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Introduction

Executive Summary

This report provides a detailed analysis of the Superstore dataset, focusing on customer behavior and product performance. The dataset did not require any data modeling as the structure was already well-organized for analysis. We performed data cleaning, developed key questions to guide the analysis, and conducted SQL queries to address both customer and product-based inquiries. Our dashboards provided a clear visual representation of the insights gained from the analysis, with the third dashboard containing filters for user interaction. Finally, we used Excel's Forecast Sheet tool to predict future trends, allowing the business to plan for upcoming sales and demand.

Key takeaways:

Customer Analysis: focused on identifying the most valuable segments and understanding how different segments behave in terms of order size, repeat purchases, and shipping preferences.

Product Analysis: Revealed the top-performing product categories and sub-categories, with a focus on seasonal spikes and regional performance.

The forecasting models: predicted future growth, particularly for the Technology and Consumer segments, enabling data-driven decisions for resource allocation and marketing strategies.

Background

The Superstore dataset is a fictional retail dataset commonly used for data analysis. It contains detailed records of customer orders, shipping preferences, and product performance. The goal of this analysis is to explore customer behavior and product sales to drive revenue growth and improve overall business performance. No data modeling was required for this dataset, as it was already well-structured for direct analysis.

Objectives:

Customer Behavior

Our mission is to understanding purchasing patterns to improve engagement, retention, and revenue.

Product Categories

Assess product sales performance to identify high-revenue categories and sub-categories, enabling data-driven decisions for optimizing marketing efforts and promotional strategies.

Dataset Overview

Order Information:

Order ID: Unique identifier for each transaction.

Order Date and Ship Date: Essential for time-based sales and shipping performance analysis.

Ship Mode: Customer-selected delivery method (Standard Class, Second Class, etc.).

Customer Information:

Customer ID: Unique identifier for each customer.

Customer Name: Key for segmentation and personalized marketing.

Segment: Customer type (Consumer, Corporate, or Home Office).

Country, City, State, Region: Geographic information for location-based analysis.

Product Information:

Product ID, Category, Sub-Category, Product Name: Data used to evaluate product sales and performance.

Sales Information:

Sales: Total revenue from each transaction.

Our Approach

3. Data Cleaning

- Before conducting the analysis, we cleaned the dataset to ensure it was accurate and usable.

First: Finding Duplicates

- A check was performed to detect duplicates, and no duplicates were found. The dataset was already well-organized, as confirmed by the following Python code:

```
if df.duplicated().sum()>0:
    print('Duplicates are present')
else:
    print('No duplicates')
```

```
No duplicates
```

Second: Handling Null Values

- **Problem:** Some customer records from Vermont were missing postal codes.
- **Solution**: The mode (most frequent postal code) for Burlington, Vermont, was used to fill in the missing data:

```
burlington_data = df[df['City'] == 'Burlington'][['City', 'State', 'Postal Code']]
print(burlington_data)
```

```
           City       State  Postal Code
683   Burlington  North Carolina      27217.0
684   Burlington  North Carolina      27217.0
1008  Burlington            Iowa      52601.0
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9800 entries, 0 to 9799
Data columns (total 18 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Row ID         9800 non-null   int64
 1   Order ID       9800 non-null   object
 2   Order Date     9800 non-null   datetime64[ns]
 3   Ship Date      9800 non-null   datetime64[ns]
 4   Ship Mode      9800 non-null   object
 5   Customer ID    9800 non-null   object
 6   Customer Name  9800 non-null   object
 7   Segment        9800 non-null   object
 8   Country        9800 non-null   object
 9   City           9800 non-null   object
 10  State          9800 non-null   object
 11  Postal Code    9789 non-null   float64
 12  Region         9800 non-null   object
 13  Product ID     9800 non-null   object
 14  Category       9800 non-null   object
 15  Sub-Category   9800 non-null   object
 16  Product Name   9800 non-null   object
 17  Sales          9800 non-null   float64
dtypes: datetime64[ns](2), float64(2), int64(1), object(13)
memory usage: 1.3+ MB
```

```
burlington_data = df[df['City'] == 'Burlington'][['City', 'State', 'Postal Code']]
print(burlington_data)
```

```
           City       State  Postal Code
683   Burlington  North Carolina      27217.0
684   Burlington  North Carolina      27217.0
1008  Burlington            Iowa      52601.0
1038  Burlington  North Carolina      27217.0
1039  Burlington  North Carolina      27217.0
1393  Burlington  North Carolina      27217.0
2234  Burlington         Vermont          NaN
2928  Burlington  North Carolina      27217.0
5065  Burlington  North Carolina      27217.0
5066  Burlington  North Carolina      27217.0
5274  Burlington         Vermont          NaN
8317  Burlington  North Carolina      27217.0
8318  Burlington  North Carolina      27217.0
8410  Burlington  North Carolina      27217.0
8798  Burlington         Vermont          NaN
9146  Burlington         Vermont          NaN
9147  Burlington         Vermont          NaN
9148  Burlington         Vermont          NaN
9209  Burlington            Iowa      52601.0
9210  Burlington            Iowa      52601.0
9386  Burlington         Vermont          NaN
9387  Burlington         Vermont          NaN
9388  Burlington         Vermont          NaN
9389  Burlington         Vermont          NaN
9741  Burlington         Vermont          NaN
```

```
burlington_mode = df[df['City'] == 'Burlington']['Postal Code'].mode()[0]
df.loc[(df['City'] == 'Burlington') & (df['State'] == 'Vermont'), 'Postal Code'] = burlington_mode
```

- **Note :** In this analysis, we used the **loc function** to update missing postal codes for Burlington, Vermont. First, we calculated the mode (most frequent value) of the postal codes for Burlington. Then, we applied loc to identify all rows where the city was Burlington and the state was Vermont, and replaced the missing values in the 'Postal Code' column with the mode. This ensured data consistency for accurate location-based analysis.

Third: Correcting Data Types

- The Order Date and Ship Date fields were converted to Datetime format to allow for accurate time-based analysis. Additionally, a Year column was created to analyze yearly trends:

```
df['Order Date'] = pd.to_datetime(df['Order Date'], format='%d/%m/%Y')
df['Ship Date'] = pd.to_datetime(df['Ship Date'], format='%d/%m/%Y')
```

Fourth: Outlier Detection

- Outliers were identified using boxplot analysis, and they represent exceptional transactions large sales. These outliers were analyzed further to understand their impact on business performance.

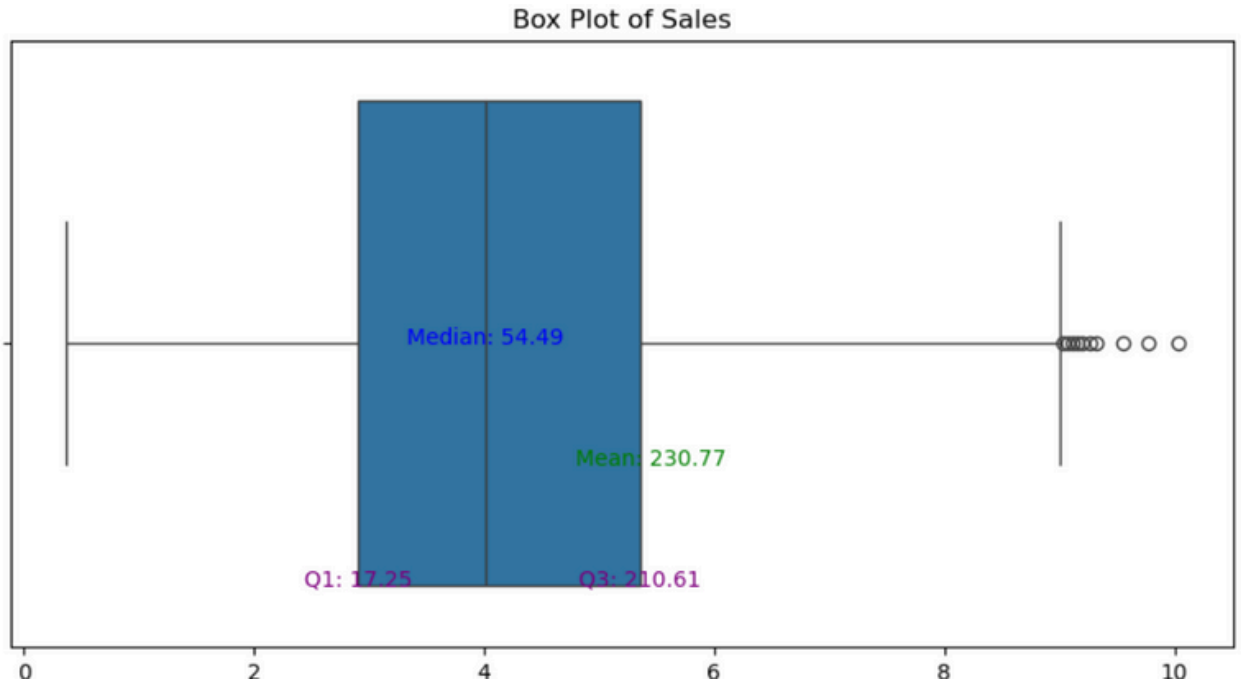
```
# Create the box plot
plt.figure(figsize=(10, 5))
sns.boxplot(x=log_sales)

# Add title and labels
plt.title("Box Plot of Sales")
#plt.xlabel("Log Sales")
#plt.ylabel("Frequency")

# Calculate the necessary statistics
min_val = np.min(df["Sales"])
max_val = np.max(df["Sales"])
q1 = df['Sales'].quantile(0.25)
q3 = df['Sales'].quantile(0.75)
mean_val = np.mean(df["Sales"])
median_val = np.median(df["Sales"])


plt.text(np.log1p(mean_val), 0.2, f'Mean: {mean_val:.2f}', horizontalalignment='center', color='green')
plt.text(np.log1p(median_val), 0, f'Median: {median_val:.2f}', horizontalalignment='center', color='blue')
plt.text(np.log1p(min_val), 0.6, f'Min: {min_val:.2f}', horizontalalignment='center', color='red')
plt.text(np.log1p(max_val), 0.6, f'Max: {max_val:.2f}', horizontalalignment='center', color='red')
plt.text(np.log1p(q1), 0.4, f'Q1: {q1:.2f}', horizontalalignment='center', color='purple')
plt.text(np.log1p(q3), 0.4, f'Q3: {q3:.2f}', horizontalalignment='center', color='purple')

plt.show()
```



- **A boxplot was created for the 'Sales' column to identify outliers.**

  The data showed a right-skewed distribution, with outliers representing unusually large transactions, possibly from bulk orders or high-value products.

  These outliers could skew the analysis by inflating average sales, leading to misinterpretations of customer behavior and product performance.

- **Possible handling methods include:**
  - **Capping:** Limiting extreme values to reduce their impact.
  - **Removing:** Excluding outliers from the dataset to focus on regular sales patterns.
  - **Separate analysis:** Analyzing outliers separately to understand their impact on the business.

4. Analysis

- **We divided the analysis into two main areas: Customer Behavior and Product Category Performance. For each area, key questions were defined to guide the SQL queries and analysis.**

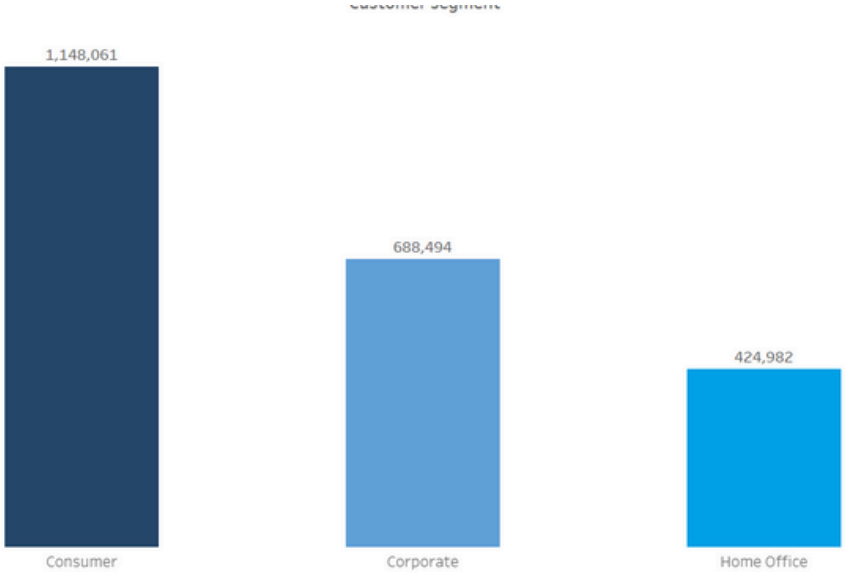
First: Customer Behavior Analysis

We focused on understanding how customer segments contribute to revenue, order sizes, and repeat purchases. The following questions were addressed:

1. Which customer segment contributes the most to revenue?

```
select Segment , round(sum(sales),2) Total_Sales
from cleaned_data2
group by segment
order by Total_Sales Desc
```

	Segment	Total_Sales
1	Consumer	1148060.53
2	Corporate	688494.07
3	Home Office	424982.18



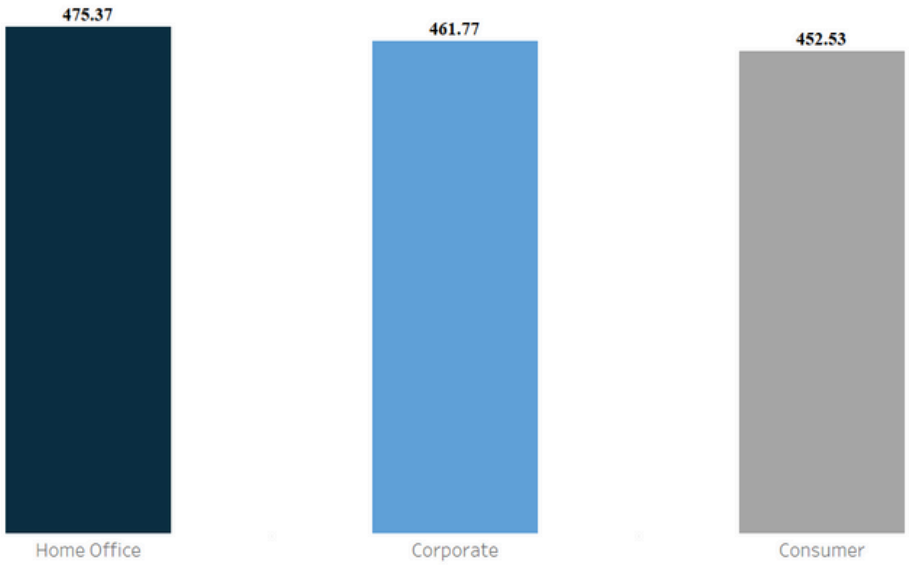
Result: The Consumer Segment contributed the most to revenue, with a total of $1,148,060. This indicates that individual consumers drive a significant portion of sales, making them a key target for marketing efforts.

First: Customer Behavior Analysis

What is the average order size by customer segment?

```
select Segment
      , round(Sum(sales)/COUNT(distinct [order id]),2) average_order_size
from cleaned_data2
group by segment
order by average_order_size desc
```

	Segment	average_order_size
1	Home Office	475.37
2	Corporate	461.77
3	Consumer	452.53



Result: The Home Office Segment had the highest average order size at $475.37, indicating that businesses in this segment tend to place larger orders compared to other segments.

Important Note

Contrasting Sales Dynamics: High Total Sales in the Consumer Segment vs. Higher Average Order Size in the Home Office Segment

Consumer Segment: While the Consumer Segment has the highest total sales ($1,148,060), this is driven by a large number of individual purchases. Consumers tend to place more frequent but smaller orders.

Home Office Segment: The Home Office Segment, on the other hand, has the highest average order size at $475.37, indicating that although they place fewer orders, these are typically larger in value.

Relationship: The two segments complement each other. Consumers generate a high volume of transactions, while Home Office customers contribute significantly through larger, less frequent orders. This combination provides both steady revenue (from consumers) and high-value transactions (from Home Offices).

- **Insights and Opportunities:**

Marketing Strategy: Focus marketing efforts on both segments. Target consumers with promotions that encourage repeat purchases, while offering tailored incentives or loyalty programs to Home Offices to capitalize on their larger orders.

Product Bundles: For Home Office customers, offering bulk discounts or product bundles could further increase order sizes.

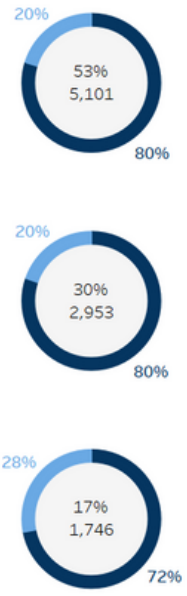
Customer Retention: Since Home Offices already place larger orders, implementing retention strategies such as personalized account management or corporate discount programs can enhance long-term business relationships.

First: Customer Behavior Analysis

What is the number of orders for each segment ?

```
select  Segment, COUNT([Order ID]) as number_of_orders
from cleaned_data2
group by Segment
```

	Segment	number_of_orders
1	Consumer	5101
2	Corporate	2953
3	Home Office	1746



Result: The Home Office Segment had the highest average order size at $475.37, indicating that businesses in this segment tend to place larger orders compared to other segments.

Important Note

Understanding the Dynamics Between Consumer and Home Office Segments: Order Volume vs. Average Order Size

Finding: The Consumer Segment had the highest number of orders, indicating a strong volume of transactions, while the Home Office Segment had the highest average order size based on sales.

Difference: The Consumer Segment generates a large number of smaller transactions, reflecting frequent purchases by individual customers. In contrast, the Home Office Segment, while placing fewer orders, tends to make larger purchases, contributing to a higher average order size.

Relationship: These two segments are interconnected. The high order volume from consumers provides steady revenue, while the high average order size from Home Office customers contributes significant value per transaction. This combination enhances overall business performance.

Relevance: Understanding this relationship is crucial for effective marketing and sales strategies. While consumers drive consistent sales, targeting Home Office customers with tailored offerings can maximize revenue potential through their larger orders. Thus, analyzing both metrics is essential for informed decision-making in resource allocation and promotional efforts.

First: Customer Behavior Analysis

What is the Proportion of Loyal and Regular Customers Relative to Total Orders?

```
SELECT
    [Customer Type],
    COUNT(*) AS Customer_Count,
    ROUND((COUNT(*) * 100.0 / (SELECT COUNT(*) FROM cleaned_data2 )), 2) AS Percentage
FROM
    cleaned_data2
GROUP BY
   [Customer Type]
```

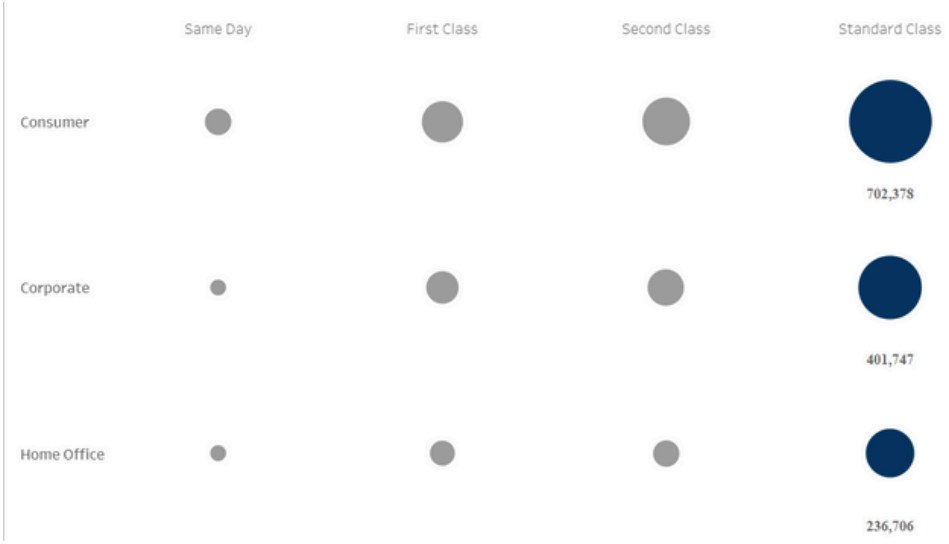
Result: The analysis revealed that the percentage of loyal customers is 79%, while regular customers account for 21%. This suggests that a significant majority of customers are repeat buyers, indicating strong customer loyalty within the Corporate Segment.

First: Customer Behavior Analysis

Do certain customer segments prefer specific shipping methods?

```
select Segment ,[ship mode],count([order id]) order_count, sum(sales)
from cleaned_data2
group by Segment ,[ship mode]
order by Segment , order_count desc
```

	Segment	ship mode	order_count	total_sales
1	Consumer	Standard Class	3031	702377.775271177
2	Consumer	Second Class	1003	230125.535160065
3	Consumer	First Class	755	158104.946645439
4	Consumer	Same Day	312	57452.2726843357
5	Corporate	Standard Class	1782	401747.405991375
6	Corporate	Second Class	589	139045.289665699
7	Corporate	First Class	468	102580.053216815
8	Corporate	Same Day	114	45121.3227184415
9	Home Office	Standard Class	1046	236706.125020981
10	Home Office	Second Class	310	80743.3529978991
11	Home Office	First Class	278	84887.256162405
12	Home Office	Same Day	112	22645.4428949356



Result: Standard Class was the preferred shipping method across all segments, but corporate clients showed a higher tendency to use First Class for faster delivery.

First: Customer Behavior Analysis

Do certain customer segments prefer specific shipping methods?

```sql
WITH MonthlySales AS (
    SELECT
        Segment,
        YEAR([Order Date]) AS OrderYear,
        MONTH([Order Date]) AS OrderMonth,
        SUM(Sales) AS TotalSales
    FROM
        cleaned_data2
    GROUP BY
        YEAR([Order Date]), MONTH([Order Date]) ,Segment
),
RankedSales AS (
    SELECT
        Segment,
        OrderYear,
        OrderMonth,
        TotalSales,
        RANK() OVER (PARTITION BY OrderYear,Segment ORDER BY TotalSales DESC) AS SalesRank
    FROM
        MonthlySales
)
SELECT
    Segment,
    OrderYear,
    OrderMonth,
    TotalSales
FROM
    RankedSales
WHERE
    SalesRank <= 3
ORDER BY
    OrderYear, Segment,TotalSales desc
```

Explanation of SQL Code

Purpose: This SQL code is designed to analyze monthly sales performance across different customer segments. Specifically, it identifies the top three segments with the highest total sales for each month and year.

How It Works:

1. MonthlySales Common Table Expression (CTE):

This section calculates the total sales for each segment, grouped by year and month.

Key Components:

YEAR([Order Date]) and MONTH([Order Date]): These functions extract the year and month from the order date, allowing for time-based aggregation.

SUM(Sales) AS TotalSales: This sums the sales figures for each combination of year, month, and segment.

The result is a summarized view of total sales per segment for each month.

2. RankedSales CTE:

This part ranks the total sales for each segment within each year.

Key Components:

RANK() OVER (PARTITION BY OrderYear, Segment ORDER BY TotalSales DESC) AS SalesRank: This function assigns a rank to each segment based on its total sales within the same year, ordering them from highest to lowest.

This ranking enables the identification of the top sales performers in each segment for every month.

3. Final Selection:

The final SELECT statement retrieves segments, years, months, and total sales from the RankedSales CTE.

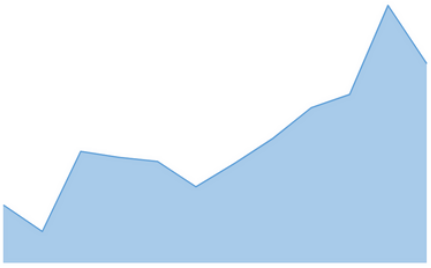
The WHERE SalesRank <= 3 clause filters the results to include only the top three segments based on sales for each month and year.

The results are ordered by year, segment, and total sales in descending order to present the highest sales figures first.

Conclusion: This SQL code provides a clear view of the best-performing segments in terms of sales on a monthly basis, enabling targeted analysis and decision-making for marketing strategies and resource allocation.

	Segment	OrderYear	OrderMonth	TotalSales
1	Consumer	2015	9	59536.8264935017
2	Consumer	2015	11	46228.4978436232
3	Consumer	2015	12	35979.4242483377
4	Corporate	2015	11	20900.2307229042
5	Corporate	2015	12	20573.5560419559
6	Corporate	2015	9	15507.7449470162
7	Home Office	2015	3	32384.3184428215
8	Home Office	2015	12	11614.0779948235
9	Home Office	2015	11	10778.9319643974
10	Consumer	2016	12	39561.97108078
11	Consumer	2016	9	38734.313282609
12	Consumer	2016	11	32423.6688239574
13	Corporate	2016	11	27299.6443556547
14	Corporate	2016	12	15929.90117383
15	Corporate	2016	9	15268.2089176178
16	Home Office	2016	12	19051.7292666435
17	Home Office	2016	11	15526.0859971046
18	Home Office	2016	9	9131.08407568932
19	Consumer	2017	12	49294.9892009497
20	Consumer	2017	11	41104.392608285
21	Consumer	2017	9	38495.127603054
22	Corporate	2017	12	35335.6858446598
23	Corporate	2017	10	32130.5444011688
24	Corporate	2017	11	26493.1799249649
25	Home Office	2017	10	17339.598212719
26	Home Office	2017	9	12895.4509665966
27	Home Office	2017	3	12644.4112565517
28	Consumer	2018	11	49566.4846957922
29	Consumer	2018	12	49433.5257019997
30	Consumer	2018	9	43759.9027414322
31	Corporate	2018	11	44357.9861465693
32	Corporate	2018	8	25678.4441123009
33	Corporate	2018	10	24877.1679894924
34	Home Office	2018	10	29705.5148932934
35	Home Office	2018	11	24013.6838222742
36	Home Office	2018	9	19183.8259179592

Consumer Segment



Corporate Segment

Home Office Segment

Result: We identified seasonal spikes in sales, particularly during the back-to-school period in September and the holiday season in November and December. These patterns were consistent across all segments but were particularly strong in the Consumer Segment.

First: Customer Behavior Analysis

Which sub-categories have the highest sales among each customer segment?

```
WITH RankedSubCategories AS (
    SELECT
        Segment,
        [Sub-Category],
        SUM(Sales) AS Total_Sales,
        ROW_NUMBER() OVER (PARTITION BY Segment ORDER BY SUM(Sales) DESC) AS Rank
    FROM  cleaned_data2

    GROUP BY
        Segment,
        [Sub-Category]
)
SELECT
    Segment,
    [Sub-Category],
    Total_Sales
FROM
    RankedSubCategories
WHERE
    Rank = 1;
```

	Segment	Sub-Category	Total_Sales
1	Consumer	Chairs	171174.095386505
2	Corporate	Chairs	95203.1516876221
3	Home Office	Phones	68209.1501820087

Purpose: This SQL code is designed to analyze sales data to identify the highest-performing sub-categories within each customer segment based on total sales.

How It Works:

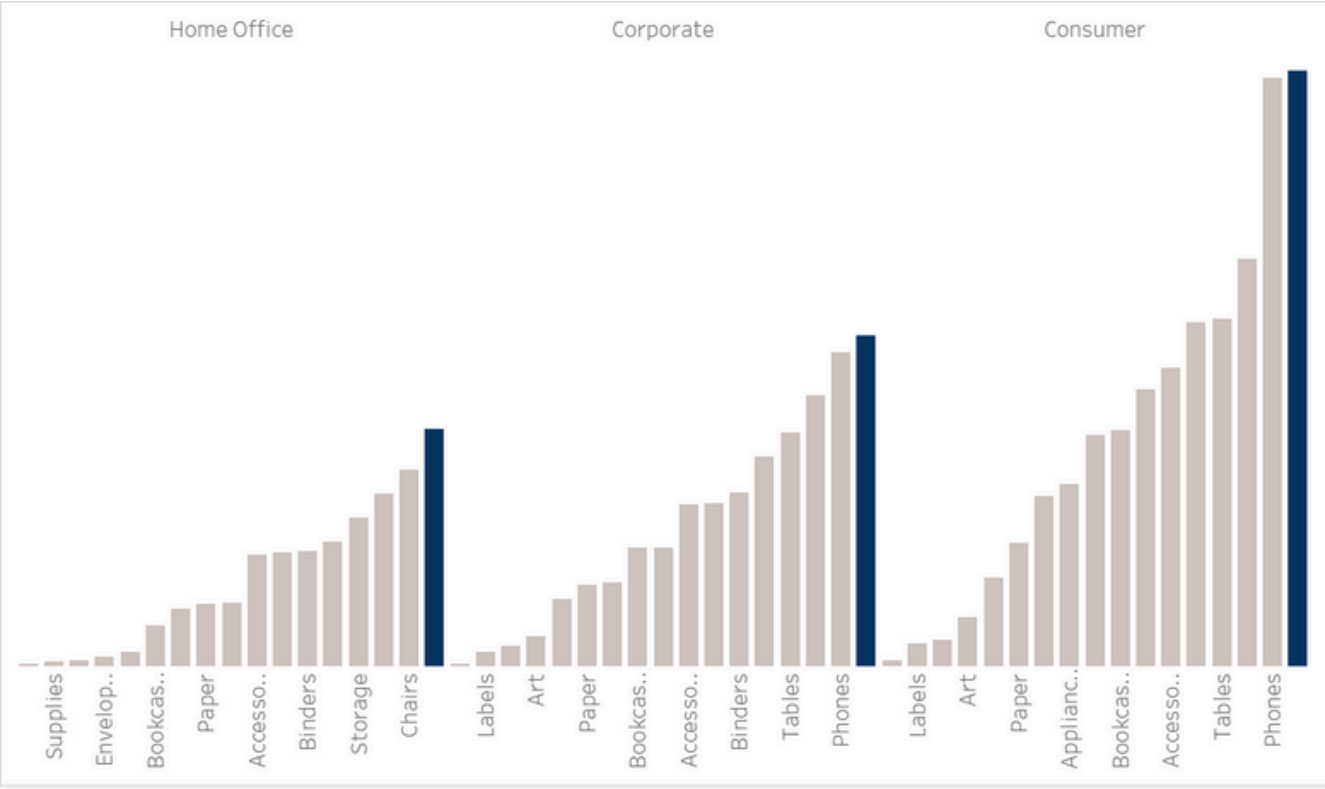
1. RankedSubCategories Common Table Expression (CTE):
This section aggregates sales data by segment and sub-category to calculate total sales.
Key Components:
SUM(Sales) AS Total_Sales: This function computes the total sales for each combination of segment and sub-category.
ROW_NUMBER() OVER (PARTITION BY Segment ORDER BY SUM(Sales) DESC) AS Rank: This function assigns a rank to each sub-category within its segment based on total sales, ordering from highest to lowest.

The result is a summarized view of total sales for each sub-category within each segment, along with a ranking that indicates the top sub-category.

2. Final Selection:
The final SELECT statement retrieves the segment, sub-category, and total sales from the RankedSubCategories CTE.
The WHERE Rank = 1 clause filters the results to include only the top sub-category for each segment based on total sales.

Results:
The analysis reveals the following top sub-categories by total sales:

- In the Consumer Segment, the highest sub-category is Chairs, with total sales of **$171,174.**
- In the Corporate Segment, the highest sub-category is also Chairs, with total sales of **$95,203.**
- In the Home Office Segment, the highest sub-category is Phones, with total sales of **$68,209**



Results:

The analysis reveals the following top sub-categories by total sales:

- In the Consumer Segment, the highest sub-category is Chairs, with total sales of **$171,174.**
- In the Corporate Segment, the highest sub-category is also Chairs, with total sales of **$95,203.**
- In the Home Office Segment, the highest sub-category is Phones, with total sales of **$68,209**

Second: Product Analysis

which product categories are the most profitable?

```
select category
       , round(sum(sales),2) Total_Sales
from cleaned_data2
group by category
order by Total_Sales desc
```

	category	Total_Sales
1	Technology	827455.87
2	Furniture	728658.57
3	Office Supplies	705422.33

Results: Technology was the most profitable product category, followed by Furniture.

Second: Product Analysis

what are the best selling sub categories within each product category

```
    WITH RankedSales AS (
SELECT   Category, [Sub-Category], ROUND(SUM(sales), 2) AS total_sales,
ROW_NUMBER() OVER (PARTITION BY Category ORDER BY SUM(sales) DESC) AS sales_rank
    FROM  cleaned_data2
    GROUP BY Category, [Sub-Category])
SELECT   Category, [Sub-Category], total_sales
FROM RankedSales
WHERE sales_rank = 1
ORDER BY total_sales DESC
```

	Category	Sub-Category	total_sales
1	Technology	Phones	327782.45
2	Furniture	Chairs	322822.73
3	Office Supplies	Storage	219343.39

Purpose: This SQL code is designed to identify the highest-performing sub-categories within each product category based on total sales.

How It Works:

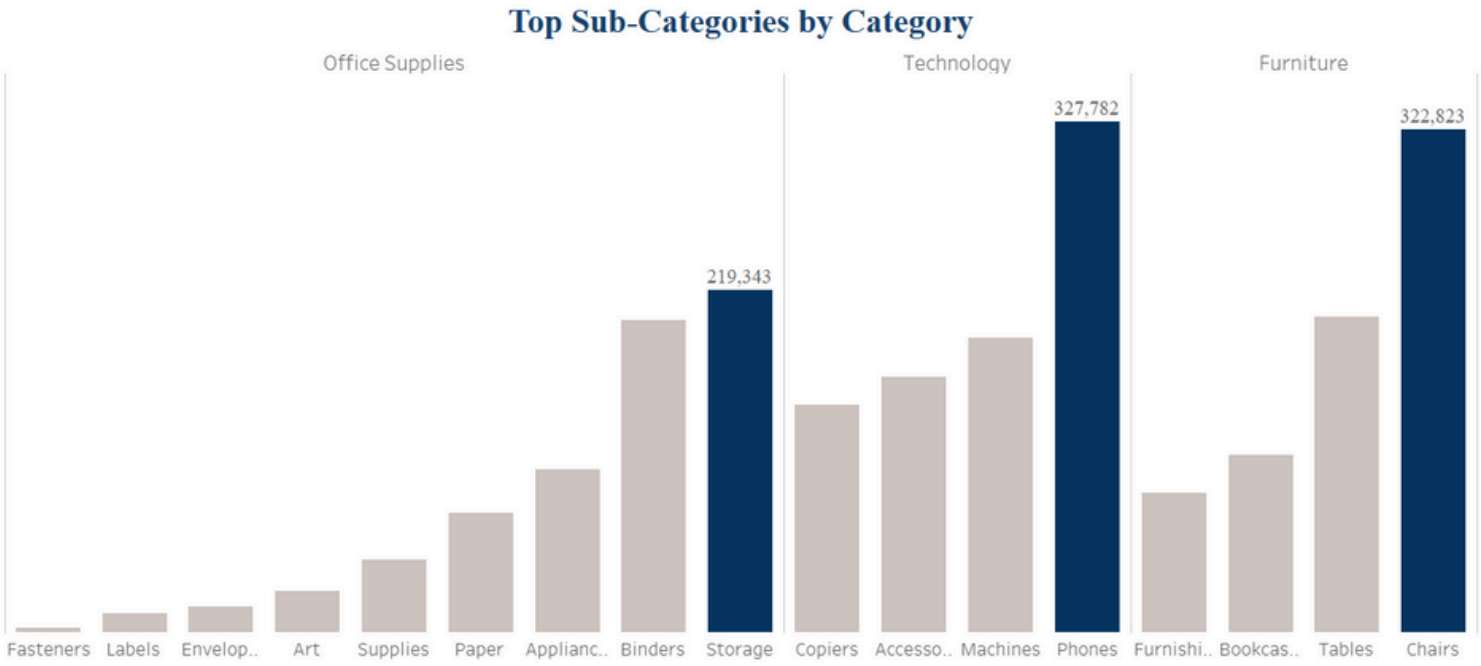
1. RankedSales Common Table Expression (CTE):
This section aggregates sales data by sub-category and category to compute total sales for each sub-category.
Key Components:
ROUND(SUM(sales), 2) AS total_sales: This function calculates the total sales for each sub-category and rounds the result to two decimal places for better readability.
ROW_NUMBER() OVER (PARTITION BY Category ORDER BY SUM(sales) DESC) AS sales_rank: This function assigns a rank to each sub-category within its respective category, ordering them from highest to lowest total sales.

The result is a detailed view of total sales for each sub-category within each category, along with a ranking indicating the top sub-category.

2. Final Selection:
The final SELECT statement retrieves the sub-category, category, and total sales from the RankedSales CTE. The WHERE sales_rank = 1 clause filters the results to include only the top sub-category for each product category based on total sales.

The results are ordered by total sales in descending order to present the highest sales figures first.

Results: Technology was the most profitable product category, followed by Furniture.



Results:

The analysis reveals the following top sub-categories by total sales:

In the Technology category, the highest sub-category is Phones, with total sales of **$327,782.44.**

In the Furniture category, the highest sub-category is Chairs, with total sales of **$322,822.73.**

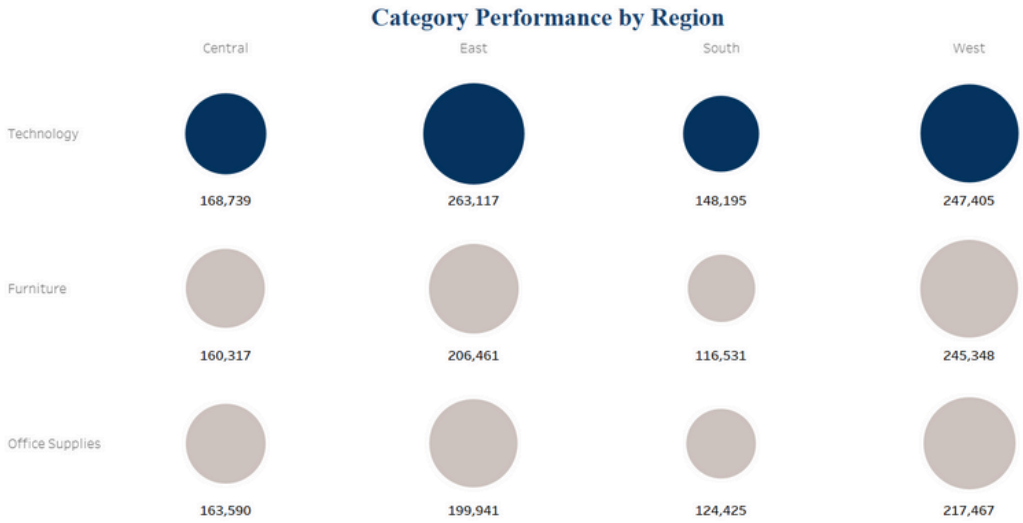
In the Office Supplies category, the highest sub-category is Storage, with total sales of **$219,343.39.**

Second: Product Analysis

How do product categories perform across different regions?

```
select Region
       ,Category
       ,round(sum(sales),2) Total_Sales
       ,DENSE_RANK() over(partition by Region order by round(sum(sales),2) desc) as Sales_Rank
from cleaned_data2
group by Region
         ,Category
order by Region , Sales_Rank
```

	Region	Category	Total_Sales	Sales_Rank
1	Central	Technology	168739.21	1
2	Central	Office Supplies	163590.24	2
3	Central	Furniture	160317.46	3
4	East	Technology	263116.53	1
5	East	Furniture	206461.39	2
6	East	Office Supplies	199940.81	3
7	South	Technology	148195.21	1
8	South	Office Supplies	124424.77	2
9	South	Furniture	116531.48	3
10	West	Technology	247404.93	1
11	West	Furniture	245348.25	2
12	West	Office Supplies	217466.51	3



Result: Technology performed best in all regions, but Furniture showed stronger performance in the West and Central regions.

Second: Product Analysis

Are there any notable sales spikes during specific months for certain products?

```
WITH MonthlySales AS (
    SELECT
        Category,
        YEAR([Order Date]) AS OrderYear,
        MONTH([Order Date]) AS OrderMonth,
        SUM(Sales) AS TotalSales
    FROM
        cleaned_data2
    GROUP BY
        YEAR([Order Date]), MONTH([Order Date]), Category
),
RankedSales AS (
    SELECT
        Category,
        OrderYear,
        OrderMonth,
        TotalSales,
        RANK() OVER (PARTITION BY OrderYear, Category ORDER BY TotalSales DESC) AS SalesRank
    FROM
        MonthlySales
)
```

```
SELECT
    Category,
    OrderYear,
    OrderMonth,
    TotalSales
FROM
    RankedSales
WHERE
    SalesRank <= 3
ORDER BY
    OrderYear, Category, TotalSales DESC;
```

Purpose: This SQL query is used to analyze the top-performing categories by sales within each year, identifying the months with the highest sales for each category.

1. MonthlySales Common Table Expression (CTE):
This part of the query aggregates the total sales for each category on a monthly basis. It groups the data by category, year, and month, and calculates the sum of sales.
Key Components:
YEAR([Order Date]) AS OrderYear and MONTH([Order Date]) AS OrderMonth: These functions extract the year and month from the order date.
SUM(Sales) AS TotalSales: This function calculates the total sales for each category per month.
The data is grouped by year, month, and category to provide a monthly sales breakdown..

2. RankedSales Common Table Expression (CTE):
This section ranks the sales figures for each category within each year. The ranking helps identify the months with the highest sales within a specific year.

Key Components:
RANK() OVER (PARTITION BY OrderYear, Category ORDER BY TotalSales DESC): This ranking function assigns a rank to each month within the same year and category, based on total sales in descending order. The month with the highest sales receives a rank of 1.

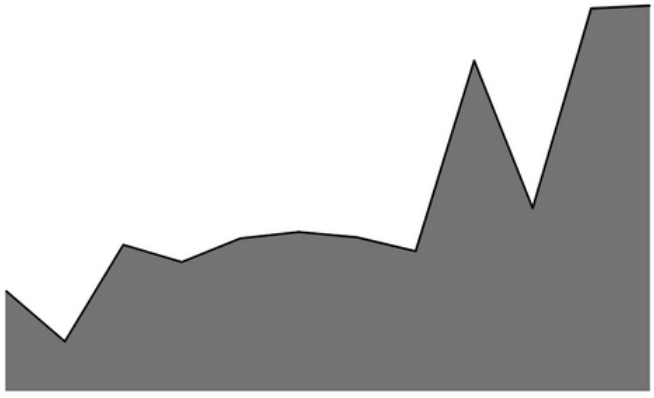
3. Final Selection:
The final SELECT statement retrieves the category, year, month, and total sales from the RankedSales CTE.
The WHERE SalesRank <= 3 clause ensures that only the top three months with the highest sales for each category within each year are selected.
The results are ordered by year, category, and total sales in descending order to present the highest sales figures first.

2024

	Category	OrderYear	OrderMonth	TotalSales
1	Furniture	2015	12	30637.3423743248
2	Furniture	2015	9	23816.4809741974
3	Furniture	2015	11	21471.0407242775
4	Office Supplies	2015	9	27423.2981255651
5	Office Supplies	2015	11	26363.1959513426
6	Office Supplies	2015	12	16956.4919661283
7	Technology	2015	3	32359.9744105339
8	Technology	2015	9	30383.7482056618
9	Technology	2015	11	30073.4238553047
10	Furniture	2016	11	30197.5003643036
11	Furniture	2016	9	25085.4230618477
12	Furniture	2016	12	22812.2513747215
13	Office Supplies	2016	11	21178.2980004549
14	Office Supplies	2016	9	19031.0550745726
15	Office Supplies	2016	12	16099.3219621181
16	Technology	2016	12	35632.0281844139
17	Technology	2016	11	23873.6008119583
18	Technology	2016	9	19017.1281394959
19	Furniture	2017	12	36604.9647674561
20	Furniture	2017	11	31783.6286377907
21	Furniture	2017	9	26755.4747447968
22	Office Supplies	2017	12	37332.9382256269
23	Office Supplies	2017	9	23013.4018874168
24	Office Supplies	2017	11	20141.8080967665
25	Technology	2017	10	31533.3734617233
26	Technology	2017	5	28832.6903800964
26	Technology	2017	5	28832.6903800964
27	Technology	2017	11	27141.0587940216
28	Furniture	2018	11	37056.7151277065
29	Furniture	2018	12	31407.4667153358
30	Furniture	2018	9	28516.7057561874
31	Office Supplies	2018	9	31607.5227885246
32	Office Supplies	2018	11	31472.3370324373
33	Office Supplies	2018	8	29799.5638329983
34	Technology	2018	11	49409.1025044918
35	Technology	2018	3	33428.6218352318
36	Technology	2018	10	32855.6629397869

Technology

Office Supplies



Furniture

September: Sales peak in September, likely due to the back-to-school season, indicating a demand for products such as technology and office supplies during this time.
November and December: Sales spike in both November and December, reflecting the holiday shopping season. This suggests that consumers are more likely to purchase high-value items, especially in categories like technology and furniture, during this period.

Optimizing Sales During Key Seasonal Peaks: September, November, and December

Maximizing September Sales: Focus on promoting back-to-school deals in September, particularly for technology and office supplies. Offering discounts or bundling products for students and professionals can help capture this seasonal demand.

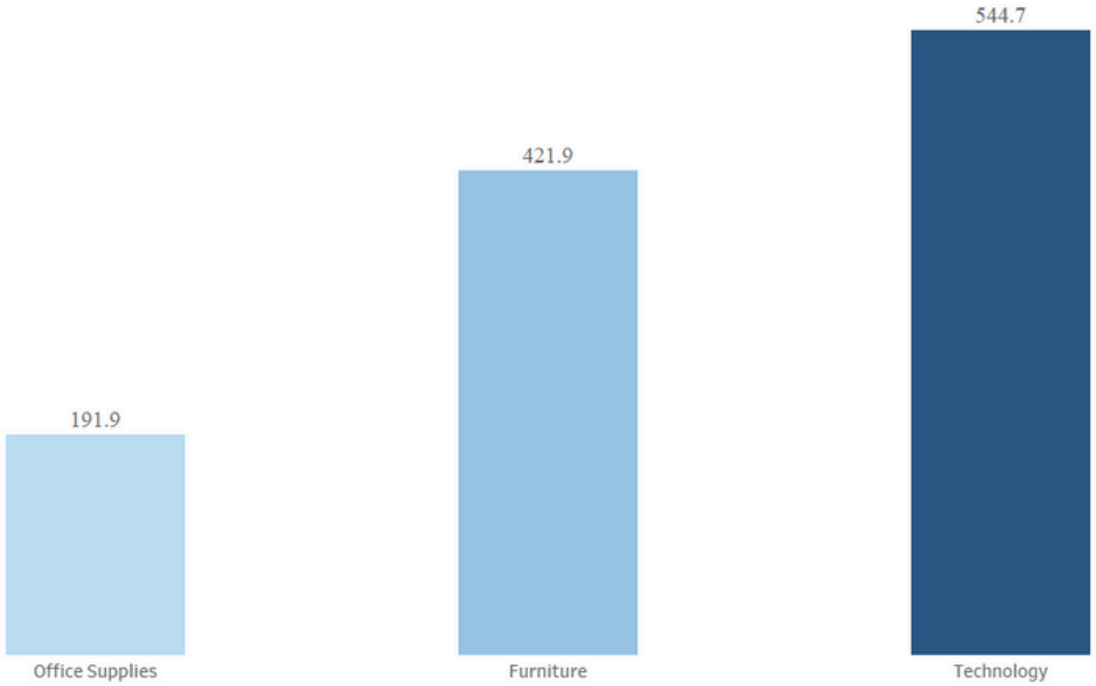
Leveraging November and December: For November and December, launch holiday promotions and marketing campaigns that highlight high-value items like technology and furniture. Consider special holiday discounts, gift bundles, and targeted ads to capitalize on increased consumer spending during the holiday season.

Second: Product Analysis

How do average sales per order vary by product category?

```
SELECT Category, ROUND(SUM(sales) / COUNT(DISTINCT [Order ID]), 2) AS avg_sales_per_order
FROM cleaned_data2
GROUP BY  Category
ORDER BY  avg_sales_per_order DESC
```

	Category	avg_sales_per_order
1	Technology	544.74
2	Furniture	421.92
3	Office Supplies	191.9



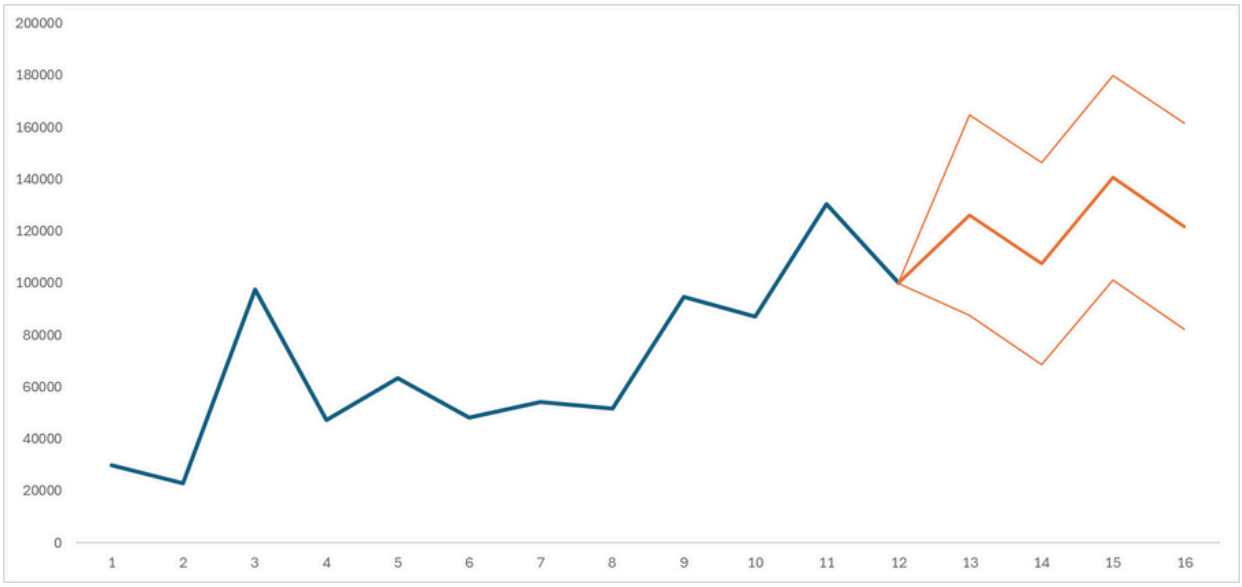
Result: Technology had the highest average sales per order, followed by Furniture, reflecting the higher price points of items in these categories.

Third: Forecasting

For forecasting, we used Excel's Forecast Sheet tool to predict future sales trends. The tool allowed us to generate time-series forecasts with confidence bounds.

Technology Forecast:

Timeline	Technol	Forecast	Lower Confidence Bound	Upper Confidence Bound
1	29774.93			
2	23084.84			
3	97500.39			
4	47285.6			
5	63450.19			
6	48180.72			
7	54131.39			
8	51673.26			
9	94854.05			
10	87031.95			
11	130497.2			
12	99991.38	99991.38	99991.38	99991.38
13		126222.05	87585.19	164858.92
14		107528.76	68581.56	146475.97
15		140582.66	101317.84	179847.49
16		121889.37	82309.47	161469.27



Third: Forecasting

The forecasting chart and the accompanying table provide insights into the future sales performance of the Technology segment. The data predicts a general upward trend in technology sales, with the highest forecasted value occurring in March (140,582 $). This steady growth indicates increasing demand for technology products over time, with March being a particularly strong month for sales.

First: Technology Forecasting

Key Insights from the Forecasting Chart:

1. Steady Growth Pattern:

- The blue line in the chart shows a consistent increase in sales over the forecast period, highlighting that demand for technology products is expected to rise steadily.
- This gradual growth aligns with technological advancements and the increasing need for tech products in both the consumer and business sectors.

2. March as a Peak Month:

- According to both the chart and the table, March is predicted to be the peak month for technology sales, with a forecasted value of 140,582.
- This could be attributed to multiple factors, such as corporate budget cycles, tech refreshes, and new product launches around this time.

3. Confidence Bounds:

- The orange lines in the chart represent the confidence intervals, showing the range within which the actual sales values are expected to fall.
- For example, in March, the lower bound of the prediction is 101,317 units, and the upper bound is 179,847 units. This indicates a level of uncertainty, which widens over time, suggesting that while March is likely to be a strong sales month, external factors could impact the exact numbers.

Third: Forecasting

4. Increasing Uncertainty:

- As shown in both the chart and the table, the confidence intervals widen as the forecast extends into the future, particularly from March onwards. This suggests that predictions become less certain over time due to market fluctuations, external factors, or unpredictable demand changes.

5. Actionable Recommendations:

Marketing & Sales Strategy for March:

- Given the peak in March sales, the company should prepare targeted marketing campaigns and ensure sufficient inventory is available during this period. Promotional efforts can be aligned with product launches or seasonal demand spikes.

Managing Uncertainty:

- Since the forecast shows increasing uncertainty in the later months, it is crucial to stay agile with inventory management and promotional tactics. Continuous monitoring of market trends and demand will help mitigate risks associated with this unpredictability.

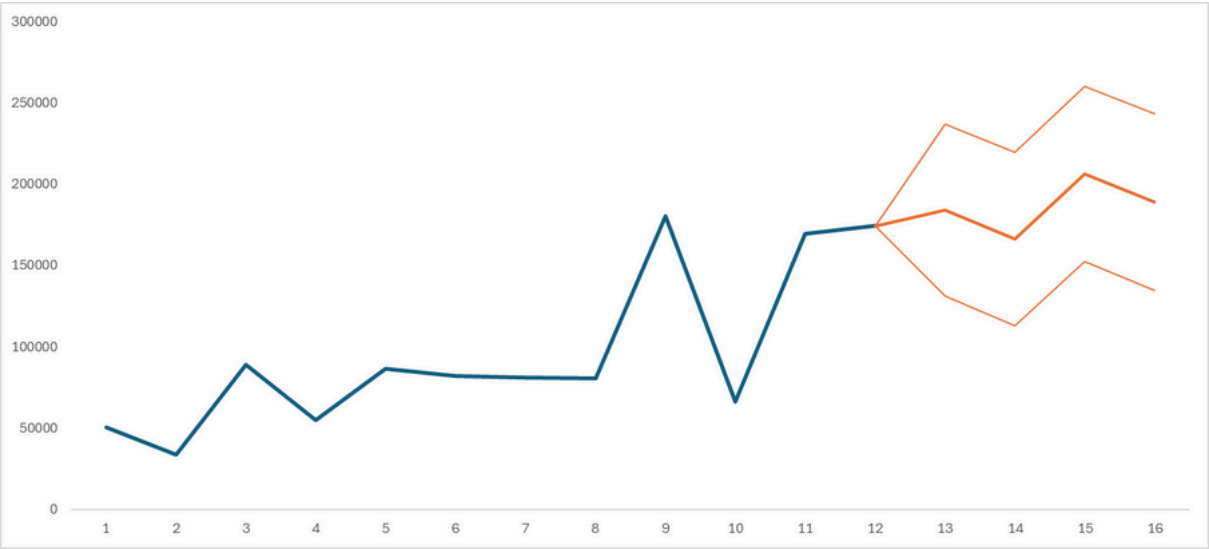
- By leveraging these insights, the company can capitalize on the forecasted demand, particularly in high-sales periods like March, while preparing for potential fluctuations in the market as indicated by the widening confidence intervals.

Third: Forecasting

For forecasting, we used Excel's Forecast Sheet tool to predict future sales trends. The tool allowed us to generate time-series forecasts with confidence bounds.

Technology Forecast:

Timeline	consum	Forecast	Lower Confidence Bound	Upper Confidence Bound
1	50273.9			
2	33446.04			
3	89174.71			
4	54774.92			
5	86406.5			
6	81911.22			
7	81008.54			
8	80591.67			
9	180526.2			
10	66353.9			
11	169323			
12	174269.9	174269.9	174269.91	174269.91
13		183965.6	130988.96	236942.25
14		166370.6	112968.39	219772.72
15		206399.1	152561.44	260236.78
16		188804.1	134534.38	243073.74



Third: Forecasting

The forecasting chart and the data table give us valuable insights into the expected consumption patterns over time for the consumer segment. The forecast shows a significant variation in future consumption with a consistent upward trajectory, particularly from December onwards. This rise in consumption is reflected in both the forecasted values and the increasing confidence intervals.

Second: Consumer Forecasting

Key Insights from the Forecasting Chart:

1. Rising Trend in Consumption:

- The initial data reveals fluctuations in consumer consumption over time. However, starting from the 12th timeline, we see a substantial jump in consumption, indicated by the blue line in the chart. This rise reflects growing consumer demand in the upcoming months.
- Insight: This pattern suggests that consumer demand is expected to accelerate, signaling that now might be the time to prepare for higher inventory levels or marketing campaigns targeted at these peak periods.

2. Confidence Intervals (Uncertainty):

- The orange lines on the chart represent the confidence bounds, displaying the upper and lower ranges for the forecast. As the timeline progresses, these intervals widen, indicating increased uncertainty regarding future consumption levels

Third: Forecasting

- For example, in the 15th timeline mark, the lower bound is approximately 152,561 units, while the upper bound extends to 260,236 units. This wide range suggests considerable variability in the expected outcome.

- Actionable Insight: To mitigate risks from this uncertainty, businesses should employ flexible strategies, allowing for rapid response to fluctuations, particularly in periods of volatile demand.

3. Key Consumption Peaks:

- From the table, we can identify that the 15th timeline has one of the highest forecasted consumptions, reaching approximately 206,399 units. This spike suggests that this period is expected to have the highest consumer demand, which could be influenced by seasonal trends, promotions, or external factors like economic growth.

- Insight: It's vital to ensure that stock levels and supply chain operations are optimized to meet this potential surge in demand.

4. Gradual Widening of Forecast Range:

- The forecast range widens after the 12th timeline, suggesting increasing uncertainty about future consumption patterns. This uncertainty could be due to changes in market conditions, consumer preferences, or unforeseen economic factors.

- Actionable Insight: Companies should monitor real-time data and market trends to adjust to potential disruptions. A robust strategy for forecasting updates will allow for greater adaptability and more precise future projections.

Third: Forecasting

Actionable Recommendations:

1. Inventory & Sales Strategy:

- Given the spike in consumption forecasted from the 12th to the 16th timeline, it is crucial to align inventory management and sales efforts accordingly. Ensuring ample stock and supply chain readiness will allow you to meet this predicted surge in demand without facing stockouts or lost sales opportunities.

2. Prepare for Demand Variability:

- With the confidence bounds widening over time, a flexible approach to inventory management is essential. Consider implementing dynamic pricing strategies or promotional activities to stimulate demand during periods of uncertainty.

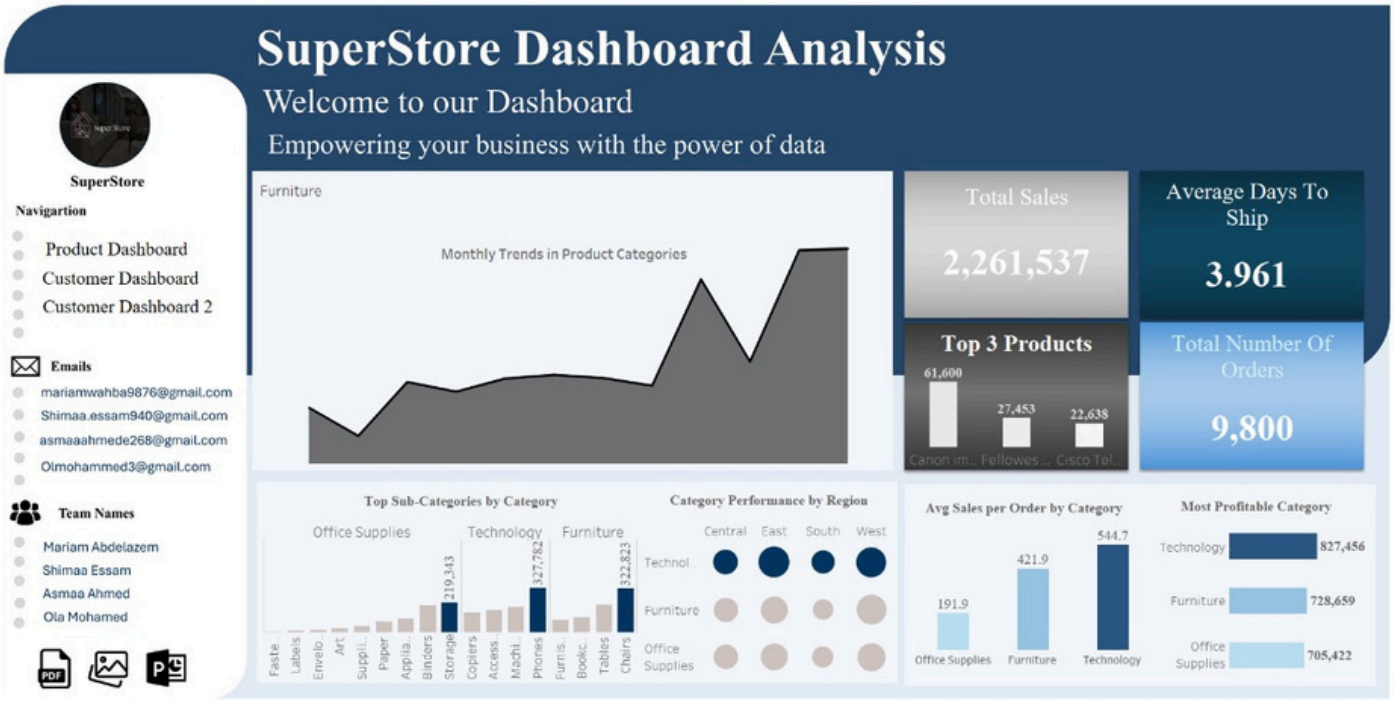
3. Agility in Marketing:

- Focus on targeted marketing initiatives in high-demand periods, particularly during the 12th to 16th timeline, when consumer activity is expected to peak. Customizing marketing campaigns during this time can maximize sales and customer engagement.

Fourth : Dashboard Visualization

- We created three interactive dashboards using Tableau to visualize the insights gained from the analysis. These dashboards provided stakeholders with an intuitive way to explore customer and product data:

1. Product Category Dashboard:



- This dashboard provides a comprehensive overview of sales performance across different product categories, including Technology, Furniture, and Office Supplies. It visualizes total sales, average sales per order, and trends across various regions.

Recommendations

Focus on Profitable Categoriese

The Technology and Furniture categories consistently performed well across all regions. By increasing inventory and marketing efforts for these categories, Superstore can capitalize on their high profitability.

Capitalize on Seasonal Sales Spikes

The data shows clear sales spikes in September, November, and December, driven by back-to-school shopping and holiday promotions. To maximize sales during these periods, Superstore should offer targeted discounts and marketing campaigns focused on high-demand products like technology and office furniture.

Enhance Customer Retention:

The analysis revealed that Corporate and Home Office segments are more likely to place repeat orders and larger orders on average. By developing loyalty programs or offering targeted promotions, Superstore can encourage these segments to continue making repeat purchases.

Optimize Shipping Strategies

The Consumer and Corporate segments show distinct shipping preferences, with Corporate clients favoring faster shipping methods. Tailoring shipping options based on customer segment preferences can improve satisfaction and streamline logistics.

Conclusion

- This report provides a comprehensive analysis of the Superstore dataset, focusing on customer behavior, product performance, and sales forecasting. By understanding key customer segments and optimizing product categories, Superstore can make informed decisions that drive revenue growth and improve customer satisfaction.

- The dashboards and forecasting models developed in this project offer powerful tools for future decision-making, helping to predict demand, manage inventory, and focus marketing efforts on the most profitable areas of the business. By implementing the recommended strategies, Superstore can continue to grow and enhance its operations.

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