df.sort_values(by='Coefficient', ascending=True)

#Display top 20 most important features
top_features = feature_importance_df.head(20)  # Adjust N as needed
plt.figure(figsize=(10, 6))
plt.bar(top_features['Feature'], top_features['Coefficient'])
plt.xlabel('Feature')
plt.ylabel('Coefficient')
plt.title('Top 20 TF-IDF Features - negative')
plt.xticks(rotation=45, ha='right')
plt.show()
```




```
feature_names = np.array(tfidf_vectorizer.get_feature_names_out())
coefficients = model.coef_.flatten()

feature_importance_df = pd.DataFrame({'Feature': feature_names,
'Coefficient': coefficients})
feature_importance_df =
feature_importance_df.sort_values(by='Coefficient', ascending=False)

top_features = feature_importance_df.head(20)
plt.figure(figsize=(10, 6))
plt.bar(top_features['Feature'], top_features['Coefficient'])
plt.xlabel('Feature')
plt.ylabel('Coefficient')
plt.title('Top 20 TF-IDF Features - positive')
plt.xticks(rotation=45, ha='right')
plt.show()
```



6. Model evaluation logistic regression and naive bayes

```
y_pred = model.predict(X_test)
accuracy1 = accuracy_score(y_test, y_pred)

print(f'Accuracy - logistic regression: {accuracy1:.2f}')

print(classification_report(y_test, y_pred))
conf_matrix1 = confusion_matrix(y_test, y_pred)
```

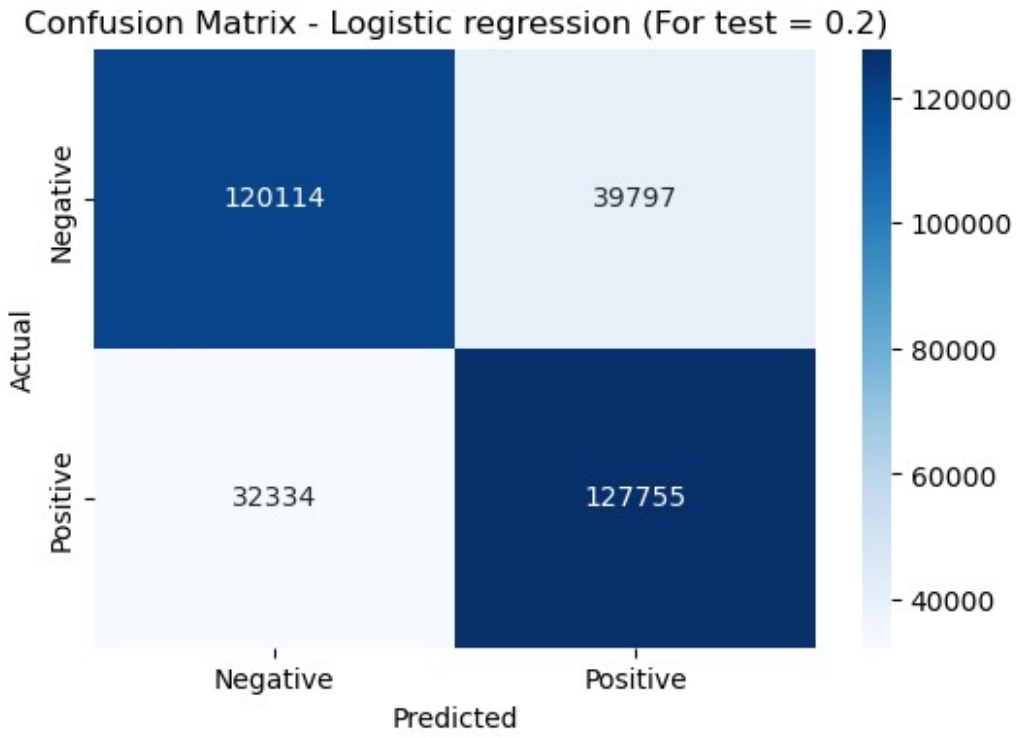
```
Accuracy - logistic regression: 0.77
              precision    recall  f1-score   support

           0       0.79      0.75      0.77    159911
           1       0.76      0.80      0.78    160089

    accuracy                           0.77    320000
   macro avg       0.78      0.77      0.77    320000
```

```
weighted avg       0.78      0.77      0.77    320000
```

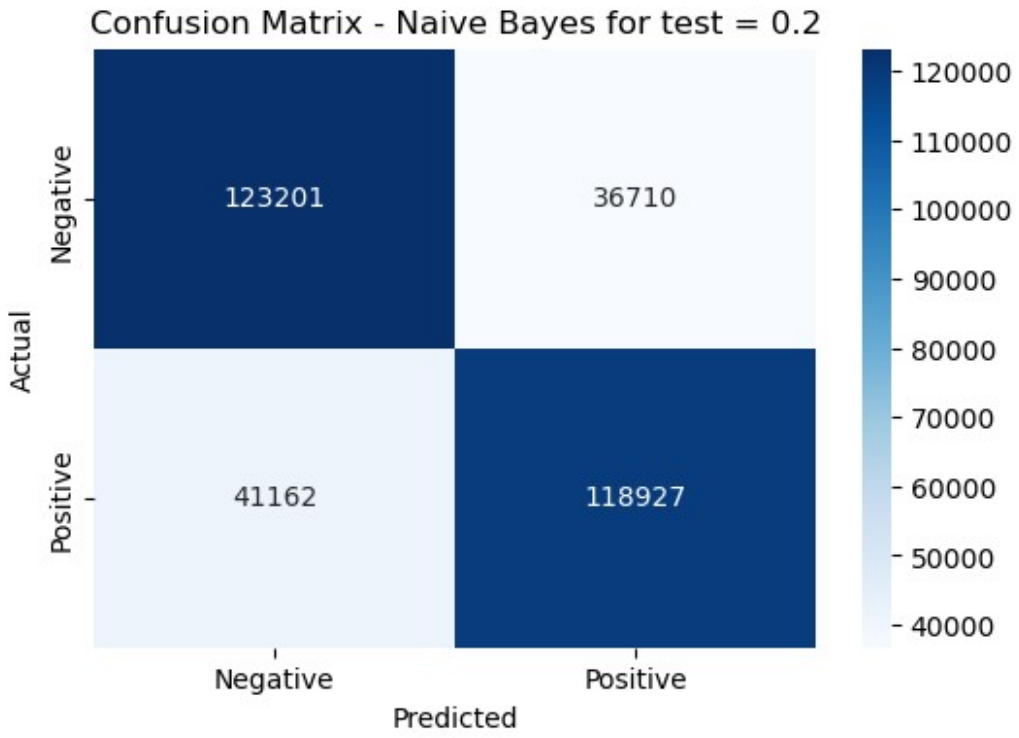
```
y_pred2 = model2.predict(X_test)
accuracy2 = accuracy_score(y_test, y_pred2)

print(f'Accuracy - Naive bayes: {accuracy2:.2f}')

print(classification_report(y_test, y_pred2))
conf_matrix2 = confusion_matrix(y_test, y_pred2)
```

```
Accuracy - Naive bayes: 0.76
              precision    recall  f1-score   support

           0       0.75      0.77      0.76    159911
           1       0.76      0.74      0.75    160089

    accuracy                           0.76    320000
   macro avg       0.76      0.76      0.76    320000
weighted avg       0.76      0.76      0.76    320000
```

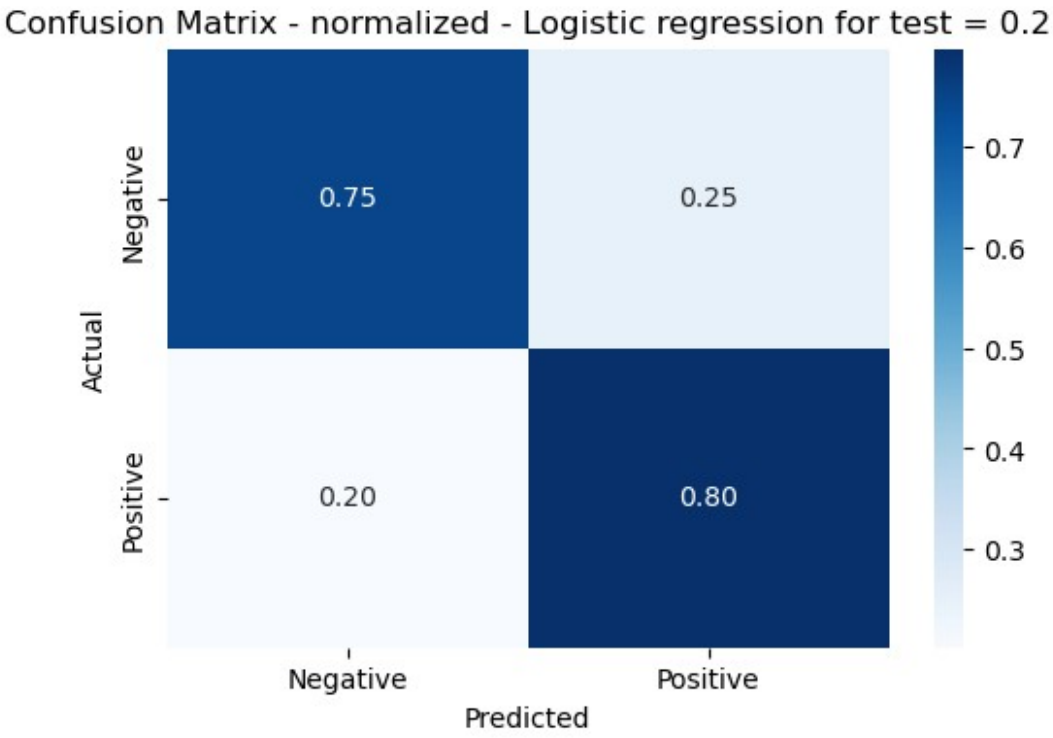
```
plt.figure(figsize=(6, 4))
sns.heatmap(conf_matrix1, annot=True, fmt='d', cmap='Blues',
xticklabels=['Negative', 'Positive'], yticklabels=['Negative',
'Positive'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - Logistic regression (For test = 0.2)')
plt.show()
```



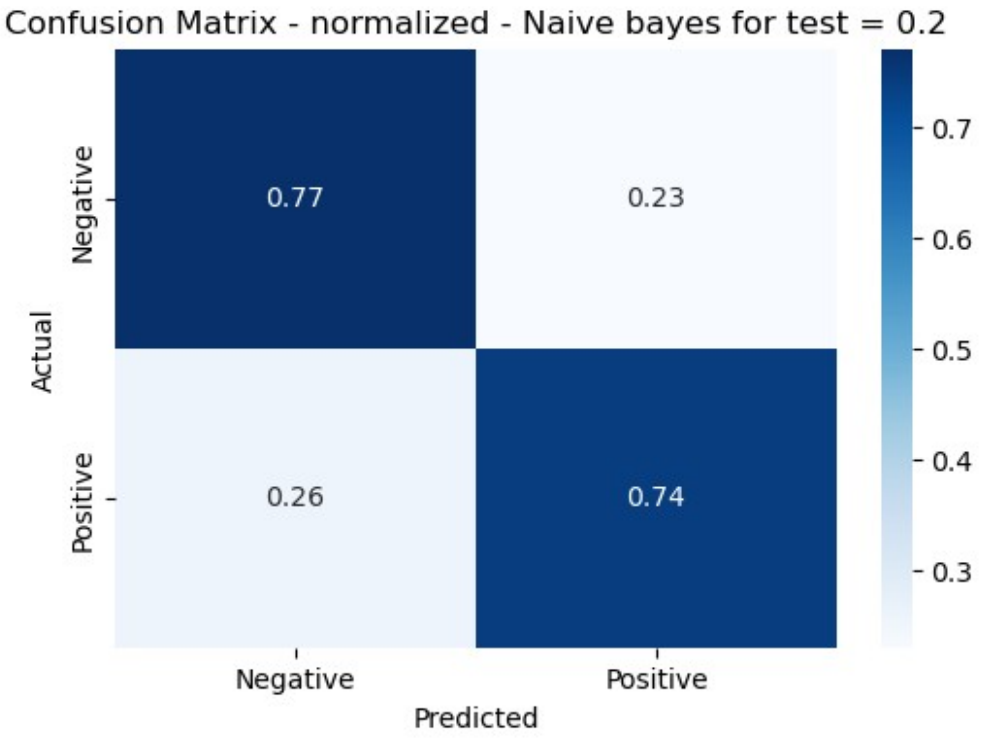

```
plt.figure(figsize=(6, 4))
sns.heatmap(conf_matrix2, annot=True, fmt='d', cmap='Blues',
xticklabels=['Negative', 'Positive'], yticklabels=['Negative',
'Positive'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - Naive Bayes for test = 0.2')
plt.show()
```




```
#creating a normalised matrix
conf_matrix1_normalised = conf_matrix1.astype('float') /
conf_matrix1.sum(axis=1)[:, np.newaxis]

plt.figure(figsize=(6, 4))
sns.heatmap(conf_matrix1_normalised, annot=True, fmt='.2f',
cmap='Blues', xticklabels=['Negative', 'Positive'],
yticklabels=['Negative', 'Positive'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - normalized - Logistic regression for
test = 0.2')
plt.show()
```




```
conf_matrix2_normalised = conf_matrix2.astype('float') /
conf_matrix2.sum(axis=1)[:, np.newaxis]

plt.figure(figsize=(6, 4))
sns.heatmap(conf_matrix2_normalised, annot=True, fmt='.2f',
cmap='Blues', xticklabels=['Negative', 'Positive'],
yticklabels=['Negative', 'Positive'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - normalized - Naive bayes for test =
0.2')
plt.show()
```



6.1 Checking how the model behaves when we change ratio of test/train set

```
#it takes a lot of time, because it now creates 33 models
'''
accuracies = []
for i in range(33):
    testsize = 0.005+i*0.03
    X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=testsize, random_state=9)
    model = LogisticRegression(max_iter=10000000)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred) #set is balanced so
accuracy can be treated as an important metric.
    print("Accuracy - Logistic regression for test size
=",round(testsize,3),"train size = ",round((1-testsize),3))
    print(classification_report(y_test, y_pred))
    conf_matrix = confusion_matrix(y_test, y_pred)
    accuracies.append(accuracy)
plt.plot(np.arange(0.005, 0.995, 0.03), accuracies, marker='o')
plt.title('Accuracy Across Different Test Sizes  - logistic
regression')
plt.xlabel('Test Size')
plt.ylabel('Accuracy')
plt.show()'''
```

```
'\naccuracies = []\nfor i in range(33):\n    testsize = 0.005+i*0.03\n
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=testsize, random_state=9)\n    model =
LogisticRegression(max_iter=10000000)\n    model.fit(X_train,
y_train)\n    y_pred = model.predict(X_test)\n    accuracy =
accuracy_score(y_test, y_pred) #set is balanced so accuracy can be
treated as an important metric.\n    print("Accuracy - Logistic
regression for test size =",round(testsize,3),"train size =
",round((1-testsize),3))\n    print(classification_report(y_test,
y_pred))\n    conf_matrix = confusion_matrix(y_test, y_pred)\n
accuracies.append(accuracy)\nplt.plot(np.arange(0.005, 0.995, 0.03),
accuracies, marker=\'o\')\nplt.title(\'Accuracy Across Different Test
Sizes  - logistic regression\')\nplt.xlabel(\'Test Size\')\
nplt.ylabel(\'Accuracy\')\nplt.show()'
```

6.2 Checking how the model behaves when the already pretrained set of vectors is used (instead of Tfidf vectorizer, WORD2VEC AND GLOVE)

6.2.1 WORD2VEC

```
'''googlenews-vectors-negative300.bin file is needed, download from
https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/view?
resourcekey=0-wjGZdNAUop6WykTtMip30g
and later change the path'''

model_path = 'GoogleNews-vectors-negative300.bin'
try:
    word_vectors = KeyedVectors.load_word2vec_format(model_path,
binary=True)
except ValueError as e:
    print(f"Error loading model: {e}")
    model = None

def get_tweet_vector(tweet):
    words = [word for word in tweet.split() if word in word_vectors]
    if not words:
        return np.zeros(300)  #vectors have 300 dimensions
    return np.mean(word_vectors[words], axis=0)

features = np.array([get_tweet_vector(tweet) for tweet in df['text']])

# Step 2: Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features, y,
test_size=0.2, random_state=9)

# Step 3: Create and train the logistic regression model
model = LogisticRegression()
```

```
model.fit(X_train, y_train)

# Step 4: Evaluate the model
y_pred = model.predict(X_test)
accuracy3 = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy3}')
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.710834375
              precision    recall  f1-score   support

           0       0.72      0.69      0.71    159911
           1       0.70      0.73      0.72    160089

    accuracy                           0.71    320000
   macro avg       0.71      0.71      0.71    320000
weighted avg       0.71      0.71      0.71    320000
```

6.2.2 GLOVE

```
'''glove vectors with 300 dimensions needed, download from
https://www.kaggle.com/datasets/thanakomsn/glove6b300dtxt'''
# Convert GloVe format to Word2Vec format
glove_file = 'glove.6B.300d.txt'  # Adjust the file path to your GloVe
file
word2vec_output_file = 'twitter.27B.300d.word2vec'
glove2word2vec(glove_file, word2vec_output_file)

word_vectors = KeyedVectors.load_word2vec_format(word2vec_output_file,
binary=False)
```

```
C:\Users\adria\AppData\Local\Temp\ipykernel_6980\21396395.py:5:
DeprecationWarning: Call to deprecated `glove2word2vec`
(KeyedVectors.load_word2vec_format(.., binary=False, no_header=True)
loads GLoVE text vectors.).
  glove2word2vec(glove_file, word2vec_output_file)
```

```
def get_tweet_vector(tweet):
    words = [word for word in tweet.split() if word in word_vectors]
    if not words:
        return np.zeros(300)
    return np.mean(word_vectors[words], axis=0)

features = np.array([get_tweet_vector(tweet) for tweet in df['text']])

X_train, X_test, y_train, y_test = train_test_split(features, y,
test_size=0.2, random_state=9)

model = LogisticRegression(max_iter=1000000)
model.fit(X_train, y_train)
```

```
y_pred = model.predict(X_test)
accuracy4 = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy4}')
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.696153125
              precision    recall  f1-score   support

           0       0.70      0.70      0.70    159911
           1       0.70      0.69      0.70    160089

    accuracy                           0.70    320000
   macro avg       0.70      0.70      0.70    320000
weighted avg       0.70      0.70      0.70    320000
```

7. Other approaches

7.1 KNN

```
model3 = KNeighborsClassifier(n_neighbors = 99) # for all data k = 99,
because it's relatively close to square root of number of all tweets

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=9)
model3.fit(X_train, y_train)

y_pred = model3.predict(X_test[0:10000])
accuracy5 = accuracy_score(y_test[0:10000], y_pred)

print(f'Accuracy: {accuracy5:.2f}')

print(classification_report(y_test[0:10000], y_pred))
```

```
Accuracy: 0.61
              precision    recall  f1-score   support

           0       0.64      0.49      0.56      5046
           1       0.58      0.72      0.65      4954

    accuracy                           0.61     10000
   macro avg       0.61      0.61      0.60     10000
weighted avg       0.61      0.61      0.60     10000
```

8. LSTM

```
train_data, test_data = train_test_split(df, test_size=0.2,
                                         random_state=9)
tokenizer = Tokenizer()
tokenizer.fit_on_texts(train_data.text)
word_index = tokenizer.word_index

vocab_size = len(tokenizer.word_index) + 1
x_train = pad_sequences(tokenizer.texts_to_sequences(train_data.text),
                        maxlen = 20)
x_test = pad_sequences(tokenizer.texts_to_sequences(test_data.text),
                       maxlen = 20)

print("Vocabulary Size :", vocab_size)
print("Training X Shape:",x_train.shape)
print("Testing X Shape:",x_test.shape)
```

```
Vocabulary Size : 228238
Training X Shape: (1279999, 20)
Testing X Shape: (320000, 20)
```

```
labels = train_data.sentiment.unique().tolist()

encoder = LabelEncoder()
encoder.fit(train_data.sentiment.to_list())

y_train = encoder.transform(train_data.sentiment.to_list())
y_test = encoder.transform(test_data.sentiment.to_list())

y_train = y_train.reshape(-1,1)
y_test = y_test.reshape(-1,1)

print("y_train shape:", y_train.shape)
print("y_test shape:", y_test.shape)
```

```
y_train shape: (1279999, 1)
y_test shape: (320000, 1)
```

```
EMBEDDING_DIM = 300
LR = 1e-3
BATCH_SIZE = 1024
EPOCHS = 1 #increasing the number will lead to overfitting

embedding_layer = tf.keras.layers.Embedding(
    vocab_size,
    EMBEDDING_DIM,
    input_length=20,
    trainable=True  #Allow the model to update the embeddings during
```

```
training
)

C:\Users\adria\AppData\Roaming\Python\Python312\site-packages\keras\
src\layers\core\embedding.py:90: UserWarning: Argument `input_length`
is deprecated. Just remove it.
  warnings.warn(
```

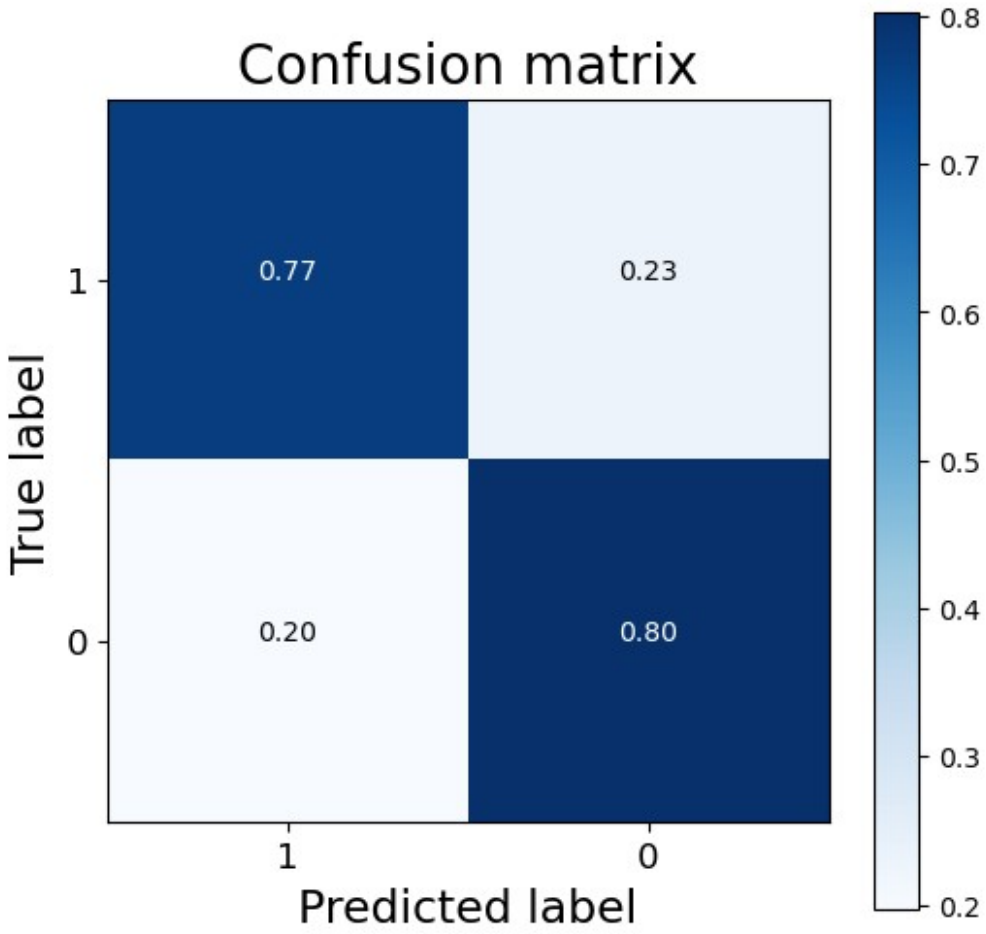
Training - LSTM

```
sequence_input = Input(shape=(20,), dtype='int32')
embedding_sequences = embedding_layer(sequence_input)
x = SpatialDropout1D(0.2)(embedding_sequences)
x = Conv1D(64, 5, activation='relu')(x)
x = Bidirectional(LSTM(64, dropout=0.2, recurrent_dropout=0.2))(x)
x = Dense(512, activation='relu')(x)
x = Dropout(0.5)(x)
x = Dense(512, activation='relu')(x)
outputs = Dense(1, activation='sigmoid')(x)
model = tf.keras.Model(sequence_input, outputs)

model.compile(optimizer=Adam(learning_rate=LR),
loss='binary_crossentropy',
              metrics=['accuracy'])
ReduceLROnPlateau = ReduceLROnPlateau(factor=0.1,
                                      min_lr = 0.01,
                                      monitor = 'val_loss',
                                      verbose = 1)

history = model.fit(x_train, y_train, batch_size=BATCH_SIZE,
epochs=EPOCHS,
                    validation_data=(x_test, y_test),
callbacks=[ReduceLROnPlateau])
```

```
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 793s 630ms/step - accuracy: 0.7430 -
loss: 0.5053 - val_accuracy: 0.7861 - val_loss: 0.4532 -
learning_rate: 0.0010
```

```
'''s, (at, al) = plt.subplots(2,1)
at.plot(history.history['accuracy'], c= 'b')
at.plot(history.history['val_accuracy'], c='r')
at.set_title('model accuracy')
at.set_ylabel('accuracy')
at.set_xlabel('epoch')
at.legend(['LSTM_train', 'LSTM_val'], loc='upper left')

al.plot(history.history['loss'], c='m')
al.plot(history.history['val_loss'], c='c')
al.set_title('model loss')
```

```
al.set_ylabel('loss')
al.set_xlabel('epoch')
al.legend(['train', 'val'], loc = 'upper left')'''
#useful only when more than 1 epoch

"s, (at, al) = plt.subplots(2,1)\nat.plot(history.history['accuracy'],
c= 'b')\nat.plot(history.history['val_accuracy'], c='r')\
nat.set_title('model accuracy')\nat.set_ylabel('accuracy')\
nat.set_xlabel('epoch')\nat.legend(['LSTM_train', 'LSTM_val'],
loc='upper left')\n\nal.plot(history.history['loss'], c='m')\
nal.plot(history.history['val_loss'], c='c')\nal.set_title('model
loss')\nal.set_ylabel('loss')\nal.set_xlabel('epoch')\
nal.legend(['train', 'val'], loc = 'upper left')"

def decode_sentiment(score):
    return 1 if score>0.5 else 0
scores = model.predict(x_test, verbose=1, batch_size=10000)
y_pred_1d = [decode_sentiment(score) for score in scores]

32/32 ━━━━━━━━━━━━━━━━━━━━ 16s 494ms/step


def plot_confusion_matrix(cm, classes,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title, fontsize=20)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, fontsize=13)
    plt.yticks(tick_marks, classes, fontsize=13)
    fmt = '.2f'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]),
range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")
    plt.ylabel('True label', fontsize=17)
    plt.xlabel('Predicted label', fontsize=17)

cnf_matrix = confusion_matrix(test_data.sentiment.to_list(),
y_pred_1d)
plt.figure(figsize=(6,6))
plot_confusion_matrix(cnf_matrix,
classes=test_data.sentiment.unique(), title="Confusion matrix")
plt.show()
```




```
report = classification_report(list(test_data.sentiment), y_pred_1d)
print(report)
accuracy6 = accuracy_score(list(test_data.sentiment), y_pred_1d)
```

```
              precision    recall  f1-score   support

           0       0.80      0.77      0.78    159911
           1       0.78      0.80      0.79    160089

    accuracy                           0.79    320000
   macro avg       0.79      0.79      0.79    320000
weighted avg       0.79      0.79      0.79    320000
```

9. COMPARISON

```
methods = ['LogReg-tfidf  ', 'NaiveB-tfidf', 'LogReg-Word2Vec',
'LogReg-Glove', 'knn', 'LSTM']
```

```
accuracy_values = [accuracy1, accuracy2, accuracy3, accuracy4,
accuracy5, accuracy6]


plt.figure(figsize=(10, 6))

plt.bar(methods, accuracy_values, color='blue')
plt.ylim(0, 1)
plt.title('Accuracy Comparison of Different Methods')

plt.xlabel('Methods')
plt.ylabel('Accuracy')
for i, value in enumerate(accuracy_values):
    plt.text(i, value, round(value,3), ha='center', va='bottom')
plt.show()
```