PRODUCT SALES ANALYSIS

DATA ANALYTICS WITH COGNOS GROUP 2

PHASE 5

PROBLEM STATEMENT:

In order to optimize inventory management and marketing strategies, our organization is faced with the challenge of effectively analyzing sales data. We need to identify top-selling products, discern peak sales periods, and understand customer preferences. This analysis is critical for making data-driven decisions that will ultimately lead to increased revenue, reduced costs, and improved customer satisfaction.

OBJECTIVES:

The objectives of conducting a product sales analysis are to gain valuable insights into your business's sales performance, customer behavior, and market trends. By setting clear objectives, you can focus your analysis efforts effectively.

Identify the goods or product groups that produce the highest sales revenue, volume, and profit margins. Prioritizing resources and marketing initiatives is aided by this knowledge.

Examine customer information to determine preferences, including preferred items, shopping habits, demographics, and geography. Marketing and product recommendations might be targeted with the help of this information.

Utilize sales data to better control inventory levels to optimize inventory management. As part of this, slow-moving items must be identified, reorder points must be optimized, and carrying costs must be decreased without stockouts.

Recognize seasonality, daily or weekly swings, and market dynamics in sales data. This facilitates preparing promotions and adjusting inventories as necessary.

DESIGN THINKING:

Design thinking is a user-centric, iterative problem-solving approach that can be applied to the process of product sales analysis to ensure that the analysis addresses the specific needs of your business and its customers.

Step1: Clearly define the problem

In order to optimize inventory management and marketing strategies, our organization is faced with the challenge of effectively analyzing sales data. We need to identify top-selling products, discern peak sales periods, and understand customer preferences. This analysis is critical for making data-driven decisions that will ultimately lead to increased revenue, reduced costs, and improved customer satisfaction.

Step2: Data collection

Use appropriate data as per the problem defined in the problem statement.

Step3: Preparing of the data

Data is gathered, and thenThe data should be cleaned and pre-processed to deal with missing values, outliers, and inconsistencies. To provide the model useful information, add new features or change current ones. For the purposes of training and assessing your model, divide the dataset into training, validation, and test sets.

STEP 4 Exploratory Data Analysis (EDA):

Perform initial data exploration to understand the basic characteristics of the sales data. Create visualizations like histograms, scatter plots, and time series graphs to identify trends, patterns, and outliers.

STEP 5 Define Objectives:

Clearly define the objectives and goals of your sales analysis. What specific insights are you seeking to gain from the analysis?

STEP 6 Top-Selling Products Analysis:

Calculate and rank products based on sales revenue, units sold, or profit margins to identify top-selling products. Analyze which products consistently perform well and whether there are seasonal variations.

STEP 7 Peak Sales Periods Analysis:

Examine sales data over time to identify peak sales periods, such as daily, weekly, or seasonally. Consider factors like holidays, promotions, and special events that influence sales peaks.

STEP 8 Customer Preferences Analysis:

Segment your customer base based on demographics, purchase history, and behavior. Analyze which products are preferred by different customer segments. Use clustering and association analysis to discover customer preferences and buying patterns.

STEP 9 Reporting and Visualization:

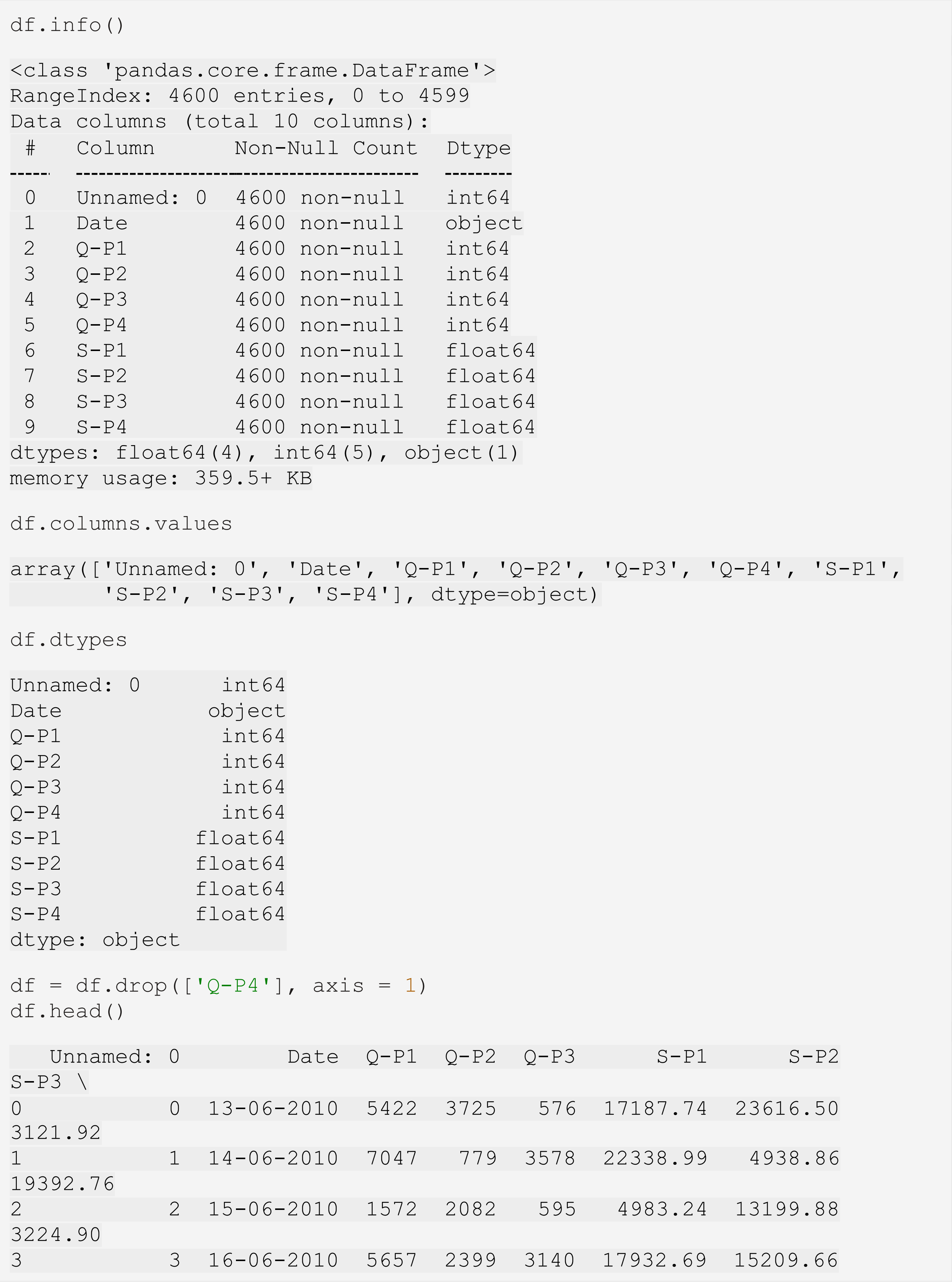
Develop dashboards and reports to track key metrics and insights.Use data visualization tools to communicate findings to stakeholders effectively.

```
import pandas as pd
import numpy as np

df = pd.read_csv('statsfinal.csv')

df.head
```

```
<bound method NDFrame.head of       Unnamed: 0        Date  Q-P1  Q-P2
Q-P3  Q-P4      S-P1      S-P2  \
0              0  13-06-2010  5422  3725   576   907  17187.74
23616.50
1              1  14-06-2010  7047   779  3578  1574  22338.99
4938.86
2              2  15-06-2010  1572  2082   595  1145   4983.24
13199.88
3              3  16-06-2010  5657  2399  3140  1672  17932.69
15209.66
4              4  17-06-2010  3668  3207  2184   708  11627.56
20332.38
...          ...         ...   ...   ...   ...   ...       ...        .
..
4595        4595  30-01-2023  2476  3419   525  1359   7848.92
21676.46
4596        4596  31-01-2023  7446   841  4825  1311  23603.82
5331.94
4597        4597  01-02-2023  6289  3143  3588   474  19936.13
19926.62
4598        4598  02-02-2023  3122  1188  5899   517   9896.74
7531.92
4599        4599  03-02-2023  1234  3854  2321   406   3911.78
24434.36

          S-P3      S-P4
0      3121.92   6466.91
1     19392.76  11222.62
2      3224.90   8163.85
3     17018.80  11921.36
4     11837.28   5048.04
...        ...       ...
4595   2845.50   9689.67
4596  26151.50   9347.43
4597  19446.96   3379.62
4598  31972.58   3686.21
4599  12579.82   2894.78

[4600 rows x 10 columns]>
```

```
df.shape
```

```
(4600, 10)
```



```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4600 entries, 0 to 4599
Data columns (total 10 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   Unnamed: 0   4600 non-null   int64  
 1   Date         4600 non-null   object 
 2   Q-P1         4600 non-null   int64  
 3   Q-P2         4600 non-null   int64  
 4   Q-P3         4600 non-null   int64  
 5   Q-P4         4600 non-null   int64  
 6   S-P1         4600 non-null   float64
 7   S-P2         4600 non-null   float64
 8   S-P3         4600 non-null   float64
 9   S-P4         4600 non-null   float64
dtypes: float64(4), int64(5), object(1)
memory usage: 359.5+ KB
```

```
df.columns.values
```

```
array(['Unnamed: 0', 'Date', 'Q-P1', 'Q-P2', 'Q-P3', 'Q-P4', 'S-P1',
       'S-P2', 'S-P3', 'S-P4'], dtype=object)
```

```
df.dtypes
```

```
Unnamed: 0      int64
Date           object
Q-P1            int64
Q-P2            int64
Q-P3            int64
Q-P4            int64
S-P1          float64
S-P2          float64
S-P3          float64
S-P4          float64
dtype: object
```

```
df = df.drop(['Q-P4'], axis = 1)
df.head()
```

```
   Unnamed: 0        Date  Q-P1  Q-P2  Q-P3      S-P1      S-P2
S-P3 \
0           0  13-06-2010  5422  3725   576  17187.74  23616.50
3121.92
1           1  14-06-2010  7047   779  3578  22338.99   4938.86
19392.76
2           2  15-06-2010  1572  2082   595   4983.24  13199.88
3224.90
3           3  16-06-2010  5657  2399  3140  17932.69  15209.66
```

```
17018.80
4            4  17-06-2010  3668  3207  2184  11627.56  20332.38
11837.28

       S-P4
0   6466.91
1  11222.62
2   8163.85
3  11921.36
4   5048.04
```

```
df[np.isnan(df['Q-P3'])]
```

```
Empty DataFrame
Columns: [Unnamed: 0, Date, Q-P1, Q-P2, Q-P3, S-P1, S-P2, S-P3, S-P4]
Index: []
```

```
df[df['Date'] == 0].index
```

```
Int64Index([], dtype='int64')
```

```
df.isnull().sum()
```

```
Unnamed: 0    0
Date          0
Q-P1          0
Q-P2          0
Q-P3          0
S-P1          0
S-P2          0
S-P3          0
S-P4          0
dtype: int64
```

```
df.drop(labels=df[df['S-P1'] == 0].index, axis=0, inplace=True)
df[df['S-P1'] == 0].index
```

```
Int64Index([], dtype='int64')
```

```
df.fillna(df["S-P3"].mean())
```

```
      Unnamed: 0        Date  Q-P1  Q-P2  Q-P3      S-P1      S-P2
S-P3 \
0              0  13-06-2010  5422  3725   576  17187.74  23616.50
3121.92
1              1  14-06-2010  7047   779  3578  22338.99   4938.86
19392.76
2              2  15-06-2010  1572  2082   595   4983.24  13199.88
3224.90
3              3  16-06-2010  5657  2399  3140  17932.69  15209.66
17018.80
4              4  17-06-2010  3668  3207  2184  11627.56  20332.38
```

```
11837.28
...         ...         ...   ...   ...   ...       ...       ...
...
4595          4595  30-01-2023  2476  3419   525   7848.92  21676.46
2845.50
4596          4596  31-01-2023  7446   841  4825  23603.82   5331.94
26151.50
4597          4597  01-02-2023  6289  3143  3588  19936.13  19926.62
19446.96
4598          4598  02-02-2023  3122  1188  5899   9896.74   7531.92
31972.58
4599          4599  03-02-2023  1234  3854  2321   3911.78  24434.36
12579.82

          S-P4
0      6466.91
1     11222.62
2      8163.85
3     11921.36
4      5048.04
...        ...
4595   9689.67
4596   9347.43
4597   3379.62
4598   3686.21
4599   2894.78

[4600 rows x 9 columns]
```

```
df.fillna(df["S-P4"].mean())
```

```
      Unnamed: 0        Date  Q-P1  Q-P2  Q-P3      S-P1      S-P2
S-P3 \
0                0  13-06-2010  5422  3725   576  17187.74  23616.50
3121.92
1                1  14-06-2010  7047   779  3578  22338.99   4938.86
19392.76
2                2  15-06-2010  1572  2082   595   4983.24  13199.88
3224.90
3                3  16-06-2010  5657  2399  3140  17932.69  15209.66
17018.80
4                4  17-06-2010  3668  3207  2184  11627.56  20332.38
11837.28
...         ...         ...   ...   ...   ...       ...       ...
...
4595          4595  30-01-2023  2476  3419   525   7848.92  21676.46
2845.50
4596          4596  31-01-2023  7446   841  4825  23603.82   5331.94
26151.50
4597          4597  01-02-2023  6289  3143  3588  19936.13  19926.62
```

```
19446.96
4598        4598  02-02-2023  3122  1188  5899   9896.74   7531.92
31972.58
4599        4599  03-02-2023  1234  3854  2321   3911.78  24434.36
12579.82

          S-P4
0      6466.91
1     11222.62
2      8163.85
3     11921.36
4      5048.04
...        ...
4595   9689.67
4596   9347.43
4597   3379.62
4598   3686.21
4599   2894.78

[4600 rows x 9 columns]
```

```
df.fillna(df["S-P2"].mean())
```

```
      Unnamed: 0        Date  Q-P1  Q-P2  Q-P3      S-P1      S-P2
S-P3 \
0              0  13-06-2010  5422  3725   576  17187.74  23616.50
3121.92
1              1  14-06-2010  7047   779  3578  22338.99   4938.86
19392.76
2              2  15-06-2010  1572  2082   595   4983.24  13199.88
3224.90
3              3  16-06-2010  5657  2399  3140  17932.69  15209.66
17018.80
4              4  17-06-2010  3668  3207  2184  11627.56  20332.38
11837.28
...          ...         ...   ...   ...   ...       ...       ...
...
4595        4595  30-01-2023  2476  3419   525   7848.92  21676.46
2845.50
4596        4596  31-01-2023  7446   841  4825  23603.82   5331.94
26151.50
4597        4597  01-02-2023  6289  3143  3588  19936.13  19926.62
19446.96
4598        4598  02-02-2023  3122  1188  5899   9896.74   7531.92
31972.58
4599        4599  03-02-2023  1234  3854  2321   3911.78  24434.36
12579.82


0      6466.91
```

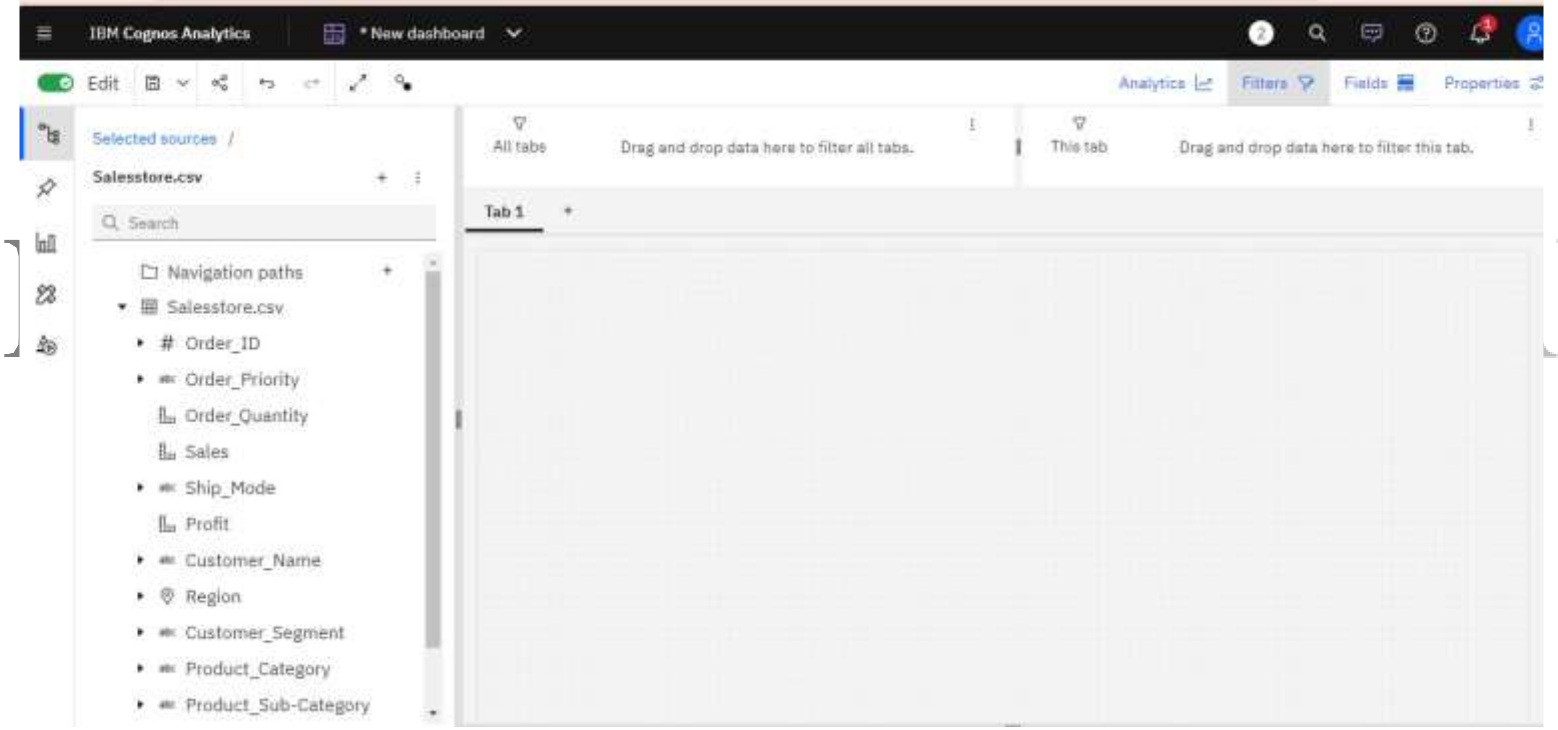
```
1      11222.62
2       8163.85
3      11921.36
4       5048.04
...         ...
4595    9689.67
4596    9347.43
4597    3379.62
4598    3686.21
4599    2894.78

[4600 rows x 9 columns]
```

```
df.isnull().sum()
```

```
Unnamed: 0     0
Date           0
Q-P1           0
Q-P2           0
Q-P3           0
S-P1           0
S-P2           0
S-P3           0
S-P4           0
dtype: int64
```

VISUALIZATION METHODS

The visualization methods is as follows:



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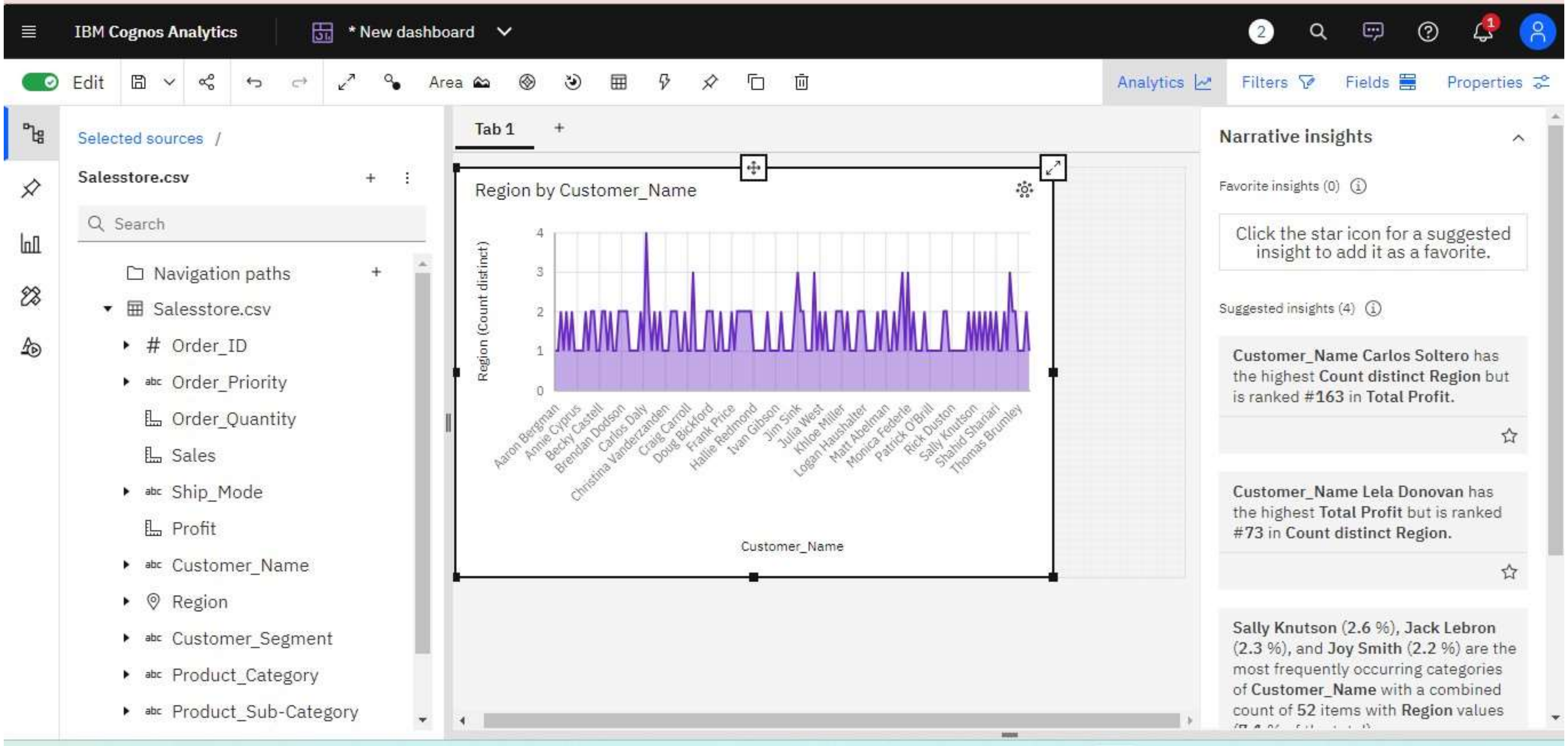
REGISTER NUMBER:421221243012



Narrative insights

Favorite insights (0)

Click the star icon for a suggested insight to add it as a favorite.

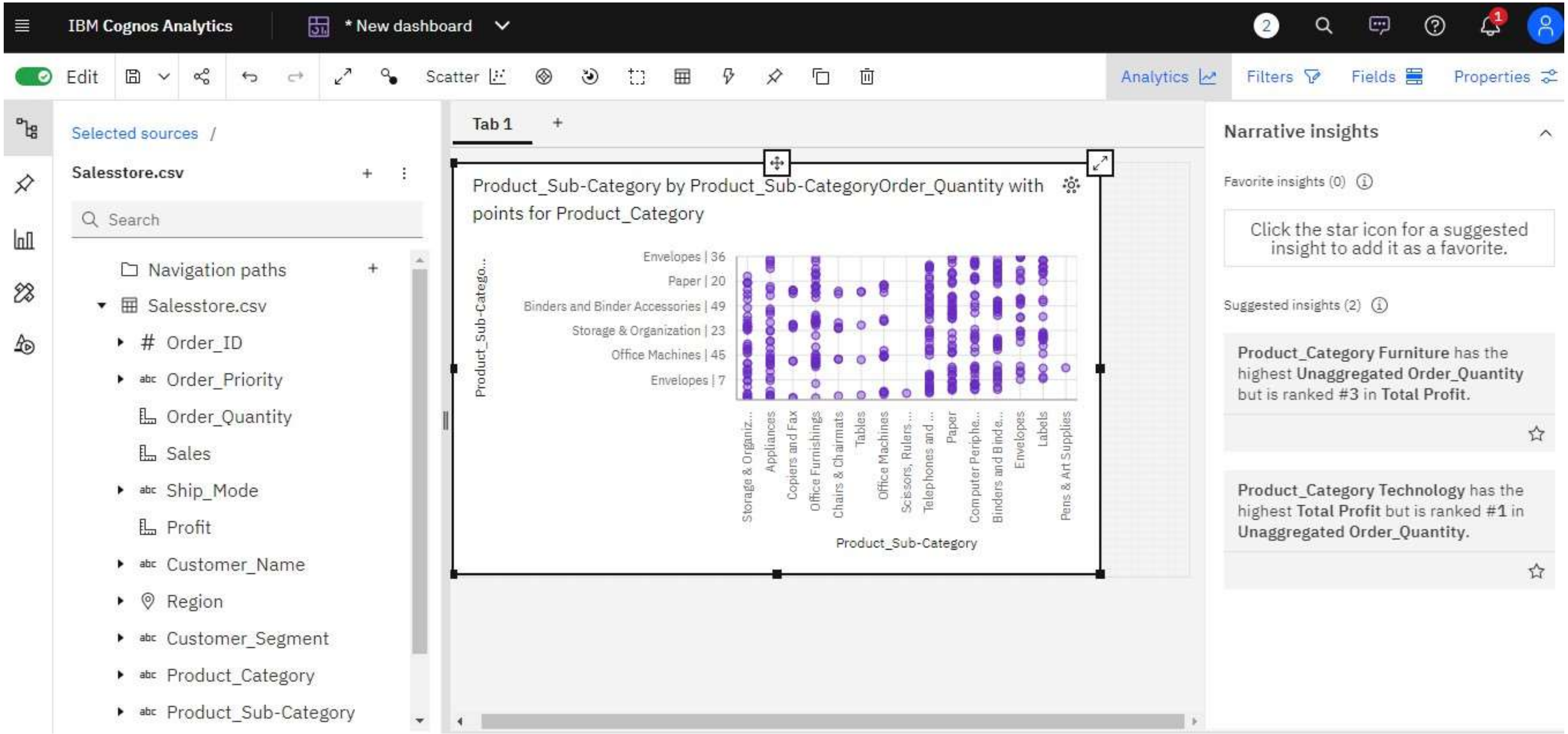
Suggested insights (4)

Customer_Name Carlos Soltero has the highest **Count distinct Region** but is ranked **#163** in **Total Profit.**

Customer_Name Lela Donovan has the highest **Total Profit** but is ranked **#73** in **Count distinct Region.**

Sally Knutson (**2.6** %), **Jack Lebron** (**2.3** %), and **Joy Smith** (**2.2** %) are the most frequently occurring categories of **Customer_Name** with a combined count of **52** items with **Region** values

COLLEGECODE:4212
REGISTER NUMBER:421221243012

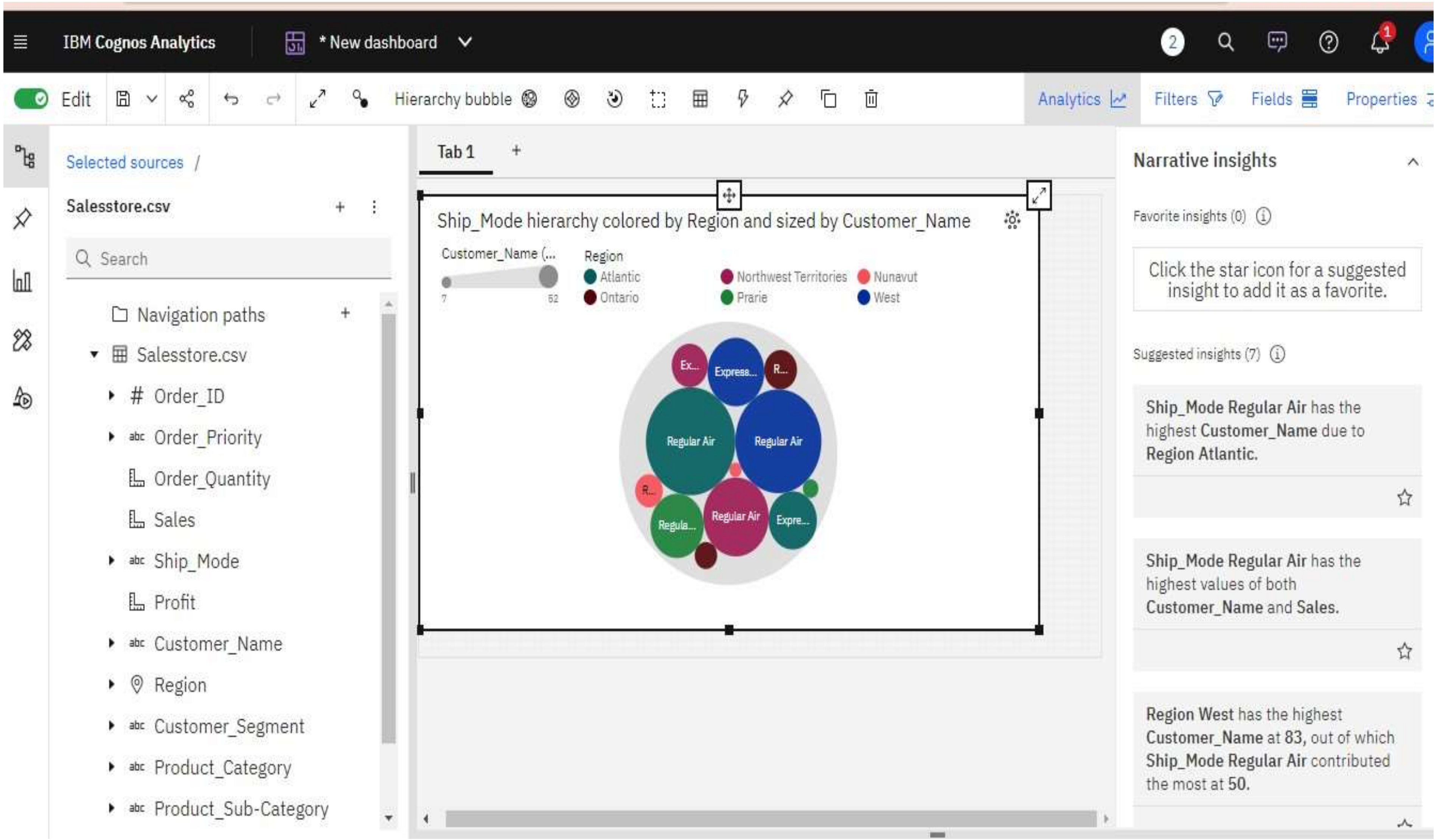


Click the star icon for a suggested insight to add it as a favorite.

Product_Category Furniture has the highest **Unaggregated Order_Quantity** but is ranked **#3** in **Total Profit**.

Product_Category Technology has the highest **Total Profit** but is ranked **#1** in **Unaggregated Order_Quantity**.

COLLEGECODE:4212
REGISTER NUMBER:421221243012



Click the star icon for a suggested insight to add it as a favorite.

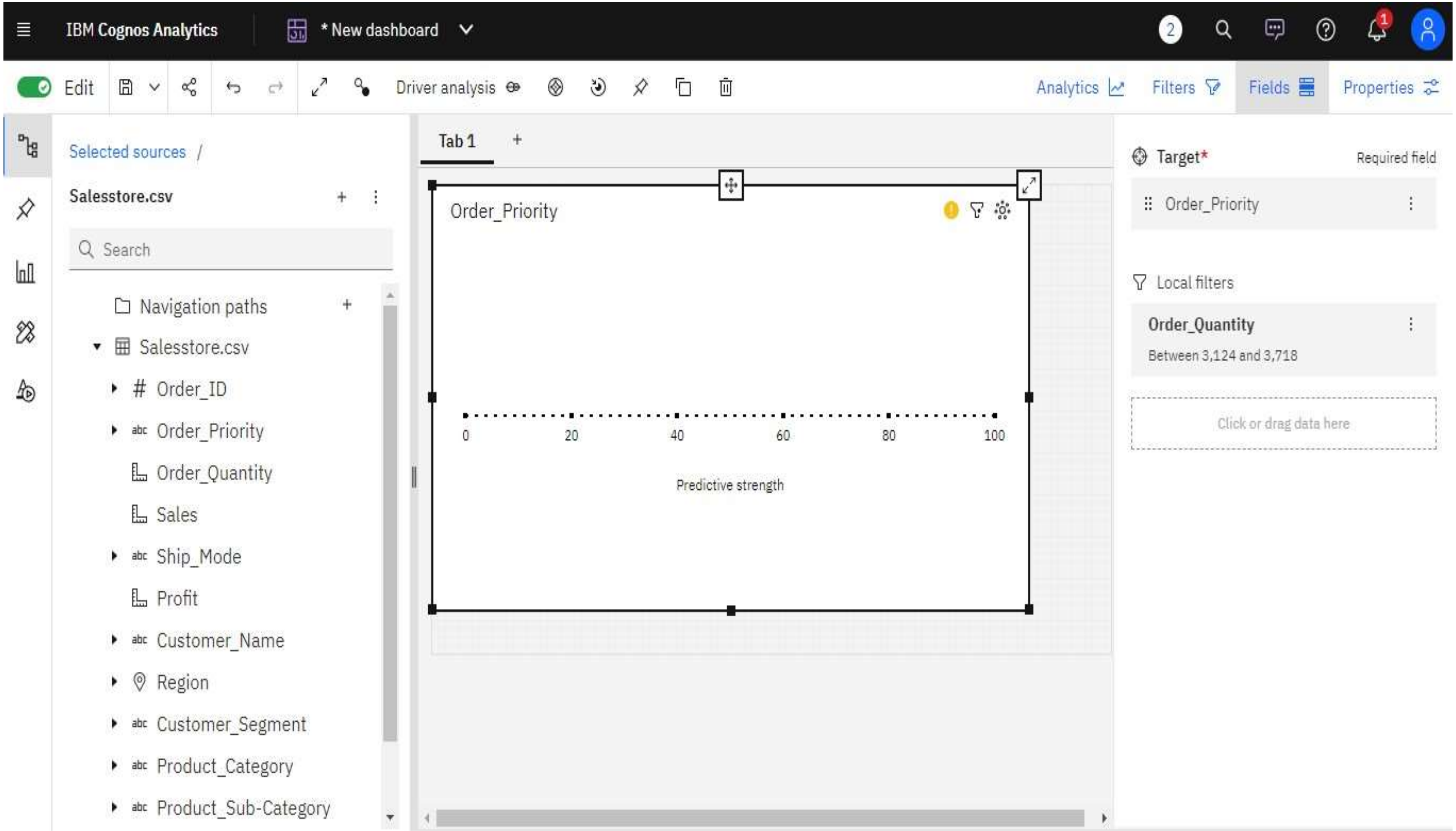
Ship_Mode Regular Air has the highest Customer_Name due to Region Atlantic.

Ship_Mode Regular Air has the highest values of both Customer_Name and Sales.

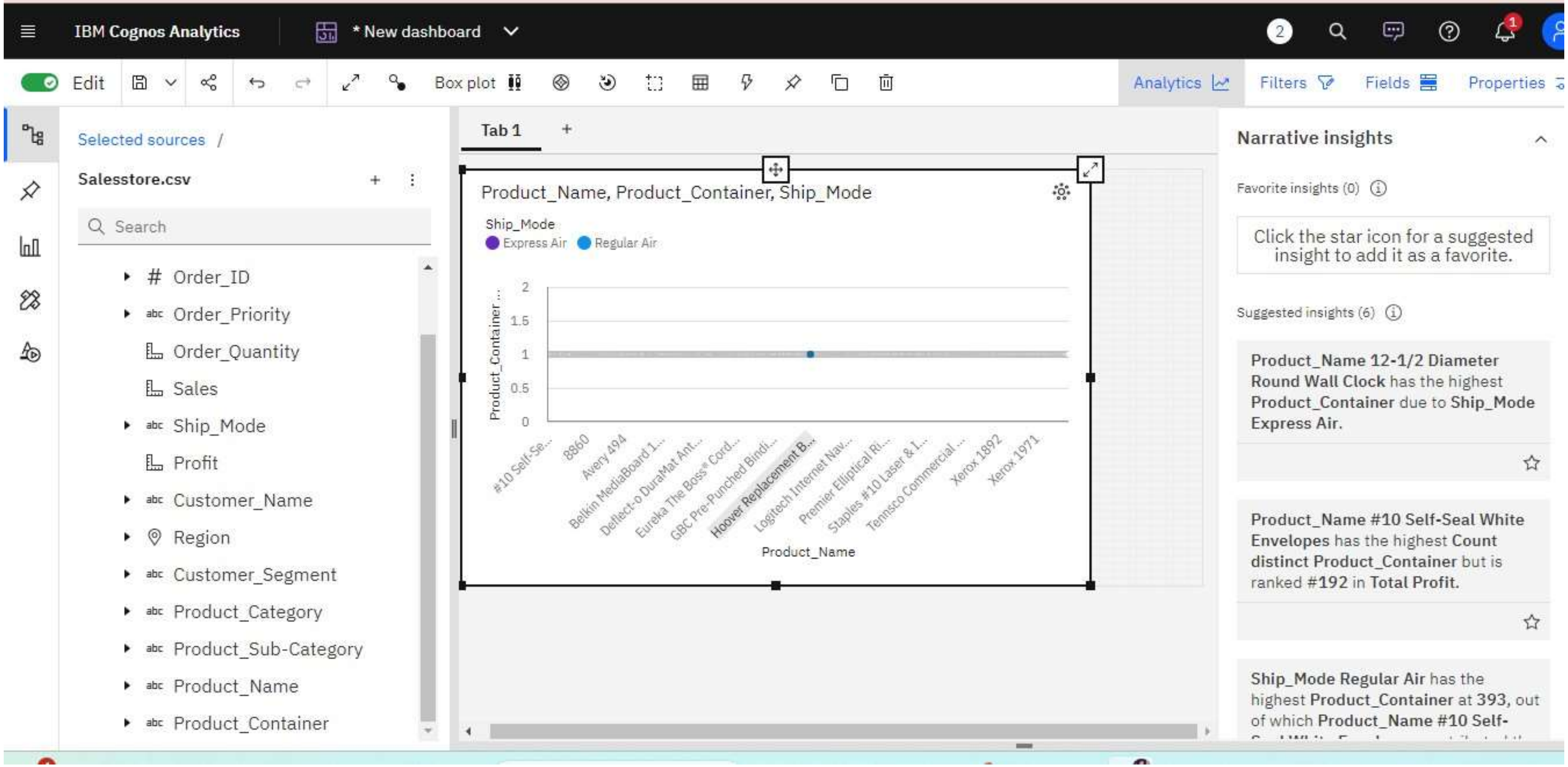
Region West has the highest Customer_Name at 83, out of which Ship_Mode Regular Air contributed the most at 50.

1q`2

COLLEGECODE:4212
REGISTER NUMBER:421221243012



COLLEGECODE:4212
REGISTER NUMBER:421221243012



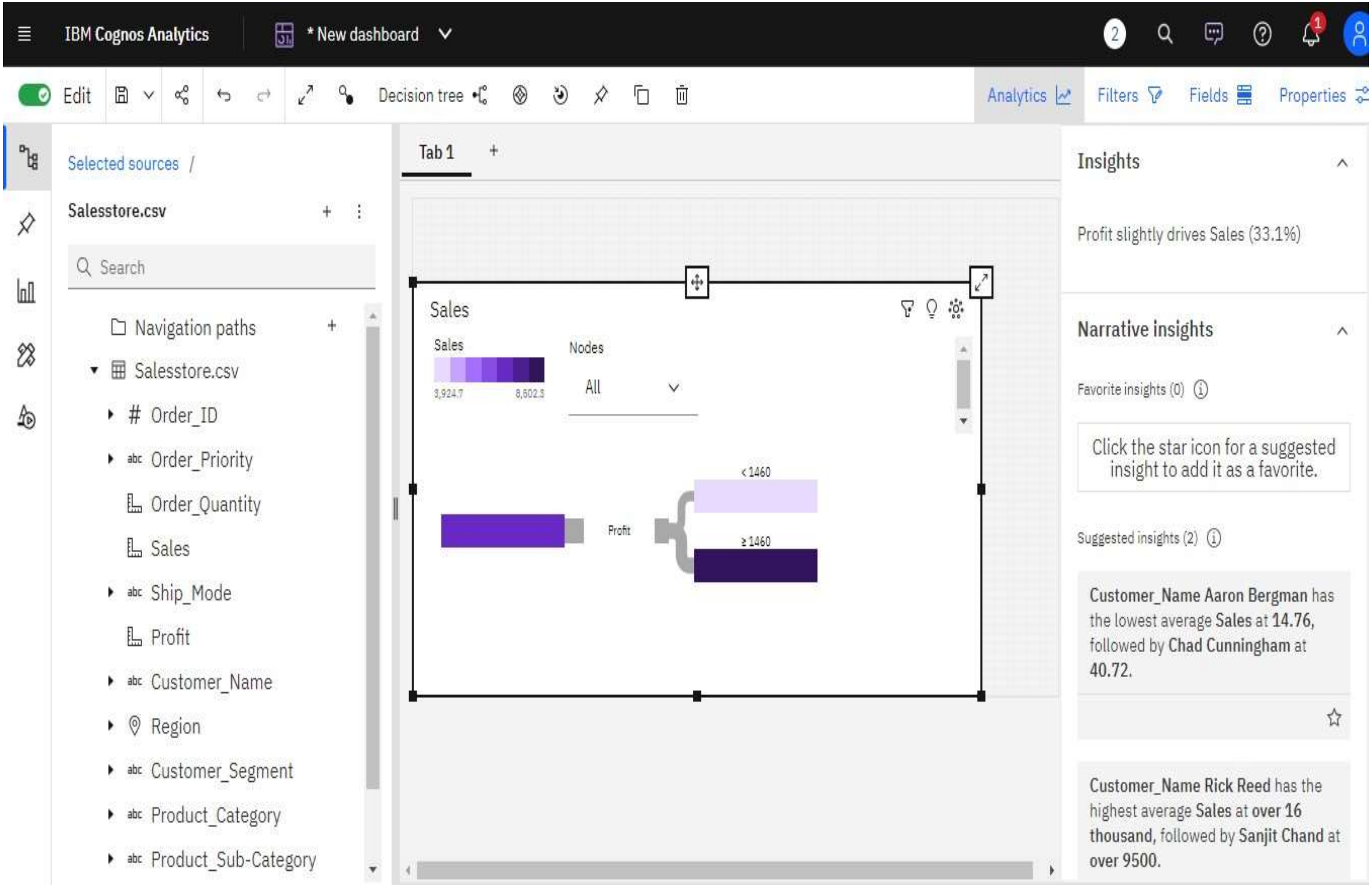
Click the star icon for a suggested insight to add it as a favorite.

Product_Name 12-1/2 Diameter Round Wall Clock has the highest **Product_Container** due to **Ship_Mode Express Air.**

Product_Name #10 Self-Seal White Envelopes has the highest **Count distinct Product_Container** but is ranked **#192** in **Total Profit.**

Ship_Mode Regular Air has the highest **Product_Container** at **393**, out of which **Product_Name #10 Self-**

COLLEGECODE:4212
REGISTER NUMBER:421221243012



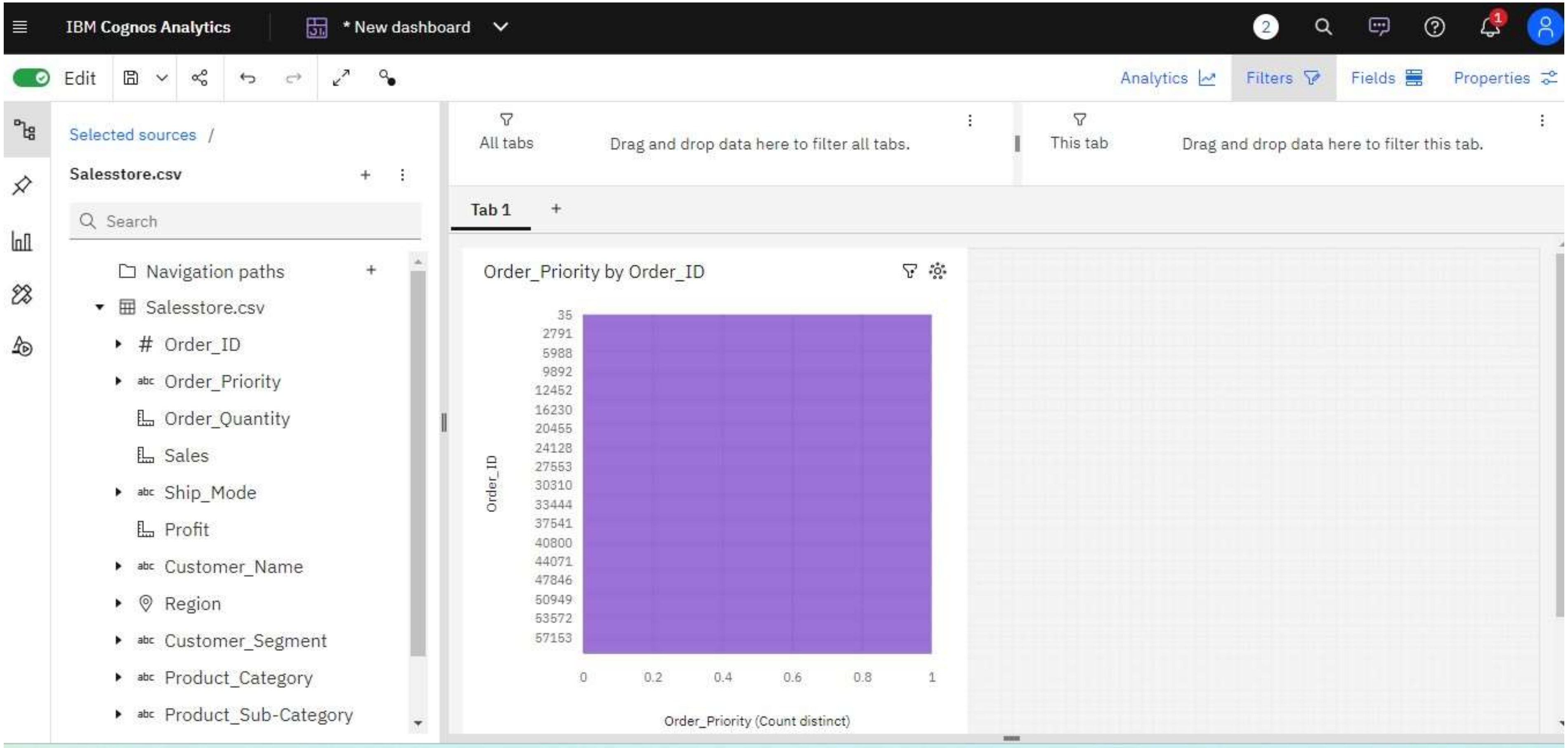
Profit slightly drives Sales (33.1%)

Click the star icon for a suggested insight to add it as a favorite.

Customer_Name Aaron Bergman has the lowest average Sales at 14.76, followed by Chad Cunningham at 40.72.

Customer_Name Rick Reed has the highest average Sales at over 16 thousand, followed by Sanjit Chand at over 9500.

COLLEGECODE:4212
REGISTER NUMBER:421221243012



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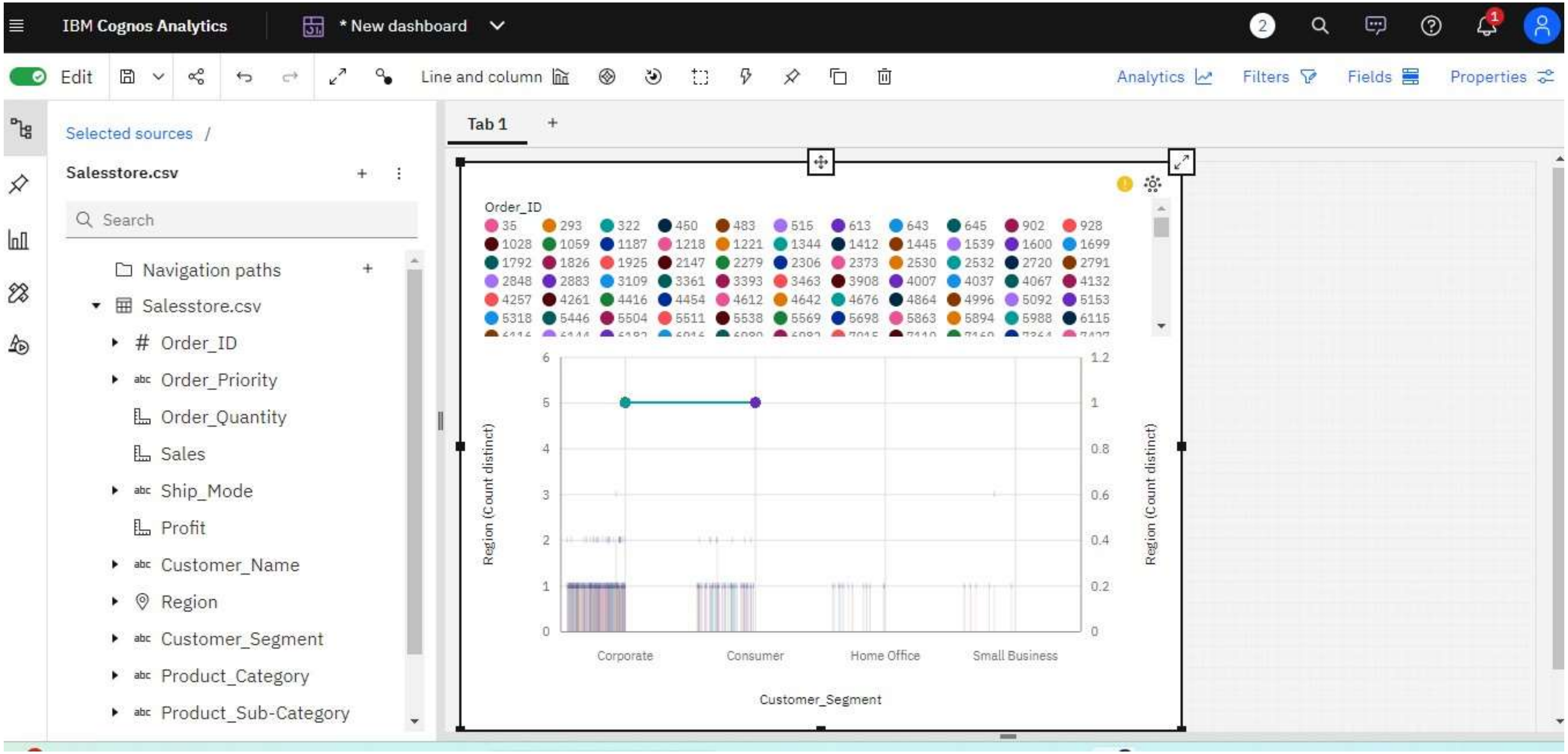

CONCLUSION

Based on the extensive analysis of your product sales data, it is evident that your product has been performing exceptionally well in the market.

With the help of data analytics, we were able to identify key patterns and customer behaviors that have contributed to this success.

It is clear that your product is meeting the needs and preferences of your target audience.

Moving forward, it would be beneficial to continue leveraging data analytics to further improve your sales strategies and capitalize on this positive trend