Importing the libraries

In [28]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import re
import seaborn as sns
```

In [29]:
```
import warnings
warnings.filterwarnings("ignore")
warnings.simplefilter("ignore")
```

Reading data

In [30]:
```
data = pd.read_csv('train_1.csv')
```

In [31]:
```
data.head()
```

Out[31]:

	Page	2015-07-01	2015-07-02	2015-07-03	2015-07-04	2015-07-05	2015-07-06	2015-07-07	2015-07-08
0	2NE1_zh.wikipedia.org_all-access_spider	18.0	11.0	5.0	13.0	14.0	9.0	9.0	22.0
1	2PM_zh.wikipedia.org_all-access_spider	11.0	14.0	15.0	18.0	11.0	13.0	22.0	11.0
2	3C_zh.wikipedia.org_all-access_spider	1.0	0.0	1.0	1.0	0.0	4.0	0.0	3.0
3	4minute_zh.wikipedia.org_all-access_spider	35.0	13.0	10.0	94.0	4.0	26.0	14.0	9.0
4	52_Hz_I_Love_You_zh.wikipedia.org_all-access_s...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

5 rows × 551 columns

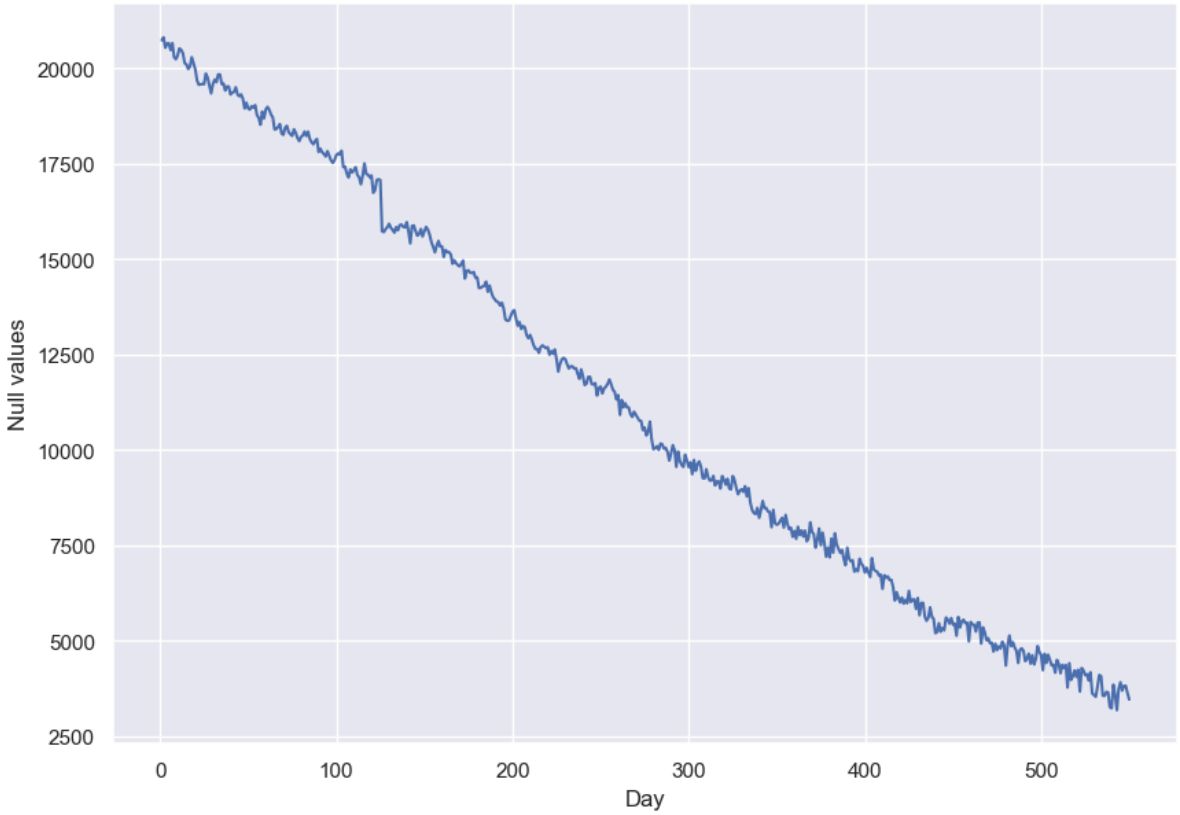
In [32]:
```
print(data.info())
```

```
<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
None
```

Checking null values with time

In [33]:
```
days = [r for r in range(1, len(data.columns))]
plt.figure(figsize=(10,7))
plt.xlabel('Day')
plt.ylabel('Null values')
plt.plot(days, data.isnull().sum()[1:])
```

Out[33]:
```
[<matplotlib.lines.Line2D at 0x22dd61a12d0>]
```



It shows that null values decrease with time indicating that some pages didnt exist previously

In [34]:
```
data.shape

data=data.dropna(thresh=300)
data.shape
```

Out[34]:
```
(133617, 551)
```

Dropping values where there isnt an entry for most days of the year and imputing rest with 0s

In [35]:
```
data=data.fillna(0)
data.tail()
```

Out[35]:

	Page	2015-07-01	2015-07-02	2015-07-03	2015-07-04	2015-07-05	2015-07-
145012	Legión_(Marvel_Comics)_es.wikipedia.org_all-ac...	0.0	0.0	0.0	0.0	0.0	0
145013	Referéndum_sobre_la_permanencia_del_Reino_Unid...	0.0	0.0	0.0	0.0	0.0	0
145014	Salida_del_Reino_Unido_de_la_Unión_Europea_es....	0.0	0.0	0.0	0.0	0.0	0
145015	Amar,_después_de_amar_es.wikipedia.org_all-acc...	0.0	0.0	0.0	0.0	0.0	0
145016	Anexo:89.º_Premios_Óscar_es.wikipedia.org_all-...	0.0	0.0	0.0	0.0	0.0	0

5 rows × 551 columns

In [20]:
```
!pip install prophet
```

```
Requirement already satisfied: prophet in c:\users\sharat\appdata\roaming\python\p
ython311\site-packages (1.1.5)
Requirement already satisfied: cmdstanpy>=1.0.4 in c:\users\sharat\appdata\roaming
\python\python311\site-packages (from prophet) (1.2.1)
Requirement already satisfied: numpy>=1.15.4 in c:\users\sharat\appdata\roaming\py
thon\python311\site-packages (from prophet) (1.26.4)
Requirement already satisfied: matplotlib>=2.0.0 in c:\users\sharat\appdata\roamin
g\python\python311\site-packages (from prophet) (3.8.3)
Requirement already satisfied: pandas>=1.0.4 in c:\users\sharat\appdata\roaming\py
thon\python311\site-packages (from prophet) (2.2.1)
Requirement already satisfied: holidays>=0.25 in c:\users\sharat\appdata\roaming\p
ython\python311\site-packages (from prophet) (0.44)
Requirement already satisfied: tqdm>=4.36.1 in c:\users\sharat\appdata\roaming\pyt
hon\python311\site-packages (from prophet) (4.66.2)
Requirement already satisfied: importlib-resources in c:\users\sharat\appdata\roam
ing\python\python311\site-packages (from prophet) (6.1.3)
Requirement already satisfied: stanio~=0.3.0 in c:\users\sharat\appdata\roaming\py
thon\python311\site-packages (from cmdstanpy>=1.0.4->prophet) (0.3.0)
Requirement already satisfied: python-dateutil in c:\users\sharat\appdata\roaming
\python\python311\site-packages (from holidays>=0.25->prophet) (2.9.0.post0)
Requirement already satisfied: contourpy>=1.0.1 in c:\users\sharat\appdata\roaming
\python\python311\site-packages (from matplotlib>=2.0.0->prophet) (1.2.0)
Requirement already satisfied: cycler>=0.10 in c:\users\sharat\appdata\roaming\pyt
hon\python311\site-packages (from matplotlib>=2.0.0->prophet) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\sharat\appdata\roamin
g\python\python311\site-packages (from matplotlib>=2.0.0->prophet) (4.49.0)
Requirement already satisfied: kiwisolver>=1.3.1 in c:\users\sharat\appdata\roamin
g\python\python311\site-packages (from matplotlib>=2.0.0->prophet) (1.4.5)
Requirement already satisfied: packaging>=20.0 in c:\users\sharat\appdata\roaming
\python\python311\site-packages (from matplotlib>=2.0.0->prophet) (24.0)
Requirement already satisfied: pillow>=8 in c:\users\sharat\appdata\roaming\python
\python311\site-packages (from matplotlib>=2.0.0->prophet) (10.2.0)
Requirement already satisfied: pyparsing>=2.3.1 in c:\users\sharat\appdata\roaming
\python\python311\site-packages (from matplotlib>=2.0.0->prophet) (3.1.2)
Requirement already satisfied: pytz>=2020.1 in c:\users\sharat\appdata\roaming\pyt
hon\python311\site-packages (from pandas>=1.0.4->prophet) (2024.1)
Requirement already satisfied: tzdata>=2022.7 in c:\users\sharat\appdata\roaming\p
ython\python311\site-packages (from pandas>=1.0.4->prophet) (2024.1)
Requirement already satisfied: colorama in c:\users\sharat\appdata\roaming\python
\python311\site-packages (from tqdm>=4.36.1->prophet) (0.4.6)
Requirement already satisfied: six>=1.5 in c:\users\sharat\appdata\roaming\python
\python311\site-packages (from python-dateutil->holidays>=0.25->prophet) (1.16.0)
```

EDA

Formatting page values to isolate page name,domain,access type and origin

Using regex

In [37]:

```python
import re

def split_page(page):
    # Define the regex pattern to extract specific components
    pattern = r'(.+?)_([a-z]+)\.wikipedia\.org_([a-z-]+)_([a-z]+)'
    match = re.match(pattern, page)
    if match:
        specific_name = match.group(1)
        language = match.group(2)
        access_type = match.group(3)
```

```
        access_origin = match.group(4)
        return specific_name, language, access_type, access_origin
    else:

        return None, None, None, None

# Apply the function to the 'Page' column of your dataframe
extracted_data = data['Page'].map(split_page)

# Unzip the extracted components and assign them to new columns
data['Specific_Name'], data['Language'], data['Access_Type'], data['Access_Origin']
```

```
                                      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
5     5566_zh.wikipedia.org_all-access_spider        12.0         7.0

   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
5         4.0         5.0        20.0         8.0         5.0        17.0

   2015-07-09  ...  2016-12-26  2016-12-27  2016-12-28  2016-12-29  \
0        26.0  ...        14.0        20.0        22.0        19.0
1        10.0  ...         9.0        30.0        52.0        45.0
2         4.0  ...         4.0         4.0         6.0         3.0
3        11.0  ...        16.0        11.0        17.0        19.0
5        24.0  ...        32.0        19.0        23.0        17.0

   2016-12-30  2016-12-31  Specific_Name  Language  Access_Type  Access_Origin
0        18.0        20.0           2NE1        zh   all-access         spider
1        26.0        20.0            2PM        zh   all-access         spider
2         4.0        17.0             3C        zh   all-access         spider
3        10.0        11.0       4minute        zh   all-access         spider
5        17.0        50.0           5566        zh   all-access         spider

[5 rows x 555 columns]
```

In [38]:
```
data.head()
```

Out[38]:

	Page	2015-07-01	2015-07-02	2015-07-03	2015-07-04	2015-07-05	2015-07-06	2015-07-07	2015-07-08	2015-07-09	...
0	2NE1_zh.wikipedia.org_all-access_spider	18.0	11.0	5.0	13.0	14.0	9.0	9.0	22.0	26.0	...
1	2PM_zh.wikipedia.org_all-access_spider	11.0	14.0	15.0	18.0	11.0	13.0	22.0	11.0	10.0	...
2	3C_zh.wikipedia.org_all-access_spider	1.0	0.0	1.0	1.0	0.0	4.0	0.0	3.0	4.0	...
3	4minute_zh.wikipedia.org_all-access_spider	35.0	13.0	10.0	94.0	4.0	26.0	14.0	9.0	11.0	...
5	5566_zh.wikipedia.org_all-access_spider	12.0	7.0	4.0	5.0	20.0	8.0	5.0	17.0	24.0	...

5 rows × 555 columns

In [39]:
```
data.groupby('Language').count()
```

Out[39]:

Language	Page	2015-07-01	2015-07-02	2015-07-03	2015-07-04	2015-07-05	2015-07-06	2015-07-07	2015-07-08	2015-07-09	...	2016-12-25	20 12
de	17362	17362	17362	17362	17362	17362	17362	17362	17362	17362	...	17362	17
en	22486	22486	22486	22486	22486	22486	22486	22486	22486	22486	...	22486	22
es	13551	13551	13551	13551	13551	13551	13551	13551	13551	13551	...	13551	13
fr	16948	16948	16948	16948	16948	16948	16948	16948	16948	16948	...	16948	16
ja	19295	19295	19295	19295	19295	19295	19295	19295	19295	19295	...	19295	19
ru	14270	14270	14270	14270	14270	14270	14270	14270	14270	14270	...	14270	14
zh	15211	15211	15211	15211	15211	15211	15211	15211	15211	15211	...	15211	15

7 rows × 554 columns

In [41]:
```
data['Language'].value_counts()
```

Out[41]:
```
en    22486
ja    19295
de    17362
fr    16948
zh    15211
ru    14270
es    13551
Name: Language, dtype: int64
```

In [42]:
```
data.isnull().sum()
```

Out[42]:
```
Page                0
2015-07-01          0
2015-07-02          0
2015-07-03          0
2015-07-04          0
                 ...
2016-12-31          0
Specific_Name    14494
Language         14494
Access_Type      14494
Access_Origin    14494
Length: 555, dtype: int64
```

In [ ]:
```
```

In [46]:
```
# Group by 'Language' and compute the mean for each language
language_mean = data.groupby('Language').mean()

# Transpose the resulting DataFrame
language_mean_transposed = language_mean.T

# Display the transposed DataFrame
(language_mean_transposed)
```

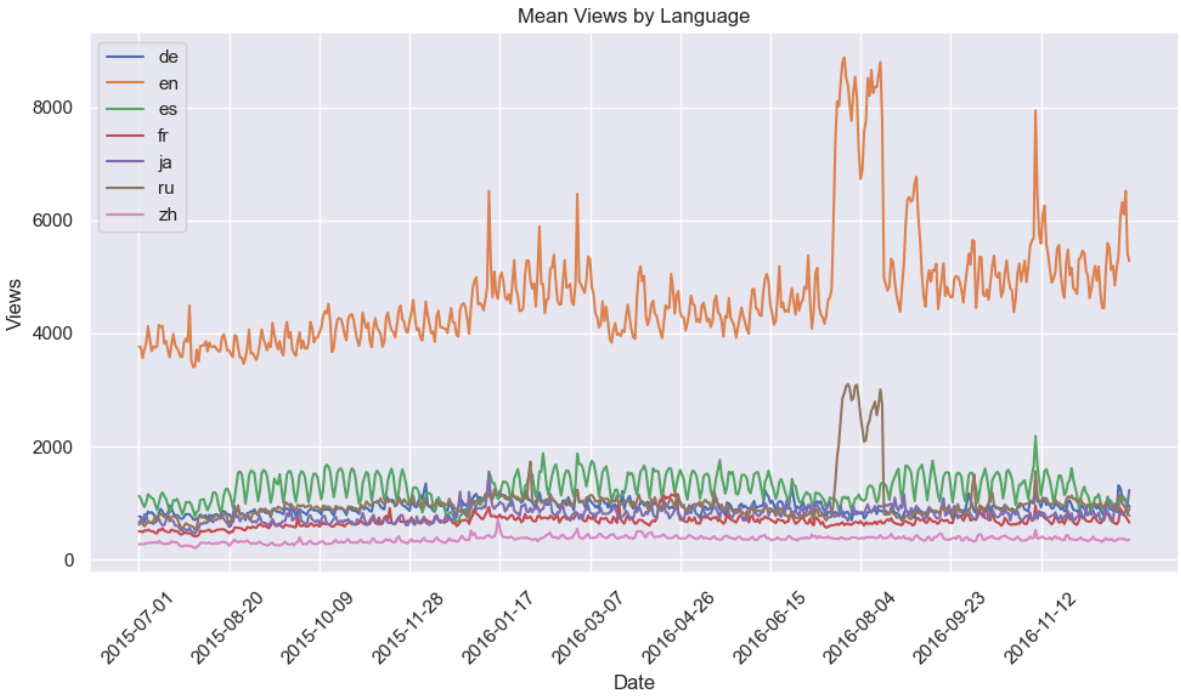
Out[46]:

Language	de	en	es	fr	ja	ru	zh
2015-07-01	763.765926	3767.328604	1127.485204	499.092872	614.637160	663.199229	272.498521
2015-07-02	753.362861	3755.158765	1077.485425	502.297852	705.813216	674.677015	272.906778
2015-07-03	723.074415	3565.225696	990.895949	483.007553	637.451671	625.329783	271.097167
2015-07-04	663.537323	3711.782932	930.303151	516.275785	800.897435	588.171829	273.712379
2015-07-05	771.358657	3833.433025	1011.759575	506.871666	768.352319	626.385354	291.977713
...	...	...	...	...	...	...	...
2016-12-27	1119.596936	6314.335275	1070.923400	840.590217	808.541436	998.374071	363.066991
2016-12-28	1062.284069	6108.874144	1108.996753	783.585379	807.430163	945.054730	369.049701
2016-12-29	1033.939062	6518.058525	1058.660320	763.209169	883.752786	909.352207	340.526330
2016-12-30	981.786430	5401.792360	807.551177	710.502773	979.278777	815.475123	342.745316
2016-12-31	937.842875	5280.643467	776.934322	654.060656	1228.720808	902.600210	352.184275

550 rows × 7 columns

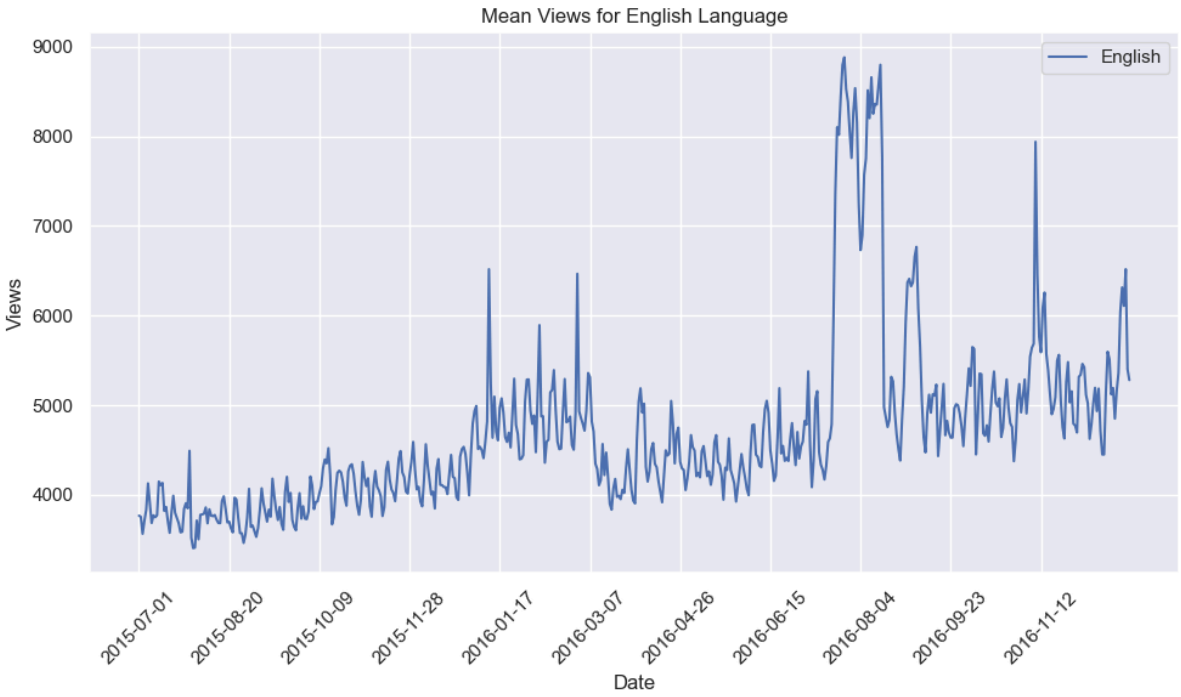
In [47]:

```
# Plotting
plt.figure(figsize=(10, 6))

# Plot each language's mean views
for language in language_mean_transposed.columns:
    plt.plot(language_mean_transposed.index, language_mean_transposed[language], la

# Set labels and title
plt.xlabel('Date')
plt.ylabel('Views')
plt.title('Mean Views by Language')
plt.legend()

# Set x-axis ticks at correct intervals
plt.xticks(language_mean_transposed.index[::50], rotation=45)

# Show plot
plt.tight_layout()
plt.show()
```



Clearly most views in english

In [49]:
```
# Filter the mean views data for only English language
english_mean_views = language_mean_transposed['en']

# Plotting
plt.figure(figsize=(10, 6))

# Plot mean views for English language
plt.plot(english_mean_views.index, english_mean_views, label='English')

# Set labels and title
plt.xlabel('Date')
plt.ylabel('Views')
plt.title('Mean Views for English Language')
plt.legend()

# Set x-axis ticks at correct intervals
plt.xticks(english_mean_views.index[::50], rotation=45)

# Show plot
plt.tight_layout()
plt.show()
```



Checking Stationarity using Dickey Fuller test

In [52]:
```
from statsmodels.tsa.stattools import adfuller

def check_stationarity(time_series):
    # Perform Dickey-Fuller test
    result = adfuller(time_series)

    # Extract test statistics and p-value
    test_statistic = result[0]
    p_value = result[1]

    # Define significance levels
    significance_levels = [0.01, 0.05, 0.1]

    # Print Dickey-Fuller test results
    print('Dickey-Fuller Test Results:')
    print(f'Test Statistic: {test_statistic}')
    print(f'p-value: {p_value}')

    # Interpretation of the test
    print('Results:')
    if p_value < significance_levels[0]:
        print("Reject the null hypothesis. Data is stationary.")
    elif p_value < significance_levels[1]:
        print("Fail to reject the null hypothesis. Data may be stationary.")
    elif p_value < significance_levels[2]:
        print("Fail to reject the null hypothesis. Data likely non-stationary.")
    else:
        print("Fail to reject the null hypothesis. Data is non-stationary.")

# Example usage:
check_stationarity(english_mean_views)
```

```
Dickey-Fuller Test Results:
Test Statistic: -2.3735629745699423
p-value: 0.1493374943735527
Results:
Fail to reject the null hypothesis. Data is non-stationary.
```

In [55]:
```
english_mean_views
```

Out[55]:
```
2015-07-01    3767.328604
2015-07-02    3755.158765
2015-07-03    3565.225696
2015-07-04    3711.782932
2015-07-05    3833.433025
                 ...
2016-12-27    6314.335275
2016-12-28    6108.874144
2016-12-29    6518.058525
2016-12-30    5401.792360
2016-12-31    5280.643467
Name: en, Length: 550, dtype: float64
```

In [56]:
```
english_mean_views_df = pd.DataFrame(english_mean_views, columns=['en'])
```

In [57]:
```
english_mean_views_df
```

Out[57]:

	en
2015-07-01	3767.328604
2015-07-02	3755.158765
2015-07-03	3565.225696
2015-07-04	3711.782932
2015-07-05	3833.433025
...	...
2016-12-27	6314.335275
2016-12-28	6108.874144
2016-12-29	6518.058525
2016-12-30	5401.792360
2016-12-31	5280.643467

550 rows × 1 columns

In [58]:
```
english_mean_views_df = english_mean_views_df.rename_axis('Language_Index')
```

In [59]:
```
english_mean_views_df
```

Out[59]:

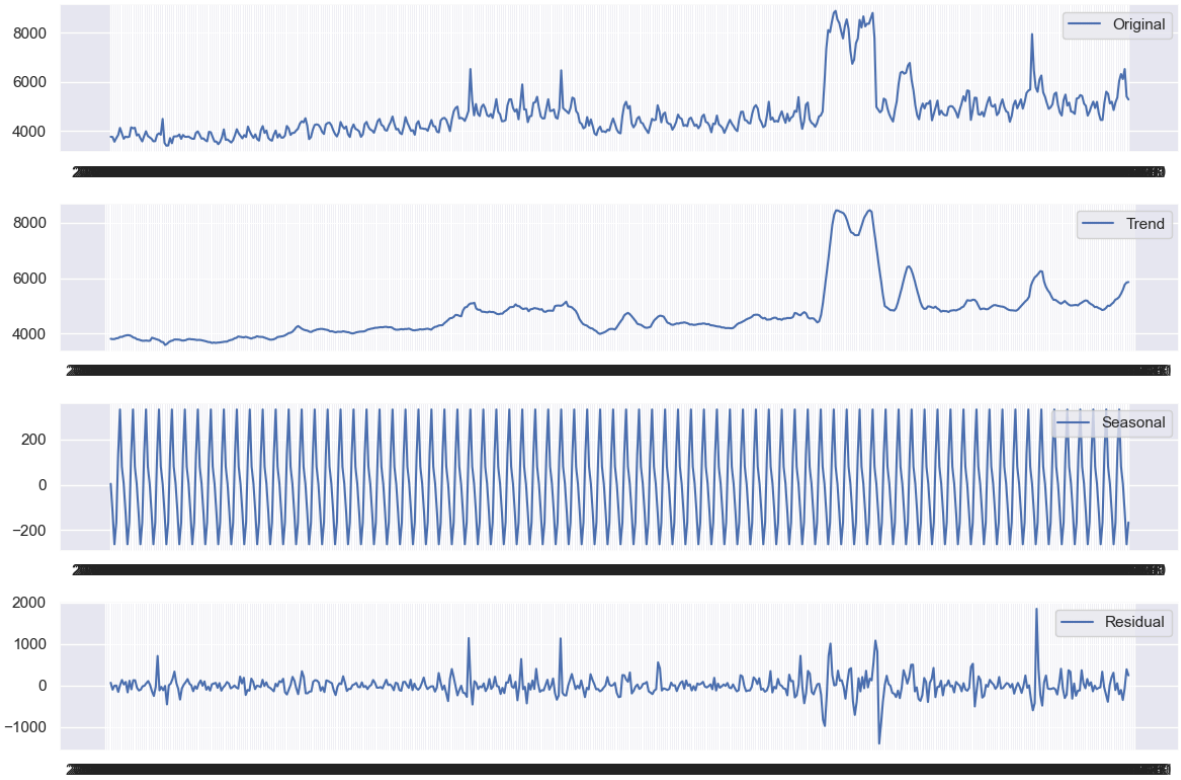
Language_Index	en
2015-07-01	3767.328604
2015-07-02	3755.158765
2015-07-03	3565.225696
2015-07-04	3711.782932
2015-07-05	3833.433025
...	...
2016-12-27	6314.335275
2016-12-28	6108.874144
2016-12-29	6518.058525
2016-12-30	5401.792360
2016-12-31	5280.643467

550 rows × 1 columns

Making it stationary using Decomposition

In [60]:

```
from statsmodels.tsa.seasonal import seasonal_decompose

# Perform seasonal decomposition
decomposition = seasonal_decompose(english_mean_views_df['en'], period=7)

# Plot original, trend, seasonal, and residual components
plt.figure(figsize=(12, 8))

# Original
plt.subplot(411)
plt.plot(english_mean_views_df.index, decomposition.observed, label='Original')
plt.legend()

# Trend
plt.subplot(412)
plt.plot(english_mean_views_df.index, decomposition.trend, label='Trend')
plt.legend()

# Seasonal
plt.subplot(413)
plt.plot(english_mean_views_df.index, decomposition.seasonal, label='Seasonal')
plt.legend()

# Residual
plt.subplot(414)
plt.plot(english_mean_views_df.index, decomposition.resid, label='Residual')
plt.legend()

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



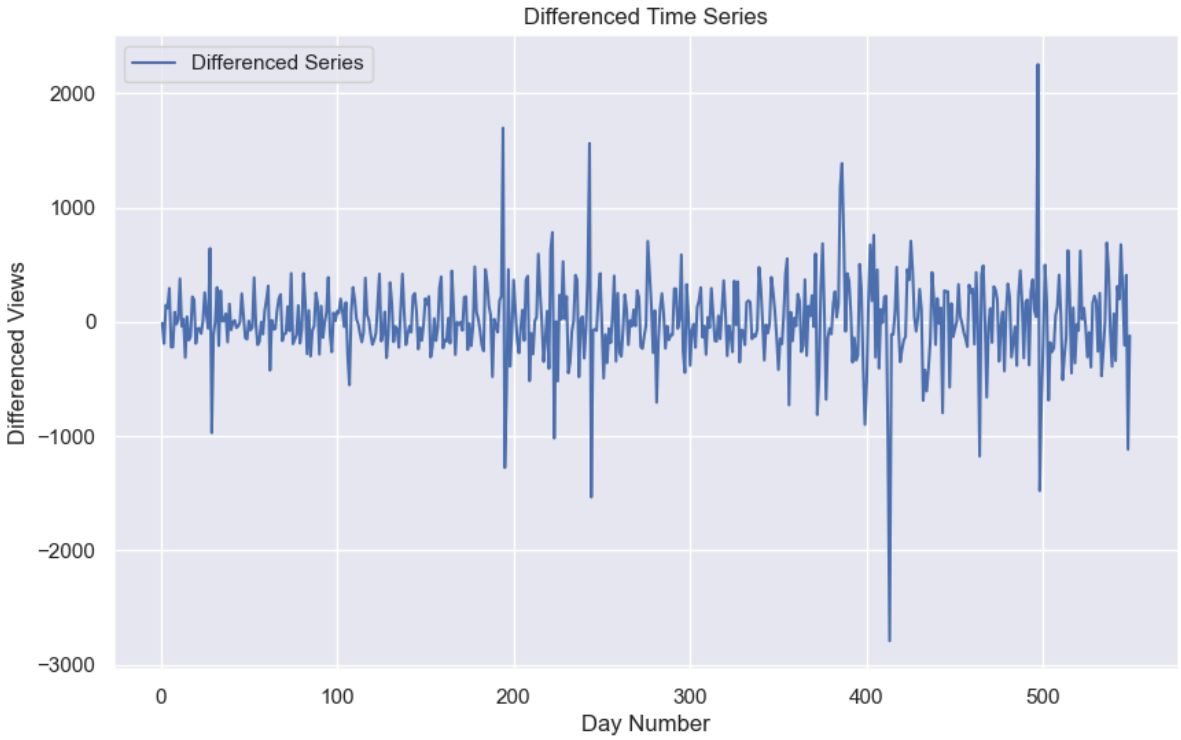
In [61]:
```
# Check for stationarity in the residual component using Dickey-Fuller test
check_stationarity(decomposition.resid.dropna())
```

```
Dickey-Fuller Test Results:
Test Statistic: -11.437315717171515
p-value: 6.3015228361645774e-21
Results:
Reject the null hypothesis. Data is stationary.
```

Removing trend and seasonality with differencing

In [62]:
```
# Perform differencing to remove trend
english_mean_views_stationary = english_mean_views_df['en'].diff().dropna()
```

In [64]:
```
# Create a sequence of day numbers
day_numbers = range(1, len(english_mean_views_stationary) + 1)

# Plot the differenced time series
plt.figure(figsize=(10, 6))
plt.plot(day_numbers, english_mean_views_stationary, label='Differenced Series')
plt.xlabel('Day Number')
plt.ylabel('Differenced Views')
plt.title('Differenced Time Series')
plt.legend()
plt.show()
```

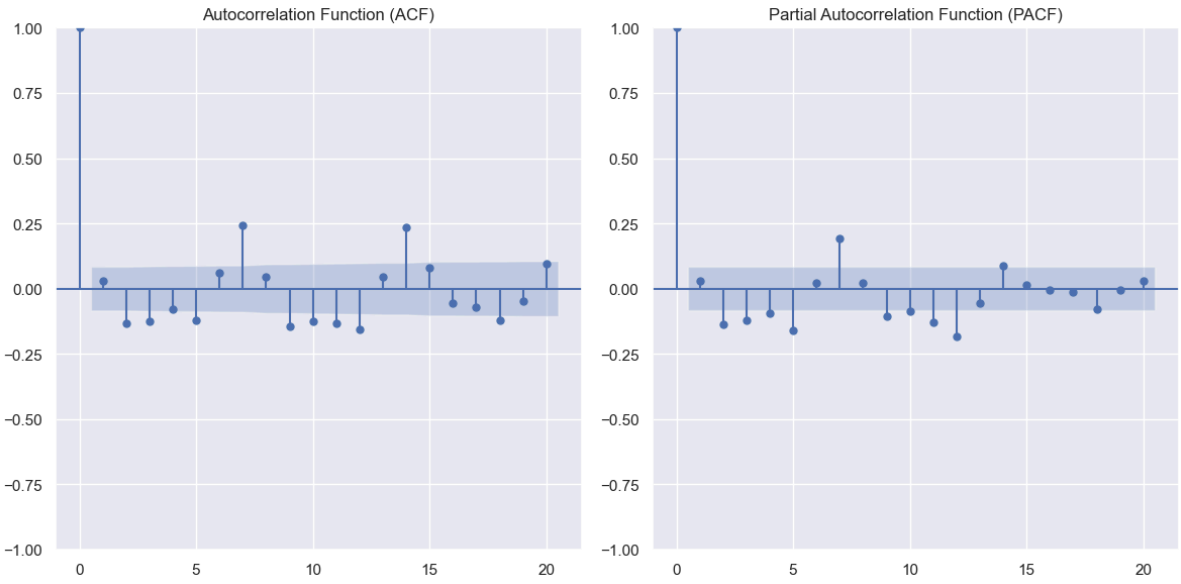


In [65]:
```
# Check for stationarity using Dickey-Fuller test
check_stationarity(english_mean_views_stationary)
```

```
Dickey-Fuller Test Results:
Test Statistic: -8.273590058493825
p-value: 4.721271966433437e-13
Results:
Reject the null hypothesis. Data is stationary.
```

Plotting the autocorreltaion and partial auto correlation functions

In [67]:
```
from matplotlib import pyplot as plt
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# Create a figure and axes with a specific size
fig, axs = plt.subplots(1, 2, figsize=(12, 6))

# Plot autocorrelation function (ACF)
plot_acf(english_mean_views_stationary, lags=20, ax=axs[0])
axs[0].set_title('Autocorrelation Function (ACF)')

# Plot partial autocorrelation function (PACF)
plot_pacf(english_mean_views_stationary, lags=20, ax=axs[1])
axs[1].set_title('Partial Autocorrelation Function (PACF)')

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

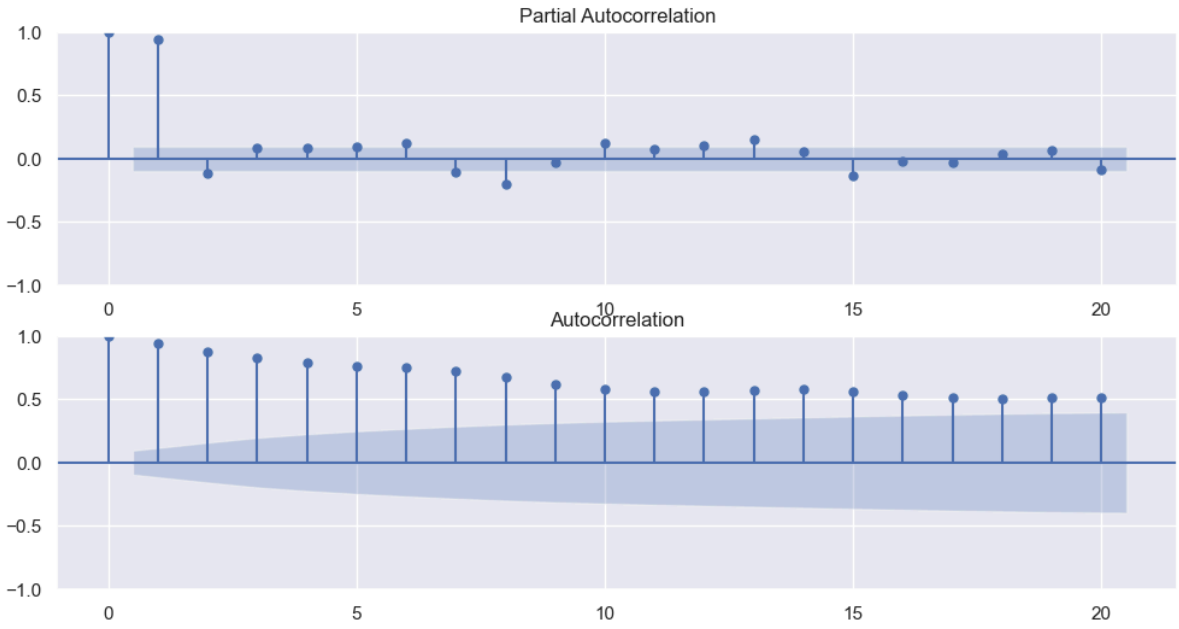


Using ARIMA model

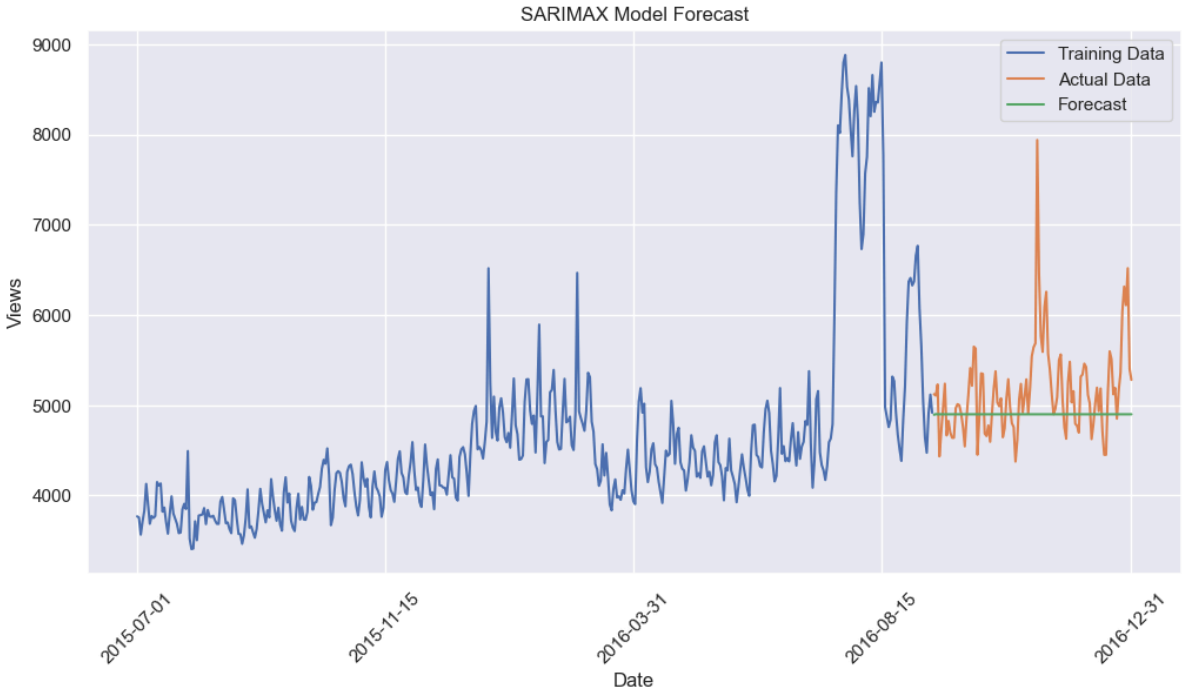
In [76]:

```
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# Plot PACF and ACF
plt.figure(figsize=(12, 6))
plt.subplot(211)
plot_pacf(train_data, ax=plt.gca(), lags=20)
plt.subplot(212)
plot_acf(train_data, ax=plt.gca(), lags=20)
plt.show()

# Determine AR and MA orders based on cut-off points
p = 1  # AR order
q = 1  # MA order
d = 1  # Differencing order

# Fit SARIMAX model
sarimax_model = SARIMAX(train_data, order=(p, d, q), seasonal_order=(0, 0, 0, 0))
sarimax_result = sarimax_model.fit()

# Make predictions
predictions = sarimax_result.predict(start=test_data.index[0], end=test_data.index[

import numpy as np

# Combine training and testing indices
all_indices = np.concatenate((train_data.index, test_data.index))

# Plot training, actual, and forecasted values
plt.figure(figsize=(12, 6))
plt.plot(train_data.index, train_data, label='Training Data')
plt.plot(test_data.index, test_data, label='Actual Data')
plt.plot(test_data.index, predictions, label='Forecast')
plt.xlabel('Date')
plt.ylabel('Views')
plt.title('SARIMAX Model Forecast')
plt.legend()

# Selecting dates to display on the x-axis
n = 5  # Number of dates to display
x_ticks_indices = np.linspace(0, len(all_indices) - 1, n).astype(int)
```

```
selected_dates = all_indices[x_ticks_indices]

# Set x-axis ticks at selected dates
plt.xticks(selected_dates, rotation=45)

plt.show()
```




```
C:\Users\Sharat\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency D will
be used.
  self._init_dates(dates, freq)
C:\Users\Sharat\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency D will
be used.
  self._init_dates(dates, freq)
```



Using SARIMAX with exog values

In [77]:
```
ex_df = pd.read_csv('Exog_Campaign_eng.csv')
ex_df.head()
```

Out[77]:

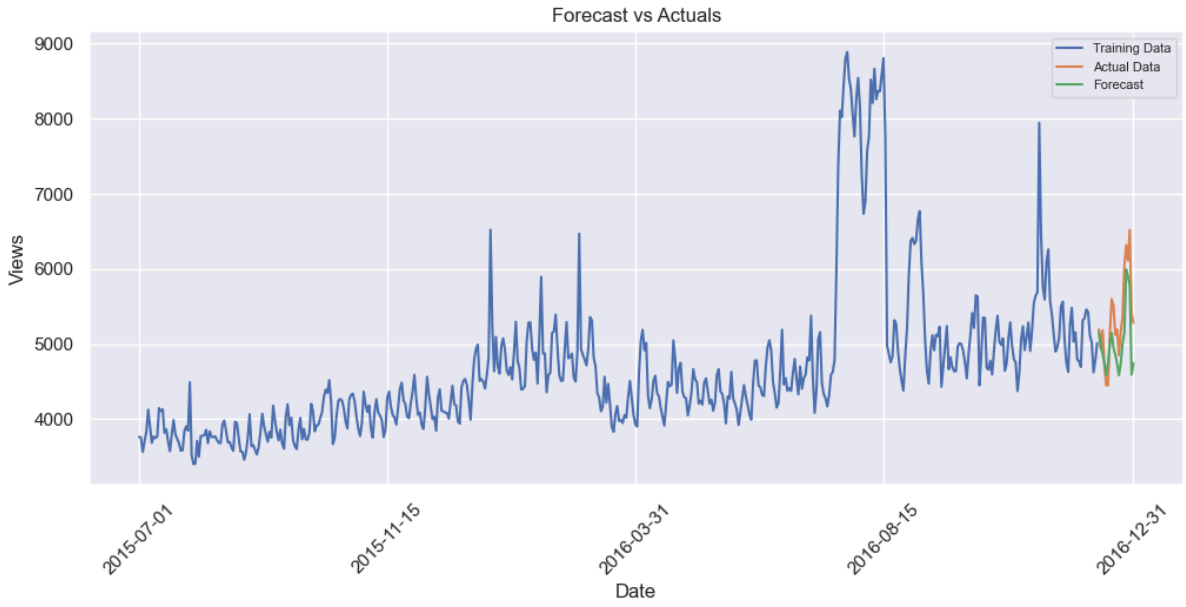
	Exog
0	0
1	0
2	0
3	0
4	0

In [84]:
```
from pandas import DataFrame
```

In [85]:
```
exog=ex_df['Exog'].to_numpy()
```

In [87]:
```
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.api as sm
import numpy as np

# Define train and test data
train = english_mean_views_df.iloc[:530]
test = english_mean_views_df.iloc[530:]

# Fit SARIMAX model with exogenous variables
model = sm.tsa.statespace.SARIMAX(train, order=(1, 1, 1), seasonal_order=(1, 1, 1,
results = model.fit()

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

# Convert forecast to pandas series
fc_series = pd.Series(forecast, index=test.index)

# Plot
plt.figure(figsize=(12, 5))
plt.plot(train, label='Training Data')
plt.plot(test, label='Actual Data')
plt.plot(fc_series, label='Forecast')
plt.title('Forecast vs Actuals')
plt.xlabel('Date')
plt.ylabel('Views')
plt.legend(fontsize=8)

# Selecting well-spaced dates to display on the x-axis
n = 5  # Number of dates to display
x_ticks_indices = np.linspace(0, len(english_mean_views_df) - 1, n).astype(int)
selected_dates = english_mean_views_df.index[x_ticks_indices]

# Set x-axis ticks at selected dates
plt.xticks(selected_dates, rotation=45)

plt.show()
```

```
C:\Users\Sharat\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency D will
be used.
  self._init_dates(dates, freq)
C:\Users\Sharat\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency D will
be used.
  self._init_dates(dates, freq)
```



In [140…

```
forecast_values = forecast22.values.ravel()
test_values = test22.values.ravel()

# Calculate MAPE
mape22 = np.mean(np.abs(forecast_values - test_values) / np.abs(test_values))
print("MAPE:", mape22)
```

```
MAPE: 0.04661381079443559
```

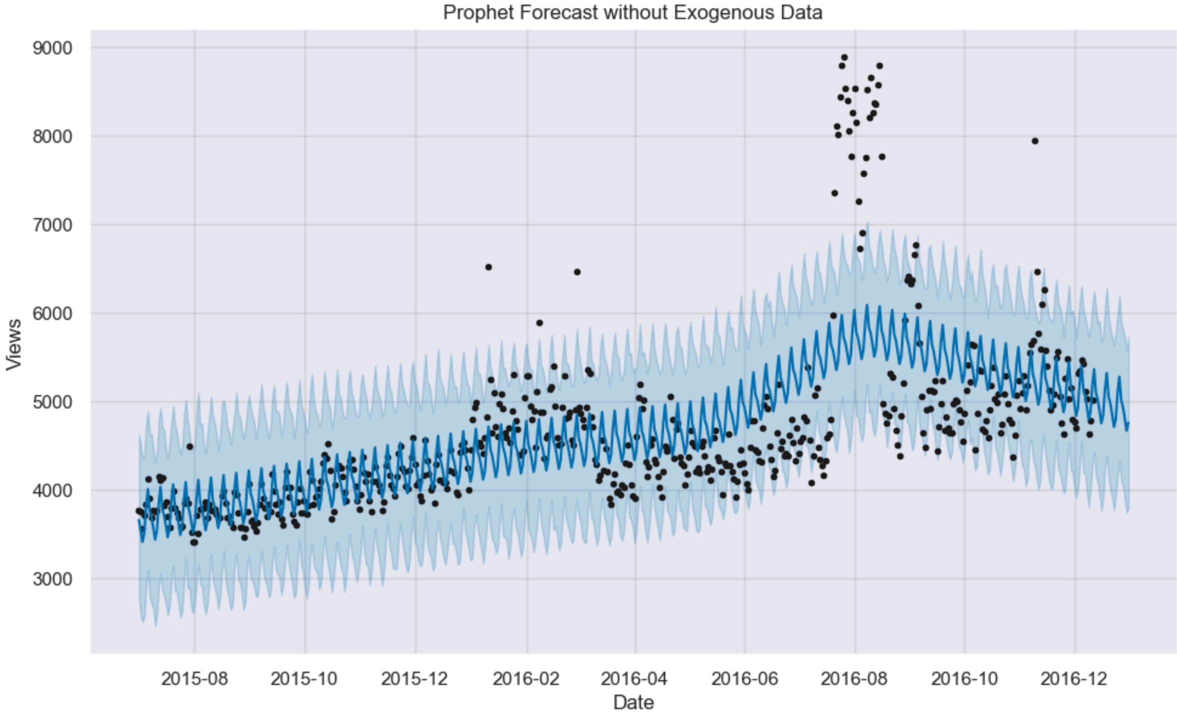
We see that we get best result from SARIMAX with MAPE of 0.0466

Using Facebook Prophet without exogenous values

In [89]:

```
# Make a copy of english_mean_views_df
df_copy = english_mean_views_df.copy()

# Reset index and rename column
df_copy.reset_index(inplace=True)
df_copy.rename(columns={'Language_Index': 'ds', 'en': 'y'}, inplace=True)

# Split into train and test sets
train_size = 530
train_df = df_copy.iloc[:train_size]
test_df = df_copy.iloc[train_size:]

# Create Prophet model without exogenous data
prophet_model = Prophet()
prophet_model.fit(train_df)

# Make forecast
future = prophet_model.make_future_dataframe(periods=len(test_df))
forecast = prophet_model.predict(future)

# Plot forecast without exogenous data
fig = prophet_model.plot(forecast)
plt.xlabel('Date')
plt.ylabel('Views')
plt.title('Prophet Forecast without Exogenous Data')
plt.show()
```

```
01:23:50 - cmdstanpy - INFO - Chain [1] start processing
01:23:52 - cmdstanpy - INFO - Chain [1] done processing
```



In [111…

```
exog
```

Out[111]:

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0,
       0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0],
      dtype=int64)
```

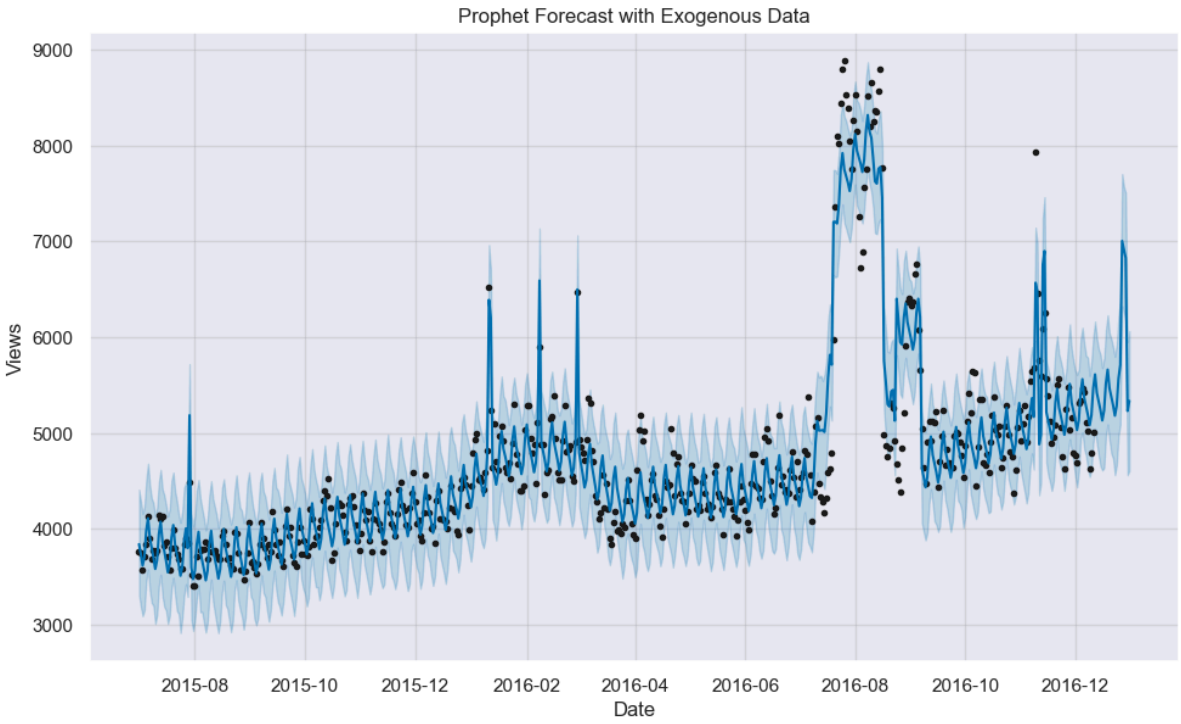
Using Facebook Prophet with exogenous values

In [116…

```
# Make a copy of english_mean_views_df
df_copy = english_mean_views_df.reset_index().copy()

# Rename columns to "ds" and "y"
df_copy.rename(columns={'Language_Index': 'ds', 'en': 'y'}, inplace=True)

# Initialize Prophet Model
model = Prophet(interval_width=0.9, weekly_seasonality=True, changepoint_prior_scal
```

```
# Convert exog array to DataFrame
exog_df = pd.DataFrame({'ds': df_copy['ds'], 'exog': exog})

# Add Exogenous Regressor
model.add_regressor('exog')

# Fit the Model (excluding last 20 rows)
model.fit(df_copy[:-20].merge(exog_df[:-20], on='ds'))

# Make Forecast (including last 20 rows)
forecast = model.predict(df_copy.merge(exog_df, on='ds'))

# Plot the Forecast
fig = model.plot(forecast)
plt.xlabel('Date')
plt.ylabel('Views')
plt.title('Prophet Forecast with Exogenous Data')
plt.show()
```

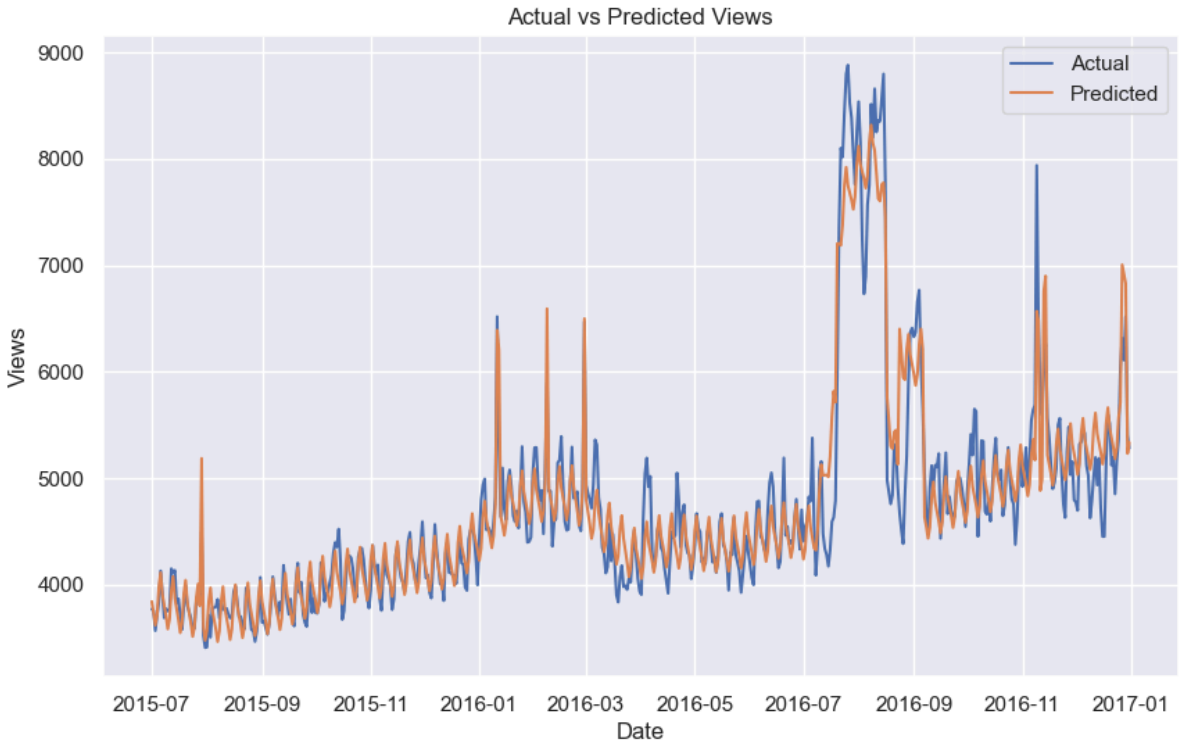
```
21:47:08 - cmdstanpy - INFO - Chain [1] start processing
21:47:09 - cmdstanpy - INFO - Chain [1] done processing
```



Poltting actual vs predicted

In [118…

```
# Convert datetime column to datetime objects
df_copy['ds'] = pd.to_datetime(df_copy['ds'])

# Plot the Forecast and Actual Values
plt.figure(figsize=(10, 6))
plt.plot(df_copy['ds'], df_copy['y'], label='Actual')
plt.plot(forecast['ds'], forecast['yhat'], label='Predicted')
plt.xlabel('Date')
plt.ylabel('Views')
plt.title('Actual vs Predicted Views')
plt.legend()
plt.show()
```



In [122…

```python
def calculate_mape(actual, predicted):
    # Calculate absolute percentage error
    abs_percentage_error = np.abs((actual - predicted) / actual)

    # Calculate mean absolute percentage error
    mape = np.mean(abs_percentage_error)

    return mape

# Calculate MAPE
mape = calculate_mape(english_mean_views_df['en'].values[-20:], forecast['yhat'].va
print("MAPE:", mape)
```

```
MAPE: 0.0663021464072997
```

Creating gridsearch function to find best model for each language

In [106…

```python
def grid_search(ts):
    p_values = range(4)  # Values of p to try
    d_values = range(4)  # Values of d to try
    q_values = range(4)  # Values of q to try

    best_mape = 100  # Initialize the best MAPE score
    best_params = [0, 0, 0]  # Initialize the best parameters (p, d, q)

    # Perform grid search
    for p in p_values:
        for d in d_values:
            for q in q_values:
                try:
                    # Fit SARIMAX model
                    model = SARIMAX(ts[:-20], order=(p, d, q))
                    model_fit = model.fit(disp=-1)

                    # Make forecast
                    fc = model_fit.forecast(20, alpha=0.02)
```

```
                    # Calculate MAPE
                    mape = np.mean(np.abs(fc.values - ts[-20:].values) / np.abs(ts[

                    # Update best MAPE and parameters if current model is better
                    if mape < best_mape:
                        best_mape = mape
                        best_params = [p, d, q]

                except:
                    pass  # Skip if model fitting fails

    return best_mape, best_params
```

In [125…

```
def all_arima(train, test, val):
    # Fit SARIMAX model
    model = SARIMAX(train, order=(val[0], val[1], val[2]))
    fitted = model.fit(disp=-1)

    # Forecast
    fc = fitted.forecast(20, alpha=0.02)

    # Convert forecast to pandas series
    fc_series = pd.Series(fc, index=test.index)

    # Plot
    plt.figure(figsize=(12,5), dpi=100)
    plt.plot(train, label='Training')
    plt.plot(test, label='Actual')
    plt.plot(fc_series, label='Forecast')
    plt.title('Forecast vs Actuals')
    plt.xlabel('Date')
    plt.ylabel('Views')
    plt.legend(loc='upper left', fontsize=8)
    plt.show()

    # Calculate MAPE and RMSE
    mape = np.mean(np.abs(fc - test) / np.abs(test))
    rmse = np.sqrt(np.mean((fc - test) ** 2))


    return fc,rmse
```

In [109…

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

In [129…

```
test.isnull().sum()
```

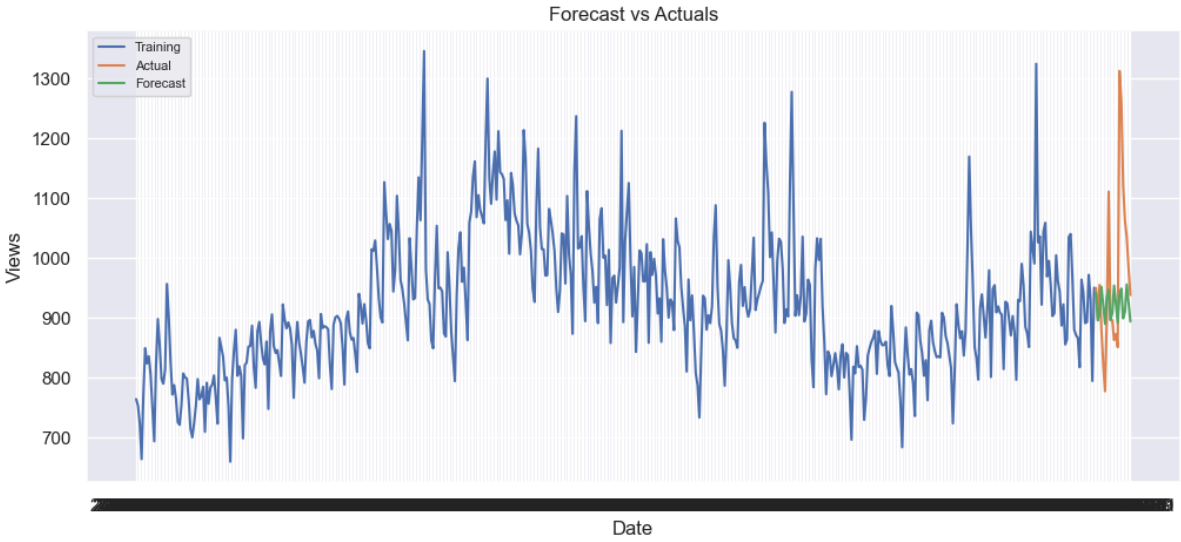
Out[129]:

```
0
```

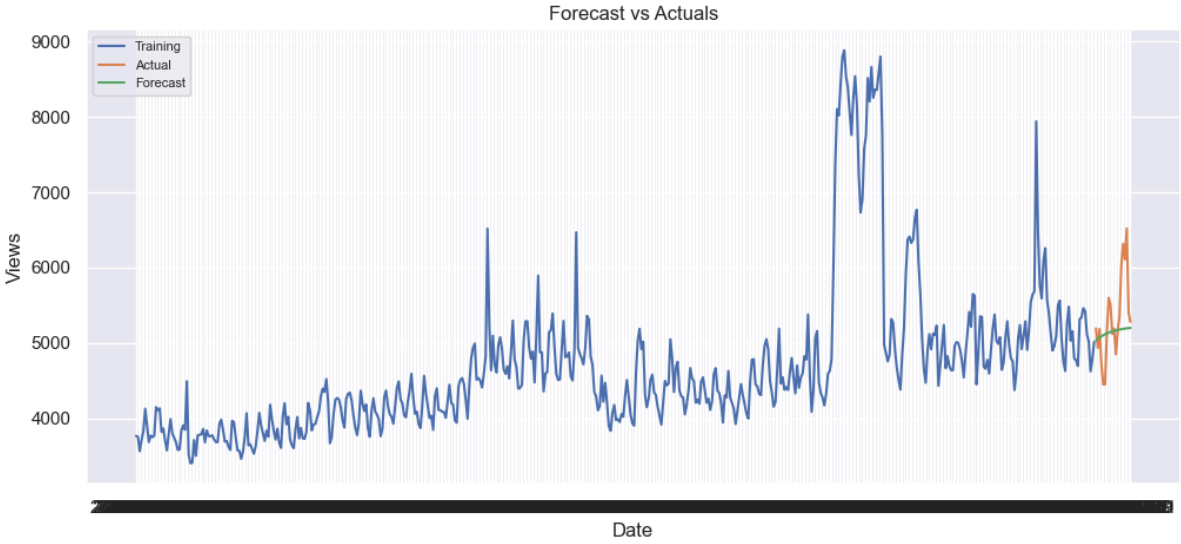
In [141…

```
views_prediction={}
for c in language_mean_transposed:
    print("language: ",c)
    kk=(language_mean_transposed[c])
    mape,val=grid_search(kk)
    print(val)
    train = kk[:530]
    test = kk[530:]
    fc,rmse=all_arima(train,test,val)
    views_prediction[c]=fc
    print("MAPE:", mape)
```

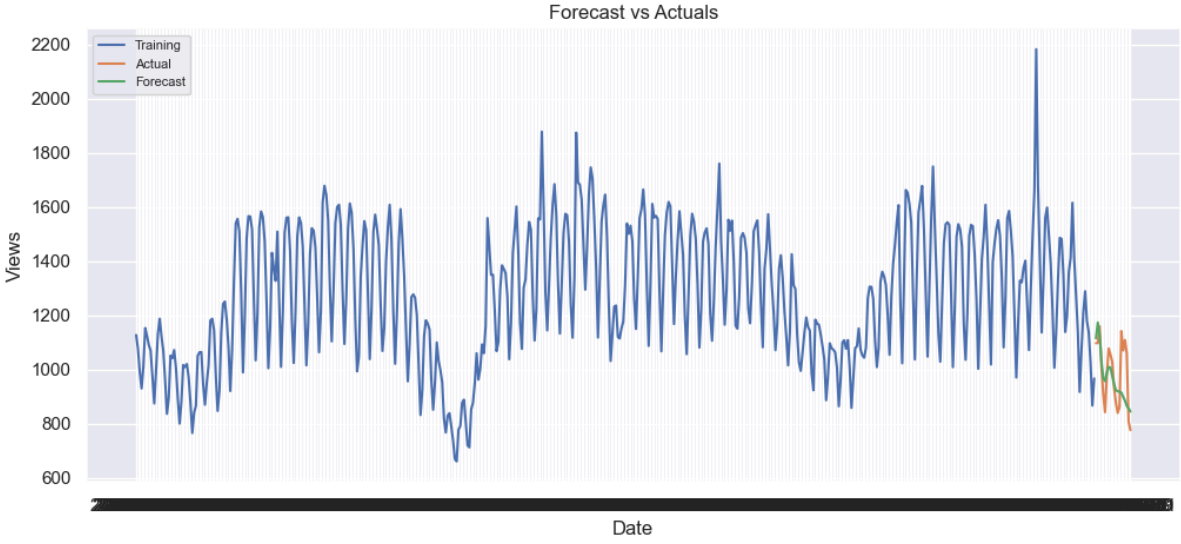
```
language:  de
[3, 2, 3]
```



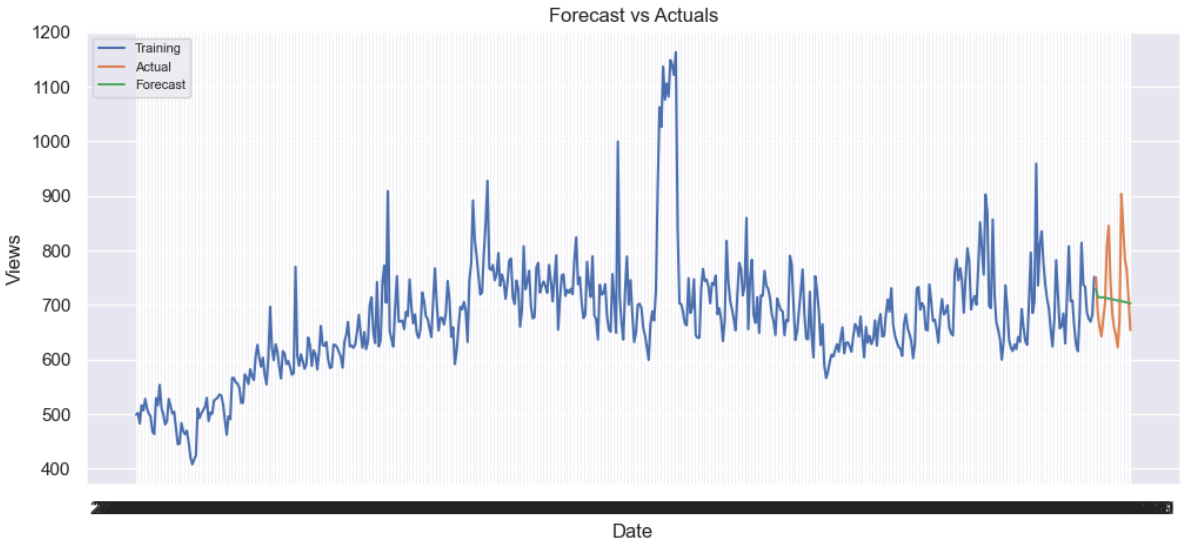

```
MAPE: 0.09353358690088856
language:  en
[1, 1, 1]
```



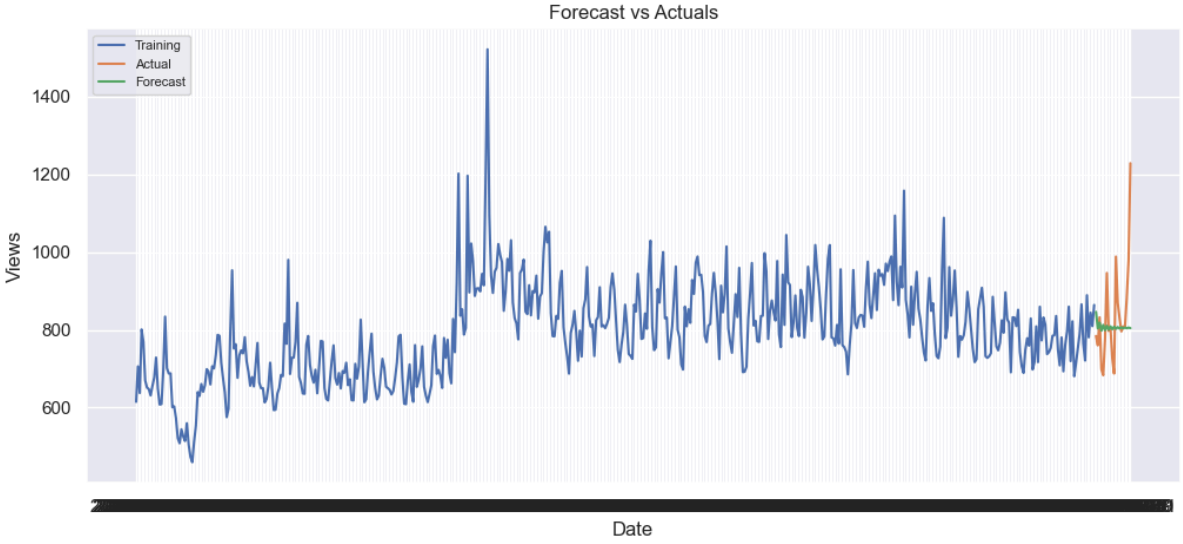

```
MAPE: 0.07223427767239152
language:  es
[3, 2, 3]
```



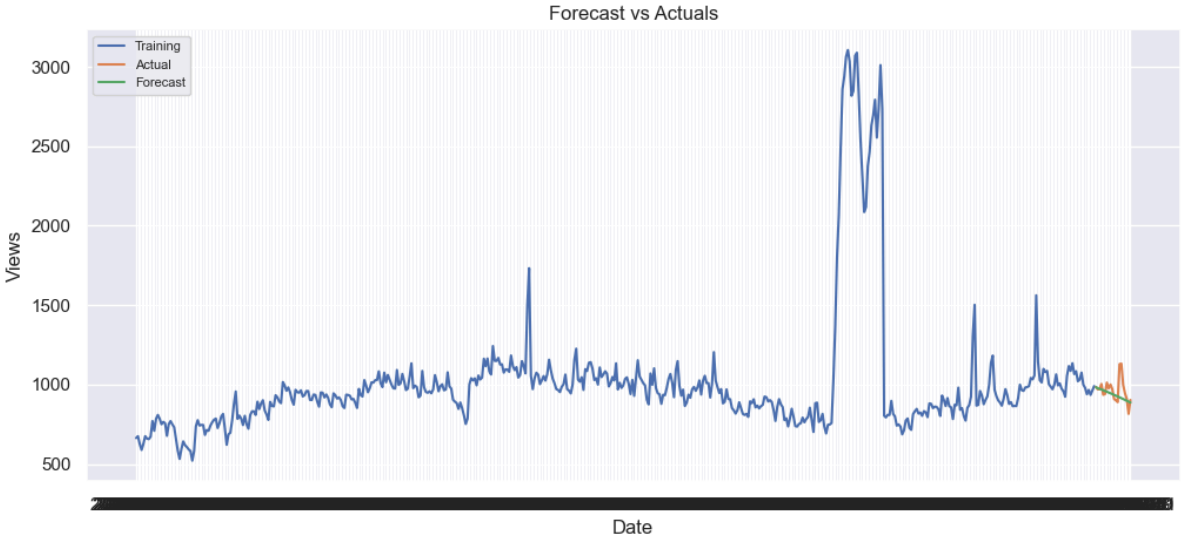

```
MAPE: 0.08062441451185409
language:  fr
[3, 0, 1]
```



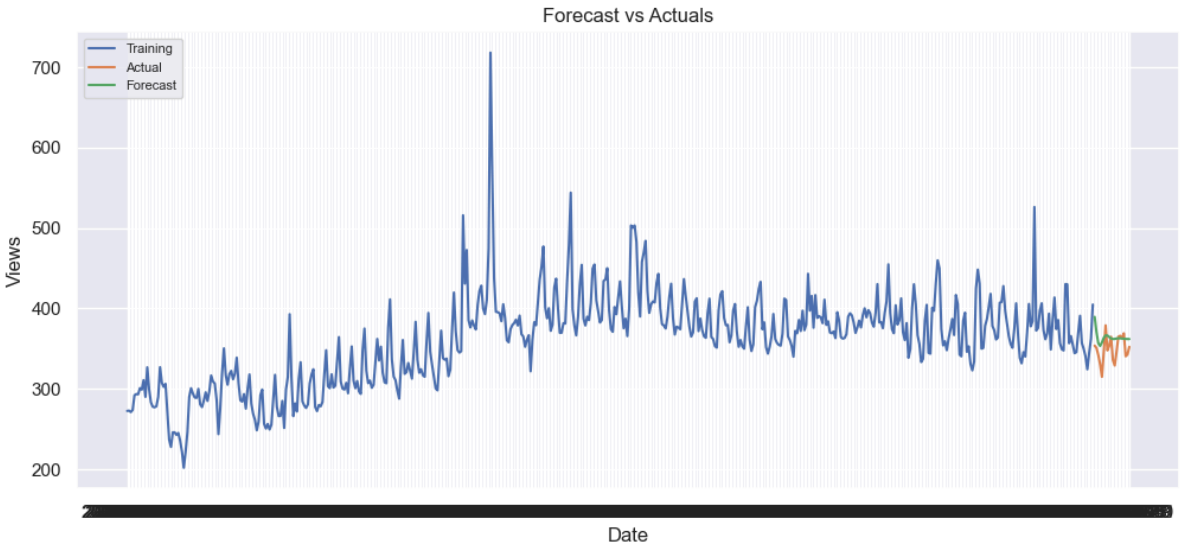
MAPE: 0.0854842610901467
language: ja
[2, 1, 2]



MAPE: 0.09361914222146142
language: ru
[3, 3, 2]



MAPE: 0.05011008837152442
language: zh
[3, 0, 3]




```
MAPE: 0.04917926933904462
```

Inferences

- English language pages are most viewed
- There are some formatting errors that give www and commons as languages
- Traffic increased and null values decreased with time
- Access type usage of mobile and desktop is similar
- There are certain spikes which are not outliers but event days
- Data is not stationary
- there is a weekly seasonality
- SARIMAX model gives best MAPE of 0.0466
- FB Prophet gave MAPE of 0.066

Recommendations

- Content Optimization: Since English language pages are the most viewed, allocate resources to optimize and enhance the quality of English-language content. Focus on creating compelling, relevant, and engaging content to maintain and further increase viewership.

- Language Identification: Address the formatting errors that incorrectly categorize URLs as languages (e.g., "www" and "commons"). Implement robust language identification algorithms to accurately classify content and avoid misinterpretations.

- Traffic Monitoring and Analysis: Continue monitoring traffic patterns over time and analyze trends to identify areas of growth and potential opportunities. Invest resources in content areas that show consistent increases in traffic and address any remaining null values to ensure data integrity.

- Mobile Optimization: Since access type usage of mobile and desktop is similar, prioritize mobile optimization strategies to cater to the growing number of users accessing content via mobile devices. Ensure that the website and content are responsive, load quickly, and provide a seamless user experience across all devices.

- Event Day Preparedness: Identify and anticipate event days that result in traffic spikes. Develop content and promotional strategies to capitalize on these spikes and maximize engagement with the audience during such events.
- Time-Series Analysis: Recognize the presence of non-stationarity and weekly seasonality in the data. Implement time-series analysis techniques, such as SARIMAX modeling, to forecast future traffic patterns accurately. Use these insights to plan content releases, promotional activities, and resource allocation effectively.
- Continuous Improvement: Emphasize a culture of continuous improvement and data-driven decision-making. Regularly review and refine content strategies, SEO techniques, and user engagement initiatives based on performance metrics and feedback from users.
- Localization and Global Reach: Explore opportunities to expand content localization efforts beyond English to cater to diverse language preferences and global audiences. Tailor content to meet the specific needs and preferences of different language-speaking communities to foster engagement and loyalty.
- Collaboration and Partnerships: Collaborate with relevant stakeholders, influencers, and communities to amplify reach and engagement. Form partnerships with local organizations or content creators to co-create content and leverage each other's networks for mutual benefit.

In [ ]: