Problem Statement

Forecasting the number of views to the pages so that you can predict and optimize the ad placement for your clients.

We are provided with the data of 145k wikipedia pages and daily view count for each of them.

The clients belong to different regions and need data on how their ads will perform on pages in different languages.

In [1]:

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

In [2]:

```
import warnings
warnings.filterwarnings("ignore")
warnings.simplefilter("ignore")
```

In [3]:

```
!gdown 1RPOLd_74kMrpkTg35X843hOrZIsSJSMF
```

```
Downloading...
From: https://drive.google.com/uc?id=1RPOLd_74kMrpkTg35X843hOrZIsSJSMF (https://drive.google.com/uc?id=1RPO
Ld_74kMrpkTg35X843hOrZIsSJSMF)
To: /content/train_1.csv
100% 278M/278M [00:04<00:00, 59.8MB/s]
```

In [4]:

```
train = pd.read_csv('train_1.csv')
```

In [5]:

```python
train.head(10)
```

Out[5]:

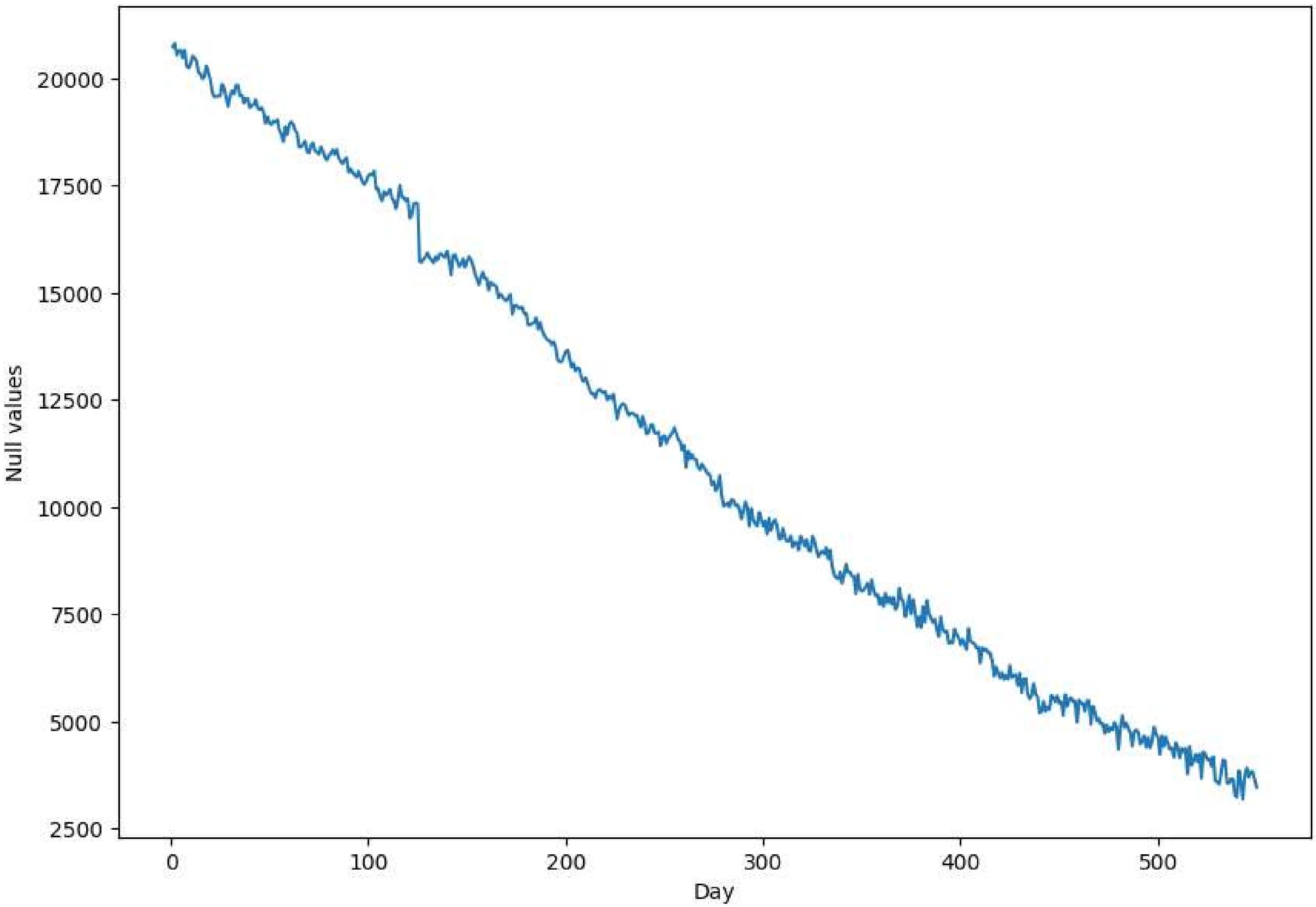
	Page	2015-07-01	2015-07-02	2015-07-03	2015-07-04	2015-07-05	2015-07-06	2015-07-07	2015-07-08	2015-07-09	...	2016-12-22	2016-12-23	2016-12-24	2016-12-25
0	2NE1_zh.wikipedia.org_all-access_spider	18.0	11.0	5.0	13.0	14.0	9.0	9.0	22.0	26.0	...	32.0	63.0	15.0	26.0
1	2PM_zh.wikipedia.org_all-access_spider	11.0	14.0	15.0	18.0	11.0	13.0	22.0	11.0	10.0	...	17.0	42.0	28.0	15.0
2	3C_zh.wikipedia.org_all-access_spider	1.0	0.0	1.0	1.0	0.0	4.0	0.0	3.0	4.0	...	3.0	1.0	1.0	7.0
3	4minute_zh.wikipedia.org_all-access_spider	35.0	13.0	10.0	94.0	4.0	26.0	14.0	9.0	11.0	...	32.0	10.0	26.0	27.0
4	52_Hz_I_Love_You_zh.wikipedia.org_all-access_s...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	48.0	9.0	25.0	13.0
5	5566_zh.wikipedia.org_all-access_spider	12.0	7.0	4.0	5.0	20.0	8.0	5.0	17.0	24.0	...	16.0	27.0	8.0	17.0
6	91Days_zh.wikipedia.org_all-access_spider	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	2.0	7.0	33.0	8.0
7	A'N'D_zh.wikipedia.org_all-access_spider	118.0	26.0	30.0	24.0	29.0	127.0	53.0	37.0	20.0	...	64.0	35.0	35.0	28.0
8	AKB48_zh.wikipedia.org_all-access_spider	5.0	23.0	14.0	12.0	9.0	9.0	35.0	15.0	14.0	...	34.0	105.0	72.0	36.0
9	ASCII_zh.wikipedia.org_all-access_spider	6.0	3.0	5.0	12.0	6.0	5.0	4.0	13.0	9.0	...	25.0	17.0	22.0	29.0

10 rows × 551 columns

Checking for reasons for null values

In [6]:
```
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:])
```

Out[6]:
```
[<matplotlib.lines.Line2D at 0x7d6e12fcc220>]
```



The null values are decreasing over time. So null values are caused because some pages were not created from the beginning.

Treating null values

In [7]:
```
train=train.dropna(how='all')
train=train.dropna(thresh=356)
```

In [8]:
```
train=train.fillna(0)
train.tail()
```

Out[8]:

	Page	2015-07-01	2015-07-02	2015-07-03	2015-07-04	2015-07-05	2015-07-06	2015-07-07	2015-07-08	2015-07-09	...	2016-12-22	2016-12-23
144994	Lucía_Hoyos_es.wikipedia.org_all-access_spider	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	3.0	2.0
144995	XXx_(película)_es.wikipedia.org_all-access_spider	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	6.0	4.0
144996	¿Volverías_con_tu_ex?_es.wikipedia.org_all-acc...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	20.0	7.0
144997	Alicia_a_través_del_espejo_(película)_es.wikip...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	10.0	24.0
144999	El_libro_de_la_selva_(película_de_2016)_es.wik...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	11.0	11.0

5 rows × 551 columns

EDA

In [9]:

```
def split_page(page):
  w = re.split('_|\.', page)

  return ' '.join(w[:-5]), w[-5], w[-2], w[-1]

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

In [10]:

```
df.head()
```

Out[10]:

	Page	2015-07-01	2015-07-02	2015-07-03	2015-07-04	2015-07-05	2015-07-06	2015-07-07	2015-07-08	2015-07-09	...	2016-12-26	2016-12-27	2016-12-28	2016-12-29	2016-12-30	201 12-:
0	2NE1_zh.wikipedia.org_all-access_spider	18.0	11.0	5.0	13.0	14.0	9.0	9.0	22.0	26.0	...	14.0	20.0	22.0	19.0	18.0	20
1	2PM_zh.wikipedia.org_all-access_spider	11.0	14.0	15.0	18.0	11.0	13.0	22.0	11.0	10.0	...	9.0	30.0	52.0	45.0	26.0	20
2	3C_zh.wikipedia.org_all-access_spider	1.0	0.0	1.0	1.0	0.0	4.0	0.0	3.0	4.0	...	4.0	4.0	6.0	3.0	4.0	17
3	4minute_zh.wikipedia.org_all-access_spider	35.0	13.0	10.0	94.0	4.0	26.0	14.0	9.0	11.0	...	16.0	11.0	17.0	19.0	10.0	11
5	5566_zh.wikipedia.org_all-access_spider	12.0	7.0	4.0	5.0	20.0	8.0	5.0	17.0	24.0	...	32.0	19.0	23.0	17.0	17.0	50

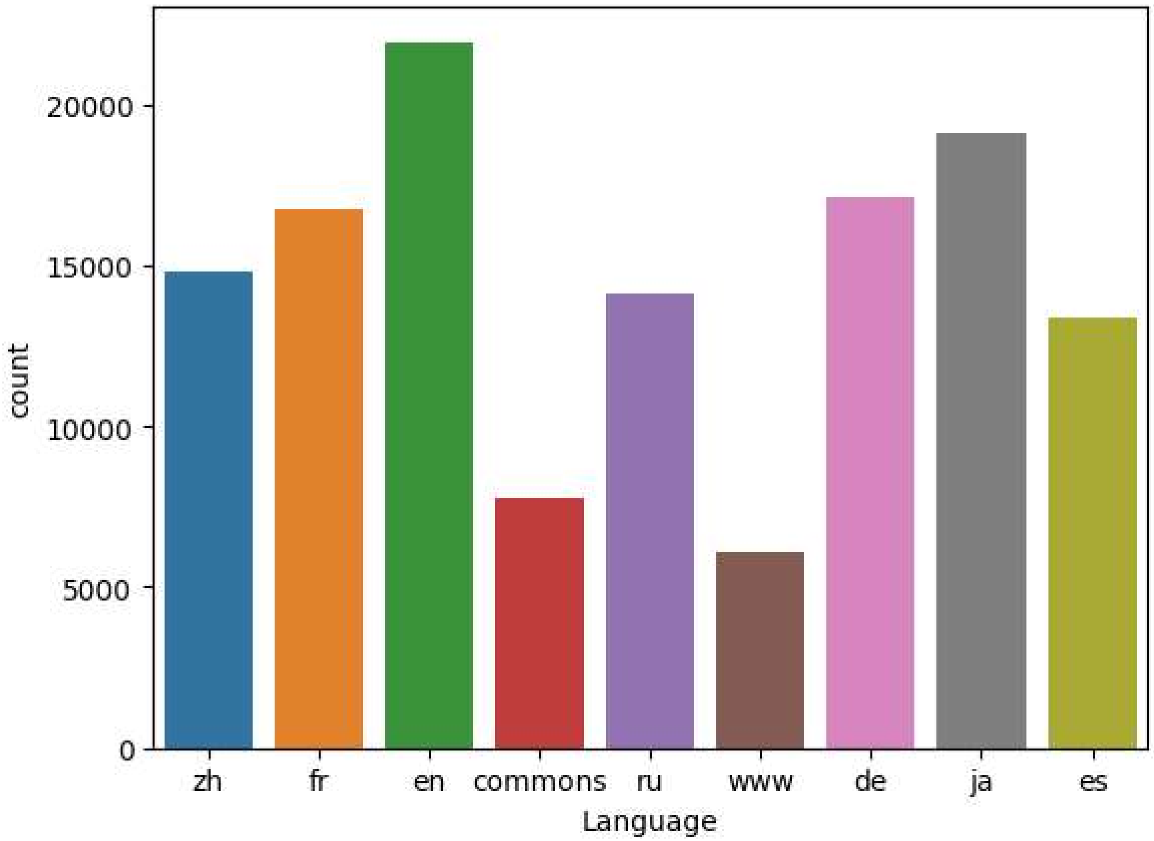
5 rows × 555 columns

In [13]:

```python
language_counts = df['Language'].value_counts()

# Create a count plot
sns.countplot(data=df, x='Language')
```

Out[13]:

```
<Axes: xlabel='Language', ylabel='count'>
```

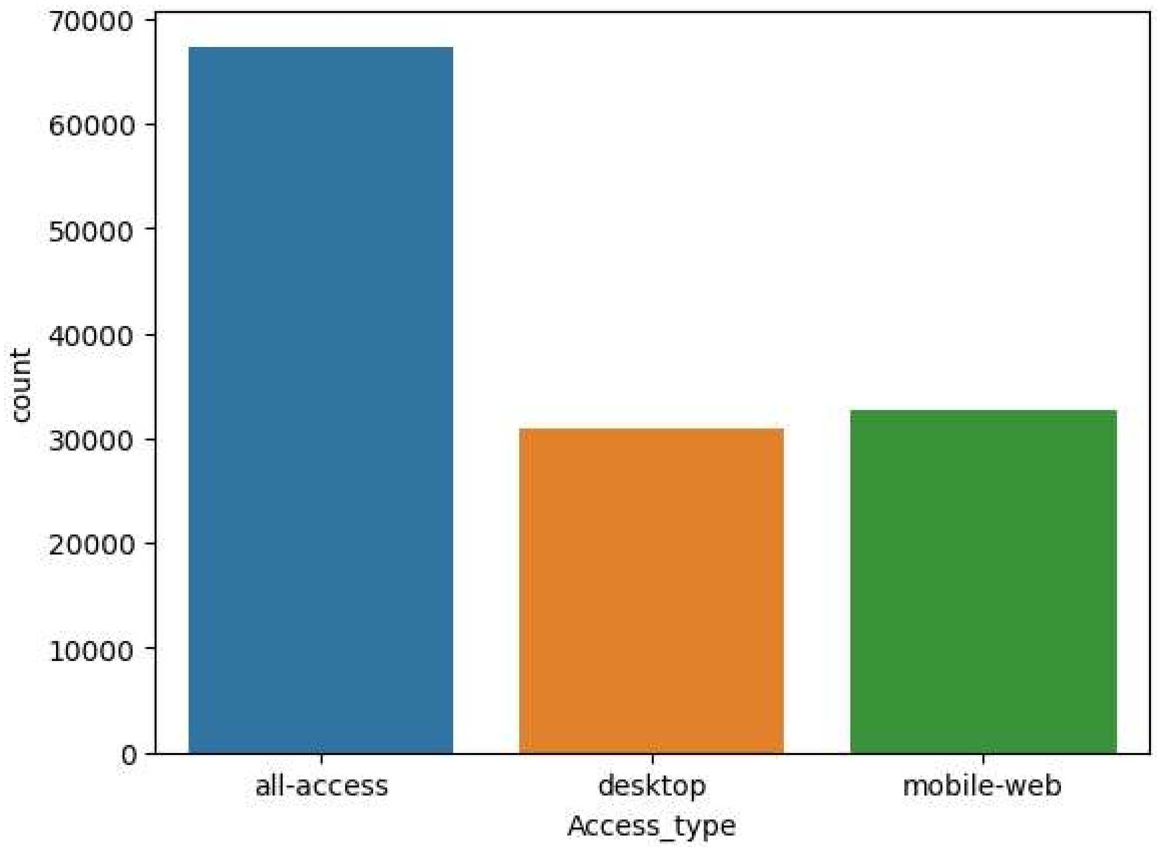


In [15]:

```
language_counts = df['Access_type'].value_counts()

# Create a count plot
sns.countplot(data=df, x='Access_type')
```

Out[15]:

```
<Axes: xlabel='Access_type', ylabel='count'>
```

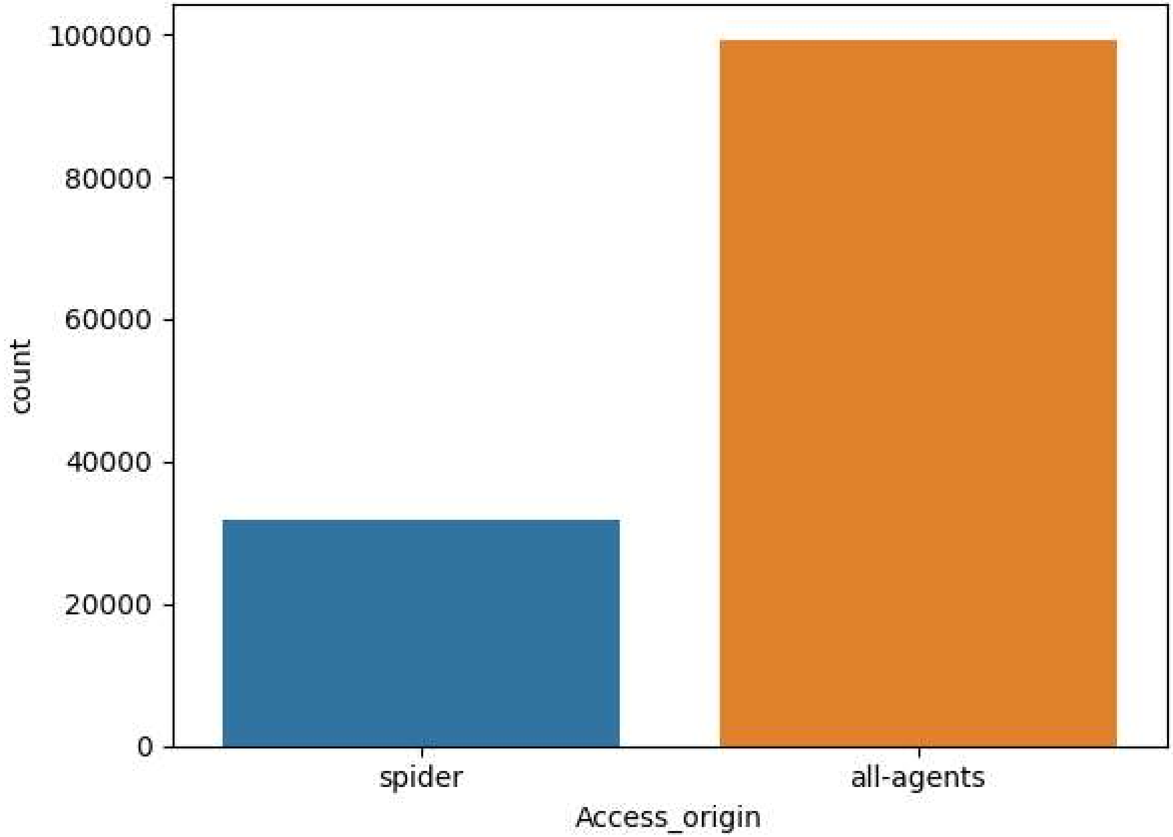


In [17]:

```
language_counts = df['Access_origin'].value_counts()

# Create a count plot
sns.countplot(data=df, x='Access_origin')
```

Out[17]:

```
<Axes: xlabel='Access_origin', ylabel='count'>
```



In [18]:
```
df.groupby('Language').count()
```

Out[18]:

	Page	2015-07-01	2015-07-02	2015-07-03	2015-07-04	2015-07-05	2015-07-06	2015-07-07	2015-07-08	2015-07-09	...	2016-12-25	2016-12-26	2016-12-27	2016-12-28	2016-12-29	2016-12-30	20 12
Language																		
commons	7213	7213	7213	7213	7213	7213	7213	7213	7213	7213	...	7213	7213	7213	7213	7213	7213	/
de	15505	15505	15505	15505	15505	15505	15505	15505	15505	15505	...	15505	15505	15505	15505	15505	15505	15
en	19744	19744	19744	19744	19744	19744	19744	19744	19744	19744	...	19744	19744	19744	19744	19744	19744	19
es	11516	11516	11516	11516	11516	11516	11516	11516	11516	11516	...	11516	11516	11516	11516	11516	11516	11
fr	14630	14630	14630	14630	14630	14630	14630	14630	14630	14630	...	14630	14630	14630	14630	14630	14630	14
ja	17172	17172	17172	17172	17172	17172	17172	17172	17172	17172	...	17172	17172	17172	17172	17172	17172	17
ru	12329	12329	12329	12329	12329	12329	12329	12329	12329	12329	...	12329	12329	12329	12329	12329	12329	12
www	5530	5530	5530	5530	5530	5530	5530	5530	5530	5530	...	5530	5530	5530	5530	5530	5530	5
zh	14187	14187	14187	14187	14187	14187	14187	14187	14187	14187	...	14187	14187	14187	14187	14187	14187	14

9 rows × 554 columns

In [19]:
```
#here we see that the languages are not treated properly as there are commons and www
```

In [20]:

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

    return 'no_lang'

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

In [21]:

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

Out[21]:

	Page	2015-07-01	2015-07-02	2015-07-03	2015-07-04	2015-07-05	2015-07-06	2015-07-07	2015-07-08	2015-07-09	...	2016-12-25	2016-12-26	2016-12-27	2016-12-28	2016-12-29	2016-12-30	2(1:
Language																		
de	17123	17123	17123	17123	17123	17123	17123	17123	17123	17123	...	17123	17123	17123	17123	17123	17123	17
en	21938	21938	21938	21938	21938	21938	21938	21938	21938	21938	...	21938	21938	21938	21938	21938	21938	21
es	13397	13397	13397	13397	13397	13397	13397	13397	13397	13397	...	13397	13397	13397	13397	13397	13397	13
fr	16717	16717	16717	16717	16717	16717	16717	16717	16717	16717	...	16717	16717	16717	16717	16717	16717	16
ja	19115	19115	19115	19115	19115	19115	19115	19115	19115	19115	...	19115	19115	19115	19115	19115	19115	1ς
no_lang	13856	13856	13856	13856	13856	13856	13856	13856	13856	13856	...	13856	13856	13856	13856	13856	13856	13
ru	14109	14109	14109	14109	14109	14109	14109	14109	14109	14109	...	14109	14109	14109	14109	14109	14109	14
zh	14791	14791	14791	14791	14791	14791	14791	14791	14791	14791	...	14791	14791	14791	14791	14791	14791	14

8 rows × 554 columns

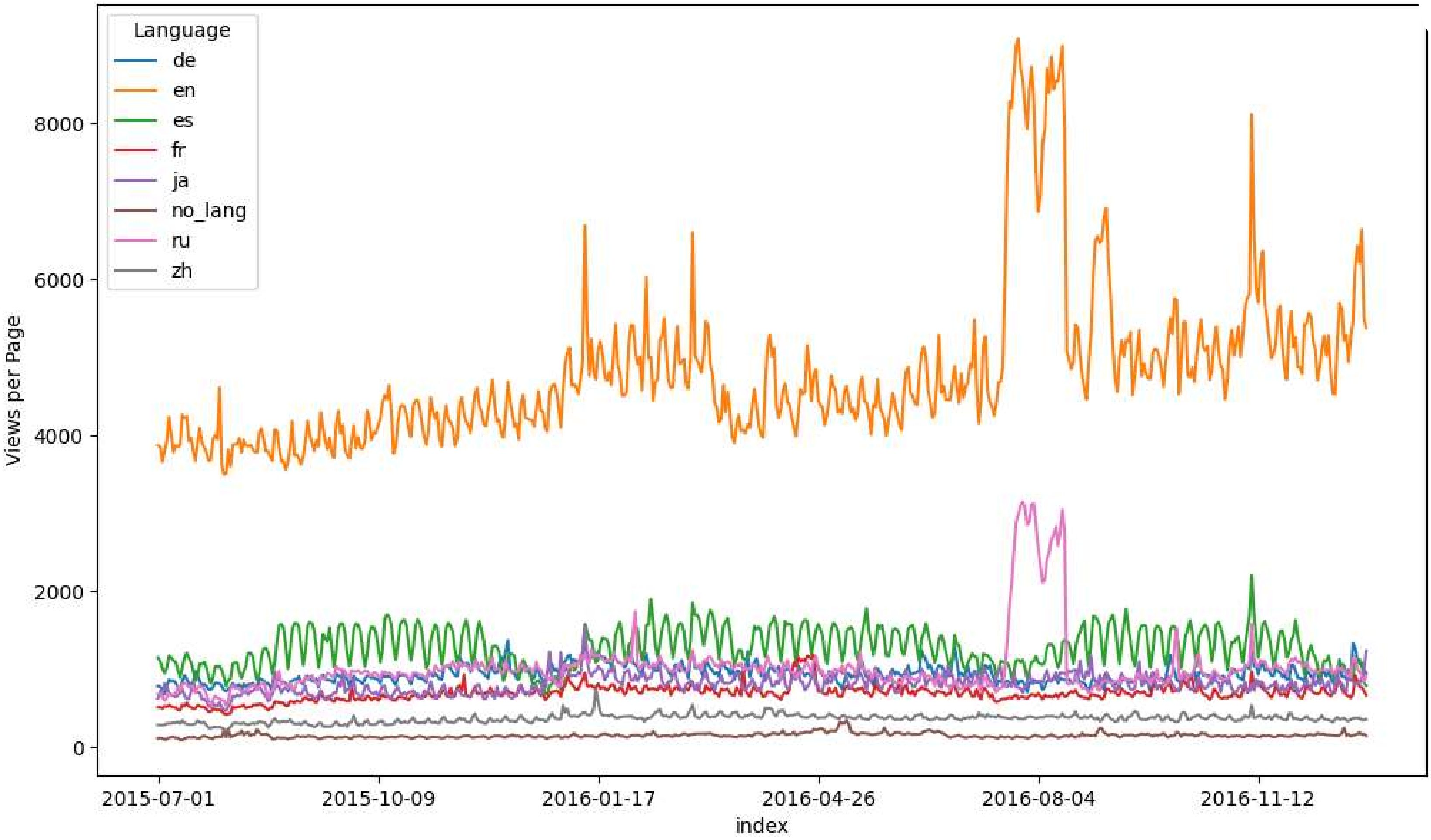
In [22]:
```
df_language=df.groupby('Language').mean().transpose()
df_language
```

Out[22]:
```
  Language          de           en           es          fr           ja     no_lang           ru          zh
2015-07-01  774.426269  3861.418270  1140.148541  505.989352   620.425007  107.428551   670.765965  280.230884
2015-07-02  763.878176  3848.940651  1089.566843  509.238500   712.459639  112.593533   682.374796  280.646745
2015-07-03  733.166910  3654.264017  1002.042323  489.659688   643.454355  106.425664   632.463605  278.785275
2015-07-04  672.798867  3804.480354   940.835112  523.400191   808.439236   90.827223   594.882132  281.481036
2015-07-05  782.125153  3929.175312  1023.180190  513.872346   775.587654  100.659353   633.532072  300.263944
       ...         ...          ...          ...         ...          ...         ...          ...         ...
2016-12-27 1123.751153  6415.150971  1078.762559  846.143028   808.217578  161.744515  1007.479977  364.880738
2016-12-28 1066.064241  6208.003464  1117.616705  774.151223   807.662046  186.088770   953.722801  371.549185
2016-12-29 1036.503358  6630.178002  1067.152571  757.718610   885.257233  157.015156   917.736339  342.295788
2016-12-30  986.052678  5490.552740   813.258789  712.405097   981.830133  162.524682   822.712028  344.481847
2016-12-31  938.918939  5367.033777   782.740240  658.079739  1230.408789  140.588265   911.081579  352.220337

550 rows × 8 columns
```

In [23]:
```
df_language.reset_index(inplace=True)
df_language.set_index('index', inplace=True)
```

In [24]:
```
df_language.plot(figsize=(12,7))
plot.ylabel('Views per Page')
```

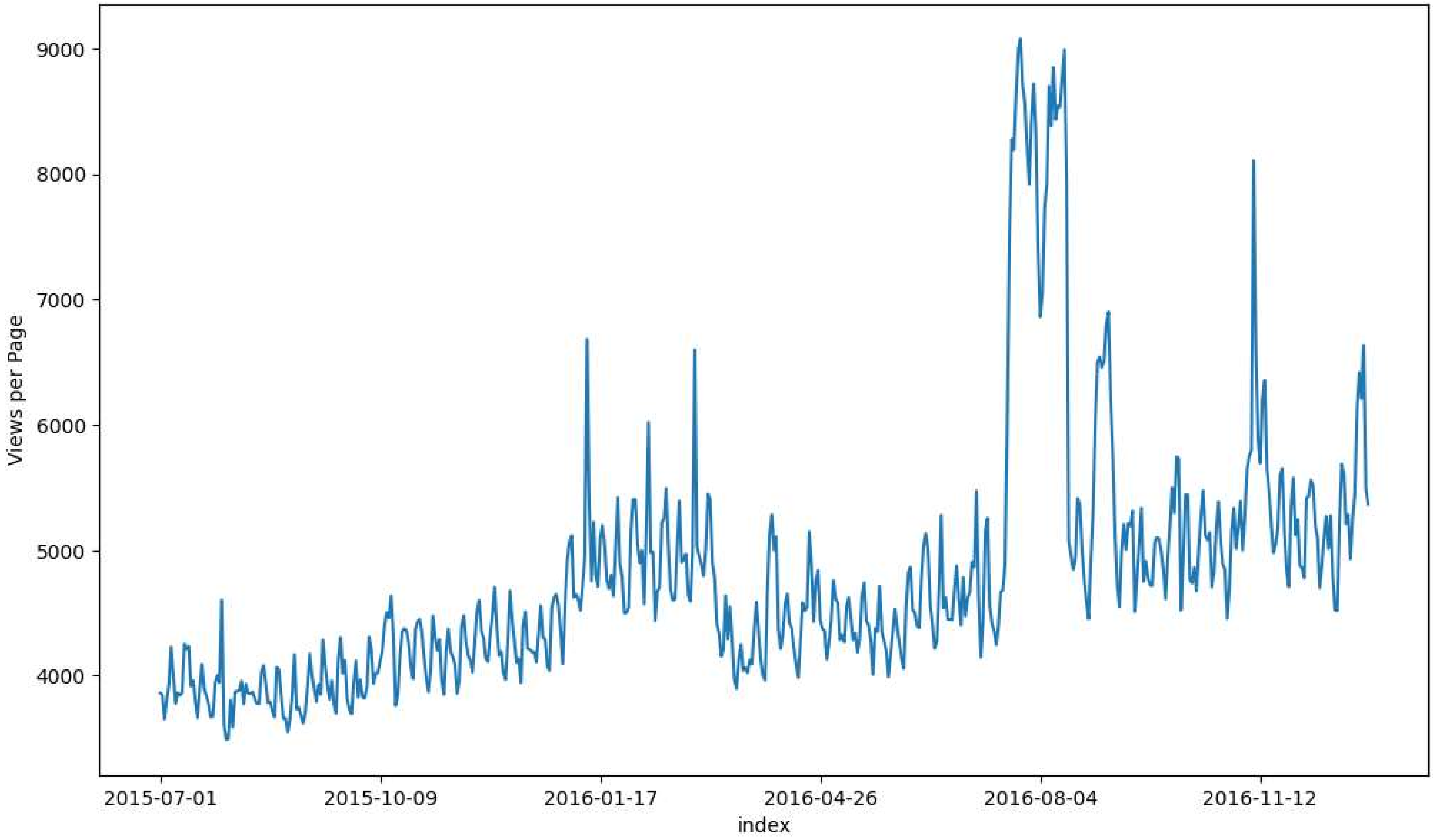
Out[24]:
```
Text(0, 0.5, 'Views per Page')
```



In [25]:
```
## English gets most amount of views followed by spanish
```

```
In [26]: # printing English
         df_language['en'].plot(figsize=(12,7))
         plot.ylabel('Views per Page')
```

```
Out[26]: Text(0, 0.5, 'Views per Page')
```



```
In [27]: total_view=df_language.copy()
```

Checking the stationarity

In [28]:
```
# Dickey-Fuller test
```

In [29]:
```
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: -2.403786
p-value: 0.140671
```

In [30]:
```
# We see that the p value is not low enough(<0.05). Therefore, we can say our series in not stationary as we
```

Making the time series stationary

In [31]:
```
ts=total_view[['en']]
```

In [32]:
```
ts = ts.reset_index()
```

In [33]:
```
ts.index = pd.to_datetime(ts.index)
```

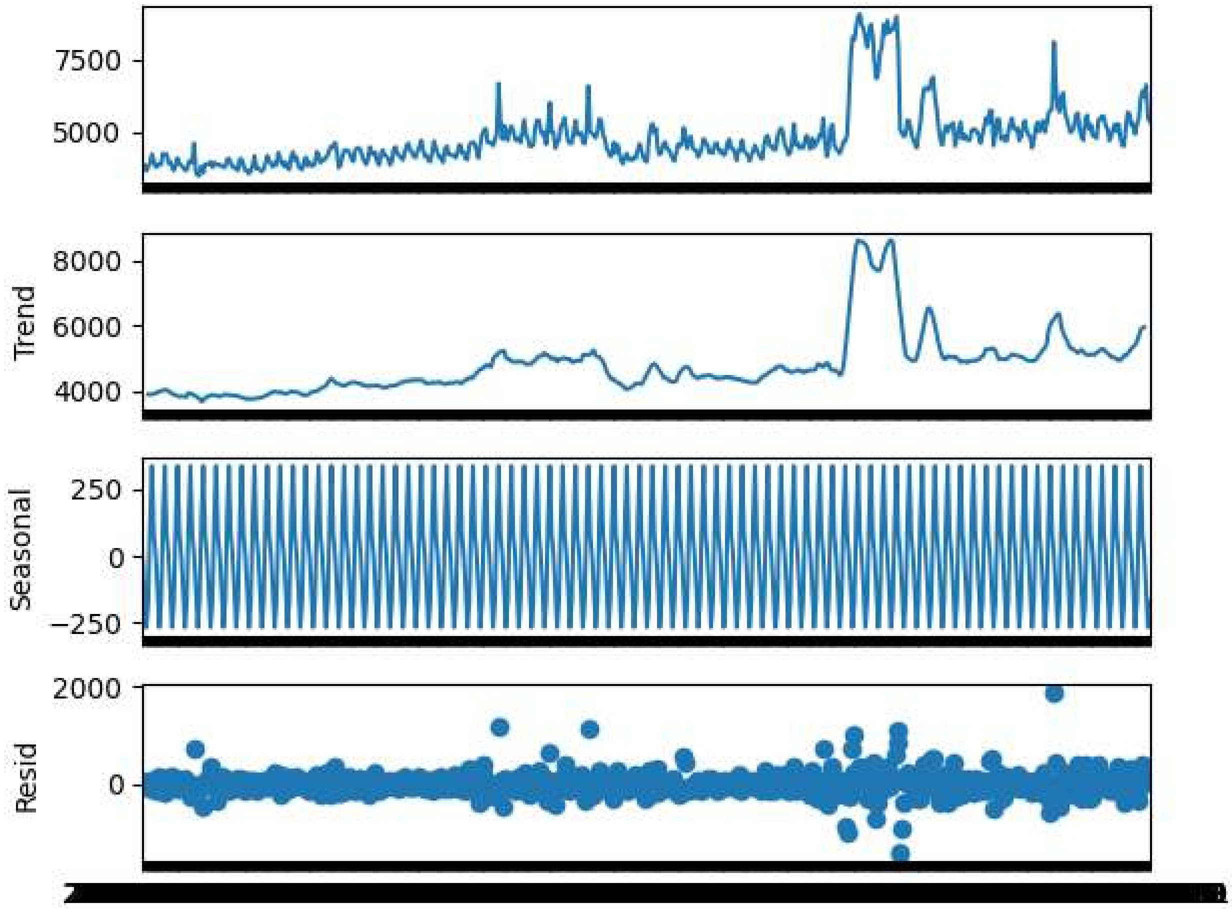
In [34]:
```
ts.set_index('index', inplace=True)
```

```
In [35]: ts
```

```
Out[35]:
Language              en
     index
2015-07-01   3861.418270
2015-07-02   3848.940651
2015-07-03   3654.264017
2015-07-04   3804.480354
2015-07-05   3929.175312
       ...           ...
2016-12-27   6415.150971
2016-12-28   6208.003464
2016-12-29   6630.178002
2016-12-30   5490.552740
2016-12-31   5367.033777

550 rows × 1 columns
```

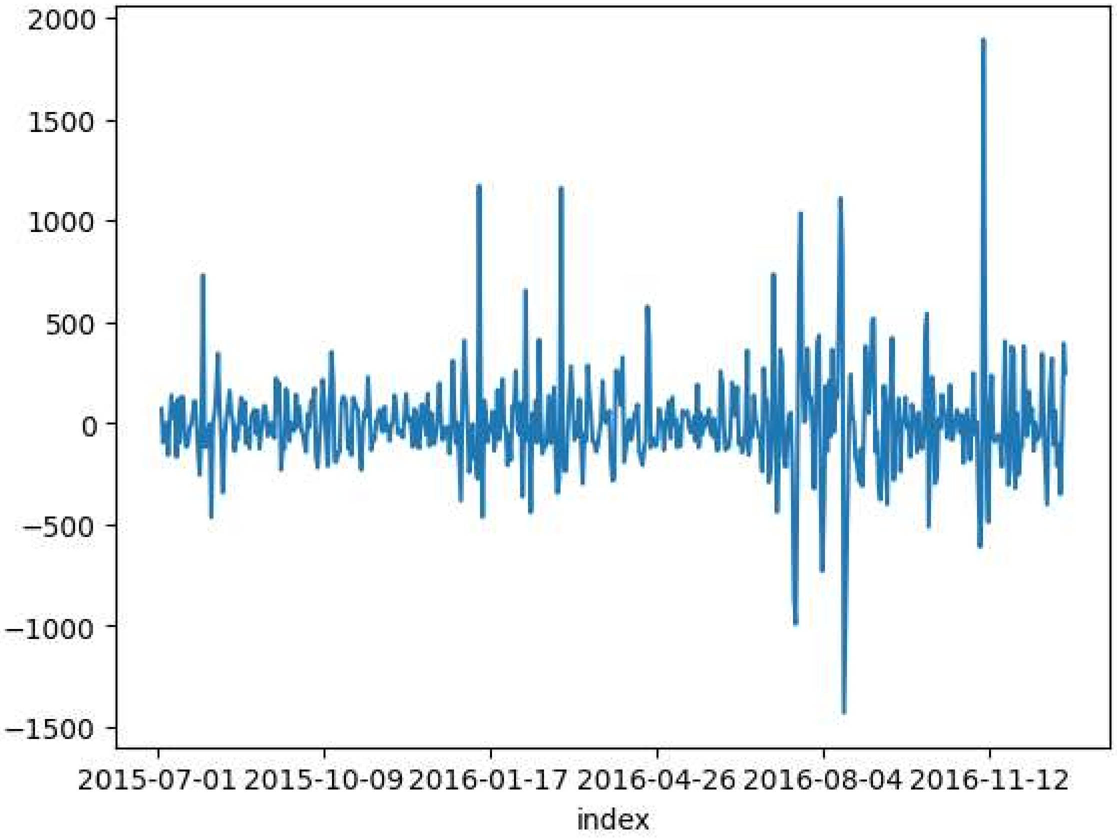
In [36]:

```
import statsmodels.api as sm
model = sm.tsa.seasonal_decompose(ts, period=7)  # Knowing the right period is V.Imp and You can use ACF to g
model.plot();
```



In [37]:
```
model.resid.plot()
```

Out[37]:
```
<Axes: xlabel='index'>
```



In [38]:
```
df_test(model.resid.dropna())
```

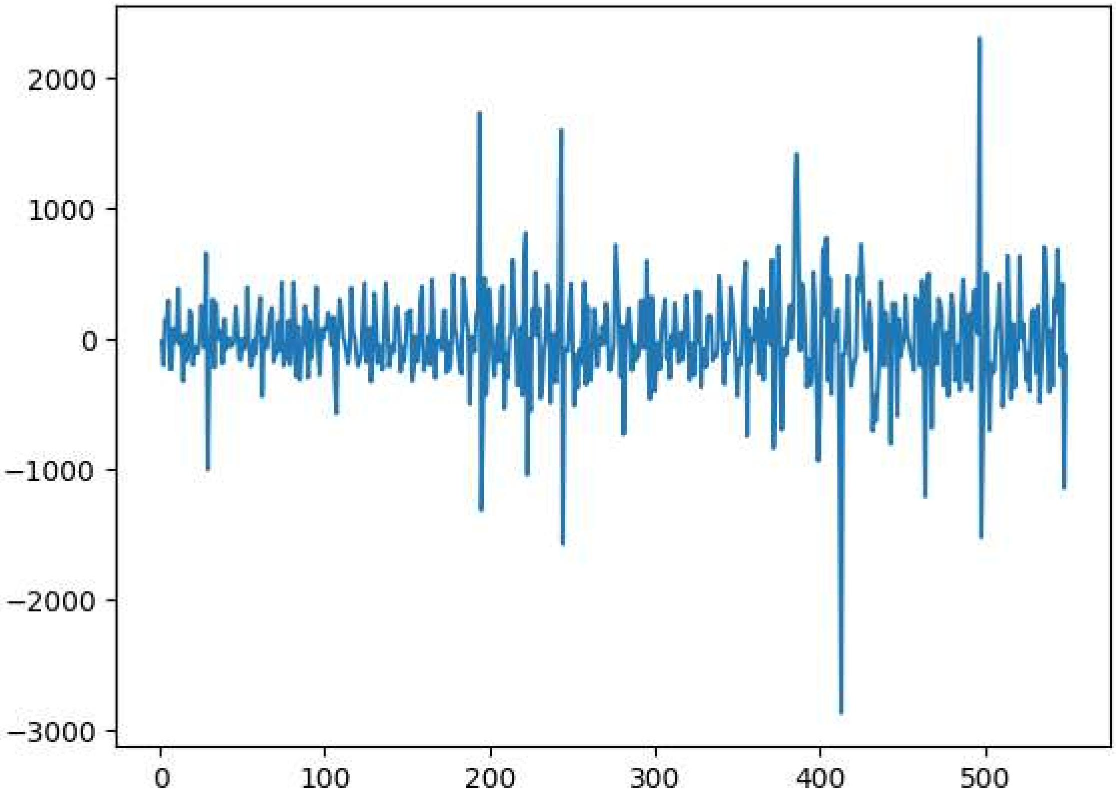
```
ADF Stastistic: -11.435041
p-value: 0.000000
```

In [39]:
```
## We can see that aur series is now stationary, we can also try diffrencing to see what results we can get.
```

Remove trend and seasonality with differencing

In [40]:

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



In [41]:

```
ts_diff.dropna(inplace=True)
df_test(ts_diff)
```

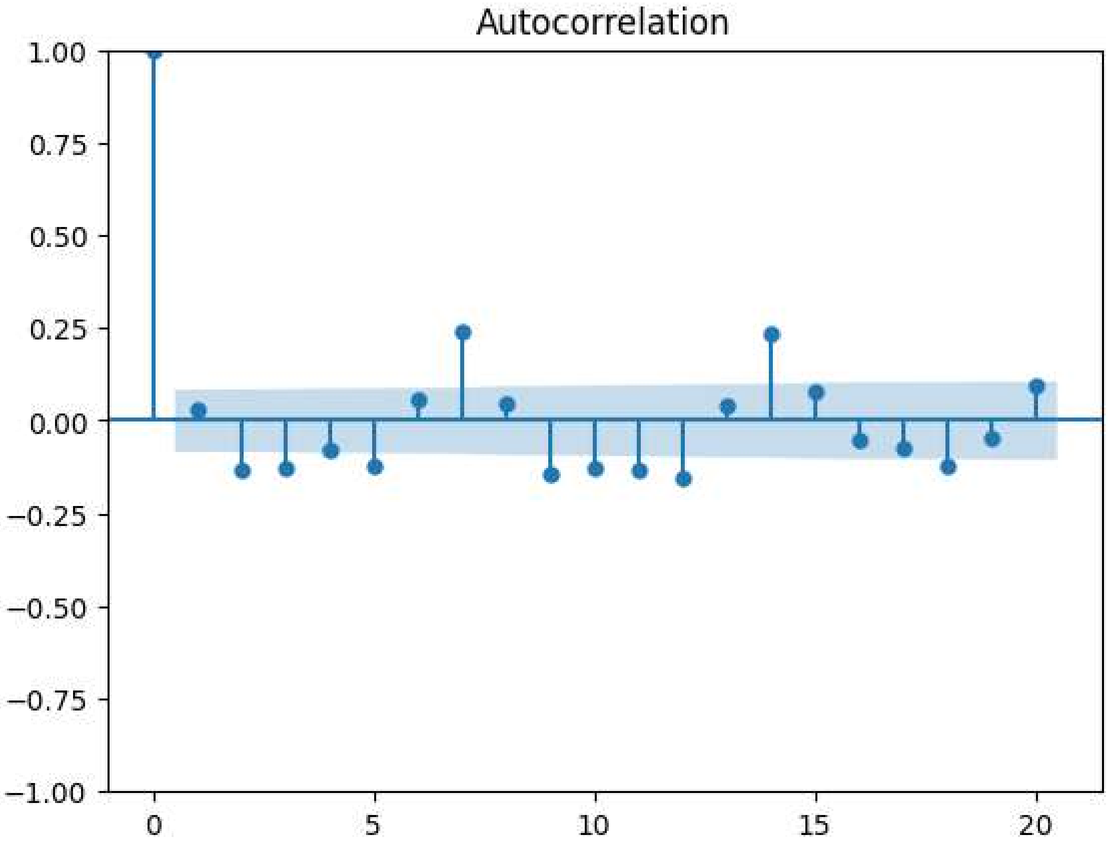
```
ADF Stastistic: -8.261352
p-value: 0.000000
```

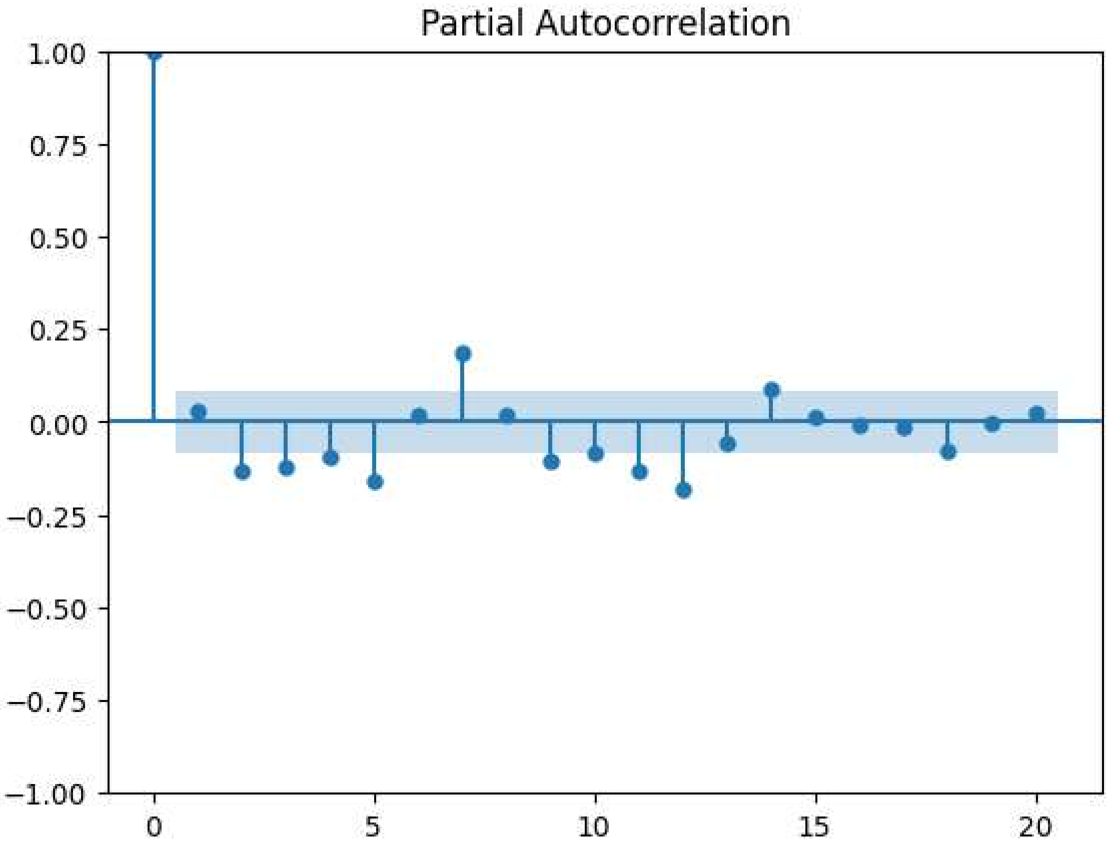
In [42]:

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

Plot the autocorreltaion and partial auto correlation functions

In [43]:
```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
acf=plot_acf(ts_diff,lags=20)
pacf=plot_pacf(ts_diff,lags=20)
```




Partial Autocorrelation
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20

In [44]:

```python
ts.diff(7) #
```

Out[44]:

Language	en
index	
2015-07-01	NaN
2015-07-02	NaN
2015-07-03	NaN
2015-07-04	NaN
2015-07-05	NaN
...	...
2016-12-27	804.087291
2016-12-28	997.424970
2016-12-29	1346.841371
2016-12-30	561.319309
2016-12-31	120.887136

550 rows × 1 columns

ARIMA MODEL

In [45]:

```python
from statsmodels.tsa.statespace.sarimax import SARIMAX
from pandas import DataFrame
```

In [46]:
```
model = SARIMAX(ts, order=(1,1,1))
model_fit = model.fit(disp=0)
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: No frequency i
nformation was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: No frequency i
nformation was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
```

In [47]:
```
model_fit.predict(12)
```

Out[47]:
```
2015-07-13    4210.297557
2015-07-14    4174.226495
2015-07-15    4197.775650
2015-07-16    3902.374198
2015-07-17    3945.629070
                  ...
2016-12-27    6062.278727
2016-12-28    6317.880194
2016-12-29    6130.967200
2016-12-30    6516.814683
2016-12-31    5480.984400
Freq: D, Name: predicted_mean, Length: 538, dtype: float64
```

In [48]:
```
train = ts[:-20]
test = ts[-20:]
```

In [49]:
```
## In ARMA family models, for getting p (Auto-regressive order) we look at PACF plot, there is a cut-off at l
```

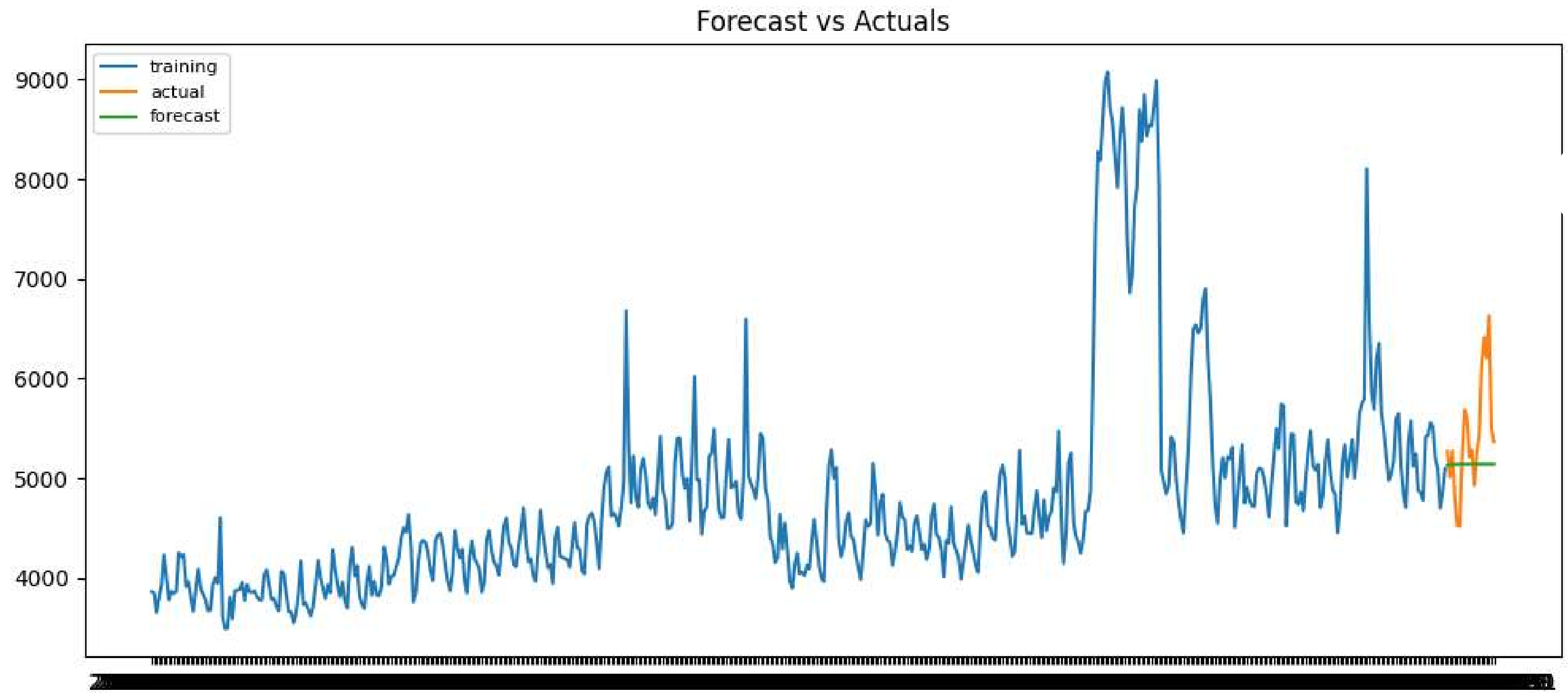
In [50]:

```
model = SARIMAX(train, order=(2, 1, 2))
fitted = model.fit(disp=-1)

# Forecast
fc = 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')
plot.legend(loc='upper left', fontsize=8)
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: No frequency i
nformation was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: No frequency i
nformation was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
```

Out[50]:

```
<matplotlib.legend.Legend at 0x7d6db1697130>
```



```
In [51]: mape = np.mean(np.abs(fc.values - test.values)/np.abs(test.values))
         rmse = np.mean((fc.values - test.values)**2)**.5
         print("mape:",mape)
         print("rsme:",rmse)
```

```
mape: 0.08213219335167705
rsme: 624.4451158083979
```

using exogenous data

In [52]:

```
ex_df = pd.read_csv('Exog_Campaign_eng.csv')
ex_df.head()
```

Out[52]:

	Exog
0	0
1	0
2	0
3	0
4	0

In [53]:

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

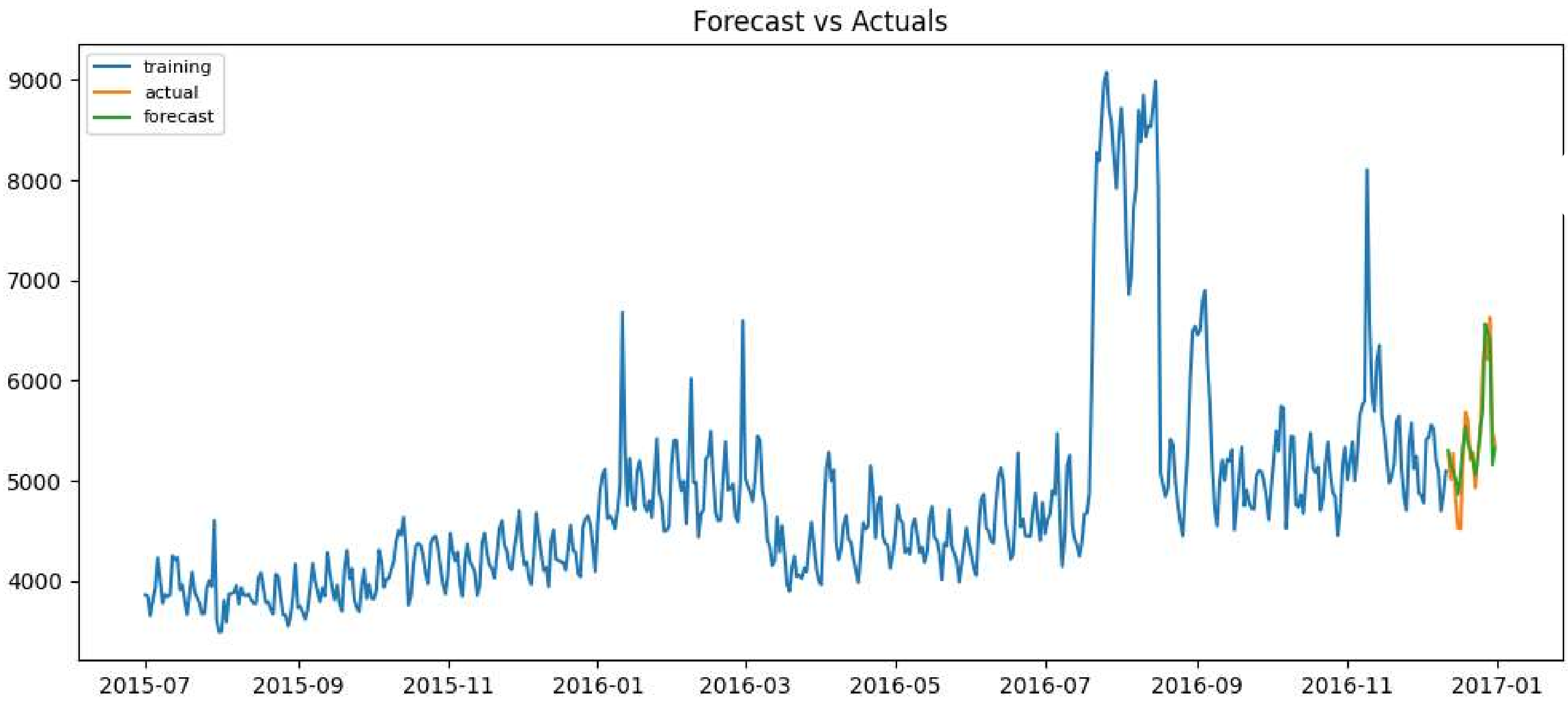
In [54]:

```
import statsmodels.api as sm
train=ts[:530]
test=ts[530:]
model=sm.tsa.statespace.SARIMAX(train,order=(1, 1, 1),seasonal_order=(1,1,1,7),exog=exog[:530])
results=model.fit()

fc=results.forecast(20,dynamic=True,exog=pd.DataFrame(exog[530:]))

# 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/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: No frequency i
nformation was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: No frequency i
nformation was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
```

Out[54]:

```
<matplotlib.legend.Legend at 0x7d6daed52080>
```



In [55]:
```
mape = np.mean(np.abs(fc.values - test.values)/np.abs(test.values))
rmse = np.mean((fc.values - test.values)**2)**.5
print("mape:",mape)
print("rsme:",rmse)
```

```
mape: 0.10347693827344548
rsme: 737.5231800914678
```

Facebook Prophet

In [56]:
```
# !pip install pystan~=2.14
# !pip install fbprophet
```

In [57]:

```
ts_df = ts.reset_index().copy()
ts_df.columns = [['ds', 'y']]
```

In [58]:

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

Out[58]:

	ds	y	exog
0	2015-07-01	3861.418270	0
1	2015-07-02	3848.940651	0
2	2015-07-03	3654.264017	0
3	2015-07-04	3804.480354	0
4	2015-07-05	3929.175312	0

In [59]:

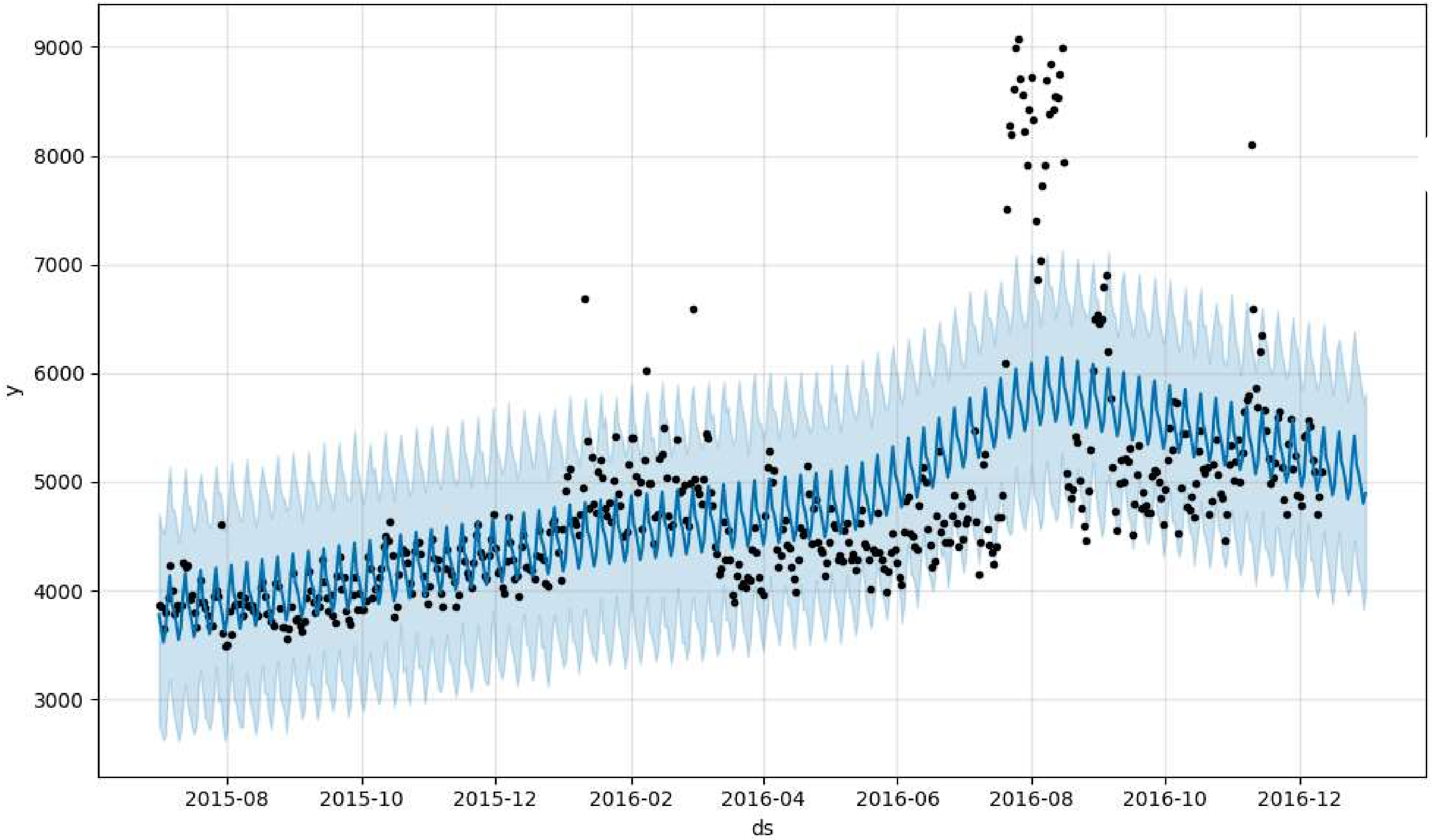
```
df2[:-20].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 530 entries, 0 to 529
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   ds      530 non-null    object 
 1   y       530 non-null    float64
 2   exog    530 non-null    int64  
dtypes: float64(1), int64(1), object(1)
memory usage: 12.5+ KB
```

In [60]:

```
from prophet 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)
```

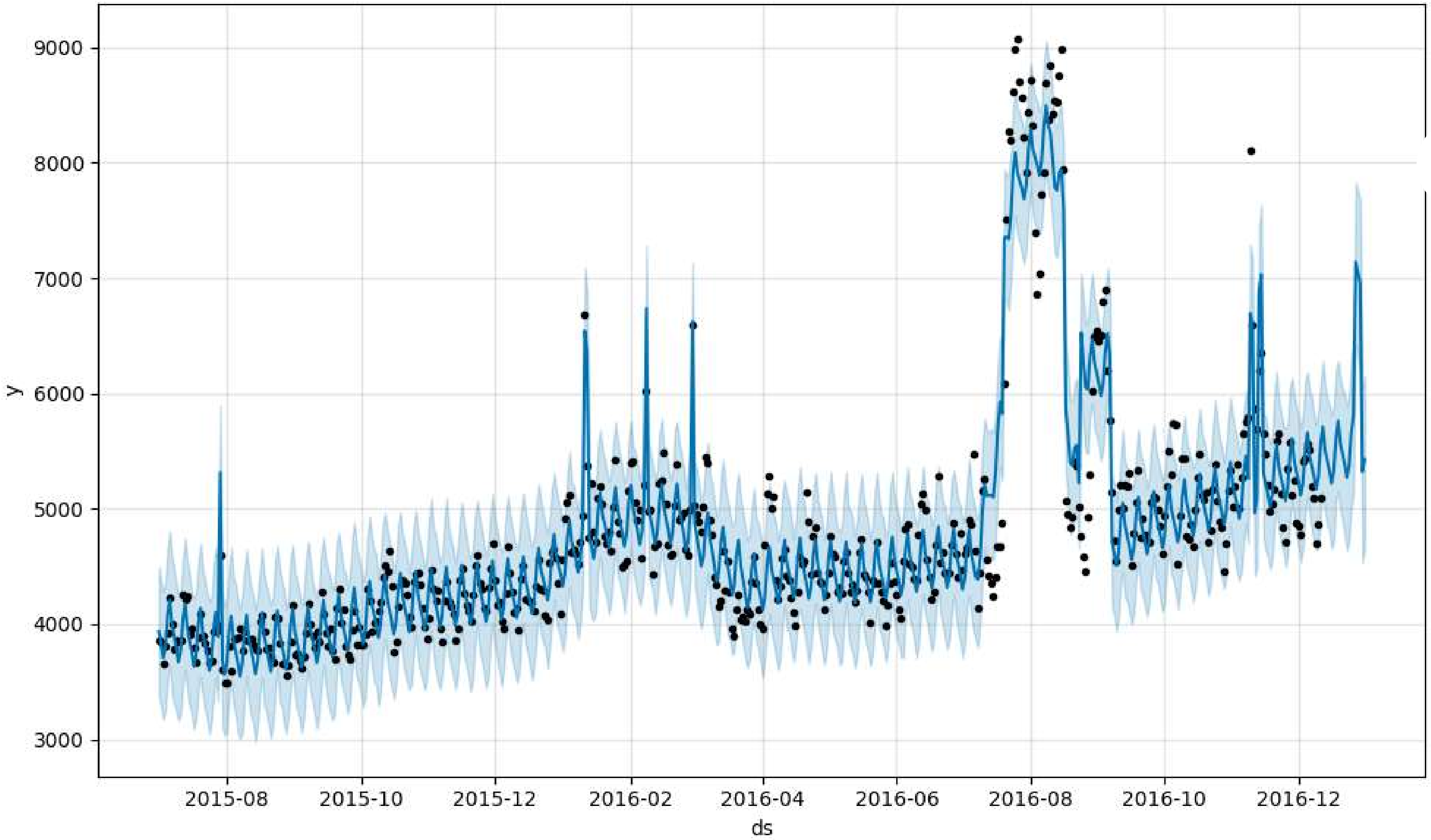
```
INFO:prophet:Disabling yearly seasonality. Run prophet with yearly_seasonality=True to override this.
INFO:prophet:Disabling daily seasonality. Run prophet with daily_seasonality=True to override this.
DEBUG:cmdstanpy:input tempfile: /tmp/tmpbugd82zr/bihxspqn.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpbugd82zr/ewtm9c_l.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.10/dist-packages/prophet/stan_model/prophet_model.bi
n', 'random', 'seed=19574', 'data', 'file=/tmp/tmpbugd82zr/bihxspqn.json', 'init=/tmp/tmpbugd82zr/ewtm9c_l.
json', 'output', 'file=/tmp/tmpbugd82zr/prophet_model92hqy3a1/prophet_model-20230928175519.csv', 'method=op
timize', 'algorithm=lbfgs', 'iter=10000']
17:55:19 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
17:55:19 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
```


9000
8000
7000
6000
5000
4000
3000
y
2015-08
2015-10
2015-12
2016-02
2016-04
2016-06
2016-08
2016-10
2016-12
ds

In [61]:

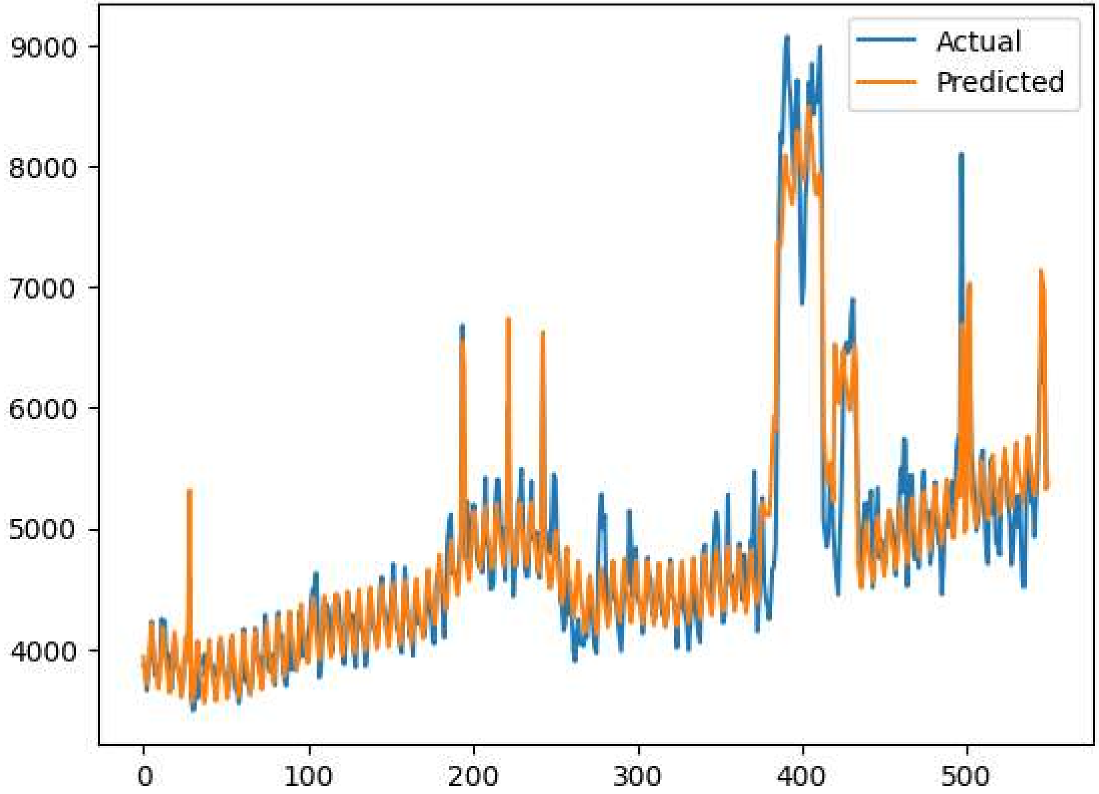
```
model2=Prophet(interval_width=0.9, weekly_seasonality=True, changepoint_prior_scale=1)
model2.add_regressor('exog')
model2.fit(df2[:-20])
forecast2 = model2.predict(df2)
fig = model2.plot(forecast2)
```

```
INFO:prophet:Disabling yearly seasonality. Run prophet with yearly_seasonality=True to override this.
INFO:prophet:Disabling daily seasonality. Run prophet with daily_seasonality=True to override this.
DEBUG:cmdstanpy:input tempfile: /tmp/tmpbugd82zr/b44qqhs1.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpbugd82zr/6mz6nkr4.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.10/dist-packages/prophet/stan_model/prophet_model.bi
n', 'random', 'seed=63734', 'data', 'file=/tmp/tmpbugd82zr/b44qqhs1.json', 'init=/tmp/tmpbugd82zr/6mz6nkr4.
json', 'output', 'file=/tmp/tmpbugd82zr/prophet_model_ejkvmlw/prophet_model-20230928175519.csv', 'method=op
timize', 'algorithm=lbfgs', 'iter=10000']
17:55:19 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
17:55:20 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
```


9000
8000
7000
6000
5000
4000
3000
y
2015-08
2015-10
2015-12
2016-02
2016-04
2016-06
2016-08
2016-10
2016-12
ds

In [62]:

```
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()
```



In [63]:

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

```
mape: 0.06757807513038254
```

Questionnaire

1. Defining the problem statements and where can this and modifications of this be used?

Forecasting the number of views to the pages so that you can predict and optimize the ad placement for your clients.

The same can be used for predicting the future sale in a online store, predicting the using pattern of streaming app etc.

2. Write 3 inferences you made from the data visualizations

The amount of null values decresing over the time. This is because some website were not there from start

There the more number of pages in English Language

The desktop and mobile user are almost similar

3. What does the decomposition of series do?

Decomposition remove trend and seasonlity from the time series data.

4. What level of differencing gave you a stationary series?

1 level of differening gave a stationary data

5. Difference between arima, sarima & sarimax.

ARIMA is a basic time series forecasting model that consist of three main component; AutoRegressive (AR), Moving Average (MA) and Residual

SARIMA is an extension of ARIMA model that takes into account easonlity in time series data

SARIMAX is an extensioin of SARIMA that allows for the inclusion of exogenous variable which are external factors that can influence the time series

6. Compare the number of views in different languages

Large number of viewers are English speaking

Followed by Chinese and Spanish

7. What other methods other than grid search would be suitable to get the model for all languages?

Random serach

Bayesian Optimization

In [63]:

```
```