E-commerce_AI Capstone Project

October 27, 2022

[1]:
```
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
# Import Essential Libraries

import pandas as pd
import numpy as np
from nltk.tokenize import WordPunctTokenizer
from sklearn.feature_extraction.text import CountVectorizer,TfidfVectorizer
from nltk.tokenize import RegexpTokenizer
from nltk.corpus import stopwords
from nltk.stem import SnowballStemmer,PorterStemmer,WordNetLemmatizer
import matplotlib.pyplot as plt
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import␣
↪accuracy_score,classification_report,confusion_matrix,roc_curve,roc_auc_score,auc
from sklearn.preprocessing import LabelBinarizer
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier,VotingClassifier
from xgboost import XGBClassifier
from sklearn.svm import SVC
from keras.models import Sequential
from keras.layers import␣
↪Dense,Dropout,Embedding,SpatialDropout1D,LSTM,GRU,Activation
from sklearn.preprocessing import label_binarize,LabelBinarizer,LabelEncoder
from sklearn.utils import class_weight
from textblob import TextBlob
import tensorflow as tf
import keras
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
from gensim.models import LdaModel
from bs4 import BeautifulSoup
import re
from gensim import corpora
import pyLDAvis.gensim_models
from wordcloud import WordCloud,STOPWORDS
```

```
import string
from sklearn.feature_extraction import text
from tensorflow.keras.preprocessing.sequence import pad_sequences
```

[3]:
```
pd.set_option('display.max_colwidth',100)
```

1 Project Task: Week 1

2 Class Imbalance Problem:

1. Perform an EDA on the dataset.

- See what a positive, negative, and neutral review looks like
- Check the class count for each class. It's a class imbalance problem.

2. Convert the reviews in Tf-Idf score.
3. Run multinomial Naive Bayes classifier. Everything will be classified as positive because of the class imbalance.

[4]:
```
# Import the train dataset

train = pd.read_csv('train_data.csv')
train.head()
```

[4]:
```
          name  \
0     All-New Fire HD 8 Tablet, 8" HD Display, Wi-Fi, 16 GB - Includes Special
Offers, Magenta
1                                             Amazon - Echo Plus w/ Built-
In Hub - Silver
2                               Amazon Echo Show Alexa-enabled Bluetooth Speaker
with 7" Screen
3  Fire HD 10 Tablet, 10.1 HD Display, Wi-Fi, 16 GB - Includes Special Offers,
Silver Aluminum
4                       Brand New Amazon Kindle Fire 16gb 7" Ips Display Tablet
Wifi 16 Gb Blue

    brand  \
0  Amazon
1  Amazon
2  Amazon
3  Amazon
4  Amazon

            categories  \
0                       Electronics,iPad & Tablets,All Tablets,Fire
Tablets,Tablets,Computers & Tablets
```

```
1  Amazon Echo,Smart Home,Networking,Home & Tools,Home Improvement,Smart Home
Automation,Voice Assi…
2  Amazon Echo,Virtual Assistant Speakers,Electronics Features,Home &
Tools,Smart Home Automation,T…
3  eBook Readers,Fire Tablets,Electronics Features,Tablets,Amazon
Tablets,College Ipads & Tablets,E…
4       Computers/Tablets & Networking,Tablets & eBook Readers,Computers &
Tablets,Tablets,All Tablets

             primaryCategories              reviews.date  \
0                  Electronics  2016-12-26T00:00:00.000Z
1         Electronics,Hardware  2018-01-17T00:00:00.000Z
2         Electronics,Hardware  2017-12-20T00:00:00.000Z
3  Office Supplies,Electronics  2017-08-04T00:00:00.000Z
4                  Electronics  2017-01-23T00:00:00.000Z

          reviews.text  \
0  Purchased on Black FridayPros - Great Price (even off sale)Very powerful and
fast with quad core…
1  I purchased two Amazon in Echo Plus and two dots plus four fire sticks and
the hub Philips hue f…
2                  Just an average Alexa option. Does show a few things on
screen but still limited.
3                                    very good product. Exactly what I wanted,
and a very good price
4  This is the 3rd one I've purchased. I've bought one for all of my nieces. No
other case compares…

              reviews.title sentiment
0            Powerful tablet  Positive
1  Amazon Echo Plus AWESOME  Positive
2                    Average   Neutral
3                Greatttttttt  Positive
4              Very durable!  Positive
```

[5]:
```python
# Import the test dataset

test = pd.read_csv('test_data.csv')
test.head()
```

[5]:
```
       name  \
0                    Fire Tablet, 7 Display, Wi-Fi, 16 GB - Includes Special
Offers, Black
1                          Amazon Echo Show Alexa-enabled Bluetooth Speaker
with 7" Screen
2  All-New Fire HD 8 Tablet, 8" HD Display, Wi-Fi, 16 GB - Includes Special
Offers, Magenta
```

```
3                  Brand New Amazon Kindle Fire 16gb 7" Ips Display Tablet Wifi
16 Gb Blue
4                          Amazon Echo Show Alexa-enabled Bluetooth Speaker
with 7" Screen

    brand  \
0  Amazon
1  Amazon
2  Amazon
3  Amazon
4  Amazon

            categories  \
0  Fire Tablets,Computers/Tablets & Networking,Tablets,All Tablets,Amazon
Tablets,Frys,Computers & …
1  Computers,Amazon Echo,Virtual Assistant Speakers,Audio & Video
Components,Electronics Features,C…
2                      Electronics,iPad & Tablets,All Tablets,Fire
Tablets,Tablets,Computers & Tablets
3       Computers/Tablets & Networking,Tablets & eBook Readers,Computers &
Tablets,Tablets,All Tablets
4  Computers,Amazon Echo,Virtual Assistant Speakers,Audio & Video
Components,Electronics Features,C…

      primaryCategories             reviews.date  \
0           Electronics  2016-05-23T00:00:00.000Z
1  Electronics,Hardware  2018-01-02T00:00:00.000Z
2           Electronics  2017-01-02T00:00:00.000Z
3           Electronics  2017-03-25T00:00:00.000Z
4  Electronics,Hardware  2017-11-15T00:00:00.000Z

          reviews.text  \
0  Amazon kindle fire has a lot of free app and can be used by any one that
wants to get online any…
1  The Echo Show is a great addition to the Amazon family. Works just like the
Echo, but with a 7" …
2                                                 Great value from Best Buy.
Bought at Christmas sale.
3  I use mine for email, Facebook ,games and to go on line. I also have down
loaded books. I use it…
4                                      This is a fantastic item & the person I
bought it for loves it.

                       reviews.title
0                  very handy device
1          Another winner from Amazon
2  simple to use and reliable so far
```

```
3                         Love it!!!
4                         Fantastic!
```

[6]:
```
# Import the test hidden dataset

test_hidden = pd.read_csv('test_data_hidden.csv')
test_hidden.head()
```

[6]:
```
       name  \
0                      Fire Tablet, 7 Display, Wi-Fi, 16 GB - Includes Special
Offers, Black
1                            Amazon Echo Show Alexa-enabled Bluetooth Speaker
with 7" Screen
2  All-New Fire HD 8 Tablet, 8" HD Display, Wi-Fi, 16 GB - Includes Special
Offers, Magenta
3                    Brand New Amazon Kindle Fire 16gb 7" Ips Display Tablet Wifi
16 Gb Blue
4                            Amazon Echo Show Alexa-enabled Bluetooth Speaker
with 7" Screen

    brand  \
0  Amazon
1  Amazon
2  Amazon
3  Amazon
4  Amazon

            categories  \
0  Fire Tablets,Computers/Tablets & Networking,Tablets,All Tablets,Amazon
Tablets,Frys,Computers & …
1  Computers,Amazon Echo,Virtual Assistant Speakers,Audio & Video
Components,Electronics Features,C…
2                       Electronics,iPad & Tablets,All Tablets,Fire
Tablets,Tablets,Computers & Tablets
3       Computers/Tablets & Networking,Tablets & eBook Readers,Computers &
Tablets,Tablets,All Tablets
4  Computers,Amazon Echo,Virtual Assistant Speakers,Audio & Video
Components,Electronics Features,C…

      primaryCategories              reviews.date  \
0           Electronics  2016-05-23T00:00:00.000Z
1  Electronics,Hardware  2018-01-02T00:00:00.000Z
2           Electronics  2017-01-02T00:00:00.000Z
3           Electronics  2017-03-25T00:00:00.000Z
4  Electronics,Hardware  2017-11-15T00:00:00.000Z

          reviews.text  \
```

```
0  Amazon kindle fire has a lot of free app and can be used by any one that
wants to get online any…
1  The Echo Show is a great addition to the Amazon family. Works just like the
Echo, but with a 7" …
2                                                  Great value from Best Buy.
Bought at Christmas sale.
3  I use mine for email, Facebook ,games and to go on line. I also have down
loaded books. I use it…
4                                       This is a fantastic item & the person I
bought it for loves it.

                       reviews.title sentiment
0                   very handy device  Positive
1          Another winner from Amazon  Positive
2  simple to use and reliable so far  Positive
3                           Love it!!!  Positive
4                          Fantastic!  Positive
```

[7]:
```python
print('Train Dataset Size :',train.shape)
print('Test Dataset Size :',test.shape)
print('Tests Hidden Dataset Size :',test_hidden.shape)
```

```
Train Dataset Size : (4000, 8)
Test Dataset Size : (1000, 7)
Tests Hidden Dataset Size : (1000, 8)
```

[8]:
```python
train.dtypes
```

[8]:
```
name                    object
brand                   object
categories              object
primaryCategories       object
reviews.date            object
reviews.text            object
reviews.title           object
sentiment               object
dtype: object
```

3 1. Perform an EDA on the dataset.

[9]:
```python
train.duplicated().sum(),test.duplicated().sum(),test_hidden.duplicated().sum()
```

[9]:
```
(58, 3, 3)
```

- Train dataset contains 58 duplicates records and test dataset contains 3 duplicate records

[10]:
```python
train = train[train.duplicated() == False]
print('Train Dataset Size :',train.shape)
```

```
Train Dataset Size : (3942, 8)
```

[11]:
```python
# Find out the information of train dataset

train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3942 entries, 0 to 3999
Data columns (total 8 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   name                3942 non-null   object
 1   brand               3942 non-null   object
 2   categories          3942 non-null   object
 3   primaryCategories   3942 non-null   object
 4   reviews.date        3942 non-null   object
 5   reviews.text        3942 non-null   object
 6   reviews.title       3932 non-null   object
 7   sentiment           3942 non-null   object
dtypes: object(8)
memory usage: 277.2+ KB
```

[12]:
```python
# Find out the information of test dataset

test_hidden.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 8 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   name                1000 non-null   object
 1   brand               1000 non-null   object
 2   categories          1000 non-null   object
 3   primaryCategories   1000 non-null   object
 4   reviews.date        1000 non-null   object
 5   reviews.text        1000 non-null   object
 6   reviews.title       997 non-null    object
 7   sentiment           1000 non-null   object
dtypes: object(8)
memory usage: 62.6+ KB
```

- Train dataset has 10 (0.25%) missing values in reviews.title and test dataset has 3 (0.03%) missing values in reviews.title

[13]:
```
# Find out is there is any missing value present or not

print(train.isna().any())
print('\n',train.isna().sum())
```

```
name                  False
brand                 False
categories            False
primaryCategories     False
reviews.date          False
reviews.text          False
reviews.title          True
sentiment             False
dtype: bool

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

3.1 See what a positive, negative, and neutral review looks like

[14]:
```
pd.set_option('display.max_colwidth',200)
```

[15]:
```
# Reviews containing Positive statement
train[train['sentiment'] == 'Positive'][['reviews.text']].head(10)
```

[15]:
```
                              reviews.text
0   Purchased on Black FridayPros - Great Price (even off sale)Very powerful and
fast with quad core processors Amazing soundWell builtCons -Amazon ads, Amazon
need this to subsidize the tablet and wi…
1   I purchased two Amazon in Echo Plus and two dots plus four fire sticks and
the hub Philips hue for lamp for the family at Christmas 2017. I‚Äôm so happy
with these purchases and learning so much w…
3
very good product. Exactly what I wanted, and a very good price
4                        This is the 3rd one I've purchased. I've bought one for
all of my nieces. No other case compares to this one. It has held protected the
tablet so many times from them dropping it.
5
This is a great product. Light weight. I wish it has wifi to download from
online.
```

```
7                                                       Purchased this for my
son. Has room to upgrade memory to allow more books & games. But the speakers
could be better or located in a better position.
8                Bought this for my mom and it was just what she needed and at a
great price. Been wanting to get an Ipad for myself, but think this might be a
great less expensive option for me as well.
10                         I got this tablet to replace my sons old one, I love
the adult/child profile and the ability to have the 2 year replacement warranty.
The case has also came in handy many times.
11
Great product for the kids gaming apps parental controls to make sure you can
monitor kids and prevent unwanted app purchases
12
Love the choice of colors. Have two kindles of my own and purchased this for a
gift.
```

[16]:
```python
# Reviews containing Negative statement
train[train['sentiment'] == 'Negative'][['reviews.text']].head(10)
```

[16]:
```
                                reviews.text
9
was cheap, can not run chrome stuff, returned to store.
97   Worthless, except as a regular echo and a poor excuse for video chat. I
love my echo devices, bathroom, pool, kitchen, other places where I may need
hands free, voice activated music and info. My …
104
Too bad Amazon turned this tablet into a big advertising tool. Many apps dont
work and the camera is not good.
121  I bought this Kindle for my 7 year old grand-daughter. I bought a warranty
for it. I bought it in August, I have already had to replace it. The charger
connection got loose and was not charging. W…
150  I am reading positive reviews and wish I could say the same. Best Buy is
great, so this is not a reflection on them, just our experience with the
product. We have had this product for just over on…
151  I have to say it was a little confusing and frustrating when i was not
getting the verification code from amazon , i waited for 20 minutes then i
requested another code, nothing… then a nother o…
249
It's a good device for children because they don't know any better
267                                                                 the speaker
voice quality is terrible compare the similar size my logitech UE BOOM.the price
is too high, even I got on promotion with $79
368                                               Needs to be a stand alone device.
I should have not required to use a tablet of Cell phone to make it work. Amazon
needs to work on the technology on device.
530                                                                        Has a
very good Bluetooth speakers sound quality is good but otherwise she's pretty
```

```
useless when it comes to get answering questions
```

[17]:
```python
# Reviews containing Neutral statement
train[train['sentiment'] == 'Neutral'][['reviews.text']].head(10)
```

[17]:
```
                                        reviews.text
2
Just an average Alexa option. Does show a few things on screen but still
limited.
6    My 7-year old daughter saved up to by this. Her brother bought the 8GB
about a year earlier, so new she needed more space. The OS is a bit clunky, and
less intuitive then on higher priced tablets,…
17
Not as good as before the old kindle, just seams to work better
59   There is nothing spectacular about this item but also nothing majorly wrong
with it. The biggest flaw is that this is geared to kids and there is no way
that I have found searching settings or onl…
95
It's unfair for me to rate this product cause I have not even taken it out of
the box to set it up.
114
I bought this as s present for my 65 year old grandma. She loves it. Very easy
to operate. No issues
146                                                                  Bought this
tablet for 8 year old. It holding up good & she loves it. She enjoys playimg her
games & being able to get on the internet.
147  bought a few kindles in the past but this time one of it came defective.
the port was bent and it was hard to charge but still possible. comes in 4
different color. was 16gb enough space for kids,…
148
Not a substitute for an iPad, but a really good tablet for reading and minimal
internet usage.
187
This device is a good if you are looking for a starter tablet for a young
individual.
```

3.2 Check the class count for each class. It’s a class imbalance problem.

[18]:
```python
train['brand'].value_counts()
```

[18]:
```
Amazon    3942
Name: brand, dtype: int64
```

[19]:
```python
train['primaryCategories'].value_counts()
```

[19]:
```
Electronics                    2562
Electronics,Hardware           1159
Office Supplies,Electronics     204
Electronics,Media                17
Name: primaryCategories, dtype: int64
```

[20]:
```
train['sentiment'].value_counts()
```

[20]:
```
Positive    3694
Neutral      158
Negative      90
Name: sentiment, dtype: int64
```

[21]:
```
pd.DataFrame(train.name.value_counts())
```

[21]:
```
                                                                     name
Amazon Echo Show Alexa-enabled Bluetooth Speaker with 7" Screen
676
All-New Fire HD 8 Tablet, 8" HD Display, Wi-Fi, 16 GB - Includes Special Offers,
Magenta                                                             628
Amazon - Echo Plus w/ Built-In Hub - Silver
483
Fire Kids Edition Tablet, 7 Display, Wi-Fi, 16 GB, Blue Kid-Proof Case
446
Brand New Amazon Kindle Fire 16gb 7" Ips Display Tablet Wifi 16 Gb Blue
340
Fire Tablet, 7 Display, Wi-Fi, 16 GB - Includes Special Offers, Black
294
Amazon Tap - Alexa-Enabled Portable Bluetooth Speaker
177
Fire Kids Edition Tablet, 7 Display, Wi-Fi, 16 GB, Green Kid-Proof Case
175
Kindle E-reader - White, 6 Glare-Free Touchscreen Display, Wi-Fi - Includes
Special Offers                                                           122
Fire HD 10 Tablet, 10.1 HD Display, Wi-Fi, 16 GB - Includes Special Offers,
Silver Aluminum                                                           82
Fire Tablet with Alexa, 7" Display, 16 GB, Magenta - with Special Offers
80
Amazon Kindle E-Reader 6" Wifi (8th Generation, 2016)
76
Amazon - Kindle Voyage - 6" - 4GB - Black
65
All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi, 32 GB - Includes Special Offers,
Blue                                                                  56
All-New Fire HD 8 Tablet, 8" HD Display, Wi-Fi, 32 GB - Includes Special Offers,
Black                                                                 45
Fire HD 8 Tablet with Alexa, 8" HD Display, 32 GB, Tangerine - with Special
```

```
Offers                                                    43
All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi, 16 GB - Includes Special Offers,
Blue                                                  35
All-New Fire HD 8 Tablet, 8" HD Display, Wi-Fi, 32 GB - Includes Special Offers,
Magenta                                              35
Kindle Oasis E-reader with Leather Charging Cover - Black, 6" High-Resolution
Display (300 ppi), Wi-Fi - Includes Special Offers    26
Amazon 9W PowerFast Official OEM USB Charger and Power Adapter for Fire Tablets
and Kindle eReaders                                   20
Amazon - Kindle Voyage - 4GB - Wi-Fi + 3G - Black
19
Kindle Oasis E-reader with Leather Charging Cover - Merlot, 6 High-Resolution
Display (300 ppi), Wi-Fi - Includes Special Offers    17
Amazon Fire TV with 4K Ultra HD and Alexa Voice Remote (Pendant Design) |
Streaming Media Player                                      2
```

[22]:
```
pd.DataFrame(train.categories.value_counts())
```

[22]:
```
                                          categories
Electronics,iPad & Tablets,All Tablets,Fire Tablets,Tablets,Computers & Tablets
628
Computers,Amazon Echo,Virtual Assistant Speakers,Audio & Video
Components,Electronics Features,Computer Accessories,Home & Tools,See more
Amazon Echo Show Smart Assistant - White,Smart Home Automat…          514
Amazon Echo,Smart Home,Networking,Home & Tools,Home Improvement,Smart Home
Automation,Voice Assistants,Amazon Home,Amazon,Smart Hub & Kits,Digital Device 3
483
Computers,Fire Tablets,Electronics Features,Computer Accessories,Tablets,Top
Rated,Amazon Tablets,Electronics,Kids' Tablets,iPad & Tablets,Cases &
Bags,Electronics, Tech Toys, Movies, Music,Compute…          446
Computers/Tablets & Networking,Tablets & eBook Readers,Computers &
Tablets,Tablets,All Tablets
340
Fire Tablets,Computers/Tablets & Networking,Tablets,All Tablets,Amazon
Tablets,Frys,Computers & Tablets,Tablets & eBook Readers
294
Fire Tablets,Tablets,All Tablets,Amazon Tablets,Computers & Tablets
231
Amazon Echo,Home Theater & Audio,MP3 MP4 Player Accessories,Electronics,Portable
Audio,Compact Radios Stereos,Smart Hubs & Wireless Routers,Featured Brands,Smart
Home & Connected Living,Home Securi…          177
Amazon Echo,Virtual Assistant Speakers,Electronics Features,Home & Tools,Smart
Home Automation,TVs Entertainment,Speakers,Smart Hub & Kits,Digital Device
3,Wireless Speakers,Smart Home,Home Improve…          162
Office,eBook Readers,Electronics Features,Walmart for
Business,Tablets,Electronics,Amazon Ereaders,Office Electronics,iPad &
Tablets,Kindle E-readers,All Tablets,Amazon Book Reader,Computers & Tablets
```

```
122
eBook Readers,Fire Tablets,Electronics Features,Tablets,Amazon Tablets,College
Ipads & Tablets,Electronics,Electronics Deals,College Electronics,Featured
Brands,All Tablets,Computers & Tablets,Back…          82
Tablets,Fire Tablets,Electronics,iPad & Tablets,Android Tablets,Computers &
Tablets,All Tablets
80
Computers,Electronics Features,Tablets,Electronics,iPad & Tablets,Kindle
E-readers,iPad Accessories,Used:Tablets,E-Readers,E-Readers &
Accessories,Computers/Tablets & Networking,Used:Computers Acce…          76
eBook Readers,Electronics Features,Walmart for Business,Tablets,See more Amazon
Kindle Voyage (Wi-Fi),Electronics,Office Electronics,iPad & Tablets,Kindle
E-readers,E-Readers & Accessories,All Tabl…          65
Fire Tablets,Tablets,Computers/Tablets & Networking,Other Computers &
Networking,Computers & Tablets,All Tablets
45
Tablets,Fire Tablets,Computers & Tablets,All Tablets
43
Fire Tablets,Tablets,All Tablets,Amazon Tablets
35
Tablets,Fire Tablets,Electronics,Computers,Computer Components,Hard Drives &
Storage,Computers & Tablets,All Tablets
35
Kindle E-readers,Electronics Features,Computers & Tablets,E-Readers &
Accessories,E-Readers,eBook Readers
26
Computers & Accessories,Tablet & E-Reader Accessories,Amazon Devices &
Accessories,Electronics,Power Adapters & Cables,Computers Features,Cell Phone
Accessories,Cell Phone Batteries & Power,Digital…          20
Computers & Tablets,E-Readers & Accessories,eBook Readers,Kindle E-readers
19
eBook Readers,E-Readers & Accessories,Amazon Book Reader,Computers &
Tablets,Amazon Ereaders,Kindle E-readers,E-Readers
17
Amazon SMP,TV, Video & Home Audio,Electronics,Electronics Deals,TVs
Entertainment,Digital Device 4,Tvs & Home Theater,Featured Brands,Video Devices
& TV Tuners,Consumer Electronics,TV & Video,Inter…          2
```

3.3 Data cleaning

[23]:
```python
train['reviews.day'] = pd.to_datetime(train['reviews.date'],format='%Y-%m-%d').
↪dt.day
train['reviews.month'] = pd.to_datetime(train['reviews.
↪date'],format='%Y-%m-%d').dt.month
train['reviews.year'] = pd.to_datetime(train['reviews.date'],format='%Y-%m-%d').
↪dt.year
```

```
test['reviews.day'] = pd.to_datetime(test['reviews.date'],format='%Y-%m-%d').dt.
↪day
test['reviews.month'] = pd.to_datetime(test['reviews.date'],format='%Y-%m-%d').
↪dt.month
test['reviews.year'] = pd.to_datetime(test['reviews.date'],format='%Y-%m-%d').
↪dt.year

test_hidden['reviews.day'] = pd.to_datetime(test_hidden['reviews.
↪date'],format='%Y-%m-%d').dt.day
test_hidden['reviews.month'] = pd.to_datetime(test_hidden['reviews.
↪date'],format='%Y-%m-%d').dt.month
test_hidden['reviews.year'] = pd.to_datetime(test_hidden['reviews.
↪date'],format='%Y-%m-%d').dt.year

train = train.drop(['brand','reviews.date'],axis=1)
test = test.drop(['brand','reviews.date'],axis=1)
test_hidden = test_hidden.drop(['brand','reviews.date'],axis=1)
```

[24]:
```
encode = LabelEncoder()

train['name'] = encode.fit_transform(train['name'])
train['categories'] = encode.fit_transform(train['categories'])
train['primaryCategories'] = encode.fit_transform(train['primaryCategories'])
train['sentiment'] = encode.fit_transform(train['sentiment'])

test['name'] = encode.fit_transform(test['name'])
test['categories'] = encode.fit_transform(test['categories'])
test['primaryCategories'] = encode.fit_transform(test['primaryCategories'])

test_hidden['name'] = encode.fit_transform(test_hidden['name'])
test_hidden['categories'] = encode.fit_transform(test_hidden['categories'])
test_hidden['primaryCategories'] = encode.
↪fit_transform(test_hidden['primaryCategories'])
test_hidden['sentiment'] = encode.fit_transform(test_hidden['sentiment'])
```

[25]:
```
train['reviews.title'].fillna(value=' ',inplace=True)
test['reviews.title'].fillna(value=' ',inplace=True)
test_hidden['reviews.title'].fillna(value=' ',inplace=True)
```

[26]:
```
tok = WordPunctTokenizer()
ps = PorterStemmer()
wnl = WordNetLemmatizer()
negations_dic = {"isn't":"is not", "aren't":"are not", "wasn't":"was not",␣
↪"weren't":"were not",
```

```
                "haven't":"have not","hasn't":"has not","hadn't":"had␣
↪not","won't":"will not",
                "wouldn't":"would not", "don't":"do not", "doesn't":"does␣
↪not","didn't":"did not",
                "can't":"can not","couldn't":"could not","shouldn't":"should␣
↪not","mightn't":"might not",
                "mustn't":"must not"}
neg_pattern = re.compile(r'\b(' + '|'.join(negations_dic.keys()) + r')\b')
def data_cleaner(text):
    text = text.replace(r"Äú",'')
    text = text.replace(r'Äù','')
    text = text.replace(r',Äô','\'')
    text = text.lower()
    text = text.replace(r',Äô','\'')
    text = neg_pattern.sub(lambda x: negations_dic[x.group()], text)
    text = re.sub("[^a-zA-Z0-9\"]", " ", text)
    word_tok=[x for x in tok.tokenize(text) if len(x) > 3]
#     word_stem = [ps.stem(i) for i in word_tok]
#     return (" ".join(word_stem).strip())
    word_lem = [wnl.lemmatize(i) for i in word_tok]
    return (" ".join(word_lem).strip())
for i in (train,test_hidden,test):
    i['reviews.text']=i['reviews.text'].apply(data_cleaner)
    i['reviews.title']=i['reviews.title'].apply(data_cleaner)
```

4 2. Convert the reviews in Tf-Idf score.

[27]:
```
tvec1 = TfidfVectorizer()
tvec2 = TfidfVectorizer()
tvec3 = TfidfVectorizer()

train1 = train.reset_index()
combine = train1.append(test_hidden,ignore_index=True,sort=False)
tvec1.fit(combine['reviews.text'])
tvec_text1 = pd.DataFrame(tvec1.transform(train1['reviews.text']).toarray())
tvec_text2 = pd.DataFrame(tvec1.transform(test_hidden['reviews.text']).
↪toarray())
tvec2.fit(combine['reviews.title'])
tvec_title1 = pd.DataFrame(tvec2.transform(train1['reviews.title']).toarray())
tvec_title2 = pd.DataFrame(tvec2.transform(test_hidden['reviews.title']).
↪toarray())
Train1 = pd.concat([train1.drop(['reviews.text','reviews.
↪title','sentiment','index'],axis=1),
                    tvec_text1, tvec_title1],axis=1)
Test_Val1 = pd.concat([test_hidden.drop(['reviews.text','reviews.
↪title','sentiment'],axis=1),
```

```
                       tvec_text2, tvec_title2],axis=1)
x_train1=Train1.values
y_train1=train['sentiment'].values
x_val1=Test_Val1.values
y_val1 = test_hidden['sentiment'].values
```

[28]:
```
print(x_train1.shape)
print(x_val1.shape)
print(y_train1.shape)
print(y_val1.shape)
```

```
(3942, 5538)
(1000, 5538)
(3942,)
(1000,)
```

[29]:
```
stop_words = stopwords.words('english')
tokenizer = RegexpTokenizer(r'[a-zA-Z\']+')
stemmer = SnowballStemmer('english')
```

[30]:
```
def tokenize(text):
    return [stemmer.stem(term) for term in tokenizer.tokenize(text.lower())]
tfidf_token =␣
 ↪TfidfVectorizer(stop_words=stop_words,tokenizer=tokenize,max_features=1000)
reviews = tfidf_token.fit_transform(train['reviews.text'])
words = tfidf_token.get_feature_names()
```

5 3. Run multinomial Naive Bayes classifier. Everything will be classified as positive because of the class imbalance.

[31]:
```
mnb_model = MultinomialNB()
mnb_model.fit(Train1.values,train1['sentiment'])
ypred = mnb_model.predict(Test_Val1.values)
y_test = test_hidden['sentiment']
print ("\nAccuracy on validation set: {:.4f}".format(accuracy_score(y_test,␣
 ↪ypred)))
print("\nClassification report : \n", classification_report(y_test, ypred))
print("\nConfusion Matrix : \n", confusion_matrix(y_test, ypred))
```

```
Accuracy on validation set: 0.9370

Classification report :
               precision    recall  f1-score   support

           0       0.00      0.00      0.00        24
```

```
           1       0.00      0.00      0.00        39
           2       0.94      1.00      0.97       937

    accuracy                           0.94      1000
   macro avg       0.31      0.33      0.32      1000
weighted avg       0.88      0.94      0.91      1000


Confusion Matrix :
 [[  0   0  24]
 [  0   0  39]
 [  0   0 937]]
```

- Everything is classified Positive label because of imbalance class.

6 Tackling Class Imbalance Problem:

4. Oversampling or undersampling can be used to tackle the class imbalance problem.
5. In case of class imbalance criteria, use the following metrices for evaluating model performance: precision, recall, F1-score, AUC-ROC curve. Use F1-Score as the evaluation criteria for this project.
6. Use Tree-based classifiers like Random Forest and XGBoost.

7 4. Oversampling or undersampling can be used to tackle the class imbalance problem.

7.1 Oversampling

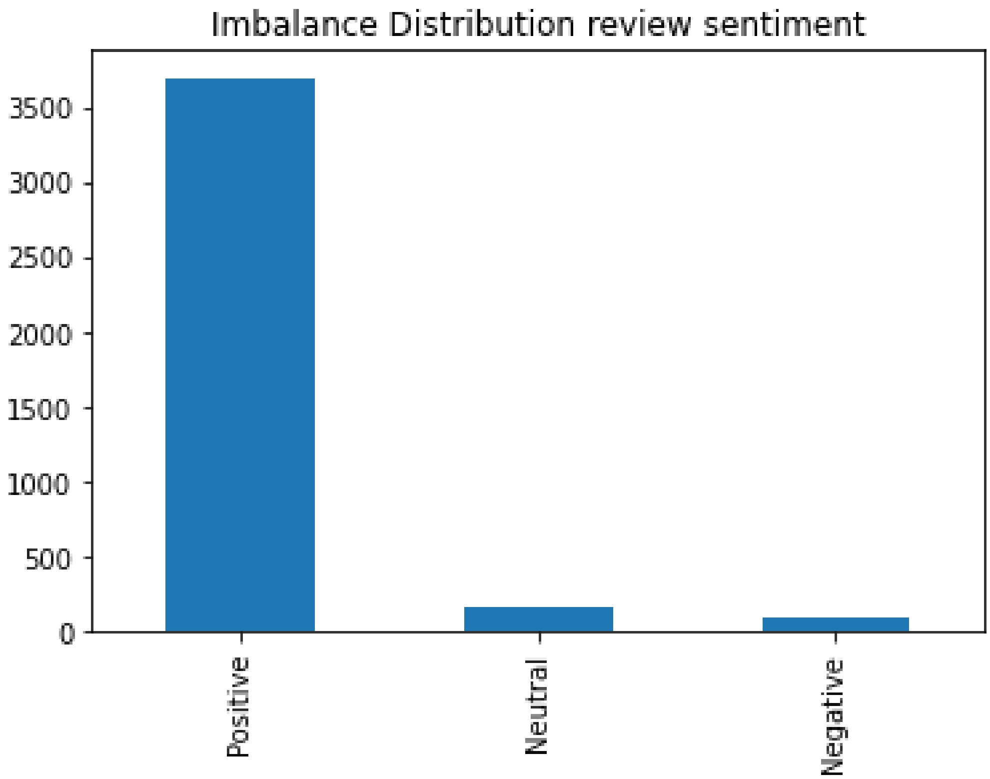
[31]:
```
train['sentiment'].value_counts()
```

[31]:
```
2    3694
1     158
0      90
Name: sentiment, dtype: int64
```

- In the train dataset has 3694(93.7%) Postive sentiment labeled, and 158(4%) has Neutral sentiment labeled, and 90(2.28%) has Negative label. So it is as imbalanced classification problem.

[32]:
```
df = train.copy()
df.sentiment.replace((2,0,1),('Positive','Negative','Neutral'),inplace=True)
df.sentiment.value_counts().plot(kind='bar')
plt.title('Imbalance Distribution review sentiment')
```

[32]:
```
Text(0.5, 1.0, 'Imbalance Distribution review sentiment')
```

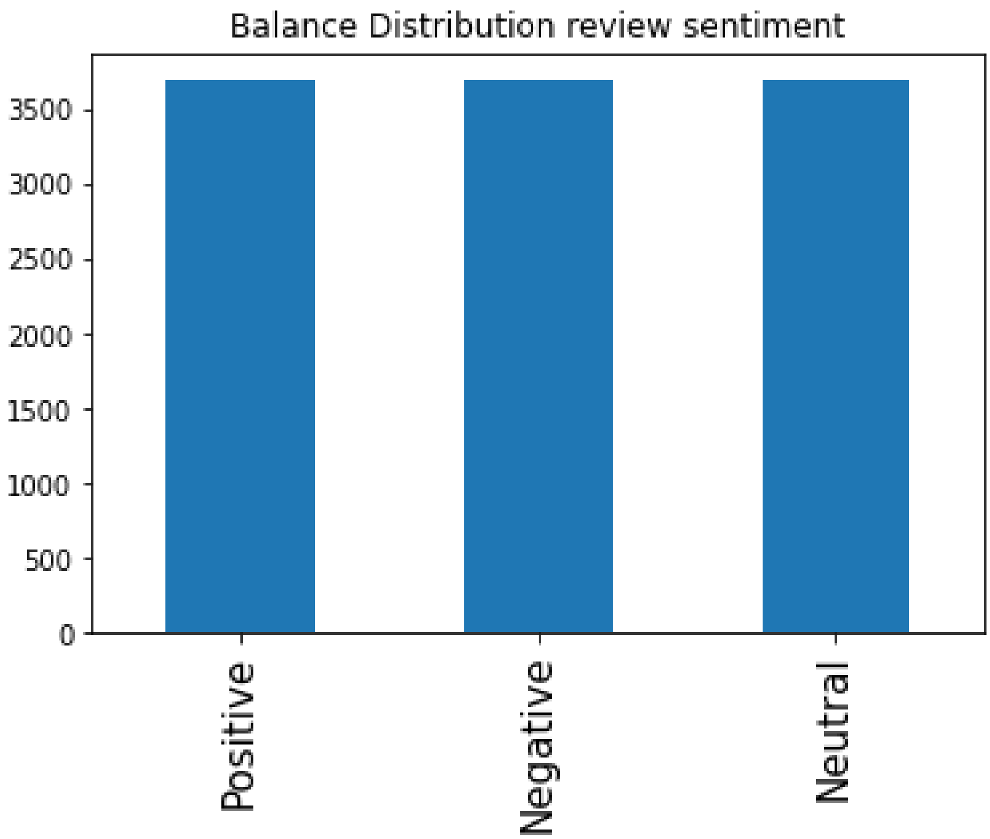


[33]:
```
count_2,count_1,count_0 = train.sentiment.value_counts()

class_2 = train[train['sentiment'] == 2]
class_1 = train[train['sentiment'] == 1]
class_0 = train[train['sentiment'] == 0]

class_0_over = class_0.sample(count_2,replace=True)
class_1_over = class_1.sample(count_2,replace=True)

train_over = pd.concat([class_2,class_0_over,class_1_over],axis=0)
print(train_over.shape)
print(train_over['sentiment'].value_counts())
```

```
(11082, 9)
2    3694
0    3694
1    3694
Name: sentiment, dtype: int64
```

[34]:
```
# Convert the sentiments

df = train_over.copy()
```

```
df.sentiment.replace((2,0,1),('Positive','Negative','Neutral'),inplace=True)
df.sentiment.value_counts().plot(kind='bar')
plt.title('Balance Distribution review sentiment')
plt.tick_params(axis='x', which='major', labelsize=15)
```

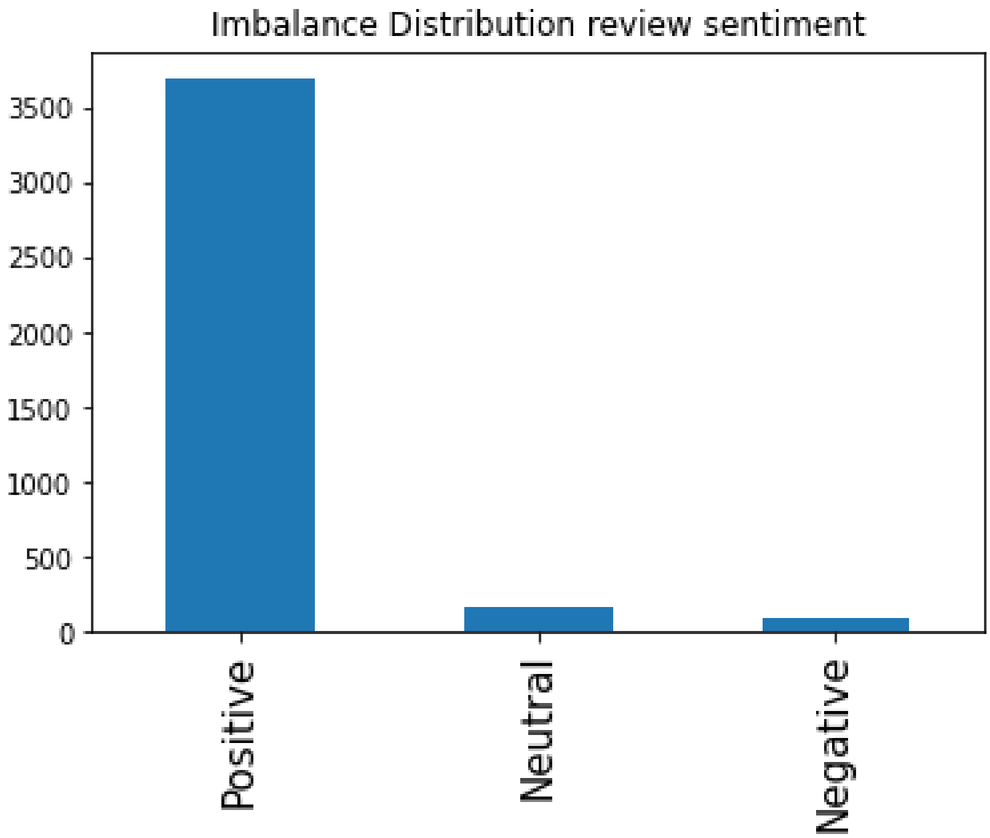


7.2 Undersampling

[35]:
```
train['sentiment'].value_counts()
```

[35]:
```
2    3694
1     158
0      90
Name: sentiment, dtype: int64
```

[36]:
```
df = train.copy()
df.sentiment.replace((2,0,1),('Positive','Negative','Neutral'),inplace=True)
df.sentiment.value_counts().plot(kind='bar')
plt.title('Imbalance Distribution review sentiment')
plt.tick_params(axis='x', which='major', labelsize=15)
```

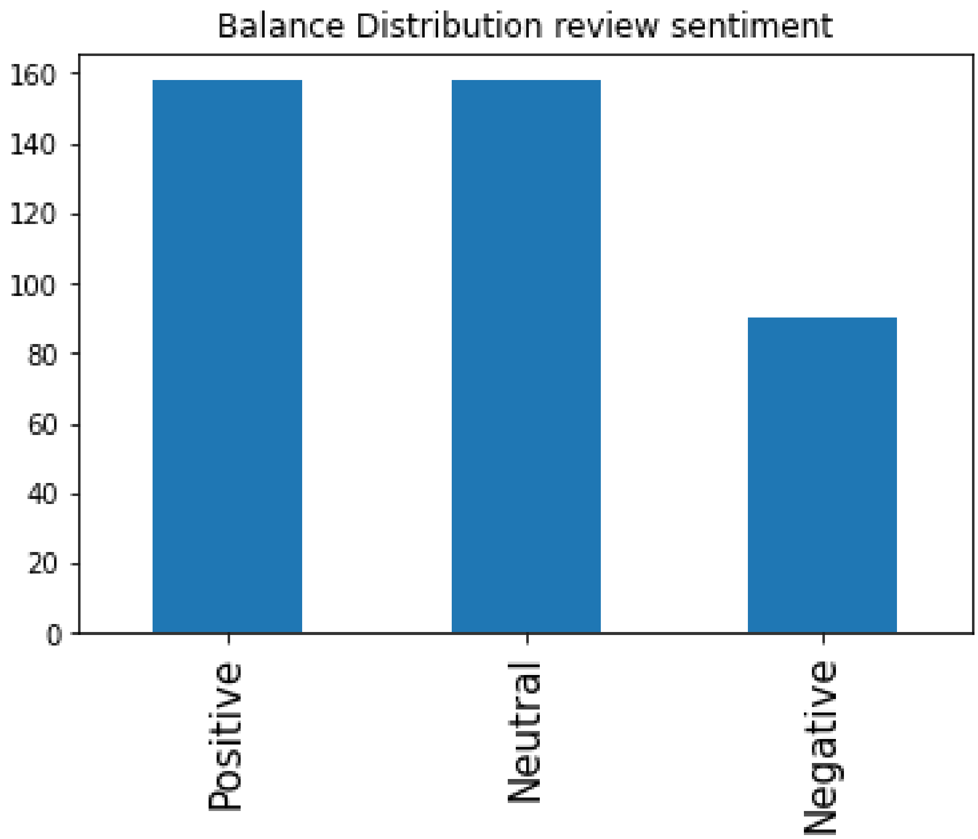


[37]:
```
count_2,count_1,count_0 = train.sentiment.value_counts()

class_2 = train[train['sentiment'] == 2]
class_1 = train[train['sentiment'] == 1]
class_0 = train[train['sentiment'] == 0]

class_2_under = class_2.sample(count_1,replace=True)

train_under = pd.concat([class_2_under,class_0,class_1],axis=0)
print(train_under.shape)
print(train_under['sentiment'].value_counts())
```

```
(406, 9)
2    158
1    158
0     90
Name: sentiment, dtype: int64
```

[38]:
```
# Convert the sentiments
df = train_under.copy()
```

```
df.sentiment.replace((2,0,1),('Positive','Negative','Neutral'),inplace=True)
df.sentiment.value_counts().plot(kind='bar')
plt.title('Balance Distribution review sentiment')
plt.tick_params(axis='x', which='major', labelsize=15)
```



7.3 TFIDF Vectorizer for under-sampled data

[39]:
```
train = train_under.reset_index(drop=True)
combine_under = train.append(test_hidden , ignore_index=True)
print(combine_under.shape)

tvec1.fit(combine_under['reviews.text'])
tvec_text1 = pd.DataFrame(tvec1.transform(train['reviews.text']).toarray())
tvec_text2 = pd.DataFrame(tvec1.transform(test_hidden['reviews.text']).
 ↪toarray())

tvec2.fit(combine_under['reviews.title'])
tvec_title1 = pd.DataFrame(tvec2.transform(train['reviews.title']).toarray())
tvec_title2 = pd.DataFrame(tvec2.transform(test_hidden['reviews.title']).
 ↪toarray())
```

```
Train = pd.concat([train.drop(['reviews.text','reviews.
 ↪title','sentiment'],axis=1),tvec_text1, tvec_title1],axis=1)
Test_Val = pd.concat([test_hidden.drop(['reviews.text','reviews.
 ↪title','sentiment'],axis=1),
                      tvec_text2, tvec_title2],axis=1)
x_train=Train.values
y_train=train['sentiment']
x_val=Test_Val.values
y_val = test_hidden['sentiment']
```

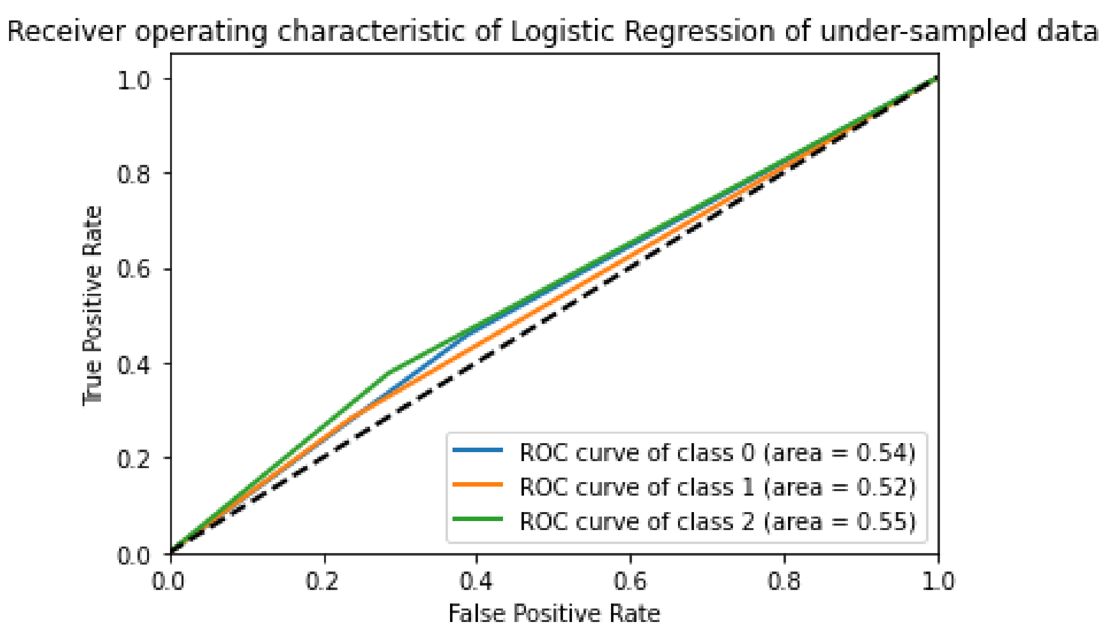
```
(1406, 9)
```

[41]:
```
lr_model = LogisticRegression(class_weight='balanced', solver='sag',␣
 ↪multi_class='multinomial', n_jobs=6,
                              random_state=40, verbose=1, max_iter=1000)
lr_model.fit(x_train,y_train)
ypred = lr_model.predict(x_val)
print ("\nAccuracy on validation set: {:.4f}".format(accuracy_score(y_val,␣
 ↪ypred)))
print("\nClassification report : \n", classification_report(y_val, ypred))
print("\nConfusion Matrix : \n", confusion_matrix(y_val, ypred))
```

```
[Parallel(n_jobs=6)]: Using backend ThreadingBackend with 6 concurrent workers.

max_iter reached after 58 seconds

Accuracy on validation set: 0.3760

Classification report :
               precision    recall  f1-score   support

           0       0.03      0.46      0.05        24
           1       0.05      0.28      0.08        39
           2       0.95      0.38      0.54       937

    accuracy                           0.38      1000
   macro avg       0.34      0.37      0.22      1000
weighted avg       0.89      0.38      0.51      1000


Confusion Matrix :
 [[ 11   7   6]
 [ 16  11  12]
 [363 220 354]]

[Parallel(n_jobs=6)]: Done   1 out of   1 | elapsed:   57.4s finished
```

[42]:
```
lb = LabelBinarizer()
lb.fit(y_val)
y_val1 = lb.transform(y_val)
y_pred1 = lb.transform(ypred)
print(roc_auc_score(y_val1, y_pred1, average='weighted'))
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(3):
    fpr[i], tpr[i], _ = roc_curve(y_val1[:, i], y_pred1[:, 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], 'k--', lw=lw)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic of Logistic Regression of␣
 ↪under-sampled data')
plt.legend(loc="lower right")
plt.show()
```

```
0.5448768816391981
```



7.4 TFIDF Vectorizer for over-sampled data

[40]:
```
train = train_over.reset_index(drop=True)

tvec1.fit(train['reviews.text'])
tvec_text1 = pd.DataFrame(tvec1.transform(train['reviews.text']).toarray())
tvec_text2 = pd.DataFrame(tvec1.transform(test_hidden['reviews.text']).
 ↪toarray())

tvec2.fit(train['reviews.title'])
tvec_title1 = pd.DataFrame(tvec2.transform(train['reviews.title']).toarray())
tvec_title2 = pd.DataFrame(tvec2.transform(test_hidden['reviews.title']).
 ↪toarray())

Train = pd.concat([train.drop(['reviews.text','reviews.
 ↪title','sentiment'],axis=1),tvec_text1, tvec_title1],axis=1)
Test_Val = pd.concat([test_hidden.drop(['reviews.text','reviews.
 ↪title','sentiment'],axis=1),
                      tvec_text2, tvec_title2],axis=1)

x_train=Train.values
y_train=train['sentiment'].values
x_val=Test_Val.values
y_val = test_hidden['sentiment'].values
```

[44]:
```
lr_model.fit(x_train,y_train)
ypred = lr_model.predict(x_val)
print ("\nAccuracy on validation set: {:.4f}".format(accuracy_score(y_val,␣
 ↪ypred)))
print("\nClassification report : \n", classification_report(y_val, ypred))
print("\nConfusion Matrix : \n", confusion_matrix(y_val, ypred))
```

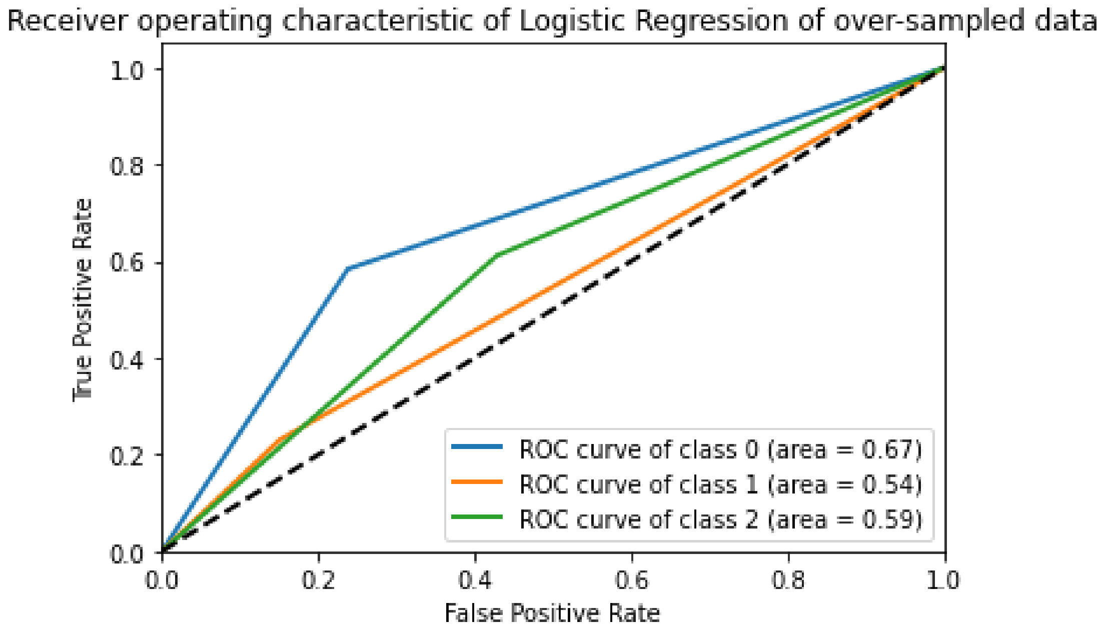
```
[Parallel(n_jobs=6)]: Using backend ThreadingBackend with 6 concurrent workers.

max_iter reached after 2204 seconds

[Parallel(n_jobs=6)]: Done   1 out of   1 | elapsed: 36.9min finished


Accuracy on validation set: 0.5960

Classification report :
               precision    recall  f1-score   support

           0       0.06      0.58      0.10        24
           1       0.06      0.23      0.09        39
```

```
           2       0.95      0.61      0.75       937

    accuracy                           0.60      1000
   macro avg       0.36      0.48      0.31      1000
weighted avg       0.90      0.60      0.70      1000


Confusion Matrix :
 [[ 14   2   8]
 [ 11   9  19]
 [221 143 573]]
```

[45]:

```python
lb = LabelBinarizer()
lb.fit(y_val)
y_val1 = lb.transform(y_val)
y_pred1 = lb.transform(ypred)
print(roc_auc_score(y_val1, y_pred1, average='weighted'))
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(3):
    fpr[i], tpr[i], _ = roc_curve(y_val1[:, i], y_pred1[:, 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], 'k--', lw=lw)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic of Logistic Regression of␣
 ↪over-sampled data')
plt.legend(loc="lower right")
plt.show()
```

```
0.5914195790392033
```



- Logostic Regression on over-sampled data is performing is better than under-sampling data.

8 5. In case of class imbalance criteria, use the following metrices for evaluating model performance: precision, recall, F1-score, AUC-ROC curve. Use F1-Score as the evaluation criteria for this project.

8.1 Multinomial Naive Bayes

[46]:
```
mnb_model = MultinomialNB()
mnb_model.fit(x_train,y_train)
ypred = mnb_model.predict(x_val)
print ("\nAccuracy on validation set: {:.4f}".format(accuracy_score(y_val,␣
 ↪ypred)))
print("\nClassification report : \n", classification_report(y_val, ypred))
print("\nConfusion Matrix : \n", confusion_matrix(y_val, ypred))

print("\nTrain Data Score : ",mnb_model.score(x_train,y_train))
print("\nTest Data Score : ",mnb_model.score(x_val,y_val))
```

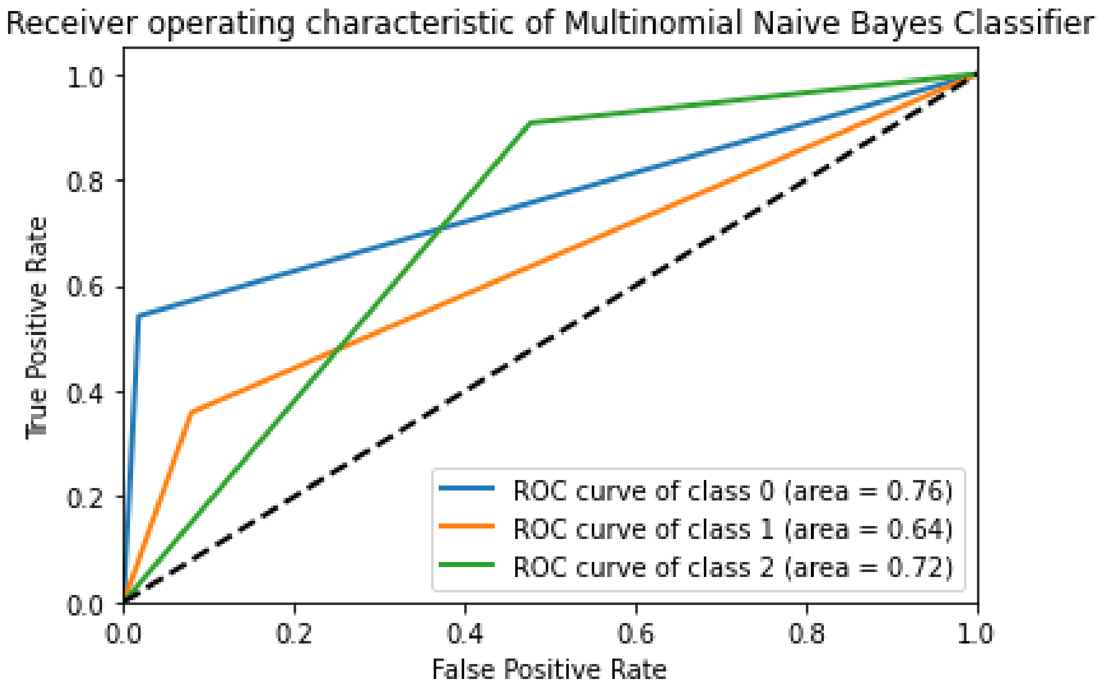
```
Accuracy on validation set: 0.8770

Classification report :
               precision    recall  f1-score   support
```

```
           0       0.43      0.54      0.48        24
           1       0.16      0.36      0.22        39
           2       0.97      0.91      0.94       937

    accuracy                           0.88      1000
   macro avg       0.52      0.60      0.54      1000
weighted avg       0.92      0.88      0.90      1000


Confusion Matrix :
 [[ 13   3   8]
 [  3  14  22]
 [ 14  73 850]]

Train Data Score :  0.9566865186789388

Test Data Score :  0.877
```

[47]:

```python
lb = LabelBinarizer()
lb.fit(y_val)
y_val1 = lb.transform(y_val)
y_pred1 = lb.transform(ypred)
print(roc_auc_score(y_val1, y_pred1, average='weighted'))
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(3):
    fpr[i], tpr[i], _ = roc_curve(y_val1[:, i], y_pred1[:, 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], 'k--', lw=lw)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic of Multinomial Naive Bayes␣
 ↪Classifier')
plt.legend(loc="lower right")
plt.show()
```

```
0.713653601910903
```



9 6. Use Tree-based classifiers like Random Forest and XGBoost.

- Note: Tree-based classifiers work on two ideologies namely, Bagging or Boosting and have fine-tuning parameter which takes care of the imbalanced class.

9.1 Random Forest Classifier

[48]:
```
rfc_model = RandomForestClassifier(n_estimators=400,random_state=11)
rfc_model.fit(x_train,y_train)
ypred = rfc_model.predict(x_val)
print ("\nAccuracy on validation set: {:.4f}".format(accuracy_score(y_val,␣
 ↪ypred)))
print("\nClassification report : \n", classification_report(y_val, ypred))
print("\nConfusion Matrix : \n", confusion_matrix(y_val, ypred))

print("\nTrain Data Score : ",rfc_model.score(x_train,y_train))
print("\nTest Data Score : ",rfc_model.score(x_val,y_val))
```

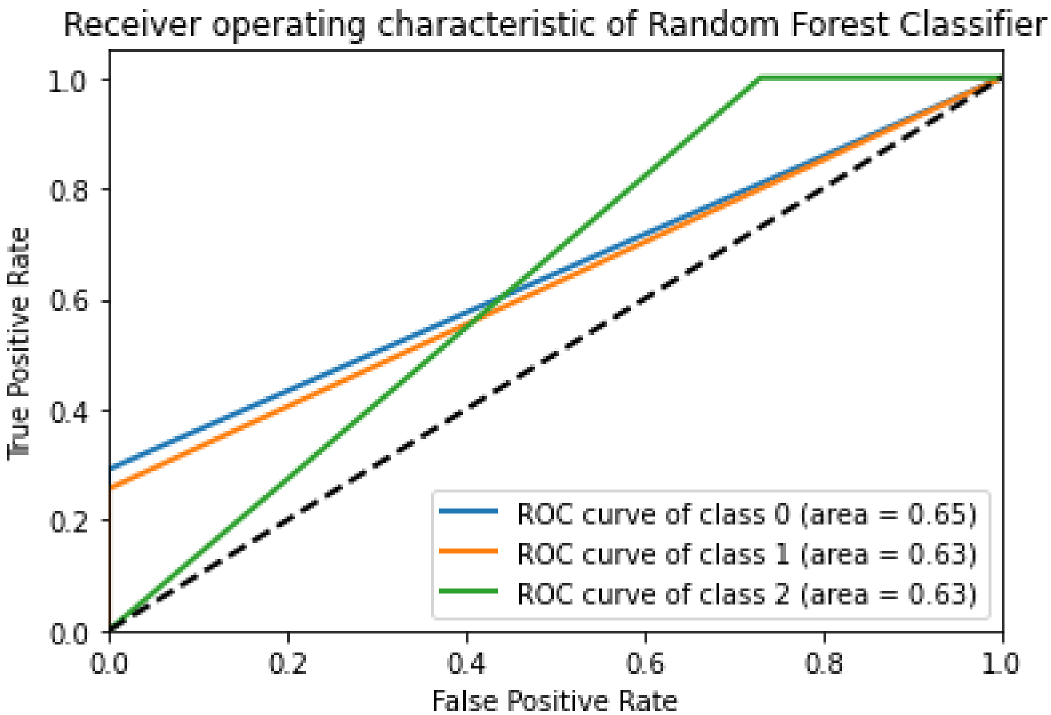
```
Accuracy on validation set: 0.9540

Classification report :
               precision    recall  f1-score   support
```

```
           0       1.00      0.29      0.45        24
           1       1.00      0.26      0.41        39
           2       0.95      1.00      0.98       937

    accuracy                           0.95      1000
   macro avg       0.98      0.52      0.61      1000
weighted avg       0.96      0.95      0.94      1000


Confusion Matrix :
 [[  7   0  17]
 [  0  10  29]
 [  0   0 937]]

Train Data Score :  1.0

Test Data Score :  0.954
```

[49]:

```
lb = LabelBinarizer()
lb.fit(y_val)
y_val1 = lb.transform(y_val)
y_pred1 = lb.transform(ypred)
print(roc_auc_score(y_val1, y_pred1, average='weighted'))
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(3):
    fpr[i], tpr[i], _ = roc_curve(y_val1[:, i], y_pred1[:, 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], 'k--', lw=lw)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic of Random Forest Classifier')
plt.legend(loc="lower right")
plt.show()
```

```
0.6349206349206349
```



9.2 XGB Classifier

[50]:
```
xgb_model = XGBClassifier(n_estimators=1000,max_depth=6)
xgb_model.fit(x_train,y_train)
ypred = xgb_model.predict(x_val)
print ("\nAccuracy on validation set: {:.4f}".format(accuracy_score(y_val,␣
 ↪ypred)))
print("\nClassification report : \n", classification_report(y_val, ypred))
print("\nConfusion Matrix : \n", confusion_matrix(y_val, ypred))

print("\nTrain Data Score : ",xgb_model.score(x_train,y_train))
print("\nTest Data Score : ",xgb_model.score(x_val,y_val))
```

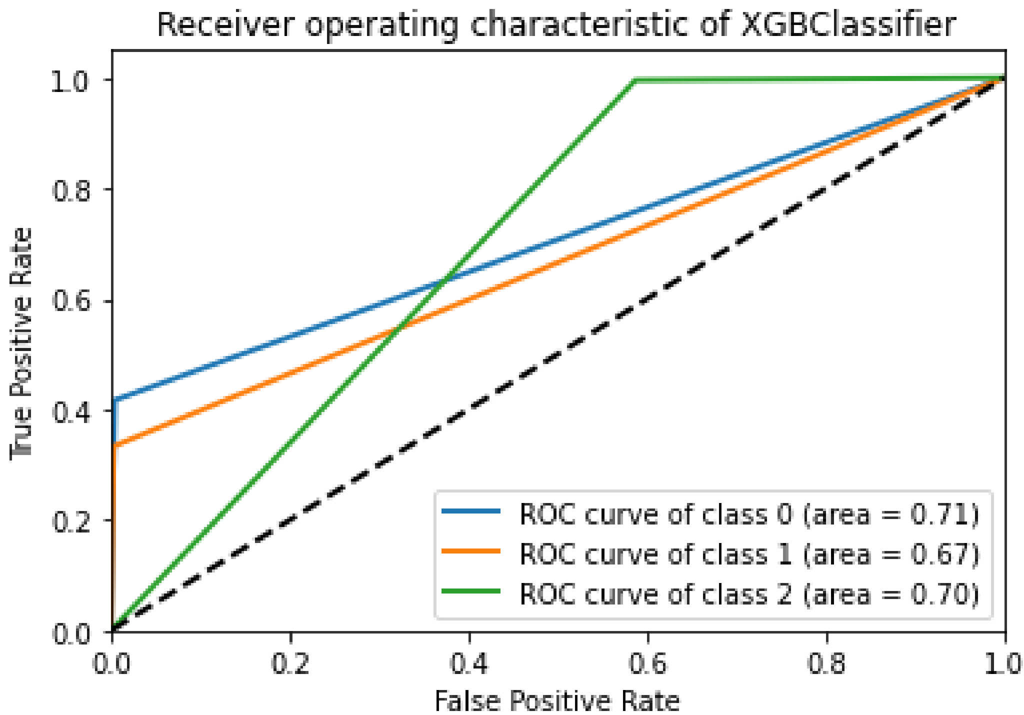
```
Accuracy on validation set: 0.9560

Classification report :
               precision    recall  f1-score   support

           0       0.71      0.42      0.53        24
           1       0.81      0.33      0.47        39
           2       0.96      1.00      0.98       937

    accuracy                           0.96      1000
```

```
   macro avg       0.83      0.58      0.66      1000
weighted avg       0.95      0.96      0.95      1000


Confusion Matrix :
 [[ 10   1  13]
 [  2  13  24]
 [  2   2 933]]

Train Data Score :  1.0

Test Data Score :  0.956
```

[51]:

```
lb = LabelBinarizer()
lb.fit(y_val)
y_val1 = lb.transform(y_val)
y_pred1 = lb.transform(ypred)
print(roc_auc_score(y_val1, y_pred1, average='weighted'))
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(3):
    fpr[i], tpr[i], _ = roc_curve(y_val1[:, i], y_pred1[:, 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], 'k--', lw=lw)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic of XGBClassifier')
plt.legend(loc="lower right")
plt.show()
```

```
0.7027391519318474
```



- We can see that XGBoost is performing better in predicting all the classes.

10 Project Task: Week 2

11 Model Selection:

1. Apply multi-class SVM's and neural nets.
2. Use possible ensemble techniques like: XGboost + oversampled_multinomial_NB.
3. Assign a score to the sentence sentiment (engineer a feature called sentiment score). Use this engineered feature in the model and check for improvements. Draw insights on the same.

12 1. Apply multi-class SVM's and neural nets.

12.1 Support Vector Machine

[52]:
```
svm_linear = SVC(kernel='linear',class_weight='balanced',random_state=11).
 ↪fit(x_train,y_train)
svm_poly = SVC(kernel='poly',class_weight='balanced',random_state=11).
 ↪fit(x_train,y_train)
svm_rbf = SVC(kernel='rbf',class_weight='balanced',random_state=11).
 ↪fit(x_train,y_train)
```

```
svm_sigmoid = SVC(kernel='sigmoid',class_weight='balanced',random_state=11).
 ↪fit(x_train,y_train)
```

[53]:
```
linear_pred = svm_linear.predict(x_val)
poly_pred = svm_poly.predict(x_val)
rbf_pred = svm_rbf.predict(x_val)
sigmoid_pred = svm_sigmoid.predict(x_val)
```

[54]:
```
print('Linear Kernel :-')
print ("\nAccuracy on validation set: {:.4f}".format(accuracy_score(y_val,␣
 ↪linear_pred)))
print("\nClassification report : \n", classification_report(y_val, linear_pred))
print("\nConfusion Matrix : \n", confusion_matrix(y_val, linear_pred))
print("\nTrain Data Score : ",svm_linear.score(x_train,y_train))
print("\nTest Data Score : ",svm_linear.score(x_val,y_val))

print('\nPolynomial Kernel :-')
print ("\nAccuracy on validation set: {:.4f}".format(accuracy_score(y_val,␣
 ↪ypred)))
print("\nClassification report : \n", classification_report(y_val, ypred))
print("\nConfusion Matrix : \n", confusion_matrix(y_val, ypred))
print("\nTrain Data Score : ",svm_poly.score(x_train,y_train))
print("\nTest Data Score : ",svm_poly.score(x_val,y_val))

print('\nrbf Kernel :-')
print ("\nAccuracy on validation set: {:.4f}".format(accuracy_score(y_val,␣
 ↪ypred)))
print("\nClassification report : \n", classification_report(y_val, ypred))
print("\nConfusion Matrix : \n", confusion_matrix(y_val, ypred))
print("\nTrain Data Score : ",svm_rbf.score(x_train,y_train))
print("\nTest Data Score : ",svm_rbf.score(x_val,y_val))

print('\nSigmoid Kernel :-')
print ("\nAccuracy on validation set: {:.4f}".format(accuracy_score(y_val,␣
 ↪ypred)))
print("\nClassification report : \n", classification_report(y_val, ypred))
print("\nConfusion Matrix : \n", confusion_matrix(y_val, ypred))
print("\nTrain Data Score : ",svm_sigmoid.score(x_train,y_train))
print("\nTest Data Score : ",svm_sigmoid.score(x_val,y_val))
```

```
Linear Kernel :-

Accuracy on validation set: 0.8860

Classification report :
               precision    recall  f1-score   support
```

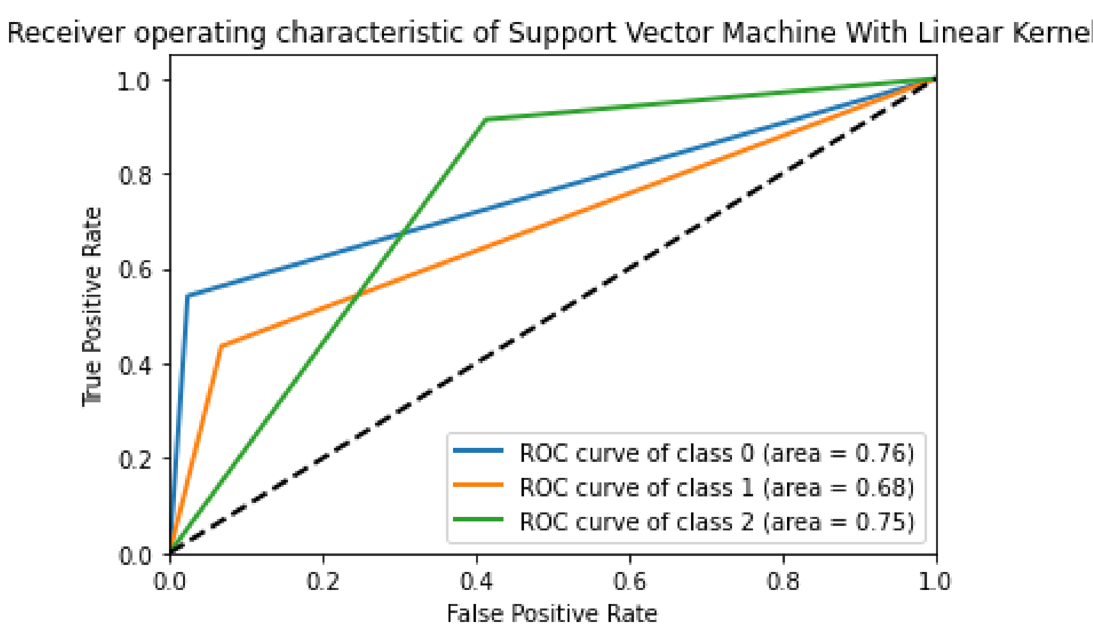
```
           0       0.36      0.54      0.43        24
           1       0.21      0.44      0.28        39
           2       0.97      0.91      0.94       937

    accuracy                           0.89      1000
   macro avg       0.51      0.63      0.55      1000
weighted avg       0.93      0.89      0.90      1000


Confusion Matrix :
 [[ 13   3   8]
 [  4  17  18]
 [ 19  62 856]]

Train Data Score :  0.8948745713770078

Test Data Score :  0.886

Polynomial Kernel :-

Accuracy on validation set: 0.9560

Classification report :
               precision    recall  f1-score   support

           0       0.71      0.42      0.53        24
           1       0.81      0.33      0.47        39
           2       0.96      1.00      0.98       937

    accuracy                           0.96      1000
   macro avg       0.83      0.58      0.66      1000
weighted avg       0.95      0.96      0.95      1000


Confusion Matrix :
 [[ 10   1  13]
 [  2  13  24]
 [  2   2 933]]

Train Data Score :  0.3767370510738134

Test Data Score :  0.459

rbf Kernel :-

Accuracy on validation set: 0.9560

Classification report :
```

```
              precision    recall  f1-score   support

           0       0.71      0.42      0.53        24
           1       0.81      0.33      0.47        39
           2       0.96      1.00      0.98       937

    accuracy                           0.96      1000
   macro avg       0.83      0.58      0.66      1000
weighted avg       0.95      0.96      0.95      1000


Confusion Matrix :
 [[ 10   1  13]
 [  2  13  24]
 [  2   2 933]]

Train Data Score :  0.38043674426998736

Test Data Score :  0.458

Sigmoid Kernel :-

Accuracy on validation set: 0.9560

Classification report :
              precision    recall  f1-score   support

           0       0.71      0.42      0.53        24
           1       0.81      0.33      0.47        39
           2       0.96      1.00      0.98       937

    accuracy                           0.96      1000
   macro avg       0.83      0.58      0.66      1000
weighted avg       0.95      0.96      0.95      1000


Confusion Matrix :
 [[ 10   1  13]
 [  2  13  24]
 [  2   2 933]]

Train Data Score :  0.3778198881068399

Test Data Score :  0.457
```

[55]:
```
lb = LabelBinarizer()
lb.fit(y_val)
```

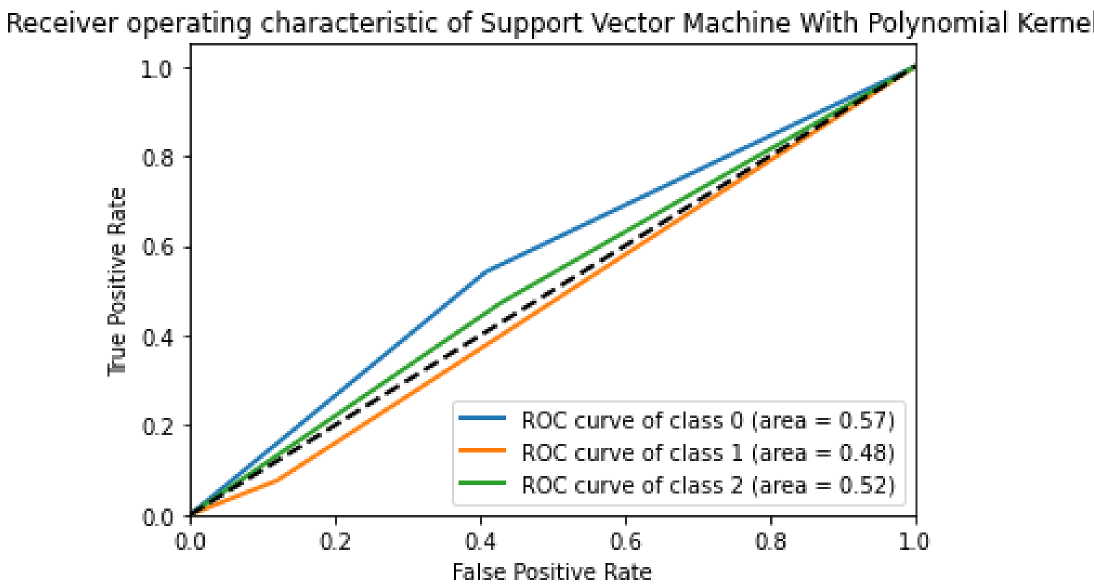
```
y_val1 = lb.transform(y_val)
y_pred1 = lb.transform(linear_pred)
print(roc_auc_score(y_val1, y_pred1, average='weighted'))
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(3):
    fpr[i], tpr[i], _ = roc_curve(y_val1[:, i], y_pred1[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

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], 'k--', lw=lw)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic of Support Vector Machine With␣
 ↪Linear Kernel')
plt.legend(loc="lower right")
plt.show()
```

0.7480490681599286



[56]:
```
lb = LabelBinarizer()
lb.fit(y_val)
y_val1 = lb.transform(y_val)
y_pred1 = lb.transform(poly_pred)
print(roc_auc_score(y_val1, y_pred1, average='weighted'))
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(3):
    fpr[i], tpr[i], _ = roc_curve(y_val1[:, i], y_pred1[:, 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], 'k--', lw=lw)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic of Support Vector Machine With␣
 ↪Polynomial Kernel')
plt.legend(loc="lower right")
plt.show()
```

```
0.5214670449643838
```



12.2 Neural Network

[57]:
```
# Simple Neural Network

model = Sequential()
model.add(Dense(units=100,activation='relu',input_dim=x_train1.shape[1]))
model.add(Dense(units=80,activation='relu'))
model.add(Dense(units=80,activation='relu'))
model.add(Dense(units=3,activation='softmax'))

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

ytrain_2 = label_binarize(y_train1, classes=[0, 1, 2])

model.fit(x_train1,ytrain_2,batch_size=512,epochs=10,verbose=1)

# Model Evaluation
ytest_2 = label_binarize(y_val1, classes=[0, 1, 2])
score = model.evaluate(x_val1,ytest_2, batch_size=512)
print('Test loss : {:.4f}'.format(score[0]))
print('Test accuracy : {:.4f}'.format(score[1]))
```

```
Epoch 1/10
8/8 [==============================] - 17s 104ms/step - loss: 6.4703 - accuracy:
0.5857
```

```
Epoch 2/10
8/8 [==============================] - 1s 132ms/step - loss: 1.0113 - accuracy:
0.9371
Epoch 3/10
8/8 [==============================] - 1s 67ms/step - loss: 0.4671 - accuracy:
0.9371
Epoch 4/10
8/8 [==============================] - 1s 65ms/step - loss: 0.3122 - accuracy:
0.9371
Epoch 5/10
8/8 [==============================] - 1s 74ms/step - loss: 0.3016 - accuracy:
0.9371
Epoch 6/10
8/8 [==============================] - 1s 64ms/step - loss: 0.2873 - accuracy:
0.9371
Epoch 7/10
8/8 [==============================] - 1s 66ms/step - loss: 0.2762 - accuracy:
0.9371
Epoch 8/10
8/8 [==============================] - 1s 68ms/step - loss: 0.2803 - accuracy:
0.9371
Epoch 9/10
8/8 [==============================] - 1s 66ms/step - loss: 0.2765 - accuracy:
0.9371
Epoch 10/10
8/8 [==============================] - 1s 62ms/step - loss: 0.2750 - accuracy:
0.9371
2/2 [==============================] - 1s 34ms/step - loss: 0.2777 - accuracy:
0.9370
Test loss : 0.2777
Test accuracy : 0.9370
```

[58]:
```
#using dropouts

model = Sequential()
model.add(Dense(units=50,activation='relu',input_dim=x_train1.shape[1]))
model.add(Dropout(0.2))
model.add(Dense(units=40,activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(units=40,activation='relu'))
model.add(Dense(units=3,kernel_initializer='normal',activation='softmax'))

model.
 ↪compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])

ytrain_2 = label_binarize(y_train1, classes=[0, 1, 2])
```

```
model.fit(x_train1,ytrain_2,batch_size=256,epochs=10,verbose=1)

# Model Evaluation
ytest_2 = label_binarize(y_val1, classes=[0, 1, 2])
score = model.evaluate(x_val1,ytest_2, batch_size=512)
print('Test loss : {:.4f}'.format(score[0]))
print('Test accuracy : {:.4f}'.format(score[1]))
```

```
Epoch 1/10
16/16 [==============================] - 5s 49ms/step - loss: 0.4780 - accuracy:
0.9069
Epoch 2/10
16/16 [==============================] - 0s 27ms/step - loss: 0.3241 - accuracy:
0.9353
Epoch 3/10
16/16 [==============================] - 0s 26ms/step - loss: 0.3016 - accuracy:
0.9363
Epoch 4/10
16/16 [==============================] - 0s 27ms/step - loss: 0.2963 - accuracy:
0.9371
Epoch 5/10
16/16 [==============================] - 0s 26ms/step - loss: 0.2901 - accuracy:
0.9371
Epoch 6/10
16/16 [==============================] - 0s 28ms/step - loss: 0.2940 - accuracy:
0.9371
Epoch 7/10
16/16 [==============================] - 0s 27ms/step - loss: 0.2920 - accuracy:
0.9371
Epoch 8/10
16/16 [==============================] - 0s 27ms/step - loss: 0.2889 - accuracy:
0.9371
Epoch 9/10
16/16 [==============================] - 1s 32ms/step - loss: 0.2874 - accuracy:
0.9371
Epoch 10/10
16/16 [==============================] - 0s 31ms/step - loss: 0.2853 - accuracy:
0.9371
2/2 [==============================] - 1s 91ms/step - loss: 0.2978 - accuracy:
0.9370
Test loss : 0.2978
Test accuracy : 0.9370
```

[59]:
```
# for over-sampled data

model = Sequential()
model.add(Dense(units=50,activation='relu',input_dim=x_train.shape[1]))
```

```python
model.add(Dense(units=150,activation='relu'))
model.add(Dense(units=40,activation='relu'))
model.add(Dense(units=3,kernel_initializer='normal',activation='softmax'))

model.
 ↪compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])

ytrain_2 = label_binarize(y_train, classes=[0, 1, 2])

model.fit(x_train,ytrain_2,batch_size=512,epochs=20,verbose=1)

# Model Evaluation
ytest_2 = label_binarize(y_val, classes=[0, 1, 2])
score = model.evaluate(x_val,ytest_2, batch_size=512)
print('Test loss : {:.4f}'.format(score[0]))
print('Test accuracy : {:.4f}'.format(score[1]))
```

```
Epoch 1/20
22/22 [==============================] - 4s 58ms/step - loss: 1.2503 - accuracy:
0.3512
Epoch 2/20
22/22 [==============================] - 1s 49ms/step - loss: 1.0960 - accuracy:
0.3688
Epoch 3/20
22/22 [==============================] - 1s 43ms/step - loss: 1.0835 - accuracy:
0.3805
Epoch 4/20
22/22 [==============================] - 1s 43ms/step - loss: 1.0677 - accuracy:
0.5337
Epoch 5/20
22/22 [==============================] - 1s 48ms/step - loss: 1.0581 - accuracy:
0.5017
Epoch 6/20
22/22 [==============================] - 1s 46ms/step - loss: 1.0410 - accuracy:
0.5191
Epoch 7/20
22/22 [==============================] - 1s 44ms/step - loss: 1.0211 - accuracy:
0.5162
Epoch 8/20
22/22 [==============================] - 1s 44ms/step - loss: 1.0024 - accuracy:
0.5112
Epoch 9/20
22/22 [==============================] - 1s 44ms/step - loss: 0.9553 - accuracy:
0.7060
Epoch 10/20
22/22 [==============================] - 1s 46ms/step - loss: 0.9147 - accuracy:
0.6742
```

```
Epoch 11/20
22/22 [==============================] - 1s 45ms/step - loss: 0.8649 - accuracy:
0.6619
Epoch 12/20
22/22 [==============================] - 1s 45ms/step - loss: 0.7595 - accuracy:
0.8066
Epoch 13/20
22/22 [==============================] - 1s 48ms/step - loss: 0.6640 - accuracy:
0.8431
Epoch 14/20
22/22 [==============================] - 1s 49ms/step - loss: 0.5577 - accuracy:
0.8558
Epoch 15/20
22/22 [==============================] - 1s 50ms/step - loss: 0.4534 - accuracy:
0.9158
Epoch 16/20
22/22 [==============================] - 1s 49ms/step - loss: 0.3700 - accuracy:
0.9433
Epoch 17/20
22/22 [==============================] - 1s 45ms/step - loss: 0.3137 - accuracy:
0.9459
Epoch 18/20
22/22 [==============================] - 1s 47ms/step - loss: 0.2386 - accuracy:
0.9749
Epoch 19/20
22/22 [==============================] - 1s 48ms/step - loss: 0.2177 - accuracy:
0.9613
Epoch 20/20
22/22 [==============================] - 1s 49ms/step - loss: 0.1744 - accuracy:
0.9723
2/2 [==============================] - 1s 72ms/step - loss: 0.3287 - accuracy:
0.8990
Test loss : 0.3287
Test accuracy : 0.8990
```

- Using drop out chances of predicting second class increases
- Using Over-sampled data for neural network does not improve the performance

13 2. Use possible ensemble techniques like: XGboost + over-sampled_multinomial_NB.

[60]:
```
model1 = MultinomialNB()
model2 =  XGBClassifier(n_estimators=1000,max_depth=6)

model = VotingClassifier(estimators=[('lr', model1), ('dt', model2)],␣
 ↪voting='hard')
```

```python
model.fit(x_train,y_train)

y_pred = model.predict(x_val)
print(confusion_matrix(y_true=y_val, y_pred=y_pred))
print(classification_report(y_true=y_val, y_pred=y_pred))
print("accuracy : ",accuracy_score(y_val, y_pred)*100)
```

```
[[ 14   2   8]
 [  4  16  19]
 [ 16  74 847]]
              precision    recall  f1-score   support

           0       0.41      0.58      0.48        24
           1       0.17      0.41      0.24        39
           2       0.97      0.90      0.94       937

    accuracy                           0.88      1000
   macro avg       0.52      0.63      0.55      1000
weighted avg       0.92      0.88      0.90      1000

accuracy :  87.7
```

- We can see that the above model performance is same as oversampled multinominal model but it increases the chances of prediction of minority class.

14 3. Assign a score to the sentence sentiment (engineer a feature called sentiment score). Use this engineered feature in the model and check for improvements. Draw insights on the same.

[61]:
```python
train['sentiment_score'] = train['reviews.text'].apply(lambda x: TextBlob(x).
 ↪sentiment)
test_hidden['sentiment_score'] = test_hidden['reviews.text'].apply(lambda x:␣
 ↪TextBlob(x).sentiment)

train['polarity'] = train['reviews.text'].apply(lambda x: TextBlob(x).
 ↪polarity+1)
test_hidden['polarity'] = test_hidden['reviews.text'].apply(lambda x:␣
 ↪TextBlob(x).polarity+1)

train.sentiment_score.head()
```

[61]:
```
0     (0.37479166666666663, 0.6791666666666667)
1    (0.45821428571428574, 0.49821428571428567)
2                   (0.69, 0.6033333333333335)
3                             (0.1875, 0.4375)
4                    (0.6000000000000001, 0.725)
```

```
Name: sentiment_score, dtype: object
```

[62]:
```
Train = pd.concat([train.drop(['reviews.text','reviews.
 ↪title','sentiment','sentiment_score'],axis=1),
                    tvec_text1, tvec_title1],axis=1)
Test_Val = pd.concat([test_hidden.drop(['reviews.text','reviews.
 ↪title','sentiment','sentiment_score'],axis=1),
                    tvec_text2, tvec_title2],axis=1)
x_train = Train.values
y_train = train['sentiment']
x_val = Test_Val.values
y_val = test_hidden['sentiment']
```

[63]:
```
mnb_model = MultinomialNB()
mnb_model.fit(x_train,y_train)

ypred = mnb_model.predict(x_val)

print ("\nAccuracy on validation set: {:.4f}".format(accuracy_score(y_val,␣
 ↪ypred)))
print("\nClassification report : \n", classification_report(y_val, ypred))
print("\nConfusion Matrix : \n", confusion_matrix(y_val, ypred))
print("\nTrain Data Score : ",mnb_model.score(x_train,y_train))
print("\nTest Data Score : ",mnb_model.score(x_val,y_val))
```

```
Accuracy on validation set: 0.8770

Classification report :
               precision    recall  f1-score   support

           0       0.45      0.54      0.49        24
           1       0.15      0.36      0.22        39
           2       0.97      0.91      0.94       937

    accuracy                           0.88      1000
   macro avg       0.52      0.60      0.55      1000
weighted avg       0.92      0.88      0.90      1000


Confusion Matrix :
 [[ 13   3   8]
 [  3  14  22]
 [ 13  74 850]]

Train Data Score :  0.9591229020032485
```

```
Test Data Score :  0.877
```

- Sentiment score does not affect on the performance.

15 Applying LSTM:

4. Use LSTM for the previous problem (use parameters of LSTM like top-word, embedding-length, Dropout, epochs, number of layers, etc.)
5. Compare the accuracy of neural nets with traditional ML based algorithms.
6. Find the best setting of LSTM (Neural Net) and GRU that can best classify the reviews as positive, negative, and neutral.

16 4. Use LSTM for the previous problem (use parameters of LSTM like top-word, embedding-length, Dropout, epochs, number of layers, etc.)

17 LSTM

- Long Short Term Memory(LSTM) Networks are a special kind of the Recurrent Neural Networks(RNN) capable of learning long-term dependencies. LSTM can be very useful in text mining problems as it involves dependencies in the sentences which can be caught in the "memory" of the LSTM.

[64]:
```
# max_features = 5000
maxlen = 80
epochs = 3
batch_size = 512

y_train2 = label_binarize(y_train1, classes=[0, 1, 2])

Xtrain = pad_sequences(x_train1, maxlen=maxlen)
Xtest = pad_sequences(x_val1, maxlen=maxlen)

model = Sequential()
model.add(Embedding(Xtrain.shape[1],128,input_length=Xtrain.shape[1]))
model.add(SpatialDropout1D(0.7))
model.add(LSTM(128))
model.add(Dense(3, activation='softmax'))
model.compile(optimizer='adam', loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])
model.summary()

model.fit(Xtrain, y_train2, epochs=epochs, batch_size=batch_size,verbose=1)

ytest_2 = label_binarize(y_val1, classes=[0, 1, 2])
score = model.evaluate(Xtest,ytest_2, batch_size=512)
```

```
print('Test loss : {:.4f}'.format(score[0]))
print('Test accuracy : {:.4f}'.format(score[1]))
```

```
Model: "sequential_3"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 80, 128)           10240

 spatial_dropout1d (SpatialD  (None, 80, 128)          0
 ropout1D)

 lstm (LSTM)                 (None, 128)               131584

 dense_12 (Dense)            (None, 3)                 387

=================================================================
Total params: 142,211
Trainable params: 142,211
Non-trainable params: 0
_________________________________________________________________
Epoch 1/3
8/8 [==============================] - 34s 2s/step - loss: 0.8840 - accuracy:
0.7737
Epoch 2/3
8/8 [==============================] - 16s 2s/step - loss: 0.3125 - accuracy:
0.9371
Epoch 3/3
8/8 [==============================] - 16s 2s/step - loss: 0.2797 - accuracy:
0.9371
2/2 [==============================] - 3s 725ms/step - loss: 0.2859 - accuracy:
0.9370
Test loss : 0.2859
Test accuracy : 0.9370
```

[65]:

```
#for over_sampled data

y_train2 = label_binarize(y_train, classes=[0, 1, 2])

Xtrain_1 = pad_sequences(x_train, maxlen=maxlen)
Xtest_1 = pad_sequences(x_val, maxlen=maxlen)

emb_dim = 128
epochs = 3
batch_size = 256
model = Sequential()
model.add(Embedding(Xtrain_1.shape[1],128,input_length=Xtrain_1.shape[1]))
```

```
model.add(SpatialDropout1D(0.7))
model.add(LSTM(64, dropout=0.7, recurrent_dropout=0.7))
model.add(Dense(3, activation='softmax'))
model.compile(optimizer='adam', loss='categorical_crossentropy',␣
 ↪metrics=['acc'])
model.fit(Xtrain_1, y_train2, epochs=epochs, batch_size=batch_size,verbose=1)

ytest_2 = label_binarize(y_val, classes=[0, 1, 2])
score = model.evaluate(Xtest_1,ytest_2, batch_size=512)
print('Test loss : {:.4f}'.format(score[0]))
print('Test accuracy : {:.4f}'.format(score[1]))
```

```
Epoch 1/3
44/44 [==============================] - 47s 867ms/step - loss: 1.1001 - acc:
0.3352
Epoch 2/3
44/44 [==============================] - 37s 841ms/step - loss: 1.0999 - acc:
0.3262
Epoch 3/3
44/44 [==============================] - 37s 835ms/step - loss: 1.1000 - acc:
0.3284
WARNING:tensorflow:5 out of the last 9 calls to <function
Model.make_test_function.<locals>.test_function at 0x0000019319163B80> triggered
tf.function retracing. Tracing is expensive and the excessive number of tracings
could be due to (1) creating @tf.function repeatedly in a loop, (2) passing
tensors with different shapes, (3) passing Python objects instead of tensors.
For (1), please define your @tf.function outside of the loop. For (2),
@tf.function has reduce_retracing=True option that can avoid unnecessary
retracing. For (3), please refer to
https://www.tensorflow.org/guide/function#controlling_retracing and
https://www.tensorflow.org/api_docs/python/tf/function for  more details.
2/2 [==============================] - 2s 284ms/step - loss: 1.0946 - acc:
0.9370
Test loss : 1.0946
Test accuracy : 0.9370
```

18 6.Find the best setting of LSTM (Neural Net) and GRU that can best classify the reviews as positive, negative, and neutral.

18.1 GRU

[66]:
```
y_train2 = label_binarize(y_train1, classes=[0, 1, 2])
epochs = 3
emb_dim = 128
batch_size = 256
model = Sequential()
model.add(Embedding(Xtrain.shape[1], emb_dim, input_length=Xtrain.shape[1]))
```

```
model.add(SpatialDropout1D(0.7))
model.add(GRU(64, dropout=0.3, recurrent_dropout=0.3))
model.add(Dense(3, activation='softmax'))

model.compile(optimizer='adam', loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])

model.fit(Xtrain, y_train2, epochs=epochs, batch_size=batch_size,verbose=1)

ytest_2 = label_binarize(y_val1, classes=[0, 1, 2])
score = model.evaluate(Xtest,ytest_2, batch_size=512)
print('Test loss : {:.4f}'.format(score[0]))
print('Test accuracy : {:.4f}'.format(score[1]))
```

```
Epoch 1/3
16/16 [==============================] - 17s 679ms/step - loss: 0.7347 -
accuracy: 0.8932
Epoch 2/3
16/16 [==============================] - 11s 663ms/step - loss: 0.3157 -
accuracy: 0.9371
Epoch 3/3
16/16 [==============================] - 10s 648ms/step - loss: 0.2813 -
accuracy: 0.9371
WARNING:tensorflow:6 out of the last 11 calls to <function
Model.make_test_function.<locals>.test_function at 0x000001931BB98AF0> triggered
tf.function retracing. Tracing is expensive and the excessive number of tracings
could be due to (1) creating @tf.function repeatedly in a loop, (2) passing
tensors with different shapes, (3) passing Python objects instead of tensors.
For (1), please define your @tf.function outside of the loop. For (2),
@tf.function has reduce_retracing=True option that can avoid unnecessary
retracing. For (3), please refer to
https://www.tensorflow.org/guide/function#controlling_retracing and
https://www.tensorflow.org/api_docs/python/tf/function for  more details.
2/2 [==============================] - 44s 277ms/step - loss: 0.2787 - accuracy:
0.9370
Test loss : 0.2787
Test accuracy : 0.9370
```

- We can see from above that LSTM and GRU models are not efficient in predicting minor classes.ANN is performing quite good in solving class imbalance problem but it cannot beat traditional ML agorithms.

19 Topic Modeling:

7. Cluster similar reviews.

- Note: Some reviews may talk about the device as a gift-option. Other reviews may be about product looks and some may highlight about its battery and performance. Try naming the clusters.

8. Perform Topic Modeling

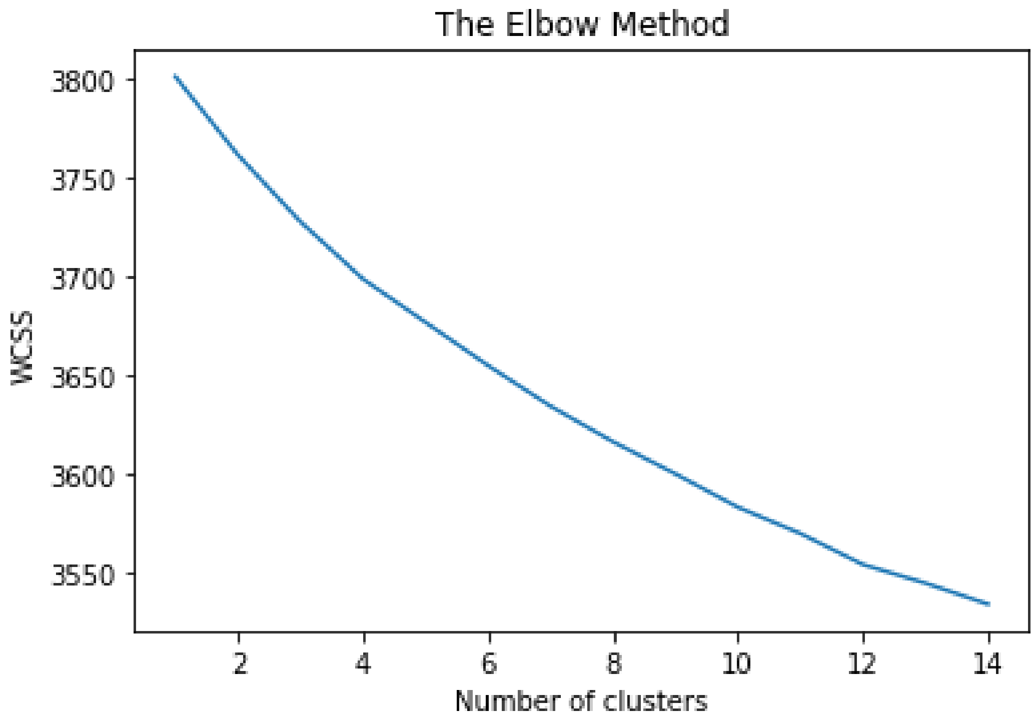
20 7. Cluster similar reviews.

- Note: Some reviews may talk about the device as a gift-option. Other reviews may be about product looks and some may highlight about its battery and performance. Try naming the clusters.

[67]:
```
print(words[200:300])
```

```
['continu', 'control', 'conveni', 'cook', 'cool', 'cord', 'cost', 'could',
'counter', 'countri', 'coupl', 'cours', 'cover', 'crack', 'crazi', 'creat',
'credit', 'crisp', 'current', 'curv', 'custom', 'daili', 'damag', 'dark',
'data', 'date', 'daughter', 'day', 'deal', 'decent', 'decid', 'defect',
'definit', 'deliv', 'descript', 'design', 'desk', 'despit', 'develop', 'devic',
'didnt', 'die', 'differ', 'difficult', 'digit', 'direct', 'disabl',
'disappoint', 'discov', 'display', 'distract', 'doe', 'dollar', 'done', 'dont',
'door', 'doorbel', 'dot', 'downfal', 'download', 'downsid', 'drain', 'drawback',
'drive', 'drop', 'durabl', 'dure', 'earli', 'earlier', 'eas', 'easi', 'easier',
'easili', 'ebook', 'echo', 'edit', 'educ', 'effect', 'effici', 'either',
'electron', 'els', 'email', 'employe', 'enabl', 'end', 'enjoy', 'enlarg',
'enough', 'entertain', 'entir', 'entri', 'equip', 'eread', 'especi', 'even',
'event', 'ever', 'everi', 'everyday']
```

[68]:
```
wcss = []
for i in range(1,15):
    kmeans =␣
↪KMeans(n_clusters=i,init='k-means++',max_iter=300,n_init=10,random_state=11)
    kmeans.fit(reviews)
    wcss.append(kmeans.inertia_)
plt.plot(range(1,15),wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



- As no proper elbow is generated, I will select the right amount of clusters by trial and error. So, I will showcase the results of different amount of clusters to find out the right amount of clusters.

21 8. Perform Topic Modeling

[41]:
```
def cleanText(raw_text, remove_stopwords=False, stemming=False,␣
↪split_text=False, \
             ):
    '''
    Convert a raw review to a cleaned review
    '''
    text = BeautifulSoup(raw_text, 'lxml').get_text()  #remove html
    letters_only = re.sub("[^a-zA-Z]", " ", text)  # remove non-character
    words = letters_only.lower().split() # convert to lower case

    if remove_stopwords: # remove stopword
        stops = set(stopwords.words("english"))
        words = [w for w in words if not w in stops]

    if stemming==True: # stemming
#         stemmer = PorterStemmer()
        stemmer = SnowballStemmer('english')
```

```
        words = [stemmer.stem(w) for w in words]

    if split_text==True:  # split text
        return (words)

    return( " ".join(words))
```

[42]:
```
doc_complete = train["reviews.text"].tolist()
doc_clean = [cleanText(doc).split() for doc in doc_complete]

dictionary = corpora.Dictionary(doc_clean)
print(dictionary)

doc_term_matrix = [dictionary.doc2bow(doc) for doc in doc_clean]
```

```
Dictionary<3974 unique tokens: ['able', 'access', 'accomplish', 'add',
'amazing']…>
```

[43]:
```
NUM_TOPICS = 11
ldamodel = LdaModel(doc_term_matrix, num_topics=NUM_TOPICS, id2word=dictionary,␣
 ↪passes=30)
```

[44]:
```
topics = ldamodel.show_topics()
for topic in topics:
    print(topic)
    print()
```

```
(4, '0.044*"show" + 0.042*"slow" + 0.032*"when" + 0.027*"returned" +
0.026*"work" + 0.025*"could" + 0.024*"plugged" + 0.023*"cloudcam" + 0.022*"very"
+ 0.022*"than"')

(0, '0.042*"echo" + 0.023*"alexa" + 0.019*"show" + 0.016*"that" + 0.016*"have" +
0.015*"screen" + 0.014*"more" + 0.014*"music" + 0.014*"like" + 0.013*"thing"')

(2, '0.070*"tablet" + 0.052*"this" + 0.039*"great" + 0.031*"kid" + 0.031*"love"
+ 0.030*"good" + 0.027*"price" + 0.024*"that" + 0.023*"bought" + 0.022*"with"')

(1, '0.029*"this" + 0.021*"bought" + 0.017*"time" + 0.017*"they" + 0.016*"ipad"
+ 0.016*"charger" + 0.016*"will" + 0.015*"that" + 0.015*"charge" +
0.014*"problem"')

(10, '0.025*"this" + 0.023*"would" + 0.020*"with" + 0.020*"device" +
0.019*"good" + 0.019*"kindle" + 0.019*"which" + 0.018*"reading" +
0.014*"battery" + 0.014*"have"')

(5, '0.041*"that" + 0.029*"with" + 0.029*"this" + 0.022*"tablet" +
0.022*"amazon" + 0.021*"about" + 0.020*"like" + 0.019*"have" + 0.017*"when" +
```

```
0.015*"game"')

(9, '0.040*"model" + 0.037*"last" + 0.032*"they" + 0.031*"kindle" + 0.031*"have"
+ 0.027*"better" + 0.025*"year" + 0.024*"quality" + 0.023*"speaker" +
0.020*"same"')

(7, '0.062*"work" + 0.045*"good" + 0.032*"with" + 0.030*"price" + 0.028*"tablet"
+ 0.028*"many" + 0.024*"camera" + 0.024*"amazon" + 0.022*"well" + 0.022*"this"')

(3, '0.059*"this" + 0.024*"tablet" + 0.023*"amazon" + 0.020*"week" +
0.018*"account" + 0.018*"apps" + 0.017*"junk" + 0.017*"google" + 0.016*"have" +
0.014*"bought"')

(8, '0.031*"this" + 0.028*"le" + 0.024*"useless" + 0.024*"work" + 0.023*"apps" +
0.023*"than" + 0.022*"have" + 0.021*"with" + 0.017*"more" + 0.016*"that"')
```

[45]:
```
word_dict = {}
for i in range(NUM_TOPICS):
    words = ldamodel.show_topic(i, topn = 20)
    word_dict["Topic # " + "{}".format(i)] = [i[0] for i in words]
```

[46]:
```
pd.DataFrame(word_dict)
```

[46]:
```
   Topic # 0 Topic # 1  Topic # 2 Topic # 3 Topic # 4   Topic # 5 Topic # 6  \
0       echo      this     tablet      this      show        that      this
1      alexa    bought       this    tablet      slow        with      very
2       show      time      great    amazon      when        this      what
3       that      they        kid      week  returned      tablet    kindle
4       have      ipad       love   account      work      amazon      with
5     screen   charger       good      apps     could       about     happy
6       more      will      price      junk   plugged        like      fire
7      music      that       that    google  cloudcam        have    tablet
8       like    charge     bought      have      very        when  friendly
9      thing   problem       with    bought      than        game      user
10      read     first       they      play   product     nothing    bought
11       doe      than  christmas      more       doe        code      have
12     light     issue       gift      work      from        ipad     would
13    having      some      child      just  actually        from   looking
14     video   product      movie     could      with        then   program
15      your    tablet       very     store      tech        time      just
16      just  charging    product      need    amazon  registered     about
17   youtube     there       year      when      best       other      year
18    device      have      thing    lasted   connect       again     every
19      with     shuts       play      used      apps       there       doe

   Topic # 7 Topic # 8  Topic # 9 Topic # 10
```

```
0        work      this      model      this
1        good        le       last     would
2        with   useless       they      with
3       price      work     kindle    device
4      tablet      apps       have      good
5        many      than     better    kindle
6      camera      have       year     which
7      amazon      with    quality   reading
8        well      more    speaker   battery
9        this      that       same      have
10       have      keep      sound   because
11     little      will       good     first
12       need      were  defective      that
13     device      fine       been      only
14       able      unit      great  internet
15     should       lot       down  download
16       nice      told      going      life
17      phone     seems    kindles      from
18    through    amazon   terrible     there
19       easy      take       this     store
```

21.0.1 Displaying Results & Getting Insights

[47]:
```
lda_display = pyLDAvis.gensim_models.
 ↪prepare(ldamodel,doc_term_matrix,dictionary,sort_topics=False)
pyLDAvis.display(lda_display)
```

[47]: <IPython.core.display.HTML object>

21.0.2 Creating Wordcloud

[48]:
```
text = ' '.join([text for text in train['reviews.text']])
wc =␣
 ↪WordCloud(width=500,height=200,background_color='black',stopwords=STOPWORDS).
 ↪generate(text)
plt.figure(figsize=(20,20),facecolor='k',edgecolor='w')
plt.imshow(wc,interpolation='bilinear')
plt.axis('off')
plt.tight_layout()
plt.show()
```

love
bought
great
easy
purchased
echo show
product
google play
kindle fire
tablet
customer service
battery life
amazon cloudcam
model kindle
last model
good tablet
really
last year
junk junk
work well
doe work
tablet kid
nice
going back
user friendly
work echo
play game
great tablet
play store
kitchen
cell phone
work great
bought newest
read book
highly recommend
external speaker
adjust brightness
someone
happy

[ ]: