Artificial Intelligence Capstone Project on E-Commerce

Project Task: Week 1

Importing libraries and datasets

In [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, AdaBoost
from xgboost import XGBClassifier

from sklearn.metrics import accuracy_score, f1_score, confusion_matrix, classification_re

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.
```

In [2]:

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

Out[2]:

name	brand	categories	primaryCategories	reviews.date	reviews.text	revie

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	name	brand	categories	primaryCategories	reviews.date	reviews.text	revie
0	All-New Fire HD 8 Tablet, 8" HD Display, Wi-Fi...	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	Electronics	2016-12-26T00:00:00.000Z	Purchased on Black FridayPros - Great Price (e...	
1	Amazon - Echo Plus w/ Built-In Hub - Silver	Amazon	Amazon Echo,Smart Home,Networking,Home & Tools...	Electronics,Hardware	2018-01-17T00:00:00.000Z	I purchased two Amazon in Echo Plus and two do...	Ama A
2	Amazon Echo Show Alexa-enabled Bluetooth Speak...	Amazon	Amazon Echo,Virtual Assistant Speakers,Electro...	Electronics,Hardware	2017-12-20T00:00:00.000Z	Just an average Alexa option. Does show a few ...	
3	Fire HD 10 Tablet, 10.1 HD Display, Wi-Fi, 16 ...	Amazon	eBook Readers,Fire Tablets,Electronics Feature...	Office Supplies,Electronics	2017-08-04T00:00:00.000Z	very good product. Exactly what I wanted, and ...	G
4	Brand New Amazon Kindle Fire 16gb 7" Ips Displ...	Amazon	Computers/Tablets & Networking,Tablets & eBook...	Electronics	2017-01-23T00:00:00.000Z	This is the 3rd one I've purchased. I've bough...	Very

In [3]:

```python
test_val= pd.read_csv("test_data_hidden.csv")
test_val.head()
```

Out[3]:

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

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

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

Out[4]:

	name	brand	categories	primaryCategories	reviews.date	reviews.text	rev
0	Fire Tablet, 7 Display, Wi-Fi, 16 GB - Include...	Amazon	Fire Tablets,Computers/Tablets & Networking,Ta...	Electronics	2016-05-23T00:00:00.000Z	Amazon kindle fire has a lot of free app and c...	v
1	Amazon Echo Show Alexa-enabled Bluetooth Speak...	Amazon	Computers,Amazon Echo,Virtual Assistant Speake...	Electronics,Hardware	2018-01-02T00:00:00.000Z	The Echo Show is a great addition to the Amazo...	w
2	All-New Fire HD 8 Tablet, 8" HD Display, Wi-Fi...	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	Electronics	2017-01-02T00:00:00.000Z	Great value from Best Buy. Bought at Christmas...	sin a
3	Brand New Amazon Kindle Fire 16gb 7" Ips Displ...	Amazon	Computers/Tablets & Networking,Tablets & eBook...	Electronics	2017-03-25T00:00:00.000Z	I use mine for email, Facebook ,games and to g...	
4	Amazon Echo Show Alexa-enabled Bluetooth Speak...	Amazon	Computers,Amazon Echo,Virtual Assistant Speake...	Electronics,Hardware	2017-11-15T00:00:00.000Z	This is a fantastic item & the person I bought...	

Exploratory Data Analysis

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

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

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

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

Out[5]: (3942, 8)

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In [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
```

In [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.

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

Reviews containing Positive Sentiments

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

Out[9]:

	reviews.text	reviews.title
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...	Powerful tablet
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...	Amazon Echo Plus AWESOME
3	very good product. Exactly what I wanted, and a very good price	Greattttttt
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.	Very durable!
5	This is a great product. Light weight. I wish it has wifi to download from online.	You will love it
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.	Great for kids or smaller needs
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.	Great tablet

	reviews.text	reviews.title
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.	Great Tablet
11	Great product for the kids gaming apps parental controls to make sure you can monitor kids and prevent unwanted app purchases	Works great
12	Love the choice of colors. Have two kindles of my own and purchased this for a gift.	great pad for both children and adults

Reviews containing Neutral Sentiments

In [10]:

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

Out[10]:

	reviews.text	reviews.title
2	Just an average Alexa option. Does show a few things on screen but still limited.	Average
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,...	OK For Entry Level Tablet
17	Not as good as before the old kindle, just seams to work better	Not as good as before
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...	Does what it says, missing one key feature
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.	Haven't set it up yet
114	I bought this as s present for my 65 year old grandma. She loves it. Very easy to operate. No issues	Solid tablet
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.	Fire tablet
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,...	Came defective
148	Not a substitute for an iPad, but a really good tablet for reading and minimal internet usage.	Good Reader
187	This device is a good if you are looking for a starter tablet for a young individual.	Good for 4 year old

Reviews containing Negative Sentiments

In [11]:

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

Out[11]:

	reviews.text	reviews.title
9	was cheap, can not run chrome stuff, returned to store.	was cheap, can not run chrome stuff, returned
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 ...	Useless screen so why pay for it?
104	Too bad Amazon turned this tablet into a big advertising tool. Many apps dont work and the camera is not good.	Amazon Fire 7 Tablet
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...	Kid's Kindle

	reviews.text	reviews.title
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...	Have never purchased a more frustrating Device
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...	not big fan
249	It's a good device for children because they don't know any better	Good for kids
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	terrible product,bad voice quality
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.	Needs to be a stand alone 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	Good Bluetooth speaker

In [12]:

```
train.sentiment.value_counts()
```

Out[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.

In [13]:

```
pd.DataFrame(train.name.value_counts())
```

Out[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

	name
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

In [ ]:

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

In [14]:

```
train.brand.value_counts() , test_val.brand.value_counts()
```

Out[14]:

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

In [15]:

```
train.primaryCategories.value_counts()
```

Out[15]:

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

In [16]:

```
test_val.primaryCategories.value_counts()
```

Out[16]:

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

In [17]:

```
pd.DataFrame(train.categories.value_counts())
```

Out[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 Automation,Electronics,TVs Entertainment,Speakers,Smart Hub & Kits,Digital Device 3,Consumer Electronics,Wireless Speakers,Home Improvement,Amazon Home,Amazon,Computer Speakers,Voice-Enabled Smart Assistants	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,Computers & Tablets	446

	categories
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 Security,Kindle Store,Electronic Components,Home Automation,Mobile Bluetooth Speakers,Home, Garage & Office,Amazon Tap,Home,Mobile Speakers,TVs & Electronics,Portable Bluetooth Speakers,Bluetooth & Wireless Speakers,Electronics Features,Frys,Speakers,Mobile,Digital Device 3,Smart Home,Home Improvement,Electronics, Tech Toys, Movies, Music,Smart Home & Home Automation Devices,Smart Hubs,MP3 Player Accessories,Home Safety & Security,Voice Assistants,Amazon Home,Alarms & Sensors,Portable Audio & Electronics,Amazon Devices,Audio,Bluetooth Speakers,MP3 Accessories,All Bluetooth & Wireless Speakers	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 Improvement,Voice Assistants,Amazon Home,Amazon	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 To College,Amazon Devices,Tablets & E-Readers	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 Accessories,iPads Tablets,All Tablets,Tablets & E-readers,Computers & Tablets,Amazon,Tablets & eBook Readers	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 Tablets,See more Amazon Kindle Voyage 4GB, Wi-Fi 3G (Unlocked...,Computers & Tablets	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 Device Accessory,Tablet Accessories,Featured Brands,Kindle Fire (2nd Generation) Accessories,Kindle Store,Power Adapters Cables,Electrical,Home,Tablets & E-Readers,Chargers Adapters,Chargers & Adapters,Electronics Features,Fire Tablet Accessories,Amazon Book Reader Accessory,Cell Phones,Amazon Device Accessories,Home Improvement,Fire (5th Generation) Accessories,Amazon Devices,Cables & Chargers	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

	categories
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,Internet & Media Streamers,Streaming Media Players,Fire TV,Streaming Devices,Amazon Devices,Amazon,See more Amazon Fire TV with Alexa Voice Remote Digital...	2

In [ ]:

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

In [18]:

```
train.dtypes
```

Out[18]:

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

Data Cleaning

In [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.montl
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.
test_val['reviews_month'] = pd.to_datetime(test_val['reviews.date'], format='%Y-%m-%d').d
test_val['reviews_year'] = pd.to_datetime(test_val['reviews.date'], format='%Y-%m-%d').dt

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()
```

Out[6]:

	name	categories	primaryCategories	reviews.text	reviews.title	sentiment	revie
0	All-New Fire HD 8 Tablet, 8" HD Display, Wi-Fi...	Electronics,iPad & Tablets,All Tablets,Fire Ta...	Electronics	Purchased on Black FridayPros - Great Price (e...	Powerful tablet	Positive	

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	name	categories	primaryCategories	reviews.text	reviews.title	sentiment	revie
1	Amazon - Echo Plus w/ Built-In Hub - Silver	Amazon Echo,Smart Home,Networking,Home & Tools...	Electronics,Hardware	I purchased two Amazon in Echo Plus and two do...	Amazon Echo Plus AWESOME	Positive	
2	Amazon Echo Show Alexa-enabled Bluetooth Speak...	Amazon Echo,Virtual Assistant Speakers,Electro...	Electronics,Hardware	Just an average Alexa option. Does show a few ...	Average	Neutral	
3	Fire HD 10 Tablet, 10.1 HD Display, Wi-Fi, 16 ...	eBook Readers,Fire Tablets,Electronics Feature...	Office Supplies,Electronics	very good product. Exactly what I wanted, and ...	Greattttttt	Positive	
4	Brand New Amazon Kindle Fire 16gb 7" Ips Displ...	Computers/Tablets & Networking,Tablets & eBook...	Electronics	This is the 3rd one I've purchased. I've bough...	Very durable!	Positive	

In [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)
```

In [8]:

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

In [9]:

```
tok = WordPunctTokenizer()
ps = PorterStemmer()
wnl = WordNetLemmatizer()
negations_dic = {"isn't":"is not", "aren't":"are not", "wasn't":"was not", "weren't":"were
                "haven't":"have not","hasn't":"has not","hadn't":"had not","won't":"will 
                "wouldn't":"would not", "don't":"do not", "doesn't":"does not","didn't":"
                "can't":"can not","couldn't":"could not","shouldn't":"should not","mightn
                "mustn't":"must not"}
Loading [MathJax]/extensions/Safe.js e.compile(r'\b(' + '|'.join(negations_dic.keys()) + r')\b')
```

```python
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)
```

In [ ]:

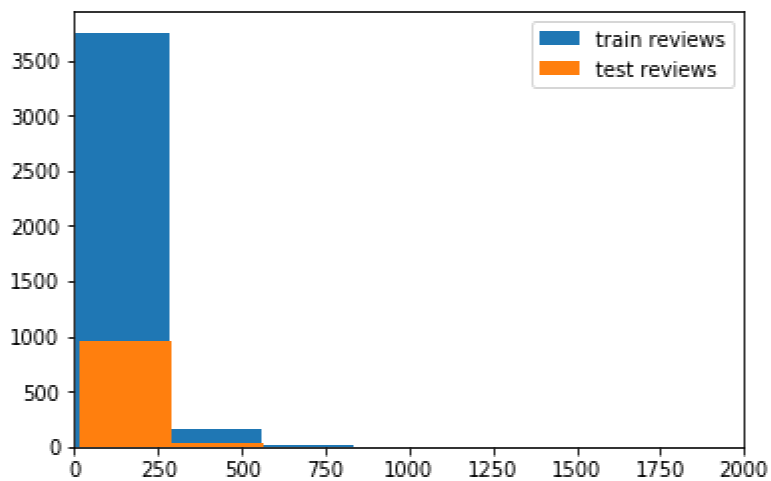
In [58]:

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

Visualization

In [23]:

```python
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()
```



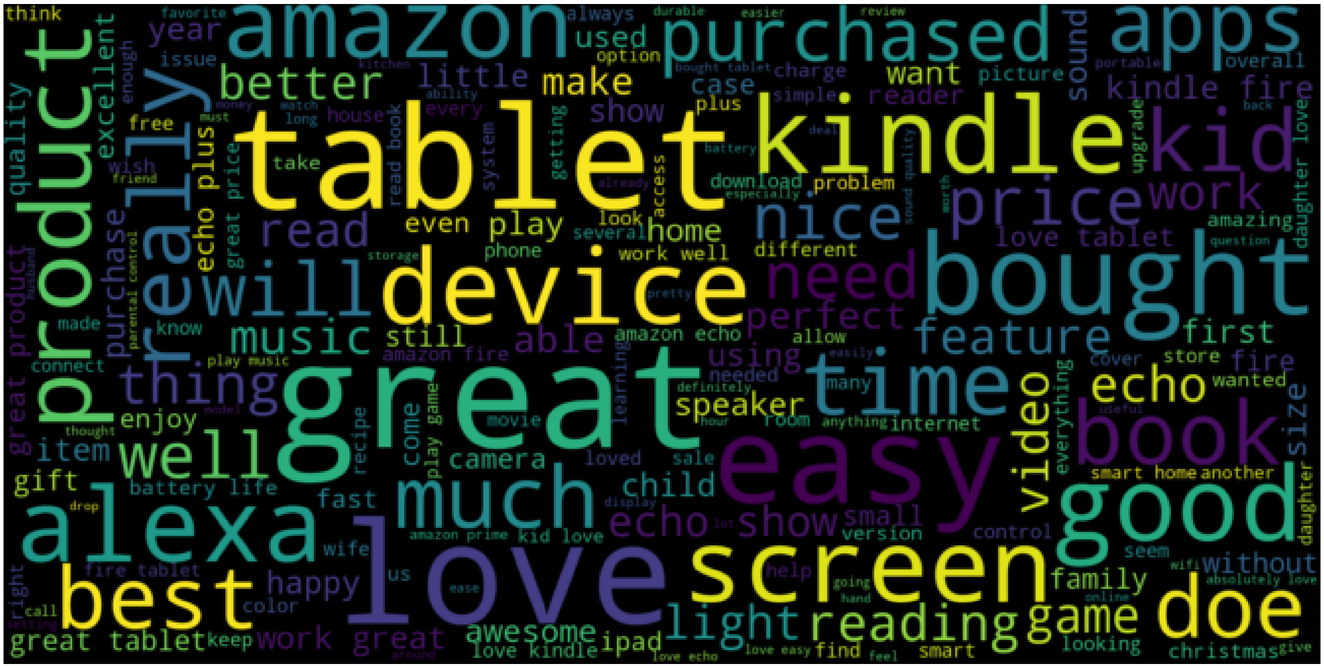
In [25]:

```python
#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'
```

In [28]:

```python
wordcloud = WordCloud(width=1600, height=800, random_state=21, max_font_size=180).generat
plt.figure(figsize=(12,10))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title(' POSITIVE REVIEWS')
```

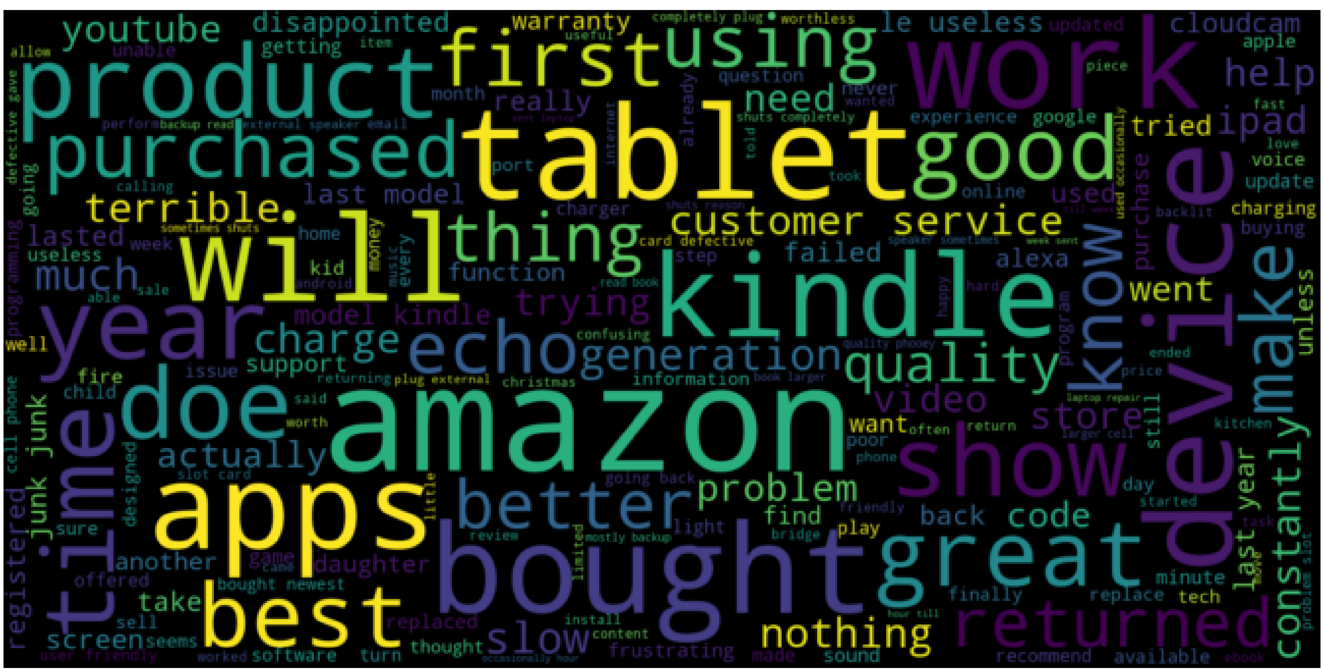
POSITIVE REVIEWS



In [29]:

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

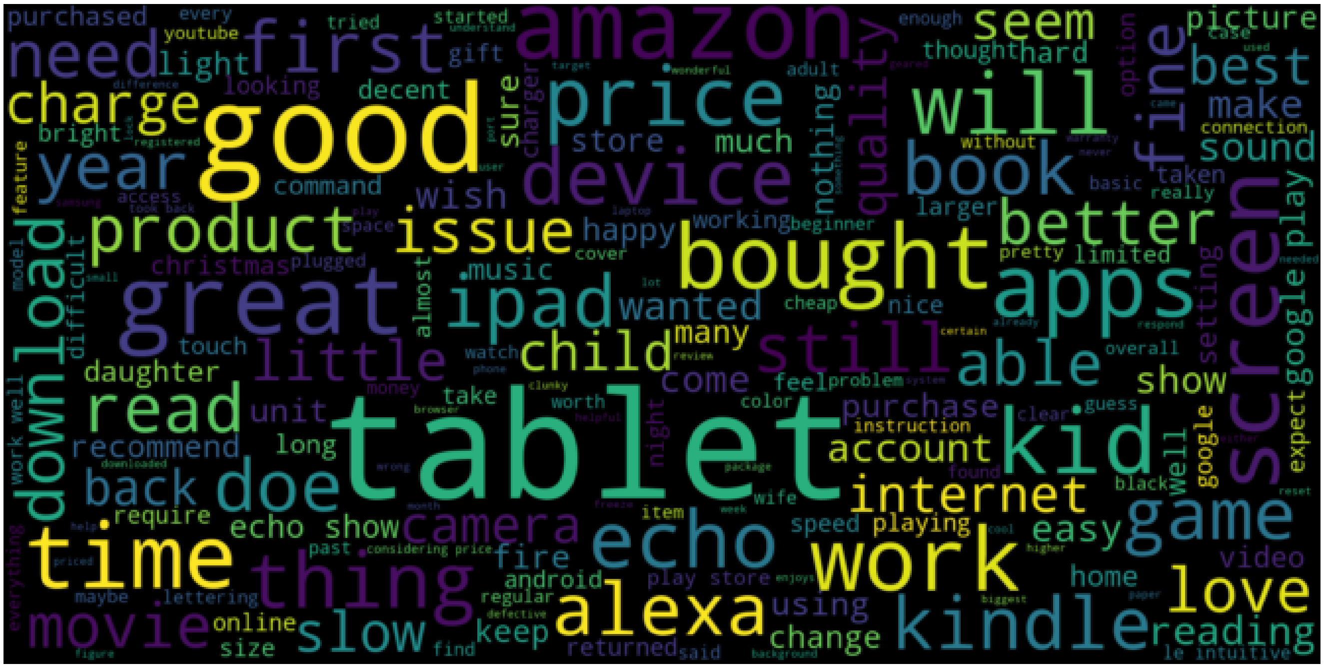
NEGATIVE REVIEWS



In [30]:

```python
wordcloud = WordCloud(height=800, width=1600, random_state=21,max_font_size=180).generate
plt.figure(figsize=(12,10))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('NEUTRAL REVIEWS')
```

NEUTRAL REVIEWS




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

TFIDF Vectorizer

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

```
In [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
Test_Val1 = pd.concat([test_val.drop(['reviews.text','reviews.title','sentiment'],axis=1)
x_train1=Train1.values
y_train1=train['sentiment'].values
x_val1=Test_Val1.values
y_val1 = test_val['sentiment'].values
```

```
In [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\']+')
```

Loading [MathJax]/extensions/Safe.js

```
def tokenize(text):
    return [stemmer.stem(word) for word in tokenizer.tokenize(text.lower())]
tvec3 = TfidfVectorizer(stop_words = stop_words, tokenizer = tokenize, max_features = 100
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: UserWar
ning: Your stop_words may be inconsistent with your preprocessing. Tokenizing the stop wor
ds generated tokens ['abov', 'afterward', 'alon', 'alreadi', 'alway', 'ani', 'anoth', 'any
on', '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', 'moreo
v', 'nobodi', 'noon', 'noth', 'nowher', 'onc', 'onli', 'otherwis', 'ourselv', 'perhap', 'p
leas', 'sever', 'sinc', 'sincer', 'sixti', 'someon', 'someth', 'sometim', 'somewher', 'the
mselv', '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))
```

Multinomial Naive Bayes

In [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: Undefin
edMetricWarning: 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: Undefin
edMetricWarning: 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: Undefin
edMetricWarning: 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

Project Task: Week 2

Tackling Class Imbalance Problem:

In [12]:

```
train.sentiment.value_counts()
```

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

In [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

In [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

In [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
```

In [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

In [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_t
Test_Val = pd.concat([test_val.drop(['reviews.text','reviews.title','sentiment'],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

In [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: ConvergenceWar
ning: 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
```

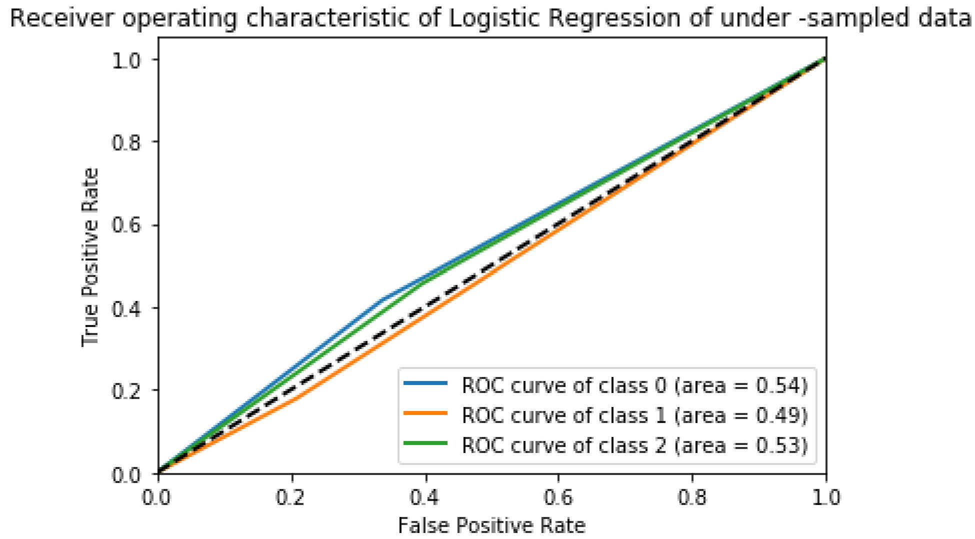
In [47]:

```
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 dat
plt.legend(loc="lower right")
plt.show()
```

```
0.5284636556242508
```



TFIDF Vectorizer for over-sampled data

In [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_t
Test_Val = pd.concat([test_val.drop(['reviews.text','reviews.title','sentiment'],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

In [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
                   0.90      0.57      0.69      1000
```

```
accuracy :  57.49999999999999
```

```
/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/sag.py:334: ConvergenceWar
ning: 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

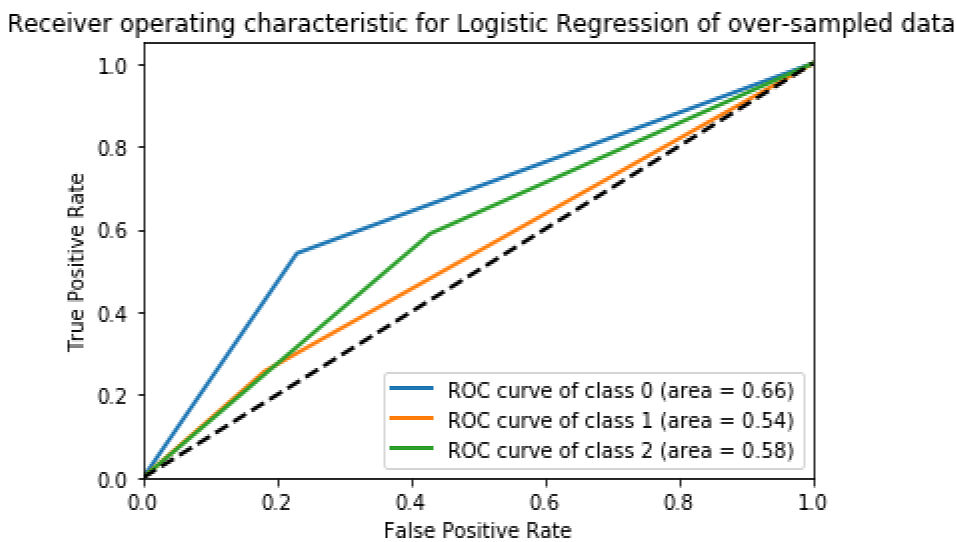
In [58]:

```python
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 dat
plt.legend(loc="lower right")
plt.show()
```

```
0.5804294901632032
```



Multinomial Naive Bayes

In [109…

```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)
```

Loading [MathJax]/extensions/Safe.js

```
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
```

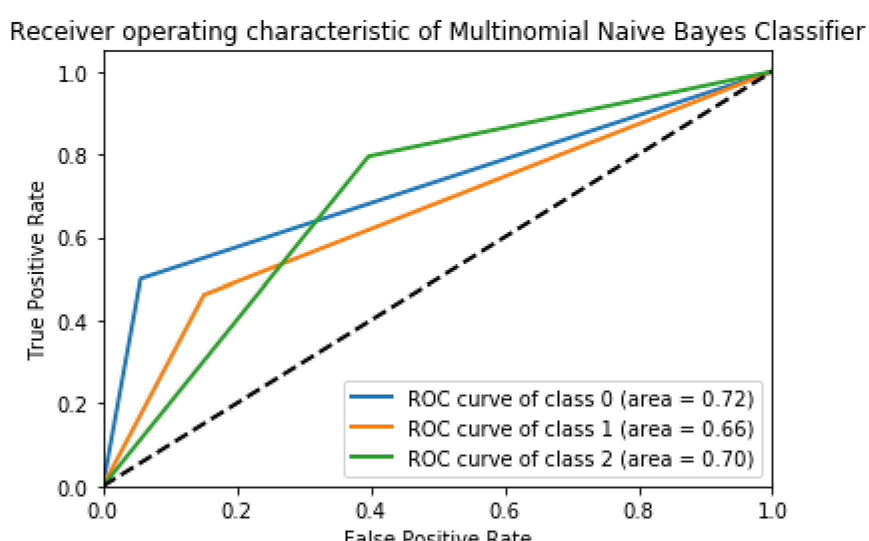
In [60]:

```
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

In [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
```

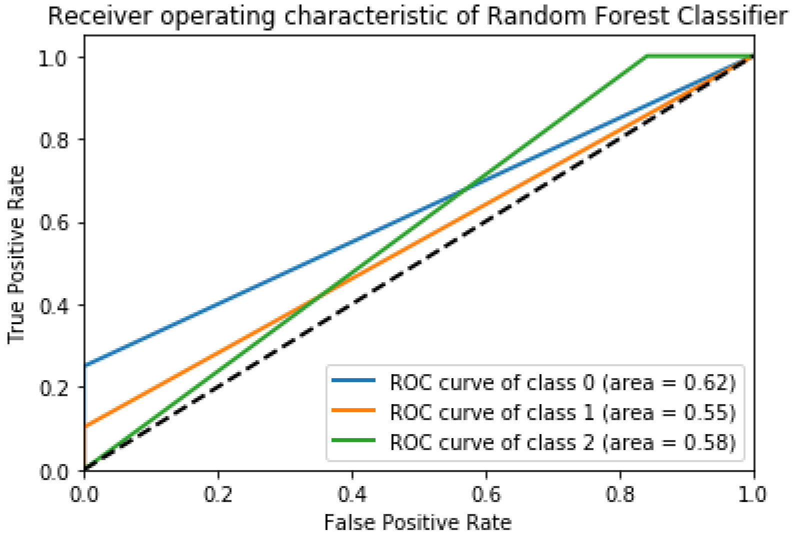
In [41]:

```
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

In [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
```

In [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])
```

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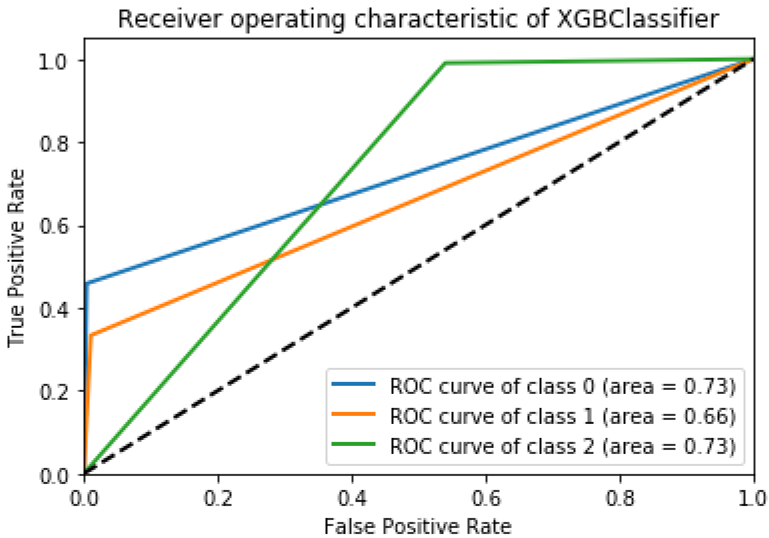
```
se Positive Rate')
```

```
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

In [54]:

```
svc = SVC(kernel='linear', class_weight='balanced', C=1.0, random_state=0).fit(x_train, y_
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
```

In [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})'
```

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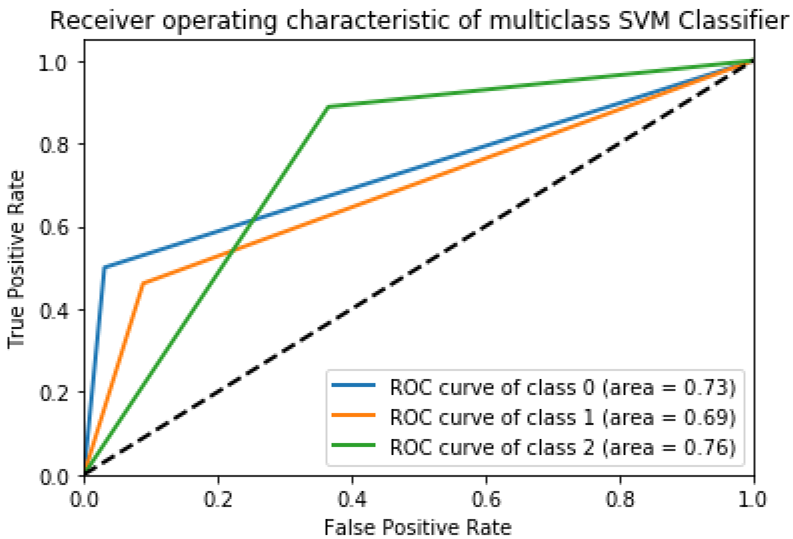
```
                 ''.format(i, roc_auc[i]))

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
```



Project Task: Week 3

Neural Network

In [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)
```

In [87]:

```
classifier = Sequential()
classifier.add(Dense(units=100,kernel_initializer='he_uniform',activation='relu',input_di
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
                   0.79      0.56      0.63      1000
```

```
weighted avg       0.94      0.95      0.94      1000
```

In [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,ver
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

In [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,ver
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

In [88]:

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

```
#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

ensemble technique using Voting Classifier: XGboost + oversampled_multinomial_NB

In [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

In [16]:

```
from textblob import TextBlob
def senti(x):
    ...Blob(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()
```

Out[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
```

In [17]:

```
Train = pd.concat([train.drop(['reviews.text','reviews.title','sentiment','senti_score'],
Test_Val = pd.concat([test_val.drop(['reviews.text','reviews.title','sentiment','senti_sc
x_train=Train.values
y_train=train['sentiment']
x_val=Test_Val.values
y_val = test_val['sentiment']
```

In [18]:

```
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

Project Task: Week 4

LSTM

In [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]))
```

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```
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: Undefin
edMetricWarning: 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: Undefin
edMetricWarning: 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: Undefin
edMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with
no predicted samples.
  'precision', 'predicted', average, warn_for)
```

In [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_wei
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/frame
work/op_def_library.py:263: colocate_with (from tensorflow.python.framework.ops) is deprec
ated and will be removed in a future version.
Instructions for updating:
led automatically by placer.
```

```
WARNING:tensorflow:From /opt/anaconda3/lib/python3.7/site-packages/keras/backend/tensorflo
w_backend.py:3445: calling dropout (from tensorflow.python.ops.nn_ops) with keep_prob is d
eprecated 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/m
ath_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: Undefin
edMetricWarning: 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: Undefin
edMetricWarning: 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: Undefin
edMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with
no predicted samples.
  'precision', 'predicted', average, warn_for)
```

In [22]:

```python
#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
```

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```
 [  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

In [16]:

```python
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: Undefin
```

```
edMetricWarning: 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: Undefin
edMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with
no predicted samples.
  'precision', 'predicted', average, warn_for)
```

In [ ]:

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

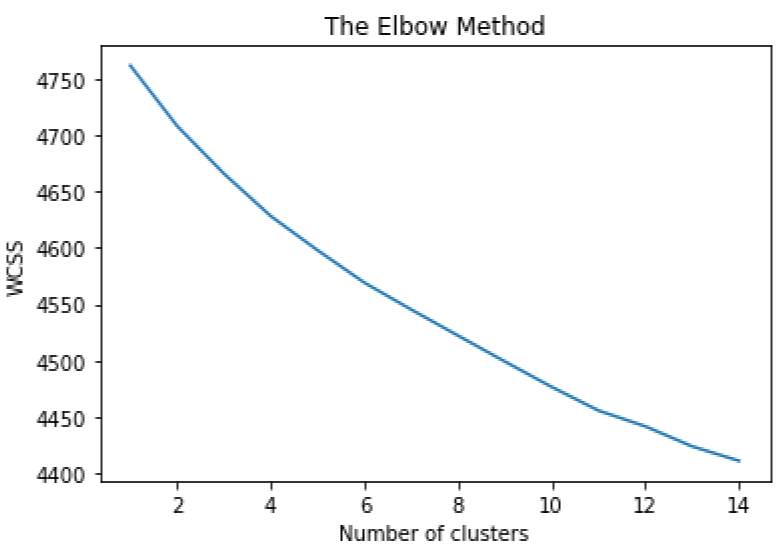
In [24]:

```
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', 'e
nviron', 'equip', 'eread']
```

In [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_
    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

Loading [MathJax]/extensions/Safe.js

```python
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, durab
l, bought, nice, best, work, price, amazon, use, qualiti, grandson, recommend, child, lear
n, enjoy
1 : echo, plus, love, alexa, amazon, great, music, sound, video, like, product, light, dev
ic, 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, p
urchas, bought, better, second, model, want, batteri, origin, replac, use, year, charg
3 : home, smart, alexa, devic, great, echo, addit, autom, control, music, amazon, love, pr
oduct, work, connect, light, purchas, video, item, easi, googl, just, hous, abl, bulb
4 : gift, love, christma, bought, purchas, great, easi, wife, perfect, tablet, absolut, ga
ve, 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, bou
ght, life, friend, need, batteri, speaker, download, just, littl, book, movi, awesom, game
6 : year, love, bought, tablet, game, purchas, easi, perfect, grandson, play, great, daugh
ter, veri, granddaught, parent, app, case, kid, warranti, christma, learn, enjoy, time, ch
ild, 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, purc
has, play, like, work, child, recommend, onli, read, best, doe, want, just, time
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lut, book, granddaught, purchas, read, great, watch, product, music, just, wife, doe, lear
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10 : good, tablet, price, product, veri, read, work, easi, kid, qualiti, pretti, great, so
und, play, game, love, recommend, nice, size, pictur, amazon, devic, speaker, batteri, chi
ld
```

13 Clusters

In [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, thin
g, listen, speaker, control, like, amazon, just, abl, sound, news, famili, weather, kitche
n
1 : game, play, love, tablet, watch, read, year, enjoy, video, book, daughter, grandson, g
reat, bought, educ, easi, movi, learn, granddaught, download, app, realli, good, time, pur
chas
2 : love, bought, gift, christma, year, purchas, grandson, birthday, absolut, daughter, ea
si, granddaught, wife, great, tablet, parent, mother, perfect, price, gave, like, grandki
d, famili, best, learn
3 : good, tablet, price, veri, product, work, qualiti, sound, easi, pretti, read, recommen
d, nice, great, pictur, love, devic, amazon, size, speaker, child, valu, realli, time, gif
t
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, ligh
t, 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, bett
er, 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, si
ze, perfect, just, carri, screen, need, wife, devic, game, watch, bought, tablet, librari
9 : veri, easi, happi, love, tablet, great, purchas, bought, pleas, product, grandson, yea
work, durabl, nice, satisfi, item, qualiti, price, use, learn, friend, rec
```

```
ommend
10 : tablet, great, price, love, app, year, need, perfect, amazon, work, purchas, daughte
r, child, bought, like, littl, best, just, nice, recommend, doe, everyth, easi, friend, ti
me
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, amazo
n, read
```

Topic Modelling

In [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
```

In [ ]: