```
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
from prophet import Prophet
import re
import warnings
warnings.filterwarnings('ignore')

# Load the datasets
train_df = pd.read_csv('train_1.csv')
exog_df = pd.read_csv('Exog_Campaign_eng.csv')

# Display initial info
print('Train Data Info:')
train_df.info()
print('\nTrain Data Head:')
print(train_df.head())

print('\nExog Data Info:')
exog_df.info()
print('\nExog Data Head:')
print(exog_df.head())
```

```
Train Data Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 145063 entries, 0 to 145062
Columns: 551 entries, Page to 2016-12-31
dtypes: float64(550), object(1)
memory usage: 609.8+ MB

Train Data Head:
                                              Page  2015-07-01  2015-07-02  \
0          2NE1_zh.wikipedia.org_all-access_spider        18.0        11.0
1           2PM_zh.wikipedia.org_all-access_spider        11.0        14.0
2            3C_zh.wikipedia.org_all-access_spider         1.0         0.0
3       4minute_zh.wikipedia.org_all-access_spider        35.0        13.0
4  52_Hz_I_Love_You_zh.wikipedia.org_all-access_s...         NaN         NaN

   2015-07-03  2015-07-04  2015-07-05  2015-07-06  2015-07-07  2015-07-08  \
0         5.0        13.0        14.0         9.0         9.0        22.0
1        15.0        18.0        11.0        13.0        22.0        11.0
2         1.0         1.0         0.0         4.0         0.0         3.0
3        10.0        94.0         4.0        26.0        14.0         9.0
4         NaN         NaN         NaN         NaN         NaN         NaN

   2015-07-09  ...  2016-12-22  2016-12-23  2016-12-24  2016-12-25  \
0        26.0  ...        32.0        63.0        15.0        26.0
1        10.0  ...        17.0        42.0        28.0        15.0
2         4.0  ...         3.0         1.0         1.0         7.0
3        11.0  ...        32.0        10.0        26.0        27.0
4         NaN  ...        48.0         9.0        25.0        13.0

   2016-12-26  2016-12-27  2016-12-28  2016-12-29  2016-12-30  2016-12-31
0        14.0        20.0        22.0        19.0        18.0        20.0
1         9.0        30.0        52.0        45.0        26.0        20.0
2         4.0         4.0         6.0         3.0         4.0        17.0
3        16.0        11.0        17.0        19.0        10.0        11.0
4         3.0        11.0        27.0        13.0        36.0        10.0

[5 rows x 551 columns]

Exog Data Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550 entries, 0 to 549
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Exog    550 non-null    int64
dtypes: int64(1)
memory usage: 4.4 KB

Exog Data Head:
   Exog
0     0
1     0
2     0
3     0
4     0
```

```
# --- Exploratory Data Analysis (EDA) ---

# Check for null values
print('\nNull values in train_df:')
print(train_df.isnull().sum().sort_values(ascending=False))

# Calculate percentage of nulls per column (date)
null_percentage = train_df.isnull().mean() * 100
print('\nPercentage of null values per date column:')
print(null_percentage[null_percentage > 0].sort_values(ascending=False))

# Visualize null value distribution over time (optional, can be large)
# plt.figure(figsize=(15, 5))
# sns.heatmap(train_df.drop('Page', axis=1).isnull(), cbar=False)
# plt.title('Null Value Distribution Over Time')
# plt.xlabel('Date')
# plt.ylabel('Page Index')
# plt.show()

# Fill null values with 0, assuming null means no views
# This is a common approach, but might need refinement based on domain knowledge
train_df.fillna(0, inplace=True)
```

```
Null values in train_df:
2015-07-02    20816
2015-07-01    20740
2015-07-07    20664
2015-07-05    20659
2015-07-04    20654
              ...
2016-12-31     3465
2016-12-20     3268
2016-12-21     3236
2016-12-24     3189
Page              0
Length: 551, dtype: int64

Percentage of null values per date column:
2015-07-02    14.349627
2015-07-01    14.297236
2015-07-07    14.244845
2015-07-05    14.241399
2015-07-04    14.237952
                ...
2016-12-12     2.438940
2016-12-31     2.388617
2016-12-20     2.252814
2016-12-21     2.230755
2016-12-24     2.198355
Length: 550, dtype: float64
```

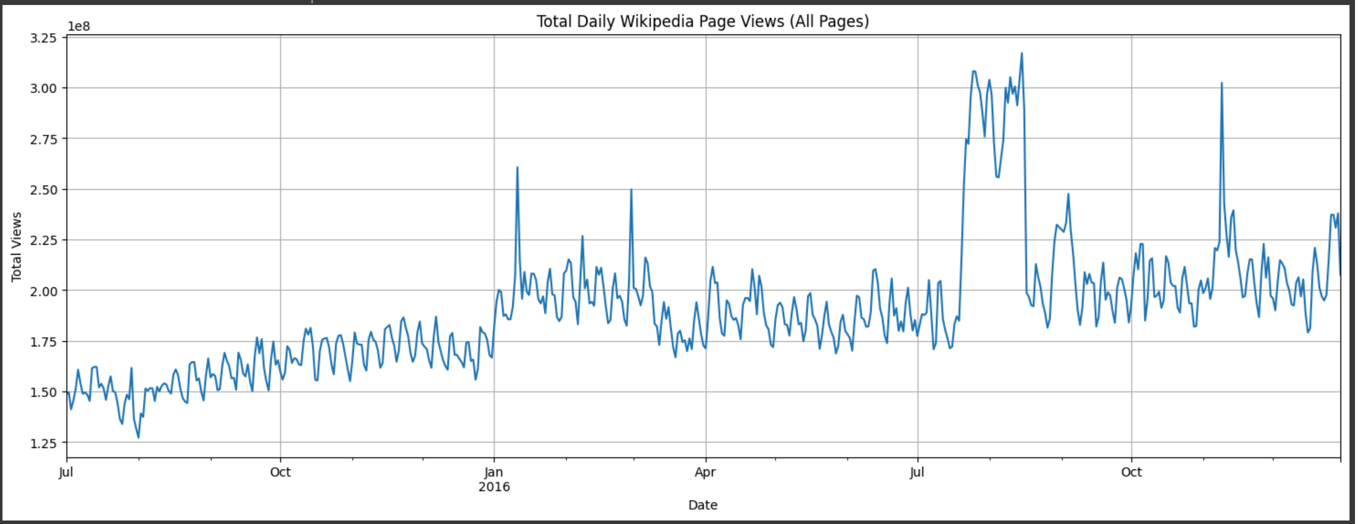
```
# Function to parse the Page column
def parse_page_name(page_name):
    match = re.match(r'(.*)_([a-z]{2}|[a-z]{2}-.*)\.wikipedia\.org_([^_]*)_([^_]*)', page_name)
    if match:
        title = match.group(1).replace('_', ' ')
        language = match.group(2)
        access_type = match.group(3)
        access_origin = match.group(4)
        return pd.Series([title, language, access_type, access_origin])
    else:
        # Handle cases that don't match the primary pattern (if any)
        # Example: Wikimedia commons pages might have a different structure
        if 'commons.wikimedia.org' in page_name:
             match_commons = re.match(r'(.*)_commons\.wikimedia\.org_([^_]*)_([^_]*)', page_name)
             if match_commons:
                 title = match_commons.group(1).replace('_', ' ')
                 language = 'commons' # Assign a specific language code
                 access_type = match_commons.group(2)
                 access_origin = match_commons.group(3)
                 return pd.Series([title, language, access_type, access_origin])
        # Fallback if no pattern matches
        return pd.Series([page_name, None, None, None])

# Apply the function to create new columns
parsed_data = train_df['Page'].apply(parse_page_name)
parsed_data.columns = ['Title', 'Language', 'AccessType', 'AccessOrigin']

# Concatenate the new columns with the original dataframe
train_df = pd.concat([train_df, parsed_data], axis=1)

# Display value counts for the new columns
```

```
print('\nLanguage Distribution:')
print(train_df['Language'].value_counts())

print('\nAccess Type Distribution:')
print(train_df['AccessType'].value_counts())

print('\nAccess Origin Distribution:')
print(train_df['AccessOrigin'].value_counts())

print('\nDataFrame with parsed columns:')
print(train_df[['Page', 'Title', 'Language', 'AccessType', 'AccessOrigin']].head())
```

```
Language Distribution:
Language
en         24108
ja         20431
de         18547
fr         17802
zh         17229
ru         15022
es         14069
commons    10555
Name: count, dtype: int64

Access Type Distribution:
AccessType
all-access    70814
mobile-web    33836
desktop       33113
Name: count, dtype: int64

Access Origin Distribution:
AccessOrigin
all-agents    104599
spider         33164
Name: count, dtype: int64

DataFrame with parsed columns:
                                              Page            Title  \
0            2NE1_zh.wikipedia.org_all-access_spider             2NE1
1             2PM_zh.wikipedia.org_all-access_spider              2PM
2              3C_zh.wikipedia.org_all-access_spider               3C
3         4minute_zh.wikipedia.org_all-access_spider          4minute
4  52_Hz_I_Love_You_zh.wikipedia.org_all-access_s...  52 Hz I Love You

  Language  AccessType AccessOrigin
0       zh  all-access       spider
1       zh  all-access       spider
2       zh  all-access       spider
3       zh  all-access       spider
4       zh  all-access       spider
```

```
# --- Data Visualization ---

# Reshape data from wide to long format for easier plotting
date_cols = train_df.columns[:-5] # Exclude Page and the parsed columns
train_melted = pd.melt(train_df,
                         id_vars=['Page', 'Title', 'Language', 'AccessType', 'AccessOrigin'],
                         value_vars=date_cols,
                         var_name='Date',
                         value_name='Views')

# Convert Date column to datetime objects
train_melted['Date'] = pd.to_datetime(train_melted['Date'])

print('\nMelted DataFrame Head:')
print(train_melted.head())

# Calculate total daily views across all pages
total_daily_views = train_melted.groupby('Date')['Views'].sum()

# Plot total daily views
plt.figure(figsize=(18, 6))
total_daily_views.plot()
plt.title('Total Daily Wikipedia Page Views (All Pages)')
plt.xlabel('Date')
plt.ylabel('Total Views')
plt.grid(True)
plt.show()
```

```
Melted DataFrame Head:
                                                Page            Title  \
0            2NE1_zh.wikipedia.org_all-access_spider             2NE1
1             2PM_zh.wikipedia.org_all-access_spider              2PM
2              3C_zh.wikipedia.org_all-access_spider               3C
3         4minute_zh.wikipedia.org_all-access_spider          4minute
4  52_Hz_I_Love_You_zh.wikipedia.org_all-access_s...  52 Hz I Love You

  Language  AccessType AccessOrigin       Date  Views
0       zh  all-access       spider 2015-07-01   18.0
1       zh  all-access       spider 2015-07-01   11.0
2       zh  all-access       spider 2015-07-01    1.0
3       zh  all-access       spider 2015-07-01   35.0
4       zh  all-access       spider 2015-07-01    0.0
```

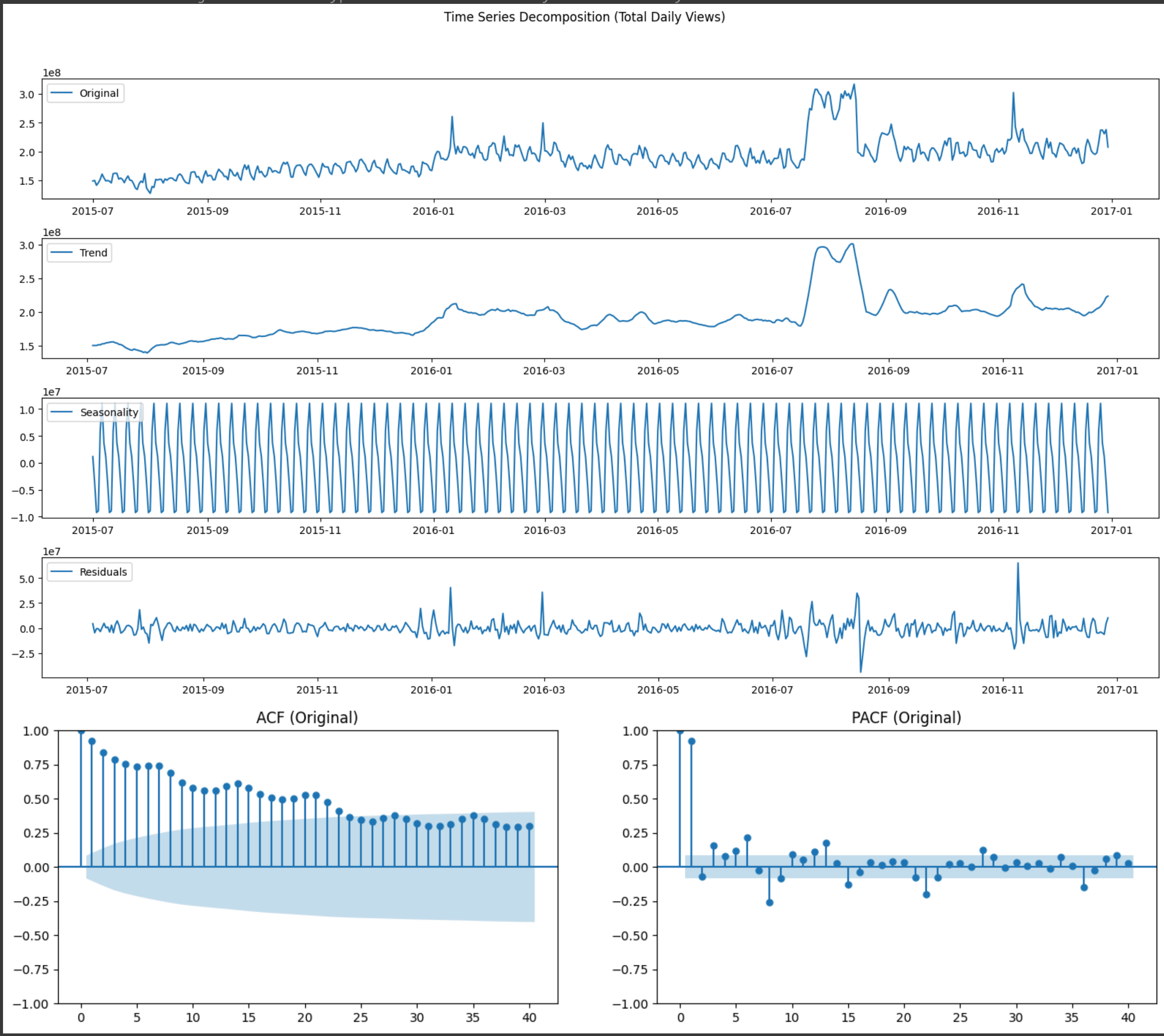



```
# Analyze views by Language
avg_views_lang = train_melted.groupby(['Date', 'Language'])['Views'].mean().unstack()

# Plot average daily views per language (Top N languages for clarity)
top_n = 7 # Adjust as needed
top_languages = train_df['Language'].value_counts().nlargest(top_n).index
plt.figure(figsize=(18, 6))
avg_views_lang[top_languages].plot(ax=plt.gca()) # Plot only top N languages
plt.title(f'Average Daily Views per Language (Top {top_n})')
plt.xlabel('Date')
plt.ylabel('Average Views')
plt.legend(title='Language', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.grid(True)
plt.tight_layout()
plt.show()

# Analyze views by Access Type
avg_views_access = train_melted.groupby(['Date', 'AccessType'])['Views'].mean().unstack()
plt.figure(figsize=(18, 6))
avg_views_access.plot(ax=plt.gca())
plt.title('Average Daily Views per Access Type')
plt.xlabel('Date')
plt.ylabel('Average Views')
plt.legend(title='Access Type', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.grid(True)
plt.tight_layout()
plt.show()

# Analyze views by Access Origin
avg_views_origin = train_melted.groupby(['Date', 'AccessOrigin'])['Views'].mean().unstack()
plt.figure(figsize=(18, 6))
avg_views_origin.plot(ax=plt.gca())
plt.title('Average Daily Views per Access Origin')
plt.xlabel('Date')
plt.ylabel('Average Views')
plt.legend(title='Access Origin', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.grid(True)
```

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

```
# --- Stationarity Check ---

# We'll use the total_daily_views for initial stationarity checks
series_to_check = total_daily_views

# Define function for ADF test
def adf_test(timeseries):
    print('Results of Dickey-Fuller Test:')
    dftest = adfuller(timeseries, autolag='AIC')
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags Used','Number of Observations Used'])
    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print(dfoutput)
    if dftest[1] <= 0.05:
        print("\nConclusion: Reject the null hypothesis. Data is likely stationary.")
    else:
        print("\nConclusion: Fail to reject the null hypothesis. Data is likely non-stationary.")

# Perform ADF test on the original series
print("--- ADF Test on Original Total Daily Views ---")
adf_test(series_to_check)

# Decompose the series
# Start with 'additive'. If variance seems to increase with the level in the original plot, try 'multiplicative'.
decomposition = seasonal_decompose(series_to_check, model='additive', period=7) # Assuming weekly seasonality (period=7)

trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid

plt.figure(figsize=(16, 10))
plt.subplot(411)
plt.plot(series_to_check, label='Original')
plt.legend(loc='upper left')
plt.subplot(412)
plt.plot(trend, label='Trend')
plt.legend(loc='upper left')
plt.subplot(413)
plt.plot(seasonal,label='Seasonality')
plt.legend(loc='upper left')
plt.subplot(414)
plt.plot(residual, label='Residuals')
plt.legend(loc='upper left')
plt.suptitle('Time Series Decomposition (Total Daily Views)')
plt.tight_layout(rect=[0, 0.03, 1, 0.95]) # Adjust layout to prevent title overlap
plt.show()

# Plot ACF and PACF for the original series
fig, axes = plt.subplots(1, 2, figsize=(16, 4))
plot_acf(series_to_check, ax=axes[0], lags=40)
plot_pacf(series_to_check, ax=axes[1], lags=40)
axes[0].set_title('ACF (Original)')
axes[1].set_title('PACF (Original)')
plt.show()
```

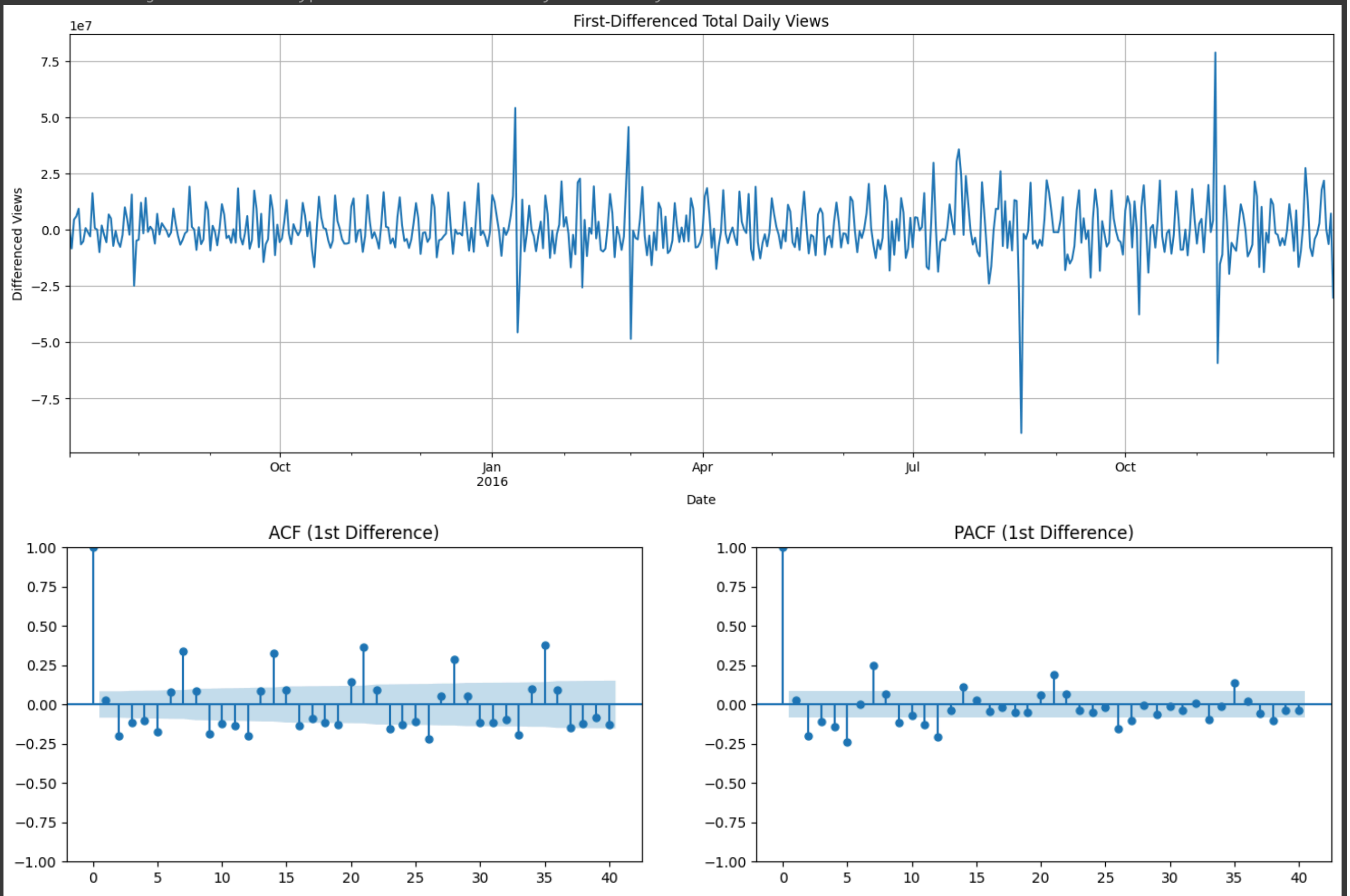
```
--- ADF Test on Original Total Daily Views ---
Results of Dickey-Fuller Test:
Test Statistic                  -2.439213
p-value                          0.130973
#Lags Used                      14.000000
Number of Observations Used    534.000000
Critical Value (1%)             -3.442655
Critical Value (5%)             -2.866968
Critical Value (10%)            -2.569661
dtype: float64

Conclusion: Fail to reject the null hypothesis. Data is likely non-stationary.
```




```
# --- Differencing for Stationarity ---

# Apply first-order differencing
```

```
# We drop NA values created by differencing
series_diff1 = series_to_check.diff().dropna()

# Perform ADF test on the first-differenced series
print("\n--- ADF Test on First-Differenced Series ---")
adf_test(series_diff1)

# Plot the differenced series
plt.figure(figsize=(18, 6))
series_diff1.plot()
plt.title('First-Differenced Total Daily Views')
plt.xlabel('Date')
plt.ylabel('Differenced Views')
plt.grid(True)
plt.show()

# Plot ACF and PACF for the first-differenced series
# These plots help determine the p and q parameters for ARIMA
fig, axes = plt.subplots(1, 2, figsize=(16, 4))
plot_acf(series_diff1, ax=axes[0], lags=40)
plot_pacf(series_diff1, ax=axes[1], lags=40)
axes[0].set_title('ACF (1st Difference)')
axes[1].set_title('PACF (1st Difference)')
plt.show()

# Note: If the series is still non-stationary after 1st differencing,
# you might need to apply second-order differencing:
# series_diff2 = series_diff1.diff().dropna()
# adf_test(series_diff2)
# Then plot ACF/PACF for series_diff2
```

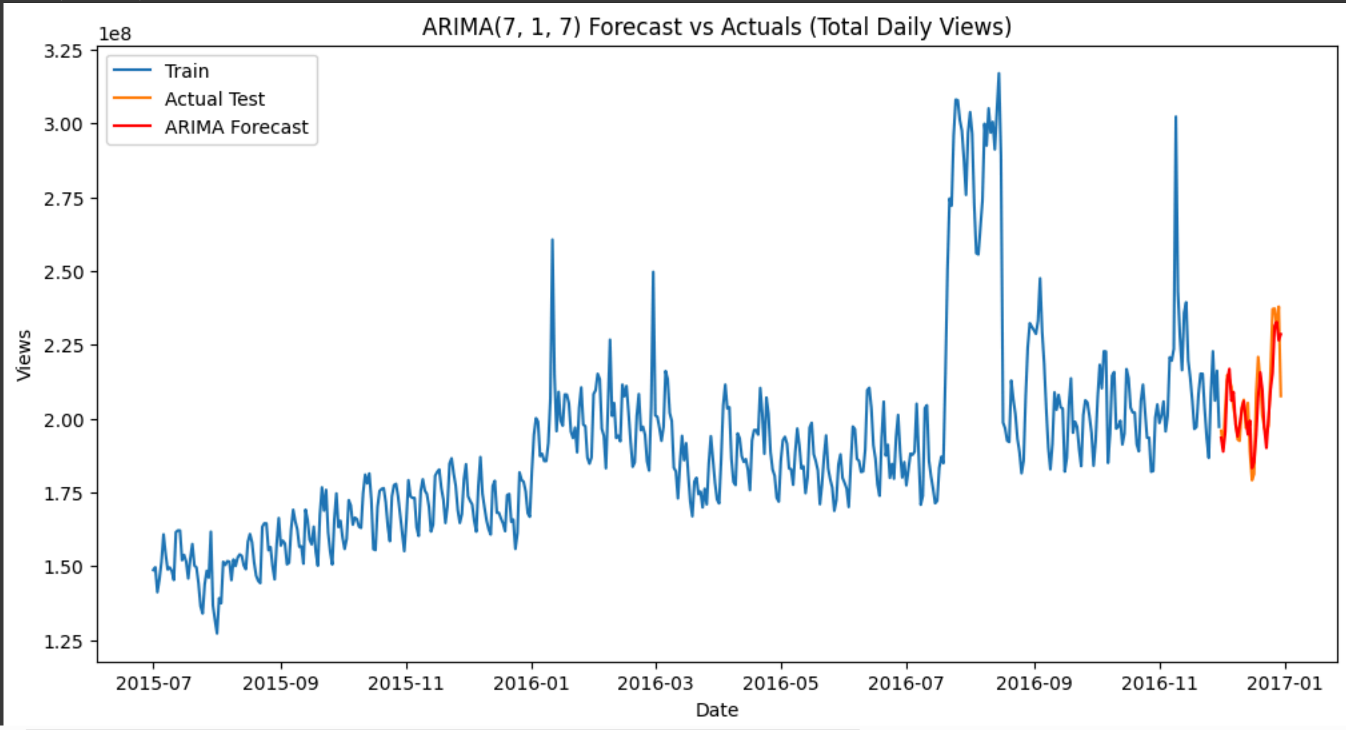
```
--- ADF Test on First-Differenced Series ---
Results of Dickey-Fuller Test:
Test Statistic                -7.883325e+00
p-value                        4.639940e-12
#Lags Used                     1.300000e+01
Number of Observations Used    5.340000e+02
Critical Value (1%)           -3.442655e+00
Critical Value (5%)           -2.866968e+00
Critical Value (10%)          -2.569661e+00
dtype: float64

Conclusion: Reject the null hypothesis. Data is likely stationary.
```




```
# --- ARIMA Modeling ---

# Define train/test split (e.g., forecast last 30 days)
forecast_days = 30
train_data = series_to_check[:-forecast_days]
test_data = series_to_check[-forecast_days:]

print(f"Training data shape: {train_data.shape}")
print(f"Testing data shape: {test_data.shape}")

# Define MAPE function
def mean_absolute_percentage_error(y_true, y_pred):
    y_true, y_pred = np.array(y_true), np.array(y_pred)
    # Avoid division by zero
    mask = y_true != 0
    # Handle cases where y_true[mask] might still contain zeros if y_pred is non-zero
    safe_true = y_true[mask]
    safe_pred = y_pred[mask]
    non_zero_mask = safe_true != 0
```

```
    if np.any(non_zero_mask):
        return np.mean(np.abs((safe_true[non_zero_mask] - safe_pred[non_zero_mask]) / safe_true[non_zero_mask])) * 100
    else:
        return 0.0 # Or np.nan, depending on how you want to handle all-zero actuals

# Define function for ARIMA modeling using walk-forward validation
# Note: Walk-forward is robust but computationally expensive as it refits the model at each step.
# For faster (but potentially less accurate) prediction, fit once and predict multiple steps.
def run_arima(train, test, order=(7, 1, 7)):
    history = [x for x in train]
    predictions = list()

    print(f"Running ARIMA{order} with walk-forward validation...")
    for t in range(len(test)):
        try:
            model = ARIMA(history, order=order)
            model_fit = model.fit() # Refit model at each step
            output = model_fit.forecast() # Forecast one step ahead
            yhat = output[0]
            predictions.append(yhat)
            obs = test[t]
            history.append(obs) # Add actual observation to history for next prediction
        except Exception as e:
            print(f"Error during ARIMA fit/forecast at step {t}: {e}")
            # Handle error, e.g., append last prediction or NaN
            predictions.append(predictions[-1] if predictions else np.nan)
            history.append(test[t]) # Still add observation

        # Optional: Print progress
        if (t+1) % 10 == 0:
             print(f'Predicted step {t+1}/{len(test)}')

    # Convert predictions to a pandas Series with the correct index
    predictions_series = pd.Series(predictions, index=test.index)

    # Evaluate forecasts
    mape = mean_absolute_percentage_error(test, predictions_series.fillna(0)) # Fill potential NaNs
    print(f'ARIMA{order} Test MAPE: %.3f' % mape)

    # Plot forecasts against actual outcomes
    plt.figure(figsize=(12, 6))
    plt.plot(train.index, train, label='Train')
    plt.plot(test.index, test, label='Actual Test')
    plt.plot(predictions_series.index, predictions_series, label='ARIMA Forecast', color='red')
    plt.title(f'ARIMA{order} Forecast vs Actuals (Total Daily Views)')
    plt.xlabel('Date')
    plt.ylabel('Views')
    plt.legend()
    plt.show()

    return predictions_series, mape

# Run ARIMA with initial parameters (p=7, d=1, q=7)
# Note: This can be time-consuming.
# The order (7,1,7) is just an example based on potential weekly patterns and assumed differencing.
# Actual order should be determined from ACF/PACF plots of the differenced series.
arima_order = (7, 1, 7)
arima_predictions, arima_mape = run_arima(train_data, test_data, arima_order)
```

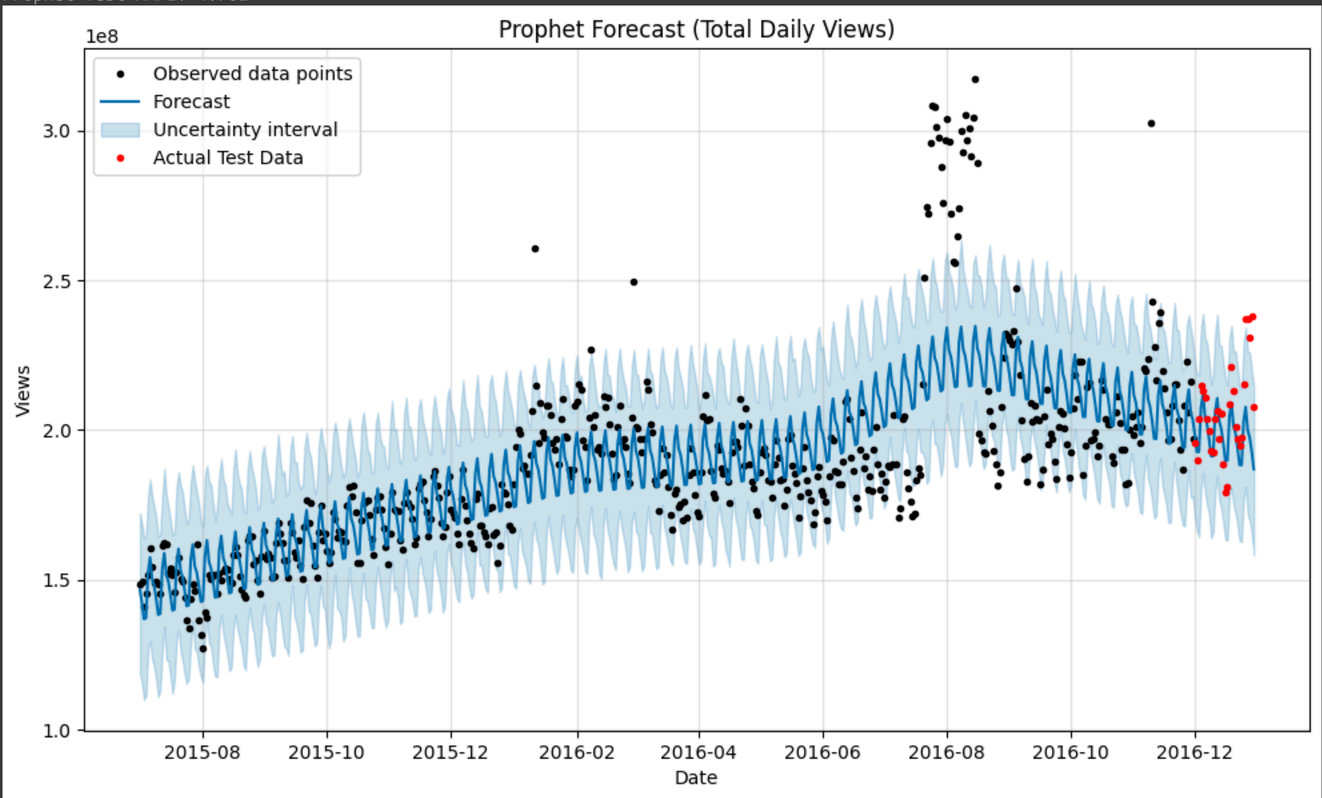
```
Training data shape: (519,)
Testing data shape: (30,)
Running ARIMA(7, 1, 7) with walk-forward validation...
Predicted step 10/30
Predicted step 20/30
Predicted step 30/30
ARIMA(7, 1, 7) Test MAPE: 2.898
```

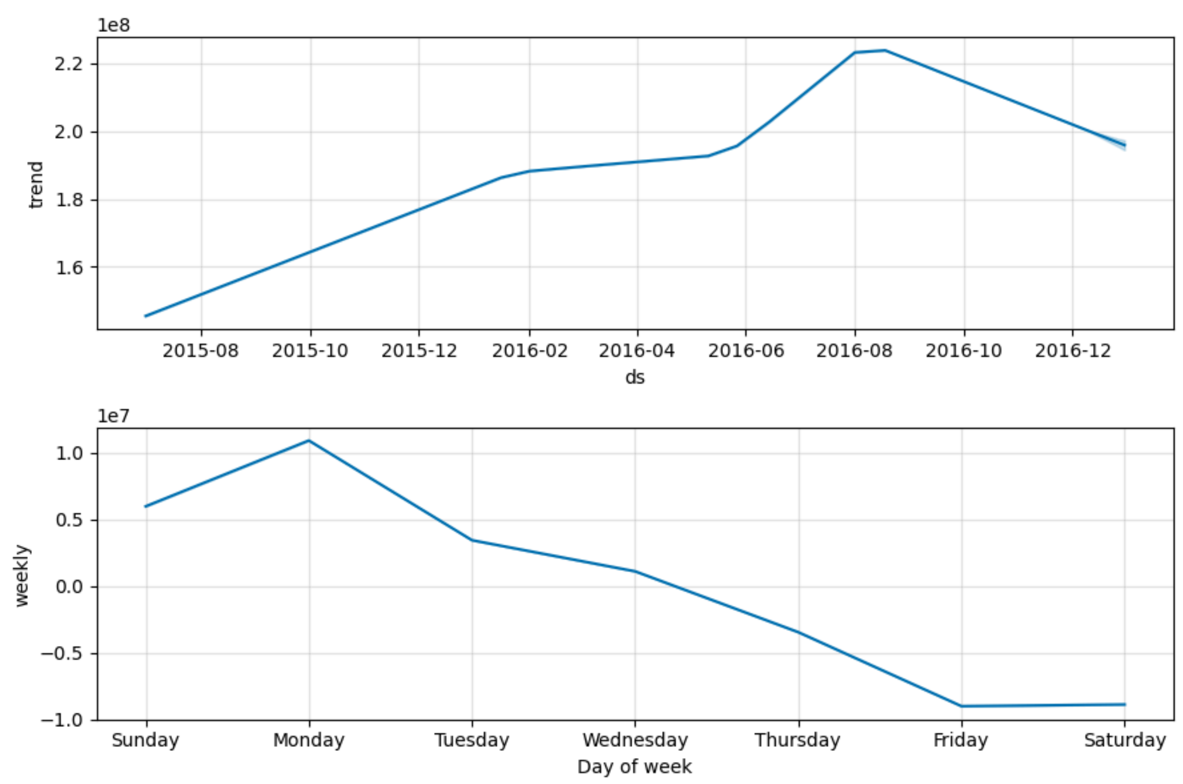



```
# --- Facebook Prophet Modeling ---

# Prepare data for Prophet (requires 'ds' and 'y' columns)
prophet_train_df = train_data.reset_index()
prophet_train_df.columns = ['ds', 'y']

# Instantiate and fit the Prophet model
# Prophet automatically detects yearly and weekly seasonality by default
print("\nRunning Prophet model...")
model_prophet = Prophet()
# Add campaign dates as holidays/events if desired (especially if running on English data)
# campaign_dates = exog_aligned[exog_aligned['Campaign'] == 1].index
# holidays = pd.DataFrame({
#   'holiday': 'campaign',
#   'ds': campaign_dates,
#   'lower_window': 0,
#   'upper_window': 1, # Assume effect lasts for a day or two
# })
# model_prophet = Prophet(holidays=holidays)

model_prophet.fit(prophet_train_df)

# Create a future dataframe for the forecast period
future = model_prophet.make_future_dataframe(periods=forecast_days)

# Generate predictions
forecast = model_prophet.predict(future)

# Extract the forecast for the test period
prophet_predictions = forecast.set_index('ds')['yhat'][-forecast_days:]

# Evaluate forecasts
prophet_mape = mean_absolute_percentage_error(test_data, prophet_predictions)
print(f'Prophet Test MAPE: %.3f' % prophet_mape)

# Plot forecasts against actual outcomes
fig1 = model_prophet.plot(forecast)
plt.title('Prophet Forecast (Total Daily Views)')
plt.xlabel('Date')
plt.ylabel('Views')
# Add actual test data points to the plot
plt.plot(test_data.index, test_data, '.r', label='Actual Test Data')
plt.legend()
plt.show()
```

```
# Plot Prophet components (trend, weekly, yearly seasonality)
fig2 = model_prophet.plot_components(forecast)
plt.show()
```

```
Running Prophet model...
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/tmpao_p1akd/svr6m3z4.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpao_p1akd/_9d93tpi.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.11/dist-packages/prophet/stan_model/prophet_model.bin', 'random', 'seed=4655
16:54:47 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
16:54:47 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
Prophet Test MAPE: 4.761
```





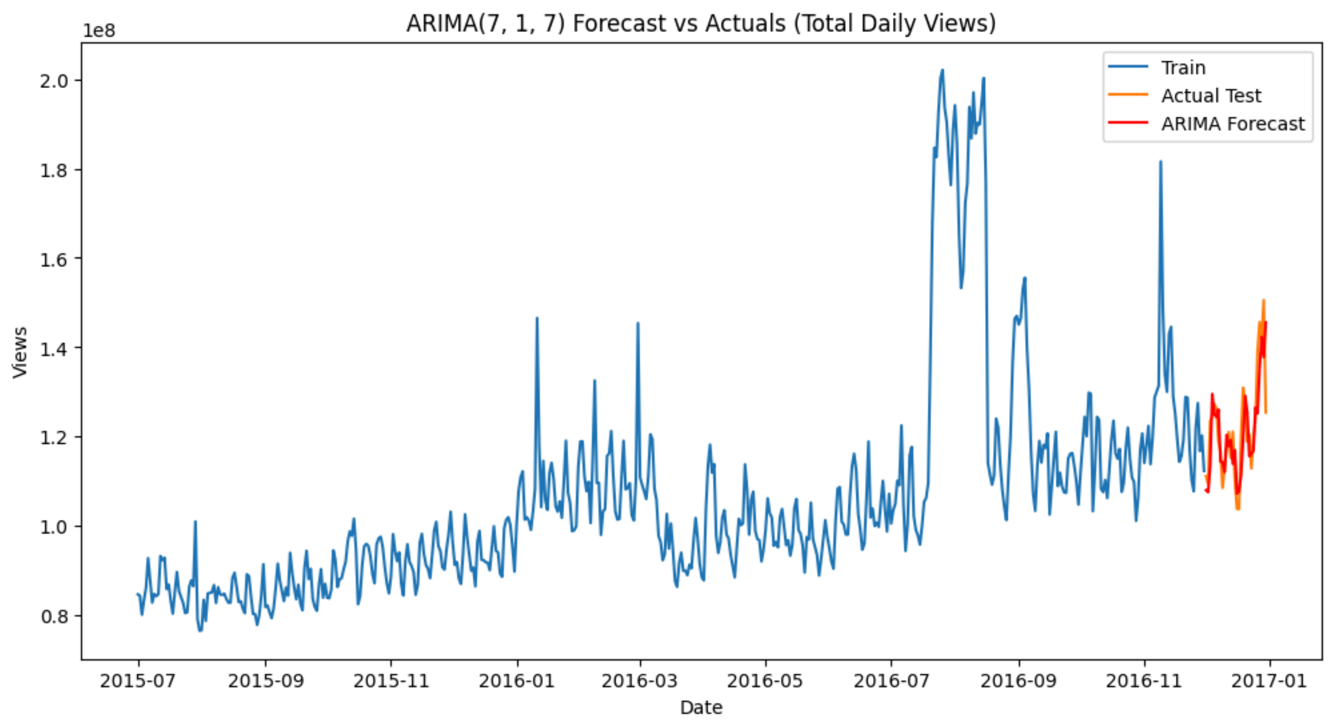
```
# --- ARIMA Parameter Tuning (Grid Search Example) ---

# Define a function to evaluate an ARIMA model using walk-forward validation
# Note: This is computationally expensive, especially within a grid search.
def evaluate_arima_model(train, test, order):
    history = [x for x in train]
    predictions = list()
    for t in range(len(test)):
        try:
            model = ARIMA(history, order=order)
            model_fit = model.fit() # Refit model at each step
            yhat = model_fit.forecast()[0]
            predictions.append(yhat)
            history.append(test[t])
        except Exception as e:
            # Suppress errors during grid search for cleaner output, return high MAPE
            # print(f"Error evaluating {order} at step {t}: {e}")
            return float('inf') # Return infinity for errors

    predictions_series = pd.Series(predictions, index=test.index)
    mape = mean_absolute_percentage_error(test, predictions_series.fillna(0))
    return mape

# Define a function to perform grid search
def grid_search_arima(train, test, p_values, d_values, q_values):
    best_score, best_cfg = float("inf"), None
    total_configs = len(p_values) * len(d_values) * len(q_values)
    count = 0
    print(f"Starting ARIMA Grid Search ({total_configs} configurations). This may take a long time...")
    for p in p_values:
        for d in d_values:
            for q in q_values:
                order = (p,d,q)
                count += 1
                try:
                    mape = evaluate_arima_model(train, test, order)
                    if mape < best_score:
                        best_score, best_cfg = mape, order
                    print(f'[{count}/{total_configs}] ARIMA{order} MAPE=%.3f (Best: {best_cfg} MAPE=%.3f)' % (mape, best_score))
                except Exception as e:
                    # This outer try-except might catch errors not handled in evaluate_arima_model
                    print(f'[{count}/{total_configs}] ARIMA{order} failed unexpectedly: {e}')
                    continue
    print('\nGrid Search Complete.')
    print('Best ARIMA%s MAPE=%.3f' % (best_cfg, best_score))
    return best_cfg, best_score

# Define parameter ranges (keep small for demonstration)
# A more thorough search would use wider ranges and potentially tools like pmdarima.auto_arima
p_values = [0, 1, 2, 7] # Include 7 based on potential weekly pattern
d_values = [1] # Assuming first differencing worked based on earlier ADF test
q_values = [0, 1, 2, 7]

# --- Run Grid Search (Commented Out By Default) ---
# Uncomment the following lines to perform the grid search.
# WARNING: This will be very time-consuming due to walk-forward validation inside the loop.
# Consider reducing p/q ranges or using a faster evaluation method for initial exploration.
# best_order, best_mape = grid_search_arima(train_data, test_data, p_values, d_values, q_values)
# if best_order:
#    print(f"\nBest ARIMA order found: {best_order} with MAPE: {best_mape:.3f}")
#    # Re-run ARIMA with potentially better parameters found from grid search
#    print("\nRe-running ARIMA with best found parameters...")
#    arima_predictions_best, arima_mape_best = run_arima(train_data, test_data, best_order)
# else:
#    print("\nGrid search did not complete successfully or was skipped.")

print("\nNote: Grid search code is present but commented out by default due to high computational cost.")
print("Uncomment the relevant lines above to perform the search.")
```

```
Note: Grid search code is present but commented out by default due to high computational cost.
Uncomment the relevant lines above to perform the search.
```

```
# --- Pipeline for Multiple Series (Example) ---

# Calculate aggregated daily views per language
lang_daily_views = train_melted.groupby(['Date', 'Language'])['Views'].sum().unstack()

# Fill potential NaNs that might appear after unstacking if a language has no pages on a day
lang_daily_views.fillna(0, inplace=True)

print("\nAggregated Daily Views per Language (Head):")
```

```
print(lang_daily_views.head())

# Define a pipeline function (using ARIMA as an example)
# Note: This uses the computationally expensive walk-forward validation from run_arima.
# For many series, consider fitting once and forecasting, or using faster models like Prophet/ML.
def forecast_pipeline(series, series_name, order=(7, 1, 7), forecast_days=30):
    print(f"\n--- Running Forecast Pipeline for: {series_name} ---")

    # Basic check for sufficient data
    if len(series) < forecast_days + 50: # Need enough data for training & model stability
        print(f"Skipping {series_name}: Insufficient data points ({len(series)}).")
        return None, None

    # Optional: Add stationarity check and dynamic order selection (e.g., auto_arima) here for a robust pipeline
    # try:
    #     adf_result = adfuller(series)
    #     if adf_result[1] > 0.05: # If not stationary
    #         # Apply differencing or use auto_arima to find d
    #         pass
    # except Exception as e:
    #     print(f"ADF test failed for {series_name}: {e}")
    #     # Handle failure - maybe skip or use default differencing

    # Split data
    train = series[:-forecast_days]
    test = series[-forecast_days:]

    # Run ARIMA (using the previously defined function)
    # In a production pipeline, you might:
    # 1. Use auto_arima to find the best order for *this specific series*.
    # 2. Choose the model (ARIMA, SARIMAX, Prophet) dynamically based on series characteristics.
    # 3. Handle exogenous variables appropriately if using SARIMAX (requires matching exog data).
    try:
        # Using the pre-defined run_arima which includes plotting (remove plot in production)
        predictions, mape = run_arima(train, test, order)
        print(f"Finished pipeline for {series_name}. MAPE: {mape:.3f}")
        return predictions, mape
    except Exception as e:
        print(f"Error running ARIMA pipeline for {series_name}: {e}")
        return None, None

# --- Apply Pipeline to Selected Languages ---

languages_to_forecast = ['en', 'ja'] # Example languages
results = {}

for lang in languages_to_forecast:
    if lang in lang_daily_views.columns:
        series = lang_daily_views[lang]
        # Use the default ARIMA order for this example pipeline.
        # Ideally, determine order per series (e.g., using auto_arima or grid search within pipeline)
        # or use a model like Prophet that doesn't require order selection.
        # The order (7,1,7) might not be optimal for 'en' or 'ja'.
        predictions, mape = forecast_pipeline(series, f"Language: {lang}", order=arima_order, forecast_days=forecast_days)
        results[lang] = {'predictions': predictions, 'mape': mape}
    else:
        print(f"\nLanguage '{lang}' not found in columns.")

# Display overall results
print("\n--- Pipeline Summary --- ")
for lang, result in results.items():
    if result.get('mape') is not None:
        print(f"Language: {lang}, MAPE: {result['mape']:.3f}")
    else:
        print(f"Language: {lang}, Forecasting failed or skipped.")
```

```
Aggregated Daily Views per Language (Head):
Language      commons          de          en          es         fr  \
Date
2015-07-01  1140821.0  13260519.0  84712190.0  15278553.0  8458638.0
2015-07-02  1178130.0  13079896.0  84438545.0  14601013.0  8512952.0
2015-07-03  1150547.0  12554042.0  80167728.0  13427632.0  8186030.0
2015-07-04   951317.0  11520379.0  83463204.0  12606538.0  8749842.0
2015-07-05  1058036.0  13392347.0  86198637.0  13710356.0  8590493.0

Language            ja         ru         zh
Date
2015-07-01  11863200.0  9463854.0  4144988.0
2015-07-02  13620792.0  9627643.0  4151189.0
2015-07-03  12305383.0  8923463.0  4123659.0
2015-07-04  15456239.0  8393214.0  4163448.0
2015-07-05  14827204.0  8938528.0  4441286.0

--- Running Forecast Pipeline for: Language: en ---
Running ARIMA(7, 1, 7) with walk-forward validation...
Predicted step 10/30
Predicted step 20/30
Predicted step 30/30
ARIMA(7, 1, 7) Test MAPE: 4.583
```




```
Finished pipeline for Language: en. MAPE: 4.583

--- Running Forecast Pipeline for: Language: ja ---
Running ARIMA(7, 1, 7) with walk-forward validation...
Predicted step 10/30
Predicted step 20/30
Predicted step 30/30
ARIMA(7, 1, 7) Test MAPE: 7.749
```