akash-adease-time-series-1

March 25, 2024

1 Ad Ease website Analytics

Dataset: Web Traffic Time Series Forecasting

Forecasting the future values of multiple time series. More specifically the problem of forecasting future web traffic for approximately 145,000 articles on britanica.

The training dataset consists of approximately 145k time series. Each of these time series represent a number of daily views of a different article, starting from July, 1st, 2015 up until December 31st, 2016. For each time series, you are provided the name of the article as well as the type of traffic that this time series represent (all, mobile, desktop, spider). You may use this metadata and any other publicly available data to make predictions. Unfortunately, the data source for this dataset does not distinguish between traffic values of zero and missing values. A missing value may mean the traffic was zero or that the data is not available for that day.

Data Dictionary:

there are two csv files given

train_1.csv :

In the csv file, each row corresponds to a particular article and each column correspond to a particular date. The values are the number of visits in that date.

Exog_Campaign_eng :

this file contaings data for the dates which had a campaign or significant event that could affect the views for that day. the data is just for pages in english.

there is a 1 for dates with campaign and 0 for remaining dates. It is to be treated as an exogenous variable for models when training and forecasting data for pages in english

Importing the libraries

[ ]:
```
!pip install --upgrade --no-cache-dir gdown
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: gdown in /usr/local/lib/python3.8/dist-packages
(4.6.0)
Requirement already satisfied: six in /usr/local/lib/python3.8/dist-packages
(from gdown) (1.15.0)
Requirement already satisfied: requests[socks] in /usr/local/lib/python3.8/dist-
```

```
packages (from gdown) (2.23.0)
Requirement already satisfied: tqdm in /usr/local/lib/python3.8/dist-packages
(from gdown) (4.64.1)
Requirement already satisfied: beautifulsoup4 in /usr/local/lib/python3.8/dist-
packages (from gdown) (4.6.3)
Requirement already satisfied: filelock in /usr/local/lib/python3.8/dist-
packages (from gdown) (3.8.0)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.8/dist-packages (from requests[socks]->gdown) (2022.9.24)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in
/usr/local/lib/python3.8/dist-packages (from requests[socks]->gdown) (1.24.3)
Requirement already satisfied: chardet<4,>=3.0.2 in
/usr/local/lib/python3.8/dist-packages (from requests[socks]->gdown) (3.0.4)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.8/dist-
packages (from requests[socks]->gdown) (2.10)
Requirement already satisfied: PySocks!=1.5.7,>=1.5.6 in
/usr/local/lib/python3.8/dist-packages (from requests[socks]->gdown) (1.7.1)
```

[ ]:
```
import pandas as pd
import numpy as np
import pylab as p
import matplotlib.pyplot as plot
from collections import Counter
import re
import os
import seaborn as sns
```

[ ]:
```
import warnings
warnings.filterwarnings("ignore")
warnings.simplefilter("ignore")
```

[ ]:
```
sns.set(rc={'figure.figsize':(11.7,8.27)})
```

[ ]:
```
import gdown
#url='https://drive.google.com/file/d/1gHYYLqLt6rMyeAyvHf1wvlQ4BLKwjv9W/view?
 ↪usp=sharing'
#url='https://drive.google.com/file/d/1SL_7DoE16m71QpjJXoQUC3cI5aHCIZLv/view?
 ↪usp=share_link'
#url='https://drive.google.com/file/d/11GQSe2Xm4vFD4Xfw3JhOoPlXnBE_LiMe/view?
 ↪usp=sharing'
url='https://drive.google.com/file/d/1CJOMYyg64x3gN52p6OqypN6UUgDnUhkm/view?
 ↪usp=sharing'

ider=url.split('/')[-2]
!gdown --id $ider
```

```
/usr/local/lib/python3.8/dist-packages/gdown/cli.py:121: FutureWarning: Option
```

```
`--id` was deprecated in version 4.3.1 and will be removed in 5.0. You don't
need to pass it anymore to use a file ID.
  warnings.warn(
Downloading…
From: https://drive.google.com/uc?id=1CJOMYyg64x3gN52p6OqypN6UUgDnUhkm
To: /content/new_train.csv
100% 425M/425M [00:03<00:00, 125MB/s]
```

[ ]:
```python
train = pd.read_csv('new_train.csv')
```

Reading the dataset and printing head and tail to get basic idea

[ ]:
```python
train.head()
```

[ ]:
```
                                          Page  2015-07-01  2015-07-02  \
0          2NE1_zh.britanica.org_all-access_spider        18.0        11.0
1           2PM_zh.britanica.org_all-access_spider        11.0        14.0
2            3C_zh.britanica.org_all-access_spider         1.0         0.0
3       4minute_zh.britanica.org_all-access_spider        35.0        13.0
4  52_Hz_I_Love_You_zh.britanica.org_all-access_s…         NaN         NaN

   2015-07-03  2015-07-04  2015-07-05  2015-07-06  2015-07-07  2015-07-08  \
0         5.0        13.0        14.0         9.0         9.0        22.0
1        15.0        18.0        11.0        13.0        22.0        11.0
2         1.0         1.0         0.0         4.0         0.0         3.0
3        10.0        94.0         4.0        26.0        14.0         9.0
4         NaN         NaN         NaN         NaN         NaN         NaN

   2015-07-09  …  2016-12-22  2016-12-23  2016-12-24  2016-12-25  \
0        26.0  …        32.0        63.0        15.0        26.0
1        10.0  …        17.0        42.0        28.0        15.0
2         4.0  …         3.0         1.0         1.0         7.0
3        11.0  …        32.0        10.0        26.0        27.0
4         NaN  …        48.0         9.0        25.0        13.0

   2016-12-26  2016-12-27  2016-12-28  2016-12-29  2016-12-30  2016-12-31
0        14.0        20.0        22.0        19.0        18.0        20.0
1         9.0        30.0        52.0        45.0        26.0        20.0
2         4.0         4.0         6.0         3.0         4.0        17.0
3        16.0        11.0        17.0        19.0        10.0        11.0
4         3.0        11.0        27.0        13.0        36.0        10.0

[5 rows x 551 columns]
```

[ ]:
```python
print(train.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 145063 entries, 0 to 145062
```

```
Columns: 551 entries, Page to 2016-12-31
dtypes: float64(550), object(1)
memory usage: 609.8+ MB
None
```

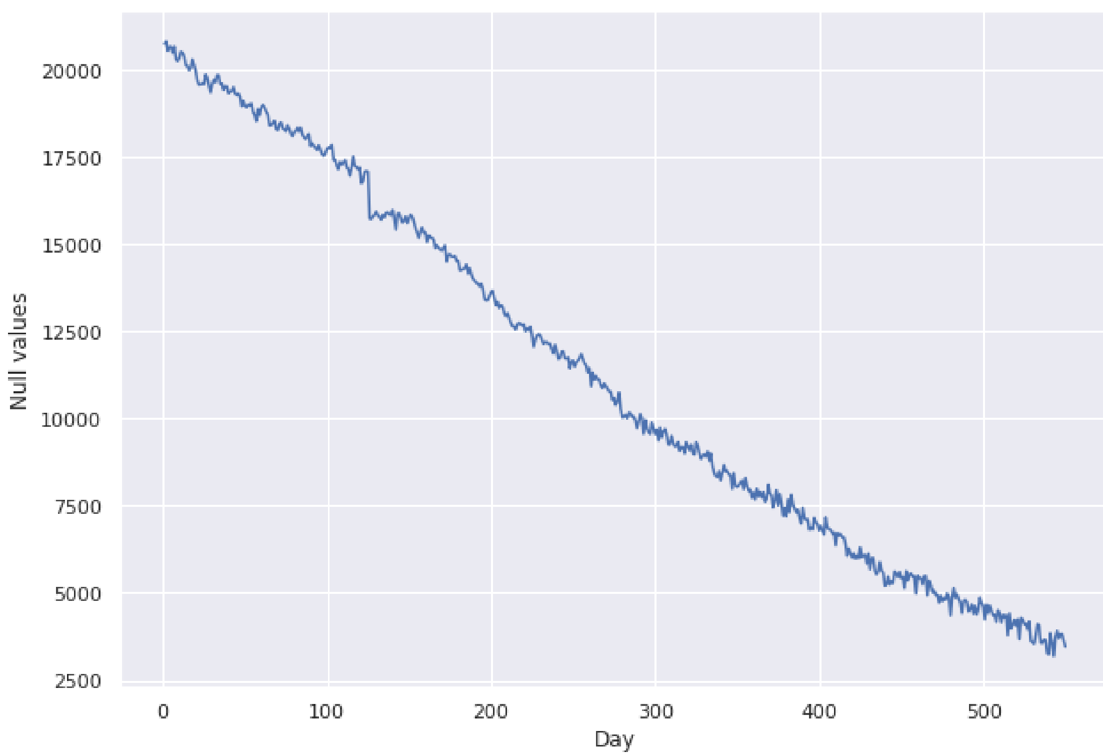
[ ]:
```
print(train.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 145063 entries, 0 to 145062
Columns: 551 entries, Page to 2016-12-31
dtypes: float64(550), object(1)
memory usage: 609.8+ MB
None
```

We can see that ther are some null values in the data, we will plot them to see how it looks

[ ]:
```
days = [r for r in range(1, len(train.columns))]
plot.figure(figsize=(10,7))
plot.xlabel('Day')
plot.ylabel('Null values')
plot.plot(days, train.isnull().sum()[1:])
```

[ ]:
```
[<matplotlib.lines.Line2D at 0x7f9af53dca90>]
```



We see that the number of nan values decrease with time.

Probable reason: Some website have all nan values in the begining, that can be due to the fact that those were created after that time so there is no traffic reading for that time

[ ]:
```
print(train.shape)
train=train.dropna(how='all')
#'all' : If all values are NA, drop that row or column.
print(train.shape)

train=train.dropna(thresh=300)
print(train.shape)
```

```
(145063, 551)
(145063, 551)
(133617, 551)
```

1. We try droping the rows that have all values as nan, none in our case.
2. We then also drop rows that have nan more than 300 days, because the time series for that would not make much sense
3. We fill all the remaining values with zero assuming there was no traffic on the date that the values are nan for.

[ ]:
```
train=train.fillna(0)
train.tail()
```

[ ]:
```
                                                     Page  2015-07-01  \
145012  Legión_(Marvel_Comics)_es.britanica.org_all-ac…         0.0
145013  Referéndum_sobre_la_permanencia_del_Reino_Unid…         0.0
145014  Salida_del_Reino_Unido_de_la_Unión_Europea_es…         0.0
145015  Amar,_después_de_amar_es.britanica.org_all-acc…         0.0
145016  Anexo:89.º_Premios_Óscar_es.britanica.org_all-…         0.0

        2015-07-02  2015-07-03  2015-07-04  2015-07-05  2015-07-06  \
145012         0.0         0.0         0.0         0.0         0.0
145013         0.0         0.0         0.0         0.0         0.0
145014         0.0         0.0         0.0         0.0         0.0
145015         0.0         0.0         0.0         0.0         0.0
145016         0.0         0.0         0.0         0.0         0.0

        2015-07-07  2015-07-08  2015-07-09  …  2016-12-22  2016-12-23  \
145012         0.0         0.0         0.0  …         7.0         3.0
145013         0.0         0.0         0.0  …         9.0        16.0
145014         0.0         0.0         0.0  …        29.0        36.0
145015         0.0         0.0         0.0  …         7.0        30.0
145016         0.0         0.0         0.0  …         0.0         0.0

        2016-12-24  2016-12-25  2016-12-26  2016-12-27  2016-12-28  \
```

```
145012         2.0        4.0        2.0        4.0        4.0
145013         8.0        3.0        6.0        3.0        3.0
145014        23.0      182.0       43.0        8.0       22.0
145015        27.0       14.0        8.0        7.0        5.0
145016         1.0        0.0        1.0        0.0        0.0

        2016-12-29  2016-12-30  2016-12-31
145012         1.0        2.0        2.0
145013        10.0       11.0        3.0
145014        13.0       18.0       14.0
145015        43.0       12.0       25.0
145016         1.0        1.0        0.0

[5 rows x 551 columns]
```

2 *EDA*

The page values are in this format

SPECIFIC NAME __ LANGUAGE.britanica.org __ ACCESS TYPE __ ACCESS ORIGIN

having information about page name, the main domain, device type used to access the page, and also the request origin(spider or browser agent)

[ ]:
```python
#Usage of Regex
def split_page(page):
    w = re.split('_|\.', page)
    print(w)
    return ' '.join(w[:-5]), w[-5], w[-2], w[-1]

split_page('2NE1_zh.britanica.org_all-access_spider')
```

```
['2NE1', 'zh', 'britanica', 'org', 'all-access', 'spider']
```

[ ]:
```
('2NE1', 'zh', 'all-access', 'spider')
```

[ ]:
```python
def split_page(page):
  w = re.split('_|\.', page)
  return ' '.join(w[:-5]), w[-5], w[-2], w[-1]

li = list(train.Page.apply(lambda x: split_page(str(x))))
df = pd.DataFrame(li)
df.columns = ['Title', 'Language', 'Access_type','Access_origin']
df = pd.concat([train, df], axis = 1)
```

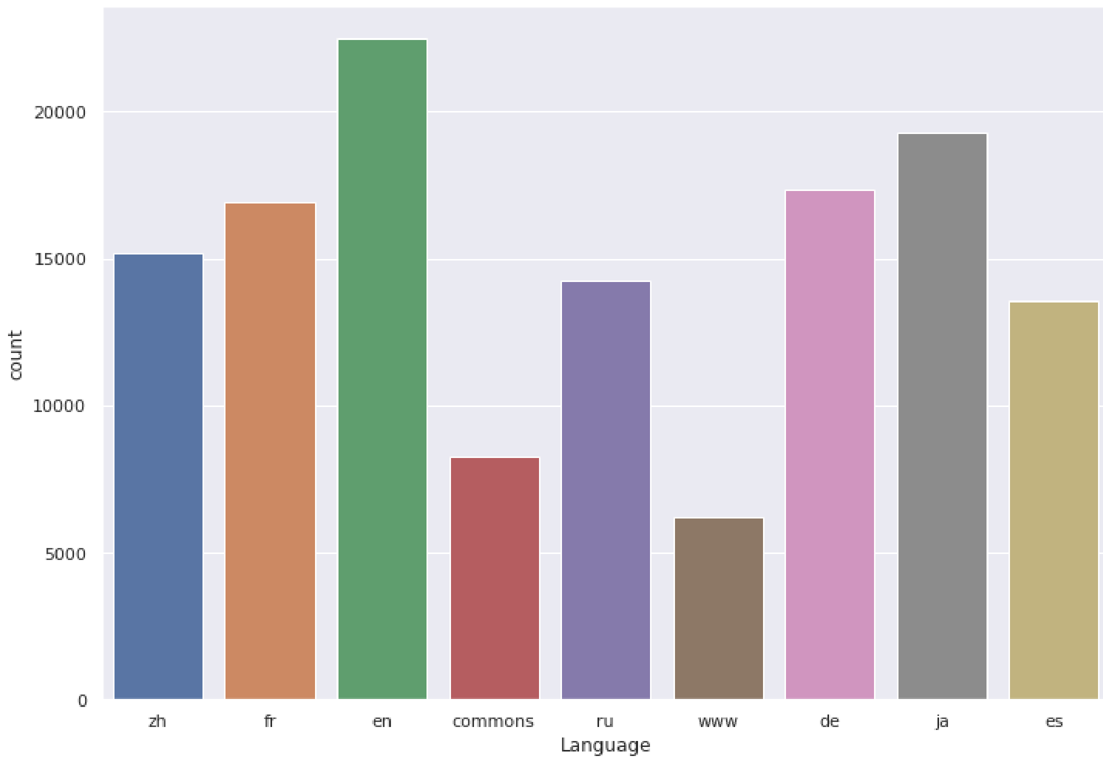
We split the page name and get that information joining it with a temporary database. below we get some rows to see the structure of the data

[ ]:
```
df.head()
```

[ ]:
```
                                       Page  2015-07-01  2015-07-02  \
0     2NE1_zh.britanica.org_all-access_spider        18.0        11.0
1      2PM_zh.britanica.org_all-access_spider        11.0        14.0
2       3C_zh.britanica.org_all-access_spider         1.0         0.0
3  4minute_zh.britanica.org_all-access_spider        35.0        13.0
4                                         NaN         NaN         NaN

   2015-07-03  2015-07-04  2015-07-05  2015-07-06  2015-07-07  2015-07-08  \
0         5.0        13.0        14.0         9.0         9.0        22.0
1        15.0        18.0        11.0        13.0        22.0        11.0
2         1.0         1.0         0.0         4.0         0.0         3.0
3        10.0        94.0         4.0        26.0        14.0         9.0
4         NaN         NaN         NaN         NaN         NaN         NaN

   2015-07-09  …  2016-12-26  2016-12-27  2016-12-28  2016-12-29  \
0        26.0  …        14.0        20.0        22.0        19.0
1        10.0  …         9.0        30.0        52.0        45.0
2         4.0  …         4.0         4.0         6.0         3.0
3        11.0  …        16.0        11.0        17.0        19.0
4         NaN  …         NaN         NaN         NaN         NaN

   2016-12-30  2016-12-31    Title  Language  Access_type  Access_origin
0        18.0        20.0     2NE1        zh   all-access         spider
1        26.0        20.0      2PM        zh   all-access         spider
2         4.0        17.0       3C        zh   all-access         spider
3        10.0        11.0  4minute        zh   all-access         spider
4         NaN         NaN     5566        zh   all-access         spider

[5 rows x 555 columns]
```

[ ]:
```
sns.countplot(df['Language'])
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9af603af10>

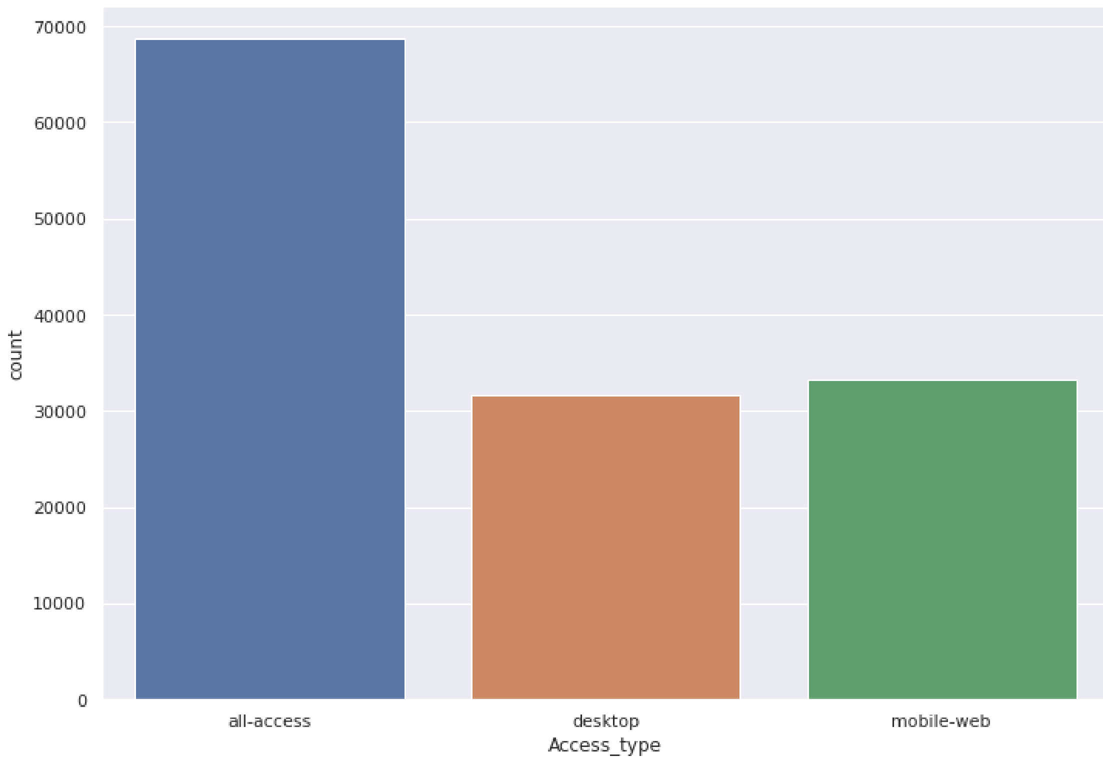


This above is the comparision number of articles in each language

{‘ja’:‘Japanese’, ‘de’:‘German’, ‘en’ : ‘English’, ‘no_lang’:‘Media_File’, ‘fr’:‘French’, ‘zh’:‘Chinese’, ‘ru’:‘Russian’, ‘es’:‘Spanish’}

[ ]:
```
sns.countplot(df['Access_type'])
```

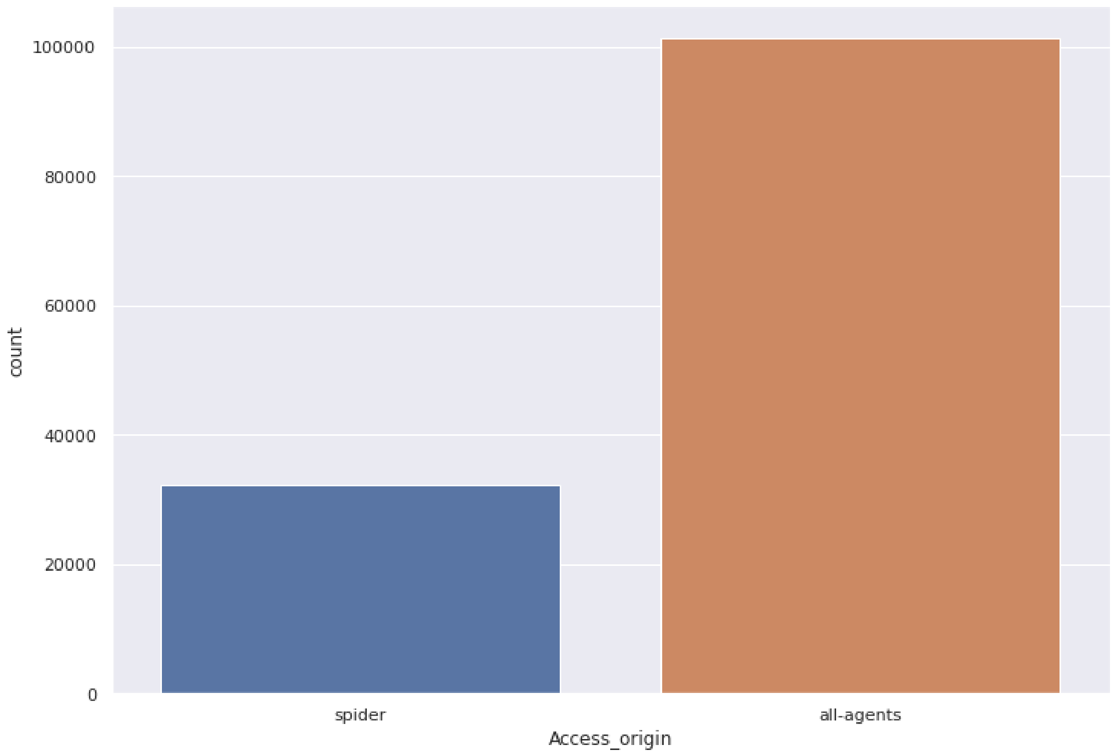
[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9af249c220>
```



This comparision shows that usage from desktop and mobile is almost the same

[ ]:
```
sns.countplot(df['Access_origin'])
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9af23f3880>



This shows that organic view is far more than that of spiders or bots

Now we want to compare the views for different languages

[ ]:
```
#here we see that the languages are not treated properly as there are commons␣
↪and www
df.groupby('Language').count()
```

[ ]:
```
          Page  2015-07-01  2015-07-02  2015-07-03  2015-07-04  2015-07-05  \
Language
commons   7672        7672        7672        7672        7672        7672
de       15946       15946       15946       15946       15946       15946
en       20758       20758       20758       20758       20758       20758
es       12268       12268       12268       12268       12268       12268
fr       15418       15418       15418       15418       15418       15418
ja       17132       17132       17132       17132       17132       17132
ru       12955       12955       12955       12955       12955       12955
www       5743        5743        5743        5743        5743        5743
zh       14845       14845       14845       14845       14845       14845

          2015-07-06  2015-07-07  2015-07-08  2015-07-09  …  2016-12-25  \
Language                                                  …
commons         7672        7672        7672        7672  …        7672
de             15946       15946       15946       15946  …       15946
```

```
en               20758       20758       20758       20758  ...       20758
es               12268       12268       12268       12268  ...       12268
fr               15418       15418       15418       15418  ...       15418
ja               17132       17132       17132       17132  ...       17132
ru               12955       12955       12955       12955  ...       12955
www               5743        5743        5743        5743  ...        5743
zh               14845       14845       14845       14845  ...       14845

          2016-12-26  2016-12-27  2016-12-28  2016-12-29  2016-12-30  \
Language
commons         7672        7672        7672        7672        7672
de             15946       15946       15946       15946       15946
en             20758       20758       20758       20758       20758
es             12268       12268       12268       12268       12268
fr             15418       15418       15418       15418       15418
ja             17132       17132       17132       17132       17132
ru             12955       12955       12955       12955       12955
www             5743        5743        5743        5743        5743
zh             14845       14845       14845       14845       14845

          2016-12-31  Title  Access_type  Access_origin
Language
commons         7672   8266         8266           8266
de             15946  17362        17362          17362
en             20758  22486        22486          22486
es             12268  13551        13551          13551
fr             15418  16948        16948          16948
ja             17132  19295        19295          19295
ru             12955  14270        14270          14270
www             5743   6228         6228           6228
zh             14845  15211        15211          15211

[9 rows x 554 columns]
```

[ ]:
```python
df[df['Language']=='commons']
```

[ ]:
```
                                                    Page  2015-07-01  \
12271    Burning_Man_en.britanica.org_desktop_all-agents      1693.0
12272    Cali_Cartel_en.britanica.org_desktop_all-agents       348.0
12273  Call_of_Duty:_Modern_Warfare_2_en.britanica.or...      806.0
12274  Calvin_Harris_en.britanica.org_desktop_all-agents      7114.0
12275     Carl_Sagan_en.britanica.org_desktop_all-agents      1808.0
...                                                  ...        ...
75274  Ash_Wednesday_en.britanica.org_mobile-web_all-...      170.0
75275  Ashley_Williams_(footballer)_en.britanica.org_...      112.0
75276  Assassin's_Creed_(film)_en.britanica.org_mobil...       28.0
75277  Aubrey_Plaza_en.britanica.org_mobile-web_all-a...     3067.0
```

```
75278  Australia_Plus_en.britanica.org_mobile-web_all…        17.0

       2015-07-02  2015-07-03  2015-07-04  2015-07-05  2015-07-06  2015-07-07  \
12271      1490.0      1186.0      1099.0      1051.0      1968.0      1874.0
12272       363.0       214.0       252.0       257.0       320.0       340.0
12273       768.0       700.0       725.0       723.0       823.0       849.0
12274      5599.0      7685.0     15844.0      9390.0      7173.0      5499.0
12275      1759.0      1838.0      1631.0      1701.0      2230.0      2052.0
…             …           …           …           …           …           …
75274       169.0       165.0       166.0       186.0       154.0       154.0
75275       102.0       135.0       147.0       120.0        89.0        90.0
75276        15.0        24.0        24.0        27.0        34.0        36.0
75277      2952.0      3459.0      3310.0      3294.0      3885.0      3830.0
75278        11.0        14.0         6.0        10.0         8.0        18.0

       2015-07-08  2015-07-09  …  2016-12-26  2016-12-27  2016-12-28  \
12271      1637.0      1842.0  …       940.0      2976.0      2447.0
12272       345.0       432.0  …      1197.0      1449.0      1376.0
12273       731.0       833.0  …       818.0       929.0       892.0
12274      6367.0      5630.0  …      1242.0      1409.0      1714.0
12275      2065.0      2002.0  …      1425.0      1730.0      1858.0
…             …           …  …         …           …           …
75274       184.0       173.0  …       475.0       444.0       389.0
75275       109.0       215.0  …       348.0       439.0       357.0
75276        35.0        22.0  …     43471.0     41147.0     38978.0
75277      3325.0      3150.0  …      4004.0      4848.0      5125.0
75278        10.0         6.0  …        12.0        17.0        18.0

       2016-12-29  2016-12-30  2016-12-31  \
12271      1648.0      1282.0       956.0
12272      1350.0      1287.0       992.0
12273       878.0       893.0       712.0
12274      1604.0      1602.0      1300.0
12275      1781.0      1718.0      1345.0
…             …           …           …
75274       382.0       362.0       393.0
75275       267.0       639.0       429.0
75276     36517.0     41760.0     38116.0
75277      4907.0      4617.0      4415.0
75278        13.0         6.0        19.0

                                                Title  Language  \
12271                                         Accueil   commons
12272                                   Atlas of Asia   commons
12273                                 Atlas of Europe   commons
12274                           Atlas of World War II   commons
12275                            Atlas of colonialism   commons
```

```
…                                                          …        …
75274    File:El jardín de las Delicias, de El Bosco jpg   commons
75275  File:Jää on kulmunud pallideks (Looduse veidru…   commons
75276  File:Reichstagsgebäude mit Weihnachtsbaum bei …   commons
75277                  Category:Images by Eugène Cattin   commons
75278                    File:Nikolaos Gyzis - Historia jpg   commons

       Access_type  Access_origin
12271   all-access         spider
12272   all-access         spider
12273   all-access         spider
12274   all-access         spider
12275   all-access         spider
…             …             …
75274      desktop     all-agents
75275      desktop     all-agents
75276      desktop     all-agents
75277      desktop     all-agents
75278      desktop     all-agents

[8266 rows x 555 columns]
```

[ ]:
```python
# Checking another way of fetching the language out of the string
def lang(Page):
    val = re.search('[a-z][a-z].britanica.org',Page)
    if val:
        #print(val)
        #print(val[0][0:2] )

        return val[0][0:2]

    return 'no_lang'

df['Language']=df['Page'].apply(lambda x: lang(str(x)))
```

[ ]:
```python
df.groupby('Language').count() #now the count has increased. You can go back␣
↪and get it sorted
```

[ ]:
```
           Page  2015-07-01  2015-07-02  2015-07-03  2015-07-04  2015-07-05  \
Language
de        17362       17362       17362       17362       17362       17362
en        22486       22486       22486       22486       22486       22486
es        13551       13551       13551       13551       13551       13551
fr        16948       16948       16948       16948       16948       16948
ja        19295       19295       19295       19295       19295       19295
no_lang   14494       14494       14494       14494       14494       14494
ru        14270       14270       14270       14270       14270       14270
```

```
zh         15211        15211        15211        15211        15211        15211

          2015-07-06  2015-07-07  2015-07-08  2015-07-09  …  2016-12-25  \
Language                                                  …
de             17362       17362       17362       17362  …       17362
en             22486       22486       22486       22486  …       22486
es             13551       13551       13551       13551  …       13551
fr             16948       16948       16948       16948  …       16948
ja             19295       19295       19295       19295  …       19295
no_lang        14494       14494       14494       14494  …       14494
ru             14270       14270       14270       14270  …       14270
zh             15211       15211       15211       15211  …       15211

          2016-12-26  2016-12-27  2016-12-28  2016-12-29  2016-12-30  \
Language
de             17362       17362       17362       17362       17362
en             22486       22486       22486       22486       22486
es             13551       13551       13551       13551       13551
fr             16948       16948       16948       16948       16948
ja             19295       19295       19295       19295       19295
no_lang        14494       14494       14494       14494       14494
ru             14270       14270       14270       14270       14270
zh             15211       15211       15211       15211       15211

          2016-12-31  Title  Access_type  Access_origin
Language
de             17362  13046        13046          13046
en             22486  22486        22486          22486
es             13551  10142        10142          10142
fr             16948  16948        16948          16948
ja             19295  16140        16140          16140
no_lang        14494  25374        25374          25374
ru             14270  14270        14270          14270
zh             15211  15211        15211          15211

[8 rows x 554 columns]
```

[ ]:
```python
df_language=df.groupby('Language').mean().transpose()
df_language
```

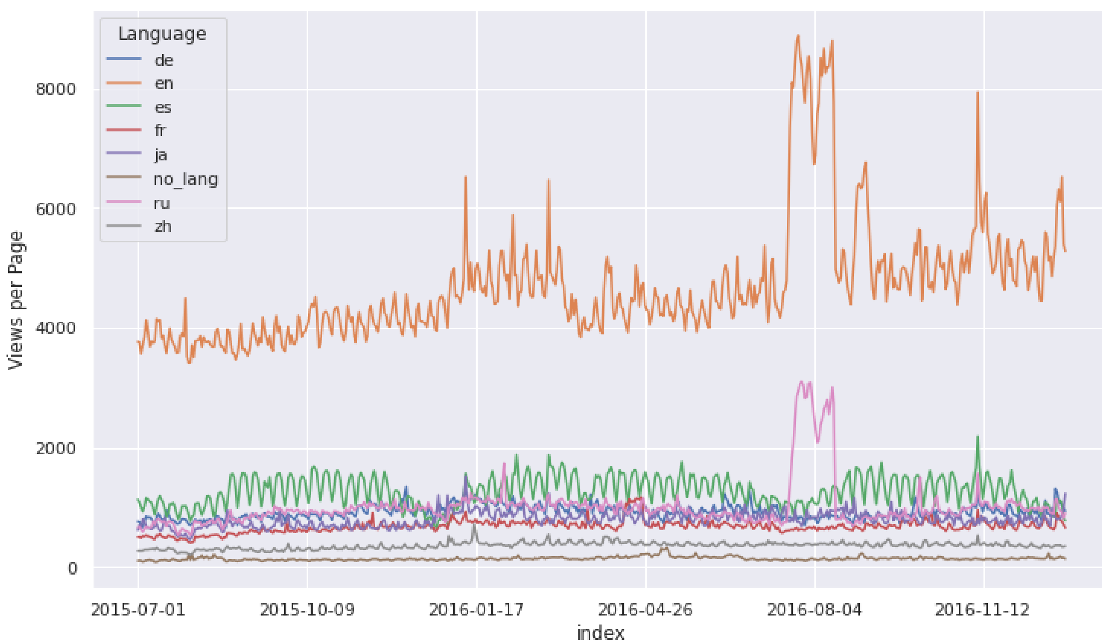
[ ]:
```
Language             de           en           es          fr          ja  \
2015-07-01   763.765926  3767.328604  1127.485204  499.092872  614.637160
2015-07-02   753.362861  3755.158765  1077.485425  502.297852  705.813216
2015-07-03   723.074415  3565.225696   990.895949  483.007553  637.451671
2015-07-04   663.537323  3711.782932   930.303151  516.275785  800.897435
2015-07-05   771.358657  3833.433025  1011.759575  506.871666  768.352319
…                   …            …            …           …           …
```

```
2016-12-27  1119.596936  6314.335275  1070.923400  840.590217   808.541436
2016-12-28  1062.284069  6108.874144  1108.996753  783.585379   807.430163
2016-12-29  1033.939062  6518.058525  1058.660320  763.209169   883.752786
2016-12-30   981.786430  5401.792360   807.551177  710.502773   979.278777
2016-12-31   937.842875  5280.643467   776.934322  654.060656  1228.720808

Language       no_lang          ru          zh
2015-07-01  102.733545  663.199229  272.498521
2015-07-02  107.663447  674.677015  272.906778
2015-07-03  101.769629  625.329783  271.097167
2015-07-04   86.853871  588.171829  273.712379
2015-07-05   96.254105  626.385354  291.977713
…                  …           …           …
2016-12-27  155.270181  998.374071  363.066991
2016-12-28  178.561267  945.054730  369.049701
2016-12-29  150.873534  909.352207  340.526330
2016-12-30  156.049193  815.475123  342.745316
2016-12-31  135.792052  902.600210  352.184275

[550 rows x 8 columns]
```

[ ]:
```
df_language.reset_index(inplace=True)
df_language.set_index('index', inplace=True)
```

[ ]:
```
df_language.plot(figsize=(12,7))
plot.ylabel('Views per Page')
```

[ ]: `Text(0, 0.5, 'Views per Page')`

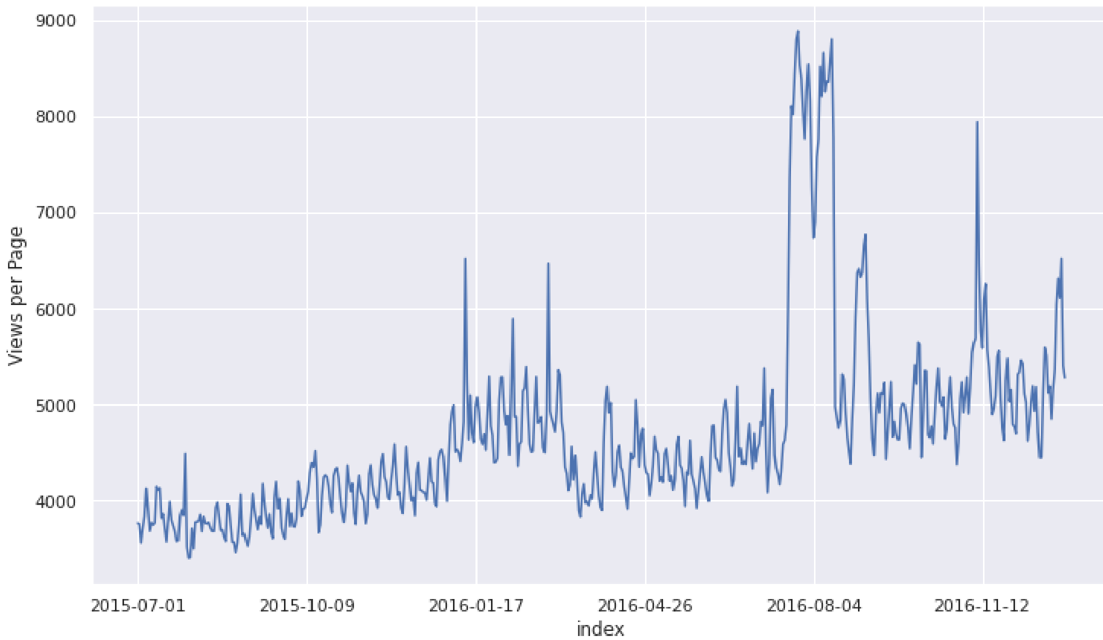


Ploting the data shows that articles in english get the most number of views as compared to different languages, there are some spikes at different times in different laguages

Ploting just for english because we are going to use this for our furthur investigation and predictions

[ ]:
```
df_language['en'].plot(figsize=(12,7))
plot.ylabel('Views per Page')
```

[ ]:
```
Text(0, 0.5, 'Views per Page')
```



[ ]:
```
total_view=df_language.copy()
```

[ ]:
```
##########################################################################################
```

3 Checking the stationarity

Dickey-Fuller test

Here the null hypothesis is that the TS is non-stationary: The test results comprise of a Test Statistic and some Critical Values for difference confidence levels.

[ ]:
```
from statsmodels.tsa.stattools import adfuller
def df_test(x):
    result=adfuller(x)
```

```
    print('ADF Stastistic: %f'%result[0])
    print('p-value: %f'%result[1])

df_test(total_view['en'])
```

```
ADF Stastistic: -2.373563
p-value: 0.149337
```

We see that the p value is not low enough(<0.05). Therefore, we can say our series in not stationary as we fail to reject the null hypothesis

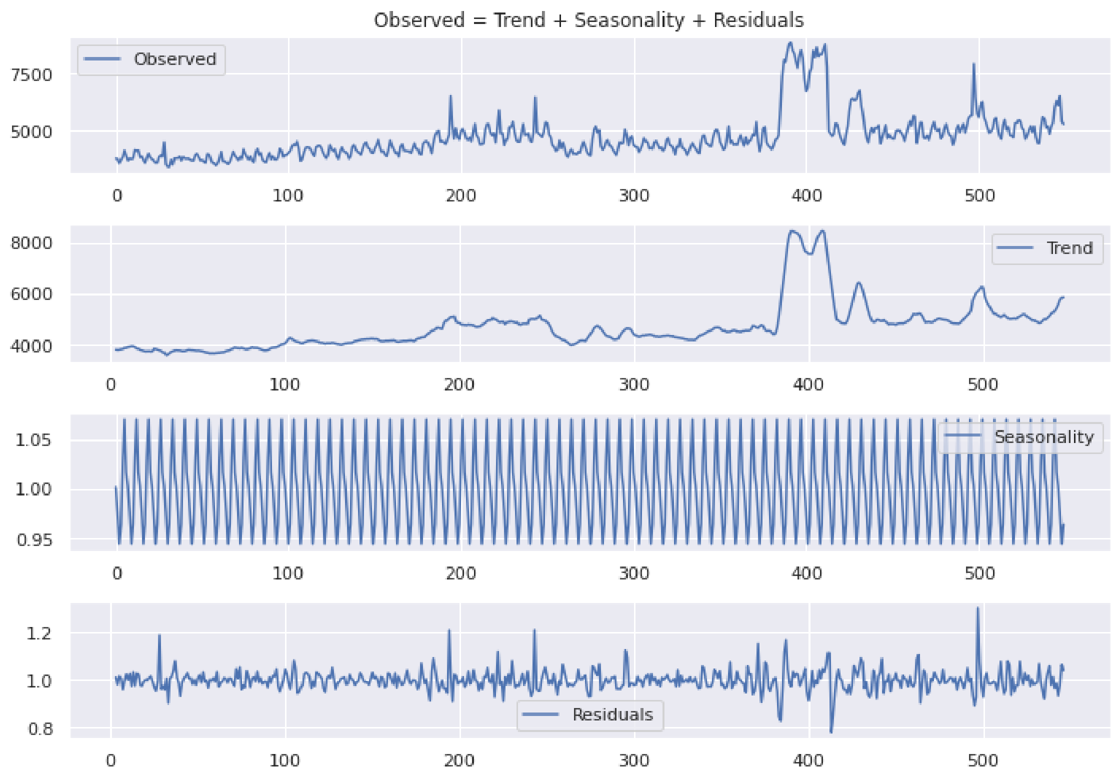
4 Making the time series stationary

[ ]:
```
ts=total_view['en']
```

4.1 1. Remove trend and seasonality with decomposition

[ ]:
```
# Naive decomposition of our Time Series as explained above
from statsmodels.tsa.seasonal import seasonal_decompose
decomposition = seasonal_decompose(ts.values, model='multiplicative',freq = 7)

""" Additive or multiplicative?
  It’s important to understand what the difference between a multiplicative␣
 ↪time series and an additive one before we go any further.

  There are three components to a time series:
  - trend how things are overall changing
  - seasonality how things change within a given period e.g. a year, month,␣
 ↪week, day
  - error/residual/irregular activity not explained by the trend or the␣
 ↪seasonal value

  How these three components interact determines the difference between a␣
 ↪multiplicative and an additive time series.

  In a multiplicative time series, the components multiply together to make the␣
 ↪time series. If you have an increasing trend, the amplitude of seasonal␣
 ↪activity increases. Everything becomes more exaggerated. This is common when␣
 ↪you’re looking at web traffic.

  In an additive time series, the components add together to make the time␣
 ↪series. If you have an increasing trend, you still see roughly the same size␣
 ↪peaks and troughs throughout the time series. This is often seen in indexed␣
 ↪time series where the absolute value is growing but changes stay relative.
```

```
"""

trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid

plot.figure(figsize=(10,7))
plot.subplot(411)
plot.title('Observed = Trend + Seasonality + Residuals')
plot.plot(ts.values,label='Observed')
plot.legend(loc='best')
plot.subplot(412)
plot.plot(trend, label='Trend')
plot.legend(loc='best')
plot.subplot(413)
plot.plot(seasonal,label='Seasonality')
plot.legend(loc='best')
plot.subplot(414)
plot.plot(residual, label='Residuals')
plot.legend(loc='best')
plot.tight_layout()
plot.show()
```



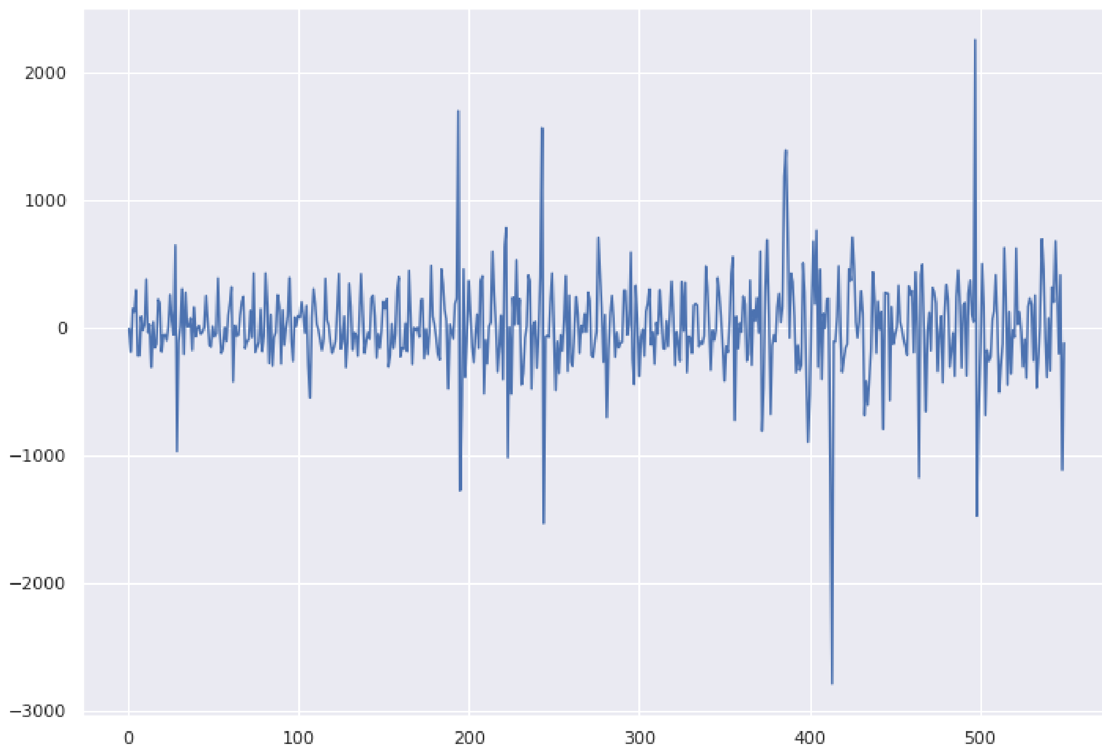
[ ]:
```
ts_decompose=pd.DataFrame(residual).fillna(0)[0].values
df_test(ts_decompose)
```

```
ADF Stastistic: -3.796320
p-value: 0.002945
```

We can see that aur series is now stationary, we can also try diffrencing to see what results we can get.

5 2. Remove trend and seasonality with differencing

[ ]:
```
ts_diff = ts - ts.shift(1)
plot.plot(ts_diff.values)
plot.show()
```



[ ]:
```
ts_diff.dropna(inplace=True)
df_test(ts_diff)
```

```
ADF Stastistic: -8.273590
p-value: 0.000000
```

Also the p value is 0. So we can say that our graph is now stationery. Now we can apply the ARIMA model

How do we choose p,d,q

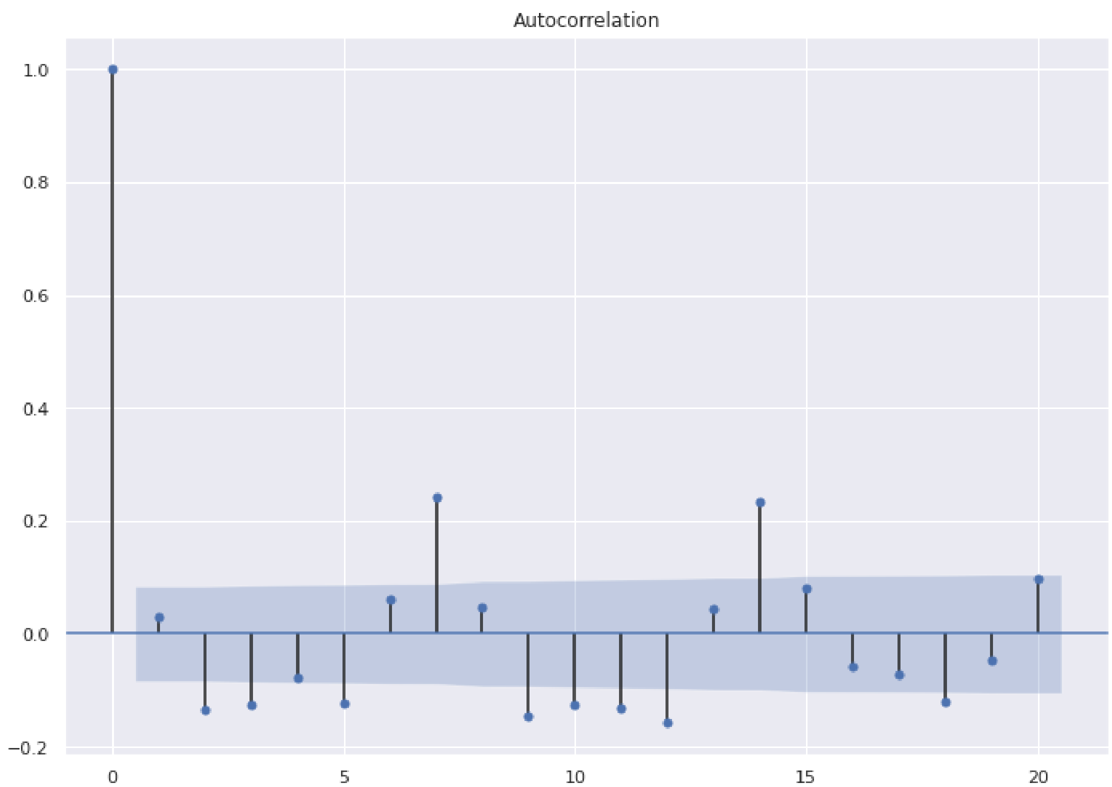
a thumb rule that for choosing the p,q values are when the lag goes below the significant level - we use PACF for p, here we see that till lag 5 there are significat lines, if we want our model to be simpler we can start with a smaller number like 3/4 - we use ACF for q. here we can see that lag 4 is below significant level so we will use till lag 3

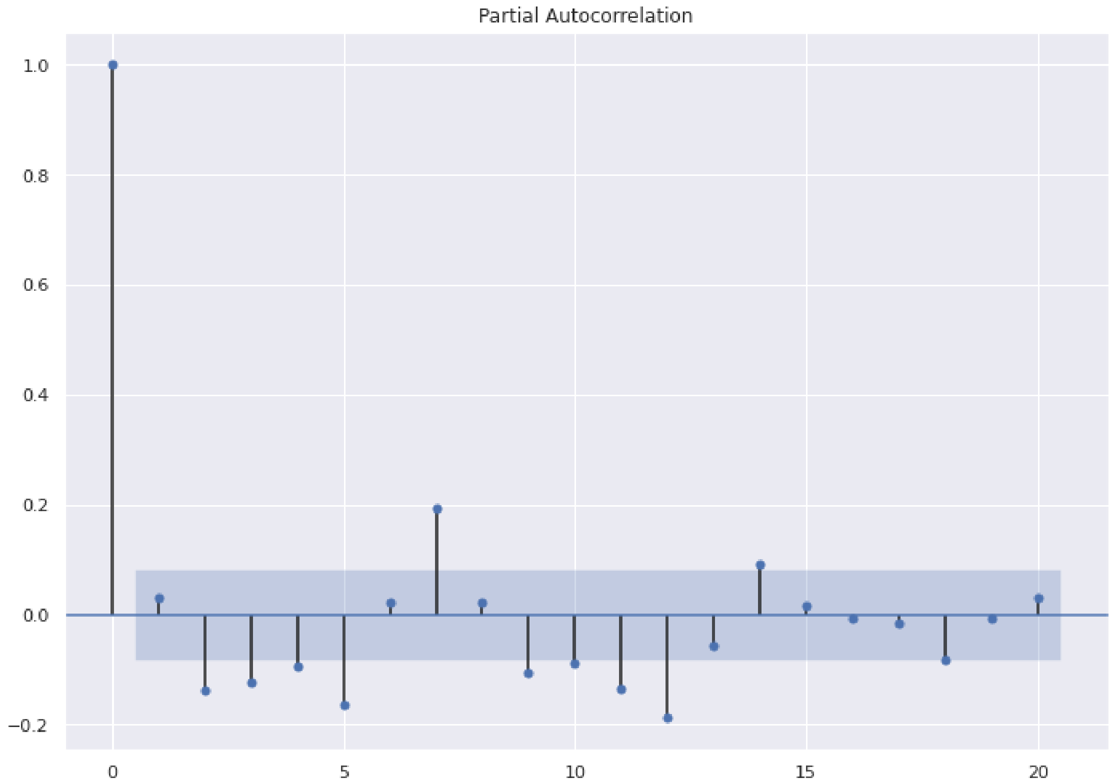
as for d we can see that at 1 diffencing the series becomes stationary so we choose d as 1

6 Plot the autocorreltaion and partial auto correlation functions

Plotting the graphs and getting the p,q,d values for arima

[ ]:
```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
acf=plot_acf(ts_diff,lags=20)
pacf=plot_pacf(ts_diff,lags=20)
```





https://people.duke.edu/~rnau/411arim3.htm

[ ]:

```

```

7 ARIMA MODEL

[ ]:

```
from statsmodels.tsa.arima_model import ARIMA
from pandas import DataFrame
```

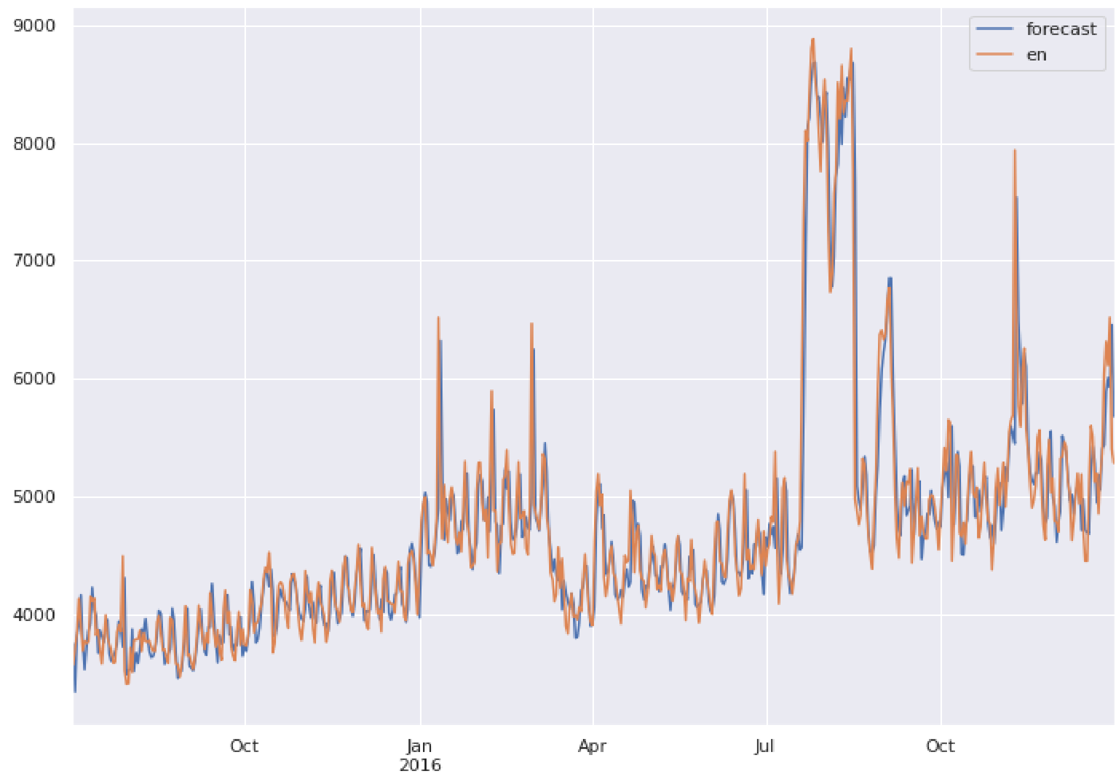
[ ]:

```
model = ARIMA(ts, order=(4,1,3))
model_fit = model.fit(disp=0)
```

```
/usr/local/lib/python3.8/dist-packages/statsmodels/tsa/base/tsa_model.py:524:
ValueWarning: No frequency information was provided, so inferred frequency D
will be used.
  warnings.warn('No frequency information was'
/usr/local/lib/python3.8/dist-packages/statsmodels/tsa/base/tsa_model.py:524:
ValueWarning: No frequency information was provided, so inferred frequency D
will be used.
  warnings.warn('No frequency information was'
/usr/local/lib/python3.8/dist-packages/statsmodels/base/model.py:547:
HessianInversionWarning: Inverting hessian failed, no bse or cov_params
```

```
available
  warnings.warn('Inverting hessian failed, no bse or cov_params '
/usr/local/lib/python3.8/dist-packages/statsmodels/base/model.py:566:
ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check
mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

[ ]:
```python
model_fit.plot_predict(dynamic=False)
"""When you set dynamic=True, the model continuously predicts one-step ahead␣
 ↪(t+1) and then for the 2nd step ahead (t+2) prediction, it appends predicted␣
 ↪value (t+1) to data, re-fits model on new expanded data then makes 2nd step␣
 ↪ahead forecast. This is called out-of-sample prediction.

When you set dynamic=False, the model sequentially predicts one-step-ahead␣
 ↪using the true value from previous time step instead of using predicted␣
 ↪value. This is called in-sample prediction.

On your first comparison of plots as you predict from 509 to 533, the reason␣
 ↪you get same plots is you are extrapolating, you do not have true values of␣
 ↪next 24 steps that you predicted therefor regardless of setting dynamic␣
 ↪either True or False model uses out-of-sample approach.

Since out-of-sample approach uses the last predicted value from the previous␣
 ↪time step to predict the next value in time, as number of steps get farther,␣
 ↪it is expected to deviate from actual values because on each step's␣
 ↪prediction fitted model learns previous predicted step's errors as well.
"""
plot.show()
```




```
[ ]:
```

Multistep forecasting

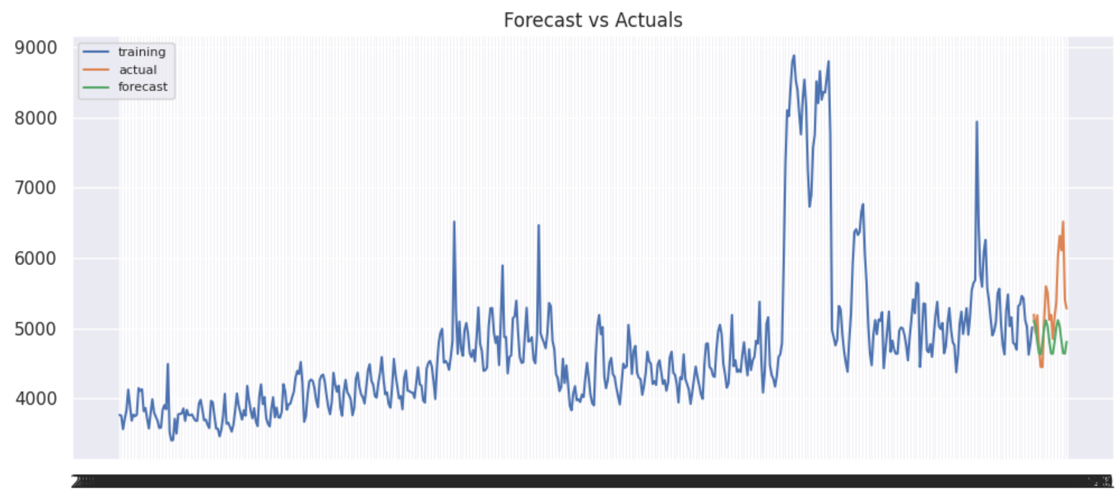
```
[ ]: train = ts[:-20]
     test = ts[-20:]
```

```
[ ]: model = ARIMA(train, order=(4, 1, 3))
     fitted = model.fit(disp=-1)

     # Forecast
     fc, se, conf = fitted.forecast(20, alpha=0.02)

     # Make as pandas series
     fc_series = pd.Series(fc, index=test.index)
     # Plot
     plot.figure(figsize=(12,5), dpi=100)
     plot.plot(train, label='training')
     plot.plot(test, label='actual')
     plot.plot(fc_series, label='forecast')

     plot.title('Forecast vs Actuals')
```

```python
plot.legend(loc='upper left', fontsize=8)
```

```
/usr/local/lib/python3.8/dist-packages/statsmodels/tsa/base/tsa_model.py:524:
ValueWarning: No frequency information was provided, so inferred frequency D
will be used.
  warnings.warn('No frequency information was'
/usr/local/lib/python3.8/dist-packages/statsmodels/tsa/base/tsa_model.py:524:
ValueWarning: No frequency information was provided, so inferred frequency D
will be used.
  warnings.warn('No frequency information was'
/usr/local/lib/python3.8/dist-packages/statsmodels/base/model.py:547:
HessianInversionWarning: Inverting hessian failed, no bse or cov_params
available
  warnings.warn('Inverting hessian failed, no bse or cov_params '
/usr/local/lib/python3.8/dist-packages/statsmodels/base/model.py:566:
ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check
mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

[ ]: <matplotlib.legend.Legend at 0x7f9aed53c340>



[ ]:
```python
mape = np.mean(np.abs(fc - test.values)/np.abs(test.values))
rmse = np.mean((fc - test.values)**2)**.5
print("mape:",mape)
print("rsme:",rmse)
```

```
mape: 0.0935492560101219
rsme: 706.602453194038
```

we can see that the model does not perform very well for multistep out sample data

from the decomposition we can see that there is a weekly seasonality and still some spikes in the residual, that may be because of some external factors, which we can take into account by using them as our exogenous variable

[ ]:
```
!gdown 1H9054-eVP9IdANPOblXwX7Nd2r_Sjf1u
```

```
Downloading…
From: https://drive.google.com/uc?id=1H9054-eVP9IdANPOblXwX7Nd2r_Sjf1u
To: /content/Exog_Campaign_eng
100% 1.10k/1.10k [00:00<00:00, 1.79MB/s]
```

[ ]:
```
ex_df = pd.read_csv('Exog_Campaign_eng')
ex_df.head()
```

[ ]:

	Exog
0	0
1	0
2	0
3	0
4	0

We get the exogenous data from this csv file for english pages

[ ]:
```
exog=ex_df['Exog'].to_numpy()
```

we will train a sarimax model for that and see if we get anyimprovements from using the two information.

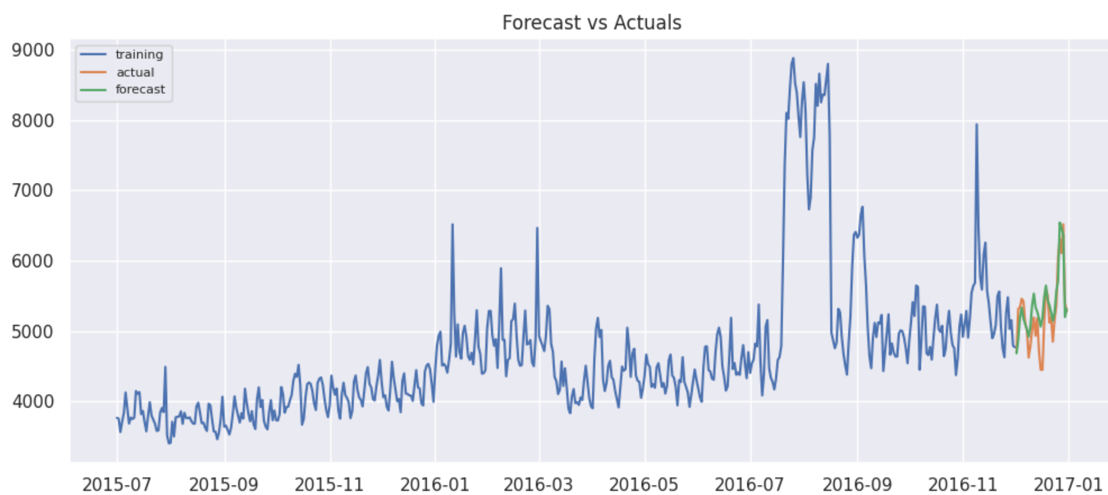
the seasonal order and the values of PDQ are based upon various trials and comparision of the models - we see a seasonality of 7 from the plots ie: weekly seasonality (from the plots we can see that afte some insignificant plots we have some significant values repeating at intervals of 7 ie: 7,14 …) - the non seasonal order we can keep the same

[ ]:
```
import statsmodels.api as sm
train=ts[:520]
test=ts[520:]
model=sm.tsa.statespace.SARIMAX(train,order=(4, 1,␣
↪3),seasonal_order=(1,1,1,7),exog=exog[:520])
results=model.fit()

fc=results.forecast(30,dynamic=True,exog=pd.DataFrame(exog[520:]))

# Make as pandas series
fc_series = pd.Series(fc)
# Plot
train.index=train.index.astype('datetime64[ns]')
test.index=test.index.astype('datetime64[ns]')
plot.figure(figsize=(12,5), dpi=100)
plot.plot(train, label='training')
plot.plot(test, label='actual')
```

```
plot.plot(fc_series, label='forecast')

plot.title('Forecast vs Actuals')
plot.legend(loc='upper left', fontsize=8)
```

```
/usr/local/lib/python3.8/dist-packages/statsmodels/tsa/base/tsa_model.py:524:
ValueWarning: No frequency information was provided, so inferred frequency D
will be used.
  warnings.warn('No frequency information was'
/usr/local/lib/python3.8/dist-packages/statsmodels/tsa/base/tsa_model.py:524:
ValueWarning: No frequency information was provided, so inferred frequency D
will be used.
  warnings.warn('No frequency information was'
/usr/local/lib/python3.8/dist-packages/statsmodels/base/model.py:566:
ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check
mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

[ ]: <matplotlib.legend.Legend at 0x7f9ae2bd5dc0>



[ ]:

[ ]:
```
mape = np.mean(np.abs(fc - test.values)/np.abs(test.values))
rmse = np.mean((fc - test.values)**2)**.5
print("mape:",mape)
print("rsme:",rmse)
```

```
mape: 0.0476009066291969
rsme: 299.17343793278815
```

The mean absolute percentage error and the root mean squared error is low

8 regression for a time series

[ ]:
```
ts_df=ts.to_frame()
ts_df.head()
```

[ ]:
```
                     en
index
2015-07-01  3767.328604
2015-07-02  3755.158765
2015-07-03  3565.225696
2015-07-04  3711.782932
2015-07-05  3833.433025
```

[ ]:
```
ts_df.reset_index(level=0, inplace=True)
ts_df['date']=pd.to_datetime(ts_df['index'])
ts_df.drop(['index'],axis=1,inplace=True)
ts_df.head()
```

[ ]:
```
            en       date
0  3767.328604 2015-07-01
1  3755.158765 2015-07-02
2  3565.225696 2015-07-03
3  3711.782932 2015-07-04
4  3833.433025 2015-07-05
```

[ ]:
```
ts_df['day_of_week']=ts_df['date'].dt.day_name()
ts_df.head()
```

[ ]:
```
            en       date day_of_week
0  3767.328604 2015-07-01   Wednesday
1  3755.158765 2015-07-02    Thursday
2  3565.225696 2015-07-03      Friday
3  3711.782932 2015-07-04    Saturday
4  3833.433025 2015-07-05      Sunday
```

[ ]:
```
ts_df=pd.get_dummies(ts_df, columns = ['day_of_week'])
```

[ ]:
```
ts_df.head()
```

[ ]:
```
            en       date  day_of_week_Friday  day_of_week_Monday  \
0  3767.328604 2015-07-01                   0                   0
1  3755.158765 2015-07-02                   0                   0
2  3565.225696 2015-07-03                   1                   0
3  3711.782932 2015-07-04                   0                   0
4  3833.433025 2015-07-05                   0                   0

   day_of_week_Saturday  day_of_week_Sunday  day_of_week_Thursday  \
```

```
0                      0                    0                      0
1                      0                    0                      1
2                      0                    0                      0
3                      1                    0                      0
4                      0                    1                      0

   day_of_week_Tuesday  day_of_week_Wednesday
0                    0                      1
1                    0                      0
2                    0                      0
3                    0                      0
4                    0                      0
```

[ ]:
```
ts_df['exog']=ex_df['Exog']
ts_df['rolling_mean']=ts_df['en'].rolling(7).mean()
```

[ ]:
```
```

[ ]:
```
ts_df=ts_df.dropna()
ts_df.head()
```

[ ]:
```
             en        date  day_of_week_Friday  day_of_week_Monday  \
6   3906.341724 2015-07-07                   0                   0
7   3685.854621 2015-07-08                   0                   0
8   3771.183714 2015-07-09                   0                   0
9   3749.860313 2015-07-10                   1                   0
10  3770.749355 2015-07-11                   0                   0

    day_of_week_Saturday  day_of_week_Sunday  day_of_week_Thursday  \
6                      0                   0                     0
7                      0                   0                     0
8                      0                   0                     1
9                      0                   0                     0
10                     1                   0                     0

    day_of_week_Tuesday  day_of_week_Wednesday  exog  rolling_mean
6                     1                      0     0   3809.528545
7                     0                      1     0   3797.889404
8                     0                      0     0   3800.178683
9                     0                      0     0   3826.555056
10                    0                      0     0   3834.978831
```

[ ]:
```
X=ts_df[['day_of_week_Friday',        'day_of_week_Monday',        'day_of_week_Saturday',
 ↪copy()
y=ts_df[['en']]

train_x = X[:-20]
```

```
test_x = X[-20:]

train_y = y[:-20]
test_y = y[-20:]
```

[ ]:
```
from sklearn.linear_model import LinearRegression

# Train and pred
model = LinearRegression()
model.fit(train_x, train_y)
y_pred = (model.predict(test_x))


mape = np.mean(np.abs(y_pred - test_y.values)/np.abs(test_y.values))
print("mape:",mape)
```

```
mape: 0.04523968736329716
```

We can see here that aur mape is better than our arima model but worse than our sarimax model

- Linear Regression Is Limited to Linear Relationships and in our case there is not a lot of linear relationship.
- it would have been better to use a regression based model for forecasting if we can build some better features.
- we have our series data and the exogenous variables, we add the day of week feature, other than that there are not a lot of features that we can build

9 using Facebook Prophet

[ ]:
```
!pip install pystan~=2.14
!pip install fbprophet
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: pystan~=2.14 in /usr/local/lib/python3.7/dist-
packages (2.19.1.1)
Requirement already satisfied: Cython!=0.25.1,>=0.22 in
/usr/local/lib/python3.7/dist-packages (from pystan~=2.14) (0.29.32)
Requirement already satisfied: numpy>=1.7 in /usr/local/lib/python3.7/dist-
packages (from pystan~=2.14) (1.21.6)
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: fbprophet in /usr/local/lib/python3.7/dist-
packages (0.7.1)
Requirement already satisfied: holidays>=0.10.2 in
/usr/local/lib/python3.7/dist-packages (from fbprophet) (0.14.2)
Requirement already satisfied: cmdstanpy==0.9.5 in
/usr/local/lib/python3.7/dist-packages (from fbprophet) (0.9.5)
```

```
Requirement already satisfied: convertdate>=2.1.2 in
/usr/local/lib/python3.7/dist-packages (from fbprophet) (2.4.0)
Requirement already satisfied: matplotlib>=2.0.0 in
/usr/local/lib/python3.7/dist-packages (from fbprophet) (3.2.2)
Requirement already satisfied: setuptools-git>=1.2 in
/usr/local/lib/python3.7/dist-packages (from fbprophet) (1.2)
Requirement already satisfied: numpy>=1.15.4 in /usr/local/lib/python3.7/dist-
packages (from fbprophet) (1.21.6)
Requirement already satisfied: tqdm>=4.36.1 in /usr/local/lib/python3.7/dist-
packages (from fbprophet) (4.64.0)
Requirement already satisfied: pystan>=2.14 in /usr/local/lib/python3.7/dist-
packages (from fbprophet) (2.19.1.1)
Requirement already satisfied: python-dateutil>=2.8.0 in
/usr/local/lib/python3.7/dist-packages (from fbprophet) (2.8.2)
Requirement already satisfied: Cython>=0.22 in /usr/local/lib/python3.7/dist-
packages (from fbprophet) (0.29.32)
Requirement already satisfied: LunarCalendar>=0.0.9 in
/usr/local/lib/python3.7/dist-packages (from fbprophet) (0.0.9)
Requirement already satisfied: pandas>=1.0.4 in /usr/local/lib/python3.7/dist-
packages (from fbprophet) (1.3.5)
Requirement already satisfied: pymeeus<=1,>=0.3.13 in
/usr/local/lib/python3.7/dist-packages (from convertdate>=2.1.2->fbprophet)
(0.5.11)
Requirement already satisfied: hijri-converter in /usr/local/lib/python3.7/dist-
packages (from holidays>=0.10.2->fbprophet) (2.2.4)
Requirement already satisfied: korean-lunar-calendar in
/usr/local/lib/python3.7/dist-packages (from holidays>=0.10.2->fbprophet)
(0.2.1)
Requirement already satisfied: pytz in /usr/local/lib/python3.7/dist-packages
(from LunarCalendar>=0.0.9->fbprophet) (2022.2.1)
Requirement already satisfied: ephem>=3.7.5.3 in /usr/local/lib/python3.7/dist-
packages (from LunarCalendar>=0.0.9->fbprophet) (4.1.3)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-
packages (from matplotlib>=2.0.0->fbprophet) (0.11.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.7/dist-packages (from matplotlib>=2.0.0->fbprophet)
(1.4.4)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in
/usr/local/lib/python3.7/dist-packages (from matplotlib>=2.0.0->fbprophet)
(3.0.9)
Requirement already satisfied: typing-extensions in
/usr/local/lib/python3.7/dist-packages (from
kiwisolver>=1.0.1->matplotlib>=2.0.0->fbprophet) (4.1.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-
packages (from python-dateutil>=2.8.0->fbprophet) (1.15.0)
```

```
[ ]: ts_df['ds']=ts_df['date']
     ts_df['y']=ts_df['en']
```

```
[ ]: df2=ts_df[['date','en','exog']].copy()
     df2.columns = ['ds', 'y', 'exog']
     df2.head()
```

```
[ ]:            ds            y  exog
     6  2015-07-07  3906.341724     0
     7  2015-07-08  3685.854621     0
     8  2015-07-09  3771.183714     0
     9  2015-07-10  3749.860313     0
     10 2015-07-11  3770.749355     0
```

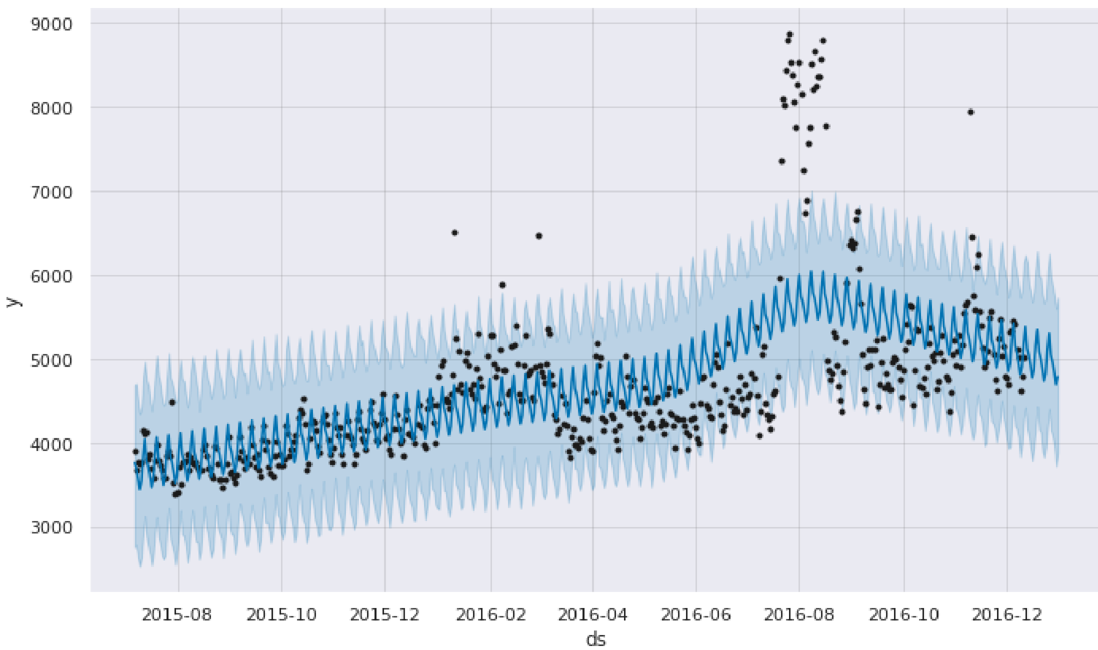
```
[ ]: df2[:-20].info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 524 entries, 6 to 529
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   ds      524 non-null    datetime64[ns]
 1   y       524 non-null    float64
 2   exog    524 non-null    int64
dtypes: datetime64[ns](1), float64(1), int64(1)
memory usage: 16.4 KB
```

prophet without exogenous

```
[ ]: from fbprophet import Prophet
     m = Prophet(weekly_seasonality=True)
     m.fit(df2[['ds', 'y']][:-20])
     future = m.make_future_dataframe(periods=20,freq="D")
     forecast = m.predict(future)
     fig = m.plot(forecast)
```

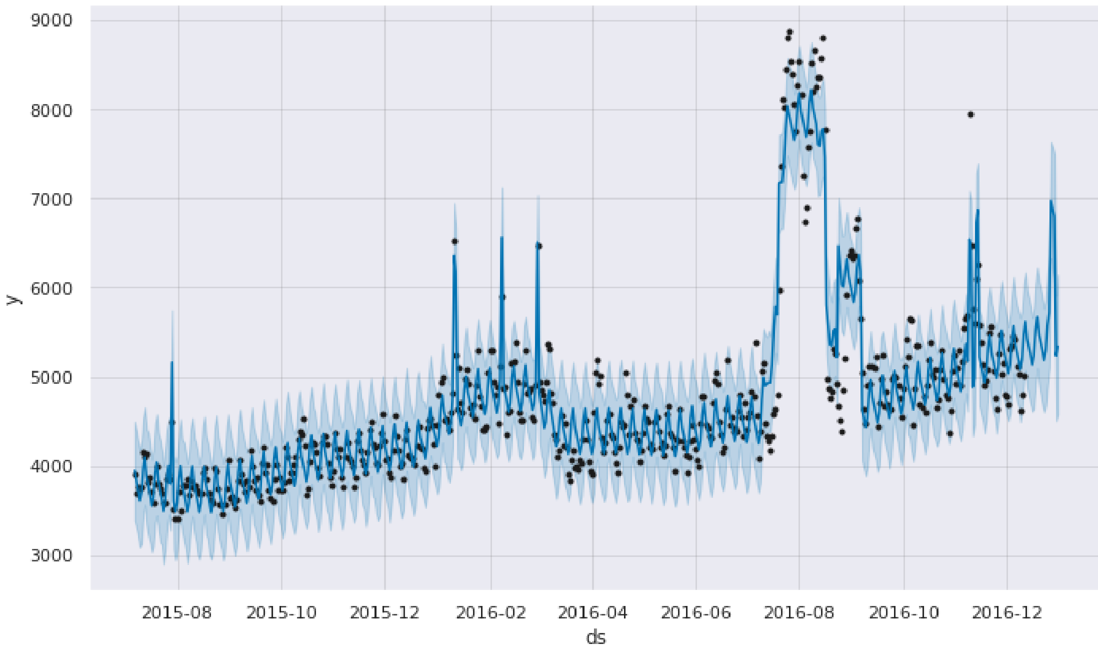
```
INFO:fbprophet:Disabling yearly seasonality. Run prophet with
yearly_seasonality=True to override this.
INFO:fbprophet:Disabling daily seasonality. Run prophet with
daily_seasonality=True to override this.
```



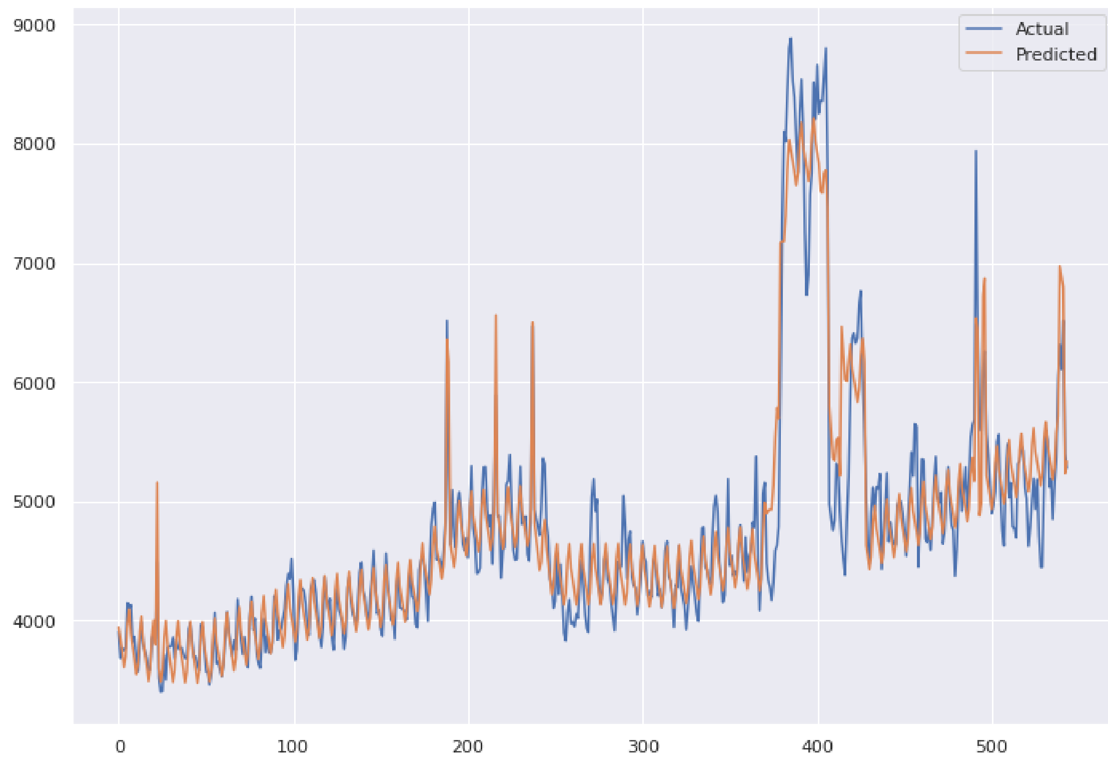
prophet with exogenous

```
[ ]: model2=Prophet(interval_width=0.9, weekly_seasonality=True,␣
      ↪changepoint_prior_scale=1)
     model2.add_regressor('exog')
     model2.fit(df2[:-20])
     forecast2 = model2.predict(df2)
     fig = model2.plot(forecast2)
```

```
INFO:fbprophet:Disabling yearly seasonality. Run prophet with
yearly_seasonality=True to override this.
INFO:fbprophet:Disabling daily seasonality. Run prophet with
daily_seasonality=True to override this.
```



[ ]:
```
y_true = df2['y'].values
y_pred = forecast2['yhat'].values

plot.plot(y_true, label='Actual')
plot.plot(y_pred, label='Predicted')
plot.legend()
plot.show()
```



[ ]:
```
mape = np.mean(np.abs(forecast2['yhat'][-20:] - df2['y'][-20:].values)/np.
 ↪abs(df2['y'][-20:].values))
print("mape:",mape)
```

```
mape: 0.06592815614410931
```

- Prophet does not perform well on non-stationary data because it is difficult to find the actual seasonality and trend of the data if the patterns are inconsistent.

10 ____

11 Comparing the predicted views for different languages

For doing this we are going to automate the procedure from loading the separate data for each langauge to doing out of sample forecasting for the next month, and then comparing the results.

[ ]:
```
def grid_search(ts):
    v=[0,1,2,3]
    mape=100
    val=[0,0,0]
    for p in v:
```

```
        for d in v:
            for q in v:
                try:
                    model = ARIMA(ts[:-20], order=(p,d,q))
                    model_fit = model.fit(disp=-1)
                    fc, se, conf = model_fit.forecast(20, alpha=0.02)
                    x = np.mean(np.abs(fc - ts[-20:].values)/np.abs(ts[-20:].
↪values))
                    if(x<mape):
                        mape=x
                        val=[p,d,q]

                except:
                    pass

    return(mape, val)
```

This functions works like a grid search for getting the best value of p,d,q by comparing the mape of all models that we create.

the values of p,d,q that give the least mape score are saved and returned

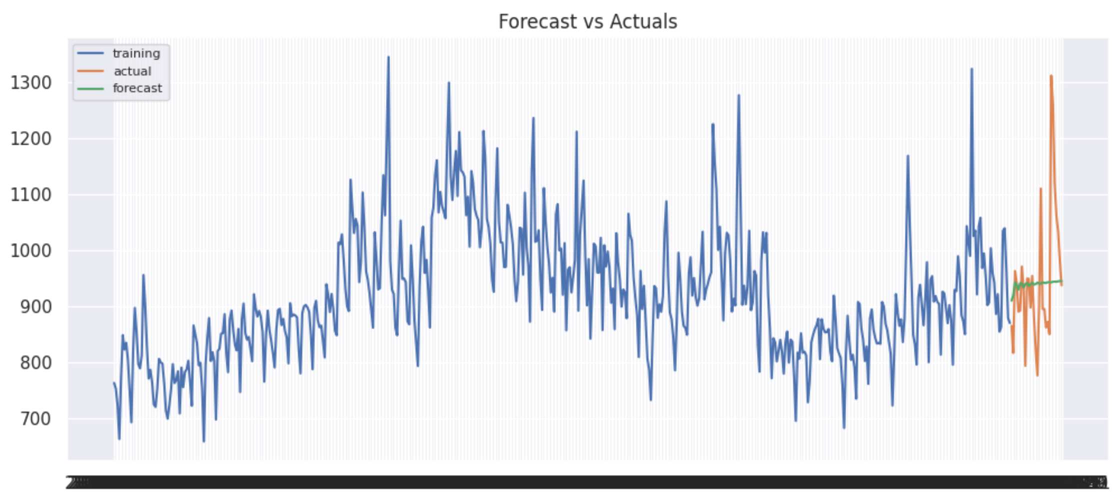
[ ]:
```
def all_arima(train,test,val):
    model = ARIMA(train, order=(val[0], val[1], val[2]))
    fitted = model.fit(disp=-1)

  # Forecast
    fc, se, conf = fitted.forecast(30, alpha=0.02)



    fc_series = pd.Series(fc, index=test.index)

  # Plot
    plot.figure(figsize=(12,5), dpi=100)
    plot.plot(train, label='training')
    plot.plot(test, label='actual')
    plot.plot(fc_series, label='forecast')
    plot.title('Forecast vs Actuals')
    plot.legend(loc='upper left', fontsize=8)
    plot.show()
    mape = np.mean(np.abs(fc - test.values)/np.abs(test.values))
    rmse = np.mean((fc - test.values)**2)**.5
    print("mape:",mape)
    print("rsme:",rmse)
    return (fc)
```

This function takes the p,d,q values that we calculated earlier and then trains a model on it, does forecast and plots them for visualization.

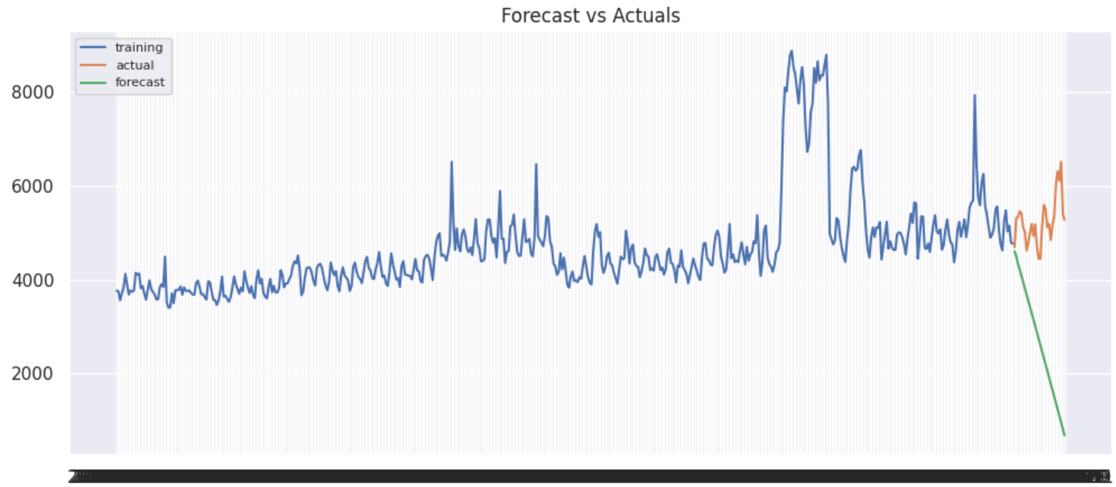
it also calculates the sum of forecased views for the next 30 days and returns it back

[ ]:
```python
import warnings
warnings.filterwarnings("ignore")
views_prediction={}
for c in total_view:
    print("language: ",c)
    ts=(total_view[c])
    mape,val=grid_search(ts)
    print(mape,val)
    train = ts[:520]
    test = ts[520:]
    fc=all_arima(train,test,val)
    views_prediction[c]=fc
```

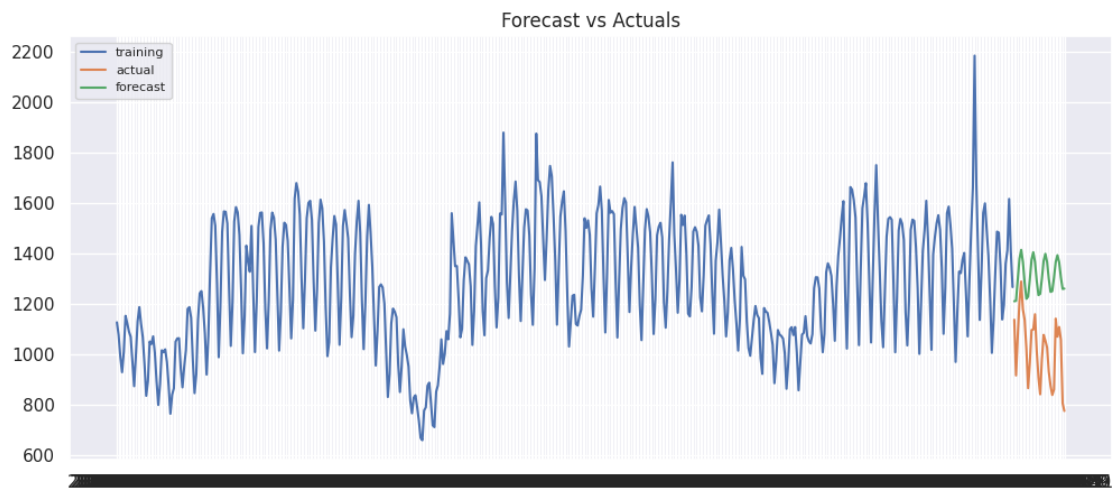
```
language:  de
0.09397758421308047 [3, 1, 3]
```



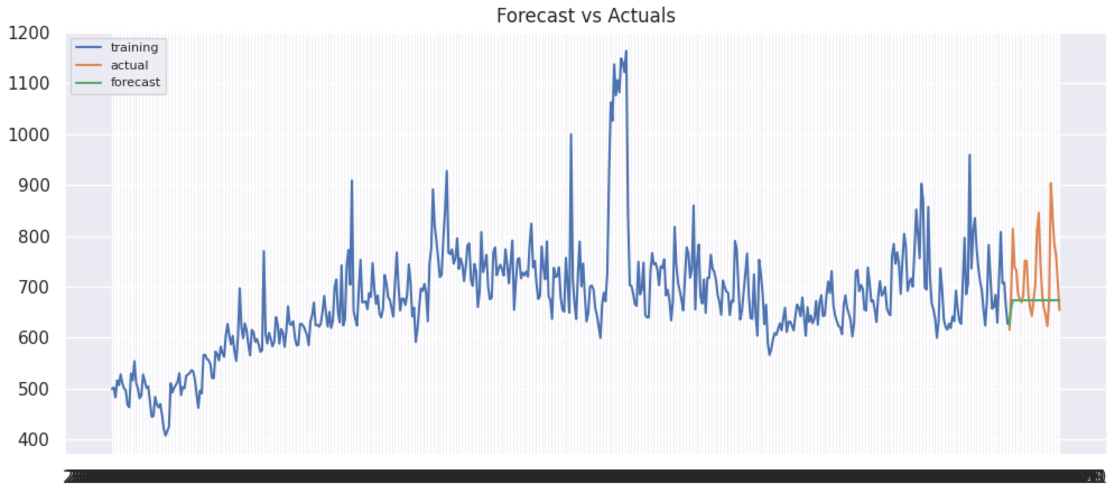

```
mape: 0.08451930259659801
rsme: 119.84846155914948
language:  en
0.07497050608151384 [3, 2, 0]
```



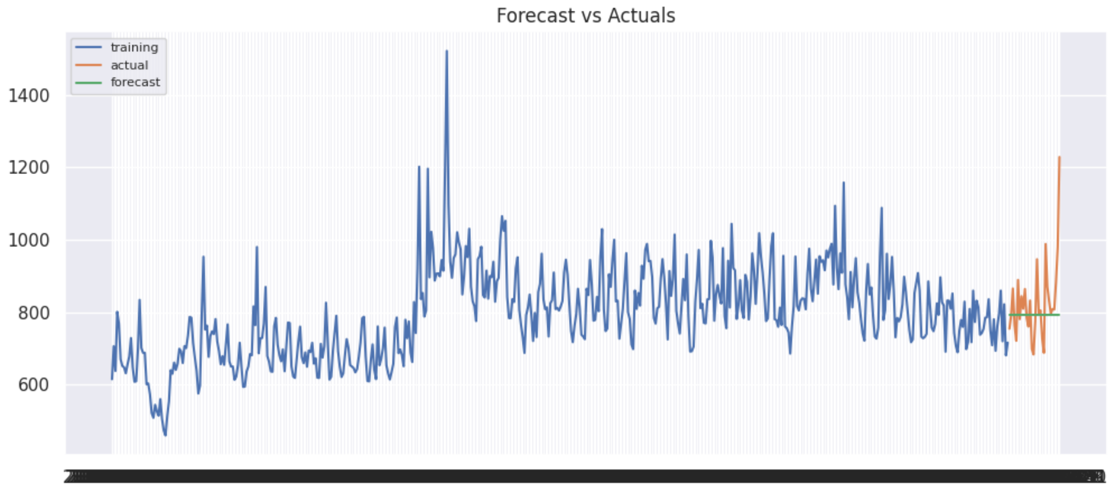
mape: 0.4781050962988165
rsme: 2972.249073736557
language: es
0.08748369803155673 [3, 1, 3]



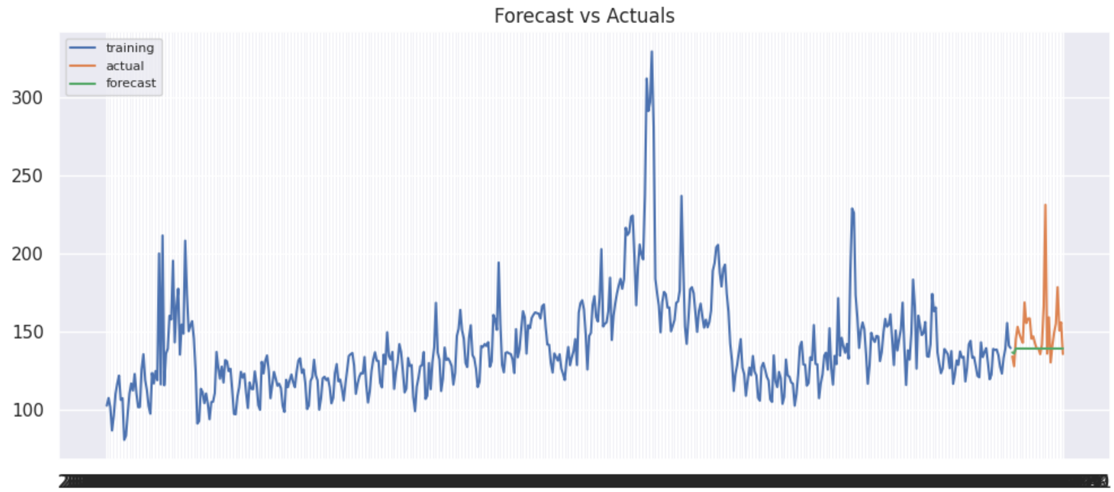
mape: 0.3032163163374593
rsme: 308.3268548323757
language: fr
0.07922539990107266 [0, 0, 2]



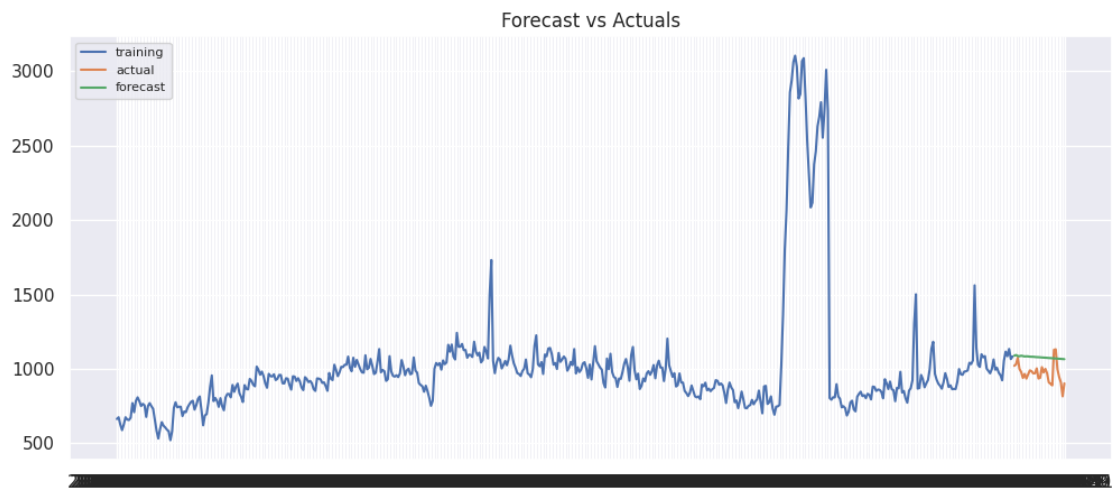
mape: 0.07316960356482773
rsme: 82.05815499130937
language: ja
0.09306005747257282 [0, 0, 0]



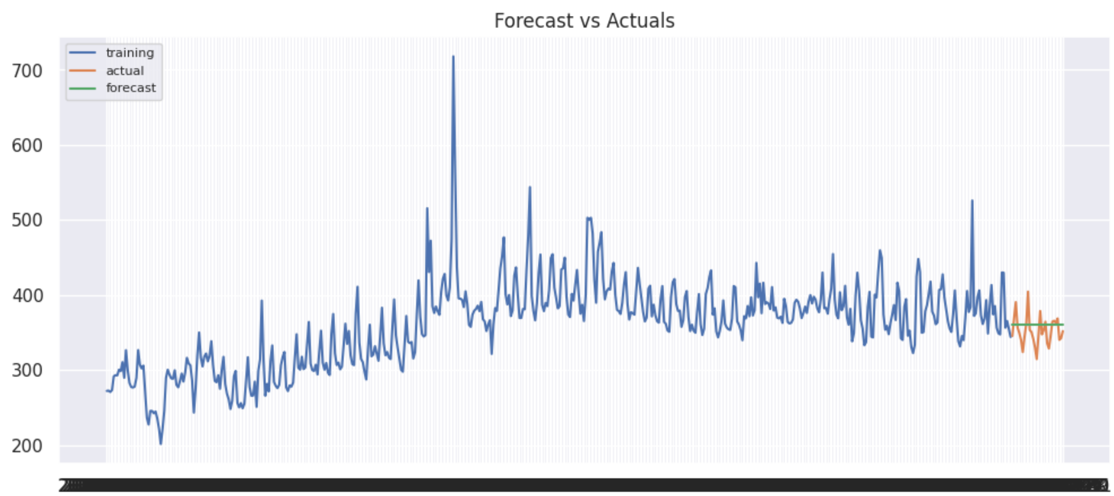
mape: 0.08086798857229117
rsme: 111.15944936830843
language: no_lang
0.07911978906564705 [0, 0, 3]




```
mape: 0.08096654200730383
rsme: 21.960681343449338
language:  ru
0.052023758161538015 [2, 2, 3]
```




```
mape: 0.1196084671042122
rsme: 122.51049610367977
language:  zh
0.04467696433881181 [0, 0, 0]
```




```
mape: 0.04704826775436991
rsme: 20.17502184263151
```

##**Difference between arima, sarima & sarimax.**

ARIMA (AutoRegressive Integrated Moving Average), SARIMA (Seasonal AutoRegressive Integrated Moving Average), and SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous factors) are all models used in time series analysis for forecasting. They are extensions or variations of the basic ARIMA model, incorporating different features to handle specific characteristics of time series data.

1. **ARIMA (AutoRegressive Integrated Moving Average):**
   - ARIMA models are used for non-seasonal time series data.
   - It combines three components: AutoRegressive (AR), Integrated (I), and Moving Average (MA).
   - AR component captures the relationship between an observation and a lagged observation in the same time series.
   - I component involves differencing the time series to make it stationary, i.e., to remove trends or seasonality.
   - MA component represents the relationship between an observation and a residual error from a moving average model applied to lagged observations.
2. **SARIMA (Seasonal AutoRegressive Integrated Moving Average):**
   - SARIMA models extend ARIMA to handle seasonal variations in time series data.
   - It includes additional seasonal AR, seasonal differencing, and seasonal MA components.
   - The seasonal AR component captures the relationship between an observation and a lagged observation from the same season.
   - Seasonal differencing is performed to remove seasonal patterns.
   - The seasonal MA component models the relationship between an observation and a residual error from a seasonal moving average model applied to lagged observations.
3. **SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous factors):**
   - SARIMAX extends SARIMA by allowing the inclusion of exogenous variables, i.e., ex-

ternal factors that can influence the time series.
- In addition to the seasonal ARIMA components, SARIMAX incorporates exogenous variables into the model.
- Exogenous variables are independent variables that are not influenced by the time series itself but may have an impact on its behavior.
- Including exogenous variables in the model can improve forecast accuracy by accounting for additional factors that may affect the time series.

In summary, ARIMA is used for non-seasonal time series, SARIMA extends ARIMA to handle seasonal patterns, and SARIMAX further extends SARIMA by allowing the inclusion of exogenous variables to better capture the complexities of real-world time series data.