load libraries

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB, GaussianNB
from imblearn.over_sampling import SMOTE
from sklearn.metrics import accuracy_score, precision_score, recall_score, roc_curve
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
from sklearn.preprocessing import label_binarize
from sklearn.metrics import roc_auc_score, auc, roc_curve
```

load data

In [2]:

```
train_data=pd.read_csv("train_data.csv")
```

In [3]:

```
train_data.head()
```

Out[3]:

	name	brand	categories	primaryCategories	reviews.date	reviews.text	re
0	All-New Fire HD 8 Tablet, 8" HD Display, Wi-Fi...	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	Electronics	2016-12-26T00:00:00.000Z	Purchased on Black FridayPros - Great Price (e...	
1	Amazon - Echo Plus w/ Built-In Hub - Silver	Amazon	Amazon Echo,Smart Home,Networking,Home & Tools...	Electronics,Hardware	2018-01-17T00:00:00.000Z	I purchased two Amazon in Echo Plus and two do...	
2	Amazon Echo Show Alexa-enabled Bluetooth Speak...	Amazon	Amazon Echo,Virtual Assistant Speakers,Electro...	Electronics,Hardware	2017-12-20T00:00:00.000Z	Just an average Alexa option. Does show a few ...	
3	Fire HD 10 Tablet, 10.1 HD Display, Wi-Fi, 16 ...	Amazon	eBook Readers,Fire Tablets,Electronics Feature...	Office Supplies,Electronics	2017-08-04T00:00:00.000Z	very good product. Exactly what I wanted, and ...	

	name	brand	categories	primaryCategories	reviews.date	reviews.text	re
4	Brand New Amazon Kindle Fire 16gb 7" Ips Displ...	Amazon	Computers/Tablets & Networking,Tablets & eBook...	Electronics	2017-01-23T00:00:00.000Z	This is the 3rd one I've purchased. I've bough...	

In [4]:
```
train_data.isna().sum()
```

Out[4]:
```
name                 0
brand                0
categories           0
primaryCategories    0
reviews.date         0
reviews.text         0
reviews.title       10
sentiment            0
dtype: int64
```

In [5]:
```
test_data=pd.read_csv("test_data.csv")
```

In [6]:
```
test_data.head()
```

Out[6]:

	name	brand	categories	primaryCategories	reviews.date	reviews.text	r
0	Fire Tablet, 7 Display, Wi-Fi, 16 GB - Include...	Amazon	Fire Tablets,Computers/Tablets & Networking,Ta...	Electronics	2016-05-23T00:00:00.000Z	Amazon kindle fire has a lot of free app and c...	
1	Amazon Echo Show Alexa-enabled Bluetooth Speak...	Amazon	Computers,Amazon Echo,Virtual Assistant Speake...	Electronics,Hardware	2018-01-02T00:00:00.000Z	The Echo Show is a great addition to the Amazo...	'
2	All-New Fire HD 8 Tablet, 8" HD Display, Wi-Fi...	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	Electronics	2017-01-02T00:00:00.000Z	Great value from Best Buy. Bought at Christmas...	
3	Brand New Amazon Kindle Fire 16gb 7" Ips Displ...	Amazon	Computers/Tablets & Networking,Tablets & eBook...	Electronics	2017-03-25T00:00:00.000Z	I use mine for email, Facebook ,games and to g...	

	name	brand	categories	primaryCategories	reviews.date	reviews.text	r
4	Amazon Echo Show Alexa-enabled Bluetooth Speak...	Amazon	Computers,Amazon Echo,Virtual Assistant Speake...	Electronics,Hardware	2017-11-15T00:00:00.000Z	This is a fantastic item & the person I bought...	

WEEK 1 TASKS

In [7]:

```
test_data.isna().sum()
```

Out[7]:

```
name                 0
brand                0
categories           0
primaryCategories    0
reviews.date         0
reviews.text         0
reviews.title        3
dtype: int64
```

In [8]:

```
test_data_hidden=pd.read_csv("test_data_hidden.csv")
```

In [9]:

```
test_data_hidden.isna().sum()
```

Out[9]:

```
name                 0
brand                0
categories           0
primaryCategories    0
reviews.date         0
reviews.text         0
reviews.title        3
sentiment            0
dtype: int64
```

In [10]:

```
train_data['sentiment'].value_counts()
```

Out[10]:

```
Positive    3749
Neutral      158
Negative      93
Name: sentiment, dtype: int64
```

In [11]:

```
test_data_hidden['sentiment'].value_counts()
```

Out[11]:

```
Positive    937
Neutral      39
Negative     24
Name: sentiment, dtype: int64
```

In [12]:

```
tf_idf=TfidfVectorizer()
```

so here test data dont have target variable and for both train and test hidden data has target variable so

we combine these both as master data

In [13]:
```
master_data=pd.concat([train_data,test_data_hidden])
```

In [14]:
```
master_data=master_data.reset_index(drop=True)
```

In [15]:
```
master_data.shape
```

Out[15]:
```
(5000, 8)
```

In [16]:
```
master_data.isna().sum()
```

Out[16]:
```
name                 0
brand                0
categories           0
primaryCategories    0
reviews.date         0
reviews.text         0
reviews.title       13
sentiment            0
dtype: int64
```

In [17]:
```
master_data.dropna(inplace=bool(1))
```

In [18]:
```
master_data.head()
```

Out[18]:

	name	brand	categories	primaryCategories	reviews.date	reviews.text	re
0	All-New Fire HD 8 Tablet, 8" HD Display, Wi-Fi...	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	Electronics	2016-12-26T00:00:00.000Z	Purchased on Black FridayPros - Great Price (e...	
1	Amazon - Echo Plus w/ Built-In Hub - Silver	Amazon	Amazon Echo,Smart Home,Networking,Home & Tools...	Electronics,Hardware	2018-01-17T00:00:00.000Z	I purchased two Amazon in Echo Plus and two do...	
2	Amazon Echo Show Alexa-enabled Bluetooth Speak...	Amazon	Amazon Echo,Virtual Assistant Speakers,Electro...	Electronics,Hardware	2017-12-20T00:00:00.000Z	Just an average Alexa option. Does show a few ...	
3	Fire HD 10 Tablet, 10.1 HD Display, Wi-Fi, 16 ...	Amazon	eBook Readers,Fire Tablets,Electronics Feature...	Office Supplies,Electronics	2017-08-04T00:00:00.000Z	very good product. Exactly what I wanted, and ...	

	name	brand	categories	primaryCategories	reviews.date	reviews.text	re
4	Brand New Amazon Kindle Fire 16gb 7" Ips Displ...	Amazon	Computers/Tablets & Networking,Tablets & eBook...	Electronics	2017-01-23T00:00:00.000Z	This is the 3rd one I've purchased. I've bough...	

In [19]:

```
master_data['sentiment'].value_counts()
```

Out[19]:

```
Positive    4673
Neutral      197
Negative     117
Name: sentiment, dtype: int64
```

In [20]:

```
X=tf_idf.fit_transform(master_data['reviews.text'])
X=X.toarray()
```

In [21]:

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(X,master_data['sentiment'], test_size
```

In [22]:

```
naive=MultinomialNB()
```

In [23]:

```
naive.fit(x_train,y_train)
```

Out[23]:

```
▾ MultinomialNB
MultinomialNB()
```

In [24]:

```
y_pred=naive.predict(x_test)
```

In [26]:

```
print(classification_report(y_pred, y_test, zero_division='warn'))
```

```
              precision    recall  f1-score   support

    Negative       0.00      0.00      0.00         0
     Neutral       0.00      0.00      0.00         0
    Positive       1.00      0.94      0.97      1497

    accuracy                           0.94      1497
   macro avg       0.33      0.31      0.32      1497
weighted avg       1.00      0.94      0.97      1497

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334:
UndefinedMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in l
abels with no true samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334:
UndefinedMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in l
abels with no true samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334:
```

```
UndefinedMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in l
abels with no true samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

In [27]:

```
tf_test_data=tf_idf.transform(test_data['reviews.text'])
tf_test_data=tf_test_data.toarray()
```

In [22]:

```
tf_idf2=TfidfVectorizer()
```

In [23]:

```
X1=tf_idf2.fit_transform(master_data['reviews.title'])
X1=X1.toarray()
```

In [24]:

```
X=pd.DataFrame(X)
X1=pd.DataFrame(X1)
```

In [25]:

```
X.shape, X1.shape
```

Out[25]: ((4987, 5401), (4987, 1392))

In [32]:

```
y_test_value=naive.predict(tf_test_data)
```

In [33]:

```
new_test_data=test_data
```

In [34]:

```
new_test_data['predicted_sentiment']=y_test_value
```

In [35]:

```
new_test_data.head()
```

Out[35]:

	name	brand	categories	primaryCategories	reviews.date	reviews.text	r
0	Fire Tablet, 7 Display, Wi-Fi, 16 GB - Include...	Amazon	Fire Tablets,Computers/Tablets & Networking,Ta...	Electronics	2016-05-23T00:00:00.000Z	Amazon kindle fire has a lot of free app and c...	
1	Amazon Echo Show Alexa-enabled Bluetooth Speak...	Amazon	Computers,Amazon Echo,Virtual Assistant Speake...	Electronics,Hardware	2018-01-02T00:00:00.000Z	The Echo Show is a great addition to the Amazo...	'
2	All-New Fire HD 8 Tablet, 8" HD Display, Wi-Fi...	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	Electronics	2017-01-02T00:00:00.000Z	Great value from Best Buy. Bought at Christmas...	

	name	brand	categories	primaryCategories	reviews.date	reviews.text	r
3	Brand New Amazon Kindle Fire 16gb 7" Ips Displ...	Amazon	Computers/Tablets & Networking,Tablets & eBook...	Electronics	2017-03-25T00:00:00.000Z	I use mine for email, Facebook ,games and to g...	
4	Amazon Echo Show Alexa-enabled Bluetooth Speak...	Amazon	Computers,Amazon Echo,Virtual Assistant Speake...	Electronics,Hardware	2017-11-15T00:00:00.000Z	This is a fantastic item & the person I bought...	

In [26]:
```
XX=pd.concat([X, X1], axis=1)
```

In [27]:
```
XX.shape
```

Out[27]:
```
(4987, 6793)
```

using smote to balance data

In [28]:
```
sm=SMOTE(random_state=43)
```

In [29]:
```
X_sm, y_sm=sm.fit_resample(X,master_data['sentiment'])
```

In [163…
```
y_sm
```

Out[163…
```
0        Positive
1        Positive
2         Neutral
3        Positive
4        Positive
           ...
14014     Neutral
14015     Neutral
14016     Neutral
14017     Neutral
14018     Neutral
Name: sentiment, Length: 14019, dtype: object
```

In [31]:
```
y_sm.value_counts()
```

Out[31]:
```
Positive    4673
Negative    4673
Neutral     4673
Name: sentiment, dtype: int64
```

Data splitting with 70 30 ratio

In [32]:
```
x_train_sm,x_test_sm,y_train_sm,y_test_sm=train_test_split(X_sm,y_sm, test_size=0.3,
```

1st model naive bayes

In [41]:
```
naive_sm=MultinomialNB()
```

In [42]:
```
naive_sm.fit(x_train_sm, y_train_sm)
```

Out[42]:
```
▾ MultinomialNB
MultinomialNB()
```

In [43]:
```
y_pred_sm=naive_sm.predict(x_test_sm)
```

In [44]:
```
y_pred_prob_naive=naive_sm.predict_proba(x_test_sm)
```

In [45]:
```
print(classification_report(y_pred_sm, y_test_sm))
```

```
              precision    recall  f1-score   support

    Negative       0.99      0.97      0.98      1428
     Neutral       0.99      0.93      0.96      1527
    Positive       0.90      0.98      0.94      1251

    accuracy                           0.96      4206
   macro avg       0.96      0.96      0.96      4206
weighted avg       0.96      0.96      0.96      4206
```

In [46]:
```
print(confusion_matrix(y_pred_sm, y_test_sm))
```

```
[[1389    0   39]
 [   0 1422  105]
 [   9   11 1231]]
```

2nd model random forest classifier

In [47]:
```
rf_sm=RandomForestClassifier(n_jobs=-1)
```

In [48]:
```
rf_sm.fit(x_train_sm, y_train_sm)
```

Out[48]:
```
▾      RandomForestClassifier
RandomForestClassifier(n_jobs=-1)
```

In [49]:
```
y_pred_sm_rf=rf_sm.predict(x_test_sm)
```

In [50]:
```
y_pred_prob_rf=rf_sm.predict_proba(x_test_sm)
```

In [51]:
```
print(classification_report(y_pred_sm_rf, y_test_sm))
```

```
              precision    recall  f1-score   support

    Negative       1.00      1.00      1.00      1395
     Neutral       0.99      1.00      0.99      1424
    Positive       1.00      0.99      0.99      1387

    accuracy                           0.99      4206
   macro avg       0.99      0.99      0.99      4206
weighted avg       0.99      0.99      0.99      4206
```

In [52]:
```
print(confusion_matrix(y_pred_sm_rf, y_test_sm))
```

```
[[1394    0    1]
 [   0 1420    4]
 [   4   13 1370]]
```

3rd model xgboost classifier

In [53]:
```
xgcl=XGBClassifier(n_jobs=-1)
```

In [36]:
```
y_sm_le=le.fit_transform(y_sm)
```

In [37]:
```
x_train_sm,x_test_sm,y_train_sm_le,y_test_sm_le=train_test_split(X_sm,y_sm_le, test_
```

In [57]:
```
xgcl.fit(x_train_sm, y_train_sm_le)
```

Out[57]:

▾ XGBClassifier

```
XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1, colsample_bytree=
1,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwis
e',
              importance_type=None, interaction_constraints='',
              learning_rate=0.300000012, max_bin=256, max_cat_to_onehot=
4,
              max_delta_step=0, max_depth=6, max_leaves=0, min_child_weig
ht=1,
```

In [58]:
```
y_pred_xgb=xgcl.predict(x_test_sm)
```

In [59]:
```
print(classification_report(y_pred_xgb, y_test_sm_le))
```

```
              precision    recall  f1-score   support

           0       1.00      0.99      1.00      1400
           1       0.99      0.99      0.99      1434
           2       0.98      0.99      0.98      1372

    accuracy                           0.99      4206
   macro avg       0.99      0.99      0.99      4206
```

```
weighted avg       0.99      0.99      0.99      4206
```

In [60]:

```
print(confusion_matrix(y_pred_xgb, y_test_sm_le))
```

```
[[1393    1    6]
 [   0 1417   17]
 [   5   15 1352]]
```

auc and roc curve for xgcl

In [34]:

```
y_test_binarize=label_binarize(y_test_sm, classes=np.unique(y_test_sm))
```

In [63]:

```
y_pred_prob_xgcl=xgcl.predict_proba(x_test_sm)
```

In [72]:

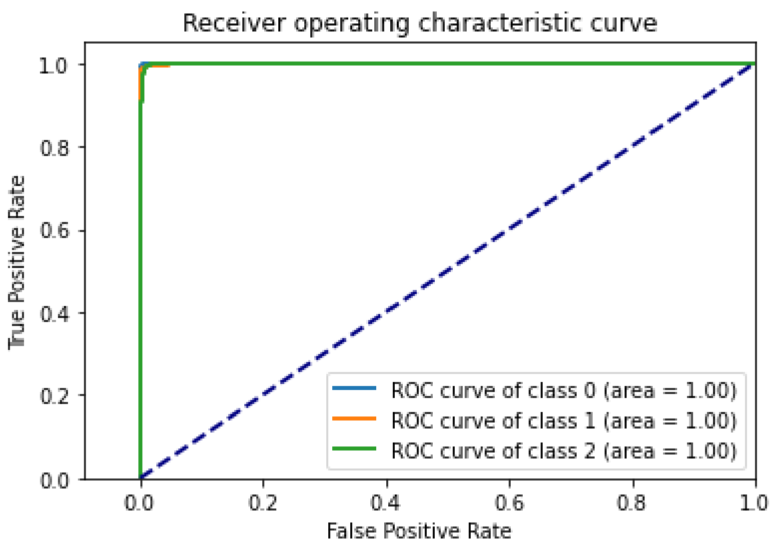
```
'''fpr={}
tpr={}
roc_auc=dict()
n_class=y_test_binarize.shape[1]
for i in range(n_class):
    fpr[i], tpr[i], _ = roc_curve(y_test_binarize[:, i], y_pred_prob_xgcl[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])
    #plt.plot(fpr[i], tpr[i], linestyle="--", color="darkorange")
    plt.plot(fpr[i], tpr[i], linestyle="--", label="%s and ROC curve (area = %0.2f)"
    plt.xlim([-0.09, 1.0])
    plt.ylim([0.0, 1.05])

fpr["micro"], tpr["micro"], _ = roc_curve(y_test_binarize.ravel(), y_pred_prob_xgcl.
roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])'''
```

Out[72]:

```
'fpr={}\ntpr={}\nroc_auc=dict()\nn_class=y_test_binarize.shape[1]\nfor i in range(n_
class):\n    fpr[i], tpr[i], _ = roc_curve(y_test_binarize[:, i], y_pred_prob_xgcl
[:, i])\n    roc_auc[i] = auc(fpr[i], tpr[i])\n    #plt.plot(fpr[i], tpr[i], linesty
le="--", color="darkorange")\n    plt.plot(fpr[i], tpr[i], linestyle="--", label="%s
and ROC curve (area = %0.2f)" %(n_class[i],roc_auc[i]))\n    plt.xlim([-0.09, 1.0])
\n    plt.ylim([0.0, 1.05])\n\nfpr["micro"], tpr["micro"], _ = roc_curve(y_test_bina
rize.ravel(), y_pred_prob_xgcl.ravel())\nroc_auc["micro"] = auc(fpr["micro"], tpr["m
icro"])'
```

In [64]:

```
fpr={}
tpr={}
roc_auc=dict()
for i in range(3):
    fpr[i], tpr[i], _ = roc_curve(y_test_binarize[:, i], y_pred_prob_xgcl[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

lw=2
for i in range(3):
    plt.plot(fpr[i], tpr[i], lw=lw,
             label='ROC curve of class {0} (area = {1:0.2f})'
             ''.format(i, roc_auc[i]))
plt.plot([0, 1], [0,1], color="navy", lw=lw, linestyle="--")
plt.xlim([-0.09, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic curve")
plt.legend(loc="lower right")
plt.show()
```



In [ ]:

```
plt.figure()
lw = 2
for i in range(3):
    plt.plot(
fpr[i],
tpr[i],
color="darkorange",
lw=lw,
label="ROC curve (area = %0.2f)" % roc_auc[i],
)

plt.plot([0, 1], [0, 1], color="navy", lw=lw, linestyle="--")
plt.xlim([-0.09, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic curve")
plt.legend(loc="lower right")
plt.show()
```

In [65]:

```
roc_auc
```

Out[65]: {0: 0.999941664730649, 1: 0.999428996939635, 2: 0.9992490928358113}

In [66]:

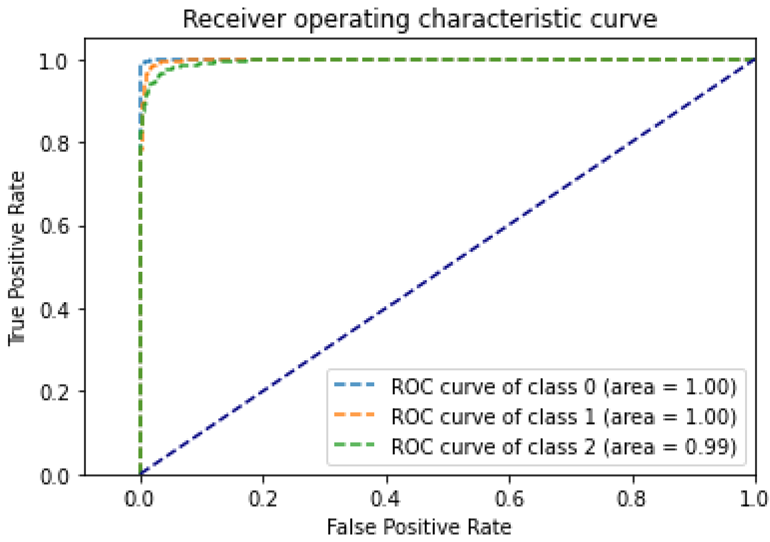
```
classes=np.unique(y_test_sm)
```

auc and roc curve for naive bayes

In [67]:

```
fpr={}
tpr={}
roc_auc=dict()
n_class=y_test_binarize.shape[1]
for i in range(n_class):
    fpr[i], tpr[i], _ = roc_curve(y_test_binarize[:, i], y_pred_prob_naive[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])
    plt.plot(fpr[i], tpr[i], linestyle="--", label='ROC curve of class {0} (area = {
             ''.format(i, roc_auc[i]))
plt.plot([0, 1], [0, 1], color="navy", linestyle="--")
plt.xlim([-0.09, 1.0])
```

```
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic curve")
plt.legend(loc="lower right")
plt.show()

#fpr["micro"], tpr["micro"], _ = roc_curve(y_test_binarize.ravel(), y_pred_prob_naiv
#roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])
```



In [ ]:

```
plt.figure()
lw = 2
i=2
plt.plot(
    fpr[i],
    tpr[i],
    color="darkorange",
    lw=lw,
    label="ROC curve (area = %0.2f)" % roc_auc[i],
)

plt.plot([0, 1], [0, 1], color="navy", linestyle="--")
plt.xlim([-0.09, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic curve")
plt.legend(loc="lower right")
plt.show()
```

In [68]:

```
roc_auc
```

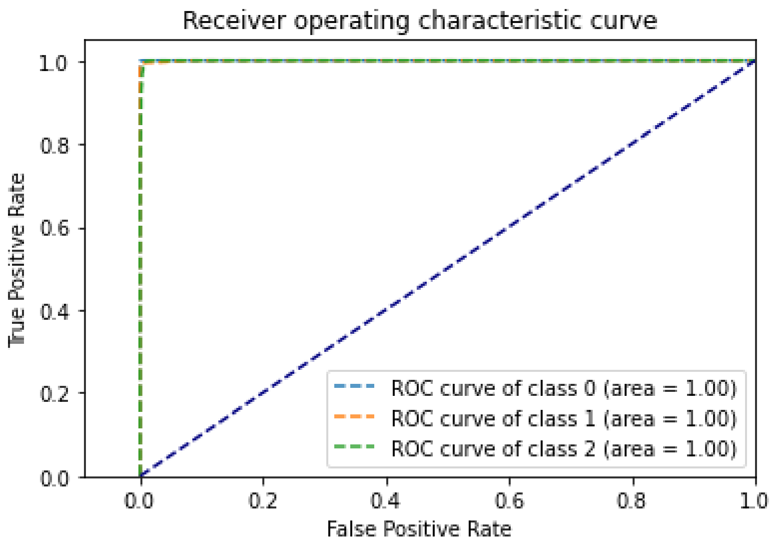
Out[68]: {0: 0.9998033413627119, 1: 0.9976344518433534, 2: 0.9947146205966411}

auc roc curve for random forest classifier

In [69]:

```
fpr={}
tpr={}
roc_auc=dict()
n_class=y_test_binarize.shape[1]
for i in range(n_class):
```

```
    fpr[i], tpr[i], _ = roc_curve(y_test_binarize[:, i], y_pred_prob_rf[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])
    #plt.plot(fpr[i], tpr[i], linestyle="--", color="darkorange")
    plt.plot(fpr[i], tpr[i], linestyle="--", label='ROC curve of class {0} (area = {
             ''.format(i, roc_auc[i]))

plt.plot([0, 1], [0, 1], color="navy", linestyle="--")
plt.xlim([-0.09, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic curve")
plt.legend(loc="lower right")
plt.show()

#fpr["micro"], tpr["micro"], _ = roc_curve(y_test_binarize.ravel(), y_pred_prob_rf.r
#roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])
```



In [ ]:

```
plt.figure()
lw = 2
plt.plot(
    fpr[2],
    tpr[2],
    color="darkorange",
    lw=lw,
    label="ROC curve (area = %0.2f)" % roc_auc[2],
)

plt.plot([0, 1], [0, 1], color="navy", linestyle="--")
plt.xlim([-0.09, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic curve")
plt.legend(loc="lower right")
plt.show()
```

In [70]:

```
roc_auc
```

Out[70]:

```
{0: 0.9999949052166506, 1: 0.999724942113275, 2: 0.999501750104364}
```

From the above 3 algorithms we can conclude that all

three algorithms are approximately given similar result

week 2 tasks

multiclass svm

In [71]:
```
from sklearn.svm import SVC
svc=SVC(kernel='linear', C=1.0, class_weight='balanced', random_state=43, probabilit
```

In [72]:
```
y_train_sm
```

Out[72]:
```
1812     Positive
1369     Positive
5379     Negative
2109     Positive
8616     Negative
           ...
2064     Positive
10517     Neutral
7985     Negative
2303     Positive
3392     Positive
Name: sentiment, Length: 9813, dtype: object
```

In [93]:
```
svc.fit(x_train_sm, y_train_sm)
```

Out[93]:
```
SVC
SVC(class_weight='balanced', kernel='linear', probability=True, random_stat
e=43)
```

In [94]:
```
y_pred_svc=svc.predict(x_test_sm)
```

In [95]:
```
y_pred_svc_prob=svc.predict_proba(x_test_sm)
```

In [96]:
```
confusion_matrix(y_pred_svc, y_test_sm)
```

Out[96]:
```
array([[1398,    0,    7],
       [   0, 1433,   39],
       [   0,    0, 1329]], dtype=int64)
```

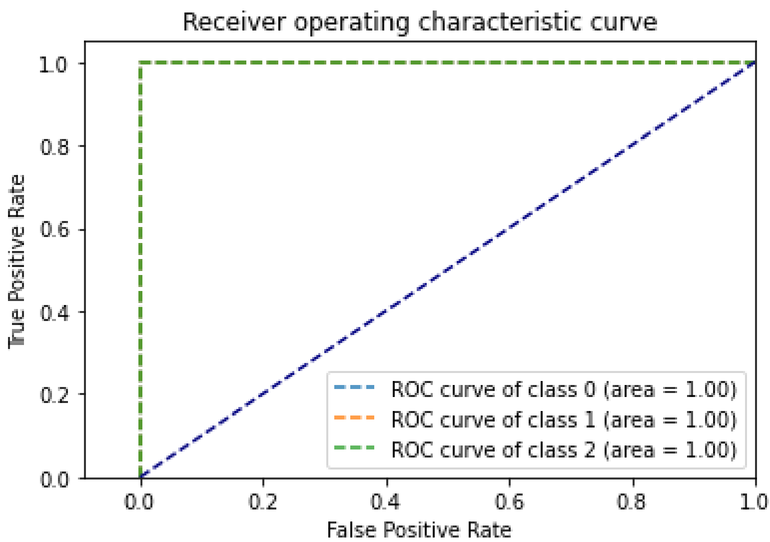
In [97]:
```
print(classification_report(y_pred_svc, y_test_sm))
```

```
              precision    recall  f1-score   support

    Negative       1.00      1.00      1.00      1405
     Neutral       1.00      0.97      0.99      1472
    Positive       0.97      1.00      0.98      1329

    accuracy                           0.99      4206
   macro avg       0.99      0.99      0.99      4206
weighted avg       0.99      0.99      0.99      4206
```

auc-roc curve for multiclass svm

In [102…

```
fpr={}
tpr={}
roc_auc=dict()
n_class=y_test_binarize.shape[1]
for i in range(n_class):
    fpr[i], tpr[i], _ = roc_curve(y_test_binarize[:, i], y_pred_svc_prob[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])
    #plt.plot(fpr[i], tpr[i], linestyle="--", color="darkorange")
    plt.plot(fpr[i], tpr[i], linestyle="--", label='ROC curve of class {0} (area = {
             ''.format(i, roc_auc[i]))

plt.plot([0, 1], [0, 1], color="navy", linestyle="--")
plt.xlim([-0.09, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic curve")
plt.legend(loc="lower right")
plt.show()
```



In [108…

```
master_data.columns
```

Out[108…

```
Index(['name', 'brand', 'categories', 'primaryCategories', 'reviews.date',
       'reviews.text', 'reviews.title', 'sentiment', 'sentimemt score',
       'polarity score'],
      dtype='object')
```

2.neural networks

In [122…

```
#!pip install textblob
```

```
Collecting textblob
  Downloading textblob-0.17.1-py2.py3-none-any.whl (636 kB)
Requirement already satisfied: nltk>=3.1 in c:\programdata\anaconda3\lib\site-packag
es (from textblob) (3.6.1)
Requirement already satisfied: regex in c:\programdata\anaconda3\lib\site-packages
(from nltk>=3.1->textblob) (2021.4.4)
Requirement already satisfied: tqdm in c:\programdata\anaconda3\lib\site-packages (f
rom nltk>=3.1->textblob) (4.59.0)
Requirement already satisfied: joblib in c:\programdata\anaconda3\lib\site-packages
(from nltk>=3.1->textblob) (1.0.1)
```

```
Requirement already satisfied: click in c:\programdata\anaconda3\lib\site-packages
(from nltk>=3.1->textblob) (7.1.2)
Installing collected packages: textblob
Successfully installed textblob-0.17.1
```

create neural network

In [33]:
```
import tensorflow as tf
from tensorflow.keras.layers import Dense, LSTM, GRU, Activation, Dropout, Embedding
from tensorflow.keras.models import Sequential
from sklearn.preprocessing import LabelBinarizer
```

In [187…
```
model=Sequential()
```

In [188…
```
model.add(Dense(units=64, activation='relu', input_dim=x_train.shape[1]))
```

In [189…
```
model.add(Dense(units=32,activation='relu'))
model.add(Dense(units=16, activation='relu'))
model.add(Dense(units=3, kernel_initializer='normal', activation='softmax'))
```

In [190…
```
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_8 (Dense)             (None, 64)                345728

 dense_9 (Dense)             (None, 32)                2080

 dense_10 (Dense)            (None, 16)                528

 dense_11 (Dense)            (None, 3)                 51

=================================================================
Total params: 348,387
Trainable params: 348,387
Non-trainable params: 0
_________________________________________________________________
```

In [191…
```
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'
```

In [122…
```
y_train_binarize=label_binarize(y_train_sm, classes=np.unique(y_train_sm))
```

In [229…
```
model.fit(x_train_sm, y_train_binarize,batch_size=128, epochs=50, verbose=1)
```

```
Epoch 1/50
77/77 [==============================] - 0s 5ms/step - loss: 6.7507e-06 - accuracy:
1.0000
Epoch 2/50
77/77 [==============================] - 0s 4ms/step - loss: 6.3709e-06 - accuracy:
1.0000
Epoch 3/50
77/77 [==============================] - 0s 4ms/step - loss: 6.0157e-06 - accuracy:
1.0000
Epoch 4/50
```

```
77/77 [==============================] - 0s 4ms/step - loss: 5.6848e-06 - accuracy:
1.0000
Epoch 5/50
77/77 [==============================] - 0s 4ms/step - loss: 5.3798e-06 - accuracy:
1.0000
Epoch 6/50
77/77 [==============================] - 0s 4ms/step - loss: 5.0833e-06 - accuracy:
1.0000
Epoch 7/50
77/77 [==============================] - 0s 4ms/step - loss: 4.8159e-06 - accuracy:
1.0000
Epoch 8/50
77/77 [==============================] - 0s 4ms/step - loss: 4.5538e-06 - accuracy:
1.0000
Epoch 9/50
77/77 [==============================] - 0s 4ms/step - loss: 4.3157e-06 - accuracy:
1.0000
Epoch 10/50
77/77 [==============================] - 0s 3ms/step - loss: 4.0871e-06 - accuracy:
1.0000
Epoch 11/50
77/77 [==============================] - 0s 4ms/step - loss: 3.8741e-06 - accuracy:
1.0000
Epoch 12/50
77/77 [==============================] - 0s 3ms/step - loss: 3.6744e-06 - accuracy:
1.0000
Epoch 13/50
77/77 [==============================] - 0s 4ms/step - loss: 3.4875e-06 - accuracy:
1.0000
Epoch 14/50
77/77 [==============================] - 0s 4ms/step - loss: 3.3100e-06 - accuracy:
1.0000
Epoch 15/50
77/77 [==============================] - 0s 4ms/step - loss: 3.1436e-06 - accuracy:
1.0000
Epoch 16/50
77/77 [==============================] - 0s 4ms/step - loss: 2.9839e-06 - accuracy:
1.0000
Epoch 17/50
77/77 [==============================] - 0s 3ms/step - loss: 2.8346e-06 - accuracy:
1.0000
Epoch 18/50
77/77 [==============================] - 0s 3ms/step - loss: 2.6964e-06 - accuracy:
1.0000
Epoch 19/50
77/77 [==============================] - 0s 4ms/step - loss: 2.5604e-06 - accuracy:
1.0000
Epoch 20/50
77/77 [==============================] - 0s 3ms/step - loss: 2.4352e-06 - accuracy:
1.0000
Epoch 21/50
77/77 [==============================] - 0s 4ms/step - loss: 2.3155e-06 - accuracy:
1.0000
Epoch 22/50
77/77 [==============================] - 0s 4ms/step - loss: 2.2038e-06 - accuracy:
1.0000
Epoch 23/50
77/77 [==============================] - 0s 4ms/step - loss: 2.0979e-06 - accuracy:
1.0000
Epoch 24/50
77/77 [==============================] - 0s 4ms/step - loss: 1.9981e-06 - accuracy:
1.0000
Epoch 25/50
77/77 [==============================] - 0s 4ms/step - loss: 1.9024e-06 - accuracy:
1.0000
Epoch 26/50
77/77 [==============================] - 0s 4ms/step - loss: 1.8098e-06 - accuracy:
1.0000
Epoch 27/50
```

```
77/77 [==============================] - 0s 4ms/step - loss: 1.7247e-06 - accuracy: 
1.0000
Epoch 28/50
77/77 [==============================] - 0s 4ms/step - loss: 1.6419e-06 - accuracy: 
1.0000
Epoch 29/50
77/77 [==============================] - 0s 4ms/step - loss: 1.5650e-06 - accuracy: 
1.0000
Epoch 30/50
77/77 [==============================] - 0s 4ms/step - loss: 1.4902e-06 - accuracy: 
1.0000
Epoch 31/50
77/77 [==============================] - 0s 4ms/step - loss: 1.4201e-06 - accuracy: 
1.0000
Epoch 32/50
77/77 [==============================] - 0s 4ms/step - loss: 1.3549e-06 - accuracy: 
1.0000
Epoch 33/50
77/77 [==============================] - 0s 4ms/step - loss: 1.2920e-06 - accuracy: 
1.0000
Epoch 34/50
77/77 [==============================] - 0s 4ms/step - loss: 1.2324e-06 - accuracy: 
1.0000
Epoch 35/50
77/77 [==============================] - 0s 4ms/step - loss: 1.1749e-06 - accuracy: 
1.0000: 0s - loss: 1.0528e-06 - accuracy
Epoch 36/50
77/77 [==============================] - 0s 4ms/step - loss: 1.1210e-06 - accuracy: 
1.0000
Epoch 37/50
77/77 [==============================] - 0s 4ms/step - loss: 1.0691e-06 - accuracy: 
1.0000
Epoch 38/50
77/77 [==============================] - 0s 4ms/step - loss: 1.0192e-06 - accuracy: 
1.0000
Epoch 39/50
77/77 [==============================] - 0s 3ms/step - loss: 9.7244e-07 - accuracy: 
1.0000
Epoch 40/50
77/77 [==============================] - 0s 4ms/step - loss: 9.2880e-07 - accuracy: 
1.0000
Epoch 41/50
77/77 [==============================] - 0s 4ms/step - loss: 8.8570e-07 - accuracy: 
1.0000
Epoch 42/50
77/77 [==============================] - 0s 5ms/step - loss: 8.4616e-07 - accuracy: 
1.0000
Epoch 43/50
77/77 [==============================] - 0s 4ms/step - loss: 8.0826e-07 - accuracy: 
1.0000
Epoch 44/50
77/77 [==============================] - 0s 5ms/step - loss: 7.7237e-07 - accuracy: 
1.0000
Epoch 45/50
77/77 [==============================] - 0s 4ms/step - loss: 7.3802e-07 - accuracy: 
1.0000
Epoch 46/50
77/77 [==============================] - 0s 4ms/step - loss: 7.0421e-07 - accuracy: 
1.0000
Epoch 47/50
77/77 [==============================] - 0s 4ms/step - loss: 6.7281e-07 - accuracy: 
1.0000
Epoch 48/50
77/77 [==============================] - 0s 4ms/step - loss: 6.4283e-07 - accuracy: 
1.0000
Epoch 49/50
77/77 [==============================] - 0s 4ms/step - loss: 6.1427e-07 - accuracy: 
1.0000
Epoch 50/50
```

```
77/77 [==============================] - 0s 4ms/step - loss: 5.8673e-07 - accuracy:
1.0000
```

Out[229…

```
<keras.callbacks.History at 0x1931e435250>
```

In [230…

```
y_pred_nn=model.predict(x_test_sm, batch_size=128)
y_pred_bool = np.argmax(y_pred_nn, axis=1)
```

In [232…

```
print(confusion_matrix(y_test_sm_le, y_pred_bool))
```

```
[[1398    0    0]
 [   0 1433    0]
 [   3   23 1349]]
```

In [233…

```
print(classification_report(y_test_sm_le, y_pred_bool))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1398
           1       0.98      1.00      0.99      1433
           2       1.00      0.98      0.99      1375

    accuracy                           0.99      4206
   macro avg       0.99      0.99      0.99      4206
weighted avg       0.99      0.99      0.99      4206
```

Use possible ensemble techniques like: XGboost + oversampled_multinomial_NB.

In [409…

```
from sklearn.ensemble import VotingClassifier
```

In [410…

```
model1=XGBClassifier(n_jobs=-1)
model2=MultinomialNB()
```

In [411…

```
vc=VotingClassifier(estimators=[('xgb',model1),('naaivebayes',model2)], voting='hard
```

In [412…

```
vc.fit(x_train_sm, y_train_sm)
```

Out[412…

```
▸ VotingClassifier
      xgb              naaivebayes
▸ XGBClassifier    ▸ MultinomialNB
```

In [413…

```
y_pred_vc=vc.predict(x_test_sm)
```

In [414…

```
confusion_matrix(y_pred_vc, y_test_sm)
```

Out[414…

```
array([[1397,    1,   44],
       [   0, 1429,  113],
       [   1,    3, 1218]], dtype=int64)
```

In [415…

```
print(classification_report(y_pred_vc, y_test_sm))
```

```
              precision    recall  f1-score   support

    Negative       1.00      0.97      0.98      1442
     Neutral       1.00      0.93      0.96      1542
    Positive       0.89      1.00      0.94      1222

    accuracy                           0.96      4206
   macro avg       0.96      0.96      0.96      4206
weighted avg       0.97      0.96      0.96      4206
```

Prepare a column called 'Sentiment Score or polarity score'

In [38]:

```
from textblob import TextBlob
```

In [39]:

```
def senti(x):
    return TextBlob(x).sentiment
def polarity(x):
    return TextBlob(x).polarity+1
```

In [40]:

```
#master_data['sentimemt_score']=master_data['reviews.text'].apply(lambda x: (TextBlo
#master_data['polarity_score']=master_data["reviews.text"].apply(lambda x: (TextBlob
```

In [41]:

```
master_data['sentiment_score']=master_data['reviews.text'].apply(senti)
master_data['polarity_score']=master_data['reviews.text'].apply(polarity)
```

In [50]:

```
#master_data.drop(['sentimemt_score','polarity_score'], axis=1, inplace=True)
```

In [42]:

```
master_data=master_data.reset_index(drop=True) ##very important
```

In [43]:

```
master_data.head()
```

Out[43]:

	name	brand	categories	primaryCategories	reviews.date	reviews.text	re
0	All-New Fire HD 8 Tablet, 8" HD Display, Wi-Fi...	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	Electronics	2016-12-26T00:00:00.000Z	Purchased on Black FridayPros - Great Price (e...	
1	Amazon - Echo Plus w/ Built-In Hub - Silver	Amazon	Amazon Echo,Smart Home,Networking,Home & Tools...	Electronics,Hardware	2018-01-17T00:00:00.000Z	I purchased two Amazon in Echo Plus and two do...	

	name	brand	categories	primaryCategories	reviews.date	reviews.text	re
2	Amazon Echo Show Alexa-enabled Bluetooth Speak...	Amazon	Amazon Echo,Virtual Assistant Speakers,Electro...	Electronics,Hardware	2017-12-20T00:00:00.000Z	Just an average Alexa option. Does show a few ...	
3	Fire HD 10 Tablet, 10.1 HD Display, Wi-Fi, 16 ...	Amazon	eBook Readers,Fire Tablets,Electronics Feature...	Office Supplies,Electronics	2017-08-04T00:00:00.000Z	very good product. Exactly what I wanted, and ...	
4	Brand New Amazon Kindle Fire 16gb 7" Ips Displ...	Amazon	Computers/Tablets & Networking,Tablets & eBook...	Electronics	2017-01-23T00:00:00.000Z	This is the 3rd one I've purchased. I've bough...	

In [44]:
```
master_data.sentiment_score.head()
```

Out[44]:
```
0      (0.36354166666666665, 0.6791666666666667)
1      (0.45821428571428574, 0.49821428571428567)
2    (-0.14047619047619045, 0.21428571428571427)
3                      (0.69, 0.6033333333333335)
4                    (0.1875, 0.2916666666666667)
Name: sentiment_score, dtype: object
```

In [45]:
```
master_data['polarity_score'].shape, XX.shape
```

Out[45]:
```
((4987,), (4987, 6793))
```

In [46]:
```
master_data.isna().sum()
```

Out[46]:
```
name                 0
brand                0
categories           0
primaryCategories    0
reviews.date         0
reviews.text         0
reviews.title        0
sentiment            0
sentiment_score      0
polarity_score       0
dtype: int64
```

In [47]:
```
data= pd.concat([master_data['polarity_score'],XX], axis=1)
```

In [48]:
```
Y=le.fit_transform(master_data['sentiment'])
```

In [49]:
```
new_x_train,new_x_test,y_train,y_test=train_test_split(data,Y, test_size=0.3, random
```

In [61]:
```
model3=MultinomialNB()
```

In [62]:
```
model3.fit(new_x_train, y_train)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:1858: FutureW
arning: Feature names only support names that are all strings. Got feature names wit
h dtypes: ['int', 'str']. An error will be raised in 1.2.
  warnings.warn(
```

Out[62]:
```
▾ MultinomialNB
MultinomialNB()
```

In [63]:
```
print(confusion_matrix(model3.predict(new_x_test), y_test))
```

```
[[   0    0    0]
 [   0    0    0]
 [  37   52 1408]]
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:1858: FutureW
arning: Feature names only support names that are all strings. Got feature names wit
h dtypes: ['int', 'str']. An error will be raised in 1.2.
  warnings.warn(
```

In [64]:
```
print(classification_report(model3.predict(new_x_test), y_test))
```

```
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         0
           1       0.00      0.00      0.00         0
           2       1.00      0.94      0.97      1497

    accuracy                           0.94      1497
   macro avg       0.33      0.31      0.32      1497
weighted avg       1.00      0.94      0.97      1497

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:1858: FutureW
arning: Feature names only support names that are all strings. Got feature names wit
h dtypes: ['int', 'str']. An error will be raised in 1.2.
  warnings.warn(
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334:
UndefinedMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in l
abels with no true samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334:
UndefinedMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in l
abels with no true samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334:
UndefinedMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in l
abels with no true samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

In [94]:
```
new_data=pd.concat([master_data['polarity_score'], X], axis=1)
```

In [96]:
```
new_x_train,new_x_test,y_train,y_test=train_test_split(new_data,Y, test_size=0.3, ra
```

from above scenario it is showing poor performance if

senti_score including in data

LSTM MODEL

In [97]:
```
epochs = 4
emb_dim = 64
batch_size = 256
model = Sequential()
model.add(Embedding(75, emb_dim, input_length=new_x_train.shape[1]))
#model.add(SpatialDropout1D(0.7))
model.add(LSTM(16, dropout=0.7, recurrent_dropout=0.7))
model.add(Dense(3, activation='softmax'))
```

```
WARNING:tensorflow:Layer lstm_2 will not use cuDNN kernels since it doesn't meet the
criteria. It will use a generic GPU kernel as fallback when running on GPU.
```

In [44]:
```
#lstm=Sequential()
```

In [ ]:
```
#lstm.add((LSTM(64, dropout=0.2, recurrent_dropout=0.3)))
```

```
WARNING:tensorflow:Layer lstm_4 will not use cuDNN kernels since it doesn't meet the
criteria. It will use a generic GPU kernel as fallback when running on GPU.
```

In [130…
```
#lstm.add(Dense(units=3, kernel_initializer='normal', activation='softmax'))
```

In [98]:
```
model.summary()
```

```
Model: "sequential_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_4 (Embedding)     (None, 5402, 64)          4800

 lstm_2 (LSTM)               (None, 16)                5184

 dense_3 (Dense)             (None, 3)                 51

=================================================================
Total params: 10,035
Trainable params: 10,035
Non-trainable params: 0
_________________________________________________________________
```

In [99]:
```
y_train_binarize=label_binarize(y_train, classes=[0,1,2])
```

In [100…
```
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'
```

In [101…
```
new_x_train.shape, y_train_binarize.shape
```

Out[101…
```
((3490, 5402), (3490, 3))
```

In [103…
```
model.fit(new_x_train, y_train_binarize, batch_size=64, epochs=epochs, verbose=2)
```

```
Epoch 1/4
```

```
55/55 - 1576s - loss: 0.7044 - accuracy: 0.8693 - 1576s/epoch - 29s/step
Epoch 2/4
55/55 - 3020s - loss: 0.2869 - accuracy: 0.9355 - 3020s/epoch - 55s/step
Epoch 3/4
55/55 - 1905s - loss: 0.2825 - accuracy: 0.9355 - 1905s/epoch - 35s/step
Epoch 4/4
55/55 - 1566s - loss: 0.2826 - accuracy: 0.9355 - 1566s/epoch - 28s/step
```

Out[103…

```
<keras.callbacks.History at 0x23218828670>
```

In [104…

```
y_pred_lstm=model.predict(new_x_test)
```

In [105…

```
y_pred_lstm_max=np.argmax(y_pred_lstm, axis=1)
```

In [113…

```
print(confusion_matrix(y_pred_lstm_max, y_test))
```

```
[[   0    0    0]
 [   0    0    0]
 [  37   52 1408]]
```

In [114…

```
print(classification_report(y_pred_lstm_max, y_test))
```

```
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         0
           1       0.00      0.00      0.00         0
           2       1.00      0.94      0.97      1497

    accuracy                           0.94      1497
   macro avg       0.33      0.31      0.32      1497
weighted avg       1.00      0.94      0.97      1497

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334:
UndefinedMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in l
abels with no true samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334:
UndefinedMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in l
abels with no true samples. Use `zero_division` parameter to control this behavior.
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C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334:
UndefinedMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in l
abels with no true samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

GRU MODEL

In [120…

```
epochs = 3
model1 = Sequential()
model1.add(Embedding(100, 128, input_length=new_x_train.shape[1]))
model1.add(SpatialDropout1D(0.7))
model1.add(GRU(32, dropout=0.3, recurrent_dropout=0.3))
model1.add(Dense(3, activation='softmax'))
```

```
WARNING:tensorflow:Layer gru_2 will not use cuDNN kernels since it doesn't meet the
criteria. It will use a generic GPU kernel as fallback when running on GPU.
```

In [121…

```
model1.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy
```

In [125…
```
hist=model.fit(new_x_train, y_train_binarize, batch_size=64, epochs=epochs, verbose=
```

```
Epoch 1/3
55/55 - 1565s - loss: 0.2823 - accuracy: 0.9355 - 1565s/epoch - 28s/step
Epoch 2/3
55/55 - 1599s - loss: 0.2825 - accuracy: 0.9355 - 1599s/epoch - 29s/step
Epoch 3/3
55/55 - 1560s - loss: 0.2823 - accuracy: 0.9355 - 1560s/epoch - 28s/step
```

In [126…
```
y_pred_gru=model1.predict(new_x_test)
```

In [127…
```
y_pred_gru_max=np.argmax(y_pred_gru, axis=1)
```

In [129…
```
print(confusion_matrix(y_pred_gru_max, y_test))
```

```
[[  37   52 1408]
 [   0    0    0]
 [   0    0    0]]
```

In [131…
```
print(classification_report(y_pred_gru_max, y_test))
```

```
              precision    recall  f1-score   support

           0       1.00      0.02      0.05      1497
           1       0.00      0.00      0.00         0
           2       0.00      0.00      0.00         0

    accuracy                           0.02      1497
   macro avg       0.33      0.01      0.02      1497
weighted avg       1.00      0.02      0.05      1497

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334:
UndefinedMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in l
abels with no true samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334:
UndefinedMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in l
abels with no true samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1334:
UndefinedMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in l
abels with no true samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

for both LSTM and GRU its not showing good performance.Some how neural network (ANN) showing good result.

In [ ]:
```
#import tensorflow as tf
#print("Num GPUs Available: ", len(tf.config.list_physical_devices('GPU')))
```

clustering

In [106…
```
from sklearn.cluster import KMeans
km3=KMeans(n_clusters=3, random_state=43)
```

In [116…
```
tf_idf3=TfidfVectorizer(max_features=2500, stop_words="english")
```

In [117…
```
km3.fit(tf_idf3.fit_transform(master_data['reviews.text']))
```

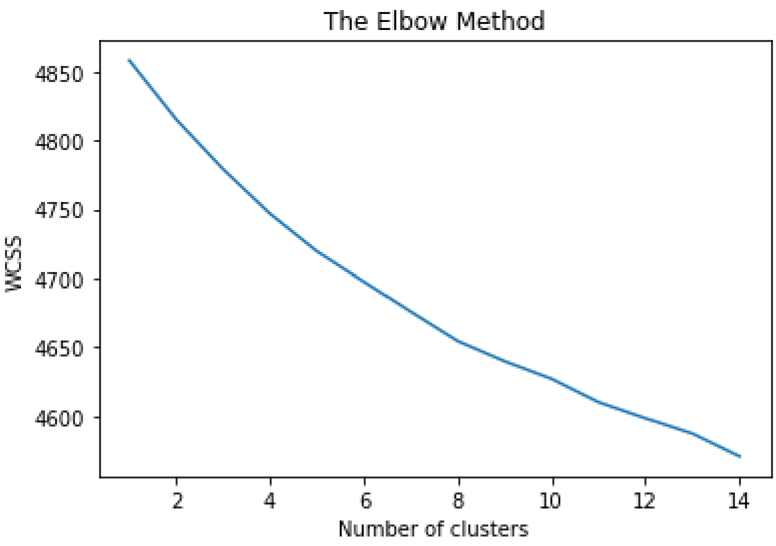
Out[117…
```
KMeans
KMeans(n_clusters=3, random_state=43)
```

In [118…
```
rev=tf_idf3.fit_transform(master_data['reviews.text'])
```

In [119…
```
words=tf_idf3.get_feature_names()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:87: FutureWa
rning: Function get_feature_names is deprecated; get_feature_names is deprecated in
1.0 and will be removed in 1.2. Please use get_feature_names_out instead.
  warnings.warn(msg, category=FutureWarning)
```

In [124…
```
wcss = []
for i in range(1,15):
    km=KMeans(n_clusters=i,init='k-means++',max_iter=300,n_init=10,random_state=43)
    km.fit(rev)
    wcss.append(km.inertia_)
plt.plot(range(1,15),wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



lets check k values 9, 10, 11

In [120…
```
km9=KMeans(n_clusters=9,init='k-means++',max_iter=300,n_init=10,random_state=43)
km9.fit(rev)
```

Out[120…
```
KMeans
KMeans(n_clusters=9, random_state=43)
```

In [121…
```
km10=KMeans(n_clusters=10,init='k-means++',max_iter=300,n_init=10,random_state=43)
km10.fit(rev)
```
Out[121…
```
KMeans
KMeans(n_clusters=10, random_state=43)
```
In [122…
```
km11=KMeans(n_clusters=11,init='k-means++',max_iter=300,n_init=10,random_state=43)
km11.fit(rev)
```
Out[122…
```
KMeans
KMeans(n_clusters=11, random_state=43)
```
In [123…
```
km9.inertia_, km10.inertia_, km11.inertia_
```
Out[123…
```
(4639.941742907345, 4627.213619830506, 4610.288669184534)
```
In [125…
```
np.unique(km9.labels_, return_counts=True)
```
Out[125…
```
(array([0, 1, 2, 3, 4, 5, 6, 7, 8]),
 array([1636,  297,  248,  538,  664,  386,  404,  424,  390], dtype=int64))
```
In [126…
```
km9.cluster_centers_.shape
```
Out[126…
```
(9, 2500)
```
In [186…
```
#most common words
how_many_words=25
common_words = km9.cluster_centers_.argsort()[:,-1:-how_many_words:-1]
for i, word_index in enumerate(common_words):
    print(str(i), ":", ",".join(words[i] for i in word_index))
```
```
0 : love,bought,like,product,gift,good,use,books,just,kids,really,read,got,buy,amazo
n,device,games,screen,christmas,purchased,better,best,time,loved
1 : loves,daughter,bought,gift,grandson,tablet,son,wife,absolutely,easy,granddaughte
r,great,purchased,got,christmas,birthday,use,games,kindle,nephew,mother,uses,durabl
e,price
2 : old,year,loves,bought,tablet,perfect,games,son,easy,grandson,great,got,granddaug
hter,yr,purchased,use,love,apps,play,christmas,years,durable,daughter,kids
3 : great,works,price,product,tablet,kids,love,recommend,buy,reading,battery,little,
gift,best,life,sound,use,just,good,features,bought,value,like,amazon
4 : tablet,good,price,apps,kids,amazon,great,use,love,play,games,perfect,need,nice,l
ike,store,little,bought,works,time,google,just,screen,size
5 : alexa,love,music,great,lights,home,ask,echo,questions,fun,things,just,family,lik
e,house,use,amazon,speaker,äôs,turn,having,screen,able,smart
6 : echo,plus,dot,love,great,amazon,music,sound,home,video,like,screen,smart,better,
tap,use,house,hue,works,just,product,features,hub,family
7 : kindle,love,books,read,reading,new,great,screen,size,best,like,old,easy,better,l
ight,bought,second,use,book,upgrade,original,just,good,really
8 : easy,use,set,great,love,product,tablet,kids,good,price,gift,recommend,fast,fun,p
erfect,books,read,super,works,light,size,sound,setup,nice
```

we can see kmeans is showing different perspective in clustering as most of data is positive reviews its showing different perspective in that positive reviews

cluster visualization

In [130…
```
from sklearn.decomposition import PCA
pca=PCA(n_components=2, random_state=43)
```

In [188…
```
reduced_features=pca.fit_transform(rev.toarray())
reduced_cluster_centers=pca.transform(km9.cluster_centers_)
```

In [189…
```
reduced_cluster_centers
```

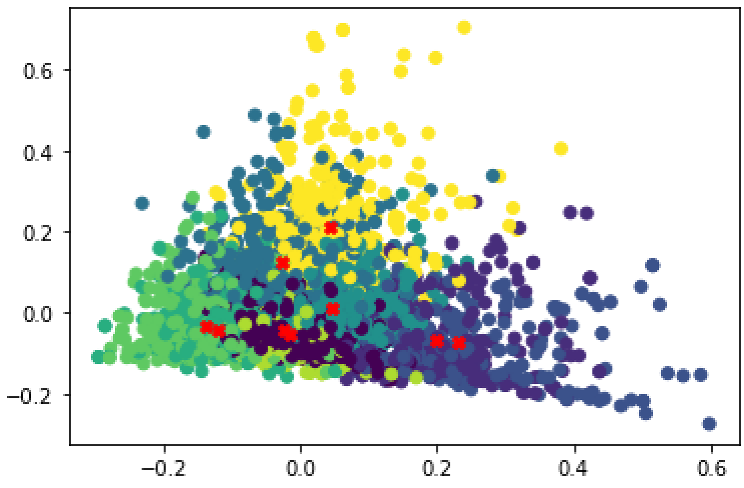
Out[189…
```
array([[-0.02497945, -0.0418664 ],
       [ 0.19996287, -0.06645549],
       [ 0.23239462, -0.07205568],
       [-0.02652184,  0.12503976],
       [ 0.04580762,  0.01326043],
       [-0.12141573, -0.04448279],
       [-0.13909127, -0.03259267],
       [-0.01366029, -0.0525048 ],
       [ 0.04242908,  0.21185648]])
```

In [190…
```
reduced_features.shape
```

Out[190…
```
(4987, 2)
```

In [191…
```
plt.scatter(reduced_features[:,0], reduced_features[:,1], c=km9.predict(rev))
plt.scatter(reduced_cluster_centers[:,0], reduced_cluster_centers[:,1], marker="X",
```

Out[191…
```
<matplotlib.collections.PathCollection at 0x2a83141d280>
```



topic modelling

in topic modelling we use 2 famous models

1. NMF(Non-Negative Matrix Factorixation)

In [151…
```
from sklearn.decomposition import NMF
nmf=NMF(n_components=4, random_state=43)
```

In [152…

```
nmf.fit(rev)
```

Out[152…

```
NMF
NMF(n_components=4, random_state=43)
```

In [161…

```
top_words=26
common_words = nmf.components_.argsort()[:,-1:-top_words:-1]
for i, word_index in enumerate(common_words):
    print(str(i), ":", ",".join(words[i] for i in word_index))
```

```
0 : great,tablet,price,good,product,works,kids,recommend,apps,little,buy,reading,nic
e,amazon,quality,sound,battery,best,value,need,features,size,does,just,like
1 : loves,bought,old,year,tablet,daughter,gift,son,grandson,christmas,games,purchase
d,got,granddaughter,perfect,wife,absolutely,kindle,birthday,uses,play,loved,mom,yr,e
njoys
2 : easy,use,set,product,setup,read,navigate,fun,super,light,fast,kindle,books,recom
mend,lightweight,convenient,really,purchased,size,happy,day,simple,reader,item,ease
3 : love,echo,alexa,kindle,music,amazon,like,screen,just,home,plus,new,play,best,rea
d,sound,device,better,smart,family,books,lights,kids,really,things
```

in above scenario tha 4 topics we can see some difference not too much but somehow a variation in topics like positive review, gifts, music and so on

2.Latent Dirichlet Allocation

In [159…

```
from sklearn.decomposition import LatentDirichletAllocation
lda=LatentDirichletAllocation(n_components=5, random_state=43)
```

In [160…

```
lda.fit(rev)
```

Out[160…

```
LatentDirichletAllocation
LatentDirichletAllocation(n_components=5, random_state=43)
```

In [158…

```
top_words=25
common_words = lda.components_.argsort()[:,-1:-top_words:-1]
for i, word_index in enumerate(common_words):
    print(str(i), ":", ",".join(words[i] for i in word_index))
```

```
0 : kindle,read,books,love,tablet,reading,great,battery,ipad,easy,screen,reader,use,
good
1 : echo,great,love,alexa,amazon,product,use,fun,best,easy,tablet,sound,things,set
2 : echo,alexa,music,great,like,love,use,home,amazon,just,screen,sound,good,works
3 : tablet,loves,great,easy,bought,use,kids,old,love,year,gift,price,product,games
```

LDA showing different perspective topics in data

with smote data

In [164…

```
X_sm, y_sm=sm.fit_resample(rev,master_data['sentiment'])
```

In [169…

```
nmf=NMF(n_components=5, random_state=43)
nmf.fit(X_sm)
```

Out[169…

```
▾ NMF
NMF(n_components=5, random_state=43)
```

In [170…

```
top_words=26
common_words = nmf.components_.argsort()[:,-1:-top_words:-1]
for i, word_index in enumerate(common_words):
    print(str(i), ":", ",".join(words[i] for i in word_index))
```

```
0 : device,work,echo,just,use,great,screen,alexa,like,buy,amazon,does,product,bough
t,love,needs,sound,friendly,easy,make,phone,things,don,home,kindle
1 : ok,year,pay,old,happy,bought,charge,tablet,charger,need,loves,christmas,price,co
nsidering,daughter,order,defective,space,time,grandson,quality,account,best,chargin
g,port
2 : week,update,customer,constantly,weak,grows,resolved,promises,junk,poorly,lowest,
magnetic,pieces,designed,kindle,means,old,services,oasis,upgrade,setting,battery,lif
e,better,lights
3 : good,tablet,apps,download,slow,kids,amazon,reading,store,price,games,app,great,p
lay,kindle,books,browser,little,google,fan,disappointed,internet,catch,movies,camera
4 : returned,apps,proprietary,worthless,did,basically,cause,install,liked,store,daug
hter,chrome,cheap,run,product,google,answers,stuff,really,confusing,like,use,owning,
ads,navigate
```

after balancing it showing different topics like in 3rd and 5th it showing negative reviews and 1st somewhat like neutral reviews etc..

In [176…

```
lda=LatentDirichletAllocation(n_components=4, random_state=43)
lda.fit(X_sm)
```

Out[176…

```
▾ LatentDirichletAllocation
LatentDirichletAllocation(n_components=4, random_state=43)
```

In [177…

```
top_words=25
common_words = lda.components_.argsort()[:,-1:-top_words:-1]
for i, word_index in enumerate(common_words):
    print(str(i), ":", ",".join(words[i] for i in word_index))
```

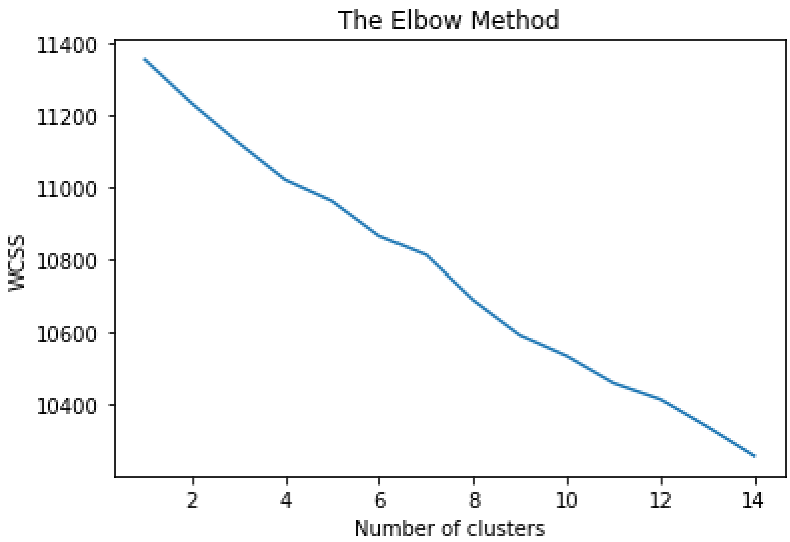
```
0 : slow,tablet,good,ok,device,ipad,like,amazon,bad,friendly,pay,children,don,didn,t
ablets,reading,work,works,apps,internet,old,better,time,know
1 : apps,amazon,tablet,good,echo,screen,alexa,just,work,does,use,kids,device,video,u
pdate,ads,download,kindle,better,needs,lots,limited,make,like
2 : charge,bought,store,just,kindle,old,tablet,charger,google,play,apps,great,going,
year,returned,wish,answers,instructions,shuts,paper,cheap,use,problem,tried
3 : great,tablet,product,easy,use,loves,love,kindle,good,returned,price,sound,reall
y,son,kids,bought,available,apps,disappointed,daughter,gift,works,quality,did
```

In [ ]:

clustering

In [178…

```
wcss = []
for i in range(1,15):
    km=KMeans(n_clusters=i,init='k-means++',max_iter=300,n_init=10,random_state=43)
    km.fit(X_sm)
    wcss.append(km.inertia_)
plt.plot(range(1,15),wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



In [184…

```
km4=KMeans(n_clusters=3,init='k-means++',max_iter=300,n_init=10,random_state=43)
km4.fit(X_sm)
```

Out[184…

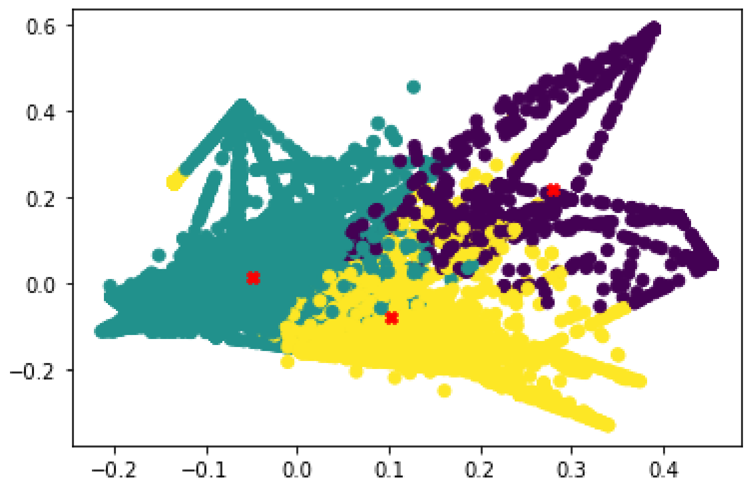
```
KMeans
KMeans(n_clusters=3, random_state=43)
```

In [185…

```
reduced_features=pca.fit_transform(X_sm.toarray())
reduced_cluster_centers=pca.transform(km4.cluster_centers_)
plt.scatter(reduced_features[:,0], reduced_features[:,1], c=km4.predict(X_sm))
plt.scatter(reduced_cluster_centers[:,0], reduced_cluster_centers[:,1], marker="X",
```

Out[185…

```
<matplotlib.collections.PathCollection at 0x2a842b5b910>
```



as we know we have three types of reviews positive, negative and neutral.

and as this one is balanced data all three clusters showing equal distribution

In [ ]:

```

```