OPTIMIZING CUSTOMER ENGAGEMENT THROUGH RFM SEGMENTATION

Presented by:

Anniza Mega

Overview

INTRODUCTION

- Hi I am Aniza Mega, and I currently work in business development at PT Yuefa Universal. Recently, I have developed a keen interest in Business Intelligence (BI) analysis and am planning to switch my career to this exciting and data-driven field. I look forward to leveraging my business development experience while diving deeper into the world of BI to drive impactful business decisions and strategies.
- This Business Intelligence (BI) project focuses on leveraging RFM (Recency, Frequency, Monetary) analysis to enhance customer segmentation. By analyzing key customer metrics, we aim to identify distinct customer segments, tailor marketing strategies, and ultimately improve customer satisfaction and retention.

PROJECT OVERVIEW

The project aims to leverage RFM analysis for customer segmentation, thereby improving marketing efficiency and customer targeting. By categorizing customers based on their purchase behavior, the marketing team can implement personalized strategies to enhance customer engagement, loyalty, and overall ROI. The initial costs include development, infrastructure, and training, while the ongoing costs cover maintenance. The projected increase in revenue and reduction in marketing costs make this a valuable investment.

[Link for detailed BRD]

PROBLEM STATMENT

In the highly competitive retail and e-commerce industry, understanding customer behavior and optimizing marketing efforts are critical for maintaining a competitive edge. Currently, the marketing team lacks actionable insights into customer purchase patterns, leading to generic and less effective marketing campaigns. This results in suboptimal customer engagement, lower response rates, and missed opportunities for revenue growth.

Link for detailed BRD

PROJECT OBJECTIVE

- Conduct RFM analysis to categorize customers based on their purchase behavior.
- Identify high-value customer segments for targeted marketing campaigns.
- Enhance customer satisfaction and loyalty through personalized marketing strategies.
- Improve response rates and ROI by focusing on valuable customers.

Link for detailed BRD

METRICS TO MEASURE

1. **RFM Scores**:
   - **Recency**: How recently a customer made a purchase.
   - **Frequency**: How often a customer makes a purchase.
   - **Monetary**: How much money a customer spends.
2. **Customer Segmentation**: Classification of customers into different segments based on RFM scores.
3. **Response Rate**: Percentage of customers who respond to marketing campaigns.
4. **Campaign ROI**: Return on investment for marketing campaigns targeted at different customer segments.

Link for detailed BRD

TOOLS

kaggle™

tableau

RFM

Make RFM to make segmentation from behaviour of customer. Our parameter is Recency , Frequency and Monetary

WHAT IS RFM?

Customer segmentation is the practice of dividing a business's customer base into distinct groups of individuals that share similar characteristics. For This project we will categorizing customers based on their purchase behavior, the marketing team can implement personalized strategies to enhance customer engagement, loyalty, and overall ROI.

WHAT IS RFM?

RFM :

- **Recency.**

Recency measures how recently a customer made a purchase. This can be determined by looking at the date of the customer’s last purchase.

- **Frequency.**

Frequency measures how often a customer makes purchases. This can be determined by looking at the number of purchases a customer has made over a period of time.

- **Monetary.**

Monetary measures how much money a customer spends on each purchase. This can be determined by looking at the total amount of money a customer has spent with the company over a period of time.

BI ANALYSYS PLAN

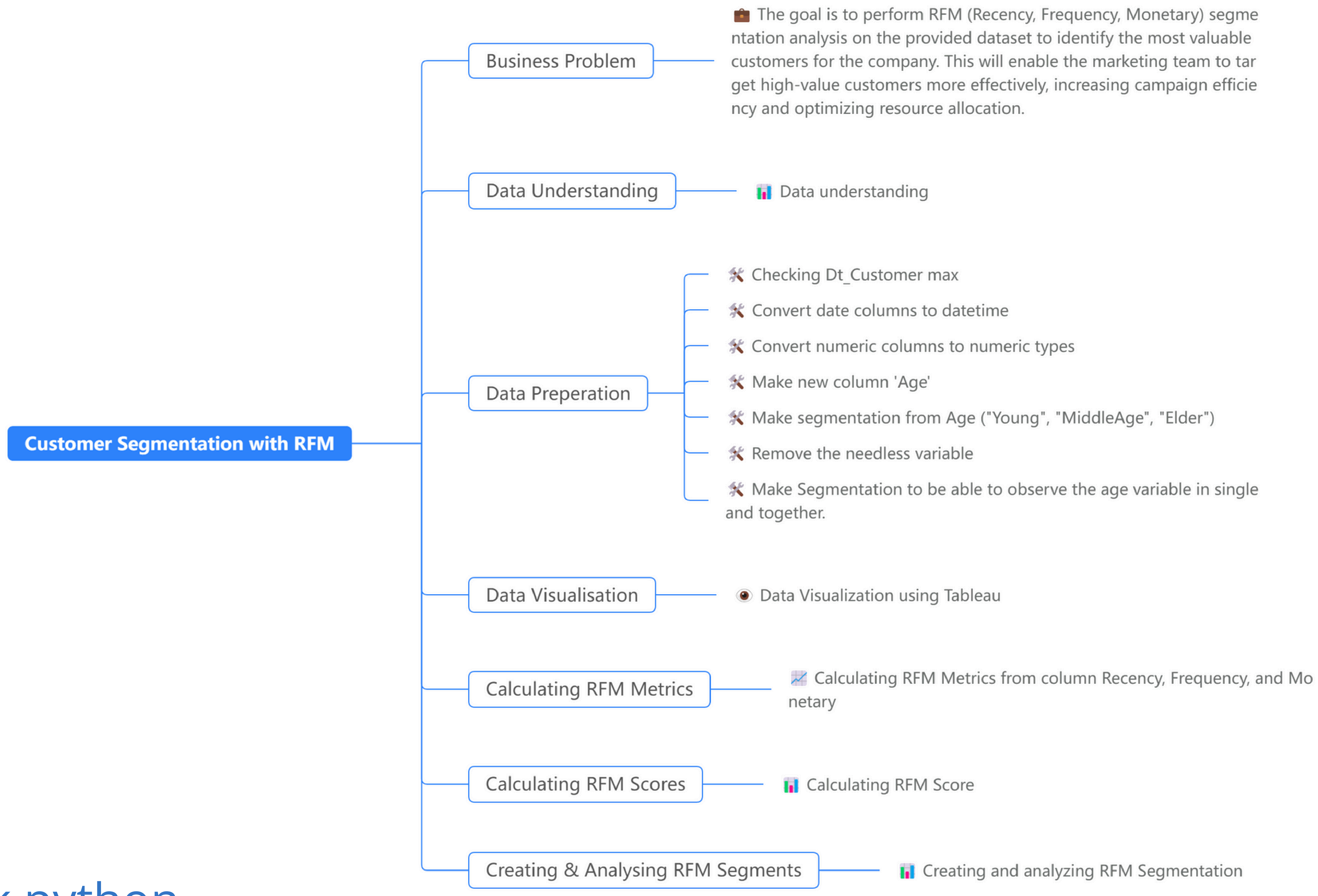
30% 30% 30%

Data Understanding

Calculate RFM based on customer behaviour

Make segmentation, Interpretation and give recomendation

FLOW CHART



[Link python]

DATA OVERVIEW

Context

A response model can provide a significant boost to the efficiency of a marketing campaign by increasing responses or reducing expenses. The objective is to predict who will respond to an offer for a product or service

ID	Year_Birth	Education	Marital_Status	Income	Kidhome	Teenhome	Dt_Customer	Recency	MntWines	MntFruits	MntMeatProducts	MntFishProducts	MntSweetProducts	MntGoldProds	NumDealsPurchases	NumWebPurchases	NumCatalogPurchases	NumStorePu
5524	1957	Graduation	Single	58138	0	0	2012-09-04	58	635	88	546	172	88	88	3	8	10	
2174	1954	Graduation	Single	46344	1	1	2014-03-08	38	11	1	6	2	1	6	2	1	1	
4141	1965	Graduation	Together	71613	0	0	2013-08-21	26	426	49	127	111	21	42	1	8	2	
6182	1984	Graduation	Together	26646	1	0	2014-02-10	26	11	4	20	10	3	5	2	2	0	
5324	1981	PhD	Married	58293	1	0	2014-01-19	94	173	43	118	46	27	15	5	5	3	
7446	1967	Master	Together	62513	0	1	2013-09-09	16	520	42	98	0	42	14	2	6	4	
965	1971	Graduation	Divorced	55635	0	1	2012-11-13	34	235	65	164	50	49	27	4	7	3	
6177	1985	PhD	Married	33454	1	0	2013-05-08	32	76	10	56	3	1	23	2	4	0	
4855	1974	PhD	Together	30351	1	0	2013-06-06	19	14	0	24	3	3	2	1	3	0	
5899	1950	PhD	Together	5648	1	1	2014-03-13	68	28	0	6	1	1	13	1	1	0	

NumDealsPurchases	NumWebPurchases	NumCatalogPurchases	NumStorePurchases	NumWebVisitsMonth	AcceptedCmp3	AcceptedCmp4	AcceptedCmp5	AcceptedCmp1	AcceptedCmp2	Complain	Z_CostContact	Z_Revenue	Response
3	8	10	4	7	0	0	0	0	0	0	3	11	1
2	1	1	2	5	0	0	0	0	0	0	3	11	0
1	8	2	10	4	0	0	0	0	0	0	3	11	0
2	2	0	4	6	0	0	0	0	0	0	3	11	0
5	5	3	6	5	0	0	0	0	0	0	3	11	0
2	6	4	10	6	0	0	0	0	0	0	3	11	0
4	7	3	7	6	0	0	0	0	0	0	3	11	0
2	4	0	4	8	0	0	0	0	0	0	3	11	0
1	3	0	2	9	0	0	0	0	0	0	3	11	1
1	1	0	0	20	1	0	0	0	0	0	3	11	0
1	1	0	2	7	0	0	0	0	0	0	3	11	0

Link of Dataset

DATA OVERVIEW

People

- ID: Customer's unique identifier
- Year_Birth: Customer's birth year
- Education: Customer's education level
- Marital_Status: Customer's marital status
- Income: Customer's yearly household income
- Kidhome: Number of children in customer's household
- Teenhome: Number of teenagers in customer's household
- Dt_Customer: Date of customer's enrollment with the company
- Recency: Number of days since customer's last purchase
- Complain: 1 if the customer complained in the last 2 years, 0 otherwise

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 29 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   ID                   2240 non-null   int64
 1   Year_Birth           2240 non-null   int64
 2   Education            2240 non-null   object
 3   Marital_Status       2240 non-null   object
 4   Income               2216 non-null   float64
 5   Kidhome              2240 non-null   int64
 6   Teenhome             2240 non-null   int64
 7   Dt_Customer          2240 non-null   object
 8   Recency              2240 non-null   int64
 9   MntWines             2240 non-null   int64
 10  MntFruits            2240 non-null   int64
 11  MntMeatProducts      2240 non-null   int64
 12  MntFishProducts      2240 non-null   int64
 13  MntSweetProducts     2240 non-null   int64
 14  MntGoldProds         2240 non-null   int64
 15  NumDealsPurchases    2240 non-null   int64
 16  NumWebPurchases      2240 non-null   int64
 17  NumCatalogPurchases  2240 non-null   int64
 18  NumStorePurchases    2240 non-null   int64
 19  NumWebVisitsMonth    2240 non-null   int64
 20  AcceptedCmp3         2240 non-null   int64
 21  AcceptedCmp4         2240 non-null   int64
 22  AcceptedCmp5         2240 non-null   int64
 23  AcceptedCmp1         2240 non-null   int64
 24  AcceptedCmp2         2240 non-null   int64
 25  Complain             2240 non-null   int64
 26  Z_CostContact        2240 non-null   int64
 27  Z_Revenue            2240 non-null   int64
 28  Response             2240 non-null   int64
dtypes: float64(1), int64(25), object(3)
memory usage: 507.6+ KB
```

DATA OVERVIEW

Product

- MntWines: Amount spent on wine in last 2 years
- MntFruits: Amount spent on fruits in last 2 years
- MntMeatProducts: Amount spent on meat in last 2 years
- MntFishProducts: Amount spent on fish in last 2 years
- MntSweetProducts: Amount spent on sweets in last 2 years
- MntGoldProds: Amount spent on gold in last 2 years

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 29 columns):
 #   Column               Non-Null Count  Dtype
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 9   MntWines             2240 non-null   int64
 10  MntFruits            2240 non-null   int64
 11  MntMeatProducts      2240 non-null   int64
 12  MntFishProducts      2240 non-null   int64
 13  MntSweetProducts     2240 non-null   int64
 14  MntGoldProds         2240 non-null   int64
 15  NumDealsPurchases    2240 non-null   int64
 16  NumWebPurchases      2240 non-null   int64
 17  NumCatalogPurchases  2240 non-null   int64
 18  NumStorePurchases    2240 non-null   int64
 19  NumWebVisitsMonth    2240 non-null   int64
 20  AcceptedCmp3         2240 non-null   int64
 21  AcceptedCmp4         2240 non-null   int64
 22  AcceptedCmp5         2240 non-null   int64
 23  AcceptedCmp1         2240 non-null   int64
 24  AcceptedCmp2         2240 non-null   int64
 25  Complain             2240 non-null   int64
 26  Z_CostContact        2240 non-null   int64
 27  Z_Revenue            2240 non-null   int64
 28  Response             2240 non-null   int64
dtypes: float64(1), int64(25), object(3)
memory usage: 507.6+ KB
```

DATA OVERVIEW

Promotion

- NumDealsPurchases: Number of purchases made with a discount
- AcceptedCmp1: 1 if customer accepted the offer in the 1st campaign, 0 otherwise
- AcceptedCmp2: 1 if customer accepted the offer in the 2nd campaign, 0 otherwise
- AcceptedCmp3: 1 if customer accepted the offer in the 3rd campaign, 0 otherwise
- AcceptedCmp4: 1 if customer accepted the offer in the 4th campaign, 0 otherwise
- AcceptedCmp5: 1 if customer accepted the offer in the 5th campaign, 0 otherwise
- Response: 1 if customer accepted the offer in the last campaign, 0 otherwise

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 29 columns):
 #   Column               Non-Null Count  Dtype
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 3   Marital_Status       2240 non-null   object
 4   Income               2216 non-null   float6
 5   Kidhome              2240 non-null   int64
 6   Teenhome             2240 non-null   int64
 7   Dt_Customer          2240 non-null   object
 8   Recency              2240 non-null   int64
 9   MntWines             2240 non-null   int64
 10  MntFruits            2240 non-null   int64
 11  MntMeatProducts      2240 non-null   int64
 12  MntFishProducts      2240 non-null   int64
 13  MntSweetProducts     2240 non-null   int64
 14  MntGoldProds         2240 non-null   int64
 15  NumDealsPurchases    2240 non-null   int64
 16  NumWebPurchases      2240 non-null   int64
 17  NumCatalogPurchases  2240 non-null   int64
 18  NumStorePurchases    2240 non-null   int64
 19  NumWebVisitsMonth    2240 non-null   int64
 20  AcceptedCmp3         2240 non-null   int64
 21  AcceptedCmp4         2240 non-null   int64
 22  AcceptedCmp5         2240 non-null   int64
 23  AcceptedCmp1         2240 non-null   int64
 24  AcceptedCmp2         2240 non-null   int64
 25  Complain             2240 non-null   int64
 26  Z_CostContact        2240 non-null   int64
 27  Z_Revenue            2240 non-null   int64
 28  Response             2240 non-null   int64
dtypes: float64(1), int64(25), object(3)
memory usage: 507.6+ KB
```

DATA OVERVIEW

Place

- NumWebPurchases: Number of purchases made through the company's website
- NumCatalogPurchases: Number of purchases made using a catalogue
- NumStorePurchases: Number of purchases made directly in stores
- NumWebVisitsMonth: Number of visits to company's website in the last month

```
<class 'pandas.core.frame.DataFrame'>
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 12  MntFishProducts      2240 non-null   int64
 13  MntSweetProducts     2240 non-null   int64
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 16  NumWebPurchases      2240 non-null   int64
 17  NumCatalogPurchases  2240 non-null   int64
 18  NumStorePurchases    2240 non-null   int64
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 21  AcceptedCmp4         2240 non-null   int64
 22  AcceptedCmp5         2240 non-null   int64
 23  AcceptedCmp1         2240 non-null   int64
 24  AcceptedCmp2         2240 non-null   int64
 25  Complain             2240 non-null   int64
 26  Z_CostContact        2240 non-null   int64
 27  Z_Revenue            2240 non-null   int64
 28  Response             2240 non-null   int64
dtypes: float64(1), int64(25), object(3)
memory usage: 507.6+ KB
```
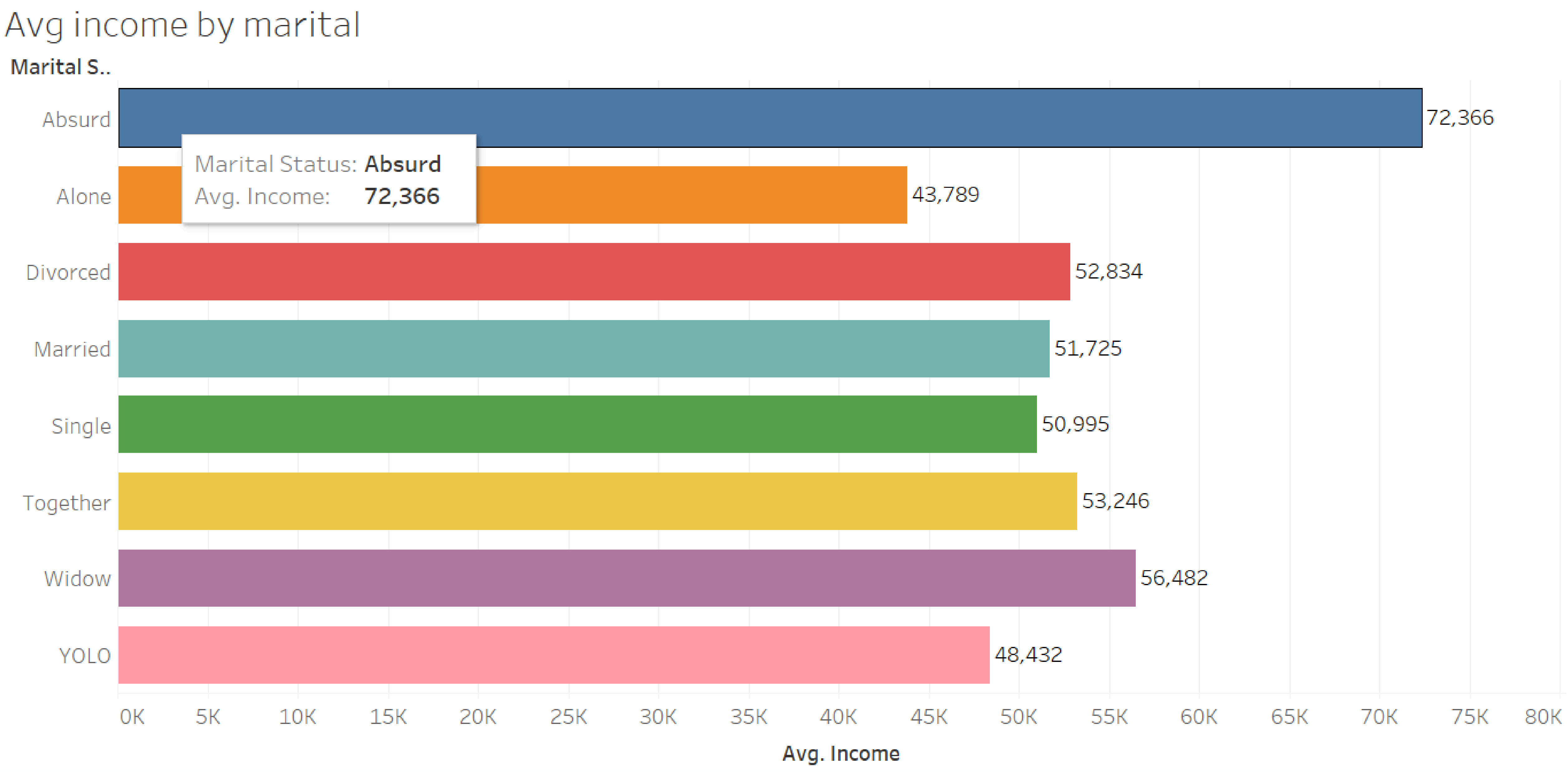
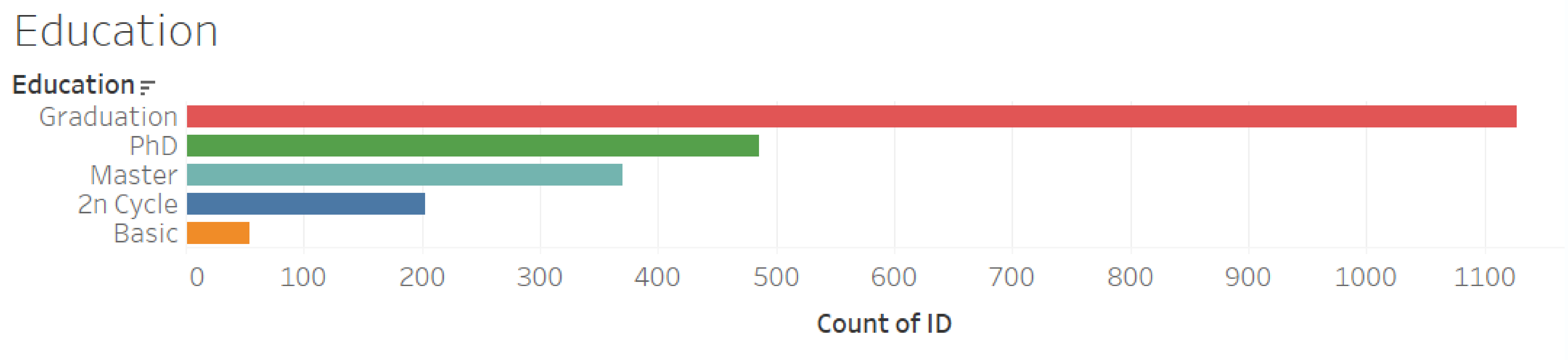

DATA VISUALIZATION

Before we make marital status segmentation to be single and together, we have visualization avg income from all customer by marital status and the result is the higest avg income come from 'absurd' status.



[Link of Tableau]

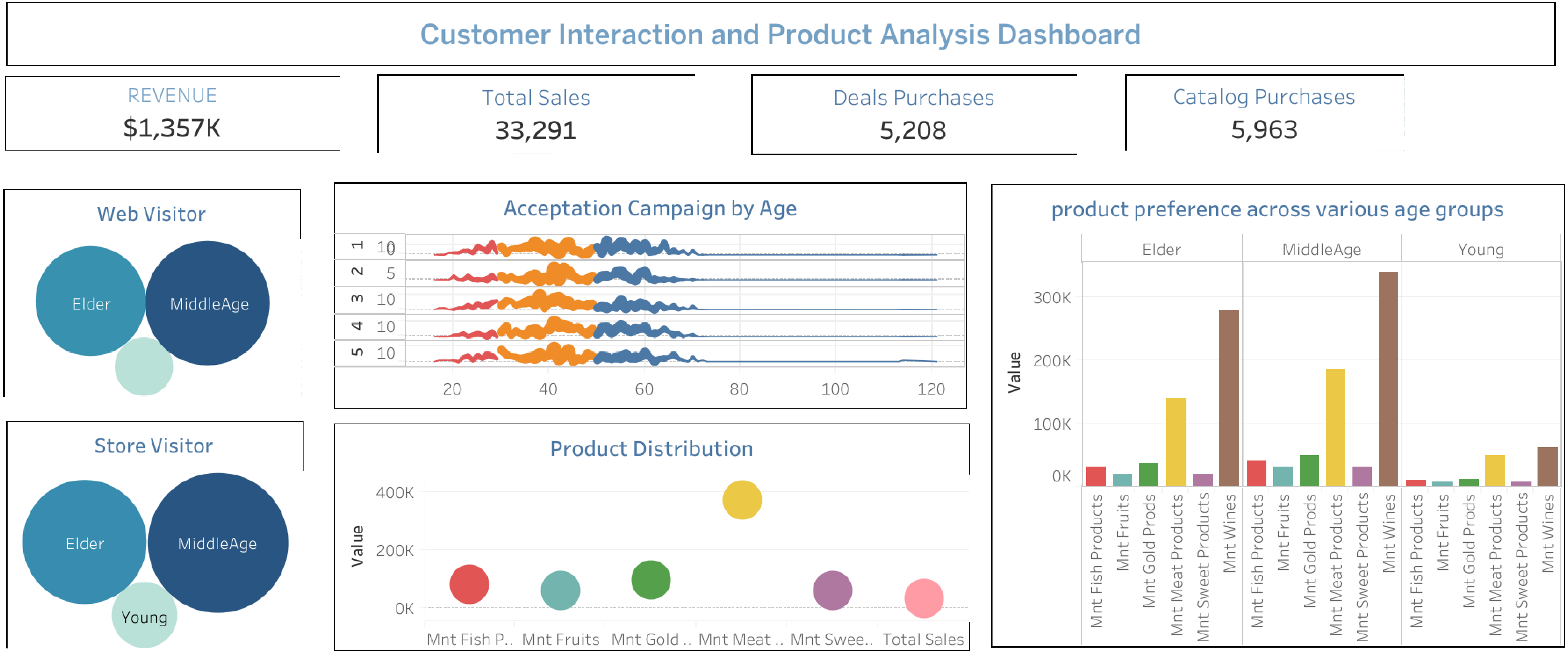
DATA VISUALIZATION



From analyzing of education visualization , our customer mostly have graduatiion or bachelor degree.

Link of Tableau

DATA VISUALIZATION



[Link of Tableau]

KEY INTERPRETATIONS

- **Age Segmentation Impact:** Both web and store visits show that MiddleAge and Elder customers are more engaged, suggesting targeted marketing strategies should focus on these age groups for higher conversion.
- **Product Preference Trends:** Wines are a clear favorite across all age groups, which can inform inventory and marketing focus.
- **Campaign Effectiveness:** The acceptance rates of campaigns by age groups can help refine future campaign targeting to improve engagement and conversion rates.
- **Revenue Drivers:** Monitoring the revenue by month and age segmentation helps in understanding seasonal trends and the impact of marketing efforts on sales.

CALCULATE RFM

```
[ ] # Recency
    df['Recency'] = df['Recency']

    # Frequency
    df['Frequency'] = df['NumDealsPurchases'] + df['NumCatalogPurchases'] + df['NumStorePurchases'] + df['NumWebPurchases']

    # Monetary
    df['Monetary'] = df['MntFishProducts'] + df['MntMeatProducts'] + df['MntFruits'] + df['MntSweetProducts'] + df['MntWines'] + df['MntGoldProds']
```

```
rfm = df[['ID','Recency', 'Frequency', 'Monetary']]
rfm.head()
```

	ID	Recency	Frequency	Monetary
0	5524	58	25	1617
1	2174	38	6	27
2	4141	26	21	776
3	6182	26	8	53
4	5324	94	19	422

From Dataset we make a new data frame that have content RFM calculation. The calculation from Recency, Frequency and Monetary.

[Python Link]

CALCULATE RFM

```
[ ] quartiles = rfm[['Recency', 'Frequency', 'Monetary']].quantile(q=[0.25, 0.5, 0.75])
    quartiles
```

	Recency	Frequency	Monetary
0.25000	24.00000	8.00000	68.75000
0.50000	49.00000	15.00000	396.00000
0.75000	74.00000	21.00000	1045.50000

Quartiles method for b scoring system RFM

Python Link

CALCULATE RFM

	ID	Recency	Frequency	Monetary	recency_score	frequency_score	monetary_score	RFM_SCORE
0	5524	58	25	1617	2	4	4	244
1	2174	38	6	27	3	1	1	311
2	4141	26	21	776	3	3	3	333
3	6182	26	8	53	3	1	1	311
4	5324	94	19	422	1	3	3	133

Using table tool and scoring system :

Find specific customer.

The simplest way to create customer segments from the RFM model is to use quartiles. We assign scores from 1 to 4 to recency, frequency, and monetary value, where 4 represents the best/highest value and 1 represents the lowest/worst value. A final RFM score is calculated by combining the individual scores.

Python Link

RFM SEGMENTATION

```
[ ] print("Best Customers: ",len(rfm[rfm['RFM_SCORE']=='444']))
    Best Customers:  51

[ ] print("Lost Customer: ",len(rfm[rfm['RFM_SCORE']=='144']))
    Lost Customer:  79

[ ] print("Lost Cheap Customer: ",len(rfm[rfm['RFM_SCORE']=='111']))
    Lost Cheap Customer:  129

[ ] print('Loyal Customers: ',len(rfm[rfm['frequency_score']==4]))
    Loyal Customers:  512

[ ] print('Big Spender: ',len(rfm[rfm['monetary_score']==4]))
    Big Spender:  560

[ ] print('Almost Lost: ',len(rfm[rfm['RFM_SCORE']==244]))
    Almost Lost:  0
```

Our RFM analysis assigns the highest score of 1 to customers with:

- Highest Recency: Most recent purchase.
- Highest Frequency: Largest number of purchases.
- Highest Monetary: Highest total spending.

Let's identify these "Champion" customers, representing our most valuable segment.

Note : using this methode make many data don't have segmentation and it caused wrong interpretation. So we try another method.

Python Link

CALCULATE RFM

Using scatter plot tool.

Segment customers using Python. Group them into 10 segments:

- * Champion : 3.4 < r <= 4, 10 < FxM <= 16
- * Loyal : 2.2 < r <= 3.4, 10 < FxM <= 16.
- * Cannot Lose Them : 1 <= r =< 2.2, 10 < FxM <= 16.
- * Potential Loyalist : 2.8 < r <= 4, 6 < FxM <= 10.
- * Need Attention : 2.2 < r <= 2.8, 6 < FxM <= 10.
- * At Risk : 1 <= r <= 2.2, 6 < FxM <= 10.
- * New Customer : 3.4 < r <= 4, 1 <= FxM <= 6.
- * Promising : 2.8 < r <= 3.4, 1 <= FxM <= 6.
- * About to Sleep : 2.2 < r <= 2.8, 1 <= FxM <= 6.
- * Hilbernating : 1 <= r <= 2.2, 1 <= FxM <= 6

	ID	Recency	Frequency	Monetary	recency_score	frequency_score	monetary_score	RFM_SCORE	ClusterCode
0	5524	58	25	1617	2	4	4	244	3
1	2174	38	6	27	3	1	1	311	8
2	4141	26	21	776	3	3	3	333	4
3	6182	26	8	53	3	1	1	311	8
4	5324	94	19	422	1	3	3	133	6
5	7446	16	22	716	4	4	3	443	1
6	965	34	21	590	3	3	3	333	4
7	6177	32	10	169	3	2	2	322	8
8	4855	19	6	46	4	1	1	411	7
9	5899	68	2	49	2	1	1	211	10

Python Link

RFM SEGMENTATION

	ID	Recency	Frequency	Monetary	recency_score	frequency_score	monetary_score	RFM_SCORE	ClusterCode	ClusterName
0	5524	58	25	1617	2	4	4	244	3	Cannot Lose them
1	2174	38	6	27	3	1	1	311	8	Promising
2	4141	26	21	776	3	3	3	333	4	Potential Loyalist
3	6182	26	8	53	3	1	1	311	8	Promising
4	5324	94	19	422	1	3	3	133	6	At risk
5	7446	16	22	716	4	4	3	443	1	Champion
6	965	34	21	590	3	3	3	333	4	Potential Loyalist
7	6177	32	10	169	3	2	2	322	8	Promising
8	4855	19	6	46	4	1	1	411	7	New Customer
9	5899	68	2	49	2	1	1	211	10	Hibernating

[Python Link]

RFM SEGMENTATION PARAMETER

```
rfm[["ClusterName", "Recency", "Frequency", "Monetary"]].groupby("ClusterName").agg(["min", "max", "mean", "count"])
```

	Recency				Frequency				Monetary			
	min	max	mean	count	min	max	mean	count	min	max	mean	count
ClusterName												
At risk	50	99	73.35862	145	10	21	18.14483	145	397	2252	723.76552	145
Cannot Lose them	50	99	73.71795	390	16	39	22.92564	390	416	2524	1278.96410	390
Champion	0	24	11.76562	192	16	44	23.10417	192	446	2349	1224.79167	192
Hibernating	50	99	74.71355	583	0	20	8.85077	583	5	1679	158.25557	583
Loyal	25	49	36.70526	190	16	43	23.32105	190	415	2525	1293.97895	190
New Customer	0	24	11.95000	300	0	19	8.56000	300	6	1044	132.11333	300
Potential Loyalist	0	49	22.50000	144	11	27	18.08333	144	277	1901	708.09028	144
Promising	25	49	37.16892	296	1	20	8.51351	296	9	963	129.62162	296

[Python Link]

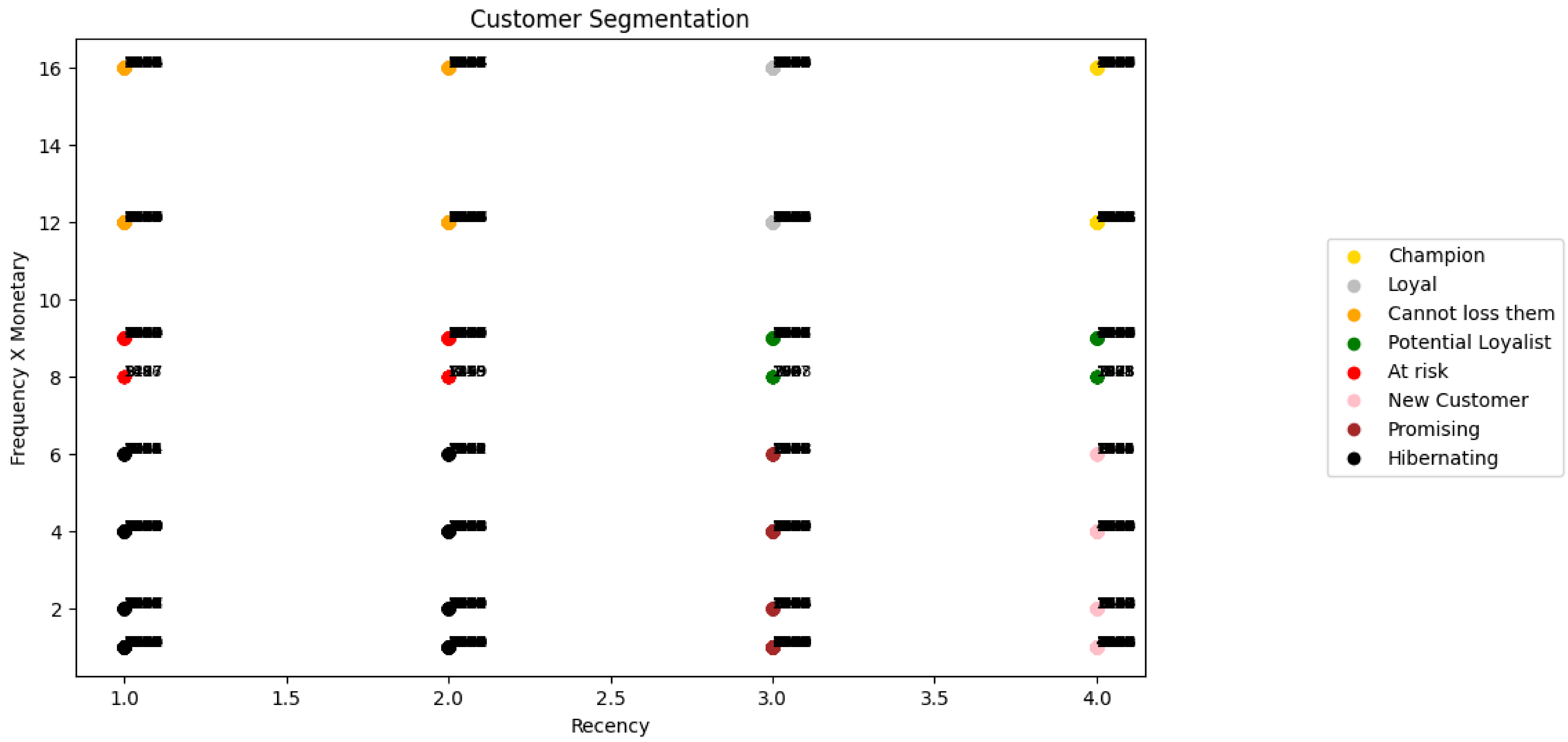
RFM SEGMENT DESCRIPTION

- **At Risk:** These customers have a high monetary value but low recency and frequency, indicating they are at risk of churning. They have spesific **Recency = (50-99 days), Frequency = (11-21 times), Monetary = ($397 - $2252)**
- **Can't Lose:** High in all RFM values, these customers are valuable and should be retained. They have spesific **Recency = (50-99 days), Frequency = (16-39 times), Monetary = ($416 - $2524)**
- **Champions:** These customers are highly active with recent purchases and high monetary value. They are the most valuable segment. They have spesific **Recency = (0-24 days), Frequency = (16-44), Monetary = ($446 - $2349)**
- **Hibernating:** Customers with low recency, frequency, and monetary value. They might have been active in the past but are currently inactive. They have spesific **Recency = (50-90 days), Frequency = (0-20 times), Monetary = ($5 - $1679)**

RFM SEGMENT DESCRIPTION

- **Loyal Customers:** High in frequency and monetary value with moderate recency. They are loyal but not recent customers. They have spesific **Recency = (25-49 days), Frequency = (16-43 times), Monetary = ($416 - $2525)**
- **New Customers:** Recently acquired customers with low RFM values. They need nurturing to become loyal customers. They have spesific **Recency = (0-24 days), Frequency = (0-19 times), Monetary = ($6 - $1044)**
- **Potential Loyalists:** These customers have moderate RFM values, indicating potential for becoming loyal. They have spesific **Recency = (0-49 days), Frequency = (11-27 times), Monetary = ($277 - $1901)**
- **Promising:** Customers with low RFM values, indicating they are new or need attention to increase their value. They have spesific **Recency = (25-49 days), Frequency = (1-20 times), Monetary = ($9 - $963)**

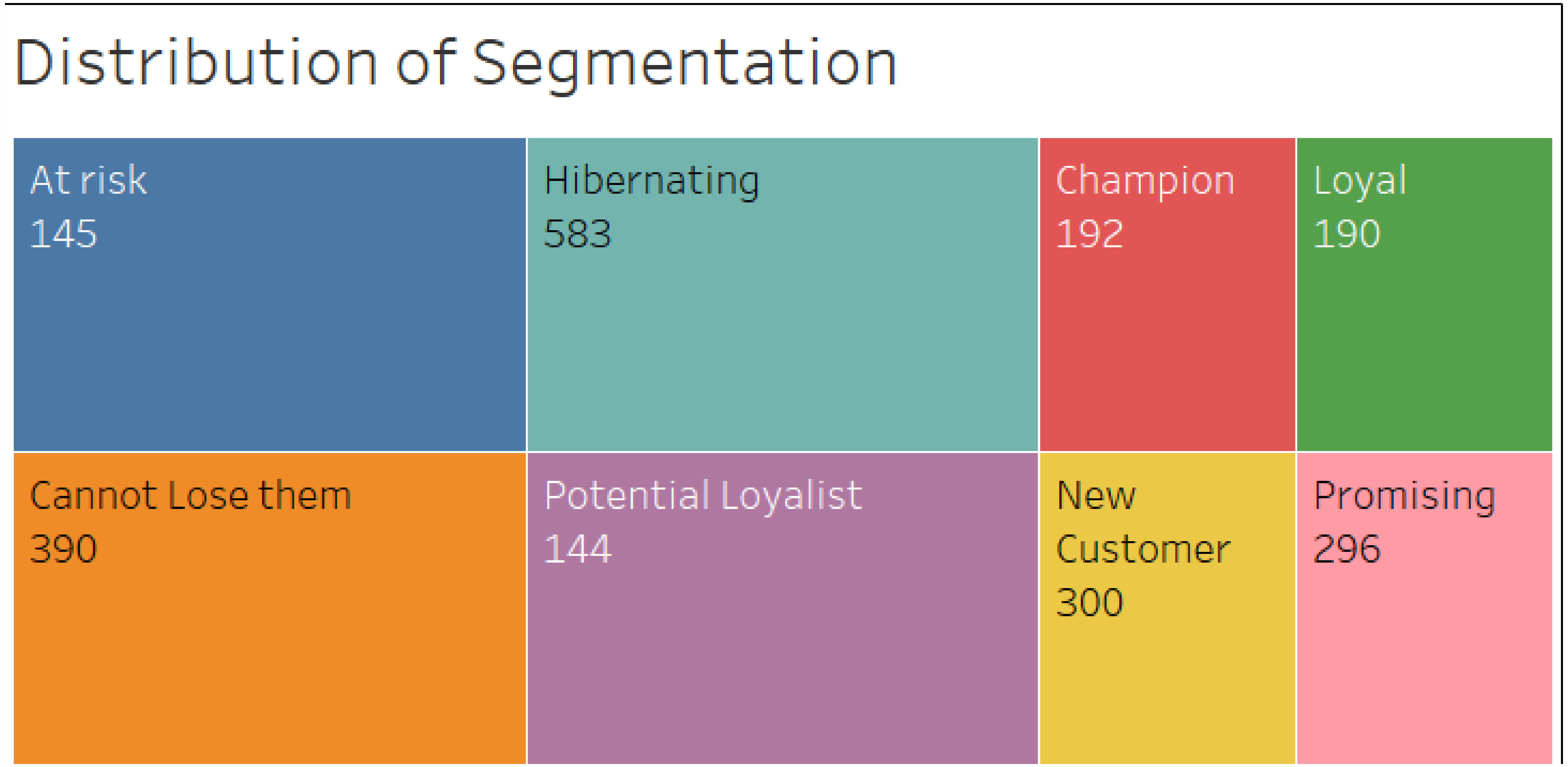
RFM VISUALIZATION



Python Link

RFM RESULT AND VISUALIZATION

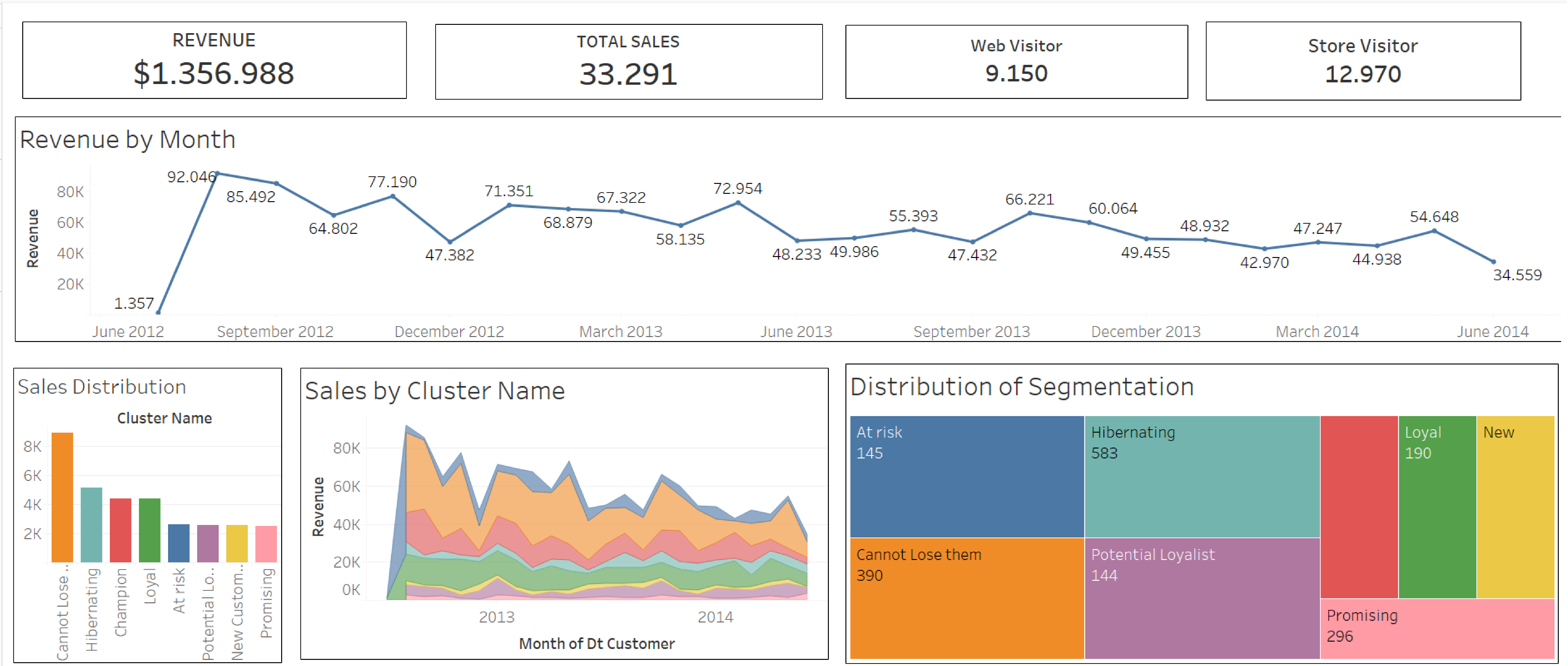
	ClusterName	ID
0	At risk	145
1	Cannot Lose them	390
2	Champion	192
3	Hibernating	583
4	Loyal	190
5	New Customer	300
6	Potential Loyalist	144
7	Promising	296



Python Link

Tableau link

MARKETING SEGMENTATION DASHBOARD



[Tableau link]

INSIGHT AND RECOMENDATION

1. **Targeting Campaigns:**
    - **Champions & Can't Lose:** Focus on loyalty programs, premium offerings, and personalized experiences to retain and maximize value.
    - **Loyal Customers:** Continue engagement with tailored promotions and rewards to maintain loyalty.
    - **Need Attention & At Risk:** Implement targeted reactivation campaigns, special offers, and personalized communications to prevent churn.
    - **Promising & About to Sleep:** Nurture these segments with welcome offers, educational content, and engagement campaigns to increase their value.
2. **Product Development:**
    - Analyze product preferences of each segment to develop new offerings or improve existing ones.
    - For example, "Champions" might prefer high-end products, while "Promising" might respond well to affordable options.
3. **Customer Experience Enhancement:**
    - Improve customer service and support, especially for high-value segments like "Champions" and "Can't Lose."
    - Implement loyalty programs and VIP services for valuable segments to enhance their experience.
4. **Retention Strategies:**
    - Create targeted retention strategies for segments like "At Risk" and "Hibernating" to re-engage and retain customers.
    - Offer exclusive deals or incentives to retain "Can't Lose" customers.

CONCLUSION

By integrating RFM segments with additional variables and a weighted analysis approach, businesses can create more targeted and effective marketing strategies. Understanding customer preferences, behavior, and satisfaction levels enables personalized campaigns that drive engagement, retention, and ultimately, revenue growth.

THANK YOU

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