

# Marketing & Retail Analysis Project

Automobile sales - Part 1

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# Problem statement

An automobile parts manufacturing company has collected data of transactions for 3 years. They do not have any in-house data science team, thus they have hired you as their consultant. Your job is to use your magical data science skills to provide them with suitable insights about their data and their customers.

## Executive Summary

- The data is regarding an automobile parts manufacturing company
- The dataset contains 2,747 records and 20 columns, with information about orders, customers, products and their sales
- The data includes various data types, such as integers, floats, objects (likely strings), and a date time column
- The data contains information about 89 customers from 19 different countries
- There are 7 product lines namely–Motorcycles, Classic Cars, Trucks and Buses, Vintage Cars, Planes, Ships and Trains, with 109 unique products
- The average order number is approximately 10,260, with an average quantity ordered of 35.1 and an average sales amount of around \$3,553. The prices range from \$26.88 to \$252.87
- The dataset includes information about customer names, contact details, and their locations, such as city, postal code, and country. The 'DEALSIZE' column suggests that most deals are categorized as "Medium"

# Data Dictionary

Column Name	Description
ORDERNUMBER	This column represents the unique identification number assigned to each order.
QUANTITYORDERED	It indicates the number of items ordered in each order.
PRICEEACH	This column specifies the price of each item in the order.
ORDERLINENUMBER	It represents the line number of each item within an order.
SALES	This column denotes the total sales amount for each order, which is calculated by multiplying the quantity ordered by the price of each item.
ORDERDATE	It denotes the date on which the order was placed.
DAYS_SINCE_LASTORDER	This column represents the number of days that have passed since the last order for each customer. It can be used to analyze customer purchasing patterns.
STATUS	It indicates the status of the order, such as "Shipped," "In Process," "Cancelled," "Disputed," "On Hold," or "Resolved"
PRODUCTLINE	This column specifies the product line categories to which each item belongs.
MSRP	It stands for Manufacturer's Suggested Retail Price and represents the suggested selling price for each item.
PRODUCTCODE	This column represents the unique code assigned to each product.
CUSTOMERNAME	It denotes the name of the customer who placed the order.
PHONE	This column contains the contact phone number for the customer.
ADDRESSLINE1	It represents the first line of the customer's address.
CITY	This column specifies the city where the customer is located.
POSTALCODE	It denotes the postal code or ZIP code associated with the customer's address.
COUNTRY	This column indicates the country where the customer is located.
CONTACTLASTNAME	It represents the last name of the contact person associated with the customer.
CONTACTFIRSTNAME	This column denotes the first name of the contact person associated with the customer.
DEALSIZE	It indicates the size of the deal or order, which are the categories "Small," "Medium," or "Large."

# Data Statistics

- The data types of these columns include int64, float64, datetime64, and object
- Notable columns include 'ORDERNUMBER,' 'QUANTITYORDERED,' 'PRICEEACH,' 'ORDERDATE,' 'SALES,' and 'DAYS\_SINCE\_LASTORDER' which appear to be related to order and sales data
- 'PRODUCTLINE,' 'MSRP,' and 'PRODUCTCODE' provide information about the product associated with each order
- Customer-related information such as 'CUSTOMERNAME,' 'PHONE,' and 'COUNTRY' is available
- Several object-type columns store textual information such as customer names, product codes, and contact details
- The 'STATUS' and 'DEALSIZE' columns also contain categorical data

```
RangeIndex: 2747 entries, 0 to 2746
Data columns (total 20 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   ORDERNUMBER                          2747 non-null   int64
1   QUANTITYORDERED                      2747 non-null   int64
2   PRICEEACH                           2747 non-null   float64
3   ORDERLINENUMBER                     2747 non-null   int64
4   SALES                               2747 non-null   float64
5   ORDERDATE                           2747 non-null   datetime64[ns]
6   DAYS_SINCE_LASTORDER                2747 non-null   int64
7   STATUS                              2747 non-null   object
8   PRODUCTLINE                         2747 non-null   object
9   MSRP                                2747 non-null   int64
10  PRODUCTCODE                         2747 non-null   object
11  CUSTOMERNAME                       2747 non-null   object
12  PHONE                              2747 non-null   object
13  ADDRESSLINE1                       2747 non-null   object
14  CITY                               2747 non-null   object
15  POSTALCODE                         2747 non-null   object
16  COUNTRY                            2747 non-null   object
17  CONTACTLASTNAME                    2747 non-null   object
18  CONTACTFIRSTNAME                   2747 non-null   object
19  DEALSIZE                           2747 non-null   object
dtypes: datetime64[ns](1), float64(2), int64(5), object(12)
memory usage: 429.3+ KB
```

# Data Statistics

	ORDERNUMBER	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	DAYS_SINCE_LASTORDER	MSRP
count	2747.000000	2747.000000	2747.000000	2747.000000	2747.000000	2747.000000	2747.000000
mean	10259.761558	35.103021	101.098951	6.491081	3553.047583	1757.085912	100.691664
std	91.877521	9.762135	42.042548	4.230544	1838.953901	819.280576	40.114802
min	10100.000000	6.000000	26.880000	1.000000	482.130000	42.000000	33.000000
25%	10181.000000	27.000000	68.745000	3.000000	2204.350000	1077.000000	68.000000
50%	10264.000000	35.000000	95.550000	6.000000	3184.800000	1761.000000	99.000000
75%	10334.500000	43.000000	127.100000	9.000000	4503.095000	2436.500000	124.000000
max	10425.000000	97.000000	252.870000	18.000000	14082.800000	3562.000000	214.000000

```
df1.duplicated().sum()  
  
0
```

```
ORDERNUMBER      0  
QUANTITYORDERED  0  
PRICEEACH         0  
ORDERLINENUMBER  0  
SALES             0  
ORDERDATE        0  
DAYS_SINCE_LASTORDER  0  
STATUS           0  
PRODUCTLINE      0  
MSRP             0  
PRODUCTCODE      0  
CUSTOMERNAME     0  
PHONE            0  
ADDRESSLINE1     0  
CITY             0  
POSTALCODE       0  
COUNTRY          0  
CONTACTLASTNAME  0  
CONTACTFIRSTNAME 0  
DEALSIZE         0  
dtype: int64
```

- The data does not contain any null values
- The data does not contain any duplicate values
- The average number of Quantity ordered per sales order is 35, with a standard deviation of 9.76
- The average price of each item is 101.09, with a standard deviation of 42.04
- The average sales amount per order is 3553.05, with a standard deviation of 1838.95
- The average time since the last order is 1757.09 days, with a standard deviation of 819.28
- The summary statistics do not indicate any red flags or abnormalities that could potentially indicate issues with the data

# Assumptions



- Each row in the data represents a unique transaction made by a customer
- The customer segments may be defined based on the purchasing frequency, amount spent, and recency of purchases (RFM Analysis)
- The marketing strategies may vary for each customer segment, and the company may need to personalize their marketing efforts accordingly
- The order date and days since last order columns are accurately calculated and last date is calculated from 01-06-2020
- The sales column is calculated as the product of quantity ordered and price each

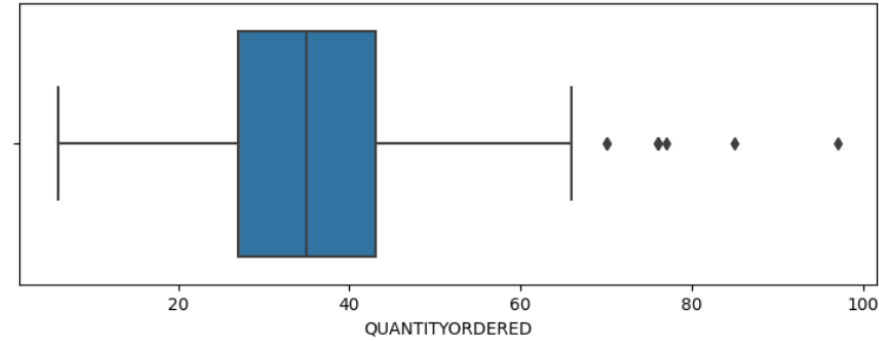
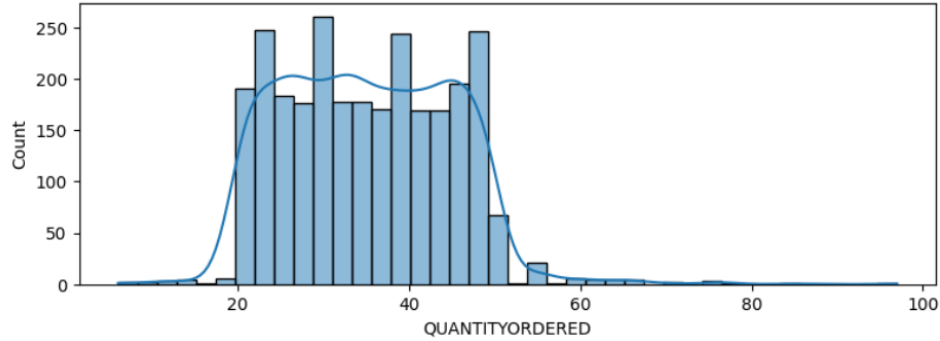
# Exploratory Analysis & Insights

Univariate and multivariate analysis

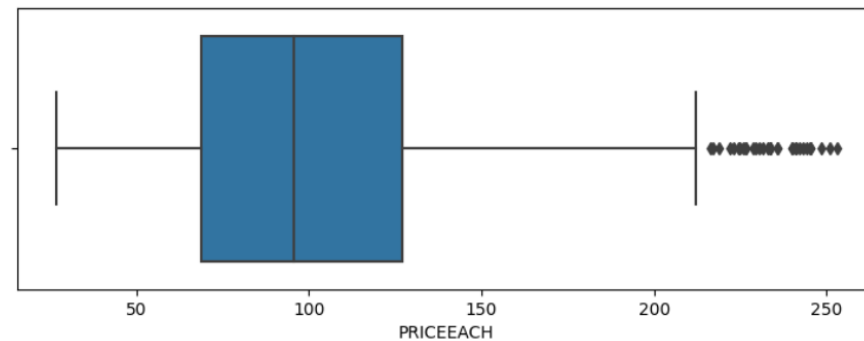
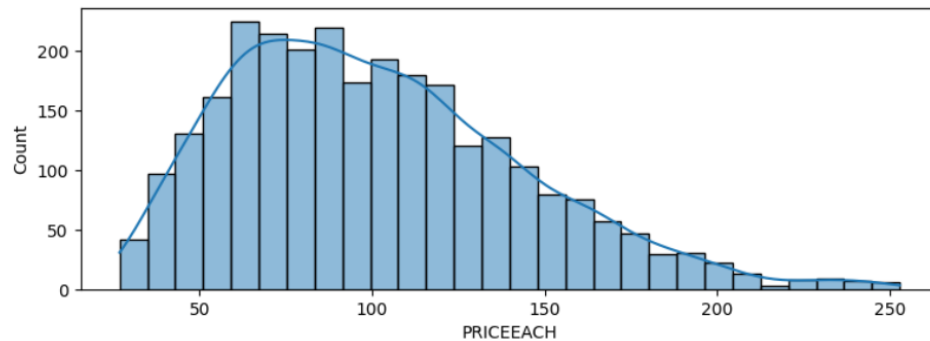
Sales Distribution



# Univariate analysis (1/2)

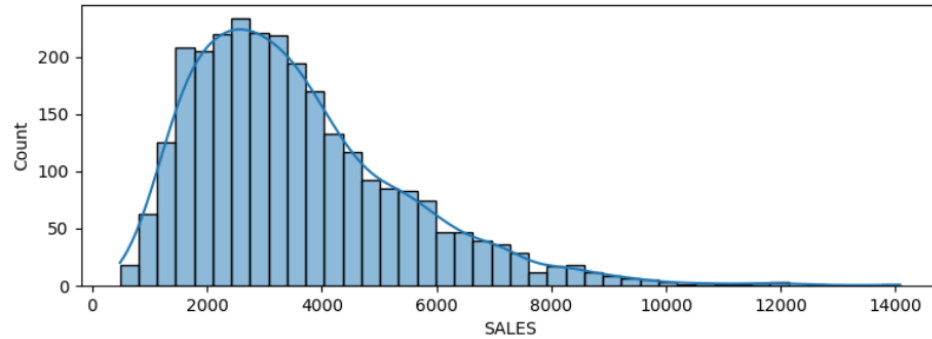


- Some outliers are present in the data of Quantity Ordered

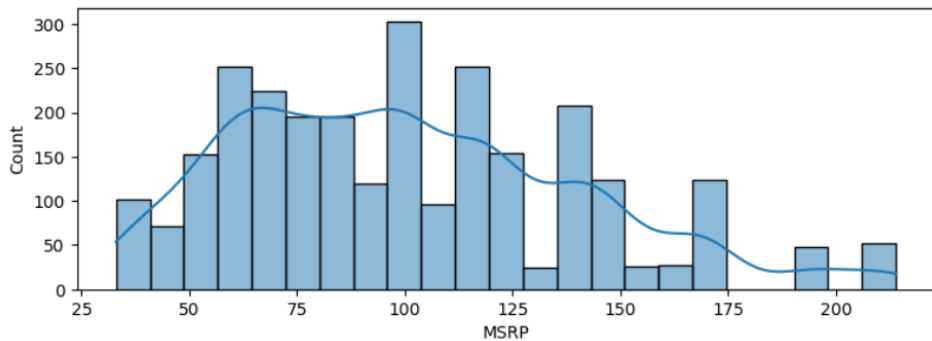
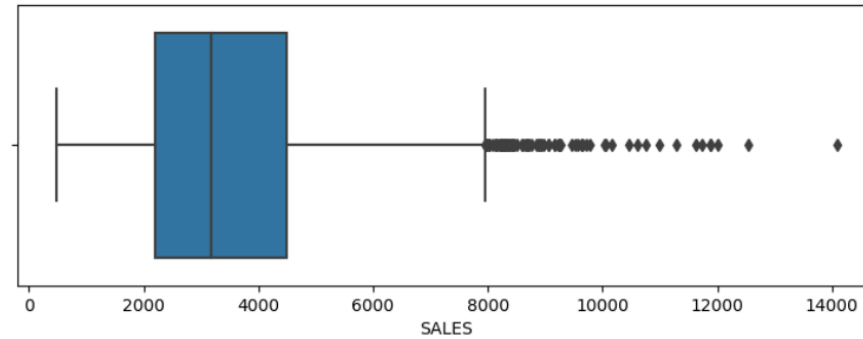


- Price of each product has majority of the outliers

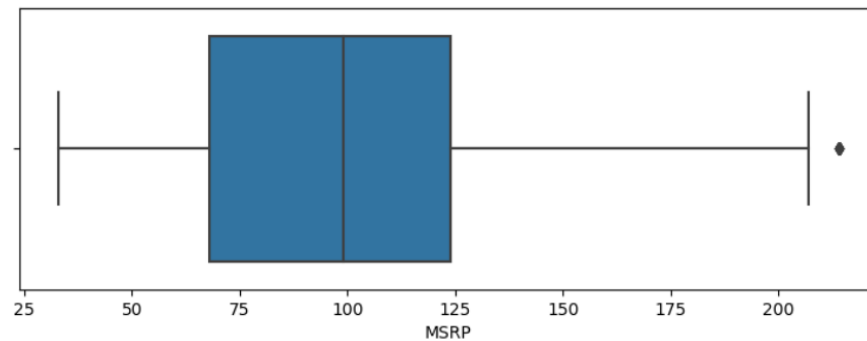
## Univariate analysis (2/2)



- We can see that sales data is skewed toward left
- There are many outliers

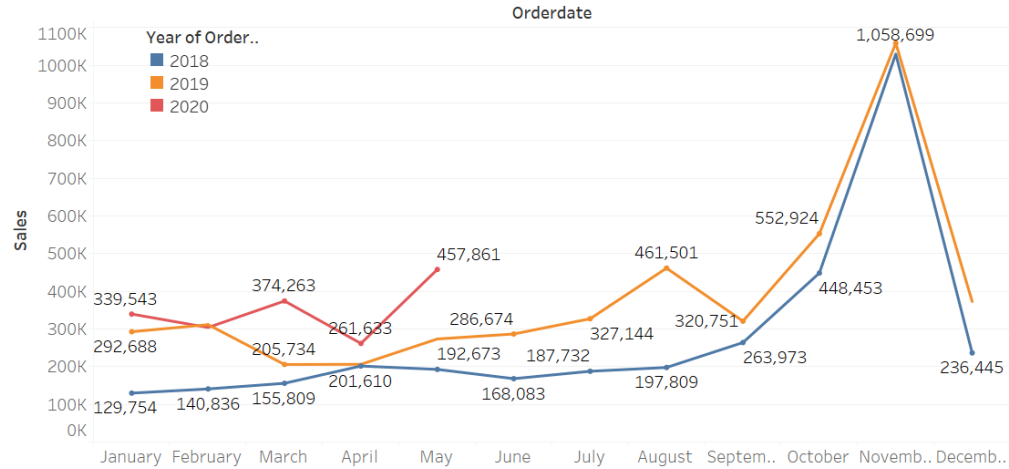


- MSRP data is skewed toward left and has outliers

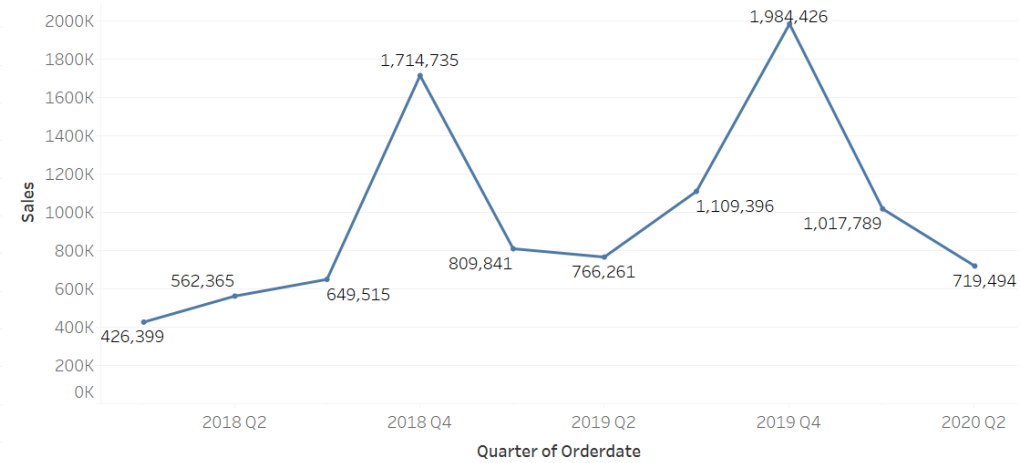


# Sales Distribution

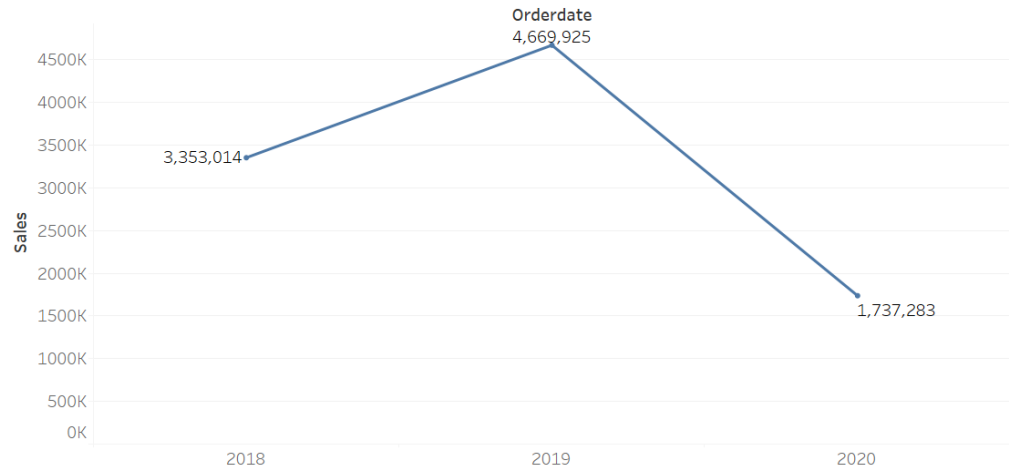
Monthly sales



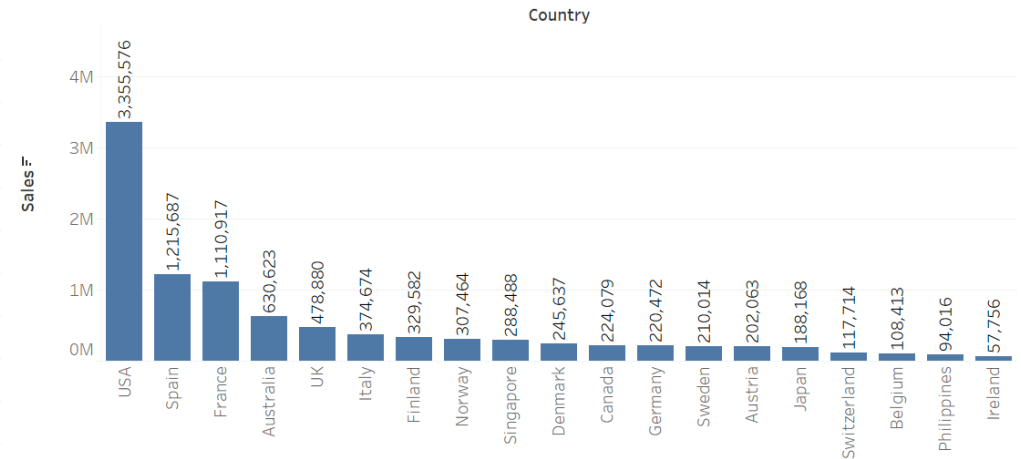
Quarterly sales



Yearly sales



Country wise sales



Note: Data consists of full years of 2018, 2019 and only first 5 months of 2020

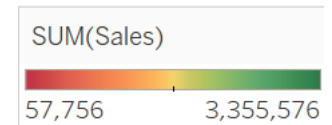
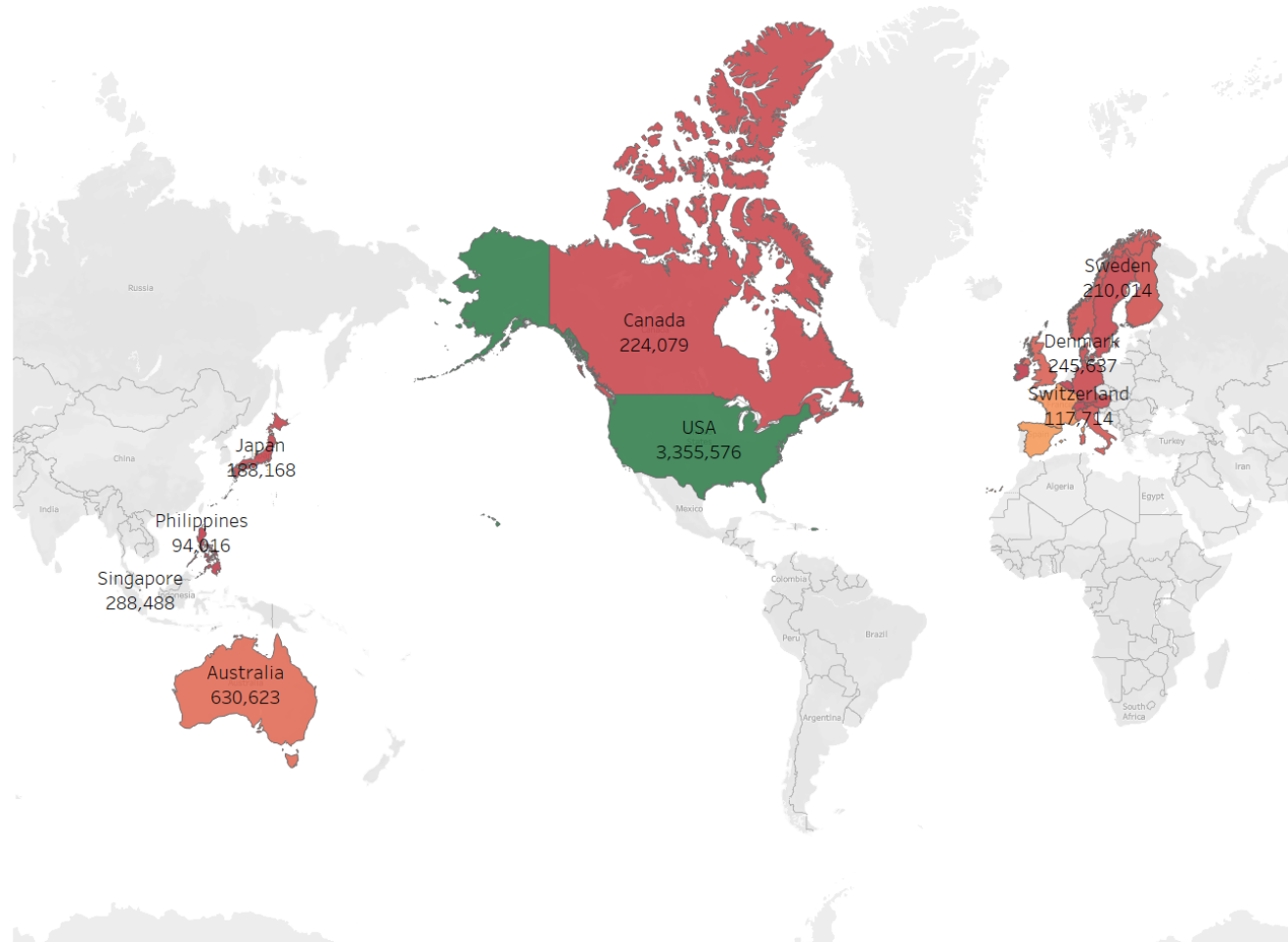
# Sales Distribution



- We can see that there is a decrease in the yearly sales.
- We can see that in the quarter 4 there is high sales as compared to other quarters
- We can see that increasing trend from January with a spike during the months of October and November
- We can also see there is always a fall in sales in the month of December
- For year 2020, the revenue for months January, February, March & May is much better than that of same months in 2018 & 2019

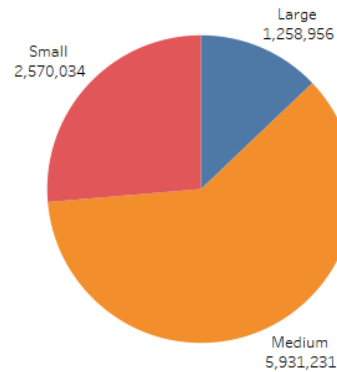
# Automobile Sales across globe

- US has the most amount of sales among the 19 countries followed by Spain and France
- USA alone accounts for 34% of the overall sales

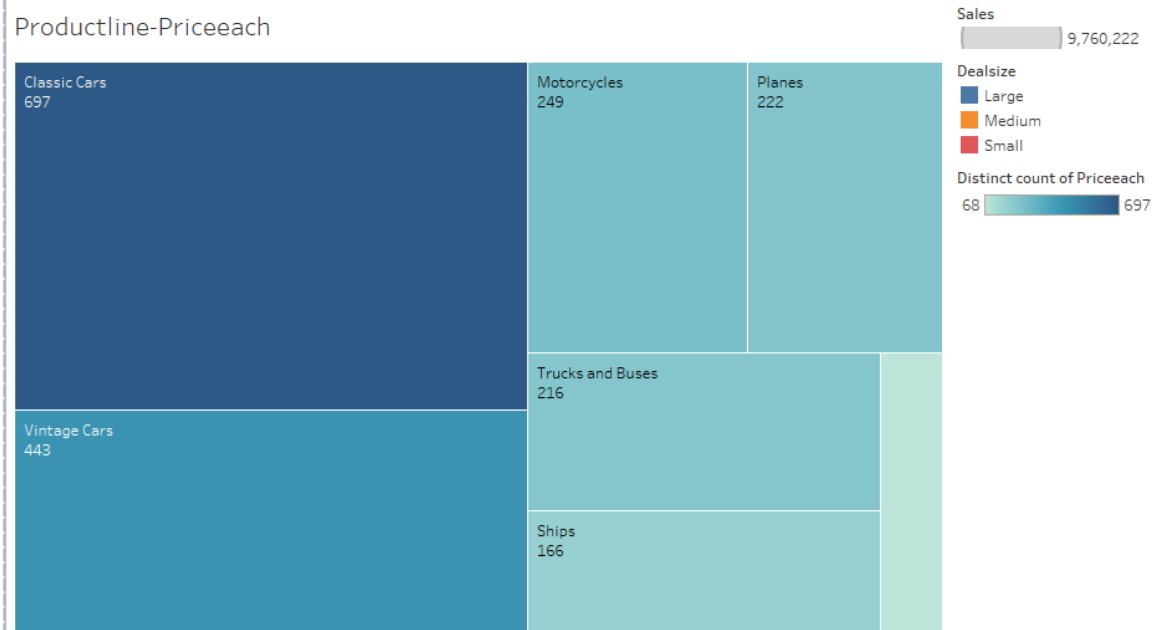


# Automobile sales considering their deal size

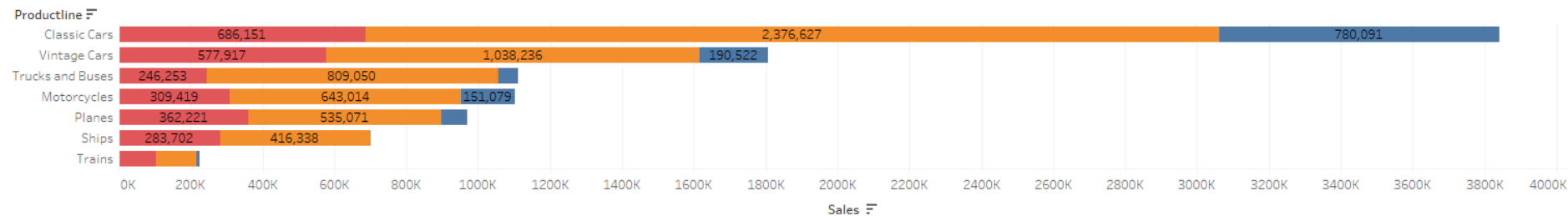
Dealsize-Sales



Productline-Priceeach



Productline-Sales



- As per the deal size, majority of the deals are medium, followed by small deals. Large deals are the lowest
- Classic Cars are the most sold vehicles with majority of all sizes of deal

# Sales percent by vehicle type and delivery status

- Classic car have highest % status as shipped followed by the status as In-Process.
- Majority of the motorcycles are having the status within the Disputed category.
- Least preferred automobile is Trains
- Within Ships, majority of the status % has been Cancelled

Sales% - By Productline

Status	Productline						
	Classic Cars	Motorcy..	Planes	Ships	Trains	Trucks and Buses	Vintage Cars
Shipped	40.19%	11.83%	9.54%	6.40%	2.39%	11.40%	18.26%
Cancelled	30.46%		18.22%	29.14%	2.61%		19.57%
On Hold	27.40%	2.79%	19.40%	13.22%	3.25%	11.28%	22.66%
Resolved	17.12%		22.91%	26.45%		13.58%	19.94%
In Process	39.91%					29.73%	30.36%
Disputed	36.02%	44.07%	5.32%	4.25%			10.34%

# Sales by Deal size and delivery status

- Majority of the status which is shipped are of Medium deal size
- Medium deal size also has the most cancelled status, followed by On Hold and then Resolved
- Small deal size also has the most cancelled status after shipped status
- Large deal size does not have any cancelled

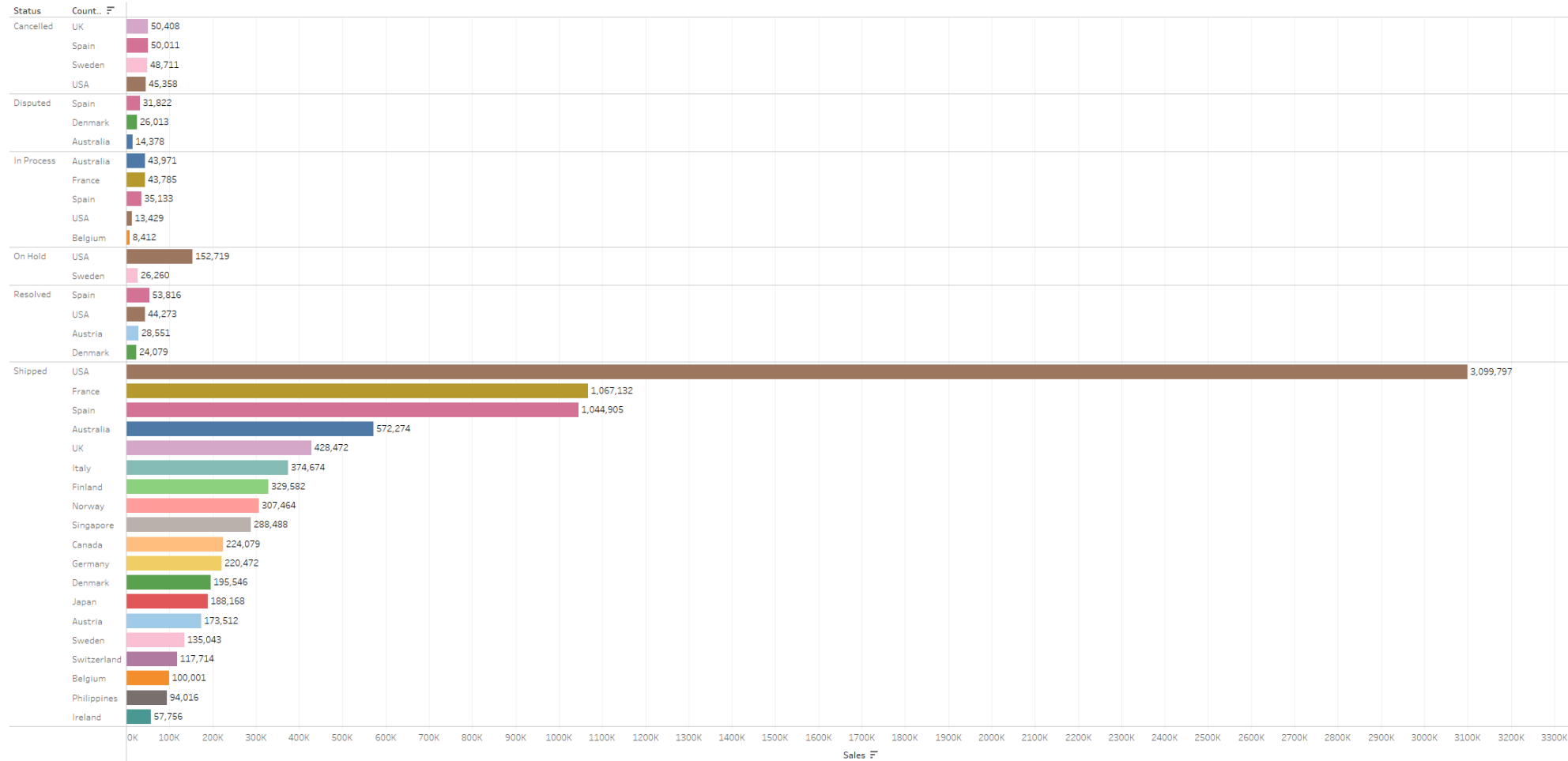
Status and Deal Size - By Sales

Deal size	Status					
	Cancelled	Disputed	In Process	On Hold	Resolved	Shipped
Large		42,747	27,152	42,941	8,885	1,137,231
Medium	137,575	22,165	83,787	106,342	103,967	5,477,396
Small	56,912	7,301	33,791	29,697	37,867	2,404,467



# Country sales by their status

Country Sales - By status



- Shipped status has majority of the countries compared to other statuses. Majority of the shipped countries include USA, France, Spain followed by Australia and others

# Customer Segmentation using RFM analysis

KNIME workflow




RFM model

# RFM Analysis

What is RFM analysis?

Recency, frequency, monetary value (RFM) is a marketing analysis tool used to identify a firm's best clients based on the nature of their spending habits

An RFM analysis evaluates clients and customers by scoring them in three categories: how recently they've made a purchase, how often they buy, and the size of their purchases

RFM Metric		
 <b>Recency</b>  The freshness of the customer activity, be it purchase or visits  E.g., Time since last order or last engaged with the product	 <b>Frequency</b>  The frequency of the customer transactions or visits  E.g., Total number of transactions or average time between transactions/engaged visits	 <b>Monetary</b>  The intentions of customer to spend or purchasing power of customers  E.g., Total or average transactions value

# Parameters used for RFM Analysis

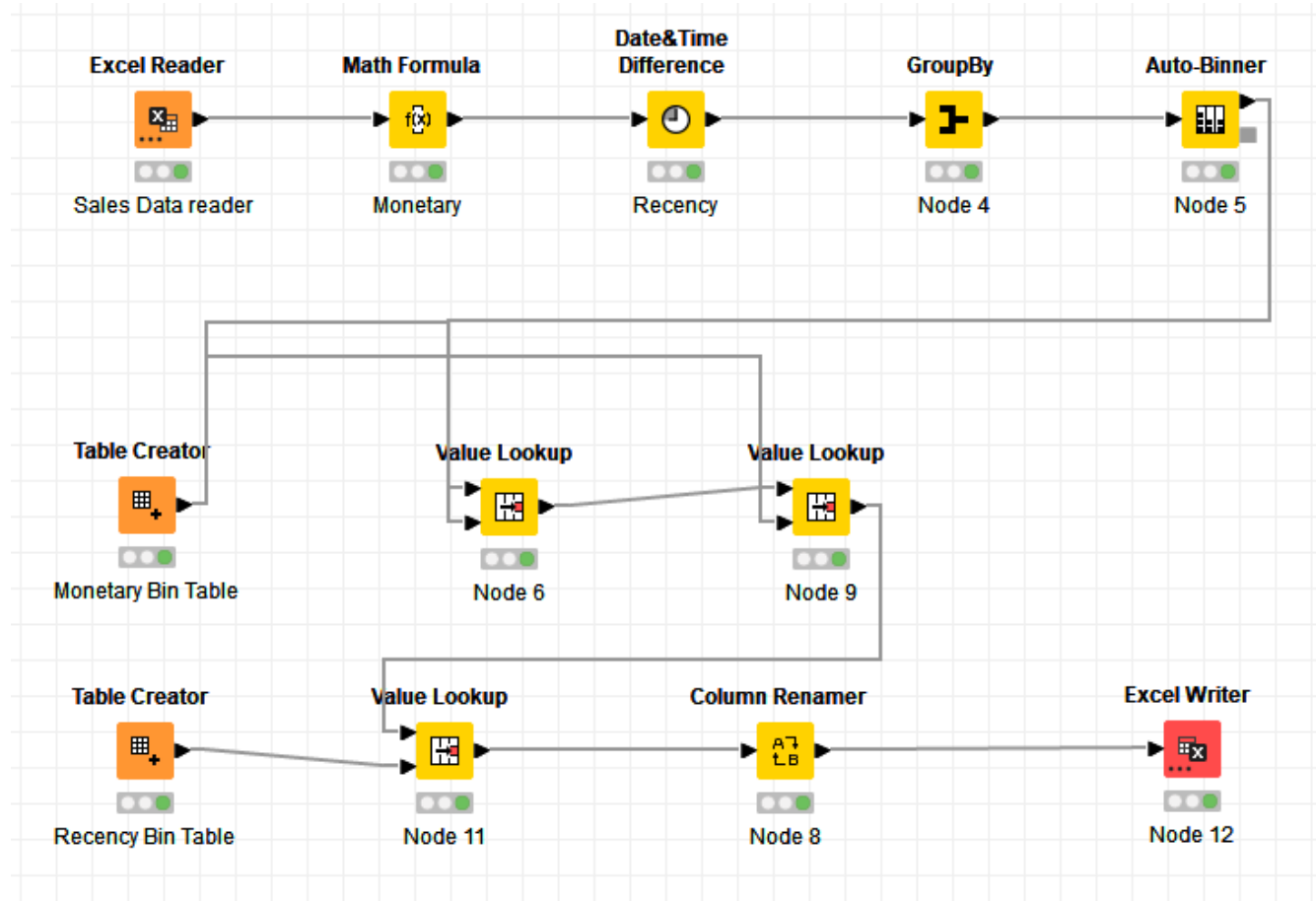
Parameter of RFM is binned into 2 groups (Frequency and Monetary) by percentiles –

- Bin 1 - 0 to 0.25 percentile = Low
- Bin 2 - 0.25 to 0.75 percentile = Medium
- Bin 3 - 0.75 to 1 percentile = High

Parameter of RFM is binned into 1 groups (Recency) by percentiles –

- Bin 1 - 0 to 0.25 percentile = High
- Bin 2 - 0.25 to 0.75 percentile = Medium
- Bin 3 - 0.75 to 1 percentile = Low
- As per instructions the column 'Days since last order' is ignored and new column Recency as '[Max(order date)-order date]'
- We have assumed '01-06-2020' as a reference date and created recency column
- Tool used: KNIME
- KNIME, the Konstanz Information Miner, is a free and open-source data analytics, reporting and integration platform

# KNIME Workflow



# KNIME Workflow

First few rows of output



CUSTOMER	ORDERNU	QUANTITY	PRICEEACH	ORDERLIN	SALES	ORDERDA	DAYS_SIN	STATUS	PRODUCT	MSRP	PRODUCT	PHONE	ADDRESS	CITY	POSTALCO	COUNTRY	CONTACT	CONTACTF	DEALSIZE	Monetary	Recency	ORDERNU	Monetary	Recency	E Monetary	Frequency	RecencyH
AV Stores,	51	34.86275	91.08451	9.019608	3094.271	#####	2969	Shipped	Vintage Ca	92.84314	S12_1108	(171) 555-	Fauntleroy Mancheste	EC2 5NT	UK	Ashworth	Victoria	Medium	157807.8	197	Bin 3	Bin 3	Bin 2	High	High	Medium	
Alpha Cog	20	34.35	101.16	4.95	3524.422	#####	2810	Shipped	Ships	97.15	S10_4757	61.77.655	1 rue Alsac Toulouse	31000	France	Roulet	Annette	Medium	70488.44	65	Bin 1	Bin 1	Bin 1	Low	Low	High	
Amica Mo	26	32.42308	110.8527	7.615385	3619.895	#####	3003	Shipped	Vintage Ca	107.6538	S10_1949	011-49885	Via Monte Torino	10100	Italy	Accorti	Paolo	Small	94117.26	266	Bin 2	Bin 2	Bin 3	Medium	Medium	Low	
Anna's De	46	31.93478	106.4241	6.434783	3347.742	#####	2939	Shipped	Classic Car	104.7174	S10_1949	02 9936 85	201 Miller North Sydr	2060	Australia	O'Hara	Anna	Small	153996.1	84	Bin 3	Bin 3	Bin 2	High	High	Medium	
Atelier gra	7	38.57143	92.23857	2	3454.28	#####	1767	Shipped	Classic Car	95.57143	S10_2016	40.32.255	54, rue Roj Nantes	44000	France	Schmitt	Carine	Medium	24179.96	189	Bin 1	Bin 1	Bin 2	Low	Low	Medium	
Australian	23	30.65217	90.04174	6.695652	2808.324	#####	2743	Shipped	Vintage Ca	88.13043	S18_1342	61-9-3844	7 Allen Str Glen Wave	3150	Australia	Connery	Sean	Small	64591.46	23	Bin 2	Bin 1	Bin 1	Low	Medium	High	
Australian	55	35.01818	104.5902	7.036364	3654.462	#####	3065	Shipped	Motorcycl	103.5273	S10_1678	03 9520 45	636 St Kild Melbourne	3004	Australia	Ferguson	Peter	Medium	200995.4	185	Bin 3	Bin 3	Bin 2	High	High	Medium	
Australian	15	36.33333	110.554	3.066667	3964.608	#####	2799	Shipped	Classic Car	111.5333	S10_1949	61-7-3844	31 Duncan South Bris	4101	Australia	Calaghan	Tony	Medium	59469.12	120	Bin 1	Bin 1	Bin 2	Low	Low	Medium	
Auto Asso	18	35.38889	99.4878	8.555556	3601.907	#####	2790	Shipped	Vintage Ca	100.3889	S10_1949	30.59.855	67, avenue Versailles	78000	France	Tonini	Daniel	Medium	64834.32	234	Bin 1	Bin 1	Bin 3	Low	Low	Low	
Auto Cana	27	37.07407	94.25519	6.333333	3450.765	#####	2742	Shipped	Motorcycl	94.85185	S10_1678	(1) 47.55.6	25, rue Lac Paris	75016	France	Perrier	Dominique	Medium	93170.66	55	Bin 2	Bin 2	Bin 1	Medium	Medium	High	
Auto-Mot	8	35.875	92.8	2	3309.908	#####	2895	Shipped	Vintage Ca	87.375	S18_3029	61755584	16780 Pon Brickhaver	58339	USA	Taylor	Leslie	Medium	26479.26	181	Bin 1	Bin 1	Bin 2	Low	Low	Medium	
Baane Mir	32	33.8125	108.5738	6.34375	3643.725	#####	3393	Shipped	Trucks and	107.4688	S10_1678	07-98 955	Erllng Skak Stavern	4110	Norway	Bergulfsen	Jonas	Medium	116599.2	209	Bin 2	Bin 2	Bin 2	Medium	Medium	Medium	
Bavarian C	14	28.64286	84.28929	7.5	2499.566	#####	2969	Shipped	Planes	82.71429	S18_1662	+49 89 61	Hansastr. Munich	80686	Germany	Donnerme	Michael	Small	34993.92	260	Bin 1	Bin 1	Bin 3	Low	Low	Low	
Blauer See	22	36.86364	108.0314	3.863636	3871.436	#####	2789	Shipped	Classic Car	105.8182	S12_1099	+49 69 66	Lyonerstr. Frankfurt	60528	Germany	Keitel	Roland	Medium	85171.59	209	Bin 2	Bin 2	Bin 2	Medium	Medium	Medium	
Boards &	3	34	89.80667	1.333333	3043.117	#####	3125	Shipped	Classic Car	92.33333	S12_3380	31055523	74097 Doug Glendale	92561	USA	Young	Leslie	Small	9129.35	114	Bin 1	Bin 1	Bin 2	Low	Low	Medium	
CAF Impor	13	36	104.9631	5.307692	3818.619	#####	3299	Shipped	Ships	106.9231	S12_1108	+34 913 72	Merchants Madrid	28023	Spain	Fernandez	Jesus	Medium	49642.05	440	Bin 1	Bin 1	Bin 3	Low	Low	Low	
Cambridge	11	32.45455	101.3291	3.272727	3287.602	#####	3095	Shipped	Vintage Ca	97.36364	S10_1949	61755555	4658 Bade Cambridge	51247	USA	Tseng	Kyung	Medium	36163.62	390	Bin 1	Bin 1	Bin 3	Low	Low	Low	
Canadian	22	31.95455	105.3409	6	3419.951	#####	2780	Shipped	Trucks and	106.4091	S10_1949	(604) 555-	1900 Oak Vancouver	V3F 2K1	Canada	Tannamuri	Yoshi	Small	75238.92	223	Bin 2	Bin 2	Bin 2	Medium	Medium	Medium	
Classic Gif	21	31.80952	103.3205	5.857143	3214.618	#####	2941	Shipped	Vintage Ca	102.4762	S10_1949	21555546	782 First St Philadelph	71270	USA	Cervantes	Francisca	Small	67506.97	231	Bin 2	Bin 1	Bin 2	Low	Medium	Medium	
Classic Leg	20	36	109.8035	4.05	3889.76	#####	2934	Shipped	Classic Car	106.65	S10_1949	21255584	5905 Pom NYC	10022	USA	Hernandez	Maria	Medium	77795.2	193	Bin 1	Bin 2	Bin 2	Medium	Low	Medium	
Clover Col	16	30.625	112.87	4.5625	3609.777	#####	2838	Shipped	Classic Car	106.875	S12_1108	+353 1862	25 Maiden Dublin	2	Ireland	Cassidy	Dean	Small	57756.43	259	Bin 1	Bin 1	Bin 3	Low	Low	Low	
Collectabl	25	38.16	91.5348	7.96	3499.569	#####	3199	Shipped	Classic Car	93.12	S10_4757	76055581	361 Furth San Diego	91217	USA	Thompson	Valarie	Medium	87489.23	461	Bin 2	Bin 2	Bin 3	Medium	Medium	Low	
Collectabl	24	33.125	97.23708	4.875	3399.083	#####	3023	Shipped	Classic Car	99.45833	S10_1949	61755585	7825 Doug Brickhaver	58339	USA	Nelson	Allen	Small	81577.98	133	Bin 2	Bin 2	Bin 2	Medium	Medium	Medium	
Corrida Au	32	36.34375	105.175	6.78125	3769.228	#####	2773	Shipped	Vintage Ca	102.625	S10_1949	(91) 555 2	C Araquil, Madrid	28023	Spain	Sommer	Martin	Medium	120615.3	213	Bin 2	Bin 3	Bin 2	High	Medium	Medium	
Cruz & So	26	36.96154	96.08	6.423077	3615.99	#####	3227	Shipped	Classic Car	97.96154	S12_1099	+63 2 555	15 McCall Makati Cit	1227 MM	Philippines	Cruz	Arnold	Medium	94015.73	198	Bin 2	Bin 2	Bin 2	Medium	Medium	Medium	
Daedalus	20	34.95	95.474	6.3	3452.621	#####	2834	Shipped	Motorcycl	94.5	S10_1678	20.16.155	184, chaus Lille	59000	France	Rance	Martine	Small	69052.41	466	Bin 1	Bin 1	Bin 3	Low	Low	Low	
Danish Wf	36	36.52778	108.0378	5.583333	4028.933	#####	2944	Shipped	Classic Car	106.4167	S10_4757	31 12 355	Vinb'tet 3 Kobenhavn	1734	Denmark	Petersen	Jytte	Medium	145041.6	47	Bin 3	Bin 3	Bin 1	High	High	High	
Diecast Cl	31	35.83871	108.5658	5.612903	3939.94	#####	2793	Shipped	Trucks and	106.5806	S10_1678	21555515	7586 Pomj Allentown	70267	USA	Yu	Kyung	Small	122138.1	2	Bin 2	Bin 3	Bin 1	High	Medium	High	
Diecast Co	18	38.61111	101.7833	7.722222	3936.654	#####	2855	Shipped	Trucks and	103.7222	S10_4962	61755525	6251 Ingle Boston	51003	USA	Franco	Valarie	Medium	70859.78	402	Bin 1	Bin 2	Bin 3	Medium	Low	Low	
Double De	12	29.75	99.10833	4.25	3001.587	#####	3267	Shipped	Vintage Ca	93.25	S10_4757	(171) 555-	120 Hanov London	WA1 1DP	UK	Hardy	Thomas	Small	36019.04	496	Bin 1	Bin 1	Bin 3	Low	Low	Low	
Dragon Sc	43	35.44186	113.1056	7.372093	4023.016	#####	3499	Shipped	Classic Car	113.4419	S10_1949	+65 221 75	Bronz Sok. Singapore	79903	Singapore	Natividad	Eric	Medium	172989.7	91	Bin 3	Bin 3	Bin 2	High	High	Medium	
Enaco Dis	23	38.34783	88.78348	6.173913	3409.211	#####	3282	Shipped	Ships	87.08696	S10_4757	(93) 203 45	Rambla de Barcelona	8022	Spain	Saavedra	Eduardo	Medium	78411.86	190	Bin 2	Bin 2	Bin 2	Medium	Medium	Medium	
Euro Shop	259	36.01158	97.3832	6.42471	3522.371	#####	2836	Shipped	Classic Car	97.01544	S10_1678	(91) 555 94	C/ Moralze Madrid	28034	Spain	Freyre	Diego	Medium	912294.1	1	Bin 3	Bin 3	Bin 1	High	High	High	

# RFM Analysis

## RFM – Output Matrix



Active



At-Risk



Inactive



Recency	Frequency	Monetary		
		High	Medium	Low
High	High	9	1	
	Medium	1	8	1
	Low		2	1
Medium	High	10	1	
	Medium	1	21	1
	Low		2	8
Low	High	1		
	Medium		7	
	Low		2	12

- RFM Segmentation is done on all 89 Customers
- Matrix shown is RFM Segregation of Customers as per:
  - High – Medium – Low
- Customers are divided as Best, Loyal, verge of churn, and Lost customers

# Best customers

- Best Customers are the ones with the highest score in each Segment
- So, Best Customers have RFM scores :
  - High - High - High
- There are 9 Customers in coming to Gold segment

CUSTOMER NAME	Recency	Frequency	Monetary
Danish Wholesale Imports	High	High	High
Euro Shopping Channel	High	High	High
L'ordine Souvenirs	High	High	High
La Rochelle Gifts	High	High	High
Mini Gifts Distributors Ltd.	High	High	High
Reims Collectables	High	High	High
Salzburg Collectables	High	High	High
Souvenirs And Things Co.	High	High	High
The Sharp Gifts Warehouse	High	High	High



# Top loyal customers

Based on RFM analysis these are the loyal customers

- We have focused on monetary value
- If we focus on these customer we can turn them in to best customers

CUSTOMERNAME	Recency	Frequency	Monetary
AV Stores, Co.	Medium	High	High
Anna's Decorations, Ltd	Medium	High	High
Australian Collectors, Co.	Medium	High	High
Dragon Souvenirs, Ltd.	Medium	High	High
Land of Toys Inc.	Medium	High	High
Muscle Machine Inc	Medium	High	High
Online Diecast Creations Co.	Medium	High	High
Rovelli Gifts	Medium	High	High
Scandinavian Gift Ideas	Medium	High	High
Technics Stores Inc.	Medium	High	High

# Verge of Churn Customers

As per RFM score we can see that these are the top customers on the verge of churning

- We should focus on these customers before we lose them
- We should try some action plan to convert them into regular customers

CUSTOMERNAME	Recency	Frequency	Monetary
Amica Models & Co.	Low	Medium	Medium
Collectable Mini Designs Co.	Low	Medium	Medium
Herkku Gifts	Low	Medium	Medium
Marta's Replicas Co.	Low	Medium	Medium
Norway Gifts By Mail, Co.	Low	Medium	Medium
Royal Canadian Collectables, Ltd.	Low	Medium	Medium
Vida Sport, Ltd	Low	Medium	Medium

# Customers who are considered as lost

According to the RFM score, we've lost customers because:

- Their recency and purchase frequency are very low
- We should conduct surveys to understand the reasons behind their departure
- Take steps to prevent future customer losses

CUSTOMERNAME	Recency	Frequency	Monetary
Auto Assoc. & Cie.	Low	Low	Low
Bavarian Collectables Imports, Co.	Low	Low	Low
CAF Imports	Low	Low	Low
Cambridge Collectables Co.	Low	Low	Low
Clover Collections, Co.	Low	Low	Low
Daedalus Designs Imports	Low	Low	Low
Double Decker Gift Stores, Ltd	Low	Low	Low
Iberia Gift Imports, Corp.	Low	Low	Low
Online Mini Collectables	Low	Low	Low
Osaka Souvenirs Co.	Low	Low	Low
Signal Collectibles Ltd.	Low	Low	Low
West Coast Collectables Co.	Low	Low	Low

# Recommendations

# Recommendations

Using RFM analysis, customers fall into four categories:

- **Best Customers:** Offer personalized recognition and exclusive incentives to maintain their loyalty.
- **Loyal Customers:** Keep them engaged with periodic discounts and offers to improve satisfaction and potentially turn them into best customers.
- **Verge of Churn Customers:** Develop action plans to prevent them from leaving by conducting surveys, offering incentives, and personalizing communication.
- **Lost Customers:** Analyze their behavior and preferences to identify reasons for departure, and use this information to prevent churn in the future and boost overall retention.

The background features abstract, overlapping geometric shapes in various shades of blue, ranging from light sky blue to deep navy blue. These shapes are primarily located on the right side of the frame, creating a modern, layered effect. The rest of the background is a solid, very light blue.

Thank you