Business Case: AdEase Time Series

Defining Problem Statement & Data Import

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.

Dataset:

https://drive.google.com/drive/folders/1mdgQscjqnCtdg7LGItomyK0abN6lcHBb

Data Dictionary:

There are two csv files given

- **train_1.csv:** In the csv file, each row corresponds to a particular article and each column corresponds to a particular date. The values are the number of visits on that date.

The page name contains data in this format: SPECIFIC NAME _ LANGUAGE.wikipedia.org _ ACCESS TYPE _ ACCESS ORIGIN having information about the page name, the main domain, the device type used to access the page, and also the request origin(spider or browser agent)

- **Exog_Campaign_eng:** This file contains data for the dates which had a campaign or significant event that could affect the views for that day. The data is just for pages in English.

There's 1 for dates with campaigns and 0 for remaining dates. It is to be treated as an exogenous variable for models when training and forecasting data for pages in English
Concepts Tested:

- Exploratory data analysis
- Time Series forecasting- ARIMA, SARIMAX, and Prophet

Analysing basic metrics

In [1]:
```
# Importing Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import warnings # supress warnings
warnings.filterwarnings('ignore')
```

Importing Data & removing non-relevant columns / duplicates

In [2]:
```
df = pd.read_csv('../Scaler/train_1.csv')
Exog_Campaign_eng = pd.read_csv('../Scaler/Exog_Campaign_eng')
```

In [3]:
```
#creating copy of dataframe for backup
data = df.copy(deep = True)
data.drop_duplicates(keep='last', inplace = True)
```

In [4]:
```
print(f'Shape of Data : {data.shape}')
print('-'*80)
print(f'Shape of exogenous variable : {Exog_Campaign_eng.shape}')
```

```
Shape of Data : (145063, 551)
--------------------------------------------------------------------------------
Shape of exogenous variable : (550, 1)
```

In [5]:
```
data.head()
```

Out[5]:

	Page	2015-07-01	2015-07-02	2015-07-03	2015-07-04	2015-07-05	2015-07-06	201... 07-(
0	2NE1_zh.wikipedia.org_all-access_spider	18.0	11.0	5.0	13.0	14.0	9.0	9
1	2PM_zh.wikipedia.org_all-access_spider	11.0	14.0	15.0	18.0	11.0	13.0	22
2	3C_zh.wikipedia.org_all-access_spider	1.0	0.0	1.0	1.0	0.0	4.0	C
3	4minute_zh.wikipedia.org_all-access_spider	35.0	13.0	10.0	94.0	4.0	26.0	14
4	52_Hz_I_Love_You_zh.wikipedia.org_all-access_s...	NaN	NaN	NaN	NaN	NaN	NaN	Na

5 rows × 551 columns

- Data for 550 Dates (1.5 Years / 18 Months) is provided for all pages

In [6]:
```
data.dtypes
```

Out[6]:
```
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
Length: 551, dtype: object
```

significance of Null Values

In [7]:
```
#Checking count of Null Values after every 25th Column in Data
data.isnull().sum()[range(1,550,25)]
```

Out[7]:
```
2015-07-01    20740
2015-07-26    19865
2015-08-20    18923
2015-09-14    18407
2015-10-09    17771
2015-11-03    15734
2015-11-28    15847
2015-12-23    14647
2016-01-17    13667
2016-02-11    12057
2016-03-07    11485
2016-04-01    10385
2016-04-26     9679
2016-05-21     9216
2016-06-15     8071
2016-07-10     7836
2016-08-04     6917
2016-08-29     6022
2016-09-23     5457
2016-10-18     4858
2016-11-12     4234
2016-12-07     4130
dtype: int64
```

In [8]:
```
#Visualizing Null-values count for all columns
plt.figure(figsize=(15, 8))
data.iloc[:, 1:-3 ].isnull().sum().plot(color='blue', linestyle='dotted')
plt.show()
```

- Above Plot indicates that NaN / Null values are decreasing with Time. Later Dates have less Null Values as compared to Older Dates.
- recent dates have lesser null values that means newer pages will have no data of prior to that page hosting date.
- We will drop the rows where more than 300 null values are present and replace remaining Null Values with 0.

In [9]:
```
data.dropna(thresh = 300, inplace = True)
print(f'Shape of Data : {data.shape}')
```

```
Shape of Data : (133617, 551)
```

In [10]:
```
data.fillna(0, inplace = True)
```

In [11]:
```
#Checking count of Null Values after every 25th Column in Data
data.isnull().sum()[range(1,550,25)]
```

Out[11]:
```
2015-07-01    0
2015-07-26    0
2015-08-20    0
2015-09-14    0
2015-10-09    0
2015-11-03    0
2015-11-28    0
2015-12-23    0
2016-01-17    0
2016-02-11    0
2016-03-07    0
2016-04-01    0
2016-04-26    0
2016-05-21    0
2016-06-15    0
2016-07-10    0
2016-08-04    0
2016-08-29    0
2016-09-23    0
2016-10-18    0
2016-11-12    0
2016-12-07    0
dtype: int64
```

Exploratory Data Analysis & Feature Engineering

Extracting Language , access type and access origin from page

In [12]:
```
# Extracting Language from page
data.Page[0]
```

Out[12]:
```
'2NE1_zh.wikipedia.org_all-access_spider'
```

In [13]:
```
import re
re.findall(r'_(.{2}).wikipedia.org_', "2NE1_zh.wikipedia.org_all-access_spider")
```

Out[13]:
```
['zh']
```

In [14]:
```
data.Page.str.findall(pat="_(.{2}).wikipedia.org_").sample(10)
```

Out[14]:
```
59454     [ja]
4528      [fr]
2199      [zh]
36112     [en]
140509    [de]
112307    [en]
120846    [ja]
100385    [ru]
63316     [zh]
22230       []
Name: Page, dtype: object
```

In [15]:
```
#Function to Extract Language from Page using Regex
def get_language(name):
    if len(re.findall(r'_(.{2}).wikipedia.org_', name)) == 1 :
```

```
        return re.findall(r'_(.{2}).wikipedia.org_', name)[0]
    else: return 'Unknown'
```

In [16]:
```
data['language'] = data['Page'].apply(get_language)
```

In [17]:
```
data["language"].unique()
```

Out[17]:
```
array(['zh', 'fr', 'en', 'Unknown', 'ru', 'de', 'ja', 'es'], dtype=object)
```

In [18]:
```
language_dict ={'de':'German',
                'en':'English',
                'es': 'Spanish',
                'fr': 'French',
                'ja': 'Japenese' ,
                'ru': 'Russian',
                'zh': 'Chinese',
                'Unknown': 'Unknown_language'}

data['language'] = data['language'].map(language_dict)
```

In [19]:
```
data["language"].unique()
```

Out[19]:
```
array(['Chinese', 'French', 'English', 'Unknown_language', 'Russian',
       'German', 'Japenese', 'Spanish'], dtype=object)
```

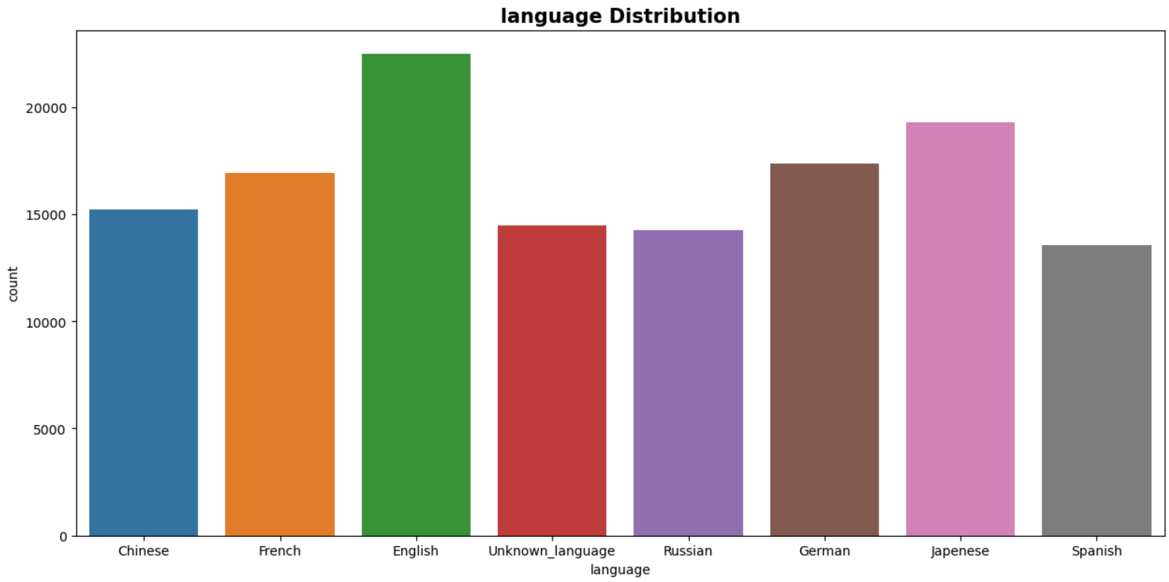
In [20]:
```
data.head()
```

Out[20]:

	Page	2015-07-01	2015-07-02	2015-07-03	2015-07-04	2015-07-05	2015-07-06	2015-07-07	2015 07-0
0	2NE1_zh.wikipedia.org_all-access_spider	18.0	11.0	5.0	13.0	14.0	9.0	9.0	22.(
1	2PM_zh.wikipedia.org_all-access_spider	11.0	14.0	15.0	18.0	11.0	13.0	22.0	11.(
2	3C_zh.wikipedia.org_all-access_spider	1.0	0.0	1.0	1.0	0.0	4.0	0.0	3.(
3	4minute_zh.wikipedia.org_all-access_spider	35.0	13.0	10.0	94.0	4.0	26.0	14.0	9.(
5	5566_zh.wikipedia.org_all-access_spider	12.0	7.0	4.0	5.0	20.0	8.0	5.0	17.(

5 rows × 552 columns

In [21]:
```
#Visualizing distribution of various languages
y = 'language'

plt.figure(figsize=(15, 7))
sns.countplot(x=data['language'] , data=data)
plt.title(f' {y} Distribution')
plt.xlabel(f'{y}')
plt.ylabel('count')
plt.title(f'{y} Distribution', fontsize = 15, fontweight = 'bold')
plt.show()
```



In [22]:
```
# unique value Language column(listed in %)
Language = data["language"].value_counts(normalize=True).map(lambda calc: round(
Language.columns = ['Language', 'Count']
Language
```

Out[22]:

	Language	Count
0	English	16.83
1	Japenese	14.44
2	German	12.99
3	French	12.68
4	Chinese	11.38
5	Unknown_language	10.85
6	Russian	10.68
7	Spanish	10.14

- 10.85% of pages have unknown language.
- 16.83% of all pages are in English which is highest.

In [23]:
```
data.loc[data['language'] == 'Unknown_language', 'Page'].sample(100).head(10)
```

Out[23]:
```
42918    Topic:Rlqs29fxd74rxtpo_www.mediawiki.org_deskt...
14376    File:Seal_of_the_President_of_the_United_State...
23209    API:Errors_and_warnings_www.mediawiki.org_mobi...
13795    Category:Vintage_photographs_of_nude_males_com...
45264    Category:Nude_girls_commons.wikimedia.org_all-...
45610    File:Olympic_rings_without_rims.svg_commons.wi...
21633    Help:Contents/he_www.mediawiki.org_mobile-web_...
45789    Category:Bollywood_films_commons.wikimedia.org...
44881    File:Speaker_Icon.svg_commons.wikimedia.org_al...
15740    File:English_Pokémon_logo.svg_commons.wikimedi...
Name: Page, dtype: object
```

- Around 10.85% of rows (~14k) don't have Language information

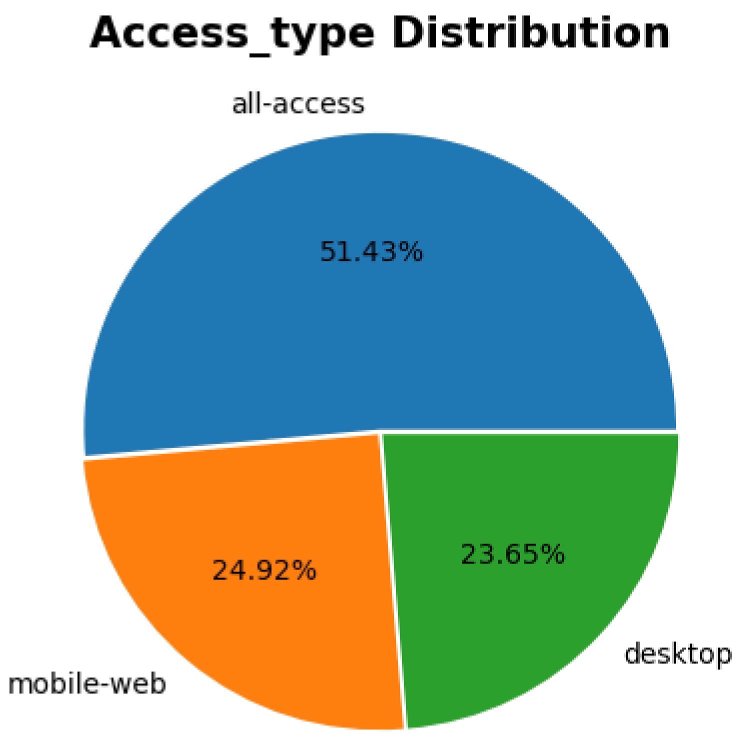
In [24]:
```
#Function to Extract Access Type from Page using Regex
def get_access_type(name):
    if len(re.findall(r'all-access|mobile-web|desktop', name)) == 1 :
        return re.findall(r'all-access|mobile-web|desktop', name)[0]
    else: return 'No Access_type'

data['Access_type'] = data['Page'].apply(get_access_type)
```

In [25]:
```
# unique value Access_Type column(listed in %)
Access_type = data["Access_type"].value_counts(normalize=True).map(lambda calc:
Access_type.columns = ['Access_type', 'Count']
Access_type
```

Out[25]:

	Access_type	Count
0	all-access	51.43
1	mobile-web	24.92
2	desktop	23.65

In [26]:
```
#Visualizing Access types Distribution
var = 'Access_type'
x = data[var].value_counts().values
y = data[var].value_counts().index

plt.pie(x, labels = y, autopct='%.2f%%',  explode = [0.01,0.01,0.01])
plt.title(f'{var} Distribution', fontsize = 15, fontweight = 'bold')
plt.show()
```



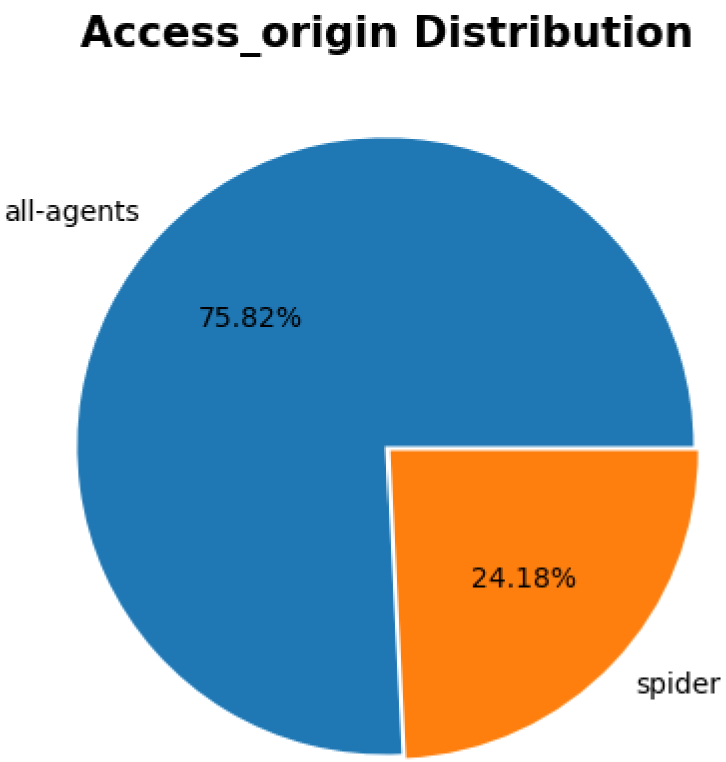
In [27]:
```
#Function to Extract Access Origin from Page using Regex
def get_access_origin(name):
    if len(re.findall(r'[ai].org_(.*)_(.*)$', name)) == 1 :
        return re.findall(r'[ai].org_(.*)_(.*)$', name)[0][1]
    else: return 'No Access_origin'

data['Access_origin'] = data['Page'].apply(get_access_origin)
```

In [28]:
```
# unique value Access_origin column(listed in %)
Access_origin = data["Access_origin"].value_counts(normalize=True).map(lambda ca
Access_origin.columns = ['Access_origin', 'Count']
Access_origin
```

Out[28]:

	Access_origin	Count
0	all-agents	75.82
1	spider	24.18

In [29]:
```
#Visualizing Access types Distribution
var = 'Access_origin'
x = data[var].value_counts().values
y = data[var].value_counts().index

plt.figure(figsize=(6, 5))
plt.pie(x, labels = y, autopct='%.2f%%',  explode = [0.01,0.01])
plt.title(f'{var} Distribution', fontsize = 15, fontweight = 'bold')
plt.show()
```



Data Pre-processing

mean page visit per language

In [30]:
```
data_language = pd.DataFrame()
data_language = data.groupby('language').mean().transpose()
data_language.drop(['Unknown_language'], inplace = True, axis = 1)
data_language.reset_index(inplace = True)
data_language.set_index('index', inplace = True)
data_language.head()
```

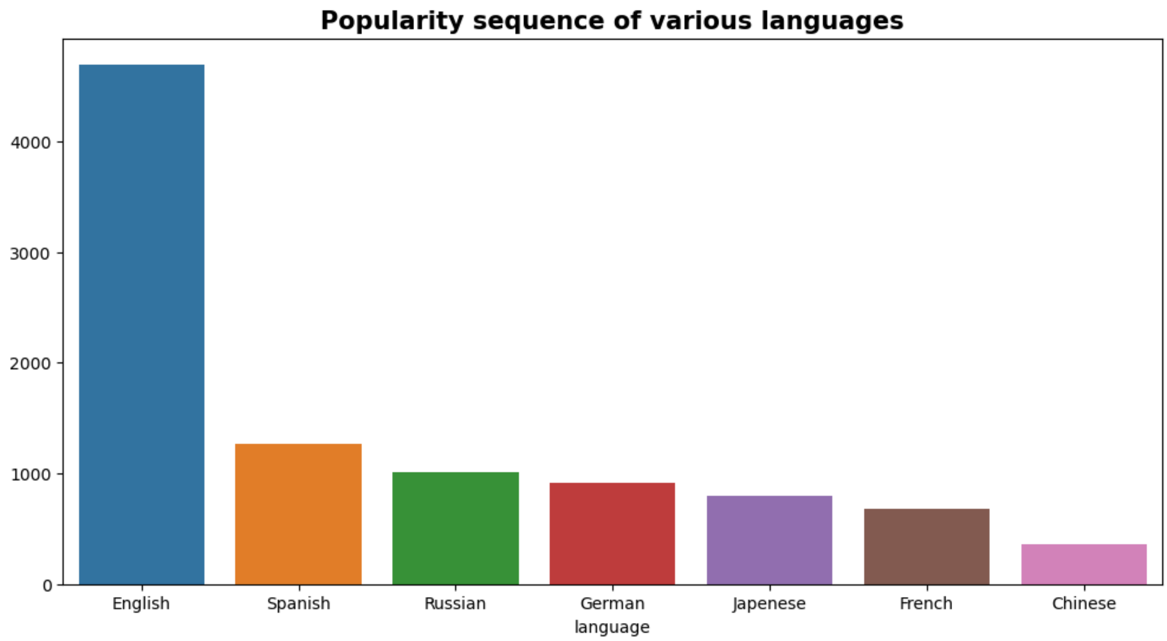
Out[30]:

language	Chinese	English	French	German	Japenese	Russian	
index							
2015-07-01	272.498521	3767.328604	499.092872	763.765926	614.637160	663.199229	112
2015-07-02	272.906778	3755.158765	502.297852	753.362861	705.813216	674.677015	107
2015-07-03	271.097167	3565.225696	483.007553	723.074415	637.451671	625.329783	99
2015-07-04	273.712379	3711.782932	516.275785	663.537323	800.897435	588.171829	93
2015-07-05	291.977713	3833.433025	506.871666	771.358657	768.352319	626.385354	101

In [31]:
```
data_language.info()
```

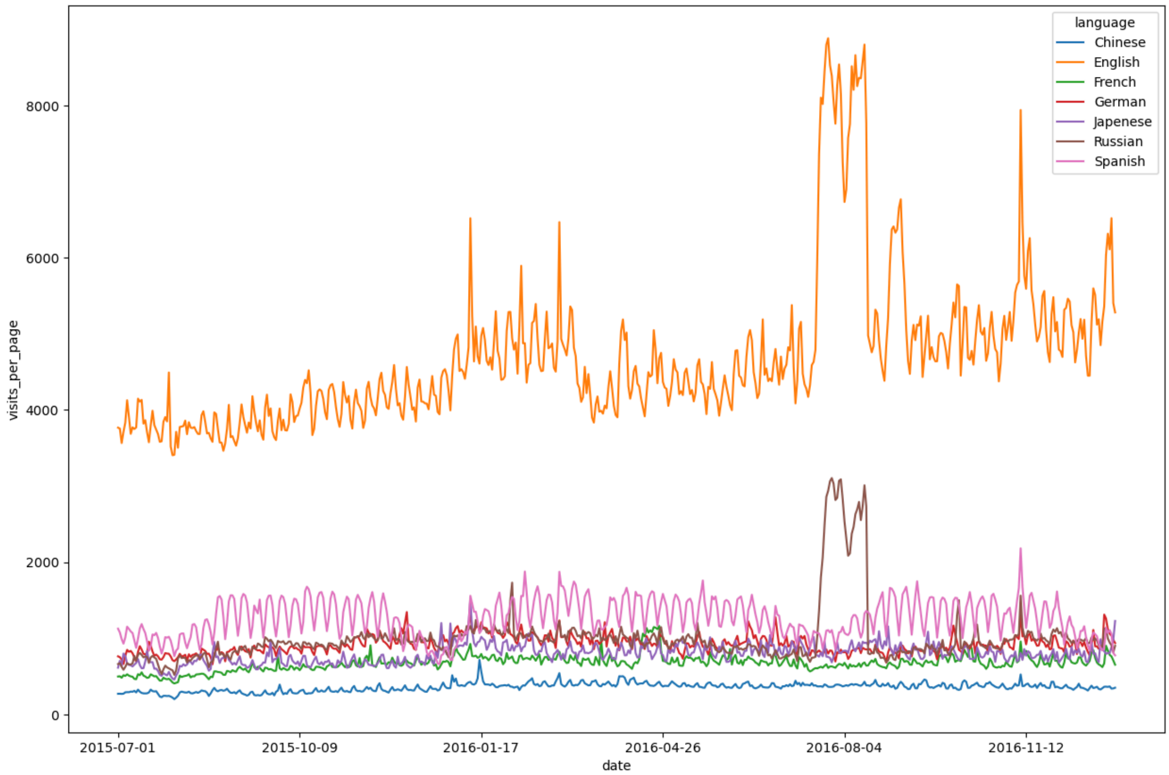
```
<class 'pandas.core.frame.DataFrame'>
Index: 550 entries, 2015-07-01 to 2016-12-31
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Chinese   550 non-null    float64
 1   English   550 non-null    float64
 2   French    550 non-null    float64
 3   German    550 non-null    float64
 4   Japenese  550 non-null    float64
 5   Russian   550 non-null    float64
 6   Spanish   550 non-null    float64
dtypes: float64(7)
memory usage: 34.4+ KB
```

In [32]:
```
x = data_language.mean().sort_values(ascending = False).index
y = data_language.mean().sort_values(ascending = False).values

plt.figure(figsize=(12, 6))
sns.barplot(x = x,y =y)
plt.title(f'Popularity sequence of various languages', fontsize = 15, fontweight
plt.show()

## Popularity sequence of various languages : English > Spanish > Russian > Germ
```



Visualising Time Series for each languages

In [33]:
```
data_language.plot(label = data_language.columns,  figsize=(15, 10))
plt.xlabel("date")
plt.ylabel("visits_per_page")
plt.show()
```



Hypothesis Testing : if Time Series is Stationary or Trending using ADF (Augmented Dickey Fuller) Test:

- Null Hypothesis: The series is Non-Stationary
- Alternative Hypothesis: The series is Stationary
- significant value : 0.05 (alpha)
- if p-value > 0.05 : we failed to reject Null hypothesis:
    - That means the series is Non-Stationart
- if p-value <= 0.05: we reject Null Hypothesis
    - that means the time series in Stationary

In [35]:
```
import statsmodels.api as sm
def Dickey_Fuller_test(ts,significances_level = 0.05):
    p_value = sm.tsa.stattools.adfuller(ts)[1]
    if p_value <= significances_level:
        print("Time Series is Stationary")
    else:
        print("Time Series is NOT Stationary")
    print("P_value is: ", p_value)
```

In [36]:
```
for Language in data_language.columns:
  print(Language)
  print(Dickey_Fuller_test(data_language[Language],significances_level = 0.05))
  print()
  print()
```

```
Chinese
Time Series is NOT Stationary
P_value is:  0.3219384419565085
None


English
Time Series is NOT Stationary
P_value is:  0.14933749437355304
None


French
Time Series is Stationary
P_value is:  0.04296020201712812
None


German
Time Series is NOT Stationary
P_value is:  0.1400503200836024
None


Japenese
Time Series is NOT Stationary
P_value is:  0.07231258891845853
None


Russian
Time Series is Stationary
P_value is:  0.0017632662037633297
None


Spanish
Time Series is Stationary
P_value is:  0.04215053463615071
None
```

- Based on DickeyFuller test of Stationarity , we can observe French, Spanish and Russian languages Pages visits Time series are stationary.
- Chinese, English , German and Japanese are not stationary.

In [37]:
```python
# Further analysing Time Series for English Language Pages Visits :
TS_English = data_language.English
```

In [38]:
```python
#define function for ADF test
from statsmodels.tsa.stattools import adfuller
def adf_test(timeseries):
    print ('Results of Dickey-Fuller Test:')
    dftest = adfuller(timeseries, autolag='AIC')
    df_output = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags
    for key, value in dftest[4].items():
```

```
        df_output['Critical Value (%s)' %key] = value
    print (df_output)
```

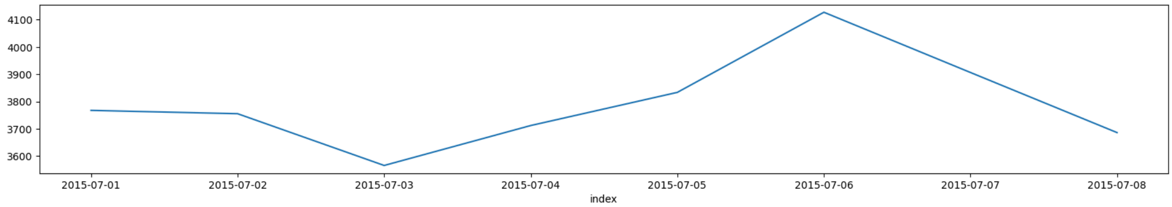
In [39]:
```
#apply adf test on the series
adf_test(TS_English)
```

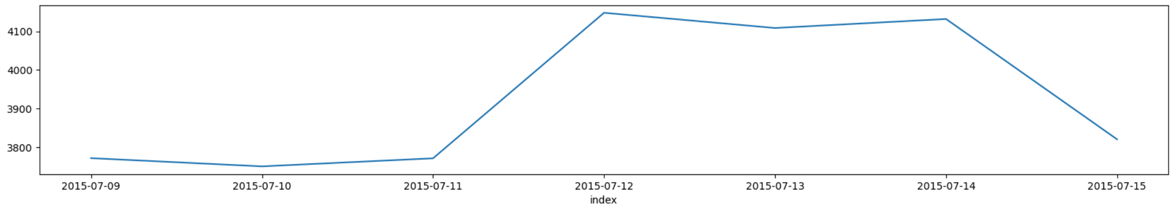
```
Results of Dickey-Fuller Test:
Test Statistic                   -2.373563
p-value                           0.149337
#Lags Used                       14.000000
Number of Observations Used     535.000000
Critical Value (1%)              -3.442632
Critical Value (5%)              -2.866957
Critical Value (10%)             -2.569655
dtype: float64
```

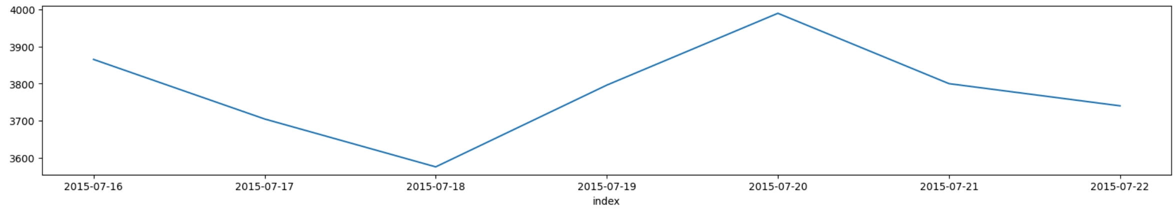
- The test statistic > critical value / p_value > 5%.
- This implies that the series is not stationary.

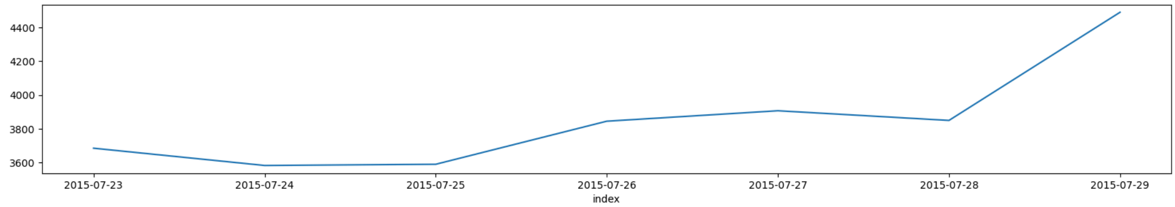
Visualising English-Language Page Visits Time Series manually to identify seasonality and period

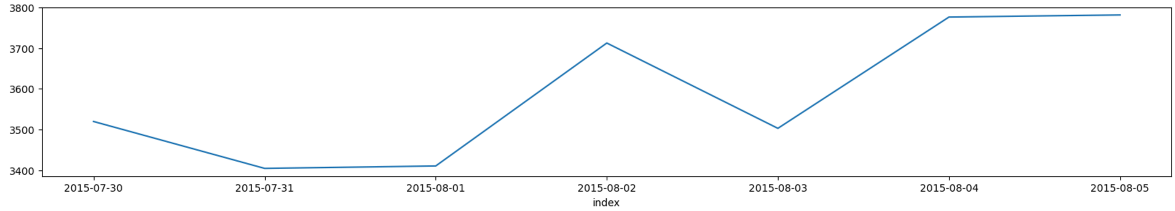
In [40]:
```
plt.rcParams['figure.figsize'] = (20, 3)

TS_English[:8].plot()
plt.show()
TS_English[8:15].plot()
plt.show()
TS_English[15:22].plot()
plt.show()
TS_English[22:29].plot()
plt.show()
TS_English[29:36].plot()
plt.show()

TS_English[36:44].plot()
plt.show()
```

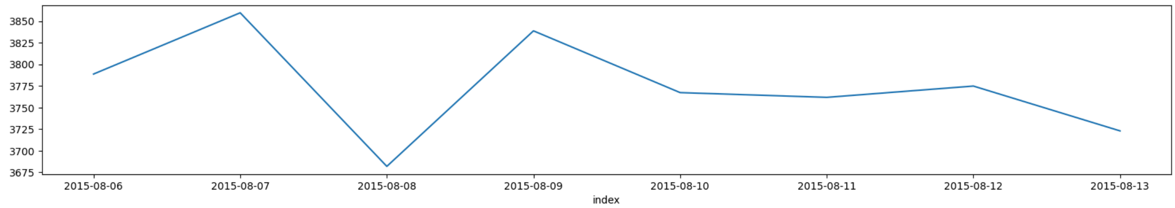












In [41]:
```
correlations = []
for lag in range(1,30):
    present = TS_English[:-lag]
    past = TS_English.shift(-lag)[:-lag]
    corrs = np.corrcoef(present,past)[0][-1]
    print(lag,corrs)
    correlations.append(corrs)
```

```
1 0.9323258278620723
2 0.8605292614028011
3 0.8077278834799054
4 0.7714189806436796
5 0.7459471144093537
6 0.7371736771608727
7 0.7196991121158116
8 0.6689152573297469
9 0.6118380346312797
10 0.5743417993048073
11 0.554221239588739
12 0.5524322164036987
13 0.5722332092818787
14 0.5862794221805331
15 0.5683714328504221
16 0.5394957974018174
17 0.5180411465322313
18 0.5060807942249275
19 0.5111672452810425
20 0.522914434987449
21 0.5211517980871624
22 0.47391333853885614
23 0.41521040939999526
24 0.3702991226846805
25 0.33878104260208974
26 0.3209256187415589
27 0.3274071758868405
28 0.33341032818913385
29 0.3139433435132756
```

Decomposing Time Series

In this case we have used Additive Model for deconstructing the time series. The term additive means individual components (trend, seasonality, and residual) are added together as shown in equation below:

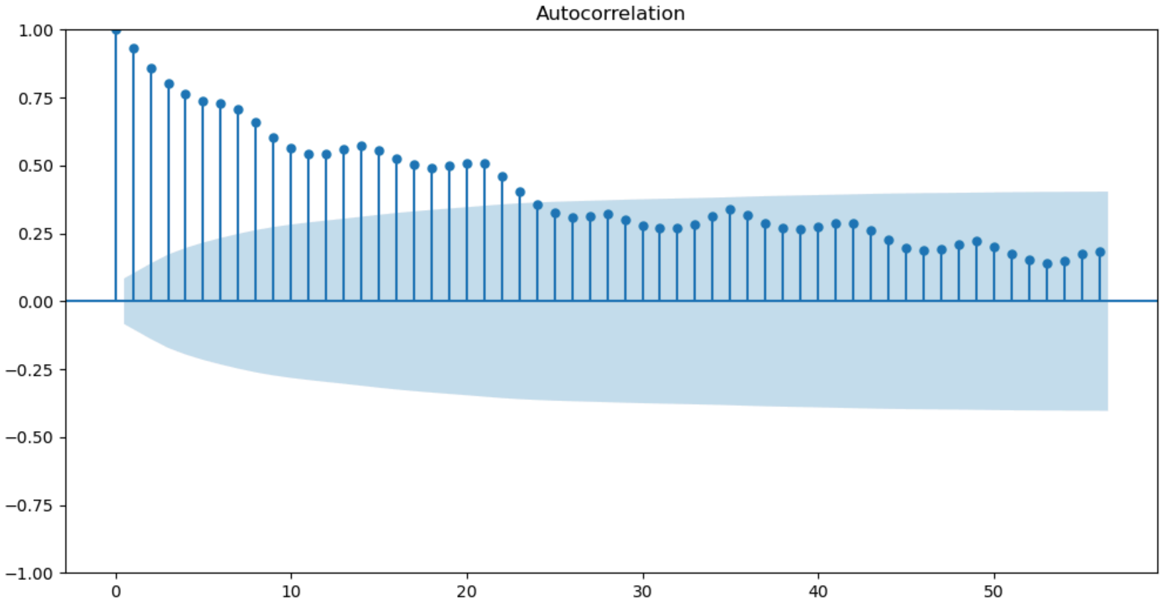
$y_t = T_t + S_t + R_t$

where

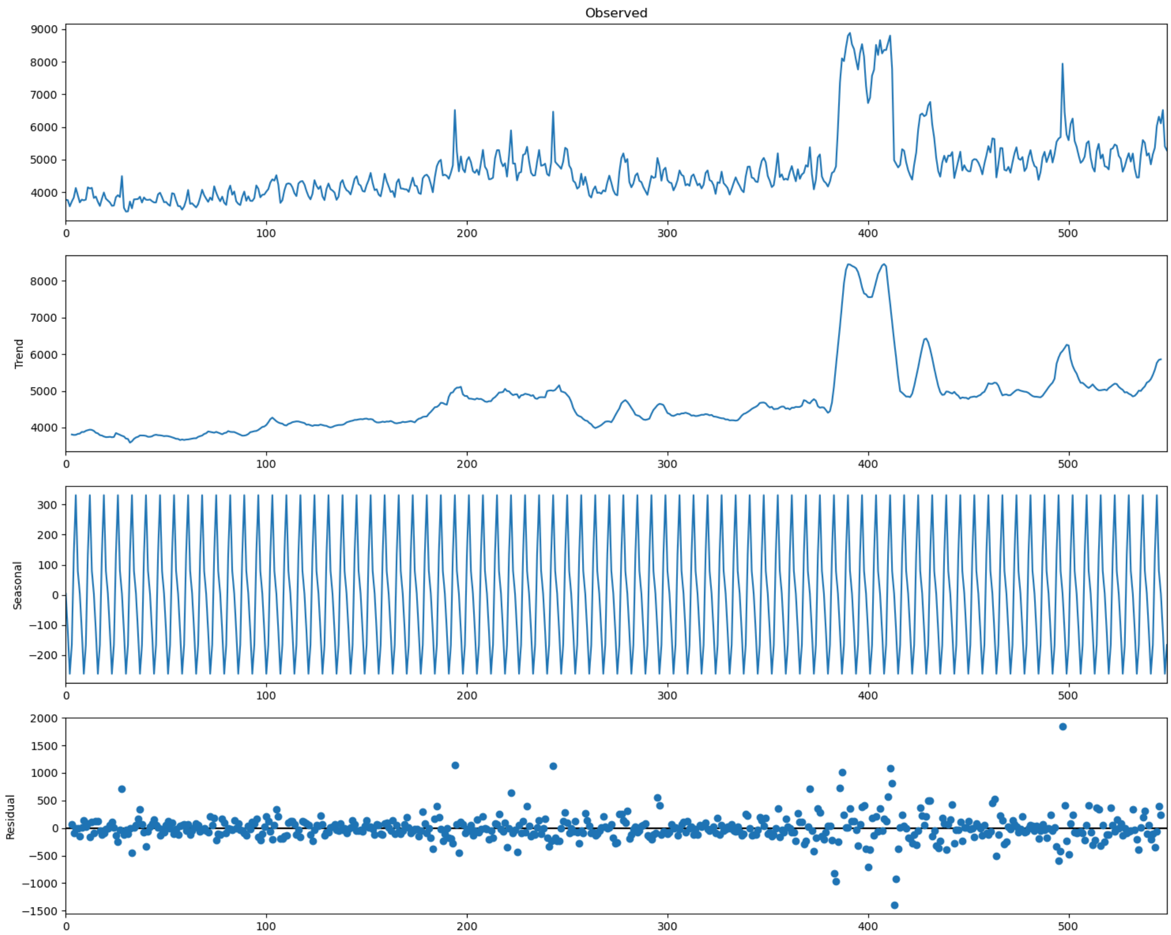
- y_t = actual value in time series
- T_t = trend in time series
- S_t = seasonality in time series
- R_t = residuals of time series

In [42]:

```
# using auto correlation function plot , to varify the period

from statsmodels.graphics.tsaplots import plot_acf,plot_pacf

plt.rcParams['figure.figsize'] = (12, 6)
plot_acf(TS_English,lags=56);
```




```
In [43]: ts_english = data_language.English.values
         from statsmodels.tsa.seasonal import seasonal_decompose
         decomposition = seasonal_decompose(ts_english, model='additive', period=7)

         fig = decomposition.plot()
         fig.set_size_inches((15, 12))
         fig.tight_layout()
         plt.show()
```




```
In [44]: residual = pd.DataFrame(decomposition.resid).fillna(0)[0].values
         adf_test(residual)
```

```
Results of Dickey-Fuller Test:
Test Statistic                 -1.152195e+01
p-value                         4.020092e-21
#Lags Used                      1.700000e+01
Number of Observations Used     5.320000e+02
Critical Value (1%)            -3.442702e+00
Critical Value (5%)            -2.866988e+00
Critical Value (10%)           -2.569672e+00
dtype: float64
```

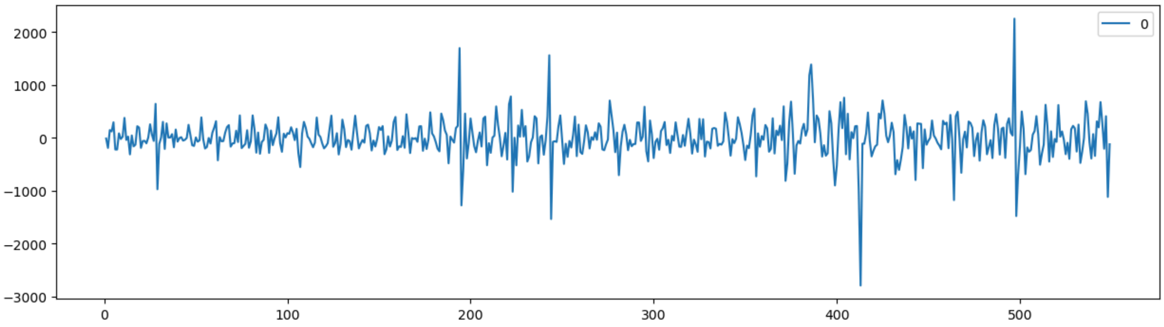
- **The test statistic < critical value / p_value < 5%.**

From ADF (Augmented Dickey Fuller) Test it can be shown that **Residuals** from time-series decomposition is **Stationary**

Estimating (p,q,d) & Interpreting ACF and PACF plots

In [45]:
```
ts_diff = pd.DataFrame(ts_english).diff(1)
ts_diff.dropna(inplace = True)
```

In [46]:
```
ts_diff.plot(figsize=(15, 4))
plt.show()
```



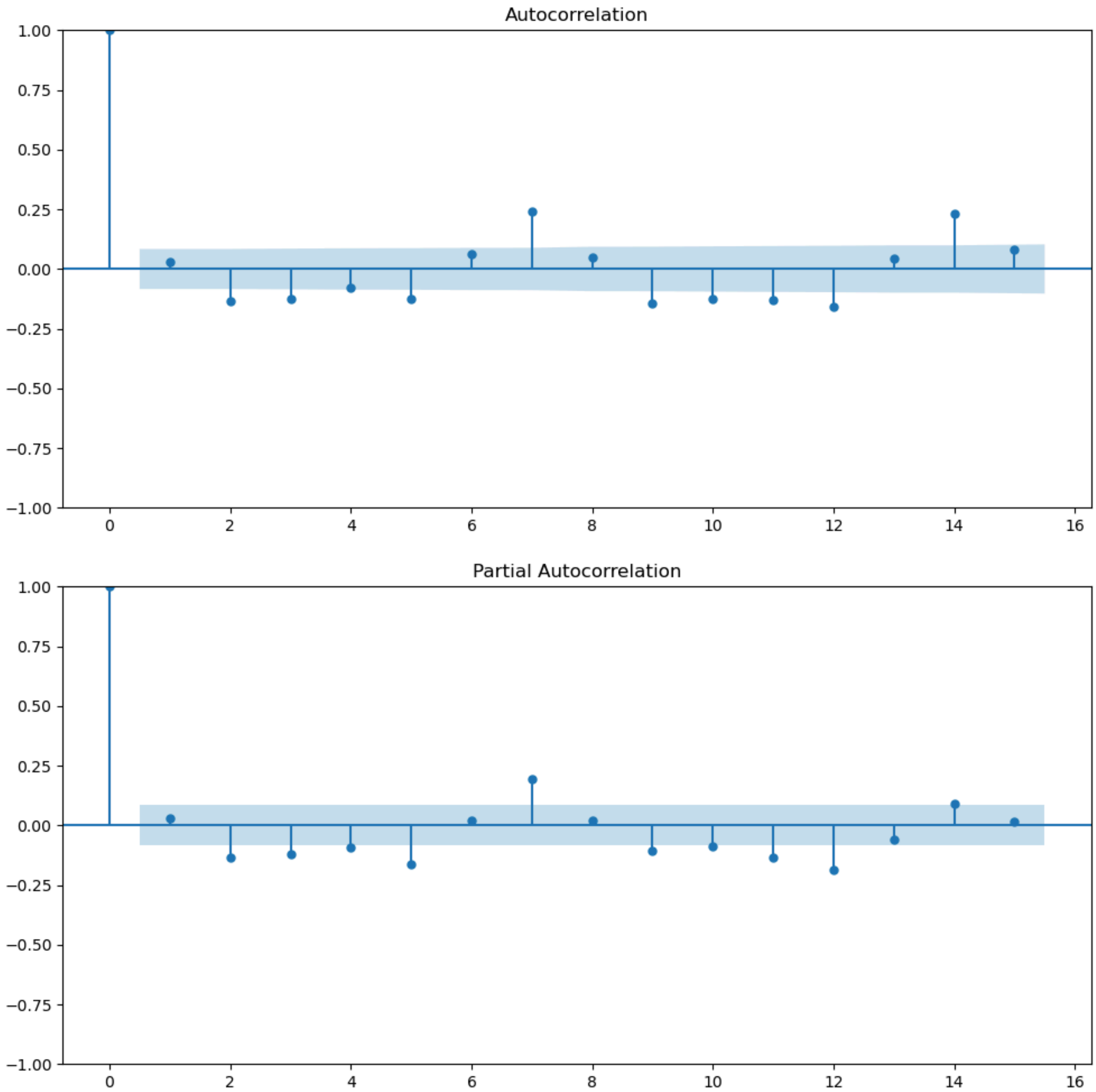
In [47]:
```
#ADF Test for differenced time-series
adf_test(ts_diff)
#p_value < 5%  ==> time series is stationary
```

```
Results of Dickey-Fuller Test:
Test Statistic                 -8.273590e+00
p-value                         4.721272e-13
#Lags Used                      1.300000e+01
Number of Observations Used     5.350000e+02
Critical Value (1%)            -3.442632e+00
Critical Value (5%)            -2.866957e+00
Critical Value (10%)           -2.569655e+00
dtype: float64
```

- After one differencing time-series becomes stationary. This indicates for ARIMA model, we can set d = 1.

In [48]:
```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

acf = plot_acf(ts_diff, lags= 15)
acf.set_size_inches((10, 5))
```

```
acf.tight_layout()
pacf = plot_pacf(ts_diff, lags= 15)
pacf.set_size_inches((10, 5))
pacf.tight_layout()
```



- ACF & PACF indicates we should choose p = 0 & q = 0. But we will start with p=1 & q=1 for base ARIMA Model

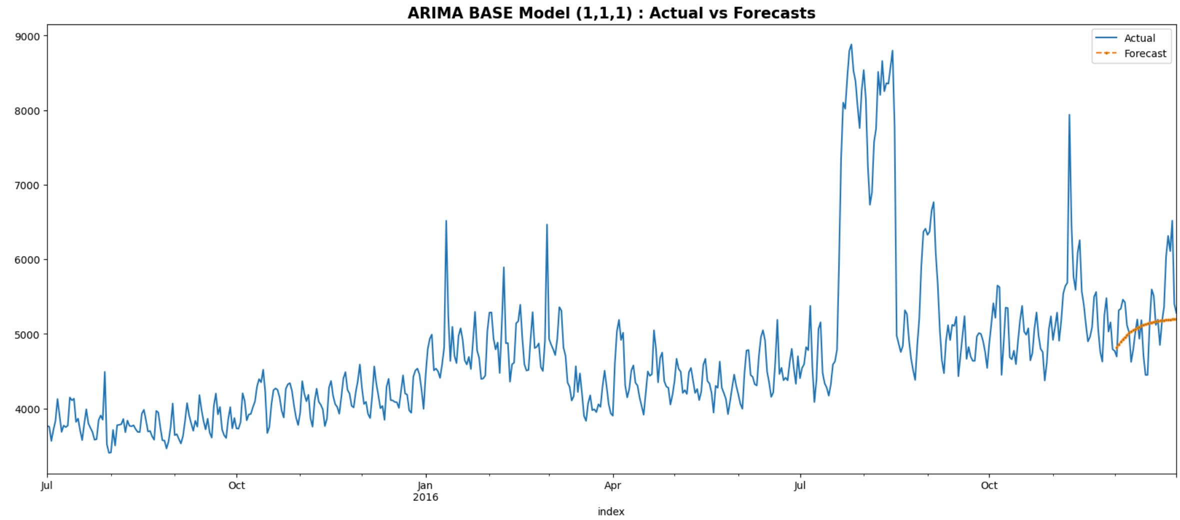
Forecasting Model Creation

ARIMA Base Model

In [49]:
```
from statsmodels.tsa.arima.model import ARIMA

import warnings # supress warnings
warnings.filterwarnings('ignore')

n = 30
time_series = data_language.English.copy(deep = True)
#Creating Base ARIMA Model with order(1,1,1)
model = ARIMA(time_series[:-n], order =(1,1,1))
```

```
model_fit = model.fit()

#Creating forecast for last n-values
forecast = model_fit.forecast(steps = n, alpha = 0.05)
```

In [50]:
```
#plotting Actual & Forecasted values
time_series.index = time_series.index.astype('datetime64[ns]')
forecast.index = forecast.index.astype('datetime64[ns]')
plt.figure(figsize = (20,8))
time_series.plot(label = 'Actual')
forecast.plot(label = 'Forecast', linestyle='dashed', marker='o',markerfacecolor
plt.legend(loc="upper right")
plt.title('ARIMA BASE Model (1,1,1) : Actual vs Forecasts', fontsize = 15, fontw
plt.show()
```



In [51]:
```
#Calculating MAPE & RMSE
actuals = time_series.values[-n:]
errors = time_series.values[-n:] - forecast.values

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

print(f'MAPE of Model : {np.round(mape,5)}')
print('-'*80)
print(f'RMSE of Model : {np.round(rmse,3)}')
```

```
MAPE of Model : 0.06691
--------------------------------------------------------------------------------
RMSE of Model : 496.72
```

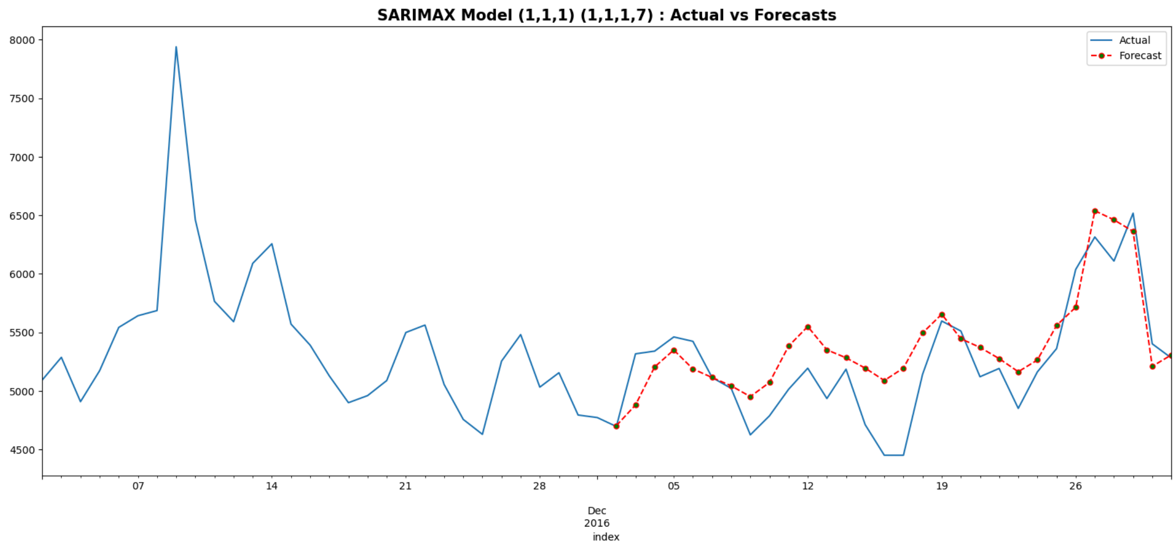
- ARIMA Base model has ~6% MAPE and RMSE ~ 500.

Creation for function for SARIMAX model

In [52]:
```
from statsmodels.tsa.statespace.sarimax import SARIMAX

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

    #Creating SARIMAX Model with order(p,d,q) & seasonal_order=(P, D, Q, s)
    model = SARIMAX(time_series[:-n], \
                    order =(p,d,q),
```

```
                        seasonal_order=(P, D, Q, s),
                        exog = exog[:-n],
                        initialization='approximate_diffuse')
    model_fit = model.fit()

    #Creating forecast for last n-values
    model_forecast = model_fit.forecast(n, dynamic = True, exog = pd.DataFrame(e

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

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

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

    print(f'MAPE of Model : {np.round(mape,5)}')
    print('-'*80)
    print(f'RMSE of Model : {np.round(rmse,3)}')
```

In [53]:
```
#Checking a SARIMAX model with seasonality (p,d,q,P,D,Q,s = 1,1,1,1,1,1,7)
exog = Exog_Campaign_eng['Exog'].to_numpy()
time_series = data_language.English
test_size= 0.1
p,d,q, P,D,Q,s = 1,1,1,1,1,1,7
n = 30
sarimax_model(time_series, n, p=p, d=d, q=q, P=P, D=D, Q=Q, s=s, exog = exog)
```




```
MAPE of Model : 0.04848
--------------------------------------------------------------------------------
RMSE of Model : 305.342
```

- SIMPLE SARIMAX model has ~4.9% MAPE and RMSE ~ 300.

- Impact of Seasonality & exogenous variable was captured properly in this model.

Searching for best parameters for SARIMAX model

Finding Best parameters for 'English' Pages

In [54]:
```
def sarimax_grid_search(time_series, n, param, d_param, s_param, exog = []):
    counter = 0
    #creating df for storing results summary
    param_df = pd.DataFrame(columns = ['serial','pdq', 'PDQs', 'mape', 'rmse'])

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

                                #Creating forecast from Model
                                model_forecast = model_fit.forecast(n, dynamic =

                                #Calculating errors for results
                                actuals = time_series.values[-n:]
                                errors = time_series.values[-n:] - model_forecas

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

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

                #print statement to check progress of Loop
                print(f'Possible Combination: {counter} out of { (len(param)**4)

    return param_df
```

In [55]:
```
#Long time to execute
#Finding best parameters for English time series
exog = Exog_Campaign_eng['Exog'].to_numpy()
time_series = data_language.English
n = 30
```

```
param = [0,1,2]
d_param = [0,1]
s_param = [7]

english_params  = sarimax_grid_search(time_series, n, param, d_param,s_param, ex
```

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

In [56]:
```
english_params.sort_values(['mape', 'rmse']).head()
```

Out[56]:

	serial	pdq	PDQs	mape	rmse
196	197	(1, 1, 1)	(2, 1, 1, 7)	0.04192	272.593
41	42	(0, 0, 2)	(0, 1, 2, 7)	0.04325	287.492
317	318	(2, 1, 2)	(1, 1, 2, 7)	0.04333	276.101
46	47	(0, 0, 2)	(1, 1, 1, 7)	0.04334	285.221
47	48	(0, 0, 2)	(1, 1, 2, 7)	0.04347	286.642

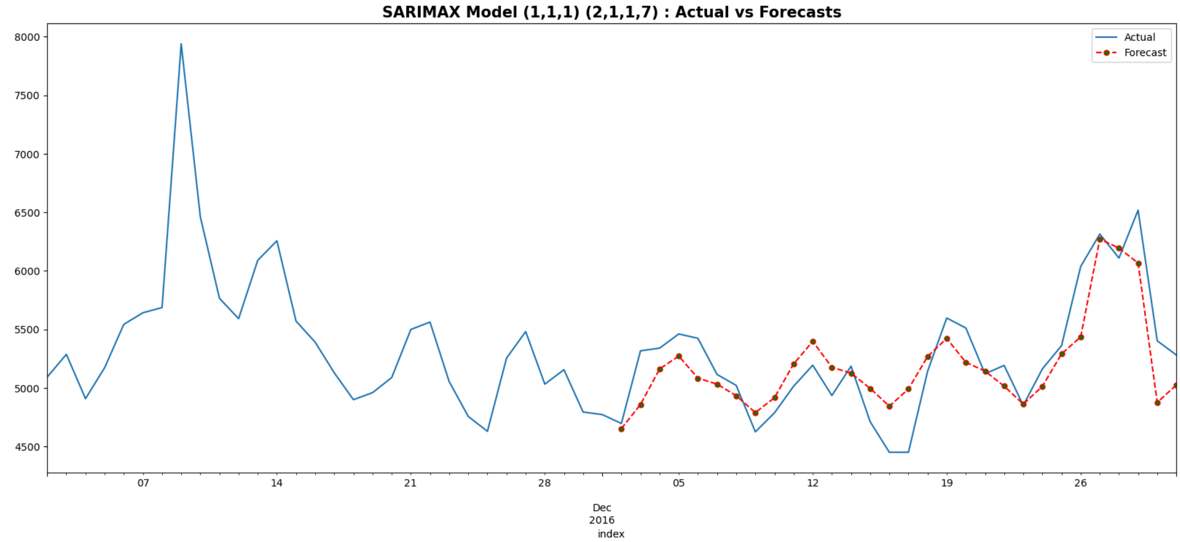
- Best Possible parameters English Time Series are pdq = (1, 1, 1) & PDQs = (2, 1, 1, 7).
- Minimum MAPE = 4.189% and corresponding RMSE = 272.188.

In [57]:
```
#Function to fetch best parameters for each language

def pipeline_sarimax_grid_search_without_exog(languages, data_language, n, param

    best_param_df  = pd.DataFrame(columns = ['language','p','d', 'q', 'P','D','Q
    for lang in languages:
        print('')
        print('')
        print(f'--------------------------------------------------------------')
        print(f'          Finding best parameters for {lang}                 ')
        print(f'--------------------------------------------------------------')
        counter = 0
        time_series = data_language[lang]
        #creating df for storing results summary
        #param_df = pd.DataFrame(columns = ['serial','pdq', 'PDQs', 'mape', 'rms
        best_mape = 100
```

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

                                    #Creating forecast from Model
                                    model_forecast = model_fit.forecast(n, dynam

                                    #Calculating errors for results
                                    actuals = time_series.values[-n:]
                                    errors = time_series.values[-n:] - model_for

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

                                    counter += 1

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

                        #print statement to check progress of Loop
                        print(f'Possible Combination: {counter} out of {(len(param)*

        best_mape = np.round(best_mape, 5)
        print(f'---------------------------------------------------------------')
        print(f'Minimum MAPE for {lang} = {best_mape}')
        print(f'Corresponding Best Parameters are {best_p , best_d, best_q, best
        print(f'---------------------------------------------------------------')

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

    return best_param_df
```

In [58]:

```
#Plotting the SARIMAX model corresponding to best parameters
exog = Exog_Campaign_eng['Exog'].to_numpy()
time_series = data_language.English
p,d,q, P,D,Q,s = 1,1,1, 2,1,1,7
n = 30
sarimax_model(time_series, n, p=p, d=d, q=q, P=P, D=D, Q=Q, s=s, exog = exog)
```




```
MAPE of Model : 0.04192
--------------------------------------------------------------------------------
RMSE of Model : 272.593
```

Creating Pipeline to search Best parameters for all Page

In [59]:
```
#long time to execute
#calculating best parameters for all languages
languages = ['Chinese', 'French', 'German', 'Japenese', 'Russian', 'Spanish']
n = 30
param = [0,1,2]
d_param = [0,1]
s_param = [7]

best_param_df = pipeline_sarimax_grid_search_without_exog(languages, data_langua
```

```
--------------------------------------------------------------
          Finding best parameters for Chinese
--------------------------------------------------------------
Possible Combination: 18 out of 324 calculated
Possible Combination: 36 out of 324 calculated
Possible Combination: 54 out of 324 calculated
Possible Combination: 72 out of 324 calculated
Possible Combination: 90 out of 324 calculated
Possible Combination: 108 out of 324 calculated
Possible Combination: 126 out of 324 calculated
Possible Combination: 144 out of 324 calculated
Possible Combination: 162 out of 324 calculated
Possible Combination: 180 out of 324 calculated
Possible Combination: 198 out of 324 calculated
Possible Combination: 216 out of 324 calculated
Possible Combination: 234 out of 324 calculated
Possible Combination: 252 out of 324 calculated
Possible Combination: 270 out of 324 calculated
Possible Combination: 288 out of 324 calculated
Possible Combination: 306 out of 324 calculated
Possible Combination: 324 out of 324 calculated
--------------------------------------------------------------
Minimum MAPE for Chinese = 0.03352
Corresponding Best Parameters are (0, 1, 1, 0, 0, 2, 7)
--------------------------------------------------------------


--------------------------------------------------------------
          Finding best parameters for French
--------------------------------------------------------------
Possible Combination: 18 out of 324 calculated
Possible Combination: 36 out of 324 calculated
Possible Combination: 54 out of 324 calculated
Possible Combination: 72 out of 324 calculated
Possible Combination: 90 out of 324 calculated
Possible Combination: 108 out of 324 calculated
Possible Combination: 126 out of 324 calculated
Possible Combination: 144 out of 324 calculated
Possible Combination: 162 out of 324 calculated
Possible Combination: 180 out of 324 calculated
Possible Combination: 198 out of 324 calculated
Possible Combination: 216 out of 324 calculated
Possible Combination: 234 out of 324 calculated
Possible Combination: 252 out of 324 calculated
Possible Combination: 270 out of 324 calculated
Possible Combination: 288 out of 324 calculated
Possible Combination: 306 out of 324 calculated
Possible Combination: 324 out of 324 calculated
--------------------------------------------------------------
Minimum MAPE for French = 0.05989
Corresponding Best Parameters are (0, 0, 2, 2, 1, 2, 7)
--------------------------------------------------------------


--------------------------------------------------------------
          Finding best parameters for German
--------------------------------------------------------------
Possible Combination: 18 out of 324 calculated
Possible Combination: 36 out of 324 calculated
```

```
Possible Combination: 54 out of 324 calculated
Possible Combination: 72 out of 324 calculated
Possible Combination: 90 out of 324 calculated
Possible Combination: 108 out of 324 calculated
Possible Combination: 126 out of 324 calculated
Possible Combination: 144 out of 324 calculated
Possible Combination: 162 out of 324 calculated
Possible Combination: 180 out of 324 calculated
Possible Combination: 198 out of 324 calculated
Possible Combination: 216 out of 324 calculated
Possible Combination: 234 out of 324 calculated
Possible Combination: 252 out of 324 calculated
Possible Combination: 270 out of 324 calculated
Possible Combination: 288 out of 324 calculated
Possible Combination: 306 out of 324 calculated
Possible Combination: 324 out of 324 calculated
--------------------------------------------------------------
Minimum MAPE for German = 0.06553
Corresponding Best Parameters are (2, 1, 0, 0, 1, 1, 7)
--------------------------------------------------------------


--------------------------------------------------------------
          Finding best parameters for Japenese
--------------------------------------------------------------
Possible Combination: 18 out of 324 calculated
Possible Combination: 36 out of 324 calculated
Possible Combination: 54 out of 324 calculated
Possible Combination: 72 out of 324 calculated
Possible Combination: 90 out of 324 calculated
Possible Combination: 108 out of 324 calculated
Possible Combination: 126 out of 324 calculated
Possible Combination: 144 out of 324 calculated
Possible Combination: 162 out of 324 calculated
Possible Combination: 180 out of 324 calculated
Possible Combination: 198 out of 324 calculated
Possible Combination: 216 out of 324 calculated
Possible Combination: 234 out of 324 calculated
Possible Combination: 252 out of 324 calculated
Possible Combination: 270 out of 324 calculated
Possible Combination: 288 out of 324 calculated
Possible Combination: 306 out of 324 calculated
Possible Combination: 324 out of 324 calculated
--------------------------------------------------------------
Minimum MAPE for Japenese = 0.07279
Corresponding Best Parameters are (0, 0, 2, 2, 0, 2, 7)
--------------------------------------------------------------


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

```
Possible Combination: 162 out of 324 calculated
Possible Combination: 180 out of 324 calculated
Possible Combination: 198 out of 324 calculated
Possible Combination: 216 out of 324 calculated
Possible Combination: 234 out of 324 calculated
Possible Combination: 252 out of 324 calculated
Possible Combination: 270 out of 324 calculated
Possible Combination: 288 out of 324 calculated
Possible Combination: 306 out of 324 calculated
Possible Combination: 324 out of 324 calculated
--------------------------------------------------------------
Minimum MAPE for Russian = 0.05261
Corresponding Best Parameters are (1, 0, 2, 2, 0, 1, 7)
--------------------------------------------------------------



--------------------------------------------------------------
          Finding best parameters for Spanish
--------------------------------------------------------------
Possible Combination: 18 out of 324 calculated
Possible Combination: 36 out of 324 calculated
Possible Combination: 54 out of 324 calculated
Possible Combination: 72 out of 324 calculated
Possible Combination: 90 out of 324 calculated
Possible Combination: 108 out of 324 calculated
Possible Combination: 126 out of 324 calculated
Possible Combination: 144 out of 324 calculated
Possible Combination: 162 out of 324 calculated
Possible Combination: 180 out of 324 calculated
Possible Combination: 198 out of 324 calculated
Possible Combination: 216 out of 324 calculated
Possible Combination: 234 out of 324 calculated
Possible Combination: 252 out of 324 calculated
Possible Combination: 270 out of 324 calculated
Possible Combination: 288 out of 324 calculated
Possible Combination: 306 out of 324 calculated
Possible Combination: 324 out of 324 calculated
--------------------------------------------------------------
Minimum MAPE for Spanish = 0.08209
Corresponding Best Parameters are (0, 1, 0, 2, 1, 0, 7)
--------------------------------------------------------------
```

In [60]:
```python
best_param_df.sort_values(['mape'], inplace = True)
best_param_df
```

Out[60]:

	language	p	d	q	P	D	Q	s	mape
0	Chinese	0	1	1	0	0	2	7	0.03352
4	Russian	1	0	2	2	0	1	7	0.05261
1	French	0	0	2	2	1	2	7	0.05989
2	German	2	1	0	0	1	1	7	0.06553
3	Japenese	0	0	2	2	0	2	7	0.07279
5	Spanish	0	1	0	2	1	0	7	0.08209

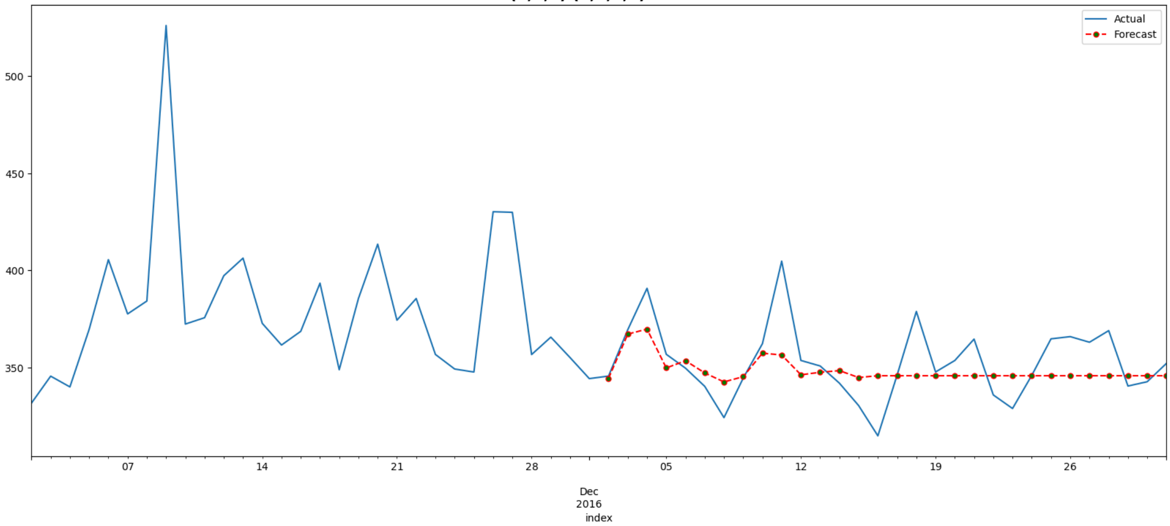
In [61]:
```
#Function to plot SARIMAX model for each Language

def plot_best_SARIMAX_model(languages, data_language, 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_language[lang]

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

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

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

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

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

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

    return 0
```

In [62]:
```
#Plotting SARIMAX model for each Language Time Series
languages = ['Chinese', 'French', 'German', 'Japenese', 'Russian', 'Spanish']
```

```python
n = 30
plot_best_SARIMAX_model(languages, data_language, n, best_param_df)
```

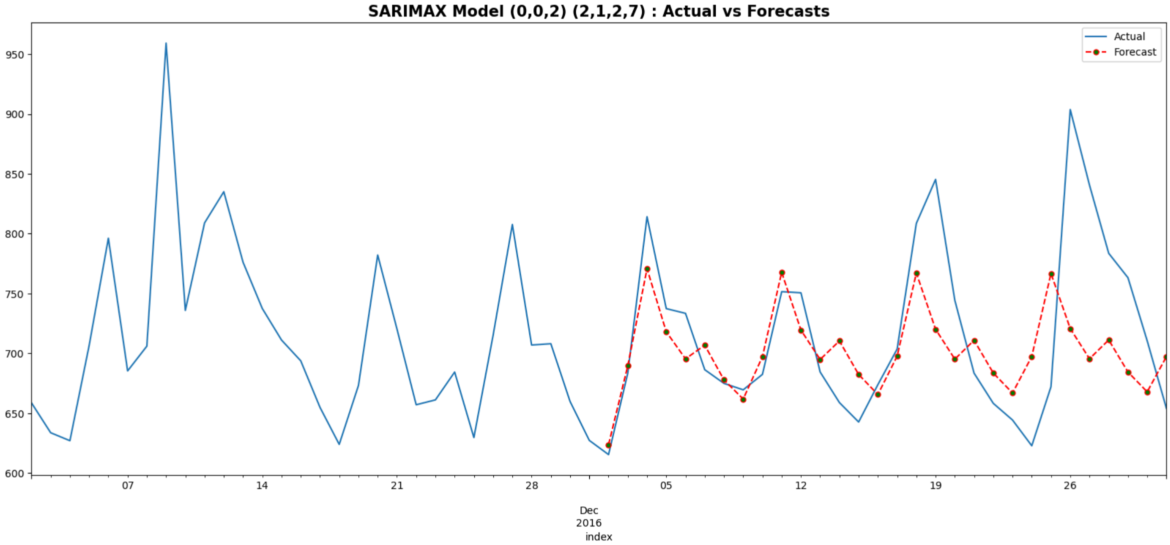
```
--------------------------------------------------------------------------------------------
        SARIMAX model for Chinese Time Series
        Parameters of Model : (0,1,1) (0,0,2,7)
        MAPE of Model       : 0.03352
        RMSE of Model       : 16.433
--------------------------------------------------------------------------------------------
```

SARIMAX Model (0,1,1) (0,0,2,7) : Actual vs Forecasts

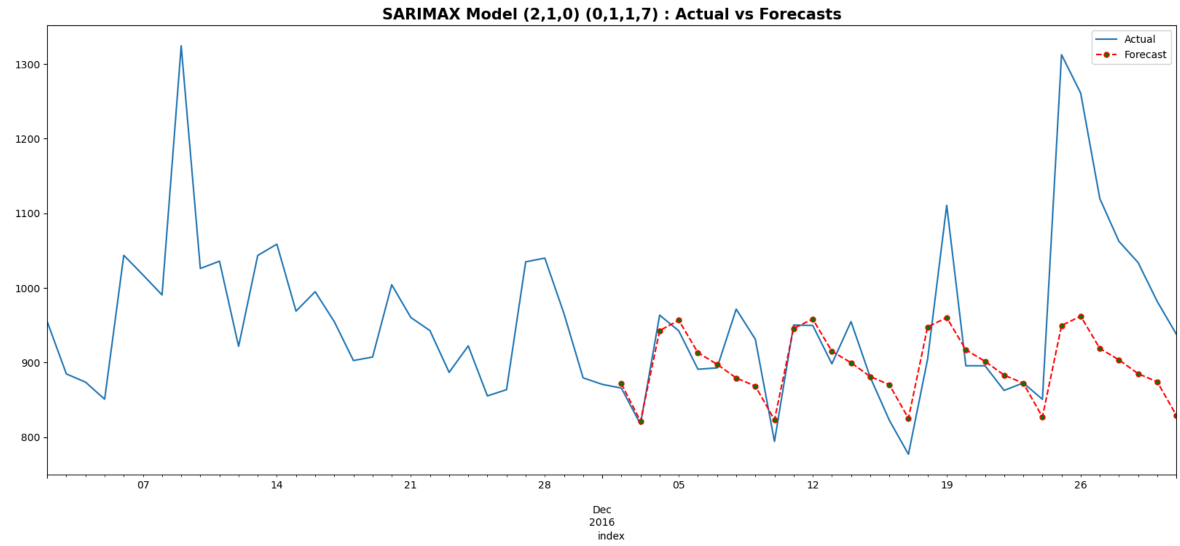



```
--------------------------------------------------------------------------------------------
        SARIMAX model for French Time Series
        Parameters of Model : (0,0,2) (2,1,2,7)
        MAPE of Model       : 0.05989
        RMSE of Model       : 62.201
--------------------------------------------------------------------------------------------
```

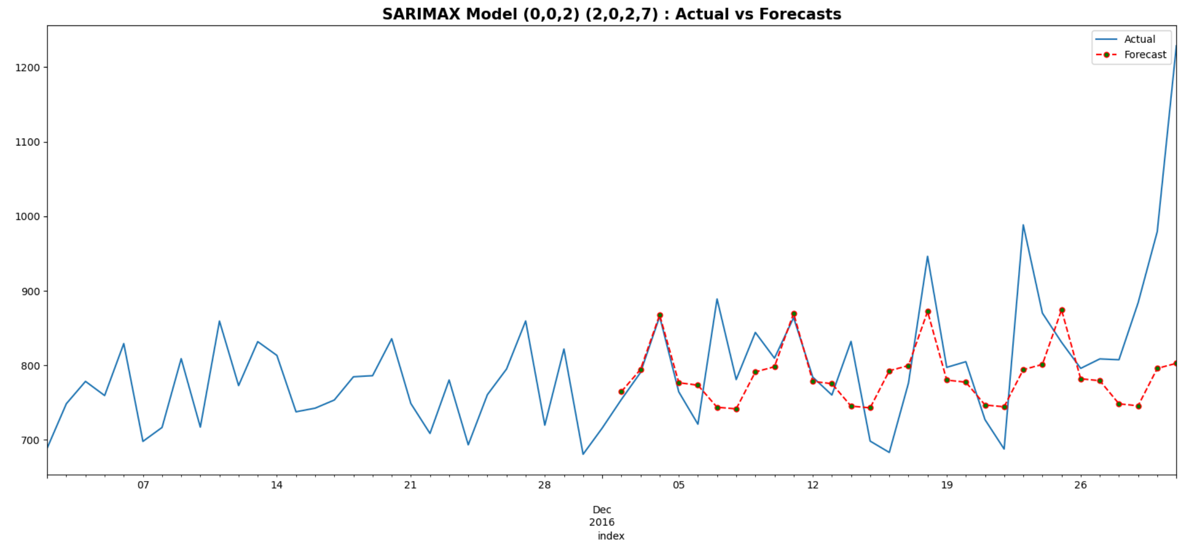
SARIMAX Model (0,0,2) (2,1,2,7) : Actual vs Forecasts



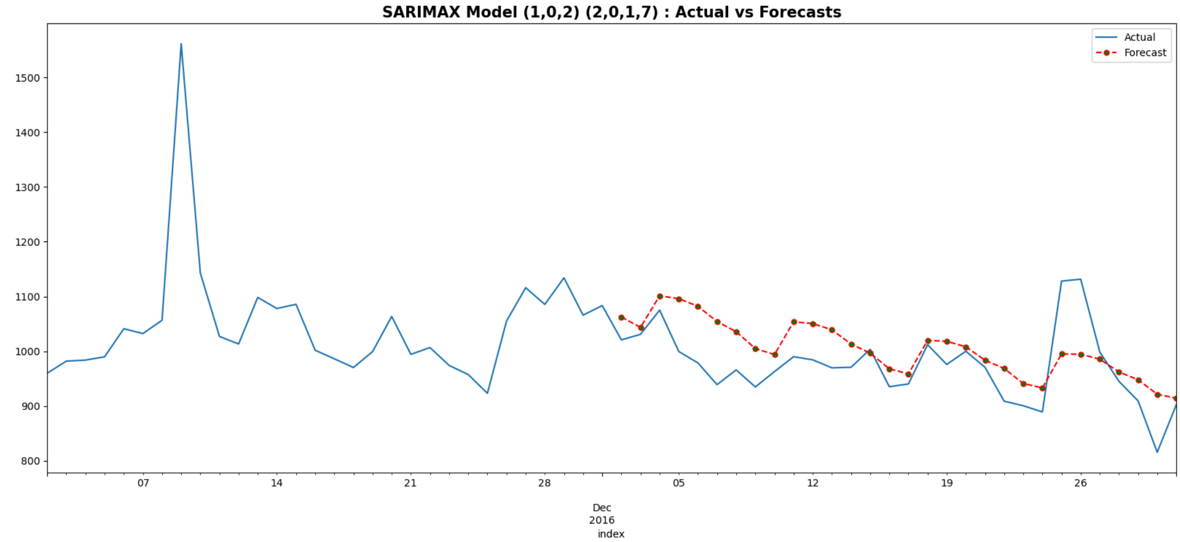
```
--------------------------------------------------------------------------------------
        SARIMAX model for German Time Series
        Parameters of Model : (2,1,0) (0,1,1,7)
        MAPE of Model       : 0.06553
        RMSE of Model       : 112.628
--------------------------------------------------------------------------------------
```



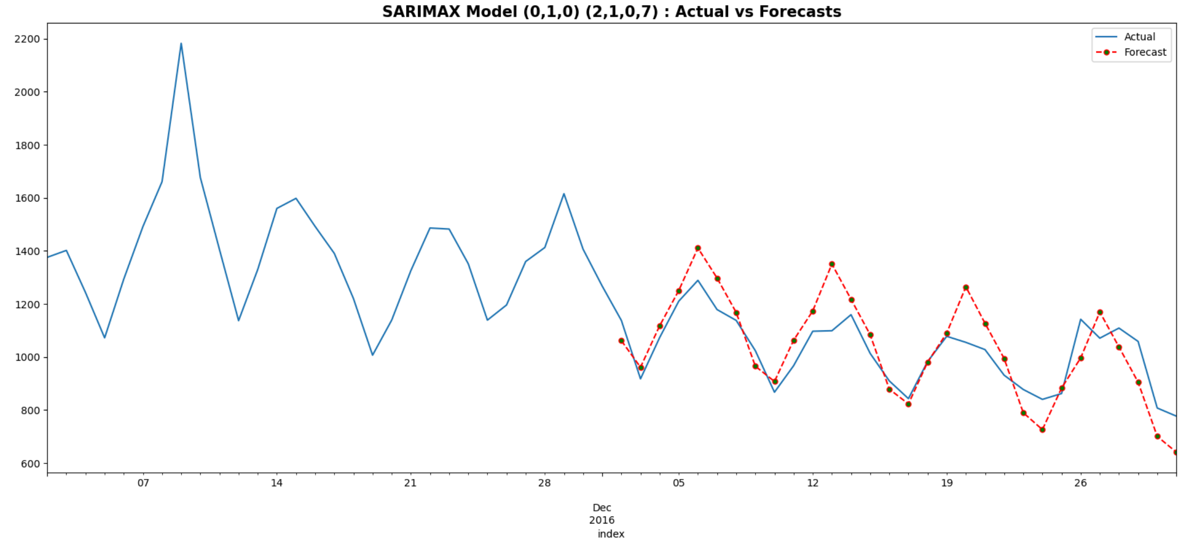

```
--------------------------------------------------------------------------------------
        SARIMAX model for Japenese Time Series
        Parameters of Model : (0,0,2) (2,0,2,7)
        MAPE of Model       : 0.07279
        RMSE of Model       : 107.14
--------------------------------------------------------------------------------------
```




```
--------------------------------------------------------------------------------------
        SARIMAX model for Russian Time Series
        Parameters of Model : (1,0,2) (2,0,1,7)
        MAPE of Model       : 0.05261
        RMSE of Model       : 63.814
--------------------------------------------------------------------------------------
```




```
--------------------------------------------------------------------------------------
        SARIMAX model for Spanish Time Series
        Parameters of Model : (0,1,0) (2,1,0,7)
        MAPE of Model       : 0.08209
        RMSE of Model       : 100.474
--------------------------------------------------------------------------------------
```



Out[62]: 0

Forecasting using Facebook Prophet

In [63]:
```python
from prophet import Prophet
```

```
Importing plotly failed. Interactive plots will not work.
```

In [64]:
```python
time_series = data_language
time_series = time_series.reset_index()
time_series = time_series[['index', 'English']]
time_series.columns = ['ds', 'y']
exog = Exog_Campaign_eng.copy(deep = True)
time_series['exog'] = exog.values
```

In [65]:
```python
time_series
```

Out[65]:

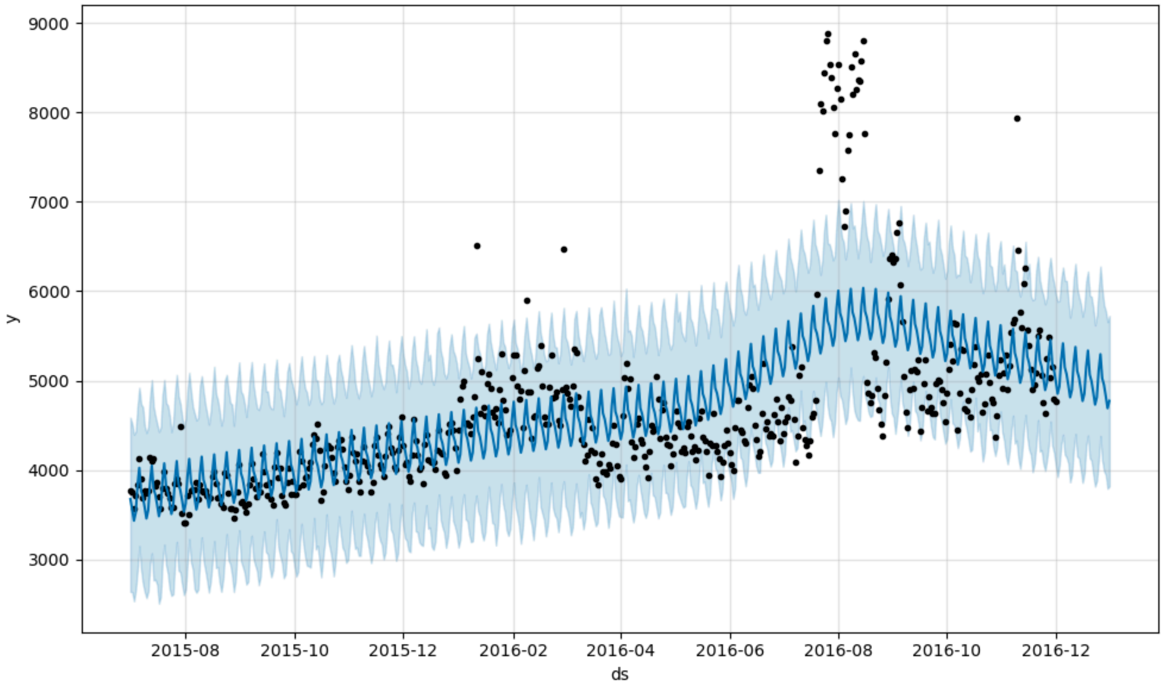
	ds	y	exog
0	2015-07-01	3767.328604	0
1	2015-07-02	3755.158765	0
2	2015-07-03	3565.225696	0
3	2015-07-04	3711.782932	0
4	2015-07-05	3833.433025	0
...	...	...	...
545	2016-12-27	6314.335275	1
546	2016-12-28	6108.874144	1
547	2016-12-29	6518.058525	1
548	2016-12-30	5401.792360	0
549	2016-12-31	5280.643467	0

550 rows × 3 columns

In [66]:

```
prophet1 = Prophet(weekly_seasonality=True)
prophet1.fit(time_series[['ds', 'y']][:-30])
future = prophet1.make_future_dataframe(periods=30, freq= 'D')
forecast = prophet1.predict(future)
fig1 = prophet1.plot(forecast)
```

```
23:16:26 - cmdstanpy - INFO - Chain [1] start processing
23:16:27 - cmdstanpy - INFO - Chain [1] done processing
```

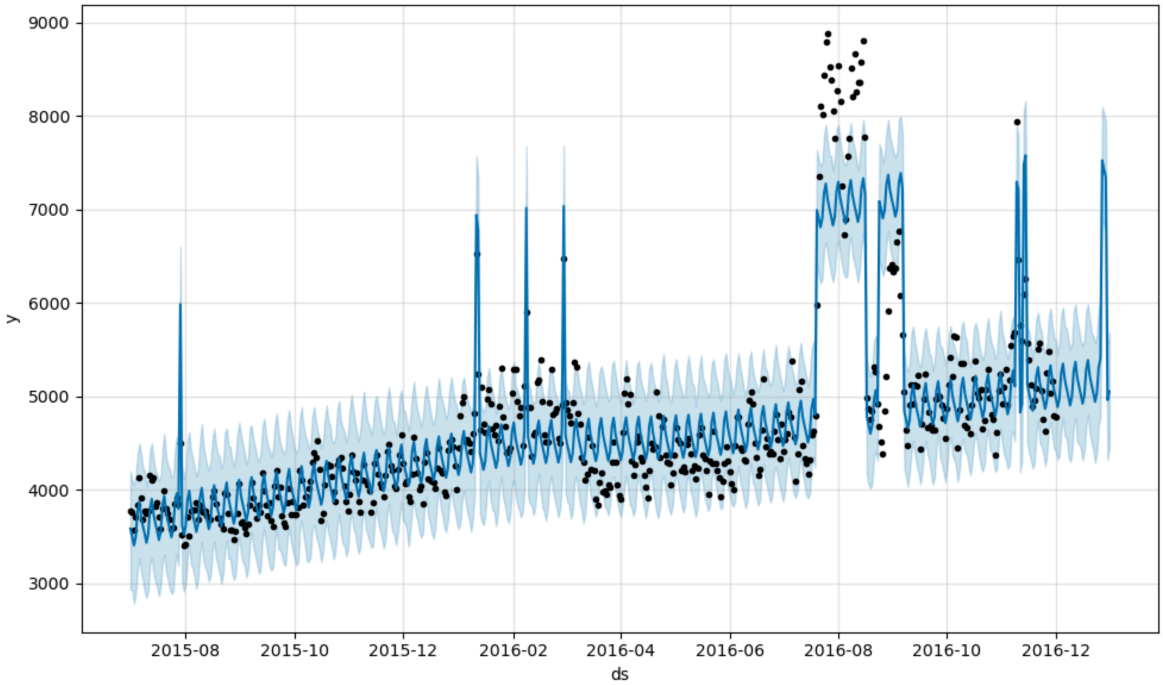


In [67]:

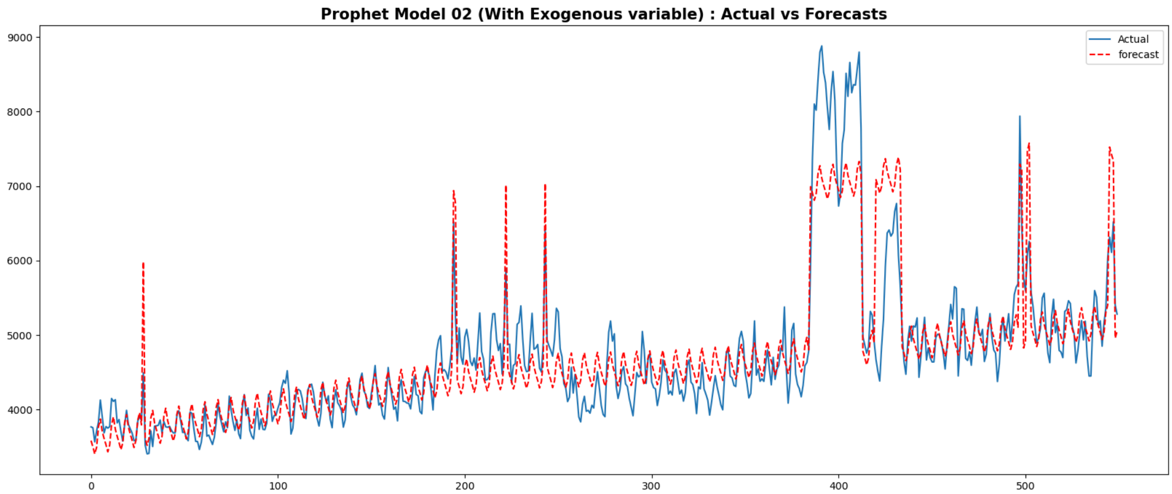
```
prophet2 = Prophet(weekly_seasonality=True)
prophet2.add_regressor('exog')
prophet2.fit(time_series[:-30])
#future2 = prophet2.make_future_dataframe(periods=30, freq= 'D')
```

```
forecast2 = prophet2.predict(time_series)
fig2 = prophet2.plot(forecast2)
```

```
23:16:29 - cmdstanpy - INFO - Chain [1] start processing
23:16:30 - cmdstanpy - INFO - Chain [1] done processing
```



In [68]:
```
actual = time_series['y'].values
forecast = forecast2['yhat'].values

plt.figure(figsize = (20,8))
plt.plot(actual, label = 'Actual')
plt.plot(forecast, label = 'forecast', color = 'red', linestyle='dashed')
plt.legend(loc="upper right")
plt.title(f'Prophet Model 02 (With Exogenous variable) : Actual vs Forecasts', f
plt.show()
```



In [69]:
```
errors = abs(actual - forecast)
mape = np.mean(errors/abs(actual))
mape
```

Out[69]: 0.059846174776769345

FB Prophet Model was created successfully. Forecast seems decent. This model is able to capture peaks because of exogenous variable.

Overall MAPE from Prophet model = ~6%

Business decisions / Recommendations

MAPE vs Visits per Language

In [70]:
```
new_row = ['English', 1,1,1,2,1,1,7, 0.04189]
best_param_df.loc[len(best_param_df)] = new_row

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

Out[70]:

	language	p	d	q	P	D	Q	s	mape
0	Chinese	0	1	1	0	0	2	7	0.03352
6	English	1	1	1	2	1	1	7	0.04189
4	Russian	1	0	2	2	0	1	7	0.05261
1	French	0	0	2	2	1	2	7	0.05989
2	German	2	1	0	0	1	1	7	0.06553
3	Japenese	0	0	2	2	0	2	7	0.07279
5	Spanish	0	1	0	2	1	0	7	0.08209

In [71]:
```
mean_visits = pd.DataFrame(data_language.mean()).reset_index()
mean_visits.columns = ['language', 'mean_visits']
df_visit_mape = best_param_df.merge(mean_visits, on = 'language')
```

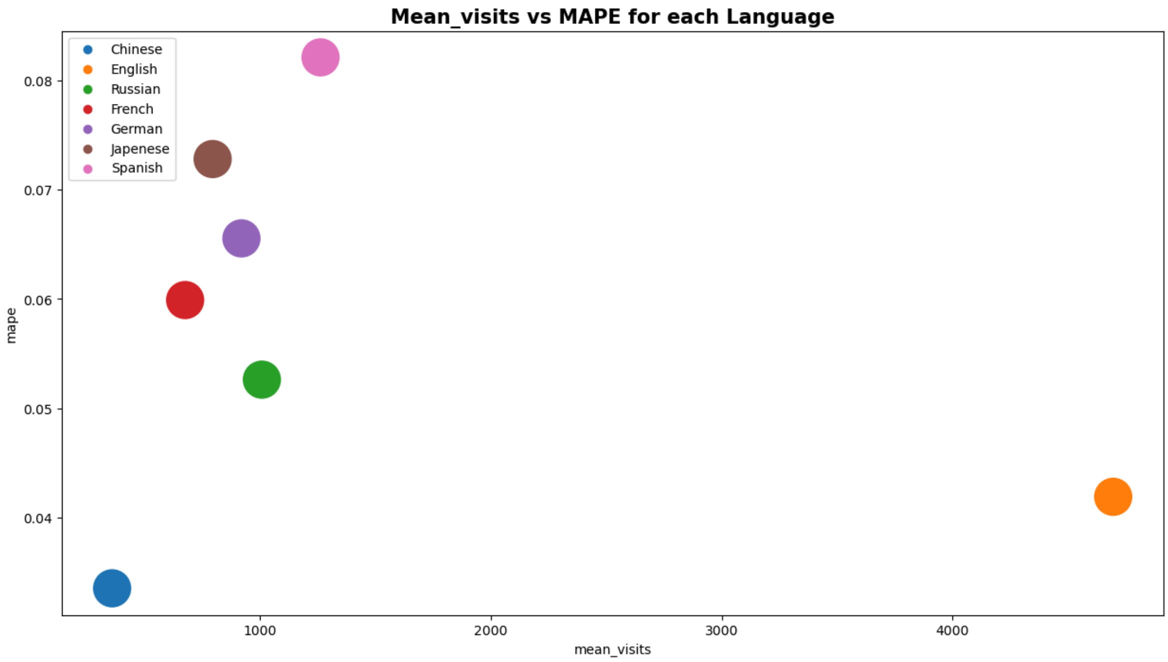
In [72]:
```
df_visit_mape
```

Out[72]:

	language	p	d	q	P	D	Q	s	mape	mean_visits
0	Chinese	0	1	1	0	0	2	7	0.03352	360.019883
1	English	1	1	1	2	1	1	7	0.04189	4696.102005
2	Russian	1	0	2	2	0	1	7	0.05261	1008.694303
3	French	0	0	2	2	1	2	7	0.05989	676.223824
4	German	2	1	0	0	1	1	7	0.06553	920.132431
5	Japenese	0	0	2	2	0	2	7	0.07279	795.415559
6	Spanish	0	1	0	2	1	0	7	0.08209	1262.718183

In [73]:
```
plt.figure(figsize = (15,8))
sns.scatterplot(x="mean_visits", y="mape", hue="language", data=df_visit_mape, s
plt.legend(loc="upper left")
```

```
plt.title(f'Mean_visits vs MAPE for each Language', fontsize = 15, fontweight =
plt.show()
```



Recommendations based on MAPE & mean_visits:

- **English** language is a clear winner. Maximum advertisement should be done on English pages. Their MAPE is low & mean visits are high.
- **Chinese** language has lowest number of visits. Advertisements on these pages should be avoided unless business has specific marketing strategy for Chinese populations.
- **Russian** language pages have decent number of visits and low MAPE. If used properly, these pages can result in maximum conversion.
- **Spanish** language has second highest number of visits but their MAPE is highest. There is a possibility advertisements on these pages won't reach the final people.
- **French, German & Japenese** have medium level of visits & medium MAPE levels. Depending on target customers advertisements should be run on these pages.

10. Questionnaire

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

- We 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. We are provided with the data of 145k wikipedia pages and daily view count for each of them. Our clients belong to different regions and need data on how their ads will perform on pages in different languages.

- By creating a proper forecasting model to predict the fluctuations of visits on pages, we can help the business team to optimise the marketing spend. If we can predict the days with higher visits properly, the business will run the ads for those specific days and still be able to reach wider audience with most optimized spend.

2. Write 3 inferences you made from the data visualizations.

- There are **7 Languages** found based on data provided. **English has highest number of pages** followed by Japanese, German & French.
- There are **3 Access types** : **All-access(51.4%)**, mobile-web (24.9%) and desktop(23.6%).
- There are **2 Access-origins**: **all-agents (75.8%)** and spider (24.2%).
- **English** language is a clear winner. Maximum advertisement should be done on English pages. Their MAPE is low & mean visits are high.
- **Chinese** language has lowest number of visits. Advertisements on these pages should be avoided unless business has specific marketing strategy for Chinese populations.
- **Russian** language pages have decent number of visits and low MAPE. If used properly, these pages can result in maximum conversion.
- **Spanish** language has second highest number of visits but their MAPE is highest. There is a possibility advertisements on these pages won't reach the final people.
- **French, German & Japanese** have medium level of visits & medium MAPE levels. Depending on target customers advertisements should be run on these pages.

3. What does the decomposition of series do?

- The decomposition of time series is a statistical task that deconstructs a time series into several components, each representing one of the underlying categories of patterns.
- There are two principal types of decomposition : Additive & Multiplicative.
- In present business case we have used Additive Model for deconstructing the time series. The term additive means individual components (trend, seasonality, and residual) are added together as shown in equation below:

$y_t = T_t + S_t + R_t$

where

- y_t = actual value in time series
- T_t = trend in time series
- S_t = seasonality in time series
- R_t = residuals of time series

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

- A non-stationary time series can be converted to a stationary time series through a technique called differencing. Differencing series is the change between consecutive data points in the series.

y'_t = y_t - y_{t-1}

This is called first order differencing.

- In some cases, just differencing once will still yield a nonstationary time series. In that case a second order differencing is required.

- Seasonal differencing is the change between the same period in two different seasons. Assume a season has period, m

y'_t = y_t - y_{t-m}

- Once the time series becomes stationary, no differencing is required.

5. Difference between arima, sarima & sarimax.

- The **ARIMA model** is an ARMA model yet with a pre-processing step included in the model that we represent using I(d). I(d) is the difference order, which is the number of transformations needed to make the data stationary. So, an ARIMA model is simply an ARMA model on the differenced time series.

- In **SARIMA models** there is an additional set of autoregressive and moving average components. The additional lags are offset by the frequency of seasonality (ex. 12 — monthly, 24 — hourly). SARIMA models allow for differencing data by seasonal frequency, yet also by non-seasonal differencing.

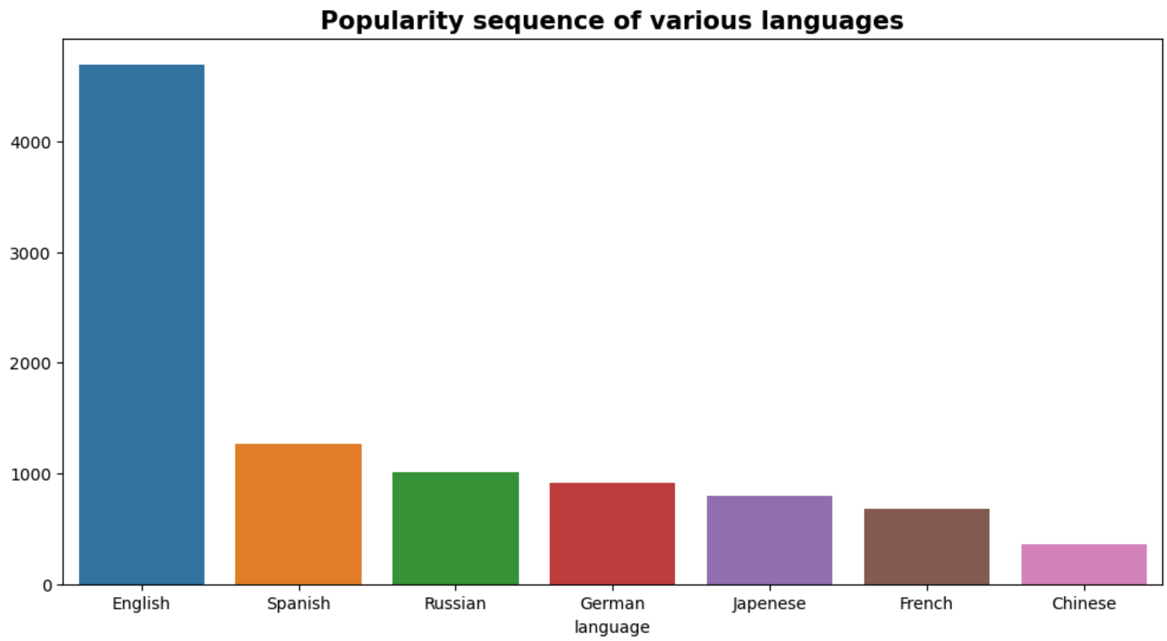
- **SARIMAX model** takes into account exogenous variables, or in other words, use external data in our forecast. Some real-world examples of exogenous variables include gold price, oil price, outdoor temperature, exchange rate.

6. Compare the number of views in different languages

- Mean number of views (Popularity sequence) of various languages have the following :

English > Spanish > Russian > German > Japanese > French > Chinese

In [74]:
```
x = data_language.mean().sort_values(ascending = False).index
y = data_language.mean().sort_values(ascending = False).values

plt.figure(figsize=(12, 6))
sns.barplot(x=x,y=y)
plt.title(f'Popularity sequence of various languages', fontsize = 15, fontweight
plt.show()
```



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

- **Deep understanding of Domain / Business or relevant experience** in the same field can be good starting point for estimating the parameters of the model intuitively.

- Second level estimation can come from **ACF & PACF plots** of the time series. We can take following steps for estimation of p, q, d:

  - Test for stationarity using the augmented dickey fuller test.
  - If the time series is stationary try to fit the ARMA model, and if the time series is non-stationary then seek the **value of d.**
  - If the data is getting stationary then draw the autocorrelation and partial autocorrelation graph of the data.
  - Draw a partial autocorrelation graph(ACF) of the data. This will help us in finding the value of p because the **cut-off point to the PACF is p**.
  - Draw an autocorrelation graph(ACF) of the data. This will help us in finding the value of q because the **cut-off point to the ACF is q**.