

SaaS Review Sentiment Analysis

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These reviews come from a trusted site which publishes user review. The purpose of this non-commercial, educational project, is to leverage this data and create a sentiment analysis using sklearn, nltk, and pandas of the mentioned review.

```
In [1]: # Libraries
import numpy as np
import pandas as pd
import re

# custom data cleaning algorithm & classification
from clean_data import clean_data

# nltk libraries for cleaning and preparing text data
from nltk.tokenize import sent_tokenize, word_tokenize
from nltk.corpus import stopwords

# creates interactive histogram plots from plotly
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.offline as py
import plotly.graph_objs as go
import plotly.tools as tls
import plotly.express as px

# to create the wordcloud
from wordcloud import WordCloud, STOPWORDS

# modify model for machine learning algorithms
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
```

```
In [2]: # system setups
%matplotlib inline
py.init_notebook_mode(connected=True)
color = sns.color_palette()
```

```
In [3]: import pandas as pd
import numpy as np
import time
import matplotlib.pyplot as plt
import seaborn as sns

# metrics
from sklearn.model_selection import train_test_split, KFold, cross_val_score
from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score
from sklearn.metrics import classification_report, confusion_matrix
```

```

# transformations
from sklearn.feature_selection import RFE
from sklearn.preprocessing import MinMaxScaler

# models
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier
from sklearn.multiclass import OneVsRestClassifier
from xgboost import XGBClassifier
from sklearn.ensemble import GradientBoostingClassifier

score_dict = {}

def score_me(mn, mc, pn, y_test):
    """
    mn : the model name you want to have (ie. mn='Linear Regression')
    mc : the variable name for the model (ie. mc=linear_regression)
    pn : predictor variable name (ie. pn=y_pred)
    """
    global model_name
    model_name = {}
    model_name['Accuracy Score'] = round(accuracy_score(y_test, pn), 4)
    model_name['Micro F1 Score'] = round(f1_score(y_test, pn, average='micro'), 4)
    model_name['Macro F1 Score'] = round(f1_score(y_test, pn, average='macro'), 4)
    model_name['Weighted F1 Score'] = round(f1_score(y_test, pn, average='weighted'), 4)
    model_name['Micro Precision Score'] = round(precision_score(y_test, pn, average='micro'), 4)
    model_name['Macro Precision Score'] = round(precision_score(y_test, pn, average='macro'), 4)
    model_name['Weighted Precision Score'] = round(precision_score(y_test, pn, average='weighted'), 4)
    model_name['Micro Recall Score'] = round(recall_score(y_test, pn, average='micro'), 4)
    model_name['Macro Recall Score'] = round(recall_score(y_test, pn, average='macro'), 4)
    model_name['Weighted Recall Score'] = round(recall_score(y_test, pn, average='weighted'), 4)
    score_dict[mn] = model_name
    print(classification_report(y_test, pn), '\n', '\n')

    plt.figure(figsize=(20, 8))
    sns.heatmap(pd.DataFrame(confusion_matrix(y_test, pn)), annot=True, fmt='g', annot_kws={"size": 15})
    plt.title(str(mn) + ' Confusion Matrix')
    plt.ylabel('Actual Label')
    plt.xlabel('Predicted Labels')
    plt.tight_layout()

    plt.show()

def Decision_Tree(X_train, y_train, X_test, y_test):
    global dctc
    dctc_start = time.time()
    dctc = DecisionTreeClassifier(random_state = 42).fit(X_train, y_train)
    dctc_predictions = dctc.predict(X_test)
    score_me('Decision Tree Classifier', dctc, dctc_predictions, y_test)

```

```

dctc_end = time.time()
compute_time_dctc = dctc_end - dctc_start
model_name['Run Time(secs)'] = round(compute_time_dctc, 3)
print('Scores:', score_dict['Decision Tree Classifier'])

def RF_Feature_Importance(X_train, y_train, X_test, y_test):
    rfc_feature_importances = pd.DataFrame(rfc.feature_importances_, index=X_train.columns,
                                           columns=['Importance']).sort_values('Importance',
                                           ascending=False)
    plt.figure(figsize=(20, 8))
    sns.barplot(x='Importance', y=rfc_feature_importances.index,
                data=rfc_feature_importances)
    plt.title('Random Forest Classifier Feature Importances', fontsize=14)
    plt.xlabel('Importance Value', fontsize=12)
    plt.show()

def Feature_Optimization_RF(X_train, y_train, X_test, y_test):
    results = pd.DataFrame(
        columns=['Number of Features', 'Accuracy Score', 'Micro F1 Score', 'Macro F1 Score', 'Weighted F1
Score',
                'Micro Precision Score', 'Macro Precision Score',
                'Weighted Precision Score', 'Micro Recall Score', 'Macro Recall Score', 'Weighted Recall
Score'])

    for index in np.arange(len(X_train.columns)):
        sel = RFE(RandomForestClassifier(random_state=42, n_jobs=-1), n_features_to_select=index + 1)
        sel.fit(X_train, y_train)
        x_train_rfe = sel.transform(X_train)
        x_test_rfe = sel.transform(X_test)
        model = RandomForestClassifier(n_estimators=50, random_state=42, n_jobs=-1)
        model.fit(x_train_rfe, y_train)
        results.loc[index] = [index + 1,
                              round(accuracy_score(y_test, model.predict(x_test_rfe)), 4),
                              round(f1_score(y_test, model.predict(x_test_rfe), average='micro'), 4),
                              round(f1_score(y_test, model.predict(x_test_rfe), average='macro'), 4),
                              round(f1_score(y_test, model.predict(x_test_rfe), average='weighted'), 4),
                              round(precision_score(y_test, model.predict(x_test_rfe), average='micro'),
4),
                              round(precision_score(y_test, model.predict(x_test_rfe), average='macro'),
4),
                              round(precision_score(y_test, model.predict(x_test_rfe),
average='weighted'), 4),
                              round(recall_score(y_test, model.predict(x_test_rfe), average='micro'), 4),
                              round(recall_score(y_test, model.predict(x_test_rfe), average='macro'), 4),
                              round(recall_score(y_test, model.predict(x_test_rfe), average='weighted'),
4)]

    return results

def Random_Forest(X_train, y_train, X_test, y_test):
    global rfc

```

```
'''returns rf_results dataframe which must be saved '''
rfc_start = time.time()
rfc = RandomForestClassifier(n_estimators=10, random_state=42, n_jobs=-1).fit(X_train, y_train)
rfc_predictions = rfc.predict(X_test)
score_me('Random Forest Classifier', rfc, rfc_predictions, y_test)

rfc_end = time.time()
compute_time_rfc = rfc_end - rfc_start
model_name['Run Time(secs)'] = round(compute_time_rfc, 3)
print('Scores:', score_dict['Random Forest Classifier'])

def Gradient_Boosting_Classifier(X_train, y_train, X_test, y_test):
    global gbc
    gbc_start = time.time()

    gbc = GradientBoostingClassifier(n_estimators=10, random_state=42).fit(X_train, y_train)

    gbc_predictions = gbc.predict(X_test)
    score_me('Gradient Boosting Classifier', gbc, gbc_predictions, y_test)

    gbc_end = time.time()
    compute_time_gbc = gbc_end - gbc_start
    model_name['Run Time(secs)'] = round(compute_time_gbc, 3)
    print('Scores:', score_dict['Gradient Boosting Classifier'])

def XG_Boost_Classifier(X_train, y_train, X_test, y_test):
    global xgc
    xgc_start = time.time()

    xgc = OneVsRestClassifier(XGBClassifier()).fit(X_train, y_train)

    xgc_predictions = xgc.predict(X_test)
    score_me('XG-Boost Classifier', xgc, xgc_predictions, y_test)

    xgc_end = time.time()
    compute_time_xgc = xgc_end - xgc_start
    model_name['Run Time(secs)'] = round(compute_time_xgc, 3)
    print('Scores:', score_dict['XG-Boost Classifier'])

def KNN_Classifier(X_train, y_train, X_test, y_test):
    global knnc
    knn_start = time.time()

    knnc = KNeighborsClassifier(n_neighbors=7, n_jobs=-1).fit(X_train, y_train)
    knn_predictions = knnc.predict(X_test)
    score_me('K-Neighbors Classifier', knnc, knn_predictions, y_test)

    knn_end = time.time()
    compute_time_knn = knn_end - knn_start
    model_name['Run Time(secs)'] = round(compute_time_knn, 3)
    print('Scores:', score_dict['K-Neighbors Classifier'])
```

```

def train_models(X_train, X_test, y_train, y_test):
    global score_dict
    score_dict = {}
    Decision_Tree(X_train, y_train, X_test, y_test)

    Gradient_Boosting_Classifier(X_train, y_train, X_test, y_test)

    XG_Boost_Classifier(X_train, y_train, X_test, y_test)

    KNN_Classifier(X_train, y_train, X_test, y_test)
    Random_Forest(X_train, y_train, X_test, y_test)

    return pd.DataFrame.from_dict(score_dict)

    if RF_O == True:
        # shows a bar chart of feature importance
        RF_Feature_Importance(X_train, y_train, X_test, y_test)
        # returns a dataframe of how features affect the performance of the RF model
        results = Feature_Optimization_RF(X_train, y_train, X_test, y_test)
        return results

score_dict_test_df = {}

def score_me_test_df(mn_t, mc_t, pn_t, y_test):
    """
    mn : the model name you want to have (ie. mn='Linear Regression')
    mc : the variable name for the model (ie. mc=linear_regression)
    pn : predictor variable name (ie. pn=y_pred)
    """
    global model_name_ts
    model_name = {}
    model_name['Accuracy Score'] = round(accuracy_score(y_test, pn_t), 4)
    model_name['Micro F1 Score'] = round(f1_score(y_test, pn_t, average='micro'), 4)
    model_name['Macro F1 Score'] = round(f1_score(y_test, pn_t, average='macro'), 4)
    model_name['Weighted F1 Score'] = round(f1_score(y_test, pn_t, average='weighted'), 4)
    model_name['Micro Precision Score'] = round(precision_score(y_test, pn_t, average='micro'), 4)
    model_name['Macro Precision Score'] = round(precision_score(y_test, pn_t, average='macro'), 4)
    model_name['Weighted Precision Score'] = round(precision_score(y_test, pn_t, average='weighted'), 4)
    model_name['Micro Recall Score'] = round(recall_score(y_test, pn_t, average='micro'), 4)
    model_name['Macro Recall Score'] = round(recall_score(y_test, pn_t, average='macro'), 4)
    model_name['Weighted Recall Score'] = round(recall_score(y_test, pn_t, average='weighted'), 4)
    score_dict_test_df[mn_t] = model_name
    print(classification_report(y_test, pn_t), '\n', '\n')

    plt.figure(figsize=(20, 8))
    sns.heatmap(pd.DataFrame(confusion_matrix(y_test, pn_t)), annot=True, fmt='g', annot_kws={"size":
15})
    plt.title(str(mn_t) + ' Confusion Matrix')
    plt.ylabel('Actual Label')
    plt.xlabel('Predicted Labels')

```

```

plt.tight_layout()

plt.show()

def run_test_df(the_target_column, the_test_data):

    target_column = the_target_column
    set_to_test = the_test_data
    model_names = {'Decision Tree Classifier':[dctc, dctc.predict(set_to_test)], 'Random Forest Classifier':[rfc, rfc.predict(set_to_test)],
                   'Gradient Boosting Classifier':[gbc, gbc.predict(set_to_test)], 'XG-Boost Classifier':[xgc, xgc.predict(set_to_test)],
                   'K-Neighbors Classifier':[knnc, knnc.predict(set_to_test)]}
    for models in model_names:
        score_me_test_df(mn_t=models, mc_t=model_names[models][0], pn_t=model_names[models][1],
y_test=the_target_column)

    model_results_ts = pd.DataFrame.from_dict(score_dict_test_df)
    return model_results_ts

# example

# train_models(classifying_set, target_column_fd, False)
# print(model_results)

# target_column_fd = bd['TARGET_CLASSES'].astype('int16')
#
# test_set = pd.read_csv('test_model.csv')
# test_set.info()
# run_X_test = classifying_set
# target_for_test = target_column_fd
# fire_dept_test_results = run_test_df(target_for_test, run_X_test)

```

```

In [11]: scrape2 = pd.read_csv('Secondscrape_2.csv')
cd = clean_data(scrape2)
cd.columns

```

```

Out[11]: Index(['app_id', 'review_date', 'review_title', 'user_role_title',
               'company_industry', 'company_size', 'score', 'app_id.1',
               'use_case_deployment_scope', 'pros', 'cons', 'roi',
               'competitors_considered', 'support_rating_usability_recommendation',
               'other_questions', 'others_used', 'app_name', 'review_feeling',
               'merged_columns'],
              dtype='object')

```

```

In [5]: test_set = pd.read_csv('real_test.csv')
real_test = clean_data(test_set)

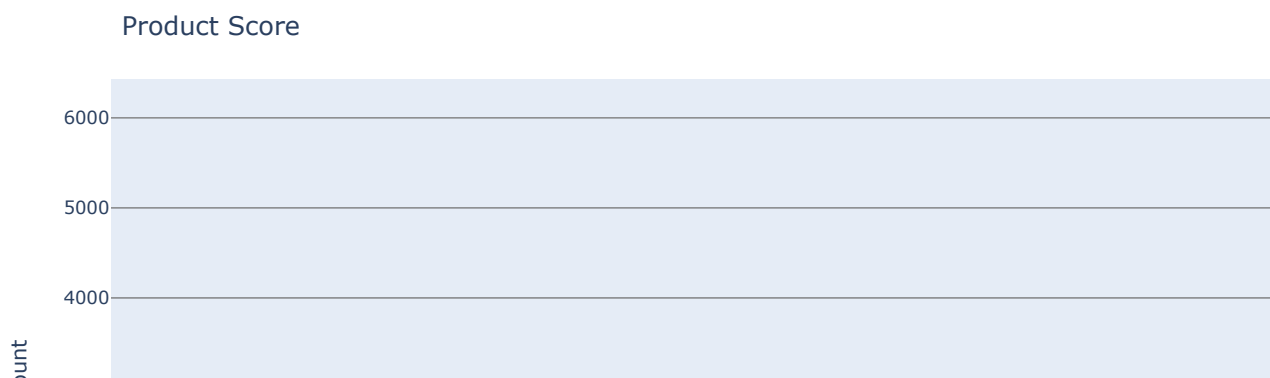
```

```

In [6]: # Product Scores
fig = px.histogram(cd, x="score")
fig.update_traces(marker_color="turquoise", marker_line_color='rgb(8,48,107)',
                  marker_line_width=1.5, opacity=.6)
fig.update_layout(title_text='Product Score')
fig.show()

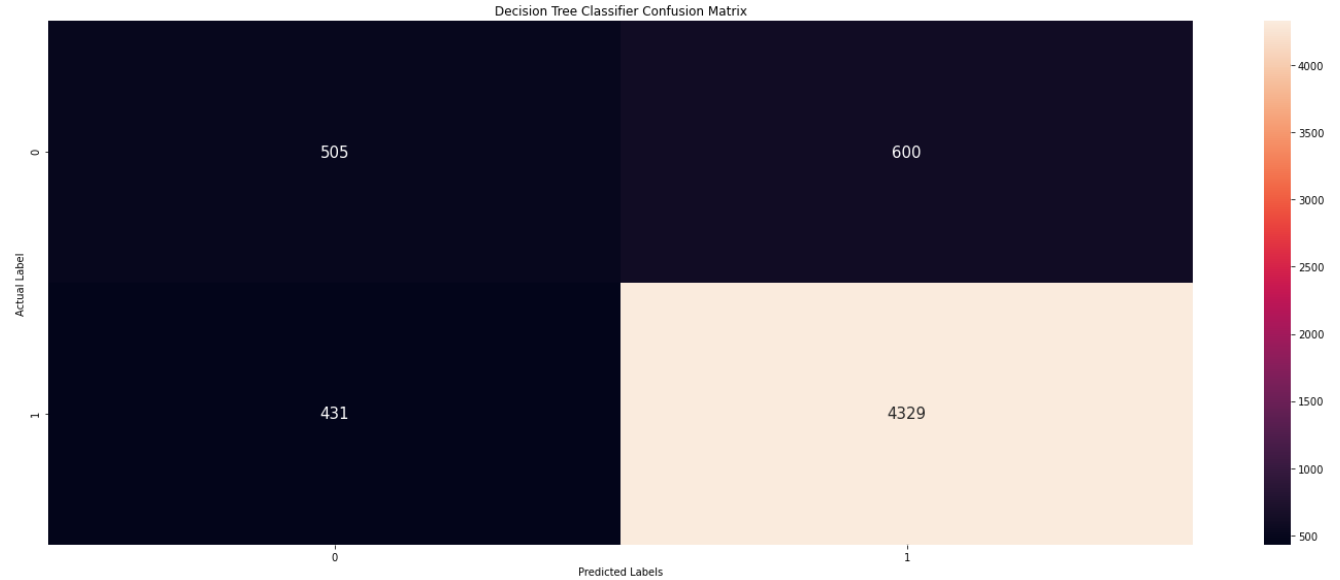
```

```
fig = px.histogram(cd, x="review_feeling")
fig.update_traces(marker_color="red", marker_line_color='rgb(8,48,107)',
                  marker_line_width=1.5, opacity=.6)
fig.update_layout(title_text='Product Score')
fig.show()
```



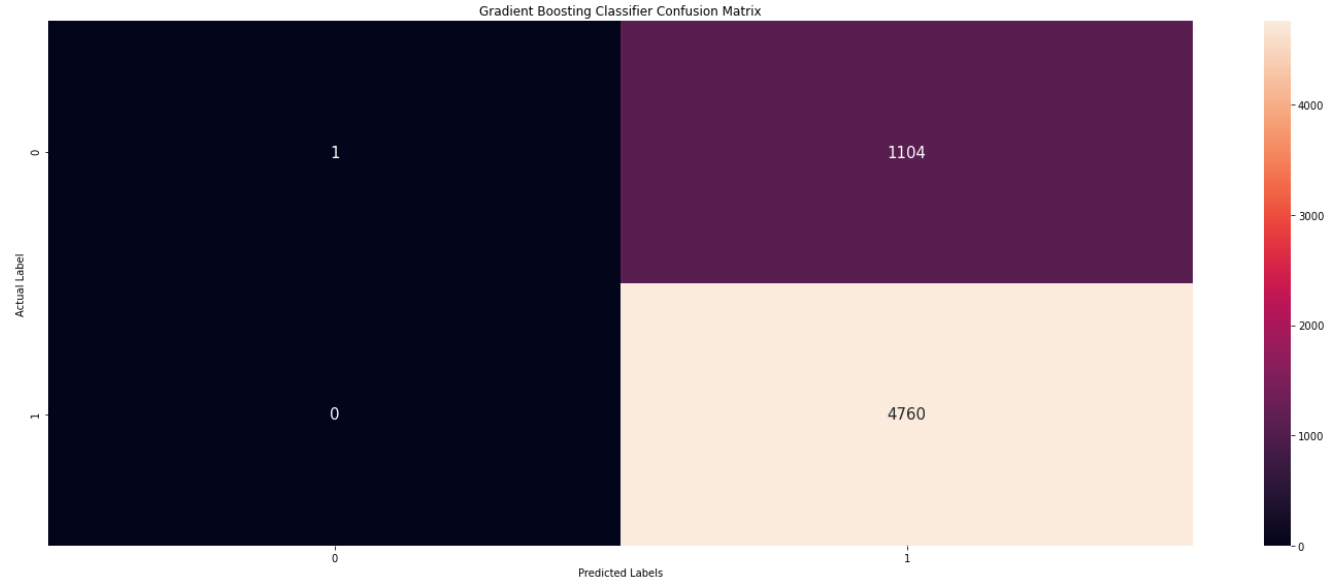
```
In [7]: long_string = ' '.join(cd['merged_columns'].tolist())
        positive_string = ' '.join(cd[cd['review_feeling'] == 1]['merged_columns'].tolist())
```

A word cloud visualization of the text "I need a tool that can help my team work together to make our data easy to use and report on". The words are arranged in a circular pattern, with "easy" and "data" being the largest. Other prominent words include "tool", "team", "work", "report", "use", "need", "help", "together", "make", "our", "and", "on", "visualization", "dashboard", "analytics", "collaboration", "communication", "integration", "software", "platform", "application", "function", "feature", "access", "update", "system", "may", "will", "quickly", "service", "us", "even", "track", "logs", "email", "one", "require", "training", "when", "use", "first", "everyday".



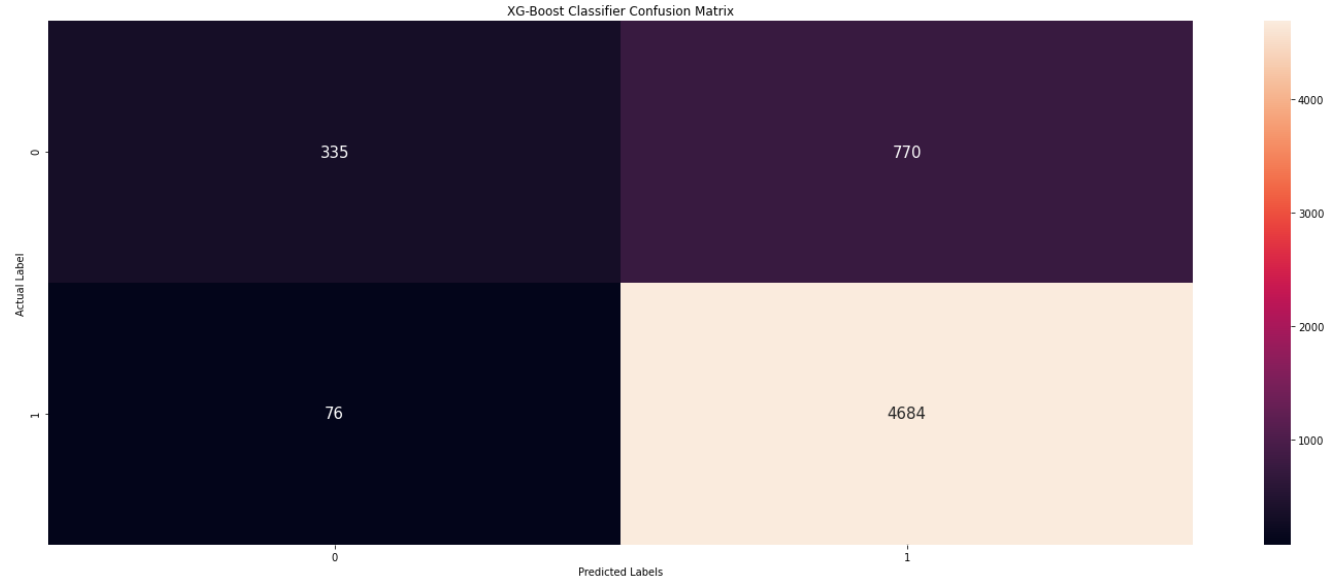
Scores: {'Accuracy Score': 0.8242, 'Micro F1 Score': 0.8242, 'Macro F1 Score': 0.6942, 'Weighted F1 Score': 0.8185, 'Micro Precision Score': 0.8242, 'Macro Precision Score': 0.7089, 'Weighted Precision Score': 0.8145, 'Micro Recall Score': 0.8242, 'Macro Recall Score': 0.6832, 'Weighted Recall Score': 0.8242, 'Run Time(secs)': 11.143}

	precision	recall	f1-score	support
0	1.00	0.00	0.00	1105
1	0.81	1.00	0.90	4760
accuracy			0.81	5865
macro avg	0.91	0.50	0.45	5865
weighted avg	0.85	0.81	0.73	5865



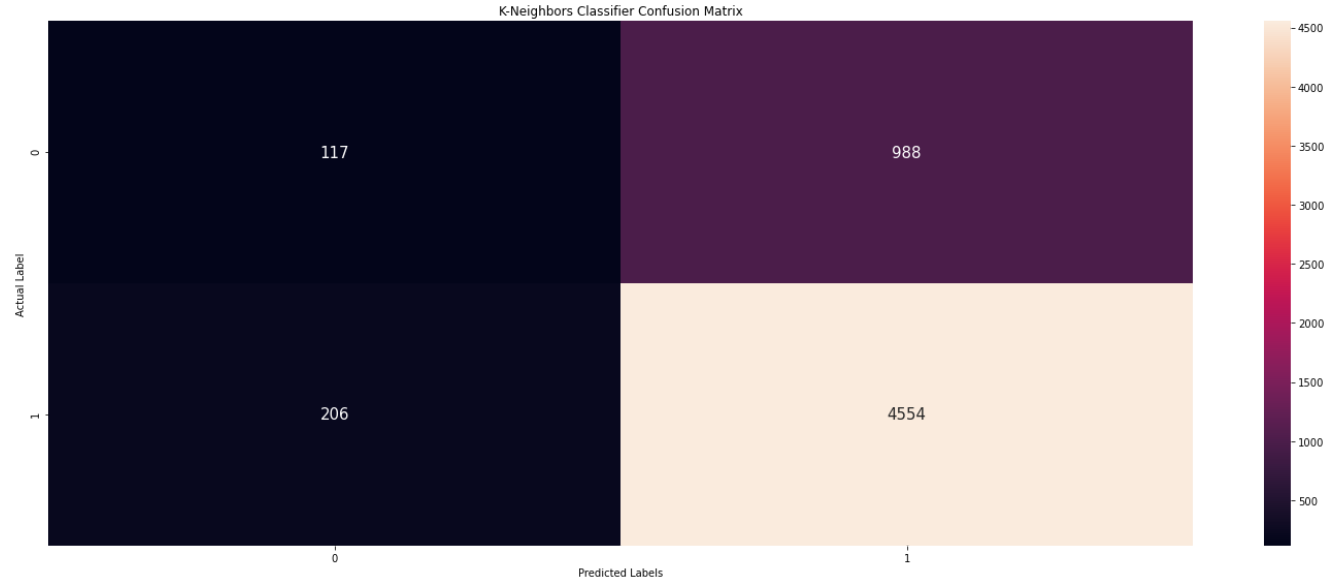
Scores: {'Accuracy Score': 0.8118, 'Micro F1 Score': 0.8118, 'Macro F1 Score': 0.4489, 'Weighted F1 Score': 0.7276, 'Micro Precision Score': 0.8118, 'Macro Precision Score': 0.9059, 'Weighted Precision Score': 0.8472, 'Micro Recall Score': 0.8118, 'Macro Recall Score': 0.5005, 'Weighted Recall Score': 0.8118, 'Run Time(secs)': 10.652}

	precision	recall	f1-score	support
0	0.82	0.30	0.44	1105
1	0.86	0.98	0.92	4760
accuracy			0.86	5865
macro avg	0.84	0.64	0.68	5865
weighted avg	0.85	0.86	0.83	5865



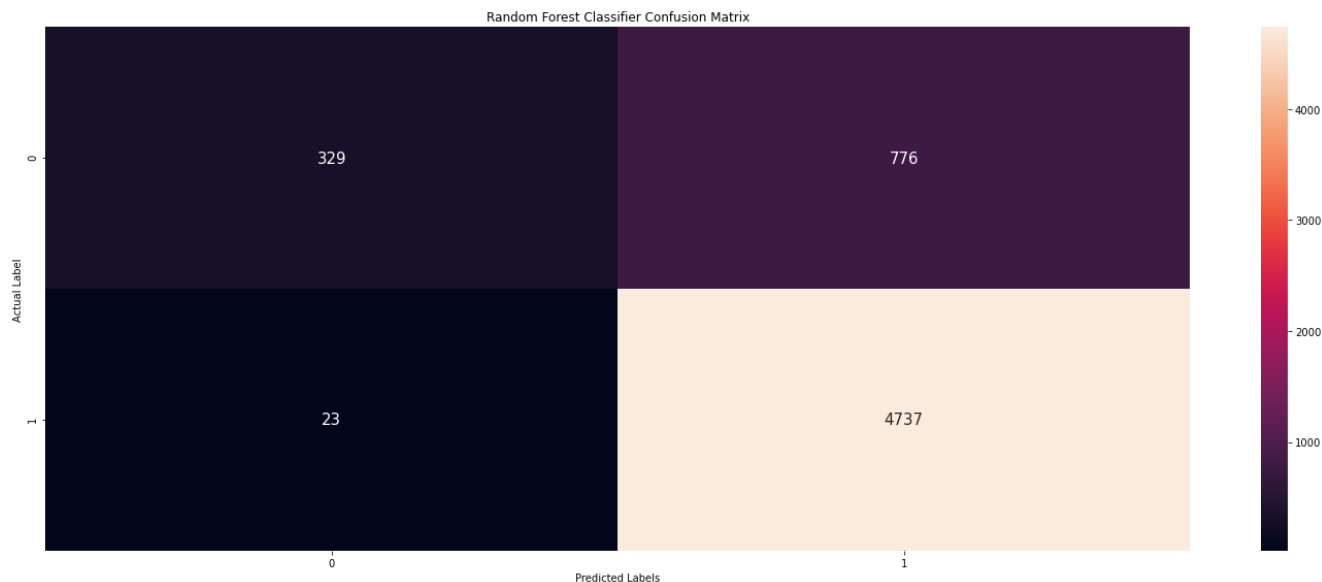
Scores: {'Accuracy Score': 0.8558, 'Micro F1 Score': 0.8558, 'Macro F1 Score': 0.6796, 'Weighted F1 Score': 0.8276, 'Micro Precision Score': 0.8558, 'Macro Precision Score': 0.837, 'Weighted Precision Score': 0.8506, 'Micro Recall Score': 0.8558, 'Macro Recall Score': 0.6436, 'Weighted Recall Score': 0.8558, 'Run Time(secs)': 5.261}

	precision	recall	f1-score	support
0	0.36	0.11	0.16	1105
1	0.82	0.96	0.88	4760
accuracy			0.80	5865
macro avg	0.59	0.53	0.52	5865
weighted avg	0.74	0.80	0.75	5865



Scores: {'Accuracy Score': 0.7964, 'Micro F1 Score': 0.7964, 'Macro F1 Score': 0.524, 'Weighted F1 Score': 0.7484, 'Micro Precision Score': 0.7964, 'Macro Precision Score': 0.592, 'Weighted Precision Score': 0.7352, 'Micro Recall Score': 0.7964, 'Macro Recall Score': 0.5313, 'Weighted Recall Score': 0.7964, 'Run Time(secs)': 2.431}

	precision	recall	f1-score	support
0	0.93	0.30	0.45	1105
1	0.86	1.00	0.92	4760
accuracy			0.86	5865
macro avg	0.90	0.65	0.69	5865
weighted avg	0.87	0.86	0.83	5865



Scores: {'Accuracy Score': 0.8638, 'Micro F1 Score': 0.8638, 'Macro F1 Score': 0.6869, 'Weighted F1 Score': 0.8336, 'Micro Precision Score': 0.8638, 'Macro Precision Score': 0.897, 'Weighted Precision Score': 0.8735, 'Micro Recall Score': 0.8638, 'Macro Recall Score': 0.6465, 'Weighted Recall Score': 0.8638, 'Run Time(secs)': 0.726}

Out[24]:

	Decision Tree Classifier	Gradient Boosting Classifier	XG-Boost Classifier	K-Neighbors Classifier	Random Forest Classifier
Accuracy Score	0.8242	0.8118	0.8558	0.7964	0.8638
Micro F1 Score	0.8242	0.8118	0.8558	0.7964	0.8638
Macro F1 Score	0.6942	0.4489	0.6796	0.5240	0.6869
Weighted F1 Score	0.8185	0.7276	0.8276	0.7484	0.8336
Micro Precision Score	0.8242	0.8118	0.8558	0.7964	0.8638
Macro Precision Score	0.7089	0.9059	0.8370	0.5920	0.8970
Weighted Precision Score	0.8145	0.8472	0.8506	0.7352	0.8735
Micro Recall Score	0.8242	0.8118	0.8558	0.7964	0.8638
Macro Recall Score	0.6832	0.5005	0.6436	0.5313	0.6465
Weighted Recall Score	0.8242	0.8118	0.8558	0.7964	0.8638
Run Time(secs)	11.1430	10.6520	5.2610	2.4310	0.7260

In [20]:

```
def new_data_test(df):
    def remove_punctuation(text):
        final = "".join(u for u in text if u not in ("?", ".", ";", ":", "!", "'", '"'))
        return final

    df['merged_columns'] = df['merged_columns'].apply(remove_punctuation)
    df = df.dropna(subset=['merged_columns'])
    df['merged_columns'] = df['merged_columns'].apply(remove_punctuation)

    index = df.index
    df['random_number'] = np.random.randn(len(index))
    train = df

    vectorizer = CountVectorizer(token_pattern=r'\b\w+\b')
    train_matrix = vectorizer.fit_transform(train['merged_columns'])

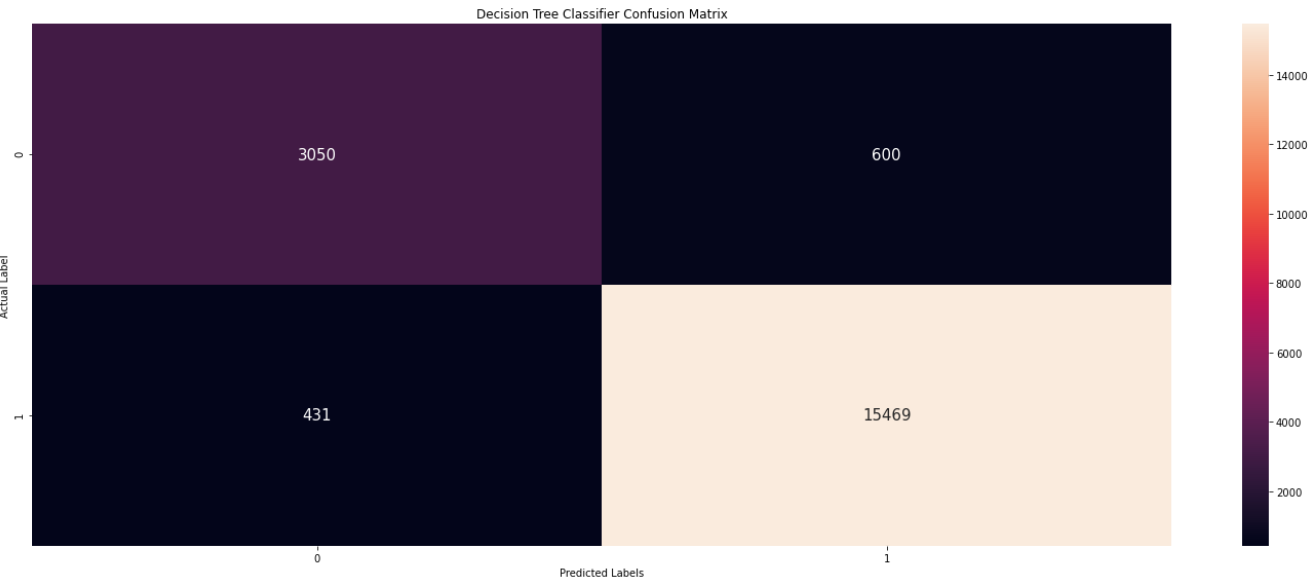
    train = train_matrix
    target = train['review_feeling']
```

```
return train, target
```

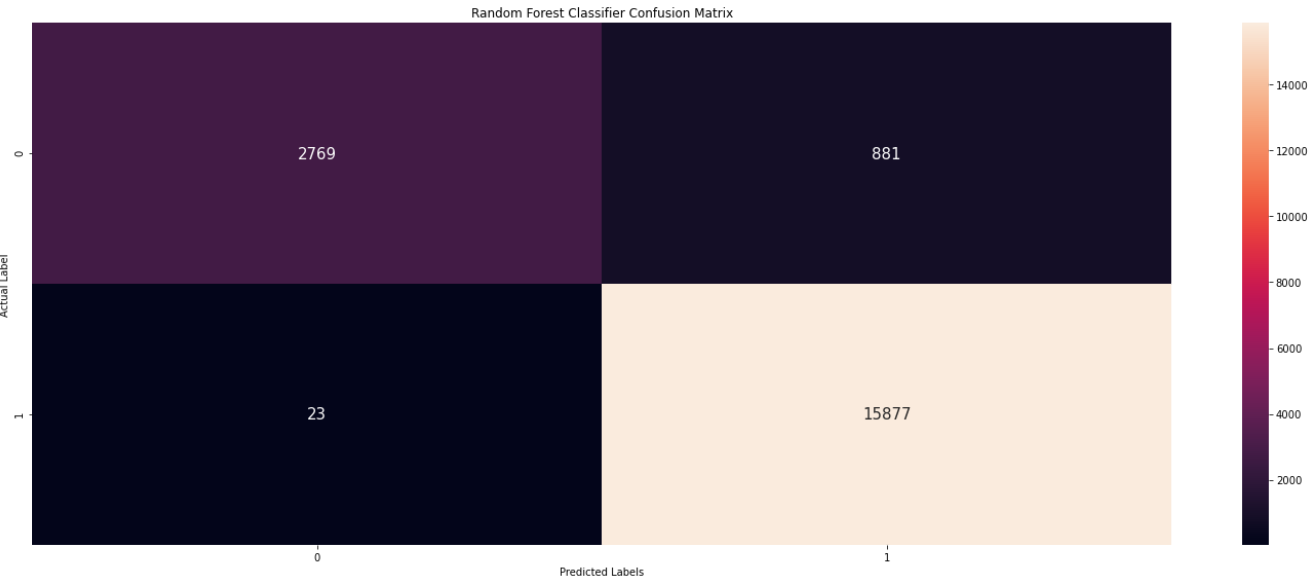
```
In [26]: traintest, targettest = process_for_ml(real_test)

test_1 = run_test_df(targettest, traintest)
test_1
```

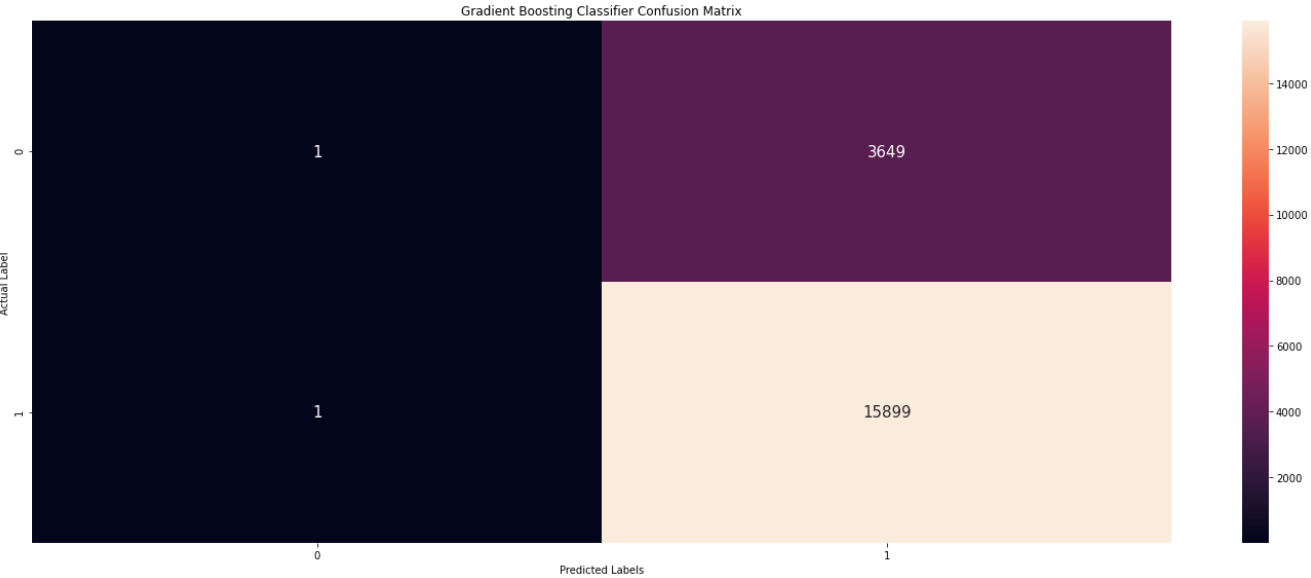
	precision	recall	f1-score	support
0	0.88	0.84	0.86	3650
1	0.96	0.97	0.97	15900
accuracy			0.95	19550
macro avg	0.92	0.90	0.91	19550
weighted avg	0.95	0.95	0.95	19550



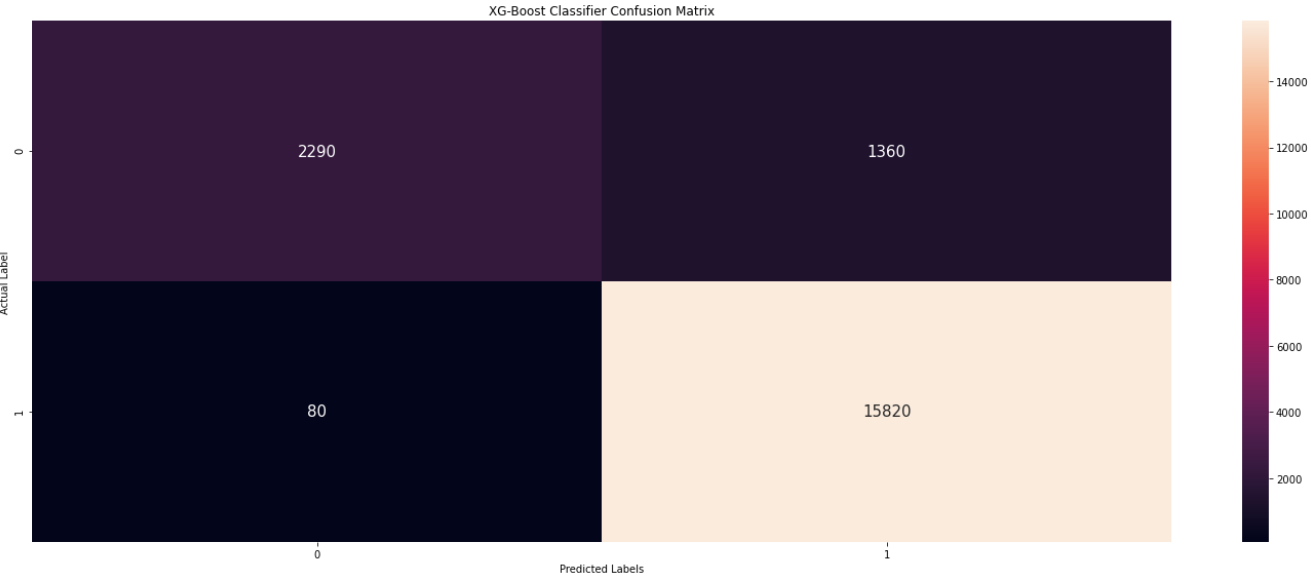
	precision	recall	f1-score	support
0	0.99	0.76	0.86	3650
1	0.95	1.00	0.97	15900
accuracy			0.95	19550
macro avg	0.97	0.88	0.92	19550
weighted avg	0.96	0.95	0.95	19550



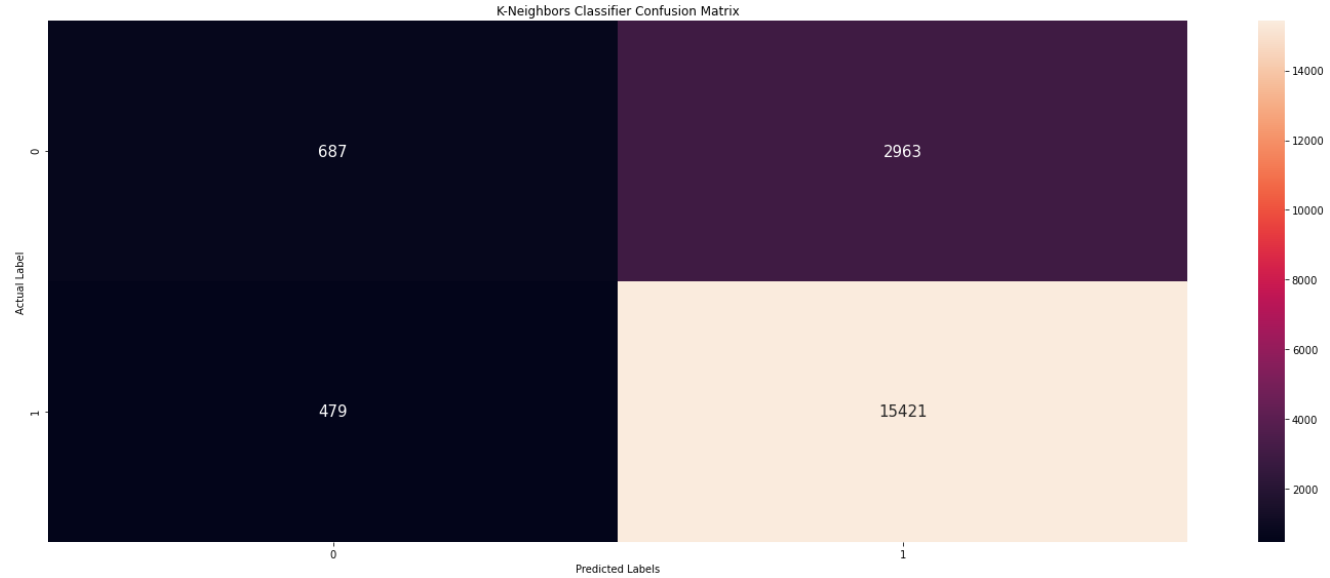
	precision	recall	f1-score	support
0	0.50	0.00	0.00	3650
1	0.81	1.00	0.90	15900
accuracy			0.81	19550
macro avg	0.66	0.50	0.45	19550
weighted avg	0.75	0.81	0.73	19550



	precision	recall	f1-score	support
0	0.97	0.63	0.76	3650
1	0.92	0.99	0.96	15900
accuracy			0.93	19550
macro avg	0.94	0.81	0.86	19550
weighted avg	0.93	0.93	0.92	19550



	precision	recall	f1-score	support
0	0.59	0.19	0.29	3650
1	0.84	0.97	0.90	15900
accuracy			0.82	19550
macro avg	0.71	0.58	0.59	19550
weighted avg	0.79	0.82	0.78	19550



Out[26]:

	Decision Tree Classifier	Random Forest Classifier	Gradient Boosting Classifier	XG-Boost Classifier	K-Neighbors Classifier
Accuracy Score	0.9473	0.9538	0.8133	0.9263	0.8239
Micro F1 Score	0.9473	0.9538	0.8133	0.9263	0.8239
Macro F1 Score	0.9116	0.9160	0.4488	0.8586	0.5925
Weighted F1 Score	0.9468	0.9513	0.7297	0.9199	0.7849
Micro Precision Score	0.9473	0.9538	0.8133	0.9263	0.8239
Macro Precision Score	0.9194	0.9696	0.6567	0.9435	0.7140
Weighted Precision Score	0.9465	0.9557	0.7548	0.9293	0.7922
Micro Recall Score	0.9473	0.9538	0.8133	0.9263	0.8239
Macro Recall Score	0.9043	0.8786	0.5001	0.8112	0.5790
Weighted Recall Score	0.9473	0.9538	0.8133	0.9263	0.8239

In []:

```
# experimental
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Flatten
from keras.layers.convolutional import Conv1D
from keras.layers.convolutional import MaxPooling1D
from keras.layers.embeddings import Embedding
from keras.preprocessing import sequence
```

```
# Padding the data samples to a maximum review length in words
max_words = 450
X_train = sequence.pad_sequences(X_train, maxlen=max_words)
X_test = sequence.pad_sequences(X_test, maxlen=max_words)
# Building the CNN Model
model = Sequential() # initilaizing the Sequential nature for CNN model
# Adding the embedding layer which will take in maximum of 450 words as input and provide a 32
dimensional output of those words which belong in the top_words dictionary
model.add(Embedding(top_words, 32, input_length=max_words))
model.add(Conv1D(32, 3, padding='same', activation='relu'))
model.add(MaxPooling1D())
```

```

model.add(Flatten())
model.add(Dense(250, activation='relu'))
model.add(Dense(1, activation='sigmoid'))

model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
model.summary()

```

```

-----
TypeError                                 Traceback (most recent call last)
<ipython-input-29-e9facc3edb23> in <module>
      1 # Padding the data samples to a maximum review length in words
      2 max_words = 450
----> 3 X_train = sequence.pad_sequences(X_train, maxlen=max_words)
      4 X_test = sequence.pad_sequences(X_test, maxlen=max_words)
      5 # Building the CNN Model

~\AppData\Roaming\Python\Python38\site-packages\tensorflow\python\keras\preprocessing\sequence.py in pad_sequences(sequences, maxlen, dtype, padding, truncating, value)
    154         or in case of invalid shape for a `sequences` entry.
    155         """
--> 156     return sequence.pad_sequences(
    157         sequences, maxlen=maxlen, dtype=dtype,
    158         padding=padding, truncating=truncating, value=value)

~\anaconda3\lib\site-packages\keras_preprocessing\sequence.py in pad_sequences(sequences, maxlen, dtype, padding, truncating, value)
     55     if not hasattr(sequences, '__len__'):
     56         raise ValueError("`sequences` must be iterable.")
--> 57     num_samples = len(sequences)
     58
     59     lengths = []

~\anaconda3\lib\site-packages\scipy\sparse\base.py in __len__(self)
    289     # non-zeros is more important. For now, raise an exception!
    290     def __len__(self):
--> 291         raise TypeError("sparse matrix length is ambiguous; use getnnz()")
    292         " or shape[0]")
    293

TypeError: sparse matrix length is ambiguous; use getnnz() or shape[0]

```

```

In [ ]: # Fitting the data onto model
        model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=2, batch_size=128, verbose=2)
        # Getting score metrics from our model
        scores = model.evaluate(X_test, y_test, verbose=0)
        # Displays the accuracy of correct sentiment prediction over test data
        print("Accuracy: %.2f%%" % (scores[1]*100))

```

In []:

In []:

In []:

In []: