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.

Importing libraries

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

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
path_1 = "/content/drive/MyDrive/Scaler Case studies/Adease casestudy/Exog_Campaign_eng"
exo_data = pd.read_csv(path_1)
```

```
path_2 = "/content/drive/MyDrive/Scaler Case studies/Adease casestudy/train_1.csv"
train_data = pd.read_csv(path_2)
```

```
#creating copy of dataframe for backup
data = train_data.copy(deep = True)
data.drop_duplicates(keep='last', inplace = True)
```

```
print('-'*80)
print(f'Shape of Data : {data.shape}')
print('-'*80)
print(f'Shape of exogenous variable : {exo_data.shape}')
print('-'*80)
```

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

```
data.sample(100).head()
```

	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
110987	Ghulam_Qadir_Jatoi_en.wikipedia.org_all-access_all-agents	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
67119	12._Juli_de.wikipedia.org_desktop_all-agents	65.0	90.0	81.0	42.0	72.0	139.0	150.0	200.0
41155	House_of_Cards_(season_3)_en.wikipedia.org_all-access_all-agents	4480.0	4262.0	4111.0	4145.0	4921.0	4661.0	4762.0	4427.0
43031	Category:MediaWiki_configuration_settings_www.mediawiki.org_desktop_all-agents	21.0	35.0	22.0	31.0	63.0	63.0	53.0	19.0
25300	Shine_(film)_fr.wikipedia.org_all-access_all-agents	24.0	32.0	32.0	39.0	50.0	33.0	20.0	30.0

```
# => Data for 550 Dates (1.5 Years / 18 Months) is provided for all pages
```

```
print('-'*80)
print('Data types of Starting Columns')
print('-'*80)
print(data.dtypes[:10])
print('-'*80)
print('Data types of Ending Columns')
print('-'*80)
print(data.dtypes[-10:])
print('-'*80)
```

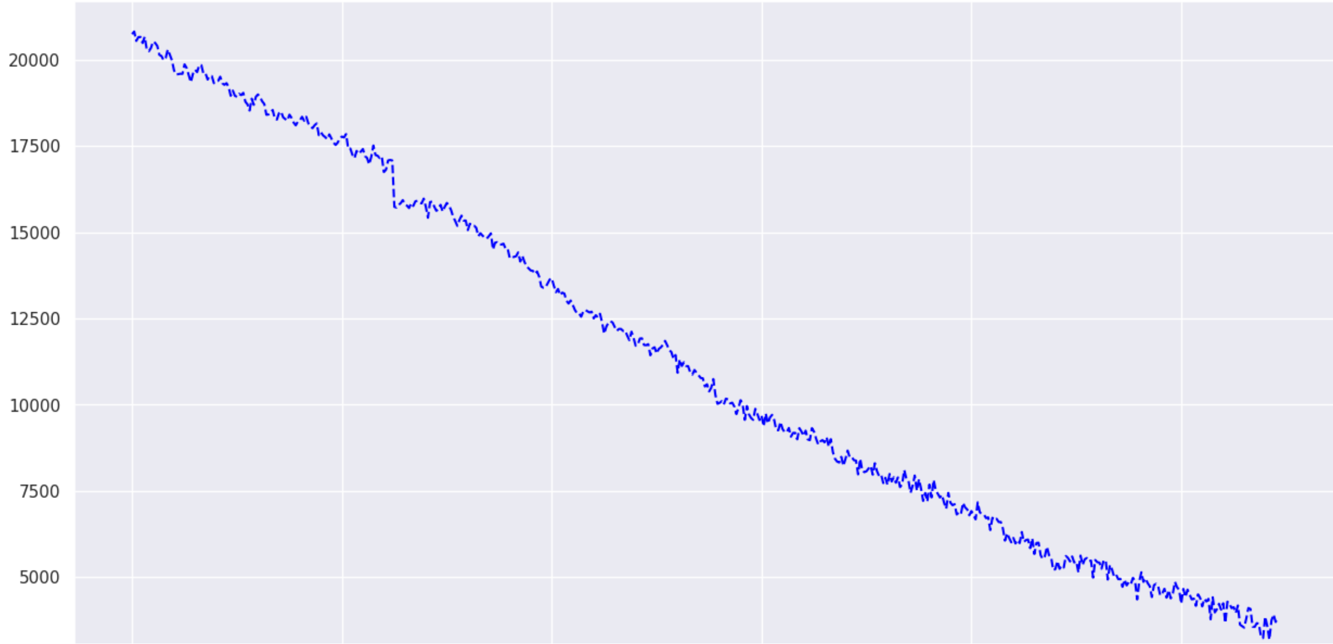
```
--------------------------------------------------------------------------------
Data types of Starting Columns
--------------------------------------------------------------------------------
Page           object
2015-07-01    float64
2015-07-02    float64
2015-07-03    float64
2015-07-04    float64
2015-07-05    float64
2015-07-06    float64
2015-07-07    float64
2015-07-08    float64
2015-07-09    float64
dtype: object
--------------------------------------------------------------------------------
Data types of Ending Columns
--------------------------------------------------------------------------------
2016-12-22    float64
2016-12-23    float64
2016-12-24    float64
2016-12-25    float64
2016-12-26    float64
2016-12-27    float64
2016-12-28    float64
2016-12-29    float64
2016-12-30    float64
2016-12-31    float64
dtype: object
--------------------------------------------------------------------------------
```

Checking null values

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

```
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
```

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



=> Above Plot indicates that NaN / Null values are decreasing with Time. Later Dates have less Null Values as compared to Older Dates.

=> This is possible as the Pages which were hosted / created towards later dates, will have null values for previous dates (dates before the page was created / hosted).

=> We will drop the rows where more than 300 null values are present and replace remaining Null Values with 0.

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

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

```
data.fillna(0, inplace = True)
```

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

```
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
```

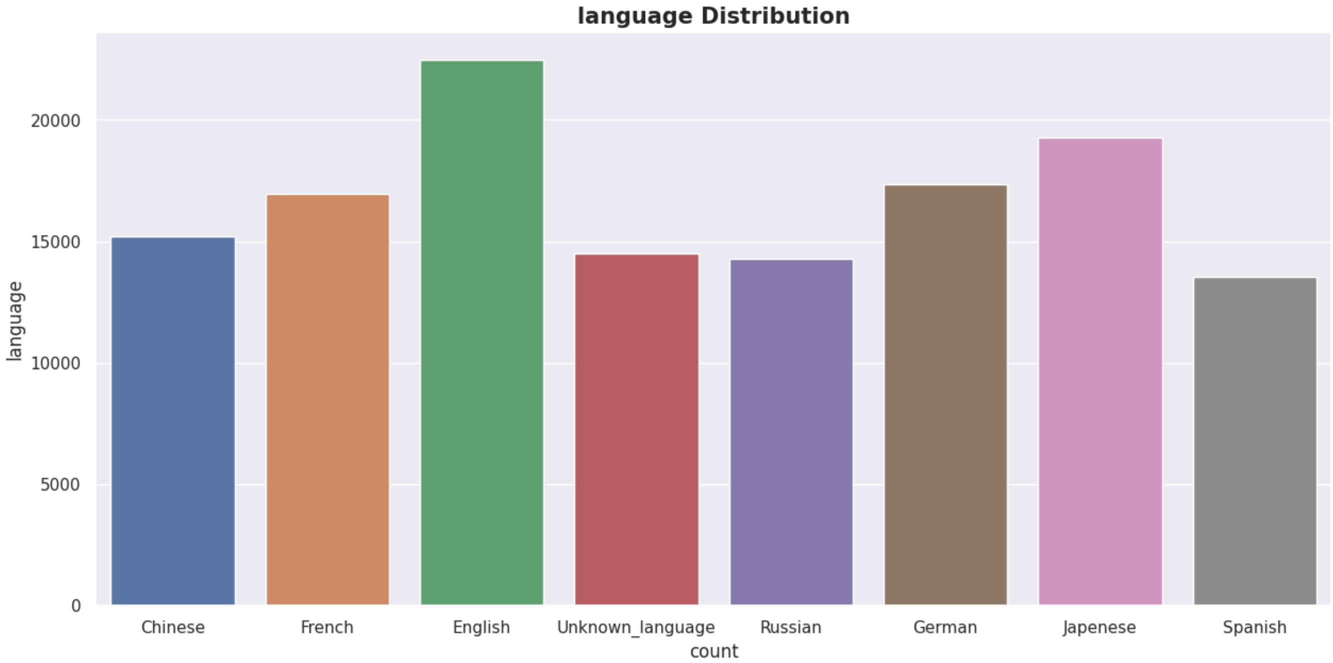
Exploratory Data Analysis & Feature Engineering

Extracting Language , Access_Type & Access_Origin from Page

```
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)


#Visualizing distribution of various languages
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()
```



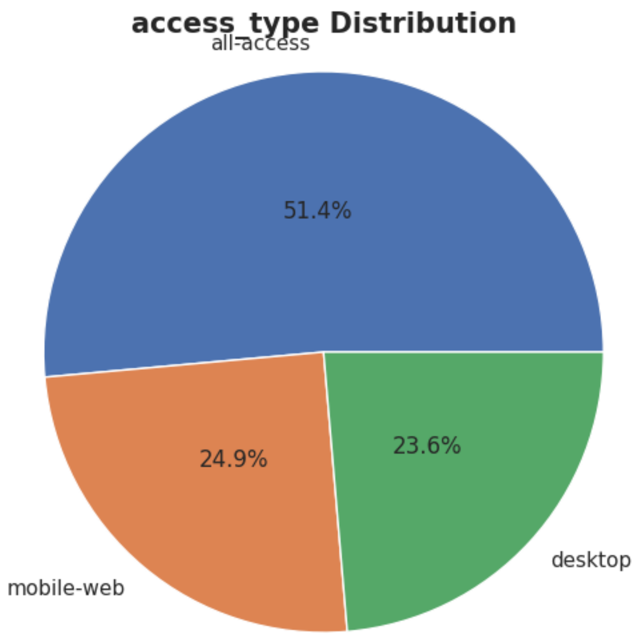

```
data.loc[data['language'] == 'Unknown_language', 'Page'].sample(100).head(10)
```

```
78579                        File:Mr._Abbot_Bitt_at_Convent.ogv_commons.wikimedia.org_mobile-web_all-agents
82607               File:Madrid_-_Acampada_Sol_-_20110519-2029.ogv_commons.wikimedia.org_desktop_all-agents
80048                                     File:Speaker_Icon.svg_commons.wikimedia.org_mobile-web_all-agents
77898                                     Category:Skin_Diamond_commons.wikimedia.org_mobile-web_all-agents
83376                                              How_to_contribute/ug_www.mediawiki.org_all-access_spider
20341                                       Special:PageTranslation_www.mediawiki.org_all-access_all-agents
45526    File:Gilbert_Stuart_Williamstown_Portrait_of_George_Washington.jpg_commons.wikimedia.org_all-acc...
45965    File:Eye_disease_simulation,_age-related_macular_degeneration.jpg_commons.wikimedia.org_all-acce...
15557                                 File:Tours_Saint-Jacques_-_195.jpg_commons.wikimedia.org_all-access_spider
78478                          File:Karl_Landsteiner,_1920s..jpg_commons.wikimedia.org_mobile-web_all-agents
Name: Page, dtype: object
```

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

```
#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)


#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=0.5)
plt.title(f'{var} Distribution', fontsize = 15, fontweight = 'bold')
plt.axis('equal')
plt.show()
```




```
#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)


#Visualizing Access Origin Distribution
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=0.5)
plt.title(f'{var} Distribution', fontsize = 15, fontweight = 'bold')
plt.axis('equal')
plt.show()
```

Data Pre-processing

Creating dataframe: mean page visit per language

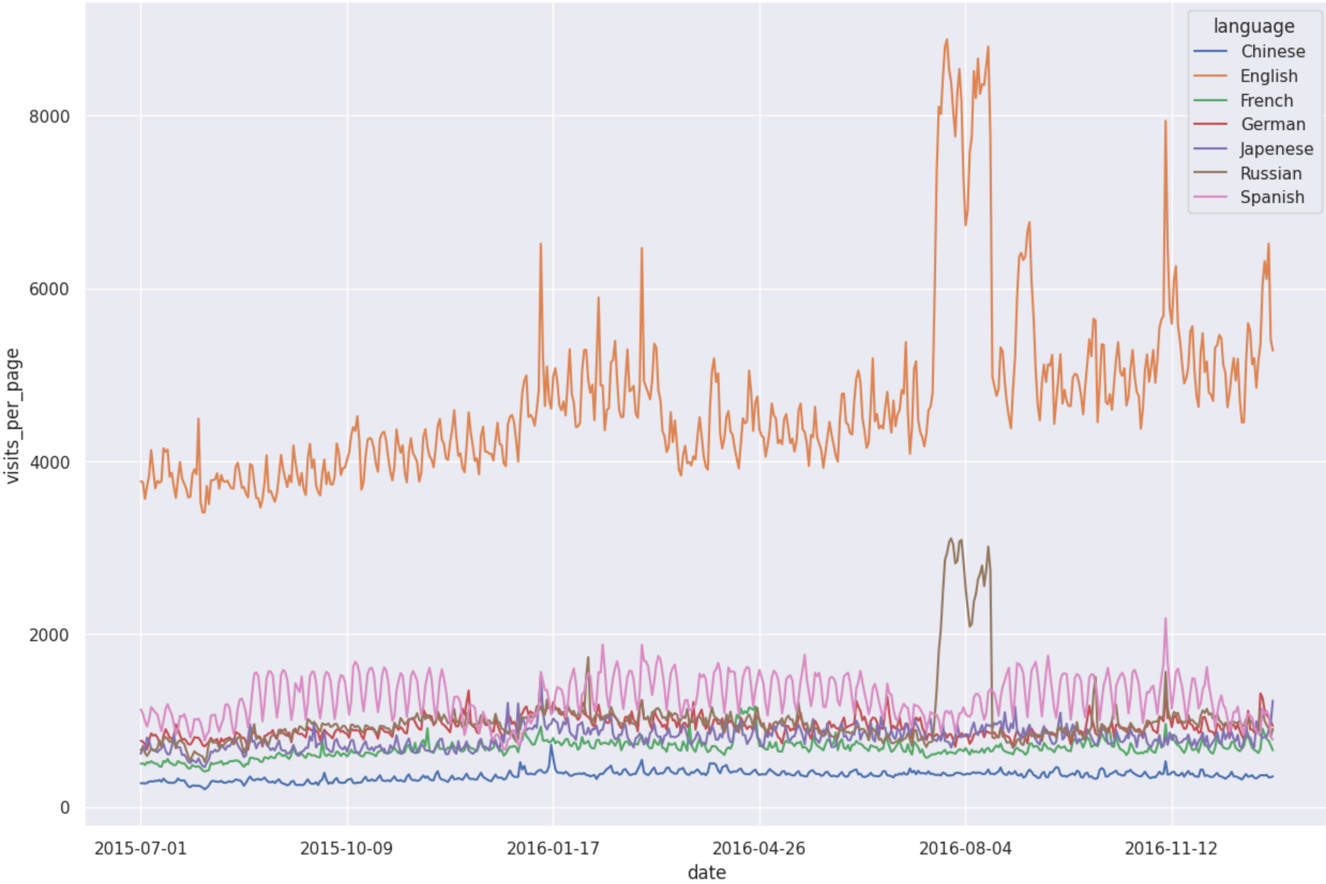
```
data_language = pd.DataFrame()
data_language = data.groupby('language').mean().transpose()
data_language.drop(['Unknown_language'], inplace = True, axis = 1)
data_language.reset_index(inplace = True)
data_language.set_index('index', inplace = True)
data_language
```

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

```
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 = 'bold')
plt.show()

## Popularity sequence of various languages : English > Spanish > Russian > German > Japenese > French > Chinese
```


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



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)

```
#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 Used','Number of Observations Used'])
    for key, value in dftest[4].items():
       df_output['Critical Value (%s)' %key] = value
    print (df_output)
```

```
#apply adf test on the series
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
```

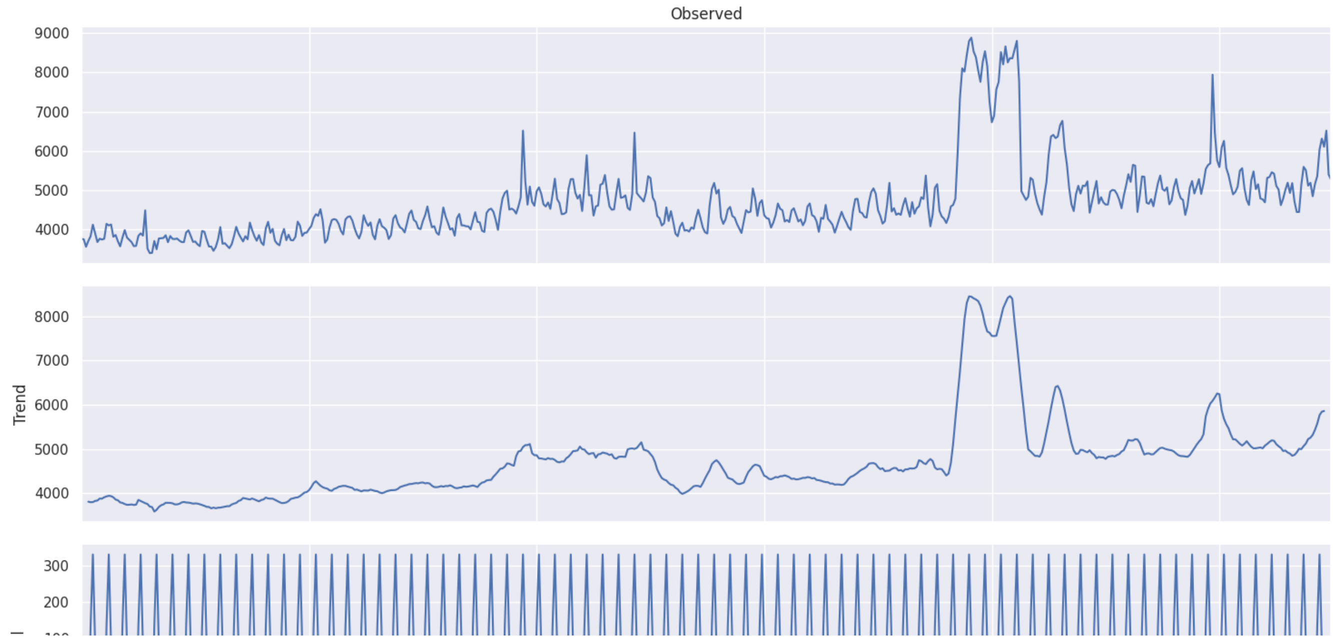
The test statistic > critical value / p_value > 5%. This implies that the series is not stationary.

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
```

```
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()
```




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

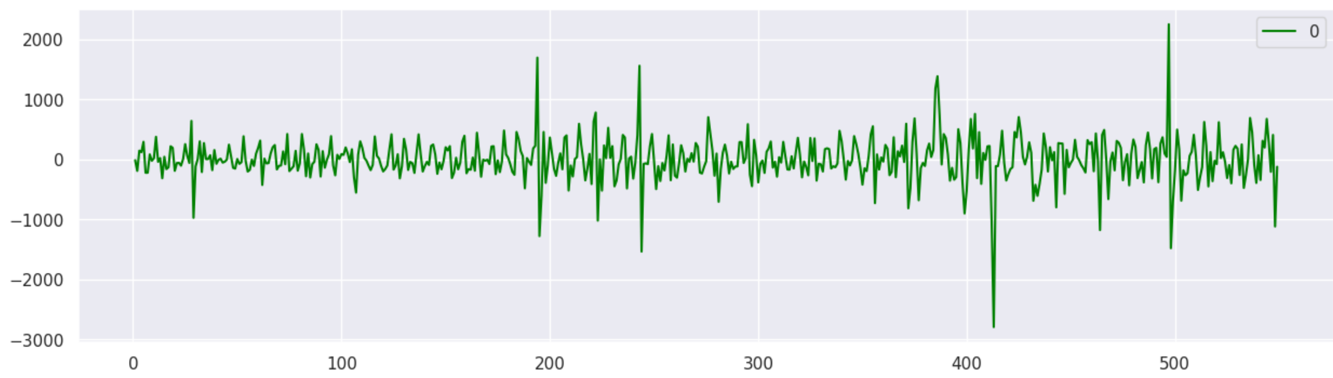
```
Results of Dickey-Fuller Test:
Test Statistic                -1.152195e+01
p-value                        4.020092e-21
#Lags Used                     1.700000e+01
Number of Observations Used    5.320000e+02
Critical Value (1%)           -3.442702e+00
Critical Value (5%)           -2.866988e+00
Critical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

```
ts_diff = pd.DataFrame(ts_english).diff(1)
ts_diff.dropna(inplace = True)
```

```
ts_diff.plot(color = 'green', figsize=(15, 4))
plt.show()
```



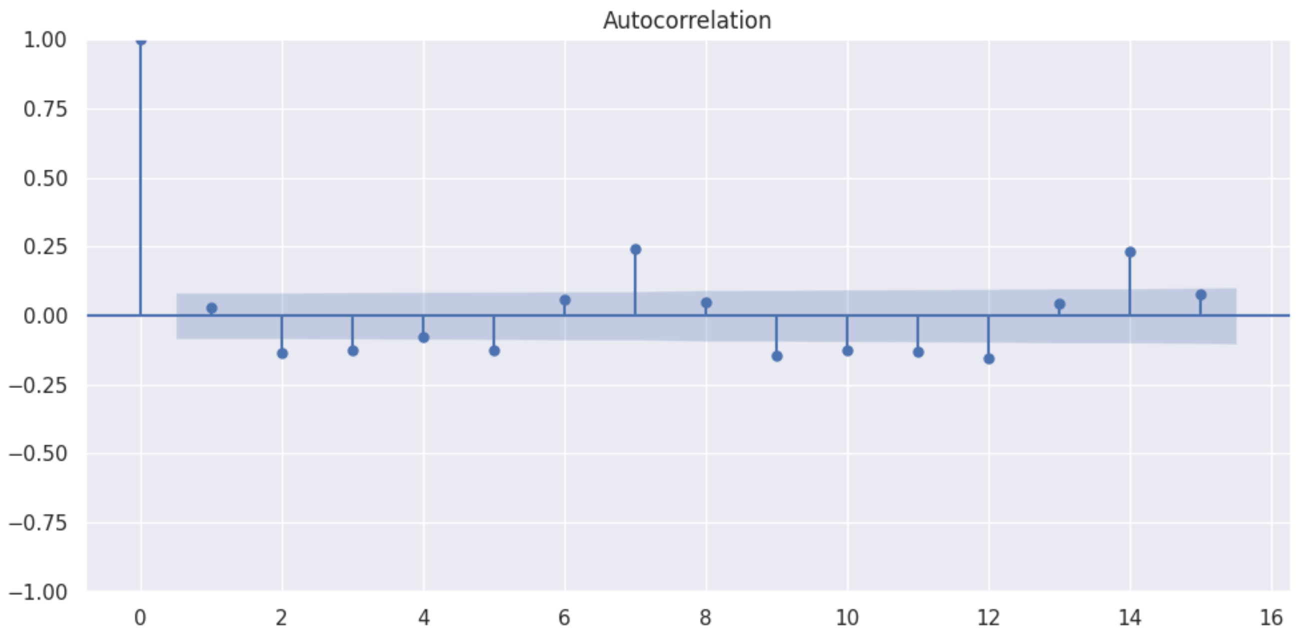

```
#ADF Test for differenced time-series
adf_test(ts_diff)
#p_value < 5%  ==> time series is stationary
```

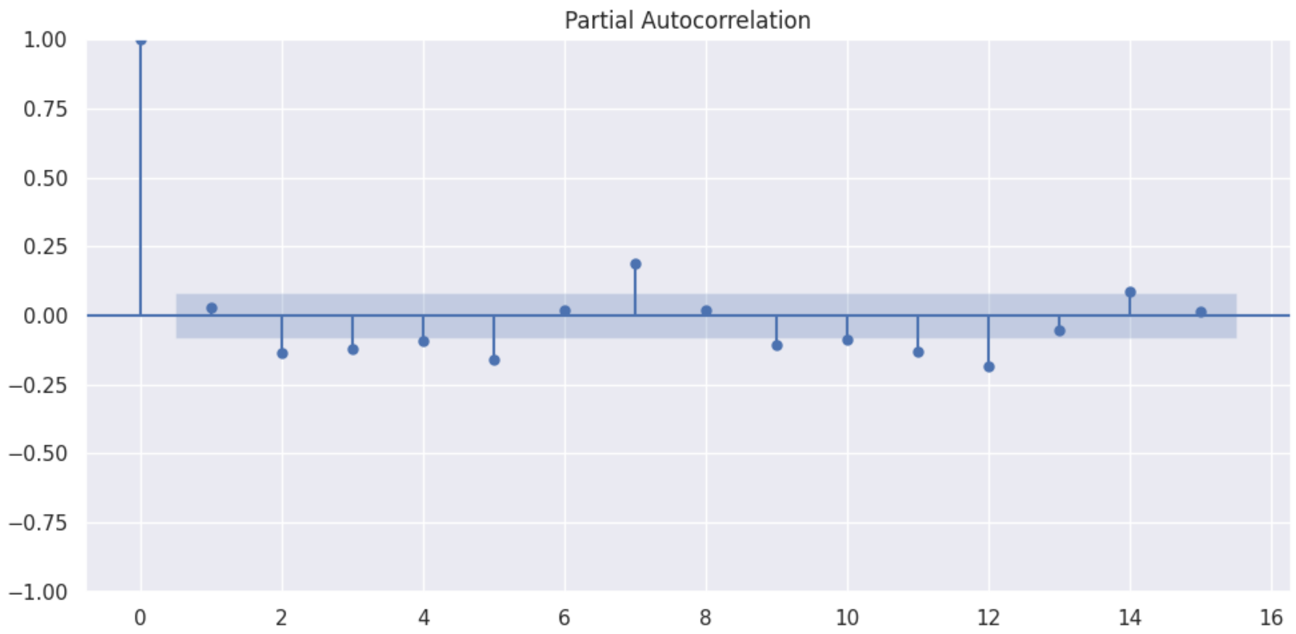
```
Results of Dickey-Fuller Test:
Test Statistic                -8.273590e+00
p-value                        4.721272e-13
#Lags Used                     1.300000e+01
```

```
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.

```
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()
```



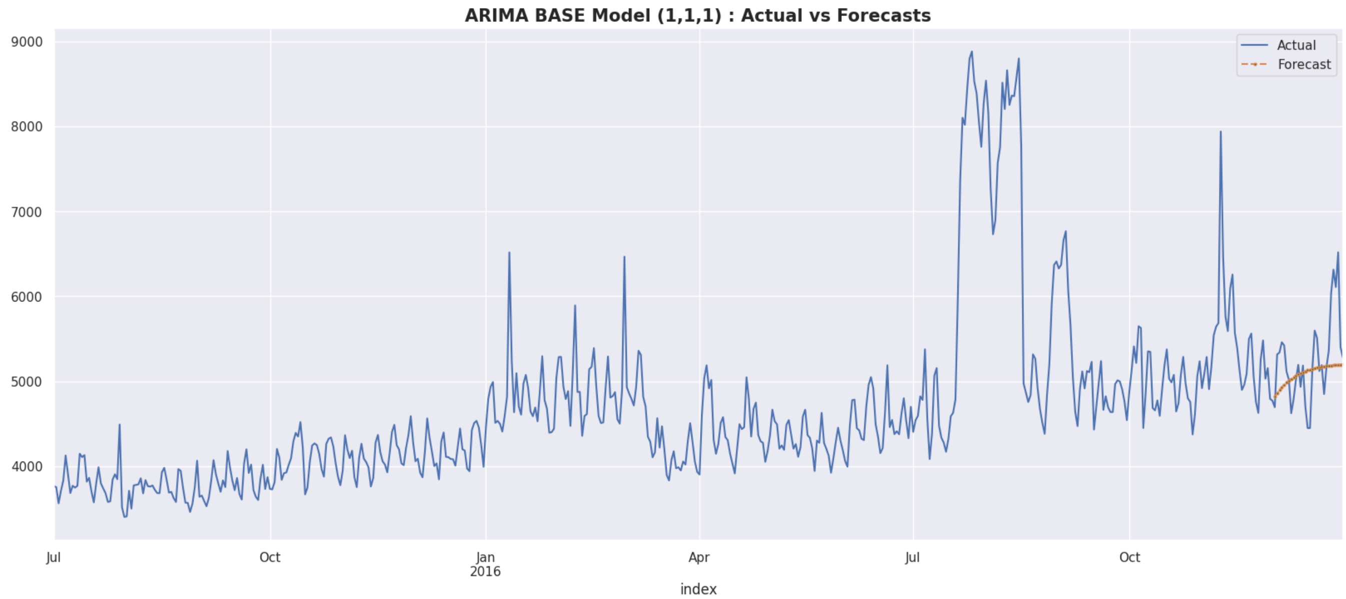


==> ACF & PACF indicates we should choose p = 0 & q = 0. But we will start with p=1 & q=1 for base ARIMA Model

Forecasting Model Creation

ARIMA Base Model

```
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)

#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='green', markersize=2)
plt.legend(loc="upper right")
plt.title('ARIMA BASE Model (1,1,1) : Actual vs Forecasts', fontsize = 15, fontweight = 'bold')
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,3)}')
print('-'*80)
```



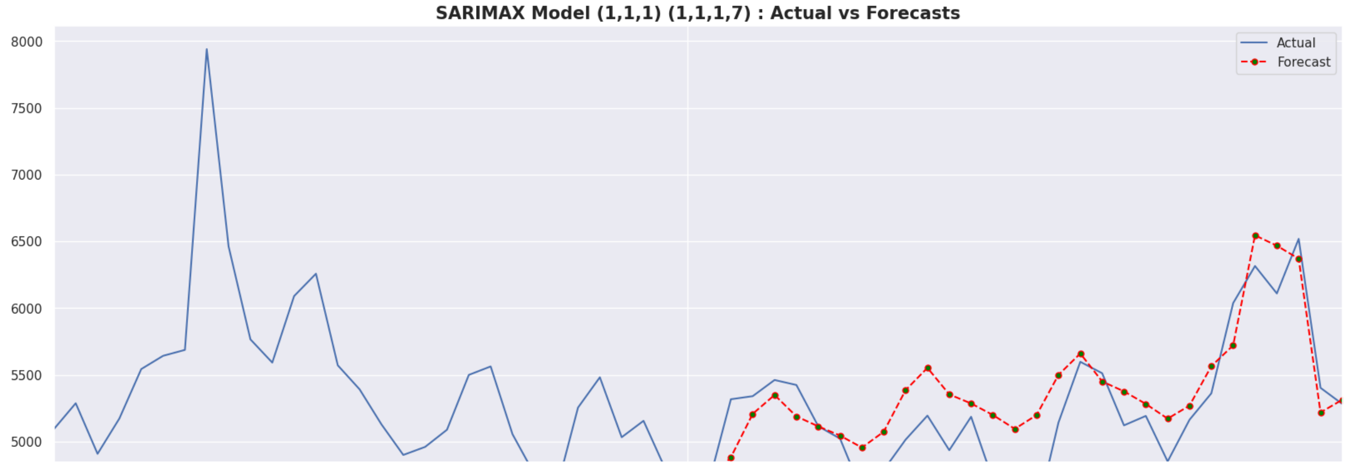

```
--------------------------------------------------------------------------------
MAPE of Model : 0.06691
--------------------------------------------------------------------------------
RMSE of Model : 496.72
--------------------------------------------------------------------------------
```

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

Creation for function for SARIMAX model

```
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(exog[-n:]))

    #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='green', markersize=5)
    plt.legend(loc="upper right")
    plt.title(f'SARIMAX Model ({p},{d},{q}) ({P},{D},{Q},{s}) : Actual vs Forecasts', fontsize = 15, fontweight = 'bold')
    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)
```

```
#Checking a SARIMAX model with seasonality (p,d,q,P,D,Q,s = 1,1,1,1,1,1,7)
exog = exo_data['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)
```



==> 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

```
MAPE of Model : 0.04884
```

Finding Best parameters for 'English' Pages

```
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_diffuse')
                                model_fit = model.fit()

                                #Creating forecast from Model
                                model_forecast = model_fit.forecast(n, dynamic = True, exog = pd.DataFrame(exog[-n:]))

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

                                #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, rmse]
                                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)*len(s_param)*(len(d_param)**2)} calculated')

    return param_df


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

exog = exo_data['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
```

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

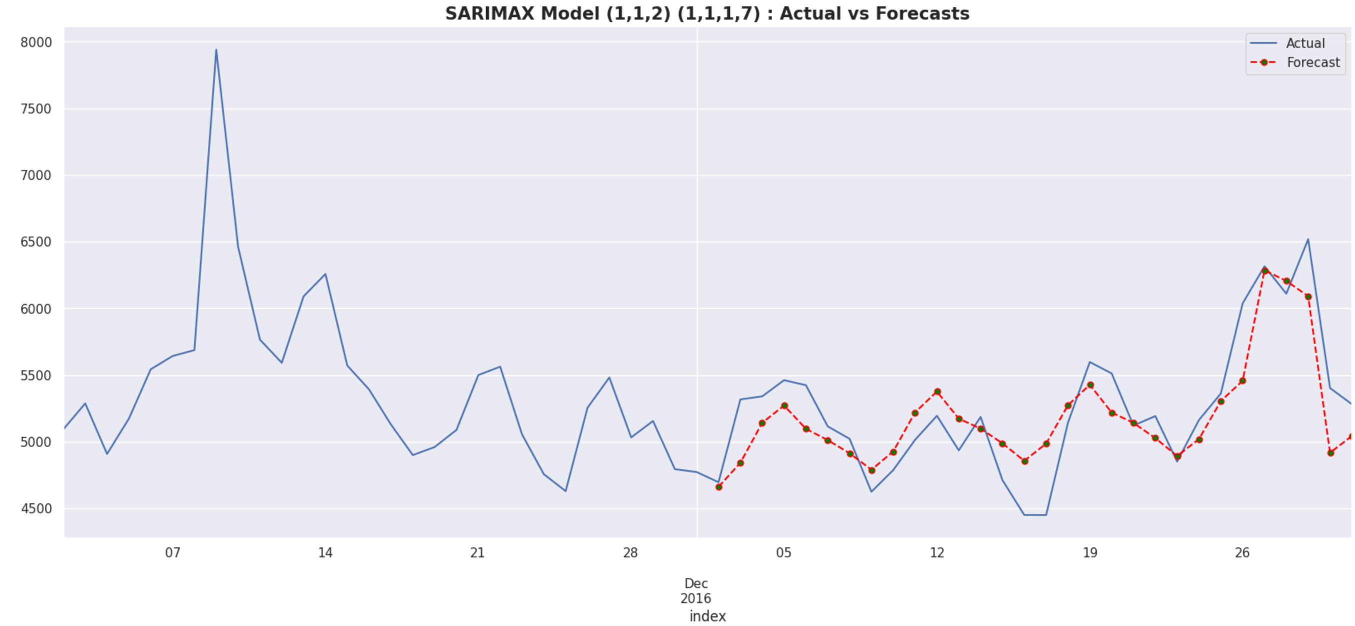
	serial	pdq	PDQs	mape	rmse
208	209	(1, 1, 2)	(1, 1, 1, 7)	0.04185	267.902
196	197	(1, 1, 1)	(2, 1, 1, 7)	0.04202	274.168
322	323	(2, 1, 2)	(2, 1, 1, 7)	0.04235	270.032
239	240	(2, 0, 1)	(0, 1, 2, 7)	0.04251	270.776
41	42	(0, 0, 2)	(0, 1, 2, 7)	0.04325	287.492

==> Best Possible parameters English Time Series are pdq = (1, 1, 2) & PDQs = (1, 1, 1, 7).

==> Minimum MAPE = 4.18% and corresponding RMSE = 267.902.

```
#Function to fetch best parameters for each language

def pipeline_sarimax_grid_search_without_exog(languages, data_language, n, param, d_param, s_param):

    best_param_df  = pd.DataFrame(columns = ['language','p','d', 'q', 'P','D','Q','s','mape'])
    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_diffuse')
                                    model_fit = model.fit()

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

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

                                    #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)*len(s_param)*(len(d_param)**2)} calculated')

        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, best_D, best_Q, best_s}')
        print(f'---------------------------------------------------------------')

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

    return best_param_df


#Plotting the SARIMAX model corresponding to best parameters
exog = exo_data['Exog'].to_numpy()
time_series = data_language.English
p,d,q, P,D,Q,s = 1,1,2, 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 : 0.04185
-----------------------------------------------------------------------------
RMSE of Model : 267.902
-----------------------------------------------------------------------------
```

Creating Pipeline to search Best parameters for all Pages

```
#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, n, param, d_param, s_param)
```

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

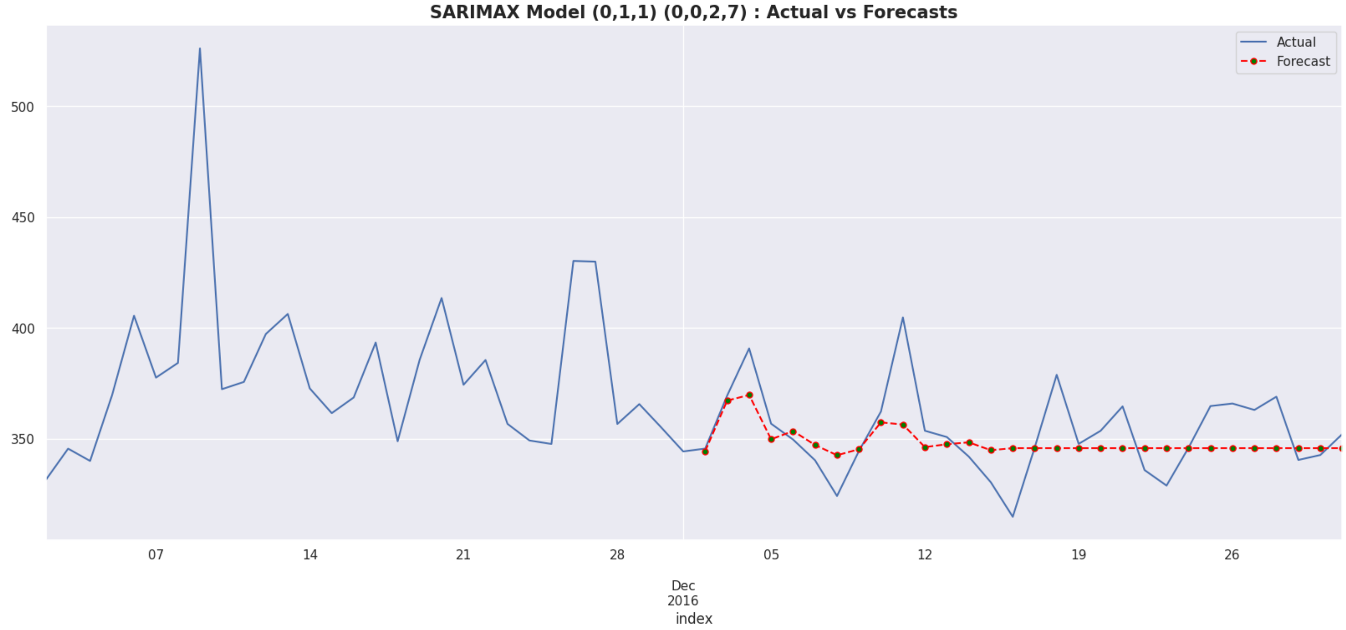
```
best_param_df.sort_values(['mape'], inplace = True)
best_param_df
```

	language	p	d	q	P	D	Q	s	mape
0	Chinese	0	1	1	0	0	2	7	0.03352

```
#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][0]
        d = best_param_df.loc[best_param_df['language'] == lang, ['d']].values[0][0]
        q = best_param_df.loc[best_param_df['language'] == lang, ['q']].values[0][0]
        P = best_param_df.loc[best_param_df['language'] == lang, ['P']].values[0][0]
        D = best_param_df.loc[best_param_df['language'] == lang, ['D']].values[0][0]
        Q = best_param_df.loc[best_param_df['language'] == lang, ['Q']].values[0][0]
        s = best_param_df.loc[best_param_df['language'] == lang, ['s']].values[0][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='green', markersize=5)
        plt.legend(loc="upper right")
        plt.title(f'SARIMAX Model ({p},{d},{q}) ({P},{D},{Q},{s}) : Actual vs Forecasts', fontsize = 15, fontweight = 'bold')
        plt.show()

    return 0


#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)
```

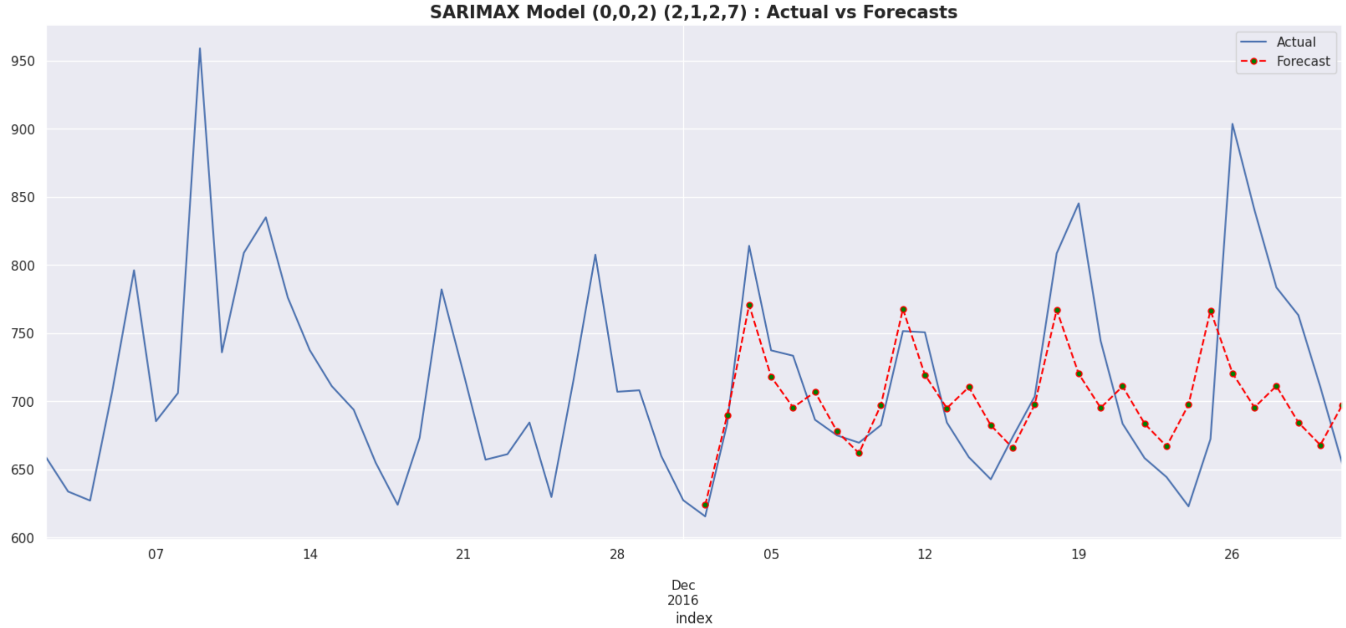
```
--------------------------------------------------------------------------------------
       SARIMAX model for Chinese Time Series
       Parameters of Model : (0,1,1) (0,0,2,7)
       MAPE of Model       : 0.03352
       RMSE of Model       : 16.433
--------------------------------------------------------------------------------------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

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



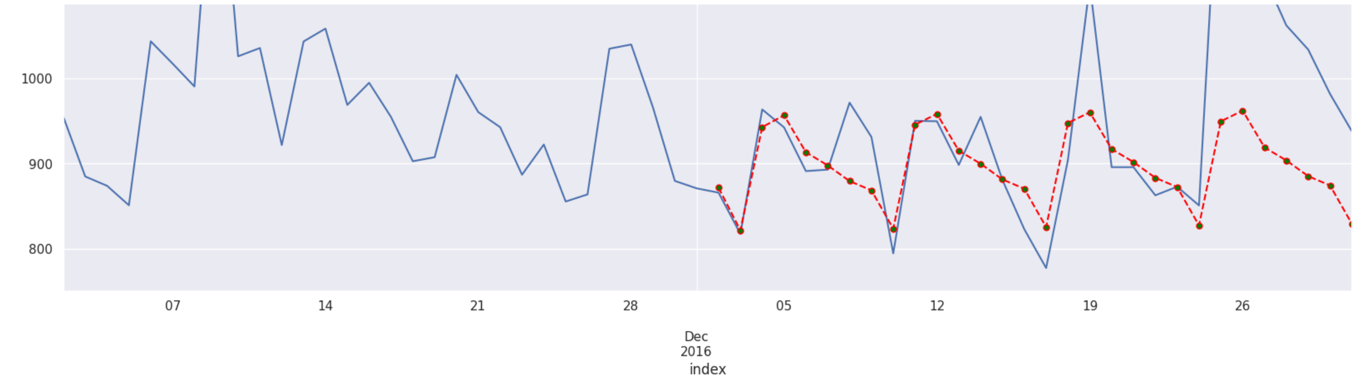

```
--------------------------------------------------------------------------------------
       SARIMAX model for French Time Series
       Parameters of Model : (0,0,2) (2,1,2,7)
       MAPE of Model       : 0.05989
       RMSE of Model       : 62.201
--------------------------------------------------------------------------------------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

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



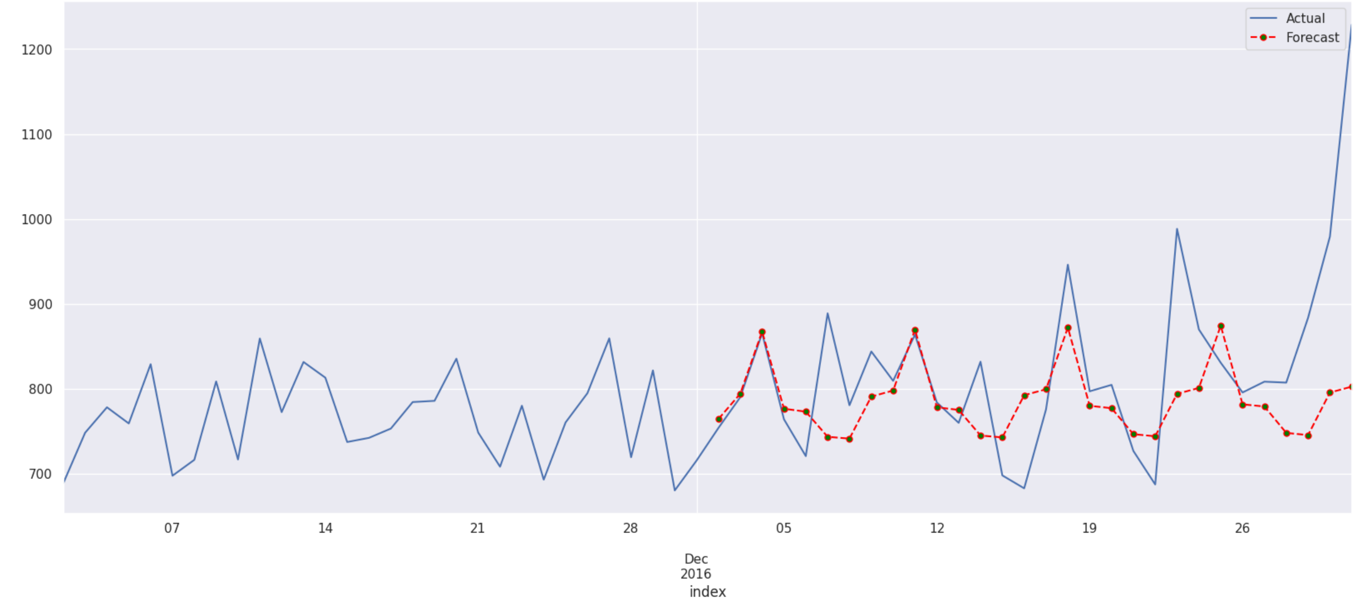

```
--------------------------------------------------------------------------------------
       SARIMAX model for German Time Series
       Parameters of Model : (2,1,0) (0,1,1,7)
       MAPE of Model       : 0.06553
       RMSE of Model       : 112.628
--------------------------------------------------------------------------------------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

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



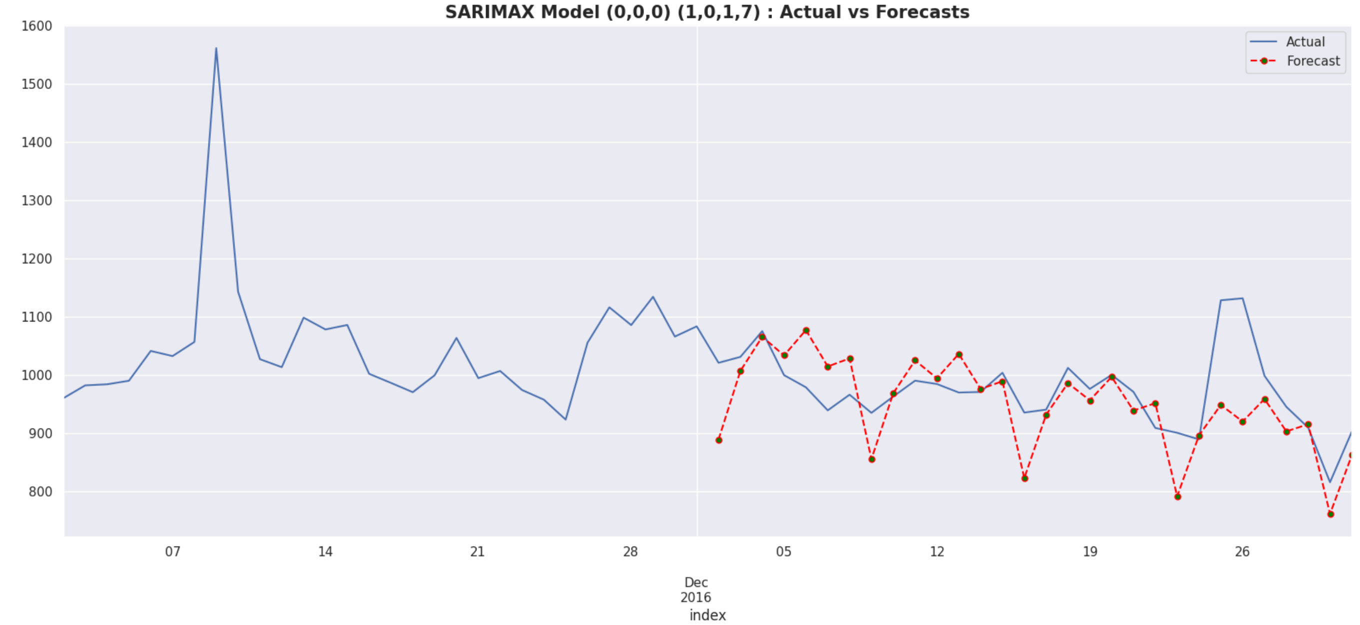

```
--------------------------------------------------------------------------------
      SARIMAX model for Japenese Time Series
      Parameters of Model : (0,0,2) (2,0,2,7)
      MAPE of Model       : 0.07278
      RMSE of Model       : 107.134
--------------------------------------------------------------------------------
```

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



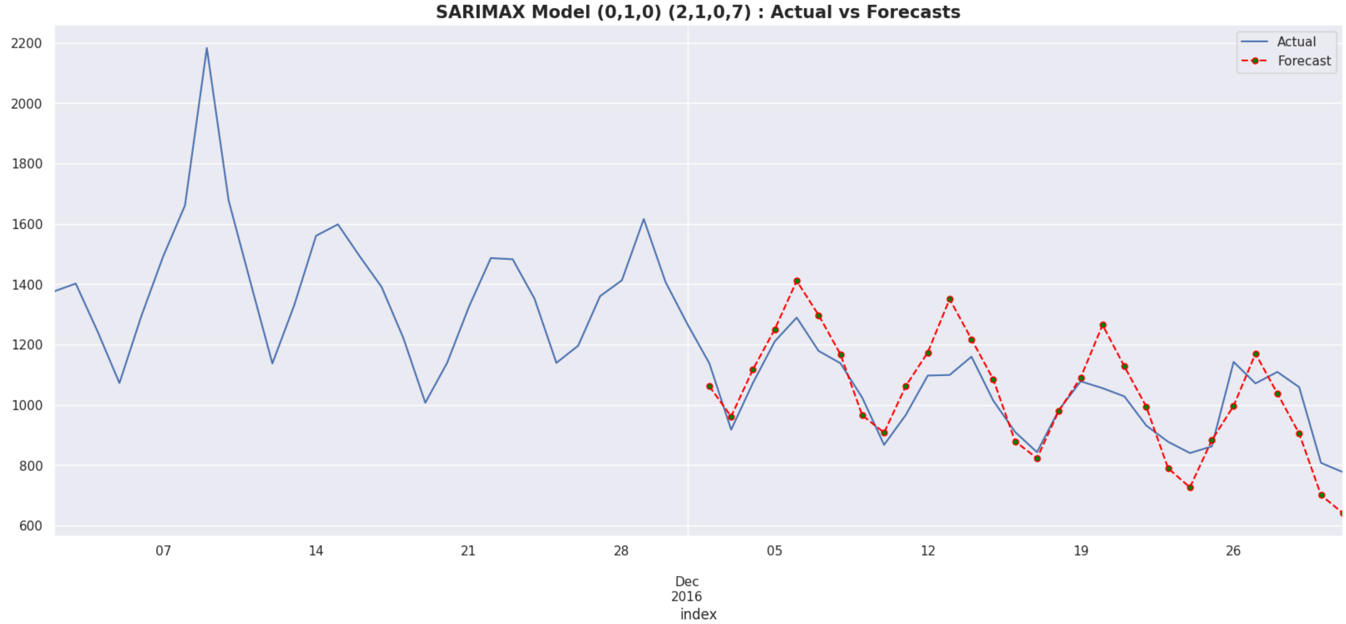

```
--------------------------------------------------------------------------------
      SARIMAX model for Russian Time Series
      Parameters of Model : (0,0,0) (1,0,1,7)
      MAPE of Model       : 0.05342
      RMSE of Model       : 74.078
--------------------------------------------------------------------------------
```

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




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

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




```
0
```

```
## Forecasting using Facebook Prophet
```

```
# np.__version__
```

```
# %pip install -c anaconda ephem
```

```
# !pip install pystan~=2.14
```

```
#pip install prophet
```

```
from prophet import Prophet
```

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

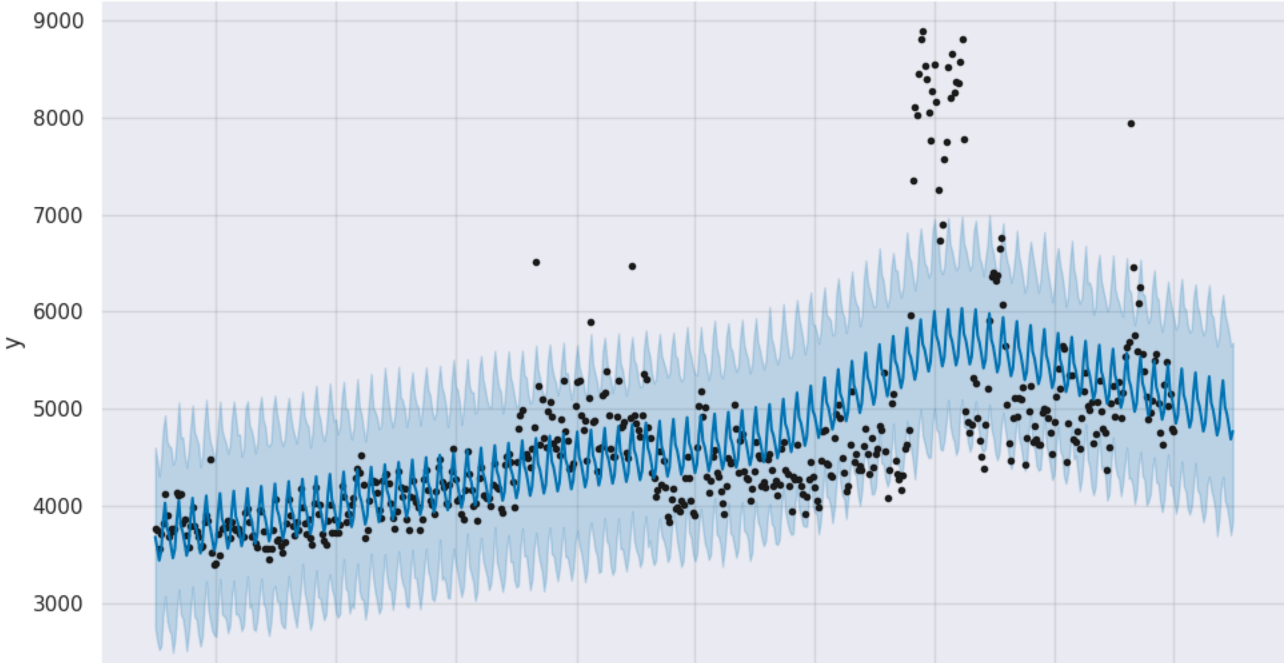
```
time_series
```

	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

```
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)
```

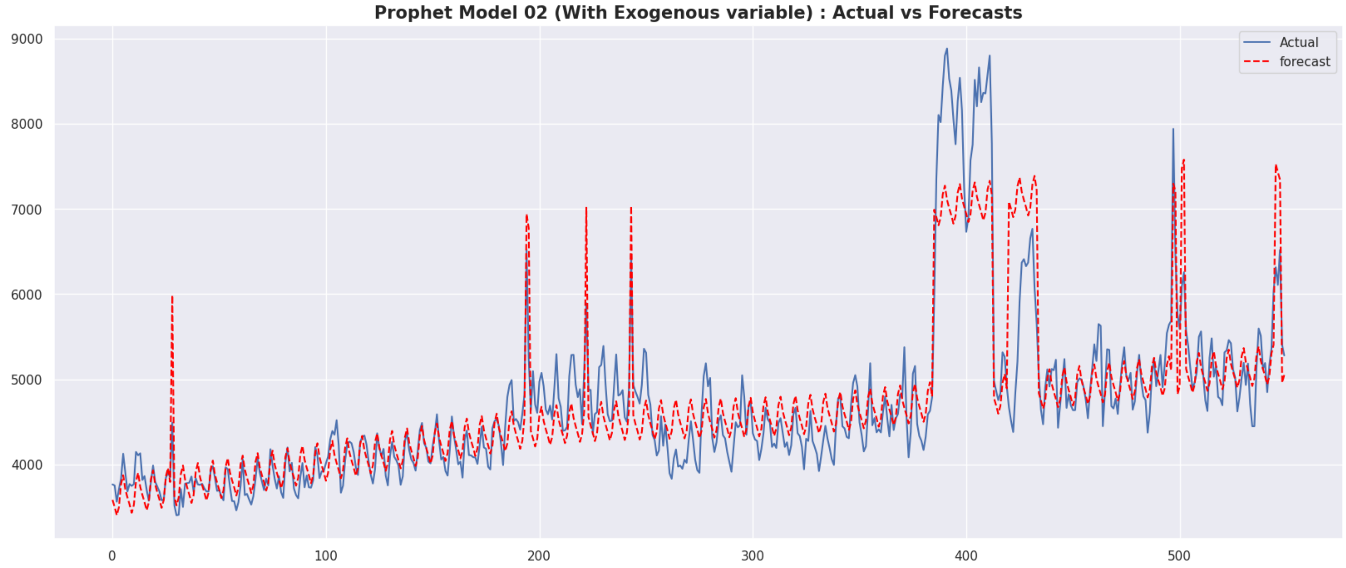
```
INFO:prophet:Disabling yearly seasonality. Run prophet with yearly_seasonality=True to override this.
INFO:prophet:Disabling daily seasonality. Run prophet with daily_seasonality=True to override this.
DEBUG:cmdstanpy:input tempfile: /tmp/tmp5wow_shg/974c856q.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmp5wow_shg/shvk9qk4.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.10/dist-packages/prophet/stan_model/prophet_model.bin', 'random', 'seed=9068
05:43:39 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
05:43:39 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
```




```
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)
```

```
INFO:prophet:Disabling yearly seasonality. Run prophet with yearly_seasonality=True to override this.
INFO:prophet:Disabling daily seasonality. Run prophet with daily_seasonality=True to override this.
DEBUG:cmdstanpy:input tempfile: /tmp/tmp5wow_shg/s7njbqx1.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmp5wow_shg/v6xq5r9b.json
DEBUG:cmdstanpy:idx 0
```

```
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', fontsize = 15, fontweight = 'bold')
plt.show()
```




```
errors = abs(actual - forecast)
mape = np.mean(errors/abs(actual))
mape
```

```
0.059768080739909364
```

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 Insights / Recommendations

MAPE vs Visits per Language

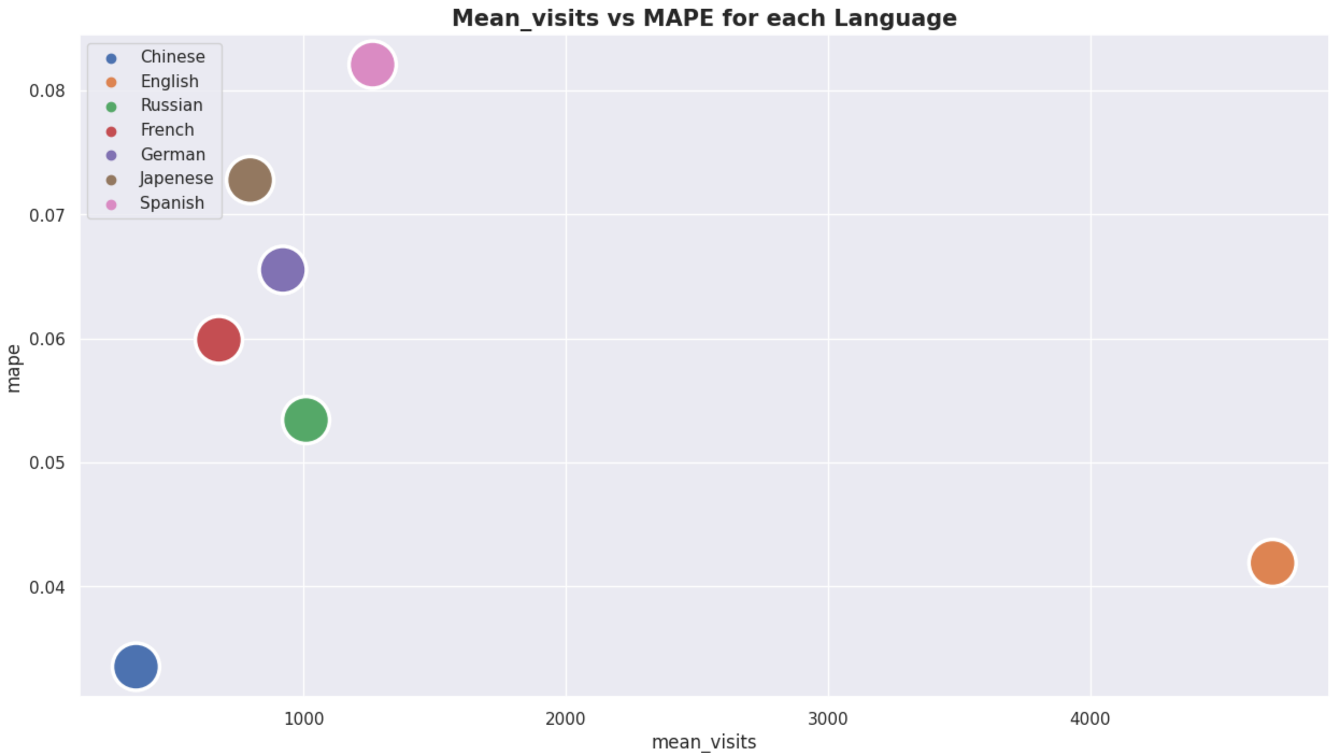
```
new_row = ['English', 1,1,1,2,1,1,7, 0.04189]
best_param_df.loc[len(best_param_df)] = new_row

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

	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	0	1	0	1	7	0.05342
1	French	0	0	2	2	1	2	7	0.05989
2	German	2	1	0	0	1	1	7	0.06553

```
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')


df_visit_mape
```

	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	0	1	0	1	7	0.05342	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	0.07278	795.415559
6	Spanish	0	1	0	2	1	0	7	0.08209	1262.718183

```
plt.figure(figsize = (15,8))
sns.scatterplot(x="mean_visits", y="mape", hue="language", data=df_visit_mape, s=1000 )
plt.legend(loc="upper left")
plt.title(f'Mean_visits vs MAPE for each Language', fontsize = 15, fontweight = 'bold')
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.
```

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 Japense, 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 & Japenese 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: 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 preprocessing 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. Equation of ARIMA model can be represented as below:

$$d_t = c + \sum_{n=1}^{p} \alpha_n d_{t-n} + \sum_{n=1}^{q} \theta_n \epsilon_{t-n} + \epsilon_t$$

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. Equation of SARIMA model can be represented as below:

$$y_t = c + \sum_{n=1}^{p} \alpha_n y_{t-n} + \sum_{n=1}^{q} \theta_n \epsilon_{t-n} + \sum_{n=1}^{P} \phi_n y_{t-sn} + \sum_{n=1}^{Q} \eta_n \epsilon_{t-sn} + \epsilon_t$$

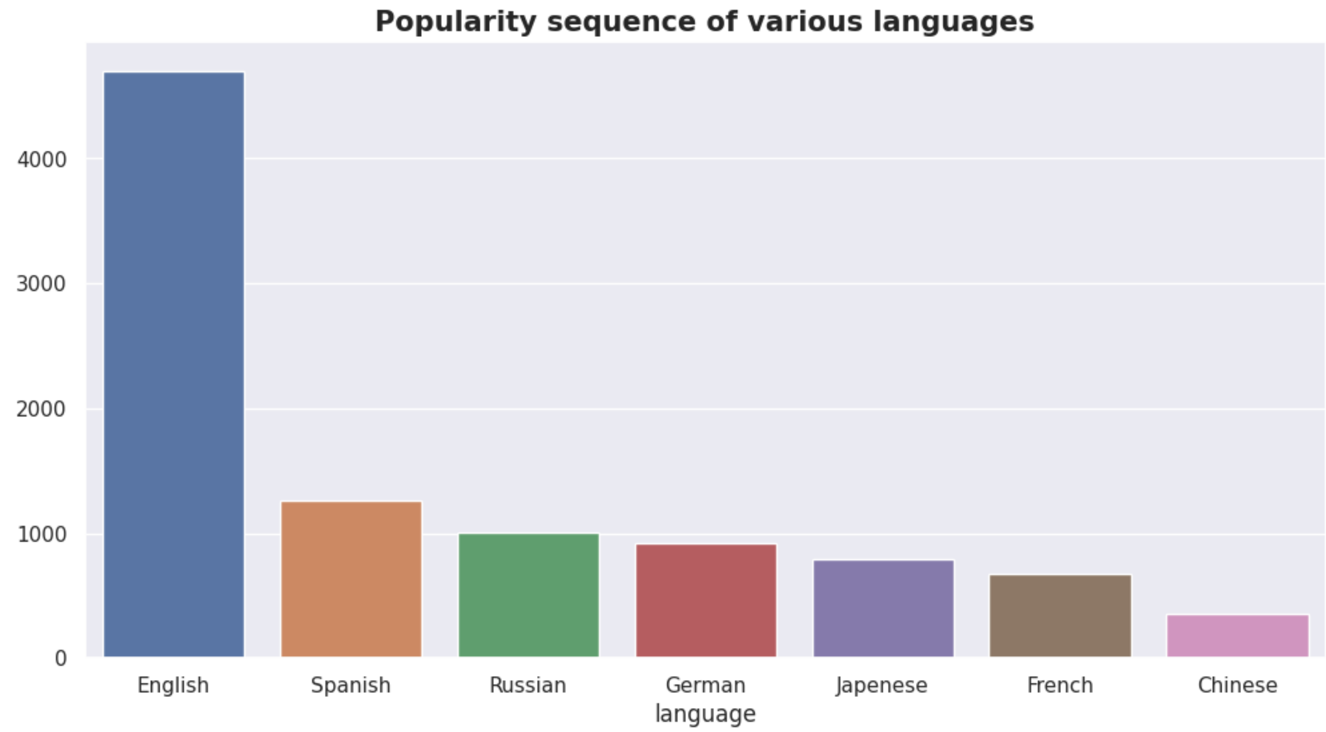
SARIMAX model takes into account exogenous variables, or in other words, use external data in our forecast. Some real-world examples of exogenous variables include gold price, oil price, outdoor temperature, exchange rate. Equation of SARIMAX model can be represented as below:

$$d_t = c + \sum_{n=1}^{p} \alpha_n d_{t-n} + \sum_{n=1}^{q} \theta_n \epsilon_{t-n} + \sum_{n=1}^{r} \beta_n x_{n_t} + \sum_{n=1}^{P} \phi_n d_{t-sn} + \sum_{n=1}^{Q} \eta_n \epsilon_{t-sn} + \epsilon_t$$

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 > Japenese > French > Chinese**

```
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 = 'bold')
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 intiuitavely.

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

1. Test for stationarity using the augmented dickey fuller test.
2. 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**.
3. If the data is getting stationary then draw the autocorrelation and partial autocorrelation graph of the data.
4. 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**.
5. 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**.