Exploration

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression, RidgeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.pipeline import make_pipeline
from sklearn.decomposition import PCA
from sklearn.datasets import fetch_lfw_people
from sklearn.ensemble import BaggingClassifier
from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
import pickle
import seaborn as sns
from sklearn.metrics import accuracy_score, confusion_matrix, mean_squared_e
from sklearn.linear_model import Ridge
from sklearn.preprocessing import OneHotEncoder
from scipy.sparse import hstack
from sklearn.preprocessing import StandardScaler
import scipy
from textblob import TextBlob
import re
import nltk
from nltk.sentiment.vader import SentimentIntensityAnalyzer
```

In [2]:
```
trainingSet = pd.read_csv("./data/train.csv")
testingSet = pd.read_csv("./data/test.csv")

print("train.csv shape is ", trainingSet.shape)
print("test.csv shape is ", testingSet.shape)
```

```
train.csv shape is  (139753, 9)
test.csv shape is  (17470, 2)
```

Feature Extraction

In [6]:
```
def process(df):
    # This is where you can do all your processing

    df['HelpfulnessRatio'] = np.where(df['HelpfulnessDenominator'] > 0,
                                      df['HelpfulnessNumerator'] / df['HelpfulnessDen

    df['NotHelpful'] = df['HelpfulnessDenominator'] - df['HelpfulnessNumerat

    df['Time'] = pd.to_datetime(df['Time'], unit='s')
    df['Year'] = df['Time'].dt.year
    df['Month'] = df['Time'].dt.month
    df['Day'] = df['Time'].dt.day
    df['DayOfWeek'] = df['Time'].dt.dayofweek

    df['Text'].fillna('', inplace=True)
```

```
df['Summary'].fillna('', inplace=True)
df["Review"] = df["Summary"] + " " + df["Text"]
df['Review'].fillna('', inplace=True)
df['ReviewLength'] = df.apply(lambda row : len(row['Review'].split()) if

df['ReviewPolarity'] = df['Review'].apply(lambda text: TextBlob(text).se
df['ReviewSubjectivity'] = df['Review'].apply(lambda text: TextBlob(text

df['NumExclamation'] = df['Review'].str.count('!')
df['NumCaps'] = df['Review'].str.findall(r'[A-Z]').str.len()
df['CapsRatio'] = df['NumCaps'] / df['ReviewLength']
df['ExclamationRatio'] = df['NumExclamation'] / df['ReviewLength']

good_words_full = ['great', 'like', 'good', 'love', 'best', 'really', 'e
df['GoodWordsRatio'] = df['Review'].apply(lambda review: sum(review.lowe

bad_words_full = ['even', 'bad', 'worst', 'awful', 'terrible', 'horrible
df['BadWordsRatio'] = df['Review'].apply(lambda review: sum(review.lower


def clean_and_split_text(text):
    # Remove any punctuation and numbers
    text = re.sub(r'[^\w\s]', '', text)
    text = re.sub(r'\d+', '', text)
    # Convert text to lowercase and split into words
    words = text.lower().split()
    return words

bad_words_set = ['even', 'bad', 'worst', 'awful', 'terrible', 'horrible'
good_words_set = ['great', 'like', 'good', 'love', 'best', 'really', 'er

df['BadWordsNum'] = df['Review'].apply(
    lambda review: sum(1 for word in clean_and_split_text(review) if wor
)

df['GoodWordsNum'] = df['Review'].apply(
    lambda review: sum(1 for word in clean_and_split_text(review) if wor
)

total_word_count = df['ReviewLength'].sum()
total_negative_word_count = sum(df['BadWordsNum'])
average_negative_word_usage = total_negative_word_count / total_word_cou
df['NegativeWordUsageDeviation'] = (
    df['BadWordsNum'] / df['ReviewLength']
) - average_negative_word_usage

nltk.download('vader_lexicon')
sid = SentimentIntensityAnalyzer()
df['PositiveScore'] = df['Review'].apply(lambda x: sid.polarity_scores(x
df['NegativeScore'] = df['Review'].apply(lambda x: sid.polarity_scores(x
df['NeutralScore'] = df['Review'].apply(lambda x: sid.polarity_scores(x)
df['CompoundScore'] = df['Review'].apply(lambda x: sid.polarity_scores(x


df = df.drop(columns=['Summary', 'Text', 'DayOfWeek', 'Day', 'Time'])
correlations = df.drop(columns=['Review', 'ProductId', 'UserId']).corr()
```

```
    print(correlations)

    return df
```

In [7]:
```
# Load the dataset
trainingSet = pd.read_csv("./data/train.csv")
```

In [8]:
```
# Process the DataFrame
train_processed = process(trainingSet)
```

```
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     /Users/doruk/nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
Score                           1.000000
ReviewPolarity                  0.466230
CompoundScore                   0.397847
PositiveScore                   0.354221
GoodWordsRatio                  0.227267
ReviewSubjectivity              0.094793
Year                            0.088850
ExclamationRatio                0.084457
NumExclamation                  0.047487
CapsRatio                       0.041387
GoodWordsNum                    0.041023
Month                          -0.009580
HelpfulnessNumerator           -0.011531
NumCaps                        -0.025855
Id                             -0.051049
ReviewLength                   -0.078221
HelpfulnessDenominator         -0.092002
HelpfulnessRatio               -0.109879
NeutralScore                   -0.138258
BadWordsNum                    -0.272797
NegativeWordUsageDeviation     -0.283034
NotHelpful                     -0.288221
BadWordsRatio                  -0.290445
NegativeScore                  -0.402475
Name: Score, dtype: float64
```

In [24]:
```
train_processed = train_processed.drop(columns=['Month'])
```

In [25]:
```
# Load test set
submissionSet = pd.read_csv("./data/test.csv")

# Merge on Id so that the test set can have feature columns as well
testX= pd.merge(train_processed, submissionSet, left_on='Id', right_on='Id')
testX = testX.drop(columns=['Score_x'])
testX = testX.rename(columns={'Score_y': 'Score'})

# The training set is where the score is not null
trainX =  train_processed[train_processed['Score'].notnull()]
trainX = trainX.dropna()

# Save the datasets with the new features for easy access later
```

```
testX.to_csv("./data/X_test.csv", index=False)
trainX.to_csv("./data/X_train.csv", index=False)
```

Creating your model

In [26]:
```
# Load training set with new features into DataFrame
X_train = pd.read_csv("./data/X_train.csv")
```

In [27]:
```
# Split training set into training and testing set
X_train, X_test, Y_train, Y_test = train_test_split(
        X_train.drop(['Score'], axis=1),
        X_train['Score'],
        test_size=1/4.0,
        random_state=42
    )

# This is where you can do more feature selection
X_train = X_train.drop(columns=['Id'])
X_test = X_test.drop(columns=['Id'])
```

In [28]:
```
# Fit the StandardScaler on the numerical columns of the training data
numerical_columns = X_train.select_dtypes(include=['int64', 'float64']).colu
scaler = StandardScaler()
scaler.fit(X_train[numerical_columns])
# Transform the training data
X_train[numerical_columns] = scaler.transform(X_train[numerical_columns])
# Transform the test data with the fitted scaler
X_test[numerical_columns] = scaler.transform(X_test[numerical_columns])
```

In [29]:
```
tfidf_transformer = TfidfVectorizer()
X_train_tfidf = tfidf_transformer.fit_transform(X_train['Review'])
# Transform the test data with the fitted transformer
X_test_tfidf = tfidf_transformer.transform(X_test['Review'])
```

In [30]:
```
# Fit OneHotEncoder on the training data
OHE = OneHotEncoder(sparse=True, handle_unknown='ignore')
ID_fitter = OHE.fit(X_train[['ProductId', 'UserId']])
# Transform both training and test data with the fitted encoder
Train_IDs = ID_fitter.transform(X_train[['ProductId', 'UserId']])
Test_IDs = ID_fitter.transform(X_test[['ProductId', 'UserId']])
```

```
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packa
ges/sklearn/preprocessing/_encoders.py:972: FutureWarning: `sparse` was rena
med to `sparse_output` in version 1.2 and will be removed in 1.4. `sparse_ou
tput` is ignored unless you leave `sparse` to its default value.
  warnings.warn(
```

In [31]:
```
X_train = X_train.drop(['ProductId','UserId'], axis=1)
X_test = X_test.drop(['ProductId','UserId'], axis=1)

X_train = X_train.drop(columns=['Review'])
X_test = X_test.drop(columns=['Review'])
```

In [46]:
```
X_train_final = hstack([X_train, Train_IDs, X_train_tfidf])
```

In [47]:
```
X_test_final = hstack([X_test, Test_IDs, X_test_tfidf])
```

In [52]:
```
# Define the parameter grid
param_grid = {
    'alpha': [1.0, 4.0, 5.0, 10.0]  # You can expand this grid as needed
}

# Initialize the Ridge model
ridge = Ridge()

# Create the GridSearchCV object
grid_search = GridSearchCV(estimator=ridge, param_grid=param_grid, scoring='

# Perform the grid search
grid_search.fit(X_train_final, Y_train)

# Retrieve the best parameters
best_alpha = grid_search.best_params_['alpha']
print(f"Best alpha parameter: {best_alpha}")

# Fit the Ridge model using the best alpha parameter
ridge_optimized = Ridge(alpha=best_alpha).fit(X_train_final, Y_train)


Y_test_predictions = ridge_optimized.predict(X_test_final).clip(1, 5)
```

```
Fitting 5 folds for each of 4 candidates, totalling 20 fits
Best alpha parameter: 4.0
```

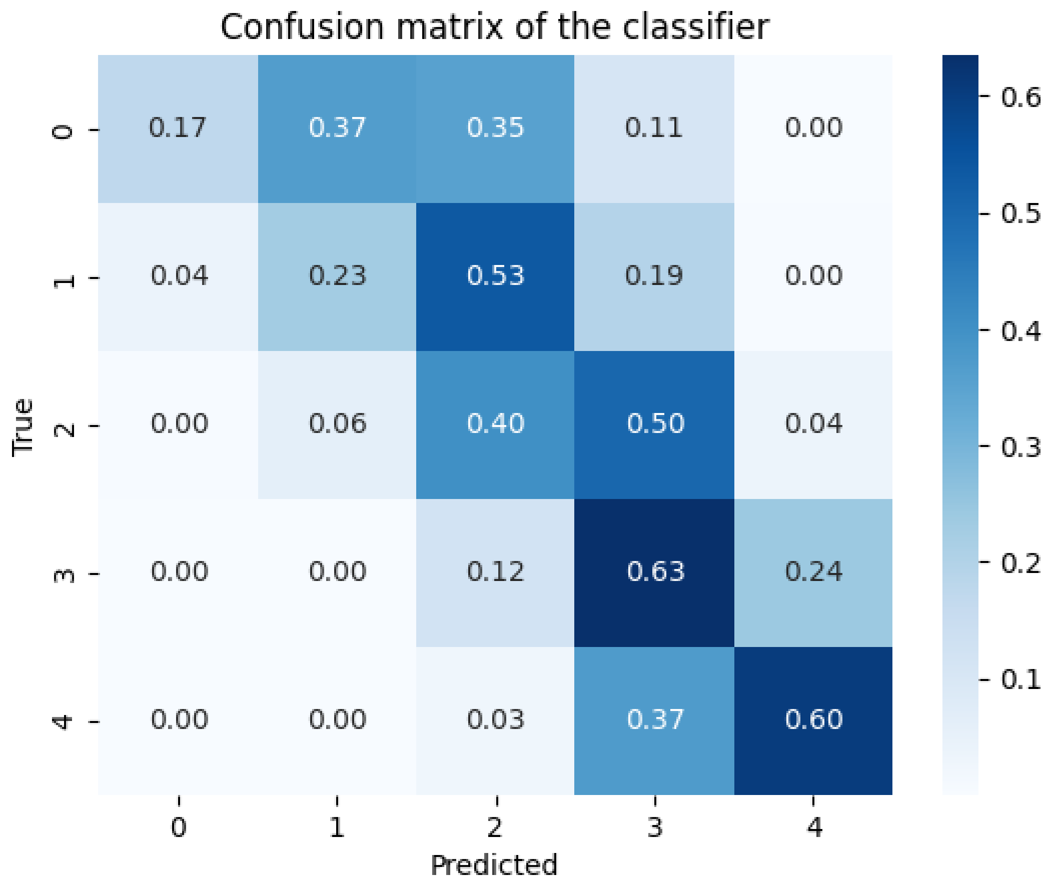
In [53]:
```
print("RMSE on testing set = ", mean_squared_error(Y_test, Y_test_predictior
```

```
RMSE on testing set =  0.5960250612885891
```

In [54]:
```
print("Accuracy on testing set =", accuracy_score(Y_test, np.round(Y_test_pr
```

```
Accuracy on testing set = 0.5372411762781721
```

In [55]:
```
cm = confusion_matrix(Y_test, np.round(Y_test_predictions), normalize='true'
sns.heatmap(cm, annot=True, fmt='.2f', cmap='Blues')
plt.title('Confusion matrix of the classifier')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```



Create the Kaggle submission

In [56]:
```
# Load the Kaggle test set
X_submission = pd.read_csv("./data/X_test.csv")
X_submission.columns
```

Out[56]:
```
Index(['Id', 'ProductId', 'UserId', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'HelpfulnessRatio', 'NotHelpful', 'Year',
       'Review', 'ReviewLength', 'ReviewPolarity', 'ReviewSubjectivity',
       'NumExclamation', 'NumCaps', 'CapsRatio', 'ExclamationRatio',
       'GoodWordsRatio', 'BadWordsRatio', 'BadWordsNum', 'GoodWordsNum',
       'NegativeWordUsageDeviation', 'PositiveScore', 'NegativeScore',
       'NeutralScore', 'CompoundScore', 'Score'],
      dtype='object')
```

In [57]:
```
# Drop 'Id' and 'Score' for scaling numerical features
X_submission_processed = X_submission.drop(columns=['Id', 'Score'])

# Separate out the numerical columns
numerical_columns_submission = X_submission_processed.select_dtypes(include=

# Scale the numerical features using the already fitted scaler
X_submission_processed[numerical_columns_submission] = scaler.transform(X_su

# Transform the test reviews using the already fitted TF-IDF vectorizer
X_submission_tfidf = tfidf_transformer.transform(X_submission_processed['Rev
```

```
# Transform 'ProductId' and 'UserId' using the already fitted OneHotEncoder
X_submission_OHE = ID_fitter.transform(X_submission_processed[['ProductId',

# Drop 'ProductId', 'UserId', and 'Review' columns before stacking
X_submission_processed = X_submission_processed.drop(columns=['ProductId', '

# Stack all features together: numerical, OneHotEncoded, and TF-IDF vectoriz
X_submission_final = hstack([X_submission_processed, X_submission_OHE, X_sub

# Make predictions using the optimized Ridge model
X_submission['Score'] = ridge_optimized.predict(X_submission_final).clip(1,

submission = X_submission[['Id', 'Score']]
# Save the submission file
submission.to_csv("./data/submission.csv", index=False)
```

Now you can upload the `submission.csv` to kaggle