Ad Ease is an ads and marketing based company helping businesses elicit maximum clicks @ minimum cost. AdEase is an ad infrastructure to help businesses promote themselves easily, effectively, and economically. The interplay of 3 AI modules - Design, Dispense, and Decipher, come together to make it this an end-to-end 3 step process digital advertising solution for all.

You are working in the Data Science team of Ad ease trying to understand the per page view report for different wikipedia pages for 550 days, and forecasting the number of views so that you can predict and optimize the ad placement for your clients. You are provided with the data of 145k wikipedia pages and daily view count for each of them. Your clients belong to different regions and need data on how their ads will perform on pages in different languages.

Dataset:

[https://drive.google.com/drive/folders/1mdgQscjqnCtdg7LGItomyK0abN6lcHBb (https://drive.google.com/drive/folders/1mdgQscjqnCtdg7LGItomyK0abN6lcHBb)](https://drive.google.com/drive/folders/1mdgQscjqnCtdg7LGItomyK0abN6lcHBb)

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 corresponds to a particular date. The values are the number of visits on that date.

The page name contains data in this format:

SPECIFIC NAME _ LANGUAGE.wikipedia.org _ ACCESS TYPE _ ACCESS ORIGIN

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

Exog_Campaign_eng: This file contains 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's 1 for dates with campaigns 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

Concepts Tested:

Exploratory data analysis

Time Series forecasting- ARIMA, SARIMAX, and Prophet

What does "good" look like?

Importing the dataset and doing usual exploratory analysis steps like checking the structure & characteristics of the dataset

Checking null values and understanding their reason.

Understanding the page name format and splitting it to get different information.

Separating different values from it like title, language, access type, and access origin.

Visualizing the data and getting inferences from them

Converting the data to a format that can be fed to the Arima model (Pivoting etc)

Checking if the data is stationary

Dickey-Fuller test

Trying different methods for stationarity.

Decomposition of series.

Differencing the series.

Plotting the ACF and PACF plots

Give insights about the characteristics of the time series.

Modeling

Creating and training the Arima model

Getting the exogenous variable and using it to train a sarimax model

Use facebook prophet for forecasting

Finding a way(grid search / etc) to find the best params for at least 1 modeling approach.

Defining functions for all of the tasks.

Comparing results for all languages and creating inferences and recommendations from them

The MAPE for previous batches has been in the range of 4-8%

Evaluation Criteria (100 points)

Importing the dataset and doing usual exploratory analysis steps like checking the structure & characteristics of the dataset (10 points)

Exploratory Data Analysis (20 points)

Separating the data

Analyzing and visualizing the data

Getting inferences

Checking stationarity (20 points)

Formatting the data for the model

Dickey fuller test

Decomposition

Differencing

Creating model training and forecasting with ARIMA, SARIMAX (20 points)

ACF and PACF plot.

Training the model.

Forecasting for different languages/regions.

Plotting the final results

Forecasting with (20 points)

Facebook prophet Creating a pipeline for working with multiple series (10 points)

Questionnaire:

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

Write 3 inferences you made from the data visualizations

What does the decomposition of series do?

What level of differencing gave you a stationary series?

Difference between arima, sarima & sarimax.

Compare the number of views in different languages

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

In [97]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

In [98]:

```
import warnings
```

In [99]:

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

In [100]:

```
# Mount Google Drive in Google Colab
from google.colab import drive
drive.mount('/content/drive')

# Download the file to your Colab runtime
!gdown --id 1qQkymAitU6l2pSe702rDUhQpoP8MUZXl

# Read the file into a pandas dataframe
import pandas as pd
df = pd.read_csv('train_1.csv')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, c
all drive.mount("/content/drive", force_remount=True).
/usr/local/lib/python3.8/dist-packages/gdown/cli.py:127: FutureWarning: Op
tion `--id` was deprecated in version 4.3.1 and will be removed in 5.0. Yo
u don't need to pass it anymore to use a file ID.
  warnings.warn(
Access denied with the following error:

        Cannot retrieve the public link of the file. You may need to chang
e
        the permission to 'Anyone with the link', or have had many accesse
s.

You may still be able to access the file from the browser:

         https://drive.google.com/uc?id=1qQkymAitU6l2pSe702rDUhQpoP8MUZXl
(https://drive.google.com/uc?id=1qQkymAitU6l2pSe702rDUhQpoP8MUZXl)
```

In [101]:

```
# df = pd.read_csv('train_1.csv')
```

In [102]:

```
exog_df = pd.read_csv('Exog_Campaign_eng .csv')
```

In [103]:

```
df.head()
```

Out[103]:

	Page	2015-07-01	2015-07-02	2015-07-03	2015-07-04	2015-07-05	2015-07-06	2015-07-07	2015-07-0
0	2NE1_zh.wikipedia.org_all-access_spider	18.0	11.0	5.0	13.0	14.0	9.0	9.0	22.
1	2PM_zh.wikipedia.org_all-access_spider	11.0	14.0	15.0	18.0	11.0	13.0	22.0	11.
2	3C_zh.wikipedia.org_all-access_spider	1.0	0.0	1.0	1.0	0.0	4.0	0.0	3.
3	4minute_zh.wikipedia.org_all-access_spider	35.0	13.0	10.0	94.0	4.0	26.0	14.0	9.
4	52_Hz_I_Love_You_zh.wikipedia.org_all-access_s...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na

5 rows × 551 columns

In [104]:

```
df.shape
```

Out[104]:

```
(66534, 551)
```

In [105]:

```
df.head()
```

Out[105]:

	Page	2015-07-01	2015-07-02	2015-07-03	2015-07-04	2015-07-05	2015-07-06	2015-07-07	2015-07-0
0	2NE1_zh.wikipedia.org_all-access_spider	18.0	11.0	5.0	13.0	14.0	9.0	9.0	22.
1	2PM_zh.wikipedia.org_all-access_spider	11.0	14.0	15.0	18.0	11.0	13.0	22.0	11.
2	3C_zh.wikipedia.org_all-access_spider	1.0	0.0	1.0	1.0	0.0	4.0	0.0	3.
3	4minute_zh.wikipedia.org_all-access_spider	35.0	13.0	10.0	94.0	4.0	26.0	14.0	9.
4	52_Hz_I_Love_You_zh.wikipedia.org_all-access_s...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na

5 rows × 551 columns

Interpretation of Null Values

```
We can infer one thing from the null values that the page is not yet created during
that time and started in between
----------------or-----------------
The page got discontinued if it has null values in the end
```

```
--------------or------------------
The page got started and discontinued in between the given timeframe
```

In [106]:

```
df.isna().sum()
```

Out[106]:

```
Page              0
2015-07-01    10607
2015-07-02    10679
2015-07-03    10602
2015-07-04    10645
              ...
2016-12-27     1602
2016-12-28     1576
2016-12-29     1620
2016-12-30     1461
2016-12-31     1607
Length: 551, dtype: int64
```

In [107]:

```
df_T = df.T
```

In [108]:

```
df_T.head()
```

Out[108]:

	0	1	2	
Page	2NE1_zh.wikipedia.org_all-access_spider	2PM_zh.wikipedia.org_all-access_spider	3C_zh.wikipedia.org_all-access_spider	4minute_zh.wik
2015-07-01	18.0	11.0	1.0	
2015-07-02	11.0	14.0	0.0	
2015-07-03	5.0	15.0	1.0	
2015-07-04	13.0	18.0	1.0	

5 rows × 66534 columns

```
There are two types of websites -- wikipedia.org --wikimedia.org
```

```
Extracting Languages from the page name
```

In [109]:

```
def get_lang(x):
    if '.wikipedia.org_' in x:
        return x.split('.wikipedia.org_')[0][-2:]
    elif '.wikimedia.org_' in x:
        return x.split('.wikimedia.org_')[0][-7:]
    else:
        return None

df['lang'] = df['Page'].apply(get_lang)
```

In [110]:

```
df.head()
```

Out[110]:

	Page	2015-07-01	2015-07-02	2015-07-03	2015-07-04	2015-07-05	2015-07-06	2015-07-07	2015-07-0
0	2NE1_zh.wikipedia.org_all-access_spider	18.0	11.0	5.0	13.0	14.0	9.0	9.0	22.
1	2PM_zh.wikipedia.org_all-access_spider	11.0	14.0	15.0	18.0	11.0	13.0	22.0	11.
2	3C_zh.wikipedia.org_all-access_spider	1.0	0.0	1.0	1.0	0.0	4.0	0.0	3.
3	4minute_zh.wikipedia.org_all-access_spider	35.0	13.0	10.0	94.0	4.0	26.0	14.0	9.
4	52_Hz_I_Love_You_zh.wikipedia.org_all-access_s...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na

5 rows × 552 columns

In [111]:

```
df.shape
```

Out[111]:

(66534, 552)

In [112]:

```
# Group the data by language and sum the timeseries data
lang_grouped = df.groupby('lang').sum()

# Transpose the dataframe to make the dates the index and the languages the columns
lang_df = lang_grouped.transpose()

# Convert the index to a datetime index
lang_df.index = pd.to_datetime(lang_df.index)

# Set the index name to 'date'
lang_df.index.name = 'date'
```

In [113]:

```
lang_df.index.min(),lang_df.index.max()
```

Out[113]:

```
(Timestamp('2015-07-01 00:00:00'), Timestamp('2016-12-31 00:00:00'))
```

We have data in the range of 1st July 2015 - 31st Dec 2016

In [114]:

```
lang_df.shape
```

Out[114]:

```
(550, 7)
```

In [115]:

```
exog_df.shape
```

Out[115]:

```
(550, 1)
```

now the exog and lang_df rows are matching

In [116]:

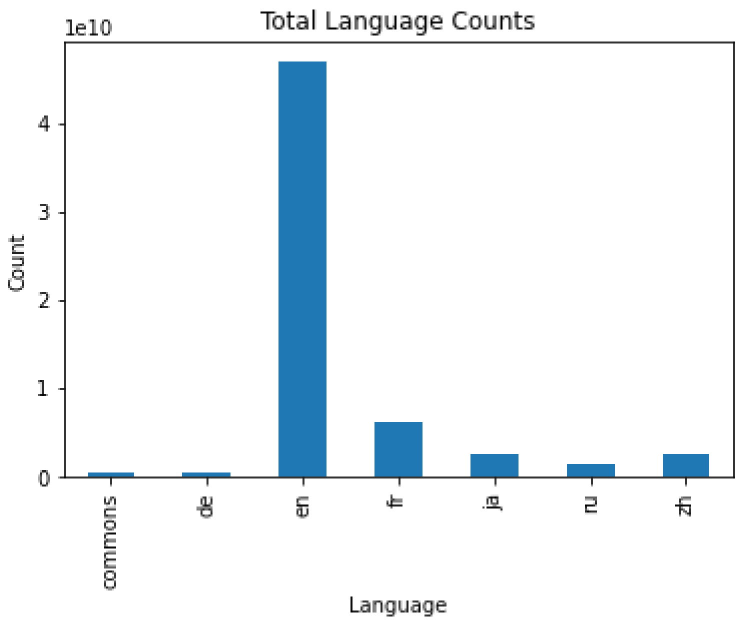
```
lang_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 550 entries, 2015-07-01 to 2016-12-31
Data columns (total 7 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   commons  550 non-null    float64
 1   de       550 non-null    float64
 2   en       550 non-null    float64
 3   fr       550 non-null    float64
 4   ja       550 non-null    float64
 5   ru       550 non-null    float64
 6   zh       550 non-null    float64
dtypes: float64(7)
memory usage: 34.4 KB
```

There are no null values in the DataFrame lang_df

In [117]:

```
import matplotlib.pyplot as plt

# get the sum of language counts for each column
lang_cols = lang_df.columns
counts = lang_df[lang_cols].sum()

# create a bar plot
fig, ax = plt.subplots()
counts.plot.bar(ax=ax)

# set the plot title and axis labels
ax.set_title('Total Language Counts')
ax.set_xlabel('Language')
ax.set_ylabel('Count')

# display the plot
plt.show()
```



In [118]:

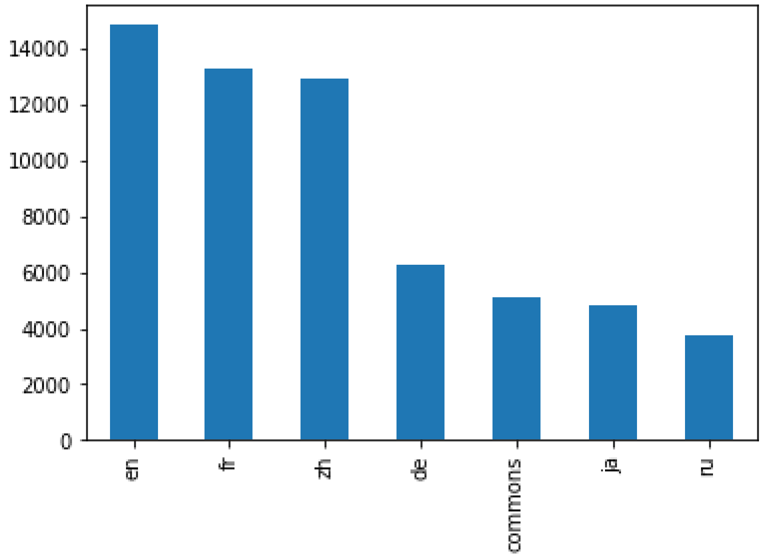
```
lang_pages = df.lang.value_counts()
```

In [119]:

```
lang_pages.plot(kind='bar')
```

Out[119]:

```
&lt;AxesSubplot:&gt;
```



Compared with all other languages, english pages have more number of visits

In [120]:

```
exog_df.set_index(lang_df.index,inplace=True)
```

In [121]:

```
#merged with Exog
merged_df = pd.merge(lang_df, exog_df, left_index=True, right_index=True)
```

In [122]:

```
merged_df
```

Out[122]:

date	commons	de	en	fr	ja	ru	zh	Exog
2015-07-01	579000.0	742302.0	66065222.0	8413729.0	3423822.0	1765720.0	3413909.0	0
2015-07-02	605257.0	698744.0	65829028.0	8479002.0	3326838.0	1776308.0	3454103.0	0
2015-07-03	593123.0	620556.0	61238929.0	8147993.0	3504746.0	1830215.0	3400769.0	0
2015-07-04	485204.0	492384.0	63041651.0	8710220.0	5200572.0	1954468.0	3336333.0	0
2015-07-05	548252.0	625341.0	65286726.0	8554550.0	4917657.0	2052188.0	3574716.0	0
...	...	...	...	...	...	...	...	...
2016-12-27	1178239.0	994183.0	113010917.0	14430822.0	4547138.0	2941859.0	5186111.0	1
2016-12-28	1322124.0	1031693.0	110388953.0	13608493.0	4473015.0	2746475.0	5240679.0	1
2016-12-29	1179010.0	1115784.0	115730191.0	13232659.0	5102968.0	2705237.0	4831297.0	1
2016-12-30	1279082.0	824192.0	98397898.0	12276415.0	6070273.0	2611825.0	4835964.0	0
2016-12-31	1113532.0	647396.0	96432986.0	11285713.0	8708195.0	3719978.0	4806224.0	0

550 rows × 8 columns

In [123]:

```
#splitting for test and training data
train_x = merged_df.loc[lang_df.index < lang_df.index[-12]].copy()
test_x = merged_df.loc[lang_df.index >= lang_df.index[-12]].copy()
```

In [124]:

```
test_x
```

Out[124]:

date	commons	de	en	fr	ja	ru	zh	Exog
2016-12-20	1198442.0	995002.0	107451595.0	12949834.0	4395424.0	2895181.0	5060070.0	0
2016-12-21	1021828.0	884494.0	98127007.0	11883184.0	4139525.0	2769093.0	5171865.0	0
2016-12-22	1032957.0	808659.0	100172430.0	11438861.0	3973725.0	2754639.0	4738674.0	0
2016-12-23	1235962.0	715057.0	90826964.0	11210366.0	6660162.0	2792881.0	4672655.0	0
2016-12-24	1027205.0	532322.0	94345332.0	10768120.0	5631341.0	3063083.0	4825119.0	0
2016-12-25	1235548.0	1356079.0	95166578.0	11618007.0	5356404.0	3875674.0	5080657.0	0
2016-12-26	1357299.0	769646.0	107480520.0	15363677.0	4546267.0	3514790.0	5116428.0	0
2016-12-27	1178239.0	994183.0	113010917.0	14430822.0	4547138.0	2941859.0	5186111.0	1
2016-12-28	1322124.0	1031693.0	110388953.0	13608493.0	4473015.0	2746475.0	5240679.0	1
2016-12-29	1179010.0	1115784.0	115730191.0	13232659.0	5102968.0	2705237.0	4831297.0	1
2016-12-30	1279082.0	824192.0	98397898.0	12276415.0	6070273.0	2611825.0	4835964.0	0
2016-12-31	1113532.0	647396.0	96432986.0	11285713.0	8708195.0	3719978.0	4806224.0	0

In [125]:

```
lang_df = train_x
```

In [126]:

```
lang_df.shape
```

Out[126]:

(538, 8)

In [127]:

```
lang_df.en.isna().sum()
```

Out[127]:

0

In [128]:

```
import statsmodels.api as sm
```

Dickey-Fuller test

In [129]:

```
sm.tsa.stattools.adfuller(lang_df.en)[1]
```

Out[129]:

```
0.14539882179746394
```

In [130]:

```
def adf_test(data, significance_level=0.05):
    pvalue = sm.tsa.stattools.adfuller(data)[1]
    if pvalue <= significance_level:
        print('Sequence is stationary')
    else:
        print('Sequence is not stationary')

adf_test(lang_df.en)
```

```
Sequence is not stationary
```

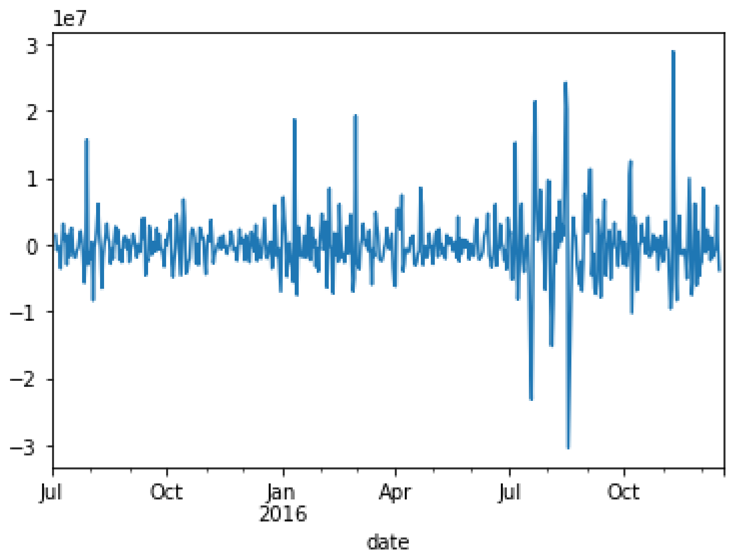
Decomposition of series.

In [131]:

```
model = sm.tsa.seasonal_decompose(lang_df.en, model='additive')
model.resid.plot()
```

Out[131]:

```
<AxesSubplot:xlabel='date'>
```



In [132]:

```
adf_test(model.resid.dropna())
```

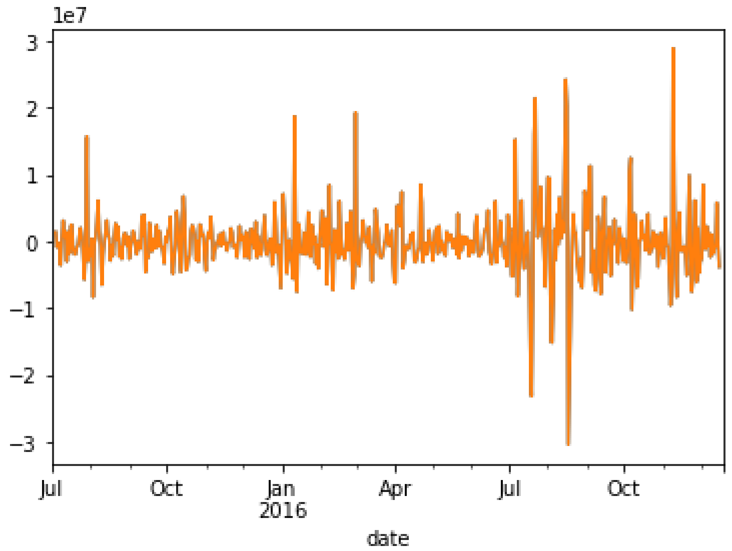
```
Sequence is stationary
```

In [133]:

```
model = sm.tsa.seasonal_decompose(lang_df.en, model='additive')
model.resid.plot()
model = sm.tsa.seasonal_decompose(lang_df.en.dropna(), model='additive')
model.resid.plot()
```

Out[133]:

```
<AxesSubplot:xlabel='date'>
```



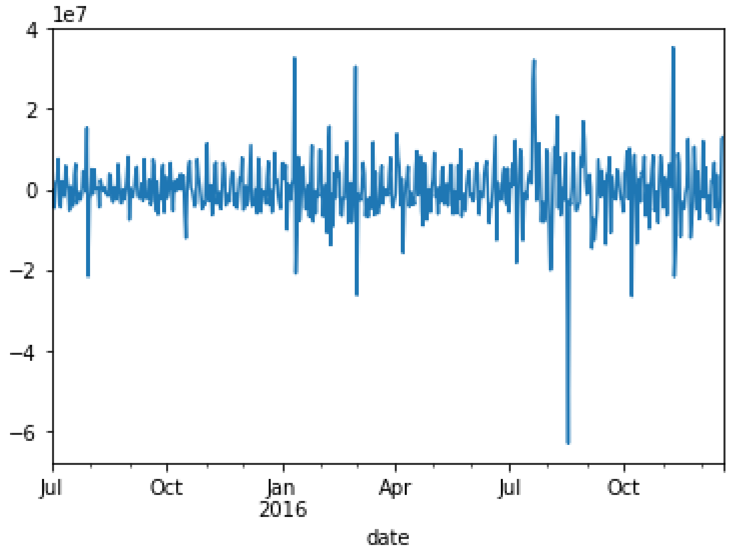
Differencing the series.

In [134]:

```
lang_df.en.diff().plot()
```

Out[134]:

```
<AxesSubplot:xlabel='date'>
```



In [135]:

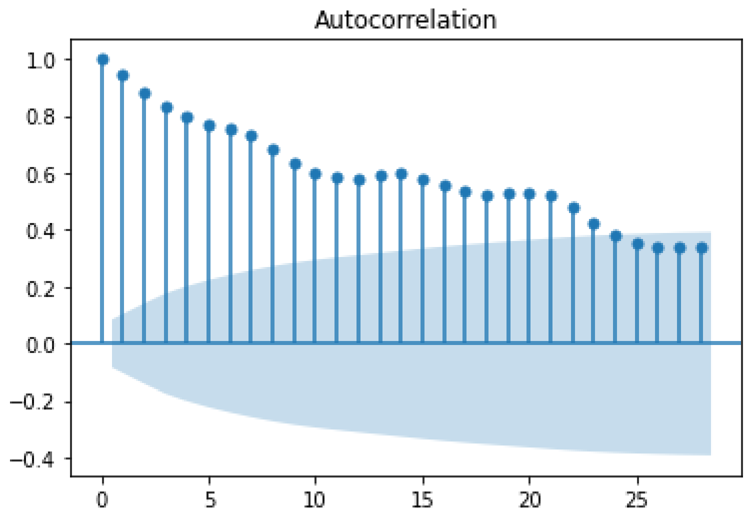
```
adf_test(lang_df.en.diff().dropna())
```

```
Sequence is stationary
```

PACF/ACF

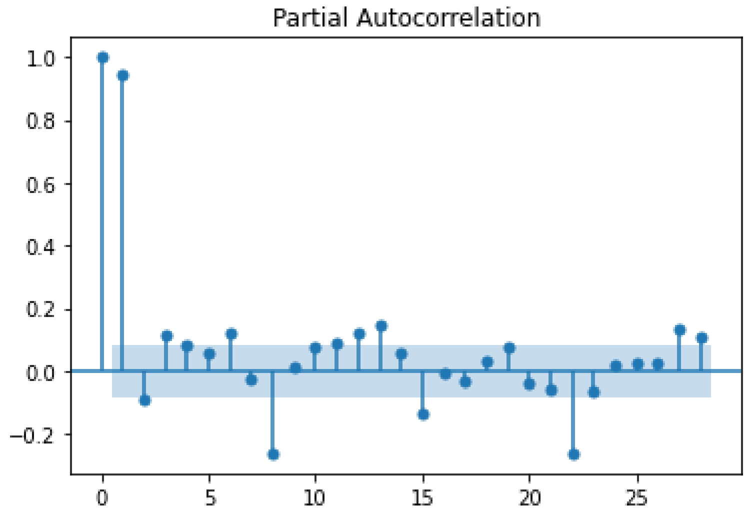
In [136]:

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
plot_acf(lang_df.en);
```



In [137]:

```
plot_pacf(lang_df.en);
```

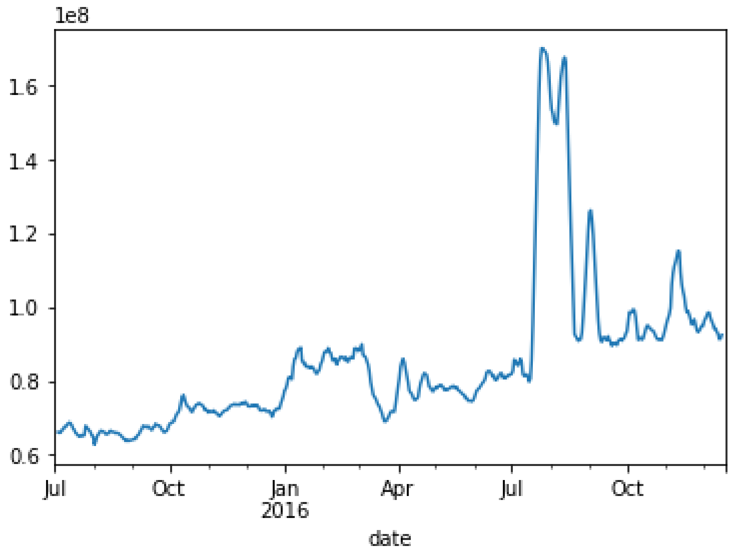


In [138]:

```
model.trend.plot()
```

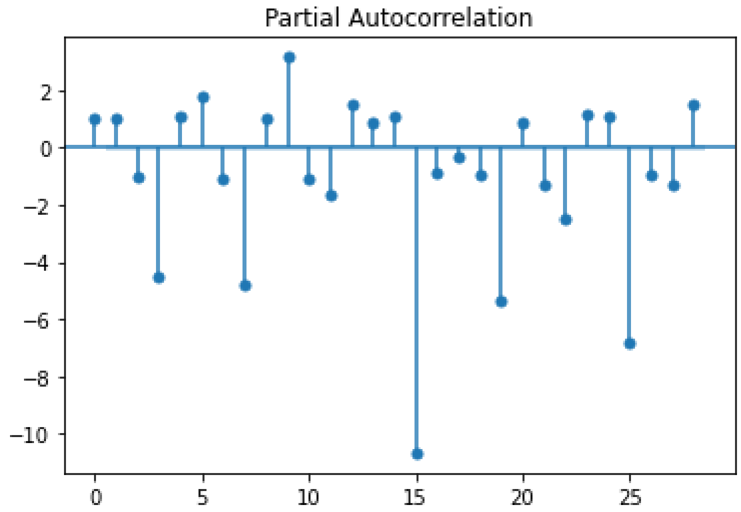
Out[138]:

```
<AxesSubplot:xlabel='date'>
```



In [139]:

```
plot_pacf(model.trend.dropna());
```

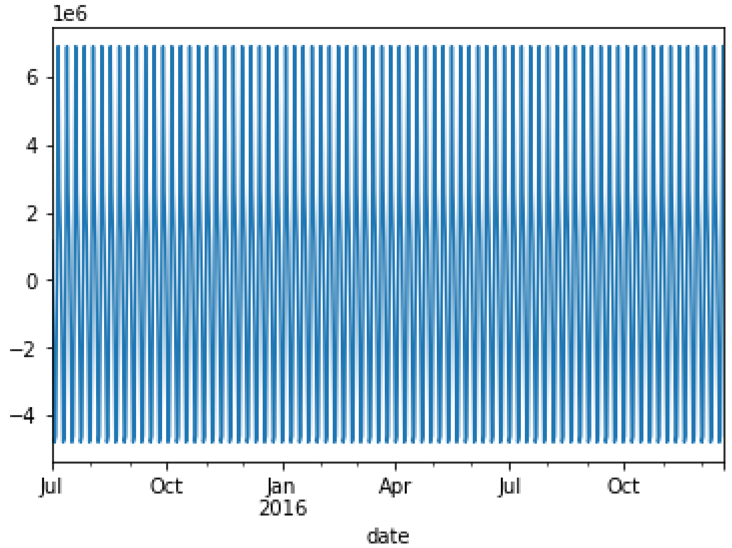


In [140]:

```
model.seasonal.plot()
```

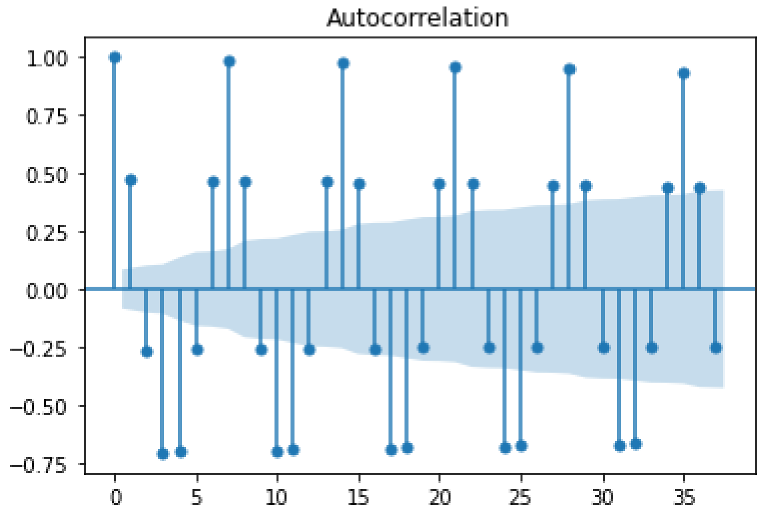
Out[140]:

```
<AxesSubplot:xlabel='date'>
```



In [141]:

```
plot_acf(model.seasonal.dropna(), lags=37);
```

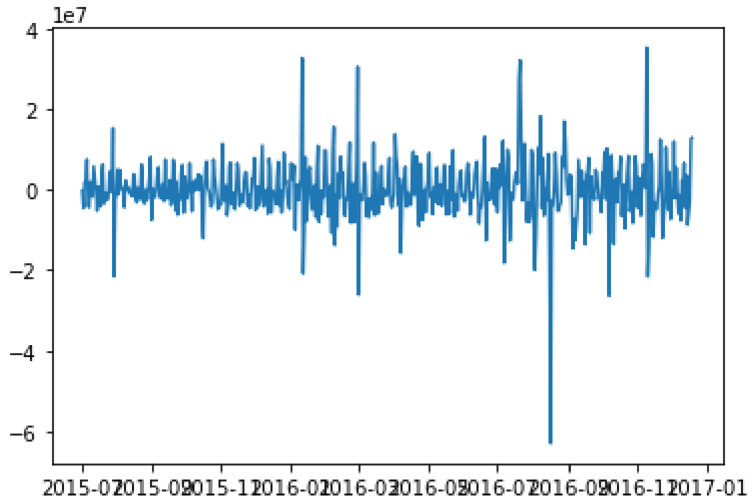


In [142]:

```
plt.plot(lang_df.en.diff())
```

Out[142]:

```
[<matplotlib.lines.Line2D at 0x7f19c683af70>]
```

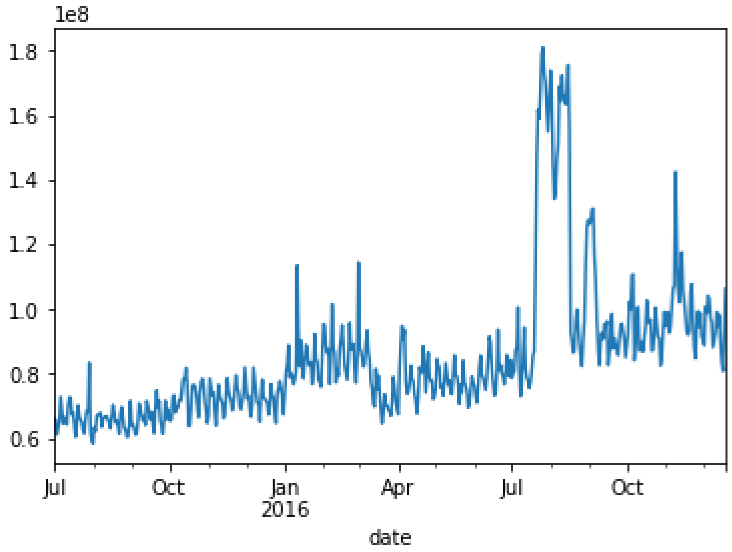


In [143]:

```
lang_df.en.plot()
```

Out[143]:

```
<AxesSubplot:xlabel='date'>
```



In [144]:

```
from sklearn.metrics import (
    mean_squared_error as mse,
    mean_absolute_error as mae,
    mean_absolute_percentage_error as mape
)
```

In [145]:

```
def performance(actual, predicted):
    print('MAE :', round(mae(actual, predicted), 3))
    print('RMSE :', round(mse(actual, predicted)**0.5, 3))
    print('MAPE:', round(mape(actual, predicted), 3))
```

In [146]:

```
from statsmodels.tsa.statespace.sarimax import SARIMAX
```

In [147]:

```
model_test_x = pd.DataFrame()
```

In [148]:

```
def predict_lang_arima(lang):
    d = 1
    min_p,min_q = 0,0
    min_mape = 101
    for p in [1,2,3,7]:
        for q in [1,2,7,12]:
            model = SARIMAX(lang_df[lang], order=(p,d,q))
            model = model.fit(disp=False)
            test_x['pred_'+lang] = model.forecast(steps=12)
#             test_x[['en','pred_'+lang]].plot(style='-o')
#             performance(test_x['pred_'+lang], test_x['en'])
            curr_mape = mape(test_x['pred_'+lang], test_x[lang])
            if curr_mape < min_mape:
                min_p,min_q,min_mape = p,q,curr_mape
    return p,q,min_mape
```

Arima for all Languages

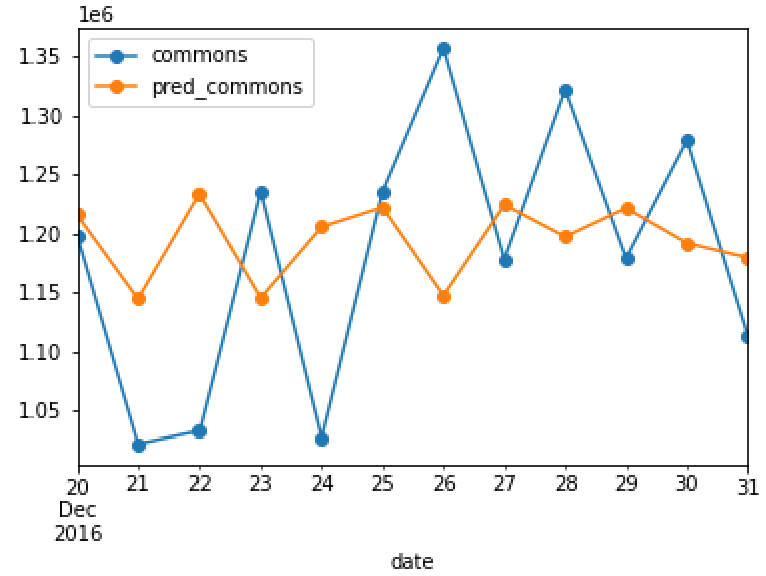
In [149]:

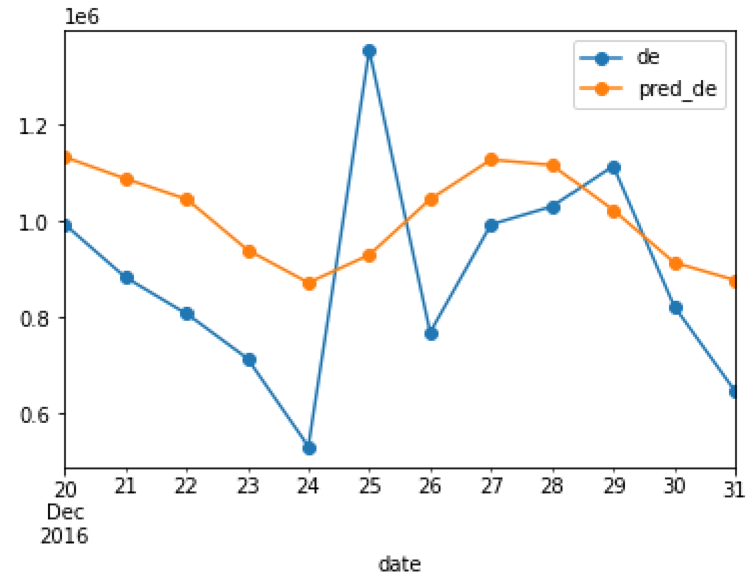
```
warnings.filterwarnings("ignore")
```

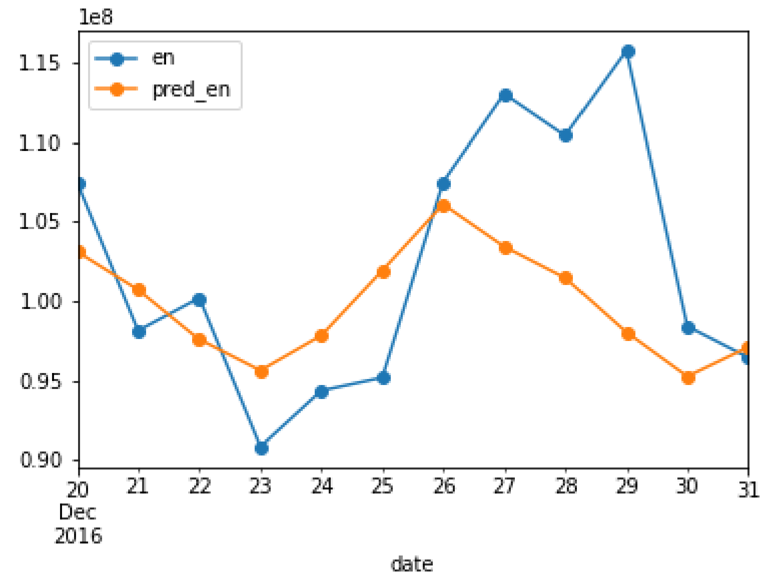
In [150]:

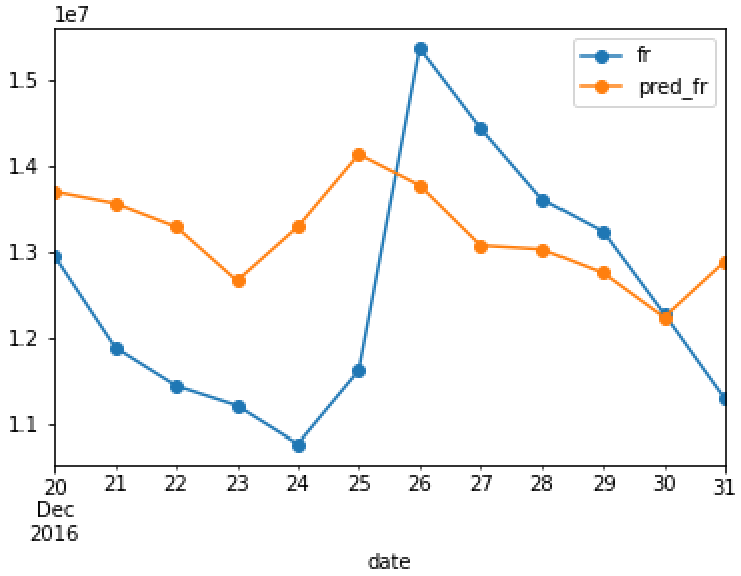
```
languages = list(lang_df.columns[:-1]) #All Languages

parameters_dict = {}

for i in languages:
    parameters_dict[i] = predict_lang_arima(i)
for key in parameters_dict.keys():
    print('{} : {}'.format(key , parameters_dict[key]))#Parameters for all languages of p

for i in languages:
    model = SARIMAX(lang_df[i], order=(parameters_dict[i][0], 1, parameters_dict[i][1]))
    model = model.fit(disp=False)
    print('----Errors for language {}----'.format(i))
    test_x['pred_'+i] = model.forecast(steps=12)

    test_x[[i,'pred_'+i]].plot(style='-o')

    performance(test_x['pred_'+i], test_x[i])
```

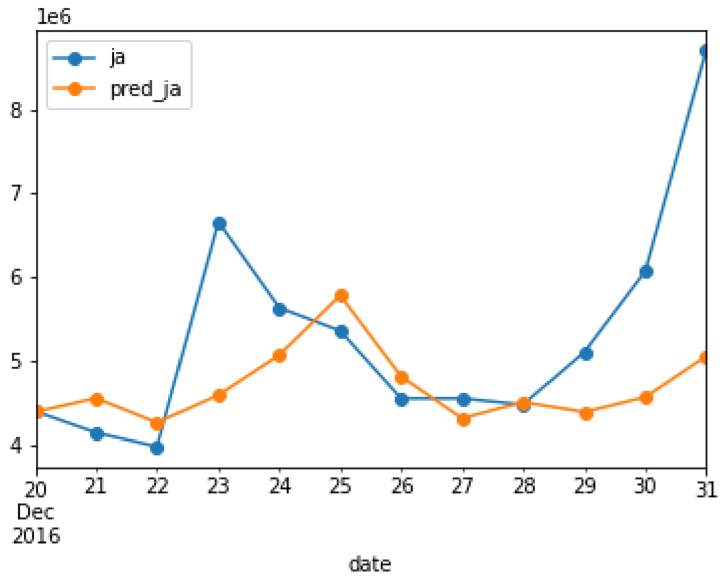
```
commons : (7, 12, 0.07471867409460274)
de : (7, 12, 0.20061822535545185)
en : (7, 12, 0.054204611279428445)
fr : (7, 12, 0.10239766037754583)
ja : (7, 12, 0.15559213608189035)
ru : (7, 12, 0.07673013689420254)
zh : (7, 12, 0.031518576387050364)
----Errors for language commons----
MAE : 99906.205
RMSE : 119410.004
MAPE: 0.084
----Errors for language de----
MAE : 207255.572
RMSE : 230727.439
MAPE: 0.212
----Errors for language en----
MAE : 5498526.358
RMSE : 7132532.98
MAPE: 0.055
----Errors for language fr----
MAE : 1367350.905
RMSE : 1556053.707
MAPE: 0.102
----Errors for language ja----
MAE : 848225.96
RMSE : 1333189.704
MAPE: 0.178
----Errors for language ru----
MAE : 236731.045
RMSE : 295361.231
MAPE: 0.077
----Errors for language zh----
MAE : 159187.96
RMSE : 201118.403
MAPE: 0.032
```

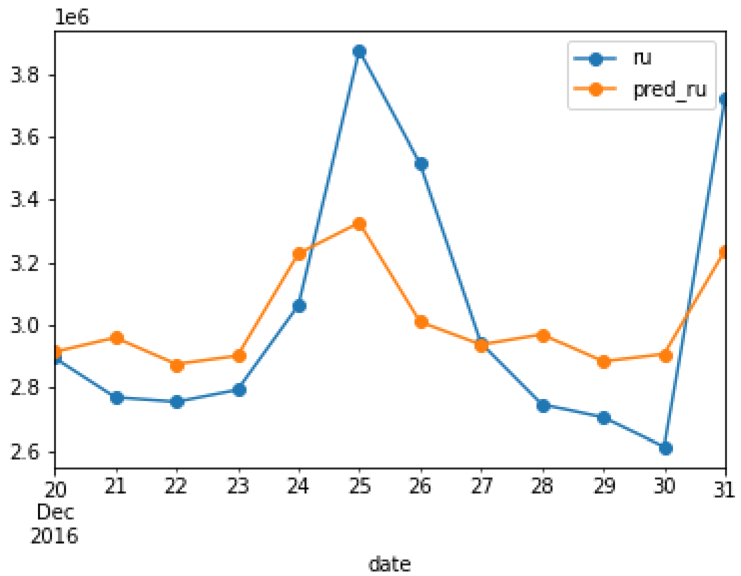

1e6
commons
pred_commons
1.35
1.30
1.25
1.20
1.15
1.10
1.05
20
Dec
2016
21
22
23
24
25
26
27
28
29
30
31
date


1e6
de
pred_de
1.2
1.0
0.8
0.6
20
Dec
2016
21
22
23
24
25
26
27
28
29
30
31
date


1e8
en
pred_en
1.15
1.10
1.05
1.00
0.95
0.90
20
Dec
2016
21
22
23
24
25
26
27
28
29
30
31
date


1e7
fr
pred_fr
1.5
1.4
1.3
1.2
1.1
20
Dec
2016
21
22
23
24
25
26
27
28
29
30
31
date


1e6
ja
pred_ja
8
7
6
5
4
20
Dec
2016
21
22
23
24
25
26
27
28
29
30
31
date


1e6
ru
pred_ru
3.8
3.6
3.4
3.2
3.0
2.8
2.6
20
Dec
2016
21
22
23
24
25
26
27
28
29
30
31
date

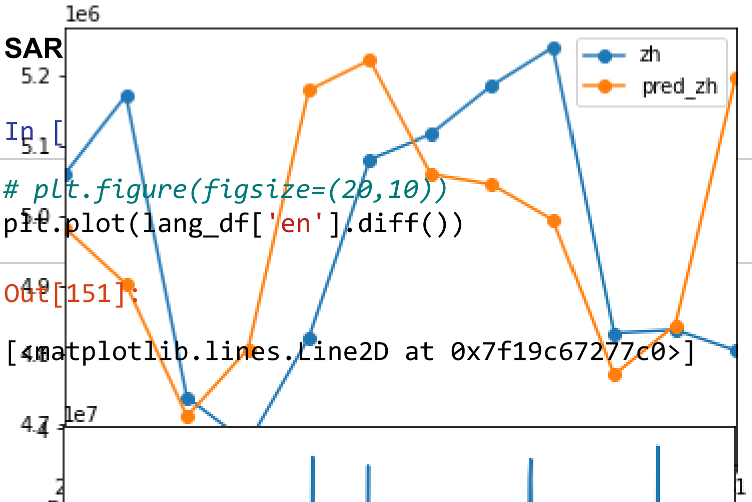
SAR

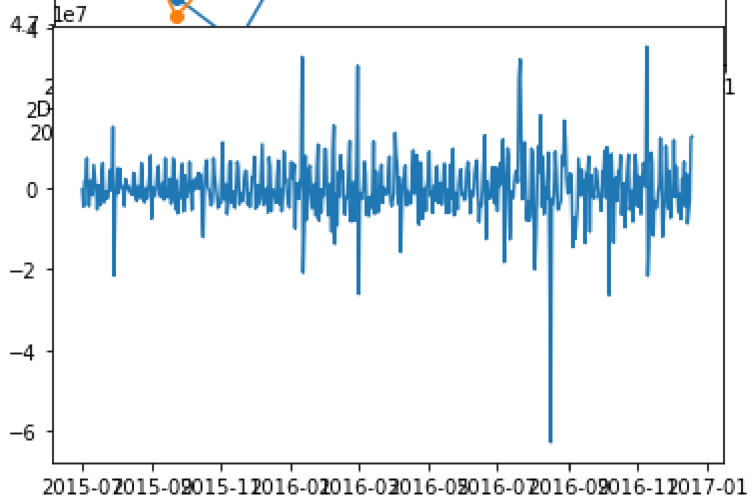
In [

```
# plt.figure(figsize=(20,10))
plt.plot(lang_df['en'].diff())
```

Out[151]:

```
[<matplotlib.lines.Line2D at 0x7f19c67277c0>]
```

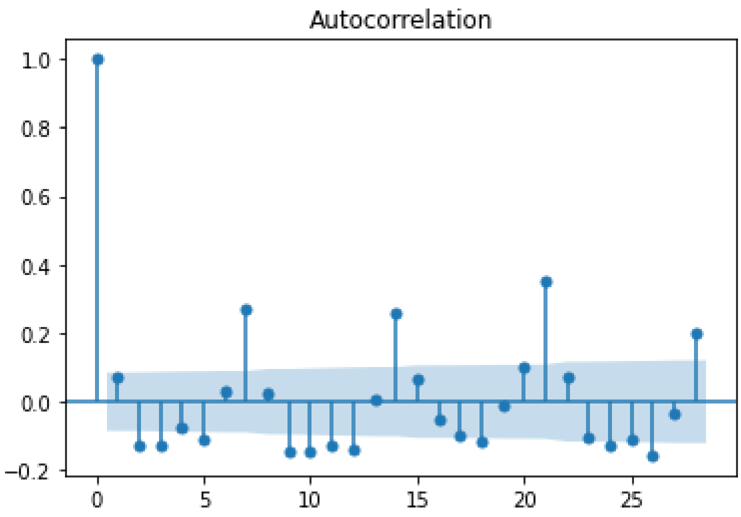


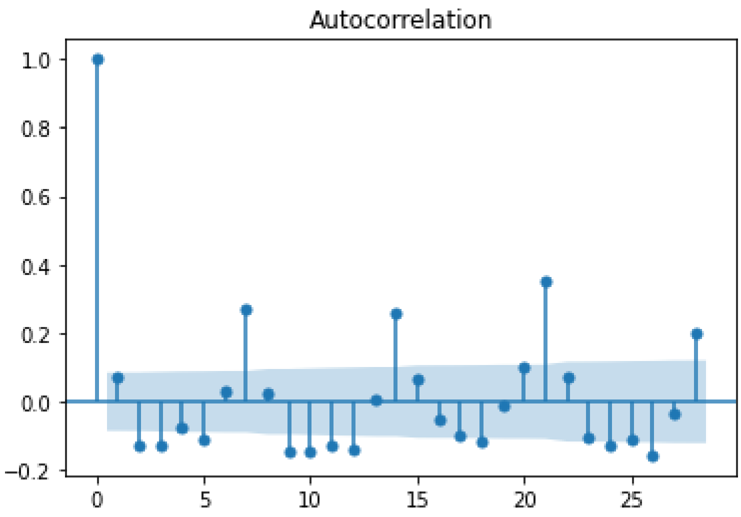


In [152]:

```
plot_acf(lang_df['en'].diff().dropna())
```

Out[152]:





In [153]:

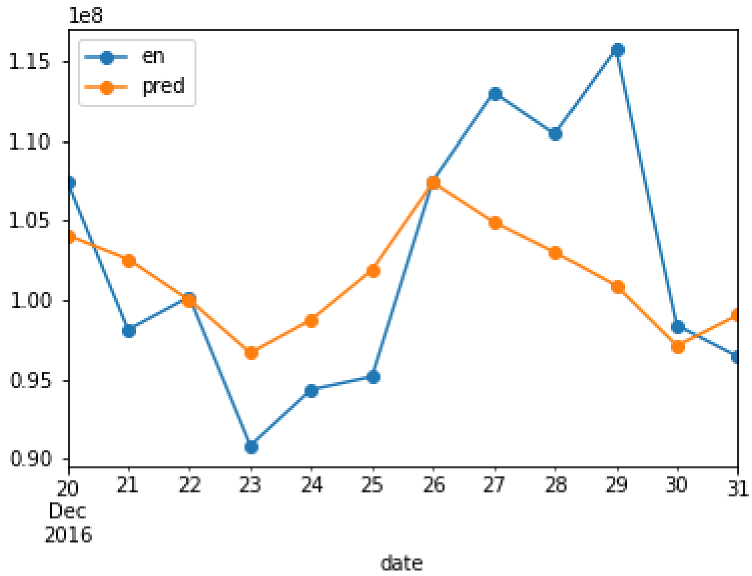
```
# plot_acf(lang_df['en'])
```

We see that there is a weekly seasonality

In [154]:

```
model = SARIMAX(lang_df.en, order=(3,1,3), seasonal_order=(3, 0, 1, 7))
model = model.fit(disp=False)


test_x['pred'] = model.forecast(steps=12)

test_x[['en','pred']].plot(style='-o')

performance(test_x['pred'], test_x['en'])
```

```
MAE : 4939798.152
RMSE : 6313157.498
MAPE: 0.049
```



In [155]:

```
lang_df.en.shape
```

Out[155]:

```
(538,)
```

In [156]:

```
lang_df.head()
```

Out[156]:

date	commons	de	en	fr	ja	ru	zh	Exog
2015-07-01	579000.0	742302.0	66065222.0	8413729.0	3423822.0	1765720.0	3413909.0	0
2015-07-02	605257.0	698744.0	65829028.0	8479002.0	3326838.0	1776308.0	3454103.0	0
2015-07-03	593123.0	620556.0	61238929.0	8147993.0	3504746.0	1830215.0	3400769.0	0
2015-07-04	485204.0	492384.0	63041651.0	8710220.0	5200572.0	1954468.0	3336333.0	0
2015-07-05	548252.0	625341.0	65286726.0	8554550.0	4917657.0	2052188.0	3574716.0	0

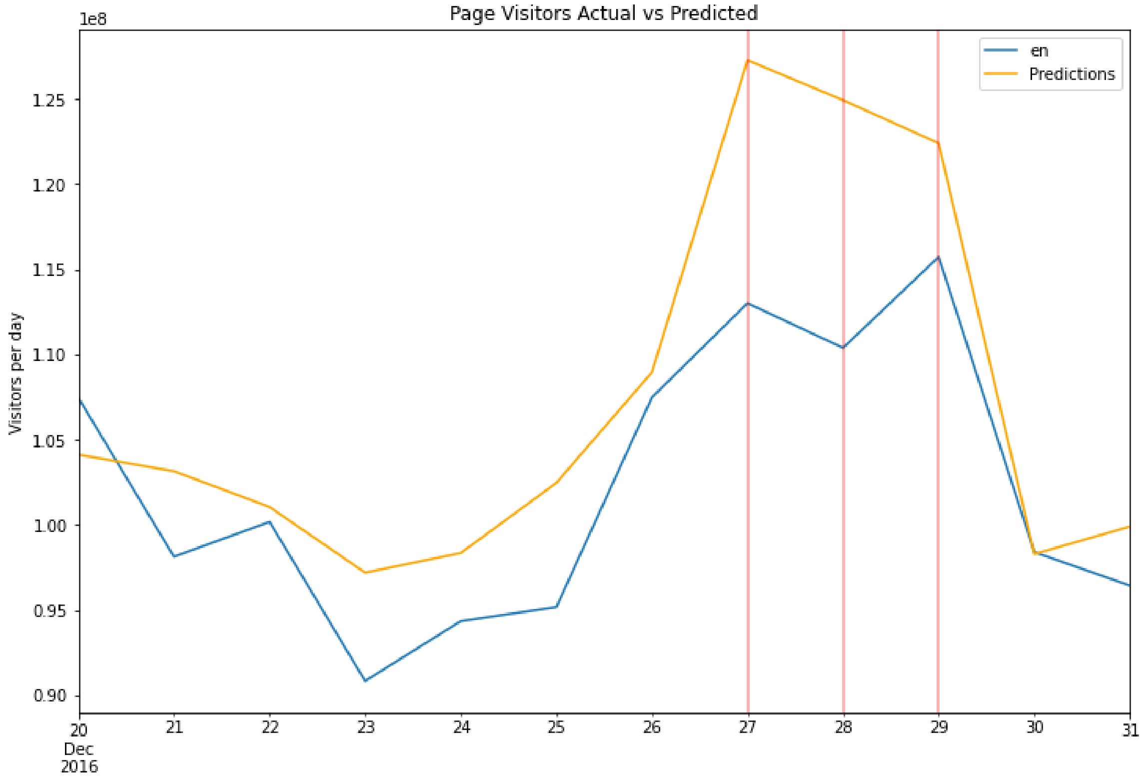
In [157]:

```
model = SARIMAX(lang_df['en'], exog=lang_df['Exog'], order=(1,1,1),seasonal_order=(3,0,2,
results = model.fit(disp=False)

exog_forecast = test_x[['Exog']]
predictions = results.predict(start=test_x.index[0], end=test_x.index[-1], exog=exog_fore
```

In [158]:

```
performance(test_x['en'], predictions)
# Plot predictions against known values
title='Page Visitors Actual vs Predicted'
ylabel='Visitors per day'
xlabel=''

ax = test_x['en'].plot(legend=True,figsize=(12,8),title=title)
predictions.plot(legend=True, color = 'orange')
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel)
for x in test_x.query('Exog==1').index:
    ax.axvline(x=x, color='red', alpha = 0.4);
```

```
MAE : 5619085.829
RMSE : 7191446.18
MAPE: 0.054
```



Prophet

In [159]:

```
from prophet import Prophet
```

In [162]:

```
df = pd.DataFrame()
df['ds'] = pd.DataFrame(lang_df.index)
```

In [163]:

```
lang_df.index
```

Out[163]:

```
DatetimeIndex(['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', '2015-07-10',
               ...
               '2016-12-10', '2016-12-11', '2016-12-12', '2016-12-13',
               '2016-12-14', '2016-12-15', '2016-12-16', '2016-12-17',
               '2016-12-18', '2016-12-19'],
              dtype='datetime64[ns]', name='date', length=538, freq=None)
```

In [164]:

```
df['y'] = lang_df['en']

df.head()
```

Out[164]:

	ds	y
0	2015-07-01	NaN
1	2015-07-02	NaN
2	2015-07-03	NaN
3	2015-07-04	NaN
4	2015-07-05	NaN

In [165]:

```
lang_df['en']
```

Out[165]:

```
date
2015-07-01     66065222.0
2015-07-02     65829028.0
2015-07-03     61238929.0
2015-07-04     63041651.0
2015-07-05     65286726.0
                  ...
2016-12-15     89581082.0
2016-12-16     83900097.0
2016-12-17     80833611.0
2016-12-18     93438972.0
2016-12-19    106338647.0
Name: en, Length: 538, dtype: float64
```

In [166]:

```
df['ds'] = pd.to_datetime(lang_df.index)
```

In [167]:

```
df['y'] = lang_df.en
```

In [168]:

```
lang_df.en.head()
```

Out[168]:

```
date
2015-07-01    66065222.0
2015-07-02    65829028.0
2015-07-03    61238929.0
2015-07-04    63041651.0
2015-07-05    65286726.0
Name: en, dtype: float64
```

In [169]:

```
p_merged_df = pd.merge(df, lang_df, left_on='ds',right_on = 'date')
p_merged_df.head()
```

Out[169]:

	ds	y	commons	de	en	fr	ja	ru	zh
0	2015-07-01	NaN	579000.0	742302.0	66065222.0	8413729.0	3423822.0	1765720.0	3413909.0
1	2015-07-02	NaN	605257.0	698744.0	65829028.0	8479002.0	3326838.0	1776308.0	3454103.0
2	2015-07-03	NaN	593123.0	620556.0	61238929.0	8147993.0	3504746.0	1830215.0	3400769.0
3	2015-07-04	NaN	485204.0	492384.0	63041651.0	8710220.0	5200572.0	1954468.0	3336333.0
4	2015-07-05	NaN	548252.0	625341.0	65286726.0	8554550.0	4917657.0	2052188.0	3574716.0

In [170]:

```
df = p_merged_df[['ds','en','Exog']]
```

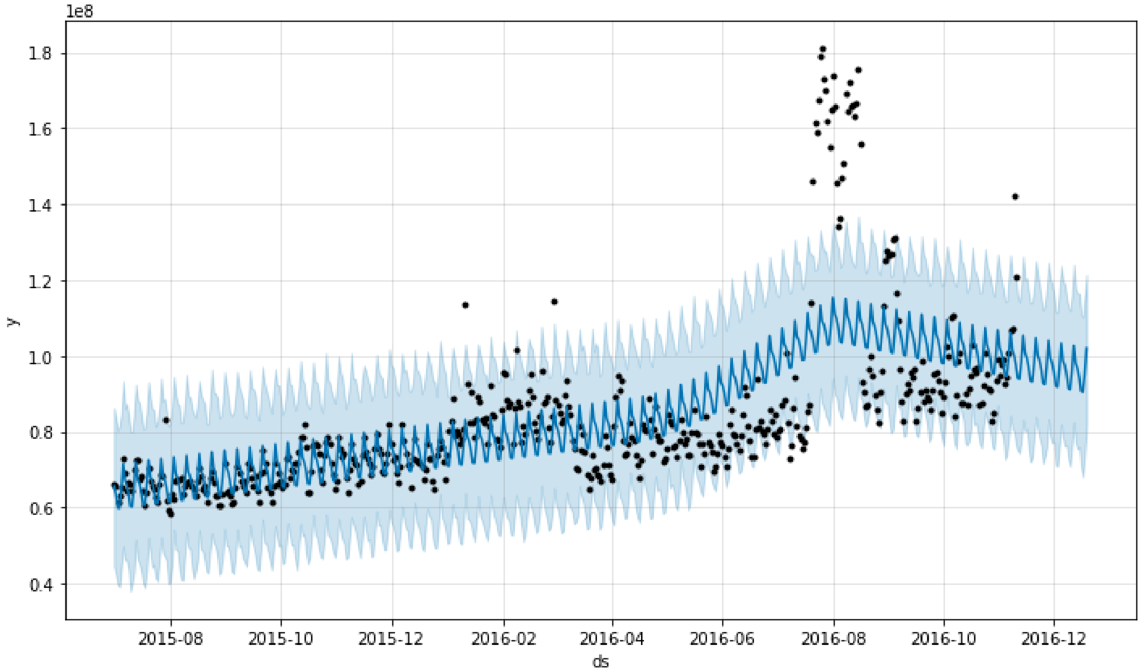
In [171]:

```
df.rename(columns={'en':'y','Exog':'holiday'},inplace=True)
```

In [172]:

```
m = Prophet()
m.fit(df[['ds', 'y']][:-39])
future = m.make_future_dataframe(periods=39, freq='D')
forecast = m.predict(future)
m.plot(forecast);
```

```
INFO:prophet:Disabling yearly seasonality. Run prophet with yearly_seasona
lity=True to override this.
INFO:prophet:Disabling daily seasonality. Run prophet with daily_seasonali
ty=True to override this.
DEBUG:cmdstanpy:input tempfile: /tmp/tmp469jh7ll/ucsz8iyu.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmp469jh7ll/u5ba5il7.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.8/dist-packages/pro
phet/stan_model/prophet_model.bin', 'random', 'seed=12063', 'data', 'file
=/tmp/tmp469jh7ll/ucsz8iyu.json', 'init=/tmp/tmp469jh7ll/u5ba5il7.json',
'output', 'file=/tmp/tmp469jh7ll/prophet_modelvjytp_eu/prophet_model-20230
226185546.csv', 'method=optimize', 'algorithm=lbfgs', 'iter=10000']
18:55:46 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
18:55:46 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
```



In [173]:

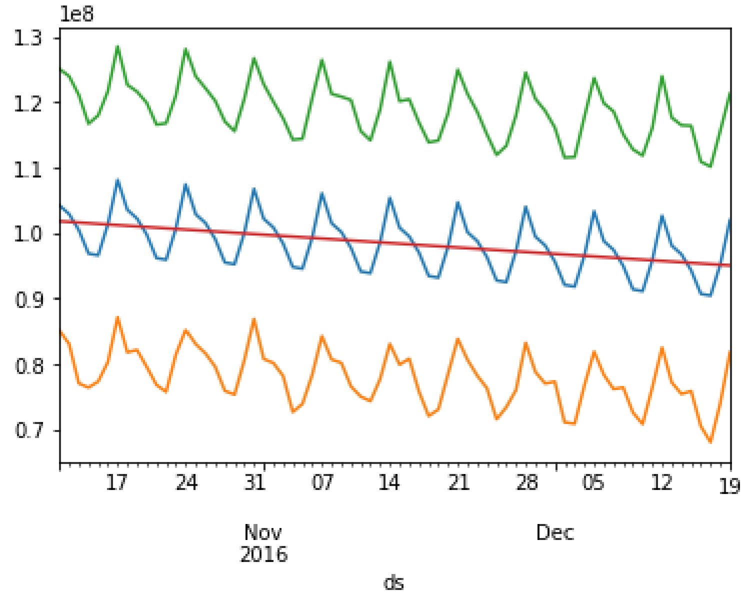
```
f = forecast.tail(70)
f.set_index('ds', inplace=True)
```

In [174]:

```
f.yhat.plot()
f.yhat_lower.plot()
f.yhat_upper.plot()
f.trend.plot()
```

Out[174]:

<AxesSubplot:xlabel='ds'>



In [175]:

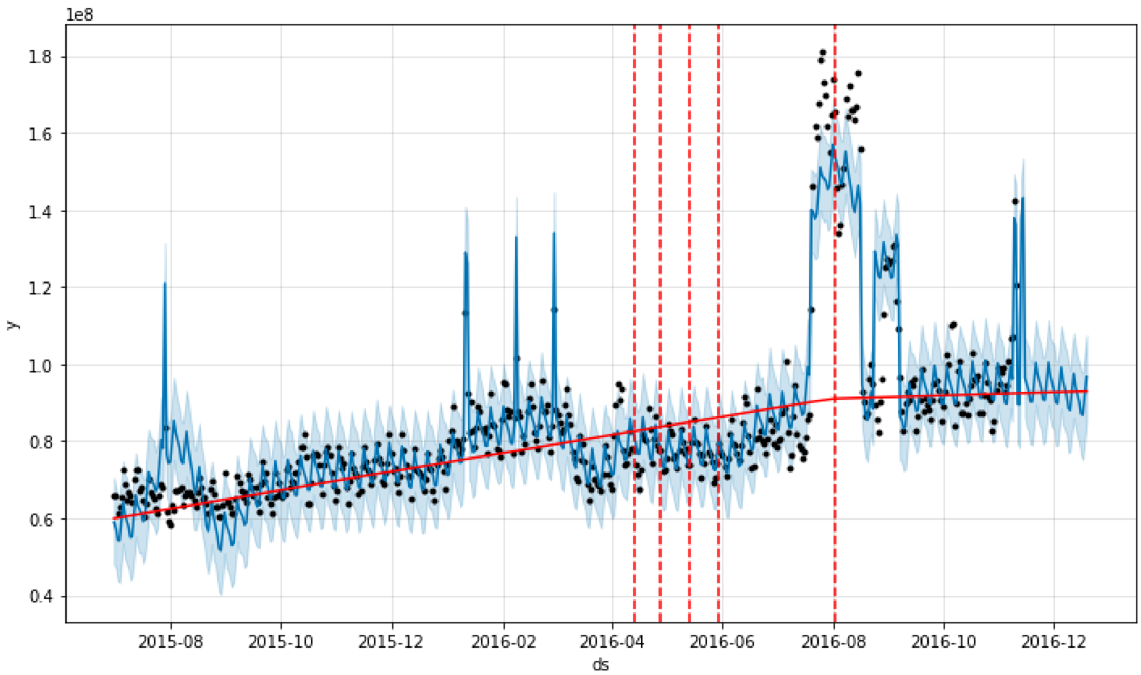
```
performance(df['y'][:-39],forecast['yhat'][:-39])
```

```
MAE : 9937098.815
RMSE : 16001870.17
MAPE: 0.103
```

In [176]:

```
from prophet.plot import add_changepoints_to_plot

model2=Prophet(yearly_seasonality=True, weekly_seasonality=True)
model2.add_regressor('holiday') #adding holidays data in the model3
model2.fit(df[:-39])
forecast2 = model2.predict(df)
fig = model2.plot(forecast2)
a = add_changepoints_to_plot(fig.gca(), m, forecast2)
```

```
INFO:prophet:Disabling daily seasonality. Run prophet with daily_seasonali
ty=True to override this.
DEBUG:cmdstanpy:input tempfile: /tmp/tmp469jh7ll/_nztnapq.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmp469jh7ll/hpb6rrlk.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.8/dist-packages/pro
phet/stan_model/prophet_model.bin', 'random', 'seed=84966', 'data', 'file
=/tmp/tmp469jh7ll/_nztnapq.json', 'init=/tmp/tmp469jh7ll/hpb6rrlk.json',
'output', 'file=/tmp/tmp469jh7ll/prophet_modelpzqqp05m/prophet_model-20230
226185547.csv', 'method=optimize', 'algorithm=lbfgs', 'iter=10000']
18:55:47 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
18:55:47 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
```



In [177]:

```
performance(df['y'][:-39],forecast2['yhat'][:-39])
```

```
MAE : 5419074.039
RMSE : 8515797.247
MAPE: 0.062
```

1) Defining the problem statements and where can this and modifications of this be used? --To Predict the page visitors for specific languages

2) Write 3 inferences you made from the data visualizations --English language pages have more number of visitors English has more number of pages Eventhough all the languages have almost same number of pages english language pages are more popualar

3) What does the decomposition of series do? -- Decomposition seperates the series into trend,seasonality and error

4) What level of differencing gave you a stationary series? -- 1st level of differencing gave a stationary series Difference between arima, sarima & sarimax.

5) Compare the number of views in different languages --English language pages have more number of visitors.

6) What other methods other than grid search would be suitable to get the model for all languages? -- we can make use of random search manually.

7) Difference between arima, sarima & sarimax. -- arima is used for stationary series sarima is to incorporate the effect of seasonality sarimax is used to add the effect of external factor in the timeseries

In [177]:

```

```

In [177]:

```

```

In [177]:

```

```

In [177]:

```

```

In [177]:

```

```