Problem Statement

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

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

In [3]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
from statsmodels.tools.sm_exceptions import ConvergenceWarning
import warnings
warnings.filterwarnings("ignore")
warnings.filterwarnings("ignore", category=UserWarning)
warnings.filterwarnings("ignore", category=ConvergenceWarning)

import scipy.stats as stats

import re
import math
import json

from sklearn.pipeline import Pipeline
from datetime import datetime

import logging

from sklearn.model_selection import train_test_split

import statsmodels.api as sm
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.graphics.tsaplots import plot_pacf
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_absolute_error as mae, mean_squared_error as
```

In [4]:
```
!gdown 1LlEcoqmNWLk_HLt3kROYWOSH3TNve0gY
!gdown 1tP3fvC_mCqoRBUUy6EhHp4nQv8pdTuho
```

```
Downloading...
From (original): https://drive.google.com/uc?id=1LlEcoqmNWLk_HLt3kROYWOSH3TNve0
gY
From (redirected): https://drive.google.com/uc?id=1LlEcoqmNWLk_HLt3kROYWOSH3TNv
e0gY&confirm=t&uuid=c8a87429-0598-496e-82e3-2f77f2f6d5be
To: /content/train_1.csv
100% 278M/278M [00:03<00:00, 79.2MB/s]
Downloading...
From: https://drive.google.com/uc?id=1tP3fvC_mCqoRBUUy6EhHp4nQv8pdTuho
To: /content/Exog_Campaign_eng
100% 1.10k/1.10k [00:00<00:00, 5.48MB/s]
```

In [5]:
```
df = pd.read_csv("train_1.csv")
df.head()
```

Out[5]:

	Page	2015-07-01	2015-07-02	2015-07-03	201
0	2NE1_zh.wikipedia.org_all-access_spider	18.0	11.0	5.0	
1	2PM_zh.wikipedia.org_all-access_spider	11.0	14.0	15.0	
2	3C_zh.wikipedia.org_all-access_spider	1.0	0.0	1.0	
3	4minute_zh.wikipedia.org_all-access_spider	35.0	13.0	10.0	
4	52_Hz_I_Love_You_zh.wikipedia.org_all-access_s...	NaN	NaN	NaN	

5 rows × 551 columns

In [6]:
```
Exog_Campaign_eng = pd.read_csv("Exog_Campaign_eng")
Exog_Campaign_eng.head()
```

Out[6]:

	Exog
0	0
1	0
2	0
3	0
4	0

In [7]:
```
df.shape
print(f"The dataset has {df.shape[0]} rows and {df.shape[1]} columns")
```

```
The dataset has 145063 rows and 551 columns
```

In [8]:
```
Exog_Campaign_eng.shape
print(f"The dataset has {Exog_Campaign_eng.shape[0]} rows and {Exog_Campaign_e
```

```
The dataset has 550 rows and 1 columns
```

In [9]:
```python
df.duplicated().sum()
```

Out[9]:
```
np.int64(0)
```

In [10]:
```python
Exog_Campaign_eng.duplicated().sum()
```

Out[10]:
```
np.int64(548)
```

In [11]:
```python
df.isna().sum().sort_values(ascending=False)
```

Out[11]:

	0
2015-07-02	20816
2015-07-01	20740
2015-07-07	20664
2015-07-05	20659
2015-07-04	20654
...	...
2016-12-31	3465
2016-12-20	3268
2016-12-21	3236
2016-12-24	3189
Page	0

551 rows × 1 columns

dtype: int64

In [12]:
```python
Exog_Campaign_eng.isna().sum().sort_values(ascending=False)
```

Out[12]:

	0
Exog	0

dtype: int64

In [13]:
```python
# Store original column names
old_cols = df.columns.copy()

# Replace spaces with underscores
df.columns = df.columns.str.replace(' ', '_')
```

```
# Find changed columns
changed_cols = [c for c, old in zip(df.columns, old_cols) if c != old]

print(f"Number of affected columns: {len(changed_cols)}")
print("Changed columns:")
print(changed_cols)
```

```
Number of affected columns: 0
Changed columns:
[]
```

Replace spaces in column names with underscores for consistency

In [14]:
```
df.nunique().sort_values(ascending=False)
```

Out[14]:

	0
Page	145063
2016-11-13	9376
2016-04-03	9305
2016-01-11	9284
2016-02-29	9202
...	...
2015-07-03	6707
2015-07-30	6642
2015-08-03	6561
2015-07-31	6524
2015-08-01	6463

551 rows × 1 columns

dtype: int64

In [15]:
```
Exog_Campaign_eng.nunique().sort_values(ascending=False)
```

Out[15]:

	0
Exog	2

dtype: int64

In [16]:
```
df.dtypes
```

Out[16]:

	0
Page	object
2015-07-01	float64
2015-07-02	float64
2015-07-03	float64
2015-07-04	float64
...	...
2016-12-27	float64
2016-12-28	float64
2016-12-29	float64
2016-12-30	float64
2016-12-31	float64

551 rows × 1 columns

dtype: object

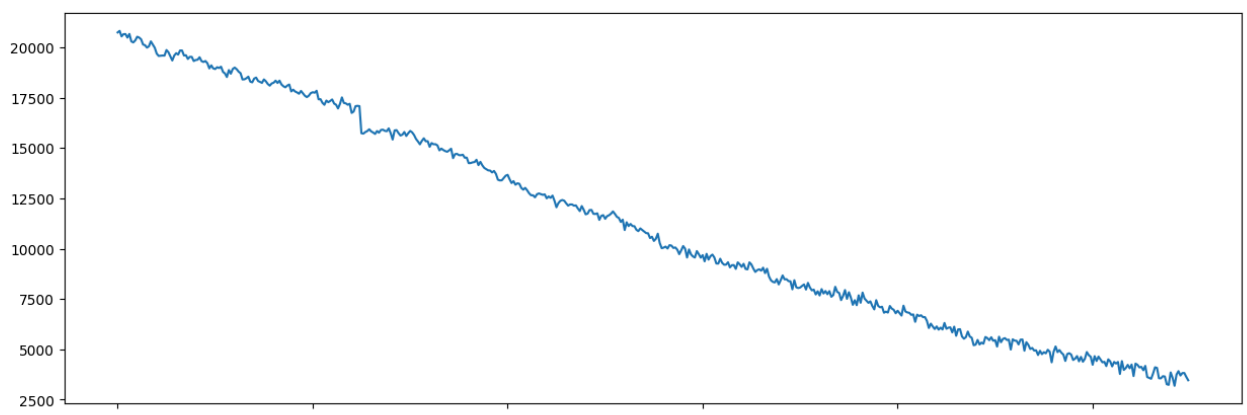
In [17]:
```
Exog_Campaign_eng.dtypes
```

Out[17]:

	0
Exog	int64

dtype: object

In [18]:
```
date_columns = df.columns[1:]
df[date_columns].isna().sum().plot(figsize=(15,5))
plt.show()
```



Insight

It can be observed that the null values keep decreasing with dates, indicating that there were no views for these dates

We can infer that the webpages which were lauched recently will not have view data prior to launch and hence can be filled with 0

In [19]:
```
df[date_columns] = df.loc[:,date_columns].fillna(0)
```

In [20]:
```
df.isna().sum()
```

Out[20]:

	0
Page	0
2015-07-01	0
2015-07-02	0
2015-07-03	0
2015-07-04	0
...	...
2016-12-27	0
2016-12-28	0
2016-12-29	0
2016-12-30	0
2016-12-31	0

551 rows × 1 columns

dtype: int64

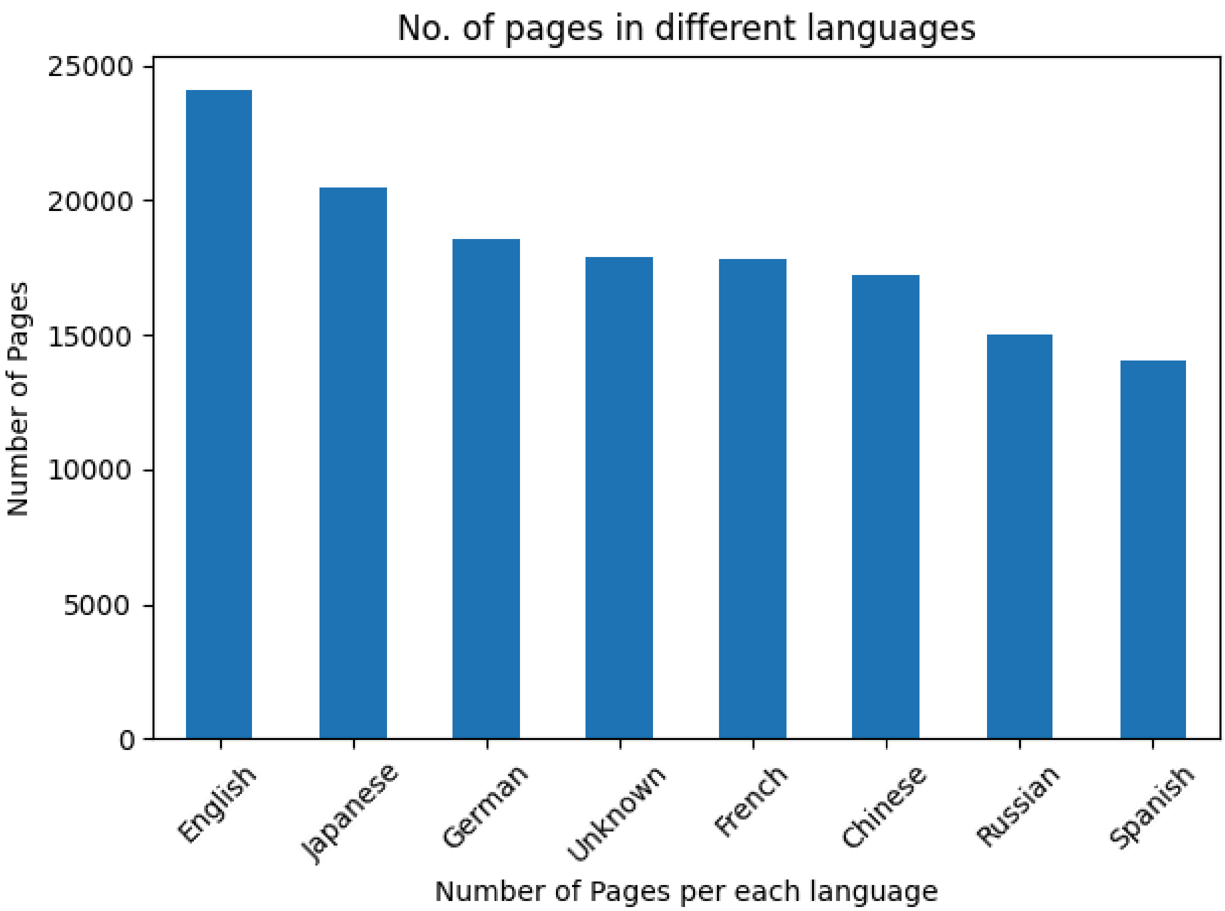
In [21]:
```
def extract_name(page):
    pattern = r'(.{0,})_(.{2}).wikipedia.org_'
    result = re.findall(pattern, page)
    if len(result) == 1:
        return result[0][0]
    else:
        return 'unknown'
df['name'] = df['Page'].apply(extract_name)
```

In [22]:
```
def extract_lang(page):
    pattern = r'(.{0,})_(.{2}).wikipedia.org_'
    result = re.findall(pattern, page)
    if len(result) == 1:
        return result[0][1]
```

```
    else:
        return 'un'
df['language'] = df['Page'].apply(extract_lang)
print(df['language'].unique())
```

```
['zh' 'fr' 'en' 'un' 'ru' 'de' 'ja' 'es']
```

In [23]:
```
lang_name_mapping={'zh':'Chinese', 'fr':'French', 'en':'English',
                   'un':'Unknown', 'ru':'Russian', 'de':'German',
                   'ja':'Japanese', 'es':'Spanish'}
df['language'] = df['language'].map(lang_name_mapping)
df['language'].value_counts().plot(kind='bar', title='No. of pages in differer
plt.tight_layout()
plt.show()
print("% of pages in different languages")
round(df['language'].value_counts(normalize=True)*100,2)
```




```
% of pages in different languages
```

Out[23]:

language	proportion
English	16.62
Japanese	14.08
German	12.79
Unknown	12.31
French	12.27
Chinese	11.88
Russian	10.36
Spanish	9.70

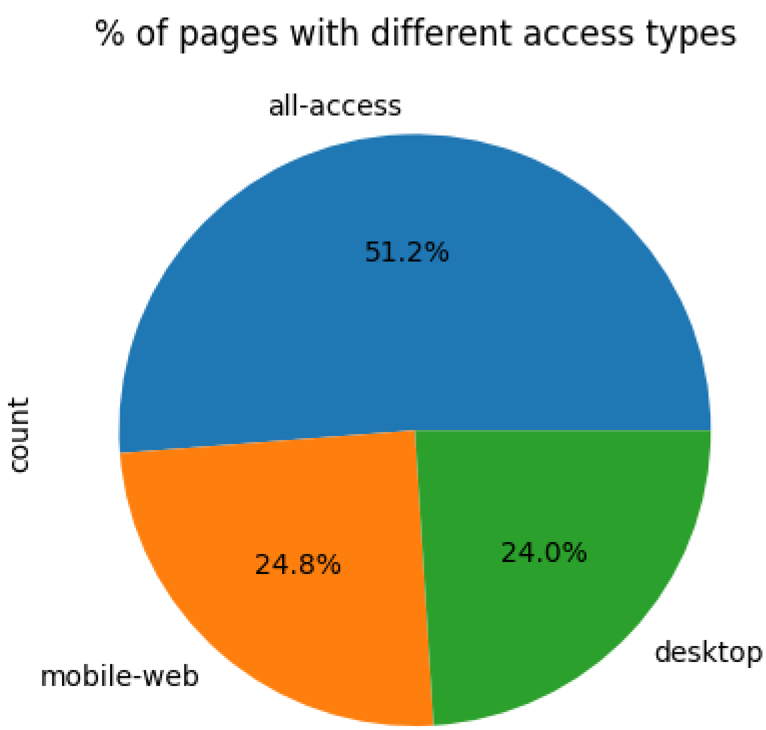
dtype: float64

Insight

Maximum number of pages, 16.62%, are in English language

In [24]:

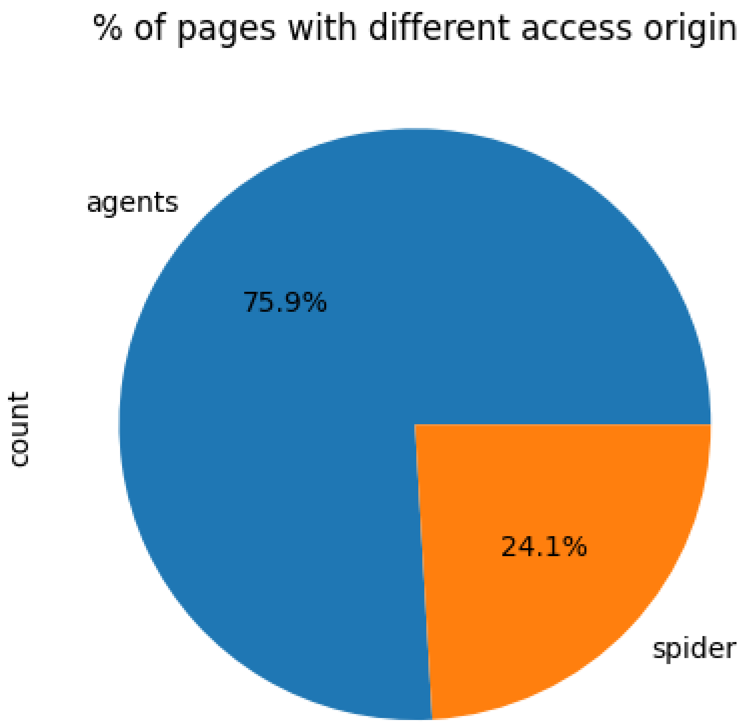
```
df['access_type'] = df['Page'].str.findall(r'all-access|mobile-web|desktop').a
df['access_type'].value_counts().plot(kind='pie', autopct='%1.1f%%', title='%
plt.show()
```



Insight

Maximum number of pages, 51.2%, have all-access access type

In [25]:
```
df['access_origin'] = df['Page'].str.findall(r'spider|agents').apply(lambda x:
df['access_origin'].value_counts().plot(kind='pie', autopct='%1.1f%%', title='
plt.show()
```



Insight

Maximum number of pages, 75.9%, have agents access origin

In [26]:
```
df_agg = df.drop(columns=['Page', 'name', 'access_type', 'access_origin']).grc
df_agg['index'] = pd.to_datetime(df_agg['index'])
df_agg = df_agg.set_index('index')
df_agg.head()
```

Out[26]:

language	Chinese	English	French	German	Japanese	Rus
index						
2015-07-01	240.582042	3513.862203	475.150994	714.968405	580.647056	629.99
2015-07-02	240.941958	3502.511407	478.202000	705.229741	666.672801	640.90
2015-07-03	239.344071	3325.357889	459.837659	676.877231	602.289805	594.02
2015-07-04	241.653491	3462.054256	491.508932	621.145145	756.509177	558.72
2015-07-05	257.779674	3575.520035	482.557746	722.076185	725.720914	595.02

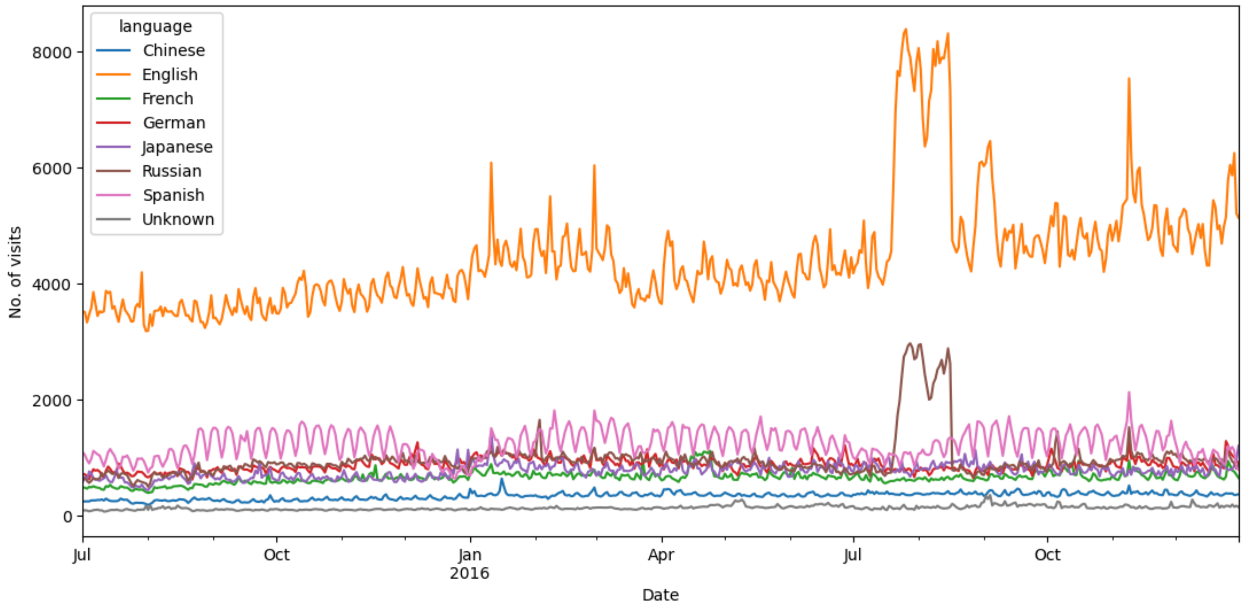
In [27]:

```
df_agg.info()
```

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

In [28]:

```
df_agg.plot(figsize=(13,6))
plt.xlabel('Date')
plt.ylabel('No. of visits')
plt.show()
```



Insight

English pages are the most visited pages follwed by Spanish

English pages have an upward trend in terms of visits

There is an unusual peak from mid of July to end of August 2016

Stationarity test

Using Augmented Dickey-Fuller test to check for stationarity

H0: The series is not stationary

H1: The series is stationary

In [29]:
```
def Dickey_Fuller_test(time_series):
    p_value = sm.tsa.stattools.adfuller(time_series)[1]
    if(p_value < 0.05):
        print('The time series is stationary')
    else:
        print('The time series is not stationary')
```

In [30]:
```
for lang in df_agg.columns:
    print(lang)
    Dickey_Fuller_test(df_agg[lang])
    print()
```

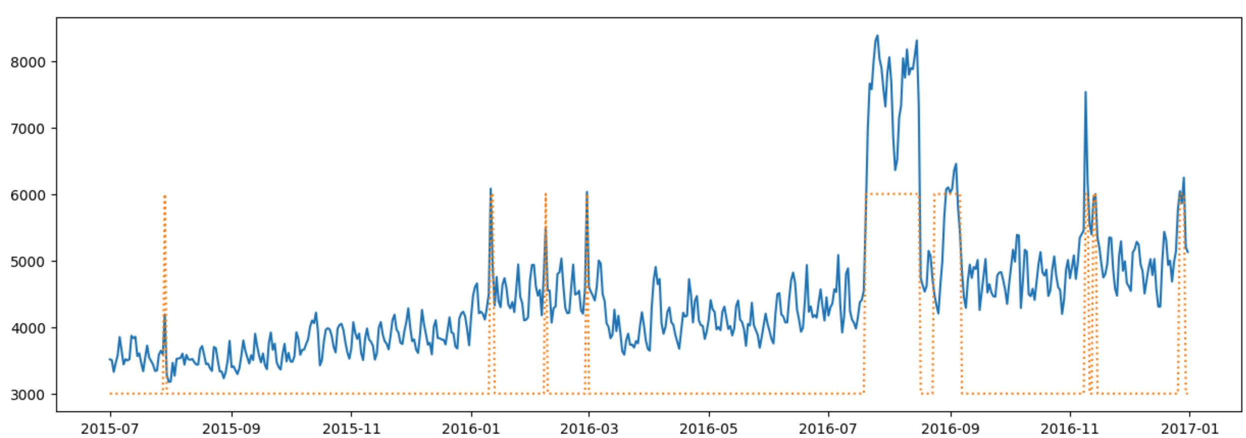
```
Chinese
The time series is not stationary

English
The time series is not stationary

French
The time series is not stationary

German
The time series is not stationary

Japanese
The time series is not stationary

Russian
The time series is stationary

Spanish
The time series is stationary

Unknown
The time series is stationary
```

Insight Based on the Augmented Dickey-Fuller test, the time series corresponding to

- Russian and Spanish language page visits are stationary
- The time series corresponding to Chinese, English, French, German and Japanese language page visits are not stationary

In [31]:

```python
ts_english = df_agg['English']
fig, ax = plt.subplots(figsize=(15, 5))
ax.plot(ts_english.index, ts_english)
ax.plot(ts_english.index, (Exog_Campaign_eng+1)*3000, ':')
plt.show()
```



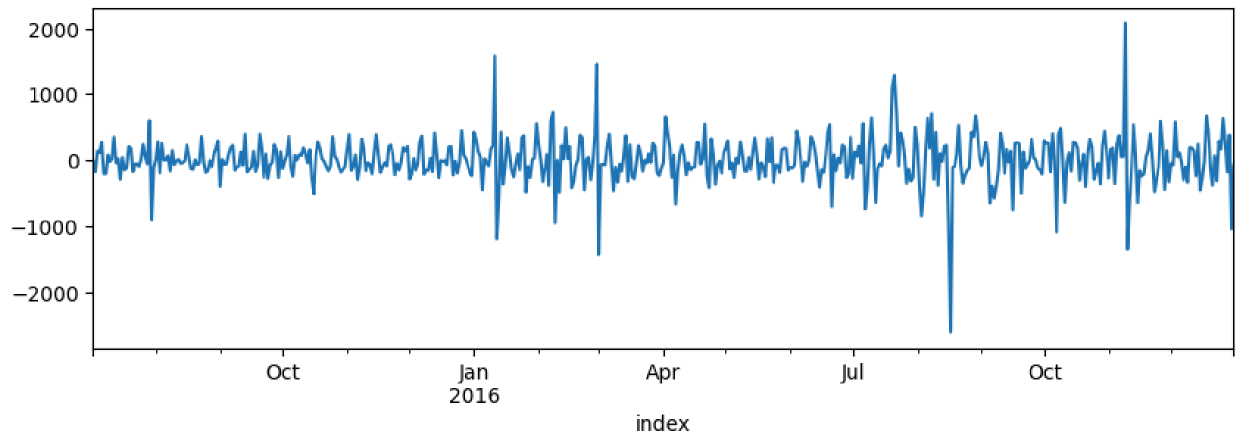
Insight

It is very clear from the above plot that the time series looks like an additive time series with linear up trend and linear sesonality

The unusual spikes in the visits are due to the special events marked by the orange peaks

> **As the trend is linear, differencing with the previous value should de-trend the time series**

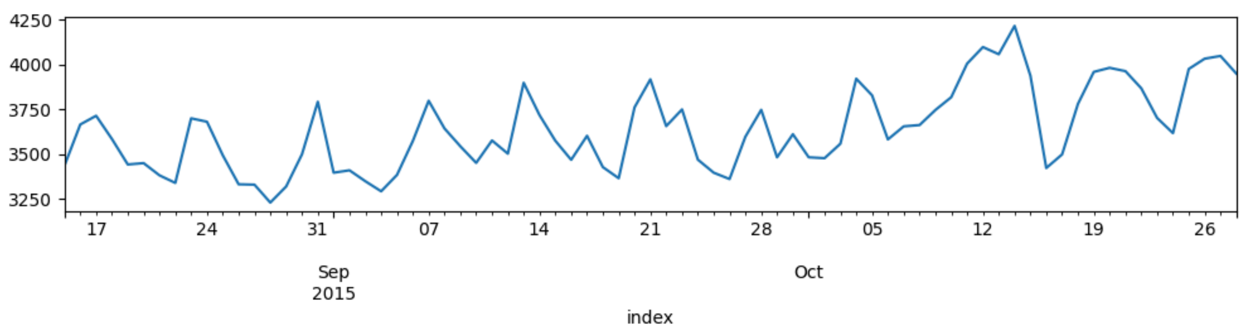
In [32]:
```
ts_english.diff(1).dropna().plot(figsize=(10,3))
plt.show()
```

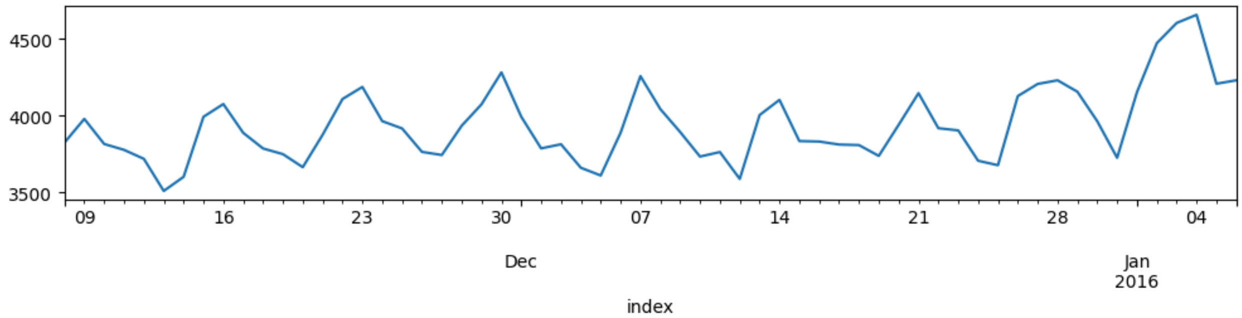


In [33]:
```
Dickey_Fuller_test(ts_english.diff(1).dropna())
```

```
The time series is stationary
```

In [34]:
```
ts_english[45:120].plot(figsize=(12,2))
plt.show()
ts_english[130:190].plot(figsize=(12,2))
plt.show()
```

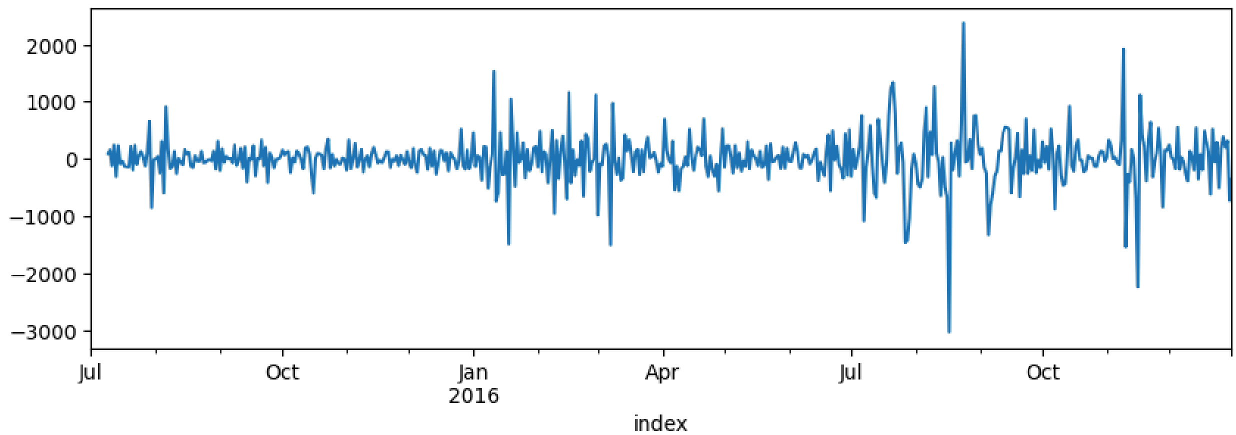




Observing the above two plots, we can conclude that there is a seasonality of 7 days. So s=7

The peaks and troughs repeat every 7 days

In [35]:
```
ts_english.diff(1).diff(7).plot(figsize=(10,3))
plt.show()
```



After removing the trend(and if required, seasonality) manually, the Augmented Dickey-Fuller test says that the time series is stationary

In [36]:
```
Dickey_Fuller_test(ts_english.diff(1).diff(7).dropna())
```

```
The time series is stationary
```

In [37]:
```
# Decompose the time series
decom = seasonal_decompose(ts_english)

# Extract components
ts_english_trend = decom.trend
ts_english_seas = decom.seasonal
ts_english_res = decom.resid

# Plot all components
plt.figure(figsize=(15, 8))

# Actual series
```

```
plt.subplot(4, 1, 1)
plt.plot(ts_english, label='Actual', color='blue')
plt.legend()

# Trend
plt.subplot(4, 1, 2)
plt.plot(ts_english_trend, label='Trend', color='orange')
plt.legend()

# Seasonal
plt.subplot(4, 1, 3)
plt.plot(ts_english_seas, label='Seasonal', color='green')
plt.legend()

# Residual
plt.subplot(4, 1, 4)
plt.plot(ts_english_res, label='Residual', color='red')
plt.legend()

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

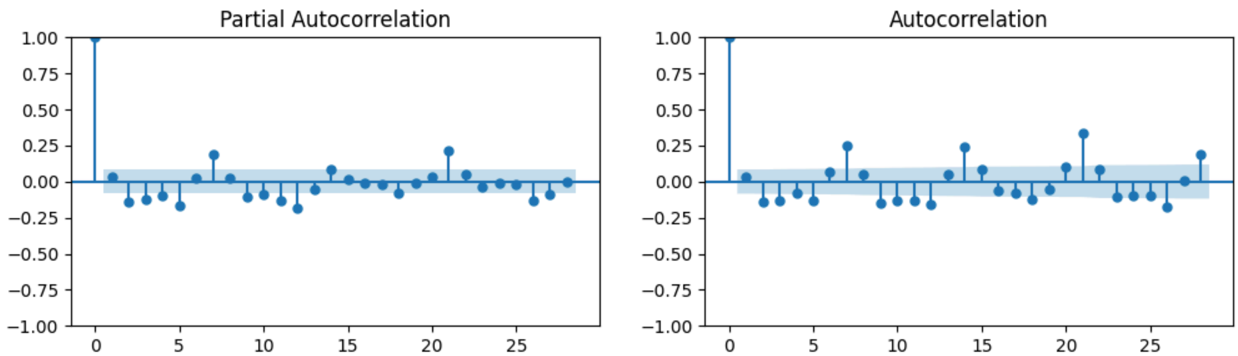
ACF and PACF plots

- The ACF plot shows the correlation of a time series with itself at different lags, while the PACF plot shows the correlation of a time series with itself at different lags, after removing the effects of the previous lag
- The ACF plot can be used to identify the order of an AR model. The order of an AR model is the number of lags that are included in the model. The ACF plot will show spikes at the lags that are included in the

model.
- The PACF plot can be used to identify the order of an MA model. The order of an MA model is the number of lags that are included in the model. The PACF plot will show spikes at the lags that are included in the model

Note: Stationary data needs to be provided to the ACF and PACF plots

In [38]:
```
fig, axs = plt.subplots(1,2, figsize=(12, 3))
plot_pacf(ax=axs[0], x=ts_english.diff(1).dropna())
plot_acf(ax=axs[1], x=ts_english.diff(1).dropna())
plt.show()
```



From the PACF plot, we can see that there are 3 significant lags, at 5, 7 and 21. So P=1,2 or 3

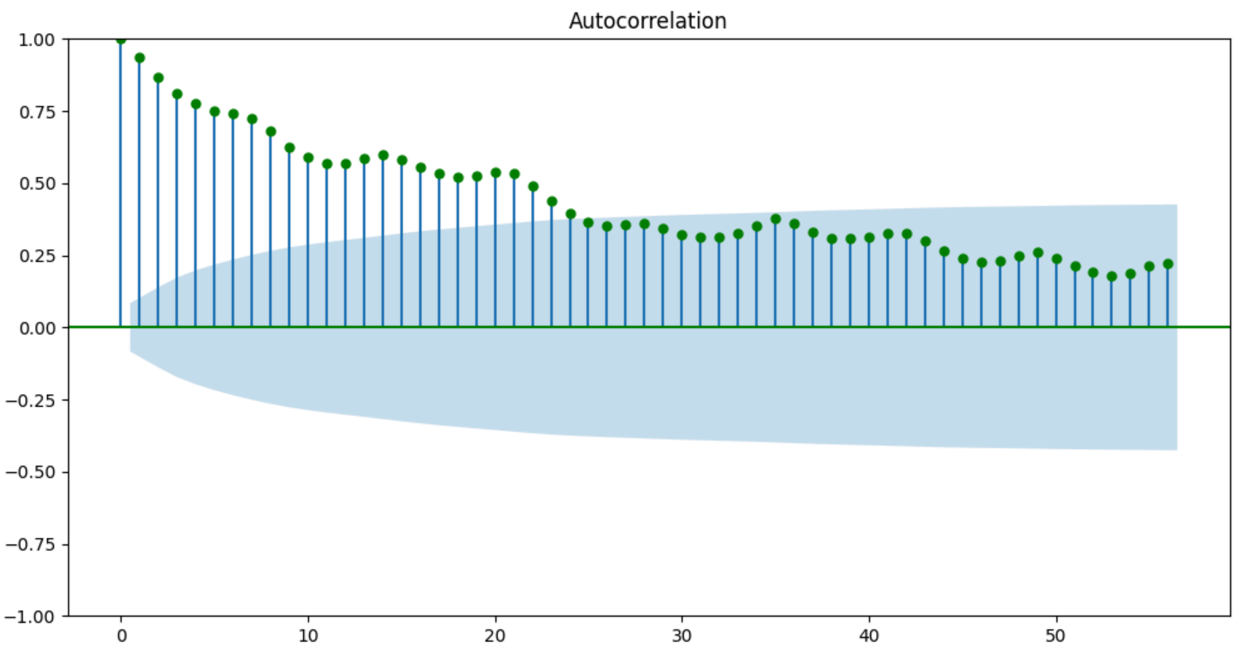
From the ACF plot, we can see that there are 3 significant lags, at 7, 14 and 21. So Q=1,2 or 3

From the PACF plot, the cut-off is right from lag 0 and same for ACF plot. hence, p and q = 0 or 1

In [39]:
```
correlations = []
for lag in range(1,30):
  present = ts_english[:-lag]
  past = ts_english.shift(-lag)[:-lag]
  corrs = np.corrcoef(present, past)[0,-1]
  print(lag,corrs)
  correlations.append(corrs)
```

```
1 0.9363434527458435
2 0.8682966716039896
3 0.8185418037184544
4 0.7846718829500342
5 0.7612561076942573
6 0.7542260641783559
7 0.7386829287516693
8 0.6912638018189877
9 0.6370978014300401
10 0.6015277501876303
11 0.5825450402423571
12 0.5812931934793534
13 0.6007266462817789
14 0.6142525351445116
15 0.5971084554755528
16 0.5693834937428246
17 0.5488401467532626
18 0.5377431132136109
19 0.5430816743411203
20 0.5552694244923043
21 0.5540623423718063
22 0.5092655604869363
23 0.45373695576813583
24 0.4112336297620323
25 0.38162860616251737
26 0.3651996316699481
27 0.3723603627302601
28 0.37818226683160033
29 0.35939242667328175
```

In [40]:
```
plt.rcParams['figure.figsize'] = (12, 6)
plot_acf(ts_english, lags=56, color='green')
plt.show()
```



In [41]:
```python
# Creating a function to print values of all these metrics.
def performance(actual, predicted, print_metrics=True):
    MAE = round(mae(actual, predicted), 3)
    RMSE = round(mse(actual, predicted)**0.5, 3)
    MAPE = round(mape(actual, predicted), 3)
    if(print_metrics==True):
        print('MAE :', MAE)
        print('RMSE :', RMSE)
        print('MAPE:', MAPE)
    return MAE, RMSE, MAPE
```

> **ARIMA MODEL**

ARIMA

- **Autoregressive Integrated Moving Average (ARIMA)** model, and extensions
- This model is the basic interface for ARIMA-type models, including those with exogenous regressors and those with seasonal components.
- The most general form of the model is:
  SARIMAX(p, d, q) × (P, D, Q, s)
  It also allows all specialized cases, including autoregressive models:
  AR(p)

Moving average models: `MA(q)`

Mixed autoregressive moving average models: `ARMA(p, q)`

Integration models: `ARIMA(p, d, q)`

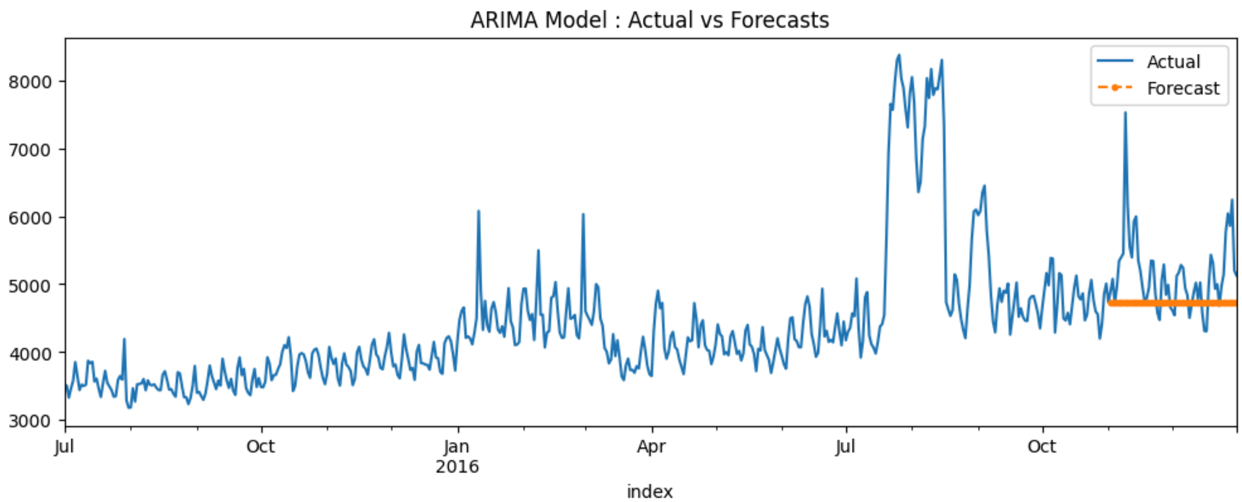
Seasonal models: `SARIMA(P, D, Q, s)`

Regression with errors that follow one of the above ARIMA-type models

In [42]:
```python
TS = ts_english.copy(deep=True)
```

In [43]:
```python
n_forecast = 60

# Fit ARIMA model
model = ARIMA(TS[:-n_forecast], order=(0, 1, 0))
model_fit = model.fit()

# Forecast next n_forecast steps
predicted = model_fit.forecast(steps=n_forecast, alpha=0.05)
```

```python
# Plot actual vs forecast
plt.figure(figsize=(12, 4))
TS.plot(label='Actual')
predicted.plot(label='Forecast', linestyle='dashed', marker='.')
plt.legend(loc="upper right")
plt.title('ARIMA Model : Actual vs Forecasts')
plt.show()

# Performance metrics
performance(TS.values[-n_forecast:], predicted.values, print_metrics=True)
```




```
MAE : 477.636
RMSE : 672.778
MAPE: 0.086
```

Out[43]: (477.636, 672.778, 0.086)

Insight

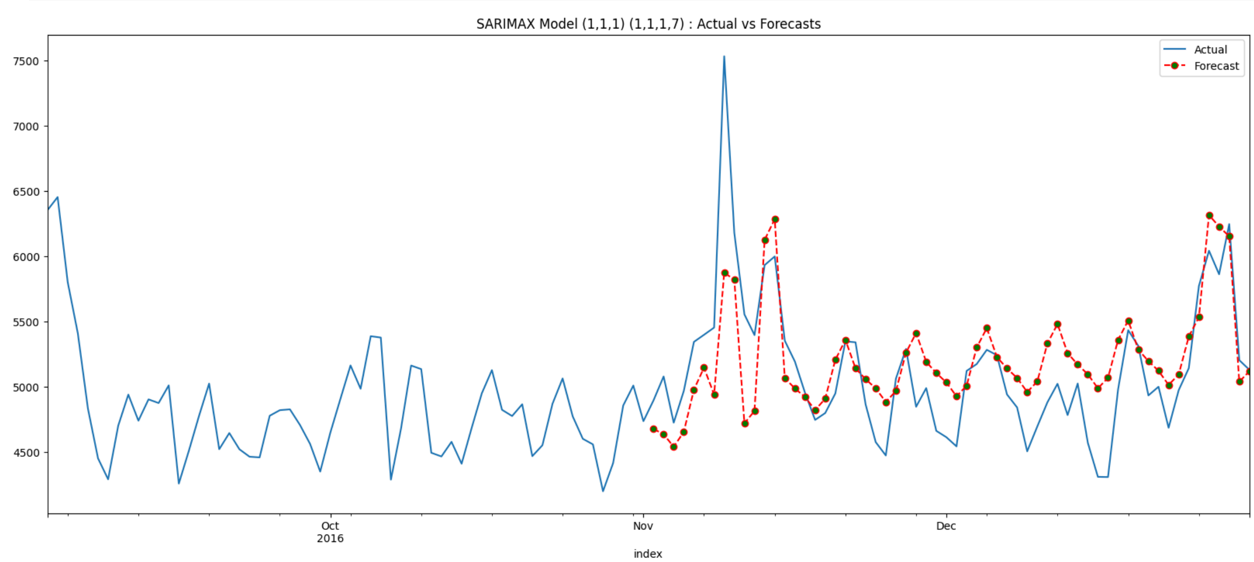
The model is not doing a good job, even for different combinations of p and q

> **SARIMAX MODEL**

In [44]:
```python
from statsmodels.tsa.statespace.sarimax import SARIMAX
```

In [45]:
```python
# Parameters
exog = Exog_Campaign_eng['Exog'].to_numpy()
p, d, q = 1, 1, 1
P, D, Q, s = 1, 1, 1, 7
n_forecast = 60

# Fit SARIMAX model
model = SARIMAX(
    TS[:-n_forecast],
    order=(p, d, q),
    seasonal_order=(P, D, Q, s),
```

```python
    exog=exog[:-n_forecast],
    initialization='approximate_diffuse'
)
model_fit = model.fit()

# Forecast last n values
model_forecast = model_fit.forecast(
    steps=n_forecast,
    dynamic=True,
    exog=pd.DataFrame(exog[-n_forecast:])
)

# Plot actual vs forecast
plt.figure(figsize=(20, 8))
TS[-120:].plot(label='Actual')
model_forecast[-120:].plot(
    label='Forecast',
    color='red',
    linestyle='dashed',
    marker='o',
    markerfacecolor='green'
)
plt.legend(loc="upper right")
plt.title(f"SARIMAX Model ({p},{d},{q}) ({P},{D},{Q},{s}) : Actual vs Forecast
plt.show()

# Performance metrics
performance(TS.values[-n_forecast:], model_forecast.values, print_metrics=True
```




```
MAE : 306.416
RMSE : 399.015
MAPE: 0.06
```

Out[45]: (306.416, 399.015, 0.06)

Insight

SARIMAX model is doing a significantly better job. We need to search for the right order values

> HyperParamter Tuning for *SARIMAX*

In [46]:
```
import time

def grid_search_sarimax(TS, n_forecast, p_list, d_list, q_list, P_list, D_list
    counter = 0
    perf_df = pd.DataFrame(columns=['serial', 'pdq', 'PDQs', 'mape', 'rmse'])

    total_combinations = (len(p_list) * len(d_list) * len(q_list) *
                          len(P_list) * len(D_list) * len(Q_list) * len(s_list

    last_print_time = time.time()  # Track last print time

    for p in p_list:
        for d in d_list:
            for q in q_list:
                for P in P_list:
                    for D in D_list:
                        for Q in Q_list:
                            for s in s_list:
                                try:
                                    model = SARIMAX(
                                        TS[:-n_forecast],
                                        order=(p, d, q),
                                        seasonal_order=(P, D, Q, s),
                                        exog=exog[:-n_forecast] if len(exog) e
                                        initialization='approximate_diffuse'
                                    )
                                    model_fit = model.fit()
                                    model_forecast = model_fit.forecast(
                                        n_forecast,
                                        dynamic=True,
                                        exog=pd.DataFrame(exog[-n_forecast:])
                                    )
                                    MAE, RMSE, MAPE = performance(
                                        TS.values[-n_forecast:],
                                        model_forecast.values,
                                        print_metrics=False
                                    )
                                    counter += 1
                                    list_row = [counter, (p, d, q), (P, D, Q,
                                    perf_df.loc[len(perf_df)] = list_row

                                    # Print only if 2 minutes passed
                                    current_time = time.time()
                                    if current_time - last_print_time >= 30:
                                        percent_done = (counter / total_combir
                                        print(f'Progress: {percent_done:.2f}%
                                        last_print_time = current_time
```

```
                                except Exception as e:
                                    # Uncomment for debugging
                                    # print(f"Error with parameters {(p,d,q,P,
                                    continue
    return perf_df
```

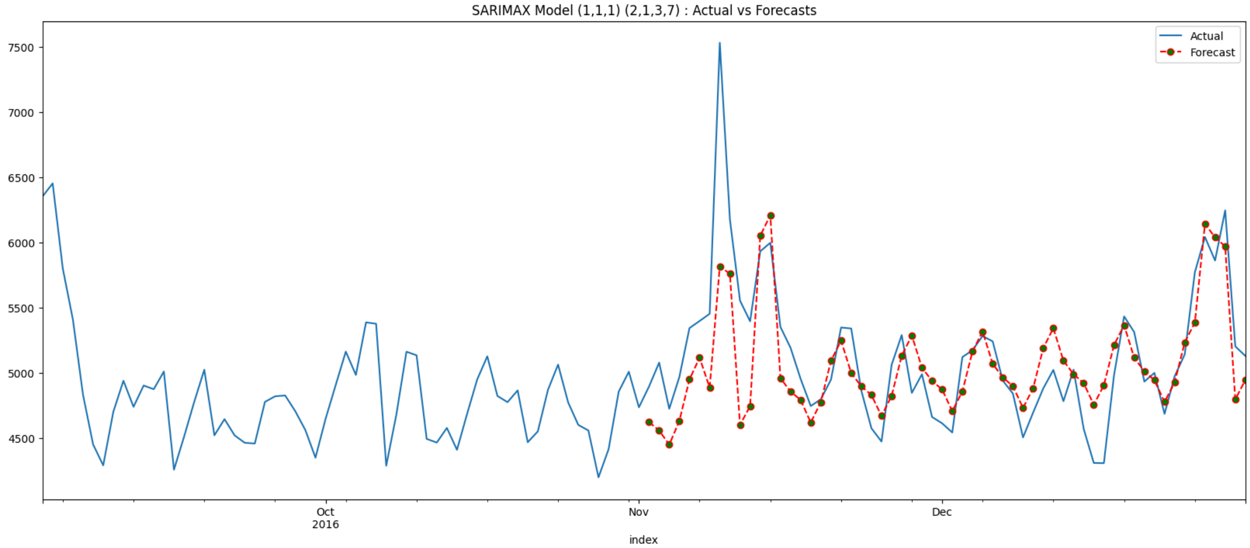
In [47]:
```
TS = ts_english.copy(deep=True)
n_forecast = 60

p_list = [0, 1]
d_list = [1]
q_list = [0, 1]

P_list = [2, 3]
D_list = [1]
Q_list = [2, 3]
s_list = [7]

exog = Exog_Campaign_eng['Exog'].to_numpy()

perf_df = grid_search_sarimax(
    TS, n_forecast,
    p_list, d_list, q_list,
    P_list, D_list, Q_list, s_list,
    exog
)

# Sort by 'mape' then 'rmse' (ascending order)
sorted_perf_df = perf_df.sort_values(['mape', 'rmse']).reset_index(drop=True)

print(sorted_perf_df)
```

```
Progress: 37.50% (6/16)
Progress: 68.75% (11/16)
Progress: 93.75% (15/16)
    serial        pdq          PDQs   mape     rmse
0       14  (1, 1, 1)  (2, 1, 3, 7)  0.051  373.568
1       12  (1, 1, 0)  (3, 1, 3, 7)  0.056  411.759
2       10  (1, 1, 0)  (2, 1, 3, 7)  0.056  412.034
3       13  (1, 1, 1)  (2, 1, 2, 7)  0.057  381.953
4       16  (1, 1, 1)  (3, 1, 3, 7)  0.057  384.402
5        6  (0, 1, 1)  (2, 1, 3, 7)  0.057  416.966
6       15  (1, 1, 1)  (3, 1, 2, 7)  0.059  392.414
7        8  (0, 1, 1)  (3, 1, 3, 7)  0.061  437.274
8        4  (0, 1, 0)  (3, 1, 3, 7)  0.061  437.976
9       11  (1, 1, 0)  (3, 1, 2, 7)  0.062  444.548
10       7  (0, 1, 1)  (3, 1, 2, 7)  0.062  444.976
11       3  (0, 1, 0)  (3, 1, 2, 7)  0.062  447.552
12       2  (0, 1, 0)  (2, 1, 3, 7)  0.063  448.904
13       5  (0, 1, 1)  (2, 1, 2, 7)  0.064  456.425
14       9  (1, 1, 0)  (2, 1, 2, 7)  0.064  456.481
15       1  (0, 1, 0)  (2, 1, 2, 7)  0.064  458.305
```

After the above experiment, p,d,q,P,D,Q,s = 1,1,1,2,1,3,7 were found to be best values with low mape

In [48]:

```
exog = Exog_Campaign_eng['Exog'].to_numpy()
p, d, q = 1, 1, 1
P, D, Q, s = 2, 1, 3, 7
n_forecast = 60

# Fit SARIMAX model
model = SARIMAX(
    TS[:-n_forecast],
    order=(p, d, q),
    seasonal_order=(P, D, Q, s),
    exog=exog[:-n_forecast],
    initialization='approximate_diffuse'
)
model_fit = model.fit()

# Forecast last n_forecast points
model_forecast = model_fit.forecast(
    steps=n_forecast,
    dynamic=True,
    exog=pd.DataFrame(exog[-n_forecast:])
)

# Plot actual vs forecast for last 120 points
plt.figure(figsize=(20, 8))
TS[-120:].plot(label='Actual')
model_forecast.plot(
    label='Forecast',
    color='red',
    linestyle='dashed',
    marker='o',
    markerfacecolor='green'
)
plt.legend(loc="upper right")
plt.title(f'SARIMAX Model ({p},{d},{q}) ({P},{D},{Q},{s}) : Actual vs Forecast
plt.show()

# Calculate and print performance metrics
performance(TS.values[-n_forecast:], model_forecast.values, print_metrics=True
```




```
MAE : 269.232
RMSE : 373.568
MAPE: 0.051
```

Out[48]: (269.232, 373.568, 0.051)

Insight

There is good improvement in the SARIMAX model after tuning the parameters

In [49]:
```
import time

def pipeline_sarimax_grid_search_without_exog(languages, data, n_forecast,
                                              p_list, d_list, q_list,
                                              P_list, D_list, Q_list, s_list):
    """
    Grid search SARIMAX with optional exogenous variables.
    Returns: results_df (all combinations) and best_param_df (best params per
    """

    results_df = pd.DataFrame(columns=['language', 'pdq', 'PDQs', 'mape'])
    best_param_df = pd.DataFrame(columns=['language', 'p', 'd', 'q', 'P', 'D',

    total_combinations = (len(p_list) * len(d_list) * len(q_list) *
                          len(P_list) * len(D_list) * len(Q_list) * len(s_list

    last_print_time = time.time()

    for lang in languages:
        TS = data[lang]

        best_mape = np.inf
        best_params = None
        counter = 0

        for p in p_list:
            for d in d_list:
```

```
                for q in q_list:
                    for P in P_list:
                        for D in D_list:
                            for Q in Q_list:
                                for s in s_list:
                                    try:
                                        # Fit SARIMAX model
                                        model = SARIMAX(
                                            TS[:-n_forecast],
                                            order=(p, d, q),
                                            seasonal_order=(P, D, Q, s),

                                            initialization='approximate_diffus
                                        )
                                        model_fit = model.fit(disp=False)

                                        # Forecast
                                        forecast = model_fit.forecast(
                                            steps=n_forecast

                                        )

                                        # Calculate MAPE
                                        actuals = TS.values[-n_forecast:]
                                        errors = actuals - forecast.values
                                        mape = np.mean(np.abs(errors) / np.abs

                                        counter += 1
                                        results_df.loc[len(results_df)] = [lar

                                        # Track best parameters
                                        if mape < best_mape:
                                            best_mape = mape
                                            best_params = (p, d, q, P, D, Q, s

                                        # Print progress every 30 seconds
                                        current_time = time.time()
                                        if current_time - last_print_time >= 3
                                            percent_done = (counter / total_co
                                            print(f"[{lang}] Progress: {percer
                                            last_print_time = current_time

                                    except Exception:
                                        continue

        # Save best parameters for this language
        if best_params:
            best_param_df.loc[len(best_param_df)] = [lang, *best_params, best_

        # Final best result for this language
        print(f"\nLanguage: {lang}")
        print(f"Best MAPE: {best_mape}")
        print(f"Best Parameters: {best_params}")
```

```python
        print("--------------------------------------------------\n")

    return results_df, best_param_df
```

In [50]:

```python
# List of time series columns
languages = df_agg.columns[:-1]
n_forecast = 60

# SARIMAX grid search parameters
p_list = [0, 1]
d_list = [1]
q_list = [0, 1]

P_list = [2, 3]
D_list = [1]
Q_list = [2, 3]
s_list = [7]

# External regressor (exogenous variable)
exog = Exog_Campaign_eng['Exog'].to_numpy()

# Run SARIMAX grid search with exogenous variable
results_df, best_param_df = pipeline_sarimax_grid_search_without_exog(
    languages, df_agg, n_forecast,
    p_list, d_list, q_list,
    P_list, D_list, Q_list, s_list
)
```

```
[Chinese] Progress: 43.75% (7/16)
[Chinese] Progress: 81.25% (13/16)

Language: Chinese
Best MAPE: 0.05093633872969188
Best Parameters: (0, 1, 1, 3, 1, 2, 7)
--------------------------------------------------

[English] Progress: 12.50% (2/16)
[English] Progress: 50.00% (8/16)
[English] Progress: 87.50% (14/16)

Language: English
Best MAPE: 0.07887191927788541
Best Parameters: (1, 1, 1, 2, 1, 3, 7)
--------------------------------------------------

[French] Progress: 25.00% (4/16)
[French] Progress: 68.75% (11/16)
[French] Progress: 100.00% (16/16)

Language: French
Best MAPE: 0.06394818305730827
Best Parameters: (1, 1, 0, 2, 1, 3, 7)
--------------------------------------------------

[German] Progress: 50.00% (8/16)
[German] Progress: 93.75% (15/16)

Language: German
Best MAPE: 0.06481826462997445
Best Parameters: (1, 1, 1, 2, 1, 2, 7)
--------------------------------------------------

[Japanese] Progress: 31.25% (5/16)
[Japanese] Progress: 75.00% (12/16)

Language: Japanese
Best MAPE: 0.05788182525341171
Best Parameters: (1, 1, 1, 2, 1, 2, 7)
--------------------------------------------------

[Russian] Progress: 12.50% (2/16)
[Russian] Progress: 50.00% (8/16)
[Russian] Progress: 87.50% (14/16)

Language: Russian
Best MAPE: 0.07029047188167518
Best Parameters: (0, 1, 0, 3, 1, 3, 7)
--------------------------------------------------

[Spanish] Progress: 25.00% (4/16)
[Spanish] Progress: 75.00% (12/16)
```

```
Language: Spanish
Best MAPE: 0.12556221070554352
Best Parameters: (1, 1, 1, 3, 1, 2, 7)
--------------------------------------------------
```

In [51]:

```python
# Sort results by MAPE then RMSE
sorted_perf_df = results_df.sort_values(['mape']).reset_index(drop=True)

# Display outputs
print(sorted_perf_df.head())  # All combinations sorted by MAPE
print("----"*20)
print(best_param_df)          # Best parameters per series
```

```
  language        pdq           PDQs      mape
0  Chinese  (0, 1, 1)  (3, 1, 2, 7)  0.050936
1  Chinese  (0, 1, 1)  (3, 1, 3, 7)  0.050952
2  Chinese  (0, 1, 1)  (2, 1, 2, 7)  0.053133
3  Chinese  (1, 1, 1)  (2, 1, 3, 7)  0.054241
4  Chinese  (1, 1, 1)  (3, 1, 2, 7)  0.054397
--------------------------------------------------------------------------------
-
   language  p  d  q  P  D  Q  s      MAPE
0   Chinese  0  1  1  3  1  2  7  0.050936
1   English  1  1  1  2  1  3  7  0.078872
2    French  1  1  0  2  1  3  7  0.063948
3    German  1  1  1  2  1  2  7  0.064818
4  Japanese  1  1  1  2  1  2  7  0.057882
5   Russian  0  1  0  3  1  3  7  0.070290
6   Spanish  1  1  1  3  1  2  7  0.125562
```

In [52]:

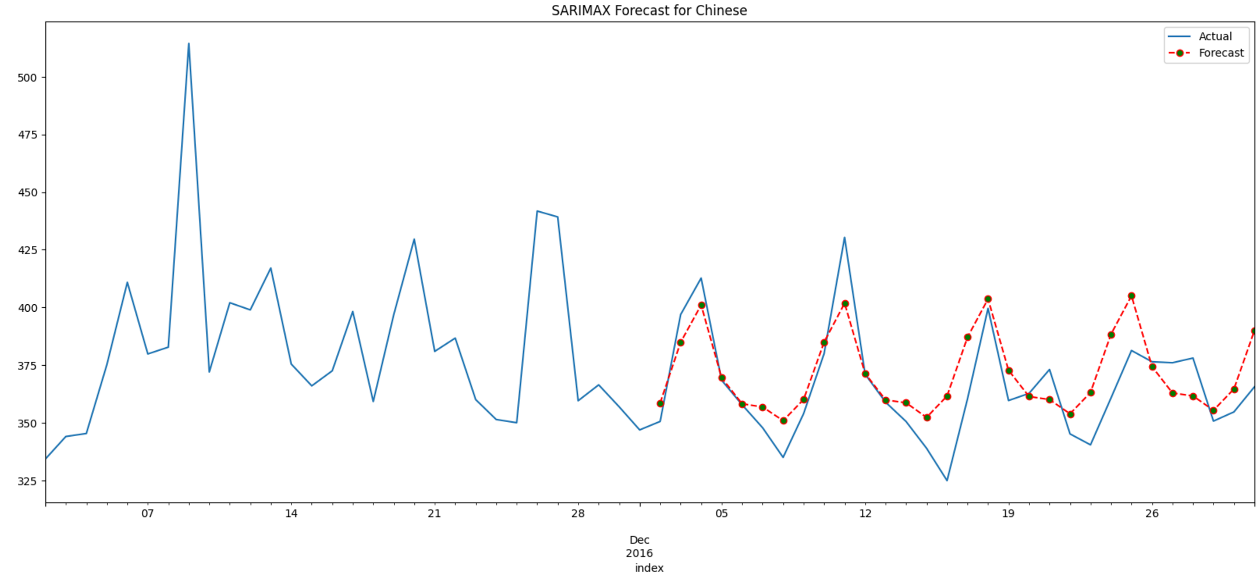
```python
def plot_best_SARIMAX_model(languages, data, n, best_param_df):
    for lang in languages:
        # Fetching respective best parameters for that language
        p = best_param_df.loc[best_param_df['language'] == lang, 'p'].values[0
        d = best_param_df.loc[best_param_df['language'] == lang, 'd'].values[0
        q = best_param_df.loc[best_param_df['language'] == lang, 'q'].values[0
        P = best_param_df.loc[best_param_df['language'] == lang, 'P'].values[0
        D = best_param_df.loc[best_param_df['language'] == lang, 'D'].values[0
        Q = best_param_df.loc[best_param_df['language'] == lang, 'Q'].values[0
        s = best_param_df.loc[best_param_df['language'] == lang, 's'].values[0

        # Creating language time series
        time_series = data[lang]

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

```
        # Forecast for last n values
        model_forecast = model_fit.forecast(n, dynamic=True)

        # Calculate MAPE & RMSE
        actuals = time_series.values[-n:]
        errors = actuals - model_forecast.values
        mape = np.mean(np.abs(errors) / np.abs(actuals))
        rmse = np.sqrt(np.mean(errors**2))

        # Print model metrics
        print("\n---------------------------------------------------")
        print(f"SARIMAX model for {lang} Time Series")
        print(f"Parameters of Model : ({p},{d},{q})  ({P},{D},{Q},{s})")
        print(f"MAPE of Model       : {np.round(mape, 5)}")
        print(f"RMSE of Model       : {np.round(rmse, 3)}")
        print("---------------------------------------------------\n")

        # Plot Actual & Forecasted values
        time_series.index = time_series.index.astype('datetime64[ns]')
        model_forecast.index = model_forecast.index.astype('datetime64[ns]')
        plt.figure(figsize=(20, 8))
        time_series[-60:].plot(label='Actual')
        model_forecast[-60:].plot(label='Forecast', color='red',
                                  linestyle='dashed', marker='o', markerfacecc
        plt.legend()
        plt.title(f"SARIMAX Forecast for {lang}")
        plt.show()
```

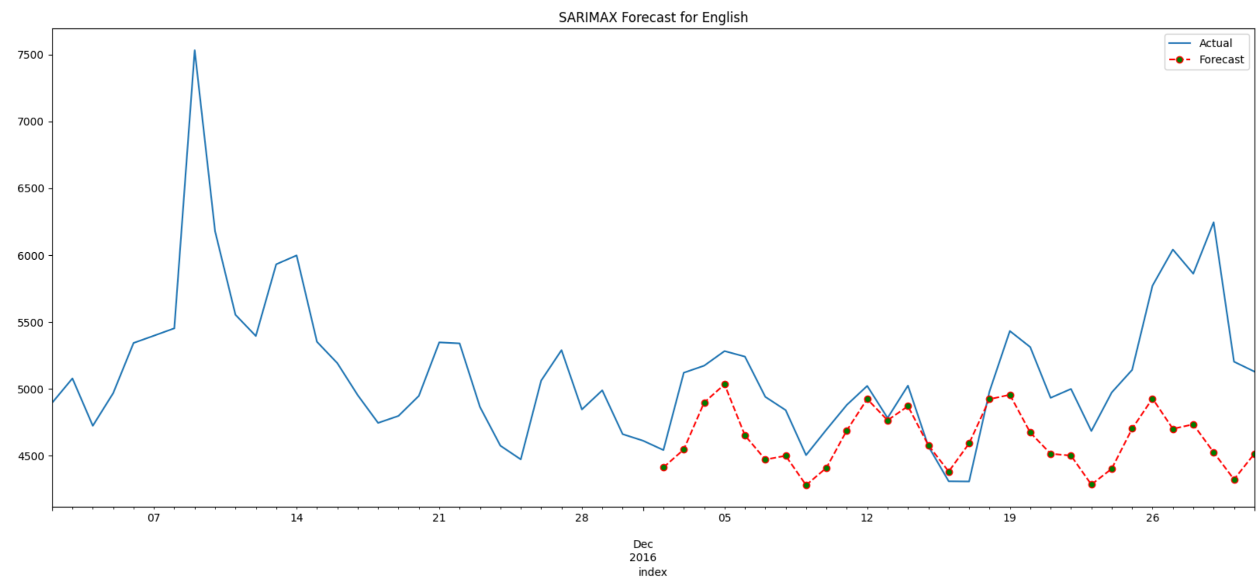
In [53]:

```
languages = df_agg.columns[:-1]
n=30
plot_best_SARIMAX_model(languages, df_agg, n, best_param_df)
```

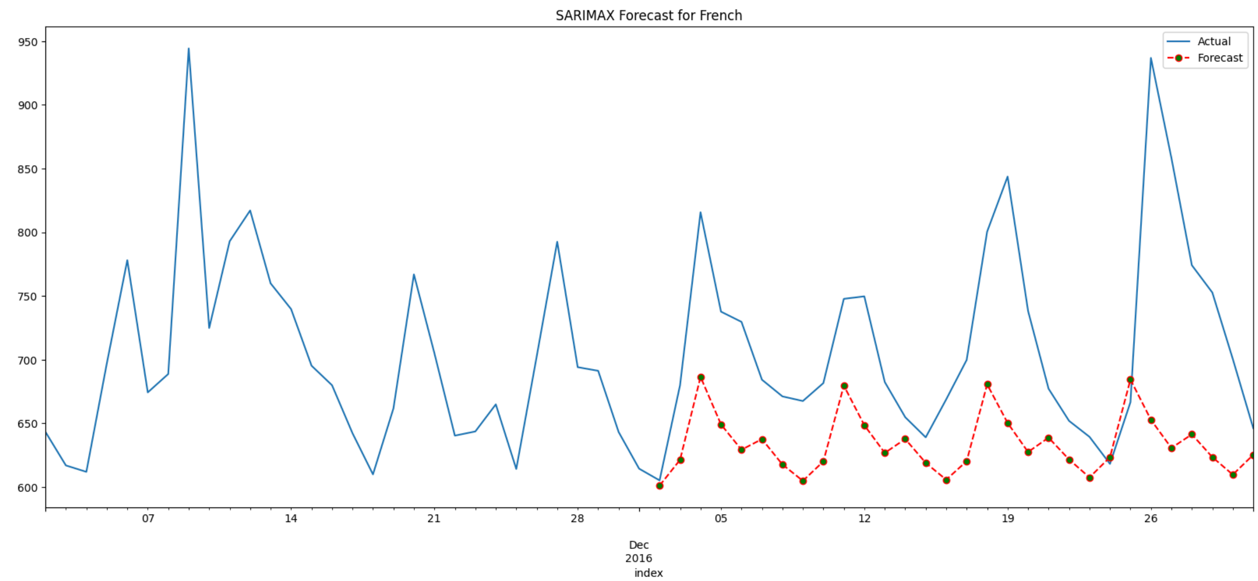
```
--------------------------------------------------
SARIMAX model for Chinese Time Series
Parameters of Model : (0,1,1)  (3,1,2,7)
MAPE of Model       : 0.0339
RMSE of Model       : 15.603
--------------------------------------------------
```



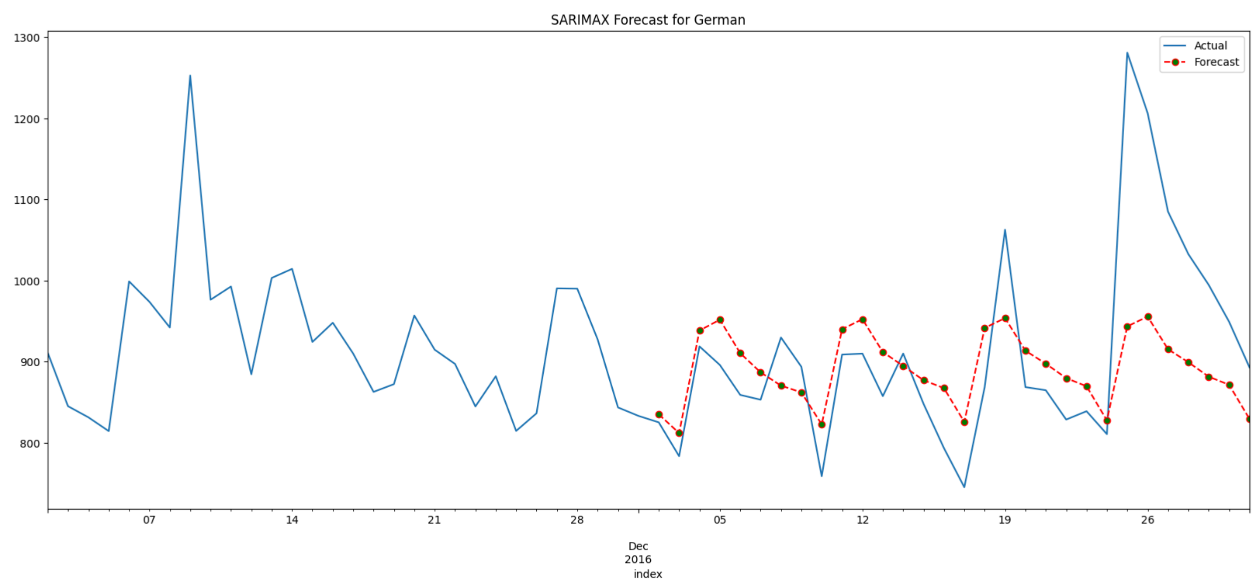

```
--------------------------------------------------
SARIMAX model for English Time Series
Parameters of Model : (1,1,1)  (2,1,3,7)
MAPE of Model       : 0.08742
RMSE of Model       : 608.108
--------------------------------------------------
```



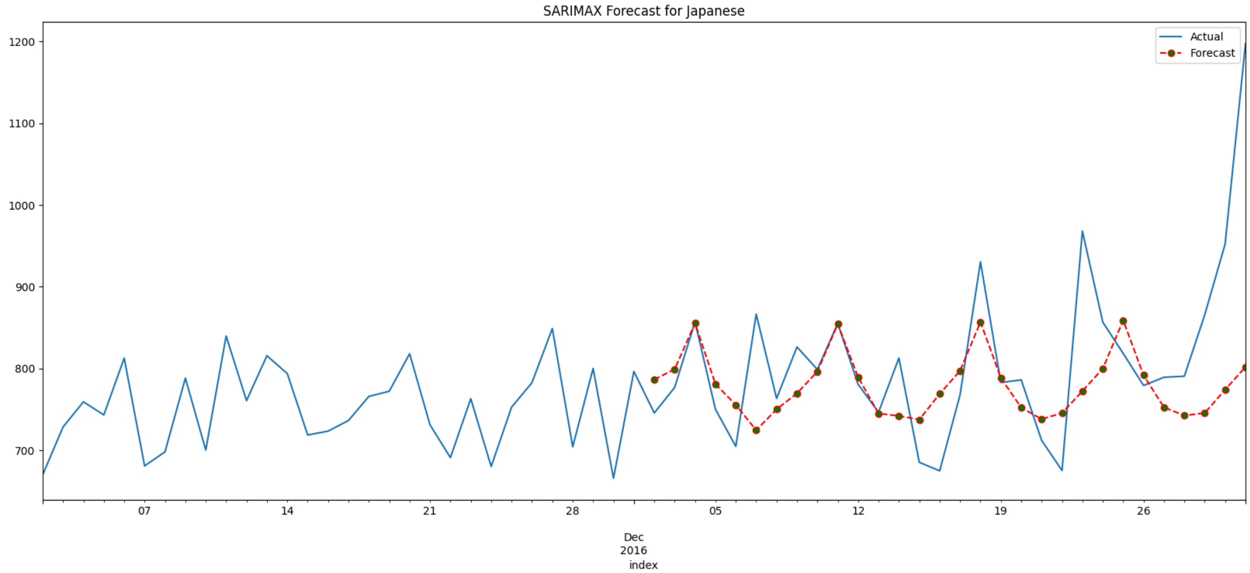

```
--------------------------------------------------
SARIMAX model for French Time Series
Parameters of Model : (1,1,0)  (2,1,3,7)
MAPE of Model       : 0.10681
RMSE of Model       : 103.769
--------------------------------------------------
```



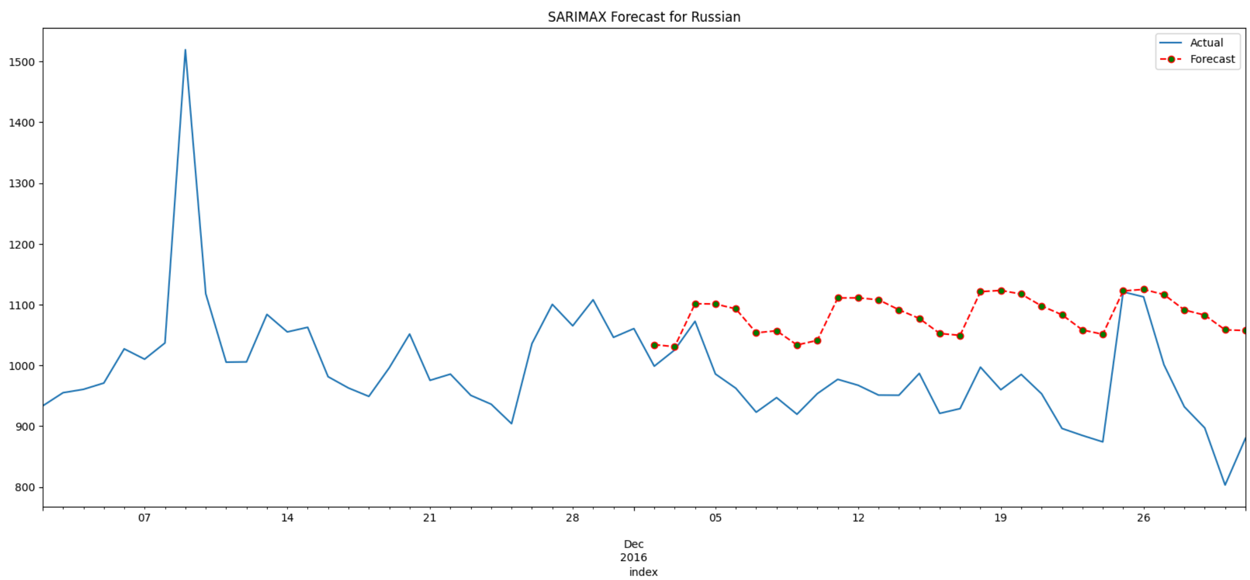

```
---------------------------------------------------
SARIMAX model for German Time Series
Parameters of Model : (1,1,1)  (2,1,2,7)
MAPE of Model       : 0.07434
RMSE of Model       : 100.974
---------------------------------------------------
```



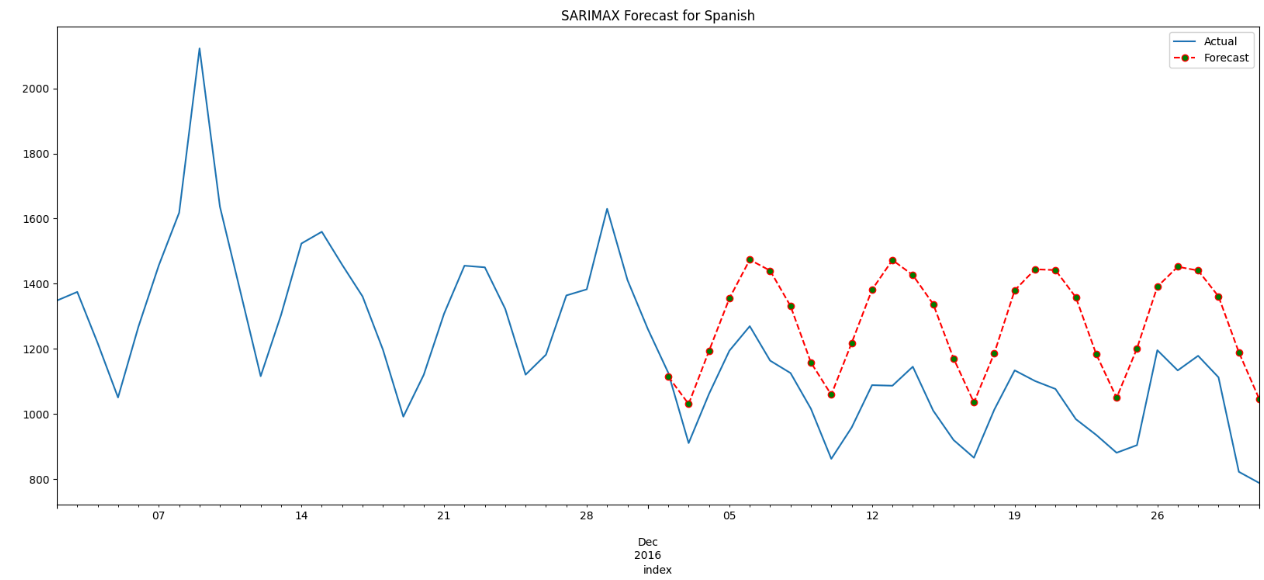

```
---------------------------------------------------
SARIMAX model for Japanese Time Series
Parameters of Model : (1,1,1)  (2,1,2,7)
MAPE of Model       : 0.07249
RMSE of Model       : 101.399
---------------------------------------------------
```




```
--------------------------------------------------
SARIMAX model for Russian Time Series
Parameters of Model : (0,1,0)  (3,1,3,7)
MAPE of Model       : 0.13227
RMSE of Model       : 135.636
--------------------------------------------------
```




```
--------------------------------------------------
SARIMAX model for Spanish Time Series
Parameters of Model : (1,1,1)  (3,1,2,7)
MAPE of Model       : 0.23868
RMSE of Model       : 257.668
--------------------------------------------------
```



Forecasting using Facebook Prophet

In [54]:
```
#!pip install numpy==1.22.4
```

In [55]:
```
!pip install prophet
```

```
Requirement already satisfied: prophet in /usr/local/lib/python3.11/dist-packag
es (1.1.7)
Requirement already satisfied: cmdstanpy>=1.0.4 in /usr/local/lib/python3.11/di
st-packages (from prophet) (1.2.5)
Requirement already satisfied: numpy>=1.15.4 in /usr/local/lib/python3.11/dist-
packages (from prophet) (2.0.2)
Requirement already satisfied: matplotlib>=2.0.0 in /usr/local/lib/python3.11/d
ist-packages (from prophet) (3.10.0)
Requirement already satisfied: pandas>=1.0.4 in /usr/local/lib/python3.11/dist-
packages (from prophet) (2.2.2)
Requirement already satisfied: holidays<1,>=0.25 in /usr/local/lib/python3.11/d
ist-packages (from prophet) (0.78)
Requirement already satisfied: tqdm>=4.36.1 in /usr/local/lib/python3.11/dist-p
ackages (from prophet) (4.67.1)
Requirement already satisfied: importlib_resources in /usr/local/lib/python3.1
1/dist-packages (from prophet) (6.5.2)
Requirement already satisfied: stanio<2.0.0,>=0.4.0 in /usr/local/lib/python3.1
1/dist-packages (from cmdstanpy>=1.0.4->prophet) (0.5.1)
Requirement already satisfied: python-dateutil in /usr/local/lib/python3.11/dis
t-packages (from holidays<1,>=0.25->prophet) (2.9.0.post0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/di
st-packages (from matplotlib>=2.0.0->prophet) (1.3.3)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-p
ackages (from matplotlib>=2.0.0->prophet) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.11/d
ist-packages (from matplotlib>=2.0.0->prophet) (4.59.0)
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.11/d
ist-packages (from matplotlib>=2.0.0->prophet) (1.4.8)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.11/dis
t-packages (from matplotlib>=2.0.0->prophet) (25.0)
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.11/dist-pack
ages (from matplotlib>=2.0.0->prophet) (11.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.11/di
st-packages (from matplotlib>=2.0.0->prophet) (3.2.3)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-p
ackages (from pandas>=1.0.4->prophet) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dis
t-packages (from pandas>=1.0.4->prophet) (2025.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packa
ges (from python-dateutil->holidays<1,>=0.25->prophet) (1.17.0)
```

In [56]:

```python
TS = ts_english.copy(deep=True).reset_index()
TS = TS[['index', 'English']]
TS.columns = ['ds', 'y']
TS['ds'] = pd.to_datetime(TS['ds'])

exog = Exog_Campaign_eng['Exog']
TS['exog'] = exog.values

TS.tail()
```

Out[56]:

	ds	y	exog
545	2016-12-27	6040.680728	1
546	2016-12-28	5860.227559	1
547	2016-12-29	6245.127510	1
548	2016-12-30	5201.783018	0
549	2016-12-31	5127.916418	0

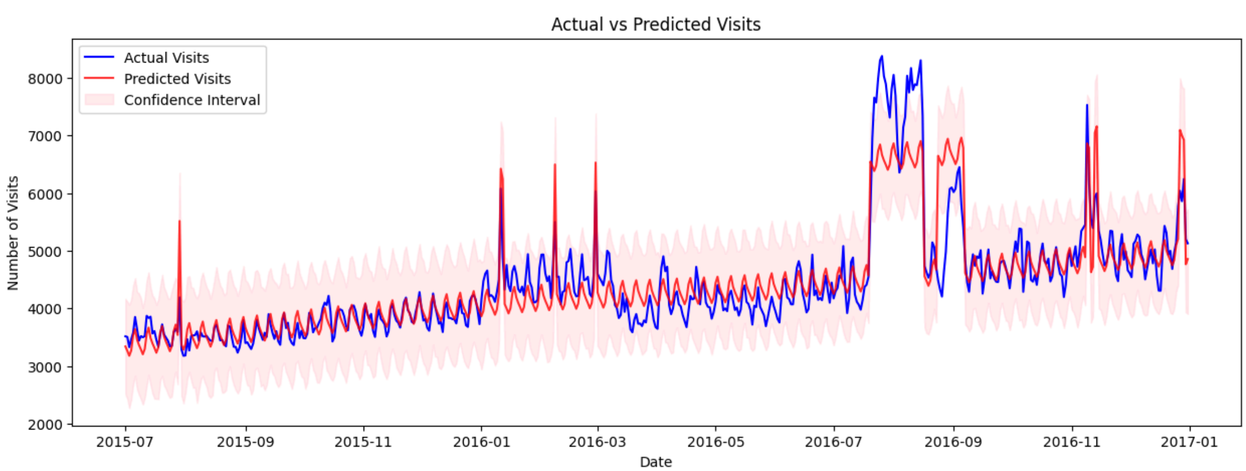
In [57]:

```python
from prophet import Prophet

# Initialize Prophet model with specified parameters
prophet_model = Prophet(
    interval_width=0.95,
    daily_seasonality=False,
    weekly_seasonality=True,
    yearly_seasonality=False
)

# Add external regressor column 'exog'
prophet_model.add_regressor('exog')

# Number of days to forecast (currently zero extension)
forecast_horizon = 0

# Fit the model on the time series data
prophet_model.fit(TS)

# Create a dataframe with future dates for prediction (here, no extension)
future_df = prophet_model.make_future_dataframe(periods=forecast_horizon)

# Add the external regressor values for these dates
future_df['exog'] = TS['exog']

# Predict future values using the model
forecast_df = prophet_model.predict(future_df)

# Merge predictions with original dataset
TS['predicted_visits'] = forecast_df['yhat']
TS['predicted_upper'] = forecast_df['yhat_upper']
TS['predicted_lower'] = forecast_df['yhat_lower']

# Evaluate performance (assuming performance() is defined elsewhere)
(_, _, _) = performance(TS['y'], TS['predicted_visits'], print_metrics=True)
```

```
DEBUG:cmdstanpy:input tempfile: /tmp/tmpgd7uit3m/eb0b0fjl.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpgd7uit3m/9why0zcf.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.11/dist-packages/prophe
t/stan_model/prophet_model.bin', 'random', 'seed=81358', 'data', 'file=/tmp/tmp
gd7uit3m/eb0b0fjl.json', 'init=/tmp/tmpgd7uit3m/9why0zcf.json', 'output', 'fil
e=/tmp/tmpgd7uit3m/prophet_modelkinv7i98/prophet_model-20250809160551.csv', 'me
thod=optimize', 'algorithm=lbfgs', 'iter=10000']
16:05:51 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
16:05:51 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
MAE : 287.417
RMSE : 441.959
MAPE: 0.06
```

In [58]:

```
# Plot actual vs predicted visits with confidence intervals
plt.figure(figsize=(15, 5))
plt.plot(TS['ds'], TS['y'], label='Actual Visits', color='blue')
plt.plot(TS['ds'], TS['predicted_visits'], label='Predicted Visits', color='re
plt.fill_between(
    TS['ds'],
    TS['predicted_lower'],
    TS['predicted_upper'],
    color='pink',
    alpha=0.3,
    label='Confidence Interval'
)

plt.xlabel('Date')
plt.ylabel('Number of Visits')
plt.title('Actual vs Predicted Visits')
plt.legend()
plt.show()
```



Insight

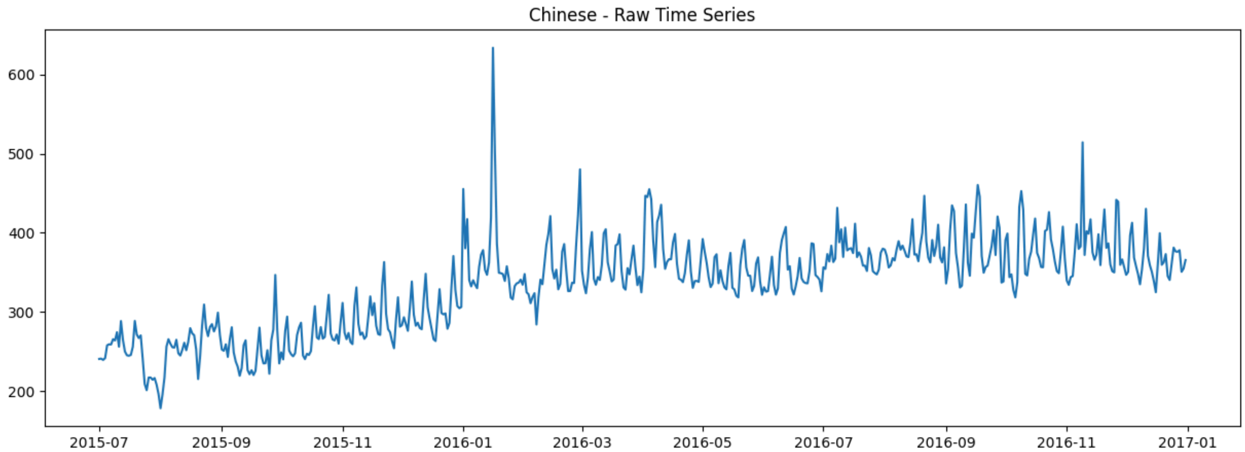
Prophet is doing an incredible job capturing the trend and unusual peaks. It is also capturing the seasonality very well

Comparison

In [59]:
```
from prophet import Prophet

# Prepare exogenous variable as numpy array
exog = Exog_Campaign_eng['Exog'].to_numpy()

# Loop through all language columns (excluding index/date columns)
for lang in df_agg.columns[:-1]:
    print(f"\nProcessing language: {lang}")

    # Step 1: Prepare time series
    TS = df_agg[lang].copy(deep=True)
    fig, ax = plt.subplots(figsize=(15, 5))
    ax.plot(TS.index, TS)
    ax.set_title(f"{lang} - Raw Time Series")
    plt.show()

    # Step 2: Prepare DataFrame for Prophet
    TS = TS.reset_index()
    TS = TS.rename(columns={"index": "ds", lang: "y"})
    TS["ds"] = pd.to_datetime(TS["ds"])

    # Add exogenous variable
    TS["exog"] = exog  # Aligns row-wise with TS

    # Step 3: Fit Prophet model with regressor
    my_model = Prophet(
        interval_width=0.95,
        daily_seasonality=False,
        weekly_seasonality=True,
        yearly_seasonality=False
    )
    my_model.add_regressor("exog")

    my_model.fit(TS)

    # Step 4: Create future dataframe (no extra periods here)
    future_dates = my_model.make_future_dataframe(periods=0)
    future_dates["exog"] = exog  # Must be provided for all prediction points

    forecast = my_model.predict(future_dates)

    # Step 5: Merge predictions
    TS["yhat"] = forecast["yhat"]
    TS["yhat_upper"] = forecast["yhat_upper"]
    TS["yhat_lower"] = forecast["yhat_lower"]

    # Step 6: Evaluate model
    (_, _, _) = performance(TS["y"], TS["yhat"], print_metrics=True)
```

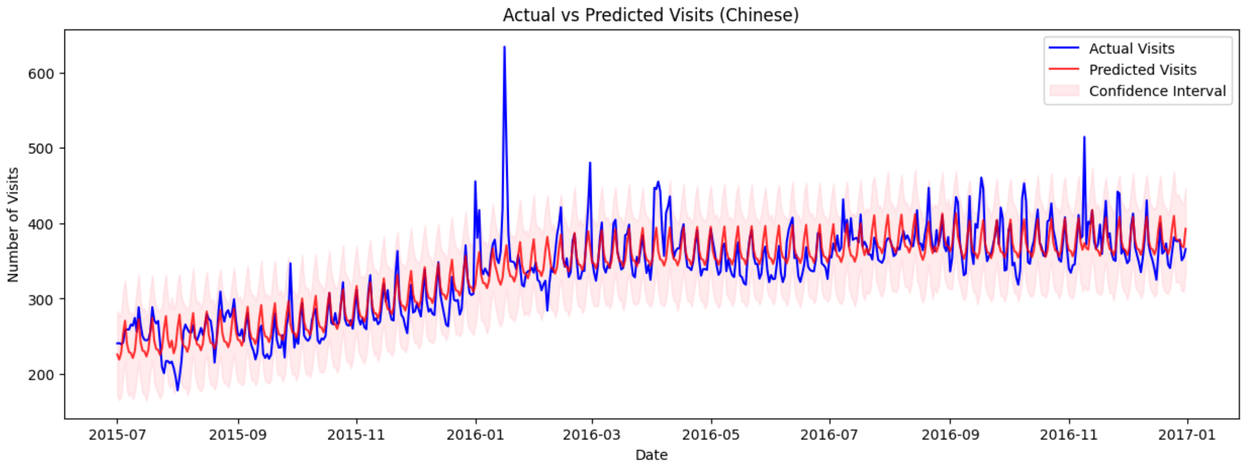
```python
# Step 7: Plot actual vs predicted visits
plt.figure(figsize=(15, 5))
plt.plot(TS["ds"], TS["y"], label="Actual Visits", color="blue")
plt.plot(TS["ds"], TS["yhat"], label="Predicted Visits", color="red", alph
plt.fill_between(
    TS["ds"], TS["yhat_lower"], TS["yhat_upper"],
    color="pink", alpha=0.3, label="Confidence Interval"
)

plt.xlabel("Date")
plt.ylabel("Number of Visits")
plt.title(f"Actual vs Predicted Visits ({lang})")
plt.legend()
plt.show()
```

```
Processing language: Chinese
```

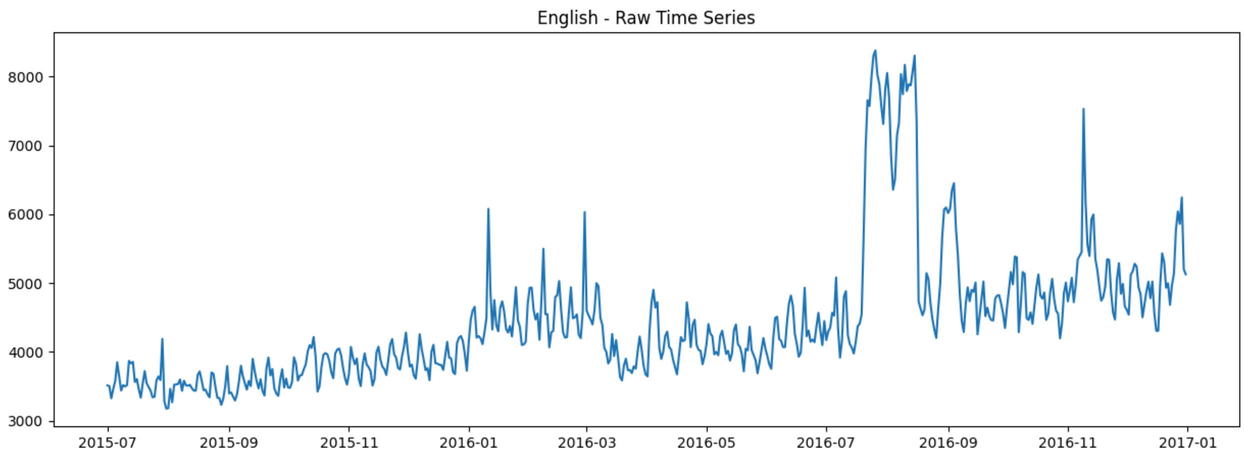



```
DEBUG:cmdstanpy:input tempfile: /tmp/tmpgd7uit3m/vg4s0c2h.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpgd7uit3m/mpjq05uv.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.11/dist-packages/prophe
t/stan_model/prophet_model.bin', 'random', 'seed=29081', 'data', 'file=/tmp/tmp
gd7uit3m/vg4s0c2h.json', 'init=/tmp/tmpgd7uit3m/mpjq05uv.json', 'output', 'fil
e=/tmp/tmpgd7uit3m/prophet_modeldwo4v4pt/prophet_model-20250809160552.csv', 'me
thod=optimize', 'algorithm=lbfgs', 'iter=10000']
16:05:52 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
16:05:52 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
```

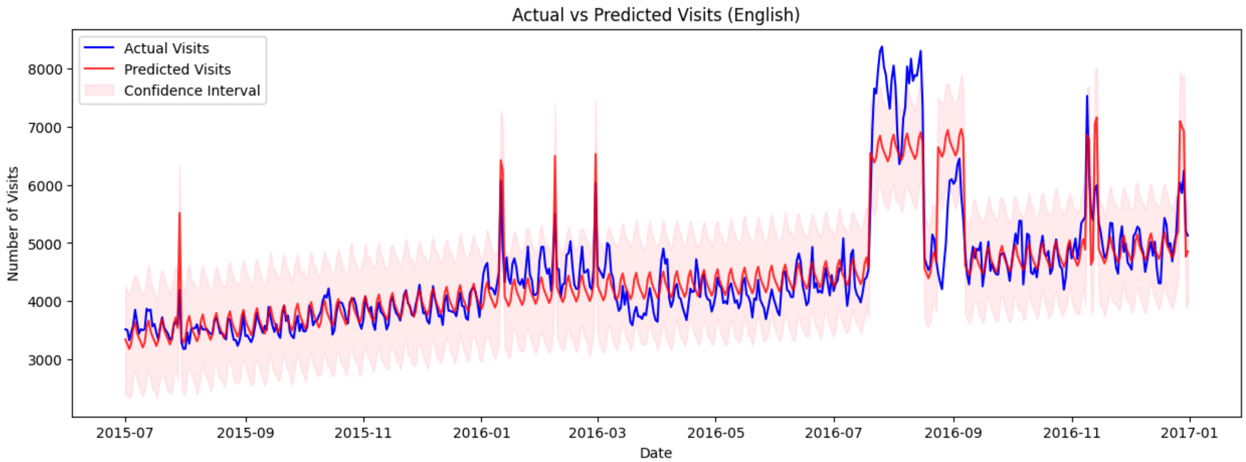
```
MAE : 19.21
RMSE : 28.605
MAPE: 0.058
```



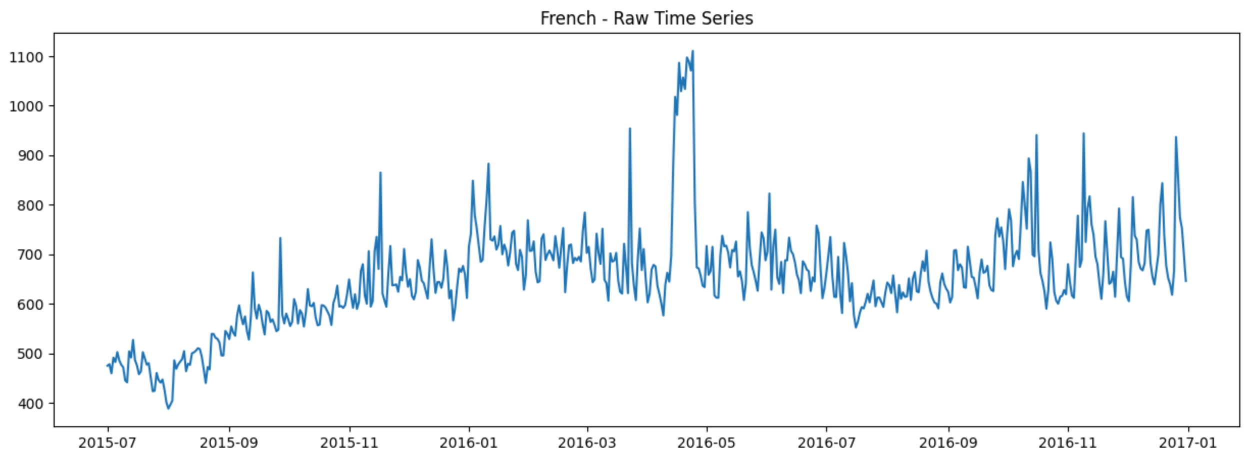

```
Processing language: English
```



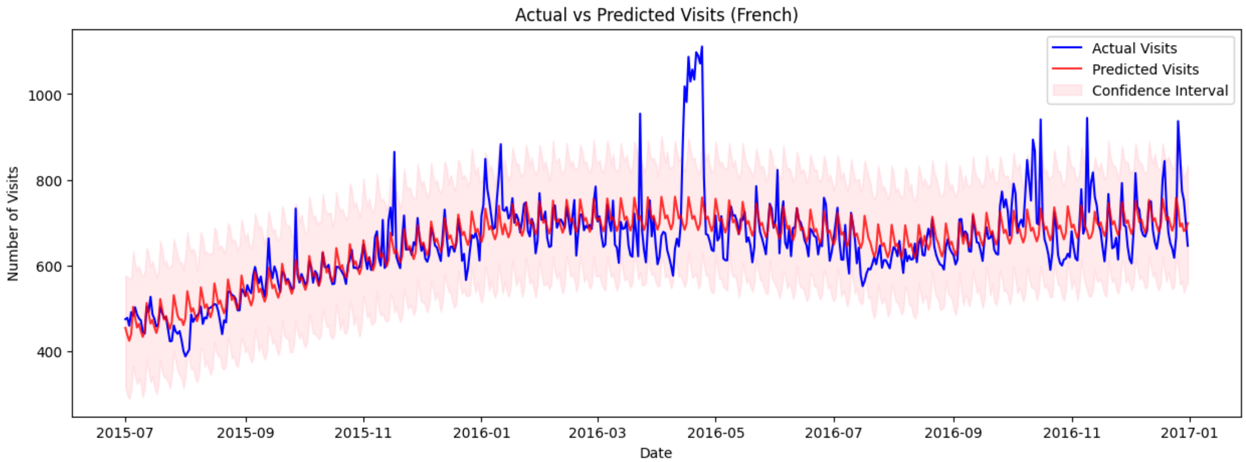

```
DEBUG:cmdstanpy:input tempfile: /tmp/tmpgd7uit3m/_2e2eips.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpgd7uit3m/s5fasmed.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.11/dist-packages/prophe
t/stan_model/prophet_model.bin', 'random', 'seed=39826', 'data', 'file=/tmp/tmp
gd7uit3m/_2e2eips.json', 'init=/tmp/tmpgd7uit3m/s5fasmed.json', 'output', 'fil
e=/tmp/tmpgd7uit3m/prophet_model1br30mu9/prophet_model-20250809160553.csv', 'me
thod=optimize', 'algorithm=lbfgs', 'iter=10000']
16:05:53 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
16:05:53 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
MAE : 287.417
RMSE : 441.959
MAPE: 0.06
```



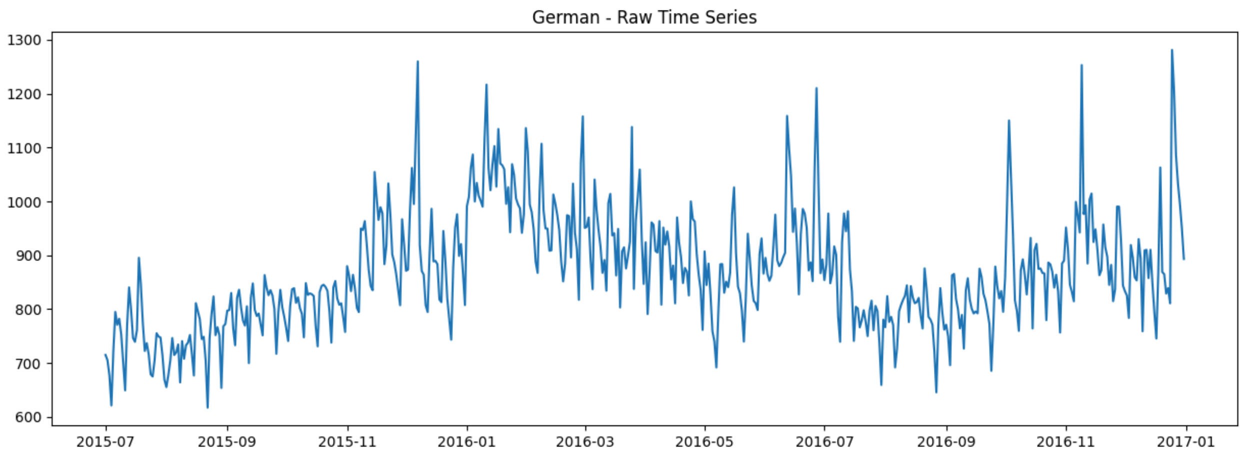

```
Processing language: French
```



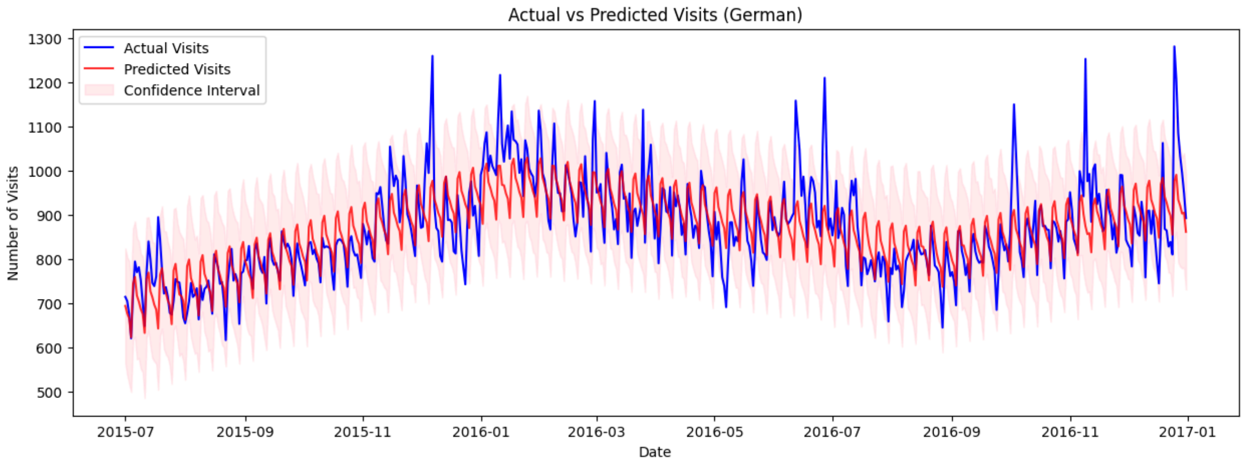

```
DEBUG:cmdstanpy:input tempfile: /tmp/tmpgd7uit3m/b03tn29m.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpgd7uit3m/0y2xqzeg.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.11/dist-packages/prophe
t/stan_model/prophet_model.bin', 'random', 'seed=86439', 'data', 'file=/tmp/tmp
gd7uit3m/b03tn29m.json', 'init=/tmp/tmpgd7uit3m/0y2xqzeg.json', 'output', 'fil
e=/tmp/tmpgd7uit3m/prophet_model9vfqjsp1/prophet_model-20250809160555.csv', 'me
thod=optimize', 'algorithm=lbfgs', 'iter=10000']
16:05:55 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
16:05:55 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
MAE : 41.967
RMSE : 69.101
MAPE: 0.061
```



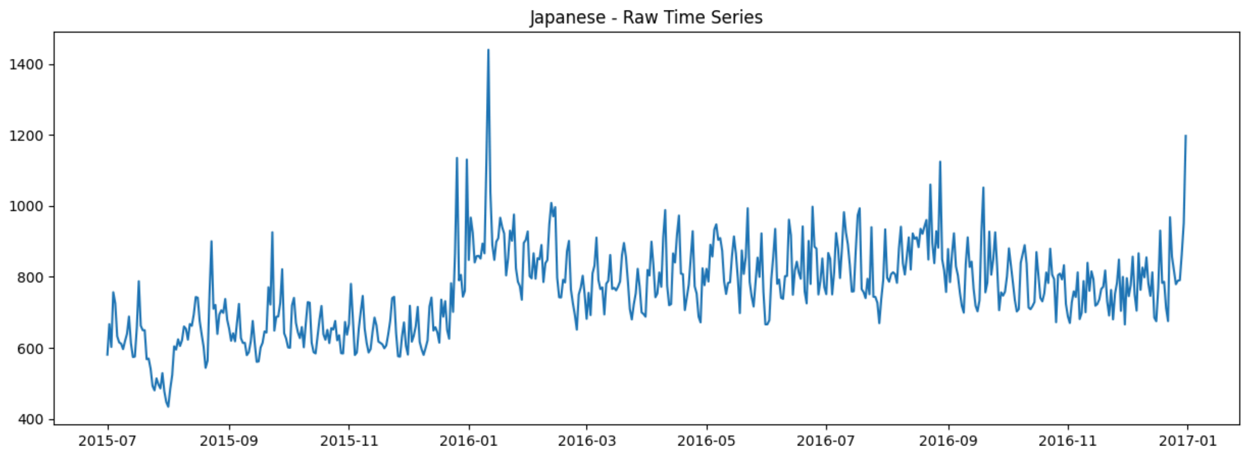
Processing language: German



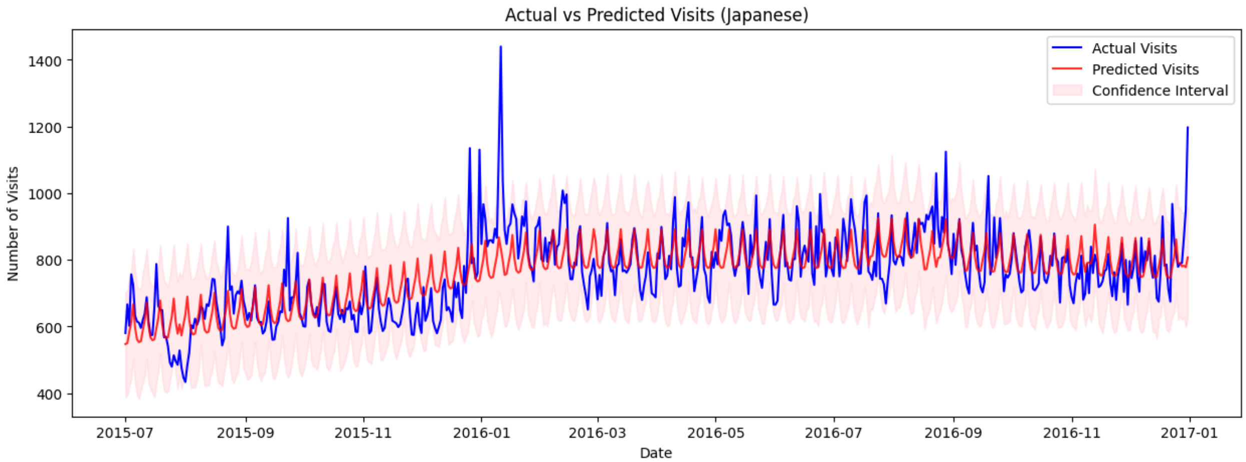

```
DEBUG:cmdstanpy:input tempfile: /tmp/tmpgd7uit3m/qobiztqy.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpgd7uit3m/44gwviwv.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.11/dist-packages/prophe
t/stan_model/prophet_model.bin', 'random', 'seed=84452', 'data', 'file=/tmp/tmp
gd7uit3m/qobiztqy.json', 'init=/tmp/tmpgd7uit3m/44gwviwv.json', 'output', 'fil
e=/tmp/tmpgd7uit3m/prophet_model95_ahrr_/prophet_model-20250809160556.csv', 'me
thod=optimize', 'algorithm=lbfgs', 'iter=10000']
16:05:56 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
16:05:56 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
MAE : 49.19
RMSE : 68.281
MAPE: 0.055
```



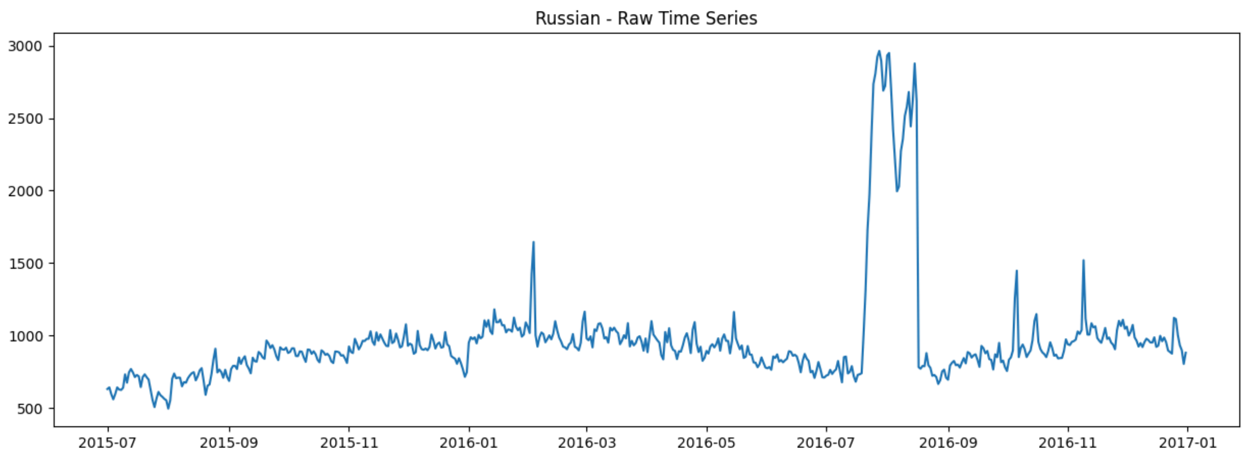
Processing language: Japanese



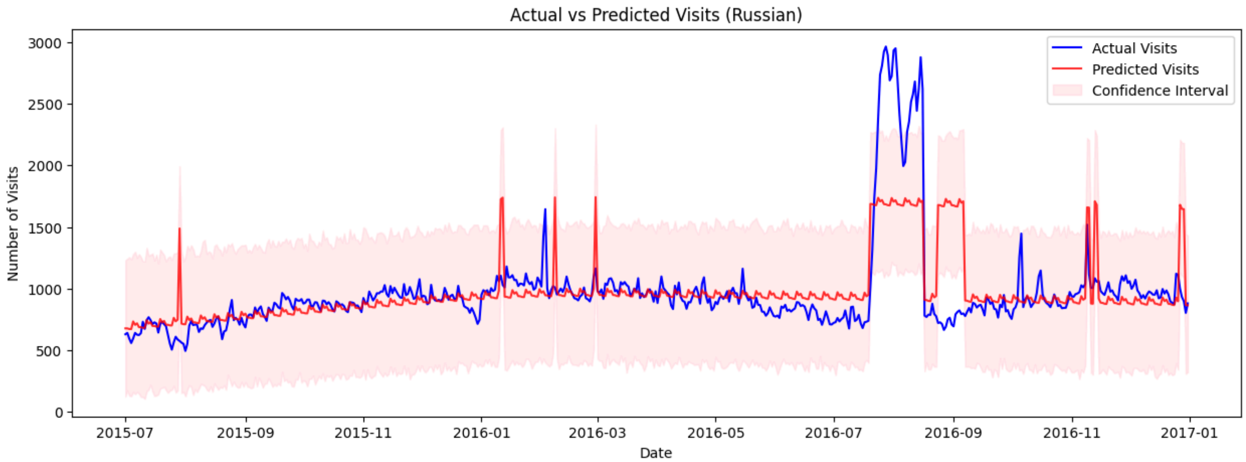

```
DEBUG:cmdstanpy:input tempfile: /tmp/tmpgd7uit3m/pg_997gq.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpgd7uit3m/yp_0ywzg.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.11/dist-packages/prophe
t/stan_model/prophet_model.bin', 'random', 'seed=57463', 'data', 'file=/tmp/tmp
gd7uit3m/pg_997gq.json', 'init=/tmp/tmpgd7uit3m/yp_0ywzg.json', 'output', 'fil
e=/tmp/tmpgd7uit3m/prophet_model42s1ruyc/prophet_model-20250809160558.csv', 'me
thod=optimize', 'algorithm=lbfgs', 'iter=10000']
16:05:58 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
16:05:58 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
MAE : 60.863
RMSE : 83.525
MAPE: 0.08
```



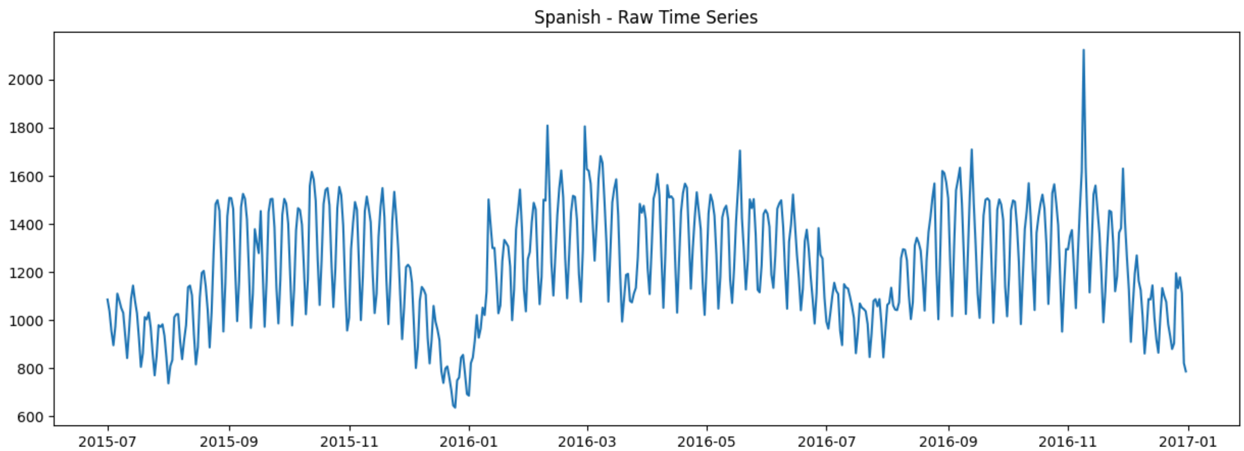

```
Processing language: Russian
```



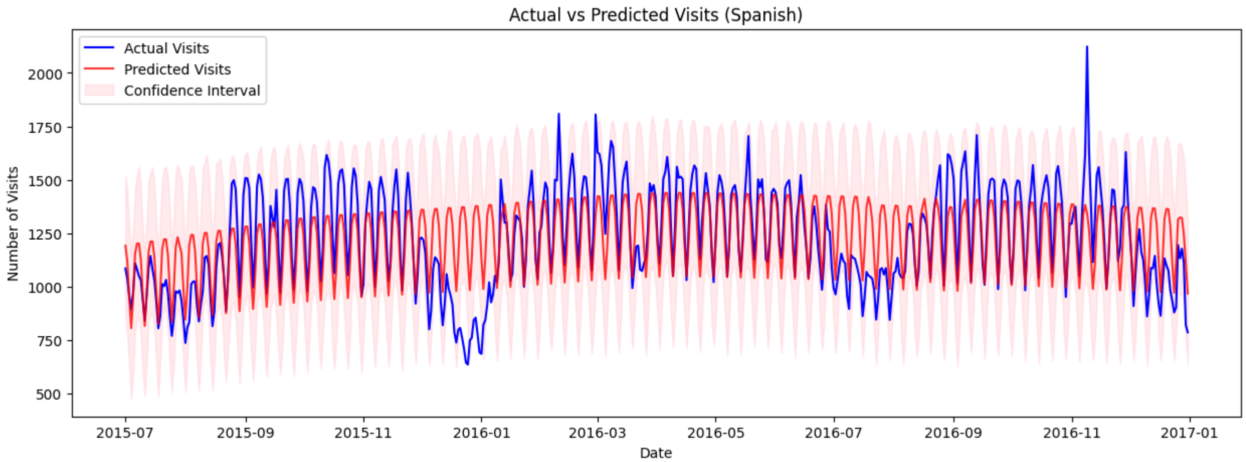

```
DEBUG:cmdstanpy:input tempfile: /tmp/tmpgd7uit3m/w1cvnxcf.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpgd7uit3m/h5z29cf2.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.11/dist-packages/prophe
t/stan_model/prophet_model.bin', 'random', 'seed=24575', 'data', 'file=/tmp/tmp
gd7uit3m/w1cvnxcf.json', 'init=/tmp/tmpgd7uit3m/h5z29cf2.json', 'output', 'fil
e=/tmp/tmpgd7uit3m/prophet_model4suicfgb/prophet_model-20250809160600.csv', 'me
thod=optimize', 'algorithm=lbfgs', 'iter=10000']
16:06:00 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
16:06:00 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
MAE : 148.58
RMSE : 285.614
MAPE: 0.143
```




```
Processing language: Spanish
```




```
DEBUG:cmdstanpy:input tempfile: /tmp/tmpgd7uit3m/wpnn6sur.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpgd7uit3m/_yl6h14g.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.11/dist-packages/prophe
t/stan_model/prophet_model.bin', 'random', 'seed=77789', 'data', 'file=/tmp/tmp
gd7uit3m/wpnn6sur.json', 'init=/tmp/tmpgd7uit3m/_yl6h14g.json', 'output', 'fil
e=/tmp/tmpgd7uit3m/prophet_modelheqdzn8q/prophet_model-20250809160604.csv', 'me
thod=optimize', 'algorithm=lbfgs', 'iter=10000']
16:06:04 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
16:06:04 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
MAE : 133.412
RMSE : 173.281
MAPE: 0.117
```



Insights

- There are 7 known language pages in the dataset - English, Japanese, German,French, Chinese, Russian and Spanish
- English has the maximum number of pages, 16.62%. This is excpected as the maximum people speak English
- Decomposition helps in understanding the underlying trend, seasonality and error(residual) in the time series data.
- As per the analysis done on English language time series data, a differencing of 1 gives a stationary series. This is also tested using Augmented Dickey-Fuller test
- As per the exogenous variable given, the visits to the English page has an unusual peak whenever the exogenous variable is 1
- The performance of AdEase will be effected by events or campaings. AdEase can use the Prophet model along with exogenous variable to improve their predictions Without the exogenous variable, it becomes impossible to make accurate predictions. This is demonstarted by the plots of other languages which do not have exogneous variable

What level of differencing gave you a stationary series?

- Typically, a first-order differencing (d=1) is applied to remove trends and achieve stationarity in many time series. If seasonality is present, seasonal differencing (e.g., differencing at lag 12 for monthly data) may also be required. The exact differencing level depends on tests like the Augmented Dickey-Fuller (ADF) test, but often:

- Non-seasonal differencing (d=1) is enough for most series,

- Seasonal differencing (D=1) at seasonal lag is used for seasonal patterns.

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

- Random Search: Samples parameter combinations randomly, often more efficient than grid search when the parameter space is large.
- Bayesian Optimization: Uses probabilistic models to select promising hyperparameters intelligently, speeding up convergence to the best model.

What does the decomposition of series do?

Decomposition splits a time series into:

- **Trend:** Long-term progression
- **Seasonality:** Repeating patterns at fixed intervals
- **Residual (Noise):** Random fluctuations after removing trend and seasonality

This clarifies underlying patterns and aids modeling.

> **ARIMA**

ARIMA (AutoRegressive Integrated Moving Average) is a forecasting model that handles time series data with trends but without strong seasonality. It is composed of three parts: AR (AutoRegression), which uses past values (lags) of the series to predict the current value; I (Integrated), which differences the series to remove trends and make it stationary; and MA (Moving Average), which uses past forecast errors to improve predictions. Its parameters are p (autoregressive order), d (degree of differencing), and q (moving average order). ARIMA is best used when the data shows a trend but no seasonal cycles, making it a simple and reliable baseline for forecasting—for example, predicting stock prices where seasonal effects are minimal.

> **SARIMA**

SARIMA (Seasonal ARIMA) extends ARIMA by directly modeling seasonality in addition to trends. It retains the non-seasonal terms (p, d, q) from ARIMA and adds seasonal terms (P, D, Q, s), where P is the seasonal autoregressive order, D is the seasonal differencing order, Q is the seasonal moving average order, and s is the number of periods per season (e.g., s=12 for monthly data with yearly seasonality). SARIMA is ideal when data has both trend and strong, repeating seasonal patterns, which ARIMA alone cannot capture. A common use case would be forecasting monthly electricity demand, where usage peaks occur in predictable cycles such as summer and winter.

SARIMAX

SARIMAX (Seasonal ARIMA with eXogenous variables) builds on SARIMA by allowing the inclusion of one or more external variables (exogenous inputs) alongside seasonal modeling. It uses the same seasonal and non-seasonal parameters but adds the “exog” term for extra predictors that can be either continuous or categorical. This is useful when the time series is influenced not only by its own history and seasonality but also by outside factors such as holidays, marketing campaigns, or weather. SARIMAX is best suited for seasonal data where known external variables can improve accuracy, such as forecasting retail sales while accounting for marketing spend, promotional events, or temperature variations.