```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Importing necessary Libraries

```
import re
import numpy as np
import pandas as pd
import gzip
import json
import nltk
from nltk.corpus import stopwords
import random
import spacy
from nltk.sentiment.vader import SentimentIntensityAnalyzer
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
from statsmodels.tsa.stattools import adfuller,acf,pacf
from statsmodels.tsa.statespace.tools import diff
from statsmodels.graphics.tsaplots import plot_acf,plot_pacf
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_squared_error
import statsmodels.api as sm
from sklearn.metrics import confusion_matrix
import warnings
warnings.filterwarnings('ignore')
```

```
# ! pip install transformers
# ! pip install wordcloud
# !pip install pyabsa
nltk.download('vader_lexicon')
nltk.download('stopwords')
nlp = spacy.load("en_core_web_sm")
```

```
[nltk_data] Downloading package vader_lexicon to /root/nltk_data...
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

1. Data Preparation

```
# for video game dataset

df_videogame_review = pd.read_json('/content/drive/MyDrive/reviews_Video_Games_5.json.gz',orient='records',lines = True)
```

```
# for android app dataset

df_android_review = pd.read_json('/content/drive/MyDrive/reviews_Apps_for_Android_5.json.gz',orient='records',lines = True)
```

```
df_android_review.head()
```

	reviewerID	asin	reviewerName	helpful	reviewText	overall	summary	unixRevie

```
df_videogame_review.head()
```

	reviewerID	asin	reviewerName	helpful	reviewText	overall	summary	unixReviewTime
0	A2HD75EMZR8QLN	0700099867	123	[8, 12]	Installing the game was a struggle (because of...	1.0	Pay to unlock content? I don't think so.	1341792000
1	A3UR8NLLY1ZHCX	0700099867	Alejandro Henao "Electronic Junky"	[0, 0]	If you like rally cars get this game you will ...	4.0	Good rally game	1372550400
					1st shipment			

shape of the android data

```
print("shape of the android app data: ",df_android_review.shape)
print("shape of the video game data: ",df_videogame_review.shape)
```

```
shape of the android app data:  (752937, 9)
shape of the video game data:  (231780, 9)
```

datatypes of the columns

```
print("for android app review")
print("----------------------------")
print(df_android_review.dtypes)
print('\n')

print("for video game review")
print("----------------------------")
print(df_videogame_review.dtypes)
```

```
for android app review
----------------------------
reviewerID         object
asin               object
reviewerName       object
helpful            object
reviewText         object
overall           float64
summary            object
unixReviewTime      int64
reviewTime         object
dtype: object


for video game review
----------------------------
reviewerID         object
asin               object
reviewerName       object
helpful            object
reviewText         object
overall           float64
summary            object
unixReviewTime      int64
reviewTime         object
dtype: object
```

Checking null values

```
print("Null values for android app review data")
print('---------------------------------------')
print(df_android_review.isnull().sum())
```

```
print('\n')

print("Null values for the video games review data")
print('-------------------------------------------')
print(df_videogame_review.isnull().sum())
```

```
Null values for android app review data
----------------------------------------
reviewerID            0
asin                  0
reviewerName      58198
helpful               0
reviewText            0
overall               0
summary               0
unixReviewTime        0
reviewTime            0
dtype: int64


Null values for the video games review data
-------------------------------------------
reviewerID           0
asin                 0
reviewerName      2813
helpful              0
reviewText           0
overall              0
summary              0
unixReviewTime       0
reviewTime           0
dtype: int64
```

Renaming asin to product id

```
df_android_review.rename(columns={'asin':'Product_id'},inplace=True)
df_videogame_review.rename(columns={'asin':'Product_id'},inplace=True)
```

```
print(df_videogame_review.columns); print(df_android_review.columns)
```

```
Index(['reviewerID', 'Product_id', 'reviewerName', 'helpful', 'reviewText',
       'overall', 'summary', 'unixReviewTime', 'reviewTime'],
      dtype='object')
Index(['reviewerID', 'Product_id', 'reviewerName', 'helpful', 'reviewText',
       'overall', 'summary', 'unixReviewTime', 'reviewTime'],
      dtype='object')
```

Dropping the nan values

```
df_app = df_android_review.dropna()
df_video = df_videogame_review.dropna()
```

Checking the null values

```
df_app.isnull().sum()
```

```
reviewerID        0
Product_id        0
reviewerName      0
helpful           0
reviewText        0
overall           0
summary           0
unixReviewTime    0
reviewTime        0
dtype: int64
```

```
df_video.isnull().sum()
```

```
reviewerID        0
Product_id        0
reviewerName      0
helpful           0
```

```
reviewText        0
overall           0
summary           0
unixReviewTime    0
reviewTime        0
dtype: int64
```

Random sampling

we have used random sampling to simplify the data as we have more than 700000 rows so need to reduce our data and by random sampling it is reduced as nearly 70k rows

```
android_data = df_app.sample(n=int(len(df_app)/10), replace=False, random_state=30)
print('Android_data shape: ',android_data.shape)
print('------------------')
games_Data = df_video.sample(n=int(len(df_video)/10), replace=False, random_state=30)
print('games_Data shape: ',games_Data.shape)
```

```
Android_data shape:  (69473, 9)
------------------
games_Data shape:  (22896, 9)
```

Resetting the index after resampling to set the index of randomly selected data

```
android_data = android_data.reset_index()
games_Data = games_Data.reset_index()
```

Preprocessing of the text for sentiment analysis

```
# function for removing punctuation,numbers present in the text data..

def clean_text(text):
  text = text.lower()
  text = re.sub("[^0-9A-Za-z\- ]+", " ", text)
  text = re.sub("(?<!\w)\d+", "", text)
  text = re.sub("-(?!\w)|(?<!\w)-", "", text)
  text = " ".join(text.split())
  text = text.lower()
  return text
```

```
android_data['reviewText'][50000]
```

```
'It's fun to mess around with but I haven't really needed to use it much. It can be touchy at times, e
specially when trying to erase one of your inputs that you may have misplaced or that they app interpr
eted incorrectly.'
```

Applying clean_text function to review and summary for removing punctuation,numbers

```
android_data['reviewText'] = android_data['reviewText'].apply(clean_text)
games_Data['reviewText'] = games_Data['reviewText'].apply(clean_text)
android_data['summary'] = android_data['summary'].apply(clean_text)
games_Data['summary'] = games_Data['summary'] .apply(clean_text)
```

```
android_data['reviewText'][50000]
```

```
'it s fun to mess around with but i haven t really needed to use it much it can be touchy at times esp
ecially when trying to erase one of your inputs that you may have misplaced or that they app interpret
ed incorrectly'
```

Removing stop words from the data

```
stop = stopwords.words('english')
android_data['reviewText'] = android_data['reviewText'].apply(lambda x: ' '.join([word for word in x.split() if word not in (stop)]))
games_Data['reviewText'] = games_Data['reviewText'].apply(lambda x: ' '.join([word for word in x.split() if word not in (stop)]))
android_data['summary'] = android_data['summary'].apply(lambda x: ' '.join([word for word in x.split() if word not in (stop)]))
games_Data['summary'] = games_Data['summary'].apply(lambda x: ' '.join([word for word in x.split() if word not in (stop)]))
```

```
android_data['reviewText'][50000]
```

```
'fun mess around really needed use much touchy times especially trying erase one inputs may misplaced
app interpreted incorrectly'
```

lemmatization of the data

```
android_data['reviewText'] = android_data['reviewText'].apply(lambda x: ' '.join([j.lemma_ for j in nlp(x)]))
games_Data['reviewText'] = games_Data['reviewText'].apply(lambda x: ' '.join([j.lemma_ for j in nlp(x)]))
android_data['summary'] = android_data['summary'].apply(lambda x: ' '.join([j.lemma_ for j in nlp(x)]))
games_Data['summary'] = games_Data['summary'].apply(lambda x: ' '.join([j.lemma_ for j in nlp(x)]))
```

```
# lemmatized text
android_data['reviewText'][50000]
```

```
'fun mess around really need use much touchy time especially try erase one input may misplace app inte
rpret incorrectly'
```

```
android_data['summary'][50000]
```

```
'fun calculator'
```

Converting our data to csv

```
android_data.to_csv('android_data.csv')
games_Data.to_csv('games_data.csv')
```

Reading the csv file

```
android_df = pd.read_csv('/content/drive/MyDrive/capestone/android_data.csv')
games_df = pd.read_csv('/content/drive/MyDrive/capestone/games_data.csv')
```

```
---------------------------------------------------------------------------
FileNotFoundError                         Traceback (most recent call last)
<ipython-input-3-a72b6f148b9e> in <module>
----> 1 android_df = pd.read_csv('/content/drive/MyDrive/capestone/android_data.csv')
      2 games_df = pd.read_csv('/content/drive/MyDrive/capestone/games_data.csv')

7 frames
/usr/local/lib/python3.7/dist-packages/pandas/io/common.py in get_handle(path_or_buf, mode, encoding,
compression, memory_map, is_text, errors, storage_options)
    705                 encoding=ioargs.encoding,
    706                 errors=errors,
--> 707                 newline="",
    708             )
    709         else:

FileNotFoundError: [Errno 2] No such file or directory:
'/content/drive/MyDrive/capestone/android_data.csv'
```

Checking the shape of the data in csv file

```
print(android_df.shape) #for android data
```

```
(69473, 11)
```

```
print(games_df.shape) #for games data
```

```
(22896, 11)
```

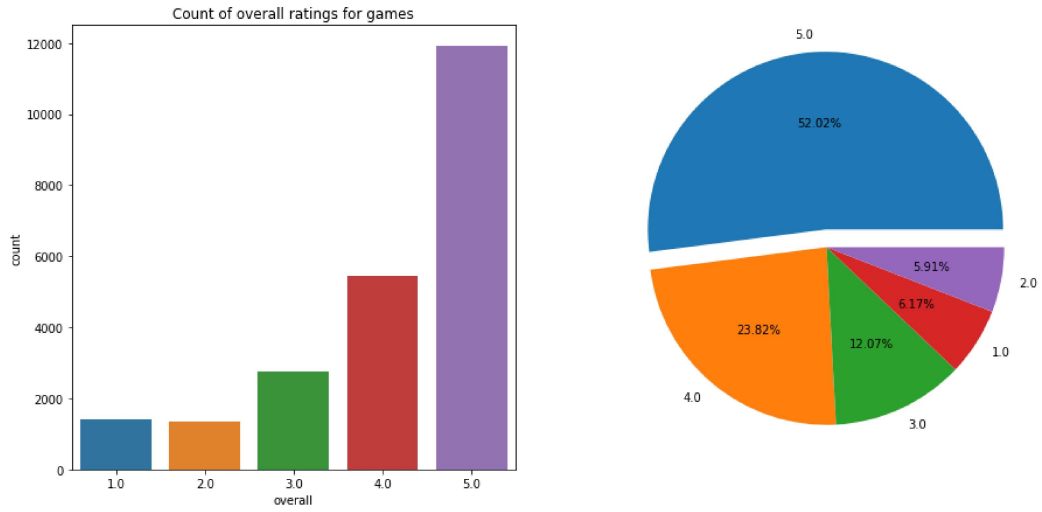
Exploratory Data Analysis (EDA)

(1) Analysis for Video Games overall rating

```
x = games_df["overall"].value_counts()          # Value counts of ratings in Video Game file
x
```

```
5.0    11911
4.0     5454
3.0     2764
1.0     1413
2.0     1354
Name: overall, dtype: int64
```

```
import seaborn as sb
fig, ax = plt.subplots(1, 2, figsize = (15, 7))
ax[0].set_title("Count of overall ratings for games")
percentage = games_df["overall"].value_counts()
labels = list(games_df["overall"].value_counts().index)

sb.countplot(x = games_df["overall"], ax = ax[0])
plt.pie(percentage,labels = labels, autopct= "%0.2f%%",explode=[0.1,0.0,0.0,0.0,0.0])

plt.show()
```



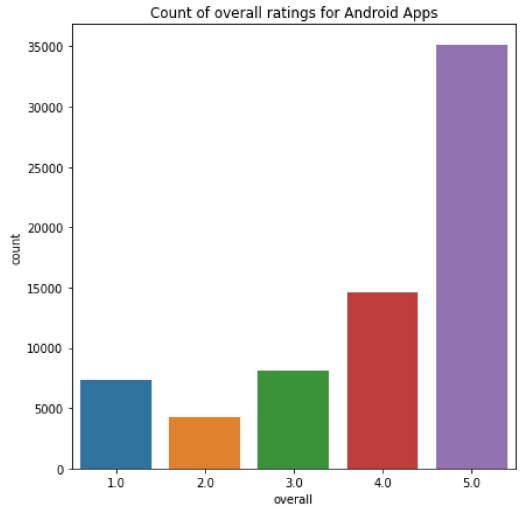
- More than half of the population are highly satisfied with the product.
- Nearly 12% of the population is not satisfied with the product.

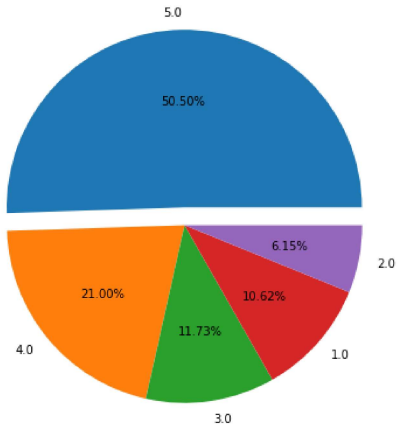
2. Analysis for Android App overall rating

```
y = android_df["overall"].value_counts()                #Counts of rating for android app file
y
```

```
5.0    35087
4.0    14586
3.0     8148
1.0     7379
2.0     4273
Name: overall, dtype: int64
```

```
fig, ax = plt.subplots(1, 2, figsize = (15, 7))
ax[0].set_title("Count of overall ratings for Android Apps")
percentage = android_df["overall"].value_counts()
labels = list(android_df["overall"].value_counts().index)

sb.countplot(x = android_df["overall"], ax = ax[0])
plt.pie(percentage,labels = labels, autopct= "%0.2f%%",explode=[0.1,0.0,0.0,0.0,0.0])

plt.show()
```





- More than half of the population are highly satisfied with the app.
- Nearly 17% of the population is not satisfied with the product.

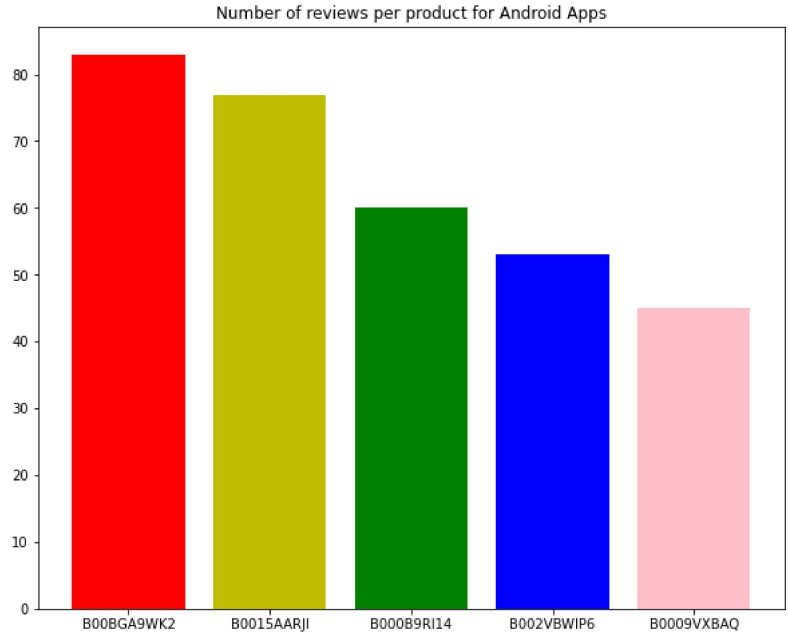
3. Analysis for Product-wise reviews of Video games

```
games_product = games_df["Product_id"].value_counts()            #Count of products with ratings
games_product
```

```
B00BGA9WK2    83
B0015AARJI    77
B000B9RI14    60
B002VBWIP6    53
B0009VXBAQ    45
              ..
B000MQQ8R6     1
B000CBCVEK     1
B000V01UOO     1
B004CQRCF4     1
B0079NGSIY     1
Name: Product_id, Length: 7468, dtype: int64
```

```
plt.figure(figsize=(10,8))
plt.bar(games_product.index[:5], games_product[:5],color=['r','y','g','b','pink'])
plt.title("Number of reviews per product for Android Apps")
```

```
Text(0.5, 1.0, 'Number of reviews per product for Android Apps')
```



- 83 reviews is the highest number of reviews which alloted to one product of video games.
- Above five games are most reviewed by people.

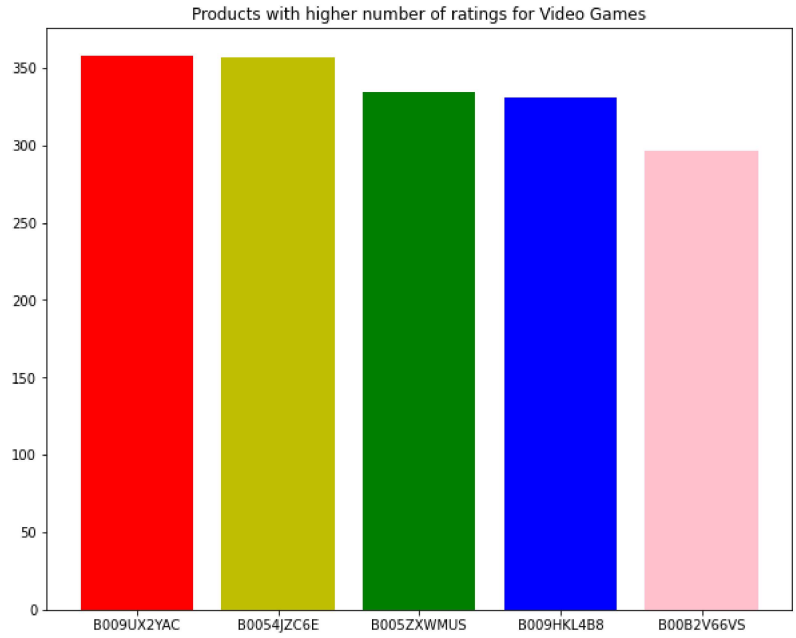
4. Analysis for Product-wise reviews of Android Apps

```
app_product = android_df["Product_id"].value_counts()            #Count of products with ratings
app_product
```

```
B009UX2YAC    358
B0054JZC6E    357
B005ZXWMUS    334
B009HKL4B8    331
B00B2V66VS    296
              ...
B005BNLRVC      1
B004V4O3V8      1
B00FDWKHRG      1
B004TNXGGE      1
B00BL8B5SG      1
Name: Product_id, Length: 9834, dtype: int64
```

```
plt.figure(figsize=(10,8))
plt.bar(app_product.index[:5], app_product[:5],color=['r','y','g','b','pink'])
plt.title("Products with higher number of ratings for Video Games")
```

```
Text(0.5, 1.0, 'Products with higher number of ratings for Video Games')
```



- 358 reviews is the highest number of reviews which alloted to one product of android apps.
- Above five apps are most reviewed by people.

2. Problem Statement 1: Sentiment Analysis

Method:1 - Vader Sentiment analysis

VADER (Valence Aware Dictionary and sEntiment Reasoner) is a lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media. VADER uses a combination of A sentiment lexicon is a list of lexical features (e.g., words) which are generally labeled according to their semantic orientation as either positive or negative. VADER not only tells about the Positivity and Negativity score but also tells us about how positive or negative a sentiment is.

Example:-

```
text = 'this product is not good'
analyzer1 = SentimentIntensityAnalyzer() # function is used from nltk library, it checks positive and negative words in the sentence
vs1 = analyzer1.polarity_scores(text) #it signifies that how data shows polarity
vs1
```

```
{'neg': 0.376, 'neu': 0.624, 'pos': 0.0, 'compound': -0.3412}
```

The Compound score is a metric that calculates the sum of all the lexicon ratings which have been normalized between -1(most extreme negative) and +1 (most extreme positive).

VADER sentiment analysis for getting Compound score.

Creating function for sentiment analysis

```
def sentimental_Score(sentence):
  analyzer = SentimentIntensityAnalyzer()
  vs = analyzer.polarity_scores(sentence)
  score=vs['compound']
  if score >= 0.6:
    return 'very pos'
  elif (score < 0.6) and (score > 0.2):
    return 'positive'
  elif (score <= 0.2) and (score >= -0.2):
    return 'neu'
  elif (score < -0.2) and (score > -0.6):
    return 'negative'
  elif score <= -0.6:
    return 'very neg'
```

```
android_df['reviewText'] = android_df['reviewText'].apply(str)
android_df['summary'] = android_df['summary'].apply(str)
games_df['reviewText'] = games_df['reviewText'].apply(str)
games_df['summary'] = games_df['summary'].apply(str)
```

Applying vader sentiment analysis to review text and summary for two categories i.e. Android apps & Video games

```
android_df['sentiment_reviewText'] = android_df['reviewText'].apply(lambda x: sentimental_Score(x))
android_df['sentiment_summaryText'] = android_df['summary'].apply(lambda x: sentimental_Score(x))
games_df['sentiment_reviewText'] = games_df['reviewText'].apply(lambda x: sentimental_Score(x))
games_df['sentiment_summaryText'] = games_df['summary'].apply(lambda x: sentimental_Score(x))
```

```
android_df.head()
```

	Unnamed: 0	index	reviewerID	Product_id	reviewerName	helpful	reviewText	overall	summ
0	0	24959	A1MDQ9NHZBXQEW	B004LZOTHU	Hearn	[0, 0]	instal application notice significant decrease...	3.0	bat k
1	1	192876	AZQ4DF43P6KD5	B006PH7WBM	Jared	[0, 1]	precious princess fool spend almost digital ju...	1.0	
2	2	82053	A13Q8F2PH26PAM	B00529IOXO	Vincent	[0, 0]	app basic easy use send picture difficult neve...	4.0	g
3	3	361845	A20IHFYO0FK8JA	B008OOYALE	art girl	[0, 0]	love wait egg hatch dragon	4.0	rev

Converting to csv

```
android_df.to_csv('android_data with sentiments.csv')
games_df.to_csv('games_data with sentiments.csv')
```

Reading the data from csv file

```
android_df = pd.read_csv('/content/drive/MyDrive/android_data with sentiments.csv',parse_dates=['reviewText'])
games_df = pd.read_csv('/content/drive/MyDrive/games_data with sentiments.csv',parse_dates=['reviewText'])
```

```
negative_android = android_df[(android_df['sentiment_reviewText']=='very neg')|(android_df['sentiment_reviewText']=='neg')]
negative_games = games_df[(games_df['sentiment_reviewText']=='very neg')|(games_df['sentiment_reviewText']=='neg')]
```

```
negative_reviews_android = negative_android.reviewText.str.cat()
negative_reviews_android
```

```
'download even though intention play rating star irritate even also go get everyone know download rate
star irritate shut stuff empty head pillah go cry nonexistent deity choice annoying d - bagok would th
ink version minecraft right wrong stupid game bounce head one platform another actually real minecraft
pocket edition check instead game stinkuse app less hour already sick every thirty second game stop ad
come ask buy something gem gold chest game nauseate get old really fast interruption enough every twen
ty second tries connect facebook post minor achievement certain friend family want read quot brian lea
rn tie shoe tribe quot twenty - seven time day game finally recover interruption get close facebook re
```

word cloud for negative android reviews

```
wordcloud_negative = WordCloud(background_color='white').generate(negative_reviews_android)
fig = plt.figure(figsize=(15,15))
ax1 = fig.add_subplot(211)
ax1.imshow(wordcloud_negative,interpolation='bilinear')
ax1.axis("off")
ax1.set_title('Android apps negative review words',fontsize=20)
```

```
Text(0.5, 1.0, 'Android apps negative review words')
```

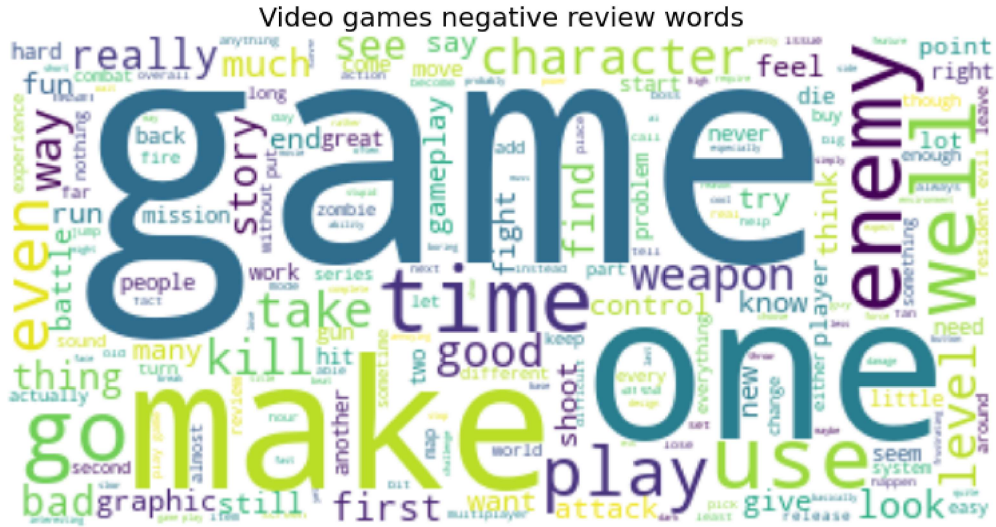
word cloud for negative video games reviews

```
negative_reviews_games = negative_games.reviewText.str.cat()
negative_reviews_games
```

```
'worth price dollar really probably buck use gamestop really hate people try price thing old be not hu
ge market video game call gamestop sell ps2 game wayy cheapfifteen year old son always check review ac
tual gamer tube purchasing video game long waste money game end bottom collection never play times bat
man arkham video game still play every onecataclysm simply mind - blow experience homeworld year ago e
ven today core gameplay tamper much grant cataclysm manage improve many aspect first game sum part add
complete whole change make basic way play game first seem exciting battle quickly become tedious examp
le technology tree add quot upgrade quot mean must take time fight search map outdated ship stop upgra
```

```
# word cloud for negative video games reviews
wordcloud_negative = WordCloud(background_color='white').generate(negative_reviews_games)
fig = plt.figure(figsize=(15,15))
ax1 = fig.add_subplot(211)
ax1.imshow(wordcloud_negative,interpolation='bilinear')
ax1.axis("off")
ax1.set_title('Video games negative review words',fontsize=20)
```

```
Text(0.5, 1.0, 'Video games negative review words')
```



Method:2 - Bert sentiment classifier

```
from transformers import pipeline
from transformers import AutoTokenizer, TFAutoModelForSequenceClassification

model_name = "nlptown/bert-base-multilingual-uncased-sentiment"
model = TFAutoModelForSequenceClassification.from_pretrained(model_name, from_pt=True)

tokenizer = AutoTokenizer.from_pretrained(model_name)
s_analyzer = pipeline('sentiment-analysis', model=model, tokenizer=tokenizer)
```

```
Downloading config.json: 100%  953/953 [00:00<00:00, 8.32kB/s]
Downloading pytorch_model.bin: 100%  638M/638M [00:14<00:00, 46.3MB/s]
All PyTorch model weights were used when initializing TFBertForSequenceClassification.

All the weights of TFBertForSequenceClassification were initialized from the PyTorch model.
If your task is similar to the task the model of the checkpoint was trained on, you can already use TFE
Downloading tokenizer_config.json: 100%  39.0/39.0 [00:00<00:00, 783B/s]
Downloading vocab.txt: 100%  851k/851k [00:00<00:00, 1.61MB/s]
Downloading special_tokens_map.json: 100%  112/112 [00:00<00:00, 2.51kB/s]
```

Example:-

```
s_analyzer('this product is bad')
```

```
[{'label': '1 star', 'score': 0.7642213702201843}]
```

```
s_analyzer('this product is good but price was very high')
```

```
[{'label': '3 stars', 'score': 0.4948844313621521}]
```

Defining the funcion for extracting the label

```
def sentiment_score_bert(sentence):
  m = s_analyzer(sentence,truncation=True)
```

```
  for i in m:
    return i['label']
```

Applying bert model to both dataframes

```
games_df['sentiment_review_bert'] = games_df['reviewText'].apply(lambda j: sentiment_score_bert(j))
android_df['sentiment_review_bert'] = android_df['reviewText'].apply(lambda j: sentiment_score_bert(j))
```

```
android_df.to_csv('android_final.csv')
games_df.to_csv('games_final.csv')
```

Model comparison by confusion matrix

we are comparing vader & bert model by plotting confusion matrix

For games data

```
games_final = pd.read_csv('/content/drive/MyDrive/games_data_final.csv') # bert result for games files
```

```
games_final = games_final.drop(columns=['Unnamed: 0','Unnamed: 0.1','Unnamed: 0.1.1','Unnamed: 0.1.1.1'],axis=1) #dropping few columns from o
```

```
# vader class
games_final.loc[games_final['sentiment_reviewText']=='very pos','vader_class'] = 5.0
games_final.loc[games_final['sentiment_reviewText']=='positive','vader_class'] = 4.0
games_final.loc[games_final['sentiment_reviewText']=='neu','vader_class'] = 3.0
games_final.loc[games_final['sentiment_reviewText']=='negative','vader_class'] = 2.0
games_final.loc[games_final['sentiment_reviewText']=='very neg','vader_class'] = 1.0
```

```
# bert class
games_final.loc[games_final['sentiment_review_bert']=='5 stars','bert_class'] = 5.0
games_final.loc[games_final['sentiment_review_bert']=='4 stars','bert_class'] = 4.0
games_final.loc[games_final['sentiment_review_bert']=='3 stars','bert_class'] = 3.0
games_final.loc[games_final['sentiment_review_bert']=='2 stars','bert_class'] = 2.0
games_final.loc[games_final['sentiment_review_bert']=='1 star','bert_class'] = 1.0
```

confusion matrix for actual rating vs vader predicted class

```
cm_vader = confusion_matrix(games_final['overall'],games_final['vader_class'],normalize='true')
```

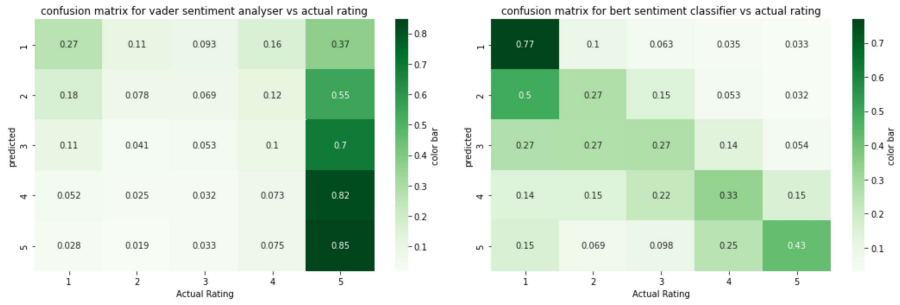
confusion matrix for actual rating vs bert predicted class

```
cm_bert = confusion_matrix(games_final['overall'],games_final['bert_class'],normalize='true')
```

```
plt.figure(figsize=(15,5))
plt.subplot(121)
sns.heatmap(cm_vader,cmap='Greens',annot=True,
            cbar_kws={'orientation':'vertical','label':'color bar'},
            xticklabels=[1,2,3,4,5],yticklabels=[1,2,3,4,5])
plt.xlabel('Actual Rating')
plt.ylabel('predicted')
plt.title('confusion matrix for vader sentiment analyser vs actual rating')
```

```
plt.subplot(122)
sns.heatmap(cm_bert,cmap='Greens',annot=True,
            cbar_kws={'orientation':'vertical','label':'color bar'},
            xticklabels=[1,2,3,4,5],yticklabels=[1,2,3,4,5])
plt.xlabel('Actual Rating')
plt.ylabel('predicted')
plt.title('confusion matrix for bert sentiment classifier vs actual rating')
```

```
plt.tight_layout()
plt.show()
```



- True positive rate is high for the bert model for all sentiments compared to vader sentiment analyser

(1) Bert model is comparatively giving true positive results than vader analysis.

(2) Vader model is giving False results by seeing in graphs that for 5-1ratings-> vader is giving 0.37 and bert is giving 0.033

For android data

```
android_final = pd.read_csv('/content/drive/MyDrive/android_df_final.csv')
android_final.drop(columns=['Unnamed: 0','Unnamed: 0.1','Unnamed: 0.1.1','Unnamed: 0.1.1.1'],axis=1,inplace=True)


# vader class
android_final.loc[android_final['sentiment_reviewText']=='very pos','vader_class'] = 5.0
android_final.loc[android_final['sentiment_reviewText']=='positive','vader_class'] = 4.0
android_final.loc[android_final['sentiment_reviewText']=='neu','vader_class'] = 3.0
android_final.loc[android_final['sentiment_reviewText']=='negative','vader_class'] = 2.0
android_final.loc[android_final['sentiment_reviewText']=='very neg','vader_class'] = 1.0

# bert class
android_final.loc[android_final['sentiment_review_bert']=='5 stars','bert_class'] = 5.0
android_final.loc[android_final['sentiment_review_bert']=='4 stars','bert_class'] = 4.0
android_final.loc[android_final['sentiment_review_bert']=='3 stars','bert_class'] = 3.0
android_final.loc[android_final['sentiment_review_bert']=='2 stars','bert_class'] = 2.0
android_final.loc[android_final['sentiment_review_bert']=='1 star','bert_class'] = 1.0
```

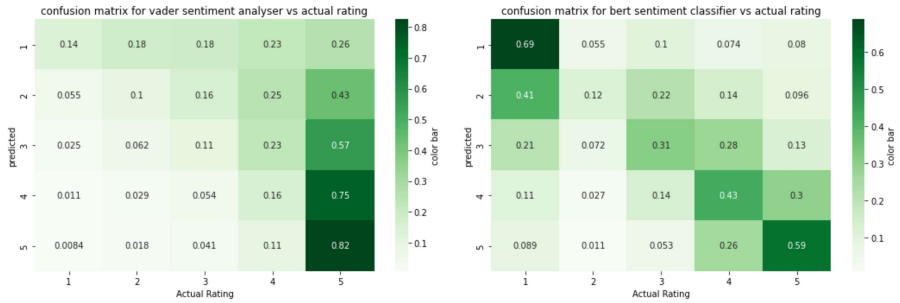
confusion matrix for actual rating vs vader predicted class

```
cm_vader = confusion_matrix(android_final['overall'],android_final['vader_class'],normalize='true')
```

confusion matrix for actual rating vs bert predicted class

```
cm_bert = confusion_matrix(android_final['overall'],android_final['bert_class'],normalize='true')


plt.figure(figsize=(15,5))
plt.subplot(121)
sns.heatmap(cm_vader,cmap='Greens',annot=True,
            cbar_kws={'orientation':'vertical','label':'color bar'},
            xticklabels=[1,2,3,4,5],yticklabels=[1,2,3,4,5])
plt.xlabel('Actual Rating')
plt.ylabel('predicted')
plt.title('confusion matrix for vader sentiment analyser vs actual rating')
```

```
plt.subplot(122)
sns.heatmap(cm_bert,cmap='Greens',annot=True,
            cbar_kws={'orientation':'vertical','label':'color bar'},
            xticklabels=[1,2,3,4,5],yticklabels=[1,2,3,4,5])
plt.xlabel('Actual Rating')
plt.ylabel('predicted')
plt.title('confusion matrix for bert sentiment classifier vs actual rating')

plt.tight_layout()
plt.show()
```



(1) Bert model is comparatively giving true positive results than vader analysis.

(2) Vader model is giving False results by seeing in graphs that for 5-1ratings-> vader is giving 0.26 and bert is giving 0.08

Reasons for negative sentiments

```
!pip install pyabsa
```

```
from pyabsa import available_checkpoints
checkpoint_map = available_checkpoints() #libraries
```

```
from pyabsa import ATEPCCheckpointManager

aspect_extractor = ATEPCCheckpointManager.get_aspect_extractor(checkpoint='english',
                                    auto_device=True)  # False means load model on CPU
```

```
# You can inference from a list of sentences or a DatasetItem from PyABSA
examples = ['Staff was very rude but food was delicious']
inference_source = examples
atepc_result = aspect_extractor.extract_aspect(inference_source=inference_source,  #
                          pred_sentiment=True,  # Predict the sentiment of extracted aspect terms
                          )
```

```
atepc_result
```

```
[{'sentence': 'Staff was very rude but food was delicious',
  'IOB': ['B-ASP', 'O', 'O', 'O', 'O', 'B-ASP', 'O', 'O'],
  'tokens': ['Staff',
   'was',
   'very',
   'rude',
   'but',
   'food',
   'was',
   'delicious'],
  'aspect': ['Staff', 'food'],
  'position': [[0, 5], [0, 5]],
  'sentiment': ['Negative', 'Positive'],
  'probs': [[0.9998047947883606,
    5.137383413966745e-05,
```

```
          0.00014384793757926673],
         [0.0004105722764506936, 3.9567938074469566e-05, 0.9995498061180115]],
        'confidence': [0.9998047947883606, 0.9995498061180115]}]
```

Reasons for video games negative labels

```
negative_game_df = games_df[(games_df['sentiment_review_bert'] == '1 star') | (games_df['sentiment_review_bert'] == '2 stars')]
```

```
n = negative_game_df["Product_id"].value_counts()  # checking no. of reviews per product
npi = n[n.values > 5].index   # taking product ids of products having no. of reviews more than 5.
```

```
examples = []                  #Step 1
for j in npi:      # considering one product at a time
  a = negative_game_df[negative_game_df['Product_id']==j]['reviewText']   # list of all reviews of one product
  for text in a:                   # considering one review at a time
    example = [text]               # text is each review in list format
    examples.append(example)       # examples contain reviews in list format
```

```
aspects = []                                            #Step 2
sentiments = []
for example in examples:                                   #Each review text
  inference_source = example
  atepc_result = aspect_extractor.extract_aspect(inference_source=inference_source,
                           pred_sentiment=True,  # extracting the aspect terms and their sentiments
                           )

  for i in atepc_result:
    aspects.append(list(i.values())[list(i.keys()).index('aspect')])     #aspects contain aspect for each review
    sentiments.append( list(i.values())[list(i.keys()).index('sentiment')])  #Sentiments contains sentiments each review
```

```
reasons = []
sentiment_reason = []
product_ids = []
for j in npi:                                          # selecting each product
  a = negative_game_df[negative_game_df['Product_id'] == j]['reviewText']
  for z,k in zip(a,range(len(sentiments))):
  #for k in range(len(sentiments)):
    for x in sentiments[k]: #  if a review contains -->   p n n [n][[n],[n]],
      if x == 'Negative':             # filter negative aspects only
        index = sentiments[k].index('Negative')         # finding the position of neg sentiment
        #print(index)
        #print(aspects[k][index])
        #print(j)
        reasons.append(aspects[k][index])              # reasons contain one aspect at a time
        sentiment_reason.append(sentiments[k][index])  # one sentiment at a time
        product_ids.append(j)                          # product id related to the same aspect
    #print("----------------------")                   # it will make duplicates
```

```
reasons, sentiment_reason
```

```
data = {'Product_id': product_ids, 'Reason': reasons, "sentiment":sentiment_reason}
product_id_games_df_r = pd.DataFrame(data)                                          # creating dataframe
```

```
product_id_games_df_r.drop_duplicates(inplace = False).head(40)  # dropping duplicate cells
```

Reasons for android apps negative labels

```
negative_android_df = android_df[(android_df['sentiment_review_bert'] == '1 star') | (android_df['sentiment_review_bert'] == '2 stars')]
```

```
m = negative_android_df["Product_id"].value_counts()
npia = m[m.values > 15].index
```

```
examples_a = []
for j in npia:
  a = negative_android_df[negative_android_df['Product_id']==j]['reviewText']
  for text in a:
```

```
    example = [text]
    examples_a.append(example)


aspects = []                                              #Step 2
sentiments = []
for example in examples_a:                                     #Each review text
  inference_source = example
  atepc_result = aspect_extractor.extract_aspect(inference_source=inference_source,  #
                           pred_sentiment=True,  # Predict the sentiment of extracted aspect terms
                           )

  for i in atepc_result:
    aspects.append(list(i.values())[list(i.keys()).index('aspect')])                        #aspects contain aspect for each review
    sentiments.append( list(i.values())[list(i.keys()).index('sentiment')])


reasons = []
sentiment_reason = []
product_ids = []
for j in npia:                                          # selecting each product
  a = negative_android_df[negative_android_df['Product_id'] == j]['reviewText']
  for z,k in zip(a,range(len(sentiments))):
  #for k in range(len(sentiments)):
    for x in sentiments[k]: # p n n [n][[n],[n]]
      if x == 'Negative':
        index = sentiments[k].index('Negative')
        #print(index)
        #print(aspects[k][index])
        #print(j)
        reasons.append(aspects[k][index])                                          # reasons contain one aspect at a time
        sentiment_reason.append(sentiments[k][index])                              # one sentiment at a time
        product_ids.append(j)                                                      # product id related to the same aspect
    #print("----------------------")                                               # it will make duplicates


data = {'Product_id': product_ids, 'Reason': reasons, "sentiment":sentiment_reason}
product_id_games_df_r = pd.DataFrame(data)                                              # creating dataframe


product_id_games_df_r.drop_duplicates(inplace = False).head(40)  # dropping duplicate cells


reasons_negative_android = pd.read_csv('/content/drive/MyDrive/capestone/Reasons for android final(in list form.csv')
reasons_negative_games = pd.read_csv('/content/drive/MyDrive/capestone/Reasons for games final.csv')



reasons_negative_android.head(5)
```

	Unnamed: 0	Product_id	Reasons
0	0	B009HKL4B8	['app', 'play', 'content']
1	24	B005ZXWMUS	['app', 'play', 'content']
2	48	B0094BB4TW	['app', 'return', 'external storage']
3	71	B008Y2FRFO	['app', 'play', 'xbox']
4	91	B00E8KLWB4	['app', 'kindle', 'action']

```
reasons_negative_games.head(5)
```

	Unnamed: 0	Product_id	Reasons
0	0	B00BGA9WK2	['graphic', 'ps4', 'size']
1	18	B00178630A	['ps4', 'size', 'graphic']
2	35	B000B9RI14	['ps4', 'size', 'graphic']
3	52	B0009VXBAQ	['ps4', 'size', 'graphic']
4	69	B004FYEZMQ	['ps4', 'size', 'console camera']

Problem statement 2 - Finding the product names

- for video games data

```
unique_product = games_final['Product_id'].value_counts()
unique_product[unique_product.values>5]
```

```
B00BGA9WK2    83
B0015AARJI    77
B000B9RI14    60
B002VBWIP6    53
B0009VXBAQ    45
              ..
B000K8YAKI     6
B000R3BNE2     6
B001UWGDC6     6
B00CMQTUY2     6
B0050SVGW8     6
Name: Product_id, Length: 910, dtype: int64
```

```
product_idd = []
product_name = []
for j in unique_product[:911].index:
  a = games_final[games_final['Product_id'] == j]['reviewText']
  for i in a:
    str1 = nlp(i)
    for b in str1.ents:
      if b.label_=='PRODUCT':
        product_idd.append(j)
        product_name.append(b.text)
```

```
d = {'Product_id':product_idd,"Product_name":product_name}
d1 = pd.DataFrame(d)
productnames = d1.groupby(by='Product_id')['Product_name'].agg(lambda x:x.value_counts().index[0])
productnames
```

```
Product_id
B00002DHEV       series4
B00002STEZ          dk64
B00002STGL       falcon2
B00004SQPD          sony
B00004SVV9        howard
                  ...
B00C71034I      spoiler1
B00DC7G0GG    nsmb games
B00DC7G2W8          mk64
B00DC7O77A         dkctf
B00ERDGMT4         cons1
Name: Product_name, Length: 108, dtype: object
```

```
product_game_name = pd.read_excel('/content/drive/MyDrive/capestone/Video_game_names.xlsx')
product_game_name
```

	Product_id	Product_name
0	B00002STEZ	dk64
1	B00005BOSF	wavebird
2	B00005MO5G	advance3
3	B0000696CZ	gta3
4	B00006FWTX	wavebird
5	B00007LV7Y	konami
6	B00009ECGK	stracraft2

- for Android app data

```
product_name_android = pd.DataFrame(productnames)
product_name_android.to_csv('product_name_android.csv')


unique_product1 = android_final['Product_id'].value_counts()
unique_product1[unique_product1.values>5]
```

```
B009UX2YAC    358
B0054JZC6E    357
B005ZXWMUS    334
B009HKL4B8    331
B00B2V66VS    296
              ...
B008REEKRA      6
B00FTJB5QK      6
B004THM08K      6
B00DU860MG      6
B006CW7I00      6
Name: Product_id, Length: 2681, dtype: int64
```

20	B003JVKHEQ	fairlv2

```
product_idd1 = []
product_name1 = []
for j in unique_product1[:2681].index:
  a = android_final[android_final['Product_id'] == j]['reviewText']
  for i in a:
    str1 = nlp(i)
    for b in str1.ents:
      if b.label_=='PRODUCT':
        product_idd1.append(j)
        product_name1.append(b.text)



d2 = {'Product_id':product_idd1,"Product_name":product_name1}
d2 = pd.DataFrame(d2)
productnames1 = d2.groupby(by='Product_id')['Product_name'].agg(lambda x:x.value_counts().index[0])
productnames1
```

```
Product_id
B004FOA84A                    atlantis
B004N2NWT2                thrive tablet
B004SJ3AXI                        pg13
B004VSC7T4                    storage3
B004XJHBCE                       tf101
B0055S348W                      mg5320
B0058OE9CS                      flext9
B00594XOZU                         kik
B005GVF95O                      droid2
B005T87QCI                           l
B005XQLBU4                thrive tablet
B005ZFOOE8                   ten eleven
B005ZTFPFQ     atari shoot missile come
B0060QU5ZS                         til
B0066T8OH0                      tetris
B006OC2ANS                        cole
B006OCM0G0                      k x x
B0075AJ3O2          samsung tab hundred
B007693VXG                        yuck
B007FFZSE6                      k nmm
B007JPG04E                      zjjsk
B007MPJQ38                      tf101
B007T8LJM4                   atlantis
B0084HDG8Y                   supernova
```

```
B008GU42KK                    atlantis
B008HU2T9K                   azada one
B008I7CVWC                     fhfhfhf
B008JK6W5K     bmw mercedes - benz game
B008KP6ENE                        sl101
B008KYLSWW                      notifie
B00902AKK4                         xoom
B00910Y1OQ                     atlantis
B00942EOGG                         ts12
B00964BWFS                     atlantis
B0098BGYM0                    discovery
B00998UF9U                            1
B00A2RZDZI                        tf101
B00AB7IA1S    toranato fan glitche game
B00AV8ZHZE                         saws3
B00AVGGYNA                 fcoldshower1
B00B4VI8MQ                  brsmithnur1
B00B99KJR0                     atlantis
B00BG3ID0Y                   hooray coin
B00BMH4GQE                          funn
B00BO0C3DW                        tf101
B00CB2837W                       tetris
B00CGTNHXA                        work2
B00CHSPB8Y                       meteor
B00CKW6FVE                       tetris
B00CZDSK7K                    families2
B00DLJ31HQ                       mosaic
B00E1GOGJK                    pic quiz
B00E1JZIGW                   discovery
B00ESNW58K                  strawberry
B00FAX6XQC            wimpy shotgun cal
B00GOZQ2E8                xp anddiamond
Name: Product_name, dtype: object
```

```
productnames1.to_csv('product_names_android1.csv')
```

```
product_android_name = pd.read_excel('/content/drive/MyDrive/capestone/Android_app_names_verified.xlsx')
product_android_name
```

1	B004SJ3AXI	pg13
2	B00594XOZU	kik
3	B005XQLBU4	thrive tablet
4	B005ZFOOE8	ten eleven
5	B005ZTFPFQ	atari shoot missile come
6	B0066T8OH0	tetris
7	B006OC2ANS	cole
8	B007693VXG	yuck
9	B007T8LJM4	atlantis
10	B0084HDG8Y	supernova
11	B008GU42KK	atlantis

Problem-3 Future Data Trends

Time series analysis for Android_df

```
# changing the Datatype of reviewTime to datetime
android_final['reviewTime'] = pd.to_datetime(android_final['reviewTime'])
games_final['reviewTime'] = pd.to_datetime(games_final['reviewTime'])


# formatting the dates
android_final['reviewTime'] = android_final['reviewTime'].dt.strftime('%m-%d-%Y')
games_final['reviewTime'] = games_final['reviewTime'].dt.strftime('%m-%d-%Y')
```

Trend of positive sentiments

Taking positive sentiments only (by bert method : ratings = 5 & 4)

```
postive_android = android_final[(android_final['bert_class']==5.0)|(android_final['bert_class']==4.0)]
```

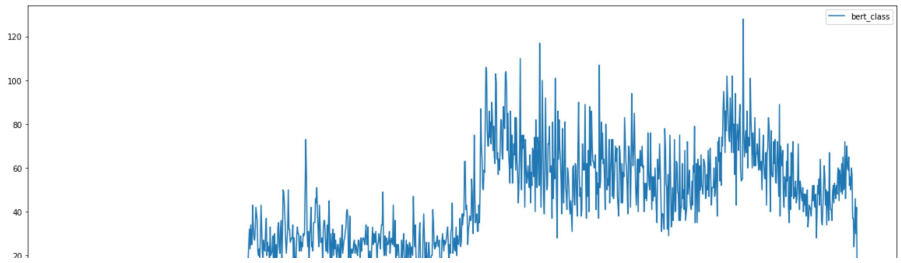
Count of positive reviews per date

```
review_positive = pd.DataFrame(postive_android.groupby(by='reviewTime')['bert_class'].count()).reset_index()
```

Converting object datatype to datetime datatype

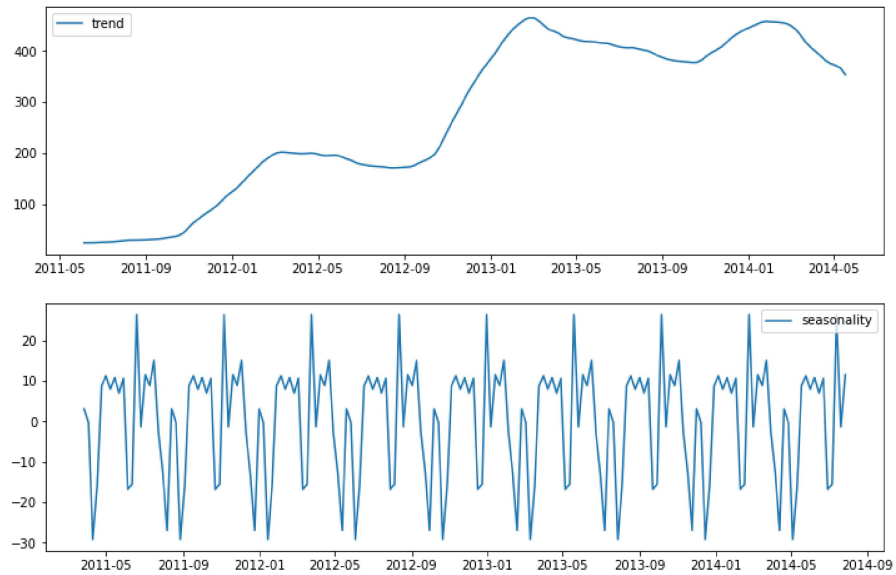
```
review_positive['reviewTime'] = pd.to_datetime(review_positive['reviewTime'])


pos_android = review_positive.sort_values(by='reviewTime',ascending=True)
pos_android = pos_android.set_index('reviewTime')


pos_android.plot(figsize=(20,8))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd0d95c7090>
```




```
pos_android = pos_android.resample('w').sum() # Resampling the data Weekly
```

```
#trend seasonality
decompose = seasonal_decompose(pos_android,period=20)

seasonality = decompose.seasonal
trend = decompose.trend

plt.subplots(figsize=(12,8))
plt.subplot(211)
plt.plot(trend,label='trend')
plt.legend(loc='best')

plt.subplot(212)
plt.plot(seasonality,label='seasonality')
plt.legend(loc='best')

plt.show()
```



- For positive sentiments :
- We have trend & seasonality both in our data.
- Since our data have seasonality, so we need to use SRIMA Model

Stationarity

```
def check_stationarity(data):
    pvalue = adfuller(data)[1]
    if pvalue < 0.05:
        ret ='data is stationary.proceed to modeling'
    else:
        ret ='data is not stationary.make it stationary'
    return(ret)


check_stationarity(pos_android)
```

```
'data is not stationary.make it stationary'
```

- since our data is not stationary
- difference the data by 1

Differencing the data

```
diff_data = pos_android - pos_android.shift()
print(diff_data)
```

```
                bert_class
reviewTime
2011-03-27         NaN
2011-04-03       -13.0
2011-04-10         0.0
2011-04-17        -2.0
2011-04-24        16.0
...                ...
2014-06-29        44.0
2014-07-06         5.0
2014-07-13        18.0
2014-07-20      -118.0
2014-07-27      -220.0

[175 rows x 1 columns]
```

```
check_stationarity(diff_data.dropna())
```

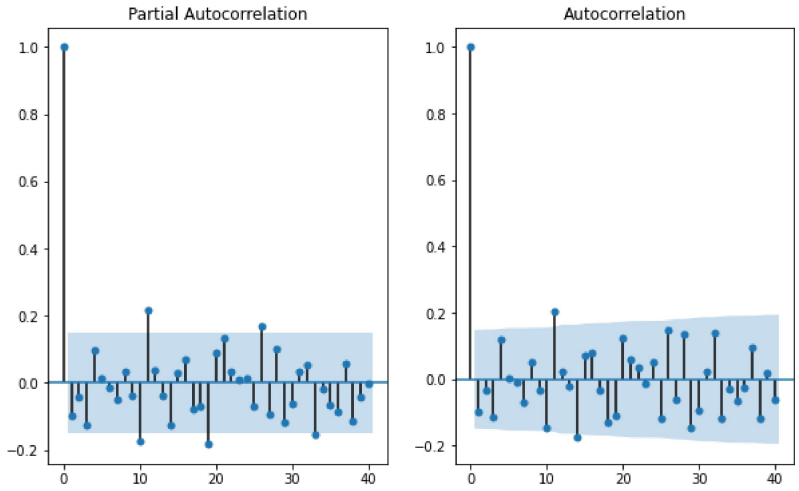
```
'data is stationary.proceed to modeling'
```

```
diff_data = diff_data.dropna()
```

```
diff_data.isnull().sum()
```

```
bert_class    0
dtype: int64
```

```
#plot for acf and pacf

fig,ax=plt.subplots(1,2,figsize=(10,6))

plot_pacf(diff_data,lags=40,ax=ax[0])
plot_acf(diff_data,lags=40,ax=ax[1])      #default Confidence level is 95%

plt.show()
```



- p,d,q,=(5,2)

- Since our data has seasonality and trend present

```
int(len(diff_data)*0.70)
```

```
121
```

spillting the data into train and test (70% & 30%)

```
rows = int(len(diff_data)*0.70)
train_data = diff_data[:rows]
test_data = diff_data[rows:]
```

Trying multiple combination of p & q values, taking values which have less error

```
#taking (p,q) as (5,2)
p = np.arange(5)
q = np.arange(2)


p_val = []
q_val = []
models= []
rmse = []
mse = []
aic_val = []
bic_val = []
p_val = []
q_val = []
mod = []
Ljung = []
count=0

for i in p:
    for j in q:
            models.append(SARIMAX(train_data,order=(i,1,j),seasonal_order=(i,1,j,15)).fit())
            p_val.append(i)
            q_val.append(j)

# for removing (p,q)(0,0)
m = models[1:]
p_v = p_val[1:]
q_v = q_val[1:]

for i in m:
    aic_val.append(i.aic)
    bic_val.append(i.bic)
    pred = i.predict(start=len(train_data), end=len(train_data)+len(test_data)-1)
    mod.append(count)
    mse.append(mean_squared_error(test_data,pred))
    rmse.append(np.sqrt(mean_squared_error(test_data,pred)))
    count = count+1

    pvalue = (sm.stats.acorr_ljungbox(i.resid,lags=[1],return_df=True))['lb_pvalue'].values
    if pvalue < 0.05:
        Ljung.append('model is not good')
    else:
         Ljung.append('model is good')


a = pd.DataFrame({'model':mod,"p":p_v,'q':q_v,"MSE":mse,"RMSE":rmse,"AIC":aic_val,"BIC":bic_val,'Ljung':Ljung})
a.sort_values(by='RMSE',ascending=True)
```

	model	p	q	MSE	RMSE	AIC	BIC	Ljung
0	0	0	1	2833.011870	53.226045	1132.661087	1140.622968	model is not good
2	2	1	1	2864.710470	53.522990	1132.160246	1145.430048	model is good

- Based on Low RMSE value, taking (p,q,d) = (1,1,1)

8	8	4	1	3218.011521	56.727520	1135.288812	1164.582376	model is good

SRIMA Model

7	7	4	0	3457.186628	58.797845	1140.702289	1164.587932	model is good

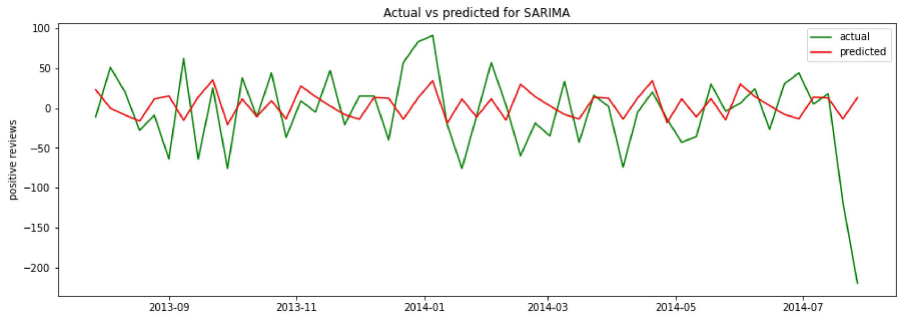
```
p=1; q=1; d=1
model = SARIMAX(train_data,order=(p,d,q),seasonal_order=(p,d,q,15)).fit()
```

3	3	2	0	4015.764415	63.370059	1166.695883	1179.965665	model is good

```
# Evaluating model performance
forcast_sarima=model.predict(start=len(train_data), end=len(train_data)+len(test_data)-1)


print(test_data.shape,forcast_sarima.shape)
```

```
(53, 1) (53,)
```

```
plt.figure(figsize=(15,5))
plt.plot(test_data,label='actual',c='g')
plt.plot(forcast_sarima,label='predicted',c='r')
plt.title('Actual vs predicted for SARIMA')
plt.ylabel('positive reviews')
plt.legend()
plt.show()
```

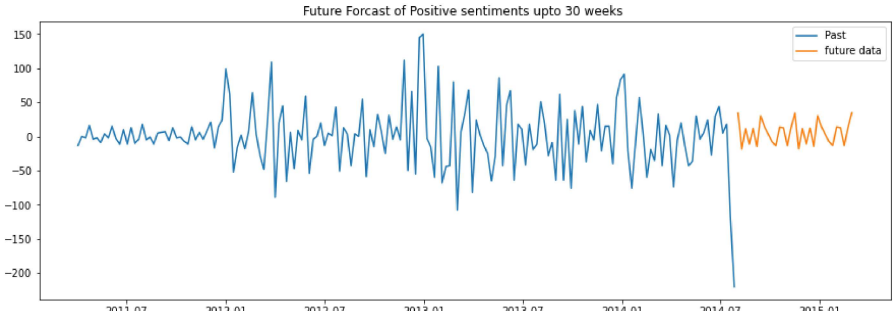


- Our Model is predicting nearly accurate values.

```
#calculating mse,rmse
mse1 = mean_squared_error(test_data,forcast_sarima)
print("ARMA model 1. p={},q={} \n\tmse = {} \n\trmse = {}".format(p,q,mse1,np.sqrt(mse1)))
```

```
ARMA model 1. p=1,q=1
        mse = 2864.710469568735
        rmse = 53.522990103027084
```

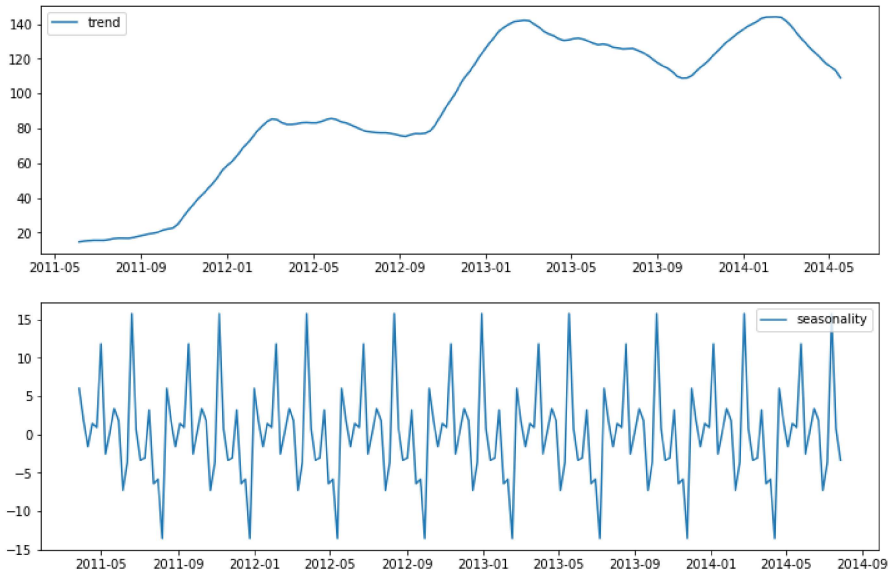
```
# future forcasting
future_forcast_sarima = model.predict(start=len(train_data), end=len(train_data)+len(test_data)+30)


plt.figure(figsize=(15,5))
plt.plot(diff_data, label='Past')
plt.plot(future_forcast_sarima[-31:], label='future data')
plt.title('Future Forcast of Positive sentiments upto 30 weeks ')
plt.legend()
plt.show()
```



- After 2014, we cannot see not many flucations in our graph.
- Its showing similar trend as our past data is showing.

Trend of Negative sentiment

```
negative_android = android_final[(android_final['bert_class']==1.0)|(android_final['bert_class']==2.0)]
review_negative = pd.DataFrame(negative_android.groupby(by='reviewTime')['sentiment_reviewText'].count()).reset_index()
review_negative['reviewTime'] = pd.to_datetime(review_negative['reviewTime'])
neg_android = review_negative.sort_values(by='reviewTime',ascending=True)
neg_android = neg_android.set_index('reviewTime')



#Resampling the data- weekly
neg_android = neg_android.resample('w').sum()


#trend seasonality
decompose = seasonal_decompose(neg_android,period=20)

seasonality = decompose.seasonal
trend = decompose.trend

plt.subplots(figsize=(12,8))
plt.subplot(211)
plt.plot(trend,label='trend')
plt.legend(loc='best')

plt.subplot(212)
plt.plot(seasonality,label='seasonality')
plt.legend(loc='best')

plt.show()
```



- For negative sentiments :

- We have trend & seasonality both in our data.
- Since our data have seasonality, so we need to use SRIMA Model

```
#stationarity checking
check_stationarity(neg_android)
```

```
'data is not stationary.make it stationary'
```

```
# since our data is not stationary
# difference the data by 1
diff_data1 = neg_android - neg_android.shift()
print(diff_data1)
```

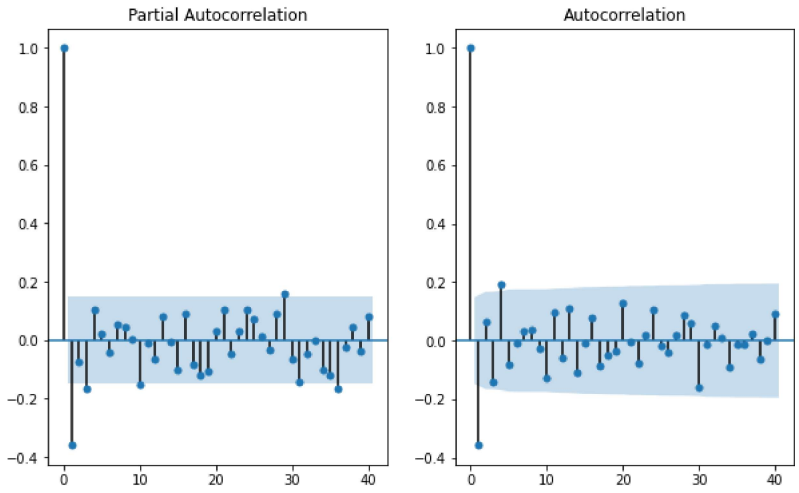
```
            sentiment_reviewText
reviewTime
2011-03-27                   NaN
2011-04-03                   5.0
2011-04-10                  -4.0
2011-04-17                  -2.0
2011-04-24                  13.0
...                          ...
2014-06-29                  -5.0
2014-07-06                  -3.0
2014-07-13                  45.0
2014-07-20                 -65.0
2014-07-27                 -59.0

[175 rows x 1 columns]
```

```
check_stationarity(diff_data1.dropna())
```

```
'data is stationary.proceed to modeling'
```

```
diff_data1 = diff_data1.dropna()
```

```
#plot for acf and pacf

fig,ax=plt.subplots(1,2,figsize=(10,6))

plot_pacf(diff_data1,lags=40,ax=ax[0])
plot_acf(diff_data1,lags=40,ax=ax[1])      #default Confidence level is 95%

plt.show()
```



p,q = 5,2

```
int(len(diff_data1)*0.70)
```

```
121
```

```
# spillting the data into train and test
rows = int(len(diff_data1)*0.70)
```

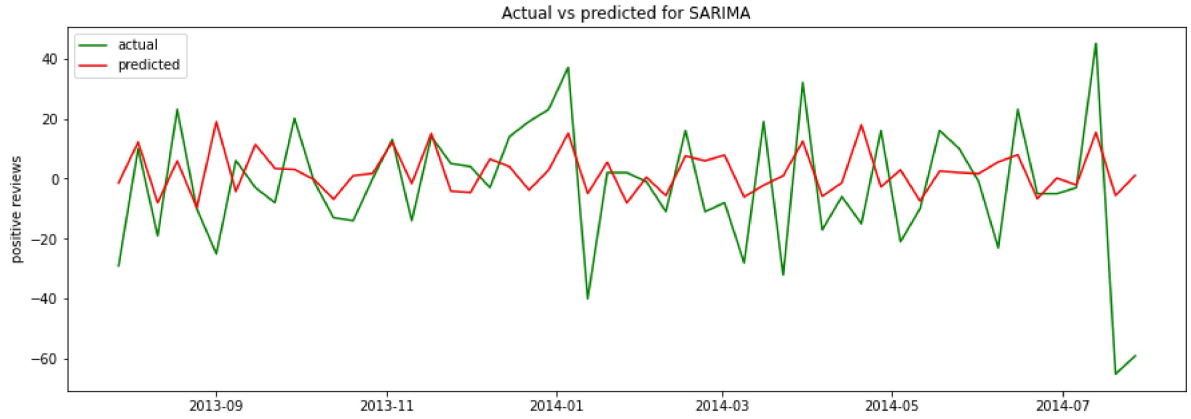
```
train_data1 = diff_data1[:rows]
test_data1 = diff_data1[rows:]


#taking (p,q) as (5,2)
p = np.arange(5)
q = np.arange(2)
d = 1

p_val = []
q_val = []
models= []
rmse = []
mse = []
aic_val = []
bic_val = []
p_val = []
q_val = []
mod = []
Ljung = []
count=0

for i in p:
    for j in q:
            models.append(SARIMAX(train_data1,order=(i,1,j),seasonal_order=(i,1,j,15)).fit())
            p_val.append(i)
            q_val.append(j)

# for removing (p,q)(0,0)
m = models[1:]
p_v = p_val[1:]
q_v = q_val[1:]

for i in m:
    aic_val.append(i.aic)
    bic_val.append(i.bic)
    pred = i.predict(start=len(train_data1), end=len(train_data1)+len(test_data1)-1)
    mod.append(count)
    mse.append(mean_squared_error(test_data1,pred))
    rmse.append(np.sqrt(mean_squared_error(test_data1,pred)))
    count = count+1

    pvalue = (sm.stats.acorr_ljungbox(i.resid,lags=[1],return_df=True))['lb_pvalue'].values
    if pvalue < 0.05:
        Ljung.append('model is not good')
    else:
         Ljung.append('model is good')



b = pd.DataFrame({'model':mod,"p":p_v,'q':q_v,"MSE":mse,"RMSE":rmse,"AIC":aic_val,"BIC":bic_val,'Ljung':Ljung})
b.sort_values(by='RMSE',ascending=True)
```

	model	p	q	MSE	RMSE	AIC	BIC	Ljung
4	4	2	1	413.004690	20.322517	953.310084	971.887807	model is good
0	0	0	1	436.700634	20.897383	976.412325	984.374206	model is not good
2	2	1	1	459.640244	21.439222	953.161062	966.430864	model is good
8	8	4	1	495.308739	22.255533	954.727459	983.921023	model is good
6	6	3	1	535.773722	23.146786	951.438910	975.324553	model is good
7	7	4	0	824.076939	28.706740	962.027188	985.912831	model is good
5	5	3	0	978.905259	31.287462	967.773353	986.351075	model is good
3	3	2	0	1380.774470	37.158774	1005.336439	1018.606241	model is good
1	1	1	0	2037.599902	45.139782	1031.967094	1039.928975	model is not good

- p,q selected based on the low rmse value

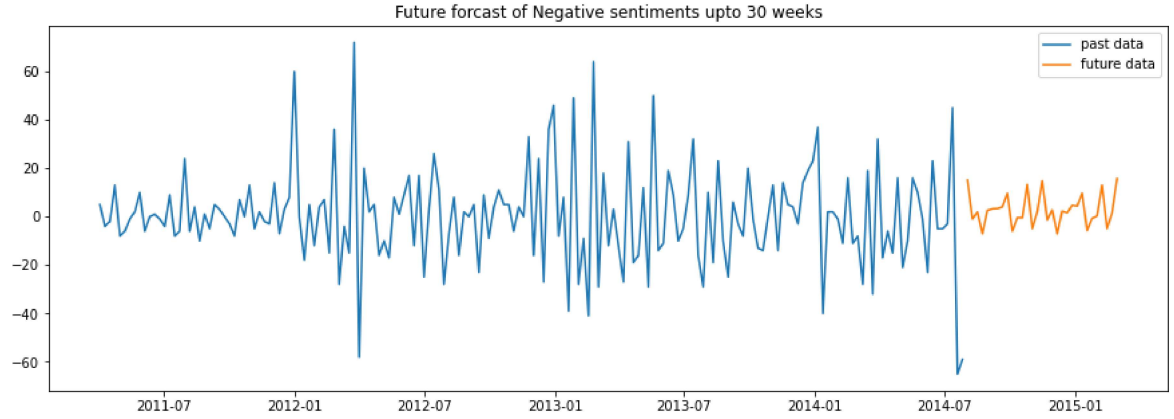
```
# building model with low rmse model
p=2; q=1; d=1
```

```
model2 = SARIMAX(train_data1,order=(p,d,q),seasonal_order=(p,d,q,15)).fit()

# Evaluating model performance
forcast_sarima2 = model2.predict(start=len(train_data1), end=len(train_data1)+len(test_data1)-1)

plt.figure(figsize=(15,5))
plt.plot(test_data1,label='actual',c='g')
plt.plot(forcast_sarima2,label='predicted',c='r')
plt.title('Actual vs predicted for SARIMA')
plt.ylabel('positive reviews')
plt.legend()
plt.show()
```



- Our Model is predicting nearly accurate values.

```
# future forcasting
future_forcast_sarima2 = model2.predict(start=len(train_data1), end=len(train_data1)+len(test_data1)+30)
plt.figure(figsize=(15,5))
plt.plot(diff_data1,label='past data')
plt.plot(future_forcast_sarima2[-31:], label='future data')
plt.title('Future forcast of Negative sentiments upto 30 weeks')
plt.legend()
plt.show()
```



- Above Graph is showing negative sentiments of android.
- It is not showing many flucations,it is showing similar trend as our past data is showing.

Trend of Neutral sentiment

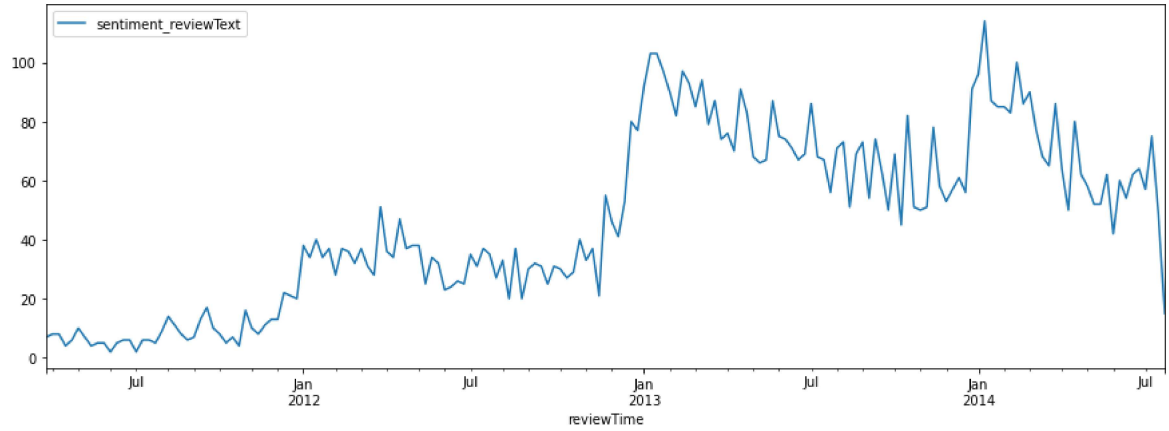
```
netural_android = android_final[(android_final['bert_class']== 3)]
review_netural = pd.DataFrame(netural_android.groupby(by='reviewTime')['sentiment_reviewText'].count()).reset_index()
review_netural['reviewTime'] = pd.to_datetime(review_netural['reviewTime'])
neu_android = review_netural.sort_values(by='reviewTime',ascending=True)
neu_android = neu_android.set_index('reviewTime')
```

Resampling by weekly

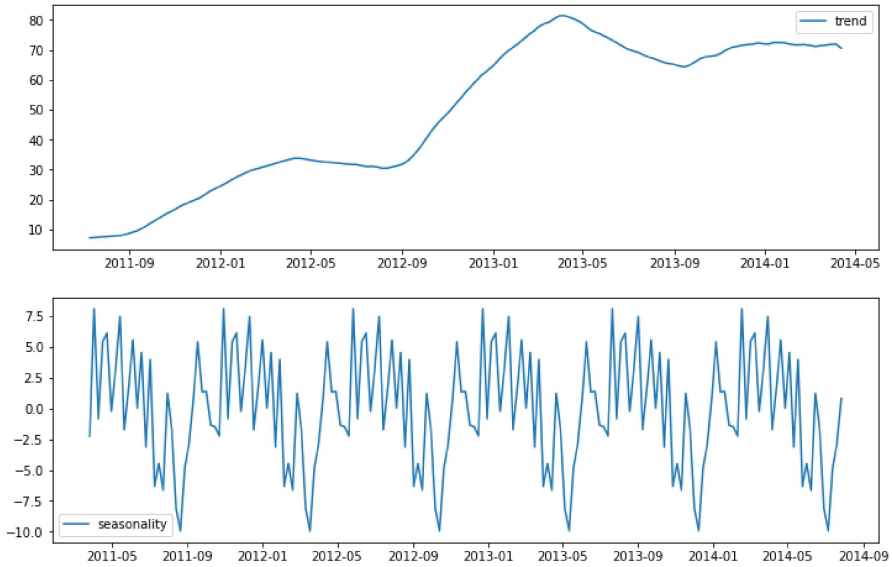
```
neu_android = neu_android.resample('w').sum()
```

```
neu_android.plot(figsize=(15,5))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd0d43c56d0>
```




```
#trend seasonality
decompose = seasonal_decompose(neu_android,period=30)

seasonality = decompose.seasonal
trend = decompose.trend

plt.subplots(figsize=(12,8))
plt.subplot(211)
plt.plot(trend,label='trend')
plt.legend(loc='best')

plt.subplot(212)
plt.plot(seasonality,label='seasonality')
plt.legend(loc='best')

plt.show()
```



- For neutral sentiments :
- We have trend & seasonality both in our data.
- Since our data have seasonality, so we need to use SRIMA Model

```
#stationarity checking
check_stationarity(neu_android)
```

```
'data is not stationary.make it stationary'
```

```
# since our data is not stationary
# difference the data by 1
diff_data2 = neu_android - neu_android.shift()
print(diff_data2)
```

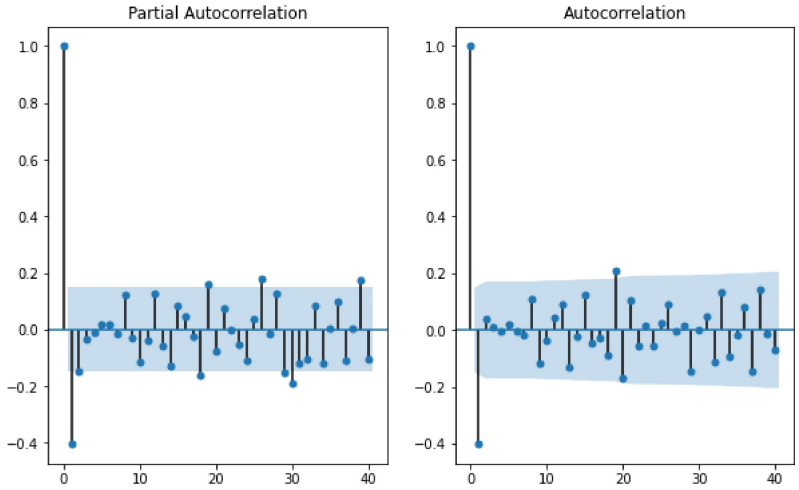
```
                sentiment_reviewText
reviewTime
2011-03-27                   NaN
2011-04-03                   1.0
2011-04-10                   0.0
2011-04-17                  -4.0
2011-04-24                   2.0
...                          ...
2014-06-29                   2.0
2014-07-06                  -7.0
2014-07-13                  18.0
2014-07-20                 -26.0
2014-07-27                 -34.0

[175 rows x 1 columns]
```

```
check_stationarity(diff_data2.dropna())
```

```
'data is stationary.proceed to modeling'
```

```
diff_data2.dropna(inplace=True)
```

```
#plot for acf and pacf

fig,ax=plt.subplots(1,2,figsize=(10,6))

plot_pacf(diff_data2,lags=40,ax=ax[0])
plot_acf(diff_data2,lags=40,ax=ax[1])      #default Confidence level is 95%

plt.show()
```



p,q = 6,2

```
int(len(diff_data2)*0.70)
```

```
121
```

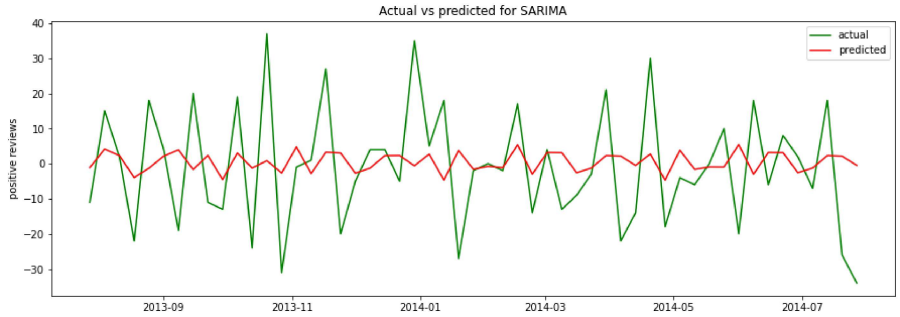
```
# spillting the data into train and test
rows = int(len(diff_data2)*0.70)
train_data2 = diff_data2[:rows]
test_data2 = diff_data2[rows:]
```

```
#taking (p,q) as (6,2)
p = np.arange(6)
q = np.arange(2)


p_val = []
q_val = []
models= []
rmse = []
mse = []
aic_val = []
bic_val = []
p_val = []
q_val = []
mod = []
Ljung = []
count=0

for i in p:
    for j in q:
            models.append(SARIMAX(train_data2,order=(i,1,j),seasonal_order=(i,1,j,15)).fit())
            p_val.append(i)
            q_val.append(j)

# for removing (p,q)(0,0)
m = models[1:]
p_v = p_val[1:]
q_v = q_val[1:]

for i in m:
    aic_val.append(i.aic)
    bic_val.append(i.bic)
    pred = i.predict(start=len(train_data2), end=len(train_data2)+len(test_data2)-1)
    mod.append(count)
    mse.append(mean_squared_error(test_data2,pred))
    rmse.append(np.sqrt(mean_squared_error(test_data2,pred)))
    count = count+1

    pvalue = (sm.stats.acorr_ljungbox(i.resid,lags=[1],return_df=True))['lb_pvalue'].values
    if pvalue < 0.05:
        Ljung.append('model is not good')
    else:
         Ljung.append('model is good')


c = pd.DataFrame({'model':mod,"p":p_v,'q':q_v,"MSE":mse,"RMSE":rmse,"AIC":aic_val,"BIC":bic_val,'Ljung':Ljung})
c.sort_values(by='RMSE',ascending=True)
```

	model	p	q	MSE	RMSE	AIC	BIC	Ljung
2	2	1	1	287.205630	16.947142	792.672055	805.941857	model is good
0	0	0	1	289.291071	17.008559	804.399477	812.361358	model is not good
4	4	2	1	312.904538	17.689108	793.226437	811.804160	model is good
6	6	3	1	314.482581	17.733657	797.197227	821.082871	model is good
8	8	4	1	317.782981	17.826469	800.505250	829.698814	model is good
7	7	4	0	320.823209	17.911538	808.981138	832.866781	model is good
10	10	5	1	323.741773	17.992826	803.338721	837.840206	model is good
5	5	3	0	339.530506	18.426354	817.636246	836.213969	model is good
9	9	5	0	367.293392	19.164900	798.273585	827.467149	model is good
3	3	2	0	373.702769	19.331393	832.872686	846.142488	model is good
1	1	1	0	942.883866	30.706414	862.089971	870.051852	model is not good

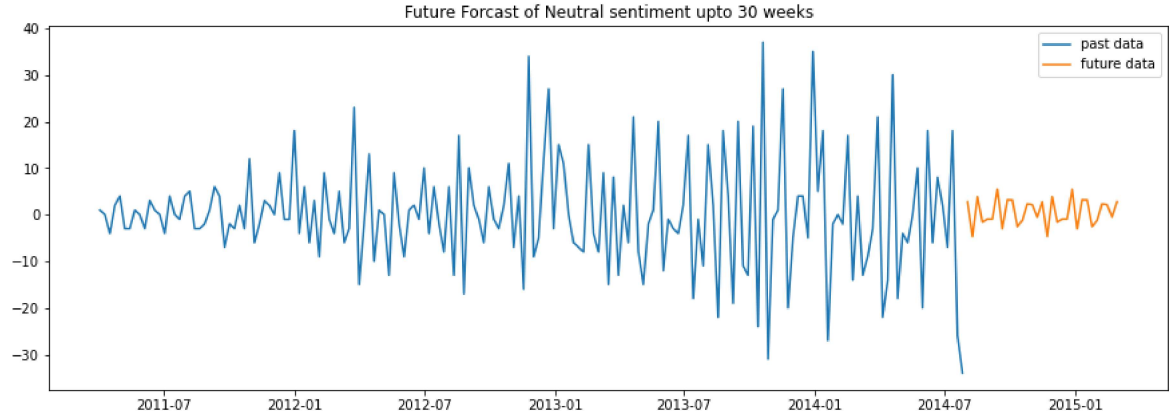
```
# building model with low rmse model
p=1; q=1; d=1
model3 = SARIMAX(train_data2,order=(p,d,q),seasonal_order=(p,d,q,15)).fit()

# Evaluating model performance
forcast_sarima3 = model3.predict(start=len(train_data2), end=len(train_data2)+len(test_data2)-1)

plt.figure(figsize=(15,5))
```

```
plt.plot(test_data2,label='actual',c='g')
plt.plot(forcast_sarima3,label='predicted',c='r')
plt.title('Actual vs predicted for SARIMA')
plt.ylabel('positive reviews')
plt.legend()
plt.show()
```



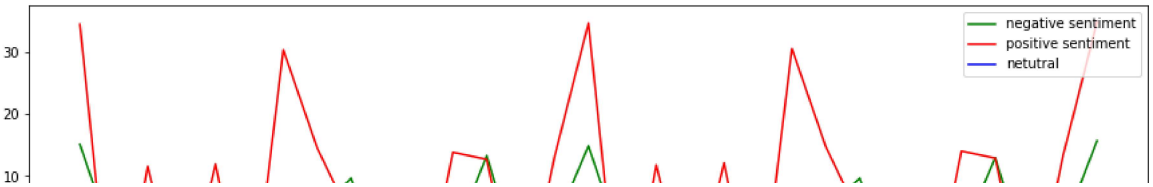
- Our Model is predicting nearly accurate values.

```
# future forcasting
future_forcast_sarima3 = model3.predict(start=len(train_data2), end=len(train_data2)+len(test_data2)+30)
plt.figure(figsize=(15,5))
plt.plot(diff_data2, label='past data')
plt.plot(future_forcast_sarima3[-31:], label='future data')
plt.title('Future Forcast of Neutral sentiment upto 30 weeks')
plt.legend()
plt.show()
```



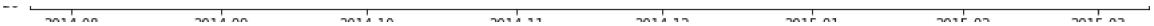
- Above Graph is showing Neutral sentiments of android.
- It is not showing many flucations,it is showing similar trend as our past data is showing.

```
# positive, negative and neutral comparision
plt.figure(figsize=(15,5))
plt.plot(future_forcast_sarima2[-31:],label='negative sentiment',c='g')
plt.plot(future_forcast_sarima[-31:],label = 'positive sentiment',c='r')
plt.plot(future_forcast_sarima3[-31:],label = 'netutral',c='b')
plt.legend()
plt.show()
```



- Positive sentiments have higher fluctuations than Negative & Neutral sentiments.
- Negative & Neutral sentiments is showing almost similar trend.

Time series analysis for video games



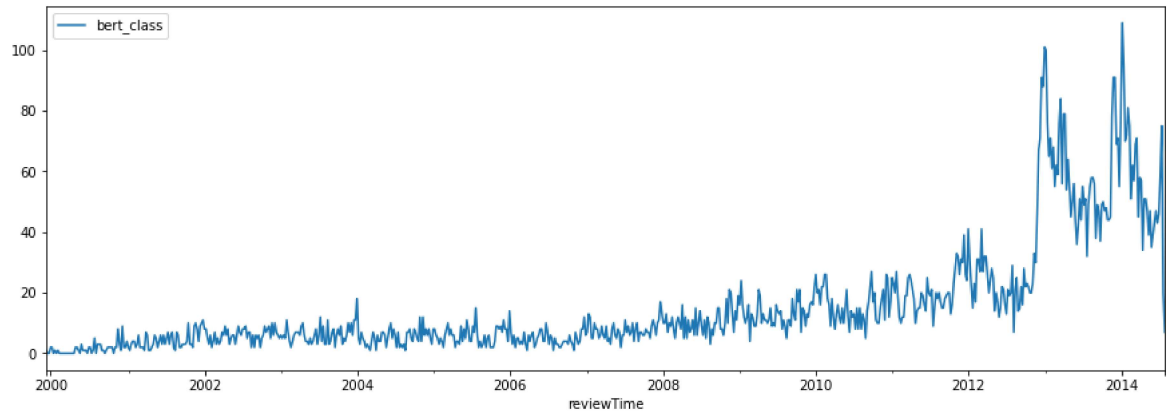
Trend for positive sentiments

```
positive_games = games_final[(games_final['bert_class']==5.0)|(games_final['bert_class']==4.0)]
review_positive = pd.DataFrame(positive_games.groupby(by='reviewTime')['bert_class'].count()).reset_index()
review_positive['reviewTime'] = pd.to_datetime(review_positive['reviewTime'])
pos_games = review_positive.sort_values(by='reviewTime',ascending=True)
pos_games = pos_games.set_index('reviewTime')
```

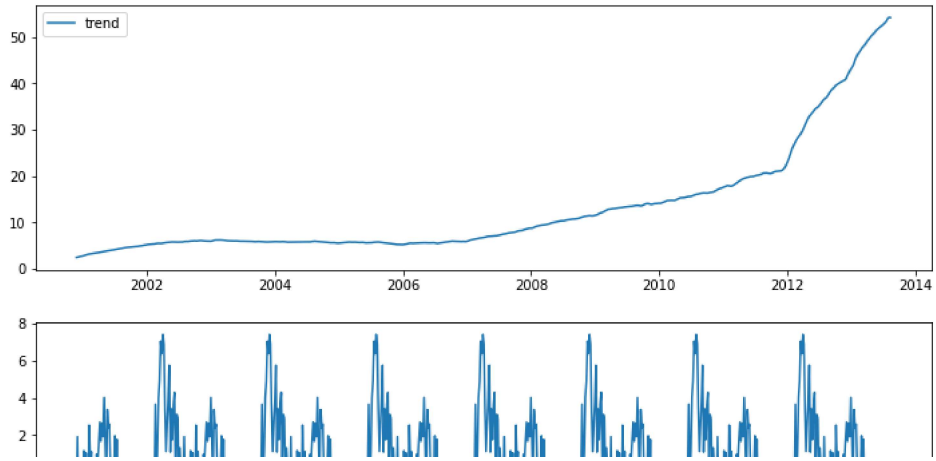
```
pos_games = pos_games.resample('w').sum()
```

```
pos_games.plot(figsize=(15,5))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd0d3ffbe90>
```




```
#trend seasonality
decompose = seasonal_decompose(pos_games,period=100)

seasonality = decompose.seasonal
trend = decompose.trend

plt.subplots(figsize=(12,8))
plt.subplot(211)
plt.plot(trend,label='trend')
plt.legend(loc='best')

plt.subplot(212)
plt.plot(seasonality,label='seasonality')
plt.legend(loc='best')

plt.show()
```



- For positive sentiments :
- We have trend & seasonality both in our data.
- Since our data have seasonality, so we need to use SRIMA Model

```
#stationarity checking
check_stationarity(pos_games)
```

```
'data is not stationary.make it stationary'
```

```
# since our data is not stationary
# difference the data by 1
diff_data1 = pos_games - pos_games.shift()
print(diff_data1)
```

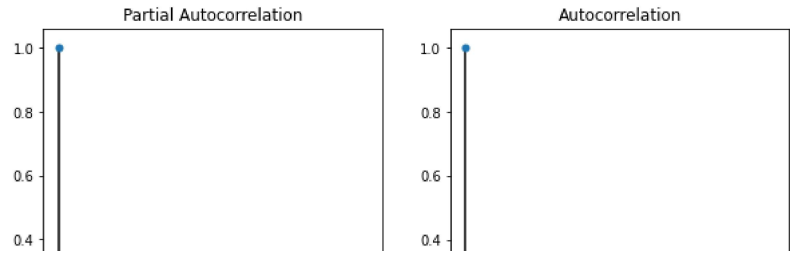
```
              bert_class
reviewTime
1999-12-12           NaN
1999-12-19          -1.0
1999-12-26           0.0
2000-01-02           2.0
2000-01-09           0.0
...                  ...
2014-06-29           3.0
2014-07-06          13.0
2014-07-13          16.0
2014-07-20         -55.0
2014-07-27         -13.0

[764 rows x 1 columns]
```

```
check_stationarity(diff_data1.dropna())
```

```
'data is stationary.proceed to modeling'
```

```
diff_data1.dropna(inplace=True)
```

```
#plot for acf and pacf

fig,ax=plt.subplots(1,2,figsize=(10,6))

plot_pacf(diff_data1,lags=10,ax=ax[0])
plot_acf(diff_data1,lags=10,ax=ax[1])      #default Confidence level is 95%

plt.show()
```



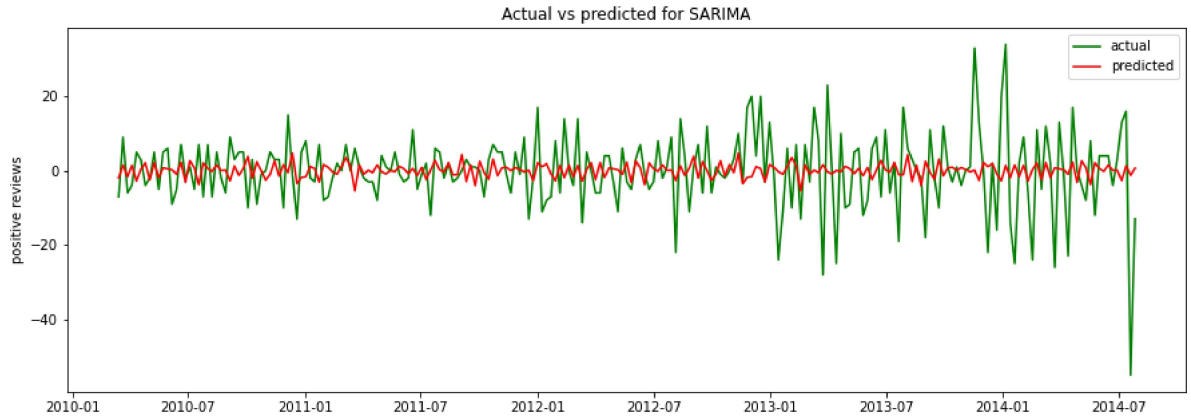
p,q = 4,2

```
# spillting the data into train and test
rows = int(len(diff_data1)*0.70)
train_data = diff_data1[:rows]
test_data = diff_data1[rows:]
```

```
#taking (p,q) as (4,2)
p = np.arange(4)
q = np.arange(2)


p_val = []
q_val = []
models= []
rmse = []
mse = []
aic_val = []
bic_val = []
p_val = []
q_val = []
mod = []
Ljung = []
count=0

for i in p:
    for j in q:
            models.append(SARIMAX(train_data,order=(i,1,j),seasonal_order=(i,1,j,15)).fit())
            p_val.append(i)
            q_val.append(j)

# for removing (p,q)(0,0)
m = models[1:]
p_v = p_val[1:]
q_v = q_val[1:]

for i in m:
    aic_val.append(i.aic)
    bic_val.append(i.bic)
    pred = i.predict(start=len(train_data), end=len(train_data)+len(test_data)-1)
    mod.append(count)
    mse.append(mean_squared_error(test_data,pred))
    rmse.append(np.sqrt(mean_squared_error(test_data,pred)))
    count = count+1

    pvalue = (sm.stats.acorr_ljungbox(i.resid,lags=[1],return_df=True))['lb_pvalue'].values
    if pvalue < 0.05:
        Ljung.append('model is not good')
    else:
         Ljung.append('model is good')


q = pd.DataFrame({'model':mod,"p":p_v,'q':q_v,"MSE":mse,"RMSE":rmse,"AIC":aic_val,"BIC":bic_val,'Ljung':Ljung})
q.sort_values(by='RMSE',ascending=True)
```

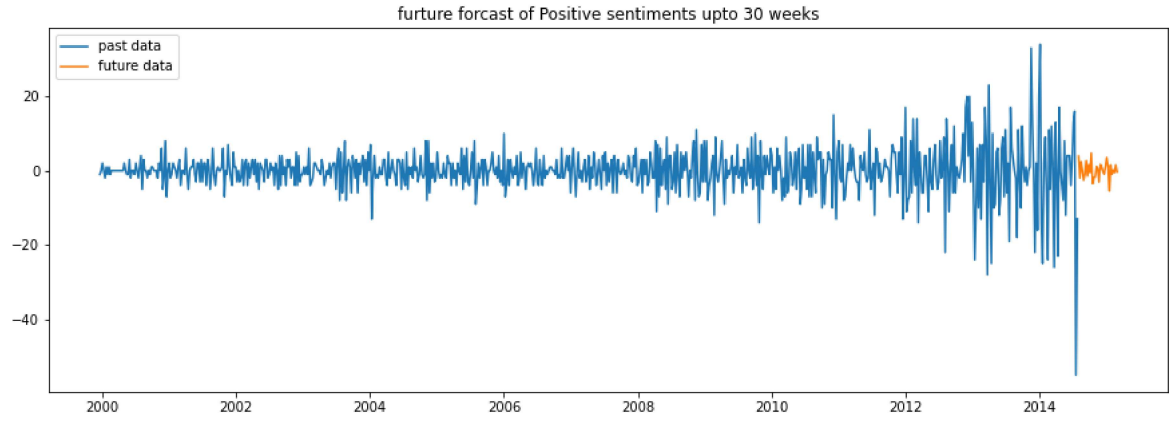
	model	p	q	MSE	RMSE	AIC	BIC	Ljung
0	0	0	1	101.700068	10.084645	2890.842985	2903.592910	model is not good

```
# building model with low rmse model
p=0; q=1; d=1
model = SARIMAX(train_data,order=(p,d,q),seasonal_order=(p,d,q,100)).fit()

# Evaluating model performance
forcast_sarima = model.predict(start=len(train_data), end=len(train_data)+len(test_data)-1)

plt.figure(figsize=(15,5))
plt.plot(test_data,label='actual',c='g')
plt.plot(forcast_sarima,label='predicted',c='r')
plt.title('Actual vs predicted for SARIMA')
plt.ylabel('positive reviews')
plt.legend()
plt.show()
```



- Our Model is predicting nearly accurate values.

```
# future forcasting
future_forcast_sarima = model.predict(start=len(train_data), end=len(train_data)+len(test_data)+30)
plt.figure(figsize=(15,5))
plt.plot(diff_data1,label='past data')
plt.plot(future_forcast_sarima[-31:],label='future data')
plt.title('furture forcast of Positive sentiments upto 30 weeks')
plt.legend()
plt.show()
```

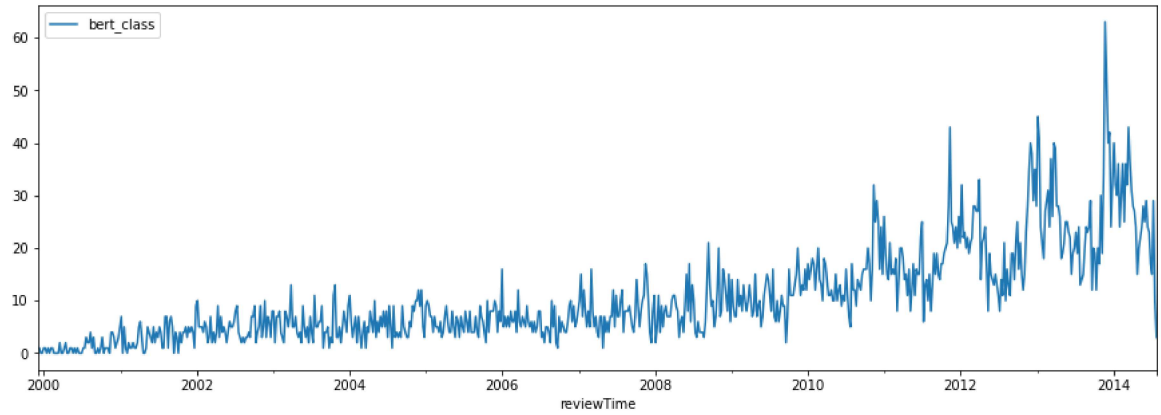


- Above Graph is showing positive sentiments of android.
- It is showing many flucations,it is showing trend depending upon the past data.

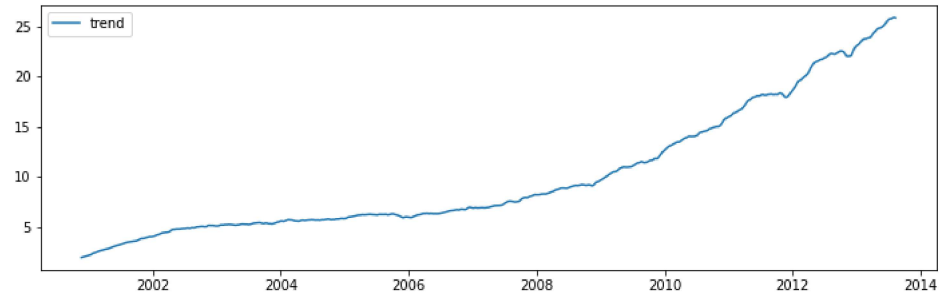
Trend for negative sentiments

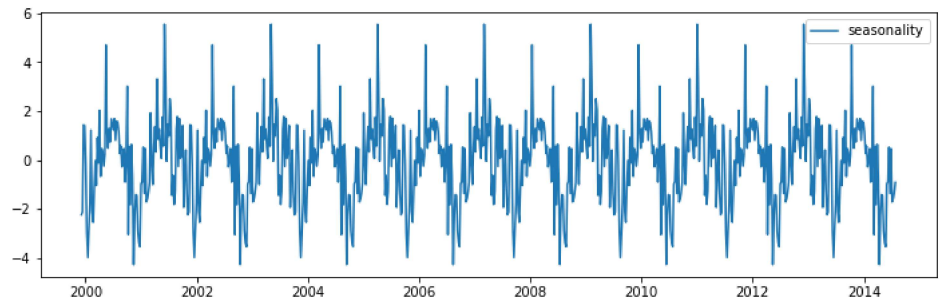
```
negative_games = games_final[(games_final['bert_class']==1.0)|(games_final['bert_class']==2.0)]
review_negative = pd.DataFrame(negative_games.groupby(by='reviewTime')['bert_class'].count()).reset_index()
review_negative['reviewTime'] = pd.to_datetime(review_negative['reviewTime'])
neg_games = review_negative.sort_values(by='reviewTime',ascending=True)
neg_games = neg_games.set_index('reviewTime')


neg_games = neg_games.resample('w').sum()


neg_games.plot(figsize=(15,5))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd0d4561750>
```




```
#trend seasonality
decompose = seasonal_decompose(neg_games,period=100)

seasonality = decompose.seasonal
trend = decompose.trend

plt.subplots(figsize=(12,8))
plt.subplot(211)
plt.plot(trend,label='trend')
plt.legend(loc='best')

plt.subplot(212)
plt.plot(seasonality,label='seasonality')
plt.legend(loc='best')

plt.show()
```





- For negative sentiments :
- We have trend & seasonality both in our data.

- Since our data have seasonality, so we need to use SRIMA Model

```
#stationarity checking
check_stationarity(neg_games)
```

```
'data is not stationary.make it stationary'
```

```
# since our data is not stationary
# difference the data by 1
diff_data2 = neg_games - neg_games.shift()
print(diff_data2)
```

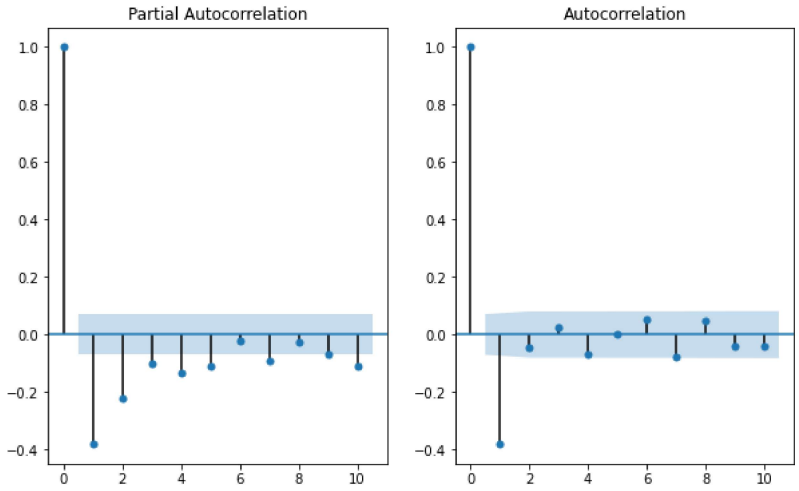
```
              bert_class
reviewTime
1999-12-05           NaN
1999-12-12           0.0
1999-12-19          -1.0
1999-12-26           0.0
2000-01-02           1.0
...                  ...
2014-06-29          -6.0
2014-07-06          -2.0
2014-07-13          14.0
2014-07-20         -19.0
2014-07-27          -7.0

[765 rows x 1 columns]
```

```
check_stationarity(diff_data2.dropna())
```

```
'data is stationary.proceed to modeling'
```

```
diff_data2.dropna(inplace=True)
```

```
#plot for acf and pacf

fig,ax=plt.subplots(1,2,figsize=(10,6))

plot_pacf(diff_data2,lags=10,ax=ax[0])
plot_acf(diff_data2,lags=10,ax=ax[1])      #default Confidence level is 95%

plt.show()
```



p,q = 7,2

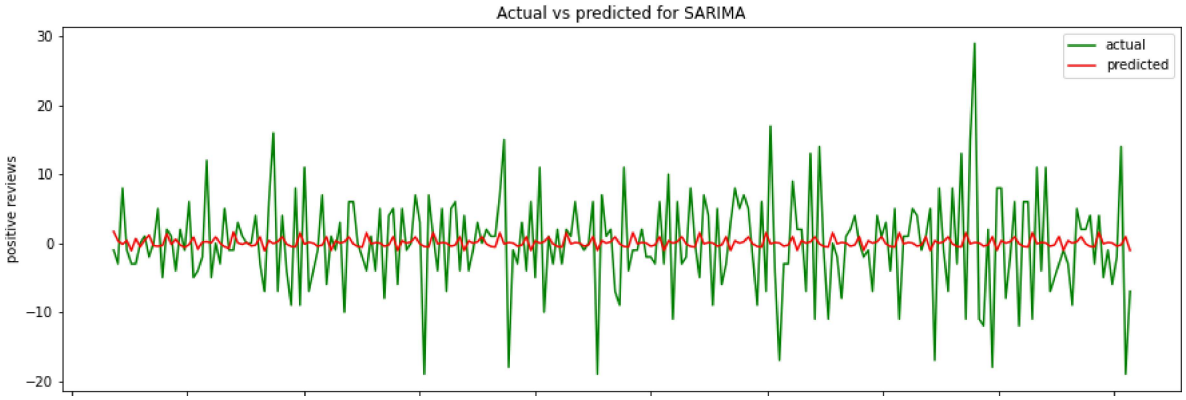
```
# spillting the data into train and test
rows = int(len(diff_data2)*0.70)
train_data1 = diff_data2[:rows]
test_data1 = diff_data2[rows:]
```

```
#taking (p,q) as (7,2)
p = np.arange(4)
```

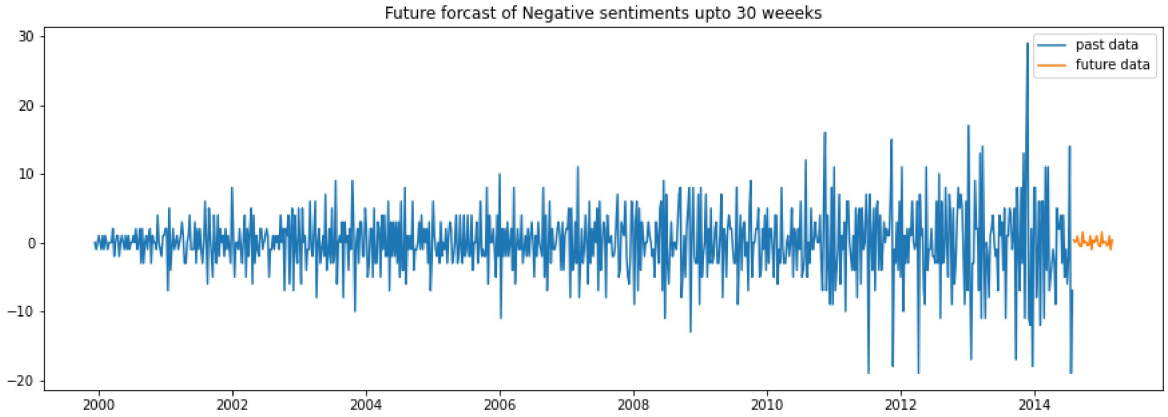
```
q = np.arange(2)


p_val = []
q_val = []
models= []
rmse = []
mse = []
aic_val = []
bic_val = []
p_val = []
q_val = []
mod = []
Ljung = []
count=0

for i in p:
    for j in q:
            models.append(SARIMAX(train_data1,order=(i,1,j),seasonal_order=(i,1,j,15)).fit())
            p_val.append(i)
            q_val.append(j)

# for removing (p,q)(0,0)
m = models[1:]
p_v = p_val[1:]
q_v = q_val[1:]

for i in m:
    aic_val.append(i.aic)
    bic_val.append(i.bic)
    pred = i.predict(start=len(train_data1), end=len(train_data1)+len(test_data1)-1)
    mod.append(count)
    mse.append(mean_squared_error(test_data1,pred))
    rmse.append(np.sqrt(mean_squared_error(test_data1,pred)))
    count = count+1

    pvalue = (sm.stats.acorr_ljungbox(i.resid,lags=[1],return_df=True))['lb_pvalue'].values
    if pvalue < 0.05:
        Ljung.append('model is not good')
    else:
         Ljung.append('model is good')


f = pd.DataFrame({'model':mod,"p":p_v,'q':q_v,"MSE":mse,"RMSE":rmse,"AIC":aic_val,"BIC":bic_val,'Ljung':Ljung})
f.sort_values(by='RMSE',ascending=True)
```

	model	p	q	MSE	RMSE	AIC	BIC	Ljung
0	0	0	1	49.531398	7.037855	2889.997683	2902.747608	model is not good
6	6	3	1	49.587175	7.041816	2710.634538	2748.884315	model is good
2	2	1	1	49.609472	7.043399	2780.029100	2801.278976	model is not good
4	4	2	1	49.732835	7.052151	2729.786814	2759.536641	model is good
5	5	3	0	53.736692	7.330532	3033.749721	3063.499548	model is not good
3	3	2	0	57.166176	7.560832	3135.413361	3156.663238	model is not good
1	1	1	0	156.724510	12.518966	3333.704087	3346.454013	model is not good

```
# building model with low rmse model
p=3; q=1; d=1
model1 = SARIMAX(train_data1,order=(p,d,q),seasonal_order=(p,d,q,15)).fit()

# Evaluating model performance
forcast_sarima2 = model1.predict(start=len(train_data1), end=len(train_data1)+len(test_data1)-1)

plt.figure(figsize=(15,5))
plt.plot(test_data1,label='actual',c='g')
plt.plot(forcast_sarima2,label='predicted',c='r')
plt.title('Actual vs predicted for SARIMA')
plt.ylabel('positive reviews')
plt.legend()
plt.show()
```




```
# future forcasting
future_forcast_sarima1 = model1.predict(start=len(train_data1), end=len(train_data1)+len(test_data1)+30)
plt.figure(figsize=(15,5))
plt.plot(diff_data2,label='past data')
plt.plot(future_forcast_sarima1[-31:],label='future data')
plt.title('Future forcast of Negative sentiments upto 30 weeeks')
plt.legend()
plt.show()
```



- Above Graph is showing negative sentiments of android.
- It is showing many flucations,it is showing trend depending upon the past data.

Trend for neutral sentiments

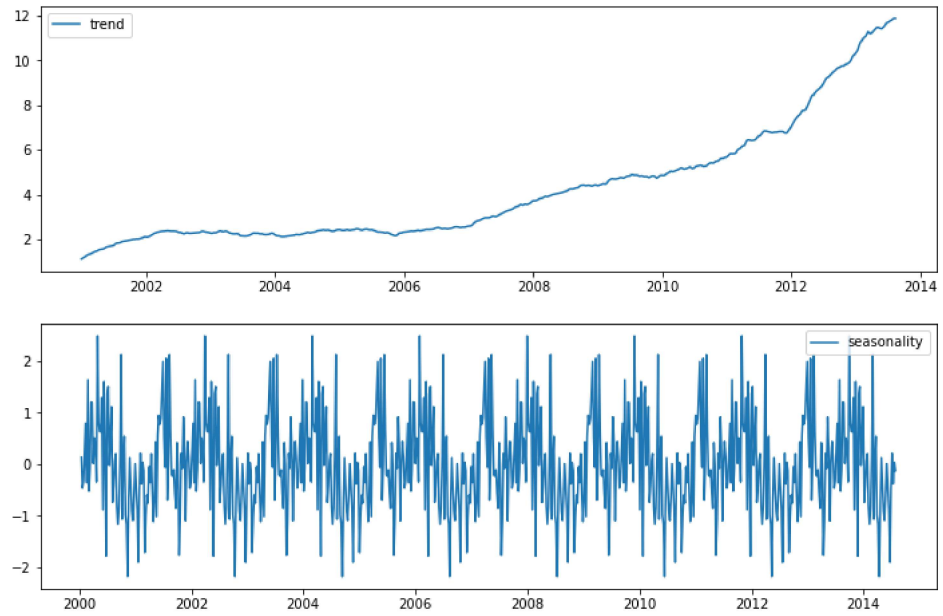
```
neutral_games = games_final[games_final['bert_class']==3.0]
review_neutral = pd.DataFrame(neutral_games.groupby(by='reviewTime')['bert_class'].count()).reset_index()
review_neutral['reviewTime'] = pd.to_datetime(review_neutral['reviewTime'])
neu_games = review_neutral.sort_values(by='reviewTime',ascending=True)
neu_games = neu_games.set_index('reviewTime')
```

```
neu_games = neu_games.resample('w').sum()
```

```
neu_games.plot(figsize=(15,5))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd0d750c0d0>
```


```
#trend seasonality
decompose = seasonal_decompose(neu_games,period=100)

seasonality = decompose.seasonal
trend = decompose.trend

plt.subplots(figsize=(12,8))
plt.subplot(211)
plt.plot(trend,label='trend')
plt.legend(loc='best')

plt.subplot(212)
plt.plot(seasonality,label='seasonality')
plt.legend(loc='best')

plt.show()
```



- For neutral sentiments :
- We have trend & seasonality both in our data.
- Since our data have seasonality, so we need to use SRIMA Model

```
#stationarity checking
check_stationarity(neu_games)
```

```
'data is not stationary.make it stationary'
```

```
# since our data is not stationary
# difference the data by 1
diff_data3 = neu_games - neu_games.shift()
print(diff_data3)
```

```
            bert_class
reviewTime
2000-01-16         NaN
2000-01-23        -2.0
2000-01-30         0.0
2000-02-06         0.0
2000-02-13         0.0
...                ...
2014-06-29        -2.0
2014-07-06         0.0
2014-07-13         6.0
2014-07-20       -11.0
2014-07-27         3.0
```

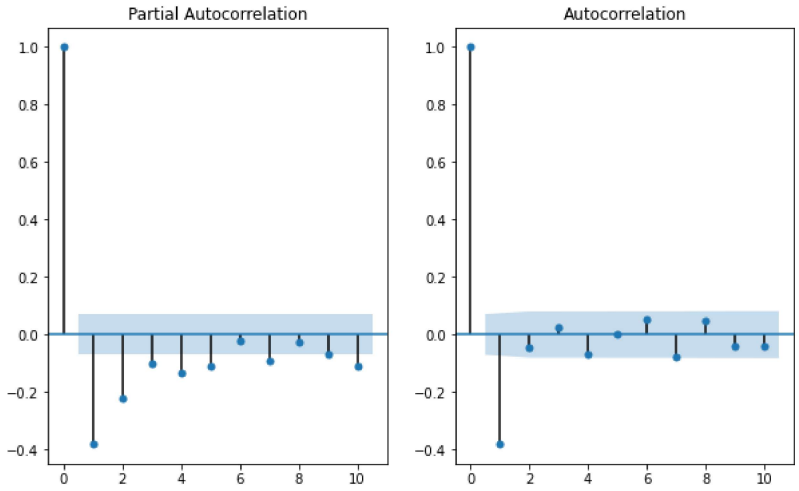
```
[759 rows x 1 columns]
```

```
check_stationarity(diff_data3.dropna())
```

```
'data is stationary.proceed to modeling'
```

```
diff_data3.dropna(inplace=True)
```

```
#plot for acf and pacf

fig,ax=plt.subplots(1,2,figsize=(10,6))

plot_pacf(diff_data2,lags=10,ax=ax[0])
plot_acf(diff_data2,lags=10,ax=ax[1])      #default Confidence level is 95%

plt.show()
```




```
# spillting the data into train and test
rows = int(len(diff_data3)*0.70)
train_data2 = diff_data3[:rows]
test_data2 = diff_data3[rows:]
```

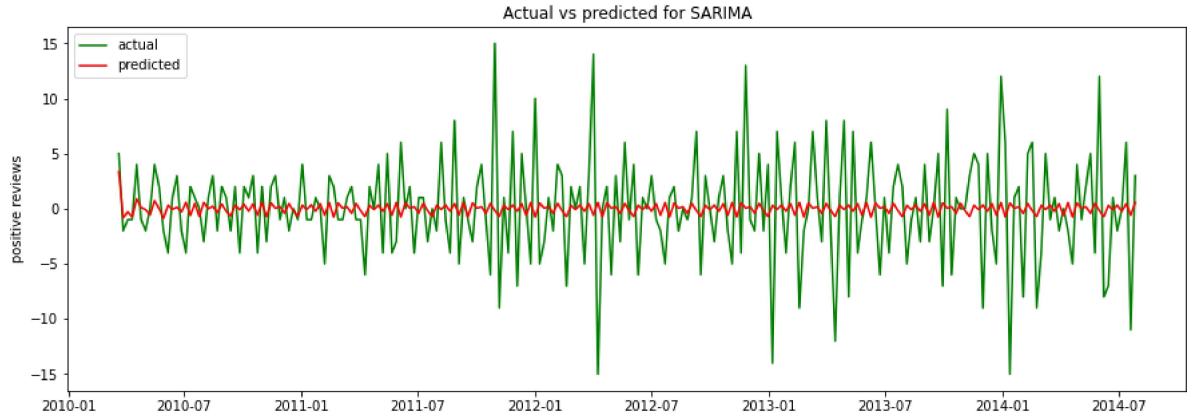
```
#taking (p,q) as (7,2)
p = np.arange(4)
q = np.arange(2)
```

```
p_val = []
q_val = []
models= []
rmse = []
mse = []
aic_val = []
bic_val = []
p_val = []
q_val = []
mod = []
Ljung = []
count=0

for i in p:
    for j in q:
            models.append(SARIMAX(train_data2,order=(i,1,j),seasonal_order=(i,1,j,15)).fit())
            p_val.append(i)
            q_val.append(j)

# for removing (p,q)(0,0)
m = models[1:]
p_v = p_val[1:]
q_v = q_val[1:]

for i in m:
```

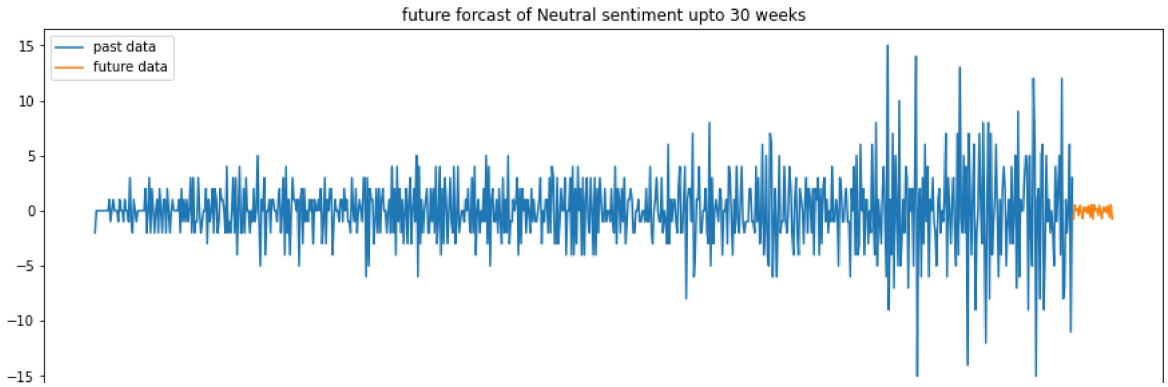
```
    aic_val.append(i.aic)
    bic_val.append(i.bic)
    pred = i.predict(start=len(train_data2), end=len(train_data2)+len(test_data2)-1)
    mod.append(count)
    mse.append(mean_squared_error(test_data2,pred))
    rmse.append(np.sqrt(mean_squared_error(test_data2,pred)))
    count = count+1

    pvalue = (sm.stats.acorr_ljungbox(i.resid,lags=[1],return_df=True))['lb_pvalue'].values
    if pvalue < 0.05:
        Ljung.append('model is not good')
    else:
         Ljung.append('model is good')


v = pd.DataFrame({'model':mod,"p":p_v,'q':q_v,"MSE":mse,"RMSE":rmse,"AIC":aic_val,"BIC":bic_val,'Ljung':Ljung})
v.sort_values(by='RMSE',ascending=True)
```

	model	p	q	MSE	RMSE	AIC	BIC	Ljung
6	6	3	1	22.152548	4.706649	2197.441192	2235.621202	model is good
4	4	2	1	22.201152	4.711810	2219.155646	2248.851209	model is good
2	2	1	1	22.269122	4.719017	2269.878302	2291.089419	model is not good
0	0	0	1	22.299114	4.722194	2383.224176	2395.950846	model is not good
5	5	3	0	140.657081	11.859894	2490.480914	2520.176476	model is not good
3	3	2	0	268.926425	16.398976	2602.801932	2624.013048	model is not good
1	1	1	0	411.521930	20.286003	2812.006748	2824.733418	model is not good

```
# building model with low rmse model
p=3; q=1; d=1
model3 = SARIMAX(train_data2,order=(p,d,q),seasonal_order=(p,d,q,15)).fit()

# Evaluating model performance
forcast_sarima3 = model3.predict(start=len(train_data2), end=len(train_data2)+len(test_data2)-1)

plt.figure(figsize=(15,5))
plt.plot(test_data2,label='actual',c='g')
plt.plot(forcast_sarima3,label='predicted',c='r')
plt.title('Actual vs predicted for SARIMA')
plt.ylabel('positive reviews')
plt.legend()
plt.show()
```

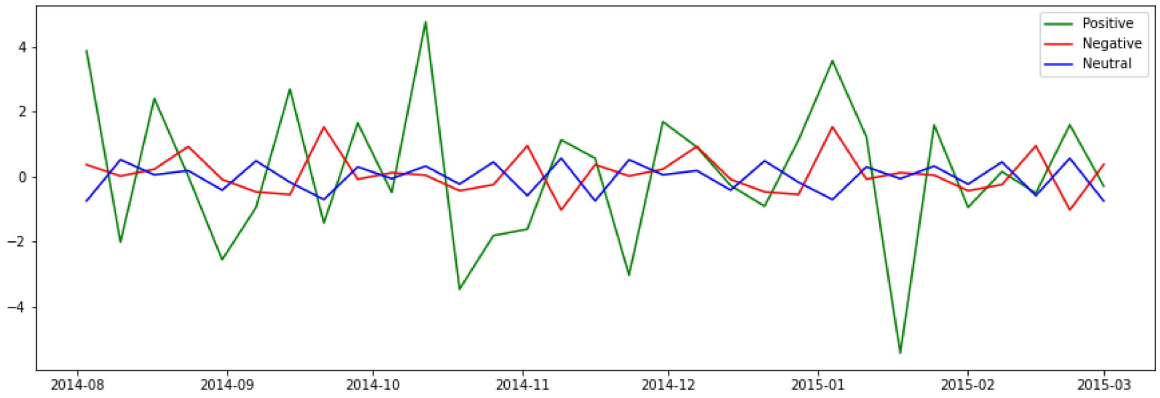



```
# future forcasting
future_forcast_sarima2 = model3.predict(start=len(train_data2), end=len(train_data2)+len(test_data2)+30)
plt.figure(figsize=(15,5))
plt.plot(diff_data3,label='past data')
plt.plot(future_forcast_sarima2[-31:],label='future data')
plt.title('future forcast of Neutral sentiment upto 30 weeks')
plt.legend()
plt.show()
```



- Above Graph is showing neutral sentiments of android.
- It is showing many flucations,it is showing trend depending upon the past data.

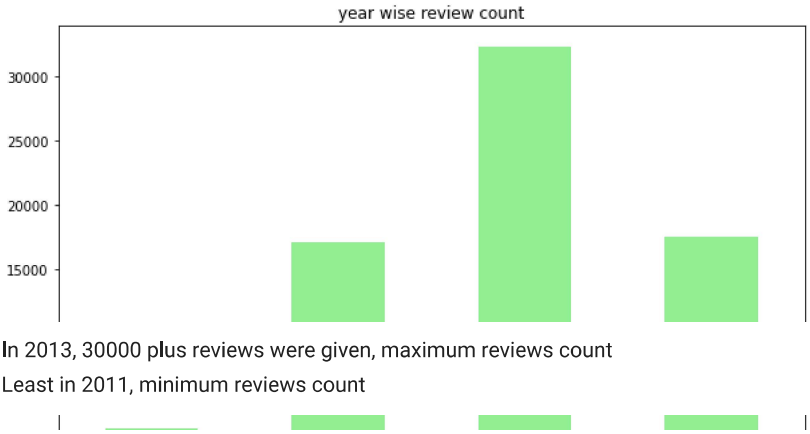
```
plt.figure(figsize=(15,5))
plt.plot(future_forcast_sarima[-31:], label='Positive', c='g')
plt.plot(future_forcast_sarima1[-31:], label='Negative', c='r')
plt.plot(future_forcast_sarima2[-31:], label='Neutral', c='b')
plt.legend()
plt.show()
```



- Positive sentiments data have more fluctuations compartively to others.
- Negative & Neutral data almost showing similar behaviour.

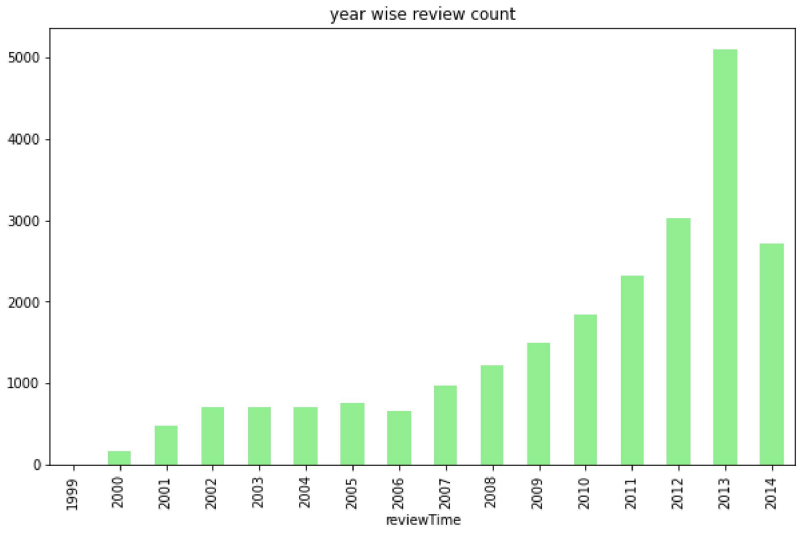
problem 4-Inter category analysis (relation between two categories)

```
android_df['reviewTime'] = pd.to_datetime(android_df['reviewTime']) #converted to datatime format

pf = android_df[['reviewTime','sentiment_reviewText']] #taking review time & sentiment review time

pf['reviewTime'] = pf['reviewTime'].dt.year #date time format

pf.rename(columns={'sentiment_reviewText':'sentiment_reviewText_android'},inplace=True) #renaming the column name

pf.groupby(pf['reviewTime'])['sentiment_reviewText_android'].count().plot(kind='bar', figsize=(10,6),color='lightgreen')
plt.title('year wise review count')
plt.show()
```



- In 2013, 30000 plus reviews were given, maximum reviews count
- Least in 2011, minimum reviews count

```
games_df['reviewTime'] = pd.to_datetime(games_df['reviewTime'])
gf = games_df[['reviewTime','sentiment_reviewText']]
gf['reviewTime'] = gf['reviewTime'].dt.year


gf.rename(columns={'sentiment_reviewText':'sentiment_reviewText_games'},inplace=True)


gf.groupby(gf['reviewTime'])['sentiment_reviewText_games'].count().plot(kind='bar', figsize=(10,6),color='lightgreen')
plt.title('year wise review count')
plt.show()
```



- In 2013, 5000 plus reviews were given, maximum reviews count
- Least in 2000, minimum reviews count

In 2013, both categories have reached at their peak performances.

```
android = pf.groupby(pf['reviewTime'])['sentiment_reviewText_android'].count()
games = gf.groupby(gf['reviewTime'])['sentiment_reviewText_games'].count()


combined = pd.concat([pd.DataFrame(games),pd.DataFrame(android)],axis=1)


combined.to_csv('year wise count of reviews.csv')
```