Predict Sentiments of Amazon Customers using Python

Title of the project:

Predict Sentiments of Amazon Customers using Python.

Description:

Hello everyone!

In this tutorial, we are going to predict the sentiments of Amazon customers using Python. We mainly use NumPy, pandas, seaborn and scikit-learn(sklearn) libraries for this purpose. We apply a Logistic Regression machine learning algorithm on our data.

It calculates the top 20 positive and negative words. Also, it gives testing accuracy, confusion matrix and model accuracy.

Prerequisites:

- 1) Dataset file of reviews with a .csv extension.
- 2) Install Jupyter Notebook or any similar working environment with the latest version of Python installed.
 - 3) Python language.
- 4) Knowledge of Python libraries like NumPy, pandas, scikit-learn(sklearn), seaborn.

Datasets:

It contains the dataset of reviews (568454, 10).

Link: Reviews.csv

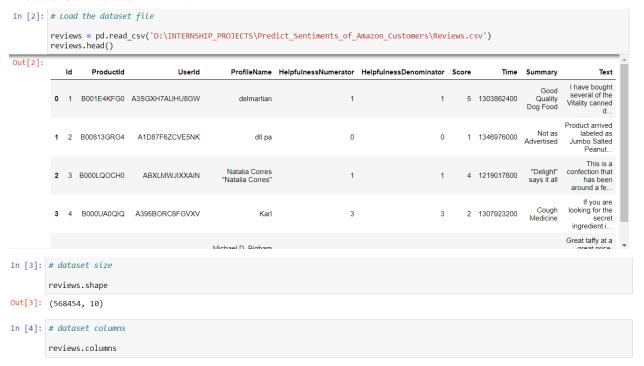
Implementation:

1) Import the required Python libraries.

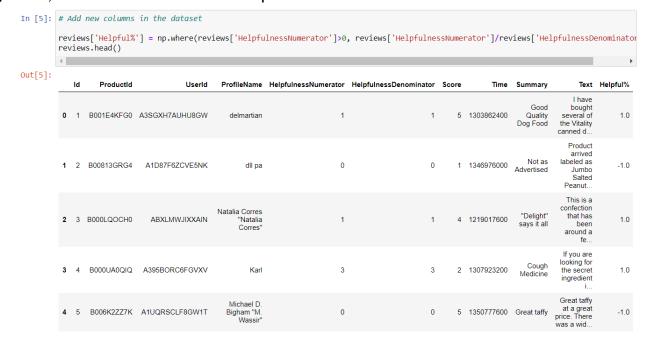
```
import libraries
import numpy as np
import pandas as pd
import seaborn as sns

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn.mirear_model import LogisticRegression
from sklearn.linear_model import togisticRegression
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.dummy import Dummyclassifier
from sklearn.feature_extraction.text import TfidfVectorizer
from imblearn.over_sampling import RandomOverSampler
from collections import Counter
from sklearn.model_selection import GridSearchCV
import warnings
warnings.filterwarnings('ignore')
```

2) Reading the dataset. It contains a <u>dataset of reviews</u>. This dataset is present in the .csv extension file.



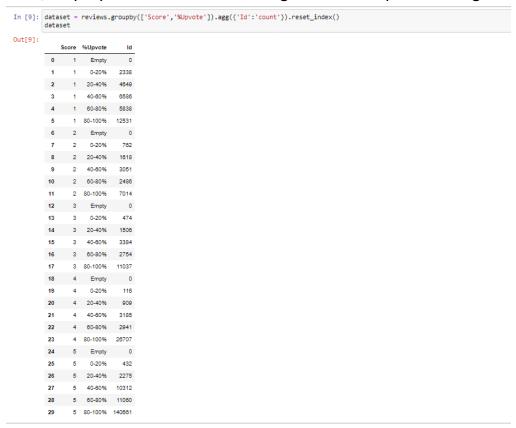
3) First, we add a new column of helpful% to our review dataset.



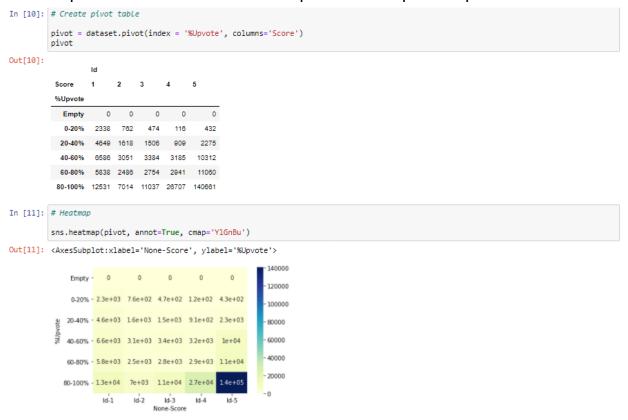
4) After that, cut the data into some slides and then analyze upvotes for different scores.

In [7]:	# Cut data into some slides # Analysis upvote for different score reviews['%Upvote'] = pd.cut(reviews['Helpful%'], bins=[-1,0, 0.2, 0.4, 0.6, 0.8, 1],											
	reviews.head()											
Out[7]:	ld	ProductId	Userld	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	Text	Helpful%	%Upvote
	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	5	1303862400	Good Quality Dog Food	I have bought several of the Vitality canned d	1.0	80-100%
	2	B00813GRG4	A1D87F6ZCVE5NK	dli pa	0	0	1	1346976000	Not as Advertised	Product arrived labeled as Jumbo Salted Peanut	-1.0	NaN
	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	4	1219017600	"Delight" says it all	This is a confection that has been around a fe	1.0	80-100%
	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	2	1307923200	Cough Medicine	If you are looking for the secret ingredient i	1.0	80-100%
	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	5	1350777600	Great taffy	Great taffy at a great price. There was a wid	-1.0	NaN

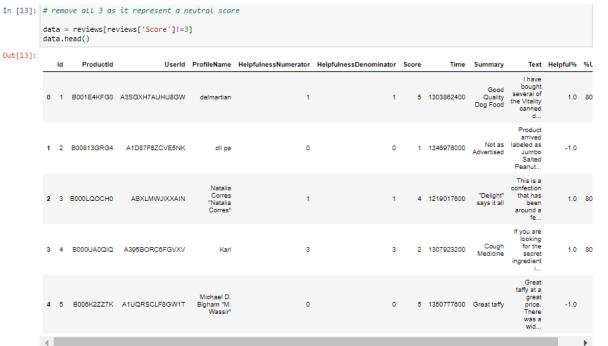
5) Next, we prepare a dataset containing scores and upvotes along with Id.



6) Create a pivot table for the dataset and plot a heatmap of this pivot table.



- 7) Now, start the calculation for prediction.
- 8) Remove reviews having a score value of 3, as it represents a neutral score.



9) Prepare 'X' and 'y' variables. 'X' represents our text data and 'y' represents the score.

```
In [15]: X = data['Text']
Out[15]: 0
                      I have bought several of the Vitality canned d...
                      Product arrived labeled as Jumbo Salted Peanut...
                      This is a confection that has been around a fe...
                      If you are looking for the secret ingredient i...
                     Great taffy at a great price. There was a wid...
          568449 Great for sesame chicken..this is a good if no... 568450 I'm disappointed with the flavor. The chocolat...
                      These stars are small, so you can give 10-15 o...
           568452 These are the BEST treats for training and rew...
568453 I am very satisfied ,product is as advertised,...
          Name: Text, Length: 525814, dtype: object
 In [16]: dict = {1:0, 2:0, 4:1, 5:1}
           y = data['Score'].map(dict)
 Out[16]: 0
           4
                       1
            568449
            568450
            568451
           568452
           568453
           Name: Score, Length: 525814, dtype: int64
```

 To predict sentiments we apply logistic regression machine learning algorithms on data.

```
In [19]: # Apply Logistic Regression to our data
cnt = CountVectorizer()
lr = LogisticRegression()
```

Apply Bag of words on data. Calculate the test accuracy and print the top
 positive and negative words.

```
In [17]: # Apply bag of words on data
          # Check accuracy for testing data
# Fetch top 20 positive and negative words
          def text_fit(X, y, nlp_model, ml_model, coeff_show=1):
              X_cnt = nlp_model.fit_transform(X)
               print('features:{}'.format(X_cnt.shape[1]))
               X_train, X_test, y_train, y_test = train_test_split(X_cnt, y)
               ml = ml_model.fit(X_train, y_train)
               print('Testing Accuracy :
               acc = ml.score(X_test, y_test)
               print(acc)
               if coeff_show==1:
                   word = cnt.get_feature_names()
coeff = ml.coef_.tolist()[0]
                   coeff_file = pd.DataFrame({'Word':word, 'Coefficient':coeff})
                   coeff_file = coeff_file.sort_values(['Coefficient', 'Word'], ascending=False)
                   print('\n')
print('Top 20 positive words: ')
                   print(coeff_file.head(20))
                   print('\n')
print('Top 20 negative words: ')
                   print(coeff_file.tail(20))
```

```
In [20]: text_fit(X,y,cnt, lr)
         features:115282
         Testing Accuracy
         0.9382369498075372
         Top 20 positive words:
                        Word Coefficient
         55155
                      hooked
                                 2.447969
         80801
                  pleasantly
                                 2.390047
         94888
                                 2.170149
                  skeptical
         35706
                   delicious
                                 2.127111
         19523
                                 2.074250
         113443
                     worried
                                 2.010215
         86940
                  refreshing
                                 1.910093
         79105
                   perfectly
                                 1.887336
         44845
                   favorites
                                 1.825904
         11025
                     awesome
                                 1.696881
         114741
                                 1.693897
                      yummy
         114673
                                 1.688697
                        yum
                   satisfied
                                 1.683484
         44544
                   fantastic
                                 1.659558
         5867
                    addicted
                                 1.650786
         79089
                                 1.643734
                     perfect
         80810
                                 1.615207
                     pleased
         43310
                   excellent
                                 1.611712
         76497
                 outstanding
                                 1.599568
         103091
                                 1.598428
                    terrific
         Top 20 negative words:
                          Word Coefficient
         88559
                      returning
                                  -1.667014
         30805
                        concept
                                  -1.741261
         46180
                     flavorless
                                  -1.760915
         11033
                         awful
                                  -1.787659
                      cancelled
         25006
                                  -1.789247
         37909
                     disgusting
                                  -1.793610
         57596
                      inedible
                                   -1.800359
         107654
                    undrinkable
                                  -1.810907
         90069
                        ruined
                                  -1.831228
                         shame
                                   -1.863703
         93250
         94968
                          skip
                                  -1.868341
         89135
                           rip
                                  -1.898396
                       terrible
         103079
                                  -1.936823
                                   -2.010035
         102272
                      tasteless
         55204
                          hopes
                                   -2.125152
         96731
                        sounded
                                   -2.134086
         114633
                yuck
disappointment
                                   -2.582982
         37630
                                   -2.719006
         37627
                  disappointing
                                   -2.974698
         113470
                          worst
                                   -3.025679
```

12) Calculate the accuracy of the model along with the confusion matrix.

```
In [18]: # Predictions

def predict(X,y,nlp_model, ml_model):
    X_cnt = nlp_model.fit_transform(X)
    X_train, X_test, y_train, y_test = train_test_split(X_cnt, y)
    ml = ml_model.fit(X_train, y_train)
    predictions = ml.predict(X_test)
    cm = confusion_matrix(predictions, y_test)
    print('Confusion Matrix: ')
    print('\n')
    acc = accuracy_score(predictions, y_test)
    print('Accuracy of the model: ')
    print(acc)
```

```
In [21]: predict(X,y,cnt,lr)

Confusion Matrix:
[[ 15106    2777]
       [ 5540 108031]]

Accuracy of the model:
    0.9367307194912289
```