adease-time-series

June 18, 2024

0.1 Problem statement:

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.

[83]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

0.2 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.

[84]:
```python
df=pd.read_csv("train_1.csv")
```

[85]:
```python
df.head()
```

[85]:
```
                                                Page  2015-07-01  2015-07-02  \
0            2NE1_zh.wikipedia.org_all-access_spider        18.0        11.0
1             2PM_zh.wikipedia.org_all-access_spider        11.0        14.0
2              3C_zh.wikipedia.org_all-access_spider         1.0         0.0
3         4minute_zh.wikipedia.org_all-access_spider        35.0        13.0
4  52_Hz_I_Love_You_zh.wikipedia.org_all-access_s…          NaN         NaN

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

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

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

[5 rows x 551 columns]
```

[86]:
```python
print("No.of rows: ", df.shape[0])
print("No.of columns: ", df.shape[1])
```

```
No.of rows:  145063
No.of columns:  551
```

[87]:
```python
df.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
```

[88]:
```
Exog_Campaign_eng = pd.read_csv("Exog_Campaign_eng")
Exog_Campaign_eng.shape
```

[88]:
```
(550, 1)
```

[89]:
```
df['Page'].value_counts()
```

[89]:
```
Page
2NE1_zh.wikipedia.org_all-access_spider
1
Rafael_Leónidas_Trujillo_es.wikipedia.org_mobile-web_all-agents
1
América_Central_es.wikipedia.org_mobile-web_all-agents
1
Física_es.wikipedia.org_mobile-web_all-agents
1
Inquisición_es.wikipedia.org_mobile-web_all-agents
1
             ..
The_First_Avenger:_Civil_War_de.wikipedia.org_all-access_spider
1
The_Fast_and_the_Furious_(Filmreihe)_de.wikipedia.org_all-access_spider
1
The_Expendables_3_de.wikipedia.org_all-access_spider
1
The_Expanse_(Fernsehserie)_de.wikipedia.org_all-access_spider
1
Francisco_el_matemático_(serie_de_televisión_de_2017)_es.wikipedia.org_all-
access_spider    1
Name: count, Length: 145063, dtype: int64
```

0.3 EDA

The page name contains data in this format:

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

Let's extract language, access type, access origin and name of each page.

Extracting language

[90]:
```
import re
```

[91]:
```
# extracting language
def Extract_Language(name):
  if len(re.findall(r'_(.{2}).wikipedia.org_', name)) == 1 :
    return re.findall(r'_(.{2}).wikipedia.org_', name)[0]
  else:
```

```
    return 'Unknown'

# Apply the function to extract the language
df['Language'] = df['Page'].map(Extract_Language)
```

[92]:
```
df['Language'].value_counts()
```

[92]:
```
Language
en         24108
ja         20431
de         18547
Unknown    17855
fr         17802
zh         17229
ru         15022
es         14069
Name: count, dtype: int64
```

[93]:
```
# Impute language names using their codes.
languages = {'de':'German',
        'en': 'English',
        'es': 'Spanish',
        'fr': 'French',
        'ja': 'Japenese' ,
        'ru': 'Russian',
        'zh': 'Chinese',
        'Unknown': 'Unknown_Language'}

df['Language']= df['Language'].map(languages)
```

Extracting ACCESS ORIGIN :

[94]:
```
df['Access_origin']=df['Page'].str.split('_').str[-1]
```

[95]:
```
df['Access_origin'].value_counts(normalize=True)
```

[95]:
```
Access_origin
all-agents    0.759325
spider        0.240675
Name: proportion, dtype: float64
```

Extracting ACCESS TYPE :

[96]:
```
df['Access_type']=df['Page'].str.split('_').str[-2]
```

[97]:
```
df['Access_type'].value_counts(normalize=True)
```

[97]:
```
Access_type
all-access    0.512295
mobile-web    0.247748
desktop       0.239958
Name: proportion, dtype: float64
```

[98]:
```
df.head()
```

[98]:
```
                                                Page  2015-07-01  2015-07-02  \
0            2NE1_zh.wikipedia.org_all-access_spider        18.0        11.0
1             2PM_zh.wikipedia.org_all-access_spider        11.0        14.0
2              3C_zh.wikipedia.org_all-access_spider         1.0         0.0
3         4minute_zh.wikipedia.org_all-access_spider        35.0        13.0
4  52_Hz_I_Love_You_zh.wikipedia.org_all-access_s…         NaN         NaN

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

   2015-07-09  …  2016-12-25  2016-12-26  2016-12-27  2016-12-28  \
0        26.0  …        26.0        14.0        20.0        22.0
1        10.0  …        15.0         9.0        30.0        52.0
2         4.0  …         7.0         4.0         4.0         6.0
3        11.0  …        27.0        16.0        11.0        17.0
4         NaN  …        13.0         3.0        11.0        27.0

   2016-12-29  2016-12-30  2016-12-31  Language  Access_origin  Access_type
0        19.0        18.0        20.0   Chinese         spider   all-access
1        45.0        26.0        20.0   Chinese         spider   all-access
2         3.0         4.0        17.0   Chinese         spider   all-access
3        19.0        10.0        11.0   Chinese         spider   all-access
4        13.0        36.0        10.0   Chinese         spider   all-access

[5 rows x 554 columns]
```

- There are some NaN values for some webpages across different dates.

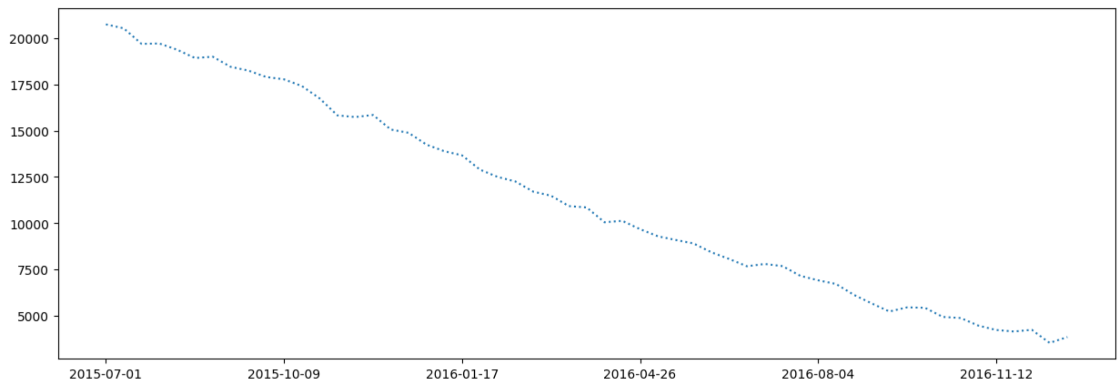
[99]:
```
df.duplicated().sum()
```

[99]:
```
0
```

[100]:
```
indexes = df.head(2).columns[1:][range(0,549,10)].values
indexes
```

[100]: array(['2015-07-01', '2015-07-11', '2015-07-21', '2015-07-31',
          '2015-08-10', '2015-08-20', '2015-08-30', '2015-09-09',
          '2015-09-19', '2015-09-29', '2015-10-09', '2015-10-19',
          '2015-10-29', '2015-11-08', '2015-11-18', '2015-11-28',
          '2015-12-08', '2015-12-18', '2015-12-28', '2016-01-07',
          '2016-01-17', '2016-01-27', '2016-02-06', '2016-02-16',
          '2016-02-26', '2016-03-07', '2016-03-17', '2016-03-27',
          '2016-04-06', '2016-04-16', '2016-04-26', '2016-05-06',
          '2016-05-16', '2016-05-26', '2016-06-05', '2016-06-15',
          '2016-06-25', '2016-07-05', '2016-07-15', '2016-07-25',
          '2016-08-04', '2016-08-14', '2016-08-24', '2016-09-03',
          '2016-09-13', '2016-09-23', '2016-10-03', '2016-10-13',
          '2016-10-23', '2016-11-02', '2016-11-12', '2016-11-22',
          '2016-12-02', '2016-12-12', '2016-12-22'], dtype=object)

[101]:
```
plt.figure(figsize=(15, 5))
df.isna().sum()[indexes].plot(linestyle='dotted')
plt.show()
```



- From the above plot, it can be observed that null values are decreasing over the time.
- These NaN values might indicate that the webpages have not yet been created on that data.

[102]:
```
# Replacing the NaN values with 0
df.fillna(0,inplace=True)
```

[103]:
```
df.isnull().sum().sum()
```

[103]: 0

[104]:
```
# Creating a copy of the dataframe
data = df.copy()
```

[105]:
```
data
```

[105]:

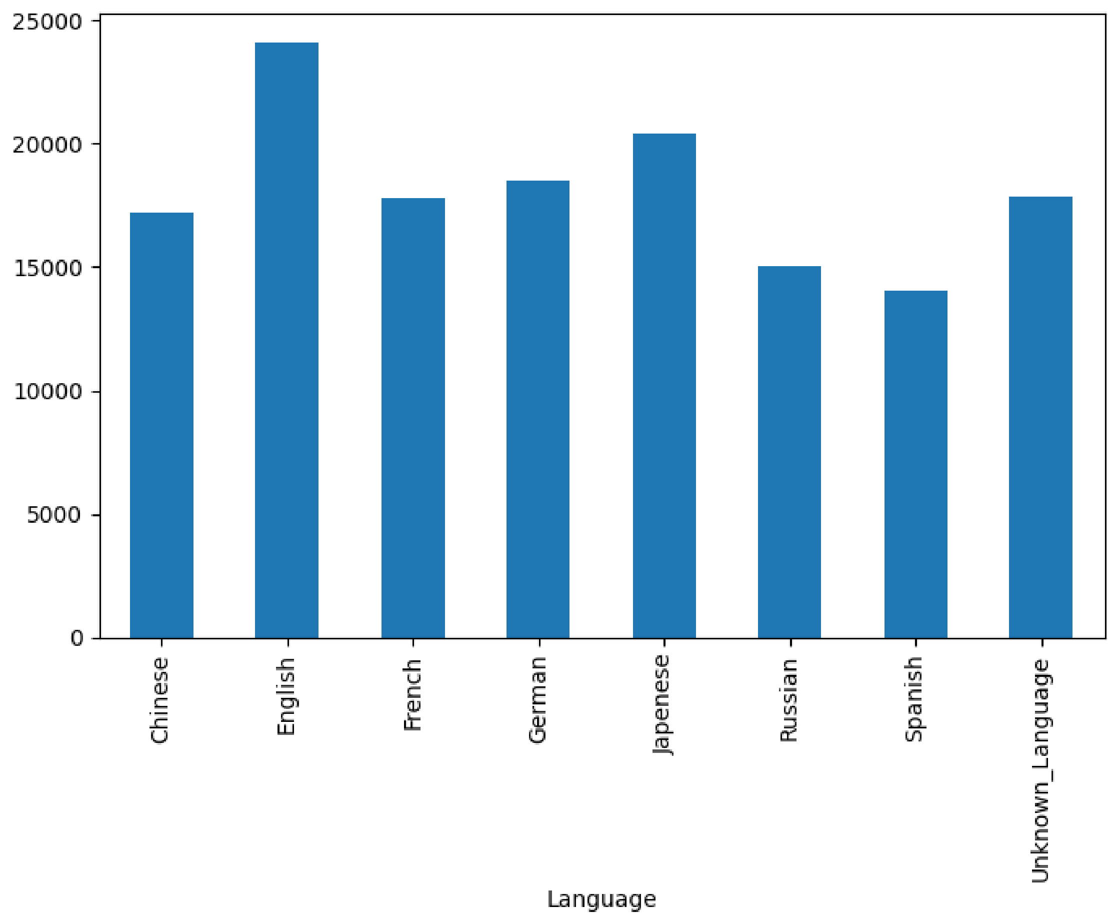
```
                                                     Page  2015-07-01  \
0                2NE1_zh.wikipedia.org_all-access_spider        18.0
1                 2PM_zh.wikipedia.org_all-access_spider        11.0
2                  3C_zh.wikipedia.org_all-access_spider         1.0
3             4minute_zh.wikipedia.org_all-access_spider        35.0
4       52_Hz_I_Love_You_zh.wikipedia.org_all-access_s…         0.0
…                                                   …         …
145058  Underworld_(serie_de_películas)_es.wikipedia.o…         0.0
145059  Resident_Evil:_Capítulo_Final_es.wikipedia.org…         0.0
145060  Enamorándome_de_Ramón_es.wikipedia.org_all-acc…         0.0
145061  Hasta_el_último_hombre_es.wikipedia.org_all-ac…         0.0
145062  Francisco_el_matemático_(serie_de_televisión_d…         0.0

        2015-07-02  2015-07-03  2015-07-04  2015-07-05  2015-07-06  \
0             11.0         5.0        13.0        14.0         9.0
1             14.0        15.0        18.0        11.0        13.0
2              0.0         1.0         1.0         0.0         4.0
3             13.0        10.0        94.0         4.0        26.0
4              0.0         0.0         0.0         0.0         0.0
…             …         …         …         …         …
145058         0.0         0.0         0.0         0.0         0.0
145059         0.0         0.0         0.0         0.0         0.0
145060         0.0         0.0         0.0         0.0         0.0
145061         0.0         0.0         0.0         0.0         0.0
145062         0.0         0.0         0.0         0.0         0.0

        2015-07-07  2015-07-08  2015-07-09  …  2016-12-25  2016-12-26  \
0              9.0        22.0        26.0  …        26.0        14.0
1             22.0        11.0        10.0  …        15.0         9.0
2              0.0         3.0         4.0  …         7.0         4.0
3             14.0         9.0        11.0  …        27.0        16.0
4              0.0         0.0         0.0  …        13.0         3.0
…             …         …         …  …         …         …
145058         0.0         0.0         0.0  …         0.0        13.0
145059         0.0         0.0         0.0  …         0.0         0.0
145060         0.0         0.0         0.0  …         0.0         0.0
145061         0.0         0.0         0.0  …         0.0         0.0
145062         0.0         0.0         0.0  …         0.0         0.0

        2016-12-27  2016-12-28  2016-12-29  2016-12-30  2016-12-31  Language  \
0             20.0        22.0        19.0        18.0        20.0   Chinese
1             30.0        52.0        45.0        26.0        20.0   Chinese
2              4.0         6.0         3.0         4.0        17.0   Chinese
3             11.0        17.0        19.0        10.0        11.0   Chinese
4             11.0        27.0        13.0        36.0        10.0   Chinese
…             …         …         …         …         …       …
145058        12.0        13.0         3.0         5.0        10.0   Spanish
```

```
145059         0.0         0.0         0.0         0.0         0.0   Spanish
145060         0.0         0.0         0.0         0.0         0.0   Spanish
145061         0.0         0.0         0.0         0.0         0.0   Spanish
145062         0.0         0.0         0.0         0.0         0.0   Spanish

        Access_origin  Access_type
0              spider   all-access
1              spider   all-access
2              spider   all-access
3              spider   all-access
4              spider   all-access
…                …          …
145058         spider   all-access
145059         spider   all-access
145060         spider   all-access
145061         spider   all-access
145062         spider   all-access

[145063 rows x 554 columns]
```

[106]:
```
data.groupby('Language')['Page'].count()
```

[106]:
```
Language
Chinese             17229
English             24108
French              17802
German              18547
Japenese            20431
Russian             15022
Spanish             14069
Unknown_Language    17855
Name: Page, dtype: int64
```

[107]:
```
plt.figure(figsize=(8,5))
data.groupby('Language')['Page'].count().plot(kind='bar')
plt.show()
```



[108]:
```
data['Language'].value_counts(normalize=True)*100
```

[108]:
```
Language
English             16.618986
Japenese            14.084225
German              12.785479
Unknown_Language    12.308445
French              12.271909
Chinese             11.876909
Russian             10.355501
Spanish              9.698545
Name: proportion, dtype: float64
```

- 16.62% of webpages are in english followed by Japanese with 14%.
- But there are more than 12% of webpages whose language is not known.

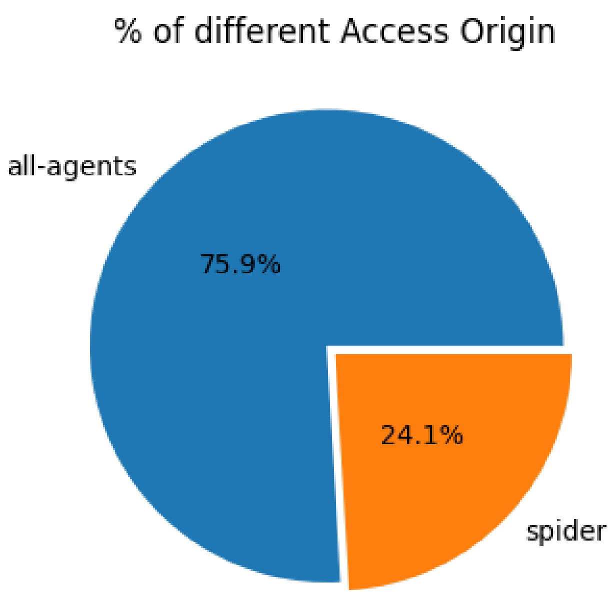
[109]:
```
data['Access_origin'].value_counts(normalize=True)*100
```

[109]: Access_origin
all-agents   75.932526
spider   24.067474
Name: proportion, dtype: float64

[110]:
```
acc_orig=data.groupby('Access_origin')['Page'].count()
acc_orig
```

[110]: Access_origin
all-agents   110150
spider   34913
Name: Page, dtype: int64

[111]:
```
plt.figure(figsize=(4,4))
plt.pie(x=acc_orig.values,labels=acc_orig.index,autopct='%1.1f%%',
 ↪pctdistance=0.5,explode=(0.05,0))
plt.title("% of different Access Origin")
plt.show()
```



- Only less than a quarter of webpages has access origin as spider.

[112]:
```
data['Access_type'].value_counts(normalize=True)*100
```

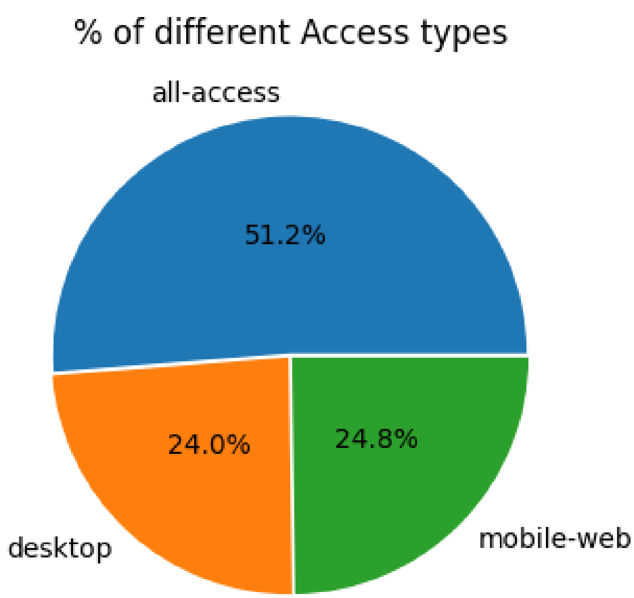
[112]: Access_type
all-access   51.229466
mobile-web   24.774753

```
desktop        23.995781
Name: proportion, dtype: float64
```

[113]:
```python
acc_type=data.groupby('Access_type')['Page'].count()
acc_type
```

[113]:
```
Access_type
all-access    74315
desktop       34809
mobile-web    35939
Name: Page, dtype: int64
```

[114]:
```python
plt.figure(figsize=(4,4))
plt.pie(x=acc_type.values,labels=acc_type.index,autopct='%1.1f%%',␣
 ↪pctdistance=0.5,explode=(0.01,0.01,0.01))
plt.title("% of different Access types")
plt.show()
```



- 24.8% of web pages have been accessed using mobile-web.
- 24% o web pages have been accesssed using desktop.
- While the remaining 51.2% is accessed by both.

[115]:
```python
data.groupby(['Access_type','Access_origin'])['Page'].count()
```

[115]:
```
Access_type  Access_origin
all-access   all-agents       39402
             spider           34913
desktop      all-agents       34809
mobile-web   all-agents       35939
Name: Page, dtype: int64
```

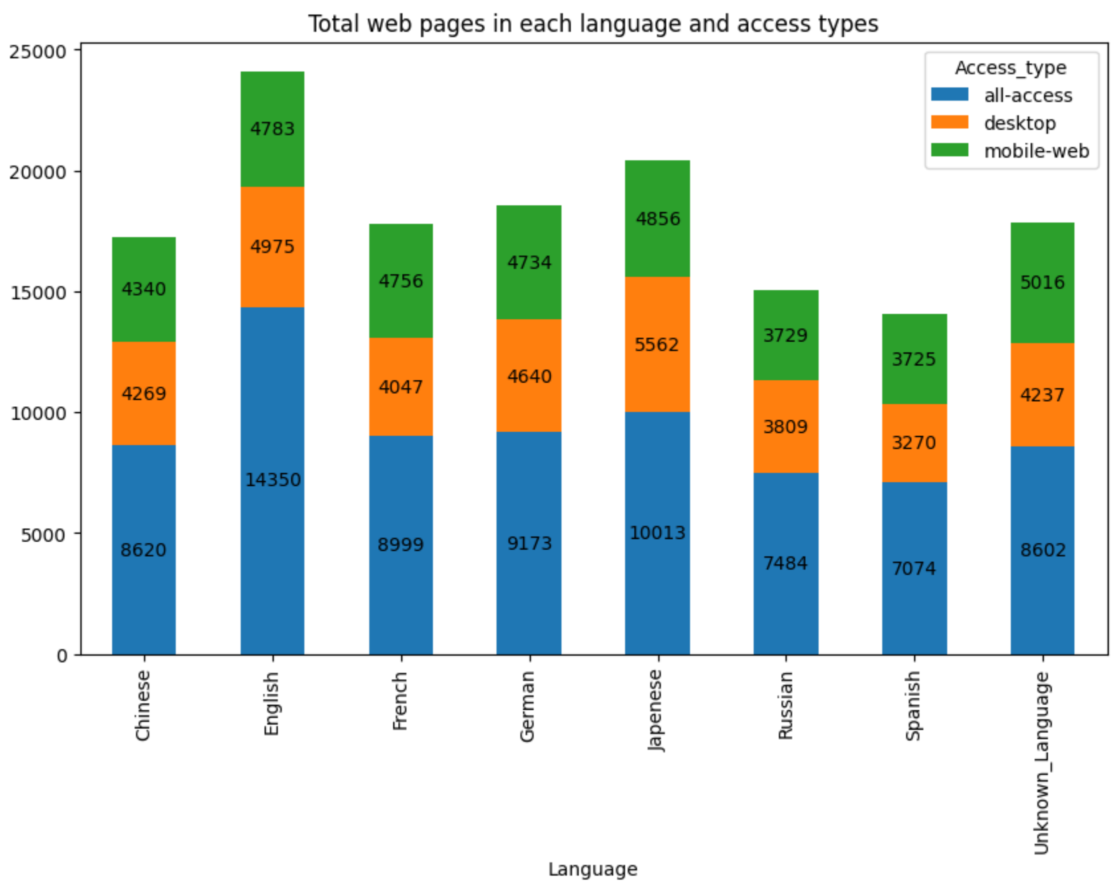
[116]:
```
data1= pd.DataFrame(data.groupby(['Language','Access_type'])['Page'].count().
 ↪unstack())
```

[117]:
```
data1
```

[117]:

Access_type	all-access	desktop	mobile-web
Language			
Chinese	8620	4269	4340
English	14350	4975	4783
French	8999	4047	4756
German	9173	4640	4734
Japenese	10013	5562	4856
Russian	7484	3809	3729
Spanish	7074	3270	3725
Unknown_Language	8602	4237	5016

[118]:
```
ax=data1.plot(kind='bar', stacked=True, figsize=(10, 6))

# Adding the annotations
for container in ax.containers:
    ax.bar_label(container, label_type='center')

plt.title("Total web pages in each language and access types")
plt.show()
```

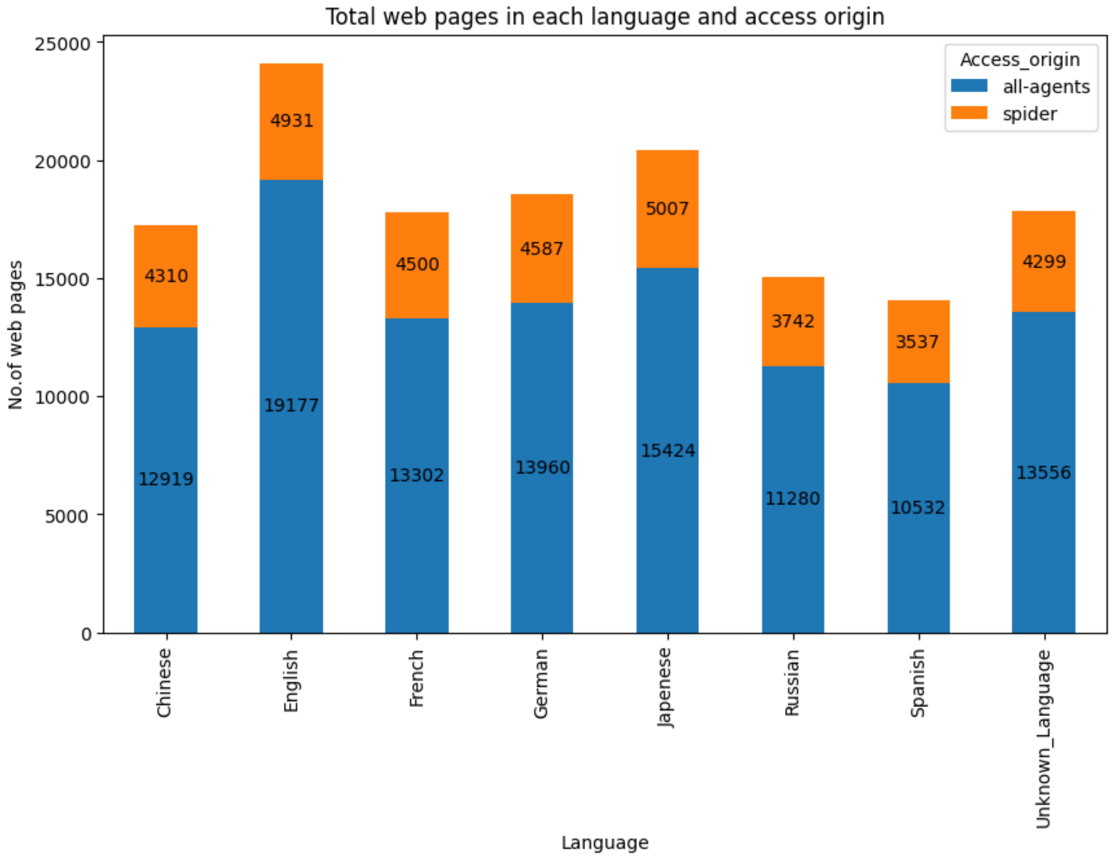


- The proportion of desktop and mobile-web access seems to be similar across different languages.

[119]:
```
data2= pd.DataFrame(data.groupby(['Language','Access_origin'])['Page'].count().
    ↪unstack())
data2
```

[119]:
```
Access_origin     all-agents  spider
Language
Chinese                12919    4310
English                19177    4931
French                 13302    4500
German                 13960    4587
Japenese               15424    5007
Russian                11280    3742
Spanish                10532    3537
Unknown_Language       13556    4299
```

[120]:
```
ax=data2.plot(kind='bar', stacked=True, figsize=(10, 6))

# Adding the annotations
for container in ax.containers:
    ax.bar_label(container, label_type='center')

plt.title("Total web pages in each language and access origin")
plt.ylabel("No.of web pages")
plt.show()
```



[121]:
```
data.head()
```

[121]:
```
                                                Page  2015-07-01  2015-07-02  \
0          2NE1_zh.wikipedia.org_all-access_spider        18.0        11.0
1           2PM_zh.wikipedia.org_all-access_spider        11.0        14.0
2            3C_zh.wikipedia.org_all-access_spider         1.0         0.0
3       4minute_zh.wikipedia.org_all-access_spider        35.0        13.0
4  52_Hz_I_Love_You_zh.wikipedia.org_all-access_s…         0.0         0.0

   2015-07-03  2015-07-04  2015-07-05  2015-07-06  2015-07-07  2015-07-08  \
```

```
0        5.0     13.0     14.0      9.0      9.0     22.0
1       15.0     18.0     11.0     13.0     22.0     11.0
2        1.0      1.0      0.0      4.0      0.0      3.0
3       10.0     94.0      4.0     26.0     14.0      9.0
4        0.0      0.0      0.0      0.0      0.0      0.0

   2015-07-09  …  2016-12-25  2016-12-26  2016-12-27  2016-12-28  \
0        26.0  …        26.0        14.0        20.0        22.0
1        10.0  …        15.0         9.0        30.0        52.0
2         4.0  …         7.0         4.0         4.0         6.0
3        11.0  …        27.0        16.0        11.0        17.0
4         0.0  …        13.0         3.0        11.0        27.0

   2016-12-29  2016-12-30  2016-12-31  Language  Access_origin  Access_type
0        19.0        18.0        20.0   Chinese         spider   all-access
1        45.0        26.0        20.0   Chinese         spider   all-access
2         3.0         4.0        17.0   Chinese         spider   all-access
3        19.0        10.0        11.0   Chinese         spider   all-access
4        13.0        36.0        10.0   Chinese         spider   all-access

[5 rows x 554 columns]
```

- Let's drop the columns access origin, acces type and page and transform it to suit for time series analysis.

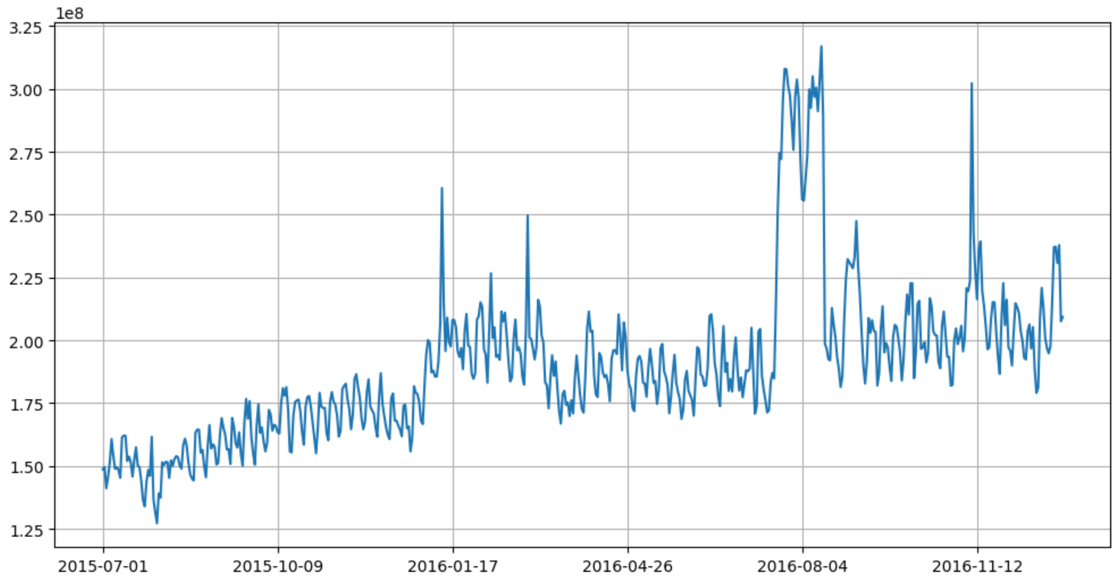
[122]:
```
data = data.drop(columns=['Page','Access_origin','Access_type'])
```

Let's plot sum of the site visits on each day.

[123]:
```
full_time_series = data.copy()
```

[124]:
```
full_time_series = full_time_series.drop('Language',axis=1)
```

[125]:
```
plt.figure(figsize=(12,6))
full_time_series.sum().plot()

plt.grid(True)
plt.show()
```



- There seems to be an upward trend in the web page visits data. This might not give a correct picture as there are different regions/languages web pages whose trend might be different from each other.
- Let's groupby language and then plot the means to find visualise the timeseries of each language.

[126]:
```python
# Groupby 'Language' and calculating the mean
mean_of_lang = data.groupby('Language').mean()
mean_of_lang
```

[126]:
```
                   2015-07-01   2015-07-02   2015-07-03   2015-07-04  \
Language
Chinese            240.582042   240.941958   239.344071   241.653491
English           3513.862203  3502.511407  3325.357889  3462.054256
French             475.150994   478.202000   459.837659   491.508932
German             714.968405   705.229741   676.877231   621.145145
Japenese           580.647056   666.672801   602.289805   756.509177
Russian            629.999601   640.902876   594.026295   558.728132
Spanish           1085.972919  1037.814557   954.412680   896.050750
Unknown_Language    83.479922    87.471857    82.680538    70.572557

                   2015-07-05   2015-07-06   2015-07-07   2015-07-08  \
Language
Chinese            257.779674   259.114864   258.832260   265.589529
English           3575.520035  3849.736021  3643.523063  3437.871080
French             482.557746   502.741209   485.945399   476.998820
German             722.076185   794.832480   770.814256   782.077641
```

```
Japenese           725.720914   632.399148   615.184181   611.462337
Russian            595.029157   640.986287   626.293436   623.360205
Spanish            974.508210  1110.637145  1082.568342  1050.669557
Unknown_Language    78.214562    89.720190    94.939457    99.096724

                   2015-07-09   2015-07-10  …   2016-12-22   2016-12-23  \
Language                                    …
Chinese            263.964420   274.414592  …   345.165129   340.420338
English           3517.459391  3497.571594  …  4997.991248  4683.314294
French             472.061903   445.495057  …   652.004719   639.459443
German             752.939990   701.702593  …   828.738017   839.025934
Japenese           596.067642   619.299300  …   675.104792   968.007733
Russian            638.550726   731.252297  …   896.352017   884.841299
Spanish           1030.841282   937.129931  …   983.568129   935.082522
Unknown_Language    86.445477    87.353906  …   131.521983   164.889051

                   2016-12-24   2016-12-25   2016-12-26   2016-12-27  \
Language
Chinese            360.738580   381.322886   376.447443   376.019618
English           4971.831757  5140.463373  5770.371661  6040.680728
French             618.215931   666.639085   936.884788   858.413100
German             810.756187  1281.088532  1206.478029  1085.095379
Japenese           856.605012   818.374725   779.114728   789.158680
Russian            874.274597  1120.990347  1112.840833  1001.209426
Spanish            880.307911   903.643685  1195.481626  1133.367901
Unknown_Language   140.363764   164.455167   165.821563   147.038925

                   2016-12-28   2016-12-29   2016-12-30   2016-12-31
Language
Chinese            378.048639   350.719427   354.704452   365.579256
English           5860.227559  6245.127510  5201.783018  5127.916418
French             774.155769   752.712954   700.543422   646.258342
German            1032.640804   994.657141   949.265649   893.013425
Japenese           790.500465   865.483236   952.018354  1197.239440
Russian            931.987685   897.282452   803.271868   880.244508
Spanish           1178.290923  1112.171085   821.671405   787.399531
Unknown_Language   186.438029   147.297004   164.540577   143.951442

[8 rows x 550 columns]
```

[127]:
```
means_data = mean_of_lang.T.reset_index()
```

[128]:
```
means_data["index"] = pd.to_datetime(means_data["index"])
means_data = means_data.set_index("index")
```

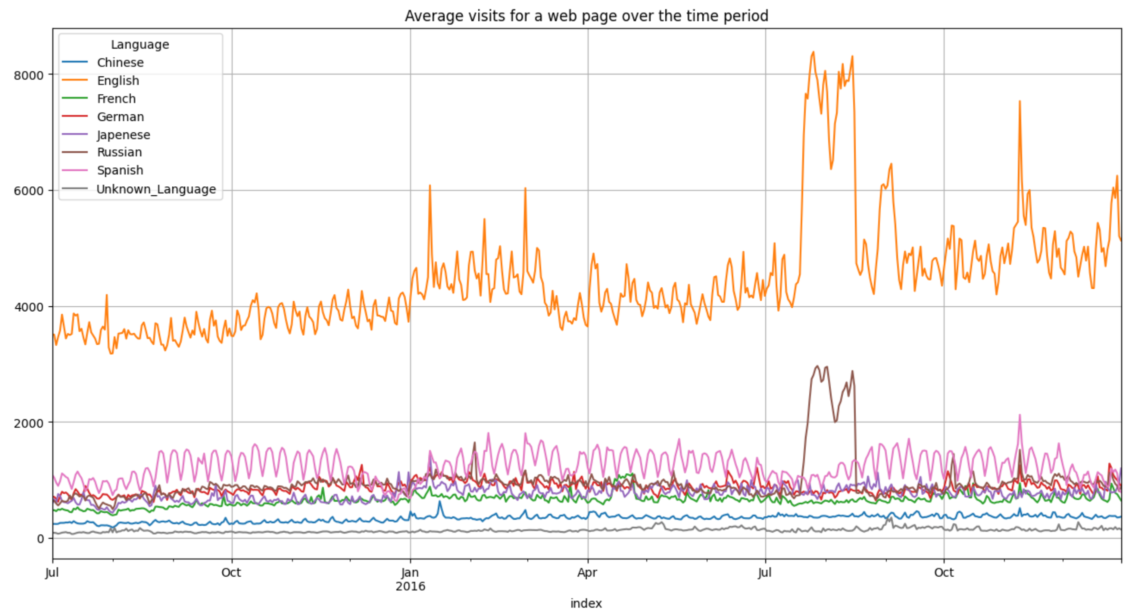
[129]:
```
means_data.head()
```

[129]:
```
Language        Chinese      English      French      German     Japenese  \
index
2015-07-01   240.582042  3513.862203  475.150994  714.968405  580.647056
2015-07-02   240.941958  3502.511407  478.202000  705.229741  666.672801
2015-07-03   239.344071  3325.357889  459.837659  676.877231  602.289805
2015-07-04   241.653491  3462.054256  491.508932  621.145145  756.509177
2015-07-05   257.779674  3575.520035  482.557746  722.076185  725.720914

Language        Russian      Spanish  Unknown_Language
index
2015-07-01   629.999601  1085.972919         83.479922
2015-07-02   640.902876  1037.814557         87.471857
2015-07-03   594.026295   954.412680         82.680538
2015-07-04   558.728132   896.050750         70.572557
2015-07-05   595.029157   974.508210         78.214562
```

[130]:
```
means_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 550 entries, 2015-07-01 to 2016-12-31
Data columns (total 8 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Chinese           550 non-null    float64
 1   English           550 non-null    float64
 2   French            550 non-null    float64
 3   German            550 non-null    float64
 4   Japenese          550 non-null    float64
 5   Russian           550 non-null    float64
 6   Spanish           550 non-null    float64
 7   Unknown_Language  550 non-null    float64
dtypes: float64(8)
memory usage: 38.7 KB
```

[131]:
```
means_data.plot(figsize=(16,8))
plt.title("Average visits for a web page over the time period")
plt.grid(True)

plt.show()
```



0.4 Is the Time Series Stationary or Trending :

Hypothesis Testing :

- Null Hypothesis: The series is Non-Stationary
- Alternative Hypothesis: The series is Stationary
- significance level : 0.05 (alpha)

[132]:
```
from statsmodels.tsa.stattools import adfuller
```

[133]:
```
# Function to perform the Dickey-Fuller test and return the p-value
def perform_adfuller(series,signficance_level):
    p_value = adfuller(series)[1]
    if p_value <= signficance_level:
        print("Time Series is Stationary")
    else:
        print("Time Series is NOT Stationary")
    print("P_value is: ", p_value)
    return p_value
```

[134]:
```
# Perform the test for each column
for column in means_data.columns:
    print(f'\nResults of Dickey-Fuller Test for {column}:')
    p_value = perform_adfuller(means_data[column],0.05)
```

```
Results of Dickey-Fuller Test for Chinese:
```

```
Time Series is NOT Stationary
P_value is:  0.44744579229311227

Results of Dickey-Fuller Test for English:
Time Series is NOT Stationary
P_value is:  0.18953359279992382

Results of Dickey-Fuller Test for French:
Time Series is NOT Stationary
P_value is:  0.051495021952457226

Results of Dickey-Fuller Test for German:
Time Series is NOT Stationary
P_value is:  0.14097382319729485

Results of Dickey-Fuller Test for Japenese:
Time Series is NOT Stationary
P_value is:  0.10257133898557619

Results of Dickey-Fuller Test for Russian:
Time Series is Stationary
P_value is:  0.0018649376536617886

Results of Dickey-Fuller Test for Spanish:
Time Series is Stationary
P_value is:  0.033588590844791

Results of Dickey-Fuller Test for Unknown_Language:
Time Series is Stationary
P_value is:  0.016293558379490952
```

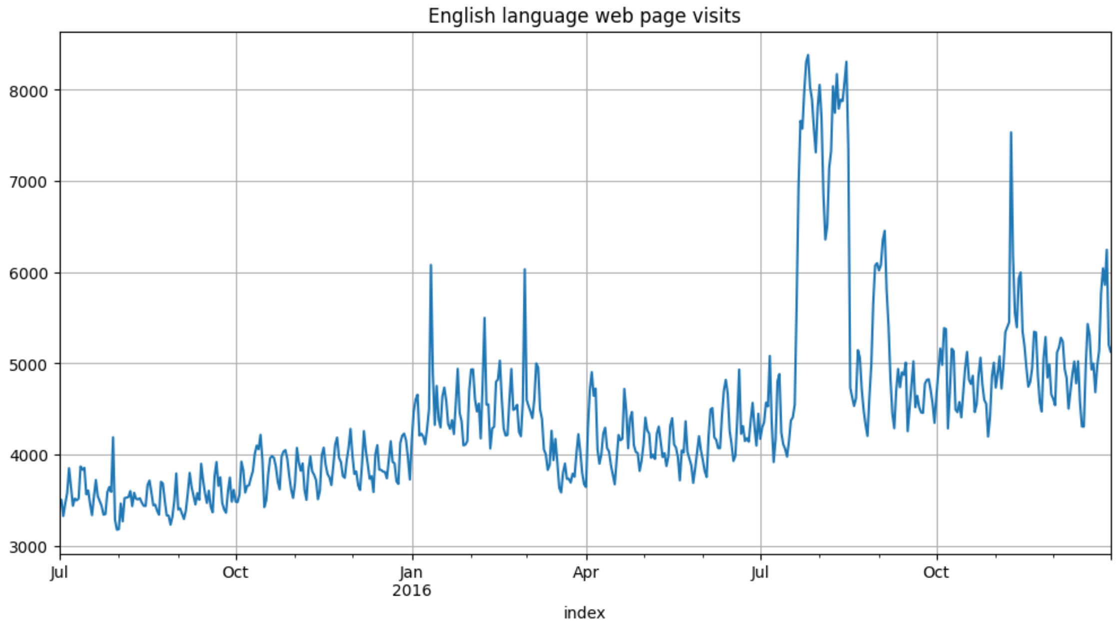
- From the above Dickey-Fuller test, it can be osberved that only the time series of Russian, spanish language site visits are stationary.

0.5 Time Series analysis for English language web pages:

- Let's create a dataset with only details of english language web pages.

[135]:
```
english_TS = means_data.English
```

[136]:
```
plt.figure(figsize=(12,6))
english_TS.plot()
plt.title("English language web page visits")
plt.grid(True)

plt.show()
```



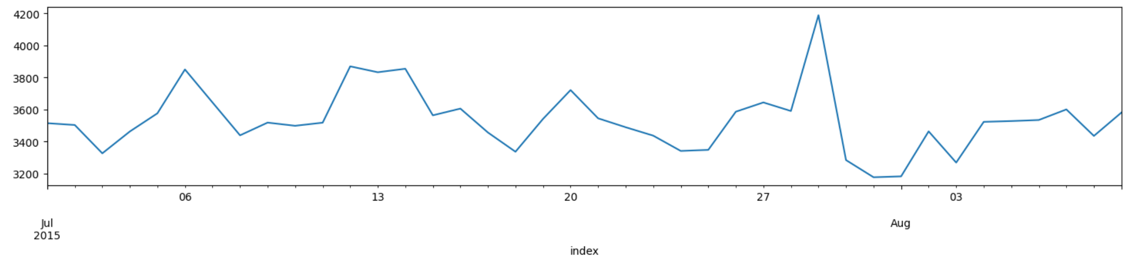
0.6 Time Series Decomposition:

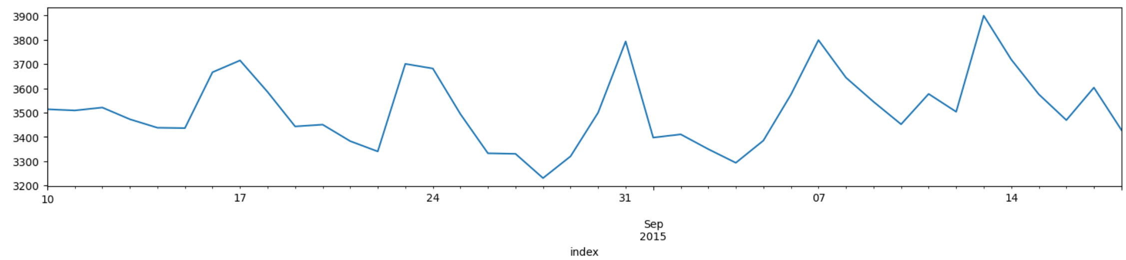
Time series = trend + seasonality + residuals(errors)

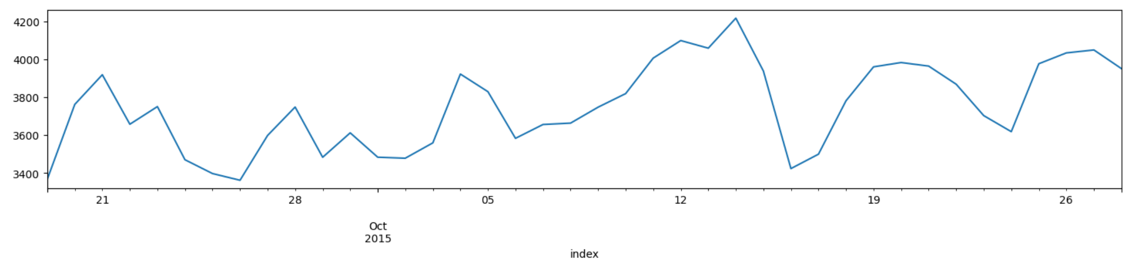
Y(t) = b(t) + s(t) + e(t)

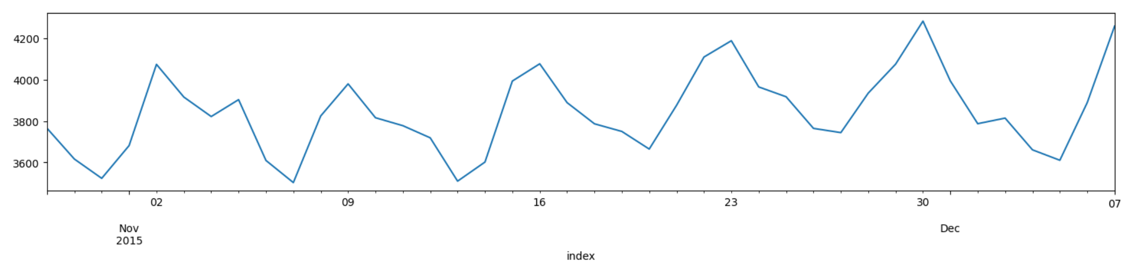
Let's check if the data has any seasonality or not by plotting smaller intervals.

[137]:
```
plt.rcParams['figure.figsize'] = (18, 3)

english_TS[:40].plot()
plt.show()

english_TS[40:80].plot()
plt.show()

english_TS[80:120].plot()
plt.show()

english_TS[120:160].plot()
plt.show()
```









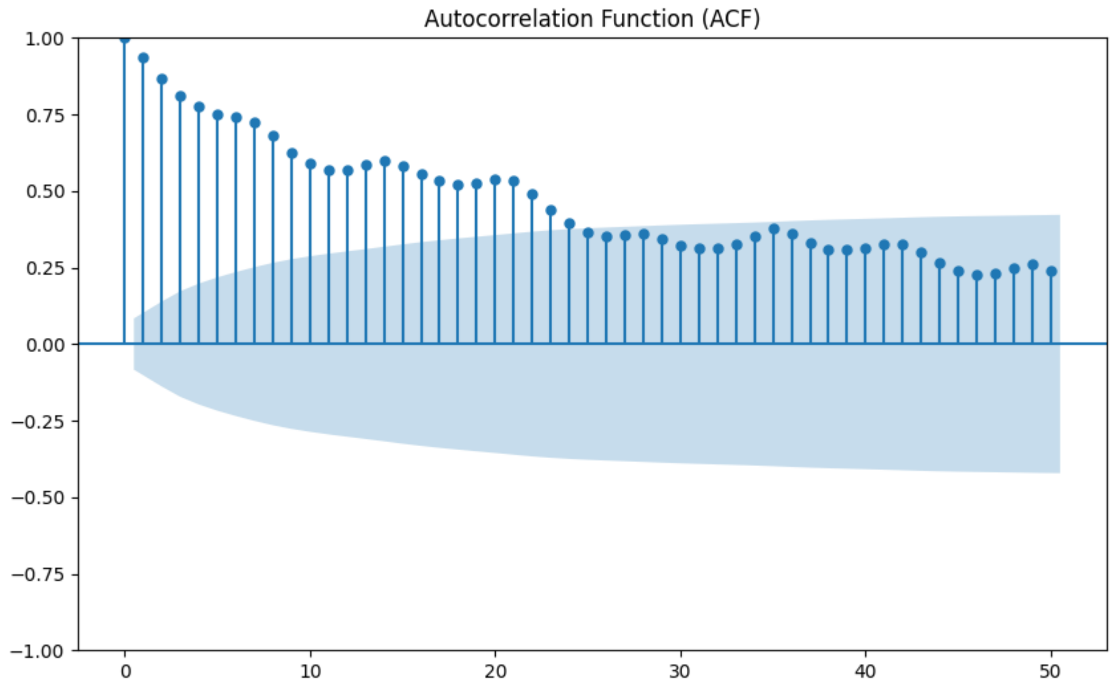
- In the above plots, we can observe that there is a local peak at almost every 7th day. So, there is a high possibility of 7 days seasonality.

Let's plot ACF and PACF

[138]:
```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
```

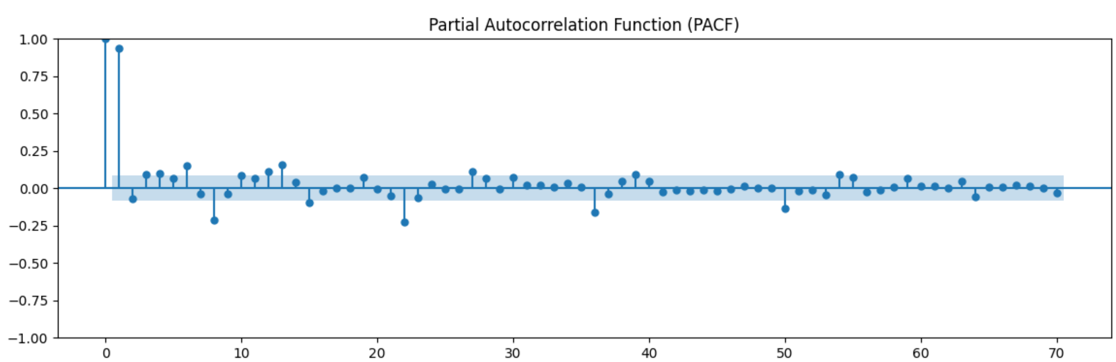
[139]:

```
# Plot ACF
fig, ax = plt.subplots(figsize=(10, 6))

plot_acf(english_TS, lags=50,ax=ax)
plt.title('Autocorrelation Function (ACF)')
plt.show()
```



[140]:

```
# Plot PACF
fig, ax = plt.subplots(figsize=(14, 4))
plot_pacf(english_TS, lags=70, method='ywm',ax=ax)
plt.title('Partial Autocorrelation Function (PACF)')
plt.show()
```



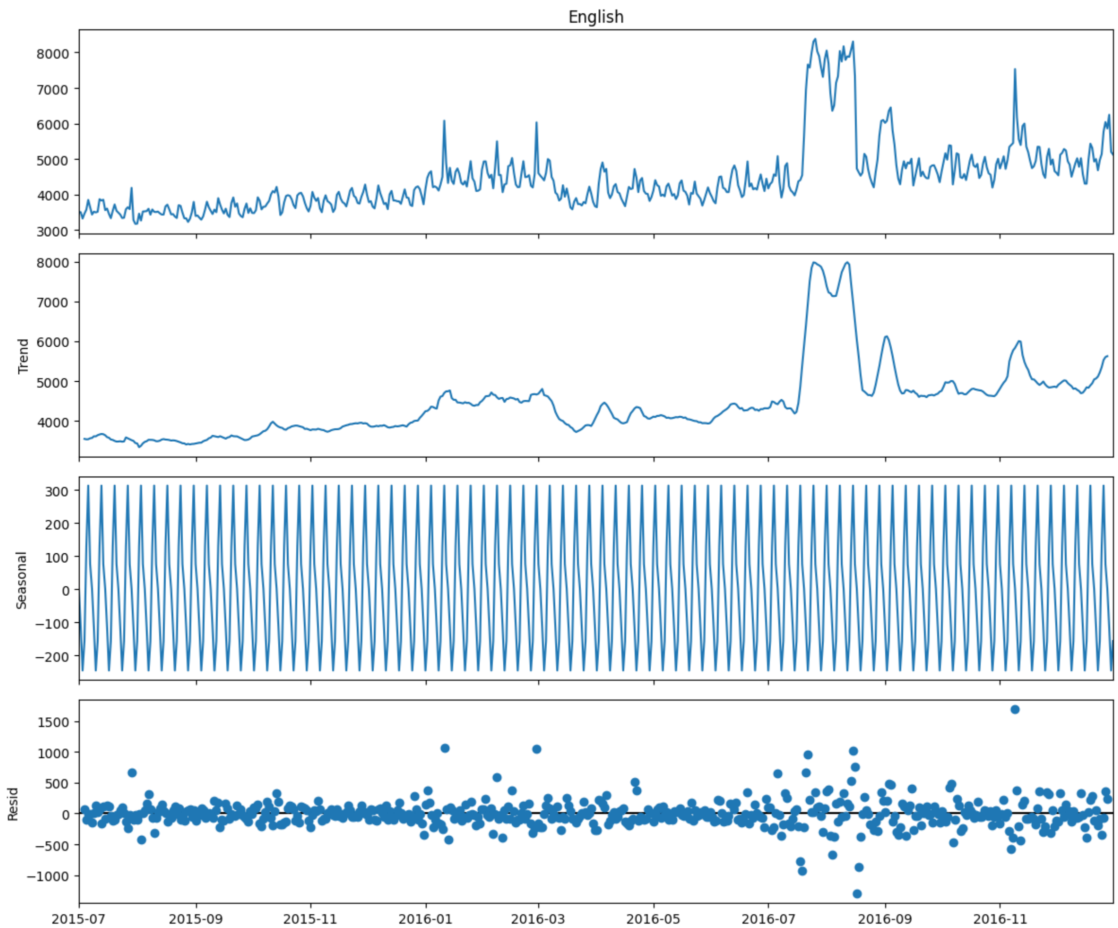
- In ACF plot, a small spikes can be observed on every 7th value. Similar pattern can also be observed in major part of PACF plot as well.

Seasonal decomposition:

[141]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
```

[142]:
```
# Perform seasonal decomposition
decomp_model = seasonal_decompose(english_TS, model='additive', period=7)
```

[143]:
```
plt.rcParams['figure.figsize'] = (12, 10)
decomp_model.plot();
```



- Let's check for the stationarity of the decomposed time series.

[144]:
```
p_value = perform_adfuller(pd.Series(decomp_model.seasonal).fillna(0),0.05)
```

```
Time Series is Stationary
P_value is:  0.0
```

[145]:
```
p_value = perform_adfuller(pd.Series(decomp_model.resid).fillna(0),0.05)
```

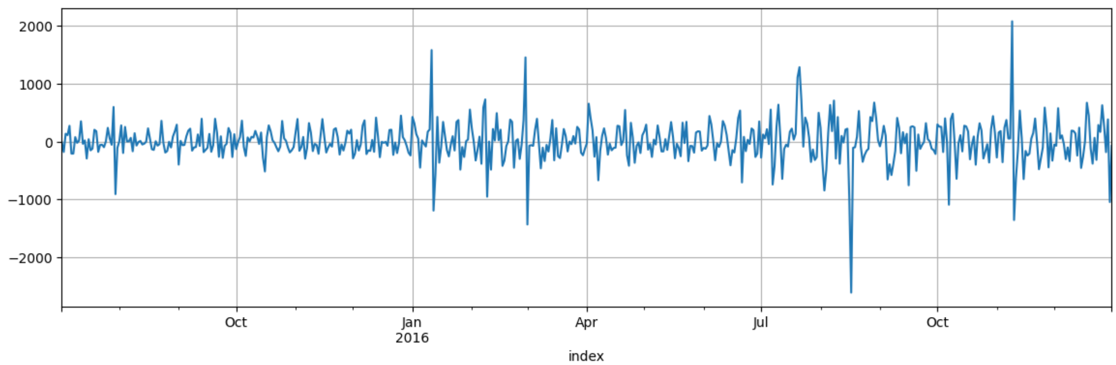
```
Time Series is Stationary
P_value is:  3.727526947812949e-21
```

- Residuals of the decomposed time series is stationary.

Time series Differencing:

[146]:
```
# Perform first-order differencing
english_TS_diff = english_TS.diff(1).dropna()
```

[147]:
```
plt.rcParams['figure.figsize'] = (14, 4)

english_TS_diff.plot()
plt.grid(True)
plt.show()
```



[148]:
```
p_value = perform_adfuller(pd.Series(english_TS_diff).fillna(0),0.05)
```

```
Time Series is Stationary
P_value is:  5.292474635436557e-13
```

0.7 Forecasting

Function to calculate model evaluation metrics

[149]:
```
from sklearn.metrics import (
    mean_squared_error as mse,
    mean_absolute_error as mae,
    mean_absolute_percentage_error as mape
)
```

[150]:
```python
# Creating a function to calculate model evaluation metrics.
def performance(actual, predicted):
    print('MAE :', round(mae(actual, predicted), 4))
    print('RMSE :', round(np.sqrt(mse(actual, predicted)), 4))
    print('MAPE:', round(mape(actual, predicted), 4))
```

Triple Exponential Smoothing:

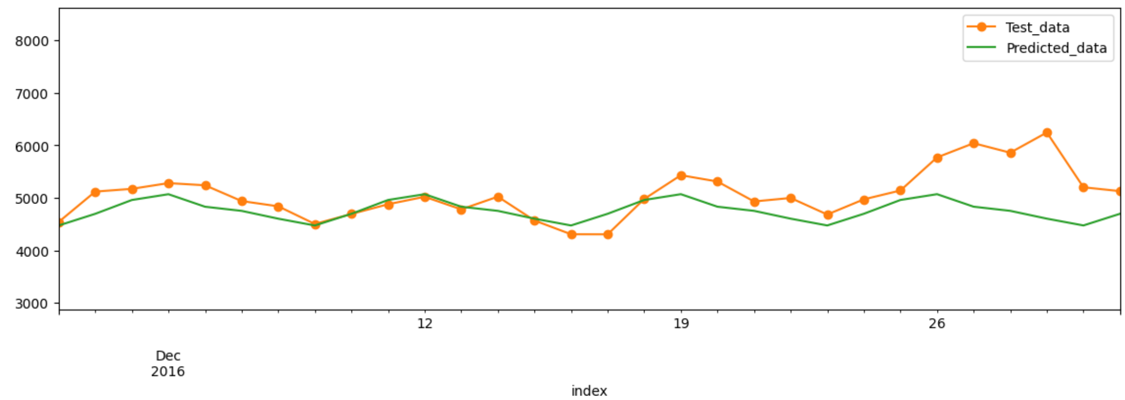
[151]:
```python
from statsmodels.tsa.holtwinters import ExponentialSmoothing
```

Train - Test Split:

[152]:
```python
train_x = english_TS.loc[english_TS.index < english_TS.index[-30]].copy()
test_x = english_TS.loc[english_TS.index >= english_TS.index[-30]].copy()
```

[153]:
```python
model = ␣
  ↪ExponentialSmoothing(train_x,trend='add',seasonal='add',seasonal_periods=7).
  ↪fit()
model.fittedvalues.plot()

# X_test.plot()
Pred = model.forecast(steps=30)
performance(test_x,Pred)

test_x.plot(style="-o",label ="Test_data")
Pred.plot(label="Predicted_data")
plt.xlim(test_x.index[0], test_x.index[-1])
plt.legend()
plt.show()
```

```
MAE : 357.7468
RMSE : 519.0338
MAPE: 0.0662
```

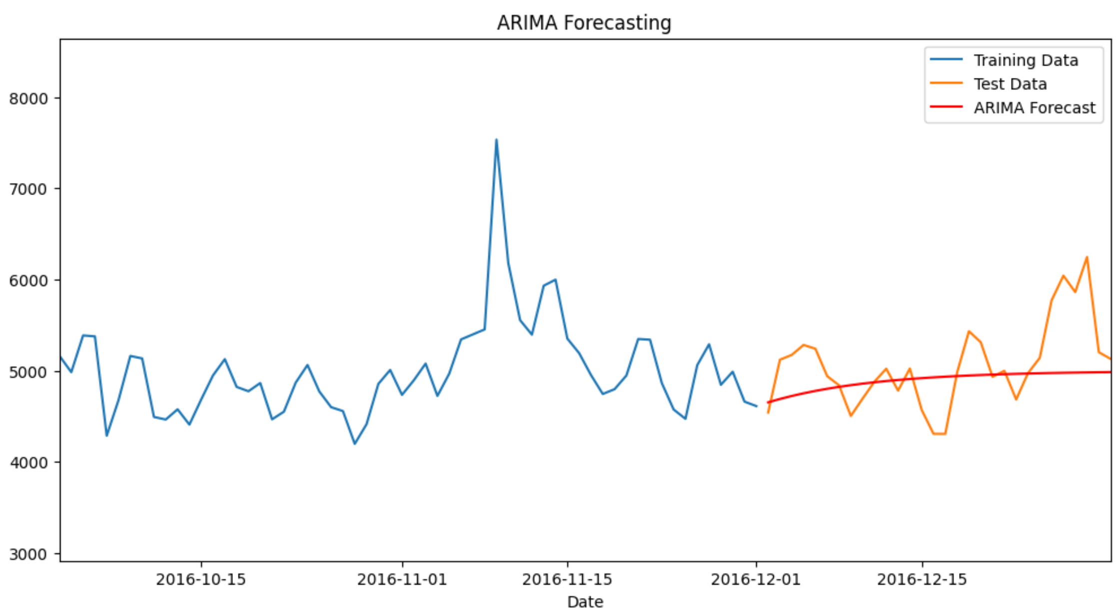


- Triple Exponential Smoothing model was able to attain MAPE of 0.0662, which is well in asked range of 4 - 8 %.

0.7.1 ARIMA:

[154]:
```
from statsmodels.tsa.arima.model import ARIMA
```

[155]:
```
# Fit ARIMA model
arima_model = ARIMA(train_x, order=(1, 1, 1))  # p=1, d=1, q=1
arima_fit = arima_model.fit()

# Forecast the next 30 days
forecast = arima_fit.forecast(steps=30)

# Plotting the results
plt.figure(figsize=(12, 6))
plt.plot(train_x.index, train_x, label='Training Data')
plt.plot(test_x.index, test_x, label='Test Data')
plt.plot(test_x.index, forecast, label='ARIMA Forecast', color='red')
plt.title('ARIMA Forecasting')
plt.xlabel('Date')
plt.xlim(train_x.index[-60], test_x.index[-1])

plt.legend()
plt.show()

performance(test_x,forecast)
```



```
MAE : 346.0364
RMSE : 472.1862
MAPE: 0.0659
```

- ARIMA model was able to attain MAPE of 0.0659, which is well in asked range of 4 - 8 %.

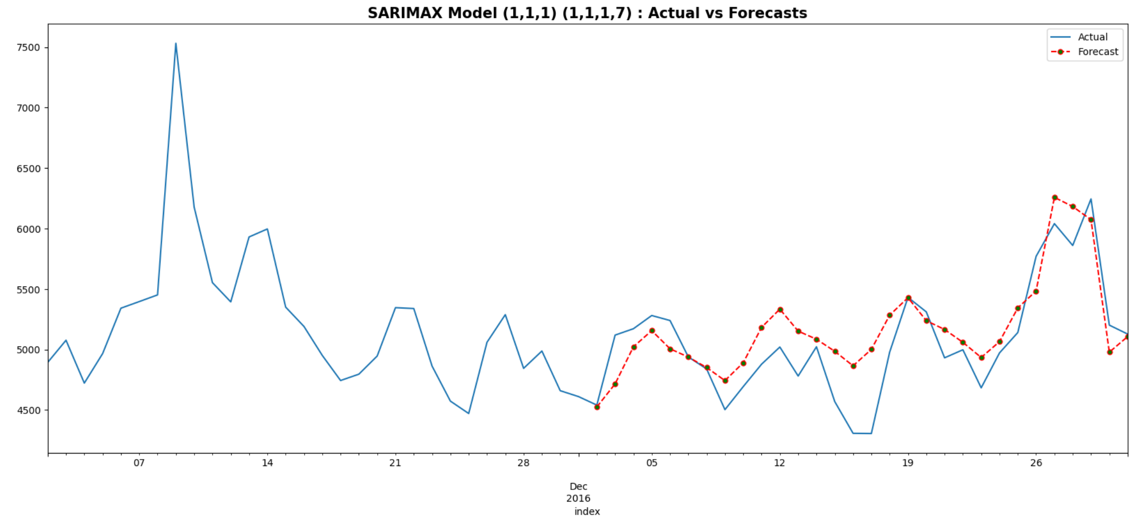
0.7.2 SARIMAX

[156]:
```
from statsmodels.tsa.statespace.sarimax import SARIMAX
```

[157]:
```
def sarimax_model(series, n, p=0, d=0, q=0, P=0, D=0, Q=0, s=0, exog = []):

    #Creating SARIMAX Model with order(p,d,q) & seasonal_order=(P, D, Q, s)
    sarimax_model = SARIMAX(series[:-n], \
                    order =(p,d,q),
                    seasonal_order=(P, D, Q, s),
                    exog = exog[:-n],
                    initialization='approximate_diffuse')
    sarimax_model_fit = sarimax_model.fit()

    #Creating forecast for last n-values
    model_forecast = sarimax_model_fit.forecast(n, dynamic = True, exog = pd.
 ↪DataFrame(exog[-n:]))

    #plotting Actual & Forecasted values

    plt.figure(figsize = (20,8))
    series[-60:].plot(label = 'Actual')
    model_forecast[-60:].plot(label = 'Forecast', color = 'red',
                              linestyle='dashed',␣
 ↪marker='o',markerfacecolor='green', markersize=5)
    plt.legend(loc="upper right")
    plt.title(f'SARIMAX Model ({p},{d},{q}) ({P},{D},{Q},{s}) : Actual vs␣
 ↪Forecasts', fontsize = 15, fontweight = 'bold')
    plt.show()
    performance(test_x,model_forecast)
```

[158]:
```
english_TS.index.freq = 'D'
```

[159]:
```
exog = Exog_Campaign_eng['Exog'].to_numpy()
p,d,q, P,D,Q,s = 1,1,1,1,1,1,7
series = english_TS
n = 30
sarimax_model(series, n, p=p, d=d, q=q, P=P, D=D, Q=Q, s=s, exog = exog)
```




```
MAE : 218.8412
RMSE : 272.9837
MAPE: 0.0446
```

Hyperparameter tuning for SARIMAX using grid search:

[160]:
```
def SARIMAX_grid_search(time_series, n, param, d_param, s_param, exog = []):
    counter = 0
    #creating df for storing results summary
    param_df = pd.DataFrame(columns = ['serial','pdq', 'PDQs', 'mape', 'rmse'])

    #Creating loop for every paramater to fit SARIMAX model
    for p in param:
        for d in d_param:
            for q in param:
                for P in param:
                    for D in d_param:
                        for Q in param:
                            for s in s_param:
                                #Creating Model
                                model = SARIMAX(time_series[:-n],
                                                order=(p,d,q),
                                                seasonal_order=(P, D, Q, s),
                                                exog = exog[:-n],
                                                ␣
↪initialization='approximate_diffuse')
                                model_fit = model.fit()

                                #Creating forecast from Model
```

```
                                model_forecast = model_fit.forecast(n, dynamic␣
↪= True, exog = pd.DataFrame(exog[-n:]))

                                #Calculating errors for results
                                actuals = time_series.values[-n:]
                                errors = time_series.values[-n:] -␣
↪model_forecast.values

                                #Calculating MAPE & RMSE
                                mape = np.mean(np.abs(errors)/ np.abs(actuals))
                                rmse = np.sqrt(np.mean(errors**2))
                                mape = np.round(mape,5)
                                rmse = np.round(rmse,3)

                                #Storing the results in param_df
                                counter += 1
                                list_row = [counter, (p,d,q), (P,D,Q,s), mape,␣
↪rmse]
                                param_df.loc[len(param_df)] = list_row

                #print statement to check progress of Loop
                print(f'Possible Combination: {counter} out of {␣
↪(len(param)**4)*len(s_param)*(len(d_param)**2)} calculated')

    return param_df
```

[161]:
```
from statsmodels.tools.sm_exceptions import ConvergenceWarning
warnings.catch_warnings()
warnings.filterwarnings("ignore", category=ConvergenceWarning)
```

[162]:
```
time_series = english_TS
n = 30
param = [0,1,2] #p,P,q,Q
d_param = [0,1] #d,D
s_param = [7] #s

english_params  = SARIMAX_grid_search(time_series, n, param, d_param,s_param,␣
↪exog)
```

```
Possible Combination: 18 out of 324 calculated
Possible Combination: 36 out of 324 calculated
Possible Combination: 54 out of 324 calculated
Possible Combination: 72 out of 324 calculated
Possible Combination: 90 out of 324 calculated
Possible Combination: 108 out of 324 calculated
Possible Combination: 126 out of 324 calculated
Possible Combination: 144 out of 324 calculated
```

```
Possible Combination: 162 out of 324 calculated
Possible Combination: 180 out of 324 calculated
Possible Combination: 198 out of 324 calculated
Possible Combination: 216 out of 324 calculated
Possible Combination: 234 out of 324 calculated
Possible Combination: 252 out of 324 calculated
Possible Combination: 270 out of 324 calculated
Possible Combination: 288 out of 324 calculated
Possible Combination: 306 out of 324 calculated
Possible Combination: 324 out of 324 calculated
```

[163]:

```
english_params.sort_values(['mape', 'rmse']).head()
```

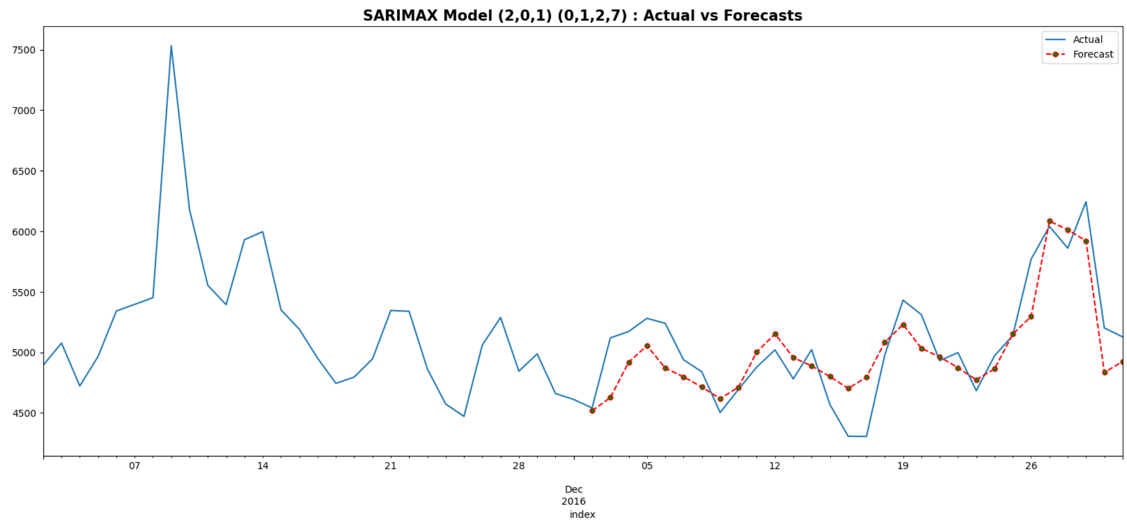
[163]:

	serial	pdq	PDQs	mape	rmse
239	240	(2, 0, 1)	(0, 1, 2, 7)	0.03936	242.880
323	324	(2, 1, 2)	(2, 1, 2, 7)	0.04025	250.688
40	41	(0, 0, 2)	(0, 1, 1, 7)	0.04199	276.311
41	42	(0, 0, 2)	(0, 1, 2, 7)	0.04206	271.577
46	47	(0, 0, 2)	(1, 1, 1, 7)	0.04212	270.079

Best Hyper parameters: 2,0,1,0,1,2,7 - Let's use the above parameters that we got after hyper parameter tuning.

[164]:

```
time_series = english_TS
p,d,q, P,D,Q,s = 2,0,1,0,1,2,7
n = 30
sarimax_model(time_series, n, p=p, d=d, q=q, P=P, D=D, Q=Q, s=s, exog = exog)
```




```
MAE : 198.5985
RMSE : 242.88
MAPE: 0.0394
```

- We are able to create a model which is able to attain MAPE of 0.0394 which is even less than the asked 4 - 8%.

[165]:
```
def sarimax_grid_search_all_lang(languages, data, n, param, d_param, s_param):

    best_param_df  = pd.DataFrame(columns = ['language','p','d', 'q',␣
↪'P','D','Q','s','mape'])
    for lang in languages:
        print('')
        print('')
        print(f'------------------------------------------------------------')
        print(f'          Finding best parameters for {lang}                 ')
        print(f'------------------------------------------------------------')
        counter = 0
        time_series = means_data[lang]
        best_mape = 100

        #Creating loop for every paramater to fit SARIMAX model
        for p in param:
            for d in d_param:
                for q in param:
                    for P in param:
                        for D in d_param:
                            for Q in param:
                                for s in s_param:
                                    #Creating Model
                                    model = SARIMAX(time_series[:-n],
                                                    order=(p,d,q),
                                                    seasonal_order=(P, D, Q, s),
                                                   ␣
↪initialization='approximate_diffuse')
                                    model_fit = model.fit()

                                    #Creating forecast from Model
                                    model_forecast = model_fit.forecast(n,␣
↪dynamic = True)


                                    #Calculating errors for results
                                    actuals = time_series.values[-n:]
                                    errors = time_series.values[-n:] -␣
↪model_forecast.values

                                    #Calculating MAPE & RMSE
                                    mape = np.mean(np.abs(errors)/ np.
↪abs(actuals))

                                    counter += 1
```

```
                                if (mape < best_mape):
                                    best_mape = mape
                                    best_p = p
                                    best_d = d
                                    best_q = q
                                    best_P = P
                                    best_D = D
                                    best_Q = Q
                                    best_s = s
                                else: pass

                #print statement to check progress of Loop
                print(f'Possible Combination: {counter} out of␣
↪{(len(param)**4)*len(s_param)*(len(d_param)**2)} calculated')

        best_mape = np.round(best_mape, 4)
        print(f'-------------------------------------------------------------')
        print(f'Minimum MAPE for {lang} = {best_mape}')
        print(f'Corresponding Best Parameters are {best_p , best_d, best_q,␣
↪best_P, best_D, best_Q, best_s}')
        print(f'-------------------------------------------------------------')

        best_param_row = [lang, best_p, best_d, best_q, best_P, best_D, best_Q,␣
↪best_s, best_mape]
        best_param_df.loc[len(best_param_df)] = best_param_row

    return best_param_df
```

[166]:

```
languages = means_data.columns
n = 30
param = [0,1,2]
d_param = [0,1]
s_param = [7]

best_param_df = sarimax_grid_search_all_lang(languages, means_data, n, param,␣
↪d_param, s_param)
```

```
--------------------------------------------------------------
          Finding best parameters for Chinese
--------------------------------------------------------------
Possible Combination: 18 out of 324 calculated
Possible Combination: 36 out of 324 calculated
Possible Combination: 54 out of 324 calculated
Possible Combination: 72 out of 324 calculated
```

```
Possible Combination: 90 out of 324 calculated
Possible Combination: 108 out of 324 calculated
Possible Combination: 126 out of 324 calculated
Possible Combination: 144 out of 324 calculated
Possible Combination: 162 out of 324 calculated
Possible Combination: 180 out of 324 calculated
Possible Combination: 198 out of 324 calculated
Possible Combination: 216 out of 324 calculated
Possible Combination: 234 out of 324 calculated
Possible Combination: 252 out of 324 calculated
Possible Combination: 270 out of 324 calculated
Possible Combination: 288 out of 324 calculated
Possible Combination: 306 out of 324 calculated
Possible Combination: 324 out of 324 calculated
--------------------------------------------------------------
Minimum MAPE for Chinese = 0.0307
Corresponding Best Parameters are (0, 1, 0, 1, 0, 2, 7)
--------------------------------------------------------------


--------------------------------------------------------------
          Finding best parameters for English
--------------------------------------------------------------
Possible Combination: 18 out of 324 calculated
Possible Combination: 36 out of 324 calculated
Possible Combination: 54 out of 324 calculated
Possible Combination: 72 out of 324 calculated
Possible Combination: 90 out of 324 calculated
Possible Combination: 108 out of 324 calculated
Possible Combination: 126 out of 324 calculated
Possible Combination: 144 out of 324 calculated
Possible Combination: 162 out of 324 calculated
Possible Combination: 180 out of 324 calculated
Possible Combination: 198 out of 324 calculated
Possible Combination: 216 out of 324 calculated
Possible Combination: 234 out of 324 calculated
Possible Combination: 252 out of 324 calculated
Possible Combination: 270 out of 324 calculated
Possible Combination: 288 out of 324 calculated
Possible Combination: 306 out of 324 calculated
Possible Combination: 324 out of 324 calculated
--------------------------------------------------------------
Minimum MAPE for English = 0.0526
Corresponding Best Parameters are (2, 0, 1, 0, 1, 2, 7)
--------------------------------------------------------------


--------------------------------------------------------------
```

```
          Finding best parameters for French
--------------------------------------------------------------
Possible Combination: 18 out of 324 calculated
Possible Combination: 36 out of 324 calculated
Possible Combination: 54 out of 324 calculated
Possible Combination: 72 out of 324 calculated
Possible Combination: 90 out of 324 calculated
Possible Combination: 108 out of 324 calculated
Possible Combination: 126 out of 324 calculated
Possible Combination: 144 out of 324 calculated
Possible Combination: 162 out of 324 calculated
Possible Combination: 180 out of 324 calculated
Possible Combination: 198 out of 324 calculated
Possible Combination: 216 out of 324 calculated
Possible Combination: 234 out of 324 calculated
Possible Combination: 252 out of 324 calculated
Possible Combination: 270 out of 324 calculated
Possible Combination: 288 out of 324 calculated
Possible Combination: 306 out of 324 calculated
Possible Combination: 324 out of 324 calculated
--------------------------------------------------------------
Minimum MAPE for French = 0.0636
Corresponding Best Parameters are (0, 0, 2, 2, 1, 2, 7)
--------------------------------------------------------------


--------------------------------------------------------------
          Finding best parameters for German
--------------------------------------------------------------
Possible Combination: 18 out of 324 calculated
Possible Combination: 36 out of 324 calculated
Possible Combination: 54 out of 324 calculated
Possible Combination: 72 out of 324 calculated
Possible Combination: 90 out of 324 calculated
Possible Combination: 108 out of 324 calculated
Possible Combination: 126 out of 324 calculated
Possible Combination: 144 out of 324 calculated
Possible Combination: 162 out of 324 calculated
Possible Combination: 180 out of 324 calculated
Possible Combination: 198 out of 324 calculated
Possible Combination: 216 out of 324 calculated
Possible Combination: 234 out of 324 calculated
Possible Combination: 252 out of 324 calculated
Possible Combination: 270 out of 324 calculated
Possible Combination: 288 out of 324 calculated
Possible Combination: 306 out of 324 calculated
Possible Combination: 324 out of 324 calculated
--------------------------------------------------------------
```

```
Minimum MAPE for German = 0.0658
Corresponding Best Parameters are (0, 1, 1, 1, 0, 1, 7)
--------------------------------------------------------------


--------------------------------------------------------------
          Finding best parameters for Japenese
--------------------------------------------------------------
Possible Combination: 18 out of 324 calculated
Possible Combination: 36 out of 324 calculated
Possible Combination: 54 out of 324 calculated
Possible Combination: 72 out of 324 calculated
Possible Combination: 90 out of 324 calculated
Possible Combination: 108 out of 324 calculated
Possible Combination: 126 out of 324 calculated
Possible Combination: 144 out of 324 calculated
Possible Combination: 162 out of 324 calculated
Possible Combination: 180 out of 324 calculated
Possible Combination: 198 out of 324 calculated
Possible Combination: 216 out of 324 calculated
Possible Combination: 234 out of 324 calculated
Possible Combination: 252 out of 324 calculated
Possible Combination: 270 out of 324 calculated
Possible Combination: 288 out of 324 calculated
Possible Combination: 306 out of 324 calculated
Possible Combination: 324 out of 324 calculated
--------------------------------------------------------------
Minimum MAPE for Japenese = 0.0712
Corresponding Best Parameters are (0, 1, 2, 2, 1, 0, 7)
--------------------------------------------------------------


--------------------------------------------------------------
          Finding best parameters for Russian
--------------------------------------------------------------
Possible Combination: 18 out of 324 calculated
Possible Combination: 36 out of 324 calculated
Possible Combination: 54 out of 324 calculated
Possible Combination: 72 out of 324 calculated
Possible Combination: 90 out of 324 calculated
Possible Combination: 108 out of 324 calculated
Possible Combination: 126 out of 324 calculated
Possible Combination: 144 out of 324 calculated
Possible Combination: 162 out of 324 calculated
Possible Combination: 180 out of 324 calculated
Possible Combination: 198 out of 324 calculated
Possible Combination: 216 out of 324 calculated
Possible Combination: 234 out of 324 calculated
```

```
Possible Combination: 252 out of 324 calculated
Possible Combination: 270 out of 324 calculated
Possible Combination: 288 out of 324 calculated
Possible Combination: 306 out of 324 calculated
Possible Combination: 324 out of 324 calculated
--------------------------------------------------------------
Minimum MAPE for Russian = 0.0427
Corresponding Best Parameters are (0, 0, 1, 2, 0, 2, 7)
--------------------------------------------------------------


--------------------------------------------------------------
          Finding best parameters for Spanish
--------------------------------------------------------------
Possible Combination: 18 out of 324 calculated
Possible Combination: 36 out of 324 calculated
Possible Combination: 54 out of 324 calculated
Possible Combination: 72 out of 324 calculated
Possible Combination: 90 out of 324 calculated
Possible Combination: 108 out of 324 calculated
Possible Combination: 126 out of 324 calculated
Possible Combination: 144 out of 324 calculated
Possible Combination: 162 out of 324 calculated
Possible Combination: 180 out of 324 calculated
Possible Combination: 198 out of 324 calculated
Possible Combination: 216 out of 324 calculated
Possible Combination: 234 out of 324 calculated
Possible Combination: 252 out of 324 calculated
Possible Combination: 270 out of 324 calculated
Possible Combination: 288 out of 324 calculated
Possible Combination: 306 out of 324 calculated
Possible Combination: 324 out of 324 calculated
--------------------------------------------------------------
Minimum MAPE for Spanish = 0.0856
Corresponding Best Parameters are (0, 1, 0, 2, 1, 0, 7)
--------------------------------------------------------------


--------------------------------------------------------------
          Finding best parameters for Unknown_Language
--------------------------------------------------------------
Possible Combination: 18 out of 324 calculated
Possible Combination: 36 out of 324 calculated
Possible Combination: 54 out of 324 calculated
Possible Combination: 72 out of 324 calculated
Possible Combination: 90 out of 324 calculated
Possible Combination: 108 out of 324 calculated
Possible Combination: 126 out of 324 calculated
```

```
Possible Combination: 144 out of 324 calculated
Possible Combination: 162 out of 324 calculated
Possible Combination: 180 out of 324 calculated
Possible Combination: 198 out of 324 calculated
Possible Combination: 216 out of 324 calculated
Possible Combination: 234 out of 324 calculated
Possible Combination: 252 out of 324 calculated
Possible Combination: 270 out of 324 calculated
Possible Combination: 288 out of 324 calculated
Possible Combination: 306 out of 324 calculated
Possible Combination: 324 out of 324 calculated
--------------------------------------------------------------
Minimum MAPE for Unknown_Language = 0.0976
Corresponding Best Parameters are (0, 1, 2, 0, 0, 0, 7)
--------------------------------------------------------------
```

- Among all the web pages, all languages achieved the required performance except for those with unknown languages.
- This could be due to multiple languages being missed during data recording, leading to them being grouped into a single time series instead of being separated.

[167]:
```
best_param_df.sort_values(['mape'], inplace = True)
best_param_df
```

[167]:

	language	p	d	q	P	D	Q	s	mape
0	Chinese	0	1	0	1	0	2	7	0.0307
5	Russian	0	0	1	2	0	2	7	0.0427
1	English	2	0	1	0	1	2	7	0.0526
2	French	0	0	2	2	1	2	7	0.0636
3	German	0	1	1	1	0	1	7	0.0658
4	Japenese	0	1	2	2	1	0	7	0.0712
6	Spanish	0	1	0	2	1	0	7	0.0856
7	Unknown_Language	0	1	2	0	0	0	7	0.0976

- So let's remove the row that contains parameters of unknown language.

[168]:
```
best_param_df = best_param_df.drop(index=7).reset_index(drop=True)
```

[169]:
```
best_param_df
```

[169]:

	language	p	d	q	P	D	Q	s	mape
0	Chinese	0	1	0	1	0	2	7	0.0307
1	Russian	0	0	1	2	0	2	7	0.0427
2	English	2	0	1	0	1	2	7	0.0526
3	French	0	0	2	2	1	2	7	0.0636
4	German	0	1	1	1	0	1	7	0.0658
5	Japenese	0	1	2	2	1	0	7	0.0712
6	Spanish	0	1	0	2	1	0	7	0.0856

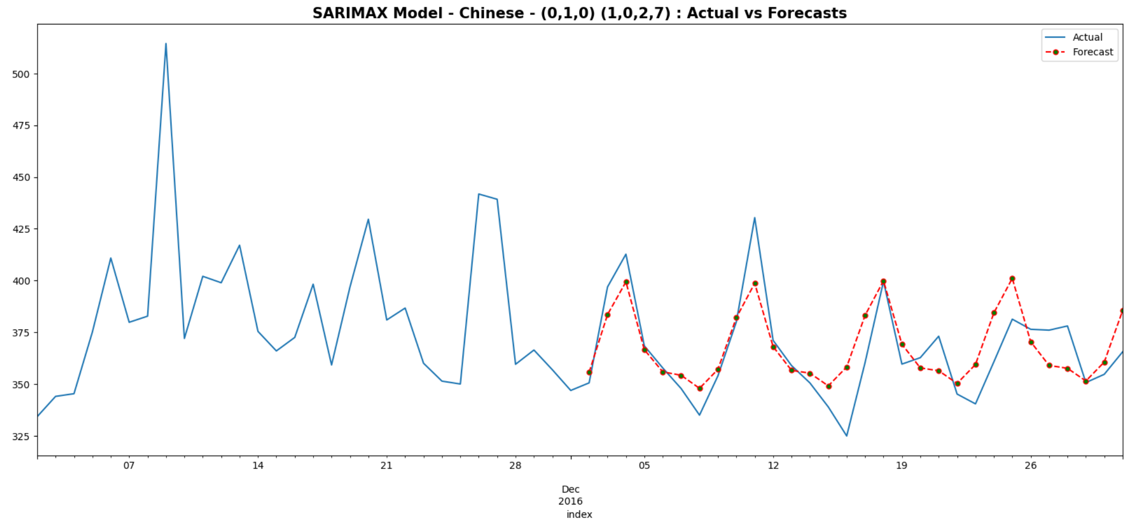
[170]:
```
def SARIMAX_model_pred_plot(languages, data, n, best_param_df):

    for lang in languages:
        #fetching respective best parameters for that language
        p = best_param_df.loc[best_param_df['language'] == lang, ['p']].
↪values[0][0]
        d = best_param_df.loc[best_param_df['language'] == lang, ['d']].
↪values[0][0]
        q = best_param_df.loc[best_param_df['language'] == lang, ['q']].
↪values[0][0]
        P = best_param_df.loc[best_param_df['language'] == lang, ['P']].
↪values[0][0]
        D = best_param_df.loc[best_param_df['language'] == lang, ['D']].
↪values[0][0]
        Q = best_param_df.loc[best_param_df['language'] == lang, ['Q']].
↪values[0][0]
        s = best_param_df.loc[best_param_df['language'] == lang, ['s']].
↪values[0][0]

        #Creating language time-series
        time_series = means_data[lang]

        #Creating SARIMAX Model with order(p,d,q) & seasonal_order=(P, D, Q, s)
        model = SARIMAX(time_series[:-n],
                        order =(p,d,q),
                        seasonal_order=(P, D, Q, s),
                        initialization='approximate_diffuse')
        model_fit = model.fit()

        #Creating forecast for last n-values
        model_forecast = model_fit.forecast(n, dynamic = True)

        #Calculating MAPE & RMSE
        actuals = time_series.values[-n:]
        errors = time_series.values[-n:] - model_forecast.values

        mape = np.mean(np.abs(errors)/ np.abs(actuals))
        rmse = np.sqrt(np.mean(errors**2))

        print('')
        print('')
       ␣
↪print(f'---------------------------------------------------------------------------------
        print(f'        SARIMAX model for {lang} Time Series                          ␣
↪                      ')
```

```
        print(f'        Parameters of Model : ({p},{d},{q}) ({P},{D},{Q},{s})  ␣
↪                          ')
        print(f'        MAPE of Model       : {np.round(mape,4)}              ␣
↪                          ')
        print(f'        RMSE of Model       : {np.round(rmse,3)}              ␣
↪                          ')
      ␣
↪print(f'--------------------------------------------------------------------------------------

        #plotting Actual & Forecasted values
        time_series.index = time_series.index.astype('datetime64[ns]')
        model_forecast.index = model_forecast.index.astype('datetime64[ns]')
        plt.figure(figsize = (20,8))
        time_series[-60:].plot(label = 'Actual')
        model_forecast[-60:].plot(label = 'Forecast', color = 'red',
                                  linestyle='dashed',␣
↪marker='o',markerfacecolor='green', markersize=5)
        plt.legend(loc="upper right")
        plt.title(f'SARIMAX Model - {lang} - ({p},{d},{q}) ({P},{D},{Q},{s}) :␣
↪Actual vs Forecasts', fontsize = 15, fontweight = 'bold')
        plt.show()
```

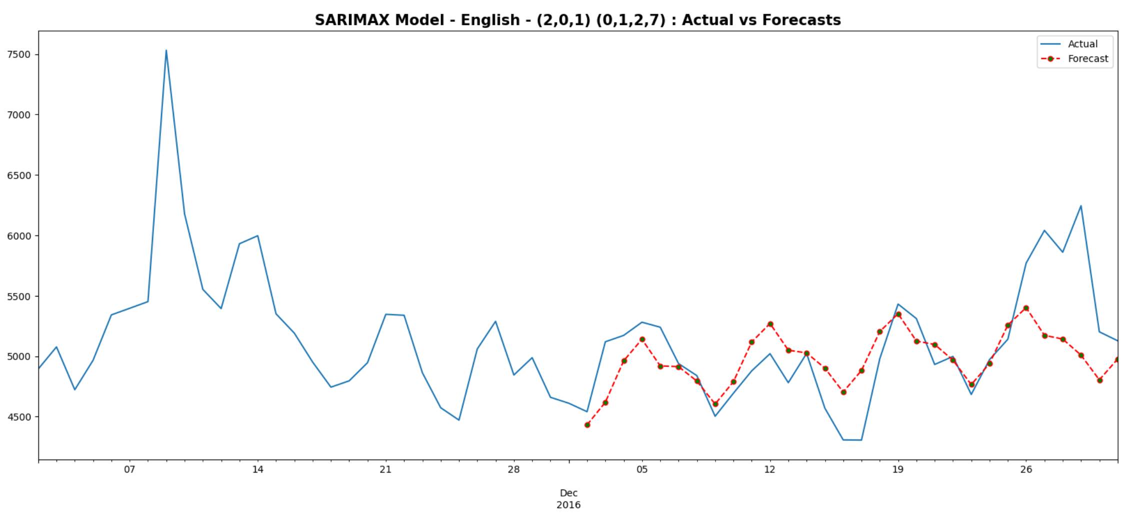
[171]:

```
#Plotting SARIMAX model for each Language Time Series
languages = means_data.columns.drop('Unknown_Language')
n = 30
SARIMAX_model_pred_plot(languages, means_data, n, best_param_df)
```

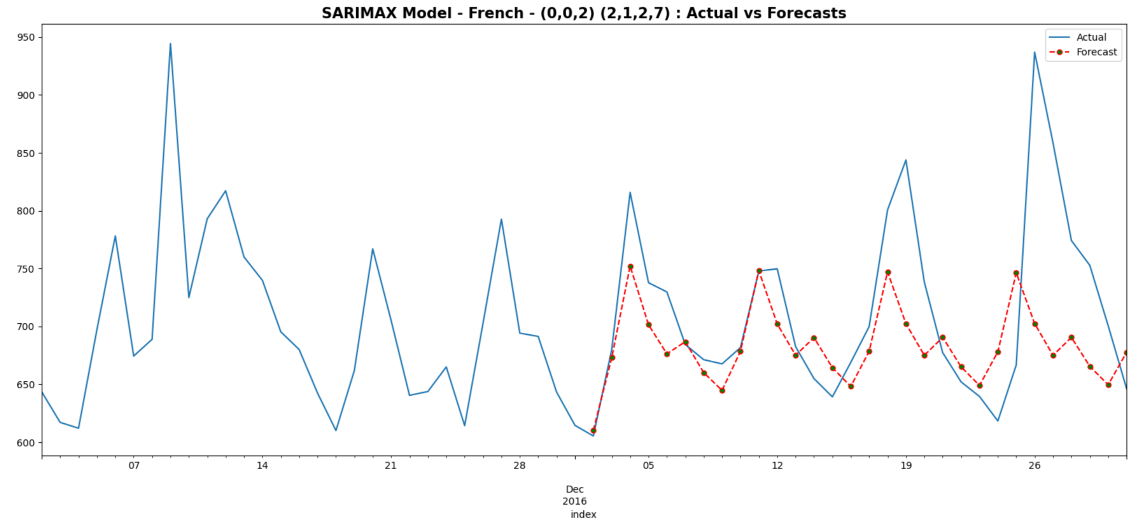
```
--------------------------------------------------------------------------------
---------
        SARIMAX model for Chinese Time Series
        Parameters of Model : (0,1,0) (1,0,2,7)
        MAPE of Model       : 0.0307
        RMSE of Model       : 14.487
--------------------------------------------------------------------------------
---------
```



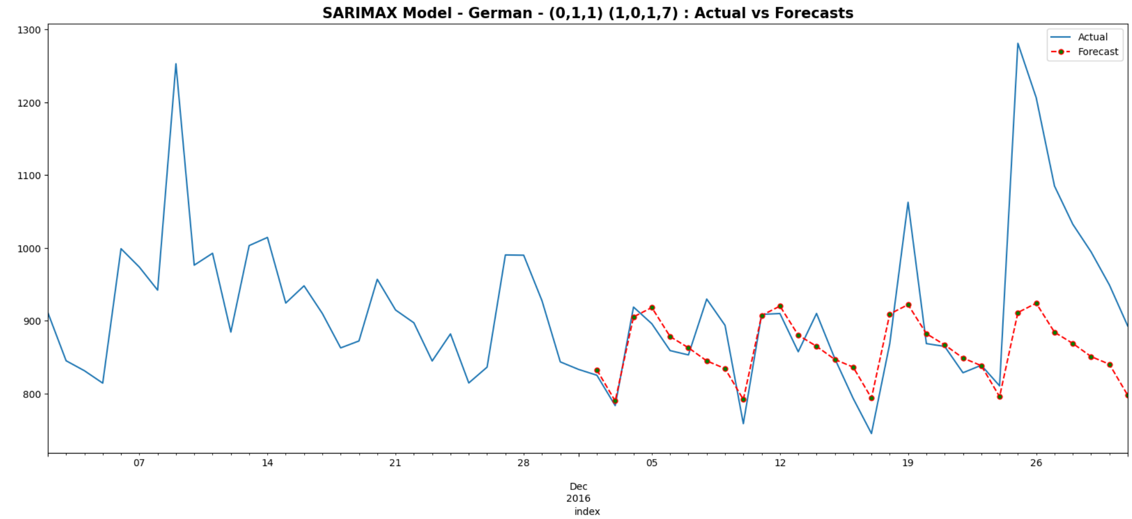
```
        SARIMAX model for English Time Series
        Parameters of Model : (2,0,1) (0,1,2,7)
        MAPE of Model       : 0.0526
        RMSE of Model       : 387.196
```



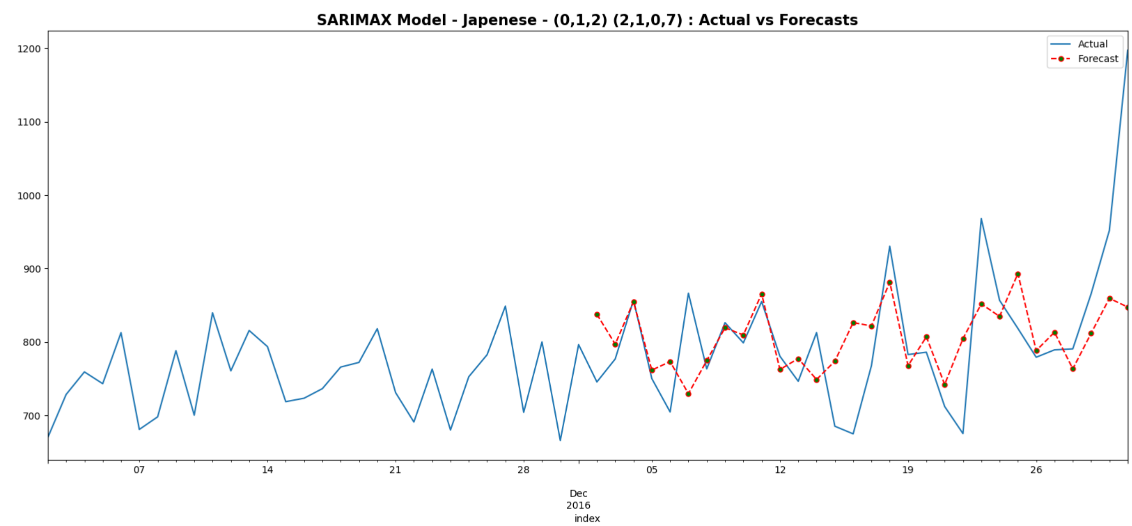
```
--------------------------------------------------------------------------------
---------
        SARIMAX model for French Time Series
        Parameters of Model : (0,0,2) (2,1,2,7)
        MAPE of Model       : 0.0636
        RMSE of Model       : 72.605
--------------------------------------------------------------------------------
---------
```



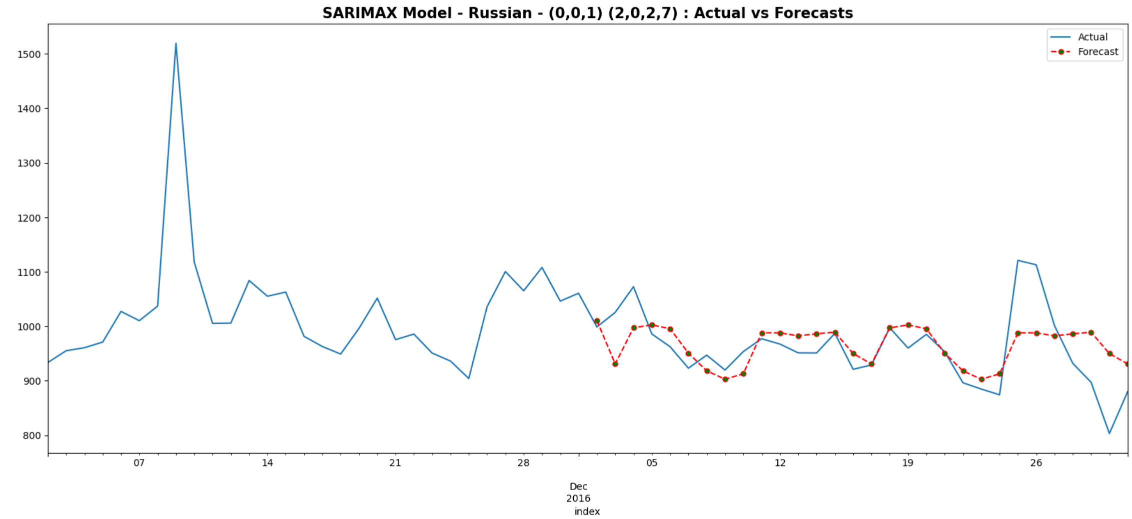

```
--------------------------------------------------------------------------------
---------
        SARIMAX model for German Time Series
        Parameters of Model : (0,1,1) (1,0,1,7)
        MAPE of Model       : 0.0658
        RMSE of Model       : 110.621
--------------------------------------------------------------------------------
---------
```



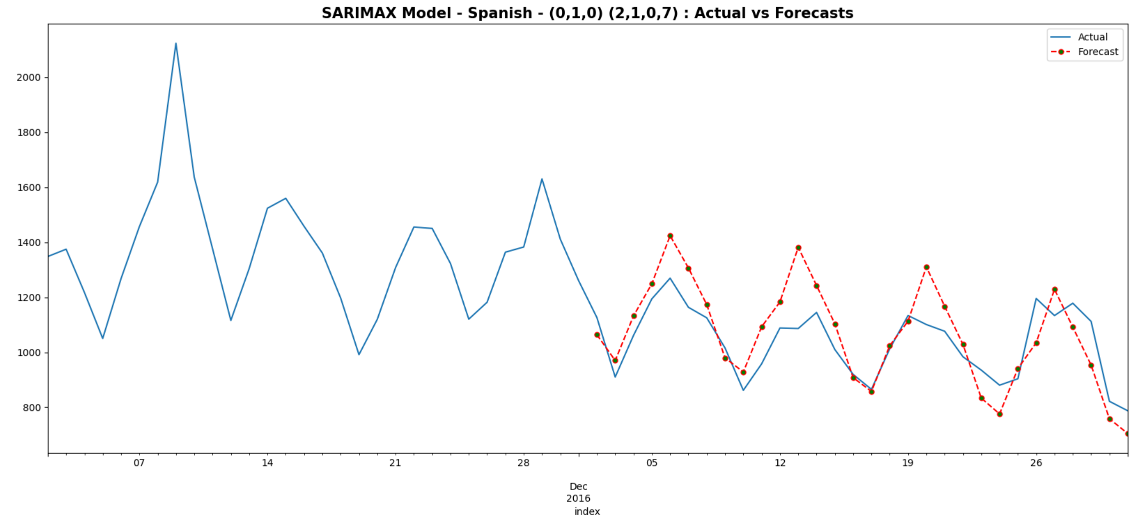

```
--------------------------------------------------------------------------------
---------
        SARIMAX model for Japenese Time Series
        Parameters of Model : (0,1,2) (2,1,0,7)
        MAPE of Model       : 0.0712
        RMSE of Model       : 90.833
--------------------------------------------------------------------------------
---------
```



```
--------------------------------------------------------------------------------
---------
        SARIMAX model for Russian Time Series
        Parameters of Model : (0,0,1) (2,0,2,7)
        MAPE of Model       : 0.0427
        RMSE of Model       : 56.737
--------------------------------------------------------------------------------
---------
```




```
--------------------------------------------------------------------------------
---------
        SARIMAX model for Spanish Time Series
        Parameters of Model : (0,1,0) (2,1,0,7)
        MAPE of Model       : 0.0856
        RMSE of Model       : 109.03
--------------------------------------------------------------------------------
---------
```



0.7.3 Facebook Prophet:

[92]:
```python
from prophet import Prophet
```

Prophet expects the data frame to have two columns: ds & y

- ds (datestamp): A column of dates
- y: The value to be forecasted

[100]:
```python
# Let's create a dataset suitable for facebook prophet.



TS_prophet = means_data.reset_index()
TS_eng_prophet = TS_prophet[['index', 'English']]
TS_eng_prophet.columns = ['ds', 'y']
exog = Exog_Campaign_eng.copy(deep = True)
TS_eng_prophet['exog'] = exog.values
```

[101]:
```python
TS_eng_prophet.head()
```

[101]:

	ds	y	exog
0	2015-07-01	3513.862203	0
1	2015-07-02	3502.511407	0
2	2015-07-03	3325.357889	0
3	2015-07-04	3462.054256	0
4	2015-07-05	3575.520035	0

[102]:
```python
TS_eng_prophet.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
```

Let's create a prophet model without using exogenous variable:

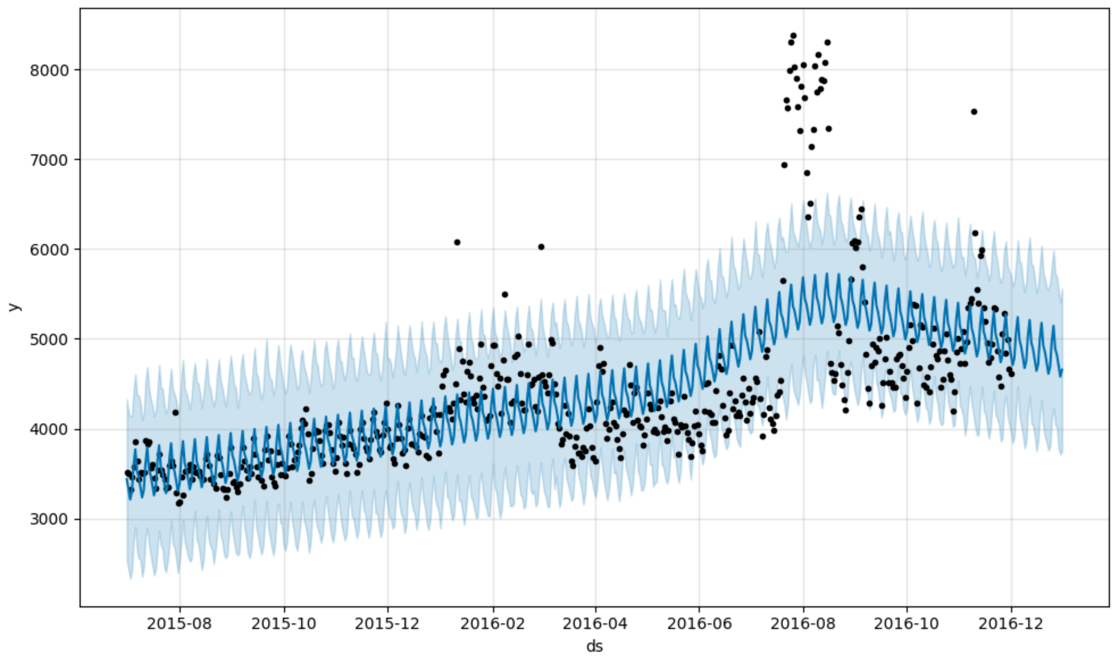
[108]:
```
warnings.filterwarnings("ignore")
```

[109]:
```
prophet_model = Prophet(weekly_seasonality=True)
prophet_model.fit(TS_eng_prophet[['ds', 'y']][:-30])

# Create a dataframe for future dates
future = prophet_model.make_future_dataframe(periods=30)  # Forecast for the␣
↪next 30 days

# Make predictions
prophet_forecast = prophet_model.predict(future)

# Plot the forecast
fig1 = prophet_model.plot(prophet_forecast)
fig1.show()

# Extract actual values for the last 30 days
y_true = TS_eng_prophet[-30:]['y'].values

# Extract forecasted values for those 30 days
y_pred = prophet_forecast[-30:]['yhat'].values

# Function to calculate MAPE
def mean_absolute_percentage_error(y_true, y_pred):
    return np.mean(np.abs((y_true - y_pred) / y_true)) * 100

# Calculate MAPE
mape = mean_absolute_percentage_error(y_true, y_pred)
print(f"MAPE: {mape:.2f}%")
```

```
INFO:prophet:Disabling yearly seasonality. Run prophet with
yearly_seasonality=True to override this.
INFO:prophet:Disabling daily seasonality. Run prophet with
daily_seasonality=True to override this.
DEBUG:cmdstanpy:input tempfile: /tmp/tmpc27s46t5/8k0qhs4c.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpc27s46t5/50ek6eq4.json
```

```
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.10/dist-
packages/prophet/stan_model/prophet_model.bin', 'random', 'seed=83290', 'data',
'file=/tmp/tmpc27s46t5/8k0qhs4c.json', 'init=/tmp/tmpc27s46t5/50ek6eq4.json',
'output',
'file=/tmp/tmpc27s46t5/prophet_modelt86_42p3/prophet_model-20240618124728.csv',
'method=optimize', 'algorithm=lbfgs', 'iter=10000']
12:47:28 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
12:47:28 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
```

```
MAPE: 6.08%
```



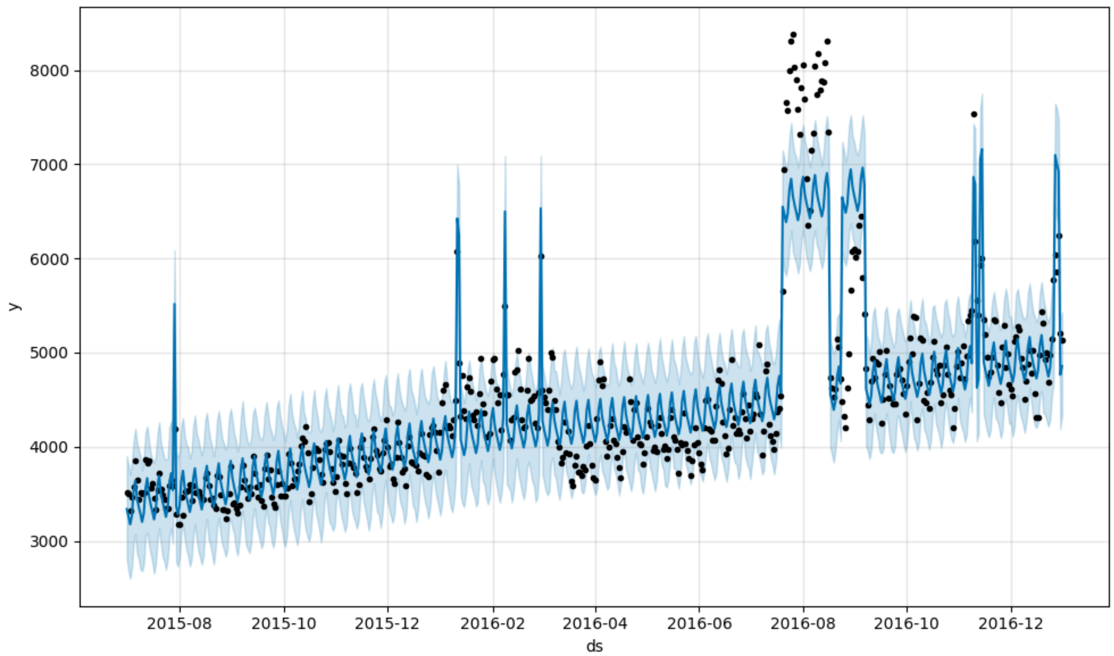
Let's create a prophet model using exogenous variable:

[116]:
```python
prophet_model = Prophet(weekly_seasonality=True)
prophet_model.add_regressor('exog')
prophet_model.fit(TS_eng_prophet)
#future2 = prophet2.make_future_dataframe(periods=30, freq= 'D')
prophet_forecast = prophet_model.predict(TS_eng_prophet)
fig = prophet_model.plot(prophet_forecast)
fig.show()

# Extracting actual values
```

```python
y_true = TS_eng_prophet['y'].values

# Extracting forecasted values
y_pred = prophet_forecast['yhat'].values

# Function to calculate MAPE
def mean_absolute_percentage_error(y_true, y_pred):
    return np.mean(np.abs((y_true - y_pred) / y_true)) * 100

# Calculate MAPE
mape = mean_absolute_percentage_error(y_true, y_pred)
print(f"MAPE: {mape:.2f}%")
```

```
INFO:prophet:Disabling yearly seasonality. Run prophet with
yearly_seasonality=True to override this.
INFO:prophet:Disabling daily seasonality. Run prophet with
daily_seasonality=True to override this.
DEBUG:cmdstanpy:input tempfile: /tmp/tmpc27s46t5/atmsmhji.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpc27s46t5/gbnx23pi.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.10/dist-
packages/prophet/stan_model/prophet_model.bin', 'random', 'seed=82862', 'data',
'file=/tmp/tmpc27s46t5/atmsmhji.json', 'init=/tmp/tmpc27s46t5/gbnx23pi.json',
'output',
'file=/tmp/tmpc27s46t5/prophet_modelqss9gco2/prophet_model-20240618130136.csv',
'method=optimize', 'algorithm=lbfgs', 'iter=10000']
13:01:36 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
13:01:36 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
```

```
MAPE: 6.01%
```



- MAPE without exog: 6.08%
- MAPE with exo: 6.01%

So, use of exogenous variable has improved the performance of the model.

0.8 Recommendations & Questionnaire:

- English has highest number of page visits followed by Japanese, so the add preference should be given in the same order.
- More than 12% of web page's language is not recorded. With better recorded data, performance of the model can be improved considerably since 12% of it missing currently.

What does the decomposition of series do?

Decomposing a time series involves breaking it down into its key components:

- Trend: This represents the overall direction in which the data is moving over a long period. It shows whether the values are generally rising, falling, or remaining stable.
- Seasonality: These are the regular patterns or cycles that repeat at consistent intervals, such as daily, monthly, or yearly. For instance, sweater sales might be higher in the winter.
- Residual (or Noise): This is what's left after removing the trend and seasonality from the data. It includes random variations and irregularities that aren't explained by the other components.

What level of differencing gave you a stationary series?

- In this case study, performing a single differencing step resulted in a stationary time series.

Difference between arima, sarima & sarimax.

ARIMA (AutoRegressive Integrated Moving Average):

- ARIMA (AutoRegressive Integrated Moving Average) is a statistical model used for time series data. It combines autoregression (using past values to predict future ones) and moving averages (using past prediction errors to forecast future values).
- ARIMA models are represented as ARIMA(p, d, q), where p indicates the number of autoregressive terms, d is the number of differences needed to make the series stationary, and q denotes the number of lagged forecast errors in the model.
- ARIMA is great for non-seasonal data that becomes stationary after differencing.

SARIMA (Seasonal ARIMA):

- SARIMA takes ARIMA and adds seasonal components to it.
- SARIMA models are represented as SARIMA(p, d, q)(P, D, Q, S). Here, p, d, and q correspond to the same parameters in ARIMA models. Additionally, P indicates the seasonal autoregression order, D is the seasonal differencing order, Q represents the seasonal moving average order, and S denotes the number of periods in a season.
- SARIMA is perfect for data with clear seasonal patterns, capturing both regular and seasonal changes.

SARIMAX (Seasonal ARIMA with eXogenous regressors):

- SARIMAX includes everything in SARIMA and also lets you add external variables that might influence your data.

- Adds the ability to include external variables, making it ideal for more complex data influenced by other factors.

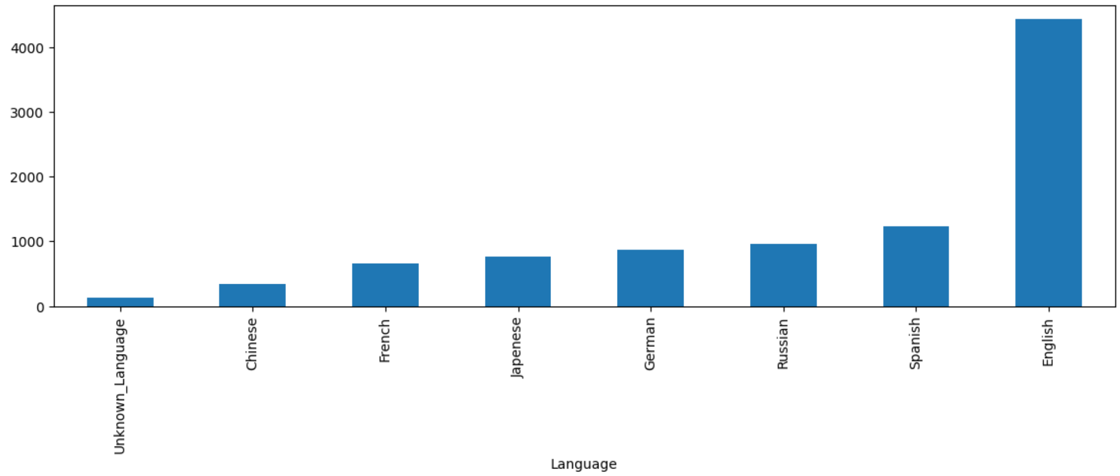
- A SARIMAX model is denoted by:

  SARIMAX(, ,)(, , ,)X

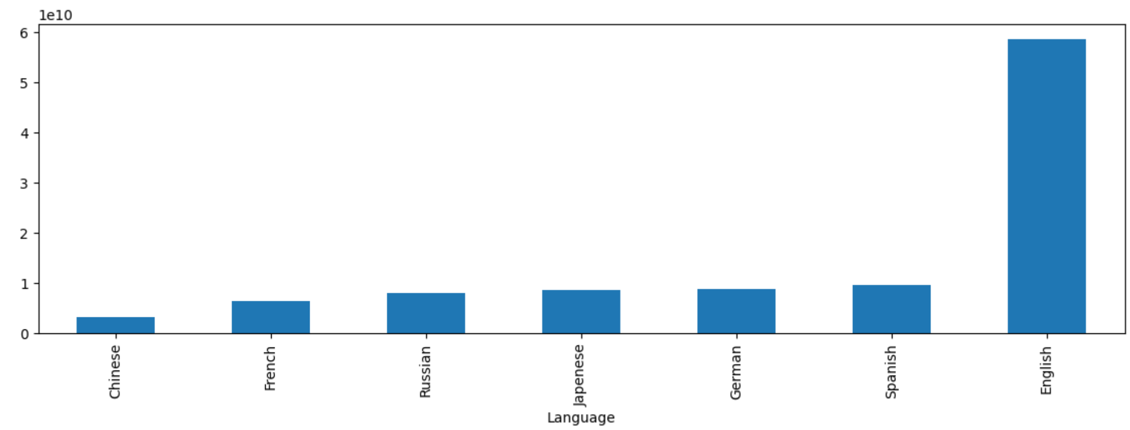
  X represents the number of exogenous variables included in the model.

Compare the number of views in different languages

[193]:
```
means_data.mean().sort_values().plot(kind = 'bar')
plt.show()
```



[195]:
```python
total = data.groupby('Language').sum().T.drop("Unknown_Language",axis = 1)

total.sum().sort_values().plot(kind = 'bar')
plt.show()
```



- Total number of visits to english pages is almost 6 times the next best language group.
- Where as the average visits is close to 4 times that of the next best language group.

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

When determining the values of p, q, and d from the ACF and PACF plots of a time series, follow these steps:

- Check the stationarity of the time series using an augmented Dickey-Fuller test.
- If the time series is stationary, proceed to fit an ARMA model. If non-stationary, determine the appropriate differencing order, d.
- Once stationarity is achieved, analyze the autocorrelation and partial autocorrelation plots of the data.
- Identify the parameter p by examining the cutoff in the partial autocorrelation plot (PACF).
- Determine the parameter q by examining the cutoff in the autocorrelation plot (ACF).