Ecommerce

1 Artificial Intelligence Capstone Project on E-Commerce

1.0.1 Project Task: Week 1

1.0.2 Importing libraries and datasets

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline

import re
from nltk import word_tokenize
from nltk.tokenize import WordPunctTokenizer
from nltk.stem.porter import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

from sklearn.feature_extraction.text import TfidfVectorizer,CountVectorizer
# import string
import warnings
# ! pip install wordcloud
#from wordcloud import WordCloud

from sklearn.preprocessing import LabelEncoder,LabelBinarizer

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LogisticRegression, RidgeClassifier,␣
↪SGDClassifier
from sklearn.naive_bayes import MultinomialNB, GaussianNB, BernoulliNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier,␣
↪GradientBoostingClassifier, AdaBoostClassifier, BaggingClassifier
```

```python
from xgboost import XGBClassifier

from sklearn.metrics import accuracy_score, f1_score, confusion_matrix,␣
↪classification_report,precision_score, recall_score,roc_curve,␣
↪roc_auc_score, auc

import tensorflow as tf
from tensorflow import keras
from sklearn.utils import class_weight
from sklearn.preprocessing import label_binarize
from keras.layers import Dense, Embedding, LSTM, SpatialDropout1D,Dropout,GRU
from keras.models import Sequential
from keras.wrappers.scikit_learn import KerasClassifier
from sklearn.model_selection import RandomizedSearchCV, KFold
from sklearn.preprocessing import MinMaxScaler
```

```
Using TensorFlow backend.
```

[2]:
```python
train = pd.read_csv("train_data.csv")
train.head()
```

[2]:
```
                                                name   brand  \
0  All-New Fire HD 8 Tablet, 8" HD Display, Wi-Fi…  Amazon
1        Amazon - Echo Plus w/ Built-In Hub - Silver  Amazon
2  Amazon Echo Show Alexa-enabled Bluetooth Speak…  Amazon
3  Fire HD 10 Tablet, 10.1 HD Display, Wi-Fi, 16 …  Amazon
4  Brand New Amazon Kindle Fire 16gb 7" Ips Displ…  Amazon

                                        categories  \
0  Electronics,iPad & Tablets,All Tablets,Fire Ta…
1  Amazon Echo,Smart Home,Networking,Home & Tools…
2  Amazon Echo,Virtual Assistant Speakers,Electro…
3  eBook Readers,Fire Tablets,Electronics Feature…
4  Computers/Tablets & Networking,Tablets & eBook…

             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 (e…
1  I purchased two Amazon in Echo Plus and two do…
2  Just an average Alexa option. Does show a few …
3  very good product. Exactly what I wanted, and …
```

```
4  This is the 3rd one I've purchased. I've bough…

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

[3]:
```python
test_val= pd.read_csv("test_data_hidden.csv")
test_val.head()
```

[3]:
```
                                                name   brand  \
0  Fire Tablet, 7 Display, Wi-Fi, 16 GB - Include…  Amazon
1  Amazon Echo Show Alexa-enabled Bluetooth Speak…  Amazon
2  All-New Fire HD 8 Tablet, 8" HD Display, Wi-Fi…  Amazon
3  Brand New Amazon Kindle Fire 16gb 7" Ips Displ…  Amazon
4  Amazon Echo Show Alexa-enabled Bluetooth Speak…  Amazon

                                          categories     primaryCategories  \
0  Fire Tablets,Computers/Tablets & Networking,Ta…           Electronics
1  Computers,Amazon Echo,Virtual Assistant Speake…  Electronics,Hardware
2  Electronics,iPad & Tablets,All Tablets,Fire Ta…           Electronics
3  Computers/Tablets & Networking,Tablets & eBook…           Electronics
4  Computers,Amazon Echo,Virtual Assistant Speake…  Electronics,Hardware

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

                                        reviews.text  \
0  Amazon kindle fire has a lot of free app and c…
1  The Echo Show is a great addition to the Amazo…
2  Great value from Best Buy. Bought at Christmas…
3  I use mine for email, Facebook ,games and to g…
4  This is a fantastic item & the person I bought…

                       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
```

[4]:
```
test= pd.read_csv("test_data.csv")
test.head()
```

[4]:
```
                                                name   brand  \
0  Fire Tablet, 7 Display, Wi-Fi, 16 GB - Include…  Amazon
1  Amazon Echo Show Alexa-enabled Bluetooth Speak…  Amazon
2  All-New Fire HD 8 Tablet, 8" HD Display, Wi-Fi…  Amazon
3  Brand New Amazon Kindle Fire 16gb 7" Ips Displ…  Amazon
4  Amazon Echo Show Alexa-enabled Bluetooth Speak…  Amazon

                                          categories     primaryCategories  \
0  Fire Tablets,Computers/Tablets & Networking,Ta…           Electronics
1  Computers,Amazon Echo,Virtual Assistant Speake…  Electronics,Hardware
2  Electronics,iPad & Tablets,All Tablets,Fire Ta…           Electronics
3  Computers/Tablets & Networking,Tablets & eBook…           Electronics
4  Computers,Amazon Echo,Virtual Assistant Speake…  Electronics,Hardware

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

                                        reviews.text  \
0  Amazon kindle fire has a lot of free app and c…
1  The Echo Show is a great addition to the Amazo…
2  Great value from Best Buy. Bought at Christmas…
3  I use mine for email, Facebook ,games and to g…
4  This is a fantastic item & the person I bought…

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

1.0.3 Exploratory Data Analysis

[17]:
```
train.duplicated().sum(), test.duplicated().sum(), test_val.duplicated().sum()
```

[17]:
```
(2, 3, 3)
```

Train dataset contains 58 duplicate records and train dataset contains 3 duplicate records.

[5]:
```
train = train[train.duplicated()==False]
train.shape
```

[5]: (3942, 8)

[6]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3942 entries, 0 to 3999
Data columns (total 8 columns):
name                  3942 non-null object
brand                 3942 non-null object
categories            3942 non-null object
primaryCategories     3942 non-null object
reviews.date          3942 non-null object
reviews.text          3942 non-null object
reviews.title         3932 non-null object
sentiment             3942 non-null object
dtypes: object(8)
memory usage: 277.2+ KB
```

[7]:
```
test_val.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 8 columns):
name                  1000 non-null object
brand                 1000 non-null object
categories            1000 non-null object
primaryCategories     1000 non-null object
reviews.date          1000 non-null object
reviews.text          1000 non-null object
reviews.title         997 non-null object
sentiment             1000 non-null object
dtypes: object(8)
memory usage: 62.6+ KB
```

Train dataset contains 10 missing values in 'reviews.title' column and test dataset contains 3 missing values in 'reviews.title' column.

[8]:
```
pd.set_option('display.max_colwidth',200)
```

Reviews containing Positive Sentiments

[9]:
```
train[train.sentiment=='Positive'][['reviews.text','reviews.title']].head(10)
```

[9]:
```
                                               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.

                            reviews.title
0                          Powerful tablet
1                 Amazon Echo Plus AWESOME
3                              Greatttttttt
4                            Very durable!
5                           You will love it
7          Great for kids or smaller needs
8                             Great tablet
10                            Great Tablet
11                              Works great
12  great pad for both children and adults
```

Reviews containing Neutral Sentiments

[10]:
```
train[train.sentiment=='Neutral'][['reviews.text','reviews.title']].head(10)
```

[10]:
```
                               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.

                                  reviews.title
2                                       Average
6                      OK For Entry Level Tablet
17                         Not as good as before
59   Does what it says, missing one key feature
95                         Haven't set it up yet
114                                 Solid tablet
146                                  Fire tablet
147                              Came defective
148                                  Good Reader
187                            Good for 4 year old
```

Reviews containing Negative Sentiments

[11]:
```
train[train.sentiment=='Negative'][['reviews.text','reviews.title']].head(10)
```

[11]:
```
                                  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

                                          reviews.title
9     was cheap, can not run chrome stuff, returned
97                Useless screen so why pay for it?
104                           Amazon Fire 7 Tablet
121                                   Kid's Kindle
150  Have never purchased a more frustrating Device
151                                    not big fan
249                                  Good for kids
267               terrible product,bad voice quality
368                 Needs to be a stand alone device
530                          Good Bluetooth speaker
```

[12]:
```
train.sentiment.value_counts()
```

[12]:
```
Positive    3694
Neutral      158
Negative      90
Name: sentiment, dtype: int64
```

Class Imbalance Problem In the train dataset, we have 3,749 (~95.1%) sentiments labeled as positive, and 1,58 (~4%) sentiments labeled as Neutral and 93(~2.35%) sentiments as Negative. So, it is an imbalanced classification problem.

[13]:
```
pd.DataFrame(train.name.value_counts())
```

[13]:
```
                                                                      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
```

[ ]:
```python
# name = pd.DataFrame(train.name.str.split(',').tolist()).stack().unique()
# name = pd.DataFrame(name,columns=['name'])
# name
```

[14]:
```python
train.brand.value_counts() , test_val.brand.value_counts()
```

[14]:
```
(Amazon    3942
 Name: brand, dtype: int64, Amazon    1000
 Name: brand, dtype: int64)
```

[15]:
```python
train.primaryCategories.value_counts()
```

[15]:
```
Electronics                      2562
Electronics,Hardware             1159
Office Supplies,Electronics       204
Electronics,Media                  17
Name: primaryCategories, dtype: int64
```

[16]:
```python
test_val.primaryCategories.value_counts()
```

[16]:
```
Electronics                      676
Electronics,Hardware             276
Office Supplies,Electronics       41
Electronics,Media                  7
Name: primaryCategories, dtype: int64
```

[17]:
```python
pd.DataFrame(train.categories.value_counts())
```

[17]:
```
                                                  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
```

[ ]:
```
# categories = pd.DataFrame(train.categories.str.split(',').tolist()).stack().
↪unique()
# categories = pd.DataFrame(categories,columns=['Categories'])
# categories
```

[18]:
```
train.dtypes
```

[18]:
```
name                  object
brand                 object
categories            object
primaryCategories     object
reviews.date          object
reviews.text          object
reviews.title         object
sentiment             object
dtype: object
```

1.0.4 Data Cleaning

[6]:
```
del train['brand']
del test_val['brand']
del test['brand']

train['reviews.date'] = train['reviews.date'].str.split('T').str[0]
test_val['reviews.date'] = test_val['reviews.date'].str.split('T').str[0]
test['reviews.date'] = test['reviews.date'].str.split('T').str[0]

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_val['reviews_day'] = pd.to_datetime(test_val['reviews.date'],␣
↪format='%Y-%m-%d').dt.day
```

```
test_val['reviews_month'] = pd.to_datetime(test_val['reviews.date'],␣
↪format='%Y-%m-%d').dt.month
test_val['reviews_year'] = pd.to_datetime(test_val['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

del train['reviews.date']
del test['reviews.date']
del test_val['reviews.date']

train.head()
```

[6]:

```
                                                name  \
0  All-New Fire HD 8 Tablet, 8" HD Display, Wi-Fi…
1        Amazon - Echo Plus w/ Built-In Hub - Silver
2  Amazon Echo Show Alexa-enabled Bluetooth Speak…
3  Fire HD 10 Tablet, 10.1 HD Display, Wi-Fi, 16 …
4  Brand New Amazon Kindle Fire 16gb 7" Ips Displ…

                                          categories  \
0  Electronics,iPad & Tablets,All Tablets,Fire Ta…
1  Amazon Echo,Smart Home,Networking,Home & Tools…
2  Amazon Echo,Virtual Assistant Speakers,Electro…
3  eBook Readers,Fire Tablets,Electronics Feature…
4  Computers/Tablets & Networking,Tablets & eBook…

             primaryCategories  \
0                  Electronics
1         Electronics,Hardware
2         Electronics,Hardware
3  Office Supplies,Electronics
4                  Electronics

                                        reviews.text  \
0  Purchased on Black FridayPros - Great Price (e…
1  I purchased two Amazon in Echo Plus and two do…
2  Just an average Alexa option. Does show a few …
3  very good product. Exactly what I wanted, and …
4  This is the 3rd one I've purchased. I've bough…

              reviews.title sentiment  reviews_day  reviews_month  \
```

```
0           Powerful tablet  Positive          26             12
1  Amazon Echo Plus AWESOME  Positive          17              1
2                   Average   Neutral          20             12
3               Greatttttttt  Positive           4              8
4             Very durable!  Positive          23              1

   reviews_year
0          2016
1          2018
2          2017
3          2017
4          2017
```

[7]:
```
name = list(set(list(train['name'])+list(test_val['name'])))
categories = list( set( list( train['categories']) +␣
 ↪list(test_val['categories'])))
primaryCategories = list(train['primaryCategories'].unique())

le_name = LabelEncoder()
le_cat = LabelEncoder()
le_pri = LabelEncoder()
le_name.fit(name)
le_cat.fit(categories)
le_pri.fit(primaryCategories)

train['name'] = le_name.transform(train.name)
train['categories'] = le_cat.transform(train.categories)
train['primaryCategories'] = le_pri.transform(train.primaryCategories)
test_val['name'] = le_name.transform(test_val.name)
test_val['categories'] = le_cat.transform(test_val.categories)
test_val['primaryCategories'] = le_pri.transform(test_val.primaryCategories)
test['name'] = le_name.transform(test.name)
test['categories'] = le_cat.transform(test.categories)
test['primaryCategories'] = le_pri.transform(test.primaryCategories)
```

[8]:
```
train['reviews.title'].fillna(value=' ',inplace=True)
test_val['reviews.title'].fillna(value=' ',inplace=True)
test['reviews.title'].fillna(value=' ',inplace=True)
```

[9]:
```
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",
```

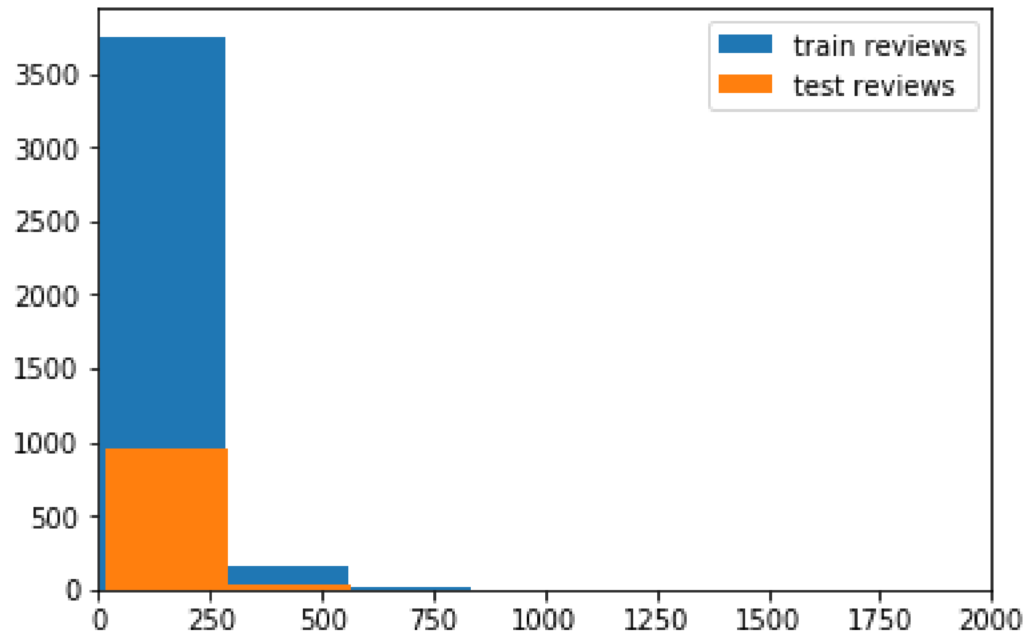
```
                "wouldn't":"would not", "don't":"do not", "doesn't":"does␣
↪not","didn't":"did not",
                "can't":"can not","couldn't":"could not","shouldn't":"should␣
↪not","mightn't":"might not",
                "mustn't":"must not"}
neg_pattern = re.compile(r'\b(' + '|'.join(negations_dic.keys()) + 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_val,test):
    i['reviews.text']=i['reviews.text'].apply(data_cleaner)
    i['reviews.title']=i['reviews.title'].apply(data_cleaner)
```

[ ]:

[58]:
```
#test[['reviews.text','reviews.title']].head(10)
```

1.0.5 Visualization

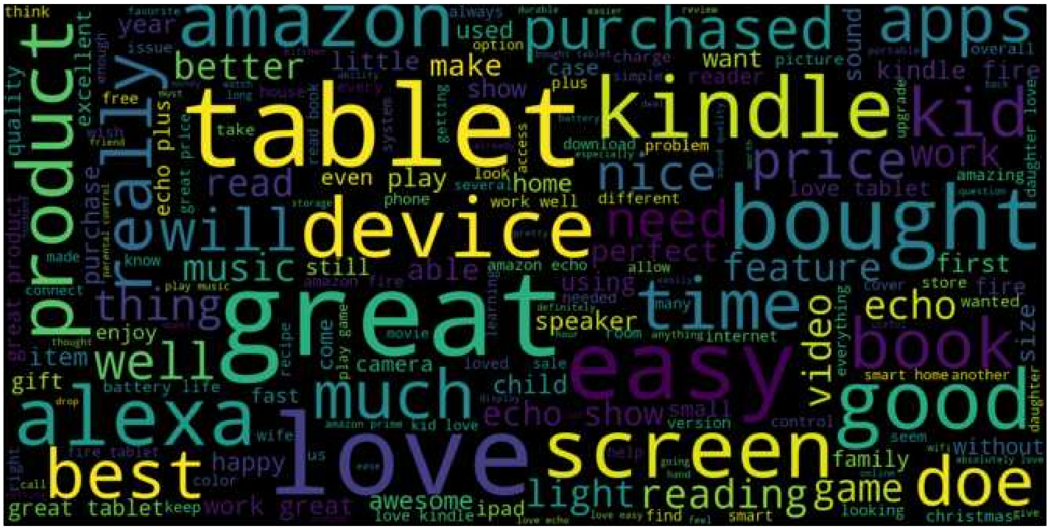
[23]:
```
train_len=train["reviews.text"].str.len()
test_len=test["reviews.text"].str.len()
plt.hist(train_len,bins=20,label="train reviews")
plt.hist(test_len,bins=20,label="test reviews")
plt.legend()
plt.xlim(0,2000)
plt.show()
```



[25]:
```
#all_text = ' '.join([text for text in train['reviews.text']])
pos_text = ' '.join([text for text in train['reviews.
↪text'][train['sentiment']=='Positive']])
neg_text = ' '.join([text for text in train['reviews.
↪text'][train['sentiment']=='Negative']])
neu_text = ' '.join([text for text in train['reviews.
↪text'][train['sentiment']=='Neutral']])
```

[28]:
```
wordcloud = WordCloud(width=1600, height=800, random_state=21,␣
↪max_font_size=180).generate(pos_text)
plt.figure(figsize=(12,10))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title(' POSITIVE REVIEWS')
plt.show()
```

POSITIVE REVIEWS

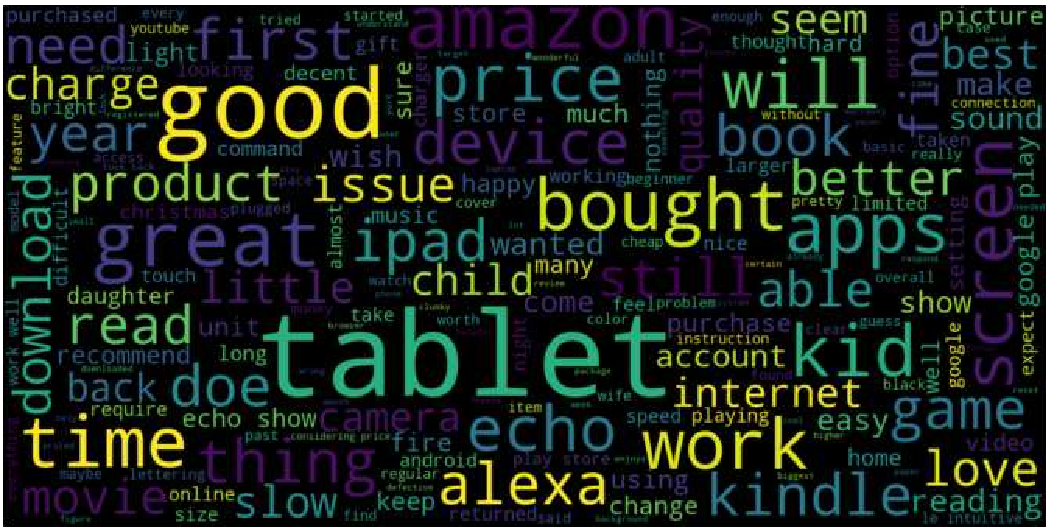



```
[29]: wordcloud = WordCloud(height=800, width=1600, random_state=21,max_font_size=180).generate(neg_text)
plt.figure(figsize=(12,10))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title(' NEGATIVE REVIEWS')
plt.show()
```

NEGATIVE REVIEWS

```
[30]: wordcloud = WordCloud(height=800, width=1600,␣
       ↪random_state=21,max_font_size=180).generate(neu_text)
      plt.figure(figsize=(12,10))
      plt.imshow(wordcloud, interpolation='bilinear')
      plt.axis('off')
      plt.title('NEUTRAL REVIEWS')
      plt.show()
```

NEUTRAL REVIEWS




```
[10]: le_senti = LabelEncoder()
      train['sentiment'] = le_senti.fit_transform(train['sentiment'])
      test_val['sentiment'] = le_senti.fit_transform(test_val['sentiment'])
```

TFIDF Vectorizer

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

```
[11]: train1 = train.reset_index()
      combi1 = train1.append(test_val,ignore_index=True,sort=False)
      tvec1.fit(combi1['reviews.text'])
      tvec_text1 = pd.DataFrame(tvec1.transform(train1['reviews.text']).toarray())
      tvec_text2 = pd.DataFrame(tvec1.transform(test_val['reviews.text']).toarray())
      tvec2.fit(combi1['reviews.title'])
      tvec_title1 = pd.DataFrame(tvec2.transform(train1['reviews.title']).toarray())
      tvec_title2 = pd.DataFrame(tvec2.transform(test_val['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_val.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_val['sentiment'].values
```

[12]:
```
from nltk.tokenize import RegexpTokenizer
from nltk.stem.snowball import SnowballStemmer
from sklearn.feature_extraction import text

punc = ['.', ',', '"', "'", '?', '!', ':', ';', '(', ')', '[', ']', '{',␣
↪'}',"%"]
stop_words = text.ENGLISH_STOP_WORDS.union(punc)

stemmer = SnowballStemmer('english')
tokenizer = RegexpTokenizer(r'[a-zA-Z\']+')

def tokenize(text):
    return [stemmer.stem(word) for word in tokenizer.tokenize(text.lower())]
tvec3 = TfidfVectorizer(stop_words = stop_words, tokenizer = tokenize,␣
↪max_features = 1000)
reviews=tvec3.fit_transform(combi1['reviews.text'])
words = tvec3.get_feature_names()
```

```
/opt/anaconda3/lib/python3.7/site-
packages/sklearn/feature_extraction/text.py:301: UserWarning: Your stop_words
may be inconsistent with your preprocessing. Tokenizing the stop words generated
tokens ['abov', 'afterward', 'alon', 'alreadi', 'alway', 'ani', 'anoth',
'anyon', 'anyth', 'anywher', 'becam', 'becaus', 'becom', 'befor', 'besid',
'cri', 'describ', 'dure', 'els', 'elsewher', 'empti', 'everi', 'everyon',
'everyth', 'everywher', 'fifti', 'forti', 'henc', 'hereaft', 'herebi', 'howev',
'hundr', 'inde', 'mani', 'meanwhil', 'moreov', 'nobodi', 'noon', 'noth',
'nowher', 'onc', 'onli', 'otherwis', 'ourselv', 'perhap', 'pleas', 'sever',
'sinc', 'sincer', 'sixti', 'someon', 'someth', 'sometim', 'somewher',
'themselv', 'thenc', 'thereaft', 'therebi', 'therefor', 'togeth', 'twelv',
'twenti', 'veri', 'whatev', 'whenc', 'whenev', 'wherea', 'whereaft', 'wherebi',
'wherev', 'whi', 'yourselv'] not in stop_words.
  'stop_words.' % sorted(inconsistent))
```

1.0.6 Multinomial Naive Bayes

[100]:
```
nb = MultinomialNB()
nb.fit(Train1.values,train1['sentiment'])
y_pred = nb.predict(Test_Val1.values)
y_val = test_val['sentiment']
print(confusion_matrix(y_true=y_val, y_pred=y_pred))
print(classification_report(y_true=y_val, y_pred=y_pred))
print(accuracy_score(y_val, y_pred)*100)
```

```
[[  0   0  24]
 [  0   0  39]
 [  0   0 937]]
              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

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

93.7
```

```
/opt/anaconda3/lib/python3.7/site-
packages/sklearn/metrics/classification.py:1143: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples.
  'precision', 'predicted', average, warn_for)
/opt/anaconda3/lib/python3.7/site-
packages/sklearn/metrics/classification.py:1143: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples.
  'precision', 'predicted', average, warn_for)
/opt/anaconda3/lib/python3.7/site-
packages/sklearn/metrics/classification.py:1143: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples.
  'precision', 'predicted', average, warn_for)
```

Everything is classified as Positive because of Imbalance Class

1.0.7 Project Task: Week 2

1.0.8 Tackling Class Imbalance Problem:

[12]:
```
train.sentiment.value_counts()
```

[12]:
```
Positive    3694
Neutral      158
Negative      90
Name: sentiment, dtype: int64
```

[17]:
```
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]
```

UnderSampling

[18]:
```
class_2_under = class_2.sample(count_1)
train_under= pd.concat([class_2_under,class_1,class_0],axis=0)
print(train_under.shape)
print(train_under.sentiment.value_counts())
```

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

OverSampling

[19]:
```
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
1    3694
0    3694
Name: sentiment, dtype: int64
```

[44]:
```
lr= LogisticRegression(C=30, class_weight='balanced', solver='sag',
                         multi_class='multinomial', n_jobs=6, random_state=40,
                         verbose=1, max_iter=1000)
```

TFIDF Vectorizer for under-sampled data

[47]:
```
train = train_under.reset_index(drop=True)
combi = train.append(test_val , ignore_index=True)
print(combi.shape)

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

tvec2.fit(combi['reviews.title'])
tvec_title1 = pd.DataFrame(tvec2.transform(train['reviews.title']).toarray())
tvec_title2 = pd.DataFrame(tvec2.transform(test_val['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_val.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_val['sentiment']
```

```
(1406, 9)
```

Logistic Regresiion for under-sampled data

[46]:
```
lr.fit(x_train,y_train)
y_pred = lr.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)
```

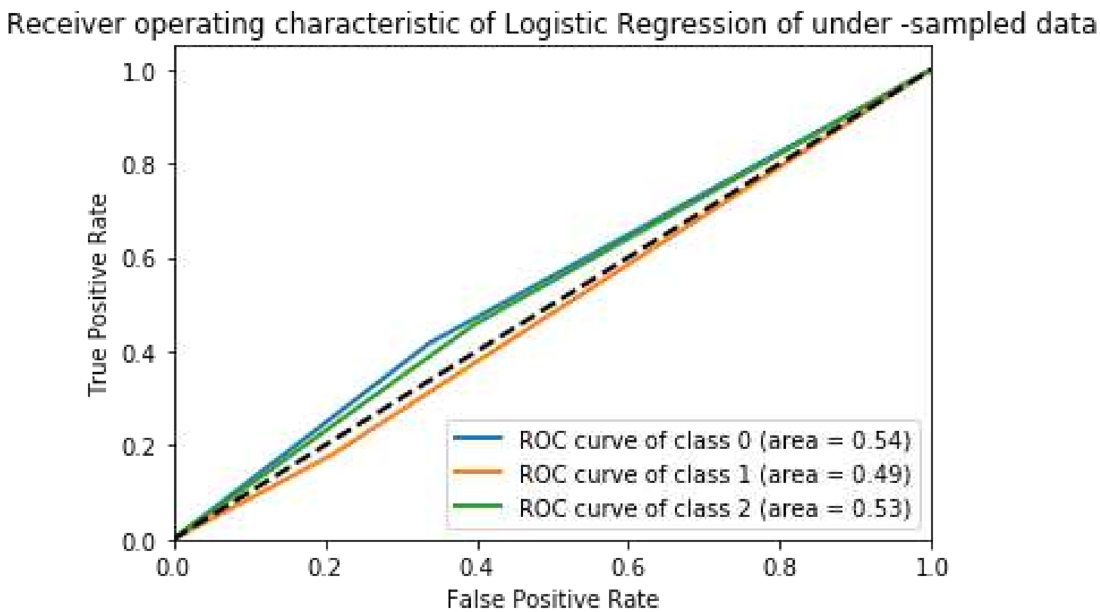
```
[Parallel(n_jobs=6)]: Using backend ThreadingBackend with 6 concurrent workers.

max_iter reached after 24 seconds
[[ 10   6   8]
 [ 15   7  17]
 [314 195 428]]
              precision    recall  f1-score   support

           0       0.03      0.42      0.06        24
           1       0.03      0.18      0.06        39
           2       0.94      0.46      0.62       937

   micro avg       0.45      0.45      0.45      1000
   macro avg       0.34      0.35      0.24      1000
weighted avg       0.89      0.45      0.58      1000
```

```
accuracy :  44.5
```

```
/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/sag.py:334:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
converge
  "the coef_ did not converge", ConvergenceWarning)
[Parallel(n_jobs=6)]: Done   1 out of   1 | elapsed:   24.4s finished
```

[47]:
```
lb = LabelBinarizer()
lb.fit(y_val)
y_val1 = lb.transform(y_val)
y_pred1 = lb.transform(y_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 Logistic Regression of under␣
 ↪-sampled data')
plt.legend(loc="lower right")
plt.show()
```

```
0.5284636556242508
```



TFIDF Vectorizer for over-sampled data

[20]:
```
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_val['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_val['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_val.drop(['reviews.text','reviews.
 ↪title','sentiment'],axis=1),tvec_text2, tvec_title2],axis=1)

Train.to_csv('Train.csv',encoding='utf-8')
Test_Val.to_csv('Test_Val.csv',encoding='utf-8')

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

Logistic Regression for over-sampled data

[56]:
```
lr.fit(x_train,y_train)
y_pred = lr.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)
```

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

```
max_iter reached after 1000 seconds
[[ 13   3   8]
 [ 10  10  19]
 [214 171 552]]
              precision    recall  f1-score   support

           0       0.05      0.54      0.10        24
           1       0.05      0.26      0.09        39
           2       0.95      0.59      0.73       937

   micro avg       0.57      0.57      0.57      1000
   macro avg       0.35      0.46      0.31      1000
weighted avg       0.90      0.57      0.69      1000

accuracy :  57.49999999999999
```

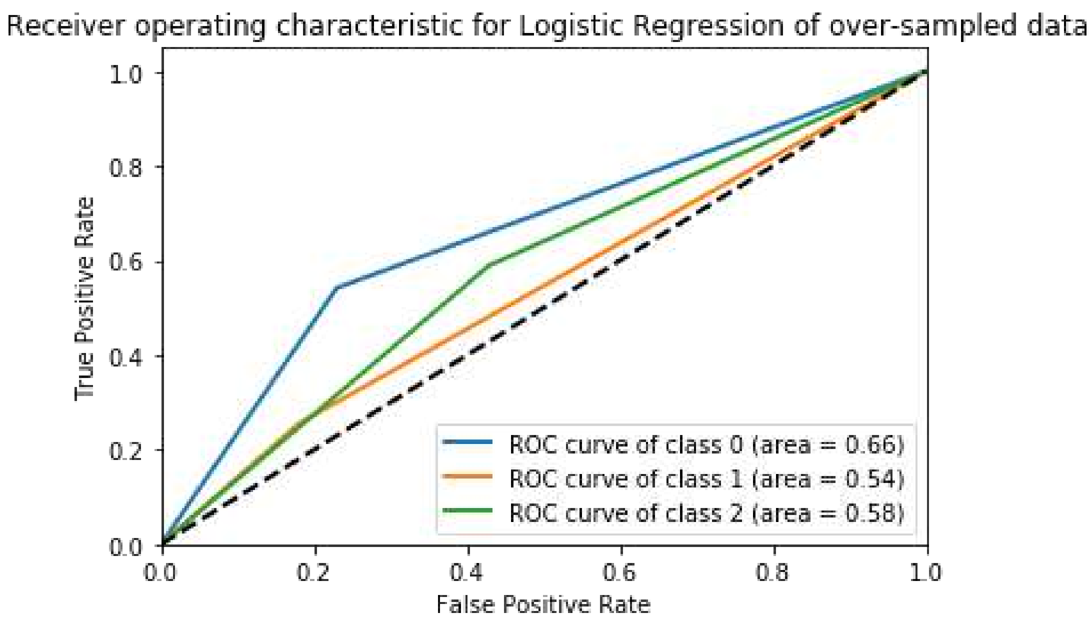
```
/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/sag.py:334:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
converge
  "the coef_ did not converge", ConvergenceWarning)
[Parallel(n_jobs=6)]: Done   1 out of   1 | elapsed: 16.7min finished
```

Logistic Regression on over-sampled data is perfroming better than under-sampled data

[58]:
```
lb = LabelBinarizer()
lb.fit(y_val)
y_val1 = lb.transform(y_val)
y_pred1 = lb.transform(y_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 for Logistic Regression of␣
 ↪over-sampled data')
plt.legend(loc="lower right")
plt.show()
```

```
0.5804294901632032
```



Multinomial Naive Bayes

[109]:
```
nb = MultinomialNB()
nb.fit(x_train,y_train)
y_pred = nb.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_score(y_val, y_pred)*100)
print(nb.score(x_train,y_train))
print(nb.score(x_val,y_val))
```

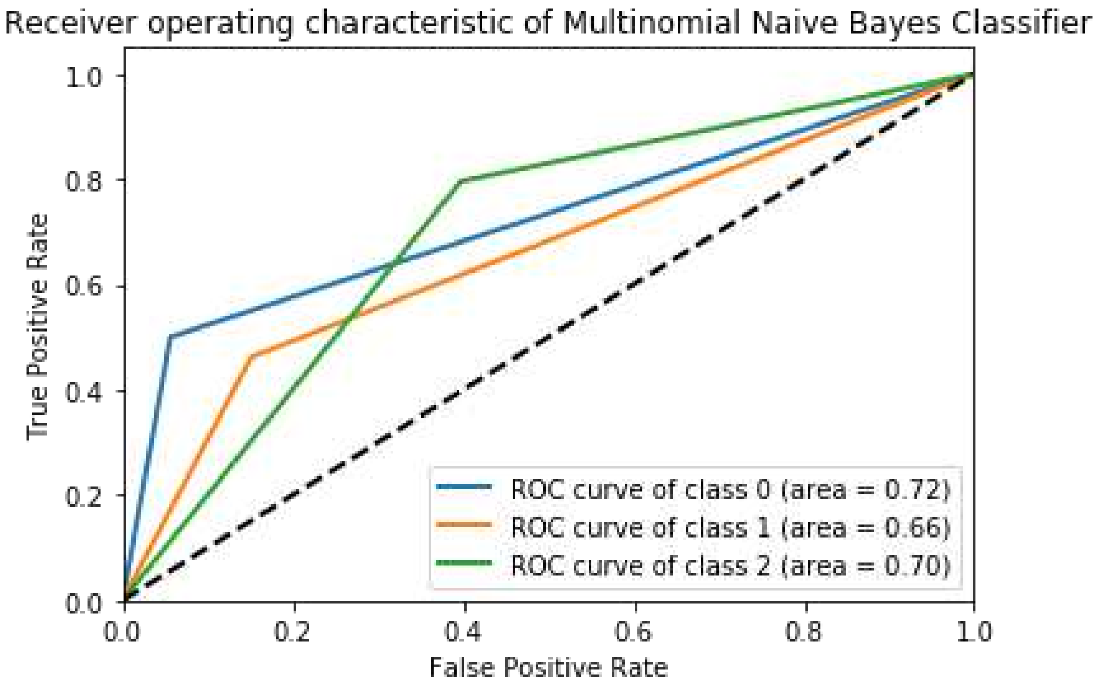
```
[[ 12   3   9]
 [  4  13  22]
```

```
 [  9  78 850]]
              precision    recall  f1-score   support

           0       0.48      0.50      0.49        24
           1       0.14      0.33      0.20        39
           2       0.96      0.91      0.94       937

   micro avg       0.88      0.88      0.88      1000
   macro avg       0.53      0.58      0.54      1000
weighted avg       0.92      0.88      0.90      1000

87.5
0.9589424291644107
0.875
```

[60]:

```
lb = LabelBinarizer()
lb.fit(y_val)
y_val1 = lb.transform(y_val)
y_pred1 = lb.transform(y_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 Multinomial Naive Bayes␣
 ↪Classifier')
plt.legend(loc="lower right")
plt.show()
```

```
0.6979688244204161
```



RandomForestClassifier

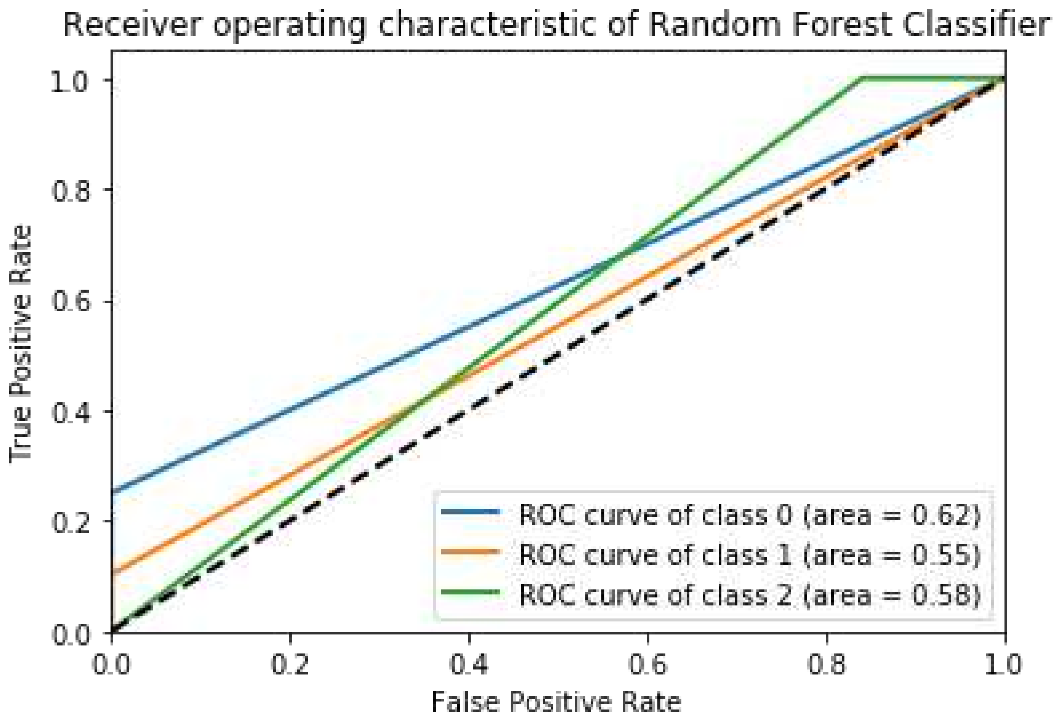
[36]:
```
rf= RandomForestClassifier(n_estimators=400,random_state=10).
 ↪fit(x_train,y_train)
y_pred=rf.predict(x_val)
print(confusion_matrix(y_true=y_val, y_pred=y_pred))
print(classification_report(y_true=y_val, y_pred=y_pred))
print('accuracy : ',accuracy_score(y_val, y_pred)*100)
print(rf.score(x_train,y_train))
print(rf.score(x_val,y_val))
```

```
[[  6   0  18]
 [  0   4  35]
 [  0   0 937]]
              precision    recall  f1-score   support

           0       1.00      0.25      0.40        24
           1       1.00      0.10      0.19        39
           2       0.95      1.00      0.97       937

   micro avg       0.95      0.95      0.95      1000
   macro avg       0.98      0.45      0.52      1000
weighted avg       0.95      0.95      0.93      1000

accuracy :  94.69999999999999
```

```
1.0
0.947
```

[41]:
```
lb = LabelBinarizer()
lb.fit(y_val)
y_val1 = lb.transform(y_val)
y_pred1 = lb.transform(y_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 Random Forest Classifier')
plt.legend(loc="lower right")
plt.show()
```

```
0.5793650793650793
```



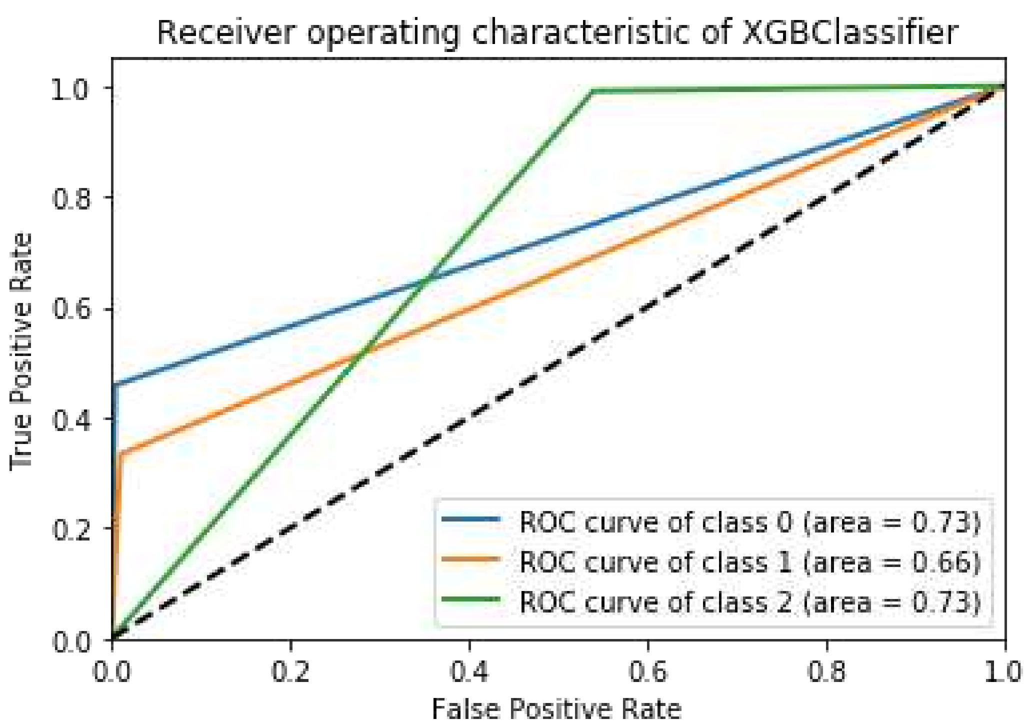
XGBClassifier

[27]:
```
xgb= XGBClassifier(n_estimators=1000,max_depth=6).fit(x_train,y_train)
y_pred=xgb.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)
```

```
[[ 11   2  11]
 [  3  13  23]
 [  1   8 928]]
              precision    recall  f1-score   support

           0       0.73      0.46      0.56        24
           1       0.57      0.33      0.42        39
           2       0.96      0.99      0.98       937

   micro avg       0.95      0.95      0.95      1000
   macro avg       0.75      0.59      0.65      1000
weighted avg       0.94      0.95      0.95      1000

95.19999999999999
1.0
0.952
```

[40]:

```
lb = LabelBinarizer()
lb.fit(y_val)
y_val1 = lb.transform(y_val)
y_pred1 = lb.transform(y_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 XGBClassifier')
plt.legend(loc="lower right")
plt.show()
```



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

multi-class SVM

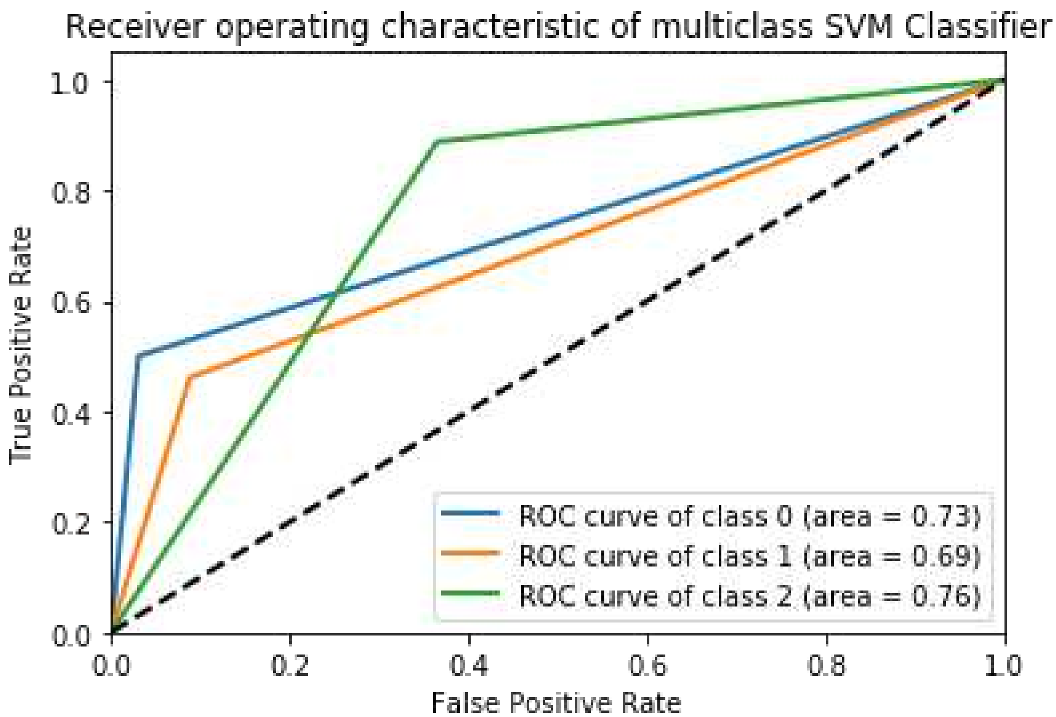
[54]:
```
svc = SVC(kernel='linear', class_weight='balanced', C=1.0, random_state=0).
 ↪fit(x_train, y_train)
y_pred=svc.predict(x_val)
print(confusion_matrix(y_true=y_val, y_pred=y_pred))
print(classification_report(y_true=y_val, y_pred=y_pred))
print("accuracy : ",accuracy_score(y_val, y_pred)*100)
```

```
[[ 12   3   9]
 [  7  18  14]
 [ 23  82 832]]
              precision    recall  f1-score   support

           0       0.29      0.50      0.36        24
           1       0.17      0.46      0.25        39
           2       0.97      0.89      0.93       937

   micro avg       0.86      0.86      0.86      1000
   macro avg       0.48      0.62      0.52      1000
weighted avg       0.93      0.86      0.89      1000

accuracy :  86.2
```

[55]:
```
lb = LabelBinarizer()
lb.fit(y_val)
y_val1 = lb.transform(y_val)
y_pred1 = lb.transform(y_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 multiclass SVM Classifier')
plt.legend(loc="lower right")
plt.show()
```

0.7578666991324146



1.0.9 Project Task: Week 3

Neural Network

[93]:
```
y_train2 = label_binarize(y_train1, classes=[0, 1, 2])
class_weights = class_weight.compute_class_weight('balanced',
                                                 np.unique(y_train1),
                                                 y_train1)
```

[87]:
```
classifier = Sequential()
classifier.
 ↪add(Dense(units=100,kernel_initializer='he_uniform',activation='relu',input_dim=x_train1.
 ↪shape[1]))
```

```
classifier.
 ↪add(Dense(units=80,kernel_initializer='he_uniform',activation='relu'))
classifier.
 ↪add(Dense(units=80,kernel_initializer='he_uniform',activation='relu'))
classifier.add(Dense(units=3,kernel_initializer='normal',activation='softmax'))
#adam = Adam(lr=0.0001)
classifier.
 ↪compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])
classifier.fit(x_train1,y_train2,batch_size=256,epochs=100,verbose=0)
y_pred = classifier.predict(x_val1, batch_size=256)
y_pred_bool = np.argmax(y_pred, axis=1)
print(confusion_matrix(y_val1, y_pred_bool))
print(classification_report(y_val1, y_pred_bool))
```

```
[[  9   1  14]
 [  0  12  27]
 [  2   7 928]]
              precision    recall  f1-score   support

           0       0.82      0.38      0.51        24
           1       0.60      0.31      0.41        39
           2       0.96      0.99      0.97       937

   micro avg       0.95      0.95      0.95      1000
   macro avg       0.79      0.56      0.63      1000
weighted avg       0.94      0.95      0.94      1000
```

[65]:
```
# Using Class-Weights
classifier = Sequential()
classifier.add(Dense(units=50,activation='relu',input_dim=x_train1.shape[1]))
classifier.add(Dense(units=40,activation='relu'))
classifier.add(Dense(units=3,kernel_initializer='normal',activation='softmax'))
classifier.
 ↪compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])
classifier.
 ↪fit(x_train1,y_train2,batch_size=256,epochs=100,class_weight=class_weights,verbose=0)
y_pred = classifier.predict(x_val1, batch_size=256)
y_pred_bool = np.argmax(y_pred, axis=1)
print(confusion_matrix(y_val1, y_pred_bool))
print(classification_report(y_val1, y_pred_bool))
```

```
[[  9   2  13]
 [  0  12  27]
 [  2   8 927]]
              precision    recall  f1-score   support
```

```
           0       0.82      0.38      0.51        24
           1       0.55      0.31      0.39        39
           2       0.96      0.99      0.97       937

   micro avg       0.95      0.95      0.95      1000
   macro avg       0.77      0.56      0.63      1000
weighted avg       0.94      0.95      0.94      1000
```

Using class-weights does not improve the performance

[73]:
```
#using dropouts
classifier = Sequential()
classifier.add(Dense(units=50,activation='relu',input_dim=x_train1.shape[1]))
classifier.add(Dropout(0.2))
classifier.add(Dense(units=40,activation='relu'))
classifier.add(Dropout(0.2))
classifier.add(Dense(units=40,activation='relu'))
classifier.add(Dense(units=3,kernel_initializer='normal',activation='softmax'))
classifier.
 ↪compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])
classifier.
 ↪fit(x_train1,y_train2,batch_size=256,epochs=100,class_weight=class_weights,verbose=0)
y_pred = classifier.predict(x_val1, batch_size=256)
y_pred_bool = np.argmax(y_pred, axis=1)
print(confusion_matrix(y_val1, y_pred_bool))
print(classification_report(y_val1, y_pred_bool))
```

```
[[  9   6   9]
 [  0  15  24]
 [  0  16 921]]
              precision    recall  f1-score   support

           0       1.00      0.38      0.55        24
           1       0.41      0.38      0.39        39
           2       0.97      0.98      0.97       937

   micro avg       0.94      0.94      0.94      1000
   macro avg       0.79      0.58      0.64      1000
weighted avg       0.94      0.94      0.94      1000
```

Using drop out chances of predicting second class increases

[88]:
```
y_train3 = label_binarize(y_train, classes=[0, 1, 2])
```

[90]:
```
#for over-sampled data
classifier = Sequential()
classifier.add(Dense(units=50,activation='relu',input_dim=x_train.shape[1]))
```

```
classifier.add(Dense(units=40,activation='relu'))
classifier.add(Dense(units=150,activation='relu'))
classifier.add(Dense(units=3,kernel_initializer='normal',activation='softmax'))
classifier.
 ↪compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])
classifier.fit(x_train,y_train3,batch_size=256,epochs=10,verbose=0)
y_pred = classifier.predict(x_val, batch_size=256)
y_pred_bool = np.argmax(y_pred, axis=1)
print(confusion_matrix(y_val, y_pred_bool))
print(classification_report(y_val, y_pred_bool))
```

```
[[ 10   1  13]
 [  0  11  28]
 [  2  11 924]]
              precision    recall  f1-score   support

           0       0.83      0.42      0.56        24
           1       0.48      0.28      0.35        39
           2       0.96      0.99      0.97       937

   micro avg       0.94      0.94      0.94      1000
   macro avg       0.76      0.56      0.63      1000
weighted avg       0.94      0.94      0.94      1000
```

Using Over-sampled data for neural network does not improve the performance

1.0.10 ensemble technique using Voting Classifier: XGboost + oversampled_multinomial_NB

[15]:
```
from sklearn.ensemble import VotingClassifier
model1 = MultinomialNB()
model2 =  XGBClassifier(n_estimators=1000,max_depth=6)
model = VotingClassifier(estimators=[('lr', model1), ('dt', model2)],␣
 ↪voting='hard')
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]
 [  3  15  21]
 [ 14  88 835]]
              precision    recall  f1-score   support

           0       0.45      0.58      0.51        24
```

```
           1       0.14      0.38      0.21        39
           2       0.97      0.89      0.93       937

   micro avg       0.86      0.86      0.86      1000
   macro avg       0.52      0.62      0.55      1000
weighted avg       0.92      0.86      0.89      1000

accuracy :  86.4
```

We can see that the above model performs almost same as oversampled multinomial model but it increases the chances of prediction of minority classes.

Sentiment Score

[16]:
```python
from textblob import TextBlob
def senti(x):
    return TextBlob(x).sentiment
def polarity(x):
    return TextBlob(x).polarity+1

train['senti_score'] = train['reviews.text'].apply(senti)
test_val['senti_score'] = test_val['reviews.text'].apply(senti)

train['polarity'] =train['reviews.text'].apply(polarity)
test_val['polarity'] = test_val['reviews.text'].apply(polarity)

train.senti_score.head()
```

[16]:
```
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: senti_score, dtype: object
```

[17]:
```python
Train = pd.concat([train.drop(['reviews.text','reviews.
 ↪title','sentiment','senti_score'],axis=1),tvec_text1, tvec_title1],axis=1)
Test_Val = pd.concat([test_val.drop(['reviews.text','reviews.
 ↪title','sentiment','senti_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_val['sentiment']
```

[18]:
```python
nb = MultinomialNB()
nb.fit(x_train,y_train)
y_pred = nb.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_score(y_val, y_pred)*100)
print(nb.score(x_train,y_train))
print(nb.score(x_val,y_val))
```

```
[[ 12   4   8]
 [  3  15  21]
 [ 10  79 848]]
              precision    recall  f1-score   support

           0       0.48      0.50      0.49        24
           1       0.15      0.38      0.22        39
           2       0.97      0.91      0.93       937

   micro avg       0.88      0.88      0.88      1000
   macro avg       0.53      0.60      0.55      1000
weighted avg       0.92      0.88      0.90      1000

87.5
0.9554232088070745
0.875
```

Sentiment Score does not have much affect on the performance

1.0.11 Project Task: Week 4

LSTM

[95]:
```
y_train2 = label_binarize(y_train1, classes=[0, 1, 2])
epochs = 4
emb_dim = 128
batch_size = 256
model = Sequential()
model.add(Embedding(100, emb_dim, input_length=x_train1.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(x_train1, y_train2, epochs=epochs, batch_size=batch_size)
y_pred = model.predict(x_val1, batch_size=100)
y_pred_bool = np.argmax(y_pred, axis=1)
print(confusion_matrix(y_val1, y_pred_bool))
print(classification_report(y_val1, y_pred_bool))
```

```
Epoch 1/4
3942/3942 [==============================] - 175s 44ms/step - loss: 0.8268 -
acc: 0.7808
```

```
Epoch 2/4
3942/3942 [==============================] - 171s 43ms/step - loss: 0.3332 -
acc: 0.9371
Epoch 3/4
3942/3942 [==============================] - 173s 44ms/step - loss: 0.2979 -
acc: 0.9371
Epoch 4/4
3942/3942 [==============================] - 171s 43ms/step - loss: 0.2867 -
acc: 0.9371
[[  0   0  24]
 [  0   0  39]
 [  0   0 937]]
              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

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


/opt/anaconda3/lib/python3.7/site-
packages/sklearn/metrics/classification.py:1143: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples.
  'precision', 'predicted', average, warn_for)
/opt/anaconda3/lib/python3.7/site-
packages/sklearn/metrics/classification.py:1143: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples.
  'precision', 'predicted', average, warn_for)
/opt/anaconda3/lib/python3.7/site-
packages/sklearn/metrics/classification.py:1143: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples.
  'precision', 'predicted', average, warn_for)
```

[15]:
```
#using clas_weights
y_train2 = label_binarize(y_train1, classes=[0, 1, 2])
class_weights = class_weight.compute_class_weight('balanced',np.
 ↪unique(y_train1),y_train1)
emb_dim = 128
epochs = 4
batch_size = 256
model = Sequential()
model.add(Embedding(x_train1.shape[1], emb_dim, input_length=x_train1.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(x_train1, y_train2, epochs=epochs,␣
↪batch_size=batch_size,class_weight=class_weights)
y_pred = model.predict(x_val1, batch_size=100)
y_pred_bool = np.argmax(y_pred, axis=1)
print(confusion_matrix(y_val1, y_pred_bool))
print(classification_report(y_val1, y_pred_bool))
```

```
WARNING:tensorflow:From /opt/anaconda3/lib/python3.7/site-
packages/tensorflow/python/framework/op_def_library.py:263: colocate_with (from
tensorflow.python.framework.ops) is deprecated and will be removed in a future
version.
Instructions for updating:
Colocations handled automatically by placer.
WARNING:tensorflow:From /opt/anaconda3/lib/python3.7/site-
packages/keras/backend/tensorflow_backend.py:3445: calling dropout (from
tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be removed
in a future version.
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 -
keep_prob`.
WARNING:tensorflow:From /opt/anaconda3/lib/python3.7/site-
packages/tensorflow/python/ops/math_ops.py:3066: to_int32 (from
tensorflow.python.ops.math_ops) is deprecated and will be removed in a future
version.
Instructions for updating:
Use tf.cast instead.
Epoch 1/4
3942/3942 [==============================] - 170s 43ms/step - loss: 0.8322 -
acc: 0.8095
Epoch 2/4
3942/3942 [==============================] - 165s 42ms/step - loss: 0.3274 -
acc: 0.9371
Epoch 3/4
3942/3942 [==============================] - 170s 43ms/step - loss: 0.3017 -
acc: 0.9371
Epoch 4/4
3942/3942 [==============================] - 173s 44ms/step - loss: 0.2816 -
acc: 0.9371
[[  0   0  24]
 [  0   0  39]
 [  0   0 937]]
              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

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

/opt/anaconda3/lib/python3.7/site-
packages/sklearn/metrics/classification.py:1143: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples.
  'precision', 'predicted', average, warn_for)
/opt/anaconda3/lib/python3.7/site-
packages/sklearn/metrics/classification.py:1143: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples.
  'precision', 'predicted', average, warn_for)
/opt/anaconda3/lib/python3.7/site-
packages/sklearn/metrics/classification.py:1143: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples.
  'precision', 'predicted', average, warn_for)
```

[22]:
```
#for over_sampled data
y_train2 = label_binarize(y_train, classes=[0, 1, 2])
emb_dim = 128
epochs = 3
batch_size = 256
model = Sequential()
model.add(Embedding(x_train.shape[1], emb_dim, input_length=x_train.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(x_train, y_train2, epochs=epochs, batch_size=batch_size)
y_pred = model.predict(x_val, batch_size=100)
y_pred_bool = np.argmax(y_pred, axis=1)
print(confusion_matrix(y_val, y_pred_bool))
print(classification_report(y_val, y_pred_bool))
```

```
Epoch 1/3
11082/11082 [==============================] - 443s 40ms/step - loss: 1.1012 -
acc: 0.3352
Epoch 2/3
```

```
11082/11082 [==============================] - 441s 40ms/step - loss: 1.1000 -
acc: 0.3302
Epoch 3/3
11082/11082 [==============================] - 438s 40ms/step - loss: 1.1004 -
acc: 0.3308
[[  0   0  24]
 [  0   0  39]
 [  0   0 937]]
              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

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


/opt/anaconda3/lib/python3.7/site-
packages/sklearn/metrics/classification.py:1143: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples.
  'precision', 'predicted', average, warn_for)
/opt/anaconda3/lib/python3.7/site-
packages/sklearn/metrics/classification.py:1143: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples.
  'precision', 'predicted', average, warn_for)
/opt/anaconda3/lib/python3.7/site-
packages/sklearn/metrics/classification.py:1143: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples.
  'precision', 'predicted', average, warn_for)
```

GRU

[16]:
```
y_train2 = label_binarize(y_train1, classes=[0, 1, 2])
epochs = 3
emb_dim = 128
batch_size = 256
model = Sequential()
model.add(Embedding(x_train1.shape[1], emb_dim, input_length=x_train1.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=['acc'])
```

```
model.fit(x_train1, y_train2, epochs=epochs, batch_size=batch_size)
y_pred = model.predict(x_val1, batch_size=100)
y_pred_bool = np.argmax(y_pred, axis=1)
print(confusion_matrix(y_val1, y_pred_bool))
print(classification_report(y_val1, y_pred_bool))
```

```
Epoch 1/3
3942/3942 [==============================] - 145s 37ms/step - loss: 0.7598 -
acc: 0.8595
Epoch 2/3
3942/3942 [==============================] - 144s 37ms/step - loss: 0.3209 -
acc: 0.9371
Epoch 3/3
3942/3942 [==============================] - 142s 36ms/step - loss: 0.2832 -
acc: 0.9371
[[  0   0  24]
 [  0   0  39]
 [  0   0 937]]
              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

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


/opt/anaconda3/lib/python3.7/site-
packages/sklearn/metrics/classification.py:1143: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples.
  'precision', 'predicted', average, warn_for)
/opt/anaconda3/lib/python3.7/site-
packages/sklearn/metrics/classification.py:1143: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples.
  'precision', 'predicted', average, warn_for)
/opt/anaconda3/lib/python3.7/site-
packages/sklearn/metrics/classification.py:1143: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples.
  'precision', 'predicted', average, warn_for)
```

[ ]:

```

```

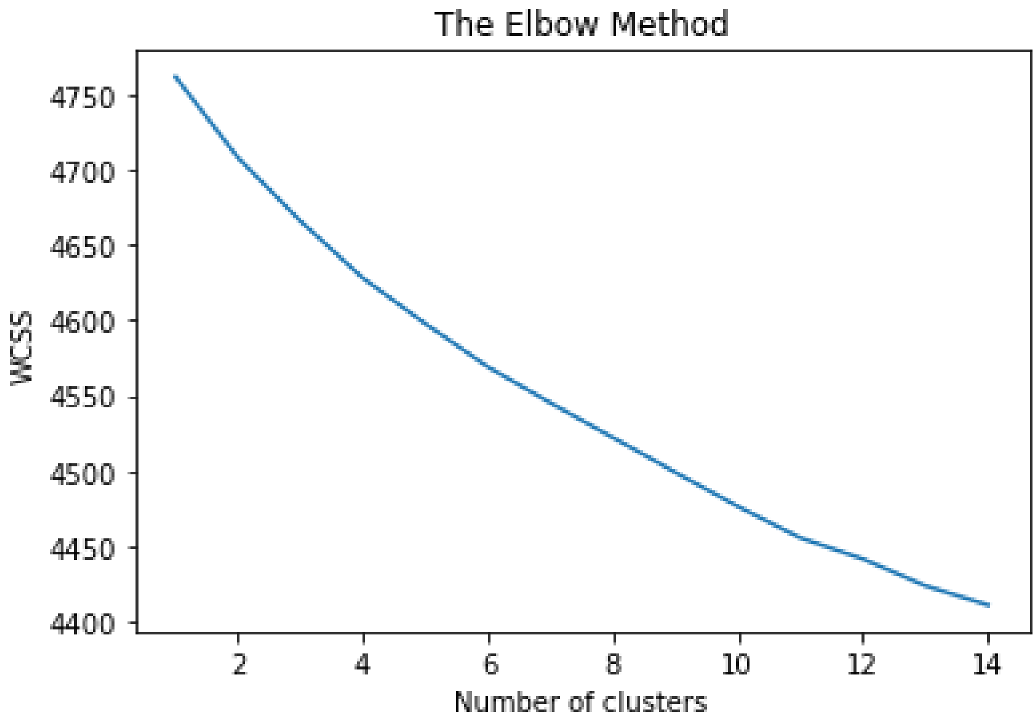
We can see from above that LSTM and GPU models iare not efficient in predicting minor classes.ANN is performing quite good in solving class imbalance problem but it cannot beat traditional ML agorithms.

Clustering of Reviews

[24]:
```
print(words[250:300])
```

```
['disappoint', 'discov', 'display', 'distract', 'doe', 'doesnt', 'dollar',
'dont', 'door', 'doorbel', 'dot', 'doubl', 'downfal', 'download', 'downsid',
'drain', 'drawback', 'drive', 'drop', 'durabl', 'dure', 'earli', 'earlier',
'eas', 'easi', 'easier', 'easili', 'ebook', 'echo', 'edg', 'edit', 'educ',
'effect', 'effici', 'effort', 'electron', 'els', 'email', 'employe', 'enabl',
'end', 'endless', 'enjoy', 'enlarg', 'entertain', 'entir', 'entri', 'environ',
'equip', 'eread']
```

[33]:
```
from sklearn.cluster import KMeans
wcss = []
for i in range(1,15):
    kmeans = ␣
↪KMeans(n_clusters=i,init='k-means++',max_iter=300,n_init=10,random_state=0,n_jobs=-1)
    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 have to select 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.

11 Clusters

[29]:
```
kmeans = KMeans(n_clusters = 11, n_init = 20, n_jobs = -1)
kmeans.fit(reviews)
# We look at 6 the clusters generated by k-means.
common_words = kmeans.cluster_centers_.argsort()[:,-1:-26:-1]
for num, centroid in enumerate(common_words):
    print(str(num) + ' : ' + ', '.join(words[word] for word in centroid))
```

```
0 : veri, easi, happi, great, product, love, tablet, help, satisfi, pleas,
purchas, durabl, bought, nice, best, work, price, amazon, use, qualiti,
grandson, recommend, child, learn, enjoy
1 : echo, plus, love, alexa, amazon, great, music, sound, video, like, product,
light, devic, work, screen, famili, hous, featur, better, just, bulb, bought,
purchas, easi, thing
2 : kindl, read, love, book, great, upgrad, easi, best, light, size, like,
screen, veri, purchas, bought, better, second, model, want, batteri, origin,
replac, use, year, charg
3 : home, smart, alexa, devic, great, echo, addit, autom, control, music,
amazon, love, product, work, connect, light, purchas, video, item, easi, googl,
just, hous, abl, bulb
```

```
4 : gift, love, christma, bought, purchas, great, easi, wife, perfect, tablet,
absolut, gave, price, product, kindl, year, kid, veri, mother, birthday, enjoy,
daughter, work, good, famili
5 : great, work, product, price, easi, recommend, kid, sound, tablet, love,
read, app, bought, life, friend, need, batteri, speaker, download, just, littl,
book, movi, awesom, game
6 : year, love, bought, tablet, game, purchas, easi, perfect, grandson, play,
great, daughter, veri, granddaught, parent, app, case, kid, warranti, christma,
learn, enjoy, time, child, good
7 : like, alexa, easi, read, screen, bought, work, use, just, amazon, devic,
enjoy, time, realli, music, play, book, doe, better, light, thing, need,
purchas, want, product
8 : tablet, great, kid, price, app, love, amazon, need, perfect, littl, game,
bought, purchas, play, like, work, child, recommend, onli, read, best, doe,
want, just, time
9 : love, bought, daughter, play, game, easi, tablet, kid, alexa, grandson,
christma, absolut, book, granddaught, purchas, read, great, watch, product,
music, just, wife, doe, learn, screen
10 : good, tablet, price, product, veri, read, work, easi, kid, qualiti, pretti,
great, sound, play, game, love, recommend, nice, size, pictur, amazon, devic,
speaker, batteri, child
```

13 Clusters

[30]:
```python
kmeans = KMeans(n_clusters = 13, n_init = 20, n_jobs = -1)
kmeans.fit(reviews)
# We look at 13 the clusters generated by k-means.
common_words = kmeans.cluster_centers_.argsort()[:,-1:-26:-1]
for num, centroid in enumerate(common_words):
    print(str(num) + ' : ' + ', '.join(words[word] for word in centroid))
```

```
0 : alexa, music, love, home, light, smart, devic, play, question, great, turn,
hous, thing, listen, speaker, control, like, amazon, just, abl, sound, news,
famili, weather, kitchen
1 : game, play, love, tablet, watch, read, year, enjoy, video, book, daughter,
grandson, great, bought, educ, easi, movi, learn, granddaught, download, app,
realli, good, time, purchas
2 : love, bought, gift, christma, year, purchas, grandson, birthday, absolut,
daughter, easi, granddaught, wife, great, tablet, parent, mother, perfect,
price, gave, like, grandkid, famili, best, learn
3 : good, tablet, price, veri, product, work, qualiti, sound, easi, pretti,
read, recommend, nice, great, pictur, love, devic, amazon, size, speaker, child,
valu, realli, time, gift
4 : kindl, love, read, great, purchas, upgrad, better, best, model, replac,
year, second, size, gift, easi, bought, veri, tablet, like, origin, screen, use,
version, light, doe
5 : batteri, life, great, long, charg, easi, tablet, read, good, kindl, longer,
love, light, screen, onli, veri, bought, amazon, fast, work, time, hour, better,
```

```
week, size
6 : like, work, easi, great, just, screen, doe, love, use, time, app, realli,
amazon, better, need, purchas, devic, bought, want, enjoy, perfect, onli, nice,
sound, size
7 : echo, plus, love, great, amazon, sound, video, music, like, alexa, home,
work, devic, product, screen, featur, famili, light, bulb, better, hous,
purchas, smart, easi, addit
8 : book, read, kindl, love, easi, great, reader, download, light, purchas,
like, want, size, perfect, just, carri, screen, need, wife, devic, game, watch,
bought, tablet, librari
9 : veri, easi, happi, love, tablet, great, purchas, bought, pleas, product,
grandson, year, help, enjoy, work, durabl, nice, satisfi, item, qualiti, price,
use, learn, friend, recommend
10 : tablet, great, price, love, app, year, need, perfect, amazon, work,
purchas, daughter, child, bought, like, littl, best, just, nice, recommend, doe,
everyth, easi, friend, time
11 : kid, great, love, tablet, easi, app, bought, good, amazon, free, price,
time, awesom, game, littl, gift, like, parent, recommend, entertain, product,
year, christma, grandson, learn
12 : great, product, work, easi, recommend, price, love, sound, best, friend,
high, gift, purchas, item, awesom, famili, qualiti, definit, veri, tablet,
devic, nice, featur, amazon, read
```

Topic Modelling

[13]:
```python
from sklearn.decomposition import LatentDirichletAllocation as LDA
# Helper function
def print_topics(model, count_vectorizer, n_top_words):
    words = count_vectorizer.get_feature_names()
    for topic_idx, topic in enumerate(model.components_):
        print("\nTopic #%d:" % topic_idx)
        print(" ".join([words[i]
                        for i in topic.argsort()[:-n_top_words - 1:-1]]))
# Tweak the two parameters below
number_topics = 10
number_words = 10
# Create and fit the LDA model
lda = LDA(n_components=number_topics, n_jobs=-1)
lda.fit(reviews)
# Print the topics found by the LDA model
print("Topics found via LDA:")
print_topics(lda, tvec3, number_words)
```

```
Topics found via LDA:

Topic #0:
tablet great kindl amazon read just good app batteri book
```

```
Topic #1:
light kindl read like page screen love turn voyag button

Topic #2:
sound look great speaker easi good need love exact just

Topic #3:
parent love great control easi tablet download book purchas kid

Topic #4:
love tablet doe everyth great price awesom work bought beat

Topic #5:
recommend great good product price tablet veri easi friend high

Topic #6:
love christma gift bought kid great present tablet grandson kindl

Topic #7:
echo alexa music home love great smart light amazon devic

Topic #8:
tablet love game play year bought daughter learn granddaught easi

Topic #9:
love easi veri happi great purchas bought camera wife kindl
```

[ ]: