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# **MRA - Main Project**

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# Problem Statement - MRA Main Project

## Part - A

### **Business Context:**

An automobile parts manufacturing company has been actively selling products to a diverse range of customers for the past three years. Despite its growth, the company lacks the in-house expertise to derive actionable insights from its transaction data. As a result, they wish to uncover hidden patterns and trends in their customer transactions. By analyzing this data, the company aims to better understand customer behavior, improve customer segmentation, and implement targeted marketing strategies. These insights will help the company not only enhance customer satisfaction but also drive revenue growth by offering more personalized and efficient services.

### **Objective:**

The primary objective of this analysis is to leverage data science techniques to:

1. Identify underlying patterns in customer purchasing behavior.
2. Segment customers based on their transactional data.
3. Provide actionable insights to optimize the company's marketing efforts.
4. Recommend personalized marketing strategies for each customer segment to maximize sales and customer retention.

### **Data Description:**

**ORDERNUMBER:** Unique identifier for each order.

**QUANTITYORDERED:** Number of items ordered in a specific transaction.

**PRICEEACH:** Price per unit of the product in the order.

**ORDERLINENUMBER:** Sequence number of the product in the order.

**SALES:** Total sales value for the order.

**ORDERDATE:** Date when the order was placed.

**DAYS\_SINCE\_LASTORDER:** Number of days since the customer's previous order.

**STATUS:** Current status of the order (e.g., Shipped, Disputed).

**PRODUCTLINE:** Product category to which the item belongs (e.g., Motorcycles, Classic Cars).

**MSRP:** Manufacturer's Suggested Retail Price for the product.

**PRODUCTCODE:** Unique identifier for the product.

**CUSTOMERNAME:** Name of the customer placing the order.

**PHONE:** Customer's contact phone number.

**ADDRESSLINE1:** Customer's primary address.

**CITY:** City of the customer's address.

**POSTALCODE:** Postal code of the customer's address.















**COUNTRY:** Country of the customer's address.

**CONTACTLASTNAME:** Last name of the customer's contact person.

**CONTACTFIRSTNAME:** First name of the customer's contact person.

**DEALSIZE:** Size category of the transaction (e.g., Small, Medium, Large).

## Summary Statistics

Column 	Exclude Column	Minimum 	Maximum 	Mean 	Standard Deviation 	Variance 	Skewness 
 ORDERNUMBER	<input type="checkbox"/>	10100	10425	10259.762	91.878	8441.479	-0.007
 QUANTITYORDERED	<input type="checkbox"/>	6	97	35.103	9.762	95.299	0.369
 PRICEEACH	<input type="checkbox"/>	26.880	252.870	101.099	42.043	1767.576	0.697
 ORDERLINENUMBER	<input type="checkbox"/>	1	18	6.491	4.231	17.897	0.575
 SALES	<input type="checkbox"/>	482.130	14082.800	3553.048	1838.954	3381751.448	1.156
 DAYS_SINCE_LASTORDER	<input type="checkbox"/>	42	3562	1757.086	819.281	671220.663	-0.003
 MSRP	<input type="checkbox"/>	33	214	100.692	40.115	1609.197	0.576








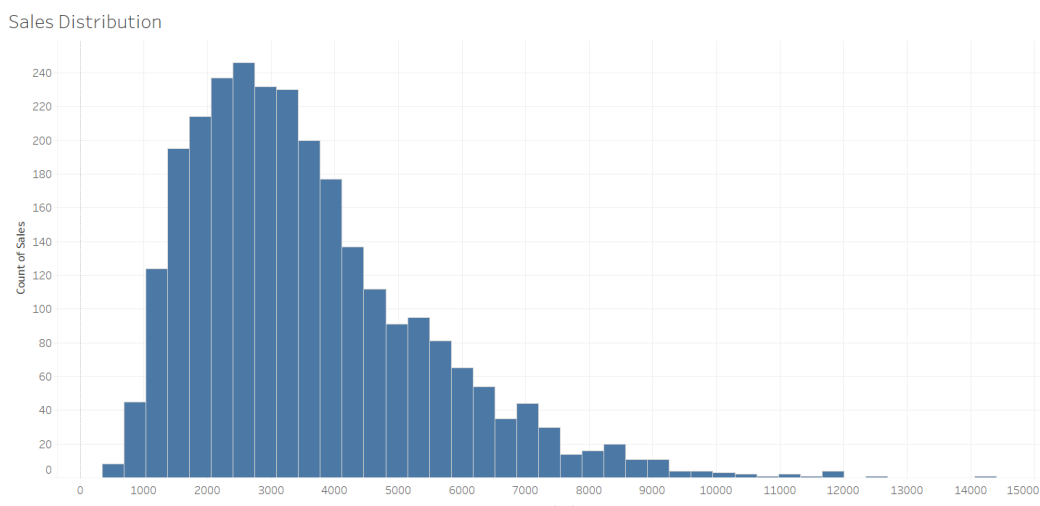
Column 	Exclude Column	No. missings 	Unique values 	All nominal values 	Frequency Bar Chart
ORDERDATE	<input type="checkbox"/>	0	246	2018-11-14, 2019-11-24, 2018-11-12, 2019-11-17, 2019-11-04, [...], 2018-04-11, 2018-10-10, 2019-08-28, 2018-04-21, 2019-04-20	
STATUS	<input type="checkbox"/>	0	6	Shipped, Cancelled, Resolved, On Hold, In Process, Disputed	
PRODUCTLINE	<input type="checkbox"/>	0	7	Classic Cars, Vintage Cars, Motorcycles, Planes, Trucks and Buses, Ships, Trains	

Table "default" - Rows: 2747		Spec - Columns: 20
Columns: 20	Column Type	Column
ORDERNUMBER	Number (integer)	0
QUANTITYORDERED	Number (integer)	1
PRICEEACH	Number (double)	2
ORDERLINENUMBER	Number (integer)	3
SALES	Number (double)	4
ORDERDATE	String	5
DAYS_SINCE_LASTORDER	Number (integer)	6
STATUS	String	7
PRODUCTLINE	String	8
MSRP	Number (double)	9
PRODUCTCODE	String	10
CUSTOMERNAME	String	11
PHONE	String	12
ADDRESSLINE1	String	13
CITY	String	14
POSTALCODE	String	15
COUNTRY	String	16
CONTACTLASTNAME	String	17
CONTACTFIRSTNAME	String	18
DEALSIZE	String	19

- There are a total of 2747 rows in the dataset with 20 variables.
- Each variable has its datatype; there are 7 numerical and 13 categorical.
- There are no missing values.

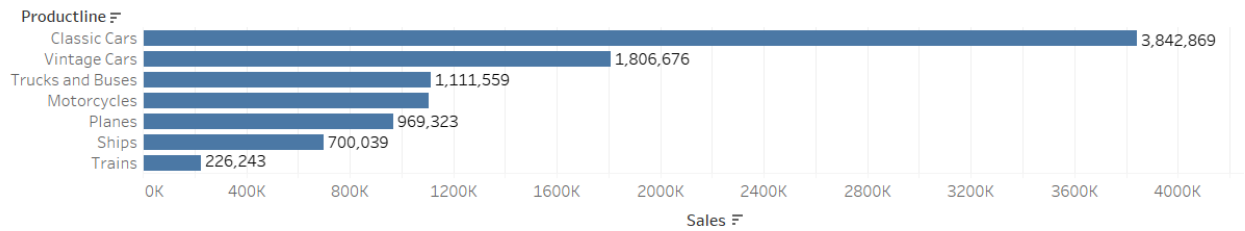
## Univariate Analysis

### 1. Sales distribution



- It is right-skewed so there are many large purchases.

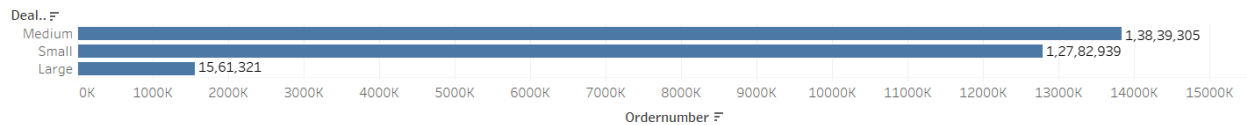
### 2. ProductLine Popularity



- Classic cars are sold higher. The sales of classic cars are much higher than the others.

### 3. Deal Size Count

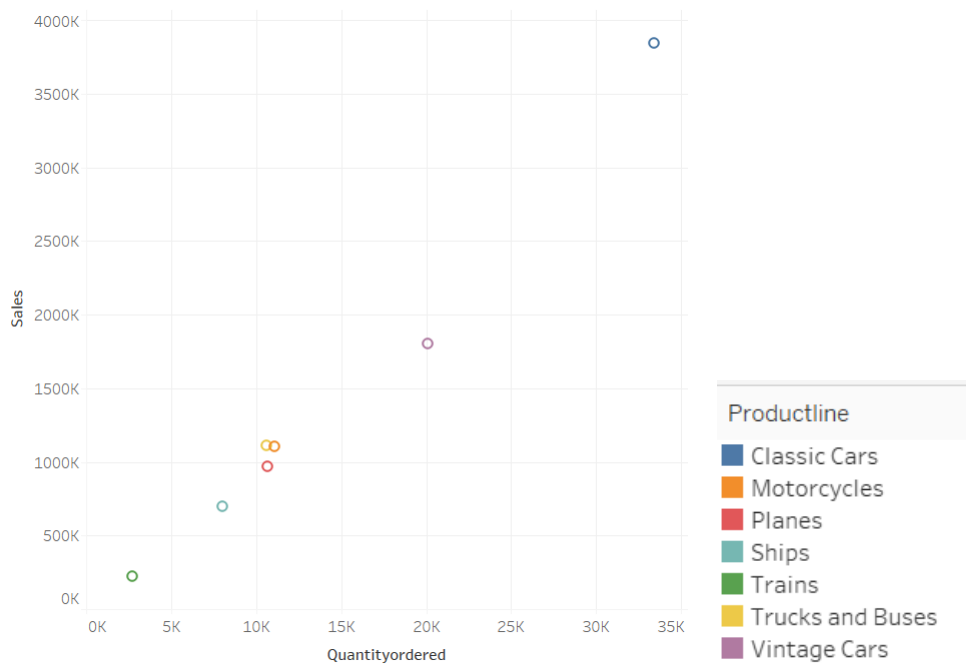
Deal size count



- Medium sized deals are most common.

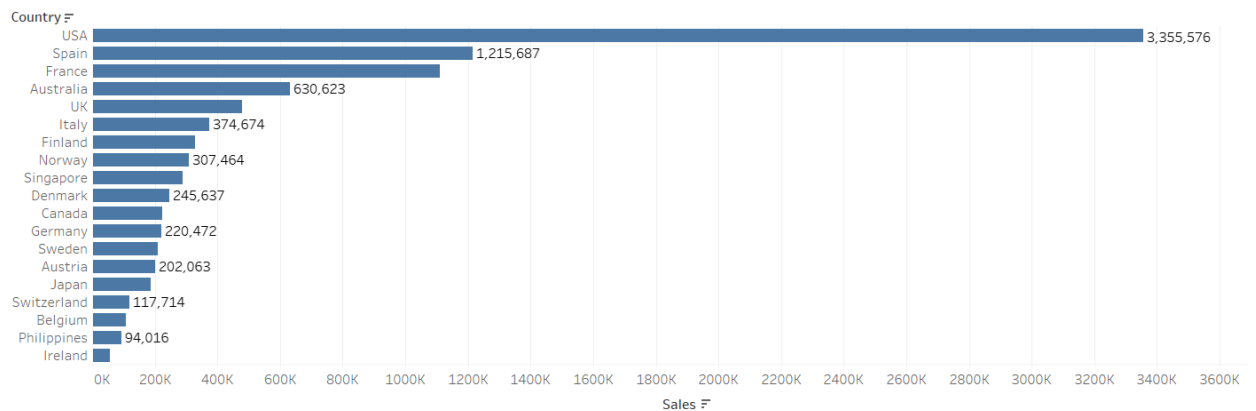
## Bivariate Analysis (Two-Variable Relationships)

### 1. Sales vs Quantity Ordered



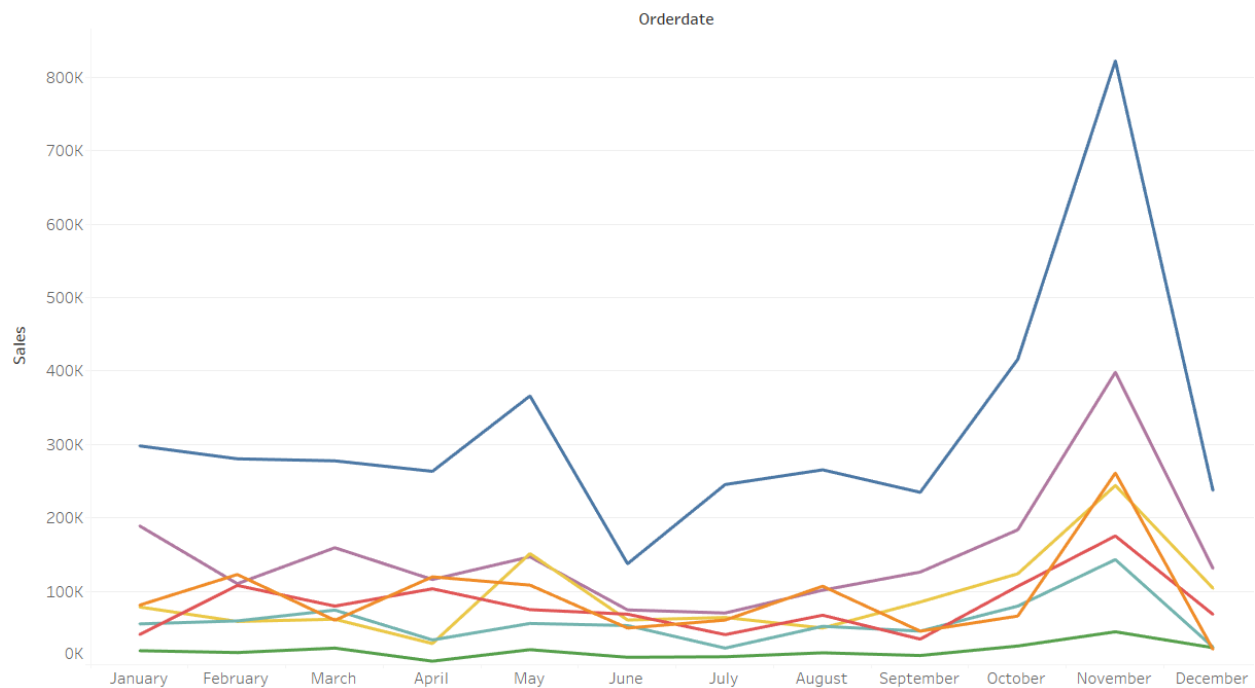
- More sales and quantities are ordered for Classic cars in the automobile sector.

## 2. Sales by Country



- USA generates the highest revenue among all.

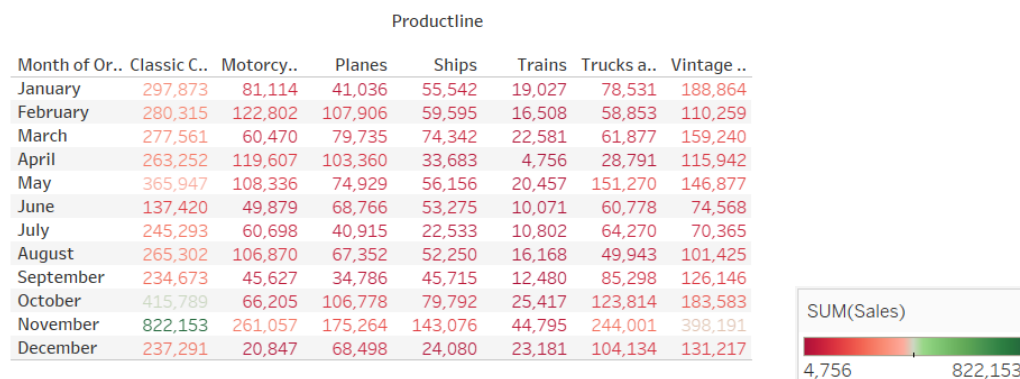
## 4. Monthly Sales Trend



- The seasonal spikes are mostly at the end of the year. The last 4 months have the highest sales for all the automobiles.

## 5. Productline vs Month : Heatmap

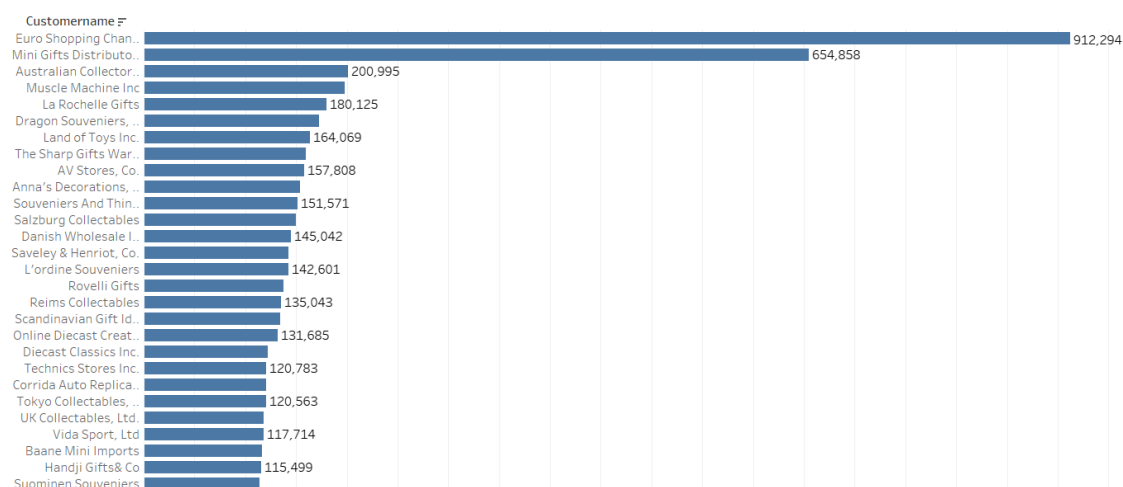
## Productline vs month



- The Classic cars are the most sold in the month of november .

## 6. Customername vs Sales

customername vs sales

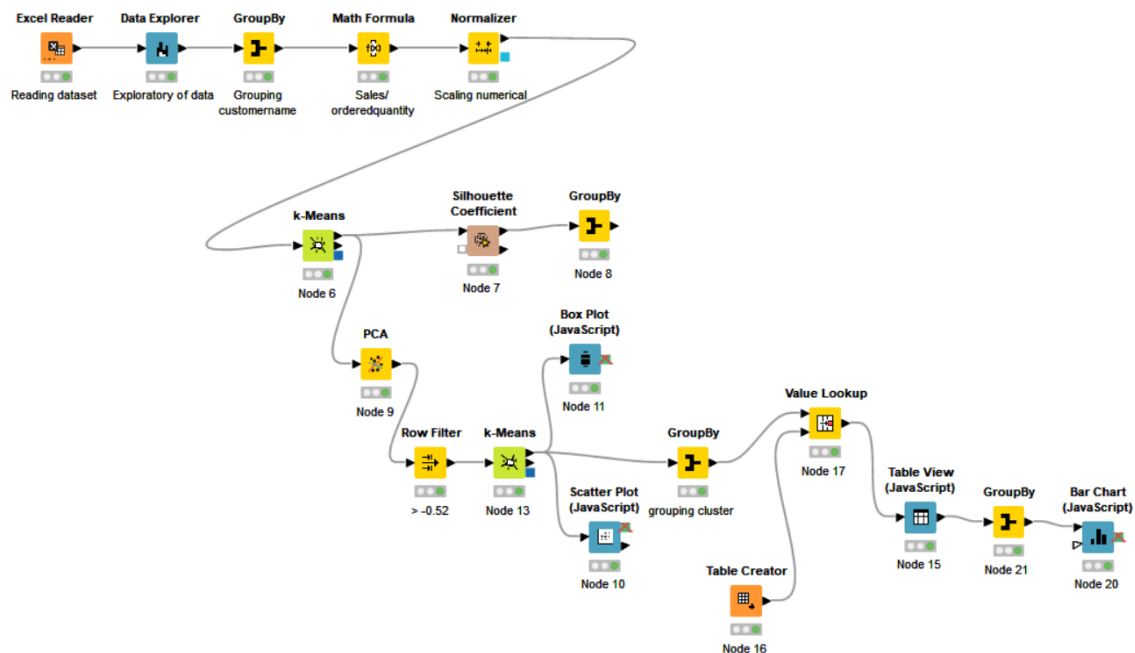


- The most valuable customers are Euro Shopping Channel with 912,294.

[https://public.tableau.com/app/profile/akshay.sreekumar8075/viz/MRA\\_main-Analysis/Dashboard1](https://public.tableau.com/app/profile/akshay.sreekumar8075/viz/MRA_main-Analysis/Dashboard1)



## Customer Segmentation using RFM analysis



After performing RFM-based clustering on the transaction data, **4 customer segments** were identified using the K-Means clustering algorithm in KNIME.

The number of clusters was determined using a combination of:

- **Elbow Method:** To identify the point of diminishing returns in the within-cluster sum of squares.
- **Business Interpretability:** Ensuring each cluster represented a distinct, actionable customer group.

The final 4 segments are:

1. **Champions** – Highly active and valuable customers

2. **Potential Loyal** – Fairly active but with lower monetary value
3. **At Risk** – Declining frequency, need re-engagement
4. **Big Spenders** – High monetary value but recent inactivity

Row ID	S Cluster	I Count(...	D Mean(S...	D Mean(...	D Mean(...	I Count*...	D Mean(S...	S segment
Row0	cluster_0	27	0.118	0.552	0.448	27	0.117	Champions
Row1	cluster_1	22	0.091	0.486	0.163	22	0.092	Potential Loyal
Row2	cluster_2	20	0.086	0.25	0.366	20	0.096	At Risk
Row3	cluster_3	18	0.071	0.428	0.766	18	0.073	Big Spenders

Q) Mention the top five customers

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Row ID	S CUSTOMERNAME	D * Sum(...	D Mean(...	D Mean(D...	D Count(...	D Sales_P...	S ▲ Cluster
Row48	Microscale Inc.	0.027	0.652	0.494	0.027	0.024	cluster_0
Row87	West Coast Collectables Co.	0.041	0.736	0.379	0.039	0.036	cluster_0
Row40	Iberia Gift Imports, Corp.	0.05	0.733	0.568	0.047	0.045	cluster_0
Row58	Online Mini Collectables	0.053	0.655	0.349	0.047	0.049	cluster_0
Row25	Daedalus Designs Imports	0.066	0.435	0.509	0.066	0.068	cluster_0

## Cluster 0 – Champions

- **Recency:** 0.1179 → Very recent buyers (good).
- **Frequency:** 0.5524 → Highest frequency.
- **Monetary:** 0.4477 → High spenders.
- **Sales per item:** 0.1168 → Consistently buying at a good value.

Best Overall Customers – Active, frequent, and high-value.

## Cluster 1 – Potential Loyal

- **Recency:** 0.0914 → Recent buyers.
- **Frequency:** 0.4863 → Moderate to high frequency.
- **Monetary:** 0.1626 → Low spenders.

Engaged but Low-Value – May be regular small buyers. These can be up-sold or nurtured into Champions through bundled discounts or targeted campaigns.

### **Cluster 2 – At Risk**

- **Recency:** 0.0863 → Recent enough (surprising for At Risk).
- **Frequency:** 0.2499 → Low frequency.
- **Monetary:** 0.3664 → Medium spenders.

Infrequent Buyers – Spend a decent amount but rarely buy. A drop in frequency could lead to churn. They are ideal for win-back offers or limited-time promotions.

### **Cluster 3 – Big Spenders**

- **Recency:** 0.0706 → Least recent (danger zone).
- **Frequency:** 0.4284 → Decent frequency.
- **Monetary:** 0.7662 → Highest spending cluster.

High Value, Low Engagement – These customers are very profitable but not recent. Immediate follow-up needed. They should be targeted with personal outreach, VIP programs, or renewal deals.

## **Problem Statement - MRA Main Project**

### **Part - B**

## **Business Context:**

In the highly competitive grocery retail industry, understanding customer buying patterns is crucial for enhancing sales, increasing customer satisfaction, and improving profitability. By identifying frequently purchased item combinations, grocery stores can craft effective marketing strategies, optimize inventory management, and tailor promotions to meet customer needs. Leveraging Point of Sale (POS) data can unlock valuable insights that drive customer-centric offerings, such as combo packs, discounts, and targeted promotions, which can increase basket size and improve customer retention. This analysis aligns with business goals by maximizing revenue, reducing operational costs, and boosting customer loyalty.

## **Objective:**

The goal is to analyze the POS transactional data to identify frequently purchased item combinations. Using association rule mining or similar techniques, the aim is to uncover patterns that will help the store create targeted combo offers and discounts, ultimately driving revenue growth by increasing customer purchases and average basket size.

## **Data Description:**

**Date:** The date when the transaction took place.

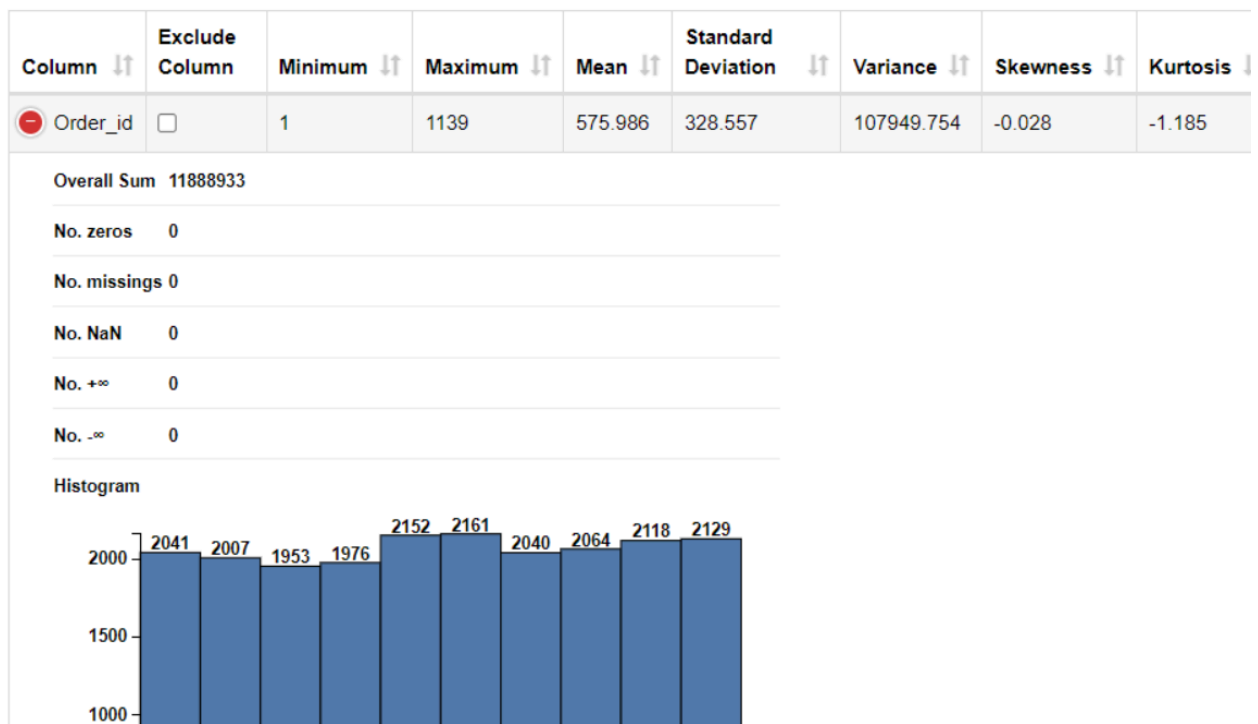
**Order\_id:** A unique identifier for each customer order.

**Product:** The individual item purchased in the transaction.

## Exploratory Data Analysis (EDA)

### Summary Statistics

- The dataset includes the following columns Date, Order\_ID,Product.
- It contains 1 numerical and 2 nominal values.
- There are a total 20641 rows.
- Dates ranging from 2018 - 2020
- There are 640 unique values.
- There are no missing values



### Q) Top 10 Frequently Purchased Products

Row ID	<b>S</b> Product	<b>D</b> Order_id
Row36	yogurt	606.167
Row30	soda	598.774
Row8	dinner rolls	595.365
Row34	tortillas	594.074
Row24	pork	593.859
Row22	paper towels	592.388
Row25	poultry	589.494
Row27	sandwich lo...	588.79
Row18	laundry det...	585.24
Row9	dishwashing...	584.842
Row0	all- purpose	584.501
Row29	soap	582.796
Row14	ice cream	582.244
Row6	cheeses	581.891

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- These are the top 10 items purchased.

#### Thresholds Used

- Minimum Support: 0.05 (5% of transactions)
- Minimum Confidence: 0.60 (60% confidence required)

#### Explanation of Metrics

- Support: Fraction of transactions containing both Items and consequent.
- Confidence: How often the consequent appears when the Items are present.
- Lift: How much more likely the consequent is with the items compared to random chance.

Row ID	D Support	D Confide...	D Lift	? Conseq...	S implies	[...] Items
rule0	0.05	0.983	0.986	?	<---	[yogurt,butter,soap]
rule1	0.05	0.64	1.7	juice	<---	[yogurt,toilet paper,aluminum foil]
rule2	0.05	1	1.004	?	<---	[yogurt,ice cream,hand soap]
rule3	0.05	0.613	1.616	coffee/tea	<---	[yogurt,cheeses,cereals]
rule4	0.05	1	1.004	?	<---	[pasta,lunch meat,pork]
rule5	0.05	0.983	0.986	?	<---	[laundry detergent,beef,pork]
rule6	0.05	0.983	0.986	?	<---	[fruits,laundry detergent,pork]
rule7	0.05	1	1.004	?	<---	[hand soap,cereals,pork]
rule8	0.05	1	1.004	?	<---	[fruits,hand soap,pork]
rule9	0.05	0.983	0.986	?	<---	[paper towels,sandwich loaves,pork]
rule10	0.05	1	1.004	?	<---	[sandwich loaves,pork,sugar]
rule11	0.05	1	1.004	?	<---	[hand soap,individual meals,sandwich bags]
rule12	0.05	1	1.004	?	<---	[all- purpose,hand soap,tortillas]
rule13	0.05	1	1.004	?	<---	[all- purpose,hand soap,bagels]
rule14	0.05	0.983	0.986	?	<---	[flour,bagels,soap]
rule15	0.05	1	1.004	?	<---	[flour,hand soap,bagels]
rule16	0.05	0.983	0.986	?	<---	[butter,spaghetti sauce,beef]
rule17	0.05	1	1.004	?	<---	[sandwich loaves,milk,sugar]
rule18	0.05	1	1.004	?	<---	[fruits,tortillas,juice]
rule19	0.05	1	1.004	?	<---	[yogurt,poultry,juice,...]
rule20	0.05	0.62	1.645	juice	<---	[yogurt,poultry,?,...]
rule21	0.05	0.613	1.666	sandwich bags	<---	[cheeses,bagels,?,...]
rule22	0.05	0.983	0.986	?	<---	[cheeses,bagels,cereals,...]
rule23	0.05	0.671	1.716	cheeses	<---	[bagels,?,cereals,...]
rule24	0.05	0.613	1.548	cereals	<---	[cheeses,bagels,?,...]
rule25	0.05	1	1.004	?	<---	[dishwashing liquid/detergent,poultry,laundry detergent,...]
rule26	0.05	0.606	1.439	poultry	<---	[dishwashing liquid/detergent,laundry detergent,?,...]
rule27	0.051	0.983	0.987	?	<---	[fruits,flour,pork]
rule28	0.051	0.983	0.987	?	<---	[butter,hand soap,pork]
rule29	0.051	1	1.004	?	<---	[pork,aluminum foil,sugar]

- If items like yogurt,toilet paper, aluminium foil they recommend for juice.
- Also for yogurt, cheese, cereals are taken they suggest coffee/tea.

## The final output table

<input type="checkbox"/>	RowID	Support	Confidence	Lift	Consequent	implies	Items
<input type="checkbox"/>	rule0	0.05004389815627744	0.9827586206896551	0.9862220871942883	?	<---	[yogurt, butter, soap]
<input type="checkbox"/>	rule1	0.05004389815627744	0.6404494382022472	1.700400722872633	juice	<---	[yogurt, toilet paper, aluminum foil]
<input type="checkbox"/>	rule2	0.05004389815627744	1	1.0035242290748898	?	<---	[yogurt, ice cream, hand soap]
<input type="checkbox"/>	rule3	0.05004389815627744	0.6129032258064516	1.6159647550776581	coffee/tea	<---	[yogurt, cheeses, cereals]
<input type="checkbox"/>	rule4	0.05004389815627744	1	1.0035242290748898	?	<---	[pasta, lunch meat, pork]
<input type="checkbox"/>	rule5	0.05004389815627744	0.9827586206896551	0.9862220871942883	?	<---	[laundry detergent, beef, pork]
<input type="checkbox"/>	rule6	0.05004389815627744	0.9827586206896551	0.9862220871942883	?	<---	[fruits, laundry detergent, pork]
<input type="checkbox"/>	rule7	0.05004389815627744	1	1.0035242290748898	?	<---	[hand soap, cereals, pork]
<input type="checkbox"/>	rule8	0.05004389815627744	1	1.0035242290748898	?	<---	[fruits, hand soap, pork]
<input type="checkbox"/>	rule9	0.05004389815627744	0.9827586206896551	0.9862220871942883	?	<---	[paper towels, sandwich loaves, pork]

Showing 1 to 10 of 8,478 entries

- Products like pork, yogurt, soap, and cereals appear in multiple strong rules.
- Certain combinations e.g., [cheeses, cereals, yogurt] => coffee/tea have high confidence and lift.
- Some rules have perfect confidence (1.00), indicating strong cross-sell potential.

