# Demand Forecasting and Inventory Optimization using Python

# Introduction

Demand Forecasting involves predicting the quantity and pattern of customer orders, which is crucial for businesses to efficiently allocate resources, manage inventory, and plan production. Accurate demand forecasting enables companies to meet customer needs, avoid overstocking or understock  and optimize their supply chain operations.

Inventory Optimization aims to strike a balance between having sufficient stock to meet demand without carrying excess inventory that ties up capital and storage space. Effective inventory optimization helps businesses reduce carrying costs, improve cash flow, and enhance customer satisfaction.

Here,we will perform these by using SARIMA Model in Jupyter Notebook.

# Solutions

## First we import required libraries and dataset.

```
[1]: import pandas as pd
     import numpy as np
     import plotly.express as px
     from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
     import matplotlib.pyplot as plt
     from statsmodels.tsa.statespace.sarimax import SARIMAX
```

```
[2]: data = pd.read_csv("C:/Users/Harsh/Downloads/demand_inventory.csv")
     print(data.head())
```

```
   Unnamed: 0        Date Product_ID  Demand  Inventory
0           0  2023-06-01         P1      51       5500
1           1  2023-06-02         P1     141       5449
2           2  2023-06-03         P1     172       5308
3           3  2023-06-04         P1      91       5136
4           4  2023-06-05         P1     198       5045
```

## There's an unnamed column in the dataset. I'll drop it.

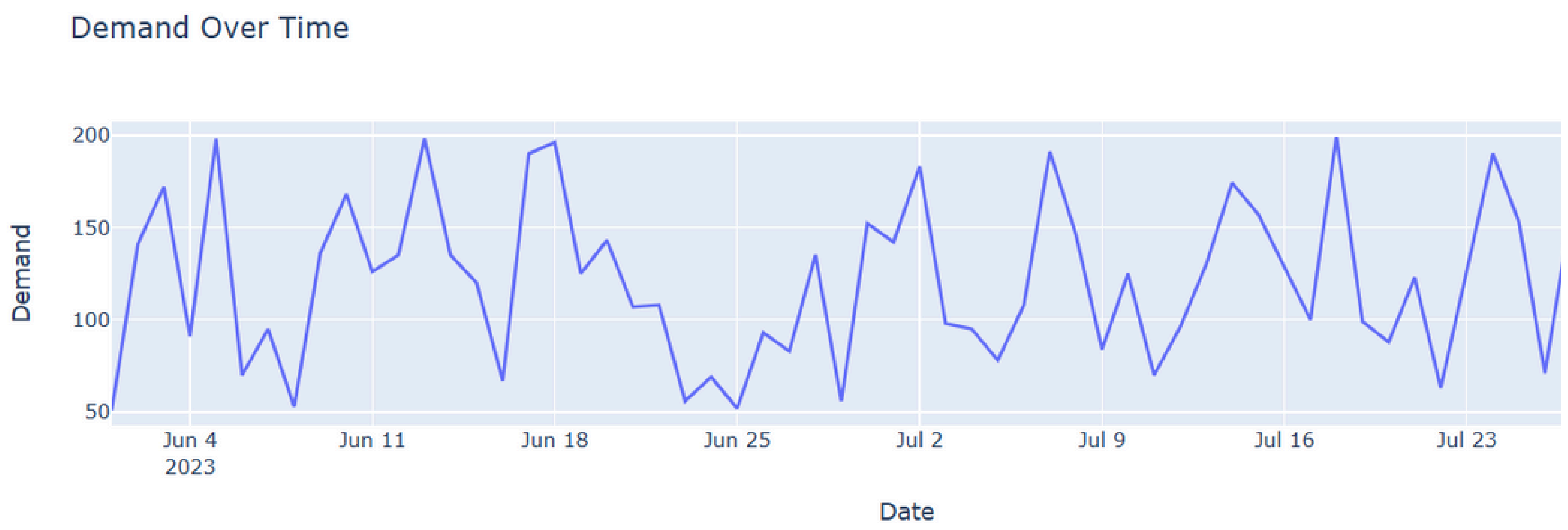
```
[3]: data = data.drop(columns=['Unnamed: 0'])
```

```
[4]: data
```

# Solutions

## Now, let’s visualize the demand & Inventoryover time: to see behaviour of demand over time .

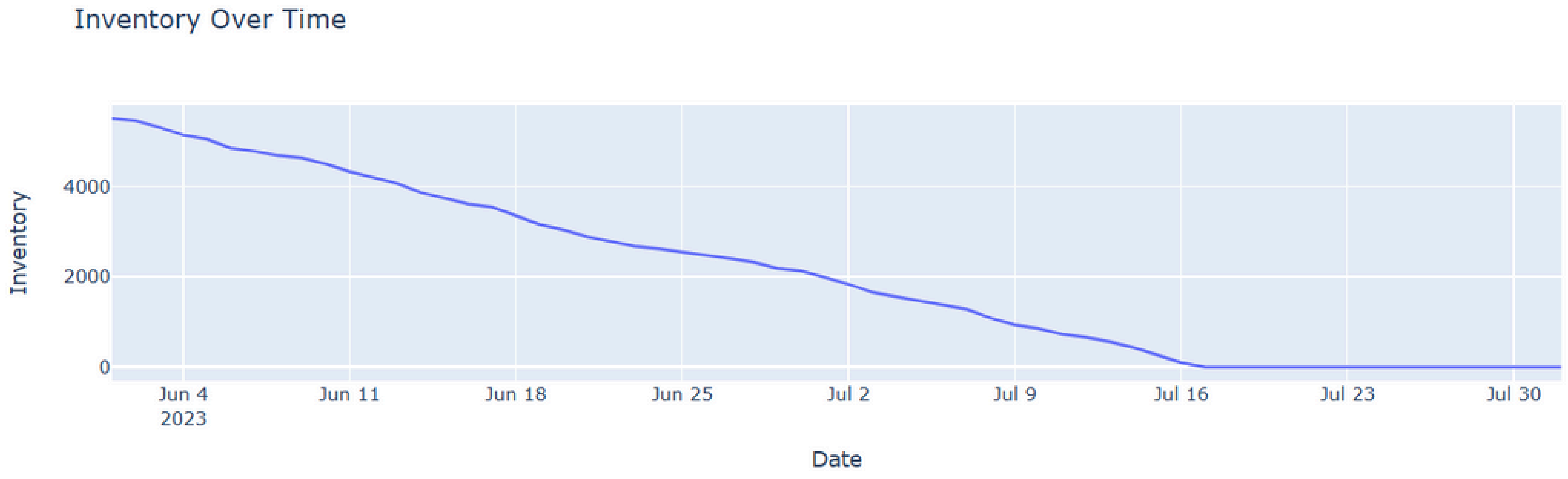
```
[5]: fig_demand = px.line(data, x='Date',
                          y='Demand',
                          title='Demand Over Time')
     fig_demand.show()
```




## Demand over time .

## Inventory over time .

```
[7]: fig_inventory = px.line(data, x='Date',
                             y='Inventory',
                             title='Inventory Over Time')
     fig_inventory.show()
```



# Solutions

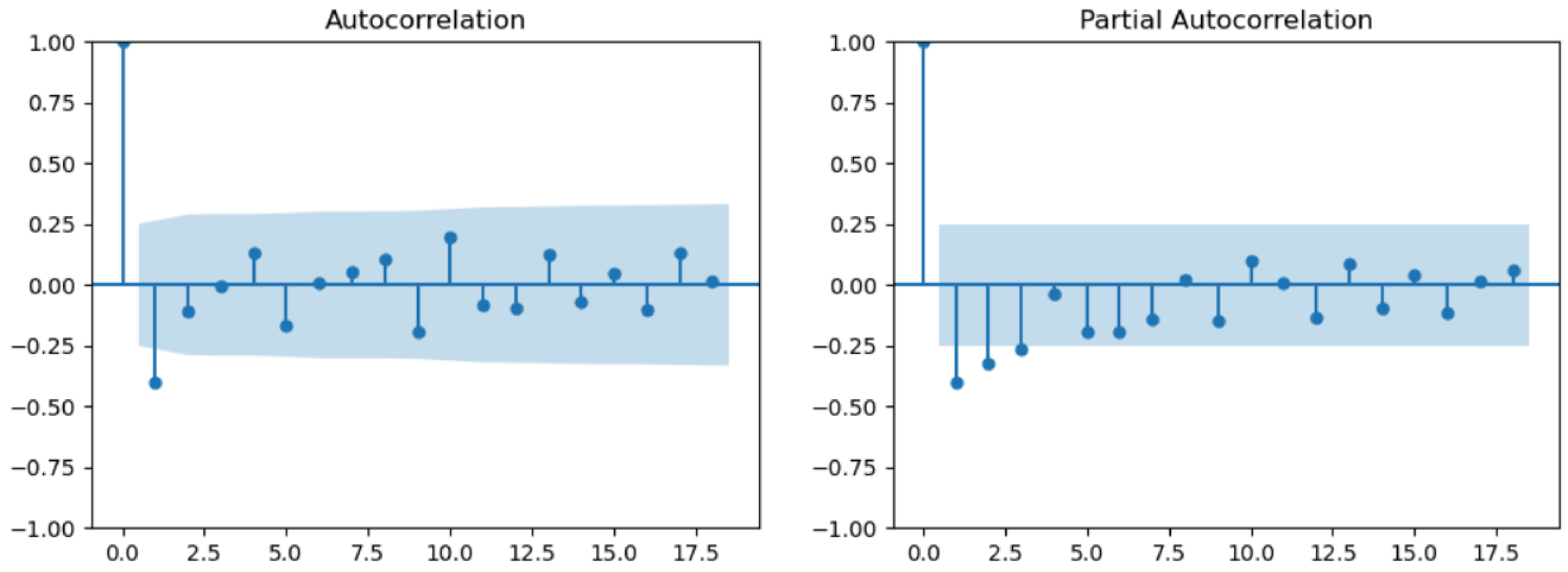
## Demand Forecasting

**We can see seasonal patterns in the demand. So we forecast the demand using SARIMA.**
**For this, first calculate the value of p and q using ACF and PACF plots: -**

```
[9]: data['Date'] = pd.to_datetime(data['Date'],
                                   )
     time_series = data.set_index('Date')['Demand']

     differenced_series = time_series.diff().dropna()

     # Plot ACF and PACF of differenced time series
     fig, axes = plt.subplots(1, 2, figsize=(12, 4))
     plot_acf(differenced_series, ax=axes[0])
     plot_pacf(differenced_series, ax=axes[1])
     plt.show()
```




**Based on the plots, we find that p=1 and q=1 & d=1. The ACF plot cuts off at lag 1, indicating q=1, and the PACF plot also cuts off at lag 1, indicating p=1. As there is a linear trend , we can set the value of d as 1 to remove the linear trend, making the time series stationary. .**

# Solutions

## Now, let’s train the model and forecast demand for the next ten days  using SARIMA model :-

[10]:

```python
order = (1, 1, 1)
seasonal_order = (1, 1, 1, 2) #2 because the data contains a time period of 2 months only
model = SARIMAX(time_series, order=order, seasonal_order=seasonal_order)
model_fit = model.fit(disp=False)

future_steps = 10
predictions = model_fit.predict(len(time_series), len(time_series) + future_steps - 1)
predictions = predictions.astype(int)
print(predictions)
```

```
C:\ProgramData\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning:

No frequency information was provided, so inferred frequency D will be used.

C:\ProgramData\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning:

No frequency information was provided, so inferred frequency D will be used.
```

```
2023-08-02    117
2023-08-03    116
2023-08-04    130
2023-08-05    114
2023-08-06    128
2023-08-07    115
2023-08-08    129
2023-08-09    115
2023-08-10    129
2023-08-11    115
Freq: D, Name: predicted_mean, dtype: int32
```

## That’s how we have trained the model and forecast demand for the next ten days using SARIMA model :-

# Solutions

## Inventory Optimization:
## Now let's optimize inventory according to the forecasted demand for the next ten days:

[11]:
```
# Create date indices for the future predictions
future_dates = pd.date_range(start=time_series.index[-1] + pd.DateOffset(days=1), periods=future_steps, freq='D')

# Create a pandas Series with the predicted values and date indices
forecasted_demand = pd.Series(predictions, index=future_dates)

# Initial inventory level
initial_inventory = 5500

# Lead time (number of days it takes to replenish inventory)
lead_time = 1 # it's different for every business, 1 is an example

# Service level (probability of not stocking out)
service_level = 0.95 # it's different for every business, 0.95 is an example
```

# Solutions

```
# Calculate the optimal order quantity using the Newsvendor formula
z = np.abs(np.percentile(forecasted_demand, 100 * (1 - service_level)))
order_quantity = np.ceil(forecasted_demand.mean() + z).astype(int)

# Calculate the reorder point
reorder_point = forecasted_demand.mean() * lead_time + z

# Calculate the optimal safety stock
safety_stock = reorder_point - forecasted_demand.mean() * lead_time

# Calculate the total cost (holding cost + stockout cost)
holding_cost = 0.1  # it's different for every business, 0.1 is an example
stockout_cost = 10  # # it's different for every business, 10 is an example
total_holding_cost = holding_cost * (initial_inventory + 0.5 * order_quantity)
total_stockout_cost = stockout_cost * np.maximum(0, forecasted_demand.mean() * lead_time - initial_inventory)

# Calculate the total cost
total_cost = total_holding_cost + total_stockout_cost

print("Optimal Order Quantity:", order_quantity)
print("Reorder Point:", reorder_point)
print("Safety Stock:", safety_stock)
print("Total Cost:", total_cost)
```

**Output :-**

```
Optimal Order Quantity: 236
Reorder Point: 235.25
Safety Stock: 114.45
Total Cost: 561.8000000000001
```

# Interpretation of Output

**1) Optimal Order Quantity: 236 –** The optimal order quantity refers to the quantity of a product that should be ordered from suppliers when the inventory level reaches a certain point. In this case, an optimal order quantity of 236 units has been calculated.

**2) Reorder Point: 235.25 –** The reorder point is the inventory level at which a new order should be placed to replenish stock before it runs out. In this case, a reorder point of 235.25 units has been calculated, which means that when the inventory reaches or falls below this level, an order should be placed to replenish stock.

**3) Safety Stock: 114.45 –** Safety stock is the additional inventory kept on hand to account for uncertainties in demand and supply. It acts as a buffer against unexpected variations in demand or lead time. In this case, a safety stock of 114.45 units has been calculated, which helps ensure that there's enough inventory to cover potential fluctuations in demand or lead time.

**4) Total Cost: 561.80 –** The total cost represents the combined costs associated with inventory management. In this case, the total cost has been calculated as approximately 561.80 units based on the order quantity, reorder point, safety stock, and associated costs.

# summary

By analyzing these values, company can make informed decisions about how much inventory to order and when to place orders to ensure a smooth supply chain and customer satisfaction while minimizing costs.

So this is how to perform Demand Forecasting and Inventory Optimization using Python. Demand Forecasting involves predicting the quantity and pattern of customer orders, which is crucial for businesses to efficiently allocate resources, manage inventory, and plan production.

Inventory Optimization aims to strike a balance between having sufficient stock to meet demand without carrying excess inventory that ties up capital and storage space.