APPENDIX

Analysis Sales Analysis using Python - CODE SNIPPET.

Adidas Sales Analysis

Project Description

This analysis aims to provide a comprehensive examination of Adidas sales data to uncover meaningful insights, predict future sales trends, and implement machine learning techniques to classify high sales performance. This project leverages various data analysis and visualization techniques, machine learning models, and time series forecasting to offer a holistic understanding of the sales dynamics.

1. Importing Libraries

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.preprocessing import StandardScaler
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
```

2. Data Loading

```
# Read and Load the csv file dataset
adidas_data = pd.read_csv("01_Adidas Sales Analysis.csv")
```

```
# Displays the first few rows of the dataset
adidas_data.head()
```

	Retailer	Retailer ID	Invoice Date	Region	State	City	Gender Type	Product Category	Price per Unit	Units Sold	Total Sales	Operating Profit	Operating Margin	Sales Method
0	Foot Locker	1185732	Tuesday, October 26, 2021	Northeast	Pennsylvania	Philadelphia	Men	Apparel	55	125	68750	24062.5	0.35	Outlet
1	Foot Locker	1185732	Wednesday, October 27, 2021	Northeast	Pennsylvania	Philadelphia	Women	Apparel	45	225	101250	30375.0	0.30	Outlet
2	Foot Locker	1185732	Thursday, October 28, 2021	Northeast	Pennsylvania	Philadelphia	Men	Street Footwear	45	475	213750	117562.5	0.55	Outlet
3	Foot Locker	1185732	Friday, October 29, 2021	Northeast	Pennsylvania	Philadelphia	Men	Athletic Footwear	45	125	56250	19687.5	0.35	Outlet
4	Foot Locker	1185732	Saturday, October 30, 2021	Northeast	Pennsylvania	Philadelphia	Women	Street Footwear	35	175	61250	24500.0	0.40	Outlet

```
# Displays the last few rows of the dataset
adidas_data.tail()
```

	Retailer	Retailer ID	Invoice Date	Region	State	City	Gender Type	Product Category	Price per Unit	Units Sold	Total Sales	Operating Profit	Operating Margin	Sales Method
9643	West Gear	1128299	Saturday, March 14, 2020	West	Nevada	Las Vegas	Women	Apparel	56	170	9520	1713.60	0.18	Outlet
9644	West Gear	1128299	Sunday, March 15, 2020	West	Nevada	Las Vegas	Men	Street Footwear	20	149	2980	1192.00	0.40	Outlet
9645	West Gear	1128299	Monday, March 16, 2020	West	Nevada	Las Vegas	Men	Athletic Footwear	31	145	4495	1123.75	0.25	Outlet
9646	West Gear	1128299	Tuesday, March 17, 2020	West	Nevada	Las Vegas	Women	Street Footwear	26	128	3328	1397.76	0.42	Outlet
9647	West Gear	1128299	Wednesday, March 18, 2020	West	Nevada	Las Vegas	Women	Athletic Footwear	26	96	2496	848.64	0.34	Outlet

3. Data Cleaning and Preprocessing

```
adidas_shape = adidas_data.shape
adidas_columns = adidas_data.columns
adidas_dtypes = adidas_data.dtypes
adidas_unique_counts = adidas_data.nunique()

print(f"Adidas shape :{adidas_shape},\n \nAdidas columns: \n{adidas_columns},\n \nAdidas dtypes: \n{adidas_dtypes}\n")
```

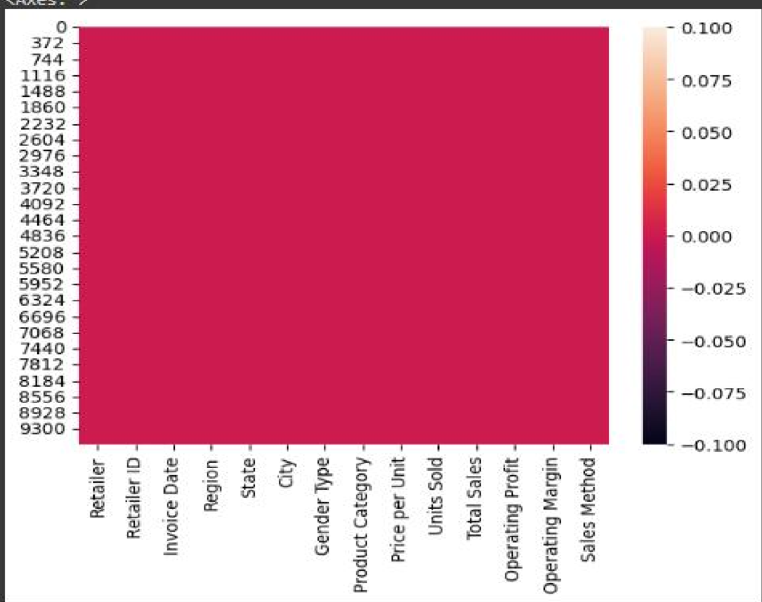
```
Adidas shape :(9648, 14),

Adidas columns:
Index(['Retailer', 'Retailer ID', 'Invoice Date', 'Region', 'State', 'City',
       'Gender Type', 'Product Category', 'Price per Unit', 'Units Sold',
       'Total Sales', 'Operating Profit', 'Operating Margin', 'Sales Method'],
      dtype='object'),

Adidas dtypes:
Retailer             object
Retailer ID           int64
Invoice Date         object
Region               object
State                object
City                 object
Gender Type          object
Product Category     object
Price per Unit        int64
Units Sold            int64
Total Sales           int64
Operating Profit    float64
Operating Margin    float64
Sales Method         object
dtype: object
```

```
# For handling missing values
adidas_missing = adidas_data.isnull()
adidas_missing_count = adidas_missing.sum()
print(adidas_missing_count)
```

```
Retailer            0
Retailer ID         0
Invoice Date        0
Region              0
State               0
City                0
Gender Type         0
Product Category    0
Price per Unit      0
Units Sold          0
Total Sales         0
Operating Profit    0
Operating Margin    0
Sales Method        0
dtype: int64
```

```
[ ] # Plot of missing values
sns.heatmap(adidas_missing)
```

<Axes: >



4. Data Analysis Techniques

```
# For descriptive statistic of the dataset
adidas_data.describe()
```

	Retailer ID	Price per Unit	Units Sold	Total Sales	Operating Profit	Operating Margin
count	9.648000e+03	9648.000000	9648.000000	9648.000000	9648.000000	9648.000000
mean	1.173850e+06	45.216625	256.930037	93273.437500	34425.244761	0.422991
std	2.636038e+04	14.705397	214.252030	141916.016727	54193.113713	0.097197
min	1.128299e+06	7.000000	0.000000	0.000000	0.000000	0.100000
25%	1.185732e+06	35.000000	106.000000	4254.500000	1921.752500	0.350000
50%	1.185732e+06	45.000000	176.000000	9576.000000	4371.420000	0.410000
75%	1.185732e+06	55.000000	350.000000	150000.000000	52062.500000	0.490000
max	1.197831e+06	110.000000	1275.000000	825000.000000	390000.000000	0.800000

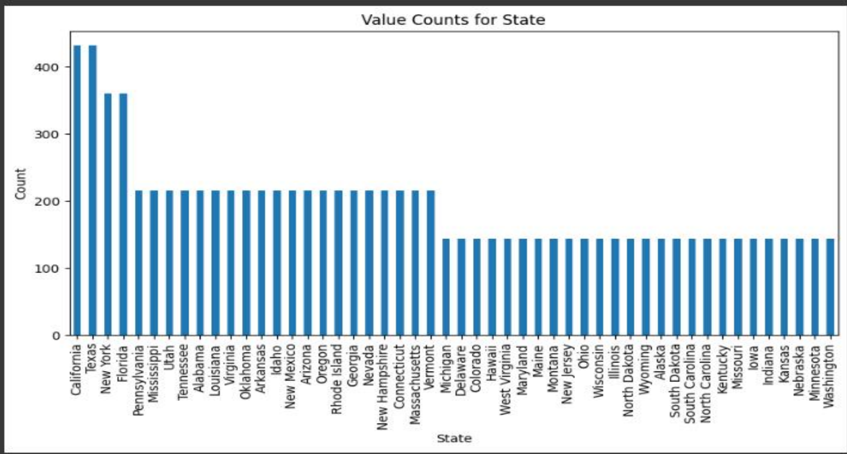
```
# Value counts of the numeric data in the dataset
adidas_count_region = adidas_data["Region"].value_counts()
adidas_count_state = adidas_data["State"].value_counts()
adidas_count_city = adidas_data["City"].value_counts()
adidas_count_gender_type = adidas_data["Gender Type"].value_counts()
adidas_count_product_category = adidas_data["Product Category"].value_counts()
adidas_count_price_per_unit = adidas_data["Price per Unit"].value_counts()
adidas_count_unit_sold = adidas_data["Units Sold"].value_counts()
adidas_count_total_sales = adidas_data["Total Sales"].value_counts()
adidas_count_operating_profit = adidas_data["Total Sales"].value_counts()
adidas_count_sales_method = adidas_data["Sales Method"].value_counts()
adidas_count_retailer = adidas_data["Retailer"].value_counts()

print(f"State Value Counts:\n \n{adidas_count_state}\n")
print(f"City Value Counts:\n \n{adidas_count_city}\n")
```

```
State Value Counts:

State
California        432
Texas             432
New York          360
Florida           360
Pennsylvania      216
Mississippi       216
Utah              216
Tennessee         216
Alabama           216
Louisiana         216
Virginia          216
Oklahoma          216
Arkansas          216
Idaho             216
New Mexico        216
Arizona           216
Oregon            216
Rhode Island      216
Georgia           216
Nevada            216
New Hampshire     216
Connecticut       216
Massachusetts     216
Vermont           216
Michigan          144
Delaware          144
Colorado          144
Hawaii            144
West Virginia     144
Maryland          144
Maine             144
Montana           144
New Jersey        144
Ohio              144
Wisconsin         144
Illinois          144
North Dakota      144
Wyoming           144
Alaska            144
South Dakota      144
South Carolina    144
North Carolina    144
Kentucky          144
Missouri          144
Iowa              144
```

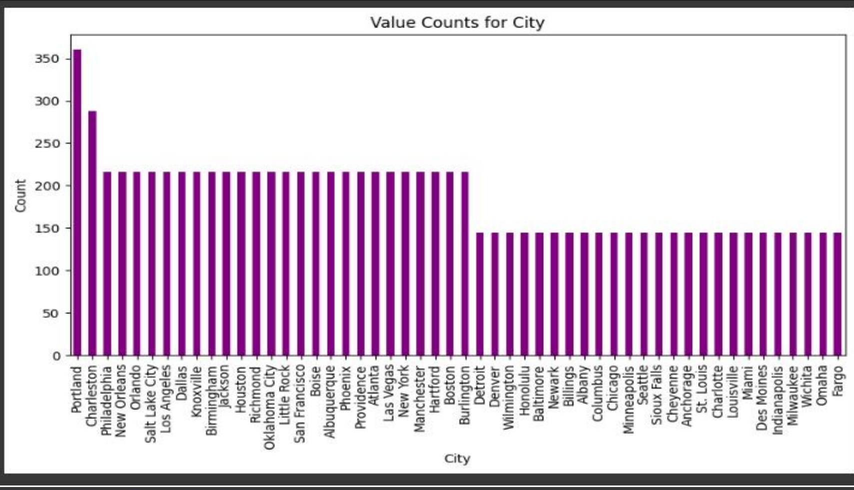
```
Indiana            144
Kansas             144
Nebraska           144
Minnesota          144
Washington         144
Name: count, dtype: int64

City Value Counts:

City
Portland           360
Charleston         288
Philadelphia       216
New Orleans        216
Orlando            216
Salt Lake City     216
Los Angeles        216
Dallas             216
Knoxville          216
Birmingham         216
Jackson            216
Houston            216
Richmond           216
Oklahoma City      216
Little Rock        216
San Francisco      216
Boise              216
Albuquerque        216
Phoenix            216
Providence         216
Atlanta            216
Las Vegas          216
New York           216
Manchester         216
Hartford           216
Boston             216
Burlington         216
Detroit            144
Denver             144
Wilmington         144
Honolulu           144
Baltimore          144
Newark             144
Billings           144
Albany             144
Columbus           144
Chicago            144
Minneapolis        144
Seattle            144
Sioux Falls        144
Cheyenne           144
Anchorage          144
St. Louis          144
Charlotte          144
Louisville         144
Miami              144
Des Moines         144
Indianapolis       144
Milwaukee          144
Wichita            144
Omaha              144
Fargo              144
Name: count, dtype: int64
```

5. Visual Insight

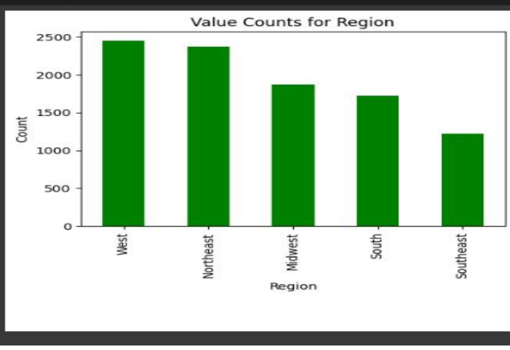
```
# Plot of Value Counts for State
plt.figure(figsize = (10, 5))
adidas_count_state.plot(kind = "bar")
plt.title("Value Counts for State")
plt.xlabel("State")
plt.ylabel("Count")
plt.show()
```



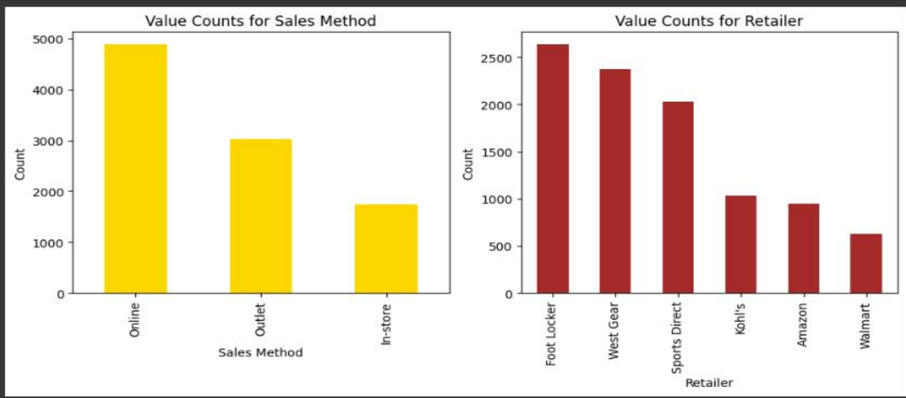

```
# Plot of Value Counts for City
plt.figure(figsize=(10, 5))
adidas_count_city.plot(kind = "bar", color = "purple")
plt.title("Value Counts for City")
plt.xlabel("City")
plt.ylabel("Count")
plt.show()
```




```
# Plot of Value Counts for Region
fig, axes = plt.subplots(1, 2, figsize=(10, 5))
adidas_count_region.plot(kind="bar", color = 'green', ax = axes[0])
axes[0].set_title("Value Counts for Region")
axes[0].set_xlabel("Region")
axes[0].set_ylabel("Count")

# Plot of Value Counts for Product Category
adidas_count_product_category.plot(kind = "bar", color = "red", ax = axes[1])
axes[1].set_title("Value Counts for Product Category")
axes[1].set_xlabel("Product Category")
axes[1].set_ylabel("Count")

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

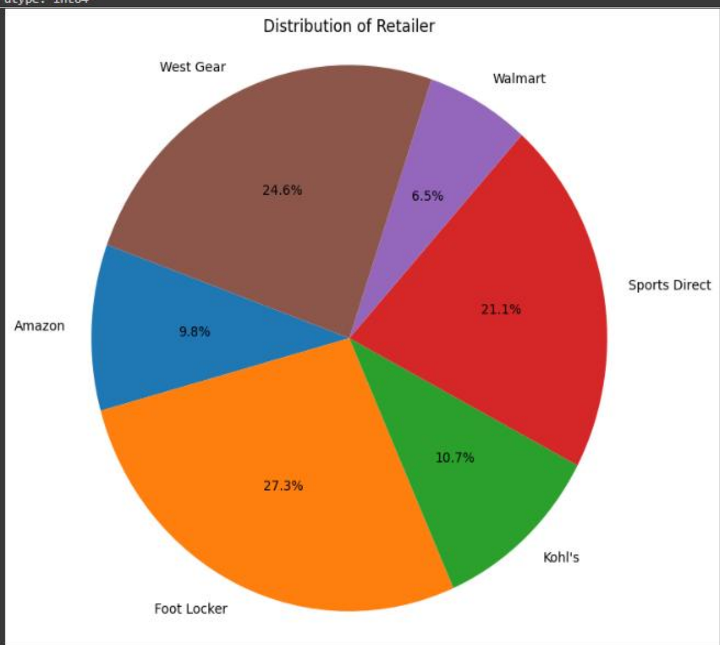


```python
# Plot of Value Counts for Sales Method
fig, axes = plt.subplots(1, 2, figsize = (10, 5))
adidas_count_sales_method.plot(kind = "bar", color = "gold", ax = axes[0])
axes[0].set_title("Value Counts for Sales Method")
axes[0].set_xlabel("Sales Method")
axes[0].set_ylabel("Count")

# Plot of Value Counts for Retailer
adidas_count_retailer.plot(kind = "bar", color = "brown", ax = axes[1])
axes[1].set_title("Value Counts for Retailer")
axes[1].set_xlabel("Retailer")
axes[1].set_ylabel("Count")

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



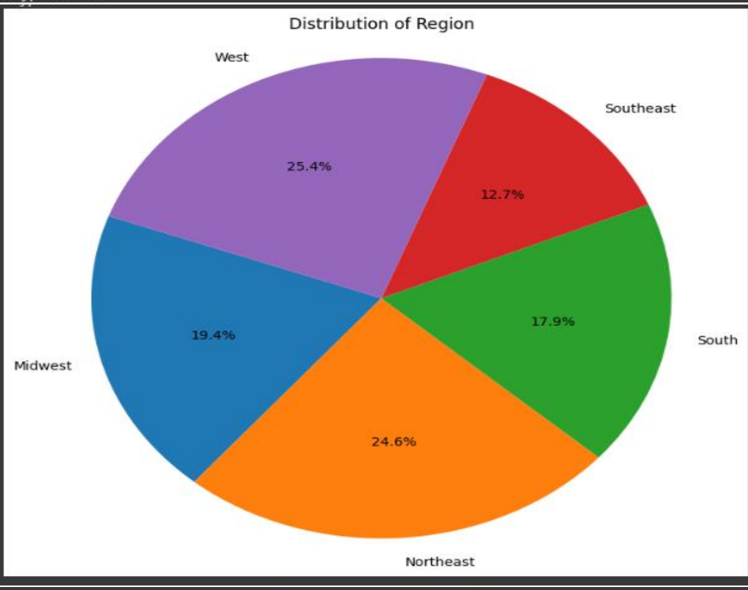

```python
retailer_size = adidas_data.groupby("Retailer").size()
print(retailer_size)

# Pie chart for Distribution of Retailer
plt.figure(figsize = (8,8))
plt.pie(retailer_size, labels= retailer_size.index, autopct= "%1.1f%%", startangle = 160)
plt.title("Distribution of Retailer")
plt.axis("equal")
plt.show()
```

```
Retailer
Amazon            949
Foot Locker      2637
Kohl's           1030
Sports Direct    2032
Walmart           626
West Gear        2374
dtype: int64
```



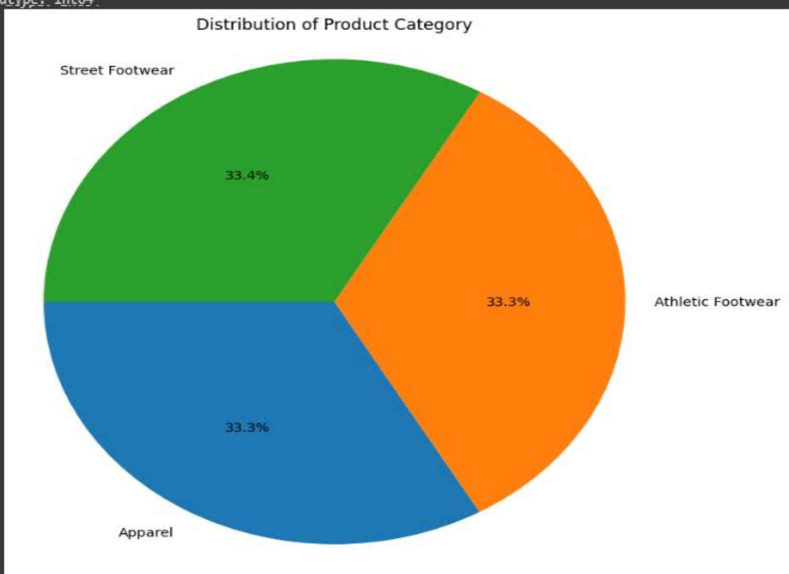
```python
region_size = adidas_data.groupby("Region").size()
print(retailer_size)

# Pie chart for Distribution of Region
plt.figure(figsize = (8,8))
plt.pie(region_size, labels= region_size.index, autopct= "%1.1f%%", startangle = 160)
plt.title("Distribution of Region")
plt.axis("equal")
plt.show()
```

```
Retailer
Amazon            949
Foot Locker      2637
Kohl's           1030
Sports Direct    2032
Walmart           626
West Gear        2374
dtype: int64
```



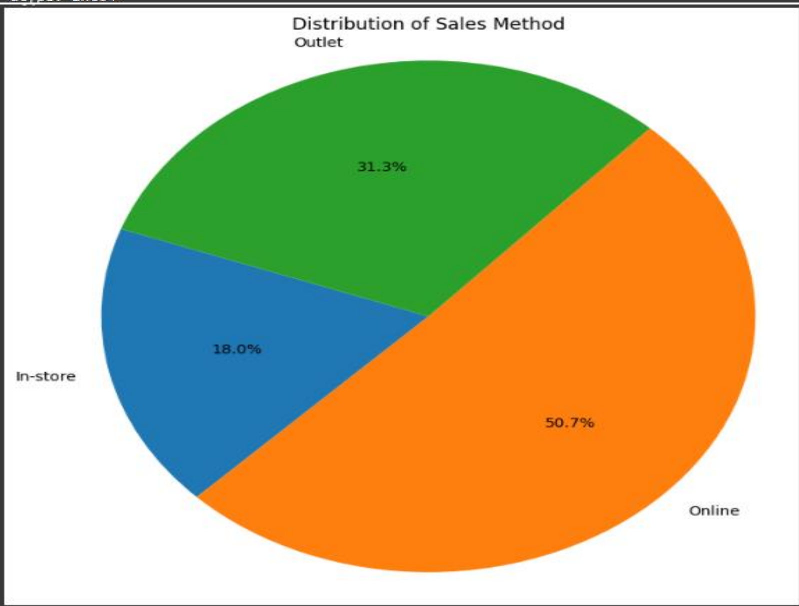

```python
product_size = adidas_data.groupby("Product Category").size()
print(product_size)

# Pie chart for Distribution of Product Category
plt.figure(figsize = (8,8))
plt.pie(product_size, labels= product_size.index, autopct= "%1.1f%%", startangle = 180)
plt.title("Distribution of Product Category")
plt.axis("equal")
plt.show()
```

```
Product Category
Apparel             3214
Athletic Footwear   3216
Street Footwear     3218
dtype: int64
```



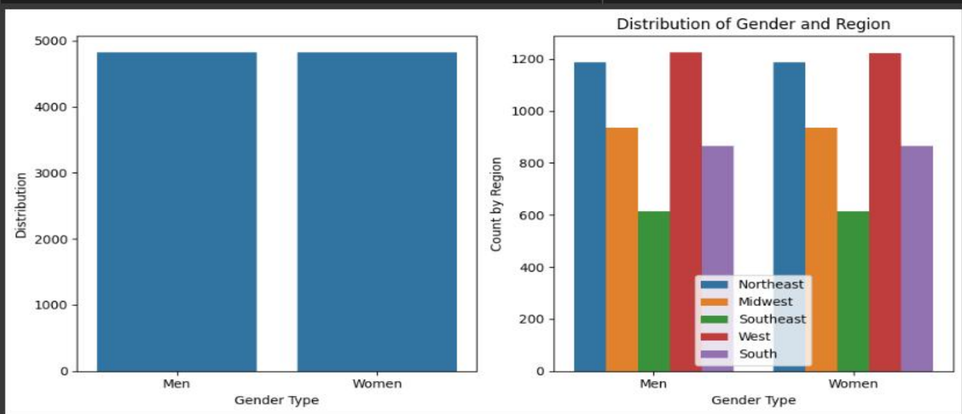
```python
method_size = adidas_data.groupby("Sales Method").size()
print(retailer_size)

# Pie chart for Distribution of Sales Method
plt.figure(figsize = (8,8))
plt.pie(method_size, labels= method_size.index, autopct= "%1.1f%%", startangle = 160)
plt.title("Distribution of Sales Method")
plt.axis("equal")
plt.show()
```

```
Retailer
Amazon           949
Foot Locker     2637
Kohl's          1030
Sports Direct   2032
Walmart          626
West Gear       2374
dtype: int64
```

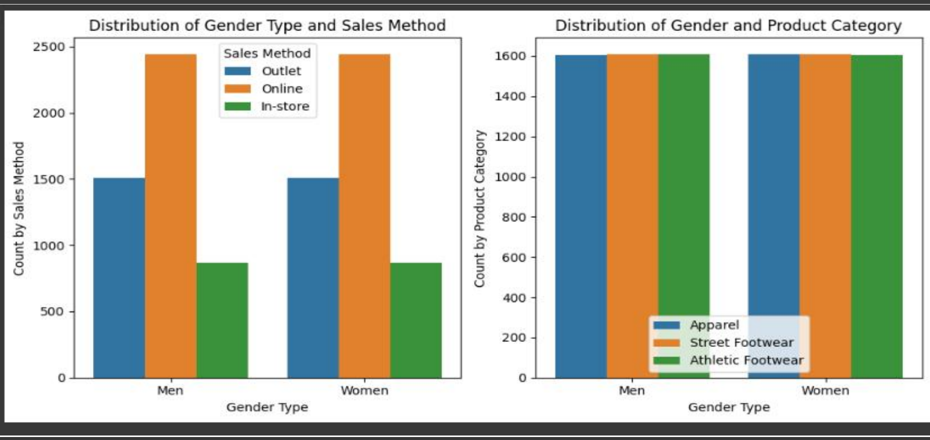


6. Data Visualization

```python
# Plot for Distribution of Gender Type
fig, axes = plt.subplots(1, 2, figsize=(10, 5))
sns.countplot(data=adidas_data, x="Gender Type", ax = axes[0])
axes[0].set_xlabel("Gender Type")
axes[0].set_ylabel("Distribution")

# Plot for Distribution of Gender Type and Region
sns.countplot(data= adidas_data, x= "Gender Type", hue = "Region", ax = axes[1])
axes[1].set_xlabel("Gender Type")
axes[1].set_ylabel("Count by Region")
axes[1].set_title("Distribution of Gender and Region")
plt.legend(loc="lower center")
plt.tight_layout()
plt.show()
```

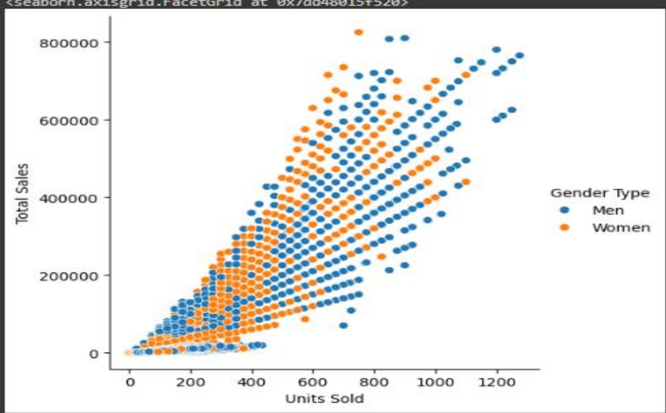


```
[ ] # Plot for Distribution of Gender Type and Sales Method
    fig, axes = plt.subplots(1, 2, figsize=(10, 5))
    sns.countplot(data = adidas_data, x = "Gender Type", hue = "Sales Method", ax = axes[0])
    axes[0].set_xlabel("Gender Type")
    axes[0].set_ylabel("Count by Sales Method")
    axes[0].set_title("Distribution of Gender Type and Sales Method")

    # Plot for Distribution of Gender Type and Product Category
    sns.countplot(data = adidas_data, x = "Gender Type", hue = "Product Category", ax = axes[1])
    axes[1].set_xlabel("Gender Type")
    axes[1].set_ylabel("Count by Product Category")
    axes[1].set_title("Distribution of Gender and Product Category")

    plt.legend(loc="lower center")
    plt.tight_layout()
    plt.show()
```




```
# Plot of Total Sales and Unit Sold per Gender Type
sns.relplot(data = adidas_data, x = "Units Sold", y = "Total Sales", hue = "Gender Type" )
```

```
<seaborn.axisgrid.FacetGrid at 0x7dd48015f520>
```



7. Implementation of Machine Learning

```
[ ] # For Data Preparation
    adidas_cleaned = adidas_data.drop(["Retailer ID", "State", "City"], axis=1)

    threshold = adidas_cleaned["Total Sales"].median()
    adidas_cleaned["High_Sales"] = (adidas_cleaned["Total Sales"] > threshold).astype(int)
    adidas_cleaned = adidas_cleaned.drop(["Total Sales"], axis=1)
    adidas_dummies = pd.get_dummies(adidas_cleaned, drop_first=True)
```

```
[ ] x = adidas_dummies.drop("High_Sales", axis=1)
    y = adidas_dummies["High_Sales"]
```

```
[ ] # Split the data into traing and test sets
    x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=42)
```

```
[ ] scaler = StandardScaler()
    x_train = scaler.fit_transform(x_train)
    x_test = scaler.transform(x_test)
```

```
[ ] model = LogisticRegression()
```

```
[ ] model.fit(x_train, y_train)
```

```
▾ LogisticRegression
LogisticRegression()
```

```
[ ] # Making prediction
    y_pred = model.predict(x_test)
```

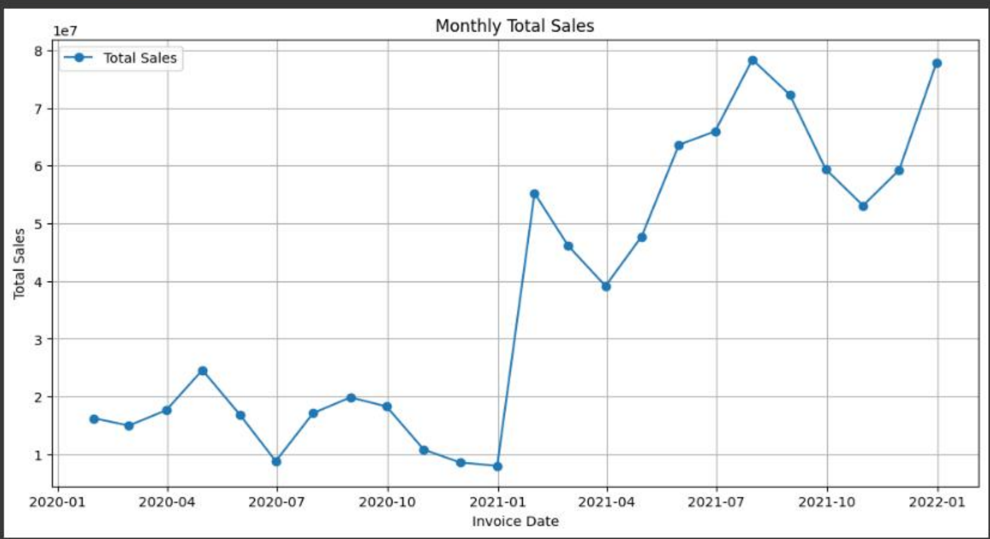
```
[ ] # Evaluate the model
    accuracy = accuracy_score(y_test, y_pred)
    conf_matrix = confusion_matrix(y_test, y_pred)
    class_report = classification_report(y_test, y_pred)

    print(f"Accuracy: {accuracy}")
    print("Confusion Matrix:")
    print(conf_matrix)
    print("Classification Report:")
    print(class_report)
```

```
Accuracy: 0.9509499136442142
Confusion Matrix:
[[1376   52]
 [  90 1377]]
Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.96      0.95      1428
           1       0.96      0.94      0.95      1467

    accuracy                           0.95      2895
   macro avg       0.95      0.95      0.95      2895
weighted avg       0.95      0.95      0.95      2895
```

8. Time Series Forecasting

```
[ ] adidas_data["Invoice Date"] = pd.to_datetime(adidas_data["Invoice Date"])
    adidas_data.set_index("Invoice Date", inplace=True)
    monthly_sales = adidas_data["Total Sales"].resample('M').sum()
```

```
[ ] plt.figure(figsize=(12, 6))
    plt.plot(monthly_sales, label="Total Sales",marker = 'o', linestyle = "-")
    plt.title("Monthly Total Sales")
    plt.xlabel("Invoice Date")
    plt.ylabel("Total Sales")
    plt.legend()
    plt.grid(True)
    plt.show()
```




```
[ ] adf_test = adfuller(monthly_sales)
    print(f"ADF Statistic: {adf_test[0]}")
    print(f"p-value: {adf_test[1]}")
```

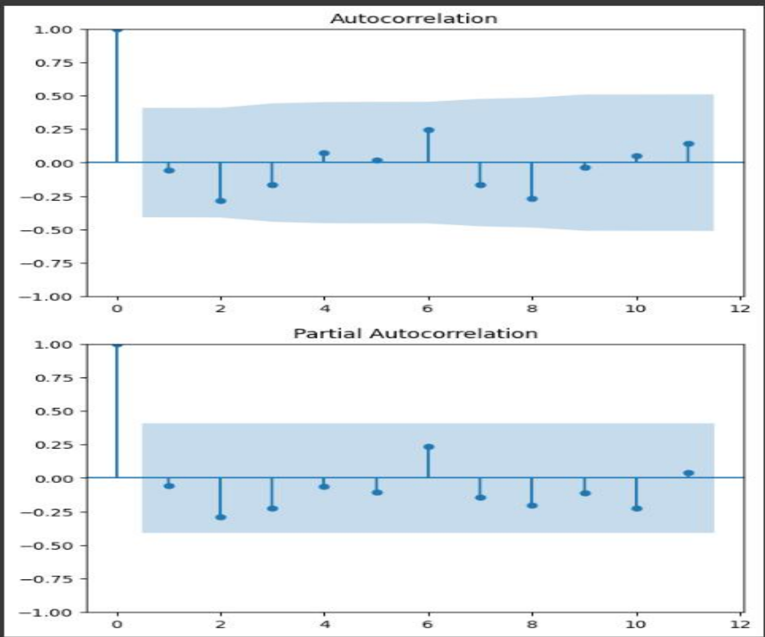
```python
adf_test = adfuller(monthly_sales)
print(f"ADF Statistic: {adf_test[0]}")
print(f"p-value: {adf_test[1]}")
```

```
ADF Statistic: -0.8391906168655257
p-value: 0.8073382697223422
```

```python
monthly_sales_diff = monthly_sales.diff().dropna()

adf_test_diff = adfuller(monthly_sales_diff)
print(f"ADF Statistic (Differenced): {adf_test_diff[0]}")
print(f"p-value (Differenced): {adf_test_diff[1]}")
```

```
ADF Statistic (Differenced): -4.594841522662277
p-value (Differenced): 0.00013202726256274837
```

```python
plot_acf(monthly_sales_diff)
plot_pacf(monthly_sales_diff)
plt.show()
```

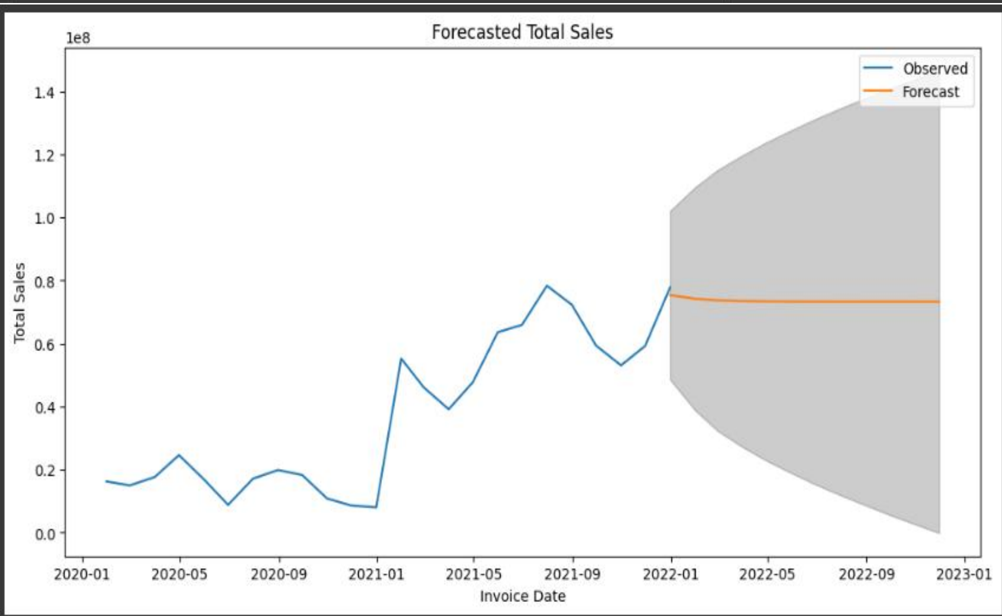



```python
# Building ARIMA Model
model = ARIMA(monthly_sales, order=(1, 1, 1))
model_fit = model.fit()
print(model_fit.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:            Total Sales   No. Observations:                   24
Model:                 ARIMA(1, 1, 1)   Log Likelihood                -408.961
Date:                Sat, 25 May 2024   AIC                            823.923
Time:                        13:44:26   BIC                            827.329
Sample:                    01-31-2020   HQIC                           824.780
                         - 12-31-2021
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.4577      2.255      0.203      0.839      -3.961       4.877
ma.L1         -0.5938      1.760     -0.337      0.736      -4.043       2.855
sigma2      1.866e+14        nan        nan        nan         nan         nan
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):                30.22
Prob(Q):                              0.97   Prob(JB):                         0.00
Heteroskedasticity (H):               4.55   Skew:                             1.85
Prob(H) (two-sided):                  0.05   Kurtosis:                         7.23
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 2.32e+46. Standard errors may be unstable.
```

```python
forecast_steps = 12  # Forecast for the next 12 months
forecast = model_fit.get_forecast(steps=forecast_steps)
forecast_index = pd.date_range(start=monthly_sales.index[-1], periods=forecast_steps, freq="M")
forecast_values = forecast.predicted_mean
forecast_conf = forecast.conf_int()
```

```python
# Plot for Forecasted Total Sales
plt.figure(figsize=(12, 6))
plt.plot(monthly_sales, label="Observed")
plt.plot(forecast_index, forecast_values, label="Forecast")
plt.fill_between(forecast_index, forecast_conf.iloc[:, 0], forecast_conf.iloc[:, 1], color="k", alpha=0.2)
plt.title("Forecasted Total Sales")
plt.xlabel("Invoice Date")
plt.ylabel("Total Sales")
plt.legend()
plt.show()
```



9. Conlusion

This analysis demonstrates the power of data science in predicting high sales for Adidas.

1. Highly Accurate Sales Prediction Model:

- A Logistic Regression model achieved an impressive 95.1% accuracy. This means it can effectively distinguish between high and low sales based on the provided data (excluding total sales).
- The chosen features within the model are highly informative when it comes to predicting sales performance.

2. Balanced Classification Performance:

- The confusion matrix reveals a well-balanced classification. The model accurately identified a large portion of both high-sales (96%) and low-sales (94%) instances in the test set.
- This balance is crucial for ensuring the model's effectiveness in real-world scenarios with a mix of sales outcomes.

3. Identifying Key Sales Drivers:

By analyzing the model coefficients, we can pinpoint the features with the strongest influence on predicting high sales. This knowledge can be invaluable for:

- Targeted Marketing: Develop marketing campaigns and promotions tailored to specific customer segments or product categories linked to high sales.
- Product Development: Focus efforts on product categories with a demonstrated association with high sales performance.
- Strategic Resource Allocation: Allocate resources (advertising budget, inventory) strategically based on predicted sales trends.

4. Enhanced Customer Targeting:

By leveraging the model's prediction capabilities, Adidas can target high-potential customers with personalized marketing strategies. This can significantly improve conversion rates and generate higher sales revenue.

5. Dynamic Resource Optimization:

The model empowers Adidas to dynamically allocate resources based on predicted sales trends. This proactive approach optimizes resource utilization (advertising budget, inventory) and maximizes return on investment.

6. Importance of Data-Driven Decision Making:

This analysis highlights the critical role of data-driven decision making. By utilizing historical sales data and building predictive models, Adidas gains valuable insights to:

- Improve sales forecasting
- Optimize resource allocation
- Enhance customer targeting
- Make strategic business decisions

Overall Impact:

This data-driven approach holds tremendous potential for Adidas to gain a competitive edge. It allows for improved sales forecasting, resource optimization, and personalized customer targeting. By continuously collecting and analyzing sales data, Adidas can refine its predictive models and stay ahead in the competitive market.

+ Code

Time Series Analysis for Adidas Sales Forecasting

Seasonality and Stationarity:

- The analysis suggests a seasonal pattern in Adidas' monthly sales data, likely influenced by holidays, back-to-school seasons, or summer vacations.
- By differencing the data (taking the difference between consecutive months), stationarity was achieved. This is a critical step for building an ARIMA model, which requires stable data.

Forecasted Sales Trend:

- The ARIMA(1, 1, 1) model predicts a modest upward trend in Adidas' total sales for the next year.

Confidence Interval and Uncertainty:

- The forecast includes a confidence interval (shaded area) that widens for future months. This indicates a higher degree of uncertainty in the predictions as we move further out in time. This is a natural limitation of time series forecasting, as predicting the future with high accuracy becomes increasingly difficult.

Benefits of Data-Driven Forecasting:

The visualization provides valuable insights for Adidas to:

- Plan Inventory: By anticipating future sales trends, Adidas can optimize inventory levels to avoid stockouts or excess inventory holding costs.
- Allocate Resources: Based on the sales forecast, Adidas can strategically allocate resources like staffing or marketing budgets to meet the anticipated demand.
- Identify Potential Issues: Significant deviations between forecasted and actual sales could signal changes in market trends or competitor activity, prompting further investigation and corrective actions. Importance of Continuous Improvement:

Overall, by continuously analyzing sales data and refining forecasting models, Adidas can gain a data-driven advantage in its business operations. This can lead to improved decision-making, optimized resource allocation, and ultimately, increased sales and profitability.

Sample Dataset - Adidas Sales Analysis

1	Retailer	Retailer ID	Invoice Date	Region	State	City	Gender Typ	Product Category	Price per Unit	Units Sold	Total Sales	Operating Profit	Operating Margin	Sales Method
2	Foot Locker	1185732	Tuesday, October 26, 2021	Northeast	Pennsylvania	Philadelphia	Men	Apparel	55	125	68750	24062.5	0.35	Outlet
3	Foot Locker	1185732	Wednesday, October 27, 2021	Northeast	Pennsylvania	Philadelphia	Women	Apparel	45	225	101250	30375	0.3	Outlet
4	Foot Locker	1185732	Thursday, October 28, 2021	Northeast	Pennsylvania	Philadelphia	Men	Street Footwear	45	475	213750	117562.5	0.55	Outlet
5	Foot Locker	1185732	Friday, October 29, 2021	Northeast	Pennsylvania	Philadelphia	Men	Athletic Footwear	45	125	56250	19687.5	0.35	Outlet
6	Foot Locker	1185732	Saturday, October 30, 2021	Northeast	Pennsylvania	Philadelphia	Women	Street Footwear	35	175	61250	24500	0.4	Outlet
7	Foot Locker	1185732	Sunday, October 31, 2021	Northeast	Pennsylvania	Philadelphia	Women	Athletic Footwear	40	50	20000	8000	0.4	Outlet
8	Foot Locker	1185732	Monday, November 1, 2021	Northeast	Pennsylvania	Philadelphia	Men	Apparel	55	125	68750	24062.5	0.35	Outlet
9	Foot Locker	1185732	Tuesday, November 2, 2021	Northeast	Pennsylvania	Philadelphia	Women	Apparel	45	225	101250	30375	0.3	Outlet
10	Foot Locker	1185732	Wednesday, November 3, 2021	Northeast	Pennsylvania	Philadelphia	Men	Street Footwear	50	445	222500	122375	0.55	Outlet
11	Foot Locker	1185732	Thursday, November 4, 2021	Northeast	Pennsylvania	Philadelphia	Men	Athletic Footwear	50	150	75000	26250	0.35	Outlet
12	Foot Locker	1185732	Friday, November 5, 2021	Northeast	Pennsylvania	Philadelphia	Women	Street Footwear	40	175	70000	28000	0.4	Outlet
13	Foot Locker	1185732	Saturday, November 6, 2021	Northeast	Pennsylvania	Philadelphia	Women	Athletic Footwear	45	25	11250	4500	0.4	Outlet
14	Foot Locker	1185732	Sunday, November 7, 2021	Northeast	Pennsylvania	Philadelphia	Men	Apparel	60	75	45000	13500	0.3	Outlet
15	Foot Locker	1185732	Monday, November 8, 2021	Northeast	Pennsylvania	Philadelphia	Women	Apparel	50	175	87500	21875	0.25	Outlet
16	Foot Locker	1185732	Tuesday, November 9, 2021	Northeast	Pennsylvania	Philadelphia	Men	Street Footwear	50	450	225000	112500	0.5	Outlet
17	Foot Locker	1185732	Wednesday, November 10, 2021	Northeast	Pennsylvania	Philadelphia	Men	Athletic Footwear	50	150	75000	22500	0.3	Outlet
18	Foot Locker	1185732	Thursday, November 11, 2021	Northeast	Pennsylvania	Philadelphia	Women	Street Footwear	40	150	60000	21000	0.35	Outlet
19	Foot Locker	1185732	Friday, November 12, 2021	Northeast	Pennsylvania	Philadelphia	Women	Athletic Footwear	45	75	33750	11812.5	0.35	Outlet
20	Foot Locker	1185732	Saturday, November 13, 2021	Northeast	Pennsylvania	Philadelphia	Men	Apparel	60	75	45000	13500	0.3	Outlet
21	Foot Locker	1185732	Sunday, November 14, 2021	Northeast	Pennsylvania	Philadelphia	Women	Apparel	50	200	100000	25000	0.25	Outlet
22	Foot Locker	1185732	Monday, November 15, 2021	Northeast	Pennsylvania	Philadelphia	Men	Street Footwear	60	470	282000	141000	0.5	Outlet
23	Foot Locker	1185732	Tuesday, November 16, 2021	Northeast	Pennsylvania	Philadelphia	Men	Athletic Footwear	60	175	105000	31500	0.3	Outlet
24	Foot Locker	1185732	Wednesday, November 17, 2021	Northeast	Pennsylvania	Philadelphia	Women	Street Footwear	55	150	82500	28875	0.35	Outlet
25	Foot Locker	1185732	Thursday, November 18, 2021	Northeast	Pennsylvania	Philadelphia	Women	Athletic Footwear	55	100	55000	19250	0.35	Outlet
26	Foot Locker	1185732	Friday, November 19, 2021	Northeast	Pennsylvania	Philadelphia	Men	Apparel	65	125	81250	24375	0.3	Outlet
27	Foot Locker	1185732	Saturday, November 20, 2021	Northeast	Pennsylvania	Philadelphia	Women	Apparel	70	250	175000	52500	0.3	Outlet
28	Foot Locker	1185732	Sunday, November 21, 2021	Northeast	Pennsylvania	Philadelphia	Men	Street Footwear	65	500	325000	178750	0.55	Outlet
29	Foot Locker	1185732	Monday, November 22, 2021	Northeast	Pennsylvania	Philadelphia	Men	Athletic Footwear	60	250	150000	52500	0.35	Outlet
30	Foot Locker	1185732	Tuesday, November 23, 2021	Northeast	Pennsylvania	Philadelphia	Women	Street Footwear	55	175	96250	38500	0.4	Outlet
31	Foot Locker	1185732	Wednesday, November 24, 2021	Northeast	Pennsylvania	Philadelphia	Women	Athletic Footwear	55	150	82500	33000	0.4	Outlet
32	Foot Locker	1185732	Thursday, November 25, 2021	Northeast	Pennsylvania	Philadelphia	Men	Apparel	65	150	97500	34125	0.35	Outlet
33	Foot Locker	1185732	Friday, November 26, 2021	Northeast	Pennsylvania	Philadelphia	Women	Apparel	70	300	210000	63000	0.3	Outlet
34	Foot Locker	1185732	Saturday, November 27, 2021	Northeast	Pennsylvania	Philadelphia	Men	Street Footwear	65	500	325000	178750	0.55	Outlet
35	Foot Locker	1185732	Sunday, November 28, 2021	Northeast	Pennsylvania	Philadelphia	Men	Athletic Footwear	60	300	180000	63000	0.35	Outlet
36	Foot Locker	1185732	Monday, November 29, 2021	Northeast	Pennsylvania	Philadelphia	Women	Street Footwear	55	225	123750	49500	0.4	Outlet
37	Foot Locker	1185732	Tuesday, November 30, 2021	Northeast	Pennsylvania	Philadelphia	Women	Athletic Footwear	55	175	96250	38500	0.4	Outlet
38	Foot Locker	1185732	Wednesday, December 1, 2021	Northeast	Pennsylvania	Philadelphia	Men	Apparel	65	200	130000	45500	0.35	Outlet
39	Foot Locker	1185732	Thursday, December 2, 2021	Northeast	Pennsylvania	Philadelphia	Women	Apparel	70	375	262500	78750	0.3	Outlet
40	Foot Locker	1185732	Friday, December 3, 2021	Northeast	Pennsylvania	Philadelphia	Men	Street Footwear	65	525	341250	187687.5	0.55	Outlet
41	Foot Locker	1185732	Saturday, December 4, 2021	Northeast	Pennsylvania	Philadelphia	Men	Athletic Footwear	60	300	180000	63000	0.35	Outlet
42	Foot Locker	1185732	Sunday, December 5, 2021	Northeast	Pennsylvania	Philadelphia	Women	Street Footwear	55	225	123750	49500	0.4	Outlet
4094	Sports Direc	1185732	Friday, October 2, 2020	Southeast	Florida	Miami	Women	Athletic Footwear	45	182	8190	3603.6	0.44	Online
4095	Sports Direc	1185732	Saturday, October 3, 2020	Southeast	Florida	Miami	Men	Apparel	57	189	10773	5386.5	0.5	Online
4096	Sports Direc	1185732	Sunday, October 4, 2020	Southeast	Florida	Miami	Women	Apparel	59	223	13157	8552.05	0.65	Online
4097	Sports Direc	1185732	Monday, October 5, 2020	Southeast	Florida	Miami	Men	Street Footwear	56	244	13664	7925.12	0.58	Online
4098	Sports Direc	1185732	Tuesday, October 6, 2020	Southeast	Florida	Miami	Men	Athletic Footwear	49	224	10976	5268.48	0.48	Online
4099	Sports Direc	1185732	Wednesday, October 7, 2020	Southeast	Florida	Miami	Women	Street Footwear	46	224	10304	3812.48	0.37	Online
4100	Sports Direc	1185732	Thursday, October 8, 2020	Southeast	Florida	Miami	Women	Athletic Footwear	49	202	9898	4355.12	0.44	Online
4101	Sports Direc	1185732	Friday, October 9, 2020	Southeast	Florida	Miami	Men	Apparel	64	195	12480	6240	0.5	Online
4102	Sports Direc	1185732	Saturday, October 10, 2020	Southeast	Florida	Miami	Women	Apparel	64	213	13632	8179.2	0.6	Online
4103	Sports Direc	1185732	Sunday, May 24, 2020	Southeast	Florida	Miami	Men	Street Footwear	63	323	20349	11395.44	0.56	Online
4104	Sports Direc	1185732	Sunday, May 24, 2020	Southeast	Florida	Miami	Men	Athletic Footwear	51	254	12954	6088.38	0.47	Online
4105	Sports Direc	1185732	Sunday, May 24, 2020	Southeast	Florida	Miami	Women	Street Footwear	52	248	12896	4771.52	0.37	Online
4106	Sports Direc	1185732	Sunday, May 24, 2020	Southeast	Florida	Miami	Women	Athletic Footwear	54	209	11286	4852.98	0.43	Online
4107	Foot Locker	1185732	Sunday, May 24, 2020	Southeast	Florida	Miami	Men	Apparel	60	202	12120	5938.8	0.49	Online
4108	Foot Locker	1185732	Sunday, May 24, 2020	Southeast	Florida	Miami	Women	Apparel	64	219	14016	8830.08	0.63	Online
4109	Foot Locker	1185732	Saturday, October 17, 2020	Southeast	Florida	Miami	Men	Street Footwear	33	131	4323	1945.35	0.45	Online
4110	Foot Locker	1185732	Sunday, October 18, 2020	Southeast	Florida	Miami	Men	Athletic Footwear	33	65	2145	858	0.4	Online
4111	Foot Locker	1185732	Monday, October 19, 2020	Southeast	Florida	Miami	Women	Street Footwear	24	63	1512	665.28	0.44	Online
4112	Foot Locker	1185732	Tuesday, October 20, 2020	Southeast	Florida	Miami	Women	Athletic Footwear	29	26	754	339.3	0.45	Online
4113	West Gear	1185732	Tuesday, January 12, 2021	Southeast	Florida	Orlando	Men	Street Footwear	41	255	10455	5750.25	0.55	Online
4114	West Gear	1185732	Tuesday, January 12, 2021	Southeast	Florida	Orlando	Men	Athletic Footwear	44	189	8316	3908.52	0.47	Online
4115	West Gear	1185732	Tuesday, January 12, 2021	Southeast	Florida	Orlando	Women	Street Footwear	32	169	5408	2055.04	0.38	Online
4116	West Gear	1185732	Tuesday, January 12, 2021	Southeast	Florida	Orlando	Women	Athletic Footwear	37	145	5365	2199.65	0.41	Online
4117	West Gear	1185732	Tuesday, January 12, 2021	Southeast	Florida	Orlando	Men	Apparel	51	165	8415	3786.75	0.45	Online
4118	West Gear	1185732	Tuesday, January 12, 2021	Southeast	Florida	Orlando	Women	Apparel	44	176	7744	5033.6	0.65	Online
4119	West Gear	1185732	Wednesday, February 10, 2021	Southeast	Florida	Orlando	Men	Street Footwear	44	234	10296	5662.8	0.55	Online
4120	West Gear	1185732	Wednesday, February 10, 2021	Southeast	Florida	Orlando	Men	Athletic Footwear	42	138	5796	2840.04	0.49	Online
4121	West Gear	1185732	Wednesday, February 10, 2021	Southeast	Florida	Orlando	Women	Street Footwear	33	174	5742	2124.54	0.37	Online
4122	Foot Locker	1185732	Saturday, January 9, 2021	Southeast	Georgia	Atlanta	Men	Street Footwear	40	1025	410000	184500	0.45	Online
4123	Foot Locker	1185732	Saturday, January 9, 2021	Southeast	Georgia	Atlanta	Men	Athletic Footwear	40	825	330000	115500	0.35	Online
4124	Foot Locker	1185732	Saturday, January 9, 2021	Southeast	Georgia	Atlanta	Women	Street Footwear	30	825	247500	61875	0.25	Online
4125	Foot Locker	1185732	Saturday, January 9, 2021	Southeast	Georgia	Atlanta	Women	Athletic Footwear	35	675	236250	70875	0.3	Online
4126	Foot Locker	1185732	Saturday, January 9, 2021	Southeast	Georgia	Atlanta	Men	Apparel	50	725	362500	126875	0.35	Online
4127	Foot Locker	1185732	Saturday, January 9, 2021	Southeast	Georgia	Atlanta	Women	Apparel	40	825	330000	165000	0.5	Online
4128	Foot Locker	1185732	Sunday, February 7, 2021	Southeast	Georgia	Atlanta	Men	Street Footwear	40	1075	430000	193500	0.45	Online
4129	Foot Locker	1185732	Sunday, February 7, 2021	Southeast	Georgia	Atlanta	Men	Athletic Footwear	40	725	290000	101500	0.35	Online
4130	Foot Locker	1185732	Sunday, February 7, 2021	Southeast	Georgia	Atlanta	Women	Street Footwear	30	775	232500	58125	0.25	Online
4131	Sports Direc	1185732	Tuesday, January 19, 2021	Southeast	Virginia	Richmond	Men	Street Footwear	34	203	6902	4210.22	0.61	Online
4132	Sports Direc	1185732	Tuesday, January 19, 2021	Southeast	Virginia	Richmond	Men	Athletic Footwear	34	154	5236	2670.36	0.51	Online
4133	Sports Direc	1185732	Tuesday, January 19, 2021	Southeast	Virginia	Richmond	Women	Street Footwear	23	149	3427	1370.8	0.4	Online
4134	Sports Direc	1185732	Tuesday, January 19, 2021	Southeast	Virginia	Richmond	Women	Athletic Footwear	29	116	3364	1682	0.5	Online
4135	Sports Direc	1185732	Tuesday, January 19, 2021	Southeast	Virginia	Richmond	Men	Apparel	43	122	5246	2727.92	0.52	Online

Google Drive Collab Code Link:

https://colab.research.google.com/drive/1-XoZiy7Bp0Xf7TTJX2hdHHFSN2hMoNXU?usp=sharingoverview

Git Hub Link:

https://judegajitos.github.io/CSST104-FINAL-EXAM/#i-project-