Arima Model

Data Preparation

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib import pyplot
from pandas import DataFrame
import os
import statsmodels.api as sm
from statsmodels.tsa.seasonal import seasonal_decompose
import math
from statsmodels.tsa.stattools import adfuller
from pmdarima import auto_arima
from pandas.plotting import autocorrelation_plot
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.tools.eval_measures import rmse
from sklearn.metrics import mean_squared_error, r2_score
from math import sqrt
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

from statsmodels.tsa.arima.model import ARIMA

pd.set_option('display.max_columns', None)

df = pd.read_csv("US_Regional_Sales_Data.csv")

df.head()
```

```
   OrderNumber Sales Channel WarehouseCode ProcuredDate OrderDate
ShipDate  \
0  SO - 000101      In-Store  WARE-UHY1004     31/12/17   31/5/18
14/6/18
1  SO - 000102        Online  WARE-NMK1003     31/12/17   31/5/18
22/6/18
2  SO - 000103   Distributor  WARE-UHY1004     31/12/17   31/5/18
21/6/18
3  SO - 000104     Wholesale  WARE-NMK1003     31/12/17   31/5/18
2/6/18
4  SO - 000105   Distributor  WARE-NMK1003      10/4/18   31/5/18
16/6/18

  DeliveryDate CurrencyCode  _SalesTeamID  _CustomerID  _StoreID
_ProductID  \
0      19/6/18          USD             6           15       259
12
```

```
1       2/7/18          USD             14          20       196
27
2       1/7/18          USD             21          16       213
16
3       7/6/18          USD             28          48       107
23
4      26/6/18          USD             22          49       111
26
```

```
   Order Quantity  Discount Applied Unit Cost Unit Price
0               5             0.075  1,001.18   1,963.10
1               3             0.075  3,348.66   3,939.60
2               1             0.050    781.22   1,775.50
3               8             0.075  1,464.69   2,324.90
4               8             0.100  1,476.14   1,822.40
```

```
df =
df.drop(['WarehouseCode','ProcuredDate','_SalesTeamID','_CustomerID','
_StoreID','DeliveryDate','ShipDate','Sales Channel','Unit
Cost','Discount Applied','_ProductID','OrderNumber'],axis=1)

df.head()
```

```
  OrderDate CurrencyCode  Order Quantity Unit Price
0   31/5/18          USD               5   1,963.10
1   31/5/18          USD               3   3,939.60
2   31/5/18          USD               1   1,775.50
3   31/5/18          USD               8   2,324.90
4   31/5/18          USD               8   1,822.40
```

```
df['OrderDate'] = pd.to_datetime(df['OrderDate'])  # Convert
'OrderDate' to datetime if not already

df['Unit Price'] = pd.to_numeric(df['Unit Price'].str.replace(',',
''), errors='coerce')

df = df.groupby('OrderDate').agg({
    'CurrencyCode': 'first',
    'Order Quantity': 'sum',
    'Unit Price': 'sum'
}).reset_index()
df['OrderDate'] = df['OrderDate'].dt.strftime('%d/%m/%y')

df
```

```
    OrderDate CurrencyCode  Order Quantity  Unit Price
0    06/01/18          USD              62     31845.1
1    07/01/18          USD              27     14974.5
2    08/01/18          USD              42     15952.7
3    09/01/18          USD              36     13949.4
4    10/01/18          USD              25     14907.5
```

```
..        ...          ...               ...         ...
940   26/12/20          USD                41     16341.3
941   27/12/20          USD                48     25547.1
942   28/12/20          USD                56     46183.1
943   29/12/20          USD                37     18632.7
944   30/12/20          USD                25     10545.8

[945 rows x 4 columns]
```

```
df.dtypes
```

```
OrderDate           object
CurrencyCode        object
Order Quantity       int64
Unit Price         float64
dtype: object
```

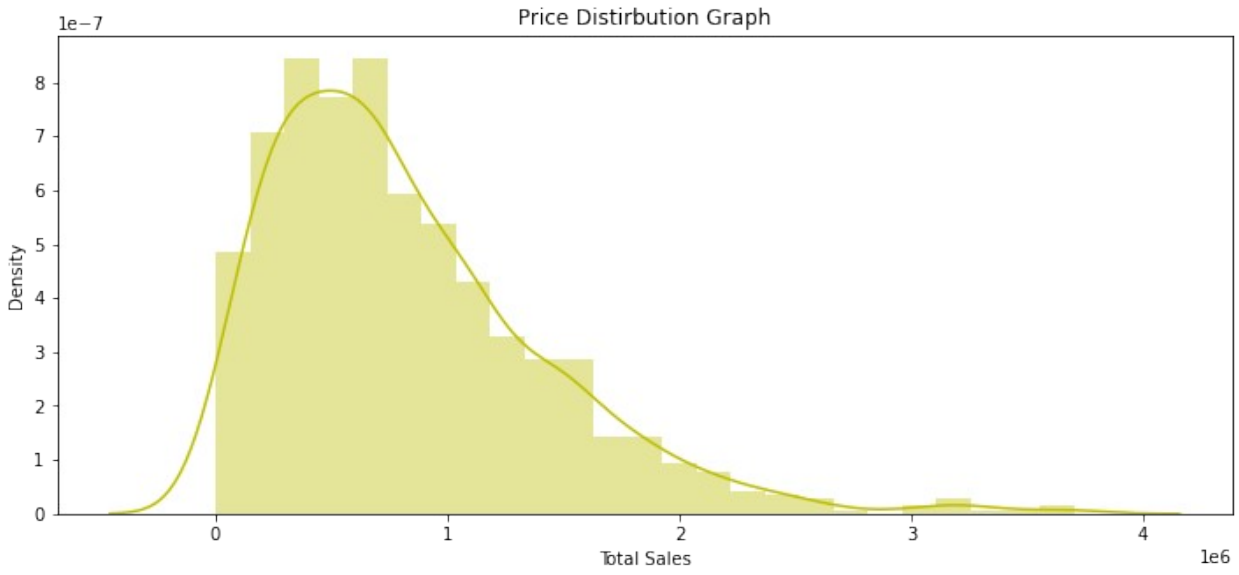
```
df['Total Sales'] = df['Unit Price'] * df['Order Quantity']
```

```
df.isna().sum()
```

```
OrderDate          0
CurrencyCode       0
Order Quantity     0
Unit Price         0
Total Sales        0
dtype: int64
```

```
df['Total Sales'] = df['Total Sales'].astype(float)
plt.figure(figsize=(12,5))
plt.title("Price Distirbution Graph")
ax = sns.distplot(df["Total Sales"], color = 'y')
```

```
C:\Users\AMAN\anaconda3\lib\site-packages\seaborn\
distributions.py:2619: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```




```
def ad_test(dataset):

    dftest = adfuller(dataset, autolag = 'AIC')

    print("1. ADF : ",dftest[0])
    print("2. P-Value : ", dftest[1])
    print("3. Num Of Lags : ", dftest[2])
    print("4. Num Of Observations Used For ADF Regression:",dftest[3])
    print("5. Critical Values :")
    for key, val in dftest[4].items():
         print("\t",key, ": ", val)


ad_test(df['Total Sales'])
```

```
1. ADF :  -31.43899449117808
2. P-Value :  0.0
3. Num Of Lags :  0
4. Num Of Observations Used For ADF Regression: 944
5. Critical Values :
      1% :  -3.4372961556318304
      5% :  -2.864606557310281
      10% :  -2.568402813173298
```

```
stepwise_fit = auto_arima(df['Total Sales'], trace=True,
suppress_warnings=True)
```

```
Performing stepwise search to minimize aic
 ARIMA(2,0,2)(0,0,0)[0] intercept   : AIC=27830.702, Time=0.72 sec
 ARIMA(0,0,0)(0,0,0)[0] intercept   : AIC=27824.465, Time=0.03 sec
 ARIMA(1,0,0)(0,0,0)[0] intercept   : AIC=27825.989, Time=0.05 sec
 ARIMA(0,0,1)(0,0,0)[0] intercept   : AIC=27825.970, Time=0.07 sec
```

```
 ARIMA(0,0,0)(0,0,0)[0]             : AIC=28832.526, Time=0.02 sec
 ARIMA(1,0,1)(0,0,0)[0] intercept   : AIC=27827.982, Time=0.13 sec

Best model:  ARIMA(0,0,0)(0,0,0)[0] intercept
Total fit time: 1.031 seconds
```

```
X = df['Total Sales']
size = int(len(X) * 0.66)
train, test = X[0:size], X[size:len(X)]
history = [x for x in train]
predictions = list()

seasonal_period = 4  # For weekly data, for example

# Calculate the moving average
moving_average = df['Total Sales'].rolling(window=seasonal_period,
min_periods=1).mean()

# Calculate the seasonal factor
seasonal_factor = df['Total Sales'] - moving_average

seasonal_factor
```

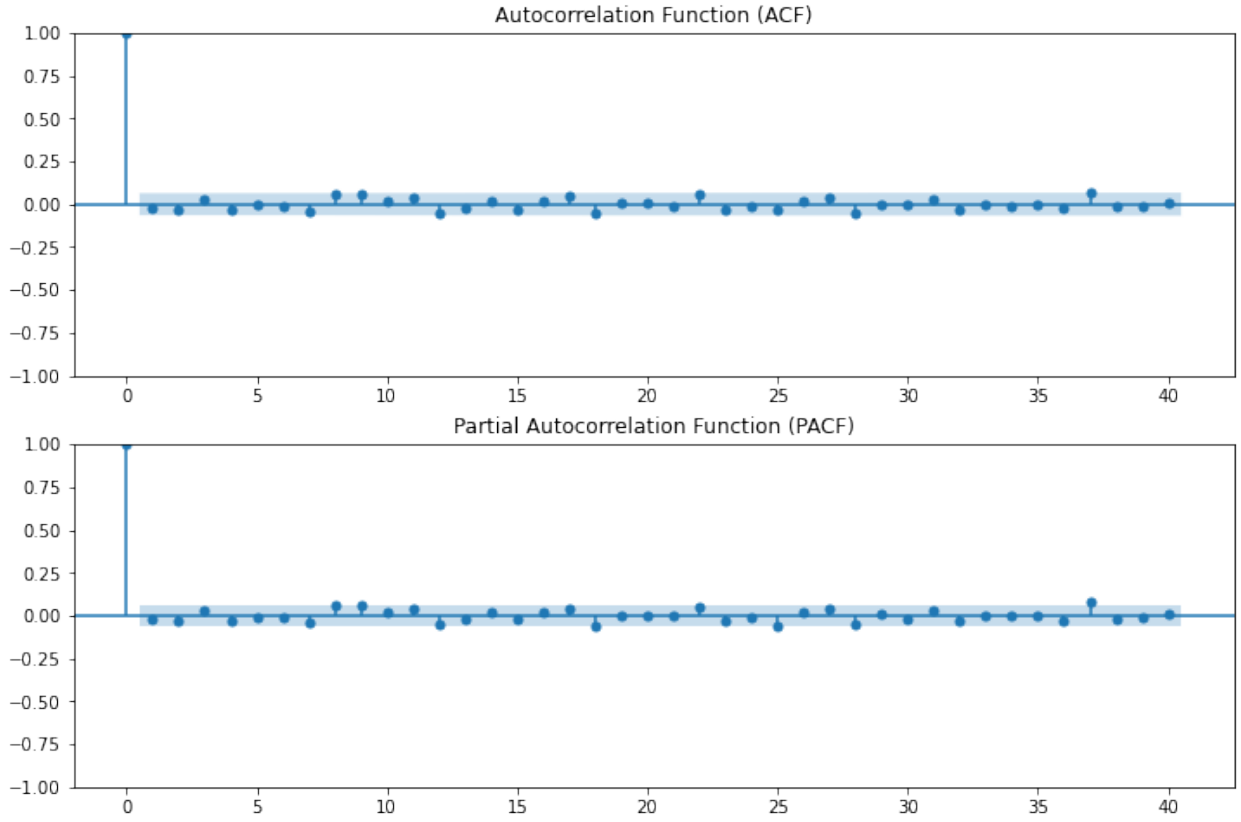
```
0      0.000000e+00
1     -7.850424e+05
2     -3.462270e+05
3     -3.855465e+05
4     -1.146102e+05
           ...
940    1.561267e+04
941    3.991625e+05
942    1.383996e+06
943   -6.035695e+05
944   -9.277473e+05
Name: Total Sales, Length: 945, dtype: float64
```

```
window_size = 10  # Replace with the appropriate window size

# Calculate the moving average
df['Moving Average'] = df['Order
Quantity'].rolling(window=window_size).mean()

# Calculate the seasonal factor
df['Seasonal Factor'] = df['Order Quantity'] - df['Moving Average']

# Drop rows with NaN values in the 'Seasonal Factor' column
df.dropna(subset=['Seasonal Factor'], inplace=True)

df
```

```
    OrderDate CurrencyCode  Order Quantity  Unit Price  Total Sales  \
9    08/02/18          USD              30     11577.6     347328.0
10   09/02/18          USD              45     13306.2     598779.0
11   10/02/18          USD              31     24099.9     747096.9
12   11/02/18          USD              39     10418.5     406321.5
13   12/02/18          USD              35     13132.0     459620.0
..        ...          ...             ...         ...          ...
940  26/12/20          USD              41     16341.3     669993.3
941  27/12/20          USD              48     25547.1    1226260.8
942  28/12/20          USD              56     46183.1    2586253.6
943  29/12/20          USD              37     18632.7     689409.9
944  30/12/20          USD              25     10545.8     263645.0

     Moving Average  Seasonal Factor
9              37.0             -7.0
10             35.3              9.7
11             35.7             -4.7
12             35.4              3.6
13             35.3             -0.3
..              ...              ...
940            42.4             -1.4
941            41.5              6.5
942            44.0             12.0
943            45.5             -8.5
944            41.9            -16.9

[936 rows x 7 columns]
```

```
fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(12, 8))

# ACF plot
plot_acf(df['Total Sales'], lags=40, ax=ax1)
ax1.set_title('Autocorrelation Function (ACF)')

# PACF plot
plot_pacf(df['Total Sales'], lags=40, ax=ax2)
ax2.set_title('Partial Autocorrelation Function (PACF)')

plt.show()
```

```
C:\Users\AMAN\anaconda3\lib\site-packages\statsmodels\graphics\
tsaplots.py:348: FutureWarning: The default method 'yw' can produce
PACF values outside of the [-1,1] interval. After 0.13, the default
will change tounadjusted Yule-Walker ('ywm'). You can use this method
now by setting method='ywm'.
  warnings.warn(
```




```
df.isna().sum()
```

```
OrderDate           0
CurrencyCode        0
Order Quantity      0
Unit Price          0
Total Sales         0
Moving Average      0
Seasonal Factor     0
dtype: int64
```

```
df['OrderDate'] = pd.to_datetime(df['OrderDate'], format='%d/%m/%y')
df.set_index('OrderDate', inplace=True)
```

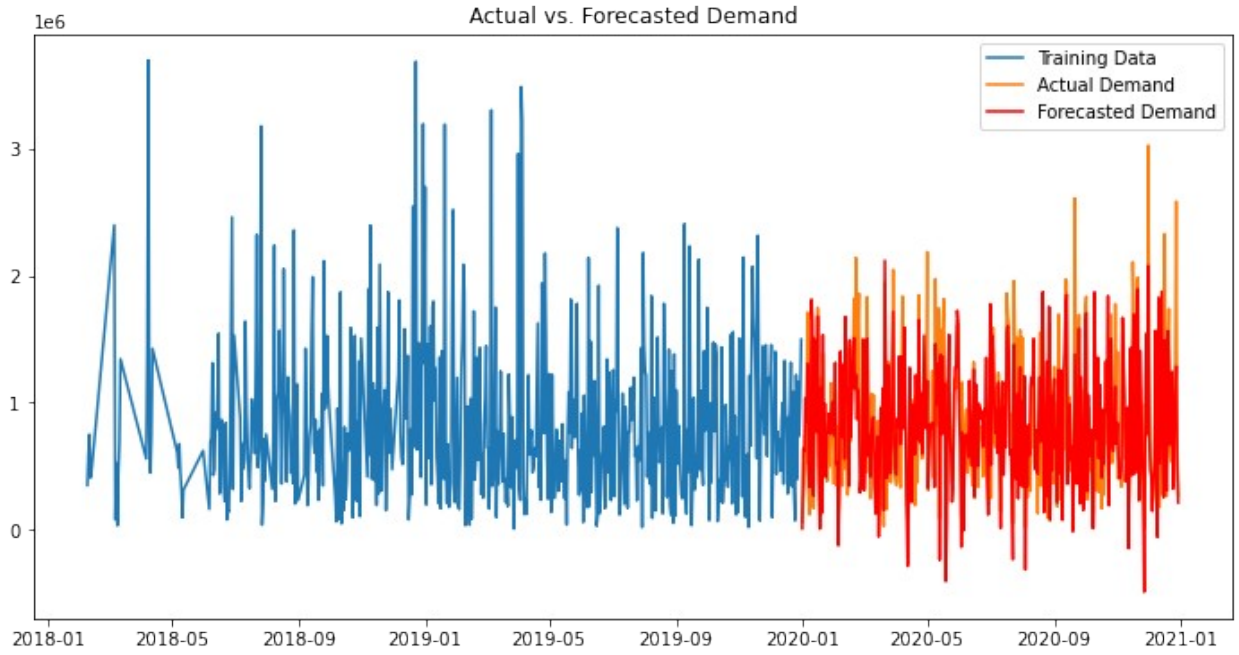
Model Training and Building

```
# Split the dataset into training and testing sets
train = df['2018-01-06':'2019-12-31']
test = df['2020-01-01':'2020-12-31']

# Define the order for the ARIMA model
p, d, q = 38, 0, 18


# Exogenous variable (external factor): 'Discount Applied'
```

```python
exog_train = train[['Seasonal Factor']]
exog_test = test[['Seasonal Factor']]

from statsmodels.tsa.statespace.sarimax import SARIMAX

# Fit the SARIMA model with exogenous variables
model = ARIMA(train['Total Sales'], order=(p, d, q), exog=exog_train)
model_fit = model.fit()

# Make predictions for the test set
forecast = model_fit.get_forecast(steps=len(test), exog=exog_test)
forecast_mean = forecast.predicted_mean

# Calculate the Root Mean Squared Error (RMSE) as a measure of model
accuracy
rmse_val = np.sqrt(mean_squared_error(test['Total Sales'],
forecast_mean))
print(f"RMSE: {rmse_val}")
r2 = r2_score(test['Total Sales'], forecast_mean)
print(f"R2 Score: {r2}")

# Plot the actual vs. forecasted values
plt.figure(figsize=(12, 6))
plt.plot(train.index, train['Total Sales'], label='Training Data')
plt.plot(test.index, test['Total Sales'], label='Actual Demand')
plt.plot(test.index, forecast_mean, label='Forecasted Demand',
color='red')
plt.legend()
plt.title('Actual vs. Forecasted Demand')
plt.show()
```

```
C:\Users\AMAN\anaconda3\lib\site-packages\statsmodels\tsa\base\
tsa_model.py:471: ValueWarning: A date index has been provided, but it
has no associated frequency information and so will be ignored when
e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\AMAN\anaconda3\lib\site-packages\statsmodels\tsa\base\
tsa_model.py:471: ValueWarning: A date index has been provided, but it
has no associated frequency information and so will be ignored when
e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\AMAN\anaconda3\lib\site-packages\statsmodels\tsa\base\
tsa_model.py:471: ValueWarning: A date index has been provided, but it
has no associated frequency information and so will be ignored when
e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\AMAN\anaconda3\lib\site-packages\statsmodels\tsa\statespace\
sarimax.py:966: UserWarning: Non-stationary starting autoregressive
parameters found. Using zeros as starting parameters.
  warn('Non-stationary starting autoregressive parameters'
```

```
C:\Users\AMAN\anaconda3\lib\site-packages\statsmodels\tsa\statespace\
sarimax.py:978: UserWarning: Non-invertible starting MA parameters
found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
C:\Users\AMAN\anaconda3\lib\site-packages\statsmodels\base\
model.py:604: ConvergenceWarning: Maximum Likelihood optimization
failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
C:\Users\AMAN\anaconda3\lib\site-packages\statsmodels\tsa\base\
tsa_model.py:834: ValueWarning: No supported index is available.
Prediction results will be given with an integer index beginning at
`start`.
  return get_prediction_index(

RMSE: 316520.263168887
R2 Score: 0.6577904808910784
```




```python
# Reset the index for the test and forecast_mean DataFrames
test = test.reset_index()
forecast_mean = forecast_mean.reset_index()

# Create a DataFrame with the actual and predicted values
actual_vs_predicted = pd.DataFrame({'Actual': test['Total Sales'],
'Predicted': forecast_mean['predicted_mean']})

# Print the DataFrame
print(actual_vs_predicted)
```

```
        Actual     Predicted
0      56139.3  4.895007e+03
1     237876.8  6.319134e+05
2     360192.0  6.146680e+05
3     746085.2  1.031459e+06
4     521434.2  8.466766e+05
..         ...           ...
360   669993.3  7.732312e+05
361  1226260.8  1.074109e+06
362  2586253.6  1.283990e+06
363   689409.9  5.222886e+05
364   263645.0  2.092405e+05

[365 rows x 2 columns]
```