

PROJECT:PRODUCT SALES ANALYSIS

PHASE 3- DEVELOPMENT PHASE 3

PREPROCESSING AND CLEANSING OF DATA

CLEANING OF DATASET:

Cleaning of the dataset includes removing duplicates,handling the missing values, handling outliers,data scaling and normalization, data visualization,data splitting and data balancing if needed.

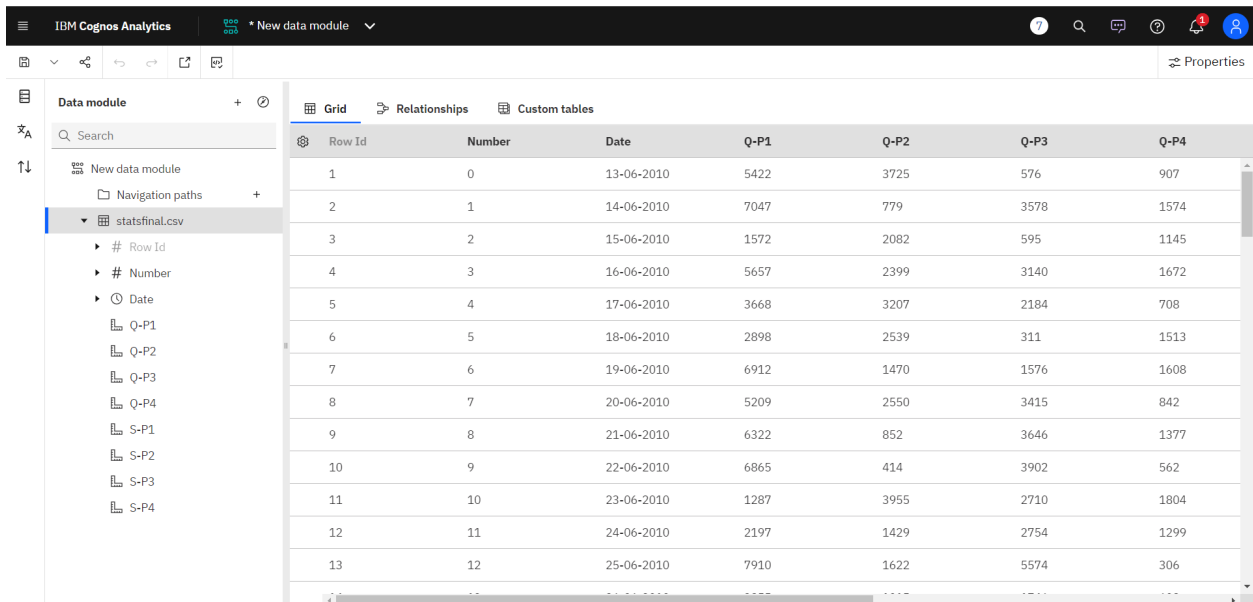
1.Removing duplicates:

```
data=data.dropna()
```

Out[8]:

	Unnamed: 0	Date	Q-P1	Q-P2	Q-P3	Q-P4	S-P1	S-P2	S-P3	S-P4
0	0	13-06-2010	5422	3725	576	907	17187.74	23616.50	3121.92	6466.91
1	1	14-06-2010	7047	779	3578	1574	22338.99	4938.86	19392.76	11222.62
2	2	15-06-2010	1572	2082	595	1145	4983.24	13199.88	3224.90	8163.85
3	3	16-06-2010	5657	2399	3140	1672	17932.69	15209.66	17018.80	11921.36
4	4	17-06-2010	3668	3207	2184	708	11627.56	20332.38	11837.28	5048.04
5	5	18-06-2010	2898	2539	311	1513	9186.66	16097.26	1685.62	10787.69
6	6	19-06-2010	6912	1470	1576	1608	21911.04	9319.80	8541.92	11465.04
7	7	20-06-2010	5209	2550	3415	842	16512.53	16167.00	18509.30	6003.46
8	8	21-06-2010	6322	852	3646	1377	20040.74	5401.68	19761.32	9818.01
9	9	22-06-2010	6865	414	3902	562	21762.05	2624.76	21148.84	4007.06

From IBM Cognos:



Row Id	Number	Date	Q-P1	Q-P2	Q-P3	Q-P4
1	0	13-06-2010	5422	3725	576	907
2	1	14-06-2010	7047	779	3578	1574
3	2	15-06-2010	1572	2082	595	1145
4	3	16-06-2010	5657	2399	3140	1672
5	4	17-06-2010	3668	3207	2184	708
6	5	18-06-2010	2898	2539	311	1513
7	6	19-06-2010	6912	1470	1576	1608
8	7	20-06-2010	5209	2550	3415	842
9	8	21-06-2010	6322	852	3646	1377
10	9	22-06-2010	6865	414	3902	562
11	10	23-06-2010	1287	3955	2710	1804
12	11	24-06-2010	2197	1429	2754	1299
13	12	25-06-2010	7910	1622	5574	306

2. Handling outliers:

On checking outliers by scatter plot .

For product1:

```
import seaborn as sns
```

```
import matplotlib.pyplot as plt
```

```
# Set some default parameters of matplotlib
```

```
plt.rcParams['figure.figsize'] = (8, 6)
```

```
plt.rcParams['figure.dpi'] = 150
```

```
# Use style froms seaborn. Try to comment the next line and see the difference in graph
```

```
sns.set()
```

```
# A regular scatter plot
```

```
plt.scatter(x=data["Q-P1"], y=data["S-P1"])
```

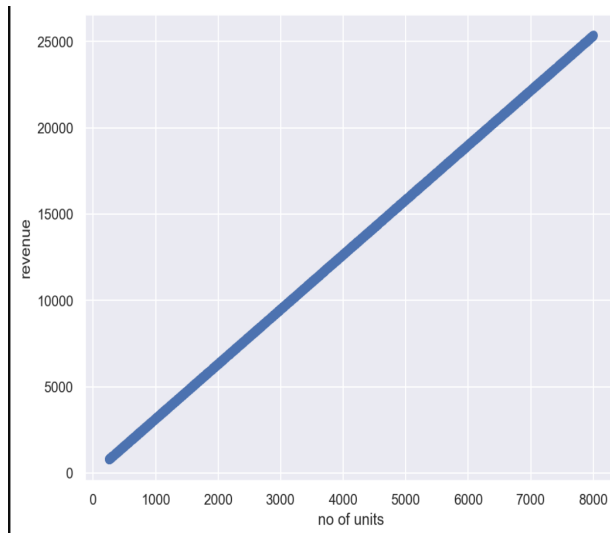
```
# Create labels for axes
```

```
plt.xlabel('no of units')
```

```
plt.ylabel('revenue')
```

```
# Display the plot on the screen
```

```
plt.show()
```



For product 2:

```
plt.rcParams['figure.figsize'] = (8, 6)
```

```
plt.rcParams['figure.dpi'] = 150
```

```
# Use style from seaborn. Try to comment the next line and see the difference in graph
sns.set()
```

```
# A regular scatter plot
```

```
plt.scatter(x=data["Q-P2"], y=data["S-P2"])
```

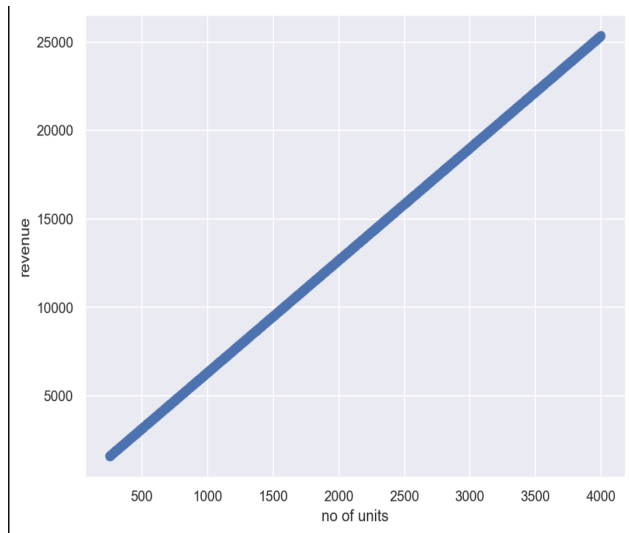
```
# Create labels for axes
```

```
plt.xlabel('no of units')
```

```
plt.ylabel('revenue')
```

```
# Display the plot on the screen
```

```
plt.show()
```



For product 3:

```
plt.rcParams['figure.figsize'] = (8, 6)
```

```
plt.rcParams['figure.dpi'] = 150
```

```
# Use style from seaborn. Try to comment the next line and see the difference in graph
sns.set()
```

```
# A regular scatter plot
```

```
plt.scatter(x=data["Q-P3"], y=data["S-P3"])
```

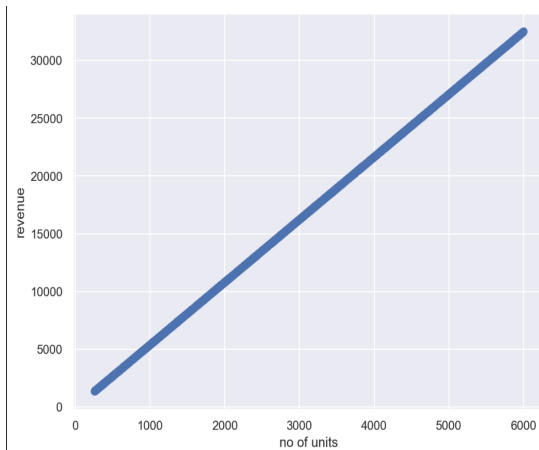
```
# Create labels for axes
```

```
plt.xlabel('no of units')
```

```
plt.ylabel('revenue')
```

```
# Display the plot on the screen
```

```
plt.show()
```



For product 4:

```
plt.rcParams['figure.figsize'] = (8, 6)
```

```
plt.rcParams['figure.dpi'] = 150
```

Use style froms seaborn. Try to comment the next line and see the difference in graph
`sns.set()`

A regular scatter plot

```
plt.scatter(x=data["Q-P4"], y=data["S-P4"])
```

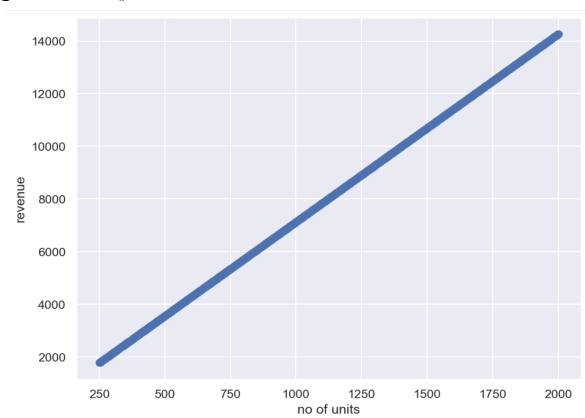
Create labels for axes

```
plt.xlabel('no of units')
```

```
plt.ylabel('revenue')
```

Display the plot on the screen

```
plt.show()
```



SUMMARY OF OUR CLEANSED DATA:

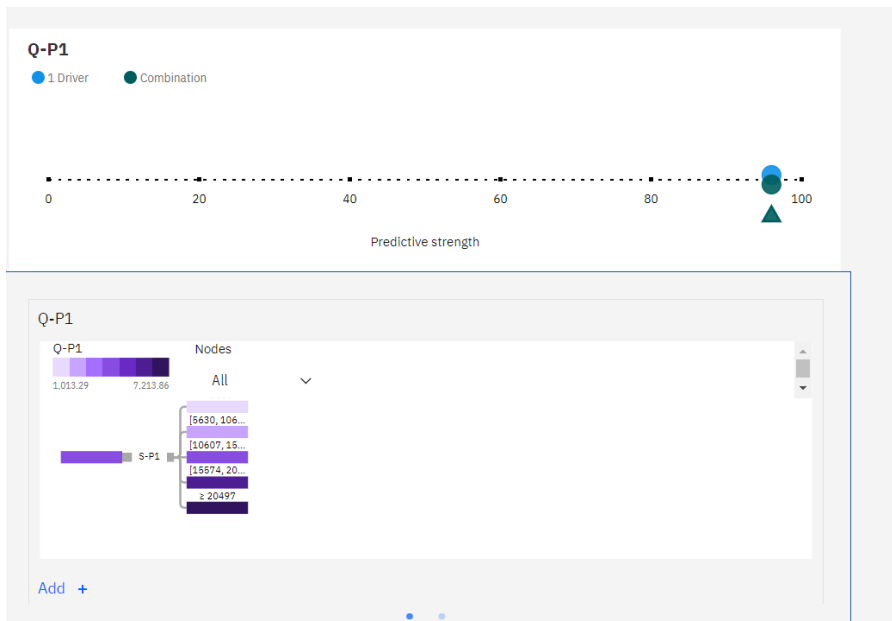
data.info()

```
<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
```

data.describe()

Accuracy of dataset performed by IBM cognos:

Q-P1

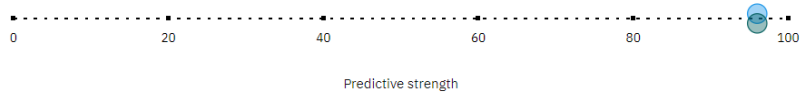


Details

S-P1 predicts Q-P1 with a strength of 96%.

Q-P1

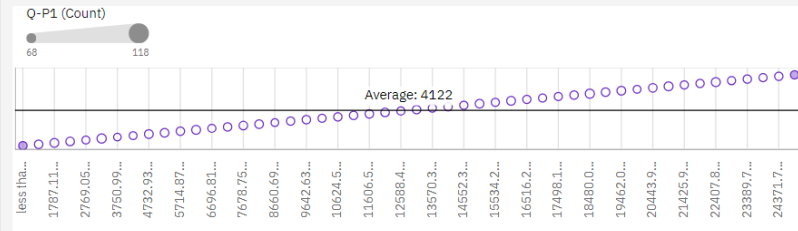
● 1 Driver ● Combination



Details

S-P1 predicts Q-P1 with a strength of 96%

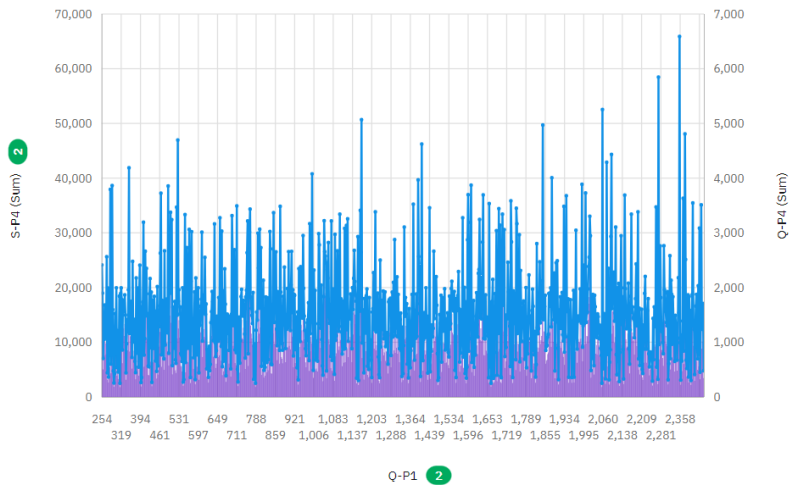
S-P1 (Group) by Q-P1 sized by Q-P1



Add +

Q-P4 and S-P4 by Q-P1

Column Line
● S-P4 (Sum) ● Q-P4 (Sum)

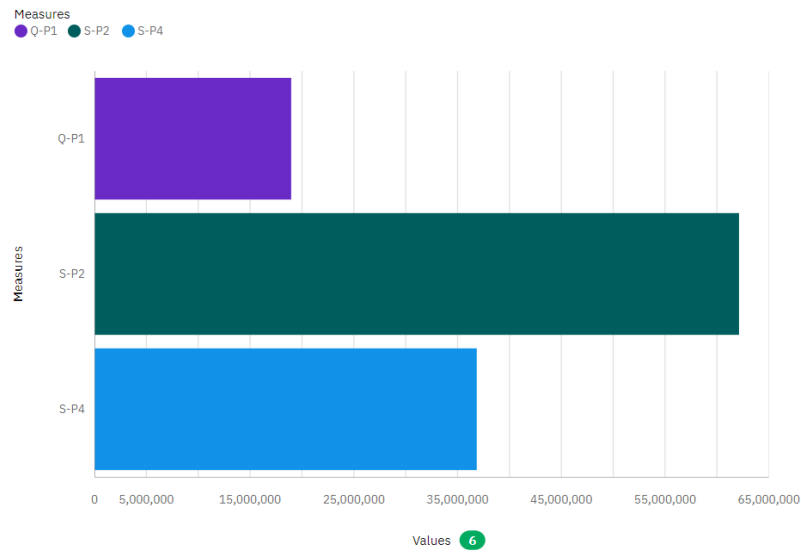


Details

Chart Insights were not computed because this visualization is based on clipped data. Consider applying a filter to reduce the number of records, and to prevent the data from being clipped, before creating the visualization.

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S-P4, S-P2 and Q-P1



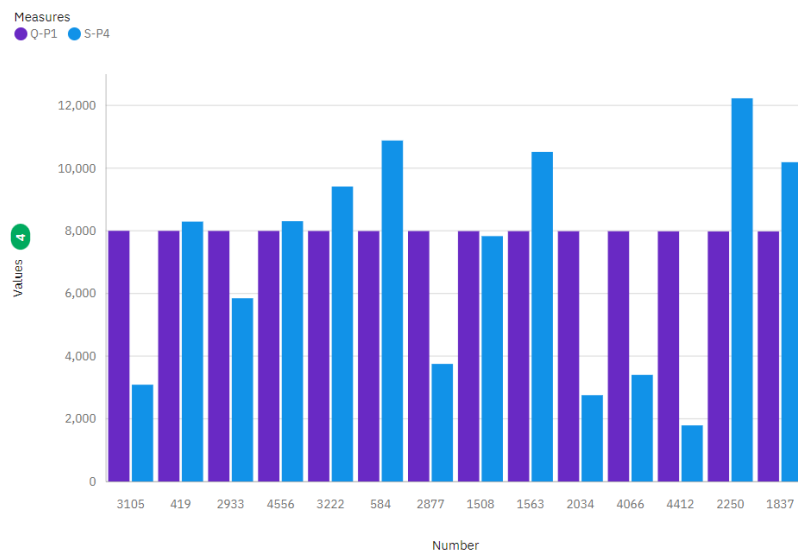
Details

The overall number of results for **S-P4** is over 4500.

The overall number of results for **S-P2** is over 4500.

The overall number of results for **Q-P1** is over 4500.

S-P4 and Q-P1 by Number



Details

The total number of results for **Q-P1**, across all **numbers**, is 14.

Over all **numbers**, the average of **Q-P1** is nearly eight thousand.

The total number of results for **S-P4**, across all **numbers**, is 14.

Across all **numbers**, the average of **S-P4** is over seven thousand.

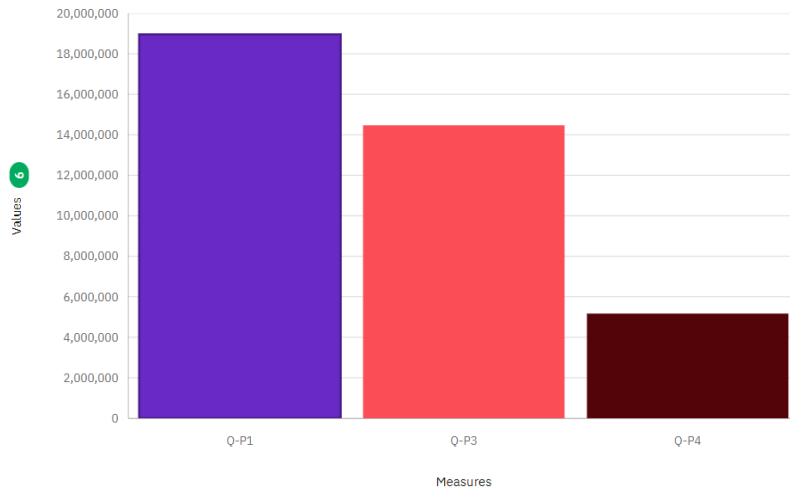
Q-P1 ranges from 7979, when **Number** is 2250, to 7998, when **Number** is 3105.

S-P4 ranges from nearly two thousand, when **Number** is 4412, to over twelve thousand, when **Number** is 2250.

Q-P4, Q-P3 and Q-P1

Measures

● Q-P1 ● Q-P3 ● Q-P4



Details

The overall number of results for **Q-P3** is over 4500.

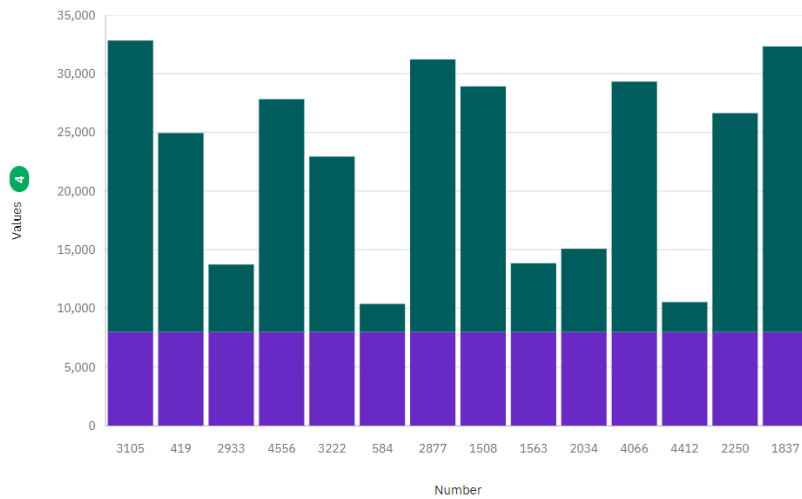
The overall number of results for **Q-P1** is over 4500.

The overall number of results for **Q-P4** is over 4500.

S-P2 and Q-P1 by Number

Measures

● Q-P1 ● S-P2



Details

Q-P1 ranges from 7979, when **Number** is 2250, to 7998, when **Number** is 3105.

S-P2 ranges from almost 2500, when **Number** is 584, to almost 25 thousand, when **Number** is 3105.

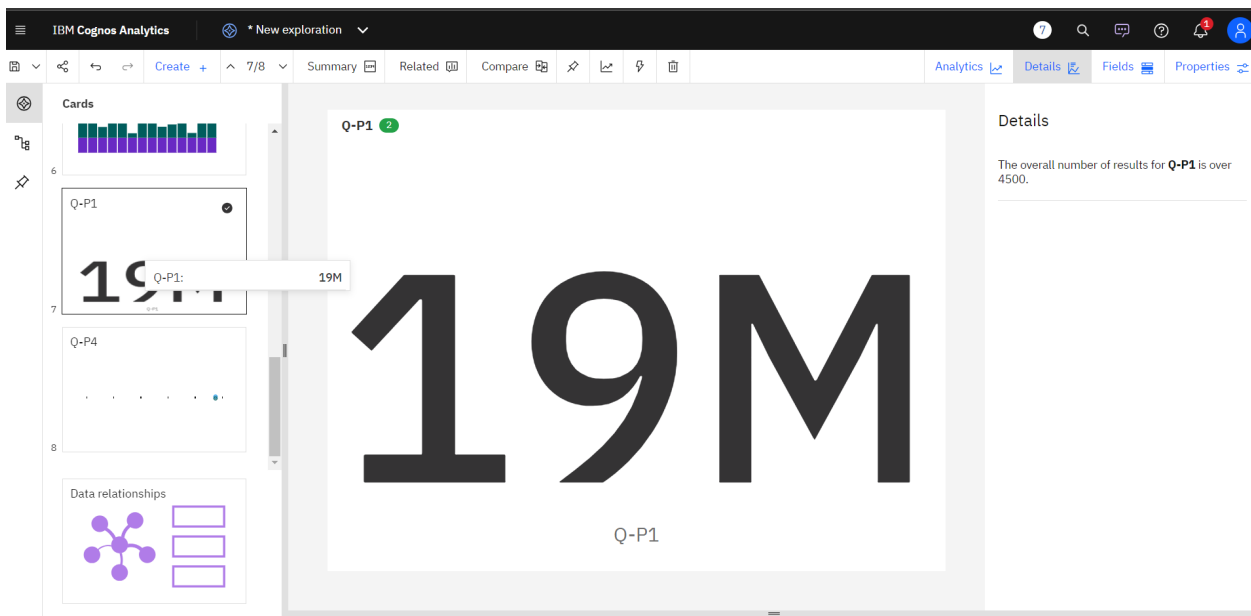
The total number of results for **S-P2**, across all **numbers**, is 14.

Over all **numbers**, the average of **S-P2** is nearly fifteen thousand.

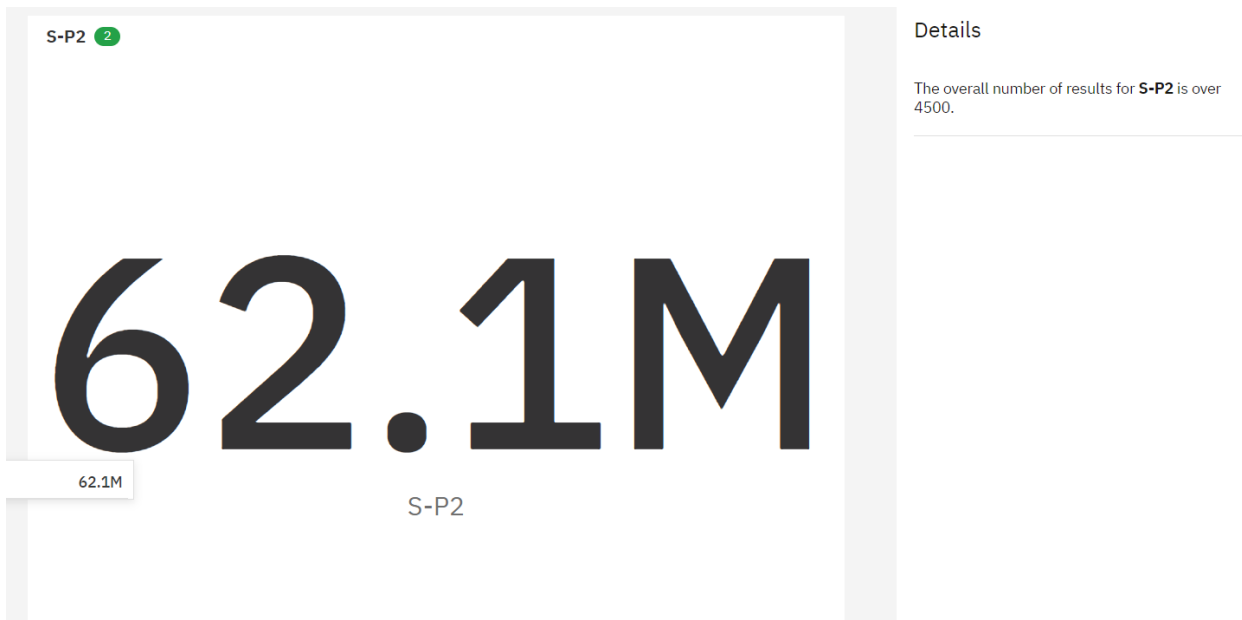
The total number of results for **Q-P1**, across all **numbers**, is 14.

Over all **numbers**, the average of **Q-P1** is nearly eight thousand.

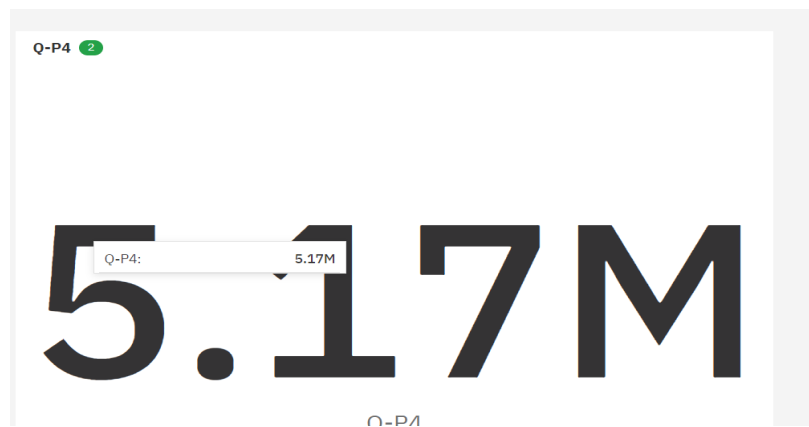
OVERALL SUMMARY IN IBM COGNOS:
Q-P1



Q-P2



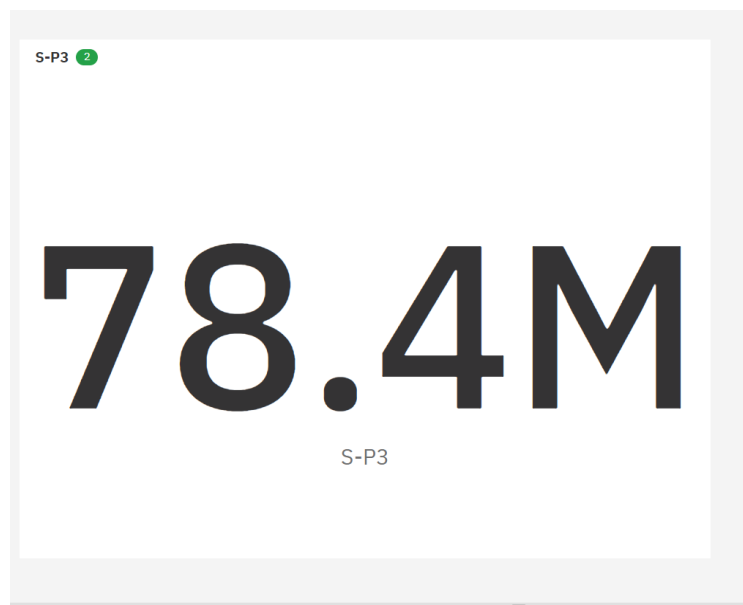
Q-P3



Details

The overall number of results for **Q-P4** is o
4500.

Q-P4



Details

The overall number of results for **S-P3** is over
4500.

CONCLUSION:

In conclusion, cleaning and preprocessing a dataset are essential steps in the data analysis and machine learning process. These steps help ensure that your data is accurate, consistent, and ready for analysis or modeling. Clean, well-preprocessed data is the foundation for meaningful and actionable insights