Amazon Product Review Sentiment Classifiers and Performance Comparison

May 2, 2022

[133]:
```
#Importing necessary libraries
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import math
import warnings

#Importing sklearn modules *
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline
from sklearn.svm import LinearSVC
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
from sklearn import metrics
from sklearn.model_selection import cross_val_score
from sklearn.metrics import plot_confusion_matrix
from sklearn.model_selection import StratifiedShuffleSplit
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.naive_bayes import MultinomialNB
from sklearn.pipeline import Pipeline
```

[134]:
```
#Remove warnings
warnings.filterwarnings('ignore')
warnings.filterwarnings("ignore", category=DeprecationWarning)
warnings.filterwarnings("ignore",category=UserWarning)
sns.set_style("whitegrid")

#Inline plottinng
%matplotlib inline

#Random number generator seeding
np.random.seed(7)
```

[135]:
```
#Importing data set
```

[136]:
```
csv = "electronics_review_data.csv"
edata = pd.read_csv(csv)
```

[137]:
```
#Viewing first two data in the data set
```

[138]:
```
edata.head(2)
```

[138]:
```
                     id                                               name  \
0  AVqkIhwDv8e3D1O-lebb  All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi,...
1  AVqkIhwDv8e3D1O-lebb  All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi,...

        asins   brand                                         categories  \
0  B01AHB9CN2  Amazon  Electronics,iPad & Tablets,All Tablets,Fire Ta...
1  B01AHB9CN2  Amazon  Electronics,iPad & Tablets,All Tablets,Fire Ta...

                                                keys manufacturer  \
0  841667104676,amazon/53004484,amazon/b01ahb9cn2...       Amazon
1  841667104676,amazon/53004484,amazon/b01ahb9cn2...       Amazon

               reviews.date     reviews.dateAdded  \
0  2017-01-13T00:00:00.000Z  2017-07-03T23:33:15Z
1  2017-01-13T00:00:00.000Z  2017-07-03T23:33:15Z

                                    reviews.dateSeen  ... reviews.doRecommend  \
0  2017-06-07T09:04:00.000Z,2017-04-30T00:45:00.000Z  ...                True
1  2017-06-07T09:04:00.000Z,2017-04-30T00:45:00.000Z  ...                True

  reviews.id  reviews.numHelpful  reviews.rating  \
0        NaN                 0.0             5.0
1        NaN                 0.0             5.0

                                  reviews.sourceURLs  \
0  http://reviews.bestbuy.com/3545/5620406/review...
1  http://reviews.bestbuy.com/3545/5620406/review...

                                        reviews.text reviews.title  \
0  This product so far has not disappointed. My c...        Kindle
1  great for beginner or experienced person. Boug...     very fast

  reviews.userCity  reviews.userProvince  reviews.username
0              NaN                   NaN           Adapter
1              NaN                   NaN            truman

[2 rows x 21 columns]
```

[139]:
```
#Copying the dataset, describing, and obtaining information on the data
```

[140]:
```
data = edata.copy()
data.describe()
```

[140]:
```
        reviews.id  reviews.numHelpful  reviews.rating  reviews.userCity  \
count          1.0        34131.000000    34627.000000               0.0
mean   111372787.0            0.630248        4.584573               NaN
std            NaN           13.215775        0.735653               NaN
min    111372787.0            0.000000        1.000000               NaN
25%    111372787.0            0.000000        4.000000               NaN
50%    111372787.0            0.000000        5.000000               NaN
75%    111372787.0            0.000000        5.000000               NaN
max    111372787.0          814.000000        5.000000               NaN

       reviews.userProvince
count                   0.0
mean                    NaN
std                     NaN
min                     NaN
25%                     NaN
50%                     NaN
75%                     NaN
max                     NaN
```

[141]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 34660 entries, 0 to 34659
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   id                    34660 non-null  object
 1   name                  27900 non-null  object
 2   asins                 34658 non-null  object
 3   brand                 34660 non-null  object
 4   categories            34660 non-null  object
 5   keys                  34660 non-null  object
 6   manufacturer          34660 non-null  object
 7   reviews.date          34621 non-null  object
 8   reviews.dateAdded     24039 non-null  object
 9   reviews.dateSeen      34660 non-null  object
 10  reviews.didPurchase   1 non-null      object
 11  reviews.doRecommend   34066 non-null  object
 12  reviews.id            1 non-null      float64
 13  reviews.numHelpful    34131 non-null  float64
 14  reviews.rating        34627 non-null  float64
 15  reviews.sourceURLs    34660 non-null  object
```

```
 16  reviews.text          34659 non-null  object
 17  reviews.title         34655 non-null  object
 18  reviews.userCity      0 non-null      float64
 19  reviews.userProvince  0 non-null      float64
 20  reviews.username      34658 non-null  object
dtypes: float64(5), object(16)
memory usage: 5.6+ MB
```

[142]:
```
#Display the unique ID of products
```

[143]:
```
data["asins"].unique()
```

[143]:
```
array(['B01AHB9CN2', 'B00VINDBJK', 'B005PB2T0S', 'B002Y27P3M',
       'B01AHB9CYG', 'B01AHB9C1E', 'B01J2G4VBG', 'B00ZV9PXP2',
       'B0083Q04TA', 'B018Y2290U', 'B00REQKWGA', 'B00IOYAM4I',
       'B018T075DC', nan, 'B00DU15MU4', 'B018Y225IA', 'B005PB2T2Q',
       'B018Y23MNM', 'B00OQVZDJM', 'B00IOY8XWQ', 'B00LO29KXQ',
       'B00QJDU3KY', 'B018Y22C2Y', 'B01BFIBRIE', 'B01J4ORNHU',
       'B018SZT3BK', 'B00UH4D8G2', 'B018Y22BI4', 'B00TSUGXKE',
       'B00L9EPT8O,B01E6AO69U', 'B018Y23P7K', 'B00X4WHP5E', 'B00QFQRELG',
       'B00LW9XOJM', 'B00QL1ZN3G', 'B0189XYY0Q', 'B01BH83OOM',
       'B00BFJAHF8', 'B00U3FPN4U', 'B002Y27P6Y', 'B006GWO5NE',
       'B006GWO5WK'], dtype=object)
```

[144]:
```
#Filtering, sorting, and structuring the data set
```

[145]:
```
print("Before {}".format(len(data)))
dataAfter = data.dropna(subset=["reviews.rating"])

# Empty values in reviews.rating removal
print("After {}".format(len(dataAfter)))
dataAfter["reviews.rating"] = dataAfter["reviews.rating"].astype(int)
```

```
Before 34660
After 34627
```

[146]:
```
#Splitting data into training and testing data set
```

[147]:
```
split = StratifiedShuffleSplit(n_splits=5, test_size=0.2)
for train_index, test_index in split.split(dataAfter,
                                           dataAfter["reviews.rating"]):
    train_data = dataAfter.reindex(train_index)
    test_data = dataAfter.reindex(test_index)
```

[148]:
```
len(train_data)
```

[148]:
```
27701
```

[149]:
```
train_data["reviews.rating"].value_counts()/len(train_data)
```

[149]:
```
5.0    0.685174
4.0    0.247031
3.0    0.043500
2.0    0.011696
1.0    0.011588
Name: reviews.rating, dtype: float64
```

[150]:
```
len(test_data)
```

[150]:
```
6926
```

[151]:
```
test_data["reviews.rating"].value_counts()/len(test_data)
```

[151]:
```
5.0    0.689864
4.0    0.244730
3.0    0.042160
1.0    0.011406
2.0    0.011118
Name: reviews.rating, dtype: float64
```

[152]:
```
#Data with review only creation
```

[153]:
```
reviews = train_data.copy()
reviews.head(2)
```

[153]:
```
                         id  \
4349   AVphgVaX1cnluZ0-DR74
30776  AV1YE_muvKc47QAVgpwE

                                                    name       asins  \
4349   Fire Tablet, 7 Display, Wi-Fi, 8 GB - Includes...  B018Y229OU
30776                                                NaN  B00U3FPN4U

                 brand                                         categories  \
4349            Amazon  Fire Tablets,Tablets,Computers & Tablets,All T...
30776  Amazon Fire Tv  Back To College,College Electronics,College Tv...

                                                    keys manufacturer  \
4349   firetablet7displaywifi8gbincludesspecialoffers...       Amazon
30776  848719057492,amazonfiretv/51454342,amazonfiret...       Amazon

                   reviews.date     reviews.dateAdded  \
4349   2015-11-28T00:00:00.000Z  2017-05-21T04:06:08Z
30776  2017-01-06T00:00:00.000Z  2017-09-20T05:35:55Z

                                        reviews.dateSeen  ...  \
```

```
4349   2017-04-30T00:26:00.000Z,2017-06-07T08:10:00.000Z  ...
30776  2017-08-25T22:21:42.763Z,2017-08-19T09:26:46.1...  ...

      reviews.doRecommend reviews.id  reviews.numHelpful  reviews.rating  \
4349                 True        NaN                 5.0             5.0
30776                True        NaN                 0.0             5.0

                                      reviews.sourceURLs  \
4349   http://reviews.bestbuy.com/3545/5025800/review...
30776  http://reviews.bestbuy.com/3545/4370400/review...

                                            reviews.text        reviews.title  \
4349   we bought this for my 11 year old daughter and...   great for all ages
30776  I have the Roku 4, and new Apple TV, this stre...  Great streaming box

      reviews.userCity  reviews.userProvince  reviews.username
4349               NaN                   NaN              Mark
30776              NaN                   NaN            Techno

[2 rows x 21 columns]
```

[154]:
```
#Review analysis
```

[155]:
```
analysis_matrix = reviews.corr()
analysis_matrix
```

[155]:
```
                      reviews.id  reviews.numHelpful  reviews.rating  \
reviews.id                   NaN                 NaN             NaN
reviews.numHelpful           NaN             1.00000        -0.04372
reviews.rating               NaN            -0.04372         1.00000
reviews.userCity             NaN                 NaN             NaN
reviews.userProvince         NaN                 NaN             NaN

                      reviews.userCity  reviews.userProvince
reviews.id                         NaN                   NaN
reviews.numHelpful                 NaN                   NaN
reviews.rating                     NaN                   NaN
reviews.userCity                   NaN                   NaN
reviews.userProvince               NaN                   NaN
```

[156]:
```
#Defining the sentiments as per rating and adding them to the data
```

[157]:
```
def sentiments(rating):
    if (rating == 5) or (rating == 4):
        return "Positive"
    elif rating == 3:
        return "Neutral"
```

```
    elif (rating == 2) or (rating == 1):
        return "Negative"

train_data["Sentiment"] = train_data["reviews.rating"].apply(sentiments)
test_data["Sentiment"] = test_data["reviews.rating"].apply(sentiments)
train_data["Sentiment"][:20]
```

[157]:

```
4349     Positive
30776    Positive
28775     Neutral
1136     Positive
17803    Positive
7336     Positive
32638    Positive
13995    Positive
6728     Negative
22009    Positive
11047    Positive
22754    Positive
5578     Positive
11673    Positive
19168    Positive
14903    Positive
30843    Positive
5440     Positive
28940    Positive
31258    Positive
Name: Sentiment, dtype: object
```

[158]:

```
# Collecting and creating set with reviews and sentiments
```

[159]:

```
X_train = train_data["reviews.text"]
X_train_targetSentiment = train_data["Sentiment"]
X_test = test_data["reviews.text"]
X_test_targetSentiment = test_data["Sentiment"]
print(len(X_train), len(X_test))
```

```
27701 6926
```

[160]:

```
# Text replacement of 'nan' with ' '
```

[161]:

```
X_train = X_train.fillna(' ')
X_test = X_test.fillna(' ')
X_train_targetSentiment = X_train_targetSentiment.fillna(' ')
X_test_targetSentiment = X_test_targetSentiment.fillna(' ')
```

[162]:

```
#Pre processing the text and checking occurance
```

[163]:
```
count_vect = CountVectorizer()
X_train_counts = count_vect.fit_transform(X_train)
X_train_counts.shape
```

[163]: (27701, 12526)

[164]:
```
#Feature extraction and tfidf transformer
```

[165]:
```
tfidf_transformer = TfidfTransformer(use_idf=False)
X_train_tfidf = tfidf_transformer.fit_transform(X_train_counts)
X_train_tfidf.shape
```

[165]: (27701, 12526)

[166]:
```
#Implementation of pipeline
```

[167]:
```
#MULTINOMIAL NAIVE BAYES CLASSIFIER Implementation and Training
```

[168]:
```
clf_multiNB_pipe = Pipeline([("vect", CountVectorizer()),
                             ("tfidf", TfidfTransformer()),
                             ("clf_nominalNB", MultinomialNB())])
clf_multiNB_pipe.fit(X_train, X_train_targetSentiment)
```

[168]:
```
Pipeline(steps=[('vect', CountVectorizer()), ('tfidf', TfidfTransformer()),
                ('clf_nominalNB', MultinomialNB())])
```

[169]:
```
#Prediction and Accuracy testing on Test Set of MNB
```

[170]:
```
predictedMultiNB = clf_multiNB_pipe.predict(X_test)
np.mean(predictedMultiNB == X_test_targetSentiment)
```

[170]: 0.9344498989315623

[171]:
```
# SUPPORT VECTOR MACHINE CLASSIFIER Implementation and Training
```

[172]:
```
clf_linearSVC_pipe = Pipeline([("vect", CountVectorizer()),
                               ("tfidf", TfidfTransformer()),
                               ("clf_linearSVC", LinearSVC())])
clf_linearSVC_pipe.fit(X_train, X_train_targetSentiment)
```

[172]:
```
Pipeline(steps=[('vect', CountVectorizer()), ('tfidf', TfidfTransformer()),
                ('clf_linearSVC', LinearSVC())])
```

[173]:
```
#Prediction and Accuracy detection of SVC
```

[174]:
```
predictedLinearSVC = clf_linearSVC_pipe.predict(X_test)
np.mean(predictedLinearSVC == X_test_targetSentiment)
```

[174]: 0.9393589373375686

[175]:
```
#LOGISTIC REGRESSION CLASSIFIER Implementation and Training
```

[176]:
```
clf_logReg_pipe = Pipeline([("vect", CountVectorizer()),
                            ("tfidf", TfidfTransformer()),
                            ("clf_logReg", LogisticRegression())])
clf_logReg_pipe.fit(X_train, X_train_targetSentiment)
```

[176]:
```
Pipeline(steps=[('vect', CountVectorizer()), ('tfidf', TfidfTransformer()),
                ('clf_logReg', LogisticRegression())])
```

[177]:
```
#Prediction and Accuracy detection of LogReg
```

[178]:
```
predictedLogReg = clf_logReg_pipe.predict(X_test)
np.mean(predictedLogReg == X_test_targetSentiment)
```

[178]: 0.9392145538550389

[179]:
```
#OPTIMAL VALUE FOR TUNING SUPPORT VECTOR MACHINE
```

[180]:
```
parameters = {'vect__ngram_range': [(1, 1), (1, 2)],
              'tfidf__use_idf': (True, False),
              }
gs_clf_LinearSVC_pipe = GridSearchCV(clf_linearSVC_pipe, parameters, n_jobs=-1)
gs_clf_LinearSVC_pipe = gs_clf_LinearSVC_pipe.fit(X_train,
                                                  X_train_targetSentiment)
```

[181]:
```
#Testing and Accuracy detection of SVM post Tuning
```

[182]:
```
predictedGS_clf_LinearSVC_pipe = gs_clf_LinearSVC_pipe.predict(X_test)
np.mean(predictedGS_clf_LinearSVC_pipe == X_test_targetSentiment)
```

[182]: 0.9408027721628646

[183]:
```
#PEROFORMANCE ANALYSIS OF VECTOR MACHINE
```

[184]:
```
for performance_analysis in (gs_clf_LinearSVC_pipe.best_score_,
                             gs_clf_LinearSVC_pipe.best_estimator_,
                             gs_clf_LinearSVC_pipe.best_params_):
        print(performance_analysis)
```

```
0.9366809937342697
Pipeline(steps=[('vect', CountVectorizer(ngram_range=(1, 2))),
                ('tfidf', TfidfTransformer()), ('clf_linearSVC', LinearSVC())])
{'tfidf__use_idf': True, 'vect__ngram_range': (1, 2)}
```

[185]:
```
#CLASSIFICATION REPORT SVC
```

[186]:
```python
print(classification_report(X_test_targetSentiment,
                            predictedGS_clf_LinearSVC_pipe))
print('Accuracy: {}'. format(accuracy_score(X_test_targetSentiment,
                             predictedGS_clf_LinearSVC_pipe)))
```

```
              precision    recall  f1-score   support

                   0.00      0.00      0.00         5
    Negative       0.67      0.25      0.36       156
     Neutral       0.47      0.11      0.18       292
    Positive       0.95      1.00      0.97      6473

    accuracy                           0.94      6926
   macro avg       0.52      0.34      0.38      6926
weighted avg       0.92      0.94      0.92      6926

Accuracy: 0.9408027721628646
```

[187]:
```python
#CLASSIFICATION REPORT LogReg
```

[188]:
```python
print(classification_report(X_test_targetSentiment,
                            predictedLogReg))
print('Accuracy: {}'. format(accuracy_score(X_test_targetSentiment,
                             predictedLogReg)))
```

```
              precision    recall  f1-score   support

                   0.00      0.00      0.00         5
    Negative       0.76      0.20      0.31       156
     Neutral       0.45      0.08      0.13       292
    Positive       0.94      1.00      0.97      6473

    accuracy                           0.94      6926
   macro avg       0.54      0.32      0.35      6926
weighted avg       0.92      0.94      0.92      6926

Accuracy: 0.9392145538550389
```

[189]:
```python
#CLASSIFICATION REPORT MNB
```

[190]:
```python
print(classification_report(X_test_targetSentiment,
                            predictedMultiNB))
print('Accuracy: {}'. format(accuracy_score(X_test_targetSentiment,
                             predictedMultiNB)))
```

```
              precision    recall  f1-score   support

                   0.00      0.00      0.00         5
    Negative       0.00      0.00      0.00       156
```

```
     Neutral       0.00      0.00      0.00       292
    Positive       0.93      1.00      0.97      6473

    accuracy                           0.93      6926
   macro avg       0.23      0.25      0.24      6926
weighted avg       0.87      0.93      0.90      6926

Accuracy: 0.9344498989315623
```

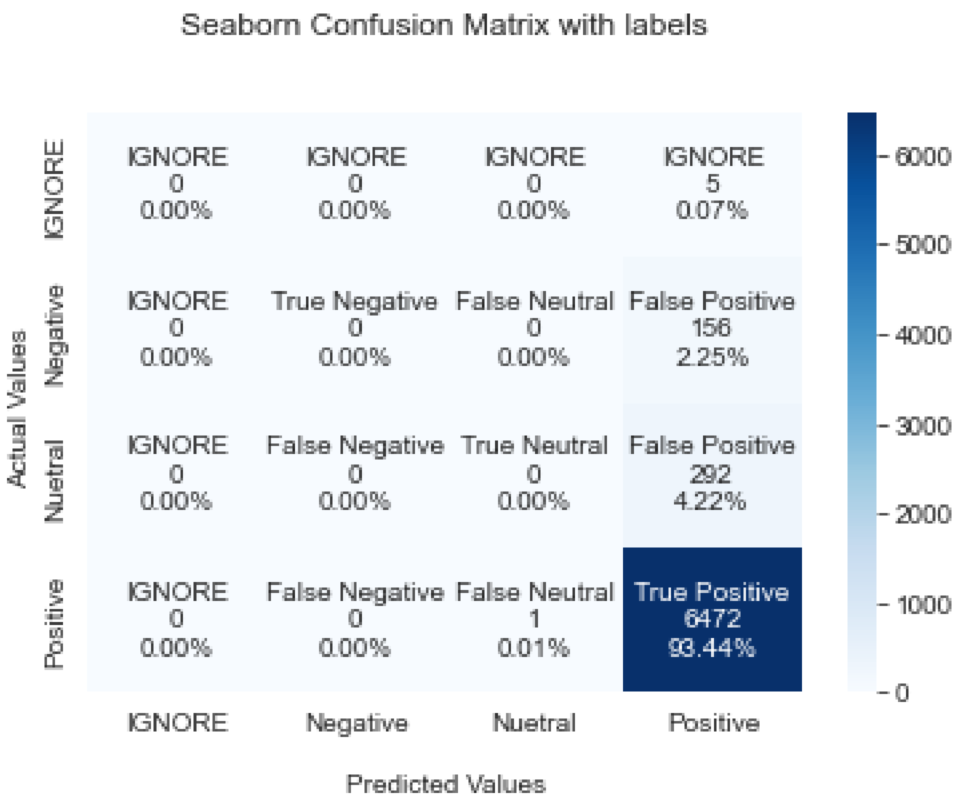
[191]:
```
#Confusion Matrix of MultiNB
```

[192]:
```
cm = metrics.confusion_matrix(X_test_targetSentiment, predictedMultiNB)
print(cm)
```

```
[[   0    0    0    5]
 [   0    0    0  156]
 [   0    0    0  292]
 [   0    0    1 6472]]
```

[193]:
```
#Confusion Matrix Tabulated Graphical Representation of MultiNB
```

[194]:
```
group_names = ['IGNORE','IGNORE','IGNORE','IGNORE','IGNORE','True␣
 ↪Negative','False Neutral','False Positive','IGNORE','False Negative','True␣
 ↪Neutral','False Positive','IGNORE','False Negative','False Neutral','True␣
 ↪Positive']

group_counts = ["{0:0.0f}".format(value) for value in
                cm.flatten()]

group_percentages = ["{0:.2%}".format(value) for value in
                     cm.flatten()/np.sum(cm)]

labels = [f"{v1}\n{v2}\n{v3}" for v1, v2, v3 in
          zip(group_names,group_counts,group_percentages)]

labels = np.asarray(labels).reshape(4,4)

ax = sns.heatmap(cm, annot=labels, fmt='', cmap='Blues')

ax.set_title('Seaborn Confusion Matrix with labels\n\n');
ax.set_xlabel('\nPredicted Values')
ax.set_ylabel('Actual Values ');


ax.xaxis.set_ticklabels(['IGNORE','Negative','Nuetral','Positive'])
ax.yaxis.set_ticklabels(['IGNORE','Negative','Nuetral','Positive'])

plt.show()
```



[195]:
```
#Confusion Matrix of SVC
```

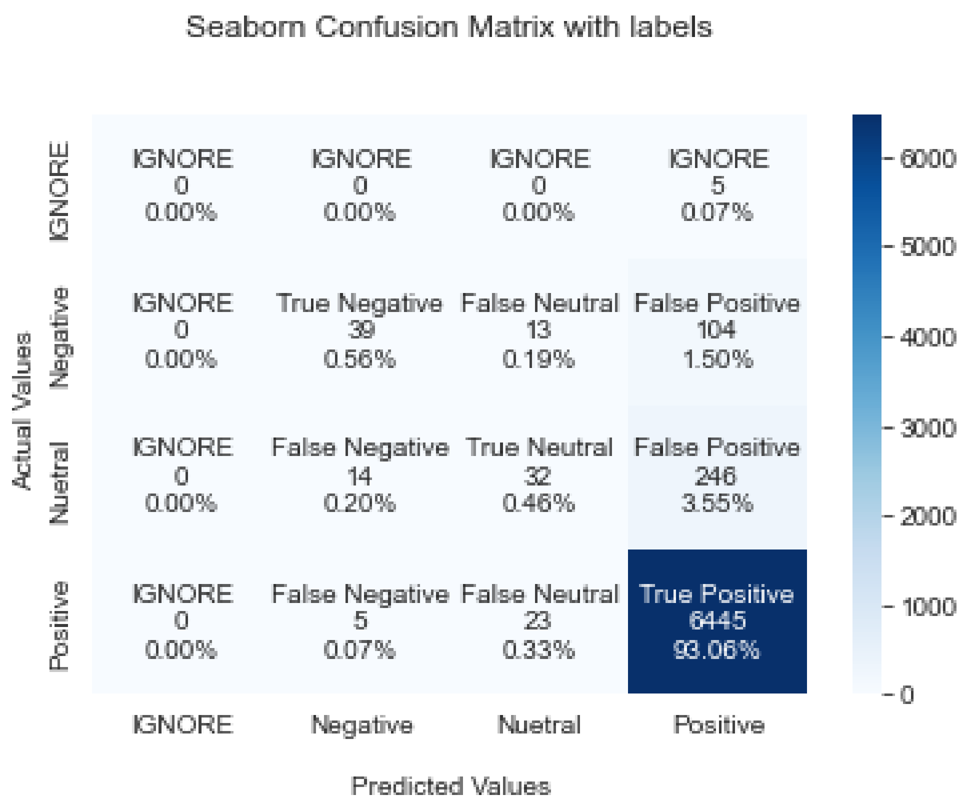
[196]:
```
cmSVC = metrics.confusion_matrix(X_test_targetSentiment,␣
 ↪predictedGS_clf_LinearSVC_pipe)
print(cmSVC)
```

```
[[   0    0    0    5]
 [   0   39   13  104]
 [   0   14   32  246]
 [   0    5   23 6445]]
```

[197]:
```
#Confusion Matrix Tabulated Graphical Representation of SVC
```

[198]:
```
group_names = ['IGNORE','IGNORE','IGNORE','IGNORE','IGNORE','True␣
 ↪Negative','False Neutral','False Positive','IGNORE','False Negative','True␣
 ↪Neutral','False Positive','IGNORE','False Negative','False Neutral','True␣
 ↪Positive']

group_counts = ["{0:0.0f}".format(value) for value in
                cmSVC.flatten()]
```

```
group_percentages = ["{0:.2%}".format(value) for value in
                     cmSVC.flatten()/np.sum(cmSVC)]

labels = [f"{v1}\n{v2}\n{v3}" for v1, v2, v3 in
          zip(group_names,group_counts,group_percentages)]

labels = np.asarray(labels).reshape(4,4)

ax = sns.heatmap(cm, annot=labels, fmt='', cmap='Blues')

ax.set_title('Seaborn Confusion Matrix with labels\n\n');
ax.set_xlabel('\nPredicted Values')
ax.set_ylabel('Actual Values ');


ax.xaxis.set_ticklabels(['IGNORE','Negative','Nuetral','Positive'])
ax.yaxis.set_ticklabels(['IGNORE','Negative','Nuetral','Positive'])

plt.show()
```



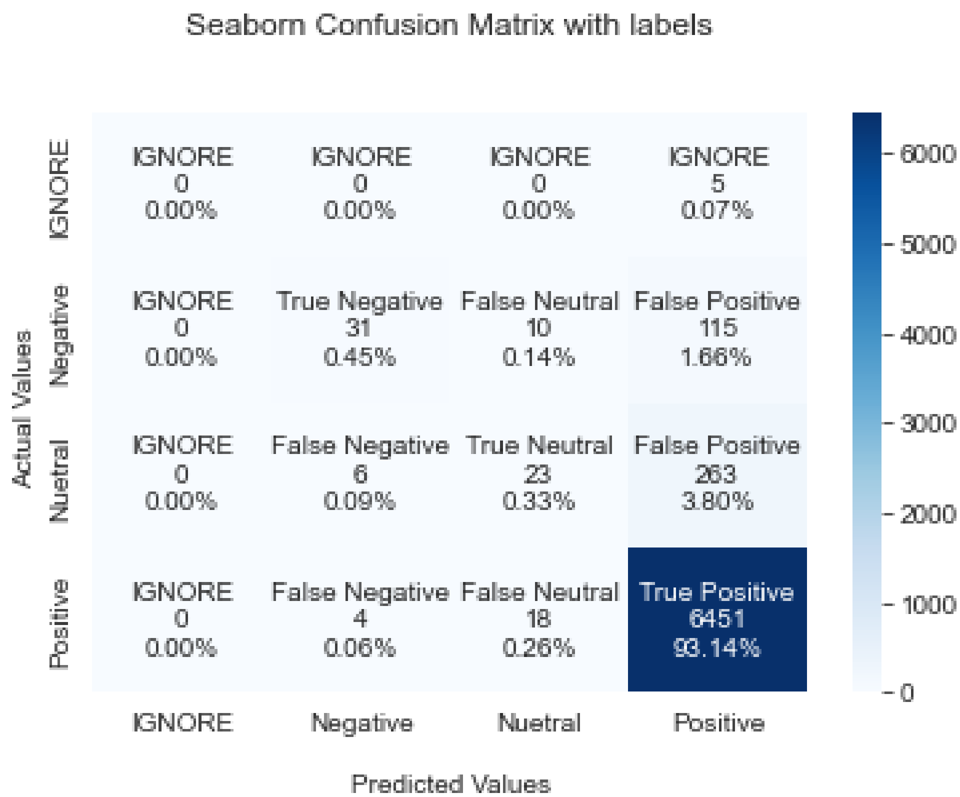
[199]:
```
#Confusion Matrix of LogReg
```

[200]:
```python
cmLR = metrics.confusion_matrix(X_test_targetSentiment, predictedLogReg)
print(cmLR)
```

```
[[   0    0    0    5]
 [   0   31   10  115]
 [   0    6   23  263]
 [   0    4   18 6451]]
```

[201]:
```python
#Confusion Matrix Tabulated Graphical Representation of LogReg
```

[202]:
```python
group_names = ['IGNORE','IGNORE','IGNORE','IGNORE','IGNORE','True␣
↪Negative','False Neutral','False Positive','IGNORE','False Negative','True␣
↪Neutral','False Positive','IGNORE','False Negative','False Neutral','True␣
↪Positive']

group_counts = ["{0:0.0f}".format(value) for value in
                cmLR.flatten()]

group_percentages = ["{0:.2%}".format(value) for value in
                     cmLR.flatten()/np.sum(cmLR)]

labels = [f"{v1}\n{v2}\n{v3}" for v1, v2, v3 in
          zip(group_names,group_counts,group_percentages)]

labels = np.asarray(labels).reshape(4,4)

ax = sns.heatmap(cmLR, annot=labels, fmt='', cmap='Blues')

ax.set_title('Seaborn Confusion Matrix with labels\n\n');
ax.set_xlabel('\nPredicted Values')
ax.set_ylabel('Actual Values ');


ax.xaxis.set_ticklabels(['IGNORE','Negative','Nuetral','Positive'])
ax.yaxis.set_ticklabels(['IGNORE','Negative','Nuetral','Positive'])

plt.show()
```



[205]:
```
inference = "Accuracy wise the Support Vector Machine (SVM) Classifier would be␣
 ↪the most optimal classifier for Amazon Product Review Sentiment Analysis."
print(inference)
```

```
Accuracy wise the Support Vector Machine (SVM) Classifier would be the most
optimal classifier for Amazon Product Review Sentiment Analysis.
```