Business Problem:

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.

Importing required packages:

In [2]:

```
import pandas as pd
import numpy as np
import math as math
import seaborn as sns
sns.set(style='whitegrid')
from scipy import stats
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
plt.rcParams['figure.figsize'] = (15, 6)
```

In [3]:

```
ad_ease_train = pd.read_csv("train_1.csv")
```

In [4]:

```
ad_ease_train
```

Out[4]:

	Page	2015-07-01	2015-07-02	2015-07-03	2015-07-04	2015-07-05	2015-07-06
0	2NE1_zh.wikipedia.org_all-access_spider	18.0	11.0	5.0	13.0	14.0	9.0
1	2PM_zh.wikipedia.org_all-access_spider	11.0	14.0	15.0	18.0	11.0	13.0
2	3C_zh.wikipedia.org_all-access_spider	1.0	0.0	1.0	1.0	0.0	4.0
3	4minute_zh.wikipedia.org_all-access_spider	35.0	13.0	10.0	94.0	4.0	26.0
4	52_Hz_I_Love_You_zh.wikipedia.org_all-access_s...	NaN	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...
145058	Underworld_(serie_de_películas)_es.wikipedia.o...	NaN	NaN	NaN	NaN	NaN	NaN
145059	Resident_Evil:_Capítulo_Final_es.wikipedia.org...	NaN	NaN	NaN	NaN	NaN	NaN
145060	Enamorándome_de_Ramón_es.wikipedia.org_all-acc...	NaN	NaN	NaN	NaN	NaN	NaN
145061	Hasta_el_último_hombre_es.wikipedia.org_all-ac...	NaN	NaN	NaN	NaN	NaN	NaN
145062	Francisco_el_matemático_(serie_de_televisión_d...	NaN	NaN	NaN	NaN	NaN	NaN

145063 rows × 551 columns

In [5]:

```
ad_ease_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
```

In [6]:

```
ad_ease_train.shape
```

Out[6]:

```
(145063, 551)
```

In [7]:

```
ad_ease_train.describe()
```

Out[7]:

	2015-07-01	2015-07-02	2015-07-03	2015-07-04	2015-07-05	2015-07-06	
count	1.243230e+05	1.242470e+05	1.245190e+05	1.244090e+05	1.244040e+05	1.245800e+05	1
mean	1.195857e+03	1.204004e+03	1.133676e+03	1.170437e+03	1.217769e+03	1.290273e+03	1
std	7.275352e+04	7.421515e+04	6.961022e+04	7.257351e+04	7.379612e+04	8.054448e+04	7
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0
25%	1.300000e+01	1.300000e+01	1.200000e+01	1.300000e+01	1.400000e+01	1.100000e+01	1
50%	1.090000e+02	1.080000e+02	1.050000e+02	1.050000e+02	1.130000e+02	1.130000e+02	1
75%	5.240000e+02	5.190000e+02	5.040000e+02	4.870000e+02	5.400000e+02	5.550000e+02	5
max	2.038124e+07	2.075219e+07	1.957397e+07	2.043964e+07	2.077211e+07	2.254467e+07	2

8 rows × 550 columns

In [8]:

```
ad_ease_train.isnull().sum().sort_values(ascending=False)
```

Out[8]:

```
2015-07-02    20816
2015-07-01    20740
2015-07-07    20664
2015-07-05    20659
2015-07-04    20654
              ...  
2016-12-31     3465
2016-12-20     3268
2016-12-21     3236
2016-12-24     3189
Page              0
Length: 551, dtype: int64
```

Exploratory Data Analysis:

Missing values:

In [9]:

```
df_null = ad_ease_train[ad_ease_train.isnull().any(axis=1)]
```

In [10]:

```
df_null.shape
```

Out[10]:

```
(27786, 551)
```

In [11]:

```
def missing_value(df):
    total_null = df.isnull().sum().sort_values(ascending=False)
    percent_null = ((df.isnull().sum()/df.shape[0])*100).sort_values(ascending = False)
    print(f"Total records in our data = {df.shape[0]}) where missing values are as follows:
    missing_data = pd.concat([total_null,percent_null.round(2)],axis=1,keys=['Total Missing
    return missing_data
```

In [12]:

```
missing_value(ad_ease_train)
```

```
Total records in our data = 145063) where missing values are as follows:
```

Out[12]:

	Total Missing	In Percent
2015-07-02	20816	14.35
2015-07-01	20740	14.30
2015-07-07	20664	14.24
2015-07-05	20659	14.24
2015-07-04	20654	14.24
...	...	...
2016-12-31	3465	2.39
2016-12-20	3268	2.25
2016-12-21	3236	2.23
2016-12-24	3189	2.20
Page	0	0.00

551 rows × 2 columns

- We have imputed the missing values with 0 as we have used the aggregation(mean) on the language for total view counts.

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

In [13]:

```
#page_details = ad_ease_train.Page.str.extract(r'(P.*)\_(P.*).wikipedia.org\_(P.*)\_(P.*)')
ad_ease_train.Page[0:10]
```

Out[13]:

```
0                2NE1_zh.wikipedia.org_all-access_spider
1                 2PM_zh.wikipedia.org_all-access_spider
2                  3C_zh.wikipedia.org_all-access_spider
3             4minute_zh.wikipedia.org_all-access_spider
4     52_Hz_I_Love_You_zh.wikipedia.org_all-access_s...
5                5566_zh.wikipedia.org_all-access_spider
6              91Days_zh.wikipedia.org_all-access_spider
7               A'N'D_zh.wikipedia.org_all-access_spider
8               AKB48_zh.wikipedia.org_all-access_spider
9               ASCII_zh.wikipedia.org_all-access_spider
Name: Page, dtype: object
```

In [14]:

```
page_details=ad_ease_train.Page.str.extract(r'(.*)\_(.*).wikipedia.org\_(.*)\_(.*)')
page_details[0:10]

#(?P.*)\_(?P.*).wikipedia.org\_(?P.*)\_(?P.*)
#page_details = ad_ease_train.Page.str.extract(r'(?P.*)\_(?P.*).wikipedia.org\_(?P.*)\_(?P.
```

Out[14]:

	0	1	2	3
0	2NE1	zh	all-access	spider
1	2PM	zh	all-access	spider
2	3C	zh	all-access	spider
3	4minute	zh	all-access	spider
4	52_Hz_I_Love_You	zh	all-access	spider
5	5566	zh	all-access	spider
6	91Days	zh	all-access	spider
7	A'N'D	zh	all-access	spider
8	AKB48	zh	all-access	spider
9	ASCII	zh	all-access	spider

In [15]:

```
page_details.columns=['topic','lang','access','type']
```

In [16]:

```
page_details[0:10]
```

Out[16]:

	topic	lang	access	type
0	2NE1	zh	all-access	spider
1	2PM	zh	all-access	spider
2	3C	zh	all-access	spider
3	4minute	zh	all-access	spider
4	52_Hz_I_Love_You	zh	all-access	spider
5	5566	zh	all-access	spider
6	91Days	zh	all-access	spider
7	A'N'D	zh	all-access	spider
8	AKB48	zh	all-access	spider
9	ASCII	zh	all-access	spider

In [17]:

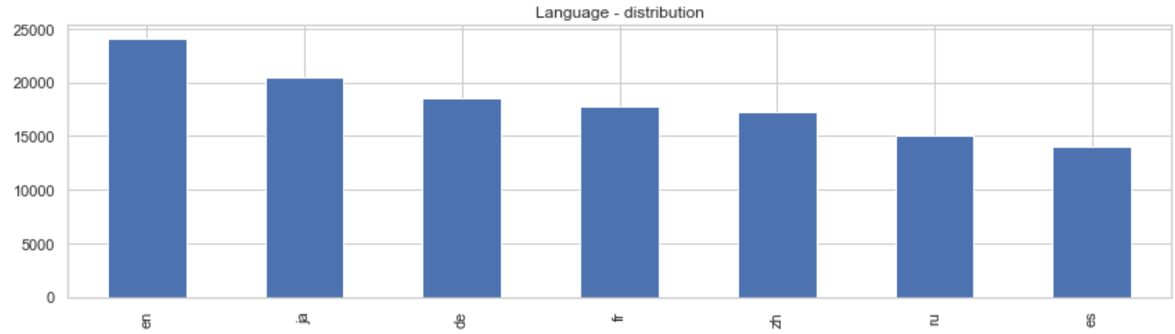
```
page_details["lang"].value_counts().sort_values(ascending  = False)
```

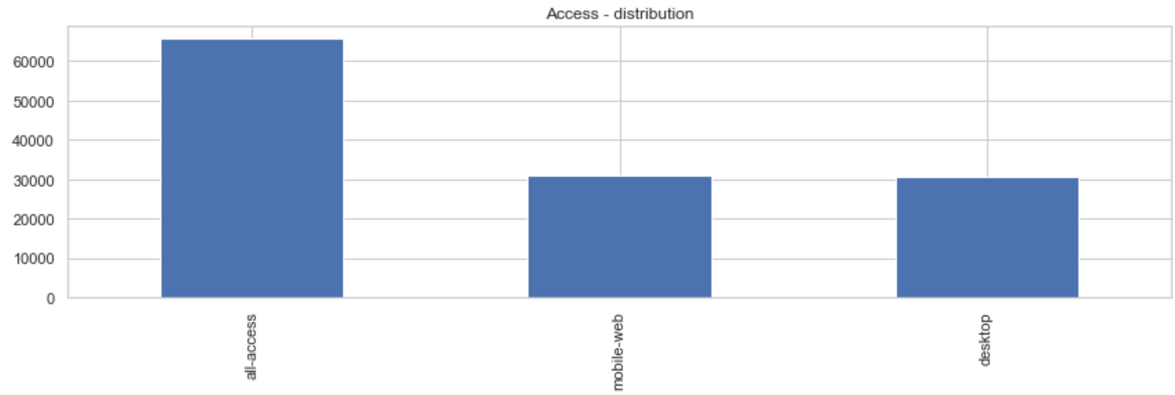
Out[17]:

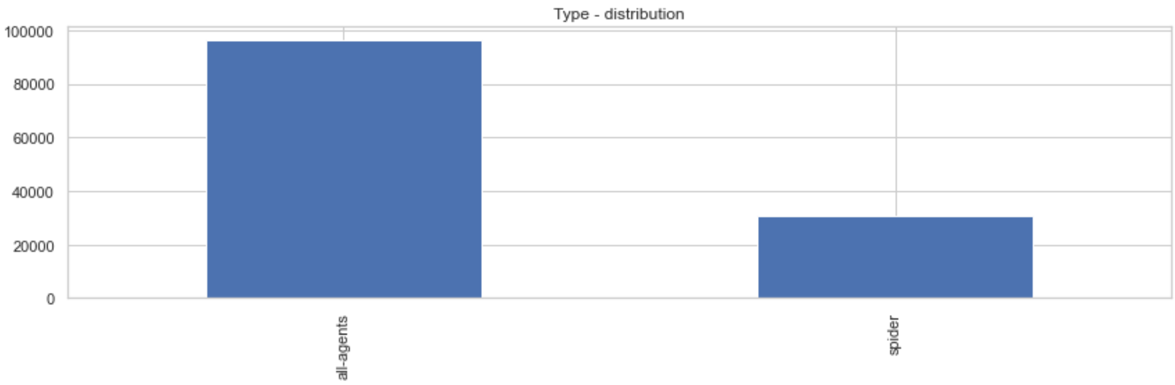
```
en    24108
ja    20431
de    18547
fr    17802
zh    17229
ru    15022
es    14069
Name: lang, dtype: int64
```

In [18]:

```
fig, ax  = plt.subplots(3,1,figsize=(12,12))

page_details["lang"].value_counts().sort_values(ascending  = False).plot.bar(ax=ax[0])
ax[0].set_title('Language - distribution')

page_details["access"].value_counts().sort_values(ascending  = False).plot.bar(ax=ax[1])
ax[1].set_title('Access - distribution')

page_details["type"].value_counts().sort_values(ascending  = False).plot.bar(ax=ax[2])
ax[2].set_title('Type - distribution')

plt.tight_layout()
```







- English webpages are the mostly viewed pages whereas Spanish(es) are the least viewed.
- All access would be prefered as we are getting maximum no. of view counts.
- The distribution type is via all agents (is preferred) as we are getting most of the views unlike via spider distribution

In [19]:

```
train_df = pd.concat([page_details, ad_ease_train],axis=1)
```

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

In [20]:

```
train_df.head(3)
```

Out[20]:

	topic	lang	access	type	Page	2015-07-01	2015-07-02	2015-07-03	2015-07-04	2015-07-05	...
0	2NE1	zh	all-access	spider	2NE1_zh.wikipedia.org_all-access_spider	18.0	11.0	5.0	13.0	14.0	...
1	2PM	zh	all-access	spider	2PM_zh.wikipedia.org_all-access_spider	11.0	14.0	15.0	18.0	11.0	...
2	3C	zh	all-access	spider	3C_zh.wikipedia.org_all-access_spider	1.0	0.0	1.0	1.0	0.0	...

3 rows × 555 columns

In [21]:

```
train_df['lang'].nunique()
```

Out[21]:

7

In [22]:

```
train_df['topic'].nunique()
```

Out[22]:

42212

In [23]:

```
train_df['access'].nunique()
```

Out[23]:

3

In [24]:

```
en_df = train_df[train_df['lang']=='en'].iloc[:,:].mean().to_frame().iloc[:,:].reset_index(
```

In [25]:

```
en_df
```

Out[25]:

	index	en
0	2015-07-01	4120.242704
1	2015-07-02	4096.969675
2	2015-07-03	3863.318780
3	2015-07-04	4020.385549
4	2015-07-05	4157.757910
...	...	...
545	2016-12-27	6189.329381
546	2016-12-28	6032.638712
547	2016-12-29	6425.295920
548	2016-12-30	5353.679346
549	2016-12-31	5180.347343

550 rows × 2 columns

In [26]:

```
lang_list=list(train_df['lang'].unique())
```

In [27]:

```
lang_list
```

Out[27]:

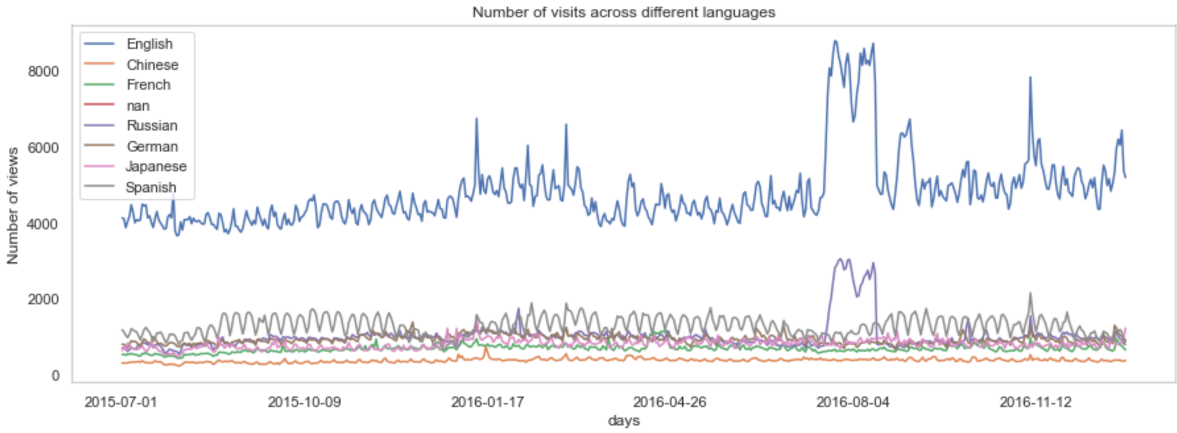
['zh', 'fr', 'en', nan, 'ru', 'de', 'ja', 'es']

In [28]:

```
df = train_df
```

In [29]:

```
all_languages = df[df['lang'] == 'en'].iloc[:,:].mean().to_frame().iloc[:,:].reset_index().
for i in df['lang'].unique():
    tdf = df[df['lang'] == i].iloc[:,:].mean().to_frame().iloc[:,:].reset_index().rename(co
    all_languages[i] = tdf[i]
all_languages.rename(columns={'en':'English','zh':'Chinese','fr':'French','na':'Media','ru'
all_languages.set_index("index").plot(kind='line',figsize=(15,5))
plt.grid()
plt.title("Number of visits across different languages")
plt.xlabel("days")
plt.ylabel("Number of views")
plt.show()
```



- As we can see, during the month of August, 2016 we are seeing a huge spike in the number of views on the web pages. As these are anamolies, we will treat these outliers using simple IQR based method.

In [30]:

```
all_languages
```

Out[30]:

	index	English	Chinese	French	NaN	Russian	German	Japanese
0	2015-07-01	4120.242704	306.174324	526.624206	NaN	694.492845	801.433519	637.635044
1	2015-07-02	4096.969675	306.180041	530.038727	NaN	706.667866	790.469330	732.300645
2	2015-07-03	3863.318780	304.711372	509.429958	NaN	654.068973	758.689914	661.188706
3	2015-07-04	4020.385549	307.106882	544.347518	NaN	615.880100	697.106317	830.489442
4	2015-07-05	4157.757910	326.373163	534.101778	NaN	655.269262	809.890360	796.904439
...	...	...	...	...	...	...	...	...
545	2016-12-27	6189.329381	380.391169	861.947656	NaN	1008.121724	1095.848843	804.676399
546	2016-12-28	6032.638712	382.556091	777.255710	NaN	938.610821	1042.817652	806.809621
547	2016-12-29	6425.295920	354.776010	755.727032	NaN	903.053531	1004.514348	883.427658
548	2016-12-30	5353.679346	358.554506	703.626382	NaN	808.817615	958.359915	970.883847
549	2016-12-31	5180.347343	369.829429	648.626656	NaN	886.737728	900.882241	1222.550930

550 rows × 9 columns

In [31]:

```
all_languages =all_languages.rename(columns={'index':'Dates'})
```

In [32]:

```
all_languages =all_languages.dropna(axis = 1)
```

In [33]:

```
all_languages
```

Out[33]:

	Dates	English	Chinese	French	Russian	German	Japanese	S
0	2015-07-01	4120.242704	306.174324	526.624206	694.492845	801.433519	637.635044	1176.
1	2015-07-02	4096.969675	306.180041	530.038727	706.667866	790.469330	732.300645	1125.
2	2015-07-03	3863.318780	304.711372	509.429958	654.068973	758.689914	661.188706	1035.
3	2015-07-04	4020.385549	307.106882	544.347518	615.880100	697.106317	830.489442	972.
4	2015-07-05	4157.757910	326.373163	534.101778	655.269262	809.890360	796.904439	1056.
...	...	...	...	...	...	...	...	
545	2016-12-27	6189.329381	380.391169	861.947656	1008.121724	1095.848843	804.676399	1138.
546	2016-12-28	6032.638712	382.556091	777.255710	938.610821	1042.817652	806.809621	1184.
547	2016-12-29	6425.295920	354.776010	755.727032	903.053531	1004.514348	883.427658	1117.
548	2016-12-30	5353.679346	358.554506	703.626382	808.817615	958.359915	970.883847	825.
549	2016-12-31	5180.347343	369.829429	648.626656	886.737728	900.882241	1222.550930	791.

550 rows × 8 columns

In [34]:

```
all_languages.Dates = pd.to_datetime(all_languages.Dates)
```

In [35]:

```
eng_df = all_languages[['Dates','English']].set_index('Dates').reset_index()
```

In [36]:

```
eng_df
```

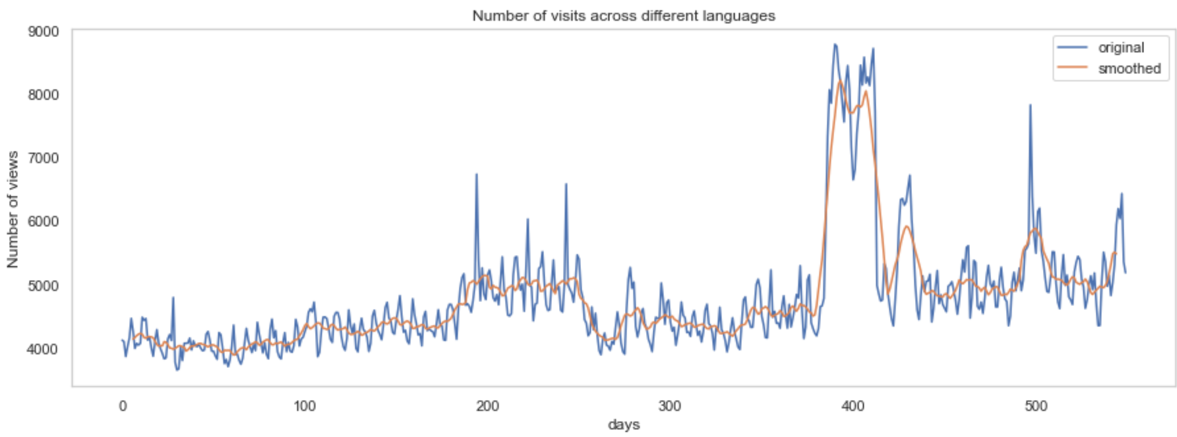
Out[36]:

	Dates	English
0	2015-07-01	4120.242704
1	2015-07-02	4096.969675
2	2015-07-03	3863.318780
3	2015-07-04	4020.385549
4	2015-07-05	4157.757910
...	...	...
545	2016-12-27	6189.329381
546	2016-12-28	6032.638712
547	2016-12-29	6425.295920
548	2016-12-30	5353.679346
549	2016-12-31	5180.347343

550 rows × 2 columns

In [37]:

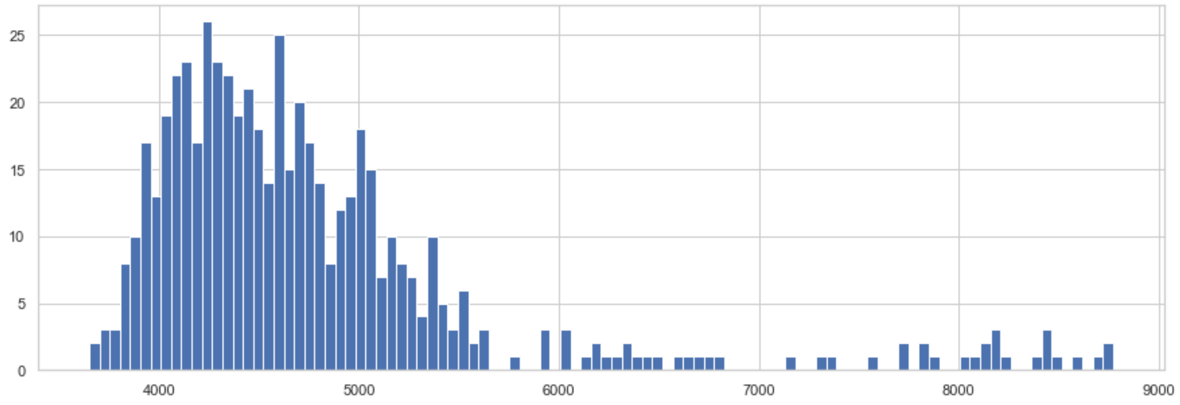
```
# centered MA: typically used for imputation
eng_df.English.plot(label='original')
eng_df.English.rolling(12, center=True).mean().plot(label='smoothed',figsize=(15,5))
plt.legend()
plt.grid()
plt.title("Number of visits across different languages")
plt.xlabel("days")
plt.ylabel("Number of views")
plt.show()
```



Percentiles based outlier removal/detection:

In [38]:

```
# Remove anamolies using percentiles
plt.figure(figsize=(15,5))
eng_df.English.hist(bins=100).plot()
plt.show()
```



In [39]:

```
eng_df.English.describe()
```

Out[39]:

```
count     550.000000
mean     4773.277263
std       926.906700
min      3650.296939
25%      4216.631281
50%      4558.549069
75%      5000.271195
max      8772.509464
Name: English, dtype: float64
```

In [40]:

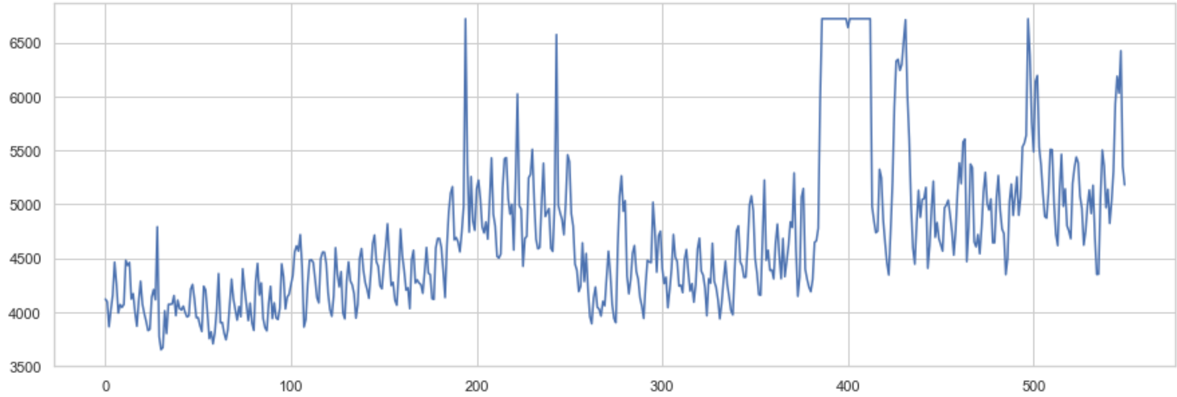
```
eng_df.English.quantile(0.95)
```

Out[40]:

```
6723.037270821685
```

In [41]:

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

eng_df.English.clip(upper=eng_df.English.quantile(0.95)).plot()
plt.show()
```



- After clipping to 95th percentile, we can clearly see the trend (increasing) in the no. of view counts.

In [42]:

```
eng_df = eng_df.English.clip(upper=eng_df.English.quantile(0.95))
```

- I have used 95th percentile to clip all the view counts beyond it as they are coming due to the fact (exogenous/any significant event)

In [43]:

```
all_languages.shape
```

Out[43]:

```
(550, 8)
```

In [44]:

```
list_lang_fin = list(all_languages.columns)
list_lang_fin
```

Out[44]:

```
['Dates',
 'English',
 'Chinese',
 'French',
 'Russian',
 'German',
 'Japanese',
 'Spanish']
```

In [45]:

```
list_lang_fin = list_lang_fin[1:]
```

In [46]:

```
list_lang_fin
```

Out[46]:

```
['English', 'Chinese', 'French', 'Russian', 'German', 'Japanese', 'Spanish']
```

In [47]:

```
final_lang_df = eng_df
for i in list_lang_fin[1:]:

    new_lang_df = all_languages[i].clip(upper=all_languages[i].quantile(0.95))
    final_lang_df = pd.concat([final_lang_df,new_lang_df], axis = 1)
```

In [48]:

```
final_lang_df
```

Out[48]:

	English	Chinese	French	Russian	German	Japanese	Spanish
0	4120.242704	306.174324	526.624206	694.492845	801.433519	637.635044	1176.993529
1	4096.969675	306.180041	530.038727	706.667866	790.469330	732.300645	1125.926357
2	3863.318780	304.711372	509.429958	654.068973	758.689914	661.188706	1035.044477
3	4020.385549	307.106882	544.347518	615.880100	697.106317	830.489442	972.426566
4	4157.757910	326.373163	534.101778	655.269262	809.890360	796.904439	1056.349179
...	...	...	...	...	...	...	...
545	6189.329381	380.391169	825.957589	1008.121724	1095.848843	804.676399	1138.872438
546	6032.638712	382.556091	777.255710	938.610821	1042.817652	806.809621	1184.690560
547	6425.295920	354.776010	755.727032	903.053531	1004.514348	883.427658	1117.971921
548	5353.679346	358.554506	703.626382	808.817615	958.359915	970.883847	825.957059
549	5180.347343	369.829429	648.626656	886.737728	900.882241	991.608202	791.449882

550 rows × 7 columns

Checking stationarity:

1.Formatting the data for the model

In [49]:

```
df = pd.concat([all_languages.iloc[:,:1], final_lang_df] , axis = 1)
df
```

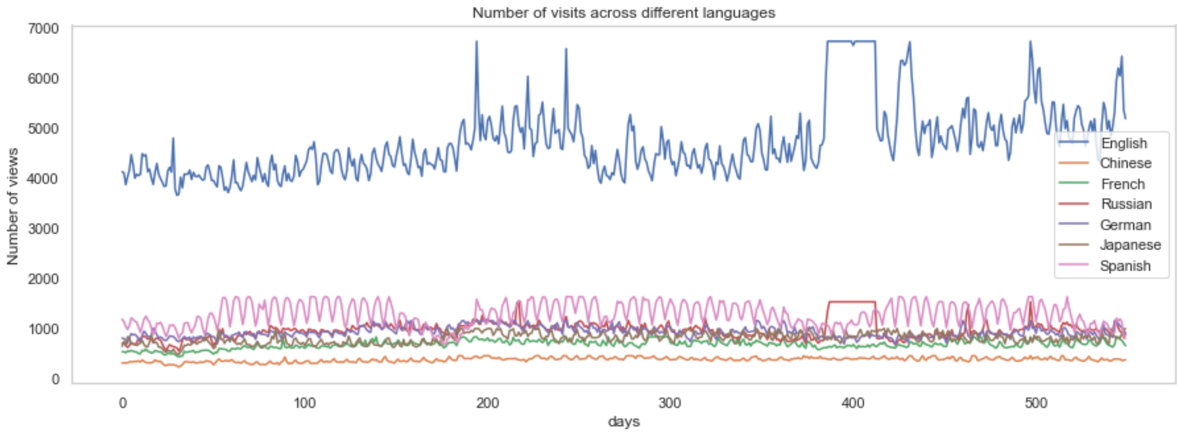
Out[49]:

	Dates	English	Chinese	French	Russian	German	Japanese	Sp
0	2015-07-01	4120.242704	306.174324	526.624206	694.492845	801.433519	637.635044	1176.9
1	2015-07-02	4096.969675	306.180041	530.038727	706.667866	790.469330	732.300645	1125.9
2	2015-07-03	3863.318780	304.711372	509.429958	654.068973	758.689914	661.188706	1035.0
3	2015-07-04	4020.385549	307.106882	544.347518	615.880100	697.106317	830.489442	972.4
4	2015-07-05	4157.757910	326.373163	534.101778	655.269262	809.890360	796.904439	1056.3
...	...	...	...	...	...	...	...	
545	2016-12-27	6189.329381	380.391169	825.957589	1008.121724	1095.848843	804.676399	1138.8
546	2016-12-28	6032.638712	382.556091	777.255710	938.610821	1042.817652	806.809621	1184.6
547	2016-12-29	6425.295920	354.776010	755.727032	903.053531	1004.514348	883.427658	1117.9
548	2016-12-30	5353.679346	358.554506	703.626382	808.817615	958.359915	970.883847	825.9
549	2016-12-31	5180.347343	369.829429	648.626656	886.737728	900.882241	991.608202	791.4

550 rows × 8 columns

In [50]:

```
final_lang_df.iloc[:,:].plot(kind='line',figsize=(15,5))
plt.grid()
plt.title("Number of visits across different languages")
plt.xlabel("days")
plt.ylabel("Number of views")
plt.show()
```



2.Dickey fuller test

In [51]:

```
from statsmodels.tsa.stattools import adfuller# ADF Test

for i in list_lang_fin:
    result = adfuller(all_languages[['Dates',i]].set_index('Dates'), autolag='AIC')
    # Extracting the values from the results:
    print(result)
    print('ADF Statistic: %f' % result[0])

    print('p-value: %f' % result[1])

    print('Critical Values:')

    for key, value in result[4].items():
        print('\t%s: %.3f' % (key, value))
    if result[0] < result[4]["5%"]:
        print (f"Reject Ho - Time Series is Stationary for {i} language page views")
    else:
        print (f"Failed to Reject Ho - Time Series is Non-Stationary for {i} language page
    print('-'*120)
    print('-'*120)
```

```
(-2.5405988735088383, 0.10590600305281189, 14, 535, {'1%': -3.44263215555209
05, '5%': -2.86695748394138, '10%': -2.5696553279762426}, 7697.34031063618)
ADF Statistic: -2.540599
p-value: 0.105906
Critical Values:
        1%: -3.443
        5%: -2.867
        10%: -2.570
Failed to Reject Ho - Time Series is Non-Stationary for English language pag
e views
----------------------------------------------------------------------------
--------------------------------------------
----------------------------------------------------------------------------
--------------------------------------------
(-2.1682373404138966, 0.21797471929344492, 19, 530, {'1%': -3.44274859335558
86, '5%': -2.8670087381529723, '10%': -2.569682641509434}, 5073.13836417610
7)
ADF Statistic: -2.168237
p-value: 0.217975
Critical Values:
        1%: -3.443
        5%: -2.867
        10%: -2.570
Failed to Reject Ho - Time Series is Non-Stationary for Chinese language pag
e views
----------------------------------------------------------------------------
--------------------------------------------
----------------------------------------------------------------------------
--------------------------------------------
(-3.089264885968547, 0.027357902773498328, 13, 536, {'1%': -3.44260912994227
4, '5%': -2.866947348175723, '10%': -2.569649926626197}, 5730.819559834136)
ADF Statistic: -3.089265
p-value: 0.027358
Critical Values:
        1%: -3.443
        5%: -2.867
        10%: -2.570
```

```
Reject Ho - Time Series is Stationary for French language page views
----------------------------------------------------------------------------
--------------------------------------------
----------------------------------------------------------------------------
--------------------------------------------
(-3.976066773544456, 0.0015411500043748221, 3, 546, {'1%': -3.44238353487127
5, '5%': -2.8668480382580386, '10%': -2.569597004924258}, 6613.514779950347)
ADF Statistic: -3.976067
p-value: 0.001541
Critical Values:
        1%: -3.442
        5%: -2.867
        10%: -2.570
Reject Ho - Time Series is Stationary for Russian language page views
----------------------------------------------------------------------------
--------------------------------------------
----------------------------------------------------------------------------
--------------------------------------------
(-2.4834127902000716, 0.11956251043822996, 16, 533, {'1%': -3.44267846724096
6, '5%': -2.8669778698997543, '10%': -2.5696661916864083}, 5890.94169324384
2)
ADF Statistic: -2.483413
p-value: 0.119563
Critical Values:
        1%: -3.443
        5%: -2.867
        10%: -2.570
Failed to Reject Ho - Time Series is Non-Stationary for German language page
views
----------------------------------------------------------------------------
--------------------------------------------
----------------------------------------------------------------------------
--------------------------------------------
(-2.8737334050595957, 0.048488815704921785, 8, 541, {'1%': -3.44249528488780
5, '5%': -2.86689723299801, '10%': -2.5696232204003677}, 6122.913108094406)
ADF Statistic: -2.873733
p-value: 0.048489
Critical Values:
        1%: -3.442
        5%: -2.867
        10%: -2.570
Reject Ho - Time Series is Stationary for Japanese language page views
----------------------------------------------------------------------------
--------------------------------------------
----------------------------------------------------------------------------
--------------------------------------------
(-3.017856656657231, 0.03326012989540662, 15, 534, {'1%': -3.442655267821600
3, '5%': -2.8669676577777548, '10%': -2.569660749624767}, 6199.097158858442
5)
ADF Statistic: -3.017857
p-value: 0.033260
Critical Values:
        1%: -3.443
        5%: -2.867
        10%: -2.570
Reject Ho - Time Series is Stationary for Spanish language page views
----------------------------------------------------------------------------
--------------------------------------------
----------------------------------------------------------------------------
--------------------------------------------
```

- Time Series is Non-Stationary for English language page views
- Time Series is Non-Stationary for Chinese language page views
- Time Series is Stationary for French language page views
- Time Series is Stationary for Russian language page views
- Time Series is Non-Stationary for German language page views
- Time Series is Stationary for Japanese language page views
- Time Series is Stationary for Spanish language page views

3. Decomposing time-series:

- English language pages:

In [52]:

```
df
```

Out[52]:

	Dates	English	Chinese	French	Russian	German	Japanese	Sp
0	2015-07-01	4120.242704	306.174324	526.624206	694.492845	801.433519	637.635044	1176.9
1	2015-07-02	4096.969675	306.180041	530.038727	706.667866	790.469330	732.300645	1125.9
2	2015-07-03	3863.318780	304.711372	509.429958	654.068973	758.689914	661.188706	1035.0
3	2015-07-04	4020.385549	307.106882	544.347518	615.880100	697.106317	830.489442	972.4
4	2015-07-05	4157.757910	326.373163	534.101778	655.269262	809.890360	796.904439	1056.3
...	...	...	...	...	...	...	...	
545	2016-12-27	6189.329381	380.391169	825.957589	1008.121724	1095.848843	804.676399	1138.8
546	2016-12-28	6032.638712	382.556091	777.255710	938.610821	1042.817652	806.809621	1184.6
547	2016-12-29	6425.295920	354.776010	755.727032	903.053531	1004.514348	883.427658	1117.9
548	2016-12-30	5353.679346	358.554506	703.626382	808.817615	958.359915	970.883847	825.9
549	2016-12-31	5180.347343	369.829429	648.626656	886.737728	900.882241	991.608202	791.4

550 rows × 8 columns

In [53]:

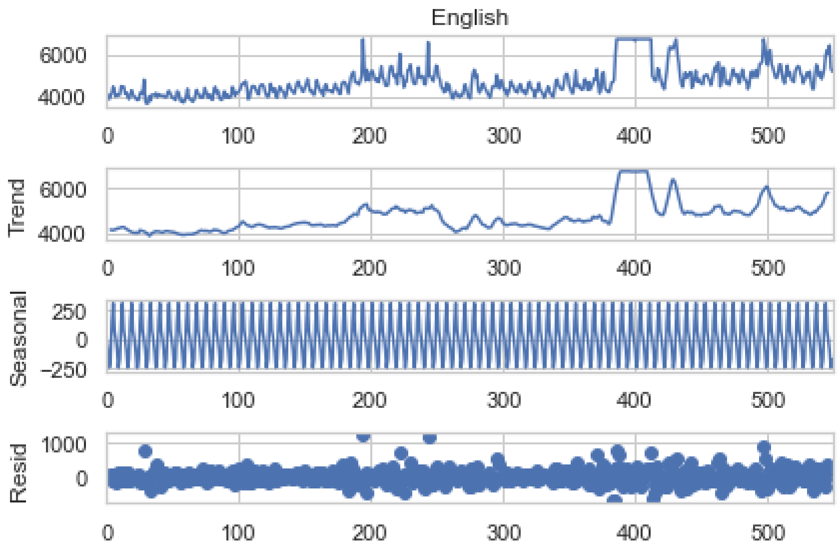
```
df.Dates = pd.to_datetime(df.Dates)
```

In [54]:

```
#additive decomposition
import statsmodels.api as sm

model = sm.tsa.seasonal_decompose(df.English, model='additive', period = 7)
```

In [55]:

```
# By default, we get the plot twice with this functionality
# We add ; to avoid seeing the plot

model.plot()
plt.show()
```

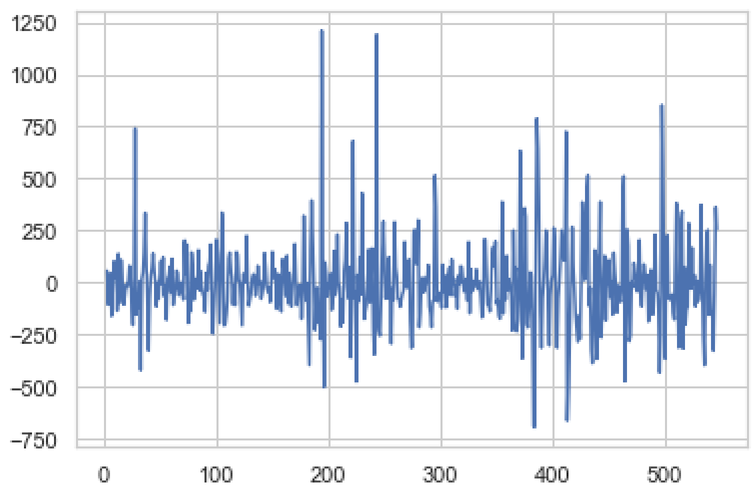


In [56]:

```
model.resid.plot()
```

Out[56]:

<AxesSubplot:>

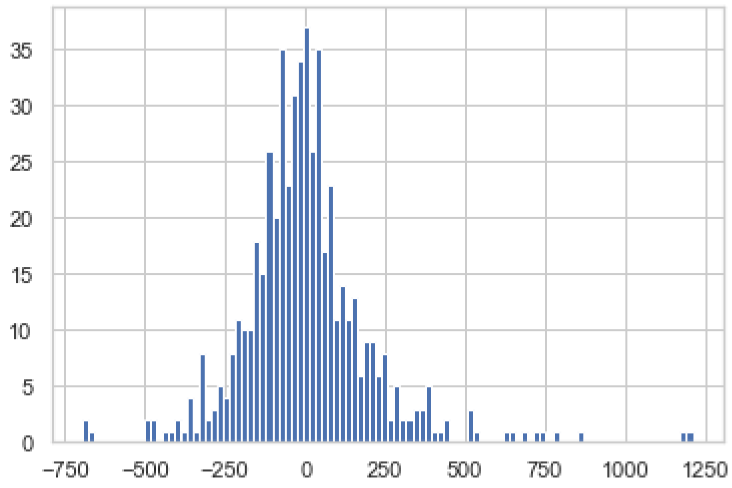


In [57]:

```
model.resid.hist(bins=100)
```

Out[57]:

<AxesSubplot:>



In [58]:

```
model.resid.mean()
```

Out[58]:

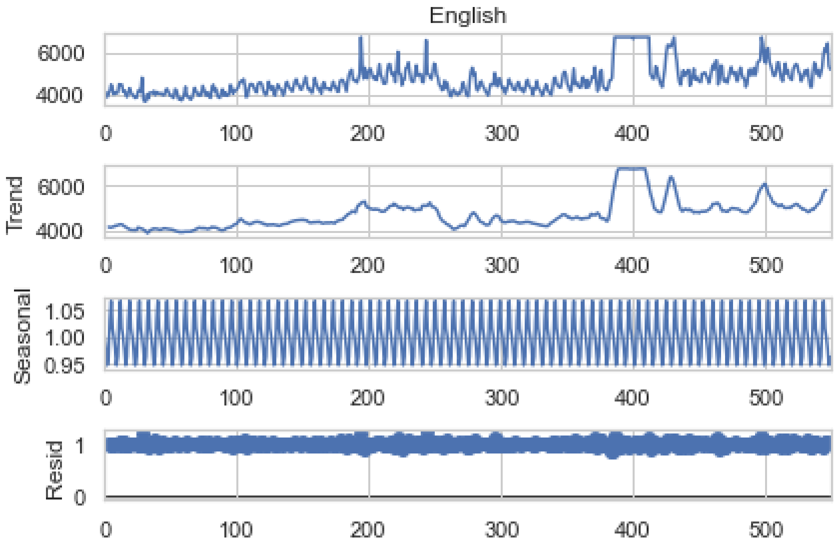
-0.08045337562489967

In [59]:

```
#multiplicative decomposition
import statsmodels.api as sm

model = sm.tsa.seasonal_decompose(df.English, model='multiplicative', period = 7)
```

In [60]:

```
# By default, we get the plot twice with this functionality
# We add ; to avoid seeing the plot

model.plot()
plt.show()
```



- As we can clearly see from the decomposition that there's a seasonality present.
- There's also an increasing trend

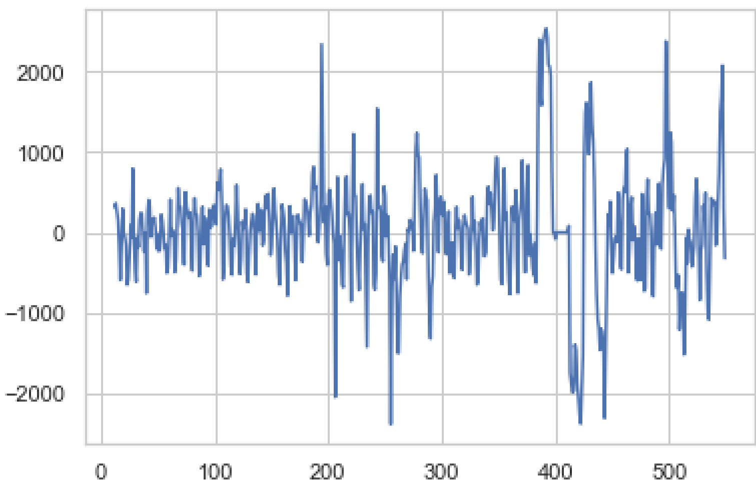
4. Differencing the series.

In [61]:

```
# de-seasonalisation
deseas = df.English.diff(12)
deseas.plot()
```

Out[61]:

```
<AxesSubplot:>
```



Creating model training and forecasting with ARIMA, SARIMAX

AutoCorrelation and PartialAutoCorrelation

In [62]:

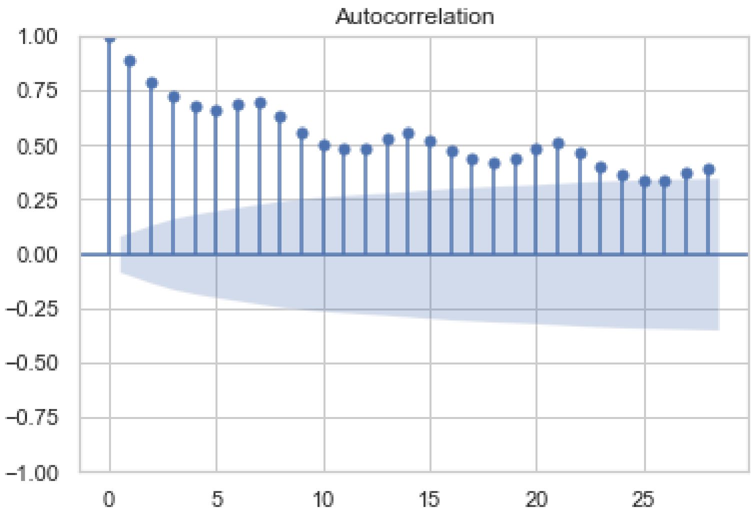
```
lag = 1
np.corrcoef(df.English[lag:],df.English.shift(lag)[lag:])[0][1]
```

Out[62]:

```
0.892969566894908
```

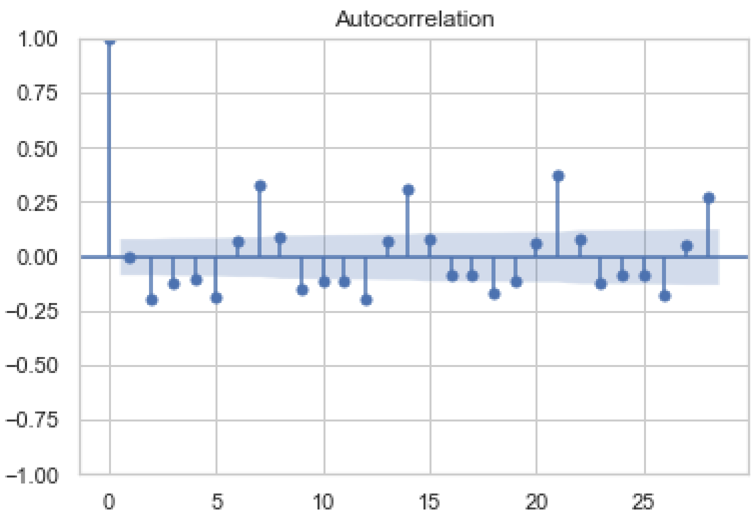
In [63]:

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
plot_acf(df.English);
```



In [64]:

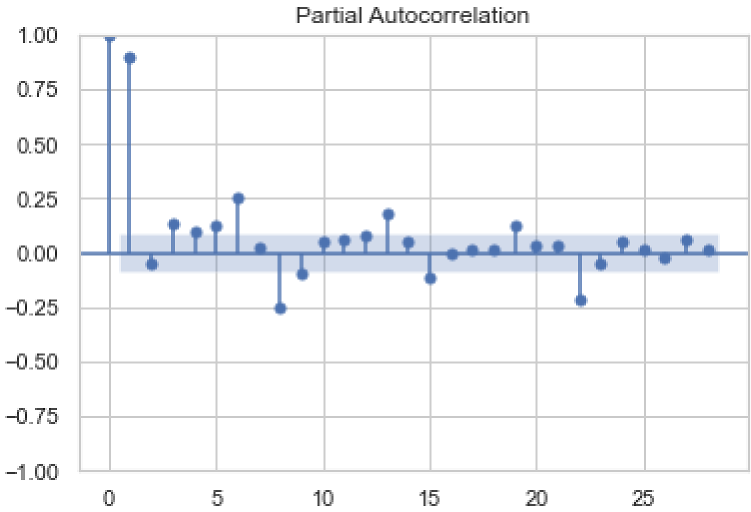
```
# for detrended time-series
plot_acf(df.English.diff().dropna());
```



- As, ACF plot is useful for identifying non-stationary time series. For a stationary time series, the ACF will drop to zero relatively quickly, while the ACF of non-stationary data decreases slowly.
- Which shows that the seasonality is of 7 days. (weekly)

In [65]:

```
# PACF
plot_pacf(df.English);
```



In [66]:

```
df_copy = df
```

In [67]:

```
df = df.set_index('Dates')
```

In [68]:

```
df
```

Out[68]:

	English	Chinese	French	Russian	German	Japanese	Spanish
Dates							
2015-07-01	4120.242704	306.174324	526.624206	694.492845	801.433519	637.635044	1176.993529
2015-07-02	4096.969675	306.180041	530.038727	706.667866	790.469330	732.300645	1125.926357
2015-07-03	3863.318780	304.711372	509.429958	654.068973	758.689914	661.188706	1035.044477
2015-07-04	4020.385549	307.106882	544.347518	615.880100	697.106317	830.489442	972.426566
2015-07-05	4157.757910	326.373163	534.101778	655.269262	809.890360	796.904439	1056.349179
...	...	...	...	...	...	...	...
2016-12-27	6189.329381	380.391169	825.957589	1008.121724	1095.848843	804.676399	1138.872438
2016-12-28	6032.638712	382.556091	777.255710	938.610821	1042.817652	806.809621	1184.690560
2016-12-29	6425.295920	354.776010	755.727032	903.053531	1004.514348	883.427658	1117.971921
2016-12-30	5353.679346	358.554506	703.626382	808.817615	958.359915	970.883847	825.957059
2016-12-31	5180.347343	369.829429	648.626656	886.737728	900.882241	991.608202	791.449882

550 rows × 7 columns

In [69]:

```
#last 50 days as test

train_x = df.loc[df.index < df.index[-50]].copy()
test_x = df.loc[df.index >= df.index[-50]].copy()
test_x.shape
```

Out[69]:

```
(50, 7)
```

In [70]:

```
test_x1 = test_x.iloc[:,:1]
test_x1.shape
```

Out[70]:

```
(50, 1)
```

In [71]:

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

# Creating a function to print values of all these metrics.
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))
```

Foundational models and trainings:

Mean model

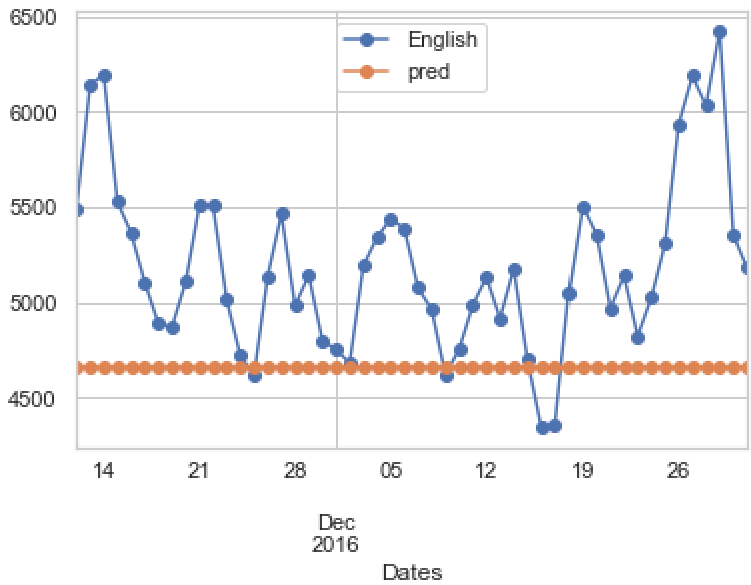
In [72]:

```
#train mean as test predicted
test_x['pred'] = train_x['English'].mean()

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

performance(test_x['English'], test_x['pred'])
plt.legend()
```

```
MAE : 562.011
RMSE : 704.079
MAPE: 0.102
```

Out[72]:

```
<matplotlib.legend.Legend at 0x2681409ad60>
```



Seasonal Naive:

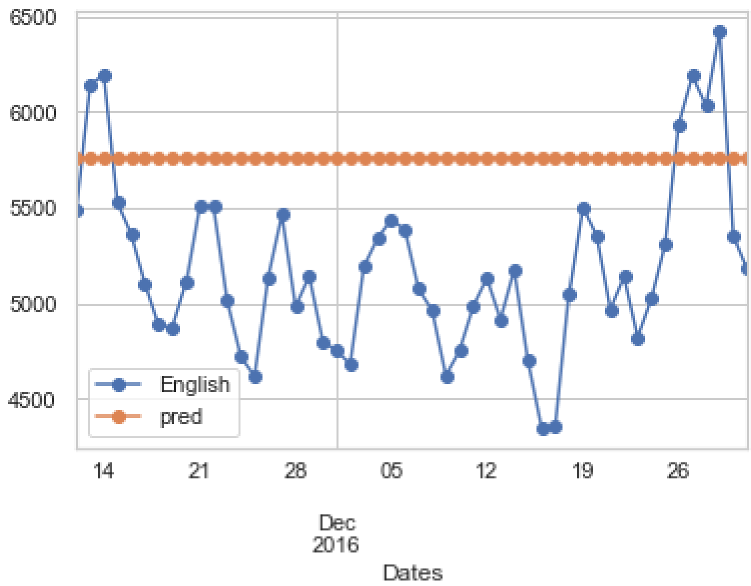
In [73]:

```
#Simple Naive
## Last value as the value at all future values: high variance model
test_x['pred'] = train_x['English'][-1]

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

performance(test_x['English'], test_x['pred'])
plt.legend()
```

```
MAE : 660.914
RMSE : 729.16
MAPE: 0.133
```

Out[73]:

```
<matplotlib.legend.Legend at 0x268140c9850>
```



In [74]:

```
test_x.index
```

Out[74]:

```
DatetimeIndex(['2016-11-12', '2016-11-13', '2016-11-14', '2016-11-15',
               '2016-11-16', '2016-11-17', '2016-11-18', '2016-11-19',
               '2016-11-20', '2016-11-21', '2016-11-22', '2016-11-23',
               '2016-11-24', '2016-11-25', '2016-11-26', '2016-11-27',
               '2016-11-28', '2016-11-29', '2016-11-30', '2016-12-01',
               '2016-12-02', '2016-12-03', '2016-12-04', '2016-12-05',
               '2016-12-06', '2016-12-07', '2016-12-08', '2016-12-09',
               '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', '2016-12-20', '2016-12-21',
               '2016-12-22', '2016-12-23', '2016-12-24', '2016-12-25',
               '2016-12-26', '2016-12-27', '2016-12-28', '2016-12-29',
               '2016-12-30', '2016-12-31'],
              dtype='datetime64[ns]', name='Dates', freq=None)
```

In [75]:

```
test_x.head(3)
```

Out[75]:

	English	Chinese	French	Russian	German	Japanese	Spanish
Dates							
2016-11-12	5487.667243	407.264755	825.682597	1017.099623	899.935765	779.382937	1128.540873
2016-11-13	6140.359217	425.872392	767.825473	1095.276586	1021.387068	835.054576	1318.801136
2016-11-14	6196.286645	382.971699	746.839165	1065.850514	1033.071648	812.220358	1540.315464

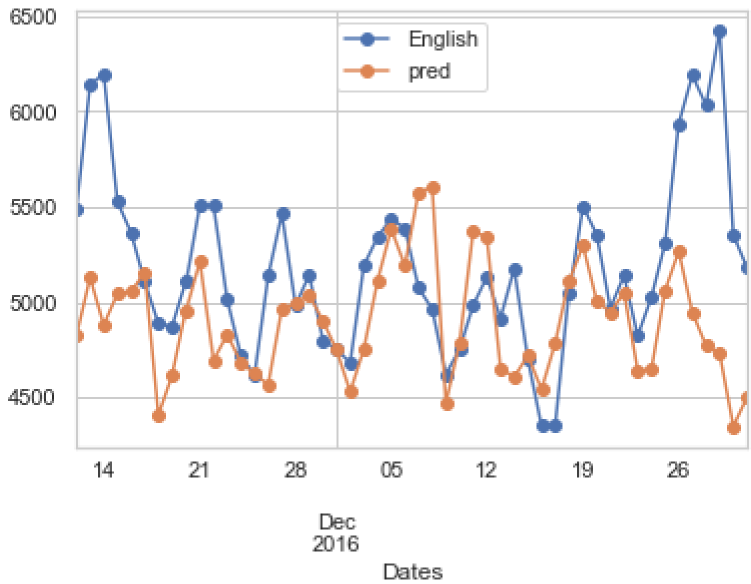
In [76]:

```
## Seasonal Naive forecast: 63 days based on ACF and PACF plots
for i in test_x.index:
    test_x.loc[i]['pred'] = train_x.loc[i - pd.DateOffset(days = 63)]['English']

test_x['English'].plot(style='-o')
test_x['pred'].plot(style='-o')
performance(test_x['English'], test_x['pred'])
plt.legend()
```

```
MAE : 398.319
RMSE : 554.8
MAPE: 0.073
```

Out[76]:

```
<matplotlib.legend.Legend at 0x2681431b2e0>
```



Moving average forecast:

In [77]:

```
train_x1 = train_x.iloc[:,:1]
```

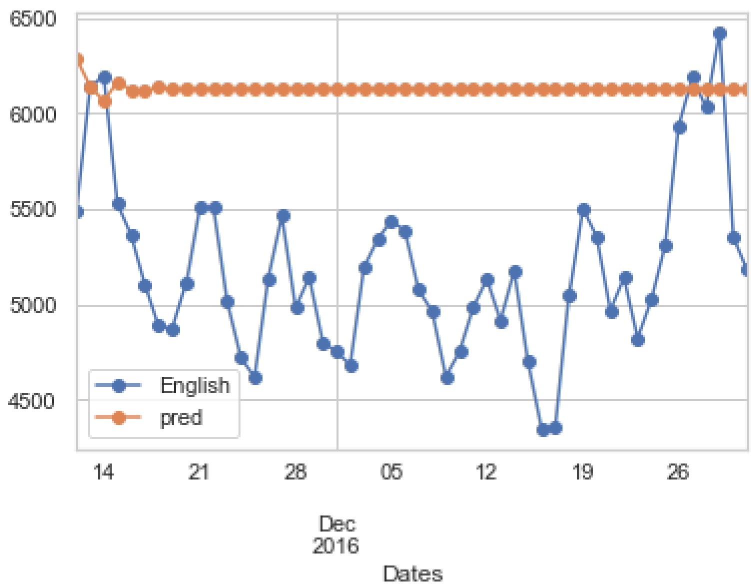
In [78]:

```
df = train_x1.copy()

df = df.append(pd.DataFrame(index = pd.date_range(start=df.index[-1], periods=50)[1:]))

pred = df.English.dropna().values

for i in range(50):
    pred = np.append(pred, pred[-3:].mean()) ##MA of window-length=3

test_x['pred'] = pred[-50:]
test_x['English'].plot(style='-o')
test_x['pred'].plot(style='-o')
performance(test_x['English'], test_x['pred'])
plt.legend()
```

```
MAE : 956.814
RMSE : 1043.618
MAPE: 0.192
```

Out[78]:

```
<matplotlib.legend.Legend at 0x26817b20d30>
```



ARIMA & SARIMA Models

ARIMA(p,d,q)

In [79]:

```
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
from sklearn.model_selection import StratifiedKFold

import datetime as dt

params = {
        'p': [1, 2, 3],
        'd': [1, 2],
        'q': [1, 2, 3],

        }
```

In [80]:

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

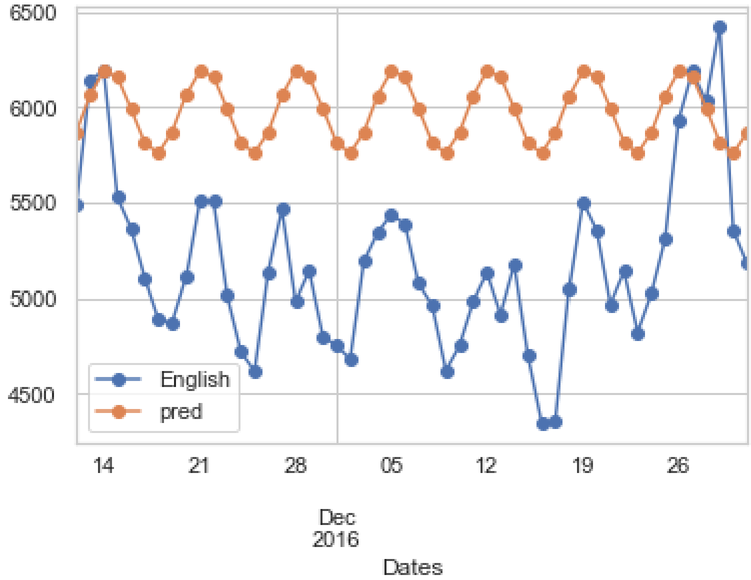
In [81]:

```
from statsmodels.tsa.statespace.sarimax import SARIMAX
model = SARIMAX(train_x.English, order=(3, 1, 3))
# RandomizedSearchCV(model, param_distributions=params)
model = model.fit(disp=False)
test_x['pred'] = model.forecast(steps=50)
test_x['English'].plot(style='-o')
test_x['pred'].plot(style='-o')
performance(test_x['English'], test_x['pred'])
plt.legend()
```

```
C:\Users\hp\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:47
1: ValueWarning: No frequency information was provided, so inferred frequenc
y D will be used.
  self._init_dates(dates, freq)
C:\Users\hp\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:47
1: ValueWarning: No frequency information was provided, so inferred frequenc
y D will be used.
  self._init_dates(dates, freq)
C:\Users\hp\anaconda3\lib\site-packages\statsmodels\base\model.py:604: Conve
rgenceWarning: Maximum Likelihood optimization failed to converge. Check mle
_retvals
  warnings.warn("Maximum Likelihood optimization failed to "

MAE : 813.327
RMSE : 880.714
MAPE: 0.163
```

Out[81]:

```
<matplotlib.legend.Legend at 0x26817b349d0>
```



SARIMA (p,d,q,P,D,Q,s)

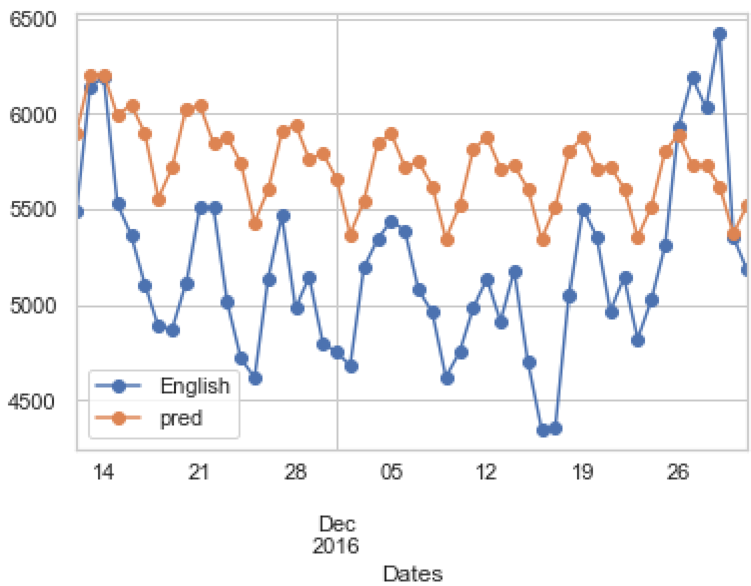
In [82]:

```
model = SARIMAX(train_x.English, order=(3, 1, 3), seasonal_order=(1,1,1,7))
model = model.fit(disp=False)
test_x['pred'] = model.forecast(steps=50)
test_x['English'].plot(style='-o')
test_x['pred'].plot(style='-o')
performance(test_x['English'], test_x['pred'])
plt.legend()
```

```
C:\Users\hp\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:47
1: ValueWarning: No frequency information was provided, so inferred frequenc
y D will be used.
  self._init_dates(dates, freq)
C:\Users\hp\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:47
1: ValueWarning: No frequency information was provided, so inferred frequenc
y D will be used.
  self._init_dates(dates, freq)
C:\Users\hp\anaconda3\lib\site-packages\statsmodels\base\model.py:604: Conve
rgenceWarning: Maximum Likelihood optimization failed to converge. Check mle
_retvals
  warnings.warn("Maximum Likelihood optimization failed to "


MAE : 603.111
RMSE : 660.853
MAPE: 0.12
```

Out[82]:

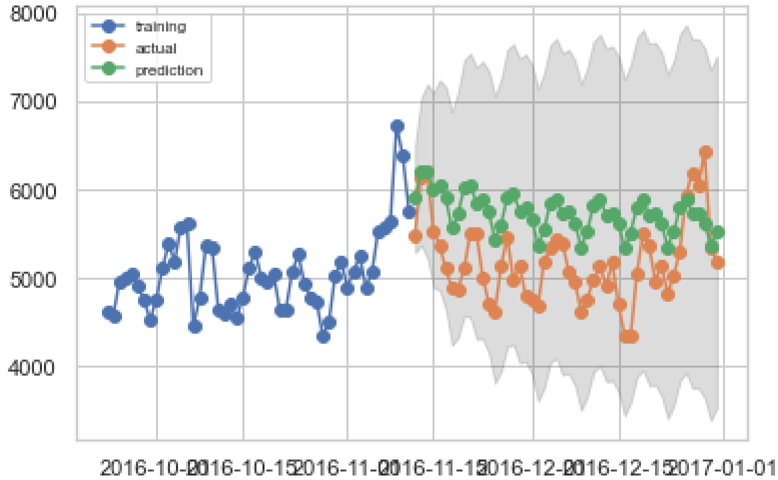
```
<matplotlib.legend.Legend at 0x26817ba8130>
```



SARIMA with 95% C.I

In [83]:

```
test_x[['lower', 'upper']] = model.get_forecast(steps=50).conf_int(0.05).values
plt.plot(train_x['English'][-50:], '-o', label='training')
plt.plot(test_x['English'], '-o', label='actual')
plt.plot(test_x['pred'], '-o', label='prediction')
plt.fill_between(test_x.index, test_x['lower'], test_x['upper'],
                 color='k', alpha=.15)
plt.legend(loc='upper left', fontsize=8)
plt.show()
```



- Confidence interval -> is huge in this case.

SARIMAX:

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

In [84]:

```
exog = pd.read_csv('Exog_Campaign_eng')
```

In [85]:

```
exog
```

Out[85]:

	Exog
0	0
1	0
2	0
3	0
4	0
...	...
545	1
546	1
547	1
548	0
549	0

550 rows × 1 columns

In [86]:

```
final_df = pd.concat([df_copy,exog], axis= 1)
final_df
```

Out[86]:

	Dates	English	Chinese	French	Russian	German	Japanese	Sp
0	2015-07-01	4120.242704	306.174324	526.624206	694.492845	801.433519	637.635044	1176.9
1	2015-07-02	4096.969675	306.180041	530.038727	706.667866	790.469330	732.300645	1125.9
2	2015-07-03	3863.318780	304.711372	509.429958	654.068973	758.689914	661.188706	1035.0
3	2015-07-04	4020.385549	307.106882	544.347518	615.880100	697.106317	830.489442	972.4
4	2015-07-05	4157.757910	326.373163	534.101778	655.269262	809.890360	796.904439	1056.3
...	...	...	...	...	...	...	...	
545	2016-12-27	6189.329381	380.391169	825.957589	1008.121724	1095.848843	804.676399	1138.8
546	2016-12-28	6032.638712	382.556091	777.255710	938.610821	1042.817652	806.809621	1184.6
547	2016-12-29	6425.295920	354.776010	755.727032	903.053531	1004.514348	883.427658	1117.9
548	2016-12-30	5353.679346	358.554506	703.626382	808.817615	958.359915	970.883847	825.9
549	2016-12-31	5180.347343	369.829429	648.626656	886.737728	900.882241	991.608202	791.4

550 rows × 9 columns

In [87]:

```
df_ind_dates = final_df.set_index('Dates')
df_ind_dates
```

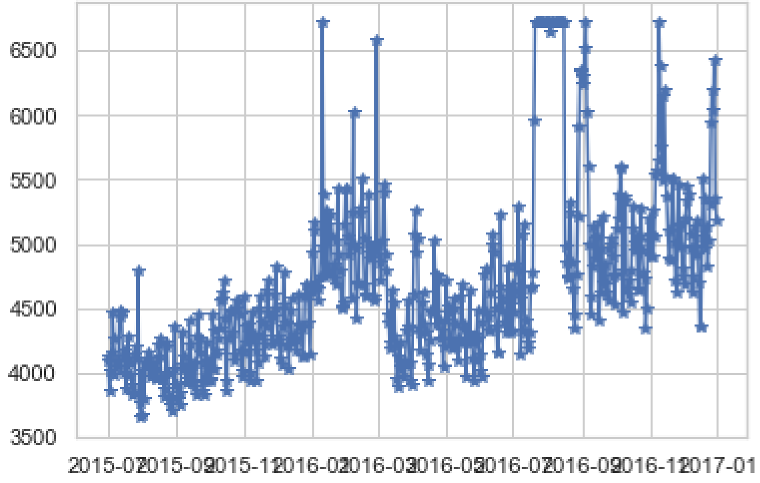
Out[87]:

	English	Chinese	French	Russian	German	Japanese	Spanish
Dates							
2015-07-01	4120.242704	306.174324	526.624206	694.492845	801.433519	637.635044	1176.993529
2015-07-02	4096.969675	306.180041	530.038727	706.667866	790.469330	732.300645	1125.926357
2015-07-03	3863.318780	304.711372	509.429958	654.068973	758.689914	661.188706	1035.044477
2015-07-04	4020.385549	307.106882	544.347518	615.880100	697.106317	830.489442	972.426566
2015-07-05	4157.757910	326.373163	534.101778	655.269262	809.890360	796.904439	1056.349179
...	...	...	...	...	...	...	...
2016-12-27	6189.329381	380.391169	825.957589	1008.121724	1095.848843	804.676399	1138.872438
2016-12-28	6032.638712	382.556091	777.255710	938.610821	1042.817652	806.809621	1184.690560
2016-12-29	6425.295920	354.776010	755.727032	903.053531	1004.514348	883.427658	1117.971921
2016-12-30	5353.679346	358.554506	703.626382	808.817615	958.359915	970.883847	825.957059
2016-12-31	5180.347343	369.829429	648.626656	886.737728	900.882241	991.608202	791.449882

550 rows × 8 columns

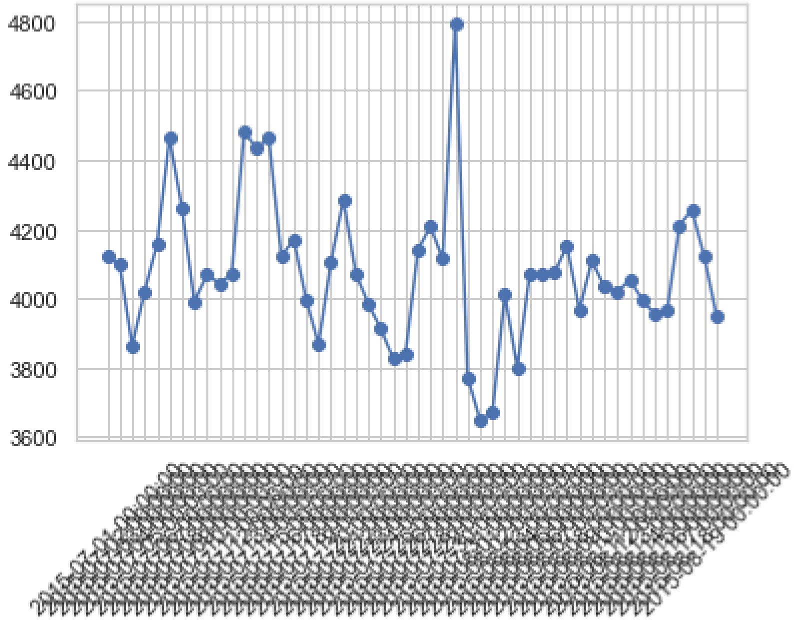
In [88]:

```
# Lets take a look at our time series plot
plt.plot(df_ind_dates.index, df_ind_dates['English'], '-*')
plt.show()
```



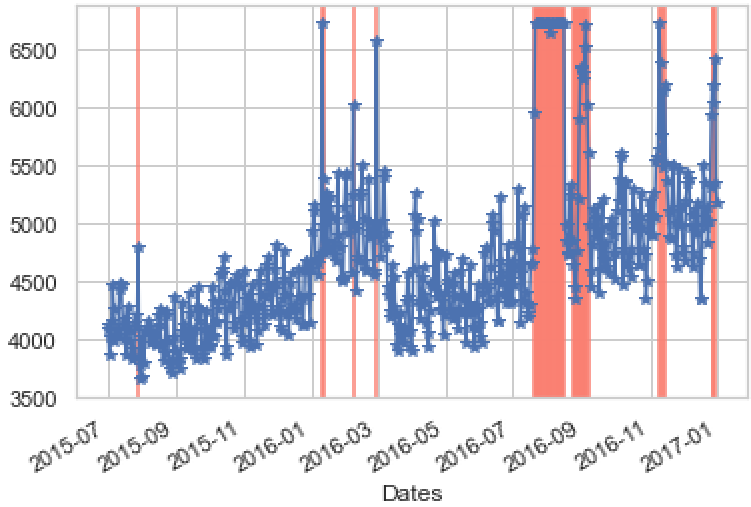
In [89]:

```
plt.plot(range(50),df_copy['English'][:50], '-o')
plt.xticks(range(0,50), df_copy['Dates'][:50],rotation = 45)
plt.show()
```



In [90]:

```
# Lets take a look at our time series plot
exog = df_ind_dates.loc[df_ind_dates.Exog==1].index
for exo in exog:
    plt.axvline(x=exo, color='#FA8072')
df_ind_dates.English.plot(style='-*')
plt.show()
```

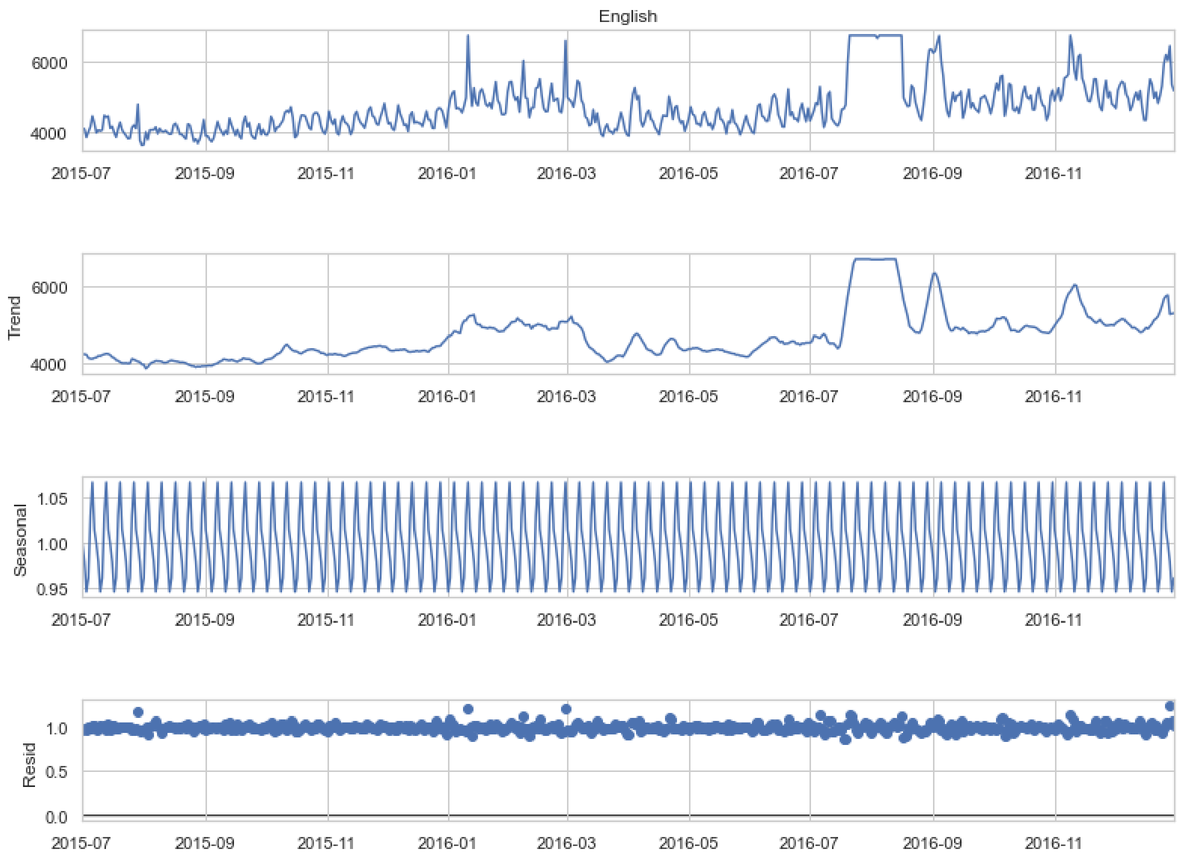


- As we can clearly see, when we had the campaign or significant event, the user view counts has peaked.
- The SARIMAX model has clearly identified the peaks due to external factors.

In [93]:

```
from statsmodels.tsa.seasonal import seasonal_decompose
result = seasonal_decompose(df_ind_dates['English'], model='multiplicative',extrapolate_tre
#,freq = 30
fig = plt.figure()
fig = result.plot()
fig.set_size_inches(12, 9)
fig.show()
```

<Figure size 432x288 with 0 Axes>



In [94]:

```
train = df_ind_dates.iloc[:500]
test = df_ind_dates.iloc[500:]
```

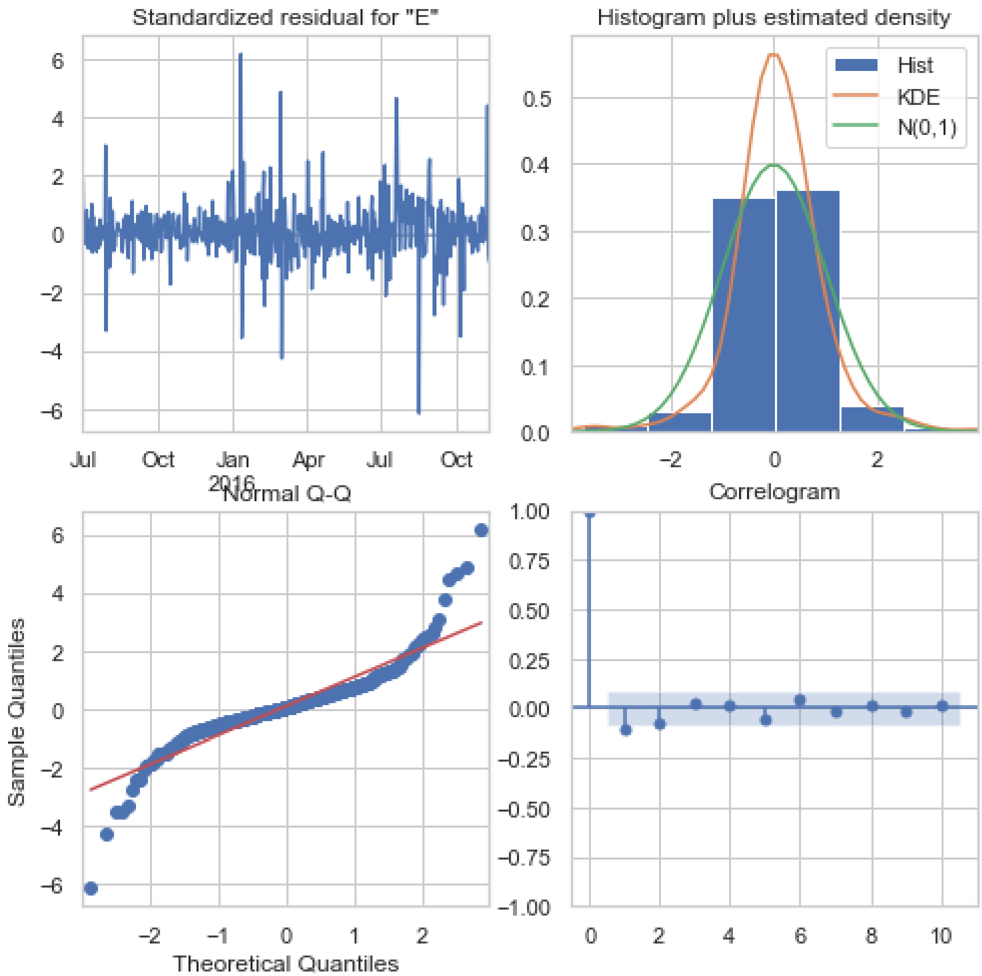
In [95]:

```
model = SARIMAX(train['English'],seasonal_order=(1,0,1,7)) # P,D, Q,s
results = model.fit()
fc = results.forecast(42)
```

```
C:\Users\hp\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:47
1: ValueWarning: No frequency information was provided, so inferred frequenc
y D will be used.
  self._init_dates(dates, freq)
C:\Users\hp\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:47
1: ValueWarning: No frequency information was provided, so inferred frequenc
y D will be used.
  self._init_dates(dates, freq)
```

In [96]:

```
results.plot_diagnostics(figsize=(8,8));
```



- With the plot_diagnostics, we can clearly see that the purely seasonal model is performing fairly well.
- Which means, there's a seasonality present.
- All residuals are within the error bound.

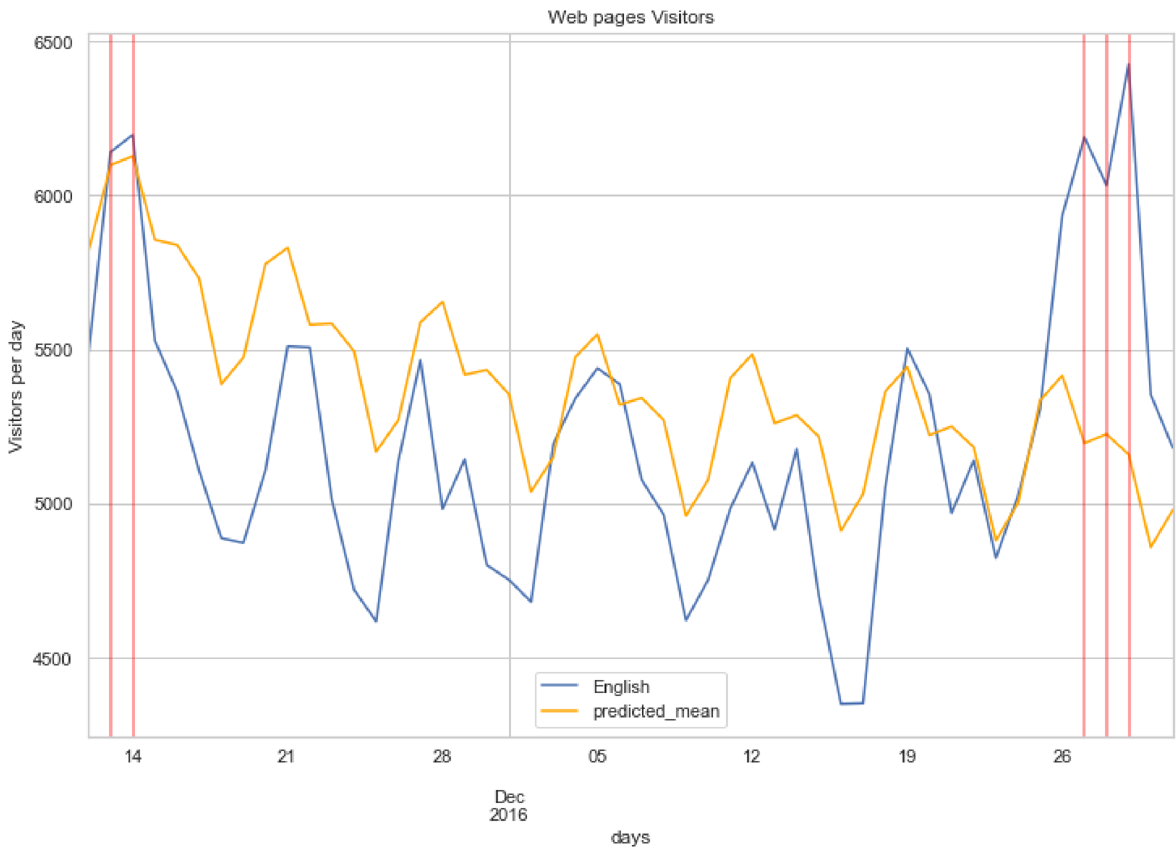
In [97]:

```
# Obtain predicted values
start=len(train)
end=len(train)+len(test)-1
predictions = results.predict(start=start, end=end)
```

In [98]:

```
performance(test['English'], predictions)
# Plot predictions against known values
title='Web pages Visitors'
ylabel='Visitors per day'
xlabel='days'
ax = test['English'].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.query('Exog==1').index:
    ax.axvline(x=x, color='red', alpha = 0.5)
```

```
MAE : 370.494
RMSE : 460.175
MAPE: 0.072
```



In [99]:

```
model = SARIMAX(train['English'],exog=train['Exog'],order=(3,1,3),seasonal_order=(1,0,1,7),
results = model.fit()
```

```
C:\Users\hp\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:47
1: ValueWarning: No frequency information was provided, so inferred frequenc
y D will be used.
  self._init_dates(dates, freq)
C:\Users\hp\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:47
1: ValueWarning: No frequency information was provided, so inferred frequenc
y D will be used.
  self._init_dates(dates, freq)
```

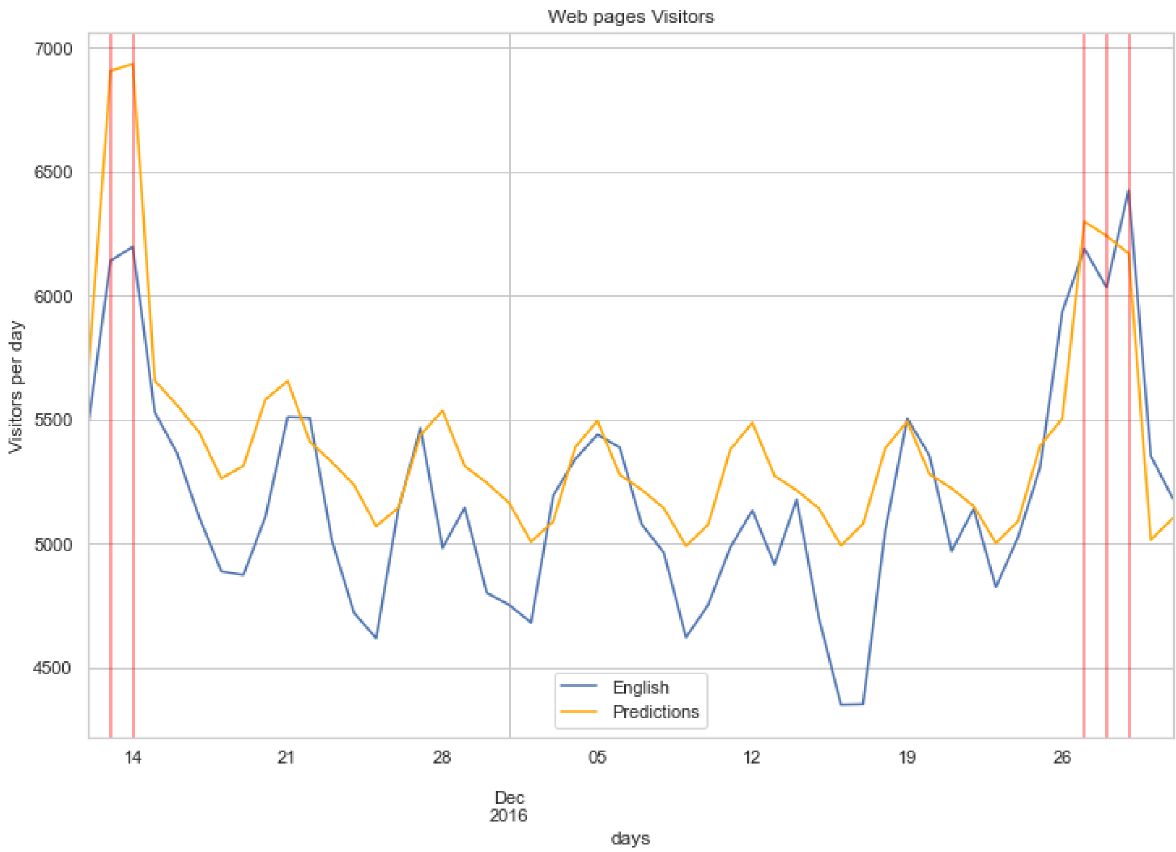
In [100]:

```
exog_forecast = test[['Exog']]  # requires two brackets to yield a shape of (50,1)
predictions = results.predict(start=start, end=end, exog=exog_forecast).rename('Predictions
```

In [101]:

```
performance(test['English'], predictions)
# Plot predictions against known values
title='Web pages Visitors'
ylabel='Visitors per day'
xlabel='days'
ax = test['English'].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.query('Exog==1').index:
    ax.axvline(x=x, color='red', alpha = 0.5)
```

```
MAE : 277.061
RMSE : 341.6
MAPE: 0.055
```



- We can a best MAPE of 5.4 % with seasonality and exogenous factors added.
- With SARIMAX, as there's huge spikes in the view counts during the campaigns and other significant events, our SARIMAX is able to detect the changes and thus the predictions are with very less MAPE(mean absolute percentage error)

Summary of all models(for English language views):

- Mean model MAPE: 10.2%
- Seasonal Naive 7.3%
- Moving average forecast: 19.2%
- ARIMA(3,1,3): 16.3%
- SARIMA(order=(3, 1, 3), seasonal_order=(1,1,1,7) : 11.4 %
- SARIMAX seasonal_order=(1,0,1,7) -MAPE: 7.2%
- SARIMAX with hyper parameter tuning: order=(3,1,3),seasonal_order=(1,0,1,7) - 5.4%

Auto ARIMA:

In [102]:

```
pip install pmdarima
```

```
Collecting pmdarimaNote: you may need to restart the kernel to use updated p
ackages.
  Downloading pmdarima-2.0.2-cp38-cp38-win_amd64.whl (571 kB)
Requirement already satisfied: setuptools!=50.0.0,>=38.6.0 in c:\users\hp\an
aconda3\lib\site-packages (from pmdarima) (49.2.0.post20200714)

Requirement already satisfied: statsmodels>=0.13.2 in c:\users\hp\anaconda3
\lib\site-packages (from pmdarima) (0.13.2)
Requirement already satisfied: numpy>=1.21.2 in c:\users\hp\anaconda3\lib\si
te-packages (from pmdarima) (1.23.1)
Requirement already satisfied: scikit-learn>=0.22 in c:\users\hp\anaconda3\l
ib\site-packages (from pmdarima) (1.1.2)
Requirement already satisfied: joblib>=0.11 in c:\users\hp\anaconda3\lib\sit
e-packages (from pmdarima) (1.1.0)
Requirement already satisfied: Cython!=0.29.18,!=0.29.31,>=0.29 in c:\users
\hp\anaconda3\lib\site-packages (from pmdarima) (0.29.21)
Requirement already satisfied: urllib3 in c:\users\hp\anaconda3\lib\site-pac
kages (from pmdarima) (1.25.9)
Requirement already satisfied: pandas>=0.19 in c:\users\hp\anaconda3\lib\sit
e-packages (from pmdarima) (1.4.3)
Requirement already satisfied: scipy>=1.3.2 in c:\users\hp\anaconda3\lib\sit
e-packages (from pmdarima) (1.9.0)
Requirement already satisfied: patsy>=0.5.2 in c:\users\hp\anaconda3\lib\sit
e-packages (from statsmodels>=0.13.2->pmdarima) (0.5.2)
Requirement already satisfied: packaging>=21.3 in c:\users\hp\anaconda3\lib
\site-packages (from statsmodels>=0.13.2->pmdarima) (21.3)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\hp\anaconda3
\lib\site-packages (from scikit-learn>=0.22->pmdarima) (2.1.0)
Requirement already satisfied: python-dateutil>=2.8.1 in c:\users\hp\anacond
a3\lib\site-packages (from pandas>=0.19->pmdarima) (2.8.1)
Requirement already satisfied: pytz>=2020.1 in c:\users\hp\anaconda3\lib\sit
e-packages (from pandas>=0.19->pmdarima) (2020.1)
Requirement already satisfied: six in c:\users\hp\anaconda3\lib\site-package
s (from patsy>=0.5.2->statsmodels>=0.13.2->pmdarima) (1.15.0)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in c:\users\hp\anaco
nda3\lib\site-packages (from packaging>=21.3->statsmodels>=0.13.2->pmdarima)
(2.4.7)
Installing collected packages: pmdarima
Successfully installed pmdarima-2.0.2
```

In [103]:

```
import pmdarima as pm
```

In [104]:

```
model = pm.auto_arima(train['English'], exogenous = train['Exog'],seasonal=True, m=12)
```

In [105]:

```
model.summary()
```

Out[105]:

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	500
Model:	SARIMAX(2, 1, 4)x(1, 0, [], 12)	**Log Likelihood**	-3525.082
Date:	Fri, 02 Dec 2022	**AIC**	7066.165
Time:	14:28:26	**BIC**	7099.866
Sample:	07-01-2015	**HQIC**	7079.390
	- 11-11-2016		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ar.L1	1.2425	0.005	263.250	0.000	1.233	1.252
ar.L2	-0.9961	0.004	-240.140	0.000	-1.004	-0.988
ma.L1	-1.4597	0.032	-45.736	0.000	-1.522	-1.397
ma.L2	1.1283	0.075	15.034	0.000	0.981	1.275
ma.L3	-0.0669	0.078	-0.862	0.389	-0.219	0.085
ma.L4	-0.1404	0.049	-2.865	0.004	-0.237	-0.044
ar.S.L12	-0.1687	0.061	-2.749	0.006	-0.289	-0.048
sigma2	9.415e+04	3794.294	24.812	0.000	8.67e+04	1.02e+05

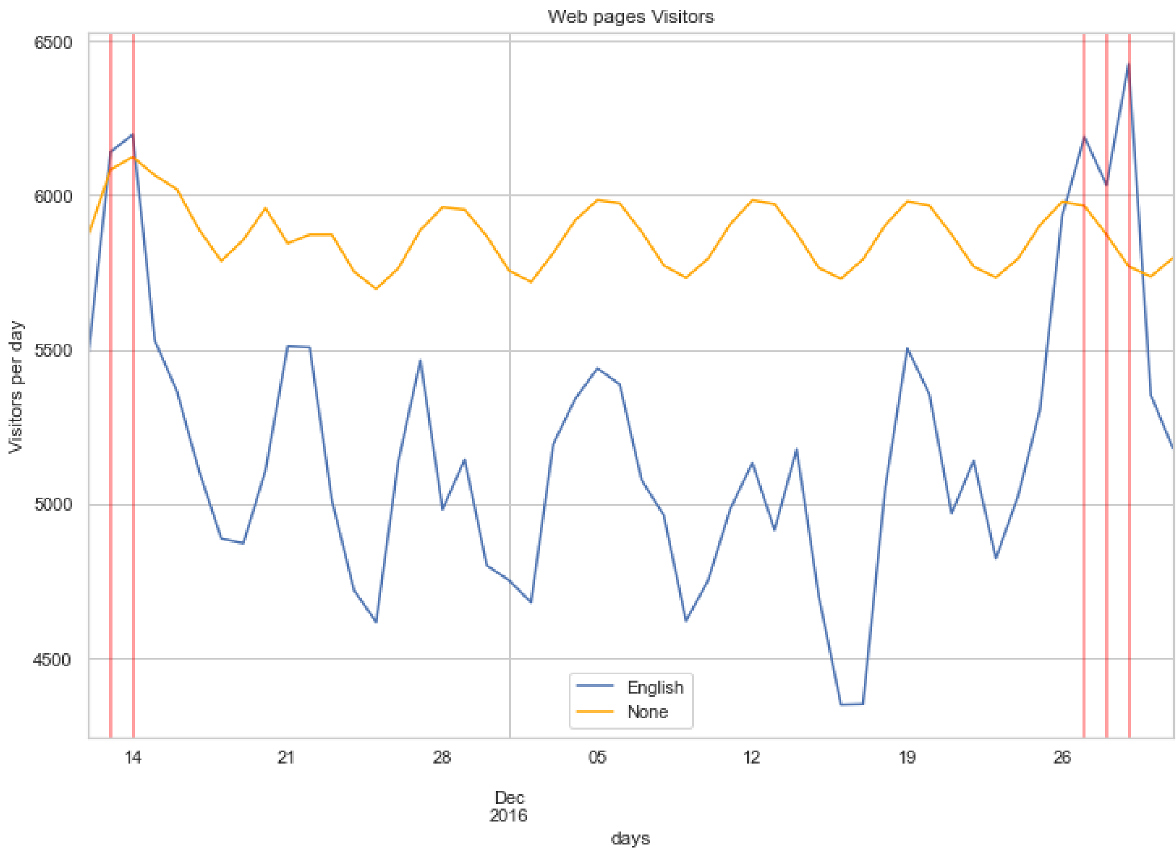
Ljung-Box (L1) (Q):	0.02	**Jarque-Bera (JB):**	1461.58
Prob(Q):	0.89	**Prob(JB):**	0.00
Heteroskedasticity (H):	3.69	**Skew:**	0.35
Prob(H) (two-sided):	0.00	**Kurtosis:**	11.35

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [106]:

```
forecasts = model.predict(test.shape[0],exogenous = test['Exog'])
performance(test['English'], forecasts)
# Plot predictions against known values
title='Web pages Visitors'
ylabel='Visitors per day'
xlabel='days'
ax = test['English'].plot(legend=True,figsize=(12,8),title=title)
forecasts.plot(legend=True,color = 'orange')
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel)
for x in test.query('Exog==1').index:
    ax.axvline(x=x, color='red', alpha = 0.5)
```

```
MAE : 723.578
RMSE : 790.322
MAPE: 0.145
```



- With Auto ARIMA along with external features, we are getting MAPE as 14.2%

- With Auto ARIMA along with external features, we are getting MAPE as 11.2%
- Which means seasonality is the most important factor even more important than the external factors

Time Series Forecasting as Linear or Non-linear Regression + innovative features:

Change points detection:

In [107]:

```
def plot_changepoints(signal, changepoints):
    for cp in changepoints:
        plt.axvline(x=cp, color='#FA8072')
    plt.plot(signal, '-*', label='signal')

    start = 0
    trends = np.array([])
    for i in changepoints:
        x = np.arange(start, i)
        y = signal[start:i]
        l1 = np.polyfit(x, y, deg=1)
        trend = x*l1[0] + l1[1]
        trends = np.append(trends, trend)
        start = i

    plt.plot(trends, label='trend')
    plt.legend()
    plt.show()
```

In [108]:

```
df_copy
```

Out[108]:

	Dates	English	Chinese	French	Russian	German	Japanese	Sp
0	2015-07-01	4120.242704	306.174324	526.624206	694.492845	801.433519	637.635044	1176.9
1	2015-07-02	4096.969675	306.180041	530.038727	706.667866	790.469330	732.300645	1125.9
2	2015-07-03	3863.318780	304.711372	509.429958	654.068973	758.689914	661.188706	1035.0
3	2015-07-04	4020.385549	307.106882	544.347518	615.880100	697.106317	830.489442	972.4
4	2015-07-05	4157.757910	326.373163	534.101778	655.269262	809.890360	796.904439	1056.3
...	...	...	...	...	...	...	...	
545	2016-12-27	6189.329381	380.391169	825.957589	1008.121724	1095.848843	804.676399	1138.8
546	2016-12-28	6032.638712	382.556091	777.255710	938.610821	1042.817652	806.809621	1184.6
547	2016-12-29	6425.295920	354.776010	755.727032	903.053531	1004.514348	883.427658	1117.9
548	2016-12-30	5353.679346	358.554506	703.626382	808.817615	958.359915	970.883847	825.9
549	2016-12-31	5180.347343	369.829429	648.626656	886.737728	900.882241	991.608202	791.4

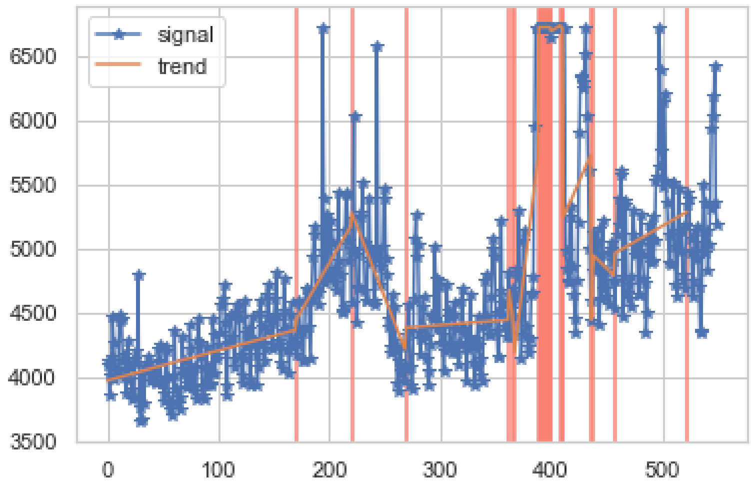
550 rows × 8 columns

In [109]:

```
df_10 = df_copy.set_index('Dates')
```

In [110]:

```
signal = df_10.English # Stationarise for mean as cost function
window=50

def get_slope(y):
    return np.polyfit(np.arange(len(y)), y, deg=1)[0]

changepoints = signal.loc[abs(signal.rolling(window, center=True).apply(get_slope).diff())

# converting to index from dates
temp = signal.reset_index()
changepoints = temp.loc[temp['Dates'].isin(changepoints)].index.tolist()

plot_changepoints(signal.values, changepoints)
```



- As we can see, there are multiple change points (around forst 175 days, 225 days, 275 days, 360 days, 400-250 days, 525 days)
- Almost all of them are due to the exogenous features (campaigns)

In [125]:

```
exog1
```

Out[125]:

	Exog
0	0
1	0
2	0
3	0
4	0
...	...
545	1
546	1
547	1
548	0
549	0

550 rows × 1 columns

Forecasting with Regression Model:

In [123]:

```
df_reg = all_languages[['Dates','English']]
df_reg['dayoftheweek'] = df_reg['Dates'].apply(lambda x : x.strftime('%a'))
df_reg['month'] = df_reg['Dates'].apply(lambda x : x.strftime('%b'))
df_reg['day'] = df_reg['Dates'].apply(lambda x : x.strftime('%d'))
df_reg['exog'] = exog1['Exog']
df_reg['year'] = df_reg['Dates'].apply(lambda x : x.strftime('%Y'))
df_reg ['dayoftheweek_mod'] = df_reg.groupby('dayoftheweek')['English'].transform("mean")
df_reg['month_mod'] = df_reg.groupby('month')['English'].transform('mean')
df_reg['day_mod'] = df_reg.groupby('day')['English'].transform('mean')
df_reg['exog_mod'] = df_reg.groupby('exog')['English'].transform('mean')
df_reg['year_mod'] = df_reg.groupby('year')['English'].transform('mean')
```

In [124]:

```
df_reg
```

Out[124]:

	Dates	English	dayoftheweek	month	day	exog	year	dayoftheweek_mod	month_m
0	2015-07-01	4120.242704	Wed	Jul	01	0	2015	4770.646066	4996.398
1	2015-07-02	4096.969675	Thu	Jul	02	0	2015	4657.967817	4996.398
2	2015-07-03	3863.318780	Fri	Jul	03	0	2015	4508.924225	4996.398
3	2015-07-04	4020.385549	Sat	Jul	04	0	2015	4582.596278	4996.398
4	2015-07-05	4157.757910	Sun	Jul	05	0	2015	4922.296453	4996.398
...	...	...	...	...	...	...	...	...	
545	2016-12-27	6189.329381	Tue	Dec	27	1	2016	4859.181033	4759.630
546	2016-12-28	6032.638712	Wed	Dec	28	1	2016	4770.646066	4759.630
547	2016-12-29	6425.295920	Thu	Dec	29	1	2016	4657.967817	4759.630
548	2016-12-30	5353.679346	Fri	Dec	30	0	2016	4508.924225	4759.630
549	2016-12-31	5180.347343	Sat	Dec	31	0	2016	4582.596278	4759.630

550 rows × 12 columns

In [126]:

```
from sklearn.model_selection import train_test_split
X = df_reg[['dayoftheweek_mod','month_mod','day_mod','exog_mod','year_mod']]
Y = df_reg['English']
```

In [127]:

```
x_train = X[:500]
x_test = X[500:]
y_train = Y[:500]
y_test = Y[500:]
```

In [128]:

```
import statsmodels.api as sm
# x_train = sm.add_constant(x_train)
# x_test = sm.add_constant(x_test
```

In [129]:

```
finalmodel = sm.OLS(y_train,x_train).fit()
print(finalmodel.summary())
```

```
                                 OLS Regression Results                                
=======================================================================================
Dep. Variable:                English   R-squared (uncentered):                   0.989
Model:                            OLS   Adj. R-squared (uncentered):              0.989
Method:                 Least Squares   F-statistic:                              8848.
Date:                Fri, 02 Dec 2022   Prob (F-statistic):                        0.00
Time:                        16:11:58   Log-Likelihood:                         -3824.3
No. Observations:                 500   AIC:                                      7659.
Df Residuals:                     495   BIC:                                      7680.
Df Model:                           5                                                  
Covariance Type:            nonrobust                                                  
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
dayoftheweek_mod     0.4601      0.105      4.389      0.000       0.254       0.666
month_mod            0.1077      0.083      1.293      0.197      -0.056       0.271
day_mod             -1.0498      0.127     -8.278      0.000      -1.299      -0.801
exog_mod             0.9519      0.036     26.797      0.000       0.882       1.022
year_mod             0.5257      0.056      9.471      0.000       0.417       0.635
==============================================================================
Omnibus:                       82.048   Durbin-Watson:                   0.508
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              547.919
Skew:                          -0.497   Prob(JB):                    1.05e-119
Kurtosis:                       8.031   Cond. No.                         71.4
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In [130]:

```
print(finalmodel.params)
```

```
dayoftheweek_mod     0.460117
month_mod            0.107668
day_mod             -1.049770
exog_mod             0.951857
year_mod             0.525677
dtype: float64
```

In [131]:

```
predictions = finalmodel.predict(x_test)
```

In [132]:

```
performance(y_test, predictions)
# Plot predictions against known values
title='Web pages Visitors of English modelled by Linear Regression'
ylabel='Visitors per day'
xlabel='days'
ax = y_test.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)
plt.show()
```

```
MAE : 452.523
RMSE : 538.464
MAPE: 0.084
```

- Linear Regression model is given the MAPE of 8.4 % which is pretty good than the complex models as well

Forecasting with FB-Prophet (Alternative to SARIMAX)

In [144]:

```
!pip install pystan~=2.14
```

```
Requirement already satisfied: pystan~=2.14 in c:\users\hp\anaconda3\lib\sit
e-packages (2.19.1.1)
Requirement already satisfied: Cython!=0.25.1,>=0.22 in c:\users\hp\anaconda
3\lib\site-packages (from pystan~=2.14) (0.29.21)
Requirement already satisfied: numpy>=1.7 in c:\users\hp\anaconda3\lib\site-
packages (from pystan~=2.14) (1.23.1)
```

In [134]:

```
df_copy
```

Out[134]:

	Dates	English	Chinese	French	Russian	German	Japanese	Sp
0	2015-07-01	4120.242704	306.174324	526.624206	694.492845	801.433519	637.635044	1176.9
1	2015-07-02	4096.969675	306.180041	530.038727	706.667866	790.469330	732.300645	1125.9
2	2015-07-03	3863.318780	304.711372	509.429958	654.068973	758.689914	661.188706	1035.0
3	2015-07-04	4020.385549	307.106882	544.347518	615.880100	697.106317	830.489442	972.4
4	2015-07-05	4157.757910	326.373163	534.101778	655.269262	809.890360	796.904439	1056.3
...	...	...	...	...	...	...	...	
545	2016-12-27	6189.329381	380.391169	825.957589	1008.121724	1095.848843	804.676399	1138.8
546	2016-12-28	6032.638712	382.556091	777.255710	938.610821	1042.817652	806.809621	1184.6
547	2016-12-29	6425.295920	354.776010	755.727032	903.053531	1004.514348	883.427658	1117.9
548	2016-12-30	5353.679346	358.554506	703.626382	808.817615	958.359915	970.883847	825.9
549	2016-12-31	5180.347343	369.829429	648.626656	886.737728	900.882241	991.608202	791.4

550 rows × 9 columns

In [135]:

```
exog1 = pd.read_csv('Exog_Campaign_eng')
```

In [136]:

```
df_copy['exog'] = exog1['Exog']
```

In [137]:

```
df_fin = df_copy[['Dates', 'English', 'exog']]
df_fin
```

Out[137]:

	Dates	English	exog
0	2015-07-01	4120.242704	0
1	2015-07-02	4096.969675	0
2	2015-07-03	3863.318780	0
3	2015-07-04	4020.385549	0
4	2015-07-05	4157.757910	0
...	...	...	...
545	2016-12-27	6189.329381	1
546	2016-12-28	6032.638712	1
547	2016-12-29	6425.295920	1
548	2016-12-30	5353.679346	0
549	2016-12-31	5180.347343	0

550 rows × 3 columns

In [138]:

```
df_fin['Dates'] = pd.to_datetime(df_fin['Dates'])
```

In [139]:

```
df_fin
```

Out[139]:

	Dates	English	exog
0	2015-07-01	4120.242704	0
1	2015-07-02	4096.969675	0
2	2015-07-03	3863.318780	0
3	2015-07-04	4020.385549	0
4	2015-07-05	4157.757910	0
...	...	...	...
545	2016-12-27	6189.329381	1
546	2016-12-28	6032.638712	1
547	2016-12-29	6425.295920	1
548	2016-12-30	5353.679346	0
549	2016-12-31	5180.347343	0

550 rows × 3 columns

In [140]:

```
df_fin['ds'] = df_fin['Dates']
df_fin['y'] = df_fin['English']
df_fin = df_fin[['ds', 'y', 'exog']]
df_fin.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550 entries, 0 to 549
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   ds      550 non-null    datetime64[ns]
 1   y       550 non-null    float64
 2   exog    550 non-null    int64
dtypes: datetime64[ns](1), float64(1), int64(1)
memory usage: 13.0 KB
```

In [141]:

```
df_fin_train = df_fin.iloc[:530]
df_fin_test = df_fin.iloc[530:]
```

In [152]:

```
#!pip install fbprophet
```

In [154]:

```
'''
from prophet import Prophet

model = Prophet(interval_width=0.95, yearly_seasonality=True, weekly_seasonality=True,
               changepoint_prior_scale=4)

#Fit the model

m = model.fit(df_fin_train)
#Make predictions
future = m.make_future_dataframe(periods=20,freq="D")
forecast3 = m.predict(future)
# plt.ylim(2500,8000)
fig = m.plot(forecast3)
'''
```

Out[154]:

```
'\nfrom prophet import Prophet\n\nmodel = Prophet(interval_width=0.95, yearl
y_seasonality=True, weekly_seasonality=True, \n               changepoint_pr
ior_scale=4)\n\n#Fit the model\n\nm = model.fit(df_fin_train)\n#Make predict
ions\nfuture = m.make_future_dataframe(periods=20,freq="D")\nforecast3 = m.p
redict(future)\n# plt.ylim(2500,8000)\nfig = m.plot(forecast3)\n'
```

In [153]:

```
df_fin_train.shape
```

Out[153]:

```
(530, 3)
```

In [155]:

```
#forecast3.head()
```

In [156]:

```
#performance(df_fin['y'][:-20],forecast3['yhat'][:-20])
```

In [157]:

```
'''
plt.plot(forecast3['ds'], forecast3['yhat'],'-*', label = 'Predictions')
plt.plot(df_fin['ds'], df_fin['y'], label = 'Actual')

plt.xlim(pd.to_datetime('2015-07-01'), pd.to_datetime('2016-12-01'))
plt.ylim(2500,8000)
for x in df_fin.query('exog==1')['ds']:
    plt.axvline(x=x, color='red', alpha = 0.5);
plt.legend()
'''
```

Out[157]:

```
"\nplt.plot(forecast3['ds'], forecast3['yhat'],'-*', label = 'Predictions')
\nplt.plot(df_fin['ds'], df_fin['y'], label = 'Actual')\n\nplt.xlim(pd.to_da
tetime('2015-07-01'), pd.to_datetime('2016-12-01'))\nplt.ylim(2500,8000)\nfo
r x in df_fin.query('exog==1')['ds']: \n    plt.axvline(x=x, color='red', al
pha = 0.5);\nplt.legend()\n"
```

- When the exogenous factors are considered along with English language view counts, we are getting MAPE as 4.2%
- FB prophet is able to determine all the change points(shown in red)

In [158]:

```
df_fin = df_fin[['ds', 'y']]
df_fin.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550 entries, 0 to 549
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   ds      550 non-null    datetime64[ns]
 1   y       550 non-null    float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 8.7 KB
```

In [159]:

```
df_fin_train = df_fin.iloc[:500]
df_fin_test = df_fin.iloc[500:]
```

In [ ]:

```
#m = Prophet()
#m.fit(df_fin_train)
```

In [ ]:

```
#future = m.make_future_dataframe(periods=50, freq = 'D')
#future.tail()
```

In [160]:

```
#forecast = m.predict(future)
#forecast[['ds', 'yhat', 'yhat_lower', 'yhat_upper']].tail()
```

In [161]:

```
df_fin_test.shape
```

Out[161]:

```
(50, 2)
```

In [162]:

```
'''
performance(df_fin_test['y'],forecast['yhat'][500:])

# Plot predictions against known values
title='Web pages Visitors of English language modelled by Prophet'
ylabel='Visitors per day'
xlabel='days'
ax = df_fin_test['y'].plot(legend=True,figsize=(12,8),title=title)
forecast['yhat'][500:].plot(legend=True,color = 'orange')
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel)
plt.show()
'''
```

Out[162]:

```
"\nperformance(df_fin_test['y'],forecast['yhat'][500:])\n\n# Plot prediction
s against known values\ntitle='Web pages Visitors of English language modell
ed by Prophet'\nylabel='Visitors per day'\nxlabel='days'\nax = df_fin_test
['y'].plot(legend=True,figsize=(12,8),title=title)\nforecast['yhat'][500:].p
lot(legend=True,color = 'orange')\nax.autoscale(axis='x',tight=True)\nax.set
(xlabel=xlabel, ylabel=ylabel)\nplt.show()\n"
```

In [163]:

```
#fig1 = m.plot(forecast)
```

- The confidence interval of the predictions is also in the range (+- 1000) views which is very great

In [164]:

```
#fig2 = m.plot_components(forecast)
```

- On monday, we have maximum number of view counts followed by a decreasing trend till friday. On weekends the view counts shoots up!!

In [ ]:

```
#from prophet.plot import plot_plotly, plot_components_plotly

#plot_plotly(m, forecast)
```

In [165]:

```
#plot_components_plotly(m, forecast)
```

- When the exogenous factors are NOT considered along with English language view counts, we are getting MAPE as 5.6%

Creating a pipeline for working with multiple series

Forecasting for different languages

In [166]:

```
df_ind_dates_train = df_ind_dates[:500]
df_ind_dates_test = df_ind_dates[500:]
```

In [167]:

```
for i in df_ind_dates.columns:
  print("Performance Metrics after Auto Arima for ",i)
  model = pm.auto_arima(df_ind_dates_train[i], exogenous = df_ind_dates_train['Exog'],seaso
  forecasts = model.predict(df_ind_dates_test.shape[0],exogenous = df_ind_dates_test['Exog'
  performance(df_ind_dates_test[i], forecasts)
  print('-'*50)
```

```
Performance Metrics after Auto Arima for  English
MAE : 723.578
RMSE : 790.322
MAPE: 0.145
--------------------------------------------------
Performance Metrics after Auto Arima for  Chinese
MAE : 29.194
RMSE : 33.117
MAPE: 0.079
--------------------------------------------------
Performance Metrics after Auto Arima for  French
MAE : 55.491
RMSE : 63.159
MAPE: 0.08
--------------------------------------------------
Performance Metrics after Auto Arima for  Russian
MAE : 129.625
RMSE : 146.541
MAPE: 0.136
--------------------------------------------------
Performance Metrics after Auto Arima for  German
MAE : 64.604
RMSE : 80.172
MAPE: 0.071
--------------------------------------------------
Performance Metrics after Auto Arima for  Japanese
MAE : 51.87
RMSE : 69.18
MAPE: 0.063
--------------------------------------------------
Performance Metrics after Auto Arima for  Spanish
MAE : 292.161
RMSE : 330.547
MAPE: 0.277
--------------------------------------------------
Performance Metrics after Auto Arima for  Exog
MAE : 0.254
RMSE : 0.318
MAPE: 770529825430761.9
--------------------------------------------------
```

- With Auto ARIMA below are the languages with decreasing order of MAPE: Japanese(6.3%) < German(6.9%) < Chinese(7.9%) < French(8%) < Russian(13.6%) < English(14.7) < Spanish(29.6%)

Questionnaire:

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

- To forecast 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.
- The modification of this can be used in case of Scaler's advertising. If Scaler Academy is willing to open it's branches in different regions, then the best time(ex. monday) and maximum digital adv capital (on english web pages, can be understood)

2) Write 3 inferences you made from the data visualizations

- English webpages are the mostly viewed pages whereas Spanish(es) are the least viewed.
- The distribution type is via all agents and is preferred as with it, we are getting most of the views unlike via spider distribution
- As we can see, during the month of August, 2016 we are seeing a huge spike in the number of views on the web pages. As these are anamolies, we will treat these outliers using simple IQR based method.

3) What does the decomposition of series do?

- The decomposition of time series is a statistical task that deconstructs a time series into several components, each representing one of the underlying categories of patterns.(ex: Trends, Seasonality, Residuals distribution)

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

- I got 3 time series (English, Japanese and German languages) as stationary with 1 level of differentiation.

5) Difference between arima, sarima & sarimax.

- ARIMA -> Differencing (detrending) and residual smoothing (moving average) are considered with order of differentiation (p,d,q)
- SARIMA -> Along with above parameters as in ARIMA, seasonality(s) and the seasonality effect on Differencing (detrending) , residual smoothing (moving average) and order of derivative is considered (p,q,d,P,Q,D,s)
- SARIMAX -> Along with SARIMA's parameters, changes due to external/exogenous factors are also considered (p,q,d,P,Q,D,s,exog)

6) Compare the number of views in different languages

- English webpages are the mostly viewed pages whereas Spanish(es) are the least viewed.
- With Auto ARIMA below are the languages with decreasing order of MAPE: Japanese(6.3%) < German(6.9%) < Chinese(7.9%) < French(8%) < Russian(13.6%) < English(14.7) < Spanish(29.6%)
- Meaning, if the advertising agency is forecasting then they will have least amount of loss in ad placements on Japanese, German web pages and most amount of losses on Spanish web pages. Keeping this in mind, Adease should allocate their digital/monetary resources on proper language's web pages.

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

- Auto ARIMA, confidence interval detection, FB Prophet are the other methods other than hyper parameter tuning (grid search) that would be suitable to get the model for all languages