Importing Data and Important Libraries

In [78]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.tsa.stattools import adfuller
import statsmodels.api as sm
import warnings
warnings.filterwarnings(action="ignore")

from sklearn.metrics import (
    mean_squared_error as mse,
    mean_absolute_error as mae,
    mean_absolute_percentage_error as mape
)
from statsmodels.tsa.statespace.sarimax import SARIMAX
import itertools
from prophet import Prophet
```

In [2]:
```
data = pd.read_csv('train_1.csv')
```

In [3]:
```
data.head()
```

Out[3]:

	Page	2015-07-01	2015-07-02	2015-07-03	2015-07-04	2015-07-05	2015-07-06	2015-07-07	2015-07-08	2015-07-09	...	2016-12-22	2016-12-23	2016-12-24	2016-12-25	2016-12-26	2016-12-27
0	2NE1_zh.wikipedia.org_all-access_spider	18.0	11.0	5.0	13.0	14.0	9.0	9.0	22.0	26.0	...	32.0	63.0	15.0	26.0	14.0	20.0
1	2PM_zh.wikipedia.org_all-access_spider	11.0	14.0	15.0	18.0	11.0	13.0	22.0	11.0	10.0	...	17.0	42.0	28.0	15.0	9.0	30.0
2	3C_zh.wikipedia.org_all-access_spider	1.0	0.0	1.0	1.0	0.0	4.0	0.0	3.0	4.0	...	3.0	1.0	1.0	7.0	4.0	4.0
3	4minute_zh.wikipedia.org_all-access_spider	35.0	13.0	10.0	94.0	4.0	26.0	14.0	9.0	11.0	...	32.0	10.0	26.0	27.0	16.0	11.0
4	52_Hz_I_Love_You_zh.wikipedia.org_all-access_s...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	48.0	9.0	25.0	13.0	3.0	11.0

5 rows × 551 columns

Feature Engineering

In [4]:

```python
def parse_page_name(page_name):
    parts = page_name.split("_")
    if len(parts) >= 4:
        title = "_".join(parts[:-3])
        language = parts[-3].split('.')[0]
        access_type = parts[-2]
        access_origin = parts[-1]
        return title, language, access_type, access_origin
    return None, None, None, None

# Apply the function to the `page_name` column and expand results into new columns
data[["Title", "Language", "Access Type", "Access Origin"]] = data["Page"].apply(parse_page_name).apply(pd.Series)
```

In [5]:

```python
data.head()
```

Out[5]:

	Page	2015-07-01	2015-07-02	2015-07-03	2015-07-04	2015-07-05	2015-07-06	2015-07-07	2015-07-08	2015-07-09	...	2016-12-26	2016-12-27	2016-12-28	2016-12-29	2016-12-30	2016-12-31
0	2NE1_zh.wikipedia.org_all-access_spider	18.0	11.0	5.0	13.0	14.0	9.0	9.0	22.0	26.0	...	14.0	20.0	22.0	19.0	18.0	20.0
1	2PM_zh.wikipedia.org_all-access_spider	11.0	14.0	15.0	18.0	11.0	13.0	22.0	11.0	10.0	...	9.0	30.0	52.0	45.0	26.0	20.0
2	3C_zh.wikipedia.org_all-access_spider	1.0	0.0	1.0	1.0	0.0	4.0	0.0	3.0	4.0	...	4.0	4.0	6.0	3.0	4.0	17.0
3	4minute_zh.wikipedia.org_all-access_spider	35.0	13.0	10.0	94.0	4.0	26.0	14.0	9.0	11.0	...	16.0	11.0	17.0	19.0	10.0	11.0
4	52_Hz_I_Love_You_zh.wikipedia.org_all-access_s...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	3.0	11.0	27.0	13.0	36.0	10.0

5 rows × 555 columns

In [6]:

```
data = data.melt(id_vars=["Page", "Title", "Language", "Access Type", "Access Origin"], var_name="Date", value_name="Value")
```

In [7]:

```
data.head()
```

Out[7]:

	Page	Title	Language	Access Type	Access Origin	Date	Value
0	2NE1_zh.wikipedia.org_all-access_spider	2NE1	zh	all-access	spider	2015-07-01	18.0
1	2PM_zh.wikipedia.org_all-access_spider	2PM	zh	all-access	spider	2015-07-01	11.0
2	3C_zh.wikipedia.org_all-access_spider	3C	zh	all-access	spider	2015-07-01	1.0
3	4minute_zh.wikipedia.org_all-access_spider	4minute	zh	all-access	spider	2015-07-01	35.0
4	52_Hz_I_Love_You_zh.wikipedia.org_all-access_s...	52_Hz_I_Love_You	zh	all-access	spider	2015-07-01	NaN

Checking Basic Metrics

In [8]:

```
data.shape
```

Out[8]:
```
(79784650, 7)
```

In [9]:
```python
data.size
```

Out[9]:
```
558492550
```

In [10]:
```python
data.isna().sum()
```

Out[10]:
```
Page                   0
Title                  0
Language               0
Access Type            0
Access Origin          0
Date                   0
Value            6192931
dtype: int64
```

In [11]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 79784650 entries, 0 to 79784649
Data columns (total 7 columns):
 #   Column         Dtype  
---  ------         -----  
 0   Page           object 
 1   Title          object 
 2   Language       object 
 3   Access Type    object 
 4   Access Origin  object 
 5   Date           object 
 6   Value          float64
dtypes: float64(1), object(6)
memory usage: 4.2+ GB
```

In [12]:
```python
data.describe()
```

Out[12]:

	Value
count	7.359172e+07
mean	1.419986e+03
std	8.669325e+04
min	0.000000e+00
25%	1.900000e+01
50%	1.470000e+02
75%	6.670000e+02
max	6.726426e+07

Some of the columns are don't have language so replacing them with unknown

In [13]:
```
data["Language"] = data["Language"].replace(["www", "commons"], "unknown")
```

In [14]:
```
(data['Date'].min() , data['Date'].max())
```

Out[14]:
```
('2015-07-01', '2016-12-31')
```

In [15]:
```
data['Date'].value_counts()
```

Out[15]:
```
Date
2016-12-31    145063
2015-07-01    145063
2015-07-02    145063
2015-07-03    145063
2015-07-04    145063
               ...
2015-07-11    145063
2015-07-10    145063
2015-07-09    145063
2015-07-08    145063
2015-07-07    145063
Name: count, Length: 550, dtype: int64
```

Quick Analysis

- Here the every date has 145063 columns so it means every page has data for every date in the dataset
- Filling the missing Nan using linear interpolation because filling the value with mean might create an discrepancy in the data

Imputing Nan values using Linear Interpolation

In [16]:
```
data['Value'] = data['Value'].interpolate(method='linear')
```

In [17]:
```
data.isna().sum()
```

Out[17]:
```
Page             0
Title            0
Language         0
Access Type      0
Access Origin    0
Date             0
Value            0
dtype: int64
```

Renaming the Language column names

In [18]:
```
data['Language'].value_counts()
```

Out[18]:
```
Language
en         13259400
ja         11237050
de         10200850
unknown     9820250
fr          9791100
zh          9475950
ru          8262100
es          7737950
Name: count, dtype: int64
```

In [19]:
```
language_map = {
    "en": "English",
    "ja": "Japanese",
    "de": "German",
```

```python
    "fr": "French",
    "zh": "Chinese",
    "ru": "Russian",
    "es": "Spanish"
}

data['Language'] = data['Language'].map(language_map)
```

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

Out[20]:

	Page	Title	Language	Access Type	Access Origin	Date	Value
0	2NE1_zh.wikipedia.org_all-access_spider	2NE1	Chinese	all-access	spider	2015-07-01	18.0
1	2PM_zh.wikipedia.org_all-access_spider	2PM	Chinese	all-access	spider	2015-07-01	11.0
2	3C_zh.wikipedia.org_all-access_spider	3C	Chinese	all-access	spider	2015-07-01	1.0
3	4minute_zh.wikipedia.org_all-access_spider	4minute	Chinese	all-access	spider	2015-07-01	35.0
4	52_Hz_I_Love_You_zh.wikipedia.org_all-access_s...	52_Hz_I_Love_You	Chinese	all-access	spider	2015-07-01	23.5

Non Graphical Analysis

In [21]:
```python
col=['Access Type', 'Access Origin', 'Language']
for i in col:
    print("Value count of :",i)
    print(data[i].value_counts())
    print()
    print("-"*100)
```

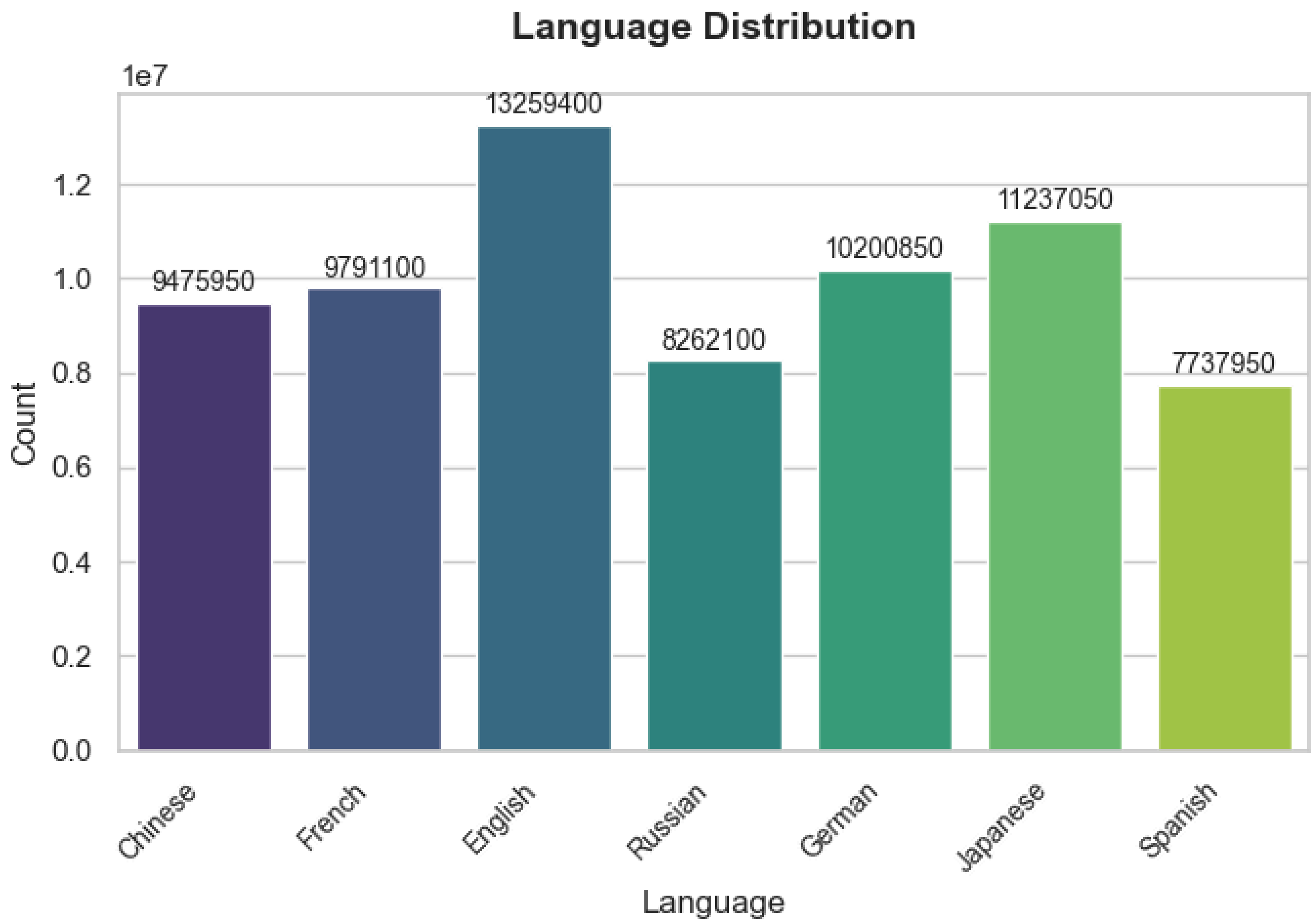
```
Value count of : Access Type
Access Type
all-access     40873250
mobile-web     19766450
desktop        19144950
Name: count, dtype: int64

----------------------------------------------------------------------------------------------------
Value count of : Access Origin
Access Origin
all-agents     60582500
spider         19202150
Name: count, dtype: int64

----------------------------------------------------------------------------------------------------
Value count of : Language
Language
English     13259400
Japanese    11237050
German      10200850
French       9791100
Chinese      9475950
Russian      8262100
Spanish      7737950
Name: count, dtype: int64

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

Graphical Analysis

In [22]:

```python
plt.figure(figsize=(7, 5))
sns.set_theme(style="whitegrid")
ax = sns.countplot(data=data, x="Language", palette="viridis")

# Add labels and a title
ax.set_title("Language Distribution", fontsize=14, fontweight='bold', pad=20)
ax.set_xlabel("Language", fontsize=12)
ax.set_ylabel("Count", fontsize=12)

# Improve readability of x-axis
plt.xticks(rotation=45, fontsize=10, ha="right")

for container in ax.containers:
```

```
    ax.bar_label(container, fmt='%d', label_type='edge', fontsize=10, padding=2)

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

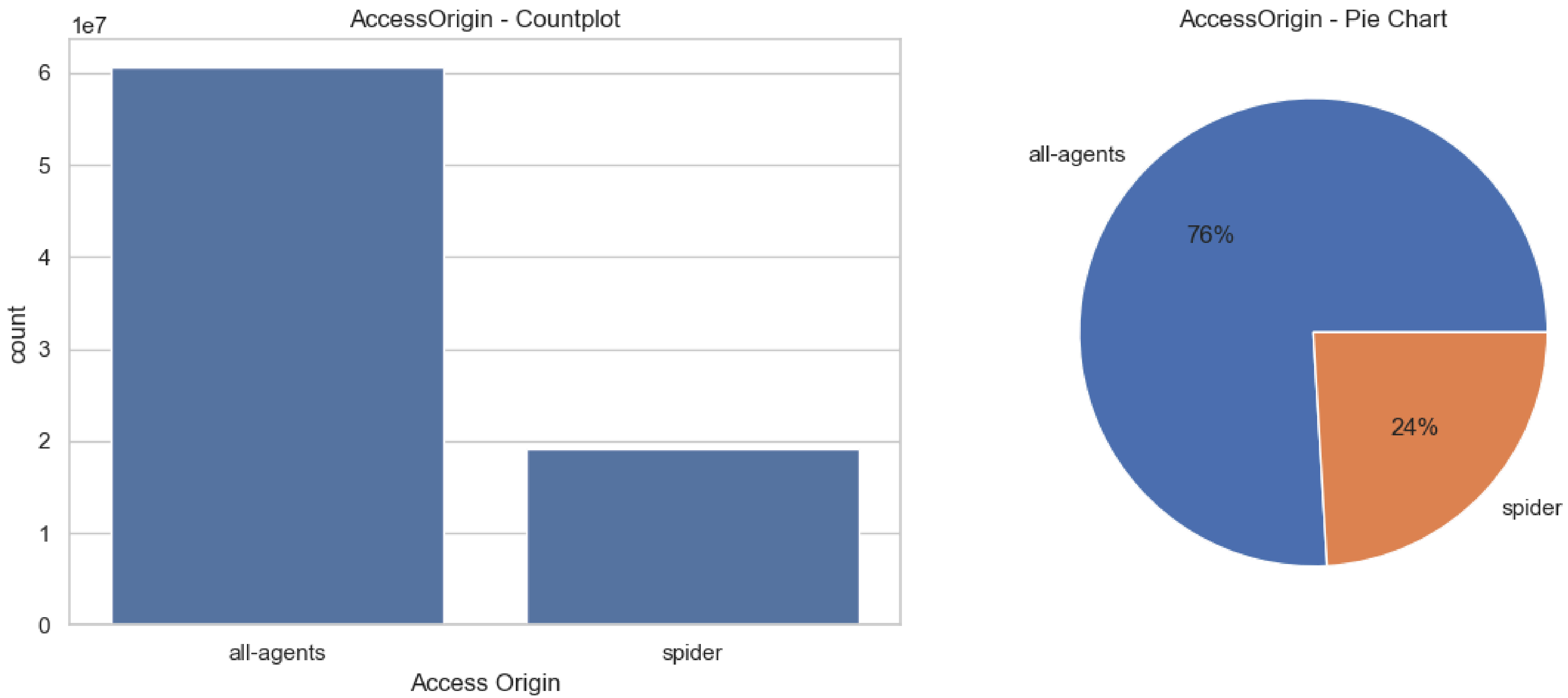


Insights:

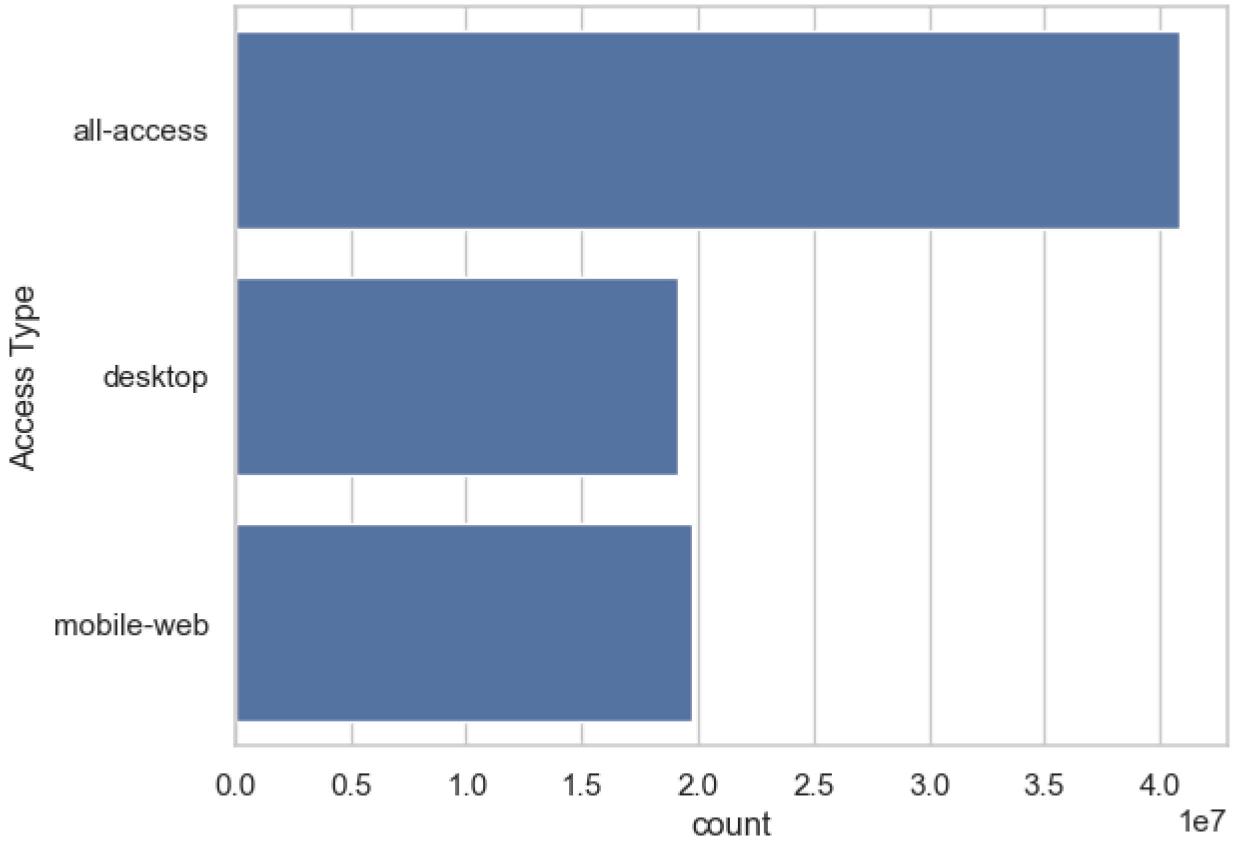
- Around 17% of the pages are in English, making it the most common language.
- Japanese comes next, with about 14% of the pages.
- The remaining languages each make up roughly 12% of the total.

In [23]:

```
fig, axes = plt.subplots(1, 2, figsize=(12, 5))

# Countplot
sns.countplot(data=data, x="Access Origin", ax=axes[0], order=data["Access Origin"].value_counts().index)
axes[0].set_title("AccessOrigin - Countplot")

# Pie chart
labels = data["Access Origin"].value_counts().index
counts = data["Access Origin"].value_counts().values

axes[1].pie(counts, labels=labels, autopct='%1.0f%%')
axes[1].set_title("AccessOrigin - Pie Chart")

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

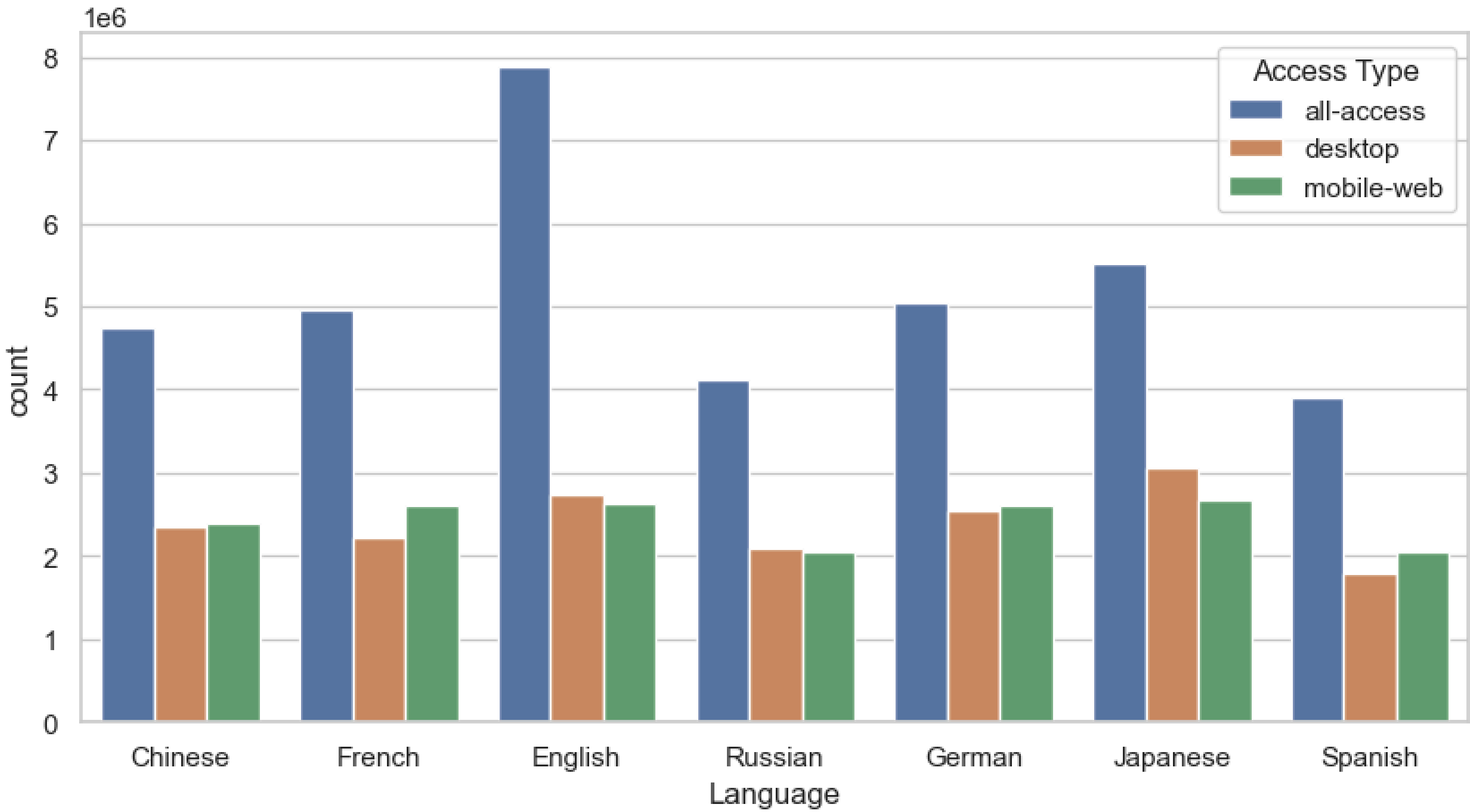


In [24]:
```
sns.countplot(y=data["Access Type"])
plt.show()
```

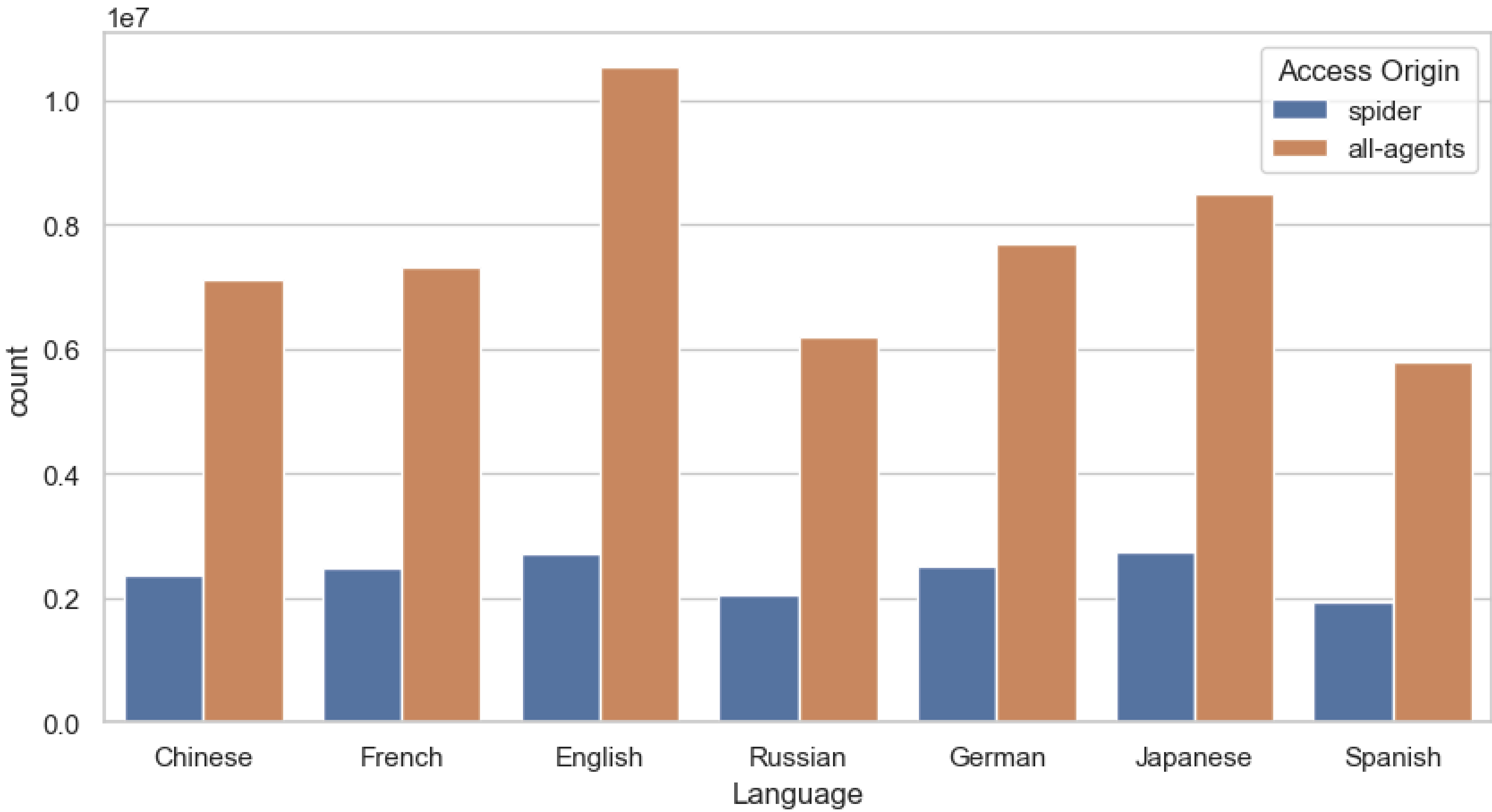


Bivariate Analysis

In [25]:
```
plt.figure(figsize=(10,5))
sns.countplot(data=data,x="Language",hue="Access Type")
plt.show()
```



In [26]:
```
plt.figure(figsize=(10,5))
sns.countplot(data=data,x="Language",hue="Access Origin")
plt.show()
```



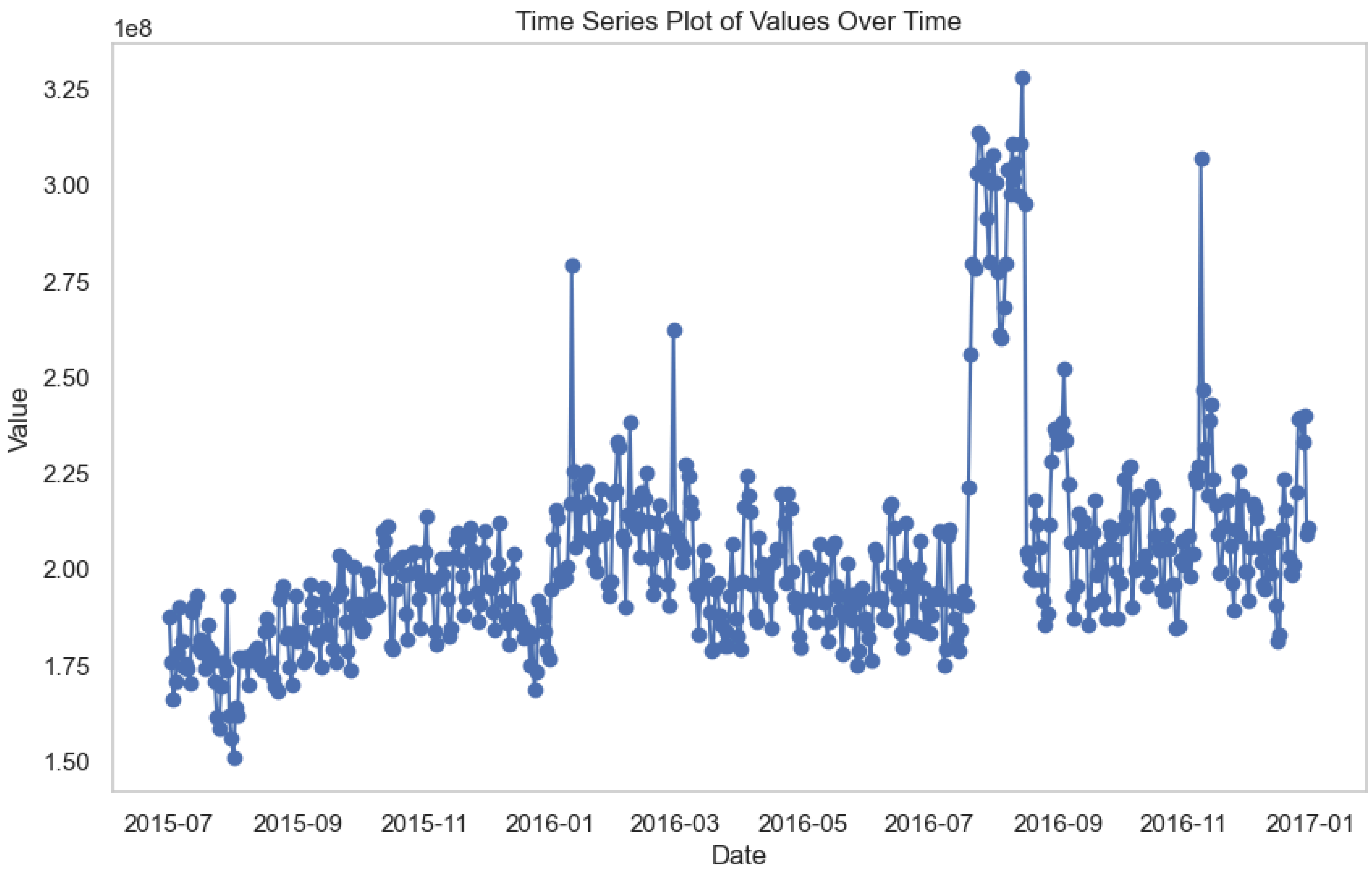
In [27]:
```
data.head()
```

Out[27]:

	Page	Title	Language	Access Type	Access Origin	Date	Value
0	2NE1_zh.wikipedia.org_all-access_spider	2NE1	Chinese	all-access	spider	2015-07-01	18.0
1	2PM_zh.wikipedia.org_all-access_spider	2PM	Chinese	all-access	spider	2015-07-01	11.0
2	3C_zh.wikipedia.org_all-access_spider	3C	Chinese	all-access	spider	2015-07-01	1.0
3	4minute_zh.wikipedia.org_all-access_spider	4minute	Chinese	all-access	spider	2015-07-01	35.0
4	52_Hz_I_Love_You_zh.wikipedia.org_all-access_s...	52_Hz_I_Love_You	Chinese	all-access	spider	2015-07-01	23.5

In [28]:

```python
data["Date"] = pd.to_datetime(data["Date"])
data_grouped = data.groupby("Date").sum(numeric_only=True).reset_index()

# Plot the time series
plt.figure(figsize=(10, 6))
plt.plot(data_grouped["Date"], data_grouped["Value"], marker='o')
plt.title("Time Series Plot of Values Over Time")
plt.xlabel("Date")
plt.ylabel("Value")
plt.grid()
plt.show()
```



In [29]:
```
data.set_index('Date', inplace=True)
```

In [30]:
```
reshaped_df = data.pivot_table(index=data.index, columns='Language', values='Value', aggfunc='mean')
```

In [31]:
```
reshaped_df.columns.name = None
```

In [32]:
```
reshaped_df
```

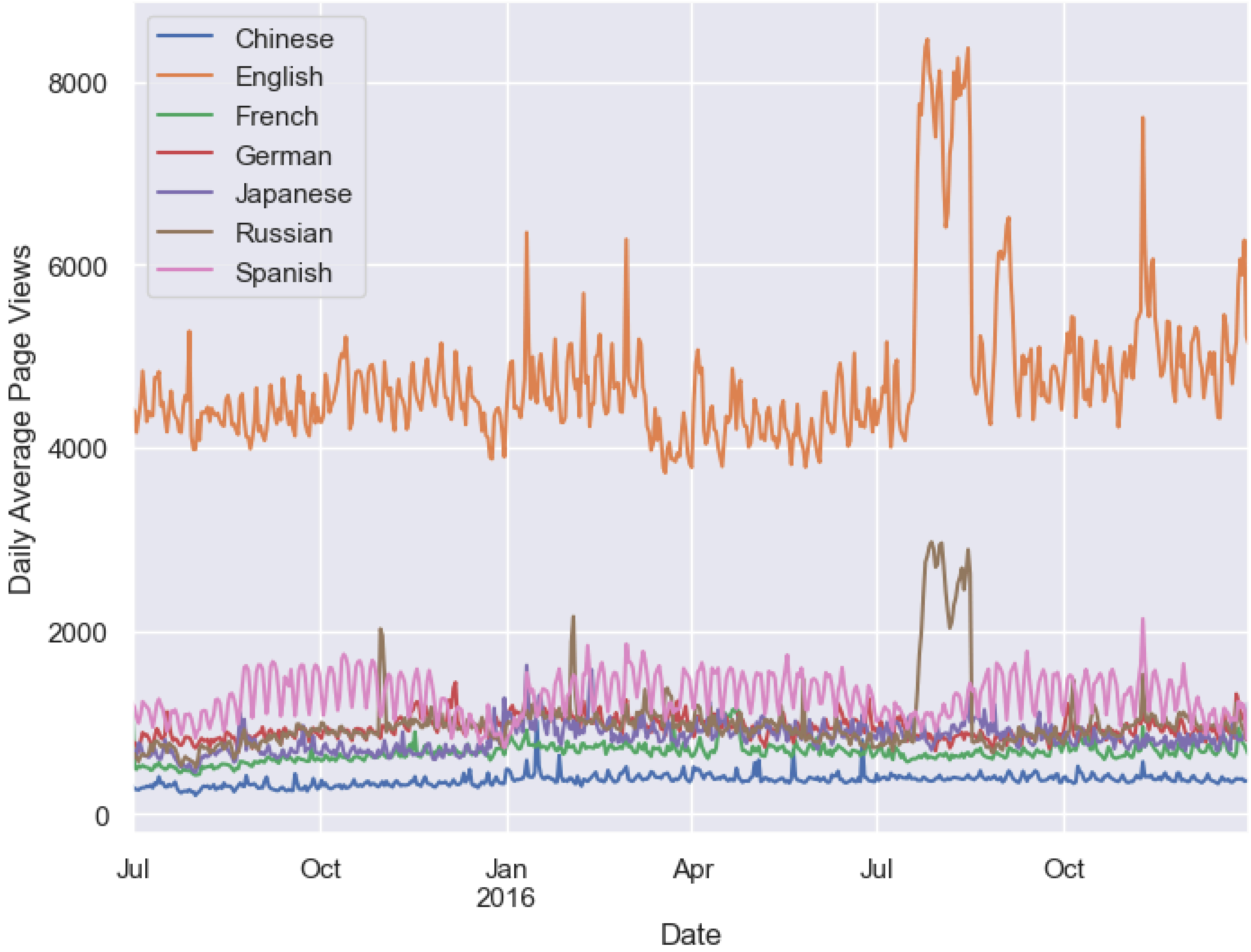
Out[32]:

Date	Chinese	English	French	German	Japanese	Russian	Spanish
2015-07-01	302.355734	4427.708334	1129.034804	790.590708	601.360077	651.452513	1209.999028
2015-07-02	268.117246	4392.444278	502.047865	775.655888	687.995484	655.053777	1160.690263
2015-07-03	267.042942	4166.937545	484.547462	745.781675	616.659299	609.369040	1056.775572
2015-07-04	259.622370	4322.986667	526.252510	678.666147	776.318452	572.553909	992.093234
2015-07-05	277.441749	4482.500642	507.830786	791.054515	750.043471	628.859743	1077.254428
...	...	...	...	...	...	...	...
2016-12-27	379.421063	6063.200286	859.794574	1116.103251	809.202535	1003.665424	1158.402587
2016-12-28	382.057316	5889.543575	776.484440	1063.900065	810.996280	934.810545	1205.360118
2016-12-29	354.920570	6268.441202	754.271205	1022.153879	887.976041	900.150945	1134.710463
2016-12-30	359.611527	5217.368425	702.872149	975.896722	959.556825	805.680469	832.056507
2016-12-31	369.184021	5139.305521	647.605466	914.112471	1215.738192	883.976202	796.098443

550 rows × 7 columns

In [33]:

```
plt.figure(figsize=(8, 6))
sns.set_theme()
reshaped_df.plot(ax=plt.gca())
plt.xlabel("Date")
plt.ylabel("Daily Average Page Views")
plt.show()
```



Insight

- English pages are the most visited pages follwed by Spanish
- English pages have an upward trend in terms of visits
- There is an unusual peak from mid of July to end of August 2016

Checking if the data is Stationary

- Null Hypothesis: Data is Not stationary
- Alternate Hypothesis: Data is stationary

In [34]:
```
def dicky_fuller(data, alpha):
    result = adfuller(data)
    if result[1] < alpha:
        print(f"The data is Stationary {result[1].round(2)}")
    else:
        print(f"The data is non stationary {result[1].round(2)}")
```

In [35]:
```
for i in reshaped_df.columns:
    print(i)
    dicky_fuller(reshaped_df[i], 0.05)
    print()
```

```
Chinese
The data is non stationary 0.22

English
The data is non stationary 0.06

French
The data is Stationary 0.03

German
The data is non stationary 0.1

Japanese
The data is non stationary 0.08

Russian
The data is Stationary 0.0

Spanish
The data is non stationary 0.05
```

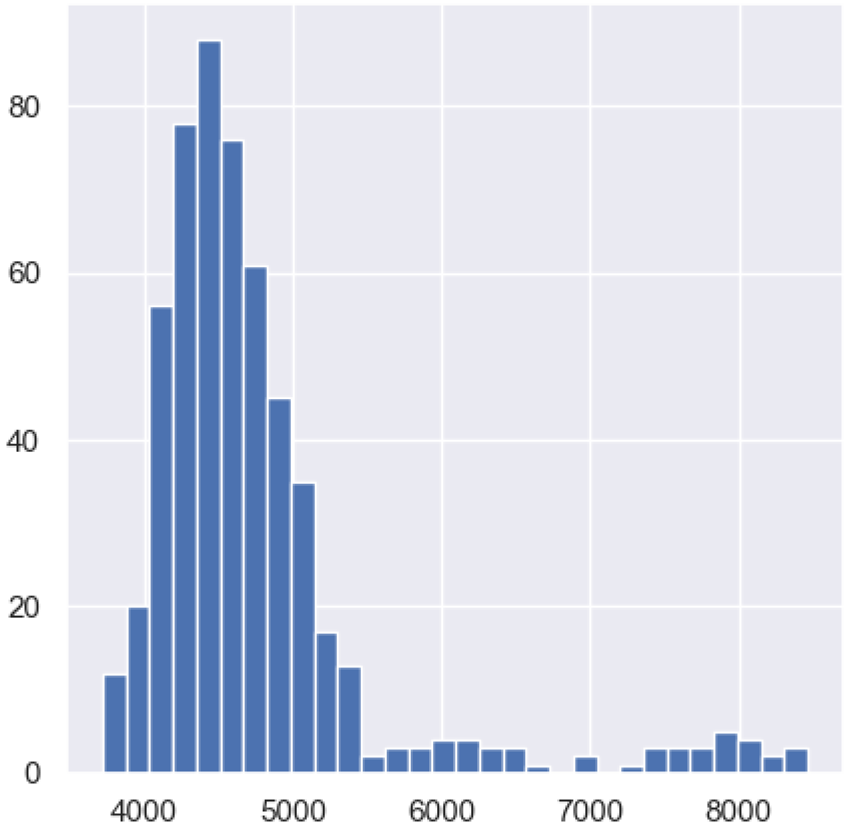
Making the data Stationary for language English only

In [36]:
```
English = reshaped_df['English']
```

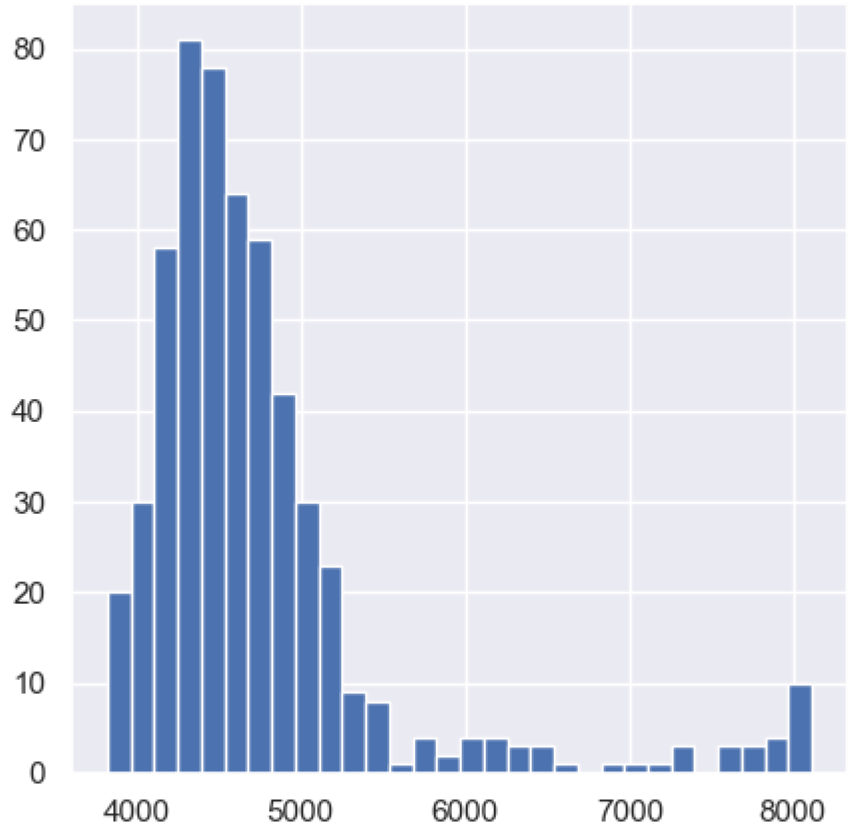
In [37]:
```
English
```

Out[37]:
```
Date
2015-07-01    4427.708334
2015-07-02    4392.444278
2015-07-03    4166.937545
2015-07-04    4322.986667
2015-07-05    4482.500642
                 ...
2016-12-27    6063.200286
2016-12-28    5889.543575
2016-12-29    6268.441202
2016-12-30    5217.368425
2016-12-31    5139.305521
Name: English, Length: 550, dtype: float64
```

In [38]:
```
plt.figure(figsize=(5,5))
English.hist(bins=30);
```



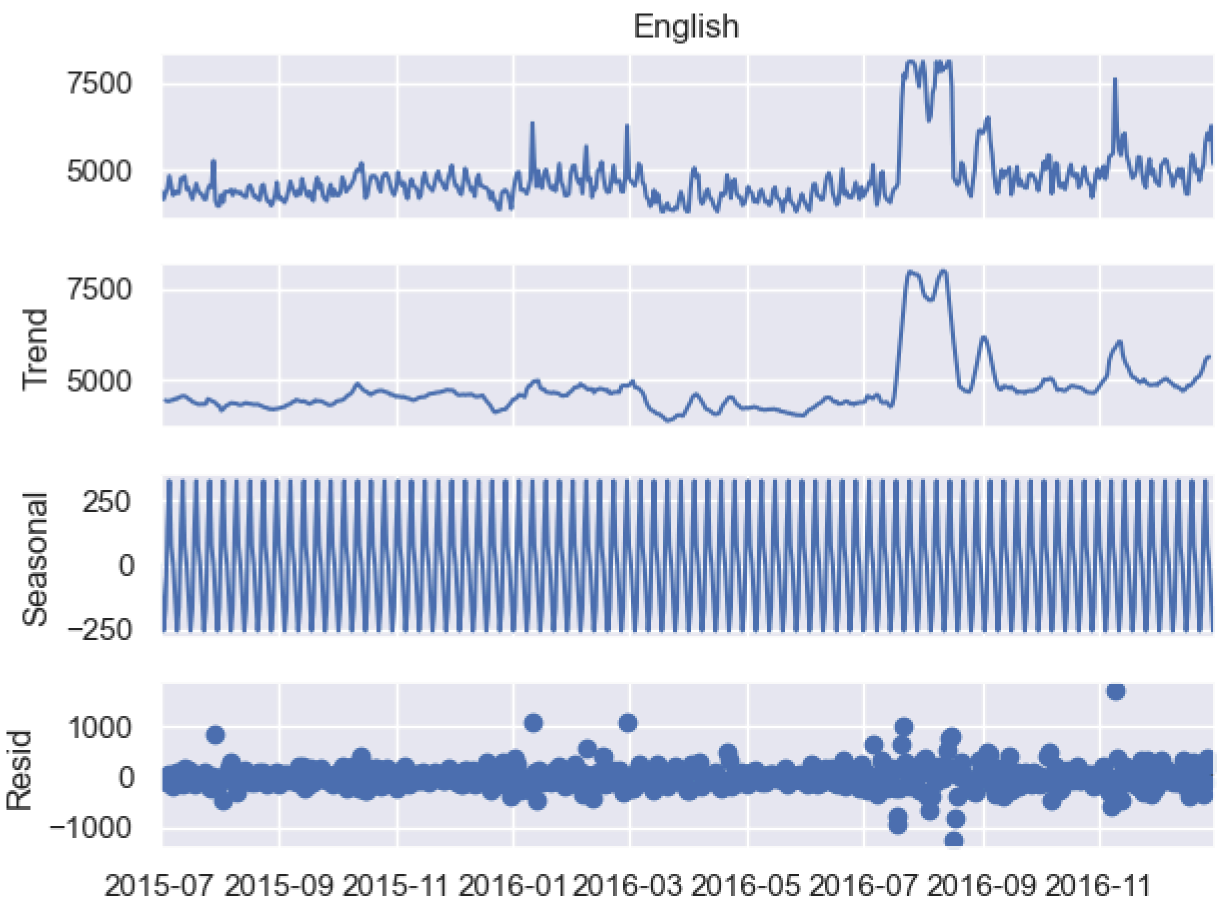
In [39]:
```
plt.figure(figsize=(5,5))
English_clipped = English.clip(lower=English.quantile(0.01),upper=English.quantile(0.99))
English_clipped.hist(bins=30);
```



Decomposing the data for english Language using Triple Exponential Smoothing

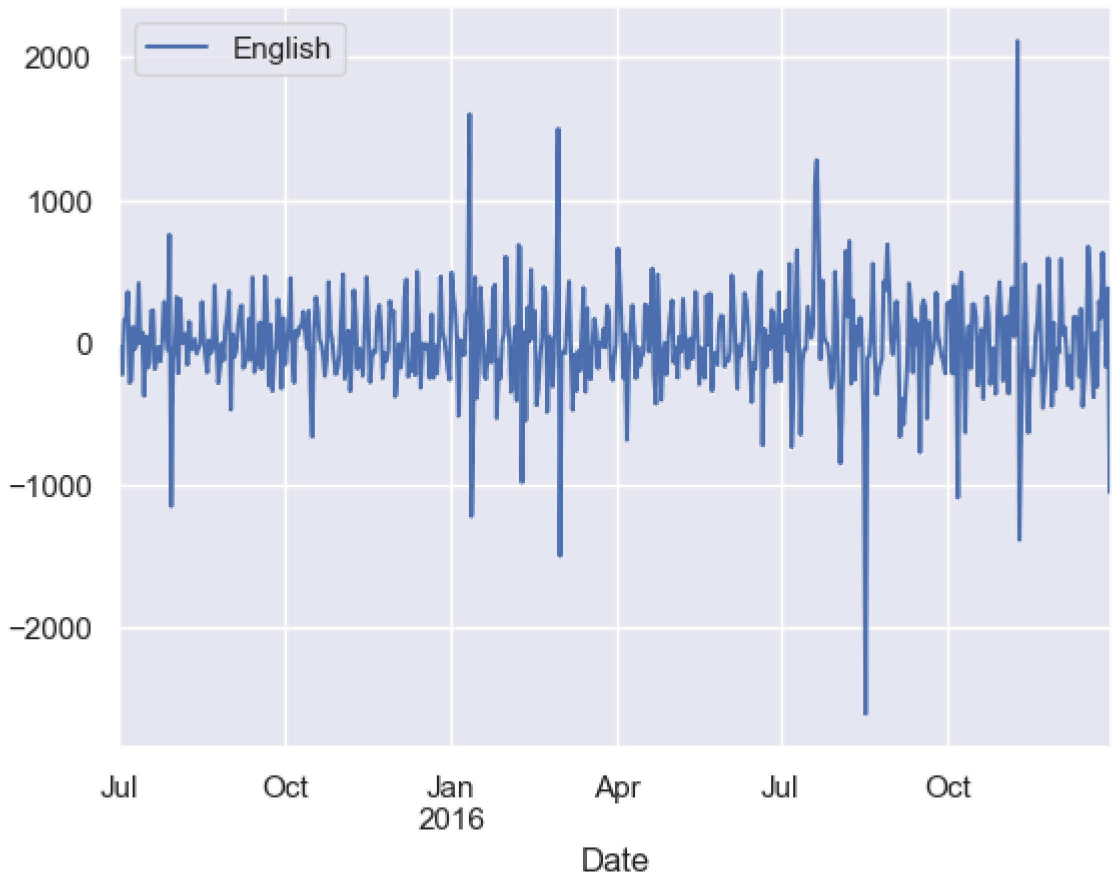
In [40]:

```
decomp_english = sm.tsa.seasonal_decompose(English_clipped)
decomp_english.plot();
```



In [41]:
```
English_clipped.diff().plot()
plt.legend()
```

Out[41]:
```
<matplotlib.legend.Legend at 0x2068b6e4910>
```



Checking the Stationary of the Data

In [42]:
```
dicky_fuller(English_clipped.diff().dropna(), 0.05)
```

```
The data is Stationary 0.0
```

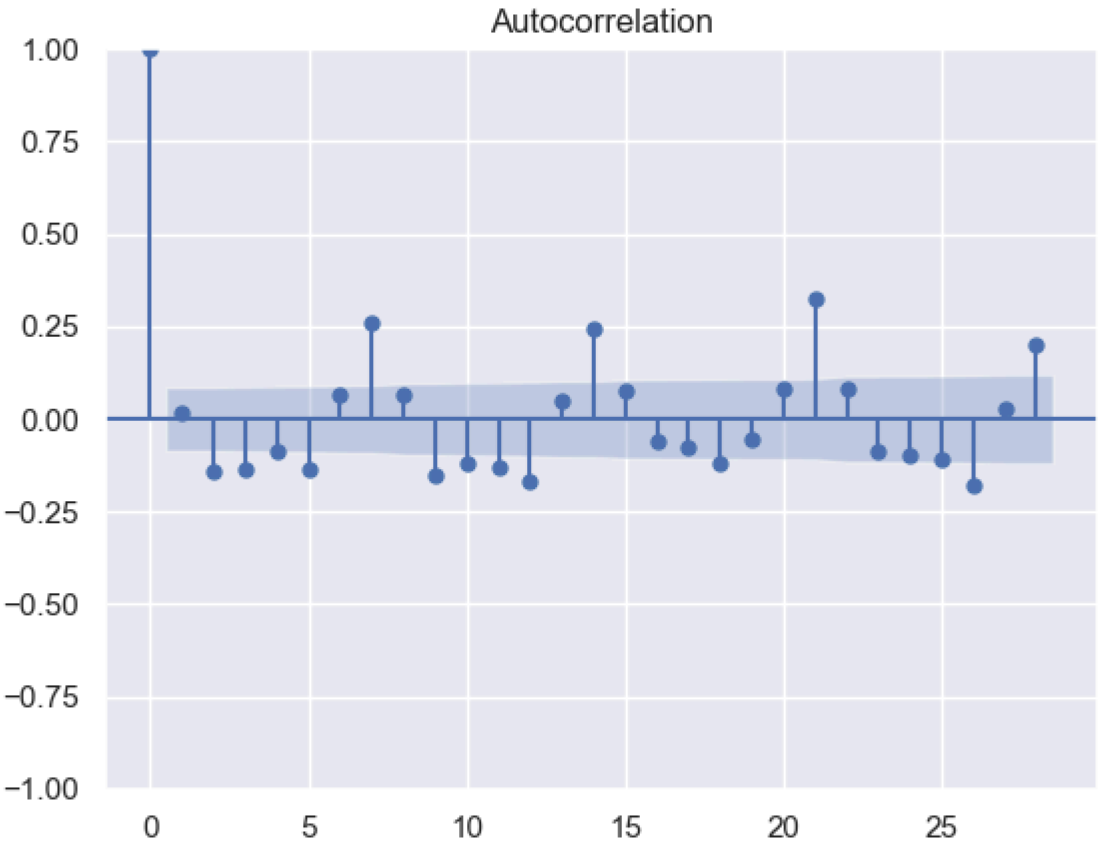
In [43]:
```
Stationary_data = English_clipped.diff().dropna()
```

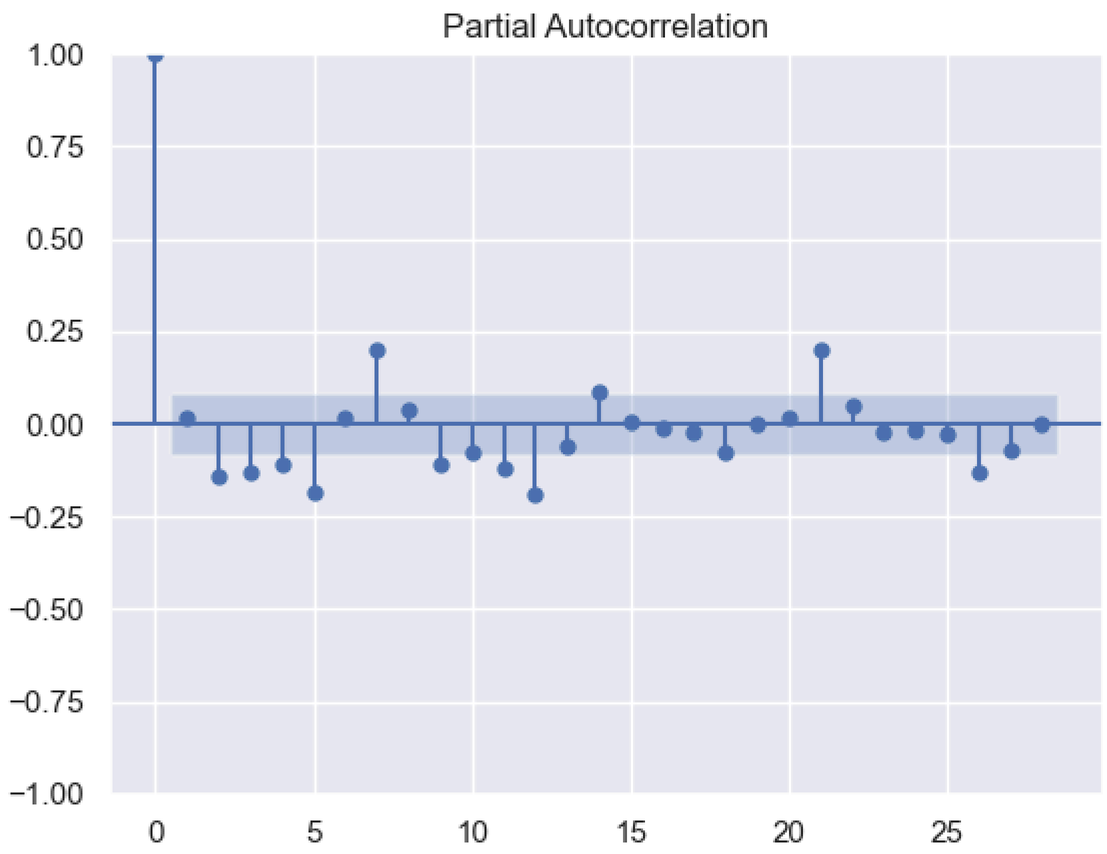
In [44]:
```
Stationary_data
```

Out[44]:
```
Date
2015-07-02      -35.264056
2015-07-03     -225.506733
2015-07-04      156.049122
2015-07-05      159.513974
2015-07-06      354.473387
                   ...
2016-12-27      279.345881
2016-12-28     -173.656711
2016-12-29      378.897627
2016-12-30    -1051.072777
2016-12-31      -78.062904
Name: English, Length: 549, dtype: float64
```

Plotting ACF and PACF plot

In [45]:
```
sm.tsa.graphics.plot_acf(Stationary_data);
sm.tsa.graphics.plot_pacf(Stationary_data);
```


Autocorrelation
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25



ACF (Autocorrelation Function):

- Significant spikes at lags 7, 14, and 21 (visible well above the confidence band).
- This pattern suggests seasonality (possibly weekly, every 7 days).
- Indicates potential values for q = 1, 2, or 3.

PACF (Partial Autocorrelation Function):

- Significant spikes at lags 7 and 21.
- Gradual decline after lag 1.
- Indicates potential values for p = 1 or 2.

Modeling

In [46]:
```
def performance(actual, predicted):
    print('MAE :', round(mae(actual, predicted), 3))
    print('RMSE :', round(mse(actual, predicted)**0.5, 3))
    print('MAPE:', round(mape(actual, predicted), 3))
```

Arima Model

In [47]:
```
X_train, X_test = Stationary_data.iloc[:-35], Stationary_data.iloc[-35:]

# Fit the ARIMA model
model = sm.tsa.ARIMA(endog=X_train, order=(1,1,1), seasonal_order=(0,0,0,0))
result = model.fit()

# Make predictions
predTest = result.forecast(len(X_test))

# Plot the predictions and the original data
predTest.plot(style="-*", label="Prediction")
Stationary_data.tail(100).plot(label="Original")
plt.ylabel("Views")
plt.xlabel("Date")
plt.legend()

# Evaluate the performance of the model
performance(X_test, predTest)
print()
```

```
MAE : 272.444
RMSE : 347.019
MAPE: 1.006
```

In [48]:
```
exog = pd.read_csv('Exog_Campaign_eng.csv')
```

In [49]:
```
X_train_exog, X_test_exog = exog.iloc[:-36], exog.iloc[-35:]
```

In [50]:
```
X_train.index = X_train_exog.index
```

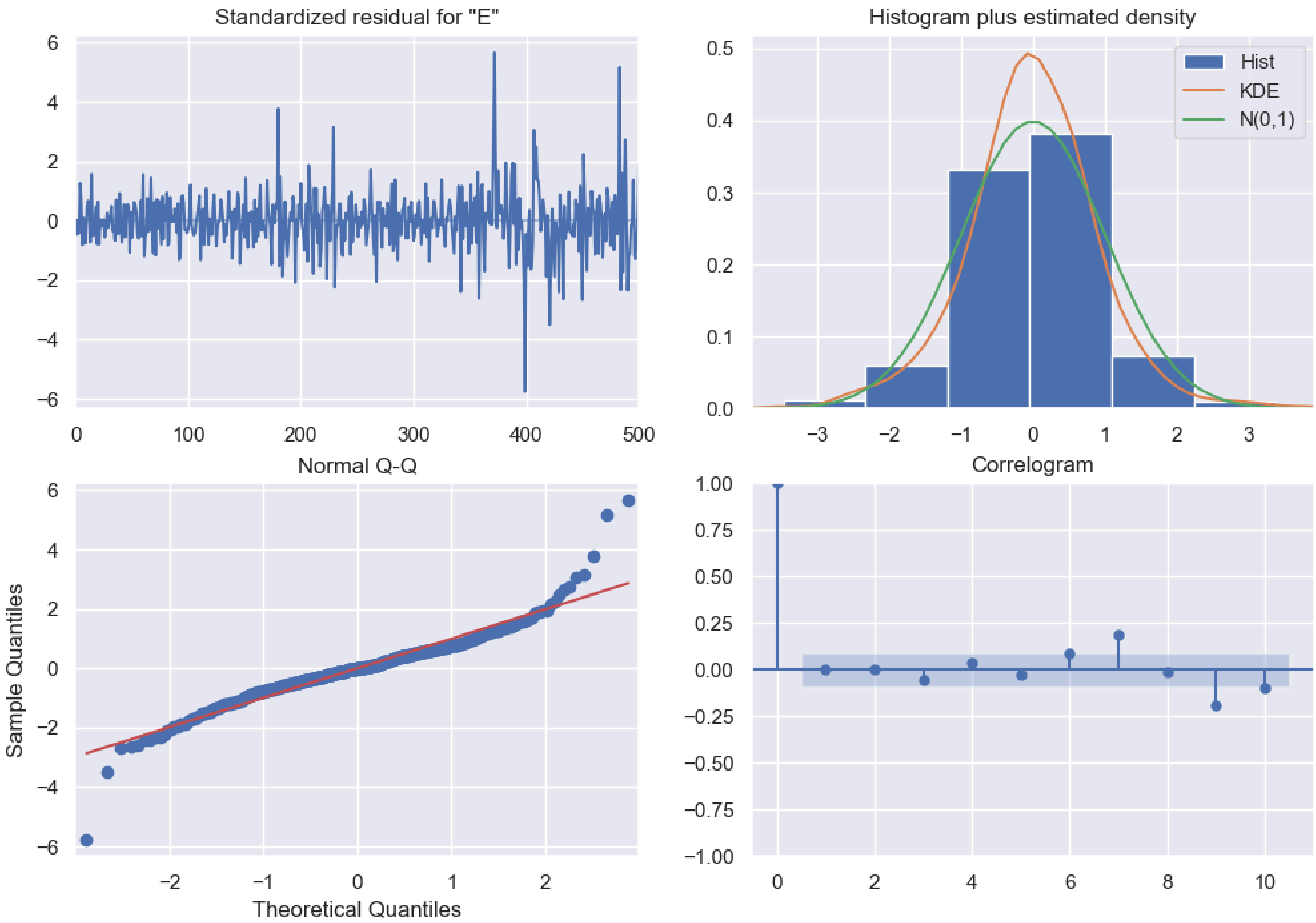
In [51]:
```
model = SARIMAX(
    X_train,
    exog=X_train_exog,
    order=(1, 1, 1),
    seasonal_order=(1, 1, 1, 12)
)
```

```python
# Fit the model
fit = model.fit(disp=False)
```

In [52]:
```python
forecast = fit.forecast(steps=len(X_test), exog=X_test_exog)
```

In [53]:
```python
print(fit.summary())

# Plot diagnostics
fit.plot_diagnostics(figsize=(12, 8))
plt.show()
```

```
                                      SARIMAX Results                                       
============================================================================================
Dep. Variable:                                English   No. Observations:                  514
Model:             SARIMAX(1, 1, 1)x(1, 1, 1, 12)   Log Likelihood               -3714.472
Date:                            Mon, 21 Apr 2025   AIC                           7440.944
Time:                                    12:11:44   BIC                           7466.243
Sample:                                         0   HQIC                          7450.871
                                            - 514                                         
Covariance Type:                              opg                                         
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
Exog       -1435.7917     57.935    -24.783      0.000   -1549.342   -1322.241
ar.L1          0.2925      0.055      5.320      0.000       0.185       0.400
ma.L1         -0.8304      0.033    -24.873      0.000      -0.896      -0.765
ar.S.L12      -0.1685      0.045     -3.781      0.000      -0.256      -0.081
ma.S.L12      -0.9846      0.090    -10.899      0.000      -1.162      -0.808
sigma2      1.504e+05   1.29e+04     11.651      0.000    1.25e+05    1.76e+05
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):               740.48
Prob(Q):                              0.96   Prob(JB):                         0.00
Heteroskedasticity (H):               4.62   Skew:                             0.27
Prob(H) (two-sided):                  0.00   Kurtosis:                         8.93
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```



In [54]:
```
performance(X_test, forecast)
```

```
MAE : 430.316
RMSE : 575.243
MAPE: 3.067
```

In [80]:
```python
X_train, X_test = English_clipped.iloc[:-35], English_clipped.iloc[-35:]
```

In [84]:
```python
X_train_exog, X_test_exog = exog.iloc[:-35], exog.iloc[-35:]
```

In [85]:
```python
X_train.index = X_train_exog.index
```

In [55]:
```python
# Define parameter ranges
p = range(0, 3)  # AR order
d = range(0, 2)  # Differencing order
q = range(0, 3)  # MA order
P = range(0, 3)  # Seasonal AR order
D = range(0, 2)  # Seasonal differencing order
Q = range(0, 3)  # Seasonal MA order
s = [12]         # Seasonal period (e.g., monthly data)

# Create all combinations of parameters
param_grid = list(itertools.product(p, d, q, P, D, Q, s))
```

In [56]:
```python
results = []

# Iterate over parameter combinations
for params in param_grid:
    try:
        # Define the SARIMAX model
        model = SARIMAX(
            X_train,
            order=(params[0], params[1], params[2]),
            seasonal_order=(params[3], params[4], params[5], params[6]),
            exog=X_train_exog  # Include exogenous variables if available
        )
        # Fit the model
        fit = model.fit(disp=False)

        # Save parameters and evaluation metric
        results.append({
            'params': params,
            'aic': fit.aic,
            'bic': fit.bic
```

```python
        })
    except Exception as e:
        # Save failed parameter combination
        results.append({
            'params': params,
            'aic': None,
            'bic': None,
            'error': str(e)
        })
```

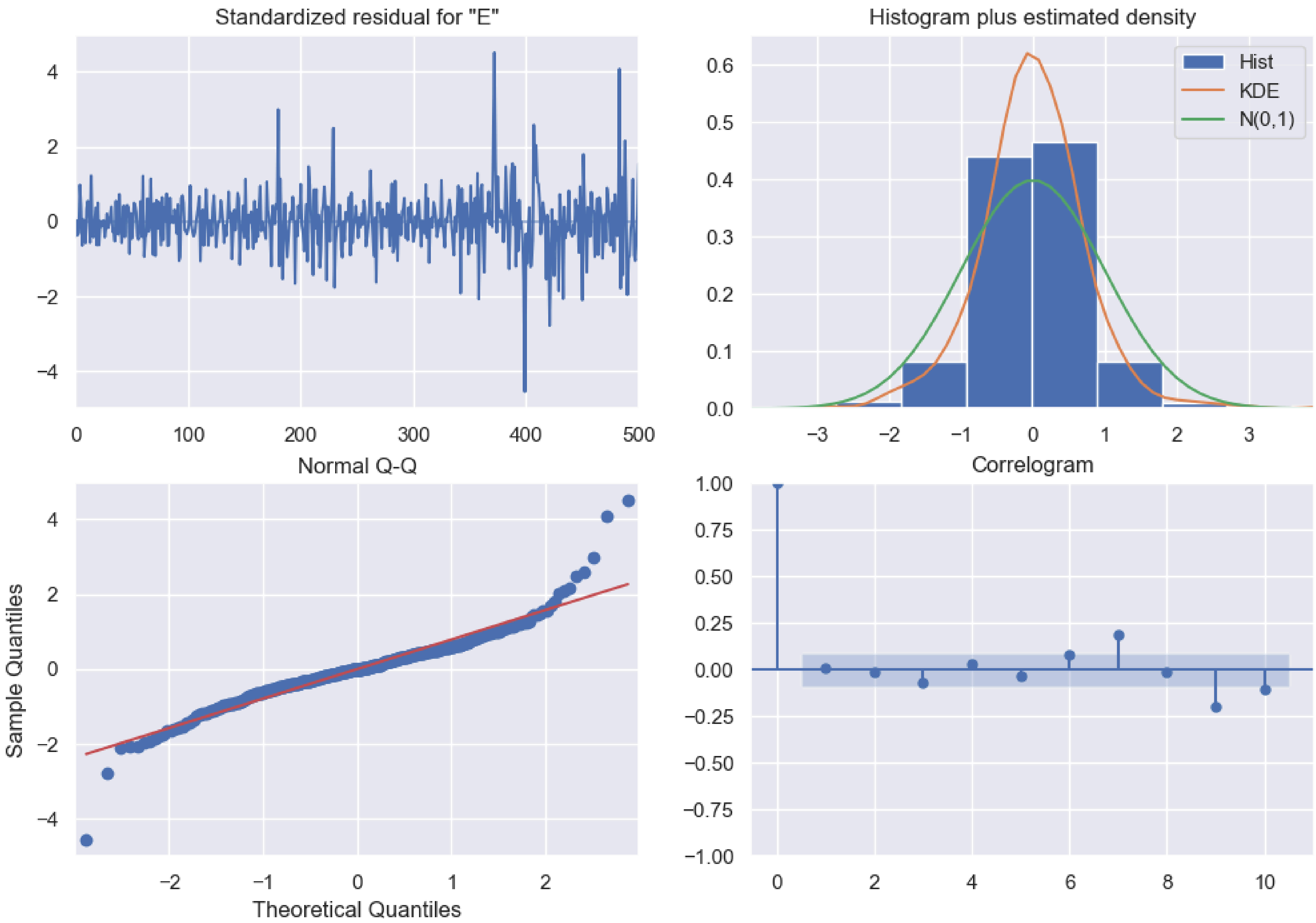
In [58]:
```python
results_df = pd.DataFrame(results)

# Drop rows with errors or NaN AIC
results_df = results_df.dropna(subset=['aic'])

# Sort by AIC
best_model = results_df.sort_values(by='aic').iloc[0]

# Display the best parameters
print("Best Parameters:", best_model['params'])
print("AIC:", best_model['aic'])
```

```
Best Parameters: (1, 0, 1, 1, 1, 2, 12)
AIC: 14.0
```

In [86]:
```python
best_params = best_model['params']

# Refit the model with best parameters
final_model = SARIMAX(
    X_train,
    order=(best_params[0], best_params[1], best_params[2]),
    seasonal_order=(best_params[3], best_params[4], best_params[5], best_params[6]),
    exog=X_train_exog
).fit(disp=False)

# Forecast using the final model
forecast = final_model.forecast(steps=len(X_test), exog=X_test_exog)
```

In [61]:
```python
print(fit.summary())

# Plot diagnostics
fit.plot_diagnostics(figsize=(12, 8))
plt.show()
```

```
                                      SARIMAX Results
==========================================================================================
Dep. Variable:                              English   No. Observations:                514
Model:             SARIMAX(2, 1, 2)x(2, 1, 2, 12)   Log Likelihood               -3739.551
Date:                            Mon, 21 Apr 2025   AIC                           7499.101
Time:                                    12:51:10   BIC                           7541.267
Sample:                                         0   HQIC                          7515.646
                                            - 514
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
Exog       -1453.9972     91.914    -15.819      0.000   -1634.145   -1273.850
ar.L1         -0.7339      0.307     -2.394      0.017      -1.335      -0.133
ar.L2          0.2659      0.116      2.283      0.022       0.038       0.494
ma.L1          0.1957      0.552      0.354      0.723      -0.887       1.278
ma.L2         -0.8035      0.455     -1.767      0.077      -1.694       0.088
ar.S.L12       0.8142      0.215      3.789      0.000       0.393       1.235
ar.S.L24       0.1643      0.085      1.931      0.053      -0.002       0.331
ma.S.L12      -1.9790      0.475     -4.169      0.000      -2.909      -1.049
ma.S.L24       0.9804      0.469      2.089      0.037       0.060       1.900
sigma2      2.399e+05      0.006   4.02e+07      0.000     2.4e+05     2.4e+05
===================================================================================
Ljung-Box (L1) (Q):                   0.03   Jarque-Bera (JB):               743.56
Prob(Q):                              0.86   Prob(JB):                         0.00
Heteroskedasticity (H):               4.64   Skew:                             0.28
Prob(H) (two-sided):                  0.00   Kurtosis:                         8.94
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 8.48e+24. Standard errors may be unstable.
```



In [87]:
```
performance(X_test, forecast)
```

```
MAE : 396.736
RMSE : 473.142
MAPE: 0.076
```

Predicting the future Values using SARIMAX

In [63]:

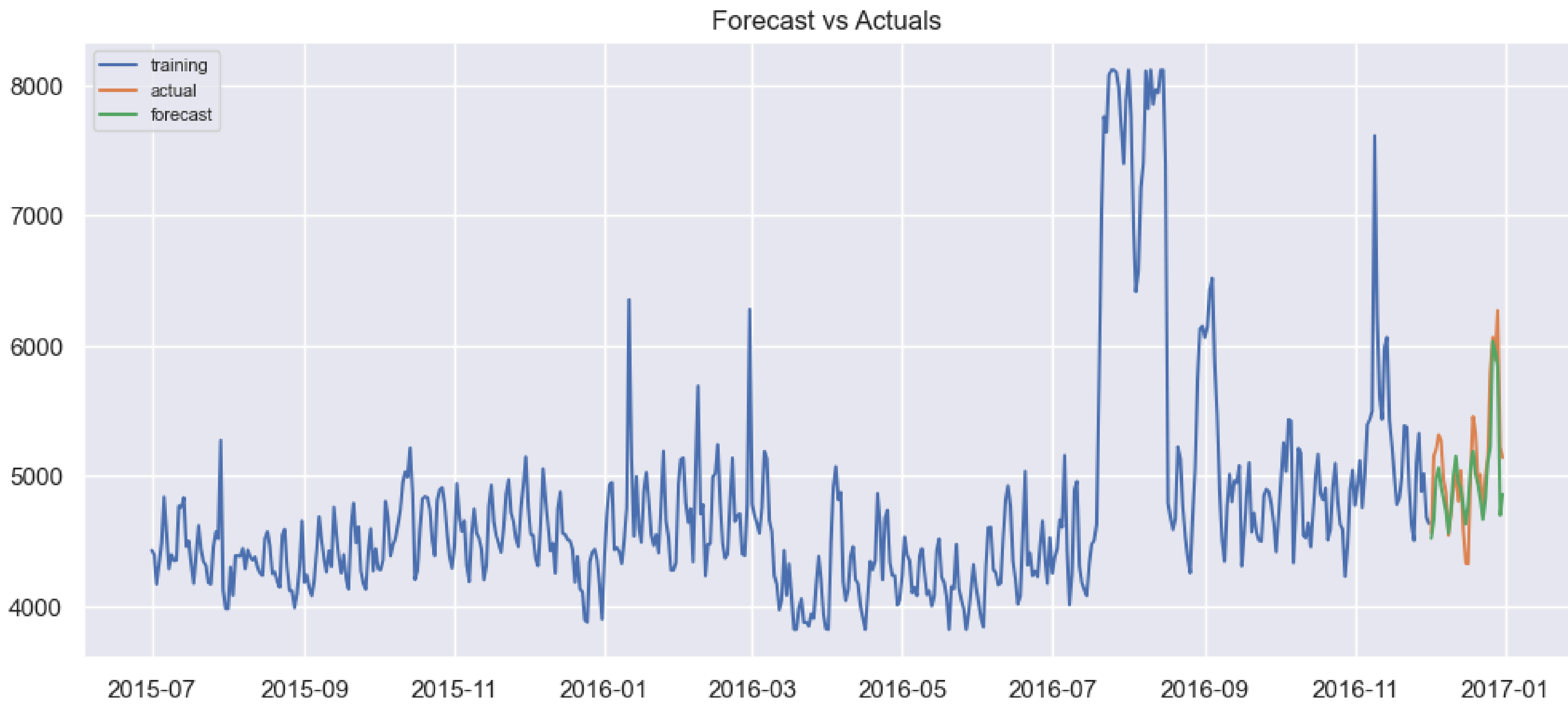
```
ex=exog['Exog'].to_numpy()
```

In [88]:

```
train=English_clipped[:520]
test=English_clipped[520:]
model=sm.tsa.statespace.SARIMAX(train,order=(4, 1, 3),seasonal_order=(1,1,1,7),exog=ex[:520])
results=model.fit()

fc=results.forecast(30,dynamic=True,exog=pd.DataFrame(ex[520:]))

# Make as pandas series
fc_series = pd.Series(fc)
# Plot
train.index=train.index.astype('datetime64[ns]')
test.index=test.index.astype('datetime64[ns]')
plt.figure(figsize=(12,5), dpi=100)
plt.plot(train, label='training')
plt.plot(test, label='actual')
plt.plot(fc_series, label='forecast')

plt.title('Forecast vs Actuals')
plt.legend(loc='upper left', fontsize=8)
```

Out[88]:

```
<matplotlib.legend.Legend at 0x206be5b5450>
```



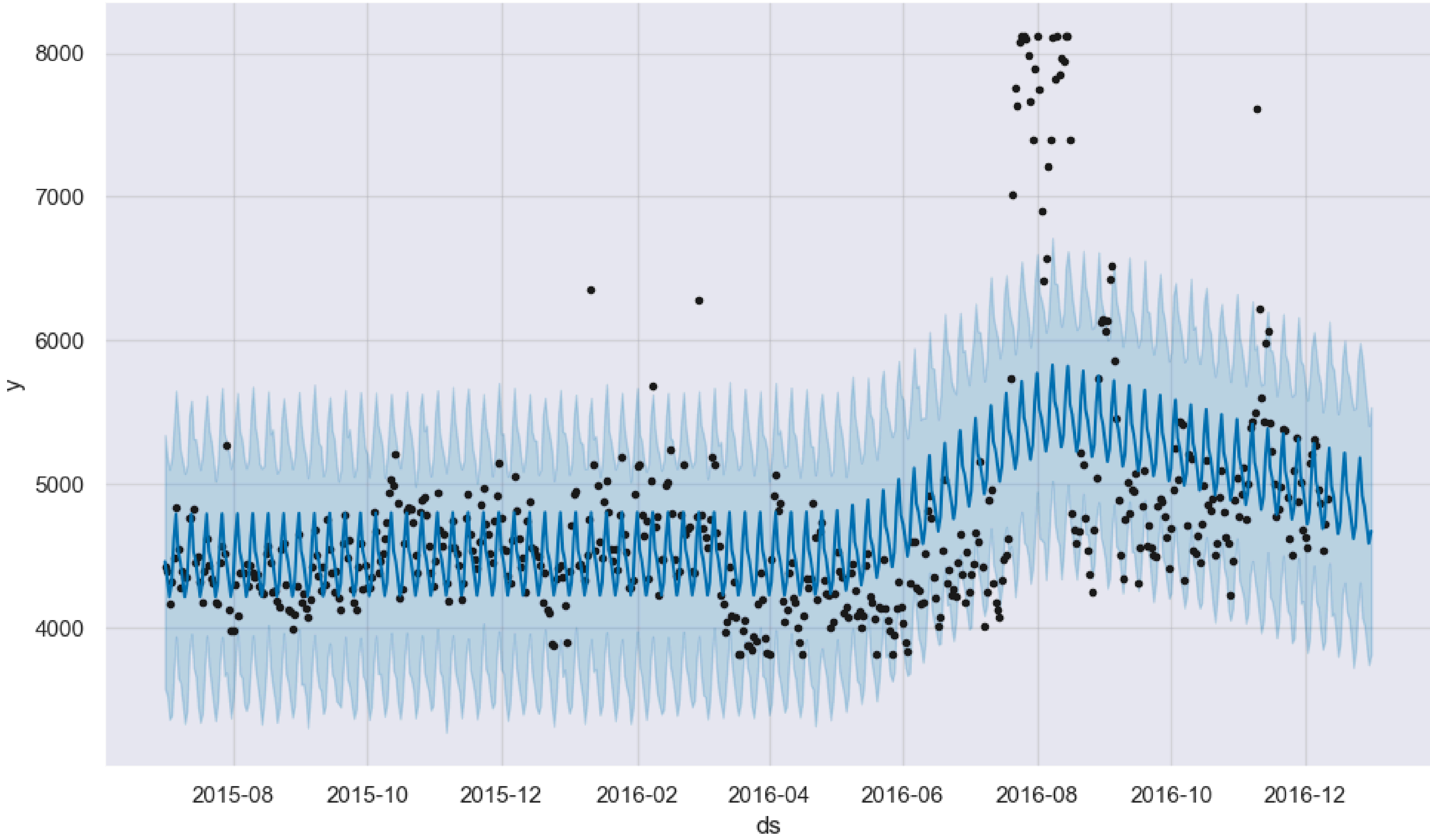
FB Prophet

In [95]:
```
df = English_clipped.reset_index()
```

In [96]:
```
df.rename(columns={'Date': 'ds', 'English': 'y'}, inplace=True)
```

In [97]:
```
m = Prophet(weekly_seasonality=True)
m.fit(df[['ds', 'y']][:-20])
future = m.make_future_dataframe(periods=20,freq="D")
forecast = m.predict(future)
fig = m.plot(forecast)
```

```
13:10:39 - cmdstanpy - INFO - Chain [1] start processing
13:10:39 - cmdstanpy - INFO - Chain [1] done processing
```



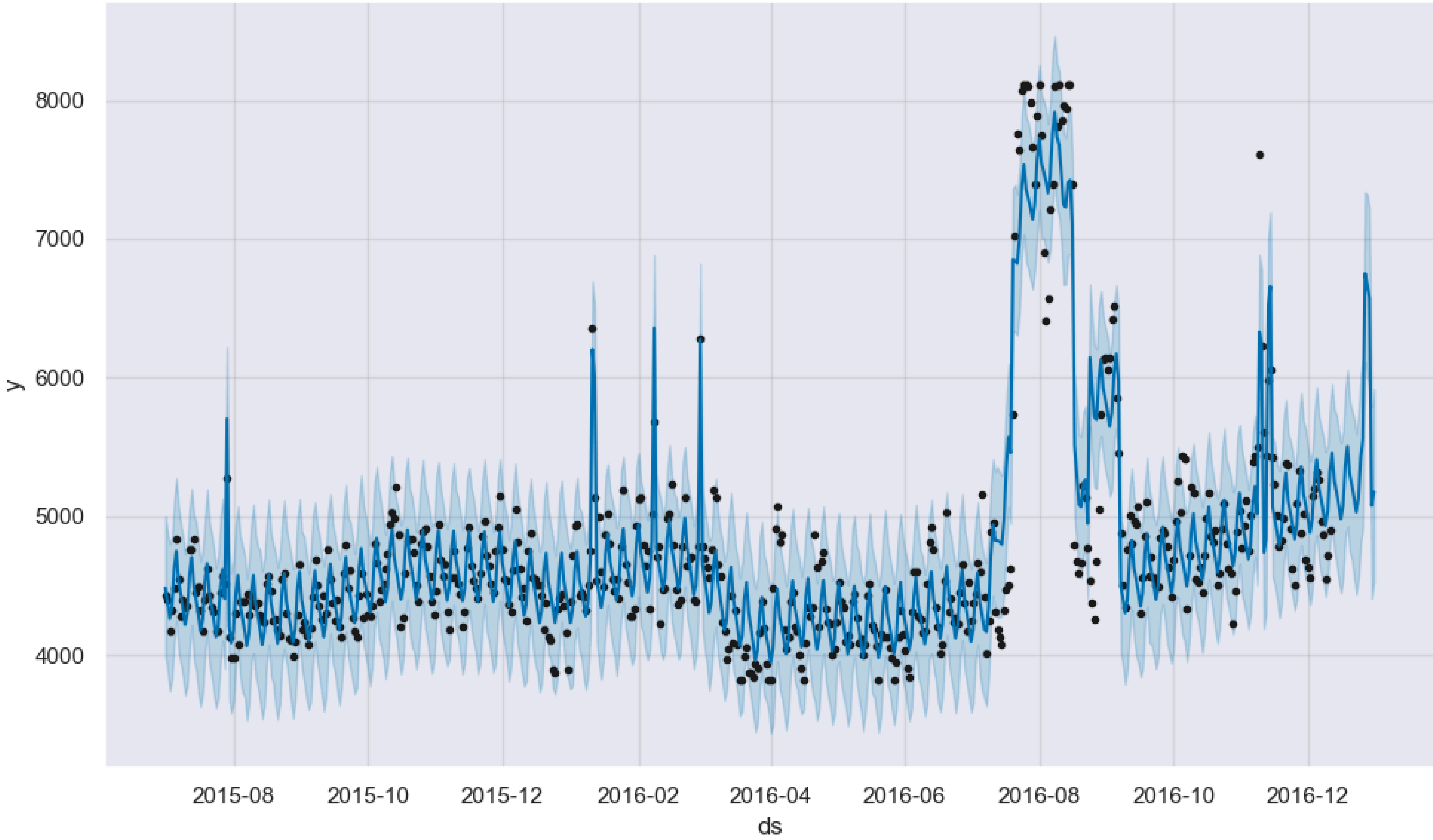
Running FB Prophet using Exogeneous Variable

In [101…
```
df['exog'] = exog
```

In [102…
```
model2=Prophet(interval_width=0.9, weekly_seasonality=True, changepoint_prior_scale=1)
model2.add_regressor('exog')
model2.fit(df[:-20])
```

```
forecast2 = model2.predict(df)
fig = model2.plot(forecast2)
```

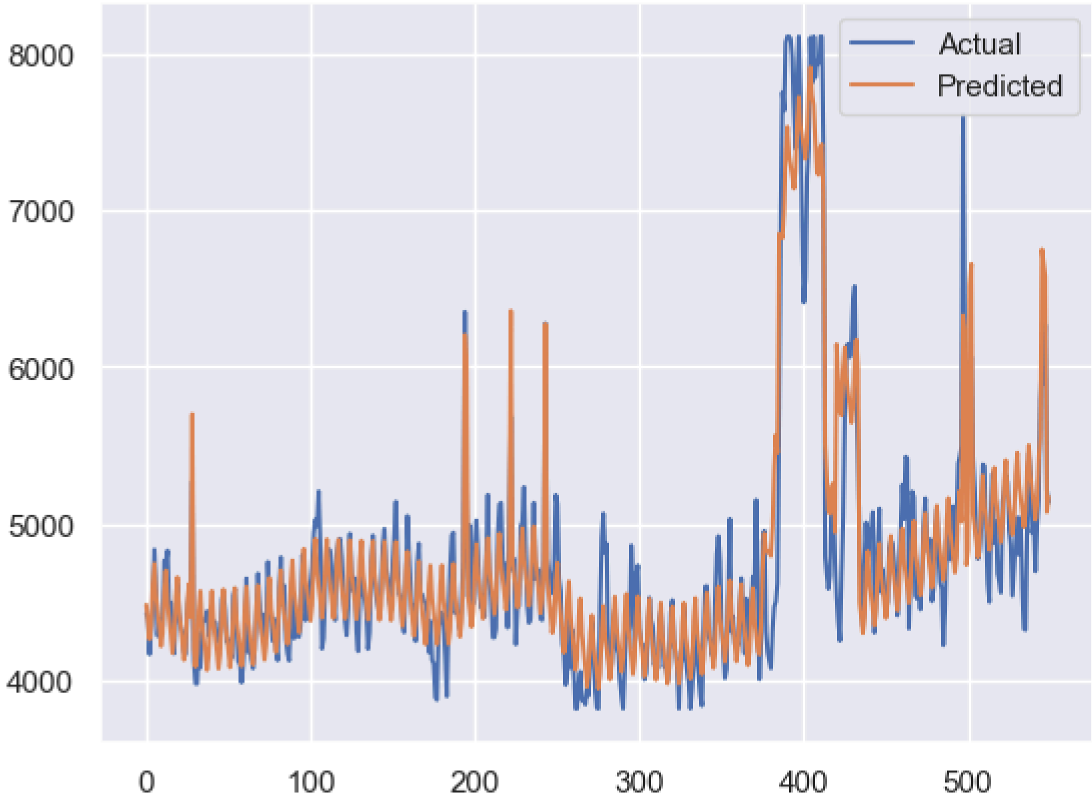
```
13:13:05 - cmdstanpy - INFO - Chain [1] start processing
13:13:06 - cmdstanpy - INFO - Chain [1] done processing
```



In [104…

```
y_true = df['y'].values
y_pred = forecast2['yhat'].values

plt.plot(y_true, label='Actual')
```

```
plt.plot(y_pred, label='Predicted')
plt.legend()
plt.show()
```



In [105…

```
mape = np.mean(np.abs(forecast2['yhat'][-20:] - df['y'][-20:].values)/np.abs(df['y'][-20:].values))
print("mape:",mape)
```

```
mape: 0.06620436903062904
```

- Fb prophet - 6.6% Mape
- Sarimax - 7.6% Mape

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.

Questions

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

- 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.

Write 3 inferences you made from the data visualizations

- All-agents access is significantly higher than spider access across all languages, with English having the highest overall count.
- Japanese and German also show high engagement from all-agents, while Spanish and Russian have the lowest counts in both categories.
- English has more pages with AccessType of all-access, different from the rest
- English pages are the most visited pages follwed by Spanish
- English pages have an upward trend in terms of visits
- There is an unusual peak from mid of July to end of August 2016

What does the decomposition of series do?

- The decomposition of a time series is a technique used to separate the series into its constituent components.

What level of differencing gave you a stationary series?

- Level 1 (diff(1))

Difference between arima, sarima & sarimax

- ARIMA:
  - Models non-seasonal time series.
  - No seasonality or external factors.
- SARIMA:
  - Extends ARIMA to handle seasonality.
  - No external factors.
- SARIMAX:
  - Extends SARIMA by including external predictors (exogenous variables).
  - Handles seasonality and external factors.

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

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

- Bayesian Optimization
- Randomized Search