Adidas Sales Analysis & Forecasting in US

March 11, 2024

Problem Statement

In navigating the dynamic retail landscape of the United States, Adidas faces the imperative to conduct a comprehensive analysis of sales and forecasting to comprehend market trends, influential factors, and future growth potential. Presently, the company encounters several challenges, including fluctuating customer demand, seasonal variations, and intense competition within the footwear and sportswear industry. Uncertainties in evolving consumer trends and external factors that may impact sales necessitate an innovative and targeted solution. Therefore, the objective of this project is to compile an in-depth analysis of past sales data, identifying patterns and key factors influencing Adidas sales in the United States. This project also aims to develop an accurate and reliable forecasting model, leveraging machine learning techniques and statistical analysis. Thus, the company can make informed decisions regarding inventory, marketing, and sales strategies, minimizing risks and enhancing operational efficiency. Through a better understanding of consumer behavior, market trends, and potential risk factors, Adidas expects to optimize their sales strategies, increase market share, and achieve sustainable growth in the U.S. market.

- The dataset utilized originates from Kaggle (Here).

Research Questions 1. What is the overall sales performance in Adidas product and retailer in the US? 2. What is the overall trend in Adidas sales in the US over the specified time period? 3.

Is there a variation in product preferences at each retailer and which retailer in the US contributes the most to Adidas profit for each product? 4. Which city, state, and region in the US contribute the most to Adidas sales, and are there any regional variations in product preferences? 5. Is there a correlation between the Units Sold, Total Sales, and Operating Profit for Adidas products in the US? 6. What is the most effective sales method to use, and what is the variation in sales methods for Adidas across different retailers? 7. How to sales Forecast w/ Arima, Sarima, & ExponentialSmoothing Holt-Winters?

1 Library and Explore Data

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.ticker import FuncFormatter
import warnings
warnings.filterwarnings("ignore")
```

[2]:
```
df = pd.read_excel(r'Adidas US Sales Datasets.xlsx',skiprows = 4)
```

[3]:
```
df
```

[3]:

	Unnamed: 0	Retailer	Retailer ID	Date	Region	State	City	Product	Price per Unit	…
0	NaN	Foot Locker	1185732	2020-01-01	Northeast	New York	New York	Men's Street Footwear	50.0	
1	NaN	Foot Locker	1185732	2020-01-02	Northeast	New York	New York	Men's Athletic Footwear	50.0	
2	NaN	Foot Locker	1185732	2020-01-03	Northeast	New York	New York	Women's Street Footwear	40.0	
3	NaN	Foot Locker	1185732	2020-01-04	Northeast	New York	New York	Women's Athletic Footwear	45.0	
4	NaN	Foot Locker	1185732	2020-01-05	Northeast	New York	New York	Men's Apparel	60.0	
…	…	…	…	…	…	…	…	…	…	…
9643	NaN	Foot Locker	1185732	2021-01-24	Northeast	New Hampshire	Manchester	Men's Apparel	50.0	
9644	NaN	Foot Locker	1185732	2021-01-24	Northeast	New Hampshire	Manchester	Women's Apparel	41.0	
9645	NaN	Foot Locker	1185732	2021-02-22	Northeast	New Hampshire	Manchester	Men's Street Footwear	41.0	
9646	NaN	Foot Locker	1185732	2021-02-22	Northeast	New Hampshire	Manchester	Men's Athletic Footwear	42.0	
9647	NaN	Foot Locker	1185732	2021-02-22	Northeast	New Hampshire	Manchester	Women's Street Footwear	29.0	

```
      Units Sold  Total Sales  Operating Profit  Operating Margin Sales Method
0           1200     600000.0         300000.00              0.50     In-store
1           1000     500000.0         150000.00              0.30     In-store
2           1000     400000.0         140000.00              0.35     In-store
3            850     382500.0         133875.00              0.35     In-store
4            900     540000.0         162000.00              0.30     In-store
…            …           …                 …                 …          …
9643          64       3200.0            896.00              0.28       Outlet
9644         105       4305.0           1377.60              0.32       Outlet
9645         184       7544.0           2791.28              0.37       Outlet
9646          70       2940.0           1234.80              0.42       Outlet
9647          83       2407.0            649.89              0.27       Outlet

[9648 rows x 14 columns]
```

[4]:
```
data = df.drop('Unnamed: 0', axis=1)
```

[5]:
```
data.isnull().sum()
```

[5]:
```
Retailer            0
Retailer ID         0
Date                0
Region              0
State               0
City                0
Product             0
Price per Unit      0
Units Sold          0
Total Sales         0
Operating Profit    0
Operating Margin    0
Sales Method        0
dtype: int64
```

[6]:
```
data.isnull().sum()
```

[6]:
```
Retailer            0
Retailer ID         0
Date                0
Region              0
State               0
City                0
Product             0
Price per Unit      0
Units Sold          0
Total Sales         0
```

```
Operating Profit    0
Operating Margin    0
Sales Method        0
dtype: int64
```

[7]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9648 entries, 0 to 9647
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Retailer          9648 non-null   object
 1   Retailer ID       9648 non-null   int64
 2   Date              9648 non-null   datetime64[ns]
 3   Region            9648 non-null   object
 4   State             9648 non-null   object
 5   City              9648 non-null   object
 6   Product           9648 non-null   object
 7   Price per Unit    9648 non-null   float64
 8   Units Sold        9648 non-null   int64
 9   Total Sales       9648 non-null   float64
 10  Operating Profit  9648 non-null   float64
 11  Operating Margin  9648 non-null   float64
 12  Sales Method      9648 non-null   object
dtypes: datetime64[ns](1), float64(4), int64(2), object(6)
memory usage: 980.0+ KB
```

[8]:
```
data.duplicated().sum()
```

[8]:
```
0
```

[9]:
```
data['Date'] = pd.to_datetime(data['Date'])
data['Month'] = data['Date'].dt.month_name().str[:3]
data['year']=data['Date'].dt.year
```

[10]:
```
data.describe()
```

[10]:
```
         Retailer ID                           Date  Price per Unit  \
count   9.648000e+03                           9648     9648.000000
mean    1.173850e+06  2021-05-10 15:20:44.776119296       45.216625
min     1.128299e+06            2020-01-01 00:00:00        7.000000
25%     1.185732e+06            2021-02-17 00:00:00       35.000000
50%     1.185732e+06            2021-06-04 00:00:00       45.000000
75%     1.185732e+06            2021-09-16 00:00:00       55.000000
max     1.197831e+06            2021-12-31 00:00:00      110.000000
std     2.636038e+04                            NaN       14.705397
```

```
        Units Sold    Total Sales  Operating Profit  Operating Margin  \
count  9648.000000    9648.000000       9648.000000       9648.000000
mean    256.930037   93273.437500      34425.244761          0.422991
min       0.000000       0.000000          0.000000          0.100000
25%     106.000000    4254.500000       1921.752500          0.350000
50%     176.000000    9576.000000       4371.420000          0.410000
75%     350.000000  150000.000000      52062.500000          0.490000
max    1275.000000  825000.000000     390000.000000          0.800000
std     214.252030  141916.016727      54193.113713          0.097197

             year
count  9648.000000
mean   2020.865050
min    2020.000000
25%    2021.000000
50%    2021.000000
75%    2021.000000
max    2021.000000
std       0.341688
```

[11]:
```
data
```

[11]:
```
         Retailer  Retailer ID       Date     Region          State  \
0     Foot Locker      1185732 2020-01-01  Northeast       New York
1     Foot Locker      1185732 2020-01-02  Northeast       New York
2     Foot Locker      1185732 2020-01-03  Northeast       New York
3     Foot Locker      1185732 2020-01-04  Northeast       New York
4     Foot Locker      1185732 2020-01-05  Northeast       New York
…           …           …         …         …             …
9643  Foot Locker      1185732 2021-01-24  Northeast  New Hampshire
9644  Foot Locker      1185732 2021-01-24  Northeast  New Hampshire
9645  Foot Locker      1185732 2021-02-22  Northeast  New Hampshire
9646  Foot Locker      1185732 2021-02-22  Northeast  New Hampshire
9647  Foot Locker      1185732 2021-02-22  Northeast  New Hampshire

            City                    Product  Price per Unit  Units Sold  \
0       New York      Men's Street Footwear            50.0        1200
1       New York    Men's Athletic Footwear            50.0        1000
2       New York    Women's Street Footwear            40.0        1000
3       New York  Women's Athletic Footwear            45.0         850
4       New York              Men's Apparel            60.0         900
…          …                         …               …          …
9643  Manchester              Men's Apparel            50.0          64
9644  Manchester            Women's Apparel            41.0         105
9645  Manchester      Men's Street Footwear            41.0         184
9646  Manchester    Men's Athletic Footwear            42.0          70
9647  Manchester    Women's Street Footwear            29.0          83
```

	Total Sales	Operating Profit	Operating Margin	Sales Method	Month	year
0	600000.0	300000.00	0.50	In-store	Jan	2020
1	500000.0	150000.00	0.30	In-store	Jan	2020
2	400000.0	140000.00	0.35	In-store	Jan	2020
3	382500.0	133875.00	0.35	In-store	Jan	2020
4	540000.0	162000.00	0.30	In-store	Jan	2020
…	…	…	…	…	…	…
9643	3200.0	896.00	0.28	Outlet	Jan	2021
9644	4305.0	1377.60	0.32	Outlet	Jan	2021
9645	7544.0	2791.28	0.37	Outlet	Feb	2021
9646	2940.0	1234.80	0.42	Outlet	Feb	2021
9647	2407.0	649.89	0.27	Outlet	Feb	2021

[9648 rows x 15 columns]

[12]:
```
data.columns
```

[12]:
```
Index(['Retailer', 'Retailer ID', 'Date', 'Region', 'State', 'City', 'Product',
       'Price per Unit', 'Units Sold', 'Total Sales', 'Operating Profit',
       'Operating Margin', 'Sales Method', 'Month', 'year'],
      dtype='object')
```

2 What is the overall sales performance in Adidas product and retailer in the US

Top Products

[13]:
```
top_product_overall = data.groupby('Product')[['Units Sold', 'Total Sales',␣
↪'Operating Profit']].sum().reset_index()
top_sold = top_product_overall.sort_values(by='Units Sold', ascending=False)
top_sales = top_product_overall.sort_values(by='Total Sales', ascending=False)
top_profit = top_product_overall.sort_values(by='Operating Profit',␣
↪ascending=False)
```

[14]:
```
top_sold
```

[14]:

	Product	Units Sold	Total Sales	Operating Profit
2	Men's Street Footwear	593320	208826244.0	82802260.62
1	Men's Athletic Footwear	435526	153673680.0	51846888.19
3	Women's Apparel	433827	179038860.0	68650970.56
5	Women's Street Footwear	392269	128002813.0	45095826.81
4	Women's Athletic Footwear	317236	106631896.0	38975784.94
0	Men's Apparel	306683	123728632.0	44763030.33

[15]:
```
top_sales
```

[15]:

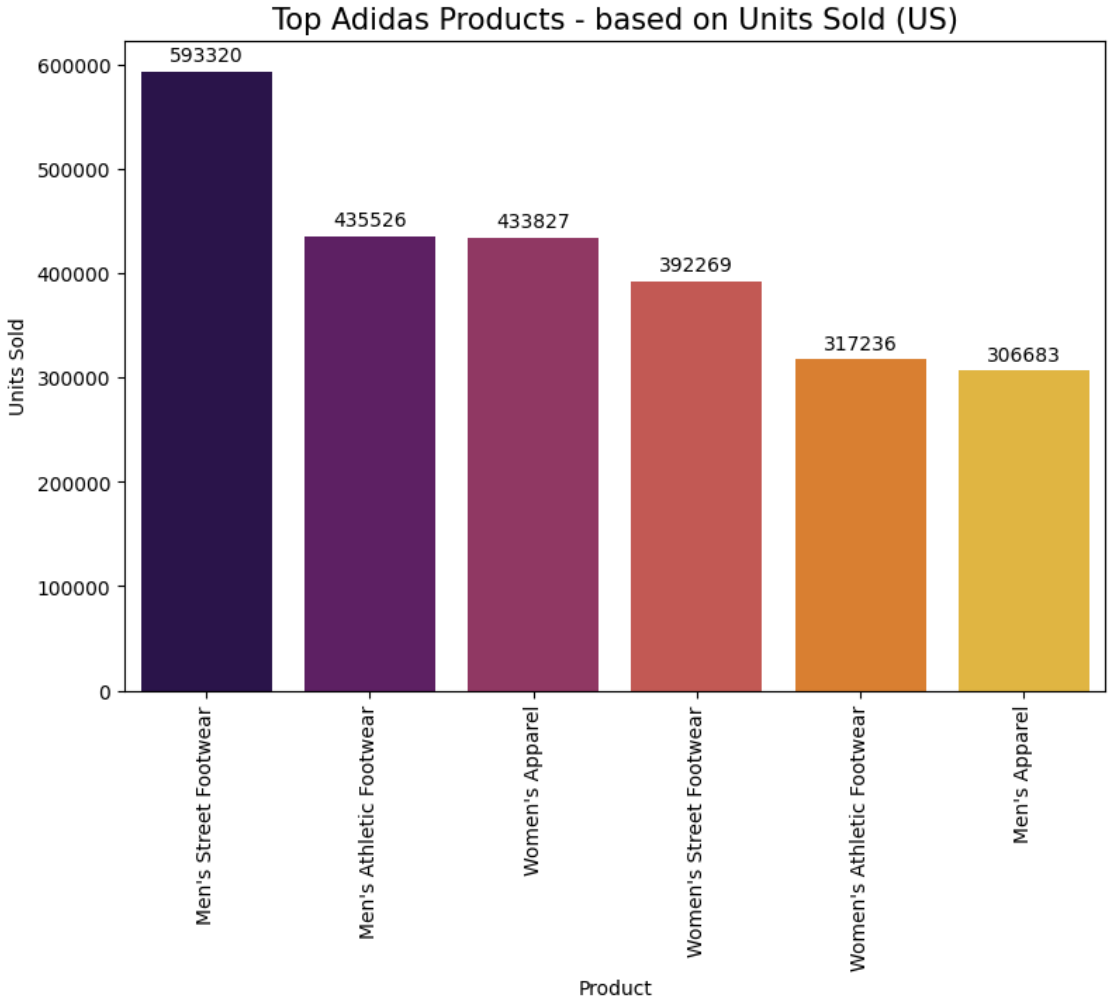
	Product	Units Sold	Total Sales	Operating Profit
2	Men's Street Footwear	593320	208826244.0	82802260.62
3	Women's Apparel	433827	179038860.0	68650970.56
1	Men's Athletic Footwear	435526	153673680.0	51846888.19
5	Women's Street Footwear	392269	128002813.0	45095826.81
0	Men's Apparel	306683	123728632.0	44763030.33
4	Women's Athletic Footwear	317236	106631896.0	38975784.94

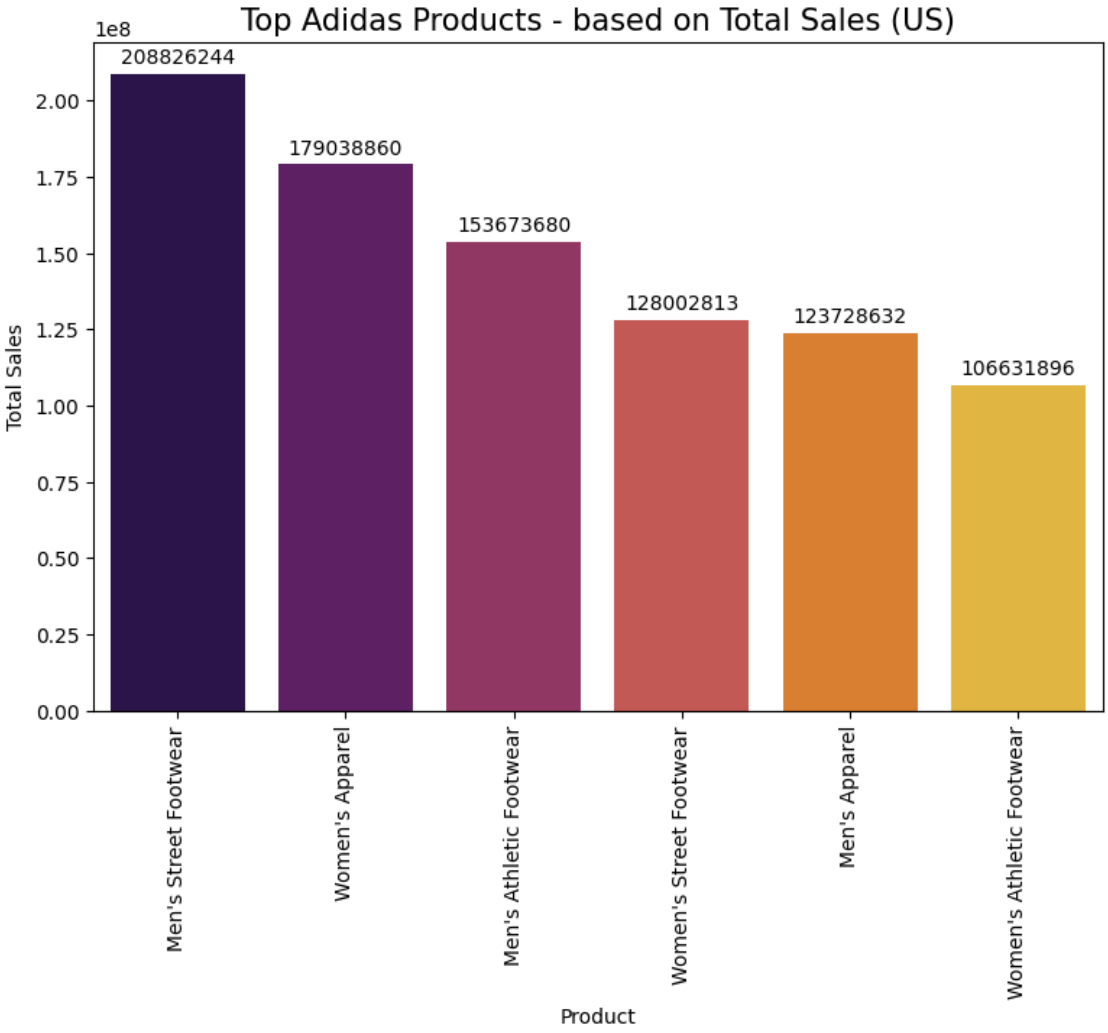
[16]:
```
top_profit
```

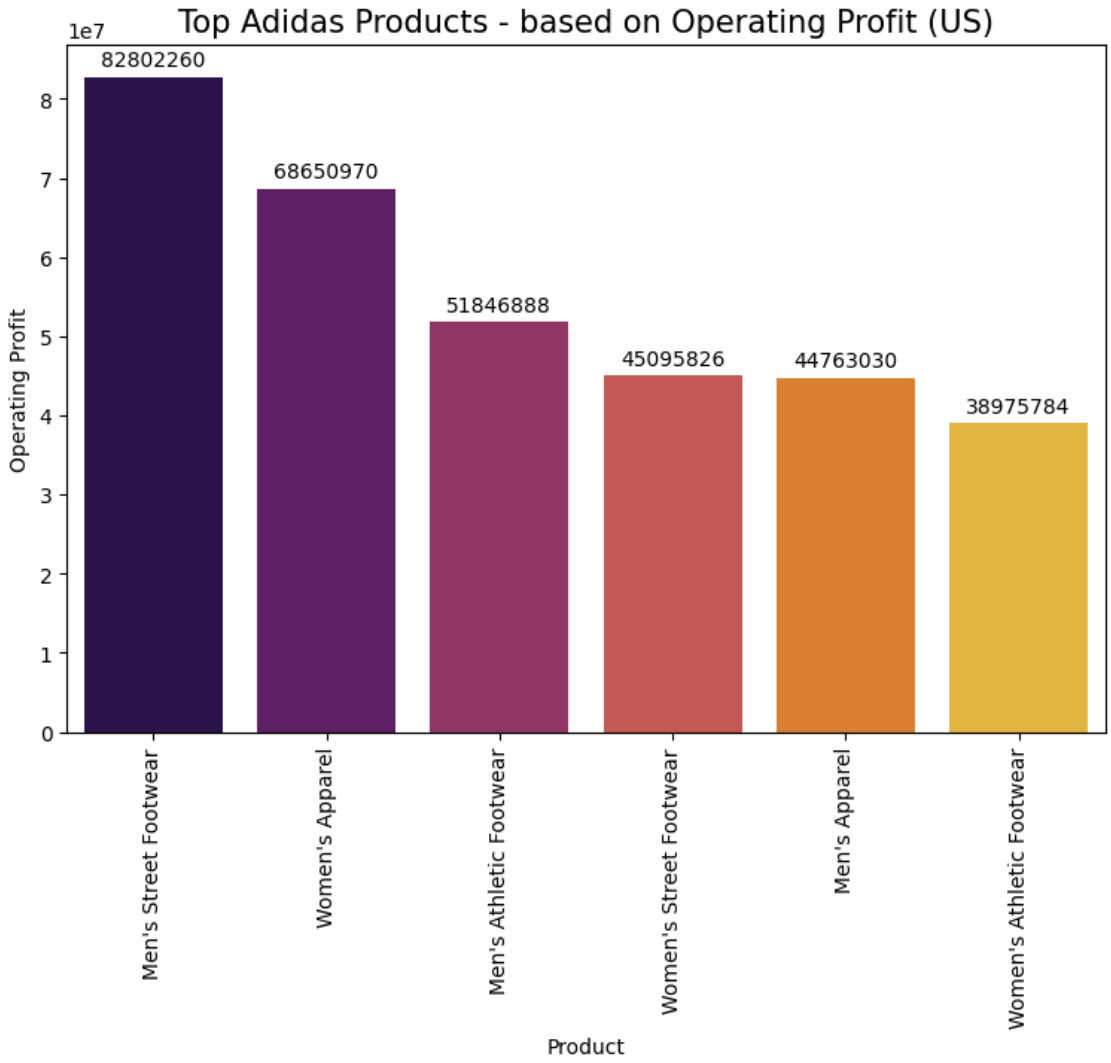
[16]:

	Product	Units Sold	Total Sales	Operating Profit
2	Men's Street Footwear	593320	208826244.0	82802260.62
3	Women's Apparel	433827	179038860.0	68650970.56
1	Men's Athletic Footwear	435526	153673680.0	51846888.19
5	Women's Street Footwear	392269	128002813.0	45095826.81
0	Men's Apparel	306683	123728632.0	44763030.33
4	Women's Athletic Footwear	317236	106631896.0	38975784.94

[17]:
```
variables = ['Units Sold', 'Total Sales', 'Operating Profit']

for variable in variables:
    top_variable = top_product_overall.sort_values(by=variable, ascending=False)

    plt.figure(figsize=(9, 6))
    ax = sns.barplot(data=top_variable, x='Product', y=variable,␣
 ↪palette='inferno')

    for container in ax.containers:
        ax.bar_label(container, fmt='%d', fontsize=10, color='black',␣
 ↪label_type='edge', padding=3)

    plt.xticks(rotation=90)
    plt.title(f"Top Adidas Products - based on {variable} (US)", size=15)
    plt.show()
```


Top Adidas Products - based on Units Sold (US)
Units Sold
600000
500000
400000
300000
200000
100000
0
593320
435526
433827
392269
317236
306683
Men's Street Footwear
Men's Athletic Footwear
Women's Apparel
Women's Street Footwear
Women's Athletic Footwear
Men's Apparel
Product


Top Adidas Products - based on Total Sales (US)
1e8
208826244
179038860
153673680
128002813
123728632
106631896
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Total Sales
Men's Street Footwear
Women's Apparel
Men's Athletic Footwear
Women's Street Footwear
Men's Apparel
Women's Athletic Footwear
Product



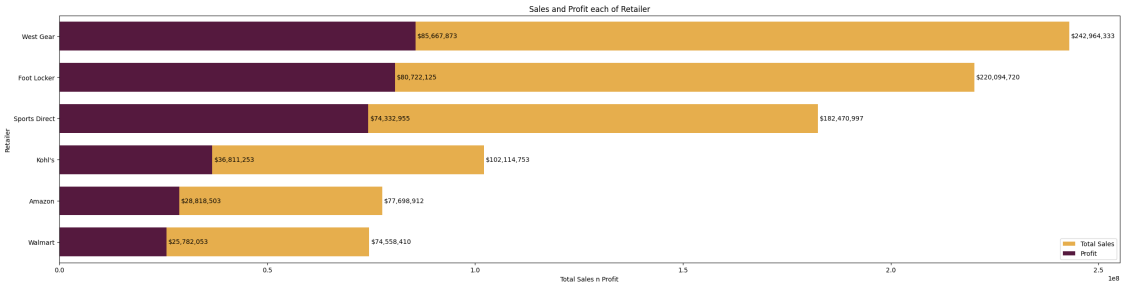
Top Retailer

[18]:
```
salesby_retail = data.groupby('Retailer')[['Total Sales', 'Operating Profit']].
  ↪sum().reset_index()
retail = salesby_retail.sort_values(by='Total Sales', ascending=False)
retail
```

[18]:

	Retailer	Total Sales	Operating Profit
5	West Gear	242964333.0	85667873.18
1	Foot Locker	220094720.0	80722124.81
3	Sports Direct	182470997.0	74332954.96
2	Kohl's	102114753.0	36811252.58
0	Amazon	77698912.0	28818503.31
4	Walmart	74558410.0	25782052.61

[19]:
```
plt.figure(figsize=(30, 7))
ax = sns.barplot(y='Retailer', x='Total Sales', data=retail, color='#FFB534',␣
 ↪edgecolor='none', width=0.7, label='Total Sales')
ax = sns.barplot(y='Retailer', x='Operating Profit', data=retail,␣
 ↪color='#5F0F40', edgecolor='none', width=0.7,  label='Profit')

def dollar_format(x, pos):
    return f"${x:,.0f}"
for container in ax.containers:
    ax.bar_label(container, fmt=FuncFormatter(dollar_format), fontsize=10,␣
 ↪color='black', label_type='edge', padding=3)

ax.set(title='Sales and Profit each of Retailer')
ax.set(ylabel='Retailer', xlabel='Total Sales n Profit')
plt.show()
```



3 What is the overall trend in Adidas sales in the US over the specified time period?

Monthwise Sales and Profit

[20]:
```
Monthwise_profit = data.groupby('Month')[['Operating Profit', 'Total Sales']].
 ↪sum().reset_index().sort_values(by='Month', ascending=False)
Monthwise_profit
```

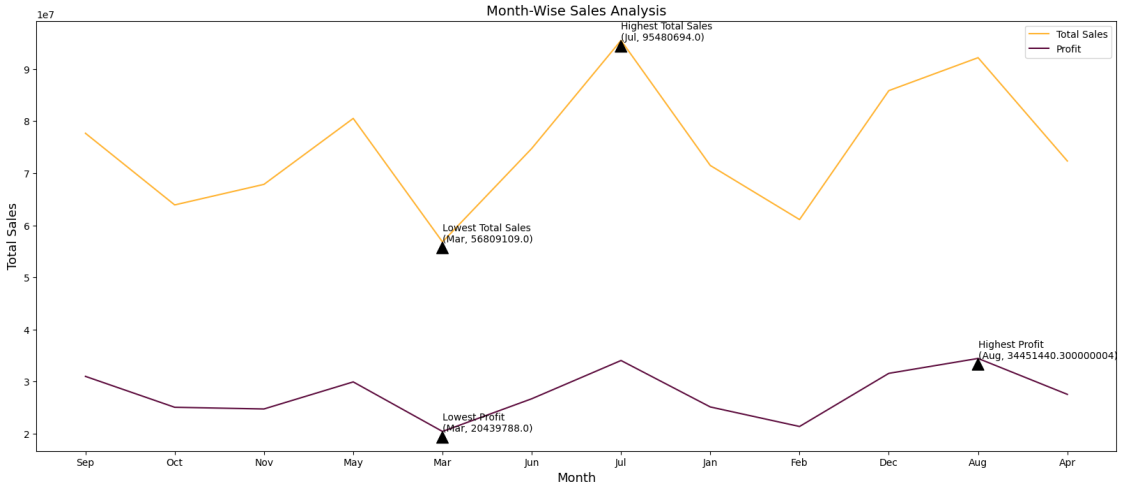
[20]:

	Month	Operating Profit	Total Sales
11	Sep	31009586.73	77661459.0
10	Oct	25078444.60	63911033.0
9	Nov	24755521.43	67857340.0
8	May	29946255.33	80507695.0
7	Mar	20439788.00	56809109.0
6	Jun	26714715.92	74747372.0
5	Jul	34054898.59	95480694.0
4	Jan	25141934.51	71479142.0
3	Feb	21392736.70	61100153.0

```
2    Dec       31590202.03   85841957.0
1    Aug       34451440.30   92166201.0
0    Apr       27559237.31   72339970.0
```

[21]:
```
plt.figure(figsize=(20, 8))

sns.lineplot(x='Month', y='Total Sales', data=Monthwise_profit,␣
 ↪color='#FFB534', label='Total Sales')
sns.lineplot(x='Month', y='Operating Profit', data=Monthwise_profit,␣
 ↪color='#5F0F40', label='Profit')

max_total_sales = Monthwise_profit.loc[Monthwise_profit['Total Sales'].idxmax()]
min_total_sales = Monthwise_profit.loc[Monthwise_profit['Total Sales'].idxmin()]

max_operating_profit = Monthwise_profit.loc[Monthwise_profit['Operating␣
 ↪Profit'].idxmax()]
min_operating_profit = Monthwise_profit.loc[Monthwise_profit['Operating␣
 ↪Profit'].idxmin()]

plt.annotate(f'Highest Total Sales\n({max_total_sales["Month"]},␣
 ↪{max_total_sales["Total Sales"]})',
             xy=(max_total_sales['Month'], max_total_sales['Total Sales']),
             xytext=(max_total_sales['Month'], max_total_sales['Total Sales'] +␣
 ↪500),
             arrowprops=dict(facecolor='black', shrink=0.05),
             fontsize=10, color='black')

plt.annotate(f'Lowest Total Sales\n({min_total_sales["Month"]},␣
 ↪{min_total_sales["Total Sales"]})',
             xy=(min_total_sales['Month'], min_total_sales['Total Sales']),
             xytext=(min_total_sales['Month'], min_total_sales['Total Sales'] -␣
 ↪500),
             arrowprops=dict(facecolor='black', shrink=0.05),
             fontsize=10, color='black')

plt.annotate(f'Highest Profit\n({max_operating_profit["Month"]},␣
 ↪{max_operating_profit["Operating Profit"]})',
             xy=(max_operating_profit['Month'], max_operating_profit['Operating␣
 ↪Profit']),
             xytext=(max_operating_profit['Month'],␣
 ↪max_operating_profit['Operating Profit'] + 500),
             arrowprops=dict(facecolor='black', shrink=0.05),
             fontsize=10, color='black')

plt.annotate(f'Lowest Profit\n({min_operating_profit["Month"]},␣
 ↪{min_operating_profit["Operating Profit"]})',
```

```
            xy=(min_operating_profit['Month'], min_operating_profit['Operating␣
 ↪Profit']),
            xytext=(min_operating_profit['Month'],␣
 ↪min_operating_profit['Operating Profit'] - 500),
            arrowprops=dict(facecolor='black', shrink=0.05),
            fontsize=10, color='black')

plt.title('Month-Wise Sales Analysis', fontsize=14)
plt.xlabel('Month', size=13)
plt.ylabel('Total Sales', size=13)
plt.legend()
plt.show()
```



Yearwise Product Sales and Profit

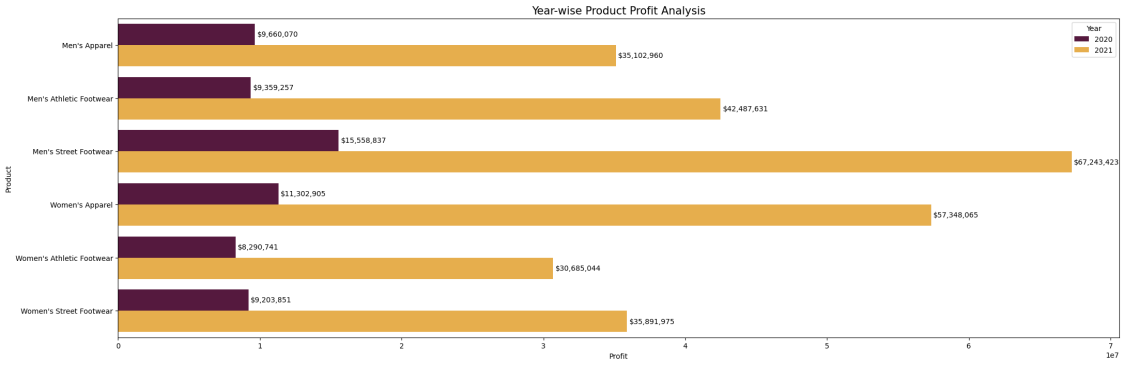
[22]:
```
yearwise= data.groupby(['year', 'Product'])[['Operating Profit', 'Total␣
 ↪Sales']].sum().reset_index()
yearwise
```

[22]:

	year	Product	Operating Profit	Total Sales
0	2020	Men's Apparel	9660070.37	26216964.0
1	2020	Men's Athletic Footwear	9359256.91	31794462.0
2	2020	Men's Street Footwear	15558837.44	37823020.0
3	2020	Women's Apparel	11302905.22	35190332.0
4	2020	Women's Athletic Footwear	8290741.17	23629892.0
5	2020	Women's Street Footwear	9203851.47	27426005.0
6	2021	Men's Apparel	35102959.96	97511668.0
7	2021	Men's Athletic Footwear	42487631.28	121879218.0
8	2021	Men's Street Footwear	67243423.18	171003224.0
9	2021	Women's Apparel	57348065.34	143848528.0

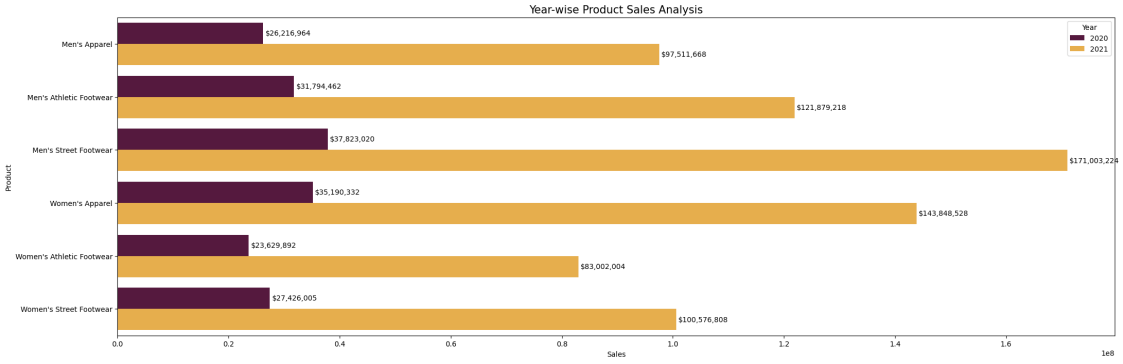
```
10  2021  Women's Athletic Footwear       30685043.77   83002004.0
11  2021    Women's Street Footwear       35891975.34  100576808.0
```

[23]:
```
custom_palette = ['#5F0F40', '#FFB534']

plt.figure(figsize=(25, 8))

ax = sns.barplot(x='Operating Profit', y='Product', hue='year', data=yearwise,␣
 ↪palette=custom_palette)

def dollar_format(x, pos):
    return f"${x:,.0f}"
for container in ax.containers:
    ax.bar_label(container, fmt=FuncFormatter(dollar_format), fontsize=10,␣
 ↪color='black', label_type='edge', padding=3)

plt.title('Year-wise Product Profit Analysis', fontsize=15)
plt.ylabel('Product')
plt.xlabel('Profit')
plt.legend(title='Year')
plt.show()
```



[24]:
```
plt.figure(figsize=(25, 8))

ax = sns.barplot(x='Total Sales', y='Product', hue='year', data=yearwise,␣
 ↪palette=custom_palette)

def dollar_format(x, pos):
    return f"${x:,.0f}"
for container in ax.containers:
    ax.bar_label(container, fmt=FuncFormatter(dollar_format), fontsize=10,␣
 ↪color='black', label_type='edge', padding=3)
```

```
plt.title('Year-wise Product Sales Analysis', fontsize=15)
plt.ylabel('Product')
plt.xlabel('Sales')
plt.legend(title='Year')
plt.show()
```



4 Is there a variation in product preferences at each retailer and which retailer in the US contributes the most to Adidas profit for each product?

[25]:
```
top_product_retail = data.groupby(['Retailer', 'Product'])[['Units Sold',␣
↪'Operating Profit']].sum().reset_index()
top_sold_retail = top_product_retail.sort_values(by=['Product', 'Units Sold'],␣
↪ascending=False)
top_profit_retail = top_product_retail.sort_values(by=['Product','Operating␣
↪Profit'], ascending=False)
top_sold_retail
```

[25]:

	Retailer	Product	Units Sold	Operating Profit
35	West Gear	Women's Street Footwear	101289	12548955.14
11	Foot Locker	Women's Street Footwear	92385	9639474.32
23	Sports Direct	Women's Street Footwear	92311	10313909.95
17	Kohl's	Women's Street Footwear	45910	5753761.30
29	Walmart	Women's Street Footwear	31745	3560034.09
5	Amazon	Women's Street Footwear	28629	3279692.01
34	West Gear	Women's Athletic Footwear	82539	10298371.50
22	Sports Direct	Women's Athletic Footwear	73697	9688746.39
10	Foot Locker	Women's Athletic Footwear	73104	8477313.73
16	Kohl's	Women's Athletic Footwear	38517	4570693.09
28	Walmart	Women's Athletic Footwear	26835	3239052.49
4	Amazon	Women's Athletic Footwear	22544	2701607.74
33	West Gear	Women's Apparel	107049	15400413.34

9	Foot Locker	Women's Apparel	104489	17192901.49
21	Sports Direct	Women's Apparel	99390	17832960.67
15	Kohl's	Women's Apparel	49012	5596172.50
27	Walmart	Women's Apparel	38002	6348451.03
3	Amazon	Women's Apparel	35885	6280071.53
8	Foot Locker	Men's Street Footwear	159081	23060809.17
32	West Gear	Men's Street Footwear	145653	20537556.88
20	Sports Direct	Men's Street Footwear	124879	15837750.43
14	Kohl's	Men's Street Footwear	66844	9219819.89
2	Amazon	Men's Street Footwear	54883	8707658.12
26	Walmart	Men's Street Footwear	41980	5438666.13
31	West Gear	Men's Athletic Footwear	111400	13228943.53
7	Foot Locker	Men's Athletic Footwear	103767	12409221.49
19	Sports Direct	Men's Athletic Footwear	100203	11935672.81
13	Kohl's	Men's Athletic Footwear	51012	5725762.60
25	Walmart	Men's Athletic Footwear	37157	4029257.65
1	Amazon	Men's Athletic Footwear	31987	4518030.11
30	West Gear	Men's Apparel	77332	13653632.79
6	Foot Locker	Men's Apparel	71543	9942404.61
18	Sports Direct	Men's Apparel	67160	8723914.71
12	Kohl's	Men's Apparel	36080	5945043.20
24	Walmart	Men's Apparel	30506	3166591.22
0	Amazon	Men's Apparel	24062	3331443.80

[26]:
```
top_profit_retail
```

[26]:

	Retailer	Product	Units Sold	Operating Profit
35	West Gear	Women's Street Footwear	101289	12548955.14
23	Sports Direct	Women's Street Footwear	92311	10313909.95
11	Foot Locker	Women's Street Footwear	92385	9639474.32
17	Kohl's	Women's Street Footwear	45910	5753761.30
29	Walmart	Women's Street Footwear	31745	3560034.09
5	Amazon	Women's Street Footwear	28629	3279692.01
34	West Gear	Women's Athletic Footwear	82539	10298371.50
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4	Amazon	Women's Athletic Footwear	22544	2701607.74
21	Sports Direct	Women's Apparel	99390	17832960.67
9	Foot Locker	Women's Apparel	104489	17192901.49
33	West Gear	Women's Apparel	107049	15400413.34
27	Walmart	Women's Apparel	38002	6348451.03
3	Amazon	Women's Apparel	35885	6280071.53
15	Kohl's	Women's Apparel	49012	5596172.50
8	Foot Locker	Men's Street Footwear	159081	23060809.17
32	West Gear	Men's Street Footwear	145653	20537556.88

20	Sports Direct	Men's Street Footwear	124879	15837750.43
14	Kohl's	Men's Street Footwear	66844	9219819.89
2	Amazon	Men's Street Footwear	54883	8707658.12
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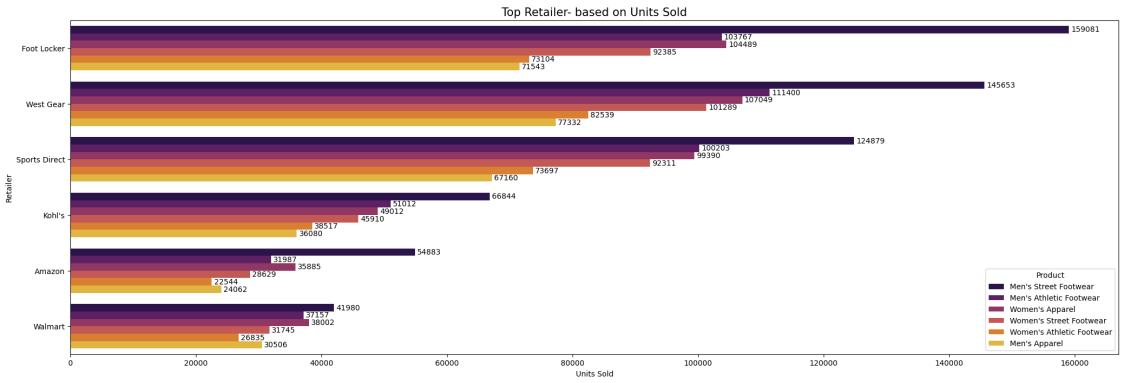
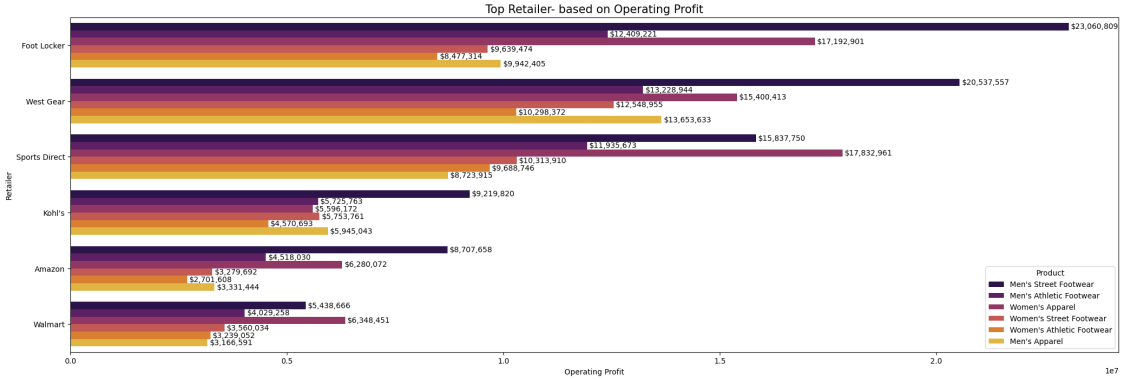
1	Amazon	Men's Athletic Footwear	31987	4518030.11
25	Walmart	Men's Athletic Footwear	37157	4029257.65
30	West Gear	Men's Apparel	77332	13653632.79
6	Foot Locker	Men's Apparel	71543	9942404.61
18	Sports Direct	Men's Apparel	67160	8723914.71
12	Kohl's	Men's Apparel	36080	5945043.20
0	Amazon	Men's Apparel	24062	3331443.80
24	Walmart	Men's Apparel	30506	3166591.22

[27]:
```
top_variable_retail = top_product_retail.sort_values(by='Units Sold',␣
↪ascending=False)

# Plotting
plt.figure(figsize=(25, 8))
ax = sns.barplot(y='Retailer', x='Units Sold', hue='Product',␣
↪data=top_variable_retail, palette='inferno')
for container in ax.containers:
    ax.bar_label(container, fmt='%d', fontsize=10, color='black',␣
↪label_type='edge', padding=3)

plt.title(f'Top Retailer- based on Units Sold', fontsize=15)
plt.ylabel('Retailer')
plt.xlabel('Units Sold')
plt.show()
```



[28]:
```
profitable_retail = top_product_retail.sort_values(by='Operating Profit',␣
 ↪ascending=False)

plt.figure(figsize=(25, 8))
ax = sns.barplot(y='Retailer', x='Operating Profit', hue='Product',␣
 ↪data=top_variable_retail, palette='inferno')
def dollar_format(x, pos):
    return f"${x:,.0f}"
for container in ax.containers:
    ax.bar_label(container, fmt=FuncFormatter(dollar_format), fontsize=10,␣
 ↪color='black', label_type='edge', padding=3)

plt.title(f'Top Retailer- based on Operating Profit', fontsize=15)
plt.ylabel('Retailer')
plt.xlabel('Operating Profit')
plt.show()
```



5 Which city, state, and region in the US contribute the most to Adidas sales, and are there any regional variations in product preferences?

[29]:
```
top_city = data.groupby('City')[['Total Sales']].sum().reset_index().
 ↪sort_values(by='Total Sales', ascending=False).head(10)
top_city
```

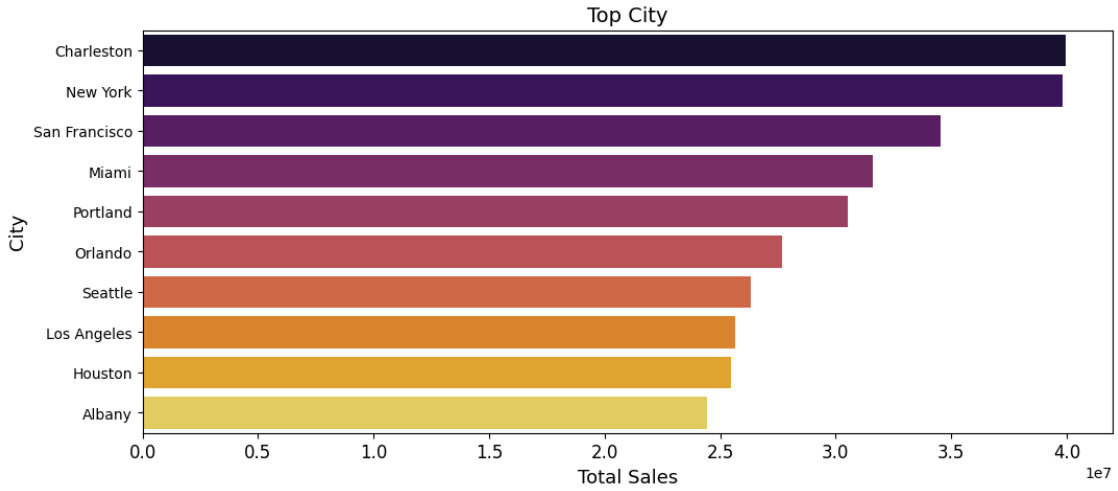
[29]:

	City	Total Sales
10	Charleston	39974797.0
35	New York	39801235.0
46	San Francisco	34539220.0
31	Miami	31600863.0
42	Portland	30545652.0

```
39        Orlando   27682851.0
47        Seattle   26330718.0
28    Los Angeles   25634913.0
22        Houston   25456882.0
0          Albany   24427804.0
```

[30]:
```
plt.figure(figsize=(12,5))
sns.barplot(x='Total Sales',y='City',data=top_city,palette = 'inferno')
plt.xticks(size= 12)
plt.title('Top City',size= 14)
plt.xlabel('Total Sales',size = 13)
plt.ylabel('City',size = 13)
```

[30]:
```
Text(0, 0.5, 'City')
```

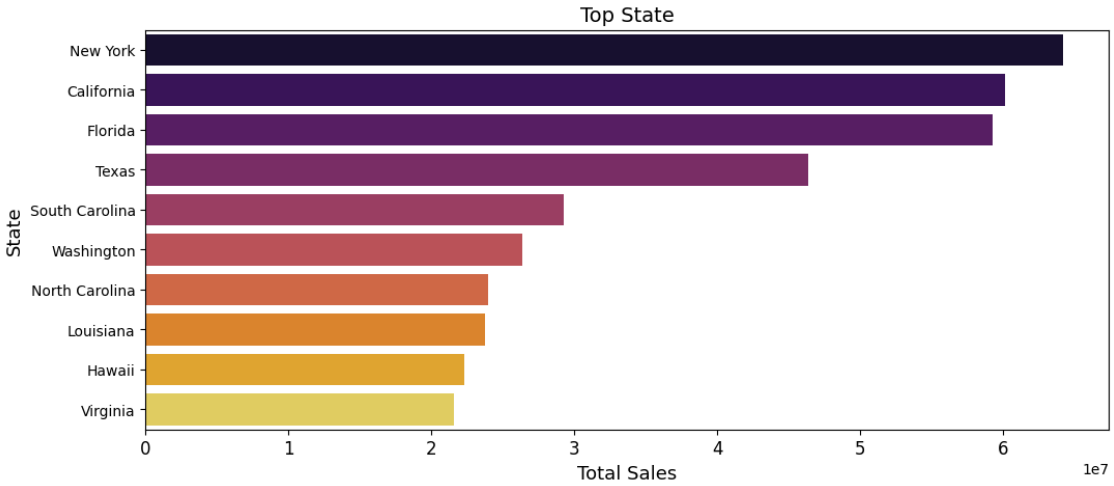


[31]:
```
top_state = data.groupby('State')[['Total Sales']].sum().reset_index().
 ↪sort_values(by='Total Sales', ascending=False).head(10)
top_state
```

[31]:
```
            State  Total Sales
31       New York   64229039.0
4      California   60174133.0
8         Florida   59283714.0
42          Texas   46359746.0
39  South Carolina   29285637.0
46      Washington   26330718.0
32  North Carolina   23956531.0
17       Louisiana   23750781.0
10          Hawaii   22282457.0
45        Virginia   21575040.0
```

[32]:
```
plt.figure(figsize=(12,5))
sns.barplot(x='Total Sales',y='State',data=top_state ,palette = 'inferno')
plt.xticks(size= 12)
plt.title('Top State',size= 14)
plt.xlabel('Total Sales',size = 13)
plt.ylabel('State',size = 13)
```

[32]:
```
Text(0, 0.5, 'State')
```

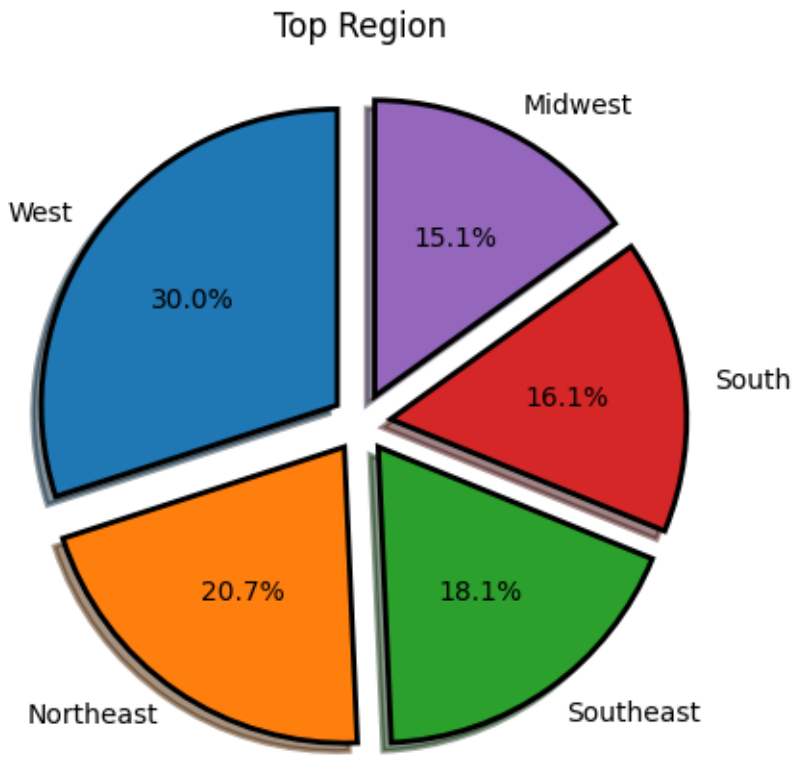


[33]:
```
salesby_region = data.groupby('Region')['Total Sales'].sum().reset_index().
 ↪sort_values(by='Total Sales', ascending=False)
salesby_region
```

[33]:

	Region	Total Sales
4	West	269943182.0
1	Northeast	186324067.0
3	Southeast	163171236.0
2	South	144663181.0
0	Midwest	135800459.0

[34]:
```
fig, ax = plt.subplots(figsize=(5, 5))
wp = {'linewidth': 2, 'edgecolor': 'black'}
explode = (0.1,) * len(salesby_region)

ax.pie(salesby_region['Total Sales'], labels=salesby_region['Region'],␣
 ↪autopct='%1.1f%%',
       shadow=True, startangle=90, wedgeprops=wp, explode=explode)
ax.set_title('Top Region')
plt.show()
```



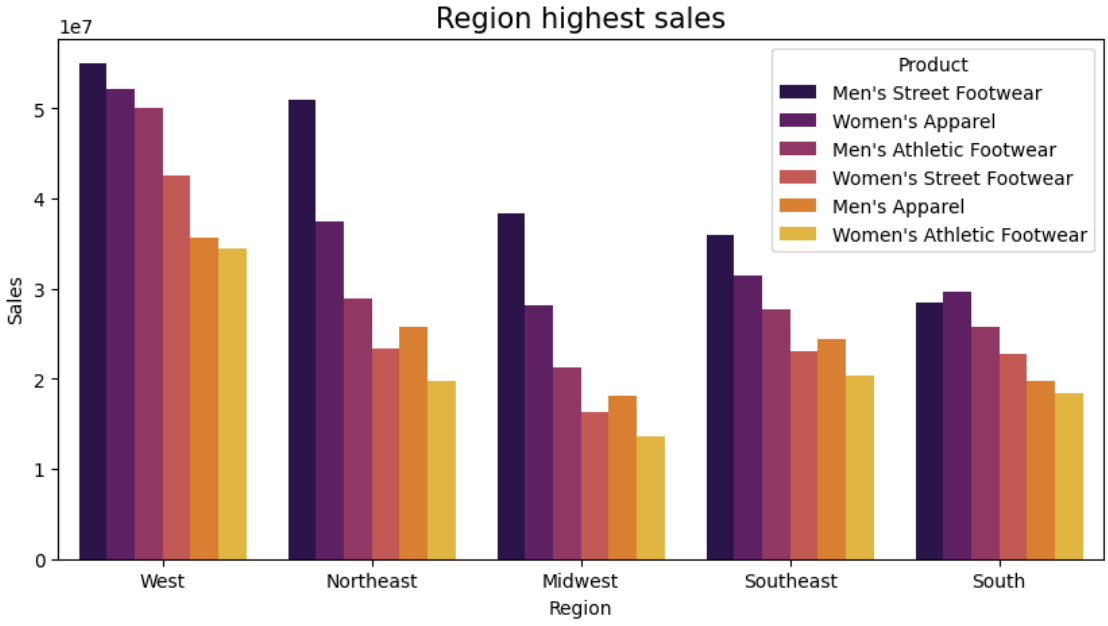
[35]:
```
product_region = data.groupby(['Region', 'Product'])[['Units Sold', 'Total␣
↪Sales']].sum()
top_product_region = product_region.sort_values(by='Total Sales',␣
↪ascending=False)
top_product_region
```

[35]:

Region	Product	Units Sold	Total Sales
West	Men's Street Footwear	150795	55014613.0
	Women's Apparel	116765	52191046.0
Northeast	Men's Street Footwear	134252	51025024.0
West	Men's Athletic Footwear	127724	50006339.0
	Women's Street Footwear	113705	42520111.0
Midwest	Men's Street Footwear	109861	38322810.0
Northeast	Women's Apparel	90048	37543083.0
Southeast	Men's Street Footwear	91867	36019236.0
West	Men's Apparel	84322	35694003.0
	Women's Athletic Footwear	93674	34517070.0
Southeast	Women's Apparel	68839	31491161.0
South	Women's Apparel	88740	29607187.0
Northeast	Men's Athletic Footwear	81474	28874237.0

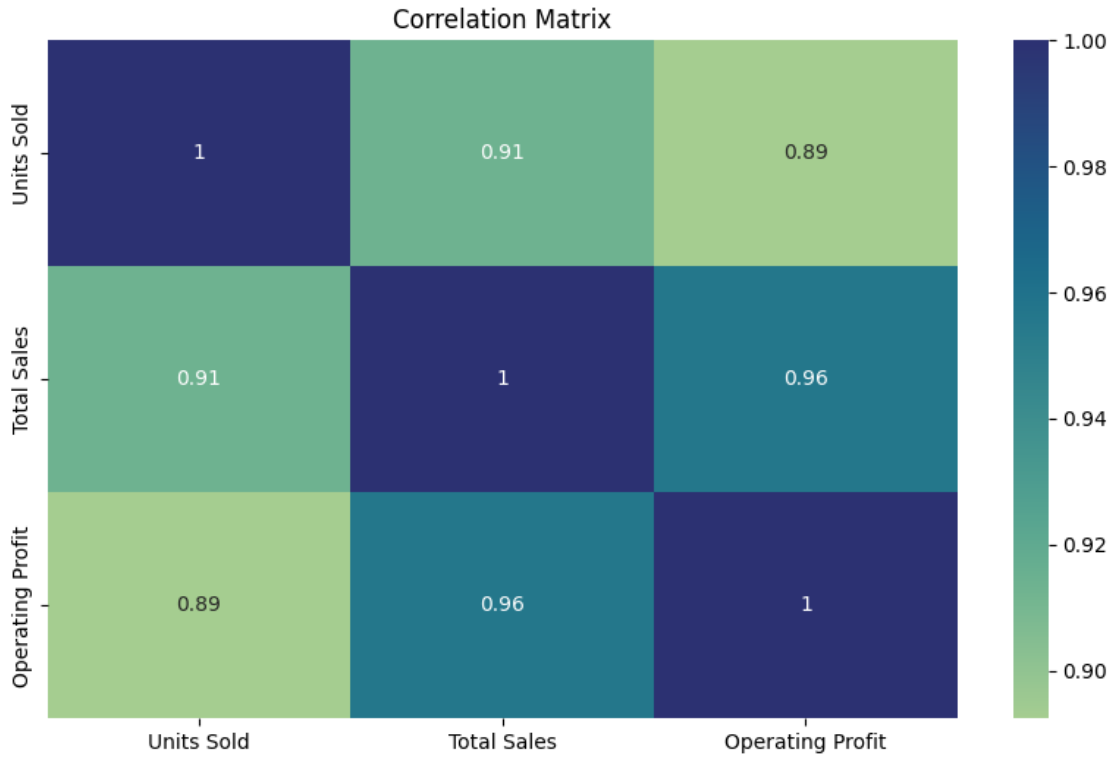
```
South     Men's Street Footwear          106545   28444561.0
Midwest   Women's Apparel                 69435   28206383.0
Southeast Men's Athletic Footwear         71129   27777020.0
Northeast Men's Apparel                   62031   25744412.0
South     Men's Athletic Footwear         90079   25710545.0
Southeast Men's Apparel                   54385   24461487.0
Northeast Women's Street Footwear         74010   23341173.0
Southeast Women's Street Footwear         65488   23119534.0
South     Women's Street Footwear         82257   22777097.0
Midwest   Men's Athletic Footwear         65120   21305539.0
Southeast Women's Athletic Footwear       55292   20302798.0
Northeast Women's Athletic Footwear       59464   19796138.0
South     Men's Apparel                   60641   19703069.0
          Women's Athletic Footwear       63998   18420722.0
Midwest   Men's Apparel                   45304   18125661.0
          Women's Street Footwear         56809   16244898.0
          Women's Athletic Footwear       44808   13595168.0
```

[36]:
```
plt.figure(figsize = (10,5))
sns.barplot(x='Region' , y= 'Total Sales' , hue = 'Product' , data =␣
 ↪top_product_region, palette = 'inferno')
plt.title('Region highest sales',fontsize=15)
plt.xlabel('Region')
plt.ylabel('Sales')
plt.show()
```



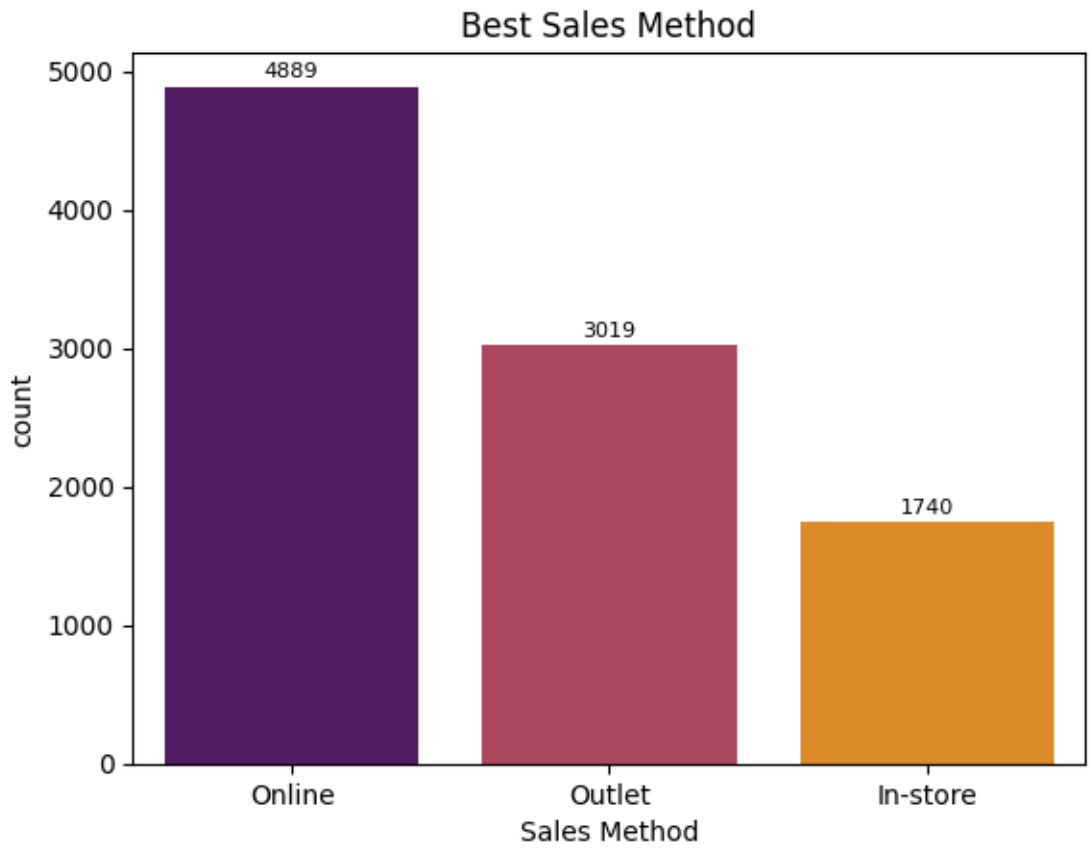
6 Is there a correlation between the Units Sold, Total Sales, and Operating Profit for Adidas products in US?

[37]:
```
correlation_matrix = df[['Units Sold', 'Total Sales', 'Operating Profit']].
 ↪corr()
plt.figure(figsize=(10, 6))
sns.heatmap(correlation_matrix, annot=True, cmap="crest")
plt.title("Correlation Matrix")
plt.show()
```



7 What is the most effective sales method to use, and what is the variation in sales methods for Adidas across different retailers?

[38]:
```
ax = sns.barplot(data=data['Sales Method'].value_counts(), palette='inferno')
for container in ax.containers:
    ax.bar_label(container, fmt='%d', fontsize=8, color='black',␣
 ↪label_type='edge', padding=2)
plt.title('Best Sales Method')
plt.show()
```



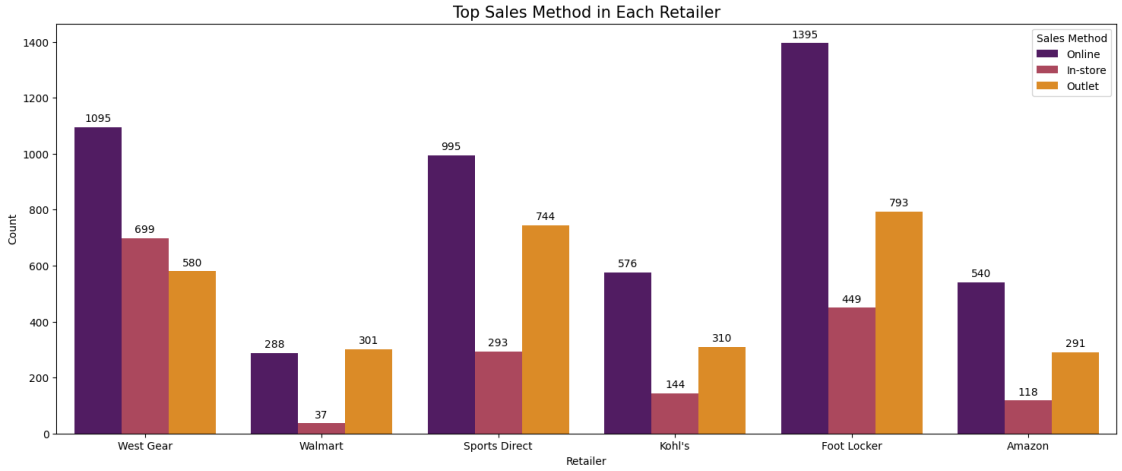
[39]:
```
best_sales = data.groupby('Retailer')['Sales Method'].value_counts().
 ↪reset_index(name='Count')
best_sales_method = best_sales.sort_values(by=['Retailer', 'Count'],␣
 ↪ascending=[False, False])
best_sales_method
```

[39]:

	Retailer	Sales Method	Count
15	West Gear	Online	1095
16	West Gear	In-store	699
17	West Gear	Outlet	580
12	Walmart	Outlet	301
13	Walmart	Online	288
14	Walmart	In-store	37
9	Sports Direct	Online	995
10	Sports Direct	Outlet	744
11	Sports Direct	In-store	293
6	Kohl's	Online	576
7	Kohl's	Outlet	310
8	Kohl's	In-store	144

```
3     Foot Locker       Online   1395
4     Foot Locker       Outlet    793
5     Foot Locker     In-store    449
0          Amazon       Online    540
1          Amazon       Outlet    291
2          Amazon     In-store    118
```

[40]:
```
# Plotting
plt.figure(figsize=(18, 7))
ax = sns.barplot(x='Retailer', y='Count', hue='Sales Method',␣
 ↪data=best_sales_method, palette='inferno')
for container in ax.containers:
    ax.bar_label(container, fmt='%d', fontsize=10, color='black',␣
 ↪label_type='edge', padding=3)

plt.title(f'Top Sales Method in Each Retailer', fontsize=15)
plt.show()
```



8 Sales Forecast w/ Arima, Sarima, & ExponentialSmoothing Holt-Winters

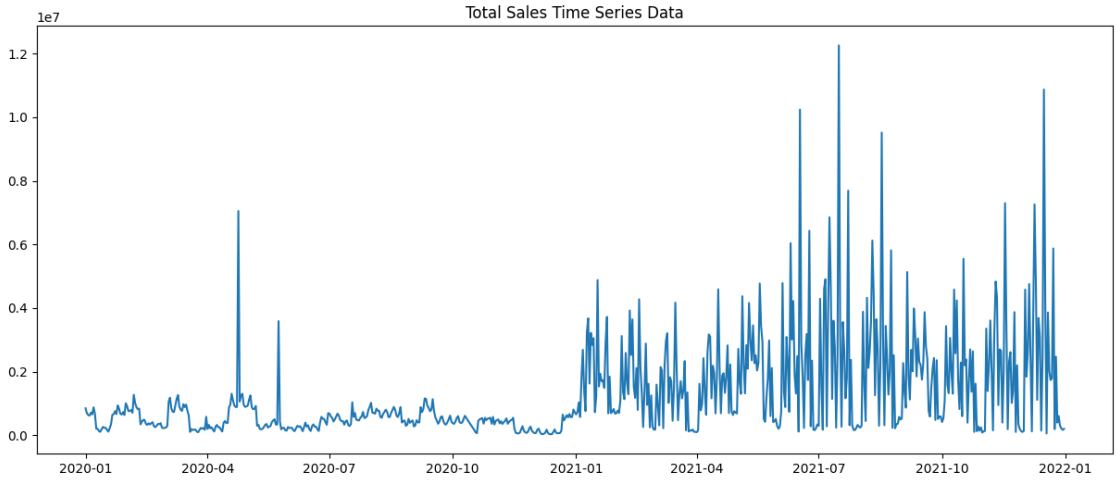
[41]:
```
grouped_data = df.groupby('Date')['Total Sales'].sum().reset_index()
grouped_data['Date'] = pd.to_datetime(grouped_data['Date'])
grouped_data
```

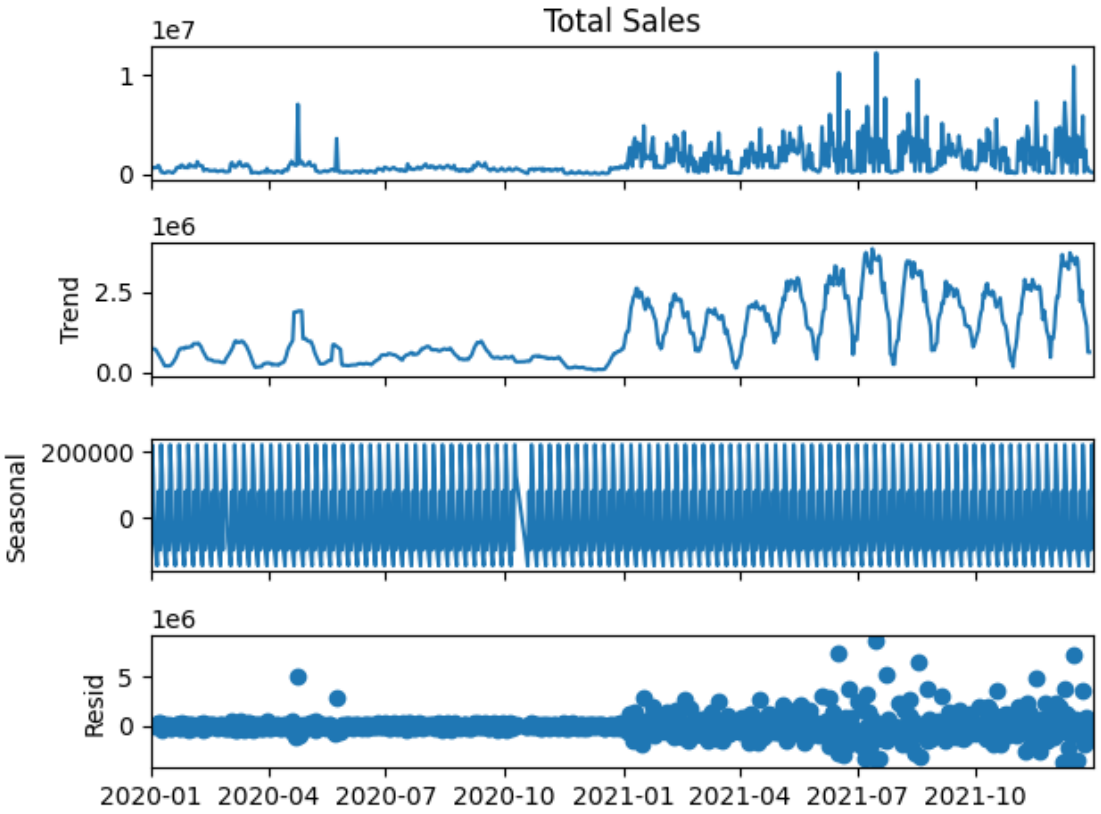
[41]:
```
        Date  Total Sales
0 2020-01-01     845141.0
1 2020-01-02     689410.0
2 2020-01-03     632573.0
3 2020-01-04     615080.0
```

```
4   2020-01-05     707829.0
..         …          …
719 2021-12-27     602353.0
720 2021-12-28     301010.0
721 2021-12-29     211109.0
722 2021-12-30     167903.0
723 2021-12-31     198659.0

[724 rows x 2 columns]
```

[42]:
```
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.tsa.holtwinters import ExponentialSmoothing
from statsmodels.tsa.seasonal import seasonal_decompose

date_sales_data = grouped_data.set_index('Date')
plt.figure(figsize=(15, 6))
plt.plot(date_sales_data['Total Sales'])
plt.title('Total Sales Time Series Data')
plt.show()

# Decompose the time series data to understand its components
result = seasonal_decompose(date_sales_data['Total Sales'], model='additive',␣
 ↪period=7)  # Adjusted period
result.plot()
plt.show()

# Define the training and testing sets
train_size = int(len(date_sales_data) * 0.8)
train, test = date_sales_data[:train_size], date_sales_data[train_size:]

# ARIMA model
order = (5, 1, 0)  # You may need to adjust these parameters based on your data␣
 ↪and analysis
arima_model = ARIMA(train, order=order)
arima_fit = arima_model.fit()
print(arima_fit.summary())
# Forecasting with ARIMA
arima_forecast = arima_fit.predict(start=len(train), end=len(train) + len(test)␣
 ↪- 1, typ='levels')

# SARIMA model
seasonal_order = (0, 1, 1, 12)  # You may need to adjust these parameters based␣
 ↪on your data and analysis
sarima_model = SARIMAX(train, order=order, seasonal_order=seasonal_order)
sarima_fit = sarima_model.fit()
print(sarima_fit.summary())
```

```
# Forecasting with SARIMA
sarima_forecast = sarima_fit.predict(start=len(train), end=len(train) +␣
 ↪len(test) - 1, typ='levels')

# Exponential Smoothing model
exponential_model = ExponentialSmoothing(train, seasonal='add',␣
 ↪seasonal_periods=7)  # Adjusted parameters
exponential_fit = exponential_model.fit()
print(exponential_fit.summary())
# Forecasting with Exponential Smoothing
exponential_forecast = exponential_fit.predict(start=len(train), end=len(train)␣
 ↪+ len(test) - 1)

# Plot the ARIMA forecast
plt.figure(figsize=(15, 6))
plt.plot(train.index, train['Total Sales'], label='Training Data')
plt.plot(test.index, test['Total Sales'], label='Actual Sales')
plt.plot(test.index, arima_forecast, label='ARIMA Forecast', linestyle='dashed')
plt.title('ARIMA Forecasting')
plt.legend()
plt.show()

# Plot the SARIMA forecast
plt.figure(figsize=(15, 6))
plt.plot(train.index, train['Total Sales'], label='Training Data')
plt.plot(test.index, test['Total Sales'], label='Actual Sales')
plt.plot(test.index, sarima_forecast, label='SARIMA Forecast',␣
 ↪linestyle='dashed')
plt.title('SARIMA Forecasting')
plt.legend()
plt.show()

# Plot the Exponential Smoothing forecast
plt.figure(figsize=(15, 6))
plt.plot(train.index, train['Total Sales'], label='Training Data')
plt.plot(test.index, test['Total Sales'], label='Actual Sales')
plt.plot(test.index, exponential_forecast, label='Exponential Smoothing␣
 ↪Forecast', linestyle='dashed')
plt.title('Exponential Smoothing Forecasting')
plt.legend()
plt.show()
```






```
c:\Users\muham\AppData\Local\Programs\Python\Python311\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:473: 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\muham\AppData\Local\Programs\Python\Python311\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: A date index has
been provided, but it has no associated frequency information and so will be
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c:\Users\muham\AppData\Local\Programs\Python\Python311\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:473: 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)
```

SARIMAX Results

Dep. Variable:	Total Sales	No. Observations:	579
Model:	ARIMA(5, 1, 0)	Log Likelihood	-8860.198
Date:	Mon, 11 Mar 2024	AIC	17732.396
Time:	09:09:34	BIC	17758.553
Sample:	0	HQIC	17742.596
	- 579		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.7643	0.030	-25.300	0.000	-0.823	-0.705
ar.L2	-0.6797	0.034	-19.781	0.000	-0.747	-0.612
ar.L3	-0.4128	0.033	-12.519	0.000	-0.477	-0.348
ar.L4	-0.2104	0.036	-5.918	0.000	-0.280	-0.141
ar.L5	-0.1689	0.026	-6.607	0.000	-0.219	-0.119
sigma2	1.218e+12	6.17e-14	1.97e+25	0.000	1.22e+12	1.22e+12

Ljung-Box (L1) (Q):	2.25	Jarque-Bera (JB):	9359.85
Prob(Q):	0.13	Prob(JB):	0.00
Heteroskedasticity (H):	9.02	Skew:	2.68
Prob(H) (two-sided):	0.00	Kurtosis:	21.97

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 1.09e+40. Standard errors may be unstable.

```
c:\Users\muham\AppData\Local\Programs\Python\Python311\Lib\site-
```

```
packages\statsmodels\tsa\base\tsa_model.py:836: ValueWarning: No supported index
is available. Prediction results will be given with an integer index beginning
at `start`.
  return get_prediction_index(
c:\Users\muham\AppData\Local\Programs\Python\Python311\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:473: 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\muham\AppData\Local\Programs\Python\Python311\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:473: 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)
```

SARIMAX Results

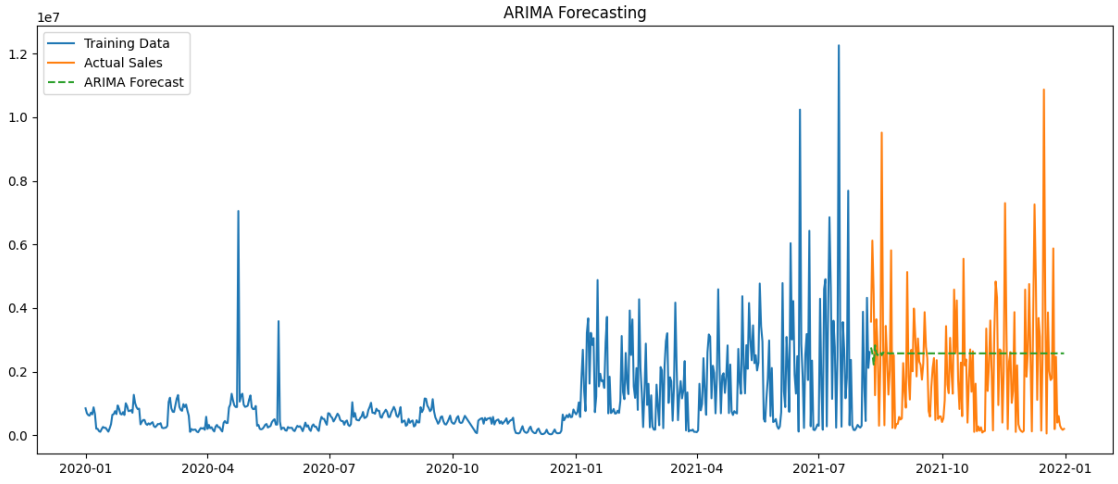
Dep. Variable:	Total Sales	No. Observations:	579
Model:	SARIMAX(5, 1, 0)x(0, 1, [1], 12)	Log Likelihood	-8753.414
Date:	Mon, 11 Mar 2024	AIC	17520.828
Time:	09:09:35	BIC	17551.198
Sample:	0	HQIC	17532.681
	- 579		
Covariance Type:	opg		

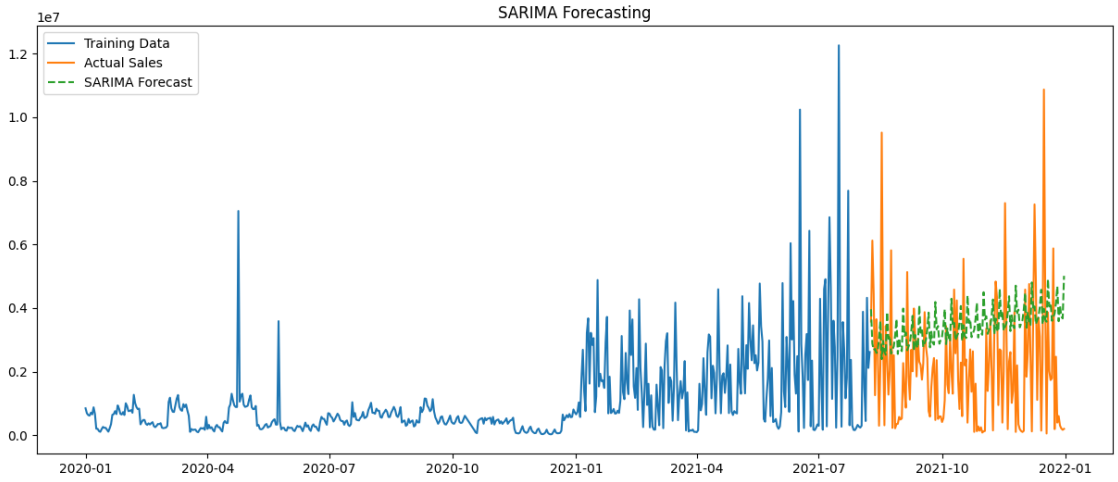
	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.7493	0.063	-11.965	0.000	-0.872	-0.627
ar.L2	-0.6676	0.071	-9.406	0.000	-0.807	-0.528
ar.L3	-0.3790	0.070	-5.386	0.000	-0.517	-0.241
ar.L4	-0.1592	0.078	-2.048	0.041	-0.312	-0.007
ar.L5	-0.1629	0.059	-2.766	0.006	-0.278	-0.047
ma.S.L12	-0.9149	0.040	-22.913	0.000	-0.993	-0.837
sigma2	2.615e+12	5.47e-14	4.78e+25	0.000	2.61e+12	2.61e+12

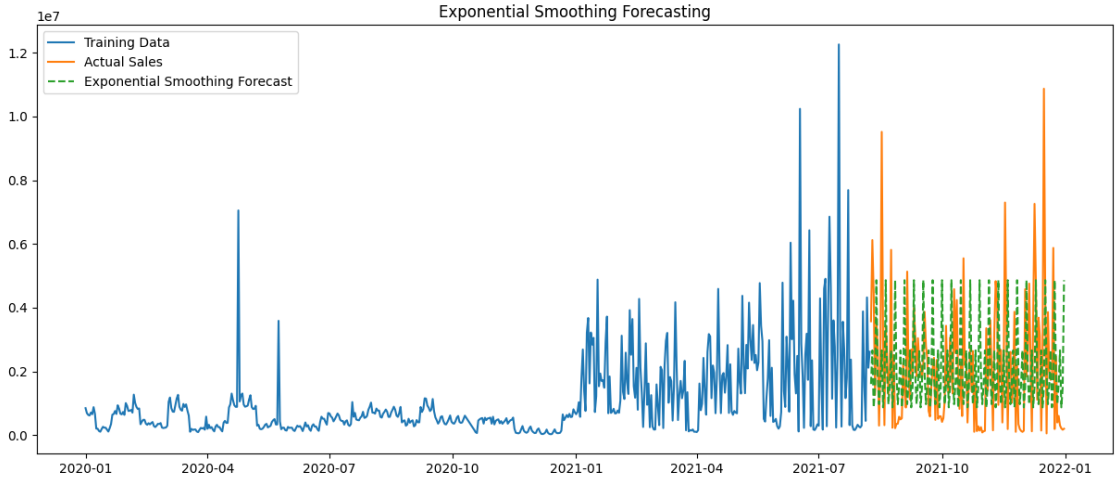
Ljung-Box (L1) (Q):	1.85	Jarque-Bera (JB):	6497.21
Prob(Q):	0.17	Prob(JB):	0.00
Heteroskedasticity (H):	8.41	Skew:	2.31

```
Prob(H) (two-sided):                  0.00   Kurtosis:
18.94
===============================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
[2] Covariance matrix is singular or near-singular, with condition number
inf. Standard errors may be unstable.
                       ExponentialSmoothing Model Results
===============================================================================
=
Dep. Variable:              Total Sales   No. Observations:
579
Model:             ExponentialSmoothing   SSE
656010821156310.125
Optimized:                         True   AIC
16088.664
Trend:                             None   BIC
16127.915
Seasonal:                      Additive   AICC
16089.129
Seasonal Periods:                     7   Date:                  Mon, 11 Mar
2024
Box-Cox:                          False   Time:
09:09:35
Box-Cox Coeff.:                    None
===============================================================================
=
                          coeff                 code              optimized
-------------------------------------------------------------------------------
-
smoothing_level               0.1700000               alpha
True
smoothing_seasonal            0.3192308               gamma
True
initial_level                 8.083e+05                 l.0
True
initial_seasons.0             54293.662                 s.0
True
initial_seasons.1            -63607.088                 s.1
True
initial_seasons.2            -13050.659                 s.2
True
initial_seasons.3            -19076.081                 s.3
True
initial_seasons.4            -30173.623                 s.4
```

```
True
initial_seasons.5            -28502.445                  s.5
True
initial_seasons.6            1.0012e+05                  s.6
True
--------------------------------------------------------------------------------
-

c:\Users\muham\AppData\Local\Programs\Python\Python311\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:836: ValueWarning: No supported index
is available. Prediction results will be given with an integer index beginning
at `start`.
  return get_prediction_index(
c:\Users\muham\AppData\Local\Programs\Python\Python311\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:473: 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\muham\AppData\Local\Programs\Python\Python311\Lib\site-
packages\statsmodels\tsa\holtwinters\model.py:917: ConvergenceWarning:
Optimization failed to converge. Check mle_retvals.
  warnings.warn(
c:\Users\muham\AppData\Local\Programs\Python\Python311\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:836: ValueWarning: No supported index
is available. Prediction results will be given with an integer index beginning
at `start`.
  return get_prediction_index(
```







[43]:
```python
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
# ARIMA
mae_arima = mean_absolute_error(test['Total Sales'], arima_forecast)
print(f'MAE for ARIMA: {mae_arima}')

# SARIMA
mae_sarima = mean_absolute_error(test['Total Sales'], sarima_forecast)
print(f'MAE for SARIMA: {mae_sarima}')

# Exponential Smoothing
mae_exponential = mean_absolute_error(test['Total Sales'], exponential_forecast)
print(f'MAE for Exponential Smoothing: {mae_exponential}')
```

```
# ARIMA
mse_arima = mean_squared_error(test['Total Sales'], arima_forecast)
print(f'MSE for ARIMA: {mse_arima}')

# SARIMA
mse_sarima = mean_squared_error(test['Total Sales'], sarima_forecast)
print(f'MSE for SARIMA: {mse_sarima}')

# Exponential Smoothing
mse_exponential = mean_squared_error(test['Total Sales'], exponential_forecast)
print(f'MSE for Exponential Smoothing: {mse_exponential}')

rmse_arima = np.sqrt(mse_arima)
rmse_sarima = np.sqrt(mse_sarima)
rmse_exponential = np.sqrt(mse_exponential)

print(f'RMSE for ARIMA: {rmse_arima}')
print(f'RMSE for SARIMA: {rmse_sarima}')
print(f'RMSE for Exponential Smoothing: {rmse_exponential}')
```

```
MAE for ARIMA: 1513423.0591785987
MAE for SARIMA: 2032261.0393489825
MAE for Exponential Smoothing: 1760107.4265754463
MSE for ARIMA: 3757834518143.952
MSE for SARIMA: 5929796040358.019
MSE for Exponential Smoothing: 5378670010677.431
RMSE for ARIMA: 1938513.481548156
RMSE for SARIMA: 2435117.2539239293
RMSE for Exponential Smoothing: 2319195.9836713737
```

[44]:
```
# Extend the time index for the next 30 days
forecast_index = pd.date_range(start=date_sales_data.index[-1] + pd.
 ↪DateOffset(1), periods=30, freq='D')

# ARIMA forecast for the next 30 days
arima_future_forecast = arima_fit.predict(start=len(date_sales_data),␣
 ↪end=len(date_sales_data) + 29, typ='levels', alpha=0.05)

# SARIMA forecast for the next 30 days
sarima_future_forecast = sarima_fit.predict(start=len(date_sales_data),␣
 ↪end=len(date_sales_data) + 29, typ='levels', alpha=0.05)

# Exponential Smoothing forecast for the next 30 days
exponential_future_forecast = exponential_fit.
 ↪predict(start=len(date_sales_data), end=len(date_sales_data) + 29)

# Plot the extended forecasts with Exponential Smoothing
```

```
plt.figure(figsize=(15, 6))
plt.plot(date_sales_data.index, date_sales_data['Total Sales'], label='Actual␣
    ↪Sales')
plt.plot(forecast_index, arima_future_forecast, label='ARIMA Forecast',␣
    ↪linestyle='dashed')
plt.plot(forecast_index, sarima_future_forecast, label='SARIMA Forecast',␣
    ↪linestyle='dashed')
plt.plot(forecast_index, exponential_future_forecast, label='Exponential␣
    ↪Smoothing Forecast', linestyle='dashed')
plt.title('Extended Forecast for the Next 30 Days')
plt.legend()
plt.show()
```

```
c:\Users\muham\AppData\Local\Programs\Python\Python311\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:836: ValueWarning: No supported index
is available. Prediction results will be given with an integer index beginning
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at `start`.
  return get_prediction_index(
c:\Users\muham\AppData\Local\Programs\Python\Python311\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:836: ValueWarning: No supported index
is available. Prediction results will be given with an integer index beginning
at `start`.
  return get_prediction_index(
```

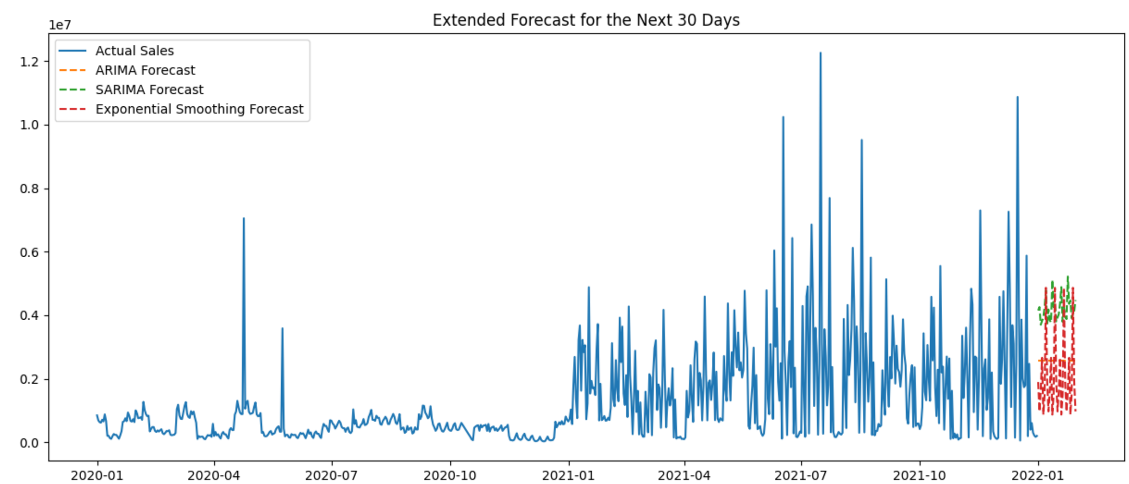

9 Conclusion

1. The results shows that the performance of Adidas products in the United States is evaluated based on Units Sold, Total Sales, and Operating Profit. Men's Street Footwear emerges as the best-selling product with 593,320 units sold. On the other hand, Men's Apparel is the least popular product with only 30,683 units sold. Additionally, Men's Street Footwear stands out with the highest sales and profit, amounting to $208,826,244.00 and $82,802,260.62, respectively.

2. The overall trend in Adidas sales in the US over the specified month-wise and year-wise analysis indicates that, on a month-wise basis, both sales and profit exhibit a fluctuating pattern. July emerges as the best-performing month and August based on profit, while March stands out as the least favorable. On a year-wise analysis, sales and profit in 2021 show improvement compared to 2020.

3. Based on Units Sold, Adidas products are predominantly sold through Gear Wear, except for Men's Street Footwear, which sees the highest sales through Foot Locker. In terms of profit, Foot Locker contributes the highest profit for Men's Street Footwear. Sports Direct leads in profit for Women's Apparel, while Gear Wear tops the list for Women's Street Footwear, Women's Athletic Footwear, Men's Athletic Footwear, and Men's Apparel.

4. The cities that contribute the most to Adidas sales in the US are Charleston, New York, and San Francisco, while the leading states are New York, California, and Florida. Additionally, the West region stands out as the top-performing region for Adidas sales in the US. Men's Street Footwear exhibits the highest sales in every region except the South, where Men's Apparel takes the lead as the best-selling product.

5. Overall, the correlation matrix suggests strong positive correlations between all three variables. This means that as Units Sold, Total Sales, and Operating Profit increase, the other two variables tend to increase as well. Here's a breakdown of the specific correlations:

    - Units Sold and Total Sales: The correlation coefficient of 0.98 indicates a very strong positive correlation. This means that as the number of units sold increases, the total sales amount also increases, and vice versa.
    - Total Sales and Operating Profit: The correlation coefficient of 0.96 also suggests a very strong positive correlation. This implies that as total sales increase, operating profit also tends to increase, and vice versa.
    - Units Sold and Operating Profit: The correlation coefficient of 0.91 represents a strong positive correlation. This suggests that as the number of units sold increases, operating profit also tends to increase, although not as strongly as the correlation between Total Sales and Operating Profit.

6. Online is the most prevalent sales method used by Adidas, this is likely due to the increasing popularity of online shopping among consumers. In-store is the second most common sales method used by Adidas, this is likely due to the convenience of shopping at physical stores and the opportunity to try products on directly. Outlets are the least common sales method for Adidas, this is likely due to the lower prices at outlets, which may attract bargain-hunting consumers.

10 Suggestions (Based on Conclusions)

1. Sales and Profit Optimization Based on Best-Least Product

By observing that Men's Street Footwear emerges as the best-selling product and Men's Apparel is the least popular, Adidas can focus on marketing strategies and boosting sales for these products. This may involve:

for Men's Street Footwear (Best-Selling): - Keep Men's Street Footwear fresh with innovative designs and collaborations. - Launch limited editions to create exclusivity and drive demand. - Develop targeted campaigns emphasizing unique features. - Implement exclusive loyalty programs for Men's Street Footwear buyers. - Explore variations within Men's Street Footwear for market diversity.

for Men's Apparel (Least Popular): - Revamp Men's Apparel with new styles aligned with trends. - Create promotions bundling Men's Apparel with other products. - Develop strategies to appeal to a broader audience. - Introduce limited-time discounts to boost Men's Apparel sales.

2. Month and Year (wise) Optimization

Adidas should align marketing strategies with seasonal trends, implementing targeted campaigns and managing inventory effectively to address the month-wise fluctuations observed in sales and profit. Specifically, focusing on peak months like July can capitalize on increased consumer activity. For year-wise improvements, the brand should analyze successful factors contributing to the growth in 2021 and develop a strategic plan accordingly.

3. Best Products at the Top Retailers

Adidas can strategically enhance its performance across different retailers by tailoring approaches to each key partner. Firstly, with Gear Wear serving as the overall sales leader, Adidas should intensify collaboration by introducing exclusive releases and joint marketing initiatives. This concerted effort aims to broaden the consumer reach and solidify the brand's presence in the market. Simultaneously, with Foot Locker dominating in Men's Street Footwear sales, Adidas should capitalize on this success through exclusive collaborations. Such collaborations can not only sustain the demand for Men's Street Footwear but also attract Foot Locker's specific customer base, creating a mutually beneficial relationship. Additionally, recognizing Sports Direct as the leader in Women's Apparel profitability, Adidas should prioritize collaborative efforts to optimize the Women's Apparel product line.

4. Regionalized Triumph: Tailored Strategies for Adidas Sales in US

Each location represents diverse consumer preferences and lifestyles, necessitating tailored marketing approaches. For instance, New York may benefit from exclusive collections and dynamic in-store experiences, while California could focus on active lifestyle campaigns. In Florida, season-specific promotions emphasizing athleisure wear for warm climates may be key. The West region's success indicates an opportunity for Adidas to tap into the innovation-driven and outdoor-focused culture, introducing technologically advanced sports gear. Additionally, in the South, where Men's Apparel leads in sales, a strategic emphasis on expanding and promoting this product line can enhance overall performance. This region-specific approach enables Adidas to strengthen its market presence, cater to diverse consumer demands, and sustain success across key cities, states, and regions in the United States.

5. Capitalize Units Sold, Sales, and Profit Correlations

To capitalize on these correlations, a strategic focus on driving Units Sold becomes pivotal. This could involve targeted marketing campaigns, product promotions, and enhanced distribution channels to stimulate sales growth. Furthermore, given the robust connection between Total Sales and Operating Profit, a holistic approach to revenue generation and cost management is essential. Strategies that optimize pricing, streamline operational efficiency, and leverage economies of scale can contribute to maximizing both Total Sales and Operating Profit. The correlation between Units Sold and Operating Profit, though slightly less strong, still underscores the importance of operational efficiency in converting sales into profitability. In essence, a comprehensive strategy that aligns marketing efforts with driving sales, while concurrently optimizing operational aspects, can harness these correlations for sustained business success.

6. Improve and Optimize Sales Method

To leverage this prevalent method, continuous enhancements to the online shopping experience, such as user-friendly interfaces, personalized recommendations, and efficient order processing, can be implemented. Additionally, targeted digital marketing campaigns and exclusive online promotions can further capitalize on the popularity of e-commerce, engaging with consumers and driving online sales growth. While online sales dominate, the acknowledgment of in-store shopping as the second most common method highlights the enduring importance of physical retail spaces. Adidas can optimize this channel by prioritizing an immersive in-store experience, incorporating innovative technologies like augmented reality for virtual try-ons, and organizing exclusive in-store events to attract foot traffic. Furthermore, emphasizing the seamless integration of online and in-store experiences, such as click-and-collect services and online-exclusive products available for in-store purchase, can create a cohesive shopping journey for consumers. Lastly, for outlets, exploring strategies to highlight the unique value proposition of outlet purchases, such as exclusive discounts or limited-edition releases, may attract bargain-seeking customers and increase the appeal of this sales channel.

THANK YOU!!!

REACH ME OUT ON:

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