MAXIMIZING ADIDAS REVENUE: SALES FORECASTS AND TREND ANALYSIS

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INTRODUCTION

This project aims to deliver a comprehensive analysis of Adidas' sales performance to identify the strategies underpinning their success in the competitive sports apparel market. Using a detailed dataset, I will examine factors including product popularity, regional sales trends, and the correlation between sales volume and profit margins. Additionally, I will develop a sales forecast model to predict future performance.

The goal is to offer actionable insights into Adidas' business model and how they maintain their industry leadership. This project holds value for marketing professionals, data analysts, financial stakeholders, and those interested in understanding the dynamics of the sports apparel industry.

REQUIREMENTS

This project analyzes the "Adidas Sales Dataset" (CSV format) obtained from Kaggle. My data analysis relied on the Google Python Colab environment, while Tableau was employed to create interactive visualizations. The dataset structure includes the following columns:

- **Retailer:** Names such as Foot Locker, Walmart, Sports Direct, and West Gear.
- **Retailer ID:** A unique identifier for each retailer.
- **Invoice Date:** The date the invoice was generated.
- **Region:** Geographic areas like West, Northeast, Southeast, South, and Mid-west.
- **Product:** Categories like Men’s and Women’s Street and Athletic Footwear, and Apparel.
- **Price per Unit:** The cost of a single item of a specific product.
- **Units Sold:** The quantity of a product sold in a specific timeframe.
- **Total Sales:** The total revenue from sales over a certain period.
- **Operating Profit:** A measure of the profitability from the main business operations.
- **Operating Margin:** A ratio indicating the profitability of the business operations.
- **Sales Method:** The channels through which sales were made, including In-store, Outlet, and Online.

	Retailer	Retailer ID	Invoice Date	Region	State	City	Product	Price per Unit	Units Sold	Total Sales	Operating Profit	Operating Margin	Sales Method
0	Foot Locker	1185732	2020-01-01	Northeast	New York	New York	Men's Street Footwear	50.0	1200	600000.0	300000.0	0.50	In-store
1	Foot Locker	1185732	2020-01-02	Northeast	New York	New York	Men's Athletic Footwear	50.0	1000	500000.0	150000.0	0.30	In-store
2	Foot Locker	1185732	2020-01-03	Northeast	New York	New York	Women's Street Footwear	40.0	1000	400000.0	140000.0	0.35	In-store
3	Foot Locker	1185732	2020-01-04	Northeast	New York	New York	Women's Athletic Footwear	45.0	850	382500.0	133875.0	0.35	In-store
4	Foot Locker	1185732	2020-01-05	Northeast	New York	New York	Men's Apparel	60.0	900	540000.0	162000.0	0.30	In-store
5	Foot Locker	1185732	2020-01-06	Northeast	New York	New York	Women's Apparel	50.0	1000	500000.0	125000.0	0.25	In-store
6	Foot Locker	1185732	2020-01-07	Northeast	New York	New York	Men's Street Footwear	50.0	1250	625000.0	312500.0	0.50	In-store
7	Foot Locker	1185732	2020-01-08	Northeast	New York	New York	Men's Athletic Footwear	50.0	900	450000.0	135000.0	0.30	Outlet
8	Foot Locker	1185732	2020-01-21	Northeast	New York	New York	Women's Street Footwear	40.0	950	380000.0	133000.0	0.35	Outlet
9	Foot Locker	1185732	2020-01-22	Northeast	New York	New York	Women's Athletic Footwear	45.0	825	371250.0	129937.5	0.35	Outlet
10	Foot Locker	1185732	2020-01-23	Northeast	New York	New York	Men's Apparel	60.0	900	540000.0	162000.0	0.30	Outlet
11	Foot Locker	1185732	2020-01-24	Northeast	New York	New York	Women's Apparel	50.0	1000	500000.0	125000.0	0.25	Outlet
12	Foot Locker	1185732	2020-01-25	Northeast	New York	New York	Men's Street Footwear	50.0	1220	610000.0	305000.0	0.50	Outlet
13	Foot Locker	1185732	2020-01-26	Northeast	New York	New York	Men's Athletic Footwear	50.0	925	462500.0	138750.0	0.30	Outlet
14	Foot Locker	1185732	2020-01-27	Northeast	New York	New York	Women's Street Footwear	40.0	950	380000.0	133000.0	0.35	Outlet

Head of the dataset

The first step towards any data analysis project/ task should be Exploratory Data Analysis (EDA).

Exploratory Data Analysis (EDA):

Exploratory Data Analysis (EDA) plays a vital role in the data analysis process. In this phase, I meticulously examined the dataset to identify trends, anomalies, and relationships. This provided insights that will guide subsequent analytical steps. EDA enabled me to detect missing data, outliers, and key correlations, and to identify significant variables. I employed various visualization techniques to understand the data's distribution and central tendencies, revealing underlying patterns.
As a result of this EDA phase, I achieved the following:

- Gain a clear understanding of the dataset’s structure, including its size and key characteristics.
- Spot and remove any duplicate entries to ensure the accuracy of our findings.
- Chart the progression of sales over different timeframes, notably years and months.
- Investigate how sales figures varied month-to-month.

This step was important and crucial in establishing a solid base for informed decision-making, enabling us to extract valuable insights from the data with greater precision and relevance.

Business problems that can be solved using this dataset:

1. Sales Performance Analysis: Which products are excelling in sales, and which are underperforming?
2. Regional Market Analysis: Which stores are experiencing strong sales, and which ones are lagging?
3. Profit Margin Analysis: Does the profit margin significantly impact sales?
4. Efficiency of Sales Methods: Which sales method is more effective — in-store or online?
5. Price Optimization: Is there a specific price range that achieves better sales than others?
6. Product Portfolio Optimization I: Determine which products are most profitable, segmented by location.
7. Market Expansion Opportunities: Assess the best and worst performing stores based on their locations.
8. Time Series Analysis: Investigate whether there has been a consistent sales trend over time or any noticeable monthly trends.
9. Predictive Sales Analysis: Develop a forecast for monthly sales.
10. Tableau Sales Dashboard

Data Cleaning and Pre-Processing:

I understand the paramount importance of data cleaning and pre-processing in ensuring the quality of any dataset. In this project, I diligently addressed inconsistencies, missing values, and formatting issues within the data. This careful preparation laid a solid foundation for subsequent analysis, guaranteeing the accuracy and relevance of all generated insights.

Importing the required Python libraries:

```
[ ]  import pandas as pd
     import matplotlib.pyplot as plt
     import plotly.express as px
     import plotly.graph_objects as go
     import seaborn as sns
     from statsmodels.tsa.seasonal import seasonal_decompose
     from statsmodels.tsa.arima.model import ARIMA
     import plotly.graph_objs as go
```

DataFrame shape:

```
[ ]  # Shape of the dataframe
     data.shape

     (9648, 13)
```

Duplicate Values

```
[ ]  # Duplicate Rows
     data.duplicated().sum()

     0
```

Duplicate Values:

Duplicate values in a dataset can lead to skewed or inaccurate analyses by artificially inflating the size of the data or creating misleading patterns.

```
[ ]  # Duplicate Rows
     data.duplicated().sum()

     0
```

Info. of the Dataset:

This method offers a comprehensive overview of the dataset, detailing its size, data integrity (non-null counts), data types, and memory usage.

```
[ ]  # Duplicate Rows
     data.duplicated().sum()
```

```
0
```

Info. of the Dataset:

This method offers a comprehensive overview of the dataset, detailing its size, data integrity (non-null counts), data types, and memory usage.

```
[ ] # Info of the dataset
    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   Invoice 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
```

Checking for Null Values:

Checking for null values involves identifying any missing or undefined data in each column. Understanding the presence and distribution of null values helps in making informed decisions about how to handle them, whether it’s through imputation, removal, or other methods.

```
[ ]  # Null values
     data.isnull().sum()

     Retailer            0
     Retailer ID         0
     Invoice 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
```

Head of the dataset:

```
# Overview of the data head
data.head()
```

	Retailer	Retailer ID	Invoice Date	Region	State	City	Product	Price per Unit	Units Sold	Total Sales	Operating Profit	Operating Margin	Sales Method
0	Foot Locker	1185732	2020-01-01	Northeast	New York	New York	Men's Street Footwear	50.0	1200	600000.0	300000.0	0.50	In-store
1	Foot Locker	1185732	2020-01-02	Northeast	New York	New York	Men's Athletic Footwear	50.0	1000	500000.0	150000.0	0.30	In-store
2	Foot Locker	1185732	2020-01-03	Northeast	New York	New York	Women's Street Footwear	40.0	1000	400000.0	140000.0	0.35	In-store
3	Foot Locker	1185732	2020-01-04	Northeast	New York	New York	Women's Athletic Footwear	45.0	850	382500.0	133875.0	0.35	In-store
4	Foot Locker	1185732	2020-01-05	Northeast	New York	New York	Men's Apparel	60.0	900	540000.0	162000.0	0.30	In-store

Tail of the dataset:

```
# Overview of the data tail
data.tail()
```

	Retailer	Retailer ID	Invoice Date	Region	State	City	Product	Price per Unit	Units Sold	Total Sales	Operating Profit	Operating Margin	Sales Method
9643	Foot Locker	1185732	2021-01-24	Northeast	New Hampshire	Manchester	Men's Apparel	50.0	64	3200.0	896.00	0.28	Outlet
9644	Foot Locker	1185732	2021-01-24	Northeast	New Hampshire	Manchester	Women's Apparel	41.0	105	4305.0	1377.60	0.32	Outlet
9645	Foot Locker	1185732	2021-02-22	Northeast	New Hampshire	Manchester	Men's Street Footwear	41.0	184	7544.0	2791.28	0.37	Outlet
9646	Foot Locker	1185732	2021-02-22	Northeast	New Hampshire	Manchester	Men's Athletic Footwear	42.0	70	2940.0	1234.80	0.42	Outlet
9647	Foot Locker	1185732	2021-02-22	Northeast	New Hampshire	Manchester	Women's Street Footwear	29.0	83	2407.0	649.89	0.27	Outlet

Removing non-numeric characters from the columns:

In order to convert data to a numeric format, it's often necessary to remove non-numeric characters such as currency symbols or commas. Occasionally, columns expected to contain numeric data may include non-numeric characters. The columns that underwent this cleaning process include Total Sales, Units Sold, Operating Profit, and Operating Margin.

```
# # Remove non-numeric characters from the columns
data['Total Sales'] = data['Total Sales'].astype(str).str.replace(r'[$, ]', '', regex=True).astype(float)
data['Units Sold'] = data['Units Sold'].astype(str).str.replace(r'[$, ]', '', regex=True).astype(float)
data['Operating Profit'] = data['Operating Profit'].astype(str).str.replace(r'[$, ]', '', regex=True).astype(float)
data['Operating Margin'] = data['Operating Margin'].astype(str).str.replace(r'[$, ]', '', regex=True).astype(float)
```

Converting Invoice Date to DateTime object:

Converting Invoice Date to a DateTime object enables precise handling of temporal data, essential for accurate date-based calculations and time-sensitive analyses.

```
[ ]  # Convert Invoice Date to DateTime Object.
     data['Invoice Date'] = pd.to_datetime(data['Invoice Date'])
```

SALES ANALYSIS:

Total revenue:

Total revenue is the total income a business generates from selling goods or services before deducting expenses. It's a key metric of financial health, calculated by multiplying the price of a product or service by the quantity sold.

```
# First lets find out the total revenue
total_revenue = data['Total Sales'].sum()
total_revenue
```

```
899902125.0
```

LET'S START BY ADDRESSING KEY BUSINESS QUESTIONS THAT WILL ASSIST ADIDAS IN IDENTIFYING ITS STRENGTHS AND AREAS FOR IMPROVEMENT.

1. Sales Performance Analysis: Which products are excelling in sales, and which are underperforming?

```
[ ] # Aggregating total sales and units sold for each product
    product_sales = data.groupby('Product').agg({'Total Sales': 'sum', 'Units Sold': 'sum'}).reset_index()

    # Sorting products by total sales in descending order to identify top-performing products
    top_performing_products = product_sales.sort_values(by='Total Sales', ascending=False).head()

    # Displaying the results
    print("Top-Performing Products:")
    top_performing_products
```

Top-Performing Products:

	Product	Total Sales	Units Sold
2	Men's Street Footwear	208826244.0	593320.0
3	Women's Apparel	179038860.0	433827.0
1	Men's Athletic Footwear	153673680.0	435526.0
5	Women's Street Footwear	128002813.0	392269.0
0	Men's Apparel	123728632.0	306683.0

```
# Sorting products by total sales in ascending order to identify underperforming products
underperforming_products = product_sales.sort_values(by='Total Sales', ascending=True).head()

print("\nUnderperforming Products:")
underperforming_products
```

Underperforming Products:

	Product	Total Sales	Units Sold
4	Women's Athletic Footwear	106631896.0	317236.0
0	Men's Apparel	123728632.0	306683.0
5	Women's Street Footwear	128002813.0	392269.0
1	Men's Athletic Footwear	153673680.0	435526.0
3	Women's Apparel	179038860.0	433827.0

KEY INSIGHT

This disparity suggests potential growth areas and indicates a need for targeted strategies to enhance the appeal of underperforming categories like Women's Athletic Footwear.

Men's Street Footwear:

Emerges as the top-performing category with robust sales amounting to $208,826,244, highlighting a strong market preference.

Women's Athletic Footwear

shows a relatively lower performance, recording sales of $106,631,896.

2. Regional Market Analysis: Which stores are experiencing strong sales, and which ones are lagging?

I grouped the data by city and retailer to analyze sales by retailer within each location. I then used the .sum() method to calculate total units sold per retailer in each city. Finally, I sorted the data in ascending order by city and descending order by units sold. This presents sales data systematically by city, highlighting top-selling retailers within each location.

```
[ ] # Group by 'City' and 'Retailer', and sum the 'Units Sold'
    three_columns_grouped = data.groupby(['City', 'Retailer'])['Units Sold'].sum().reset_index()

    # Sorting the results within each city to find the top and worst performing retailers
    three_columns_sorted = three_columns_grouped.sort_values(by=['City', 'Units Sold'], ascending=[True, False])

    # Getting the top performing retailer in each city
    top_performers = three_columns_sorted.groupby('City').head(1)

    # Getting the worst performing retailer in each city
    worst_performers = three_columns_sorted.groupby('City').tail(1)
```

```
[ ] # Display the results
    print("Top Performing Retailers in Each City:")
    top_performers.head()
```

Top Performing Retailers in Each City:

	City	Retailer	Units Sold
1	Albany	West Gear	47133.0
2	Albuquerque	Kohl's	43752.0
4	Anchorage	Amazon	26749.0
7	Atlanta	Sports Direct	41414.0
8	Baltimore	Foot Locker	9322.0

```
[ ]
print("\nWorst Performing Retailers in Each City:")
worst_performers.head()
```

```
Worst Performing Retailers in Each City:
```

	City	Retailer	Units Sold
0	Albany	Kohl's	10053.0
3	Albuquerque	Sports Direct	8881.0
5	Anchorage	Foot Locker	4066.0
6	Atlanta	Foot Locker	14977.0
10	Baltimore	West Gear	5647.0

KEY INSIGHT

Conversely, the lowest performers are Kohl’s in Albany and Sports Direct in Albuquerque, with sales of 10,053 and 8,881 units respectively.

West Gear in Albany

Top performer in Albany, selling 47,133 units.

Kohl’s in Albuquerque

Top performer in Albuquerque, selling 43,752 units.

3. Profit Margin Analysis: Does the Operating profit significantly impact sales?

To address the query, I have two potential methods. Firstly, I could construct detailed tables and graphs to facilitate an in-depth analysis. Alternatively, I could assess the correlation between Operating Profit and Total Sales. A positive correlation would suggest a 'yes' answer, while a negative correlation would imply a 'no.'

```
# Correlation bewtween Operating Profit and Total Sales
correlation = data['Operating Profit'].corr(data['Total Sales'])
correlation
```

```
0.9563074349716087
```

0.9563 correlation indicates a strong positive correlation between Total Sales and Operating Profit.

```
[ ] # Correlation bewtween Operating Profit and Total Sales
correlation = data['Operating Profit'].corr(data['Units Sold'])
correlation
```

```
0.8923793765537961
```

KEY INSIGHT

A strong operating profit is closely linked with higher total sales and a greater number of units sold, suggesting that efficient operational management plays a crucial role in driving sales success.

Correlation between operating profit and total sales

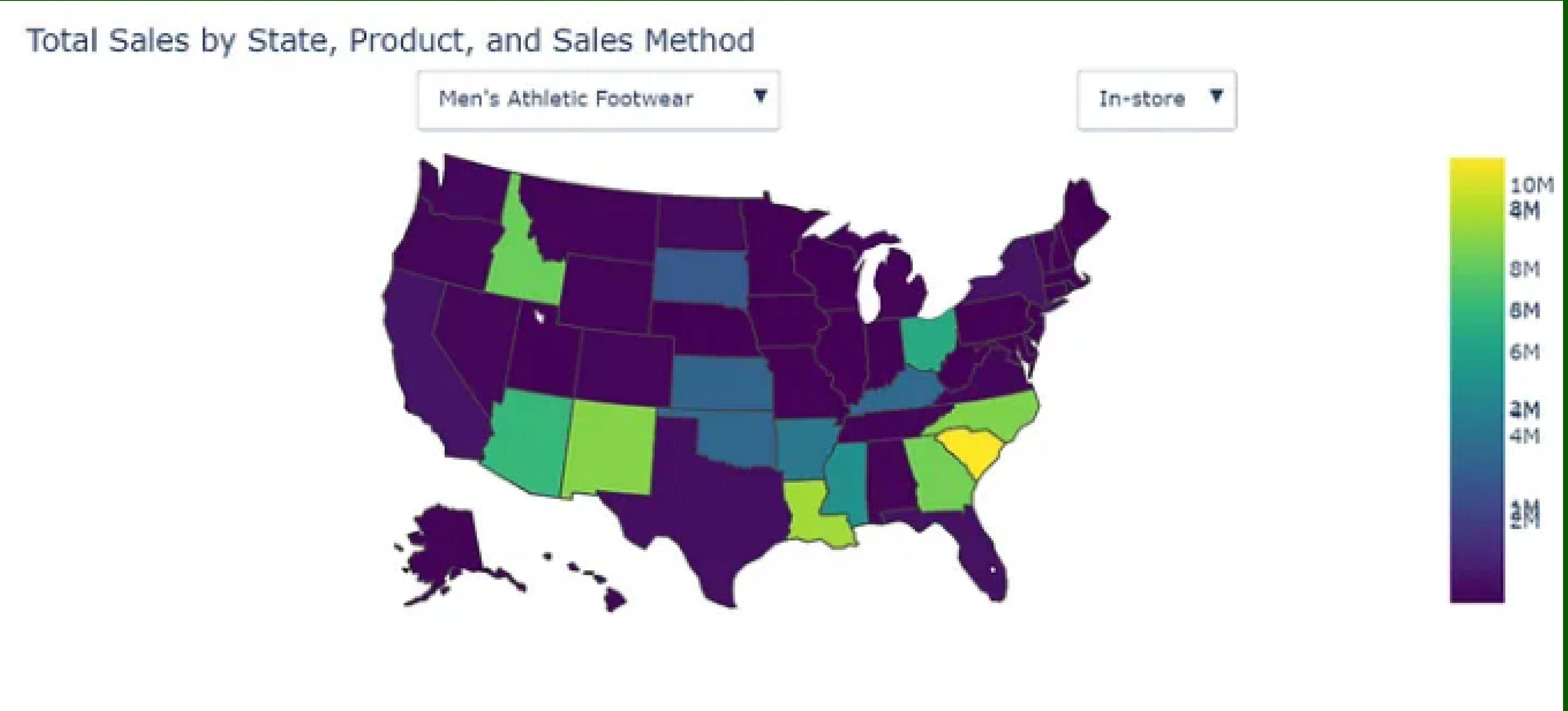
0.9563

Correlation between operating profit and units sold

0.8923

4. Efficiency of Sales Methods: Which sales method is more effective — in-store or online?

To tackle this question, I have utilized a library in Python called Plotly.



Choropleth map of the US indicating relation b/w Products, Sales methods, and Units sold in the US.

1. First I begin by cleansing the ‘Total Sales’ data, removing currency symbols and converting the values to float for numeric analysis.
2. A choropleth map is created using Plotly, with separate traces added for each unique product and sales method combination, showing total sales by U.S. state.
3. The layout is enhanced with dropdown menus for product and sales method selection, enabling interactive visualization of sales data across different categories and methods.
4. The final output is a dynamic, interactive visualization showing total sales across various states, differentiated by products and sales methods.

	Total Sales	Operating Profit	Operating Margin
Sales Method			
In-store	356643750.0	1.275913e+08	0.357756
Online	247672882.0	9.655518e+07	0.389850
Outlet	295585493.0	1.079883e+08	0.365337

Interpretation of the table:

1. Total Sales:

- In-store: $356,643,750
- Online: $247,672,882
- Outlet: $295,585,493

2. Operating Profit:

- In-store: $127,591,300 (approx)
- Online: $96,555,180 (approx)
- Outlet: $107,988,300 (approx)

3. Operating Margin

- In-store: 0.357756 (or 35.78%)
- Online: 0.389850 (or 38.99%)
- Outlet: 0.365337 (or 36.53%)

KEY INSIGHT

When deciding which sales method is more effective, it depends on what the business prioritizes. If the focus is on maximizing total revenue and profit, then in-store sales are more effective. However, if the focus is on efficiency in terms of profit generated per dollar of sales, then online sales are more effective.

In terms of Total Sales and Operating Profit:

In-store sales method is the most effective, generating the highest total sales and operating profit.

Correlation between operating profit and units sold

Online sales are the most effective, indicating that although the total sales and operating profit are lower than in-store, the profitability relative to the sales generated is higher.

5. Price Optimization: Is there a specific price range that achieves better sales than others?

To answer this question, I analyzed the data based on different price ranges. Here’s the breakdown to my approach.
1. Defining Price Bins: I begin by creating bins for price ranges, with intervals of $10 up to $130.
2. Categorizing Prices: A new column ‘Price Range’ is added to our dataset, categorizing each product into these defined price bins based on its ‘Price per Unit’.
3. Aggregating Sales Data: I then group the data by these price ranges and calculate the sum of ‘Total Sales’ for each range.
4. Sorting for Insights: To identify which price range yields the highest sales, I sort the aggregated data in descending order of ‘Total Sales’.
5. Final Analysis: The sorted results offer a clear view of sales performance across different price ranges, enabling us to pinpoint the most and least profitable pricing tiers in our product range.

	Price Range	Total Sales
4	(40, 50]	220666307.0
5	(50, 60]	210865002.0
6	(60, 70]	190679285.0
3	(30, 40]	134726187.0
7	(70, 80]	52787579.0
8	(80, 90]	33547420.0
2	(20, 30]	29636023.0
9	(90, 100]	14468685.0
1	(10, 20]	6574478.0
11	(110, 120]	3080000.0
10	(100, 110]	2785706.0
0	(0, 10]	85453.0
12	(120, 130]	0.0

KEY INSIGHT

Very low-priced products (below $20) and higher-priced products (above $90) show significantly lower sales. This might be due to various factors like perceived value, product quality, target customer segment, or availability.

The highest total sales are in the price range of $40 to $50 ($220,666,307), indicating that products priced within this range are very popular or in high demand. This could indicate a sweet spot for pricing where customers are more willing to purchase.

6. Product Portfolio Optimization I: Determine which products are most profitable, segmented by location.

Retailers can significantly increase earnings by identifying top-performing products in each city and adjusting pricing accordingly. This targeted approach benefits both retailers and manufacturers like Adidas by maximizing profits.

Best and Worst Performing Cities for Each Product:

	Product	City	Total Sales
0	Men's Apparel	New York	6835166.0
1	Men's Apparel	Omaha	530197.0
2	Men's Athletic Footwear	New York	6301528.0
3	Men's Athletic Footwear	Omaha	942983.0
4	Men's Street Footwear	Charleston	9479502.0
5	Men's Street Footwear	Omaha	2131074.0
6	Women's Apparel	Charleston	8147789.0
7	Women's Apparel	Omaha	1202661.0
8	Women's Athletic Footwear	New York	5201048.0
9	Women's Athletic Footwear	Omaha	465677.0
10	Women's Street Footwear	San Francisco	5549840.0
11	Women's Street Footwear	Omaha	656446.0

Sales and Profitability Analysis by Location

KEY INSIGHTS:

Albany:

‘Women’s Apparel’ and ‘Men’s Street Footwear’ are highly profitable, with profit margins around 49% and 46%, respectively.

Omaha:

Consistently shows the lowest sales across various products, suggesting limited market penetration or demand.

New York:

Excels in sales of ‘Men’s Apparel’, ‘Men’s Athletic Footwear’, and ‘Women’s Athletic Footwear’, indicating a strong market for these products.

7. Data-Driven Expansion: Location Analysis for Growth

Evaluating how stores perform in various locations leads to better decision-making, optimized resource allocation, insightful consumer targeting, and ultimately, a stronger competitive edge.

Store Performance by City:

	City	Retailer	Total Sales	Operating Profit	Profit Margin
1	Albany	West Gear	20735165.0	8062399.80	0.388827
0	Albany	Kohl's	3692639.0	1367451.11	0.370318
2	Albuquerque	Kohl's	17065965.0	5783668.15	0.338901
3	Albuquerque	Sports Direct	2799051.0	954392.26	0.340970
4	Anchorage	Amazon	13365025.0	4143804.75	0.310048

Store Performance by City

KEY INSIGHTS:

1.Top Performers:

In Albany, ‘West Gear’ emerges as the top performer with a total sales of approximately $20.7 million and a profit margin of about 38.9%. This is significantly higher than ‘Kohl’s’ in the same city, which has a total sales of around $3.7 million with a profit margin of 37%.
In Albuquerque, ‘Kohl’s’ leads with a total sales of $17.1 million and a profit margin of approximately 33.9%.

2. Profit Margins Analysis:

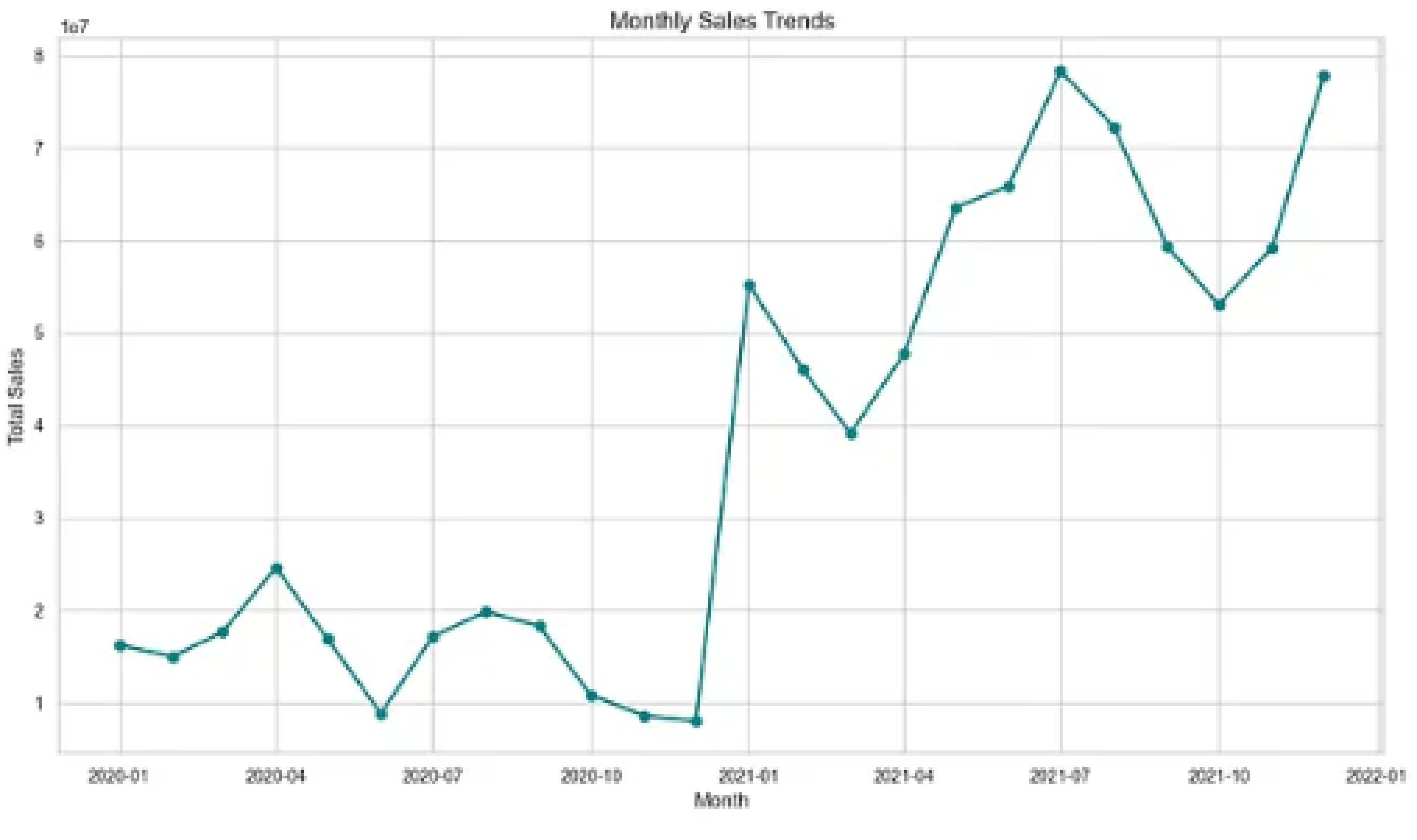
Profit margins vary across cities and stores. While ‘West Gear’ in St. Louis has a high profit margin of 40.1%, other stores like ‘Amazon’ in Anchorage show lower profit margins (31%).

3. Sales vs. Profit Margins:

There is not always a direct correlation between high sales and high profit margins. For instance, ‘Kohl’s’ in Wichita has higher sales than ‘Foot Locker’ in the same city, yet their profit margins are fairly close (35.3% for Kohl’s vs. 34.9% for Foot Locker).

8. Investigating Sales Trends and Seasonality in Adidas Data.

The time series analysis of sales data reveals insightful trends, including seasonal fluctuations highlighted by the month-to-month variations and visually represented in the plot.



Monthly Sales Trend

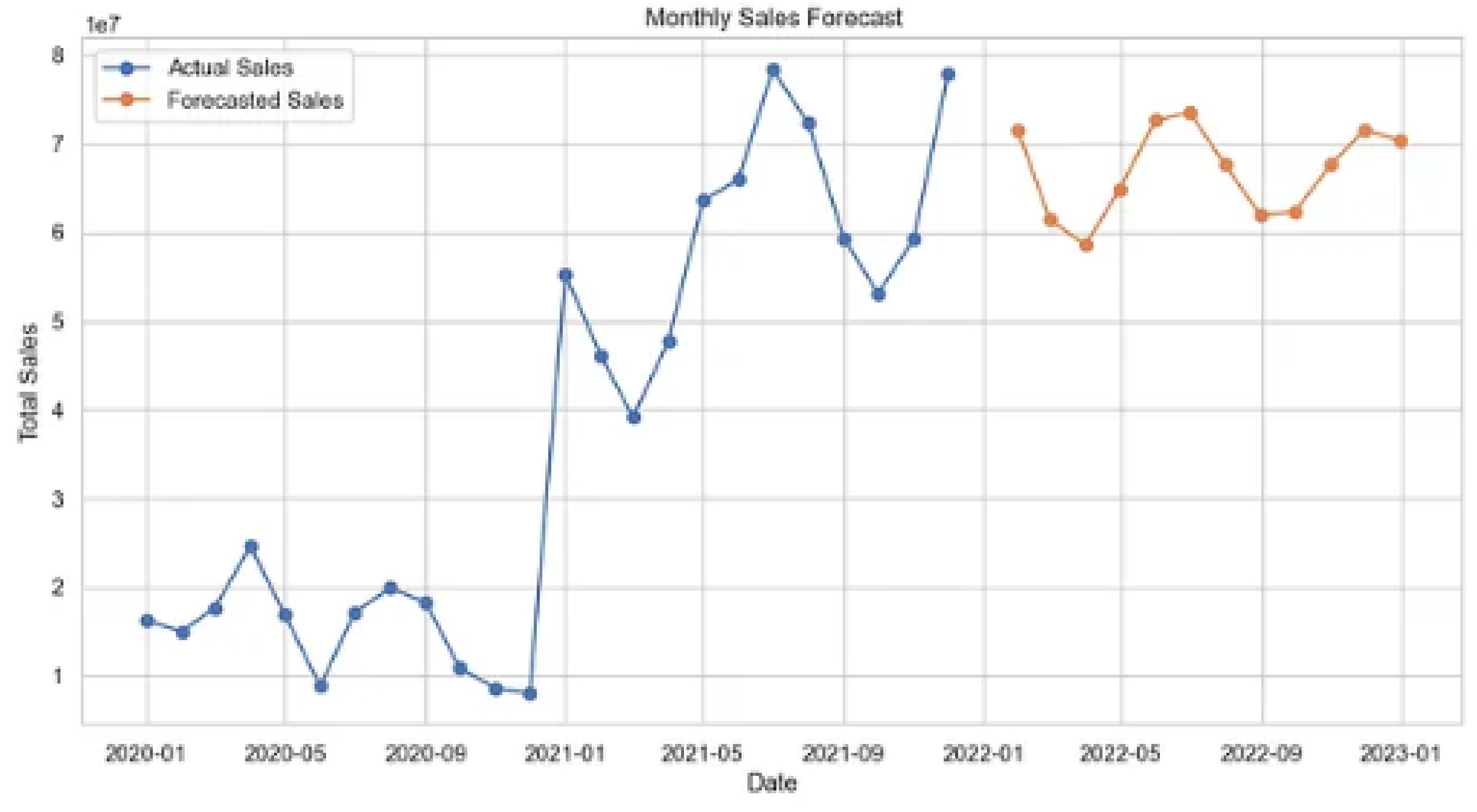
KEY INSIGHT

Monthly sales data from January 2020 to January 2022 exhibit significant variability with notable peaks around April 2021 and consistent increases in December and April of each year, potentially correlating with holiday seasons and sales promotions.

This analysis suggests that while sales exhibit seasonal patterns, there’s no steady long-term growth or decline, indicating the need for a more nuanced approach to sales strategy that accounts for these periodic fluctuations.

9.Using Time Series Analysis for Monthly Sales Forecasting

I've used an ARIMA model to forecast monthly sales for the next year, factoring in historical trends and seasonality. This approach goes beyond simple projections, providing strategic value for the business. It informs efficient resource allocation, helps anticipate market changes, and promotes adaptability. The fitted ARIMA model (2,1,2) predicts sales for the next 12 months, and a visualization combines historical and forecasted data. This offers a clear picture of expected sales performance, facilitating strategic planning and resource management.



Prediction / Forecast of the Monthly Sales

KEY INSIGHT

The graph displays actual and forecasted monthly sales from January 2020 to March 2023. Actual sales peak at 7 million in April 2021 and show volatility, while forecasted sales predict a steadier pattern, mostly ranging between 4 to 6 million, without the extremes seen in actual sales. The forecasted data smoothens the peaks and valleys, indicating a stable sales environment for future planning.

10.Optimize Sales Strategy with a Tableau Dashboard

Using Salesforce's Tableau, I created a dashboard to provide a concise and comprehensive overview of key findings from the Adidas dataset. This dashboard demonstrates the power of Business Intelligence tools for extracting valuable, data-driven conclusions.

Dashboard

CONCLUSION

Adidas' sales analysis reveals a strong market position with room for further growth. To maintain its competitive edge, Adidas should prioritize product innovation, targeted marketing, a seamless omnichannel experience, and a strong commitment to sustainability. These insights, combined with a customer-centric approach, will ensure Adidas' continued leadership in the sportswear industry, delivering exceptional products and experiences to its global customer base.

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REFERENCES

Data Source: https://www.kaggle.com/datasets/heemalichaudhari/adidas-sales-dataset?resource=download

Github Link: https://github.com/Nate374/Nathan_Musowoya-Adidas-Sales-Report

THANK YOU