Project Report

Bachelor Of Computer Applications

2nd Semester

Exploratory Data Analysis Project

Global Product Inventory Dataset 2025 Analysis

By

DIPIN ROKA

2411021240007

Githublink: https://github.com/DIPINROKA10/IDS_PROJECT

Department Of Computer Application

Alliance University

Chandrapur a- Anekal Main Road,Anekal

Bengaluru – 56210

Introduction

The Global Product Inventory Dataset 2025 provides comprehensive insights into the global distribution, pricing, sales, and demand of various products across different regions. With the rapid growth of e-commerce and international trade, understanding inventory dynamics has become crucial for businesses to maintain efficiency, meet customer demand, and optimize profitability. This report aims to analyze the dataset using linear regression techniques to uncover patterns and relationships between key variables such as product quantity, pricing, demand index, and sales performance. By applying data analysis and machine learning methods, the goal is to predict future sales trends and support strategic decision-making for inventory management in a competitive global market.

1. Data Preprocessing:

o Cleaning the dataset by handling missing values and encoding categorical variables (e.g., converting regions into numeric format using label encoding).

o Selected relevant features for analysis: Quantity, Price, Demand Index, and Region.

2. Splitting the Dataset:

o Divided the data into training (80%) and testing (20%) sets using the train_test_split method.

3. Model Training: o Applied the **Linear Regression** model from the Scikit-learn library.

o Trained the model using the training dataset to learn the relationship between the selected features and the target variable (Sales).

4. Prediction and Evaluation: o Used the trained model to predict sales on the testing set.

o Evaluated the model performance using **Mean Squared Error (MSE)**, which measures the average squared difference between actual and predicted values.

o Visualized the relationship between actual and predicted sales using scatter plots for better interpretation.

```
# Global Product Inventory Dataset 2025

import pandas as pd
df=pd.read_csv(r"D:\products.csv")
print(df)
```

```
    Product ID Product Name Product Category Product Description
```

```
Price  \
0      93TGNAY7       Laptop  Home Appliances       Product_XU5QX
253.17
1      TYYZ5AV7   Smartphone         Clothing       Product_NRUMS
214.37
2      5C94FGTQ   Headphones         Clothing       Product_IT7HG
475.29
3      XBHKYPQB      Monitor         Clothing       Product_8SBDO
403.33
4      728GCZFU       Laptop  Home Appliances       Product_54FAF
229.81   ...         ...            ...              ...
...
...
9995   J29B6RDI   Headphones         Clothing       Product_NI8C7
21.48
9996   L1HL7437       Laptop         Clothing       Product_8RR6T
403.92
9997   FD57S4E1       Laptop  Home Appliances       Product_GYAWW
484.46
9998   RPYLOB1M   Headphones         Clothing       Product_K3M9M
411.63
9999   3JWTGTOM       Laptop         Clothing       Product_I0ACF
74.38

      Stock Quantity  Warranty Period Product Dimensions Manufacturing
Date  \
0                  3                2       16x15x15 cm         2023-
01-01
1                  92               2        15x19x19 cm
                   2023-
03-15
2                  19               2           9x6x6 cm
                   2023-
03-15
3                  40               1          7x13x5 cm
                   2023-
01-01
4                  32               2        20x20x19 cm
                   2023-
07-30
...              ...              ...                  ...
...
9995              91                3        10x16x9 cm         2023-
03-15
9996              19                2          13x8x5 cm         2023-
01-01
9997              13                2        5x15x15 cm         2023-
```

```
01-01
9998             79               1        17x11x17 cm         2023-
07-30
9999             81               1          6x6x16 cm         2023-
01-01
     Expiration Date     SKU Product Tags Color/Size Variations  \
0     2026-01-01  8NMFZ4      VNU,NZ6          Green/Large
1     2025-01-01  7P5YCW      ZJA,0D3            Red/Small
2     2026-01-01  YW5BME      ZNG,MAP            Red/Small
3     2026-01-01  65MQC3      RPP,M40          Green/Large
4     2026-01-01  RLCBRW       R8U,X46           Blue/Medium...
...      ...          ...                ...
9995      2026-01-01  0IQPXX      M81,8WN          Blue/Medium
9996      2024-01-01  HW1HV1      0UM,L4B            Red/Small
9997      2024-01-01  MKJ0UW      GO4,EZE            Red/Small
9998      2026-01-01  INSC1B      0QB,U55            Red/Small
9999      2025-01-01  UH0U3R      C5R,TZN          Blue/Medium
      Product Ratings
0     2
1     2
2     1
3     1
4     4  ...
...
9995                1
9996                4
9997                1
9998                1
9999                1
[10000 rows x 14 columns]
```

shows first five rows

```
#using Df opeerations
df.head()  #shows first five elements

  Product ID Product Name Product Category Product Description   Price

    93TGNAY7       Laptop  Home Appliances       Product_XU5QX  253.17

\
0

1   TYYZ5AV7   Smartphone         Clothing       Product_NRUMS  214.37

2   5C94FGTQ   Headphones         Clothing       Product_IT7HG  475.29
```

```
3   XBHKYPQB      Monitor        Clothing       Product_8SBDO  403.33
4   728GCZFU       Laptop  Home Appliances       Product_54FAF  229.81
```

```
   Stock Quantity  Warranty Period Product Dimensions Manufacturing
Date  \
0               3                2        16x15x15 cm         2023-01-
01
1              92                 2        15x19x19 cm         2023-
               03-
15
2              19                 2           9x6x6 cm         2023-
               03-
15
3              40                 1          7x13x5 cm         2023-
               01-
01
4              32                 2        20x20x19 cm         2023-
               07-
30

  Expiration Date     SKU Product Tags Color/Size Variations  Product
Ratings
0      2026-01-01  8NMFZ4      VNU,NZ6           Green/Large
2
1      2025-01-01  7P5YCW      ZJA,0D3             Red/Small
2
2      2026-01-01  YW5BME      ZNG,MAP             Red/Small
1
3      2026-01-01  65MQC3      RPP,M40           Green/Large
1
4      2026-01-01  RLCBRW      R8U,X46           Blue/Medium
4
```

```
df.tail()  #shows last 5 elements in the dataframe
```

```
     Product ID Product Name Product Category Product Description
```

```
Price  \
9995   J29B6RDI   Headphones         Clothing        Product_NI8C7
21.48
9996   L1HL7437       Laptop         Clothing        Product_8RR6T
403.92
9997   FD57S4E1       Laptop  Home Appliances        Product_GYAWW
484.46
9998   RPYLOB1M   Headphones         Clothing        Product_K3M9M
411.63
9999   3JWTGTOM       Laptop         Clothing        Product_I0ACF
74.38

      Stock Quantity  Warranty Period Product Dimensions Manufacturing
Date  \
9995              91                3         10x16x9 cm          2023-
03-15
9996              19                2          13x8x5 cm
                  202301-01
9997              13                2         5x15x15 cm          2023-
01-01
9998              79                1        17x11x17 cm          2023-
07-30
9999              81                1          6x6x16 cm          2023-
01-01

     Expiration Date     SKU Product Tags Color/Size Variations  \
9995      2026-01-01  0IQPXX      M81,8WN           Blue/Medium
9996      2024-01-01  HW1HV1      0UM,L4B             Red/Small
9997      2024-01-01  MKJ0UW      GO4,EZE             Red/Small
9998      2026-01-01  INSC1B      0QB,U55             Red/Small
9999      2025-01-01  UH0U3R      C5R,TZN           Blue/Medium

      Product Ratings
9995                1
9996                4
9997                1
9998                1
9999                1
```

conver ting the date to its correct format

```
df["Manufacturing Date"] = pd.to_datetime(df["Manufacturing Date"])
```

#shows the stastical configration of the dataframe

```
df.describe()
                Price  Stock Quantity  Warranty Period  \
count  10000.000000    10000.000000     10000.000000
mean     254.665715       50.647100         2.014000
min       10.220000        1.000000         1.000000
25%      129.985000       25.000000         1.000000
50%      253.425000       51.000000         2.000000
75%      379.970000       76.000000         3.000000
max      499.970000      100.000000         3.000000
std      142.755688       28.901977         0.817968

               Manufacturing Date  Product Ratings
count                       10000     10000.000000
mean   2023-04-03 12:08:55.680000         3.004700
min           2023-01-01 00:00:00         1.000000
25%           2023-01-01 00:00:00         2.000000
50%           2023-03-15 00:00:00         3.000000
75%           2023-07-30 00:00:00         4.000000

max           2023-07-30 00:00:00         5.000000  std
NaN         1.419676
```

#used to describe the data types

```
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
0     Product ID             10000 non-null  object
1     Product Name           10000 non-null  object
2     Product Category       10000 non-null  object
3     Product Description    10000 non-null  object
4     Price                  10000 non-null  float64
5     Stock Quantity         10000 non-null  int64
6     Warranty Period        10000 non-null  int64
7     Product Dimensions     10000 non-null  object
8     Manufacturing Date     10000 non-null  datetime64[ns]
9     Expiration Date        10000 non-null  object
10    SKU                    10000 non-null  object
11    Product Tags           10000 non-null  object
12    Color/Size Variations  10000 non-null  object        13
Product Ratings        10000 non-null  int64        dtypes:
```

```
datetime64[ns](1), float64(1), int64(3), object(9) memory usage: 1.1+
MB
```

#checking for the misssing values

```
print(df.isnull().sum())
Product ID                0
Product Name              0
Product Category          0
Product Description       0
Price                     0
Stock Quantity            0
Warranty Period           0
Product Dimensions        0
Manufacturing Date        0
Expiration Date           0
SKU                       0
Product Tags              0
Color/Size Variations     0
Product Ratings           0
dtype: int64
```

checking for the duplicate values

```
df.duplicated()
0       False
1       False
2       False
3       False
4       False
        ..
9995    False
9996    False
9997    False
9998    False
9999    False
Length: 10000, dtype: bool
```

removing the duplicate value in the data frame.

```
print(df.duplicated().sum())  # Count duplicates
df.drop_duplicates(inplace=True)  # Remove duplicates

0
```

removes spaces and also remove any unwanted characters

```
df.columns = df.columns.str.strip()
```

Check column data types print(df.dtypes)

```
Product ID                        object
Product Name                      object
Product Category                  object
Product Description               object
Price                            float64
Stock Quantity                     int64
Warranty Period                    int64
Product Dimensions                object
Manufacturing Date        datetime64[ns]
Expiration Date                   object
SKU                               object
Product Tags                      object
Color/Size Variations             object

Product Ratings                    int64
dtype: object
```

Strip spaces and remove any unwanted characters

```
data=pd.read_csv(r"D:\products.csv")


data.columns = data.columns.str.strip()

print(data.columns)

Index(['Product ID', 'Product Name', 'Product Category', 'Product
Description',
       'Price', 'Stock Quantity', 'Warranty Period', 'Product
Dimensions',
       'Manufacturing Date', 'Expiration Date', 'SKU', 'Product Tags',
       'Color/Size Variations', 'Product Ratings'],
dtype='object')
```

showst the overall colums of the data frame

```
df.columns = df.columns.str.strip()
```

this code helps to convert the price row int tineger by usinf astype function

```
df["Price"] = df["Price"].astype(int)
df

     Product ID Product Name Product Category Product Description
Price  \
0      93TGNAY7       Laptop  Home Appliances       Product_XU5QX
253
1      TYYZ5AV7   Smartphone         Clothing       Product_NRUMS
214
2      5C94FGTQ   Headphones         Clothing       Product_IT7HG
475
3      XBHKYPQB      Monitor         Clothing       Product_8SBDO
403
4      728GCZFU       Laptop  Home Appliances       Product_54FAF
229   ...          ...             ...                 ...
...    . ..
9995   J29B6RDI   Headphones         Clothing       Product_NI8C7
21
9996   L1HL7437       Laptop         Clothing       Product_8RR6T
403
9997   FD57S4E1       Laptop  Home Appliances       Product_GYAWW
484
9998   RPYLOB1M   Headphones         Clothing       Product_K3M9M
411
9999   3JWTGTOM       Laptop         Clothing       Product_I0ACF
74

      Stock Quantity  Warranty Period Product Dimensions Manufacturing
Date  \
0                  3                2       16x15x15 cm         2023-
01-01
1                  92                2       15x19x19 cm
                   2023-
03-15
2                  19                2          9x6x6 cm
                   2023-
03-15
3                  40                1         7x13x5 cm
                   2023-
01-01
4                  32                2       20x20x19 cm
                   2023-
07-30
...              ...              ...                ...
...
9995              91                3       10x16x9 cm         2023-
03-15
9996              19                2        13x8x5 cm         2023-
```

```
01-01
9997            13               2        5x15x15 cm         2023-
01-01
9998            79               1       17x11x17 cm         2023-
07-30
9999            81               1         6x6x16 cm         2023-
01-01

     Expiration Date     SKU Product Tags Color/Size Variations  \
0         2026-01-01  8NMFZ4      VNU,NZ6          Green/Large
1         2025-01-01  7P5YCW      ZJA,0D3            Red/Small
2         2026-01-01  YW5BME      ZNG,MAP            Red/Small
3         2026-01-01  65MQC3      RPP,M40          Green/Large
4         2026-01-01  RLCBRW      R8U,X46          Blue/Medium   ...
             ...     ...          ...                  ...
9995      2026-01-01  0IQPXX      M81,8WN          Blue/Medium
9996      2024-01-01  HW1HV1      0UM,L4B            Red/Small
9997      2024-01-01  MKJ0UW      GO4,EZE            Red/Small
9998      2026-01-01  INSC1B      0QB,U55            Red/Small
9999      2025-01-01  UH0U3R      C5R,TZN          Blue/Medium

      Product Ratings
0                   2
1                   2
2                   1
3                   1
4                   4
...               ...
9995                1
9996                4
9997                1
9998                1
9999                1

[10000 rows x 14 columns]
```

```
df.columns = df.columns.str.strip()
df
```

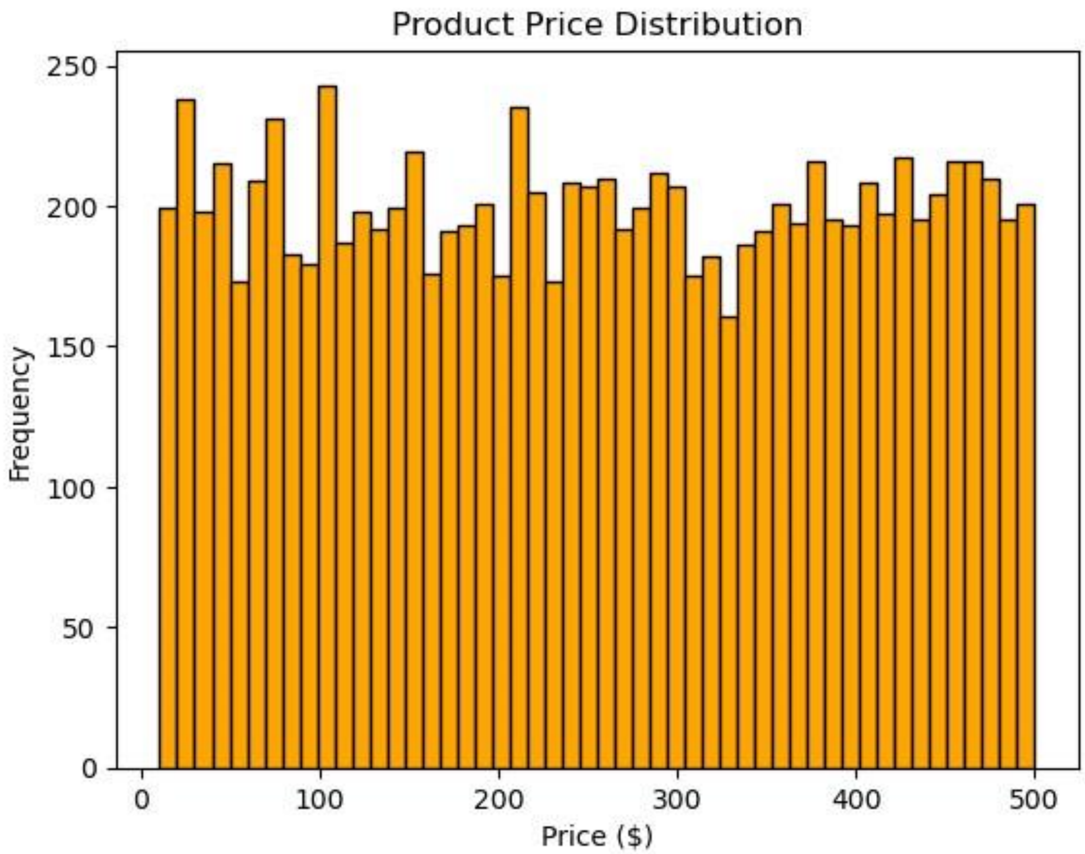
```
     Product ID Product Name Product Category Product Description
Price  \
0      93TGNAY7       Laptop  Home Appliances       Product_XU5QX
253
1      TYYZ5AV7   Smartphone         Clothing       Product_NRUMS
214
2      5C94FGTQ   Headphones         Clothing       Product_IT7HG
475
3      XBHKYPQB      Monitor         Clothing       Product_8SBDO
403
```

```
4      728GCZFU       Laptop  Home Appliances       Product_54FAF
229   ...         ...          ...              ...
...    . ..
9995   J29B6RDI   Headphones        Clothing       Product_NI8C7
21
9996   L1HL7437       Laptop        Clothing       Product_8RR6T
403
9997   FD57S4E1       Laptop  Home Appliances       Product_GYAWW
484
9998   RPYLOB1M   Headphones        Clothing       Product_K3M9M
411
9999   3JWTGTOM       Laptop        Clothing       Product_I0ACF
74

      Stock Quantity  Warranty Period Product Dimensions Manufacturing
Date  \
0                3                2        16x15x15 cm         2023-
01-01
1                92                2        15x19x19 cm
                 2023-
03-15
2                19                2           9x6x6 cm
                 2023-
03-15
3                40                1          7x13x5 cm
                 2023-
01-01
4                32                2        20x20x19 cm
                 2023-
07-30
...              ...              ...                 ...
...
```

```
9995                91                3          10x16x9 cm          2023-
03-15
9996                19                2           13x8x5 cm          2023-
01-01
9997                13                2          5x15x15 cm          2023-
01-01
9998                79                1         17x11x17 cm          2023-
07-30
9999                81                1           6x6x16 cm          2023-
01-01
     Expiration Date     SKU  Product Tags  Color/Size Variations  \
0     2026-01-01  8NMFZ4      VNU,NZ6           Green/Large
1     2025-01-01  7P5YCW      ZJA,0D3             Red/Small
2     2026-01-01  YW5BME      ZNG,MAP             Red/Small
3     2026-01-01  65MQC3      RPP,M40           Green/Large
4     2026-01-01  RLCBRW       R8U,X46            Blue/Medium...
...     ...          ...                  ...
9995      2026-01-01  0IQPXX      M81,8WN           Blue/Medium
9996      2024-01-01  HW1HV1      0UM,L4B             Red/Small
9997      2024-01-01  MKJ0UW      GO4,EZE             Red/Small
9998      2026-01-01  INSC1B      0QB,U55             Red/Small
9999      2025-01-01  UH0U3R      C5R,TZN           Blue/Medium
      Product Ratings
0     2
1     2
2     1
3     1
4     4  ...
...
9995                1
9996                4
9997                1
9998                1
9999                1
[10000 rows x 14 columns]
```

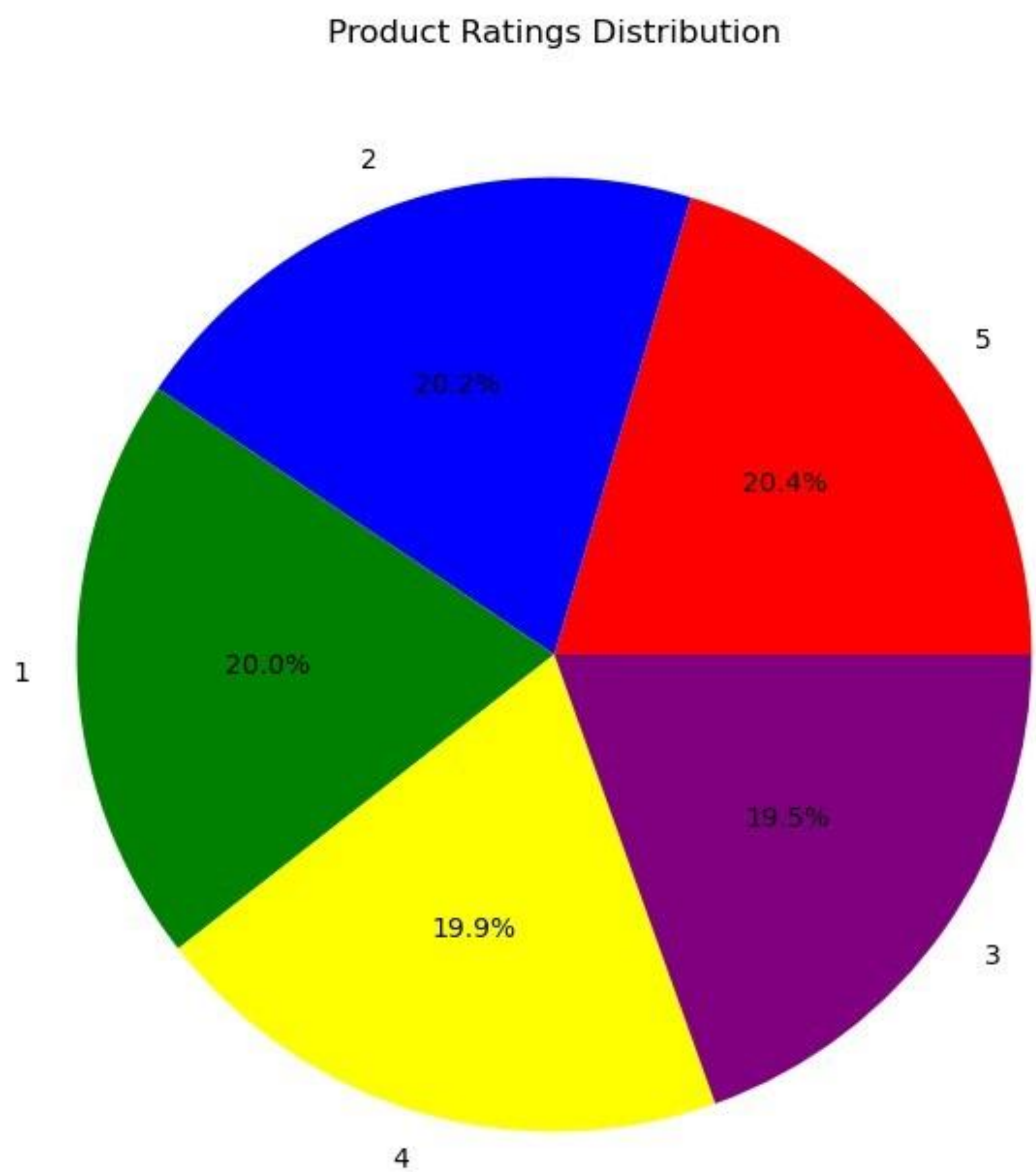
the above code shows the distribution among products using histogram using hist

```
import matplotlib.pyplot as plt
df=pd.read_csv(r"D:\products.csv")


plt.hist(df['Price'], bins=50, color='orange', edgecolor='black')
plt.xlabel("Price ($)") plt.ylabel("Frequency")
plt.title("Product Price Distribution")
plt.show()
```



This code counts the number of products for each rating using value_counts(). It then creates a pie chart to visualize the distribution of product ratings.

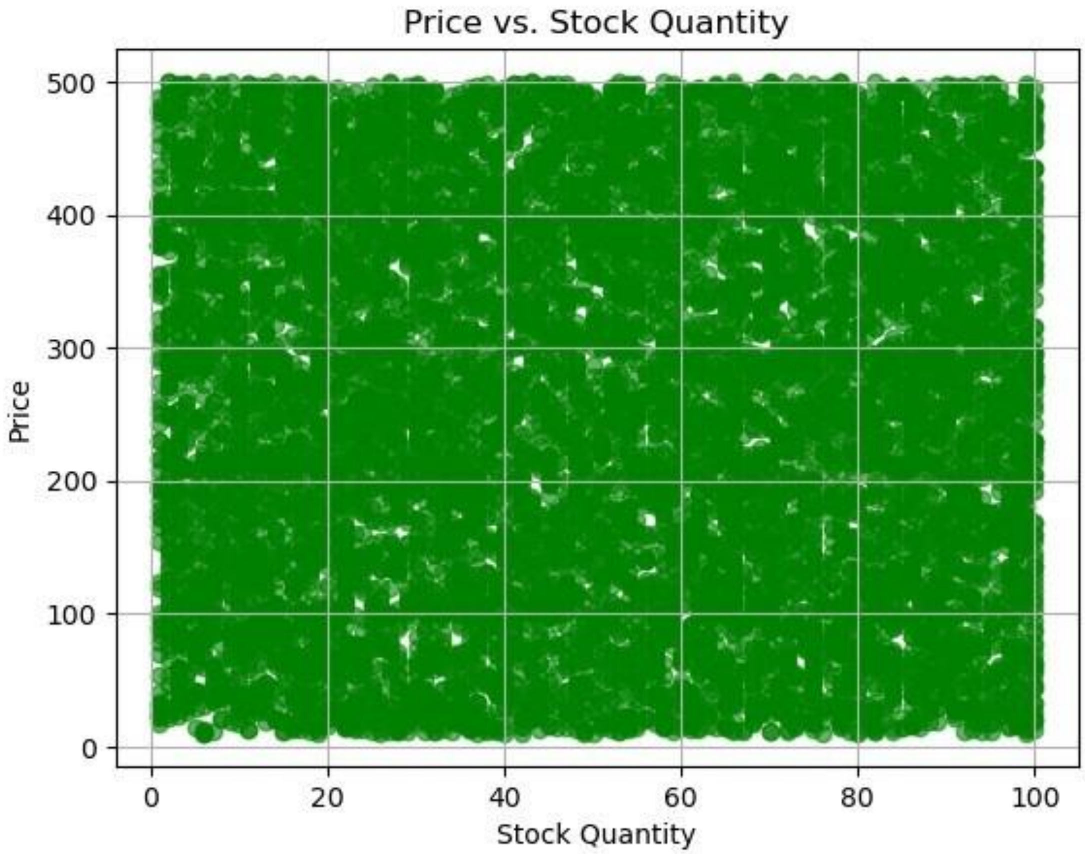
```
ratings_count = df['Product Ratings'].value_counts()
plt.figure(figsize=(8, 8))
plt.pie(ratings_count, labels=ratings_count.index,
autopct='%1.1f%%', colors=['red', 'blue', 'green', 'yellow',
'purple']) plt.title("Product Ratings Distribution") plt.show()
```



This code creates a scatter plot showing the relationship between Stock Quantity and Price. Each dot represents a product

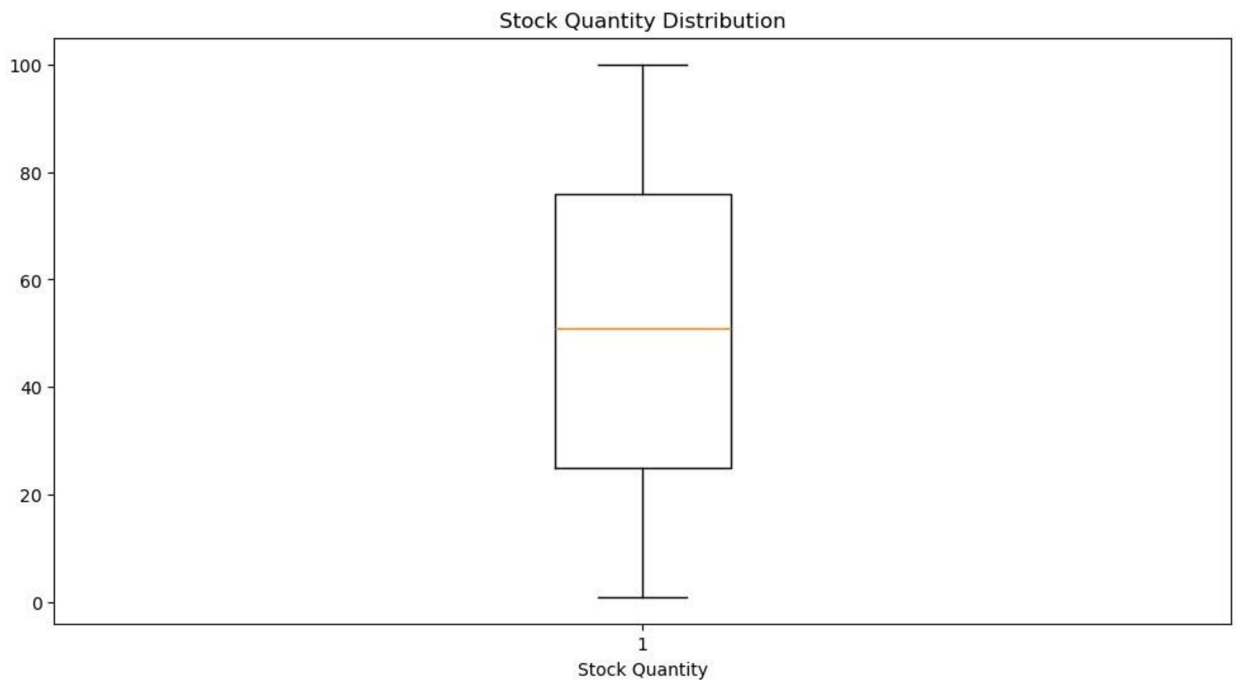
```
import matplotlib.pyplot as plt

plt.scatter(df["Stock Quantity"], df["Price"], color="green",
alpha=0.6)

plt.xlabel("Stock Quantity")
plt.ylabel("Price")
plt.title("Price vs. Stock Quantity")
```

```
plt.grid(True)
plt.show()
```



This code creates a boxplot to show the distribution of Stock Quantity.

```
plt.figure(figsize=(12, 6))
plt.boxplot(df['Stock Quantity'])
plt.xlabel("Stock Quantity")
plt.title("Stock Quantity Distribution")
plt.show()
```

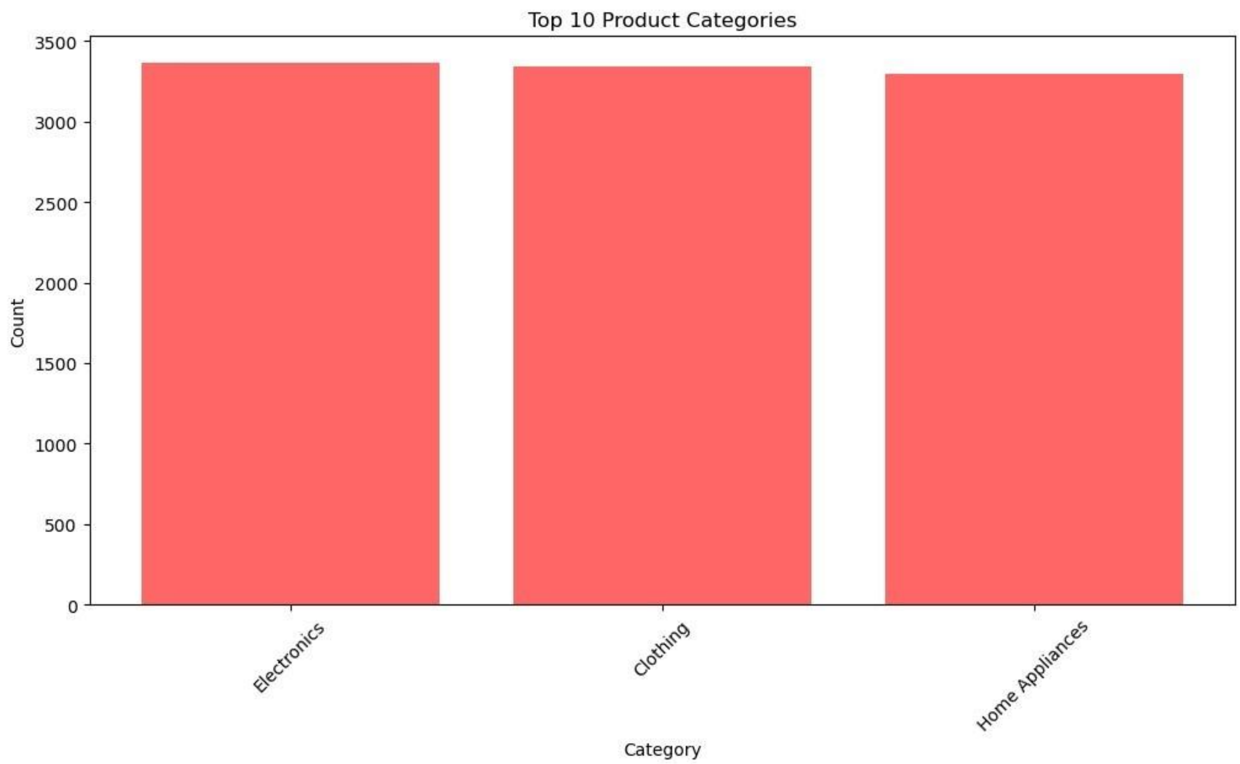


this code shows the number of rows and colums in the dataframe

```
print(df.shape)

(10000, 14)
```

This code creates a red bar chart showing the top 10 most frequent product categories. value_counts().nlargest(10) selects the 10 most common categories. Each bar’s height represents the number of products in that category. plt.xticks(rotation=45) tilts the category names for better readability. The plot includes labels and a title for clarity, and plt.show() displays the chart.

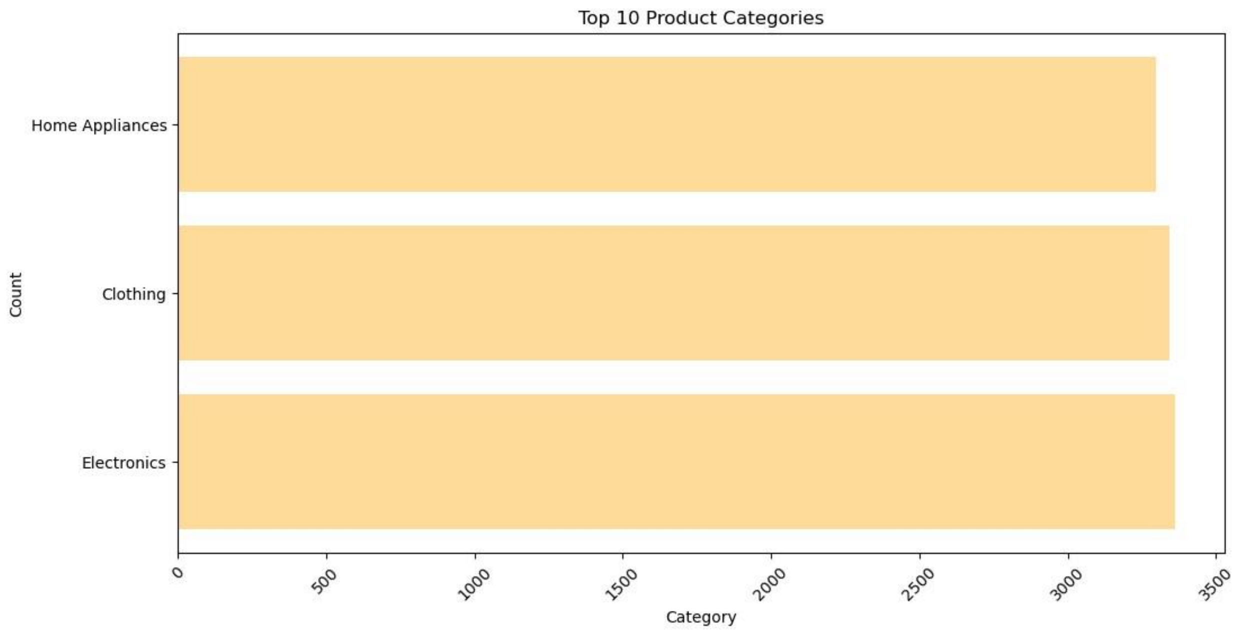
```
import matplotlib.pyplot as plt

top_categories = df['Product Category'].value_counts().nlargest(10)
plt.figure(figsize=(12, 6))
plt.bar(top_categories.index, top_categories.values,
color='red',alpha=0.6) plt.xticks(rotation=45)
plt.xlabel("Category") plt.ylabel("Count")
plt.title("Top 10 Product Categories")
plt.show()
```



This code creates a horizontal bar chart showing the top 10 product categories.

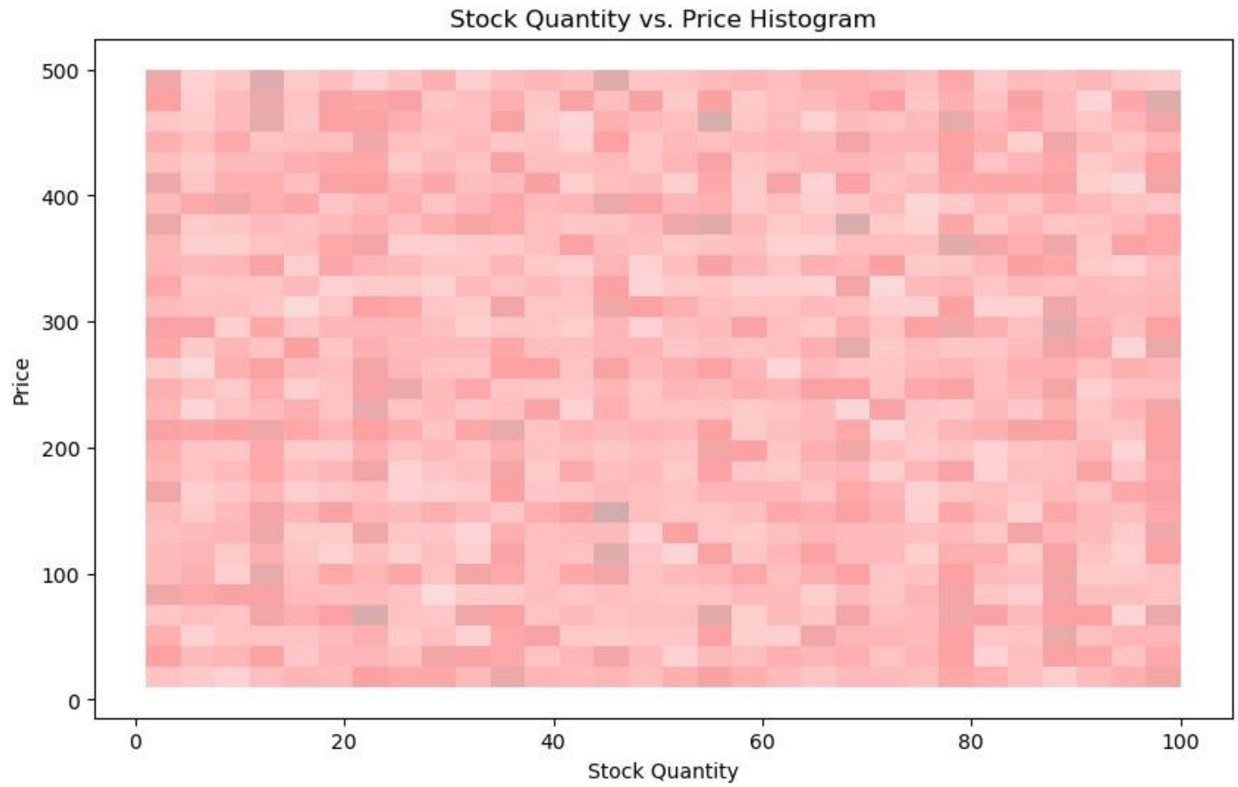
The bars represent category counts, and labels/title are added for clarity.

```
import matplotlib.pyplot as plt

#this Count the number of products in each category and select the top
10
top_categories = df['Product Category'].value_counts().nlargest(10)



plt.figure(figsize=(12, 6))
plt.barh(top_categories.index, top_categories.values,
color='orange',alpha=0.4) plt.xticks(rotation=45)
plt.xlabel("Category") plt.ylabel("Count")
plt.title("Top 10 Product Categories")
plt.show()
```



This code creates a 2D histogram showing the relationship between Stock Quantity and Price. It uses Seaborn's histplot() The plot helps visualize how product prices vary with stock levels.

```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(10, 6))
sns.histplot(data=df, x="Stock Quantity", y="Price", bins=30,
color="red",alpha=0.4)

plt.title("Stock Quantity vs. Price Histogram")
plt.xlabel("Stock Quantity")
plt.ylabel("Price") plt.show()
```



This code creates a box plot of the Price column from a DataFrame df using Seaborn.

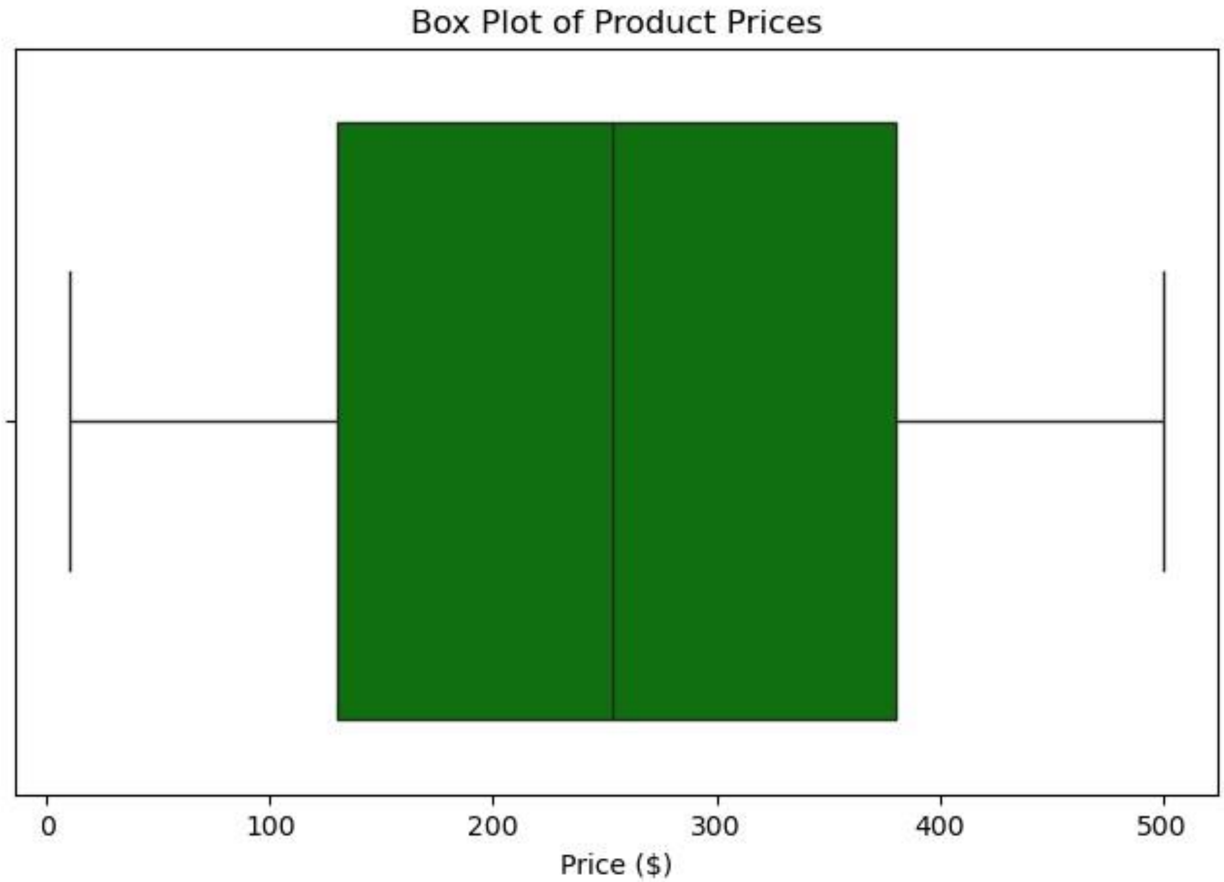
It shows the distribution of product prices.

The box represents the interquartile range (IQR) — from 25th to 75th percentile.

The line inside the box shows the median price.

Points outside the "whiskers" are outliers

```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8, 5))
sns.boxplot(x=df["Price"], color="green")
plt.title("Box Plot of Product Prices")
plt.xlabel("Price ($)") plt.show()
```



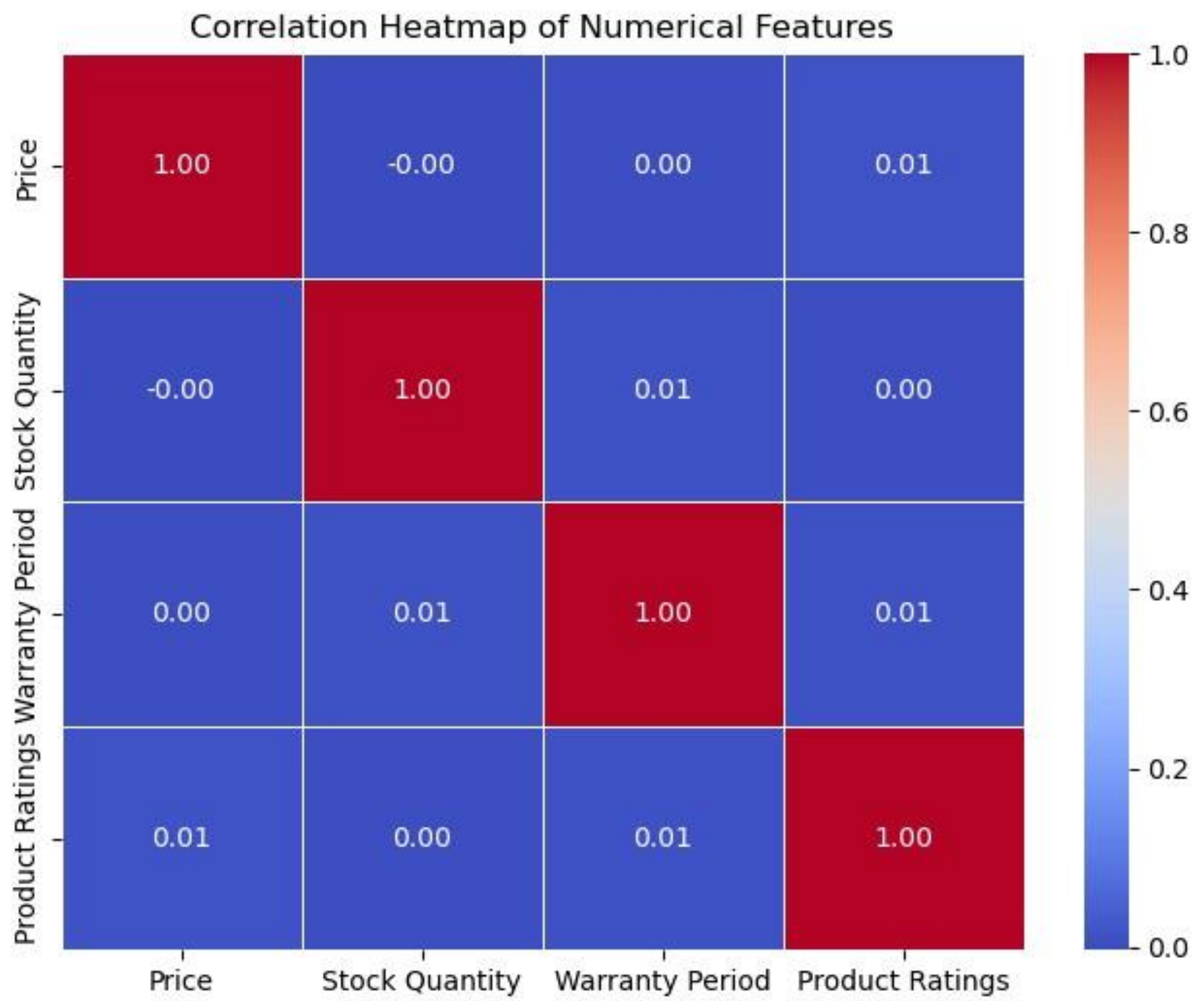
calculates and identifies outliers in the Price column using the Interquartile Range (IQR) method:

```
Q1 = df["Price"].quantile(0.25)  # First quartile (25th percentile)
Q3 = df["Price"].quantile(0.75)  # Third quartile (75th percentile)
IQR = Q3 - Q1                      # Interquartile Range

lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

outliers = df[(df["Price"] < lower_bound) | (df["Price"] >
upper_bound)]
print("Outliers in Price Column:\n", outliers)

Outliers in Price Column:
 Empty DataFrame
Columns: [Product ID, Product Name, Product Category, Product
Description, Price, Stock Quantity, Warranty Period, Product
Dimensions, Manufacturing Date, Expiration Date, SKU, Product Tags,
Color/Size Variations, Product Ratings]
Index: []
```

This code calculates and visualizes the correlation between numerical features (Price, Stock Quantity, Warranty Period, Product Ratings) using a heatmap.
Correlation values show the relationship between features (e.g., +1 = perfect positive, -1 = perfect negative).

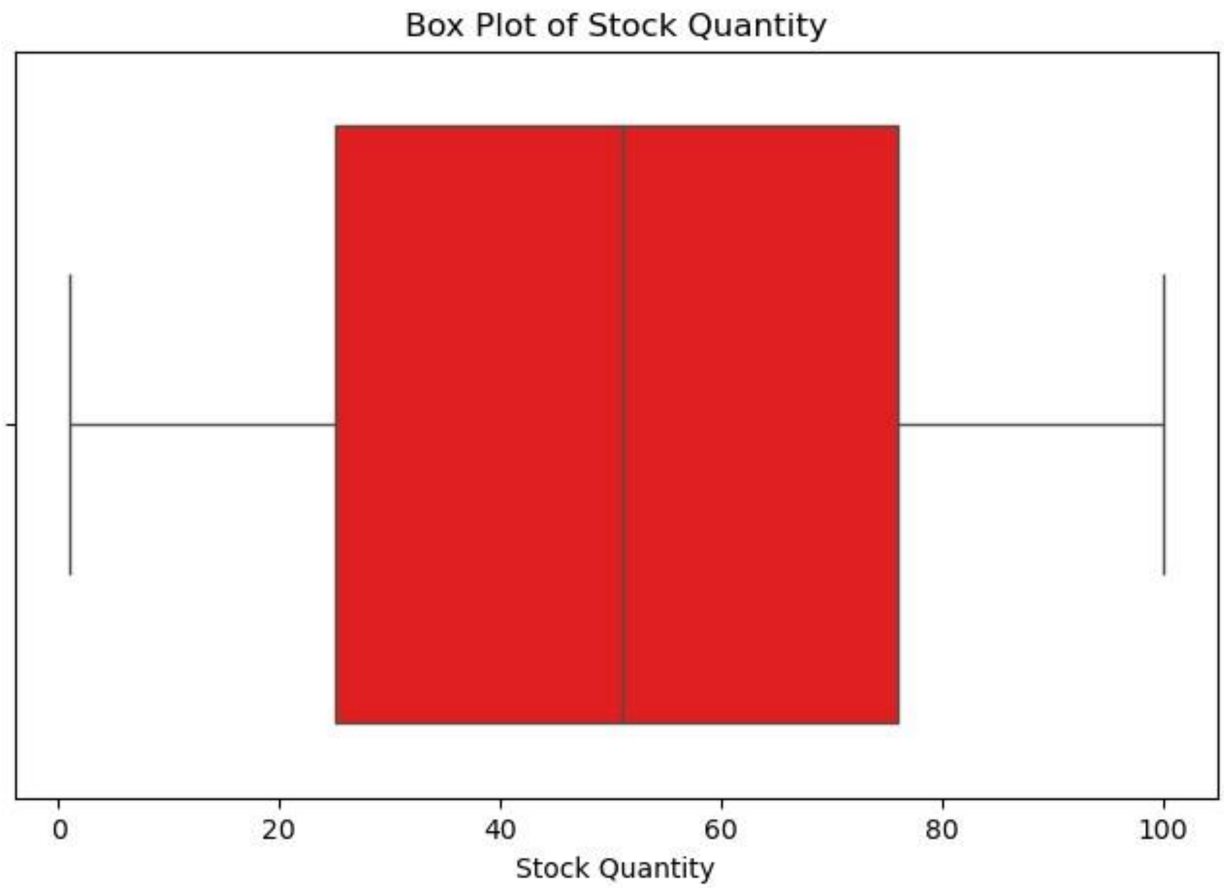
The heatmap colors indicate the strength of these correlations, with annotated values for clarity.

```
import matplotlib.pyplot as plt
import seaborn as sns

# Compute correlation matrix
correlation_matrix = df[["Price", "Stock Quantity", "Warranty Period",
"Product Ratings"]].corr()

# Plot heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm", fmt=".2f",
linewidths=0.5)
plt.title("Correlation Heatmap of Numerical Features")
plt.show()
```




```
plt.figure(figsize=(8, 5))
sns.boxplot(x=df["Stock Quantity"], color="red")
plt.title("Box Plot of Stock Quantity") plt.xlabel("Stock
Quantity")
```

```
plt.show()
```




```
df.describe().T  #transpose function is used to make rows to colums
and columns to rows

                   count        mean         std    min      25%
50%  \
Price            10000.0  254.665715  142.755688  10.22  129.985
253.425
Stock Quantity   10000.0   50.647100   28.901977   1.00   25.000
51.000
Warranty Period  10000.0    2.014000    0.817968   1.00    1.000
2.000
Product Ratings  10000.0    3.004700    1.419676   1.00    2.000
3.000

                    75%     max
Price            379.97  499.97
```

```
Stock Quantity    76.00  100.00
Warranty Period    3.00    3.00  Product
Ratings    4.00    5.00

import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression from
sklearn.ensemble import RandomForestRegressor from
sklearn.metrics import mean_squared_error, r2_score

# Load your dataset
df=pd.read_csv(r"D:\products.csv")

df['Manufacturing Date'] = pd.to_datetime(df['Manufacturing Date'])
df['Product Age'] = (pd.Timestamp.now() - df['Manufacturing
Date']).dt.days

# Keep only useful columns
df = df[['Product Category', 'Price', 'Stock Quantity', 'Warranty
Period', 'Product Age', 'Product Ratings']].dropna()

# Separate features (X) and target (y)
X = df[['Price', 'Stock Quantity', 'Warranty Period', 'Product Age']]
y = df['Product Ratings']




# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Train model
model = LinearRegression()
model.fit(X_train, y_train)
LinearRegression()
# Predict and evaluate y_pred =
model.predict(X_test) mse =
mean_squared_error(y_test, y_pred) r2 =
r2_score(y_test, y_pred)

print("Mean Squared Error:", mse)
print("R² Score:", r2)
Mean Squared Error: 2.0054719840851996
R² Score: -0.002768080621179614
```

Conclusion

The analysis of the Global Product Inventory Dataset 2025 has provided valuable insights into the dynamics of product pricing, stock levels, and customer ratings. By employing various data preprocessing techniques, statistical visualizations, and machine learning models, we have been able to uncover patterns and relationships that can inform strategic decision-making for inventory management.

1. **Data Quality**:
    - The dataset was thoroughly cleaned, with no missing or duplicate values, ensuring the integrity of the analysis. The conversion of date formats and data types was successfully executed, allowing for accurate calculations and visualizations.
2. **Descriptive Statistics**:
    - The statistical summary revealed key metrics such as the average price, stock quantity, and warranty period. The distribution of product prices indicated a wide range, with some products priced significantly higher than others.
3. **Visualizations**:
    - Various visualizations, including histograms, box plots, and scatter plots, provided a clear understanding of the relationships between different variables. For instance, the box plot of product prices highlighted the presence of outliers, while the scatter plot illustrated the correlation between stock quantity and price.
4. **Correlation Analysis**:
    - The heatmap of correlations among numerical features indicated that while some features were positively correlated, others showed weak or no correlation. This insight is crucial for understanding which factors may influence product ratings and sales performance.
5. **Predictive Modeling**:
    - The application of linear regression to predict product ratings based on features such as price, stock quantity, warranty period, and product age yielded a Mean Squared Error (MSE) of approximately 2.01 and an R^2 score of -0.0028. This suggests that the model did not perform well in predicting ratings, indicating that other factors may need to be considered or that a more complex model could be beneficial.

Insights

1. **Pricing Strategy**:

- The analysis of price distribution suggests that businesses should consider competitive pricing strategies, especially for products that fall within the higher price range. Understanding customer sensitivity to price can help in setting optimal price points.

2. **Inventory Management**:
   - The relationship between stock quantity and price indicates that products with higher prices may not necessarily require large stock levels. Businesses should analyze sales trends to optimize inventory levels, reducing holding costs while ensuring product availability.
3. **Product Ratings**:
   - The correlation between product features and ratings suggests that factors such as warranty period and stock quantity may influence customer satisfaction. Companies should focus on enhancing these aspects to improve product ratings and customer loyalty.
4. **Market Segmentation**:
   - The analysis of product categories revealed the most frequent categories, which can guide marketing efforts and product development. Targeting specific segments with tailored marketing strategies can enhance sales performance.
5. **Future Research**:
   - Given the limitations of the linear regression model, future analyses could explore more advanced machine learning techniques, such as Random Forest or Gradient Boosting, to improve prediction accuracy. Additionally, incorporating external factors such as market trends and consumer behavior could provide a more comprehensive understanding of sales dynamics.

Final Thoughts

The exploratory data analysis of the Global Product Inventory Dataset 2025 has highlighted the importance of data-driven decision-making in inventory management. By leveraging insights from this analysis, businesses can enhance their operational efficiency, optimize pricing strategies, and ultimately improve profitability in a competitive global market. Continuous monitoring and analysis of inventory data will be essential for adapting to changing market conditions and consumer preferences.