AdEase

December 26, 2024

0.1 About AdEase

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.

0.2 Business Problem

The primary objective is to accurately forecast the number of views for each Wikipedia page to optimize ad placement strategies. By predicting future page views, Ad Ease can ensure that ads are placed on pages with high traffic, thereby maximizing visibility and engagement for their clients.

0.3 Importing Required Libraries

[1]:
```
import pandas as pd
import numpy as np
import itertools

from matplotlib import pyplot as plt
import seaborn as sns

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

import statsmodels.api as sm
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

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

```python
import warnings
warnings.filterwarnings('ignore')
```

```
c:\Users\ganelnu\AppData\Local\miniconda3\envs\learnings\lib\site-
packages\tqdm\auto.py:21: TqdmWarning: IProgress not found. Please update
jupyter and ipywidgets. See
https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

0.4 Read Dataset

[2]:
```python
df = pd.read_csv('../data/train_1.csv')
```

[3]:
```python
df.head()
```

[3]:
```
                                                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]
```

[4]:
```
df.shape
```

[4]: (145063, 551)

[5]:
```
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
```

[6]:
```
df.describe().T
```

[6]:
```
                count         mean           std  min   25%    50%    75%  \
2015-07-01  124323.0  1195.856567  72753.518671  0.0  13.0  109.0  524.0
2015-07-02  124247.0  1204.003638  74215.145424  0.0  13.0  108.0  519.0
2015-07-03  124519.0  1133.675969  69610.224744  0.0  12.0  105.0  504.0
2015-07-04  124409.0  1170.437324  72573.513699  0.0  13.0  105.0  487.0
2015-07-05  124404.0  1217.769300  73796.116656  0.0  14.0  113.0  540.0
…                …            …             …   …    …      …      …
2016-12-27  141362.0  1678.301870  92324.820056  0.0  23.0  162.0  668.0
2016-12-28  141241.0  1633.965605  91858.307668  0.0  24.0  163.0  654.0
2016-12-29  141237.0  1684.307717  90142.656814  0.0  23.0  160.0  649.0
2016-12-30  141428.0  1467.943378  81554.814146  0.0  23.0  154.0  635.0
2016-12-31  141598.0  1478.282137  88735.672589  0.0  21.0  136.0  561.0

                   max
2015-07-01  20381245.0
2015-07-02  20752194.0
2015-07-03  19573967.0
2015-07-04  20439645.0
2015-07-05  20772109.0
…                  …
2016-12-27  26916991.0
2016-12-28  27025053.0
2016-12-29  26073819.0
2016-12-30  24363967.0
2016-12-31  26149541.0

[550 rows x 8 columns]
```

[7]:
```
df.isna().sum()
```

[7]:
```
Page              0
2015-07-01    20740
2015-07-02    20816
2015-07-03    20544
```

```
2015-07-04    20654
              …
2016-12-27     3701
2016-12-28     3822
2016-12-29     3826
2016-12-30     3635
2016-12-31     3465
Length: 551, dtype: int64
```

[8]:
```
df['missing'] = df.isna().sum(axis=1)
df[['Page', 'missing']].head(20)
```

[8]:

	Page	missing
0	2NE1_zh.wikipedia.org_all-access_spider	0
1	2PM_zh.wikipedia.org_all-access_spider	0
2	3C_zh.wikipedia.org_all-access_spider	0
3	4minute_zh.wikipedia.org_all-access_spider	0
4	52_Hz_I_Love_You_zh.wikipedia.org_all-access_s…	291
5	5566_zh.wikipedia.org_all-access_spider	0
6	91Days_zh.wikipedia.org_all-access_spider	365
7	A'N'D_zh.wikipedia.org_all-access_spider	0
8	AKB48_zh.wikipedia.org_all-access_spider	0
9	ASCII_zh.wikipedia.org_all-access_spider	0
10	ASTRO_zh.wikipedia.org_all-access_spider	31
11	Ahq_e-Sports_Club_zh.wikipedia.org_all-access_…	0
12	All_your_base_are_belong_to_us_zh.wikipedia.or…	0
13	AlphaGo_zh.wikipedia.org_all-access_spider	212
14	Android_zh.wikipedia.org_all-access_spider	0
15	Angelababy_zh.wikipedia.org_all-access_spider	0
16	Apink_zh.wikipedia.org_all-access_spider	0
17	Apple_II_zh.wikipedia.org_all-access_spider	0
18	As_One_zh.wikipedia.org_all-access_spider	0
19	B-PROJECT_zh.wikipedia.org_all-access_spider	351

[9]:
```
df['Page'].duplicated().sum()
```

[9]: 0

[10]:
```
df[df['Page'].str.contains('.wikipedia.org') == False].shape
```

[10]: (17855, 552)

[11]:
```
df['Page'].str.contains('.wikipedia.org').value_counts(normalize=True)
```

[11]:
```
Page
True     0.876916
False    0.123084
Name: proportion, dtype: float64
```

[12]:
```
date_range = df.columns.to_list()
date_range = [date_ for date_ in date_range if date_ not in (['Page',␣
↪'missing'])]
date_range = pd.to_datetime(date_range)

print('Min date:', date_range.min())
print('Max date:', date_range.max())
print('Total days:', len(date_range))
```

```
Min date: 2015-07-01 00:00:00
Max date: 2016-12-31 00:00:00
Total days: 550
```

[13]:
```
wiki_df = df[df['Page'].str.contains('.wikipedia.org') == True]
wiki_df.shape
```

[13]:
```
(127208, 552)
```

0.4.1 Observations

Shape and Structure:

- The dataset consists of 145,063 rows and 551 columns.
- It represents daily views for 145,000 Wikipedia pages over a period of 550 days.
- Each row corresponds to the daily view counts of a specific page for each day.
- The data spans from July 1, 2015, to September 10, 2016, covering a total of 550 days.

Missing Data:

- The dataset contains missing values, indicating that there were no views recorded for specific pages on certain days.

Pages Details:

- There are no duplicate pages in the dataset.
- The dataset includes pages from domains other than wikipedia.org.
- There are over 17,855 non-Wikipedia pages, which constitute approximately 12% of the total pages.

0.5 Page Name Formatting

[14]:
```
wiki_df[['TITLE', 'LANGUAGE']] = wiki_df['Page'].str.split('.wikipedia.org_').
↪str.get(0).str.rsplit('_', n=1, expand=True)
wiki_df[["_",'ACCESS_TYPE',  'ACCESS_ORIGIN']] = wiki_df['Page'].str.
↪rsplit('_', n=2, expand=True)
wiki_df = wiki_df.drop('_', axis=1)
```

```
wiki_df['LANGUAGE'] = wiki_df['LANGUAGE'].str.upper()
```

[15]:
```
wiki_df.sample(5)
```

[15]:
```
                                                     Page  2015-07-01  \
62362            _zh.wikipedia.org_desktop_all-agents        73.0
133980              _ja.wikipedia.org_all-access_spider         3.0
28291          _zh.wikipedia.org_all-access_all-agents       244.0
142939       Tom_Hanks_es.wikipedia.org_all-access_spider        18.0
76256   Thor:_The_Dark_World_en.wikipedia.org_mobile-w…      2669.0

        2015-07-02  2015-07-03  2015-07-04  2015-07-05  2015-07-06  \
62362         74.0        71.0        67.0        96.0        77.0
133980         8.0         8.0         9.0         1.0         5.0
28291        168.0       224.0       200.0       224.0       214.0
142939        21.0         5.0         7.0         9.0        10.0
76256       2259.0      2139.0      2274.0      4054.0      2975.0

        2015-07-07  2015-07-08  2015-07-09  …  2016-12-27  2016-12-28  \
62362         66.0        54.0        63.0  …        95.0       113.0
133980        14.0         4.0         8.0  …        94.0       126.0
28291        185.0       176.0       149.0  …       167.0       203.0
142939         8.0         9.0        48.0  …        10.0        55.0
76256       1840.0      1651.0      1923.0  …      2254.0      2057.0

        2016-12-29  2016-12-30  2016-12-31  missing                 TITLE  \
62362        125.0       152.0        93.0        0
133980       159.0       108.0       105.0        0
28291        155.0       167.0       157.0        0
142939        26.0        40.0        21.0        0             Tom_Hanks
76256       1939.0      2046.0      2471.0        0  Thor:_The_Dark_World

        LANGUAGE  ACCESS_TYPE  ACCESS_ORIGIN
62362         ZH      desktop     all-agents
133980        JA   all-access         spider
28291         ZH   all-access     all-agents
142939        ES   all-access         spider
76256         EN   mobile-web     all-agents

[5 rows x 556 columns]
```

[16]:
```
wiki_df['TITLE'].value_counts().reset_index()
```

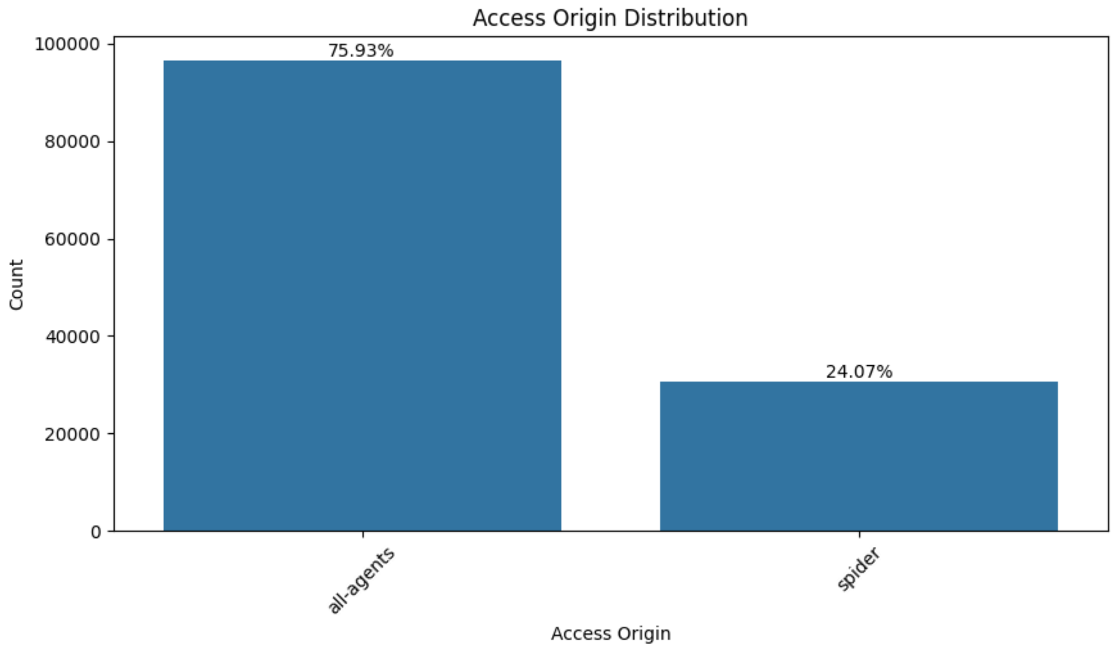
[16]:
```
                                                   TITLE  count
0                                               Facebook     28
1                                                YouTube     28
2                                         Special:Search     27
```

```
3                                                    Google     27
4                                                    IPhone     24
…                                                     …     …
42207                                              Paul_Klee      1
42208  LVIII_Festival_Internacional_de_la_Canción_de_…      1
42209                                             Paul_Guers      1
42210                                           Paul_Bourget      1
42211                                         Jabrill_Peppers      1

[42212 rows x 2 columns]
```

[17]:

```python
access_origin_counts = wiki_df['ACCESS_ORIGIN'].value_counts()
access_origin_percent = wiki_df['ACCESS_ORIGIN'].value_counts(normalize=True)

print(access_origin_counts, access_origin_percent)

plt.figure(figsize=(10, 5))
ax = sns.countplot(data=wiki_df, x='ACCESS_ORIGIN', order=access_origin_counts.
 ↪index)
plt.title('Access Origin Distribution')
plt.xlabel('Access Origin')
plt.ylabel('Count')
plt.xticks(rotation=45)

# Add percentages to the bars
for p in ax.patches:
    height = p.get_height()
    percentage = f'{100 * height / len(wiki_df):.2f}%'
    ax.annotate(percentage, (p.get_x() + p.get_width() / 2., height),
                ha='center', va='center', xytext=(0, 5), textcoords='offset␣
 ↪points')

plt.show()
```

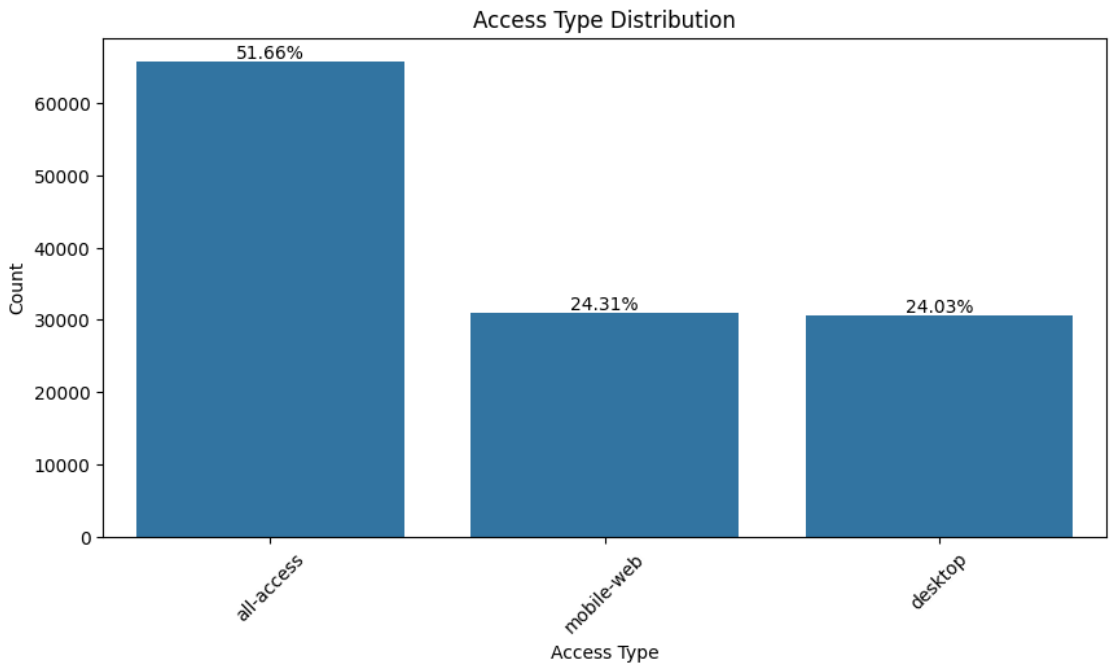
```
ACCESS_ORIGIN
all-agents    96594
spider        30614
Name: count, dtype: int64 ACCESS_ORIGIN
all-agents    0.759339
spider        0.240661
Name: proportion, dtype: float64
```



[18]:
```
access_origin_counts = wiki_df['ACCESS_TYPE'].value_counts()
access_origin_percent = wiki_df['ACCESS_TYPE'].value_counts(normalize=True)

print(access_origin_counts, access_origin_percent)

plt.figure(figsize=(10, 5))
ax = sns.countplot(data=wiki_df, x='ACCESS_TYPE', order=access_origin_counts.
 ↪index)
plt.title('Access Type Distribution')
plt.xlabel('Access Type')
plt.ylabel('Count')
plt.xticks(rotation=45)

# Add percentages to the bars
for p in ax.patches:
    height = p.get_height()
    percentage = f'{100 * height / len(wiki_df):.2f}%'
    ax.annotate(percentage, (p.get_x() + p.get_width() / 2., height),
                ha='center', va='center', xytext=(0, 5), textcoords='offset␣
 ↪points')

plt.show()
```

```
ACCESS_TYPE
all-access    65713
mobile-web    30923
```

```
desktop        30572
Name: count, dtype: int64 ACCESS_TYPE
all-access     0.516579
mobile-web     0.243090
desktop        0.240331
Name: proportion, dtype: float64
```

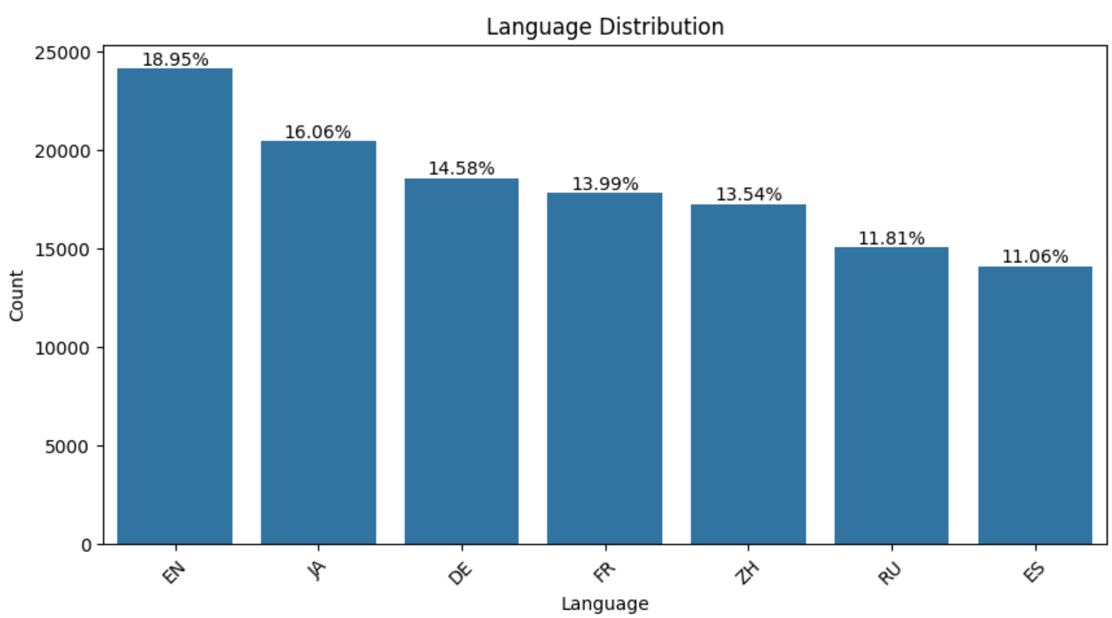


[19]:

```
access_origin_counts = wiki_df['LANGUAGE'].value_counts()
access_origin_percent = wiki_df['LANGUAGE'].value_counts(normalize=True)

print(access_origin_counts, access_origin_percent)

plt.figure(figsize=(10, 5))
ax = sns.countplot(data=wiki_df, x='LANGUAGE', order=access_origin_counts.index)
plt.title('Language Distribution')
plt.xlabel('Language')
plt.ylabel('Count')
plt.xticks(rotation=45)

# Add percentages to the bars
for p in ax.patches:
    height = p.get_height()
    percentage = f'{100 * height / len(wiki_df):.2f}%'
    ax.annotate(percentage, (p.get_x() + p.get_width() / 2., height),
```

```
                    ha='center', va='center', xytext=(0, 5), textcoords='offset␣
↪points')

plt.show()
```

```
LANGUAGE
EN    24108
JA    20431
DE    18547
FR    17802
ZH    17229
RU    15022
ES    14069
Name: count, dtype: int64 LANGUAGE
EN    0.189516
JA    0.160611
DE    0.145801
FR    0.139944
ZH    0.135440
RU    0.118090
ES    0.110598
Name: proportion, dtype: float64
```



0.5.1 Observations

Page Name Format: The format for page names is as follows: SPECIFIC NAME _ LANGUAGE.wikipedia.org _ ACCESS TYPE _ ACCESS ORIGIN.

- Access Origin:
  - Approximately 75% of the traffic originates from All Agents.
  - Around 24% of the traffic comes from Spiders.
- Access Type:
  - About 50% of the traffic is from All Agents.
  - Mobile web and desktop each account for around 24% of the remaining traffic.
- Language Distribution:
  - English (EN) pages constitute 18% of the total pages.
  - Japanese (JA) pages make up 16% of the total pages.
  - German (DE) pages account for 14% of the total pages.
  - French (FR) pages represent 13% of the total pages.
  - Chinese (ZH) pages also contribute 13% of the total pages.
  - Russian (RU) pages make up 11% of the total pages.
  - Spanish (ES) pages account for 11% of the total pages.

---

[20]:
```
wiki_df
```

[20]:
```
                                                     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…         NaN
…                                                     …           …
145058  Underworld_(serie_de_películas)_es.wikipedia.o…         NaN
145059  Resident_Evil:_Capítulo_Final_es.wikipedia.org…         NaN
145060  Enamorándome_de_Ramón_es.wikipedia.org_all-acc…         NaN
145061  Hasta_el_último_hombre_es.wikipedia.org_all-ac…         NaN
145062  Francisco_el_matemático_(serie_de_televisión_d…         NaN

        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              NaN         NaN         NaN         NaN         NaN
…              …          …          …          …          …
145058         NaN         NaN         NaN         NaN         NaN
145059         NaN         NaN         NaN         NaN         NaN
145060         NaN         NaN         NaN         NaN         NaN
145061         NaN         NaN         NaN         NaN         NaN
145062         NaN         NaN         NaN         NaN         NaN

        2015-07-07  2015-07-08  2015-07-09  …  2016-12-27  2016-12-28  \
0              9.0        22.0        26.0  …        20.0        22.0
1             22.0        11.0        10.0  …        30.0        52.0
```

```
2                0.0          3.0          4.0  …          4.0          6.0
3               14.0          9.0         11.0  …         11.0         17.0
4                NaN          NaN          NaN  …         11.0         27.0
…                  …            …            …  …            …            …
145058           NaN          NaN          NaN  …         12.0         13.0
145059           NaN          NaN          NaN  …          NaN          NaN
145060           NaN          NaN          NaN  …          NaN          NaN
145061           NaN          NaN          NaN  …          NaN          NaN
145062           NaN          NaN          NaN  …          NaN          NaN

        2016-12-29  2016-12-30  2016-12-31  missing  \
0             19.0        18.0        20.0        0
1             45.0        26.0        20.0        0
2              3.0         4.0        17.0        0
3             19.0        10.0        11.0        0
4             13.0        36.0        10.0      291
…                …           …           …        …
145058         3.0         5.0        10.0      544
145059         NaN         NaN         NaN      550
145060         NaN         NaN         NaN      550
145061         NaN         NaN         NaN      550
145062         NaN         NaN         NaN      550

                                                    TITLE  LANGUAGE  \
0                                                    2NE1        ZH
1                                                     2PM        ZH
2                                                      3C        ZH
3                                                 4minute        ZH
4                                         52_Hz_I_Love_You        ZH
…                                                       …         …
145058                    Underworld_(serie_de_películas)        ES
145059                    Resident_Evil:_Capítulo_Final        ES
145060                            Enamorándome_de_Ramón        ES
145061                            Hasta_el_último_hombre        ES
145062  Francisco_el_matemático_(serie_de_televisión_d…        ES

        ACCESS_TYPE  ACCESS_ORIGIN
0        all-access         spider
1        all-access         spider
2        all-access         spider
3        all-access         spider
4        all-access         spider
…                 …              …
145058   all-access         spider
145059   all-access         spider
145060   all-access         spider
145061   all-access         spider
```

```
145062    all-access         spider

[127208 rows x 556 columns]
```

0.6 Model Ready Dataset Preparation

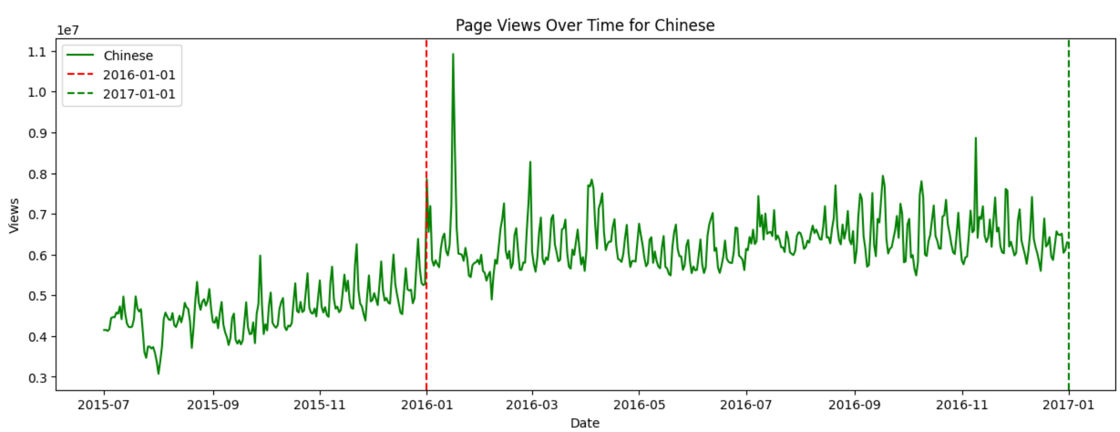
[21]:
```python
date_views_df = pd.DataFrame()
date_views_df['Date'] = date_range

for lang in wiki_df['LANGUAGE'].unique():
    lang_df = wiki_df[wiki_df['LANGUAGE'] == lang]
    lang_df = lang_df.drop(['Page', 'missing', 'TITLE', 'LANGUAGE',␣
 ↪'ACCESS_TYPE', 'ACCESS_ORIGIN'], axis=1)
    lang_df = lang_df.sum(axis=0)
    date_views_df[lang] = lang_df.values

date_views_df
```

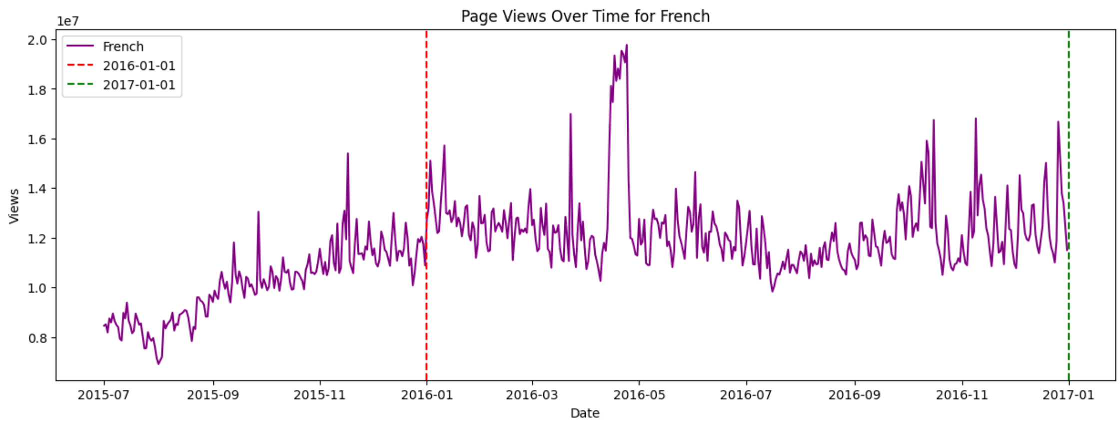
[21]:
```
           Date         ZH          FR           EN          RU          DE  \
0    2015-07-01  4144988.0   8458638.0   84712190.0   9463854.0  13260519.0
1    2015-07-02  4151189.0   8512952.0   84438545.0   9627643.0  13079896.0
2    2015-07-03  4123659.0   8186030.0   80167728.0   8923463.0  12554042.0
3    2015-07-04  4163448.0   8749842.0   83463204.0   8393214.0  11520379.0
4    2015-07-05  4441286.0   8590493.0   86198637.0   8938528.0  13392347.0
..          …          …           …            …           …           …
545  2016-12-27  6478442.0  15281470.0  145628731.0  15040168.0  20125264.0
546  2016-12-28  6513400.0  13781521.0  141278366.0  14000319.0  19152389.0
547  2016-12-29  6042545.0  13399796.0  150557534.0  13478977.0  18447906.0
548  2016-12-30  6111203.0  12471074.0  125404585.0  12066750.0  17606030.0
549  2016-12-31  6298565.0  11504691.0  123623809.0  13223033.0  16562720.0

             JA          ES
0    11863200.0  15278553.0
1    13620792.0  14601013.0
2    12305383.0  13427632.0
3    15456239.0  12606538.0
4    14827204.0  13710356.0
..          …           …
545  16123301.0  15945353.0
546  16150715.0  16577375.0
547  17682688.0  15647135.0
548  19450687.0  11560095.0
549  24460799.0  11077924.0

[550 rows x 8 columns]
```

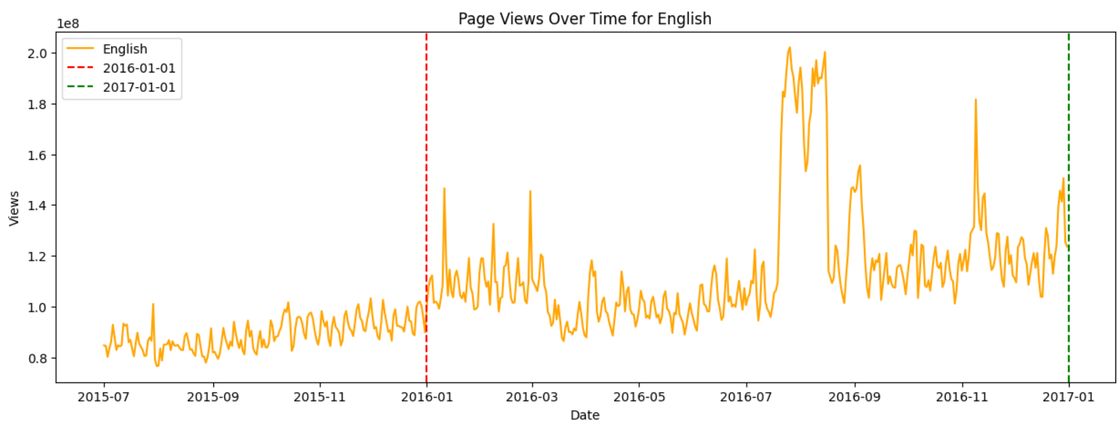
[22]:
```
date_views_df.isna().sum()
```

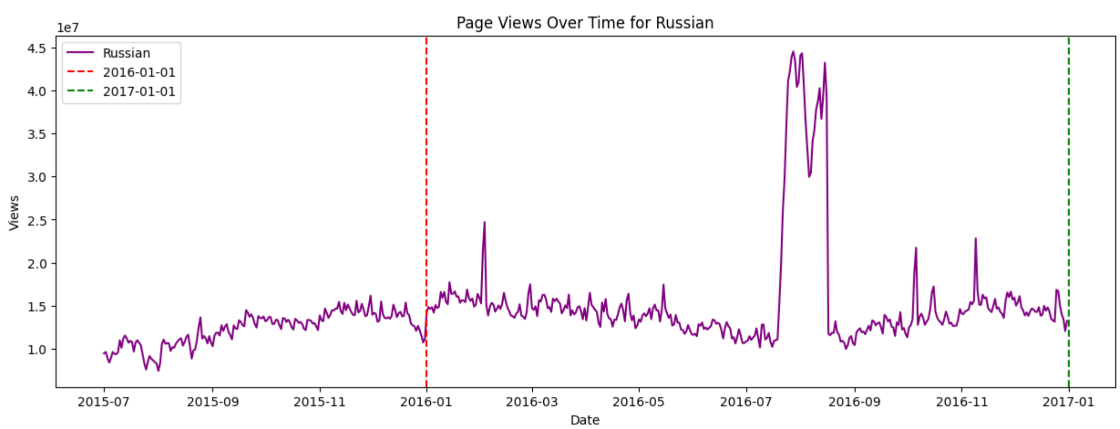
[22]:
```
Date     0
ZH       0
FR       0
EN       0
RU       0
DE       0
JA       0
ES       0
dtype: int64
```

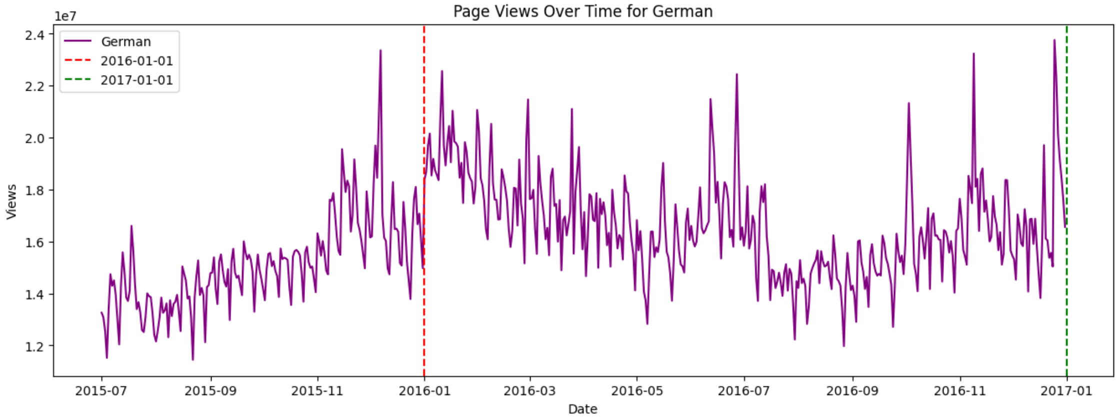
[23]:
```
languages = wiki_df['LANGUAGE'].unique().tolist()
languages.remove('EN')

lang_map = {'ZH': 'Chinese', 'EN': 'English', 'RU': 'Russian', 'FR': 'French',␣
↪'DE': 'German', 'JA': 'Japanese', 'ES': 'Spanish'}

# plot for each language

for lang in wiki_df['LANGUAGE'].unique().tolist():
    plt.figure(figsize=(15, 5))
    plt.plot(date_views_df['Date'], date_views_df[lang], label=lang_map[lang],␣
↪color=np.random.choice(['red', 'green', 'blue', 'yellow', 'orange',␣
↪'purple']))
    plt.title(f'Page Views Over Time for {lang_map[lang]}')
    plt.axvline(x=pd.to_datetime('2016-01-01'), color='r', linestyle='--',␣
↪label='2016-01-01')
    plt.axvline(x=pd.to_datetime('2017-01-01'), color='g', linestyle='--',␣
↪label='2017-01-01')
    plt.xlabel('Date')
    plt.ylabel('Views')
    plt.legend()
plt.show()
```

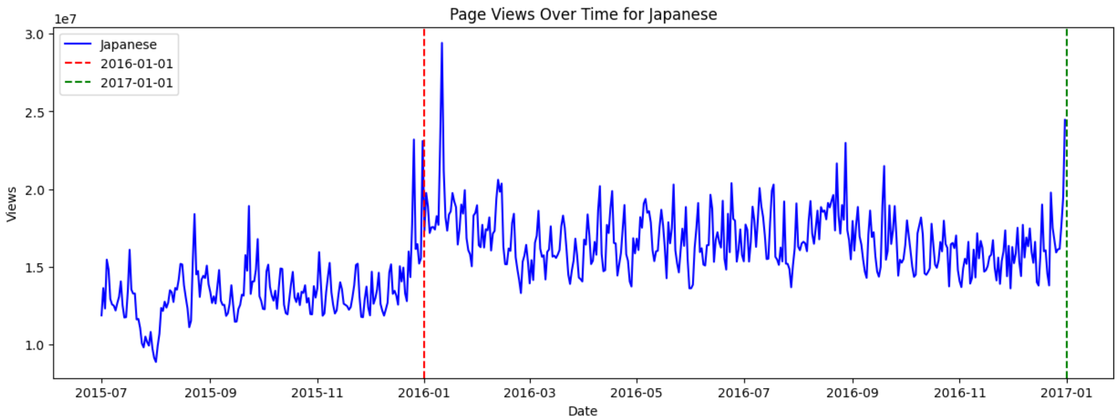


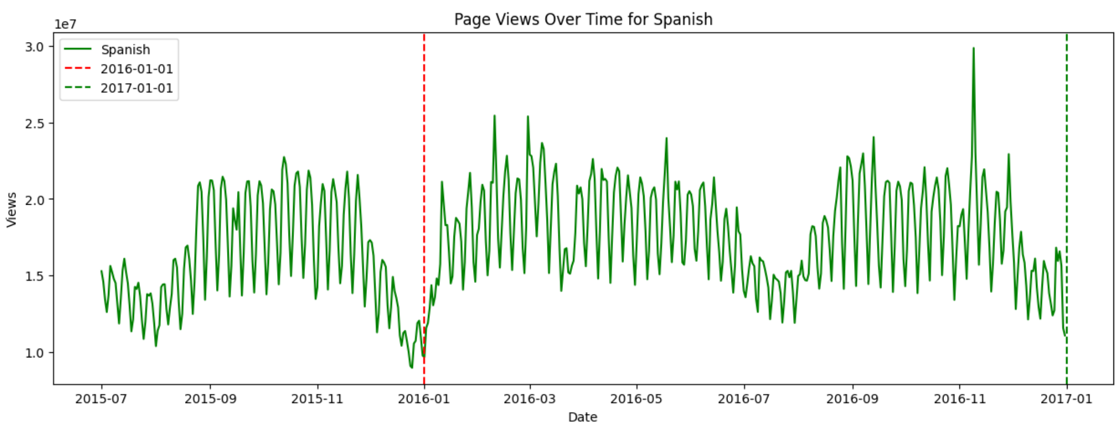

Page Views Over Time for French
1e7
French
2016-01-01
2017-01-01
Views
Date
2.0
1.8
1.6
1.4
1.2
1.0
0.8
2015-07
2015-09
2015-11
2016-01
2016-03
2016-05
2016-07
2016-09
2016-11
2017-01


Page Views Over Time for English
1e8
English
2016-01-01
2017-01-01
Views
Date
2.0
1.8
1.6
1.4
1.2
1.0
0.8
2015-07
2015-09
2015-11
2016-01
2016-03
2016-05
2016-07
2016-09
2016-11
2017-01


Page Views Over Time for Russian
1e7
Russian
2016-01-01
2017-01-01
Views
Date
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
2015-07
2015-09
2015-11
2016-01
2016-03
2016-05
2016-07
2016-09
2016-11
2017-01







0.6.1 Observations

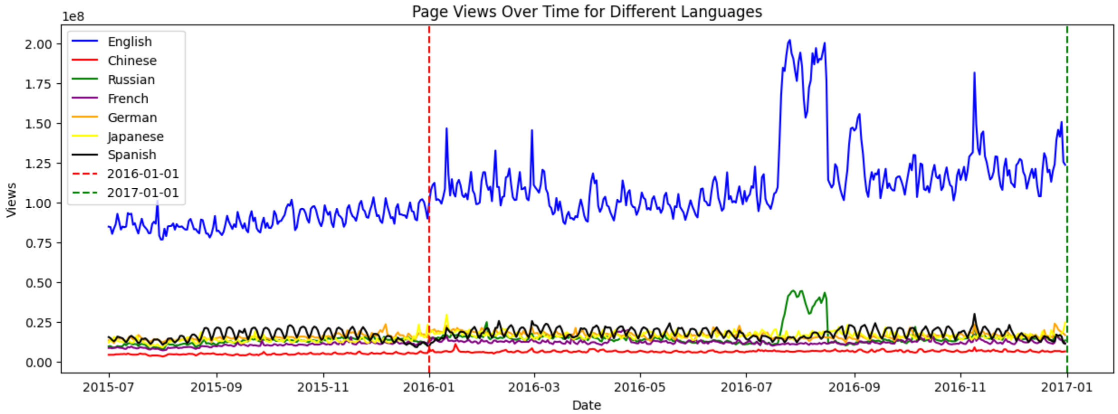
Null Check:

- There are no null values present after transforming the data.

Data Series:

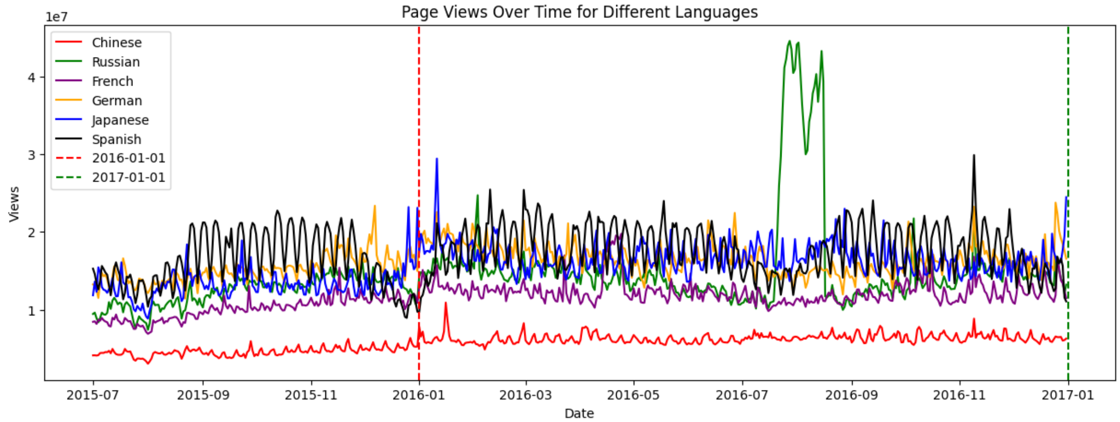
- Chinese: The data exhibits an additive increasing trend.
- English: The data shows an additive increasing trend with noticeable peaks during specific periods.
- Russian: The data appears to be more stationary.
- French: The data follows an increasing trend before 2016. From 2016 to 2017, the data remains within a range, with a few intermediate peaks.
- German: The data displays a seasonal up and down trend.
- Japanese: TThe data appears to be more stationary.
- Spanish: The data exhibits a seasonal up and down trend.

[24]:
```
plt.figure(figsize=(15, 5))
plt.plot(date_views_df['Date'], date_views_df['EN'], label='English',␣
 ↪color='blue')
plt.plot(date_views_df['Date'], date_views_df['ZH'], label='Chinese',␣
 ↪color='red')
plt.plot(date_views_df['Date'], date_views_df['RU'], label='Russian',␣
 ↪color='green')
plt.plot(date_views_df['Date'], date_views_df['FR'], label='French',␣
 ↪color='purple')
plt.plot(date_views_df['Date'], date_views_df['DE'], label='German',␣
 ↪color='orange')
plt.plot(date_views_df['Date'], date_views_df['JA'], label='Japanese',␣
 ↪color='yellow')
plt.plot(date_views_df['Date'], date_views_df['ES'], label='Spanish',␣
 ↪color='black')
plt.title('Page Views Over Time for Different Languages')

plt.axvline(x=pd.to_datetime('2016-01-01'), color='r', linestyle='--',␣
 ↪label='2016-01-01')
plt.axvline(x=pd.to_datetime('2017-01-01'), color='g', linestyle='--',␣
 ↪label='2017-01-01')
plt.xlabel('Date')
plt.ylabel('Views')
plt.legend()

plt.show()
```



[25]:

```
plt.figure(figsize=(15, 5))
plt.plot(date_views_df['Date'], date_views_df['ZH'], label='Chinese',␣
 ↪color='red')
plt.plot(date_views_df['Date'], date_views_df['RU'], label='Russian',␣
 ↪color='green')
plt.plot(date_views_df['Date'], date_views_df['FR'], label='French',␣
 ↪color='purple')
plt.plot(date_views_df['Date'], date_views_df['DE'], label='German',␣
 ↪color='orange')
plt.plot(date_views_df['Date'], date_views_df['JA'], label='Japanese',␣
 ↪color='blue')
plt.plot(date_views_df['Date'], date_views_df['ES'], label='Spanish',␣
 ↪color='black')
plt.title('Page Views Over Time for Different Languages')

plt.axvline(x=pd.to_datetime('2016-01-01'), color='r', linestyle='--',␣
 ↪label='2016-01-01')
plt.axvline(x=pd.to_datetime('2017-01-01'), color='g', linestyle='--',␣
 ↪label='2017-01-01')
plt.xlabel('Date')
plt.ylabel('Views')
plt.legend()

plt.show()
```



Compare the number of views in different languages

- English has higher number of daily views compare to any other language
- Chinese has less daily views compare to other languages

0.6.2 Stationary Check

[26]:
```
date_views_df.set_index('Date', inplace=True)
date_views_df
```

[26]:
```
                   ZH          FR           EN          RU          DE  \
Date
2015-07-01  4144988.0   8458638.0   84712190.0   9463854.0  13260519.0
2015-07-02  4151189.0   8512952.0   84438545.0   9627643.0  13079896.0
2015-07-03  4123659.0   8186030.0   80167728.0   8923463.0  12554042.0
2015-07-04  4163448.0   8749842.0   83463204.0   8393214.0  11520379.0
2015-07-05  4441286.0   8590493.0   86198637.0   8938528.0  13392347.0
…                 …          …            …          …           …
2016-12-27  6478442.0  15281470.0  145628731.0  15040168.0  20125264.0
2016-12-28  6513400.0  13781521.0  141278366.0  14000319.0  19152389.0
2016-12-29  6042545.0  13399796.0  150557534.0  13478977.0  18447906.0
2016-12-30  6111203.0  12471074.0  125404585.0  12066750.0  17606030.0
2016-12-31  6298565.0  11504691.0  123623809.0  13223033.0  16562720.0

                    JA          ES
Date
2015-07-01  11863200.0  15278553.0
2015-07-02  13620792.0  14601013.0
2015-07-03  12305383.0  13427632.0
2015-07-04  15456239.0  12606538.0
2015-07-05  14827204.0  13710356.0
…                  …           …
```

```
2016-12-27  16123301.0  15945353.0
2016-12-28  16150715.0  16577375.0
2016-12-29  17682688.0  15647135.0
2016-12-30  19450687.0  11560095.0
2016-12-31  24460799.0  11077924.0

[550 rows x 7 columns]
```

[27]:
```python
def check_stationarity(time_series):

    # Perform the Augmented Dickey-Fuller test
    adf_result = adfuller(time_series)

    # Extract the test statistic, p-value, and critical values
    test_statistic = adf_result[0]
    p_value = adf_result[1]
    critical_values = adf_result[4]

    # Determine if the series is stationary
    if p_value < 0.05:
        print('The time series is stationary.')
    else:
        print('The time series is not stationary.')

    # Return the results as a dictionary
    return {
        'ADF Test Statistic': test_statistic,
        'p-value': p_value,
        'Critical Values': critical_values
    }
```

[28]:
```python
# Check stationarity for each language

for lang in wiki_df['LANGUAGE'].unique().tolist():
    print(f'Language: {lang_map[lang]}')
    check_stationarity(date_views_df[lang])
    print("-"*50, '\n')
```

```
Language: Chinese
The time series is not stationary.
--------------------------------------------------

Language: French
The time series is not stationary.
--------------------------------------------------

Language: English
```

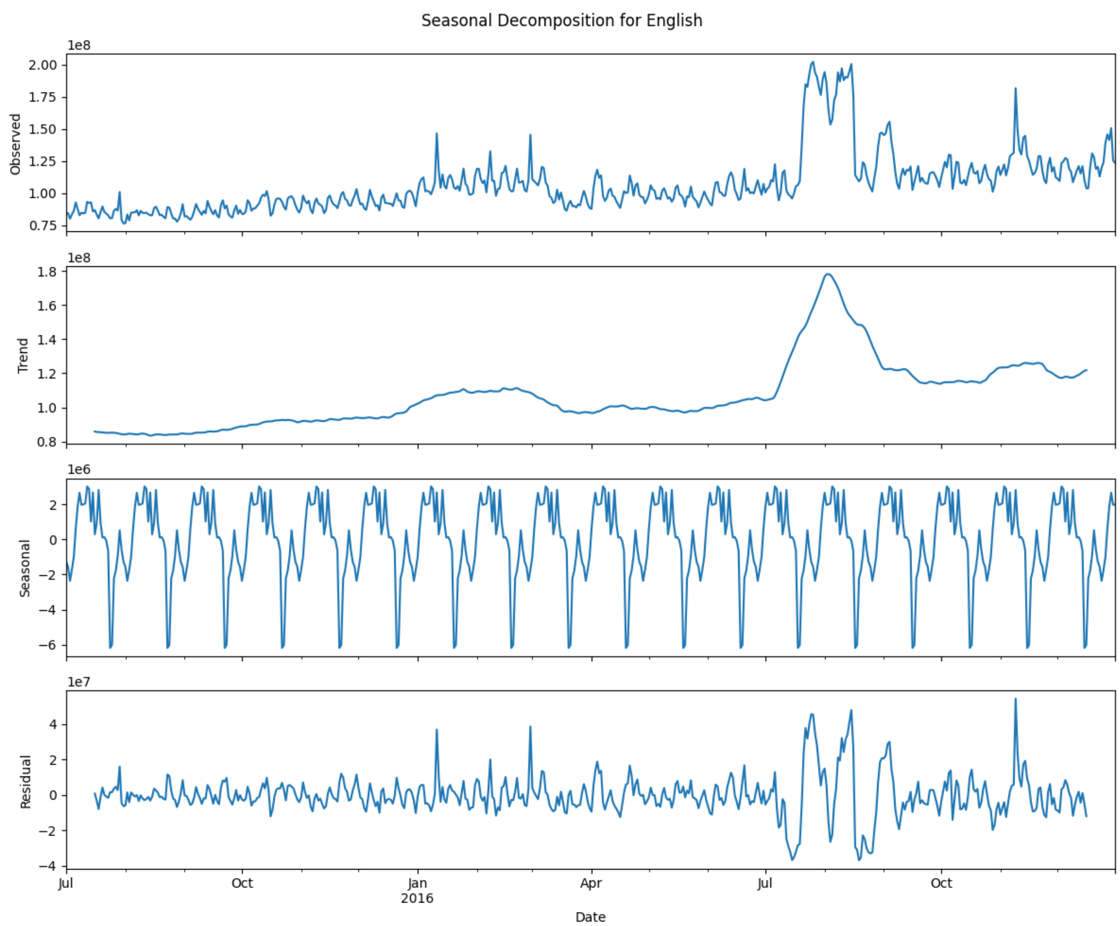
```
The time series is not stationary.
--------------------------------------------------

Language: Russian
The time series is stationary.
--------------------------------------------------

Language: German
The time series is not stationary.
--------------------------------------------------

Language: Japanese
The time series is not stationary.
--------------------------------------------------

Language: Spanish
The time series is stationary.
--------------------------------------------------
```

0.6.3 Seasonality Check

[29]:
```python
def check_seasonality(language, frequency=30):

    # Decompose the time series
    decomposition = seasonal_decompose(date_views_df[language],␣
↪model='additive', period=frequency)

    # Plot the decomposition

    fig, (ax1, ax2, ax3, ax4) = plt.subplots(4, 1, figsize=(12, 10),␣
↪sharex=True)

    plt.suptitle('Seasonal Decomposition for ' + lang_map[language])
    decomposition.observed.plot(ax=ax1, legend=False)
    ax1.set_ylabel('Observed')

    decomposition.trend.plot(ax=ax2, legend=False)
    ax2.set_ylabel('Trend')

    decomposition.seasonal.plot(ax=ax3, legend=False)
    ax3.set_ylabel('Seasonal')

    decomposition.resid.plot(ax=ax4, legend=False)
    ax4.set_ylabel('Residual')
    ax4.set_xlabel('Date')
```

```
    plt.tight_layout()
    plt.show()

    return {
        'Trend': decomposition.trend,
        'Seasonal': decomposition.seasonal,
        'Residual': decomposition.resid
    }
```

[30]:
```
_ = check_seasonality('EN', frequency=30)
```



0.7 English Page

Decomposition

- Decomposition of a time series is a statistical method used to break down a time series into its constituent components.

- Trend Component
- Seasonal Component
- Cyclical Component
- Irregular Component

[31]:
```
# Take the first difference of the time series

for lang in wiki_df['LANGUAGE'].unique().tolist():
    date_views_df[lang+'_diff'] = date_views_df[lang].diff()
```

[32]:
```
# Perform the ADF test on a specific column, e.g., 'EN'
result = adfuller(date_views_df['EN'])

# Print the results
print('ADF Statistic:', result[0])
print('p-value:', result[1])
print('Critical Values:')
for key, value in result[4].items():
    print(f'   {key}: {value}')
```

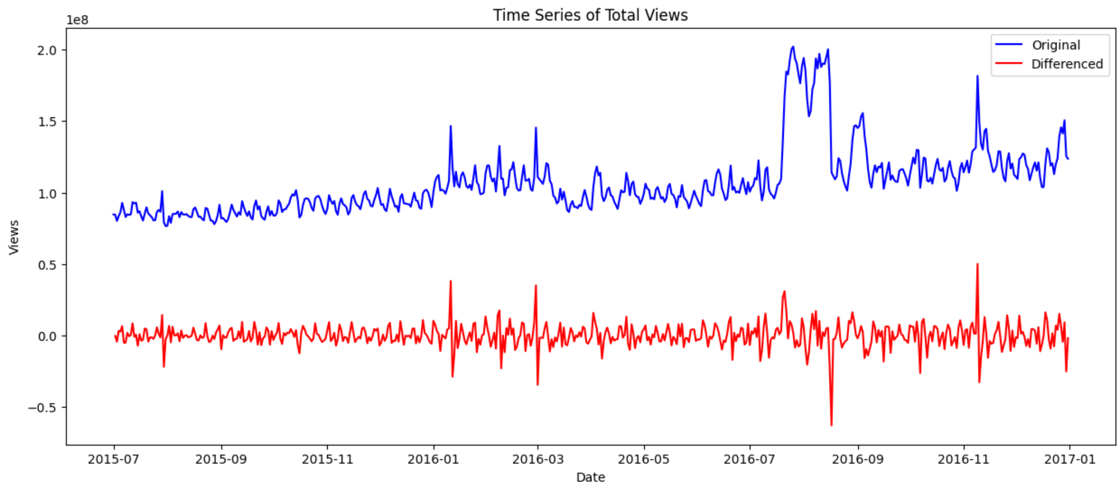
```
ADF Statistic: -2.2472840057446666
p-value: 0.18953359279992876
Critical Values:
   1%: -3.4426321555520905
   5%: -2.86695748394138
   10%: -2.5696553279762426
```

[33]:
```
result_diff = adfuller(date_views_df['EN_diff'].dropna())

# Print the results
print('ADF Statistic (Differenced):', result_diff[0])
print('p-value (Differenced):', result_diff[1])
print('Critical Values (Differenced):')
for key, value in result_diff[4].items():
    print(f'   {key}: {value}')
```

```
ADF Statistic (Differenced): -8.254153104895686
p-value (Differenced): 5.2924746354369e-13
Critical Values (Differenced):
   1%: -3.4426321555520905
   5%: -2.86695748394138
   10%: -2.5696553279762426
```

[34]:
```
# Plot the time series
plt.figure(figsize=(15, 6))
plt.plot(date_views_df['EN'], label='Original', color='blue')
plt.plot(date_views_df['EN_diff'], label='Differenced', color='red')
plt.title(f'Time Series of Total Views')
plt.xlabel('Date')
```

```
plt.ylabel('Views')
plt.legend()
plt.show()
```



What level of differencing gave you a stationary series?

- Differencing of level 1 makes the data stationary series

0.7.1 Observations

Original Data:

- Since the ADF statistic (-2.2472840057446666) is higher than the critical values at the 1%, 5%, and 10% levels, and the p-value (0.18953359279992876) is greater than 0.05, we fail to reject the null hypothesis.

This means that the original time series is not stationary.

Differenced Data:

- For the differenced time series, the ADF statistic (-8.254153104895686) is much lower than the critical values at the 1%, 5%, and 10% levels, and the p-value (5.2924746354369e-13) is significantly less than 0.05.

Therefore, we reject the null hypothesis, indicating that the differenced time series is stationary.

Conclusion

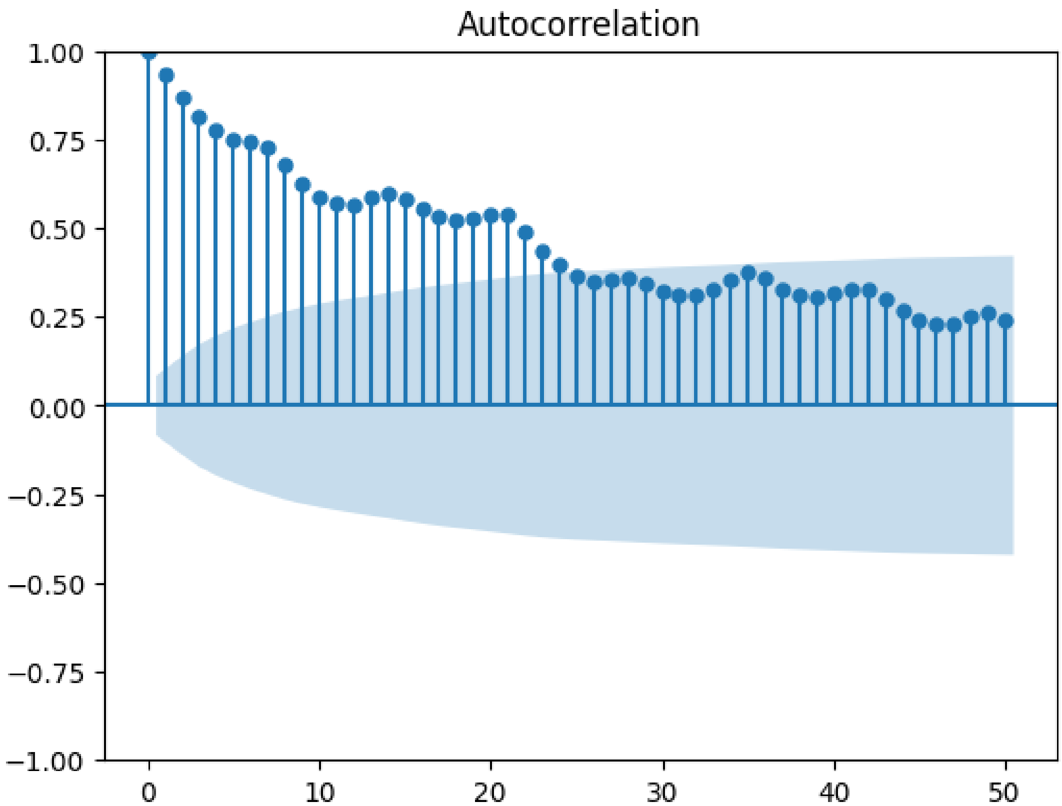
- Since the original time series is not stationary, but the differenced time series is stationary, you should use the differenced data for your ARIMA model.

Differencing the data has effectively removed the non-stationarity, making it suitable for time series forecasting.

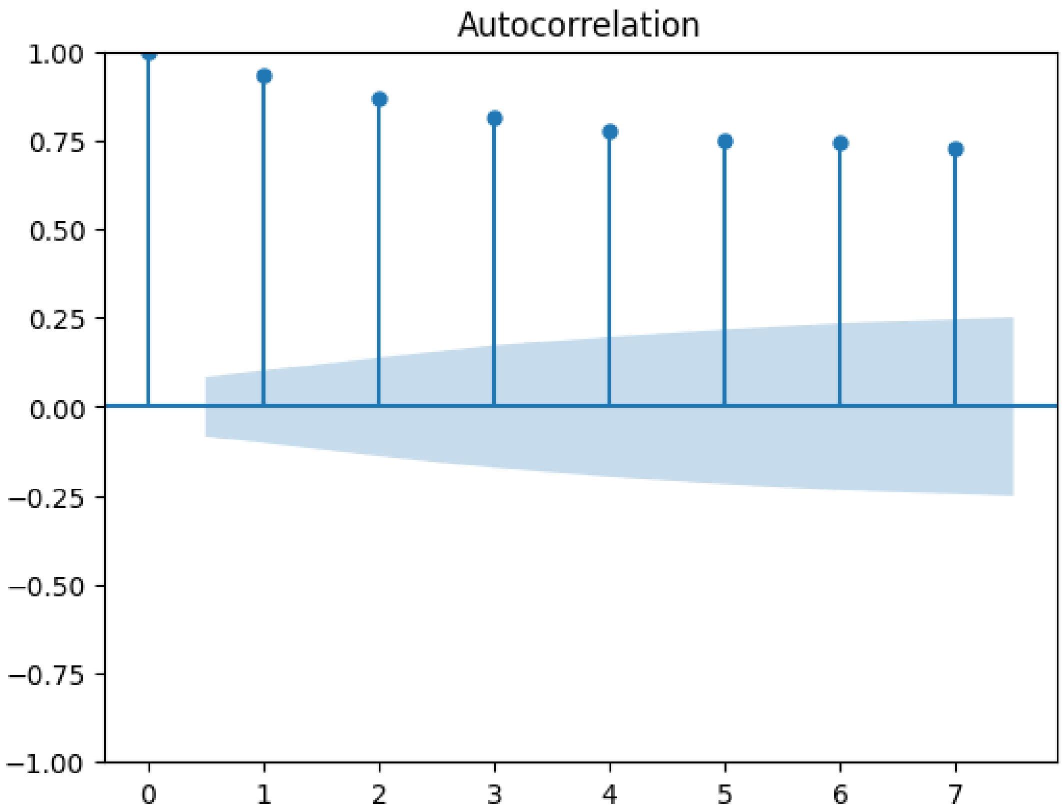
0.7.2 ACF and PACF plots

[35]:
```
# Plot ACF
plt.figure(figsize=(15, 6))
plot_acf(date_views_df['EN'], lags=50)
plt.show()
```

```
<Figure size 1500x600 with 0 Axes>
```

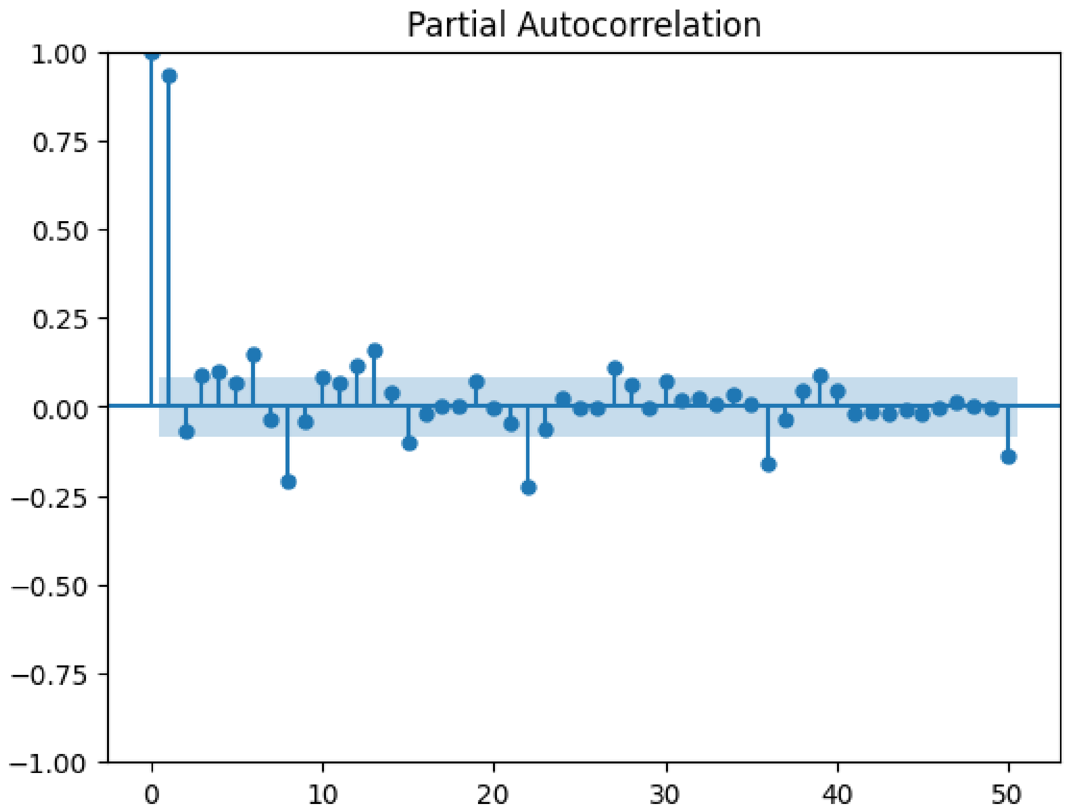


[36]:
```
plot_acf(date_views_df['EN'], lags=7)
plt.show()
```



[37]:
```
# Plot PACF
plt.figure(figsize=(15, 6))
plot_pacf(date_views_df['EN'], lags=50, method='ywm')
plt.show()
```

```
<Figure size 1500x600 with 0 Axes>
```



Observations

ACF Plot:

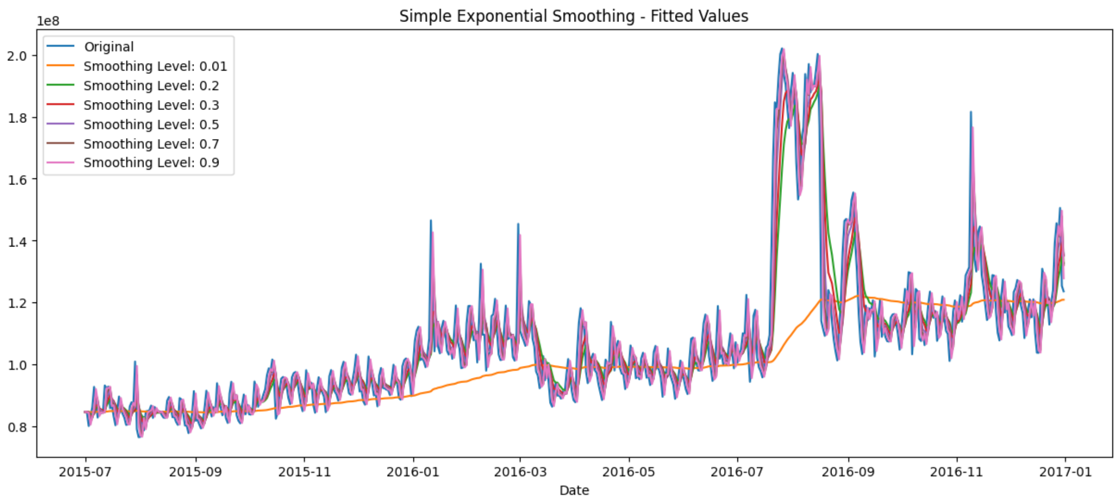
- The ACF plot shows a seasonal peak every 7 days, indicating a weekly trend.

0.7.3 Exoponential Smoothing

[38]:
```
smoothing_level_values = [0.01, 0.2, 0.3,  0.5,  0.7,  0.9]


# Plot the original data and the fitted values
plt.figure(figsize=(15, 6))
plt.plot(date_views_df['EN'], label='Original')


for sl in smoothing_level_values:
    model = sm.tsa.SimpleExpSmoothing(date_views_df['EN']).
 ↪fit(smoothing_level=sl)
    fitted_values = model.fittedvalues
    mse_ = mse(date_views_df['EN'], fitted_values)
```

```
    print(f'Smoothing Level: {sl} - MSE: {mse_}')
    plt.plot(fitted_values, label=f'Smoothing Level: {sl}')

plt.xlabel('Date')
plt.title('Simple Exponential Smoothing - Fitted Values')
plt.legend()
plt.show()
```

```
Smoothing Level: 0.01 - MSE: 377731906645562.56
Smoothing Level: 0.2 - MSE: 126560396928220.38
Smoothing Level: 0.3 - MSE: 105104189964734.28
Smoothing Level: 0.5 - MSE: 84682462480172.02
Smoothing Level: 0.7 - MSE: 75008289560125.16
Smoothing Level: 0.9 - MSE: 70179797415225.4
```



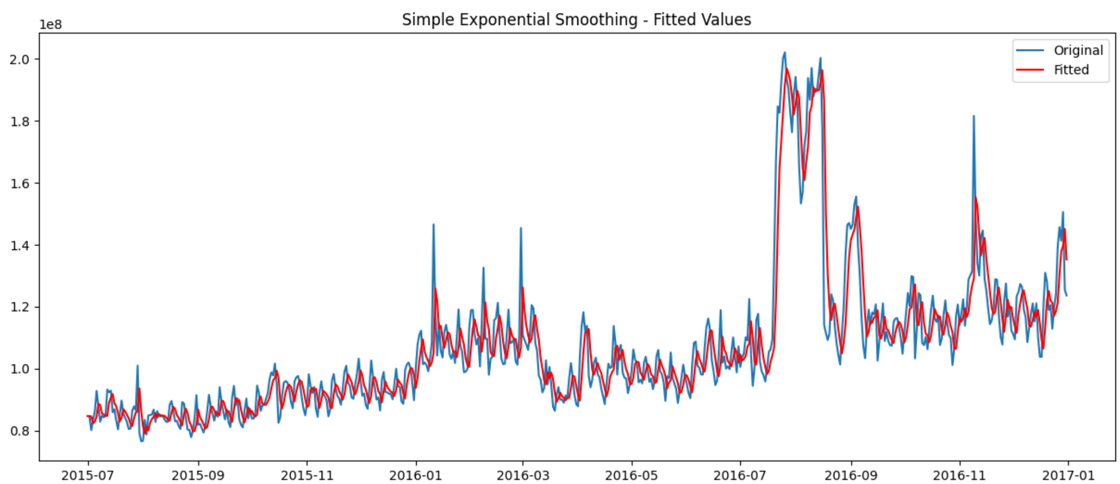
Observations

- By using a smoothing level of 0.5, you should achieve a good balance between capturing the trend and seasonality while avoiding overfitting.

[39]:
```
optimal_model = sm.tsa.SimpleExpSmoothing(date_views_df['EN']).
 ↪fit(smoothing_level=0.5)

# Extract the fitted values
fitted_values = optimal_model.fittedvalues

# Print the optimal smoothing level
print(f'Optimal Smoothing Level: {optimal_model.model.
 ↪params["smoothing_level"]}')
```

```python
# Plot the original data and the fitted values
plt.figure(figsize=(15, 6))
plt.plot(date_views_df['EN'], label='Original')
plt.plot(fitted_values, color='red', label='Fitted')
plt.title('Simple Exponential Smoothing - Fitted Values')
plt.legend()
plt.show()

mae_ = mae(date_views_df['EN'], fitted_values)
mse_ = mse(date_views_df['EN'], fitted_values)
rmse = np.sqrt(mse_)

print(f'MAE: {mae_}')
print(f'MSE: {mse_}')
print(f'RMSE: {rmse}')
```

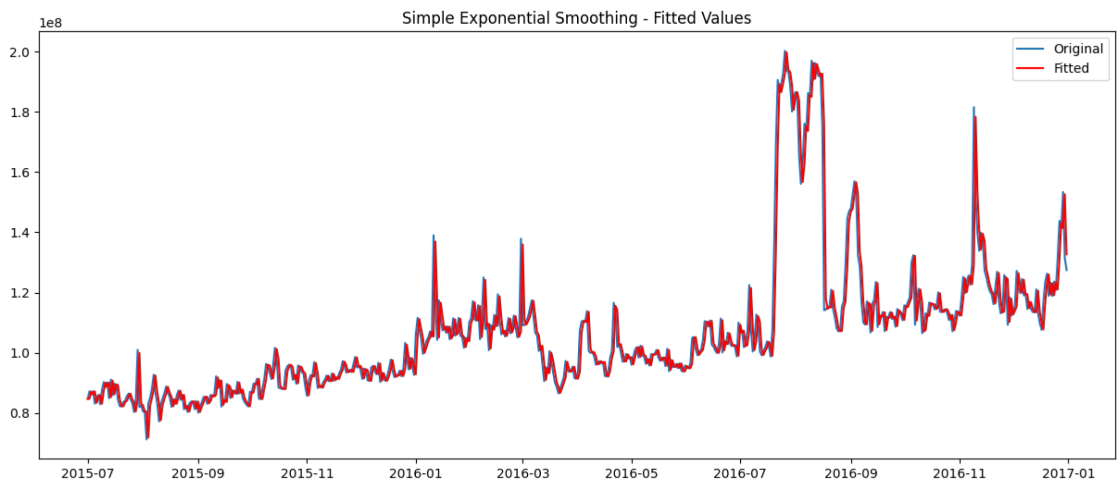
```
Optimal Smoothing Level: 0.5
```




```
MAE: 6368108.346375721
MSE: 84682462480172.02
RMSE: 9202307.454121059
```

[40]:
```python
# Prepare the EN time series, De-seasoning
decomposition = seasonal_decompose(date_views_df['EN'], model='additive',␣
 ↪period=7)
date_views_df['EN_deseasoned'] = date_views_df['EN'] - decomposition.seasonal

# Fit the model
optimal_model = sm.tsa.SimpleExpSmoothing(date_views_df['EN_deseasoned']).fit()

# Extract the fitted values
```

```python
fitted_values = optimal_model.fittedvalues

# Plot the original data and the fitted values
plt.figure(figsize=(15, 6))
plt.plot(date_views_df['EN_deseasoned'], label='Original')
plt.plot(fitted_values, color='red', label='Fitted')
plt.title('Simple Exponential Smoothing - Fitted Values')
plt.legend()
plt.show()

mae_ = mae(date_views_df['EN_deseasoned'], fitted_values)
mse_ = mse(date_views_df['EN_deseasoned'], fitted_values)
rmse = np.sqrt(mse_)

print(f'MAE: {mae_}')
print(f'MSE: {mse_}')
print(f'RMSE: {rmse}')
```

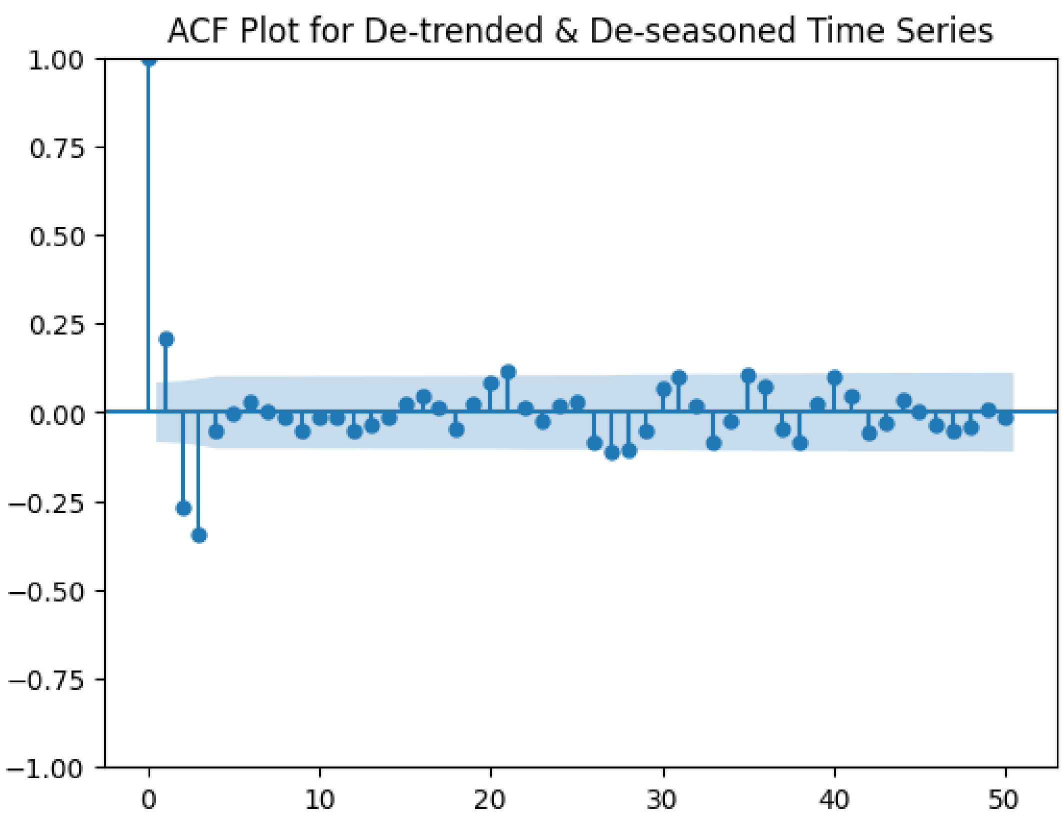



```
MAE: 4283515.4418008905
MSE: 51044489960174.23
RMSE: 7144542.669770699
```

[41]:
```python
# Decompose the time series
decomposition = seasonal_decompose(date_views_df['EN'], model='additive',␣
  ↪period=7)
trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid

# Remove trend and seasonality
```

```
detrended_deseasoned = date_views_df['EN'] - trend - seasonal

# Drop NaN values resulting from the decomposition
detrended_deseasoned.dropna(inplace=True)

plt.figure(figsize=(10, 6))
plot_acf(detrended_deseasoned, lags=50)
plt.title('ACF Plot for De-trended & De-seasoned Time Series')
plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```



Observations

- By using a weekly seasonal decomposition, we should achieve a good balance between capturing the trend and seasonality while avoiding overfitting.

Difference between ARIMA, SARIMA & SARIMAX

Model	Seasonality	Exogenous Variables	Complexity
ARIMA	Does not handle seasonality.	Does not include exogenous variables.	Simpler model, suitable for non-seasonal data.
SARIMA	Handles seasonality by including seasonal components.	Does not include exogenous variables.	More complex due to the inclusion of seasonal components.
SARIMAX	Handles seasonality and also includes exogenous variables.	Includes exogenous variables, allowing for the incorporation of external predictors.	Most complex, as it includes both seasonal components and exogenous variables.

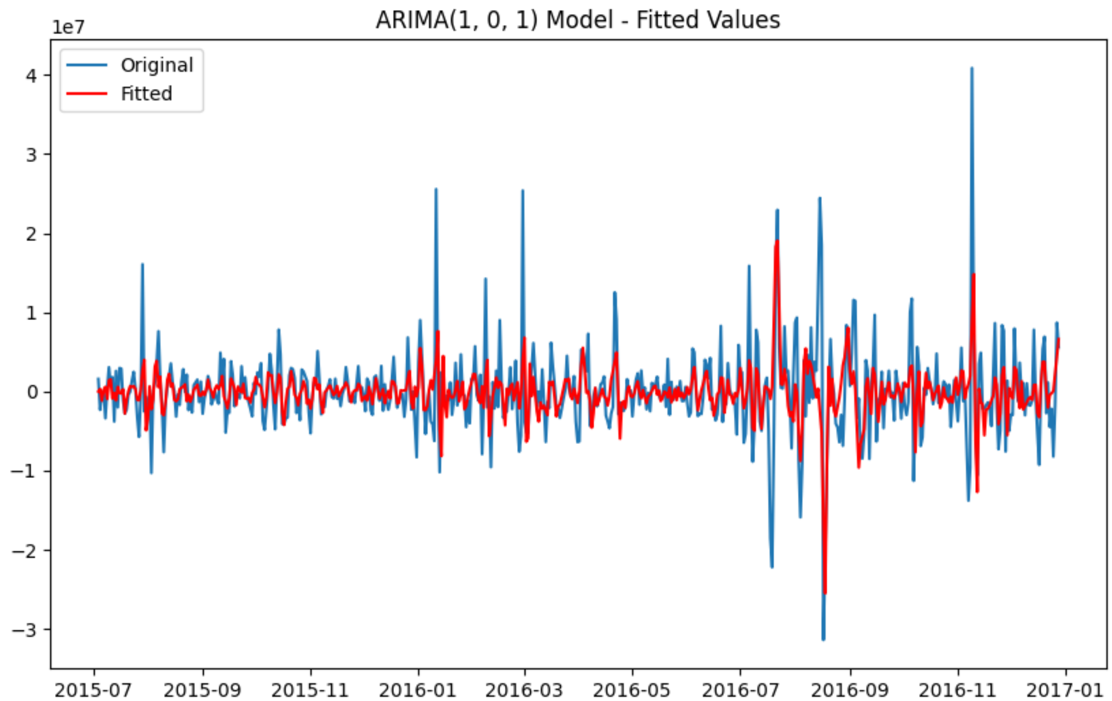
0.7.4 Train with ARIMA

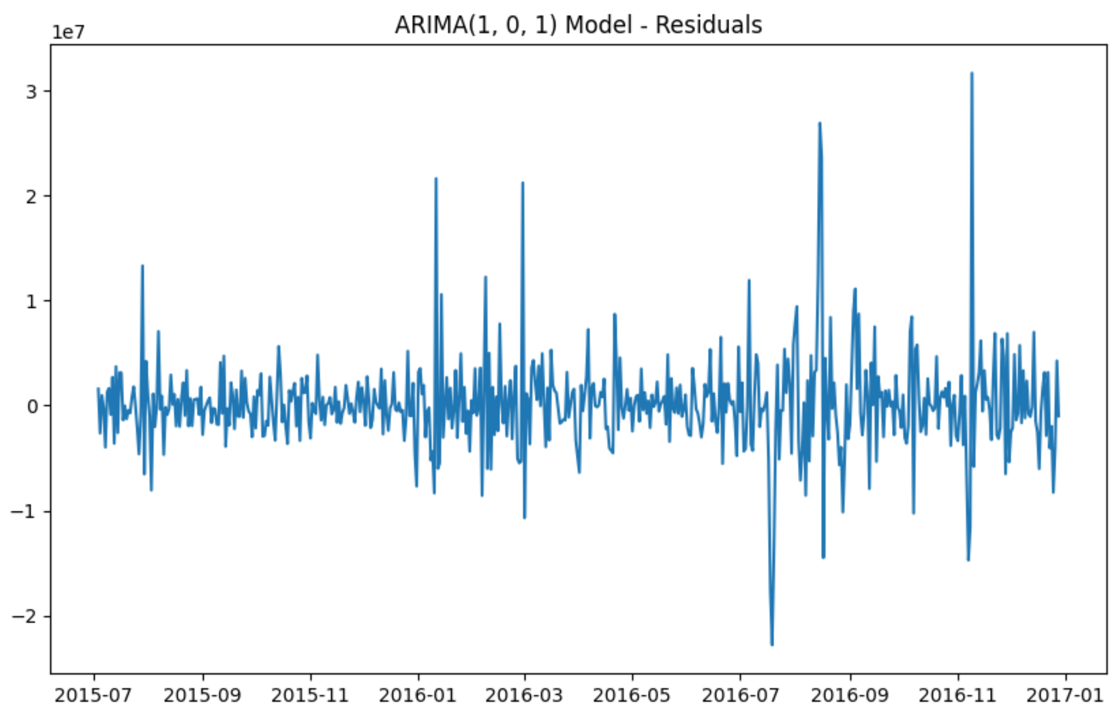
[42]:

```python
# Fit the ARIMA model
model = ARIMA(detrended_deseasoned, order=(1, 0, 7)).fit()

# Summary of the model
print(model.summary())

# Plot the original and fitted values
plt.figure(figsize=(10, 6))
plt.plot(detrended_deseasoned, label='Original')
plt.plot(model.fittedvalues, label='Fitted', color='red')
plt.title('ARIMA(1, 0, 1) Model - Fitted Values')
plt.legend()
plt.show()

# Calculate the residuals
residuals = detrended_deseasoned - model.fittedvalues

# Plot the residuals
plt.figure(figsize=(10, 6))
plt.plot(residuals)
plt.title('ARIMA(1, 0, 1) Model - Residuals')
plt.show()
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  544
Model:                 ARIMA(1, 0, 7)   Log Likelihood               -9104.330
Date:                Thu, 26 Dec 2024   AIC                          18228.661
Time:                        15:08:48   BIC                          18271.650
Sample:                    07-04-2015   HQIC                         18245.468
                         - 12-28-2016
Covariance Type:                  opg
```

```
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const      -3012.6970   3170.793     -0.950      0.342   -9227.338    3201.944
ar.L1         -0.5803      0.908     -0.639      0.523      -2.361       1.200
ma.L1          0.6379      0.910      0.701      0.483      -1.146       2.422
ma.L2         -0.3898      0.079     -4.914      0.000      -0.545      -0.234
ma.L3         -0.7619      0.385     -1.980      0.048      -1.516      -0.008
ma.L4         -0.3841      0.496     -0.774      0.439      -1.357       0.589
ma.L5         -0.0693      0.118     -0.587      0.557      -0.301       0.162
ma.L6         -0.0052      0.054     -0.097      0.923      -0.111       0.101
ma.L7         -0.0252      0.066     -0.383      0.702      -0.154       0.104
sigma2      2.108e+13   4.68e-06   4.51e+18      0.000    2.11e+13    2.11e+13
================================================================================
===
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):
2969.85
Prob(Q):                              0.98   Prob(JB):
0.00
Heteroskedasticity (H):               6.39   Skew:
1.26
Prob(H) (two-sided):                  0.00   Kurtosis:
14.16
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
[2] Covariance matrix is singular or near-singular, with condition number
2.13e+33. Standard errors may be unstable.
```


ARIMA(1, 0, 1) Model - Fitted Values
1e7
Original
Fitted
4
3
2
1
0
−1
−2
−3
2015-07
2015-09
2015-11
2016-01
2016-03
2016-05
2016-07
2016-09
2016-11
2017-01


ARIMA(1, 0, 1) Model - Residuals
1e7
3
2
1
0
−1
−2
2015-07
2015-09
2015-11
2016-01
2016-03
2016-05
2016-07
2016-09
2016-11
2017-01

[43]:
```
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))
```

[44]:
```
performance(detrended_deseasoned, model.fittedvalues)
```

```
MAE : 2833352.615
RMSE : 4474010.161
MAPE: 3.559
```

Interpretation :

- The model includes one autoregressive term (AR(1)) and seven moving average terms (MA(1) to MA(7)).
- The constant term and most of the AR and MA coefficients are not statistically significant (p-value > 0.05), except for MA(2) and MA(3), which are significant at the 5% level.
- The high value of the variance of residuals (sigma2) indicates substantial variability in the residuals.

Overall, while the model captures some aspects of the data, the lack of significance in most coefficients and the non-normality of residuals suggest that there may be room for improvement in the model.

0.7.5 Train SARIMAX model

[45]:
```
exog_df = pd.read_csv('../data/Exog_Campaign_eng.csv')
exog_df.shape
```

[45]:
```
(550, 1)
```

[46]:
```
print(exog_df.isna().sum())
exog_df.head()
```

```
Exog    0
dtype: int64
```

[46]:

	Exog
0	0
1	0
2	0
3	0
4	0

[47]:
```
exog_df.index = pd.to_datetime(date_range)
exog_df.head()
```

[47]:

	Exog
2015-07-01	0
2015-07-02	0

```
2015-07-03    0
2015-07-04    0
2015-07-05    0
```

Train Test Data Split

[48]:
```python
days_to_forecast = 30
train_max_date = date_views_df.index[-days_to_forecast]



train_x = date_views_df.loc[date_views_df.index < date_views_df.
 ↪index[-days_to_forecast]].copy()
test_x = date_views_df.loc[date_views_df.index >= date_views_df.
 ↪index[-days_to_forecast]].copy()

train_exog = exog_df.loc[exog_df.index < exog_df.index[-days_to_forecast]].
 ↪copy()
test_exog = exog_df.loc[exog_df.index >= exog_df.index[-days_to_forecast]].
 ↪copy()
```

[49]:
```python
# train with exog variable
sarima_model = SARIMAX(train_x['EN'], exog=train_exog['Exog'] ,order=(1, 0, 7),␣
 ↪seasonal_order=(1, 1, 1, 12)).fit(disp=False)

# Summary of the model
print(sarima_model.summary())
```

```
                                      SARIMAX Results
================================================================================
============
Dep. Variable:                                    EN   No. Observations:
520
Model:             SARIMAX(1, 0, 7)x(1, 1, [1], 12)   Log Likelihood
-8834.228
Date:                               Thu, 26 Dec 2024   AIC
17692.456
Time:                                       15:08:52   BIC
17743.221
Sample:                                   07-01-2015   HQIC
17712.362
                                        - 12-01-2016
Covariance Type:                                 opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
Exog        4.534e+07   2.08e-09   2.18e+16      0.000    4.53e+07    4.53e+07
ar.L1          0.9915      0.009    110.778      0.000       0.974       1.009
```

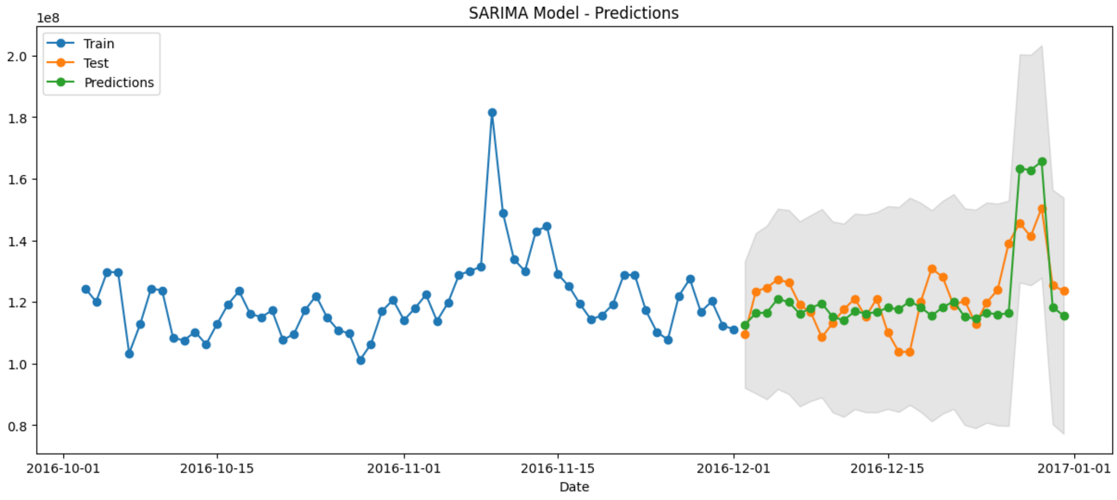
```
ma.L1         -0.2112      0.047     -4.489      0.000      -0.303      -0.119
ma.L2         -0.2467      0.057     -4.320      0.000      -0.359      -0.135
ma.L3         -0.1378      0.067     -2.052      0.040      -0.270      -0.006
ma.L4         -0.0905      0.071     -1.282      0.200      -0.229       0.048
ma.L5         -0.1394      0.076     -1.841      0.066      -0.288       0.009
ma.L6         -0.0087      0.085     -0.103      0.918      -0.174       0.157
ma.L7          0.1051      0.081      1.300      0.193      -0.053       0.263
ar.S.L12      -0.0744      0.070     -1.069      0.285      -0.211       0.062
ma.S.L12      -0.9064      0.051    -17.667      0.000      -1.007      -0.806
sigma2      1.097e+14   2.67e-16   4.11e+29      0.000     1.1e+14     1.1e+14
================================================================================
===
Ljung-Box (L1) (Q):                   0.79   Jarque-Bera (JB):
898.23
Prob(Q):                              0.37   Prob(JB):
0.00
Heteroskedasticity (H):               2.96   Skew:
-0.93
Prob(H) (two-sided):                  0.00   Kurtosis:
9.24
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
[2] Covariance matrix is singular or near-singular, with condition number
1.73e+45. Standard errors may be unstable.
```

[50]:
```python
test_x['pred'] = sarima_model.forecast(steps=days_to_forecast , exog =
 ↪test_exog['Exog'])
test_x[['lower', 'upper']] = sarima_model.get_forecast(steps =
 ↪days_to_forecast,  exog = test_exog['Exog']).conf_int(0.05).values

print("Performance: ")
performance(test_x['EN'], test_x['pred'])
```

```
Performance:
MAE : 7937487.603
RMSE : 9992041.242
MAPE: 0.064
```

[51]:
```python
plt.figure(figsize=(15, 6))

plt.plot(train_x['EN'][-60:], label='Train', linestyle='-', marker='o')
plt.plot(test_x['EN'], label='Test', linestyle='-', marker='o')
plt.plot(test_x['pred'], label='Predictions', linestyle='-', marker='o')
```

```
plt.fill_between(test_x.index, test_x['lower'], test_x['upper'],
                 color='k', alpha=.10)

plt.xlabel('Date')
plt.title('SARIMA Model - Predictions')
plt.legend()
plt.show()
```



Interpretation :

- SARIMAX has a significantly lower AIC (17692.456) compared toARIMA (18228.661), indicating a better fit.
- SARIMAX also has a lower BIC (17743.221) and HQIC (17712.362) compared to ARIMA (BIC: 18271.650, HQIC: 18245.468), further supporting a better fit.
- SARIMAX has a higher Log Likelihood (-8834.228) compared to ARIMA (-9104.330), indicating a better fit.

It has significantly lower AIC, BIC, and a higher Log Likelihood compared to ARIMA. Therefore, SARIMAX is selected as the best model for the given data.

0.7.6 Train Prophet model

[52]:
```
prop_df = date_views_df[['EN']].reset_index()
prop_df.columns = ['ds', 'y']
prop_df.head()
```

[52]:

	ds	y
0	2015-07-01	84712190.0
1	2015-07-02	84438545.0
2	2015-07-03	80167728.0
3	2015-07-04	83463204.0

```
4 2015-07-05  86198637.0
```

[53]:
```python
prop_df['ds'] = pd.to_datetime(prop_df['ds'])
prop_df['exo'] = exog_df['Exog'].values

prop_df.head()
```

[53]:
```
          ds           y  exo
0 2015-07-01  84712190.0    0
1 2015-07-02  84438545.0    0
2 2015-07-03  80167728.0    0
3 2015-07-04  83463204.0    0
4 2015-07-05  86198637.0    0
```

[54]:
```python
train_df = prop_df[:-days_to_forecast]
test_df = prop_df[-days_to_forecast:]

train_df.shape, test_df.shape
```

[54]:
```
((520, 3), (30, 3))
```

[55]:
```python
m = Prophet(yearly_seasonality=True, weekly_seasonality=True)
m.add_regressor('exo')
m.fit(train_df)

future_dates = m.make_future_dataframe(periods=len(test_df))

# Add the exogenous variable to the future dataframe
future_dates['exo'] = pd.concat([train_df['exo'], test_df['exo']]).
 ↪reset_index(drop=True)

# Make predictions
forecast = m.predict(future_dates)
forecast.tail()
```

```
15:08:53 - cmdstanpy - INFO - Chain [1] start processing
15:08:53 - cmdstanpy - INFO - Chain [1] done processing
```

[55]:
```
            ds         trend    yhat_lower    yhat_upper   trend_lower  \
545 2016-12-27  1.171097e+08  1.533145e+08  1.766247e+08  1.170519e+08
546 2016-12-28  1.171317e+08  1.513925e+08  1.743926e+08  1.170695e+08
547 2016-12-29  1.171537e+08  1.496566e+08  1.736910e+08  1.170878e+08
548 2016-12-30  1.171757e+08  1.046439e+08  1.269367e+08  1.171049e+08
549 2016-12-31  1.171977e+08  1.068367e+08  1.295274e+08  1.171209e+08

      trend_upper  additive_terms  additive_terms_lower  additive_terms_upper  \
545  1.171638e+08    4.773298e+07          4.773298e+07          4.773298e+07
546  1.171906e+08    4.603620e+07          4.603620e+07          4.603620e+07
```

```
547  1.172171e+08   4.443917e+07          4.443917e+07          4.443917e+07
548  1.172445e+08  -1.254610e+06         -1.254610e+06         -1.254610e+06
549  1.172716e+08   1.181872e+06          1.181872e+06          1.181872e+06

              exo  …        weekly  weekly_lower  weekly_upper  \
545  4.383312e+07  …  1.691483e+06  1.691483e+06  1.691483e+06
546  4.383312e+07  … -4.894587e+05 -4.894587e+05 -4.894587e+05
547  4.383312e+07  … -2.575789e+06 -2.575789e+06 -2.575789e+06
548  0.000000e+00  … -4.926220e+06 -4.926220e+06 -4.926220e+06
549  0.000000e+00  … -2.975503e+06 -2.975503e+06 -2.975503e+06

           yearly  yearly_lower  yearly_upper  multiplicative_terms  \
545  2.208379e+06  2.208379e+06  2.208379e+06                   0.0
546  2.692540e+06  2.692540e+06  2.692540e+06                   0.0
547  3.181841e+06  3.181841e+06  3.181841e+06                   0.0
548  3.671611e+06  3.671611e+06  3.671611e+06                   0.0
549  4.157375e+06  4.157375e+06  4.157375e+06                   0.0

     multiplicative_terms_lower  multiplicative_terms_upper          yhat
545                         0.0                         0.0  1.648427e+08
546                         0.0                         0.0  1.631679e+08
547                         0.0                         0.0  1.615929e+08
548                         0.0                         0.0  1.159211e+08
549                         0.0                         0.0  1.183796e+08

[5 rows x 25 columns]
```

[56]:

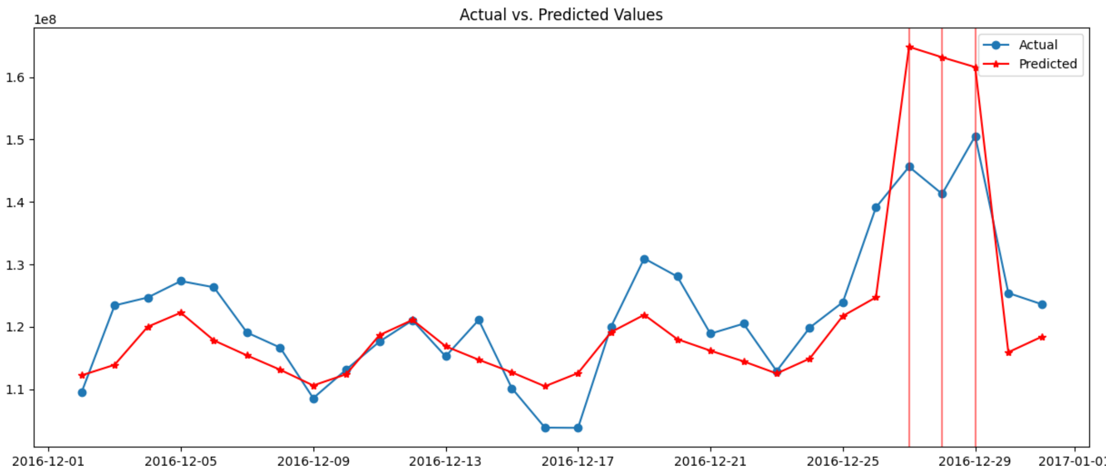
```
forecast_test = forecast[-len(test_df):]

# Calculate evaluation metrics
y_true = test_df['y'].values
y_pred = forecast_test['yhat'].values

performance(y_true, y_pred)
```

```
MAE : 6168372.58
RMSE : 8106833.47
MAPE: 0.048
```

[57]:

```
# Plot the actual vs. predicted values
plt.figure(figsize=(15, 6))
plt.plot(test_df['ds'], y_true, label='Actual', marker='o')
plt.plot(test_df['ds'], y_pred, label='Predicted', color='red', marker='*')

for x in test_df.query('exo==1')['ds']:
    plt.axvline(x=x, color='red', alpha = 0.5);

plt.title('Actual vs. Predicted Values')
```

```
plt.legend()
plt.show()
```



[58]:
```
fig1 = plot_plotly(m, forecast)
fig1.show()

# Plot the forecast components
fig2 = plot_components_plotly(m, forecast)
fig2.show()
```

Interpretation :

- Facebook's Prophet has the lower MAPE of 0.048 compare to the SARIMAX's MAPE of 0.064
- This indicates that Prophet better fits the given data

0.8 Train Other Languages

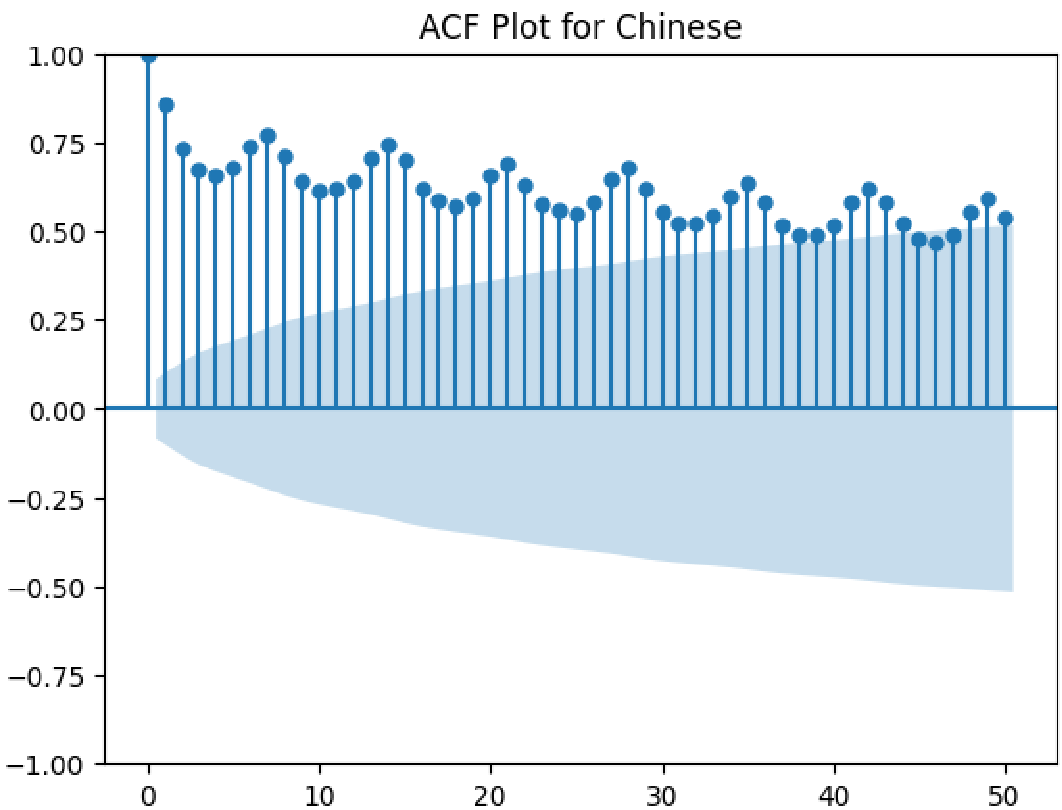
[59]:
```
lang_map
```

[59]:
```
{'ZH': 'Chinese',
 'EN': 'English',
 'RU': 'Russian',
 'FR': 'French',
 'DE': 'German',
 'JA': 'Japanese',
 'ES': 'Spanish'}
```

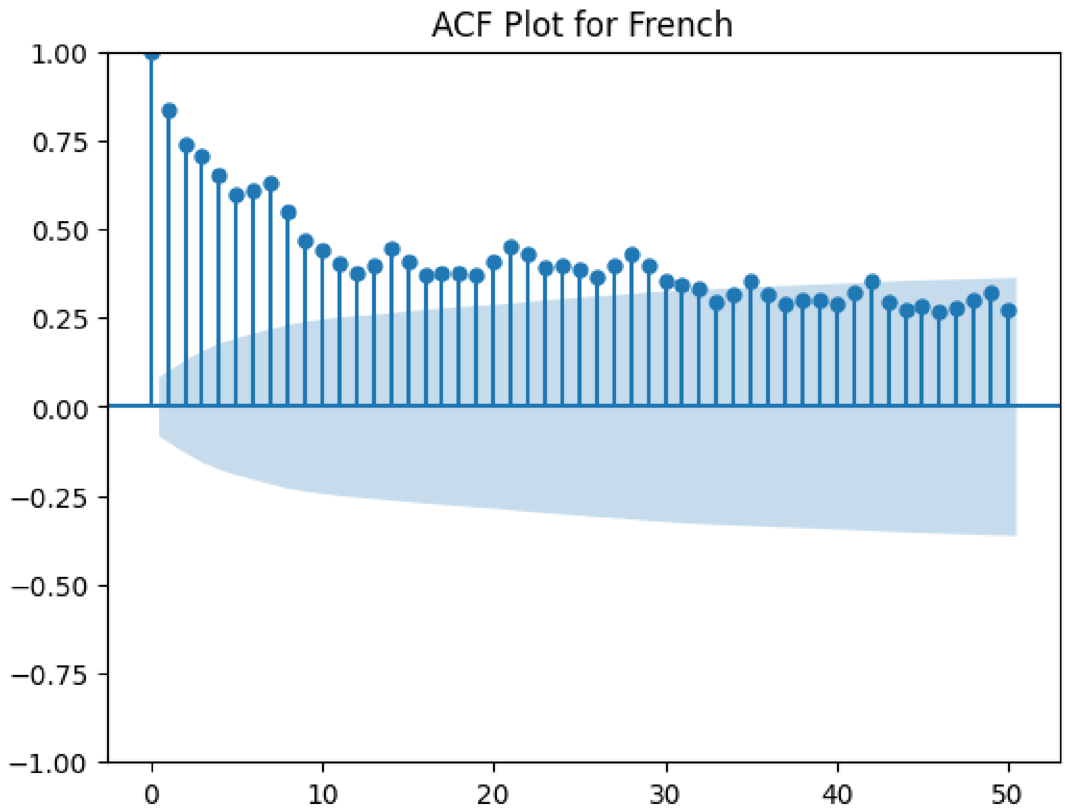
[60]:
```
# Plot ACF
def plot_acf_language(lang):
    plt.figure(figsize=(15, 6))
    plot_acf(date_views_df[lang], lags=50)
    plt.title(f'ACF Plot for {lang_map[lang]}')
    plt.show()
```

[61]:
```
for lang in languages:
    plot_acf_language(lang)
```

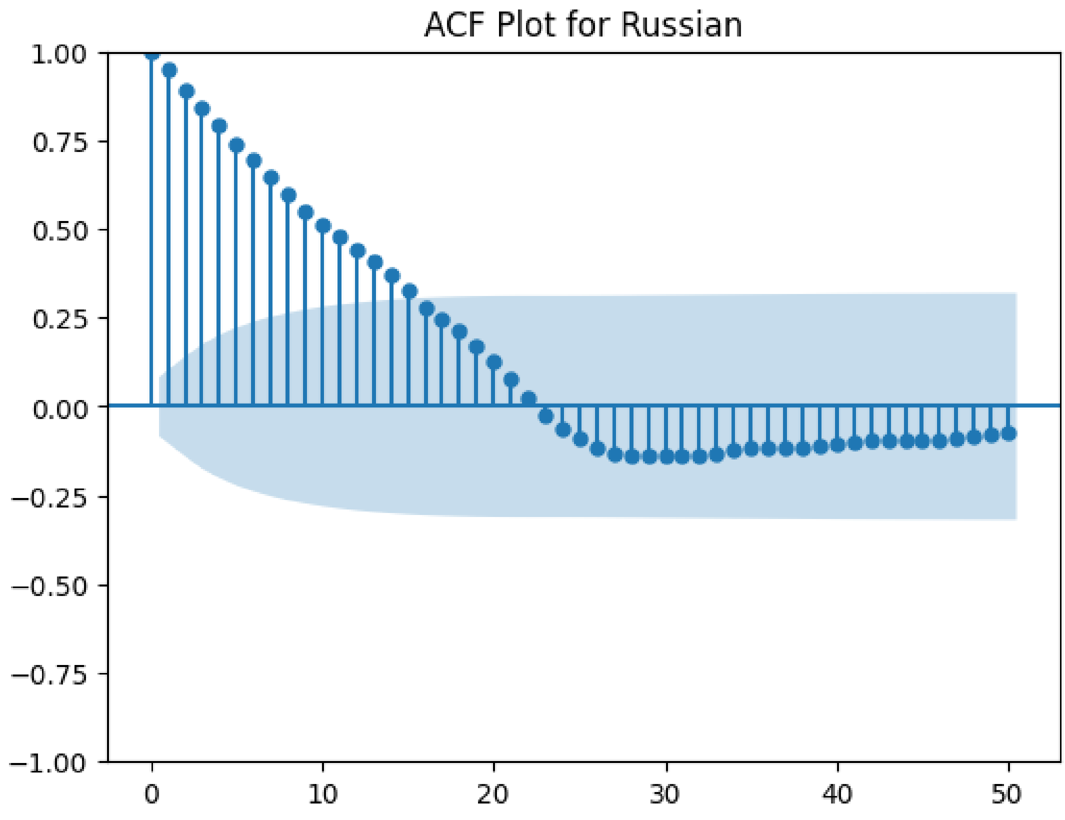
```
<Figure size 1500x600 with 0 Axes>
```



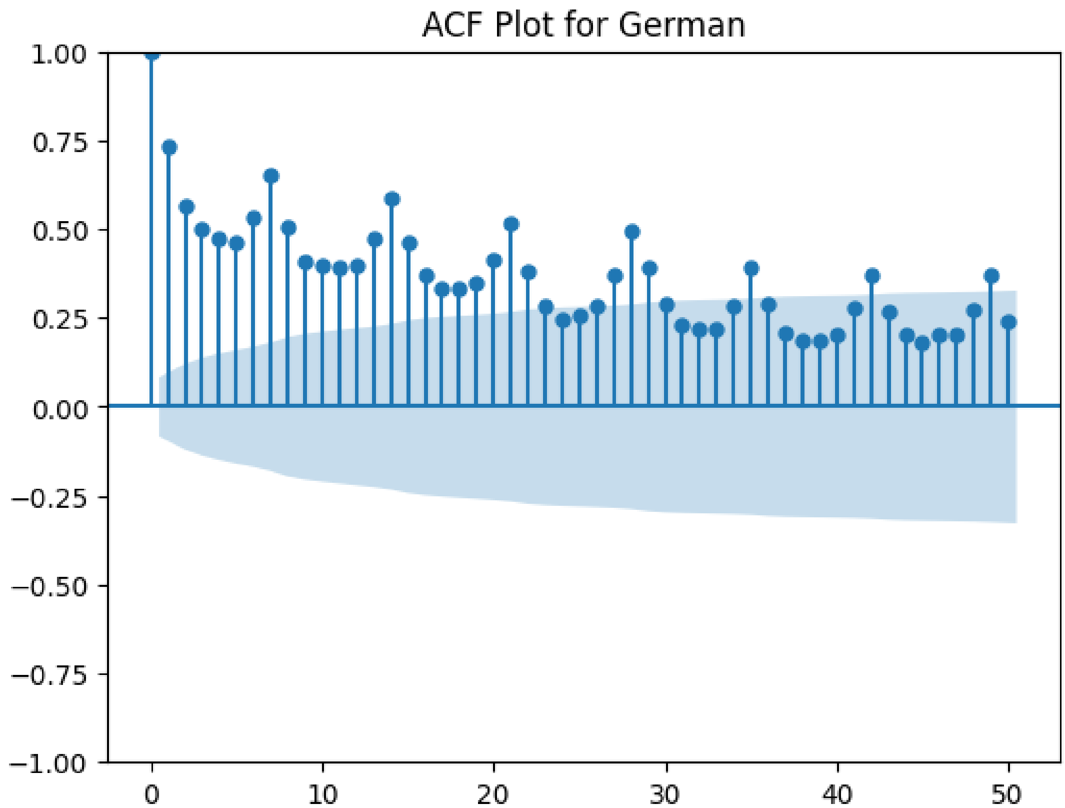

```
<Figure size 1500x600 with 0 Axes>
```



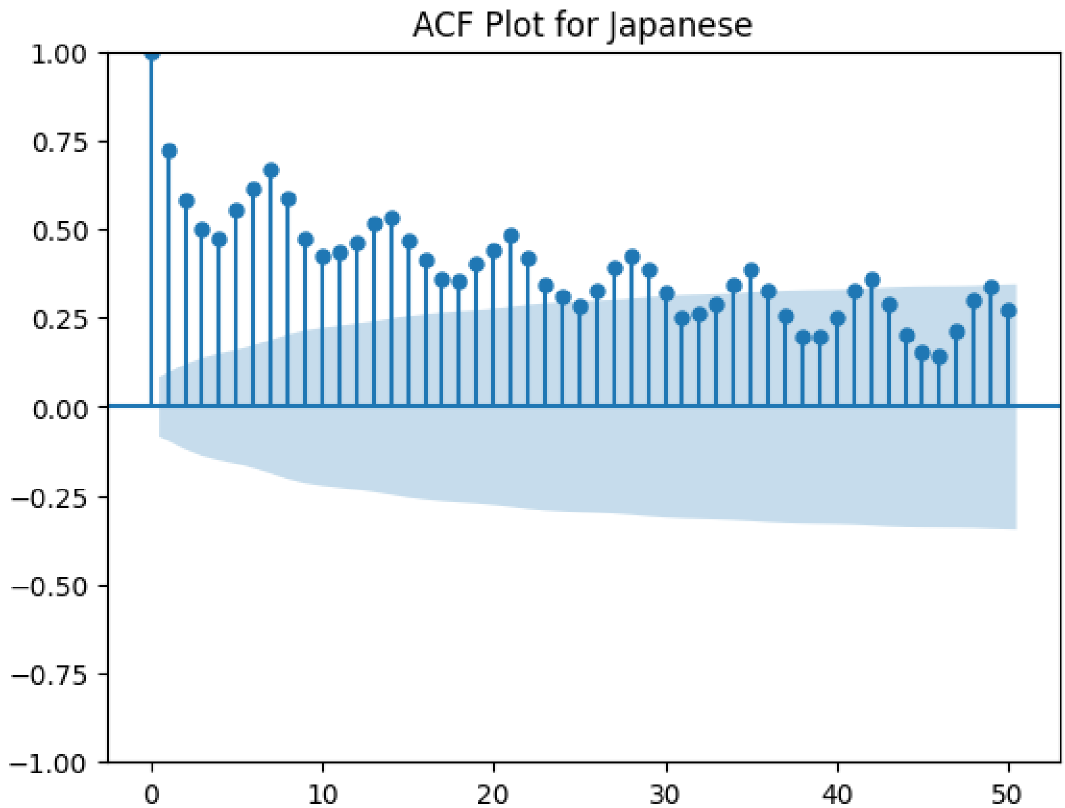
<Figure size 1500x600 with 0 Axes>



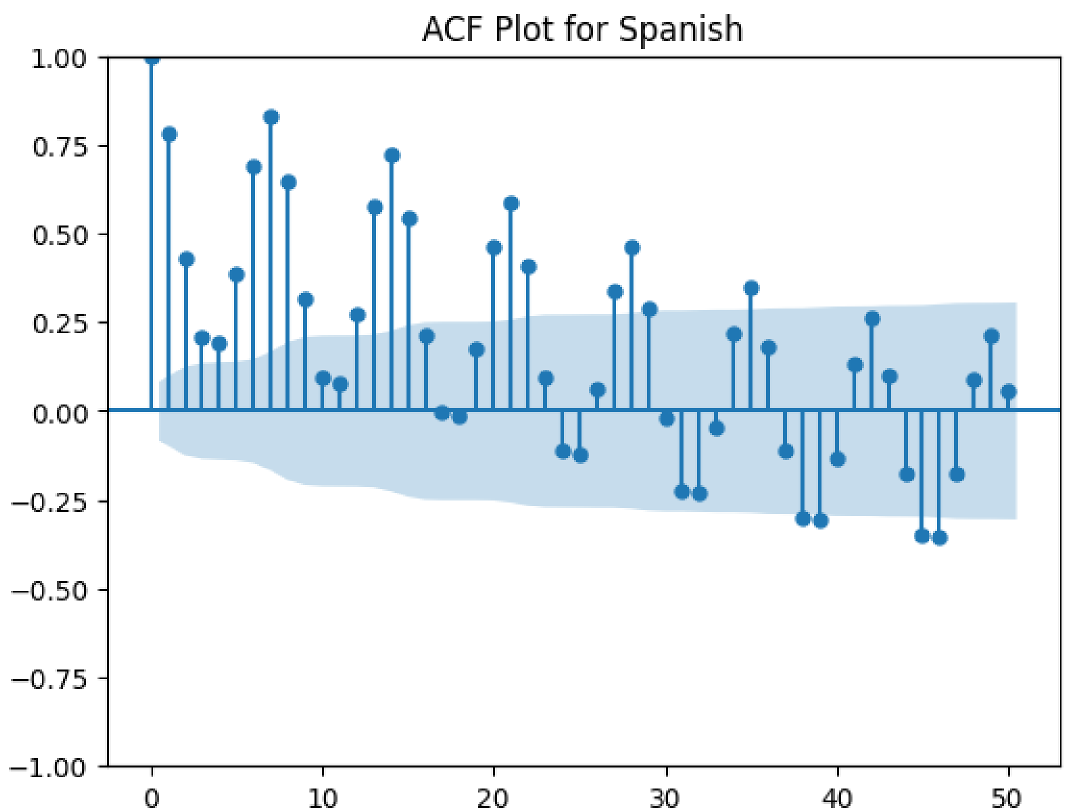

```
<Figure size 1500x600 with 0 Axes>
```




```
<Figure size 1500x600 with 0 Axes>
```




```
<Figure size 1500x600 with 0 Axes>
```



Observations

ACF Plot:

- The ACF plot shows a seasonal peak every 7 days, indicating a weekly trend for all language expect Russian.

0.8.1 Training Pipeline for Other Languages

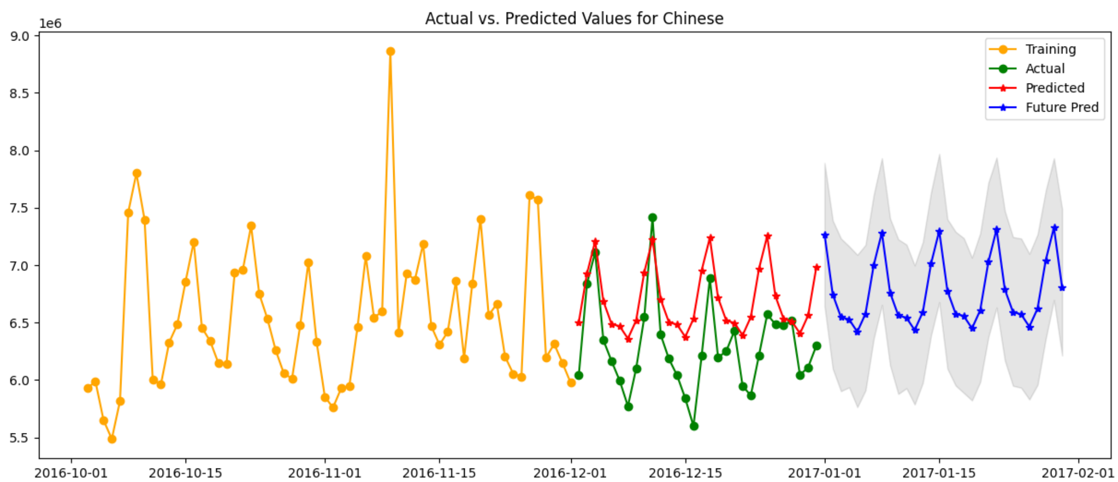
[62]:
```
# Create a pipeline to forecast the views for all languages
languages = ['ZH', 'FR', 'RU', 'DE', 'JA', 'ES']

def forecast_pipeline(df, days_to_forecast=30):
    date_views_df = df.copy()

    # Initialize the forecast dataframe
    forecast_df = pd.DataFrame()

    for lang in languages:
```

```
    print("*"*50, lang, "*"*50)
    print(f'Forecasting for {lang}...')
    prop_df = date_views_df[[lang]].reset_index()
    prop_df.columns = ['ds', 'y']
    prop_df['ds'] = pd.to_datetime(prop_df['ds'])

    train_df = prop_df[:-days_to_forecast]
    test_df = prop_df[-days_to_forecast:]

    # Initialize the model
    yearly_seasonality = True if lang in ['DE','JA', 'ES'] else False
    # weekly_seasonality = True if lang not in ['ZH', 'FR', 'RU'] else False
    m = Prophet(yearly_seasonality=yearly_seasonality,␣
↪weekly_seasonality=True)
    m.fit(train_df)

    future_dates = m.make_future_dataframe(periods=len(test_df))

    forecast = m.predict(future_dates)
    forecast_test = forecast[-len(test_df):]

    y_true = test_df['y'].values
    y_pred = forecast_test['yhat'].values

    print(f'Performance for {lang}:')
    performance(y_true, y_pred)

    # Future predications
    future_dates = m.make_future_dataframe(periods=len(test_df)+30)

    forecast = m.predict(future_dates)
    forecast_future = forecast[-len(test_df)+30:]
    forecast_future = forecast_future[-30:]

    # Plot the actual vs. predicted values
    plt.figure(figsize=(15, 6))
    plt.plot(train_df['ds'][-60:], train_df['y'][-60:], label='Training',␣
↪marker='o', color='orange')
    plt.plot(test_df['ds'], y_true, label='Actual', marker='o',␣
↪color='green')
    plt.plot(test_df['ds'], y_pred, label='Predicted', color='red',␣
↪marker='*')
    plt.plot(forecast_future['ds'], forecast_future['yhat'], label='Future␣
↪Pred', color='blue', marker='*')

    plt.fill_between(forecast_future['ds'], forecast_future['yhat_lower'],␣
↪forecast_future['yhat_upper'],
```

```
                    color='k', alpha=.10)

        plt.title(f'Actual vs. Predicted Values for {lang_map[lang]}')
        plt.legend()
        plt.show()


        predictation_df = forecast_future[['ds', 'yhat', 'yhat_lower',␣
↪'yhat_upper']]
        predictation_df['Language'] = lang
        forecast_df = pd.concat([forecast_df, predictation_df])

        print("*"*50, lang, "*"*50)
        print("\n\n")


    return forecast_df
```

[63]:
```
forecast_df = forecast_pipeline(date_views_df, days_to_forecast=30)
```

```
15:08:55 - cmdstanpy - INFO - Chain [1] start processing

************************************************** ZH
**************************************************
Forecasting for ZH…

15:08:56 - cmdstanpy - INFO - Chain [1] done processing

Performance for ZH:
MAE : 407575.774
RMSE : 466456.482
MAPE: 0.066
```



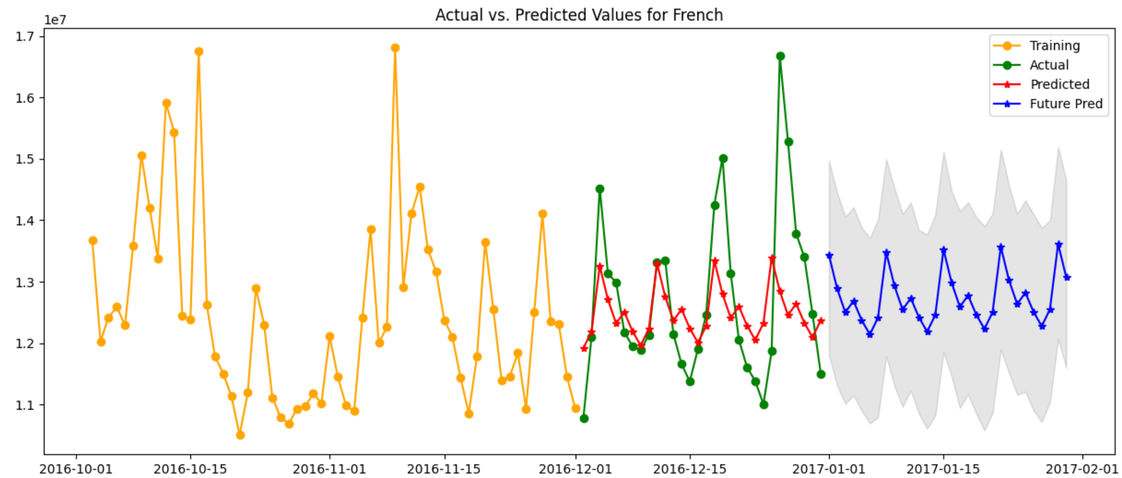
15:08:56 - cmdstanpy - INFO - Chain [1] start processing

** ZH
****

** FR
****
Forecasting for FR…

15:08:56 - cmdstanpy - INFO - Chain [1] done processing

Performance for FR:
MAE : 862881.13
RMSE : 1200957.325
MAPE: 0.065



15:08:57 - cmdstanpy - INFO - Chain [1] start processing

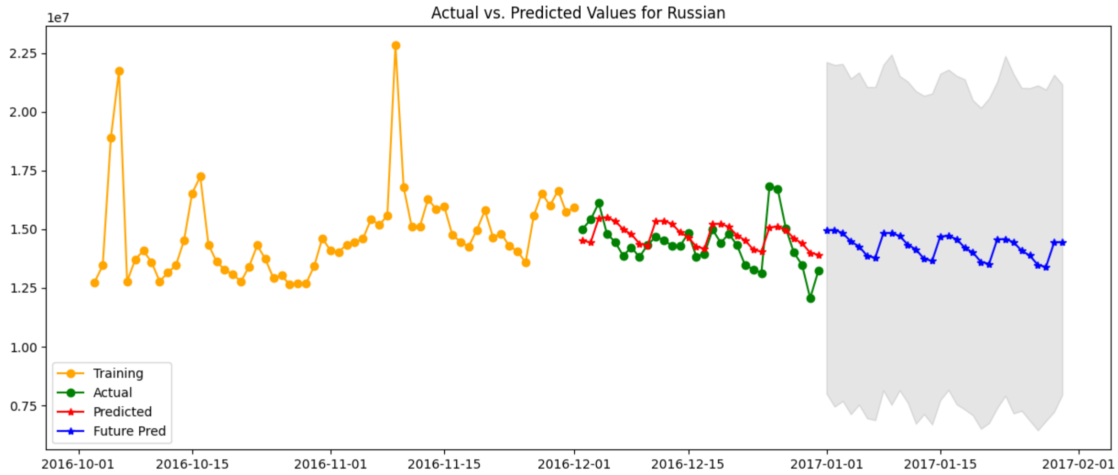
** FR
****

** RU
****
Forecasting for RU…

15:08:57 - cmdstanpy - INFO - Chain [1] done processing

Performance for RU:
MAE : 730035.637

RMSE : 857906.314
MAPE: 0.051



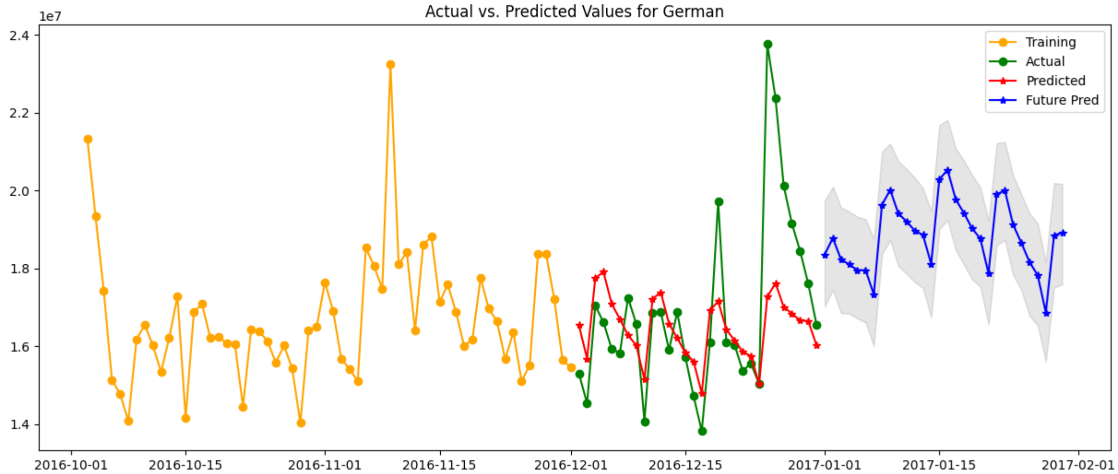
15:08:57 - cmdstanpy - INFO - Chain [1] start processing

** RU
****

** DE
****
Forecasting for DE…

15:08:58 - cmdstanpy - INFO - Chain [1] done processing

Performance for DE:
MAE : 1253507.612
RMSE : 1864050.865
MAPE: 0.068

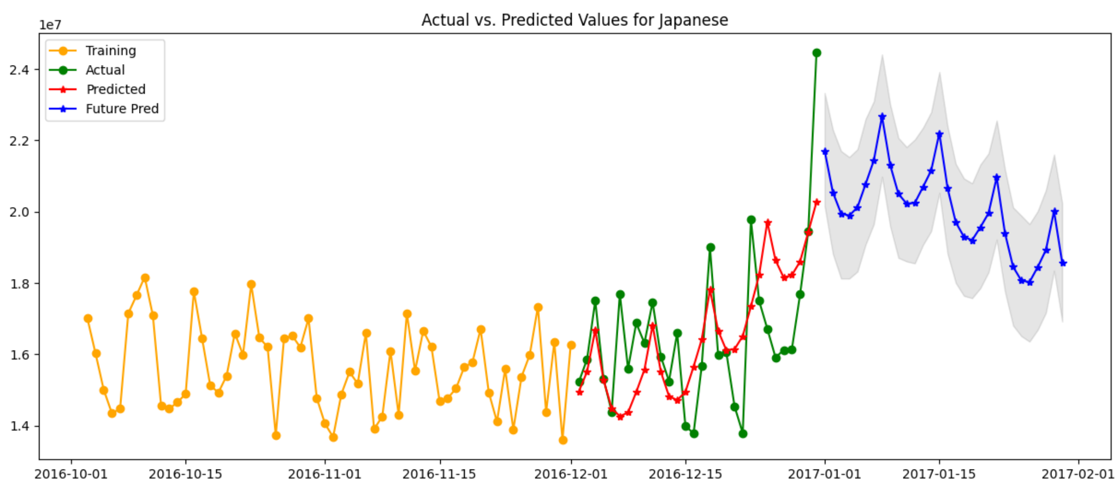



```
************************************************** DE
**************************************************
```

```
************************************************** JA
**************************************************
Forecasting for JA…
```

```
15:08:58 - cmdstanpy - INFO - Chain [1] start processing
15:08:59 - cmdstanpy - INFO - Chain [1] done processing
```

```
Performance for JA:
MAE : 1340179.469
RMSE : 1724722.937
MAPE: 0.08
```

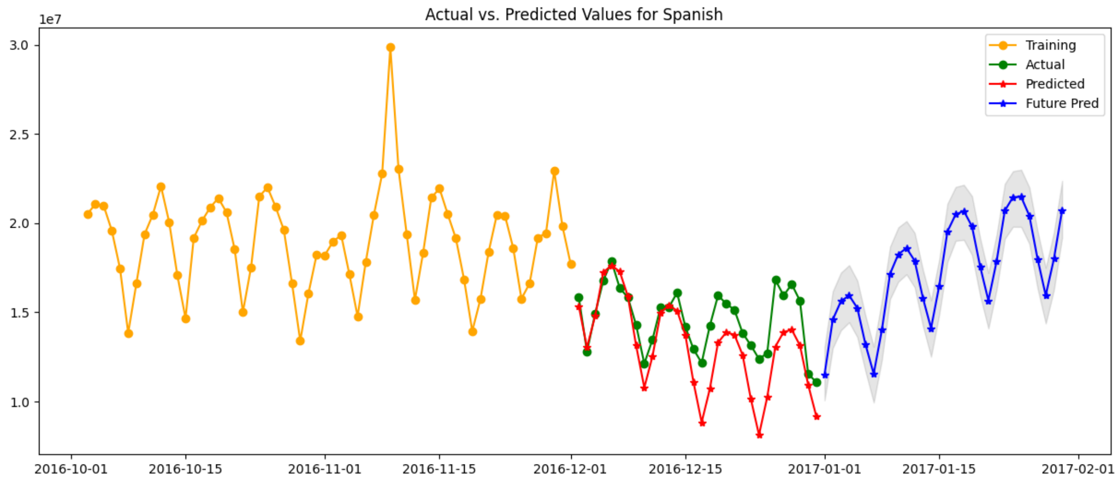


```
************************************************** JA
**************************************************
```

```
************************************************** ES
**************************************************
Forecasting for ES…
```

```
15:08:59 - cmdstanpy - INFO - Chain [1] start processing
15:08:59 - cmdstanpy - INFO - Chain [1] done processing
```

```
Performance for ES:
MAE : 1551037.646
RMSE : 1959009.507
MAPE: 0.11
```




```
************************************************** ES
**************************************************
```

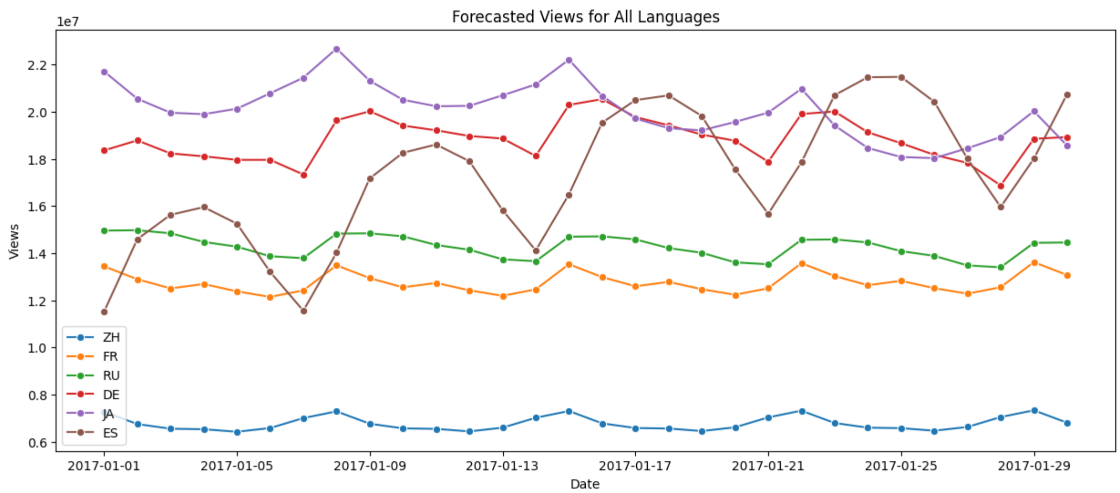
[64]:
```
forecast_df
```

[64]:

	ds	yhat	yhat_lower	yhat_upper	Language
550	2017-01-01	7.268116e+06	6.641686e+06	7.889181e+06	ZH
551	2017-01-02	6.745295e+06	6.098049e+06	7.388785e+06	ZH
552	2017-01-03	6.547396e+06	5.902415e+06	7.232366e+06	ZH
553	2017-01-04	6.526421e+06	5.935316e+06	7.163889e+06	ZH
554	2017-01-05	6.419308e+06	5.763440e+06	7.089671e+06	ZH

```
..         ...           ...           ...           ...        ...
575 2017-01-26  2.042219e+07  1.884725e+07  2.200515e+07        ES
576 2017-01-27  1.800063e+07  1.634525e+07  1.955320e+07        ES
577 2017-01-28  1.595430e+07  1.437772e+07  1.749687e+07        ES
578 2017-01-29  1.800505e+07  1.627398e+07  1.949654e+07        ES
579 2017-01-30  2.073857e+07  1.921922e+07  2.238004e+07        ES

[180 rows x 5 columns]
```

[65]:
```python
plt.figure(figsize=(15, 6))
sns.lineplot(data=forecast_df, x='ds', y='yhat', hue='Language', marker='o')
plt.title('Forecasted Views for All Languages')
plt.xlabel('Date')
plt.ylabel('Views')
plt.legend()
plt.show()
```



Observations

Model Performance Comparsion:

Language	MAE	RMSE	MAPE
ZH	407575.774	466456.482	0.066
FR	862881.13	1200957.325	0.065
RU	730035.637	857906.314	0.051
DE	1253507.612	1864050.865	0.068
JA	1340179.469	1724722.937	0.08
ES	1551037.646	1959009.507	0.11

- Spanish (ES) has slightly higher MAPE, indicating the model hasn't fit very well with the data. There is a room for improvement.

Fine Tune ES Model

[66]:
```
prop_df = date_views_df[['ES']].reset_index()
prop_df.columns = ['ds', 'y']
prop_df['ds'] = pd.to_datetime(prop_df['ds'])

train_df = prop_df[:-days_to_forecast]
test_df = prop_df[-days_to_forecast:]

# Initialize the model
# yearly_seasonality = True if lang in ['DE','JA', 'ES'] else False
# weekly_seasonality = True if lang not in ['ZH', 'FR', 'RU'] else False
m = Prophet(yearly_seasonality=True, weekly_seasonality=True)
m.fit(train_df)

future_dates = m.make_future_dataframe(periods=len(test_df))

forecast = m.predict(future_dates)
forecast_test = forecast[-len(test_df):]

y_true = test_df['y'].values
y_pred = forecast_test['yhat'].values

print(f'Performance for {"ES"}:')
performance(y_true, y_pred)
```

```
15:09:00 - cmdstanpy - INFO - Chain [1] start processing
15:09:00 - cmdstanpy - INFO - Chain [1] done processing
```

```
Performance for ES:
MAE : 1551037.646
RMSE : 1959009.507
MAPE: 0.11
```

[67]:
```
p = d = q = range(0, 3)
pdq = list(itertools.product(p, d, q))
seasonal_pdq = [(x[0], x[1], x[2], 12) for x in pdq]

best_mape = float("inf")
best_order = None
best_seasonal_order = None

for param in pdq:
    for param_seasonal in seasonal_pdq:
        try:
```

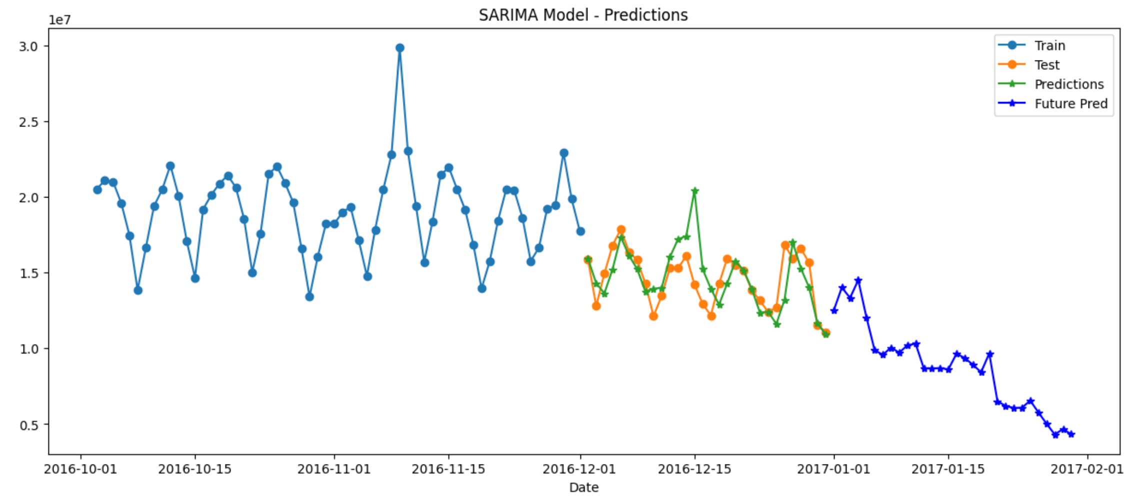
```
            mod = SARIMAX(train_x['ES'], order=param,␣
↪seasonal_order=param_seasonal, enforce_stationarity=False,␣
↪enforce_invertibility=False)
            results = mod.fit(disp=False)
            pred = results.forecast(steps=days_to_forecast)
            current_mape = mape(test_x['ES'], pred)
            # print(f'Order: {param} Seasonal Order: {param_seasonal} - MAPE:␣
↪{current_mape}')
            if current_mape < best_mape:
                best_mape = current_mape
                best_order = param
                best_seasonal_order = param_seasonal
        except:
            continue

print(f'Best order: {best_order}')
print(f'Best seasonal_order: {best_seasonal_order}')
print(f'Best MAPE: {best_mape}')
```

```
Best order: (0, 2, 2)
Best seasonal_order: (2, 1, 2, 12)
Best MAPE: 0.08277353567242449
```

[68]:
```
mod = SARIMAX(train_x['ES'], order=(0, 2, 2), seasonal_order=(2, 1, 2, 12),␣
↪enforce_stationarity=False, enforce_invertibility=False)
results = mod.fit(disp=False)
pred = results.forecast(steps=days_to_forecast)
performance(test_x['ES'], pred)

plt.figure(figsize=(15, 6))

plt.plot(train_x['ES'][-60:], label='Train', linestyle='-', marker='o')
plt.plot(test_x['ES'], label='Test', linestyle='-', marker='o')
plt.plot(pred, label='Predictions', linestyle='-', marker='*')

future_dates = results.forecast(steps=len(test_df)+30)
forecast_future = future_dates[-30:]

plt.plot(forecast_future.index, forecast_future.values, label='Future Pred',␣
↪color='blue', marker='*')

plt.xlabel('Date')
plt.title('SARIMA Model - Predictions')
plt.legend()
plt.show()
```

```
MAE : 1202152.52
RMSE : 1722478.842
```

```
MAPE: 0.083
```



Observations

Best Parameter for SARIMAX model:

- **Order**: (0, 2, 2)
- **Seasonal Order**: (2, 1, 2, 12)

MAPE

- **MAPE**: 0.08277353567242449

SARIMAX Model better fits the ES (MAPE - 0.082) data compare to Prophet Model (MAPE - 0.11)

Model Performance:

Language	MAE	RMSE	MAPE
EN (English)	6168372.58	8106833.47	0.048
RU (Russian)	730035.637	857906.314	0.051
FR (French)	862881.13	1200957.325	0.065
ZH (Chinese)	407575.774	466456.482	0.066
DE (German)	1253507.612	1864050.865	0.068
JA (Japanese)	1340179.469	1724722.937	0.08
ES (Spanish)	1202152.52	1722478.847	0.083

0.8.2 Conclusion:

- The Prophet model was used to forecast the views for the Wikipedia pages in different languages.
- The model was trained on the historical data and used the exogenous variable to improve the predictions.
- The model was evaluated using the MAPE metric.
- The model was used to forecast the views for the next 30 days.
- The SARIMAX model was used to forecast the views for the Spanish Wikipedia page.

Recommendations :

- **Implement Advanced Forecasting Models**
  - *Adopt SARIMAX Models*: Given the superior performance of SARIMAX models in capturing both seasonal patterns and external influences, Adease should implement these models for more accurate and reliable forecasts.
  - *Continuous Model Evaluation*: Regularly evaluate and update the forecasting models to ensure they remain accurate and relevant as new data becomes available.
- **Leverage Exogenous Variables**
  - *Incorporate External Factors*: Identify and integrate key external variables (e.g., economic indicators, marketing campaigns, competitor activities) that can influence business metrics. This will enhance the predictive power of the models.
- **Enhance Data Quality and Management**
  - *Data Cleaning and Preprocessing*: Ensure that the data used for forecasting is clean, accurate, and up-to-date. Implement robust data preprocessing pipelines to handle missing values, outliers, and other data quality issues.
- **Regular Review and Adjustment**
  - *Periodic Review:* Conduct regular reviews of the forecasting models and their performance. Adjust the models as needed to account for any changes in the business environment or data patterns.

[ ]:

```

```