impoting libraries:

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style = "darkgrid")
pd.set_option("display.max_columns",None)
pd.options.display.max_colwidth = 100

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

In [2]:
```
raw_data = pd.read_csv(r"C:\Users\lenovo\Downloads\train_1.csv")
exo_var = pd.read_csv(r"C:\Users\lenovo\Downloads\Exog_Campaign_eng")
```

In [3]:
```
data = raw_data.copy(deep = True)
```

In [4]:
```
data.sample(100).head()
```

Out[4]:

	Page	2015-07-01	2015-07-02	2015-07-03	2015-07-04	2015-07-05	2015-07-06	2015-07-07	2015-07-08	201 07-(
56606	市川実日子_ja.wikipedia.org_mobile-web_all-agents	166.0	259.0	622.0	533.0	457.0	283.0	306.0	239.0	272
92278	Florida_Cup_2017_es.wikipedia.org_all-access_all-agents	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
68672	Malaria_de.wikipedia.org_desktop_all-agents	578.0	552.0	501.0	372.0	515.0	635.0	638.0	707.0	606
117873	The_World's_End_de.wikipedia.org_mobile-web_all-agents	75.0	61.0	106.0	131.0	208.0	81.0	74.0	77.0	109
64696	西部世界_zh.wikipedia.org_desktop_all-agents	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na

In [5]:
```
data.duplicated().sum()
data.drop_duplicates(keep="last",inplace=True)
```

In [6]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 145063 entries, 0 to 145062
Columns: 551 entries, Page to 2016-12-31
dtypes: float64(550), object(1)
memory usage: 610.9+ MB
```

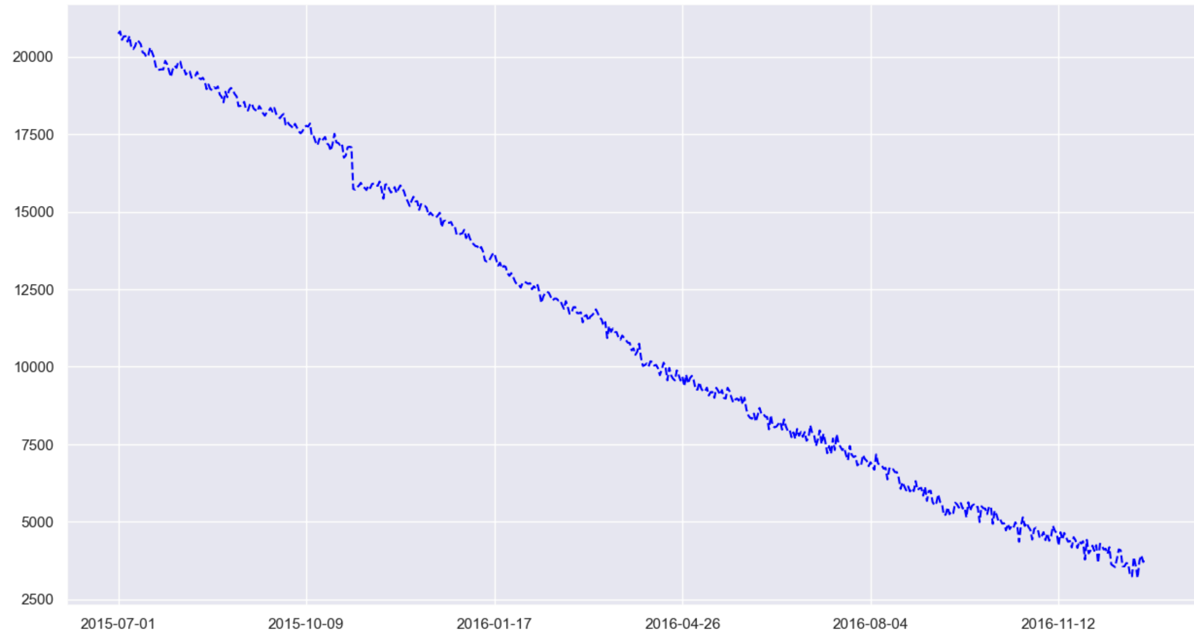
In [7]:
```
print("-"*80)
print(f"shape of the Data: {data.shape}")
print("-"*80)
print(f"Shape of the Exogenous variable:{exo_var.shape}")
print("-"*80)
```

```
--------------------------------------------------------------------------------
shape of the Data: (145063, 551)
--------------------------------------------------------------------------------
Shape of the Exogenous variable:(550, 1)
--------------------------------------------------------------------------------
```

In [8]:
```
(data.isnull().sum()[range(1,550,25)]/len(data)*100)
```

Out[8]:
```
2015-07-01    14.297236
2015-07-26    13.694050
2015-08-20    13.044677
2015-09-14    12.688970
2015-10-09    12.250539
2015-11-03    10.846322
2015-11-28    10.924219
2015-12-23    10.096992
2016-01-17     9.421424
2016-02-11     8.311561
2016-03-07     7.917250
2016-04-01     7.158959
2016-04-26     6.672273
2016-05-21     6.353102
2016-06-15     5.563790
2016-07-10     5.401791
2016-08-04     4.768273
2016-08-29     4.151300
2016-09-23     3.761814
2016-10-18     3.348890
2016-11-12     2.918732
2016-12-07     2.847039
dtype: float64
```

In [9]:
```
plt.figure(figsize=(15,8))
data.iloc[:,1:-3].isnull().sum().plot(color="blue",linestyle="dashed")
plt.show()
```



In [10]:
```
data.dropna(thresh = 300 , inplace=True)
print(data.shape)
```

```
(133617, 551)
```

In [11]:
```
data.fillna(0,inplace = True)
```

In [12]:
```
(data.isnull().sum()[range(1,550,25)]/len(data)*100)
```

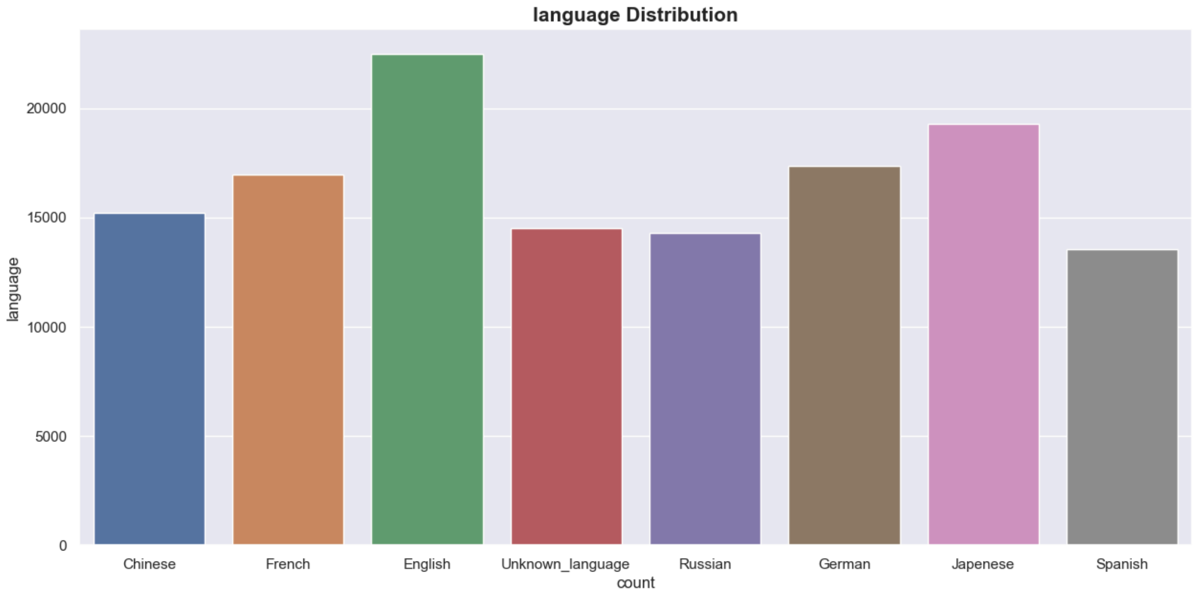
Out[12]:
```
2015-07-01    0.0
2015-07-26    0.0
2015-08-20    0.0
2015-09-14    0.0
2015-10-09    0.0
2015-11-03    0.0
2015-11-28    0.0
2015-12-23    0.0
2016-01-17    0.0
2016-02-11    0.0
2016-03-07    0.0
2016-04-01    0.0
2016-04-26    0.0
2016-05-21    0.0
2016-06-15    0.0
2016-07-10    0.0
2016-08-04    0.0
2016-08-29    0.0
2016-09-23    0.0
2016-10-18    0.0
2016-11-12    0.0
2016-12-07    0.0
dtype: float64
```

2. Exploratory Data Analysis & Feature Engineering

2.1 Extracting Language , Access_Type & Access_Origin from Page

In [13]:
```
import re

#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_language'

data['language'] = data['Page'].apply(get_language)


language_dict ={'de':'German',
                'en':'English',
                'es': 'Spanish',
                'fr': 'French',
                'ja': 'Japenese' ,
                'ru': 'Russian',
                'zh': 'Chinese',
                'Unknown_language': 'Unknown_language'}

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

In [14]:
```
y = "language"

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



In [15]:
```
(data.loc[data['language'] == 'Unknown_language', 'Page'].sample(100).head(10))
```

Out[15]:
```
79199    Category:Videos_of_female_masturbation_commons.wikimedia.org_mobile-web_all-agents
79516                File:MimiRogersApr09.jpg_commons.wikimedia.org_mobile-web_all-agents
80499                           Category:Belief_commons.wikimedia.org_desktop_all-agents
84451                              Skin:Nostalgia_www.mediawiki.org_all-access_spider
82992                               API:Allpages_www.mediawiki.org_all-access_spider
22361                    User_talk:Grind24_www.mediawiki.org_mobile-web_all-agents
43760                             UNC_links_www.mediawiki.org_desktop_all-agents
78384           File:Gnome-dev-camera.svg_commons.wikimedia.org_mobile-web_all-agents
80176        File:Chicxulub-animation.gif_commons.wikimedia.org_mobile-web_all-agents
19802                          Git/Workflow_www.mediawiki.org_all-access_all-agents
Name: Page, dtype: object
```

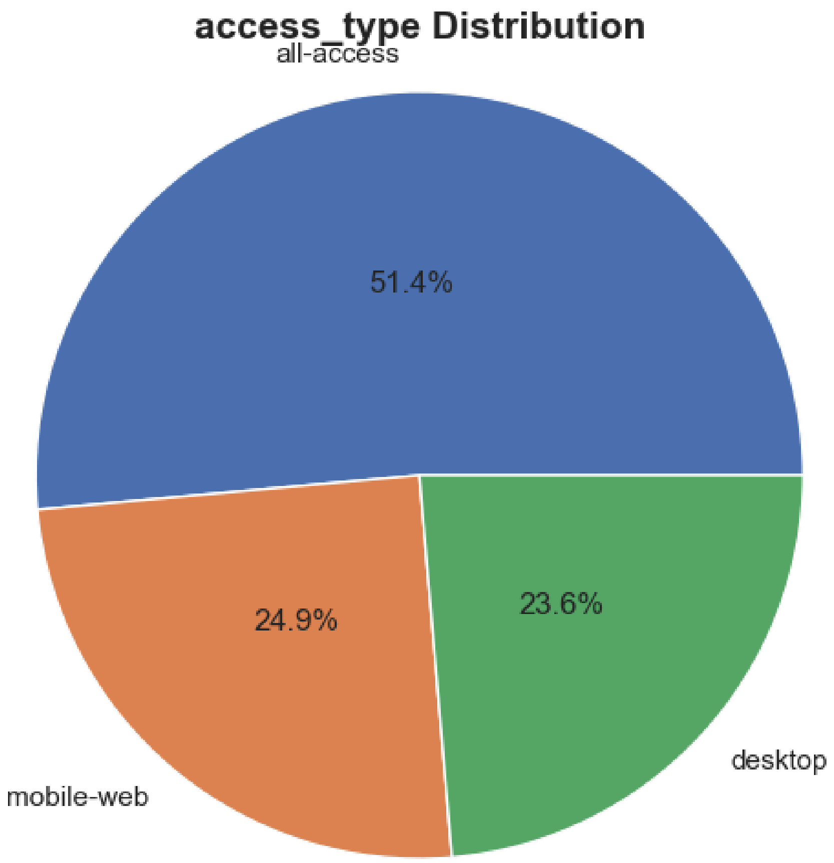
=> Around 10.8% of rows (~14k) don't have Language information

In [16]:

```
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 [17]:

```
# visualizing access types Distribution
var = "access_type"
x = data[var].value_counts().values
y = data[var].value_counts().index

plt.figure(figsize=(7,6))
plt.pie(x,labels = y, center = (0,0), radius= 1.5, autopct="%1.1f%%", pctdistance=
plt.title(f"{var} Distribution", fontsize = 15, fontweight= "bold")
plt.axis("equal")
plt.show()
```

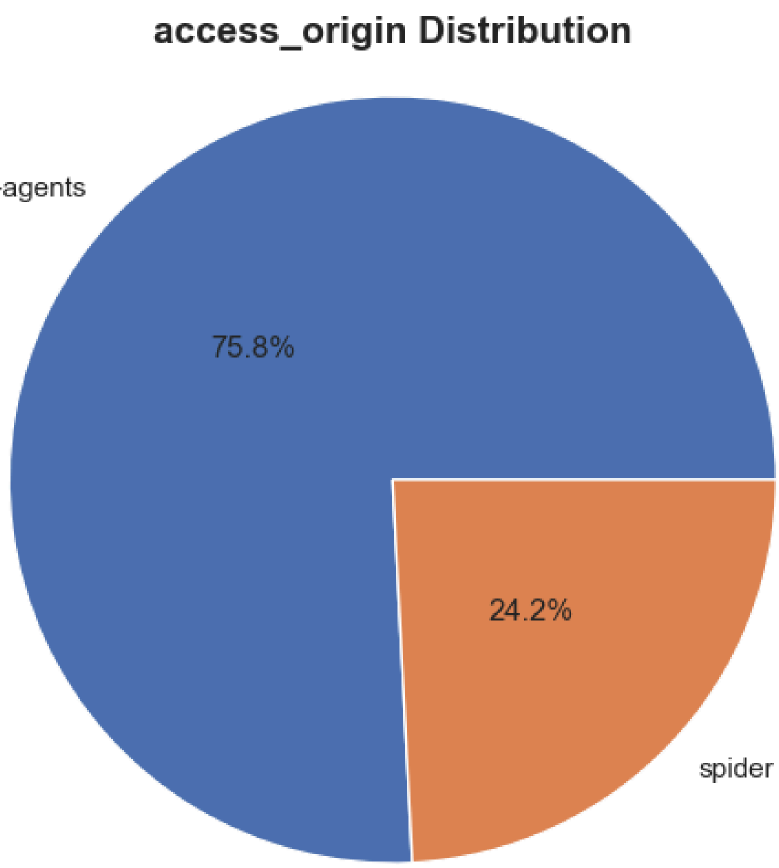


In [18]:

```
# 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 [19]:

```
var = "access_origin"
x = data[var].value_counts().values
y = data[var].value_counts().index

plt.figure(figsize=(7,6))
plt.pie(x,labels = y, center = (0,0), radius= 1.5, autopct="%1.1f%%", pctdistance=
plt.title(f"{var} Distribution", fontsize = 15, fontweight= "bold")
plt.axis("equal")
plt.show()
```



3. Data Pre-processing

3.1 Creating dataframe: mean page visit per language

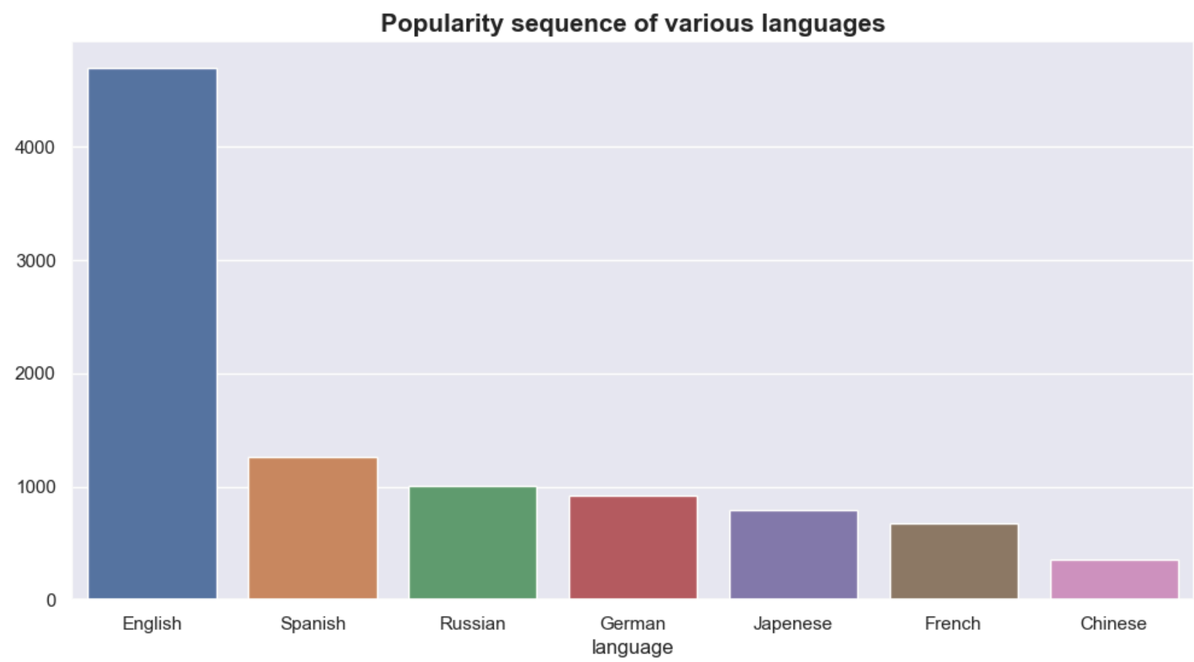
In [20]:
```
data_language = pd.DataFrame()
data_language = data.groupby('language').mean().transpose()
data_language.drop(['Unknown_language'], inplace = True, axis = 1)
data_language.reset_index(inplace = True)
data_language.set_index('index', inplace = True)
data_language
```

Out[20]:

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

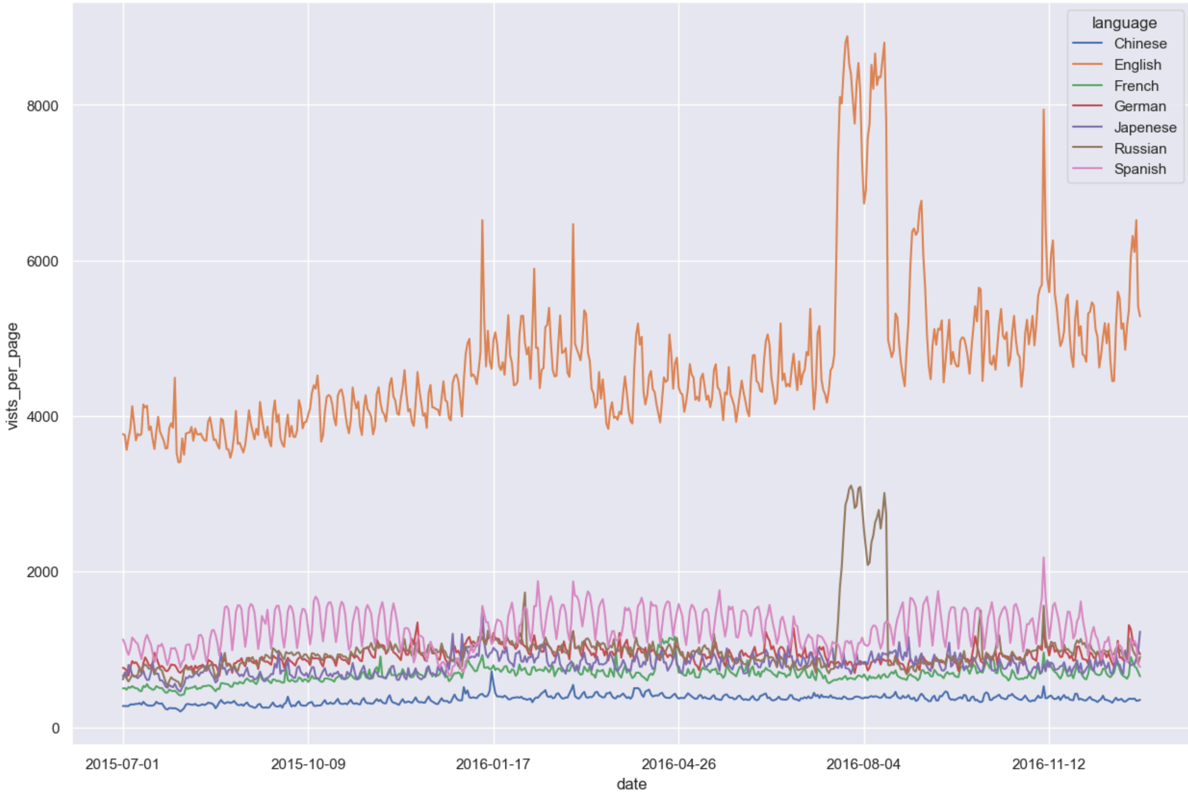
550 rows × 7 columns

In [21]:
```
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()


```



In [22]:

```
data_language.plot(label = data_language.columns,figsize=(15,10))
plt.xlabel("date")
plt.ylabel("vists_per_page")
plt.show()
```



4. Checking Stationarity using ADF (Augmented Dickey Fuller) Test

ADF Test

- **Null Hypothesis**: The series has a unit root (value of a=1). The series is non-stationary.
- **Alternate Hypothesis**: The series has no unit root. The series is stationary.
- If we fail to reject the null hypothesis, we can say that the series is non-stationary.
- If p_value < 0.05 (alpha) or test statistic is less than the critical value, then we can reject the null hypothesis (aka the series is stationary)

In [23]:

```
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 Us
    for key, value in dftest[4].items():

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

In [24]:
```
adf_test(data_language["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.**

5. 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:

yt = Tt + St + Rt

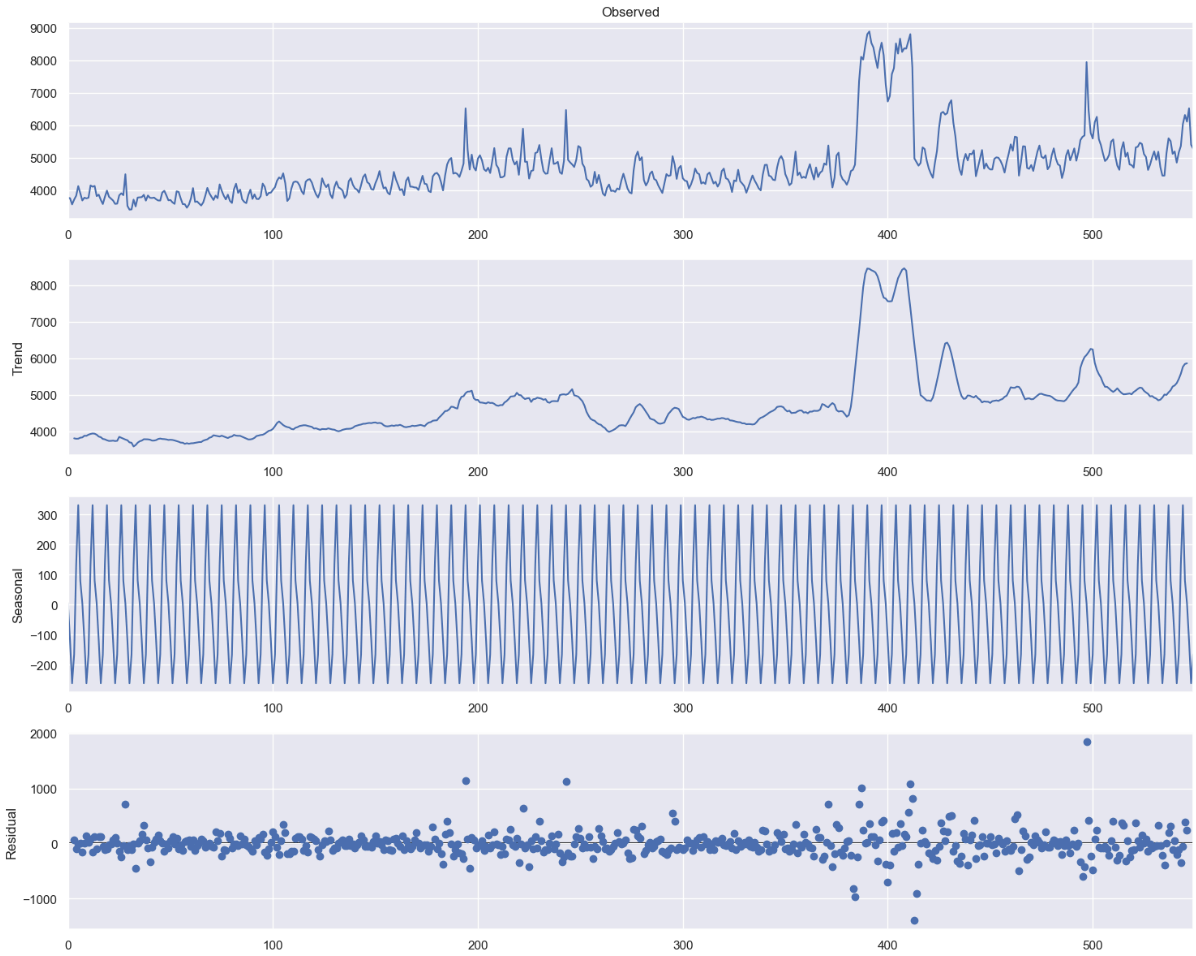
where

- **yt** = actual value in time series
- **Tt** = trend in time series
- **St** = seasonality in time series
- **Rt** = residuals of time series

In [25]:
```
ts_english = data_language.English.values
```

In [26]:

```python
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 [27]:

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

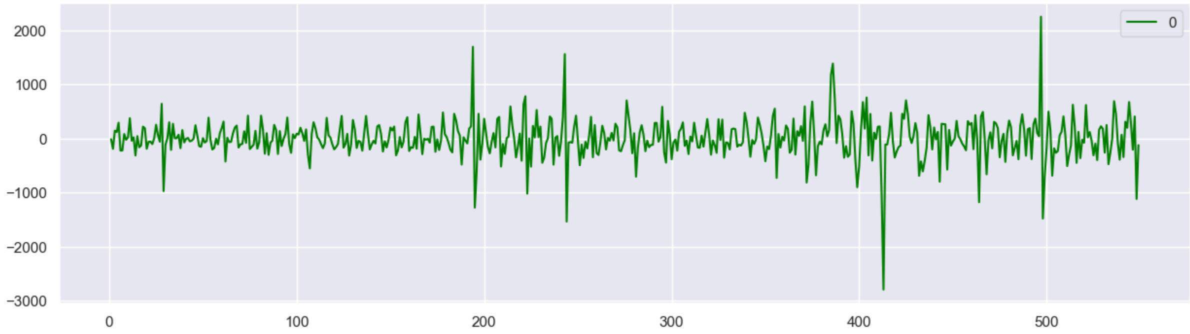
```
Results of Dickey-Fuller Test:
Test Statistic                -1.152195e+01
p-value                        4.020092e-21
#Lags Used                     1.700000e+01
Number of Observations Used    5.320000e+02
Critical Value (1%)           -3.442702e+00
Critical Value (5%)           -2.866988e+00
Critical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

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

In [28]:
```
ts_diff = pd.DataFrame(ts_english).diff(1)
ts_diff.dropna(inplace= True)
```

In [29]:
```
ts_diff.plot(color = "green",figsize=(15,4))
plt.show()
```

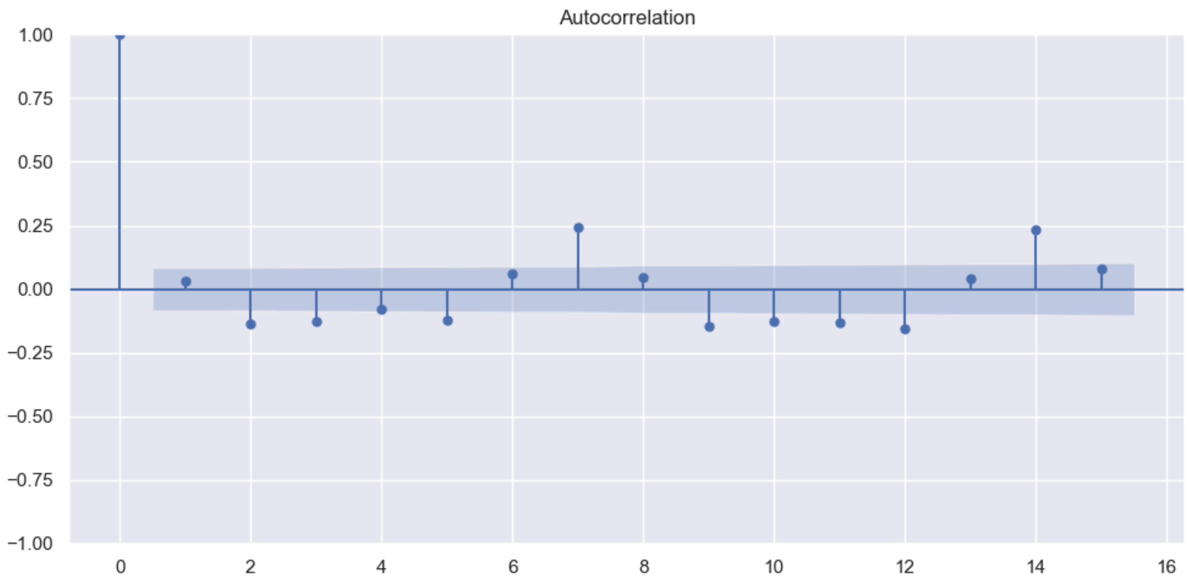


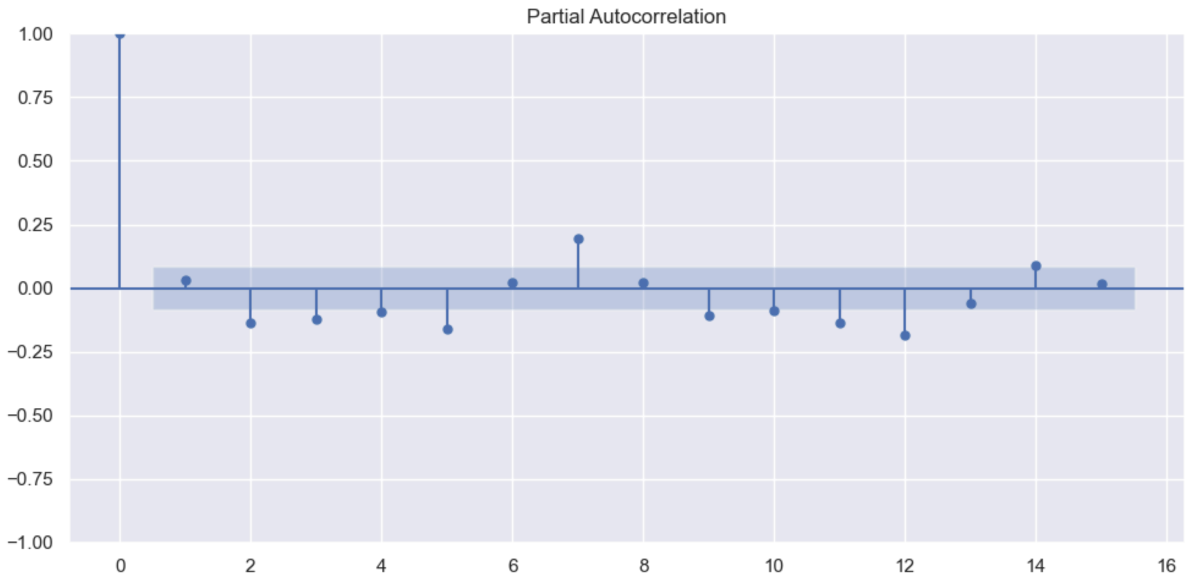
In [30]:
```
#ADF Test for differenced time-series
adf_test(ts_diff)
#p_value < 5%  ==> time series is stationary
```

```
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 [31]:
```
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()
```





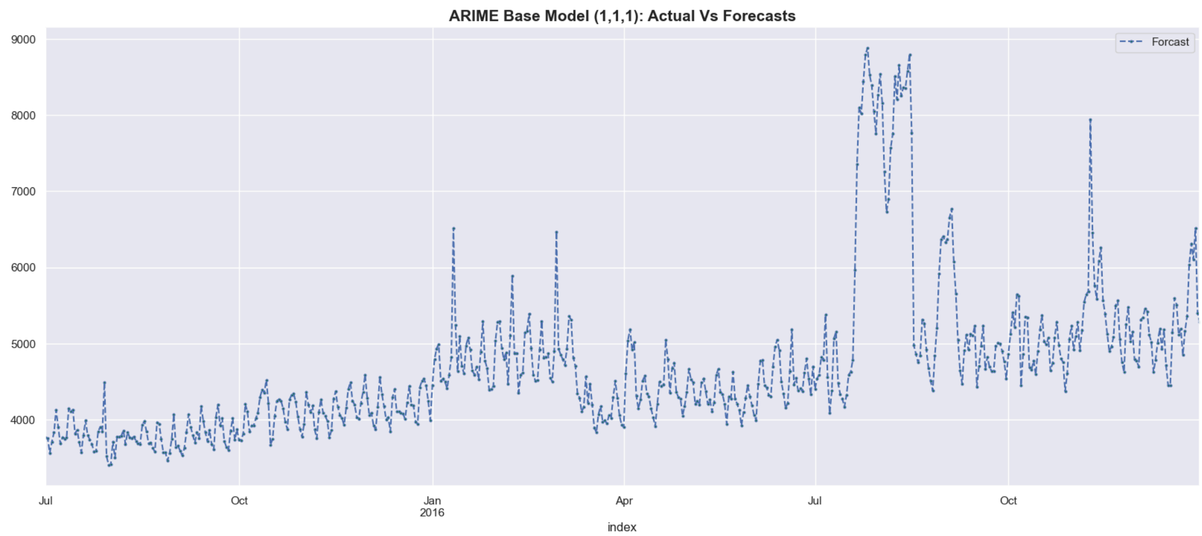
==> ACF & PACF indicates we should choose p = 0 & q = 0. But we will start with p=1 & q=1 for base ARIMA Model==> ACF & PACF indicates we should choose p = 0 & q = 0. But we will start with p=1 & q=1 for base ARIMA Model

7. Forecasting Model Creation

7.1 ARIMA Base Model

In [32]:

```
from statsmodels.tsa.arima.model import ARIMA

import warnings
warnings.filterwarnings("ignore")

n=30
time_series = data_language.English.copy(deep=True)

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)

#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 = "Forcast", linestyle = "dashed", marker="o",markerfacecol
plt.legend(loc= "upper right")
plt.title("ARIME Base Model (1,1,1): Actual Vs Forecasts", fontsize = 15, fontweig
plt.show()



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




```
--------------------------------------------------------------------------------
MAPE of Model : 0.06691
--------------------------------------------------------------------------------
RMSE of Model : 496.72036
--------------------------------------------------------------------------------
```

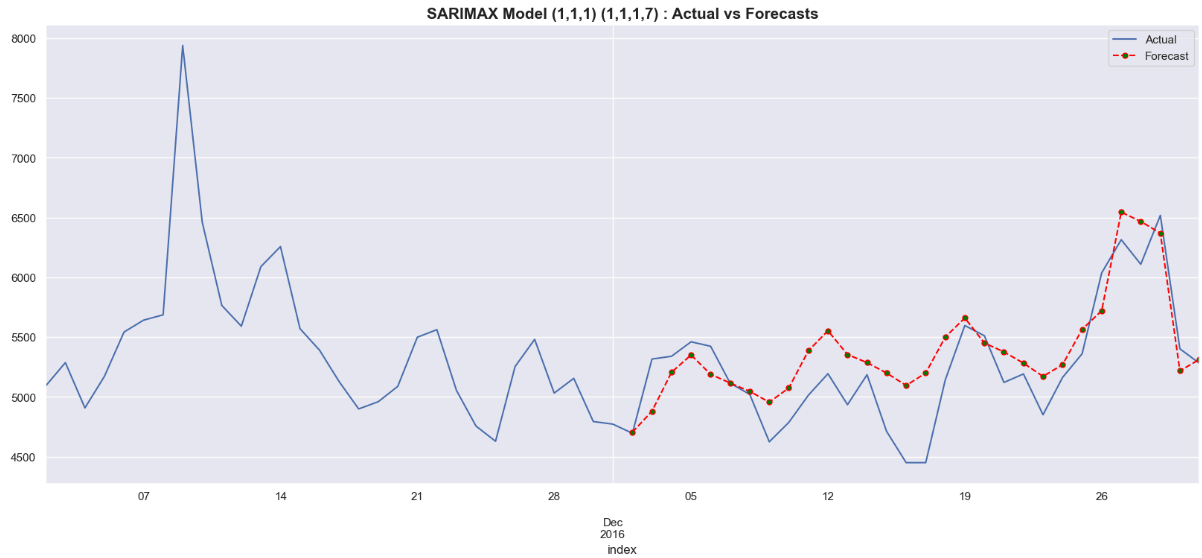
==> **ARIMA Base model has ~6% MAPE and RMSE ~ 500.**

In [33]:

```
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(exo

    #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='gree
    plt.legend(loc="upper right")
    plt.title(f'SARIMAX Model ({p},{d},{q}) ({P},{D},{Q},{s}) : Actual vs Forecast
    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('-'*80)
    print(f'MAPE of Model : {np.round(mape,5)}')
    print('-'*80)
    print(f'RMSE of Model : {np.round(rmse,3)}')
    print('-'*80)
```

In [34]:

```

#Checking a SARIMAX model with seasonality (p,d,q,P,D,Q,s = 1,1,1,1,1,1,7)
exog = exo_var['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 : 0.04899
--------------------------------------------------------------------------------
RMSE of Model : 307.897
--------------------------------------------------------------------------------
```

=> **SIMPLE SARIMAX model has ~4.9% MAPE and RMSE ~ 300.**

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

In [35]:

```
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_diffus
                                model_fit = model.fit()

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

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

                                #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, rms
                                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)*l

    return param_df
```

In [36]:

```
#long time to execute
#Finding best parameters for English time series

exog = exo_var['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, exog
```

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

In [37]:

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

Out[37]:

	serial	pdq	PDQs	mape	rmse
196	197	(1, 1, 1)	(2, 1, 1, 7)	0.04198	273.438
298	299	(2, 1, 1)	(1, 1, 1, 7)	0.04281	273.662
215	216	(1, 1, 2)	(2, 1, 2, 7)	0.04308	269.523
41	42	(0, 0, 2)	(0, 1, 2, 7)	0.04325	287.493
46	47	(0, 0, 2)	(1, 1, 1, 7)	0.04332	285.475

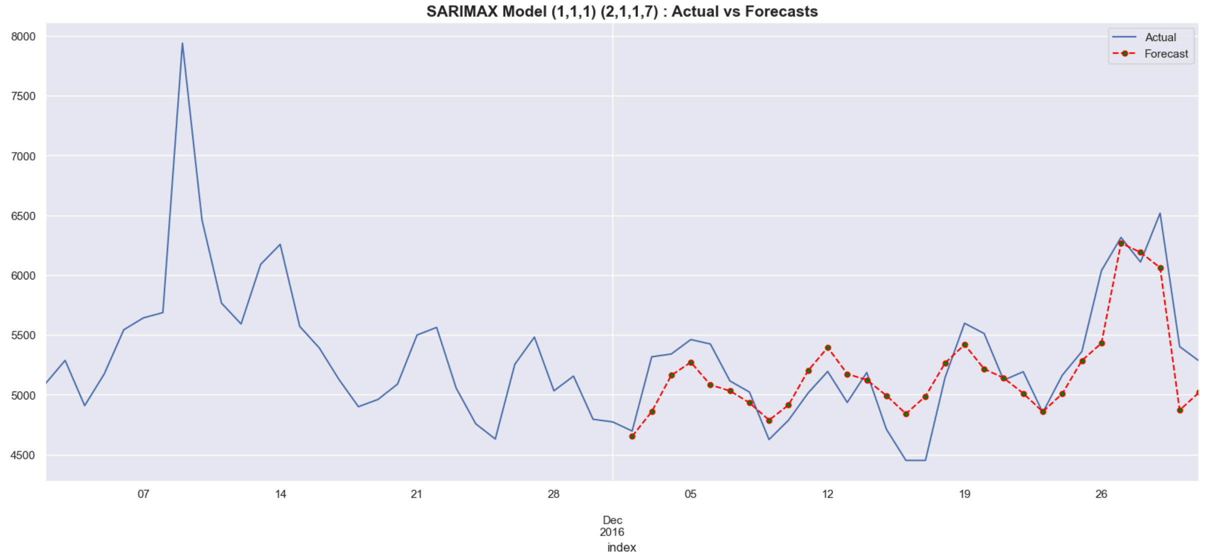
In [38]:

```
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', 'rmse'
        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_di
                                    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_forec

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

                                    counter += 1

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

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

        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_P
        print(f'--------------------------------------------------------------')

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

```

```
    return best_param_df
```

In [39]:

```
#Plotting the SARIMAX model corresponding to best parameters
exog = exo_var['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 : 0.04198
--------------------------------------------------------------------------------
RMSE of Model : 273.438
--------------------------------------------------------------------------------
```

7.4 Creating Pipeline to search Best parameters for all Pages

In [40]:
```
#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_language
```

```
-------------------------------------------------------------
          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 = 0.0735
Corresponding Best Parameters are (1, 0, 1, 1, 1, 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 = 0.05133
Corresponding Best Parameters are (0, 0, 2, 2, 0, 1, 7)
```

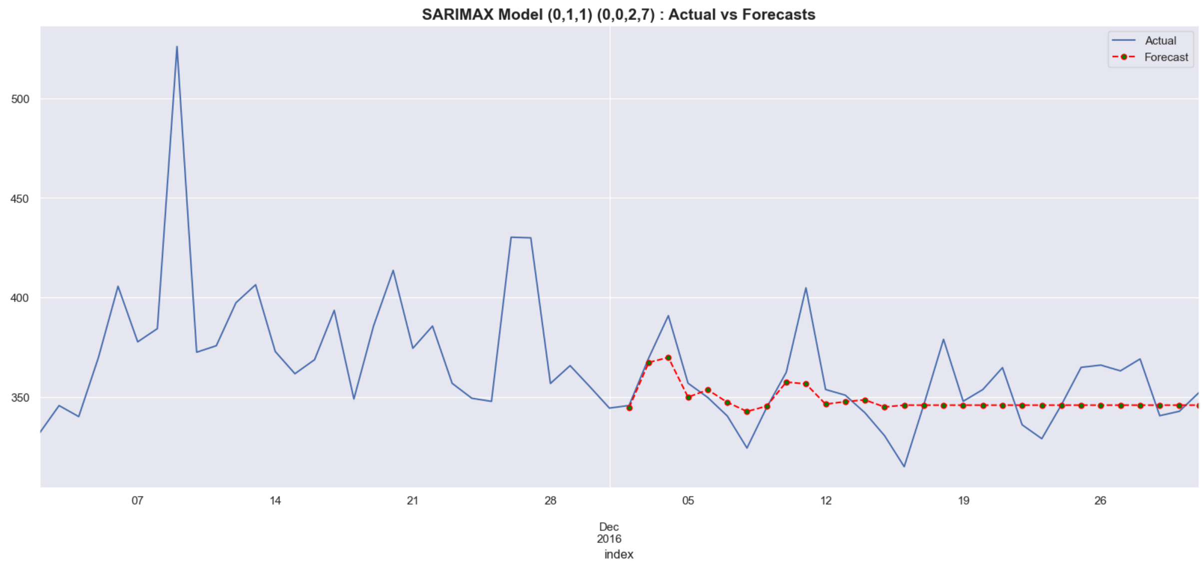
```
-------------------------------------------------------------


-------------------------------------------------------------
          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 [41]:

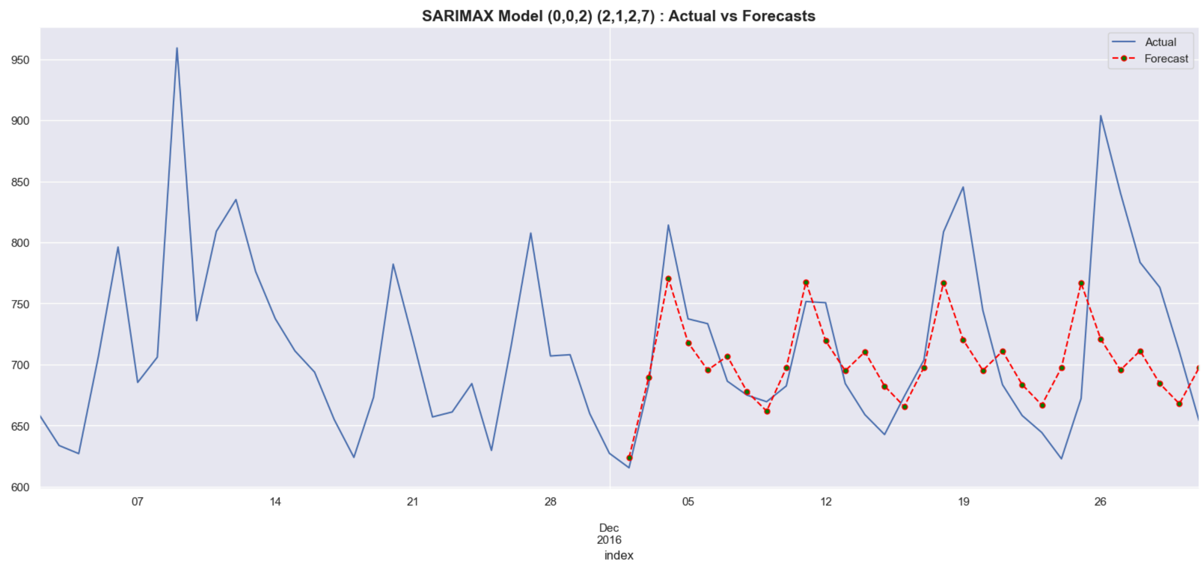
```python
#Function to plot SARIMAX model for each Language

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 Fore
        plt.show()

    return 0
```

In [42]:
```
#Plotting SARIMAX model for each Language Time Series
languages = ['Chinese', 'French', 'German', 'Japenese', 'Russian', 'Spanish']
n = 30
plot_best_SARIMAX_model(languages, data_language, n, best_param_df)
```

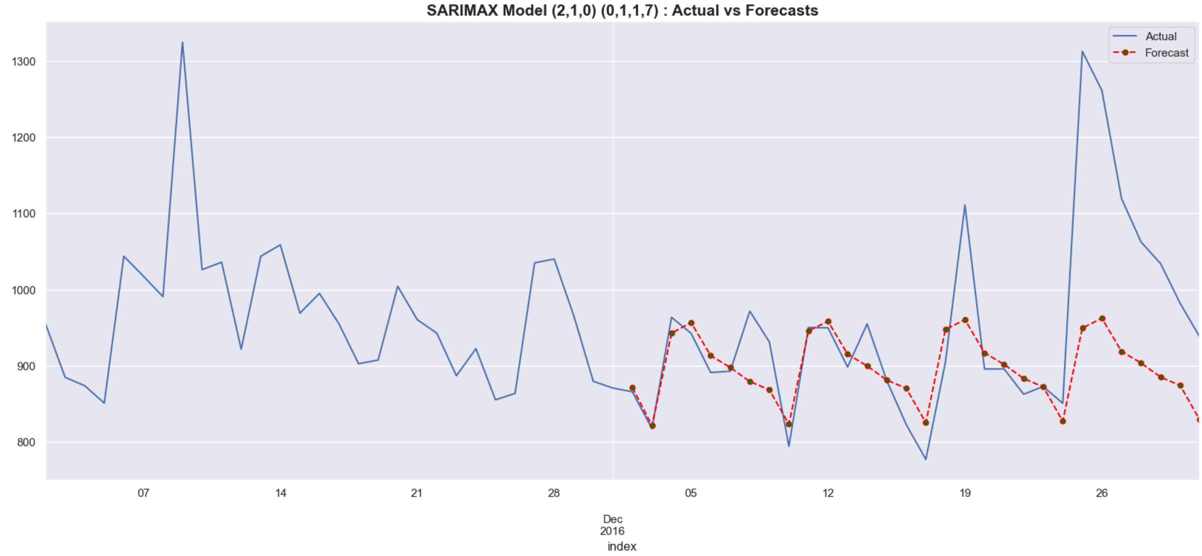
```
------------------------------------------------------------------------------------
----
        SARIMAX model for Chinese Time Series
        Parameters of Model : (0,1,1) (0,0,2,7)
        MAPE of Model       : 0.03352
        RMSE of Model       : 16.433
------------------------------------------------------------------------------------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



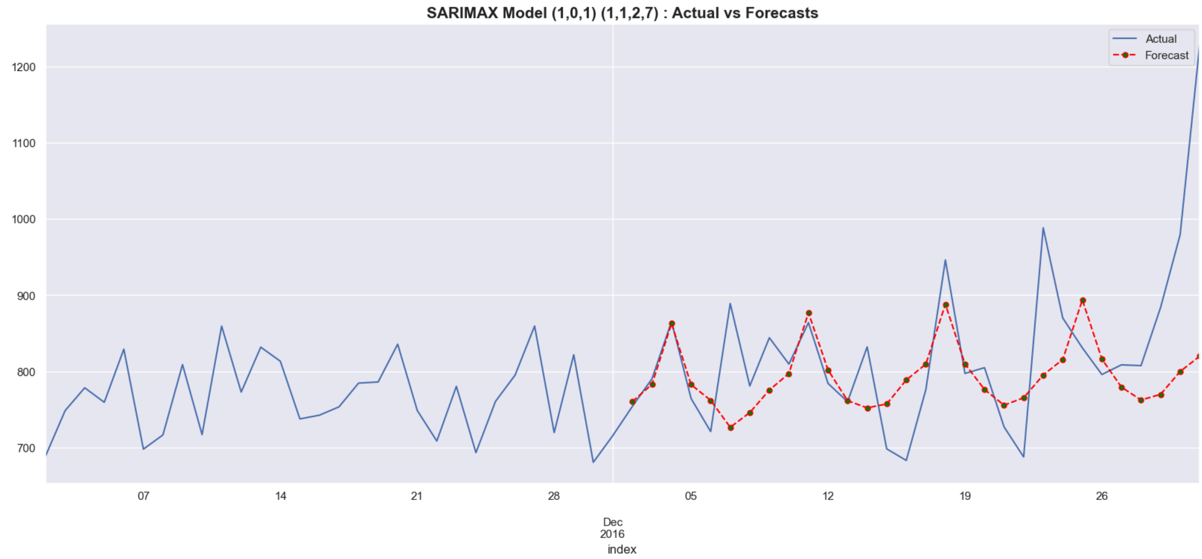

```
------------------------------------------------------------------------------------
----
        SARIMAX model for French Time Series
        Parameters of Model : (0,0,2) (2,1,2,7)
        MAPE of Model       : 0.05989
        RMSE of Model       : 62.201
------------------------------------------------------------------------------------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



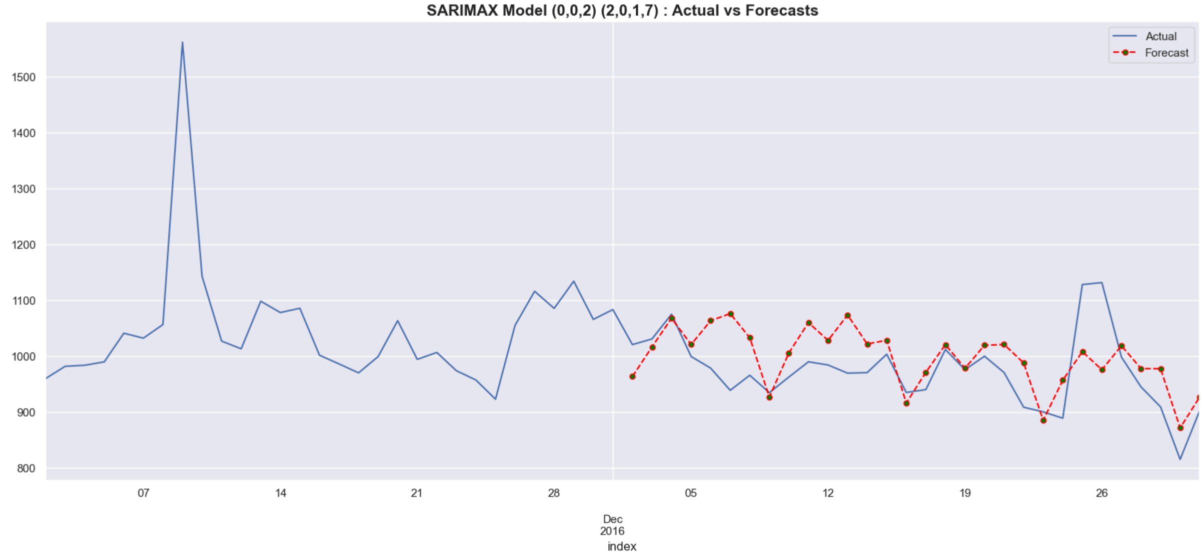
```
--------------------------------------------------------------------------------
----
       SARIMAX model for German Time Series
       Parameters of Model : (2,1,0) (0,1,1,7)
       MAPE of Model       : 0.06553
       RMSE of Model       : 112.628
--------------------------------------------------------------------------------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



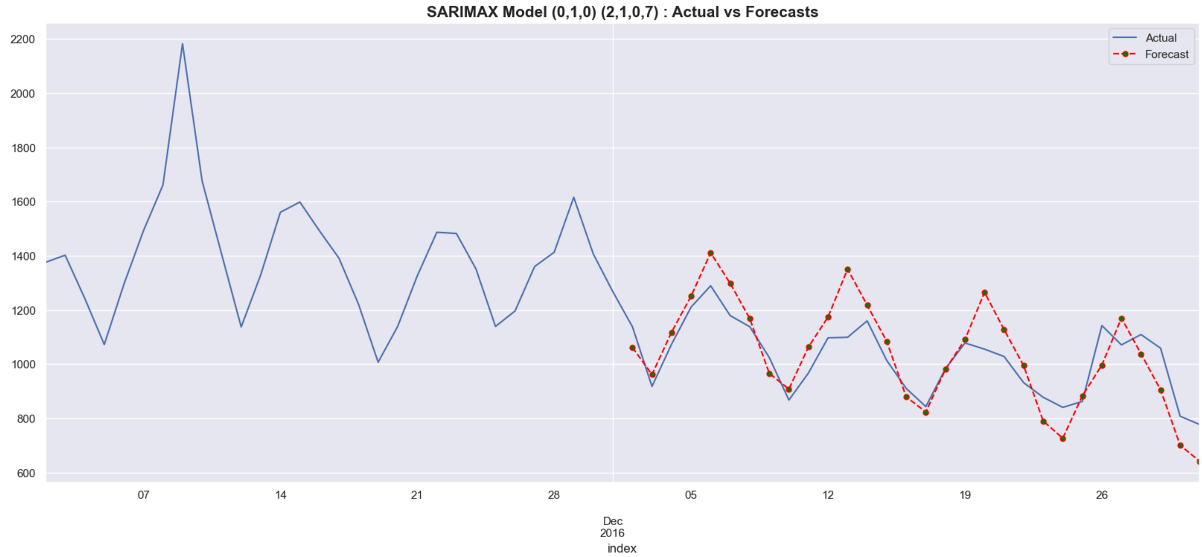

```
--------------------------------------------------------------------------------
----
       SARIMAX model for Japenese Time Series
       Parameters of Model : (1,0,1) (1,1,2,7)
       MAPE of Model       : 0.0735
       RMSE of Model       : 104.629
--------------------------------------------------------------------------------
----
```



```
--------------------------------------------------------------------------------------
----
        SARIMAX model for Russian Time Series
        Parameters of Model : (0,0,2) (2,0,1,7)
        MAPE of Model       : 0.05133
        RMSE of Model       : 63.586
--------------------------------------------------------------------------------------
----
```




```
--------------------------------------------------------------------------------------
----
        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[42]: 0

8. Forecasting using Facebook Prophet

In [51]:
```
from prophet import Prophet
```

In [52]:
```
time_series = data_language
time_series = time_series.reset_index()
time_series = time_series[['index', 'English']]
time_series.columns = ['ds', 'y']
exog = exo_var.copy(deep = True)
time_series['exog'] = exog.values
```

In [53]:
```
time_series
```

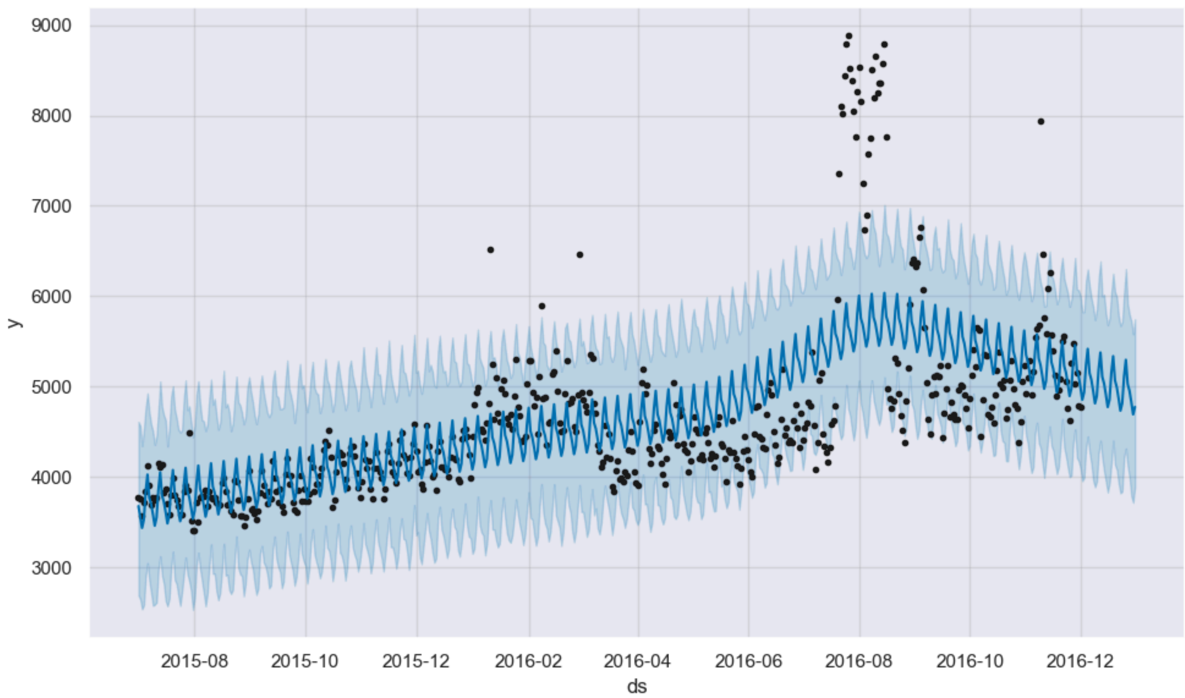
Out[53]:

	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 [54]:
```
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)
```

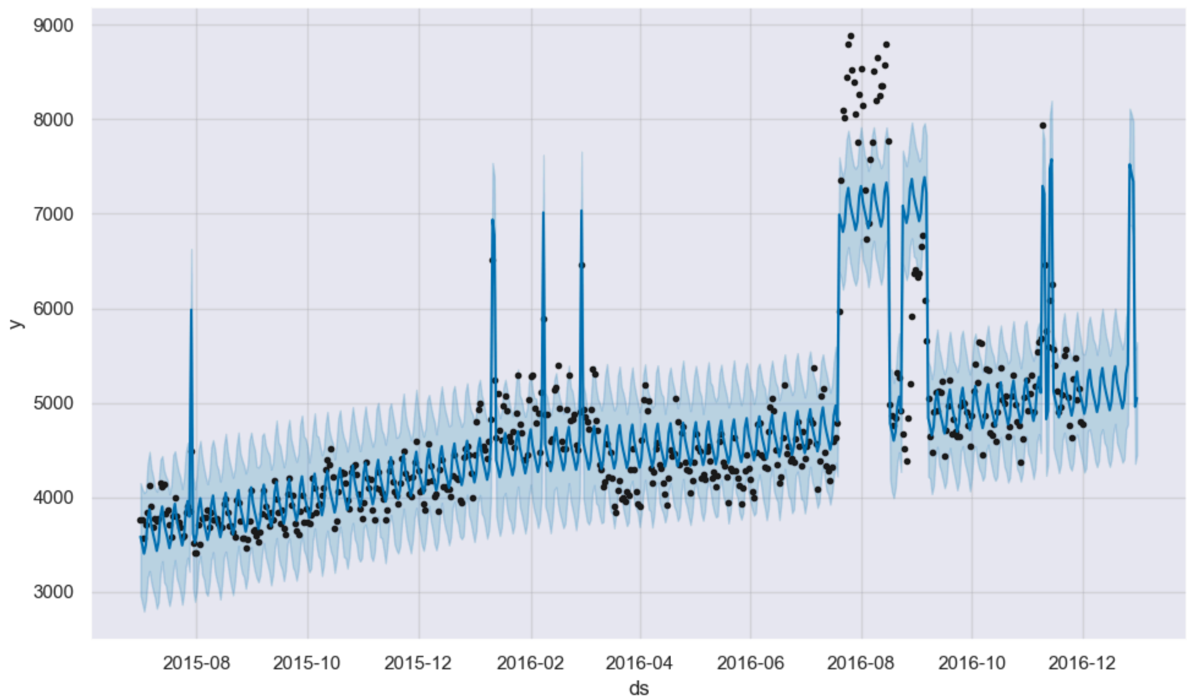
```
20:14:48 - cmdstanpy - INFO - Chain [1] start processing
20:14:49 - cmdstanpy - INFO - Chain [1] done processing
```



In [55]:

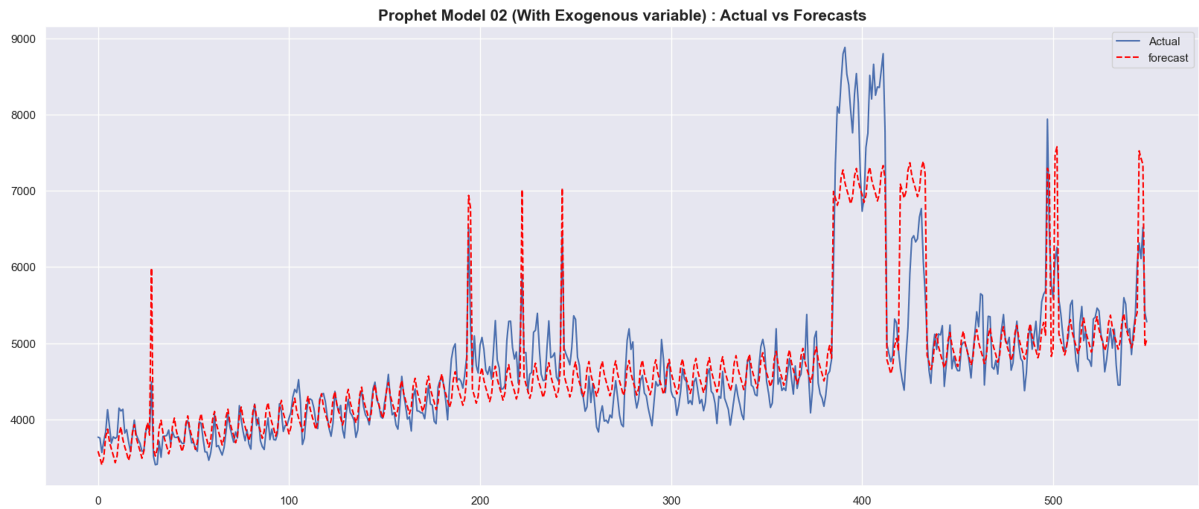
```
prophet2 = Prophet(weekly_seasonality=True)
prophet2.add_regressor('exog')
prophet2.fit(time_series[:-30])
#future2 = prophet2.make_future_dataframe(periods=30, freq= 'D')
forecast2 = prophet2.predict(time_series)
fig2 = prophet2.plot(forecast2)
```

```
20:14:53 - cmdstanpy - INFO - Chain [1] start processing
20:14:53 - cmdstanpy - INFO - Chain [1] done processing
```



In [56]:

```
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', fon
plt.show()
```



In [57]:
```
errors = abs(actual - forecast)
mape = np.mean(errors/abs(actual))
mape
```

Out[57]: 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%

9. Business decisions / Recommendations

9.1 MAPE vs Visits per Language

In [58]:
```
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[58]:

	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	0	0	2	2	0	1	7	0.05133
1	French	0	0	2	2	1	2	7	0.05989
2	German	2	1	0	0	1	1	7	0.06553
3	Japenese	1	0	1	1	1	2	7	0.07350
5	Spanish	0	1	0	2	1	0	7	0.08209

In [59]:
```
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')
```

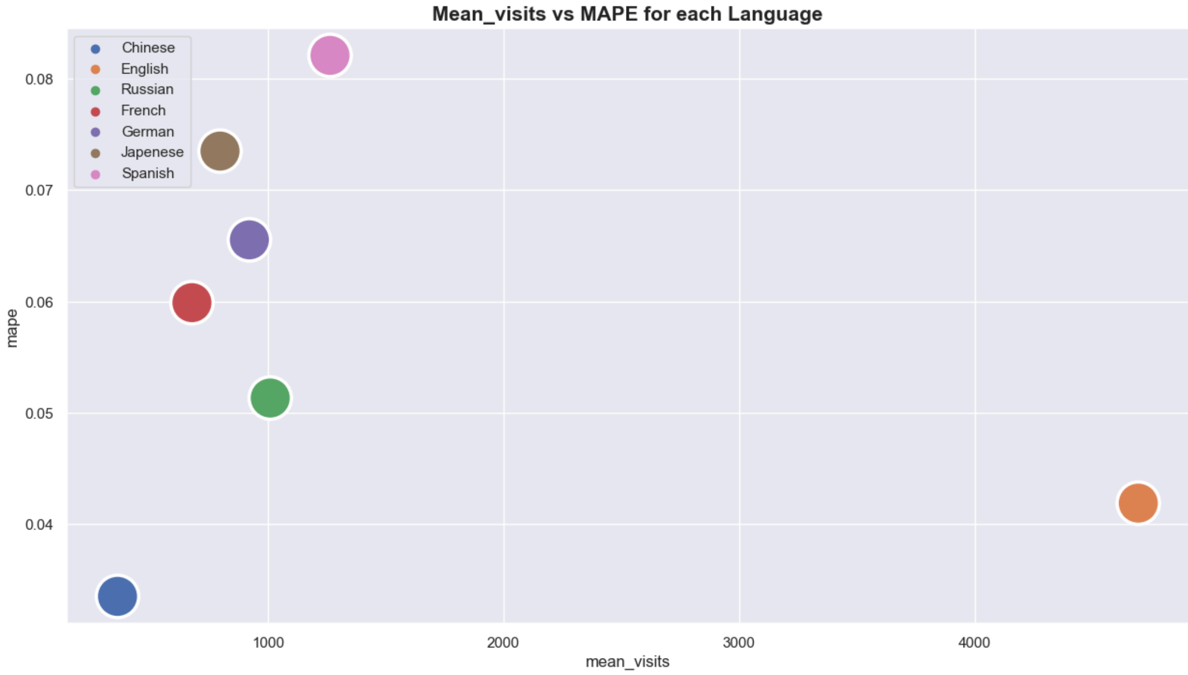
In [60]:
```
df_visit_mape
```

Out[60]:

	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	0	0	2	2	0	1	7	0.05133	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	1	0	1	1	1	2	7	0.07350	795.415559
6	Spanish	0	1	0	2	1	0	7	0.08209	1262.718183

In [61]:

```
plt.figure(figsize = (15,8))
sns.scatterplot(x="mean_visits", y="mape", hue="language", data=df_visit_mape, s=1
plt.legend(loc="upper left")
plt.title(f'Mean_visits vs MAPE for each Language', fontsize = 15, fontweight = 'b
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.