Marketing Segmentation

Data Analysis and Visualization Business Report

Unsupervised Learning

10/6/24

Contents / Agenda

Executive Summary

In order for our marketing efforts to be successful and have a better return on investment dollars spent, we must have an understanding of certain aspects of who our customer is.

This information will have a direct consequence on the type of sales and marketing strategies we need to implement.

The goal of this analysis is to understand our existing customers purchasing habits and define the most profitable customer segments based on these purchasing habits.

The information extracted from the data will tell about the customers' behaviors, characteristics, and unique needs which will be used to craft an effective marketing campaign and product strategies.

This analysis revealed 2 sets of strongly correlated categories which hold the most monetary value.

- food and wine
- deals and online

It is my recommendation to first focus our marketing campaign on these 2 areas by offering a combination of the two and also a cross combination.

As an example, the data shows food and wine is a winning combination. I also suggest a cross combination offering of food deals with online wine sales in order to bringer a strong segment of one market into another area of focus.

Promoting highly-correlated products could potentially lead to increased overall sales.

There is enough data to use this information for multiple marketing campaigns across various customer groups.

Data Overview

All data types are correct

24 numerical columns (all discrete, except income = continuous)
(some numerical columns are categorical)

3 object columns (2 = categorical, 1 = date)

Missing values are not significant.

numerical = income has 1%

categorical = no missing customers in the categorical data
2240/2240

DATA COLLECTION YEAR = 2016

Data Shape

- Original data shape: (2240, 27)

- Filtered data shape: (2240, 27)
  This is a copy created to look at outliers.

MADE SOME ADJUSTMENTS TO THE FILTERED DATA SET

Condensed some categories

Education:
Placed "2n Cycle" in the "Master" category

Marital_Status:
Placed "Alone", "Absurd, "YOLO" in "Single" category

Added
“quarter” category to look at enrollment dates

Removed
income outliers

NEW Filtered data shape: (2182, 28)

Separated into 2 data sets due to significant outliers

No outlier data shape: (1336, 28)

- separated significant outliers in monetary food purchase categories

Outlier only data shape: (846, 28)

- created a new data set with significant outliers to use as a segmentation category

Exploratory Data Analysis and Data Preprocessing

Univariate Analysis of Income (histogram and box plot)

- Range approx 35 - 80k
- Histogram and box plot showed outliers
- income for those were 118k
- Were 8 customers in that group
- Checked to see what income percentage 99.5% of customers were under.
    - 99.5% are below $102,145 so I am removing these 8 from the data set.

Univariate Analysis of Amt Spent on Food Items (histogram)

- Alot of people spent a very small amount where few people spent a much lesser amount

Univariate Analysis of Categorical Data (bar plot)

- 64.4% customers are in a relationship
- Education is nearly 50/50 degree vs no degree
- Most without children or teens, although not an overwhelming marginal difference
- If they do have a child, it's only 1

FEATURE ENGINEERING TECHNIQUES

- Combined kids in the home and teens in the home into one category = Kids
- Combined marital status into 2 categories of single or relationship and is now = Relationship Status
- Created a new category which combines the Relationship Status + Kids to = Family Size
- Combined the amounts spent on all food categories to = Expenses which = 1435
- Combined all the modes of purhcases into one category = Number of Total Purchases = 137
- Took the enrollment dates to create a number of days a customer has been with the company to = 1089
- Dropped some columns not needed in order to create models.
- Created AVG INCOME IN RANGES
    - 0.0 - 25,000
        - 12,500

- 25,000 - 50,000
    - 37,500

- 50,000 - 75,000
    - 62,500

- 75,000 - 100,000
    - 87,500

FEATURE ENGINEERING OBSERVATION

A larger family size contributes to an increase in income.

- larger households are consistent with those in a relationship
- more than one adult is contributing to the household income.

Observations

Upper and Lower 5 Observations

AGE RANGE

- birth years between 1946 & 1984

EDUCATION

- Grad - Phd - Master

FAMILY DYNAMICS

- married - single -together - divorced
- 0 to 2 kids home - 2 = 1946 (caring for grandkids)
- teens home 0 - 1 (54,67,46,56,54 - caring for grandkids)
- income between 26,645 (1984) & 71,613

ENROLLMENT DATE WITH COMPANY

- 2012 - 2014

- 1st Q = 5, 2nd Q = 2, 3 Q = 1, 4 Q = 1

DAYS SINCE LAST PURCHASE (recency)
- 8 = 1 teen home, 1956, master, 69k, $428 in wine
- 94 = 81, phd, 1 child, 58k, $173 wine

MODE OF PURCHASE
- catalog purchase (most all on low end)
  - 0 = 1984, 1 child, lowest income
  - 10 = 1957, 58k, single, 635 wine, 58 days since last buy
- store purchase 2 - 13

FREQUENCY
- visit /mo 3 - 7

CAMPAIGN OPT INS
- 1st campaign = 1 accept
- 2nd campaign = 0 accepts
- 3rd campaign = 0 accepts
- 4th campaign = 1 accept
- 5th campaign = 0 accepts
- response (campaign) (accepted) = 0

*last campaign (assuming would be 6) is missing from data.
  - Head and tail showed 2 accepted “last” marketing
  - 5th campaign = 0 accepts
  - is the last one accounted for in my data

COMPLAINTS = 0

OVERALL CATEGORICAL OBSERVATIONS

HISTOGRAM & BOX PLOT ANALYSIS OBSERVATION:
- 2 groups of customers have emerged
  - 1. Typical (majority) who spent small amount

- 2. Outlier (minority) who spent nearly as much as the typical grouping

STRATEGY:
1. segment customers
    A. typical purchaser group
    B. outlier purchaser group

OBSERVATION:
Filtered data shape - has outliers: (2182, 28)
No outlier data shape: (1336, 28)
Outlier only data shape: (846, 28)

- Total observations in the 2 new data sets = 2182
- 28 original columns

2. Use clustering on these 2 to better understand the relationship with the other categories

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INCOME OBSERVATIONS

- Outliers are beyond the 118k whisker
- Majority is under 102k
- count and % are insignificant

STRATEGY: Filter out outliers
CONCLUSION:

- Histogram data is now evenly distributed

FIRST CATEGORY TO FILTER OUTLIERS

Income 1974 unique (use this in range form)
HISTOGRAM & BOX PLOT OBSERVATION:
Upper Whisker Limit: 118350.5
99.5% of observations in 'Income' are under: 102145.75
Number of outliers in 'Income': 8 out of 2240

Outlier Percentage in 'Income': 0.36%

WINE PRODUCT OBSERVATIONS

- Performed 2 paces of outlier removal and data is still skewed

STRATEGY: Will need to use other method of standardization

SECOND CATEGORY TO FILTER OUTLIERS

MntWines 776 (use this for an avg)

HISTOGRAM & BOX PLOT OBSERVATION:

Upper Whisker Limit: 1226.5
99.5% of observations in 'MntWines' are under: 1374.35
Number of outliers in 'MntWines': 35 out of 2232
Outlier Percentage in 'MntWines': 1.57%

- OBSERVATION:
  - Outliers make up very small percentage of data
- DECISION:
  - Filter out outliers
- CONCLUSION:
  - Filtering out the outliers didn't evenly distribute the data.

RECHECKED DUE TO OUTLIERS REMAINING IN THE NEW BOXPLOT. DID A SECOND ITERATION OF FILTERING BASED ON THE NUMBERS BELOW

Upper Whisker Limit: 1173.0
Number of outliers in 'MntWines': 15 out of 2197
Outlier Percentage in 'MntWines': 0.68%

- OBSERVATION:
  - This took care of most of the outliers

CONCLUSION:

- Data is still skewed.

FRUIT PRODUCT OBSERVATIONS

- 10% of the data are outliers
- I am not filtering the outliers

STRATEGY: Create 2 categories from this group

THIRD CATEGORY TO FILTER OUT OUTLIERS

MntFruits 158 (use this for an avg)

HISTOGRAM & BOX PLOT OBSERVATION:

Upper Whisker Limit: 80
99.5% of observations in 'MntFruits' are under: 185.0
Number of outliers in 'MntFruits': 224 out of 2182
Outlier Percentage in 'MntFruits': 10.27%

- OBSERVATION:
  - Upper whisker is 80 and box plot shows concentration is in the lower range
  - However the percentage observations indicate a large amount was spent outside the upper limit.
  - Removing second run of outliers in the Wine category didn't have a huge effect on the stats for the next category of fruit.
    - The whisker limit and % observations were nearly unaffected. It decreased number of outliers by 20 and the outlier percentage decrease was approx. 1%

MEAT PRODUCT OBSERVATIONS

- Not filtering outliers

STRATEGY: Create 2 categories from this group

FOURTH CATEGORY TO FILTER OUT OUTLIERS

MntMeatProducts 558 (use this for an avg)

HISTOGRAM & BOX PLOT OBSERVATION:

Upper Whisker Limit: 520.0
99.5% of observations in 'MntMeatProducts' are under: 936.38
Number of outliers in 'MntMeatProducts': 191 out of 2182
Outlier Percentage in 'MntMeatProducts': 8.75%

- OBSERVATION:

- Upper whisker @ 520
- Difference in upper whisker limit and 99.5% = 416
- Need to look at this group

FISH PRODUCT OBSERVATIONS

- Not filtering outliers

STRATEGY: Create 2 categories from this group

FIFTH CATEGORY TO FILTER OUT OUTLIERS

MntFishProducts 182 (use this for an avg)

HISTOGRAM & BOX PLOT:

Upper Whisker Limit: 118.0
99.5% of observations in 'MntFishProducts' are under: 242.38
Number of outliers in 'MntFishProducts': 231 out of 2182
Outlier Percentage in 'MntFishProducts': 10.59%

- OBSERVATION:
  - upper whisker @118
  - Difference in upper whisker limit and 99.5% = 124
  - Need to look at this group

SWEET PRODUCT OBSERVATIONS

- Not filtering the outliers

STRATEGY: Create 2 categories from this group

SIXTH CATEGORY TO FILTER OUT OUTLIERS

MntSweetProducts 177 (use this for an avg)

HISTOGRAM & BOX PLOT:

Upper Whisker Limit: 78.5
99.5% of observations in 'MntSweetProducts' are under: 192.0
Number of outliers in 'MntSweetProducts': 252 out of 2182

Outlier Percentage in 'MntSweetProducts': 11.55%

- OBSERVATION:
  - upper whisker @ 78.5
  - Difference in upper whisker limit and 99.5% = 113.5
  - Need to look at this group

GOLD PRODUCT OBSERVATIONS

- Not filtering the outliers

STRATEGY: Create 2 categories from this group

SEVENTH CATEGORY TO FILTER OUT OUTLIERS

MntGoldProds 213 (use this for an avg)

HISTOGRAM & BOX PLOT:

Upper Whisker Limit: 126.5

99.5% of observations in 'MntGoldProds' are under: 241.10

Number of outliers in 'MntGoldProds': 197 out of 2182

Outlier Percentage in 'MntGoldProds': 9.03%

- OBSERVATION:
  - upper whisker @ 126.5
  - Difference in upper whisker limit and 99.5% = 114.60
  - Need to look at this group

FAMILY DYNAMICS OBSERVATIONS

- 64.4% customers are in a relationship/have a family grouping
- Education is nearly 50/50 degree vs no degree
- Standard characteristic - children
  - Outlier characteristic - no children

- Education & Marital Status —> Income
  - Outliers have more income than the Standard group by up to 30k more

- Outlier income same for PhD, Master, Graduation & all marital statuses

STRATEGY: grouping = children / no children
higher income = no children
75k+ - no children
50 - 75k - 1-2 children
less than 50k - 2-3 children

Education ~~5~~ 4 unique (not relevant to looking at habits)(decision tree)

UNIQUE DATA & BAR PLOT OBSERVATION

UNFILTERED DATA

- Graduation = 50.4% = graduation
- Master = 25.6% = masters
- PhD = 21.6% = Phd
- Basic = 2.4%

NO OUTLIERS

- Same order
- Percentage difference not significant

OUTLIERS ONLY

- Same order
- Percentage difference not significant

CONCLUSION:

- Outliers not a factor for this grouping

CATEGORICAL CORRELATION OBSERVATION

Education & Income - Earning from greatest to least

NO OUTLIERS

- PhD - 45k
- Master - 40k
- Graduation - 38k
- Basic - 20k

OUTLIERS

- PhD -69k
- Graduation - 68,5k
- Master - 68k
- Basic - 31k

**Combined Together + Married to = Relationship*
and Single, Divorced, and Widow to = Single

Marital_Status ~~8~~ 5 unique (not relevant to looking at habits)(decision tree)

UNIQUE DATA & BAR PLOT OBSERVATION

UNFILTERED DATA

- Married = 38.6%
- Together = 25.8%
- Single = 21.8%
- Divorced = 10.3%
- Widow = 3.4%

NO OUTLIERS

- Same order
- Percentage difference not significant

OUTLIERS ONLY

- Same order
- Percentage difference not significant

CONCLUSION:

- Outliers not a factor for this grouping

CATEGORICAL CORRELATION OBSERVATION

Marital Status & Income - Earning from greatest to least

NO OUTLIERS

- Widow - 45k
- Married - 40k
- Divorced - 40k
- Together - 38k
- Single - 37k

OUTLIERS

- Married - 69k
- Together - 68,5k
- Divorced - 68,5k
- Single - 68k
- Widow - 67k

**Combined Kidhome and Teenhome to = Kids*

Kidhome 3 unique (0 - 2 range) (could be relevant to looking at habits) (decision tree)

UNIQUE DATA & BAR PLOT OBSERVATION

UNFILTERED DATA

- 0 = 57.7%
- 1 = 40.1%
- 2 = 2.2%

NO OUTLIERS

- 0 = 36.8%
- 1 = 59.8%
- 2 = 3.4%

OUTLIERS ONLY

- 0 = 88.9%
- 1 = 10.8%
- 2 = .4%

CONCLUSION: dominant

- 0 = Outlier group
- 1 = Standard group
- 2 = Standard group - but small %
- Outlier Characteristic
  - no children
- Standard Characteristic
- children

Teenhome 3 unique (0 - 2 range) (could be relevant to looking at habits) (decision tree)

UNIQUE DATA & BAR PLOT OBSERVATION

UNFILTERED DATA

- 0 = 51.6%
- 1 = 46.1%
- 2 = 2.3%

NO OUTLIERS

- 0 = 45.7%
- 1 = 51.8%
- 2 = 2.5%

OUTLIERS ONLY

- 0 = 59.9%
- 1 = 38.2%
- 2 = 1.9%

CONCLUSION: dominant

- 0 = Outlier group
- 1 = Standard group
- 2 = Standard group - but small %
- Outlier Characteristic
  - no children
- Standard Characteristic
  - children

**Assigned Relationship Status a numerical value, then combined Relationship Status + Kids to = Family Size.*

CUSTOMER ENROLLMENT DATE OBSERVATIONS

- small degree of variance amongst the quarters
- 4th Q had more enrollments
- 3rd Q had the least
- 1st enrollment = 1089 days
- last enrollment = 26 days

STRATEGY: Although there is a 2 approaches: to raise 3rd Q enrollment and/or to capitalize on 4th Q when customers enrollment has historically been higher.

Dt_Customer 663 unique

*(*Already know there are 69 unique observations. Want to know the enrollment count in each quarter to see if there is an pattern we can capitalize on.)

UNIQUE DATA & BAR PLOT OBSERVATION

UNFILTERED DATA

- 4 = 26.7% 174
- 1 = 25.9% 163
- 2 = 24.3% 170
- 3 = 23.1% 156

NO OUTLIERS

- 1 = 25.7%
- 2 = 25.4%
- 3 = 22.2%

- 4 = 26.6%

OUTLIERS ONLY

- 1 = 26.5%
- 2 = 22.7%
- 3 = 24%
- 4 = 26.8%

CONCLUSION:

- Overall well balanced

COMPLAINT OBSERVATIONS

- Basically no complaints in the past 2 years
- Happy customers

STRATEGY: Capitalize on this in the marketing campaign

Complain 2 unique (0 or 1 - not relevant to looking at habits)(decision tree)

UNIQUE DATA & BAR PLOT OBSERVATION

UNFILTERED DATA

- 99.1 % complaint free in past 2 years.

NO OUTLIERS

- NO Percentage difference

OUTLIERS ONLY

- NO Percentage difference

CONCLUSION:

- Outliers are not a factor for this grouping

AGE OBSERVATIONS

- Customers caring for grandchildren

STRATEGY: Capitalize on the pain points of older customers with younger children to care for

- easy, diverse, healthy meals
- items kids can help themselves with

Year_Birth 59 unique

HEAD & TAIL OBSERVATION:

- Some older customers have children and/or teens in the home
- Check age and children in the home. Could be a market segment.

UNIQUE OBSERVATION:

- Broad customer age range.
- Look at habits of older customers vs habits of younger customers.

RECENTLY VISITED OBSERVATIONS

- The recency of visits to the store didn't show to have an impact on their purchasing habits

Recency 100 unique

HEAD & TAIL OBSERVATION:

- Do frequent shoppers spend more money on indulgences, such as wine?

UNIQUE OBSERVATION:

- 100 unique amounts of time
  - out of the 2240 customers
- Segment into what these ranges are
- Get an idea of numbers on possibly who shops often vs who doesn't shop often
- Use this to compare to
  - where they shop
  - when they shop
  - ex: shop weekly & mostly in store

MODE OF PURCHASE OBSERVATIONS

- Balanced across modes
- Number of products purchased by the customers = 137 avg

STRATEGY: Craft marketing offers to the shopping mode for the age group based on the driving factor for that segment

The total.

Maximum Amount Per Purchase: 137.0

NumDealsPurchases 15 (use this for avg / range / in ratio to)

NumCatalogPurchases 14 (use this for avg / range / in ratio to)
NumStorePurchases 14 (use this for avg / range / in ratio to)
NumWebPurchases 15 (use this for avg / range / in ratio to)

NumWebVisitsMonth 16 (use this for avg / range / in ratio to)
HEAD & TAIL OBSERVATION:

- See if there is a correlation to customers who have been enrolled a long time and how often they are shopping.

CAMPAIGN OPT IN OBSERVATIONS

*last campaign (assuming would be 6) is missing from data.

- Head and tail showed 2 accepted “last” marketing
- 5th campaign = 0 accepts
- is the last one accounted for in my data

STRATEGY: The last campaign had more opt ins than others so mirror similarities

AcceptedCmp3 2 (0 or 1 - not relevant to looking at habits)(decision tree)
AcceptedCmp4 2 (0 or 1 - not relevant to looking at habits)(decision tree)
AcceptedCmp5 2 (0 or 1 - not relevant to looking at habits)(decision tree)
AcceptedCmp1 2 (0 or 1 - not relevant to looking at habits)(decision tree)
AcceptedCmp2 2 (0 or 1 - not relevant to looking at habits)(decision tree)
Response 2 (0 or 1 - not relevant to looking at habits)(decision tree)
HEAD & TAIL OBSERVATION:

- 1st campaign = 1 accept
- 2nd campaign = 0 accepts
- 3rd campaign = 0 accepts
- 4th campaign = 1 accept
- 5th campaign = 0 accepts
- response (campaign) (accepted) = 0

OVERALL OBSERVATION

- Maximum amount of products purchased per purchase = 137
- Max expenses for all categories past 2 yrs = 1435
- Amount / purchase, distributed over time = more frequent shoppers average spending less
- Higher earners spend more.
- Expenses, distributed over time = 2-4 wks for majority
- Larger family size = increase in income
- Max days customer has been with company = 1035
- Max time with no engagement = 1089 days

Model Building

Comparison of Techniques and their Performances

I used the filtering method for outliers because it creates a view of the original DataFrame, not a new DataFrame. The whole of the data frame is needed for running certain models so I wanted to maintain the integrity of the true dataset.

Even though some categories remain highly skewed after filtering out the outliers, I opted to not standardize the data in that category because doing so would significantly affect the relationship with the other categories. I

need to see their relationship with the other categories to accurately segment customers.

I ran comparison in categories without outliers and with outliers, documented the findings, then filtered outliers and removed unnecessary variables in order to run models.

SCATTER PLOT OBSERVATION

- There is a positive correlation between income and expenses. As income increases, so does the amount of expenses the customer has in the store.

HEATMAP OBSERVATION

- Grouped and iterated over and over based on the heat map findings before irrelevant variables were removed

STRATEGY: The last campaign had more opt ins than others so mirror similarities. Use the common connections within the groups to craft personal and custom targeted offers.

Complain Least
- Yr Birth
- Money Spent on Gold Prods
- Wine
- Kids in Home
- Teens in Home
- Income

Number of Store Purchases
- Money Spent on Meat
- Kids in Home
- Money Spent on Gold Prod

Number of Web Purchases

Money Spent on Gold Prod
Money Spent on Meat
Number of Purchases Catalog

Number of Web Visits / Mo
Income
Number of Deals Purchased

Money Spent on Wine
Income
Number Web Purchases
Number of Store Purchases
Number of Catalog Purchases
Accepted Campaign 3

Response to Last Campaign
Accepted Campaign 3
Recency Since Last Purchase

Money Spent on Fruit
Money Spent on Sweets
Money Spent on Fish

Accepted Campaign 5
Accepted Campaign 1
Accepted Campaign 2

- Heat map findings after irrelevant variables were removed

Strong Positive Correlations:

- Wine & Overall Total:

    - Customers who spend more on wine have higher total spending across all product categories.
    - Wine is likely a significant part of the total spending.

- Fruit, Meat Products, Fish Products, Sweet Products, GoldProds & Overall Total:
    - Customers who purchase more of these products tend to spend more overall.

Moderate Positive Correlations:

- Number of Deals Purchased & Number of Web Purchases:
    - Moderate correlation
    - Customers who make more purchases using deals also make more purchases online.

- Number of Web Visits per Month & Number of Web Purchases:
    - Customers who visit the website more often tend to make more purchases online.

Weak or No Correlations:

- Most other feature combinations show weak or no significant correlations, implying that they are relatively independent of each other. For example, Recency (number of days since last purchase) has little correlation with most other features.

OVERALL HEATMAP OBSERVATION:

The heatmap indicates overall spending is mostly on wine and other product categories. Customers who engage more with deals and online purchases tend

to have higher overall spending. Recency of purchases doesn't seem to have a strong relationship with spending habits in this dataset.

CLUSTERING OBSERVATION

- T-SNE clustering showed organized groups tracking along a predictable pattern.
- PCA was performed to organize the data along an even scale for all categories
- 3 categories emerged enabling the perfect environment for K Means clustering.

CLUSTERING & BOX PLOT PROFILING OBSERVATION

- As a whole, this method didn’t have any stand out categories as to why this method gave any insight into segmentation.

Proposal for the Final Solution Design

Heatmap and K Means clustering are the best models to use for segmentation.

The heat map gave clear correlations between categories.

K Means clearly showed 3 saturated categories of customers.

Conclusions

By using past information to learn about customer engagement with various marketing activities, above the line activities and below the line campaigns, and targeted personalized offers, a successful marketing campaign can be built around what resonates with the customer base.

A main marketing campaign can be developed and slightly modified for each of the saturated categories of customers

Recommendations

There are 2 sets of strongly correlated categories which hold the most monetary value.

- food and wine
- deals and online

Focusing on promoting highly-correlated products could potentially lead to increased overall sales.

It is my recommendation to begin with these 2 areas by offering a combination of the two and also a cross combination.

As an example, the data shows food and wine is a winning combination. I also suggest a cross combination offering of food deals with online wine sales in order to bringer a strong segment of one market into another area of focus.

Appendix

CHECKING ORIGINAL DATA SET AND FILTERED DATA SET BEFORE ANY CHANGES

original_data

#	Column	Count	Non-Null	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	NumCatalogPurchas	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	Response	2240	non-null	int64

dtypes: float64(1), int64(23), object(3)

filtered_data_copy

#	Column	Count	Non-Null	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	Response	2240	non-null	int64

dtypes: float64(1), int64(23), object(3)

NUMERIC SUMMARY

```
ID  Year_Birth     Income  Kidhome  Teenhome  Recency  MntWines  \
count   2240.00     2240.00    2216.00  2240.00   2240.00  2240.00   2240.00
mean    5592.16     1968.81   52247.25     0.44      0.51    49.11    303.94
std     3246.66       11.98   25173.08     0.54      0.54    28.96    336.60
min        0.00     1893.00    1730.00     0.00      0.00     0.00      0.00
25%     2828.25     1959.00   35303.00     0.00      0.00    24.00     23.75
50%     5458.50     1970.00   51381.50     0.00      0.00    49.00    173.50
75%     8427.75     1977.00   68522.00     1.00      1.00    74.00    504.25
max    11191.00     1996.00  666666.00     2.00      2.00    99.00   1493.00

       MntFruits  MntMeatProducts  MntFishProducts  ...  NumCatalogPurchases
\
count    2240.00          2240.00          2240.00  ...              2240.00
mean       26.30           166.95            37.53  ...                 2.66
std        39.77           225.72            54.63  ...                 2.92
min         0.00             0.00             0.00  ...                 0.00
25%         1.00            16.00             3.00  ...                 0.00
50%         8.00            67.00            12.00  ...                 2.00
75%        33.00           232.00            50.00  ...                 4.00
max       199.00          1725.00           259.00  ...                28.00

       NumStorePurchases  NumWebVisitsMonth  AcceptedCmp3  AcceptedCmp4  \
count            2240.00            2240.00       2240.00       2240.00
mean                5.79               5.32          0.07          0.07
std                 3.25               2.43          0.26          0.26
min                 0.00               0.00          0.00          0.00
25%                 3.00               3.00          0.00          0.00
50%                 5.00               6.00          0.00          0.00
75%                 8.00               7.00          0.00          0.00
max                13.00              20.00          1.00          1.00

       AcceptedCmp5  AcceptedCmp1  AcceptedCmp2  Complain  Response
count       2240.00       2240.00       2240.00   2240.00   2240.00
mean           0.07          0.06          0.01      0.01      0.15
std            0.26          0.25          0.11      0.10      0.36
min            0.00          0.00          0.00      0.00      0.00
25%            0.00          0.00          0.00      0.00      0.00
50%            0.00          0.00          0.00      0.00      0.00
75%            0.00          0.00          0.00      0.00      0.00
max            1.00          1.00          1.00      1.00      1.00

[8 rows x 24 columns]
```

CHECKING ORIGINAL DATA SET AND FILTERED DATA SET AFTER CHANGES

- Red shows 2 categories which were condensed and one category added for quarter of enrollment

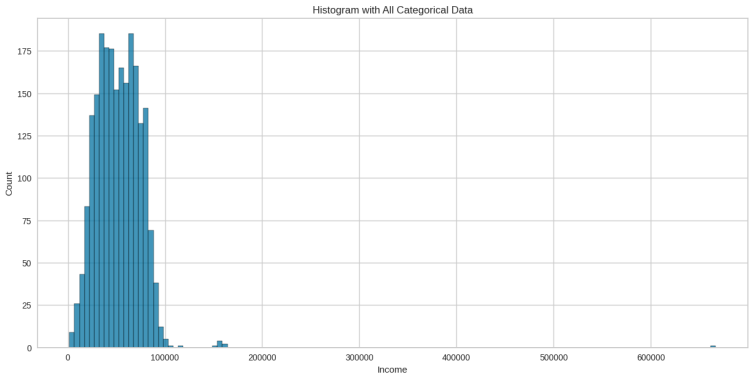
original_data

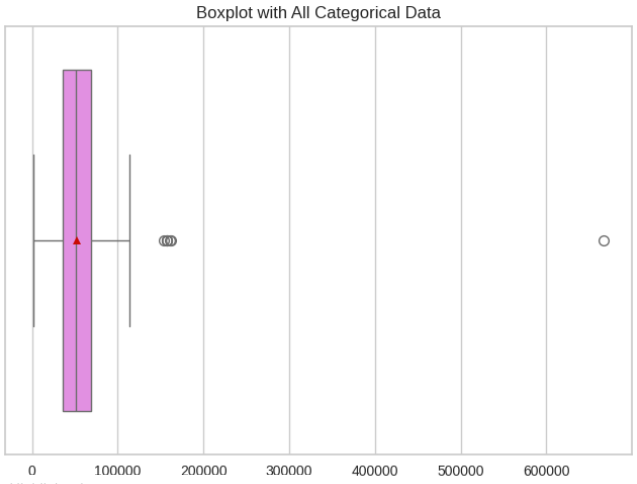
Column	Unique Values
ID	2240
Year_Birth	59
Education	5
Marital_Status	8
Income	1974
Kidhome	3
Teenhome	3
Dt_Customer	663
Recency	100
MntWines	776
MntFruits	158
MntMeatProducts	558
MntFishProducts	182
MntSweetProducts	177
MntGoldProds	213
NumDealsPurchases	15
NumWebPurchases	15
NumCatalogPurchases	14
NumStorePurchases	14
NumWebVisitsMonth	16
AcceptedCmp3	2
AcceptedCmp4	2
AcceptedCmp5	2
AcceptedCmp1	2
AcceptedCmp2	2
Complain	2
Response	2

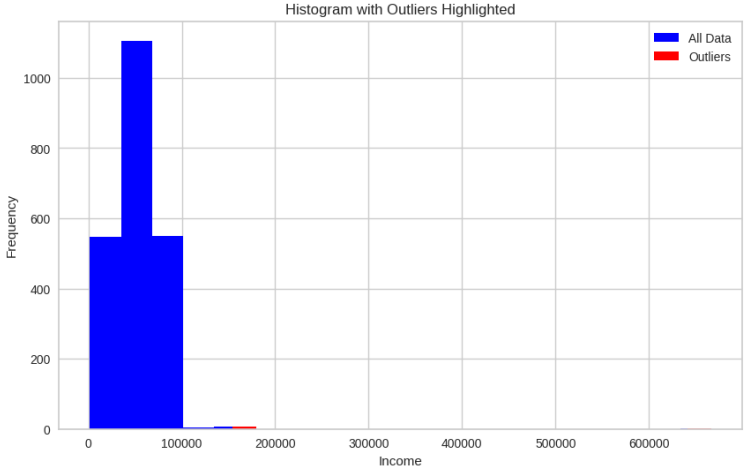
filtered_data

Column	Unique Values
ID	2240
Year_Birth	59
Education	4
Marital_Status	5
Income	1974
Kidhome	3
Teenhome	3
Dt_Customer	663
Recency	100
MntWines	776
MntFruits	158
MntMeatProducts	558
MntFishProducts	182
MntSweetProducts	177
MntGoldProds	213
NumDealsPurchases	15
NumWebPurchases	15
NumCatalogPurchases	14
NumStorePurchases	14
NumWebVisitsMonth	16
AcceptedCmp3	2
AcceptedCmp4	2
AcceptedCmp5	2
AcceptedCmp1	2
AcceptedCmp2	2

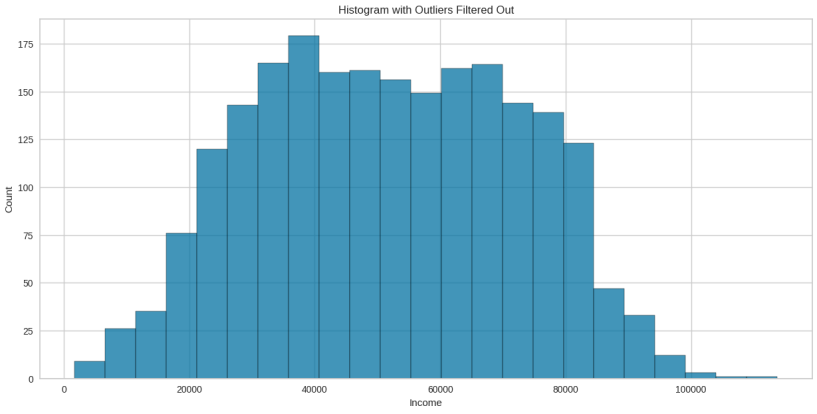
INCOME

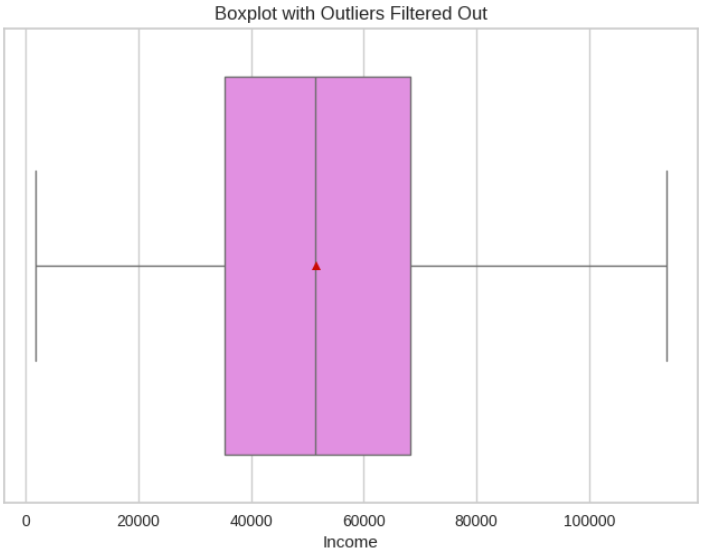






AFTER OUTLIER FILTERING

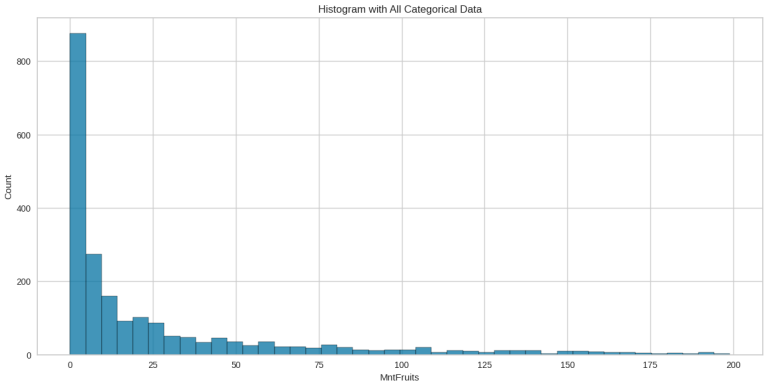


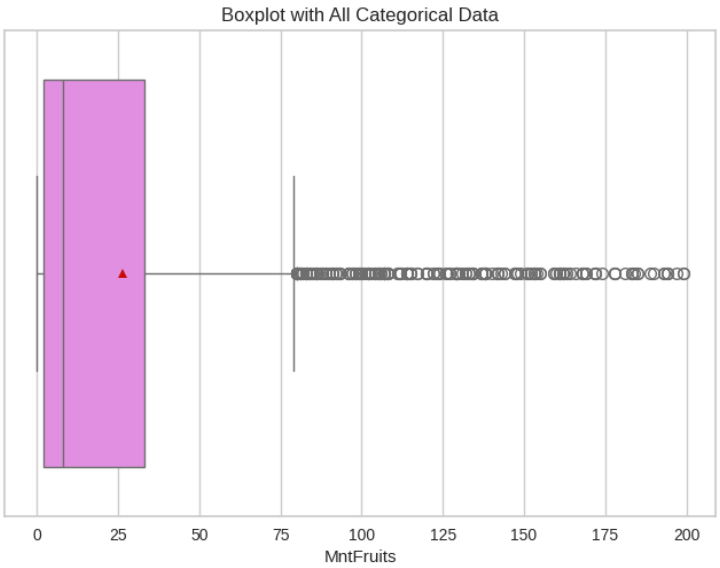


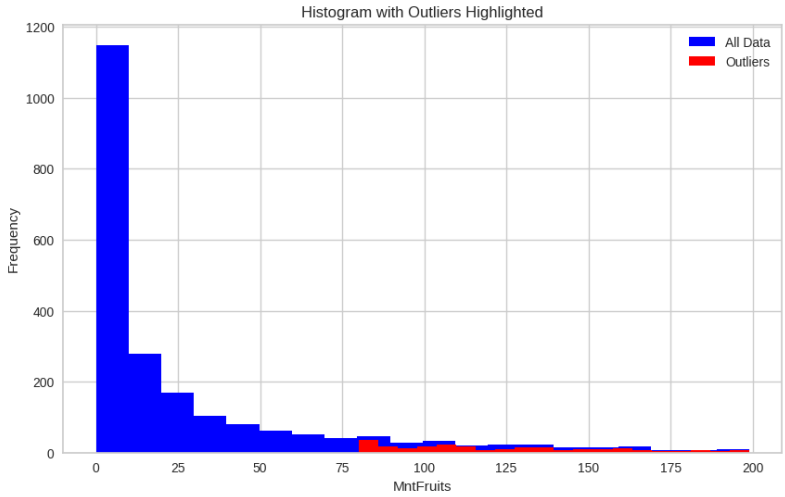

```
Original data shape: (2240, 27)
```
(removed 58 outliers)


```
Filtered data shape: (2232, 28)
```

MONEY SPENT ON FRUIT

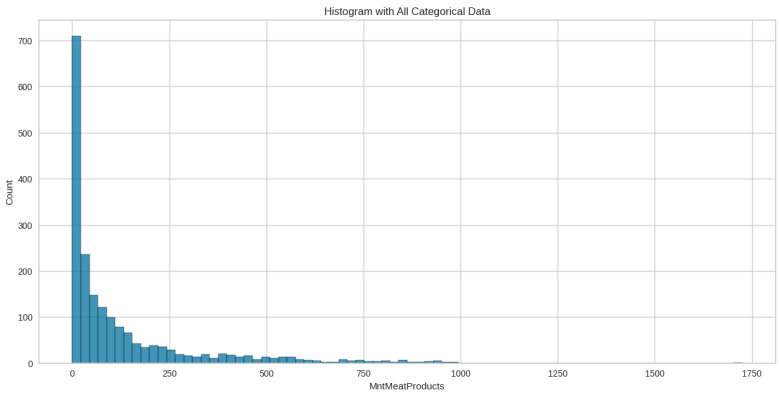


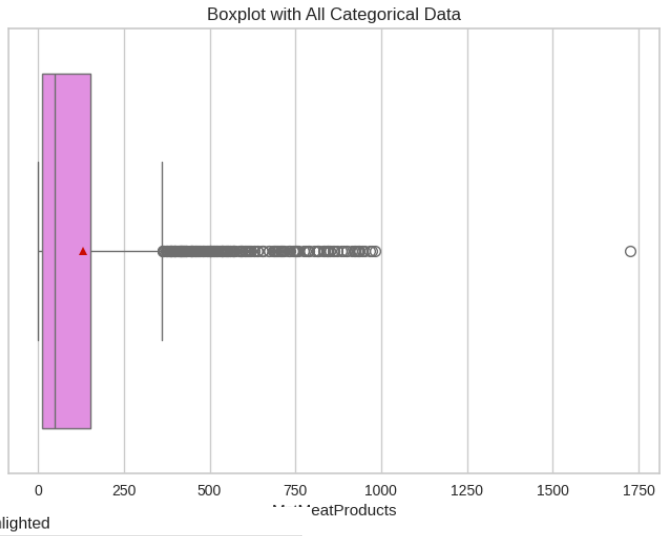


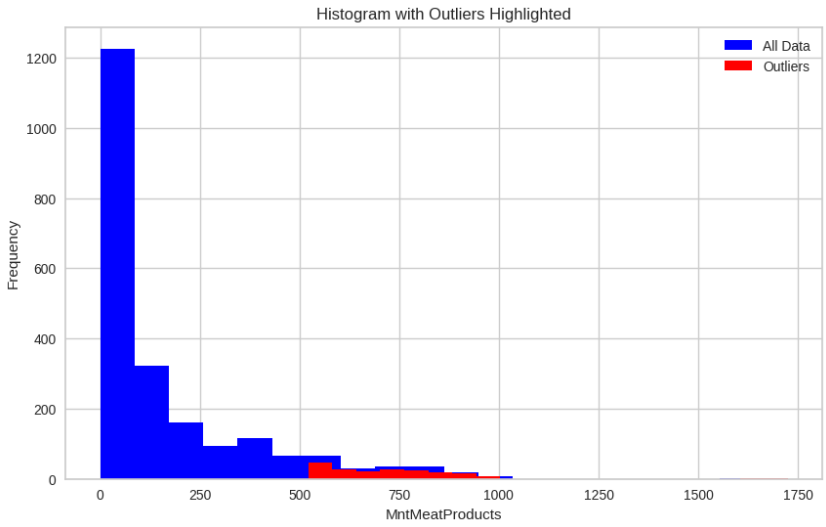



```
Original data shape: (2240, 27)
Filtered data shape: (2182, 28)
```

MONEY SPENT ON MEAT

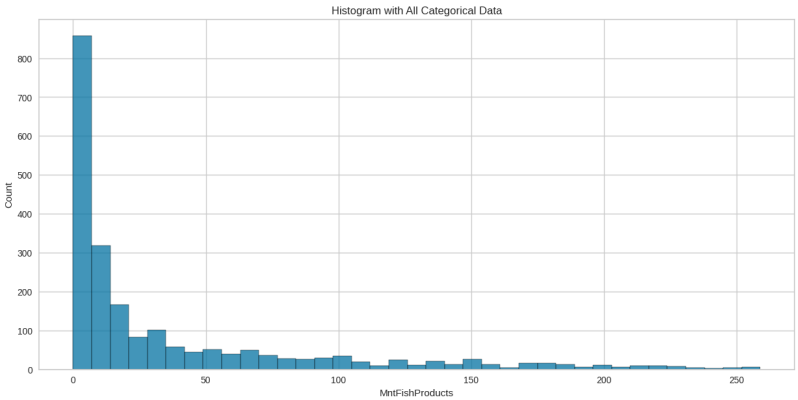


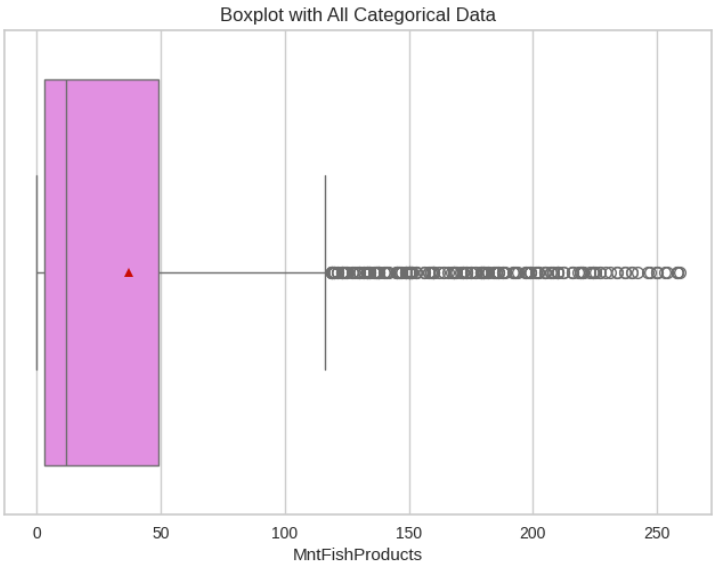


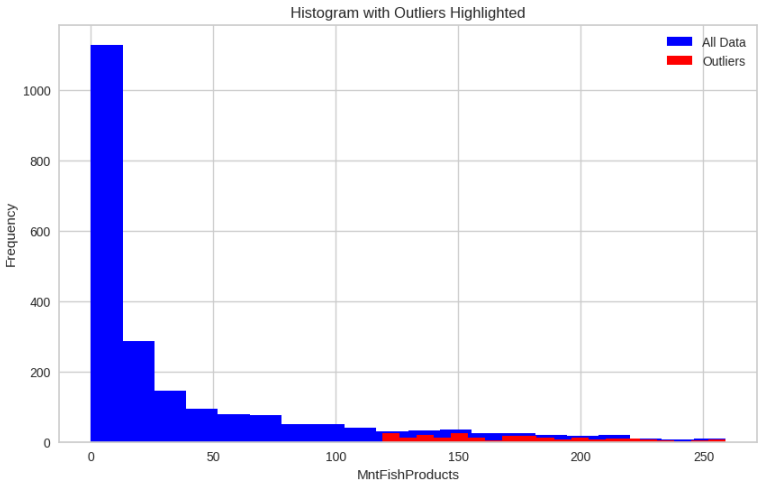



```
Original data shape: (2240, 27)
Filtered data shape: (2182, 28)
```

MONEY SPENT OF FISH

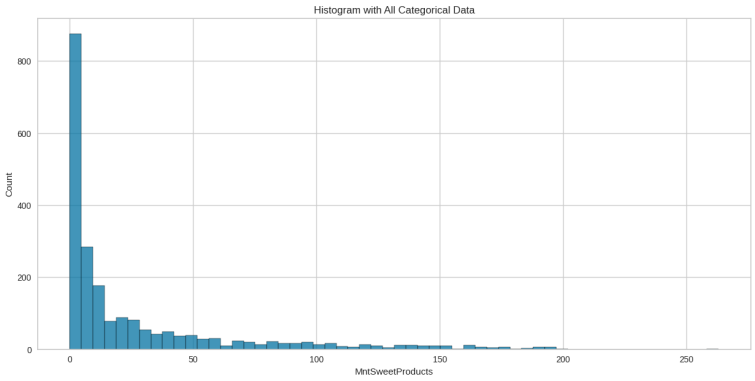


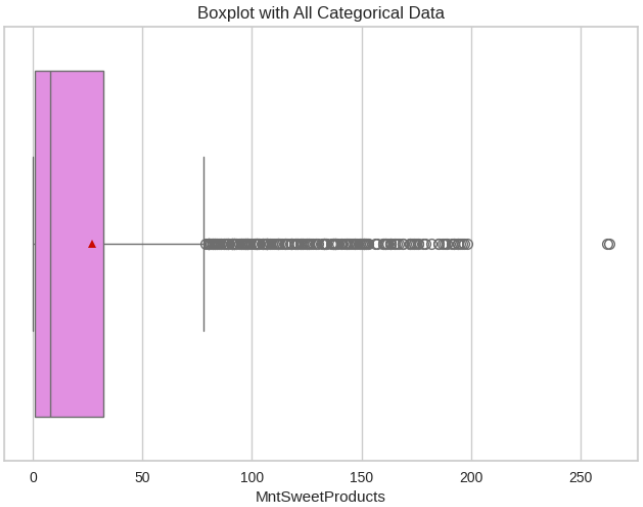


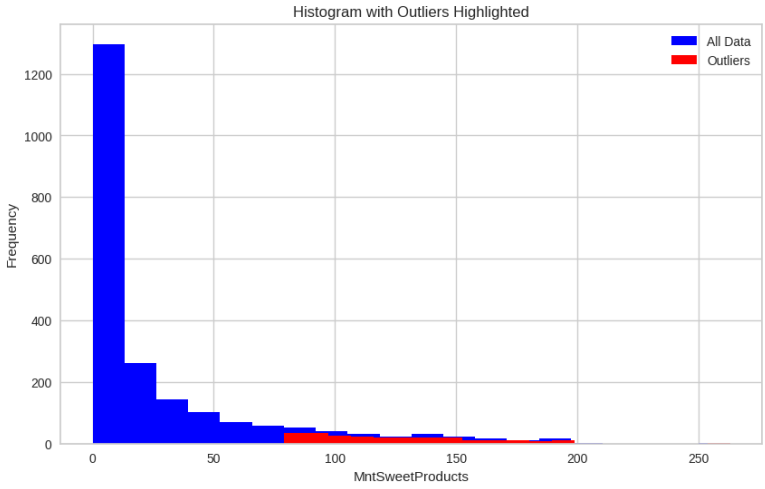



```
Original data shape: (2240, 27)
Filtered data shape: (2182, 28)
```

MONEY SPENT ON SWEETS

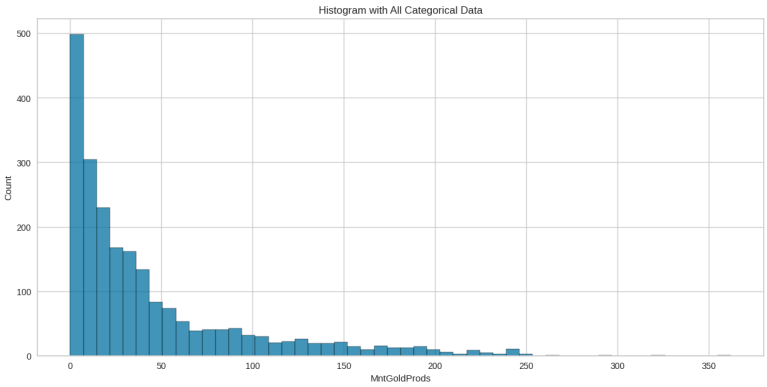


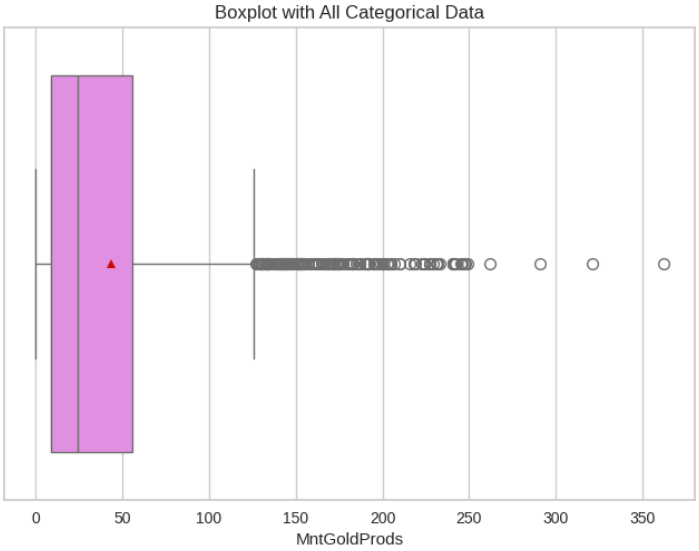


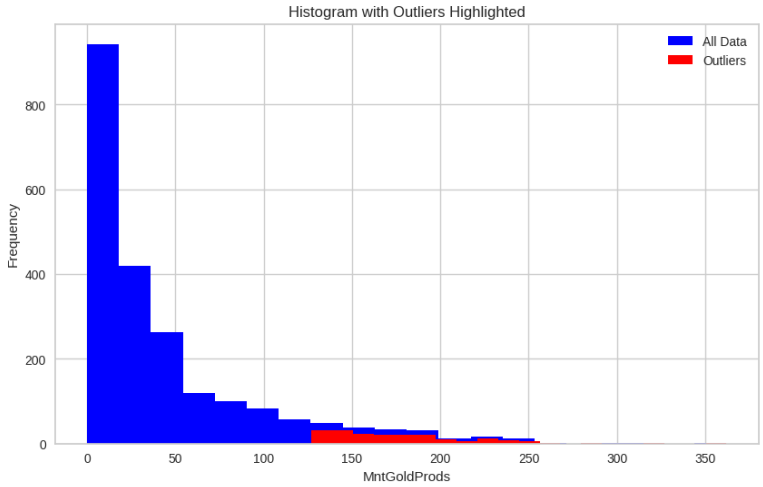



```
Original data shape: (2240, 27)
Filtered data shape: (2182, 28)
```

MONEY SPENT ON GOLD PRODUCTS



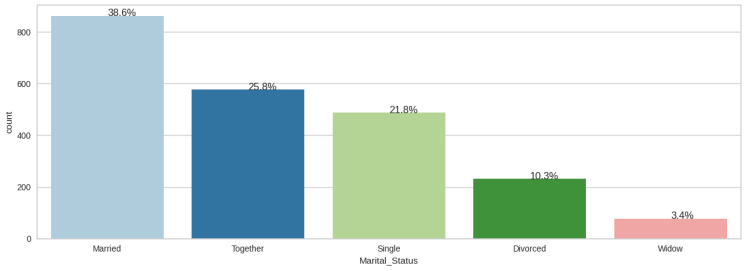


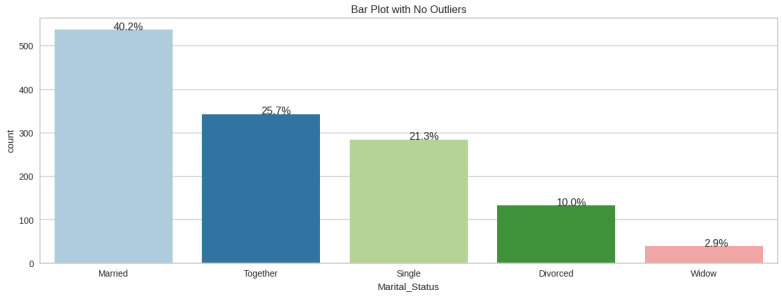


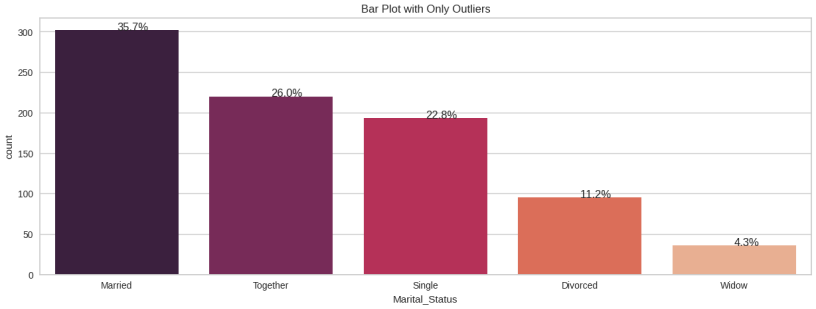

```
Original data shape: (2240, 27)
Filtered data shape: (2182, 28)
```

CHECKING :
NO OUTLIERS DATA SET ~ AND ~ ONLY OUTLIERS DATA SET

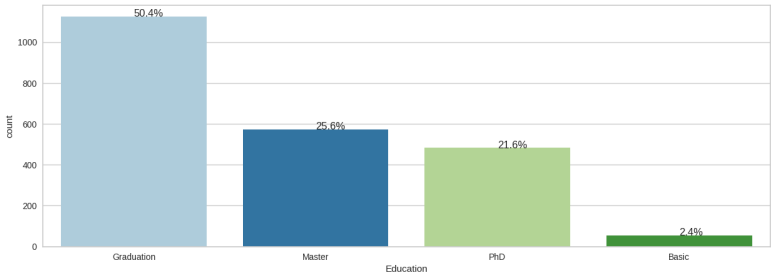
Bar plot for 'Marital_Status'

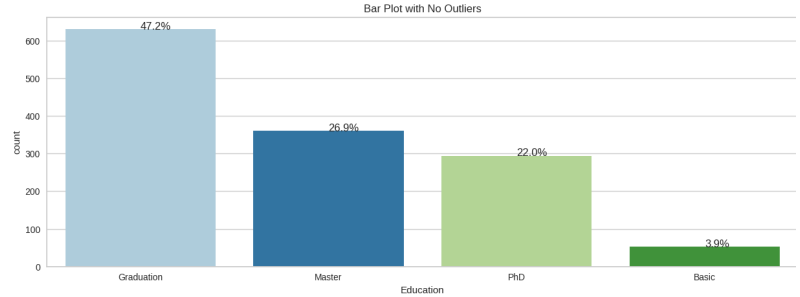


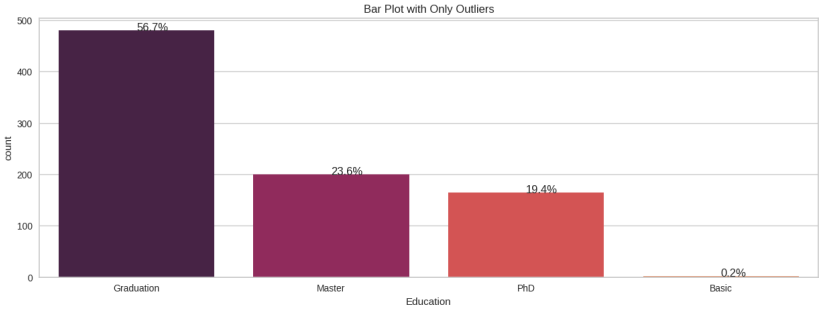




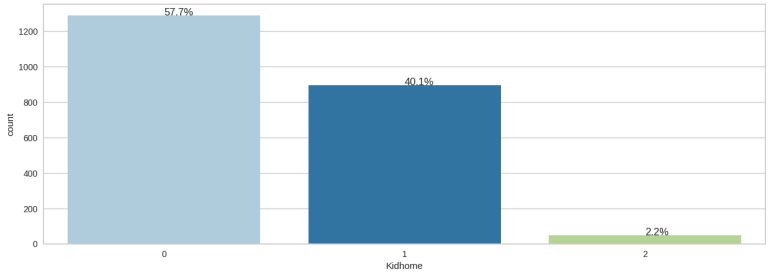
Bar plot for 'Education'

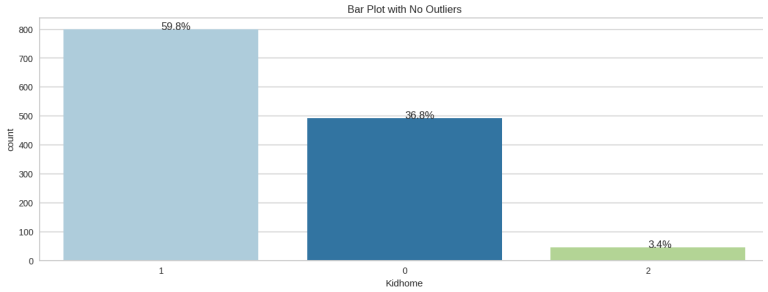


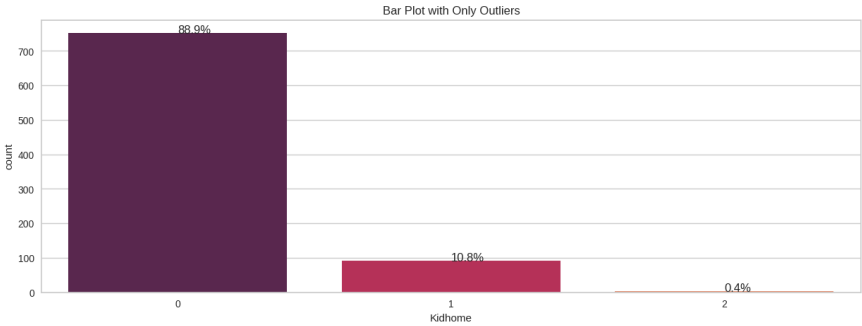




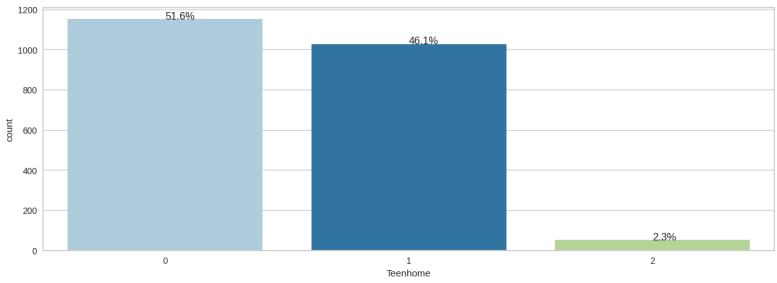
Bar plot for ‘Kidhome'

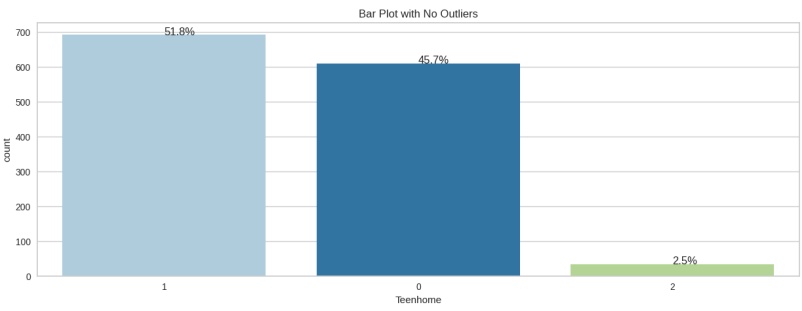


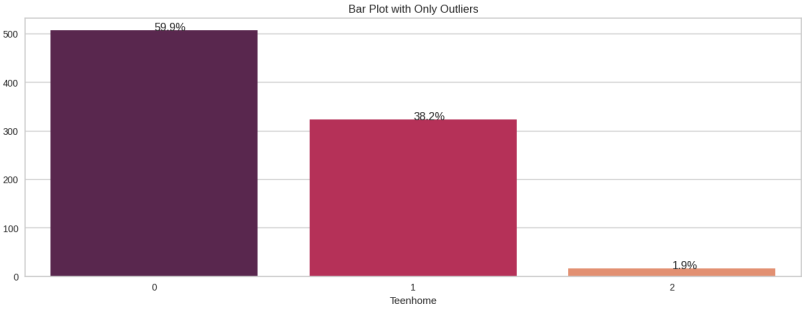




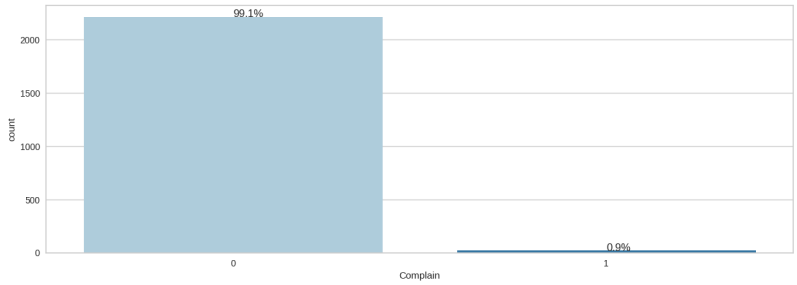
Bar plot for ‘Teenhome’

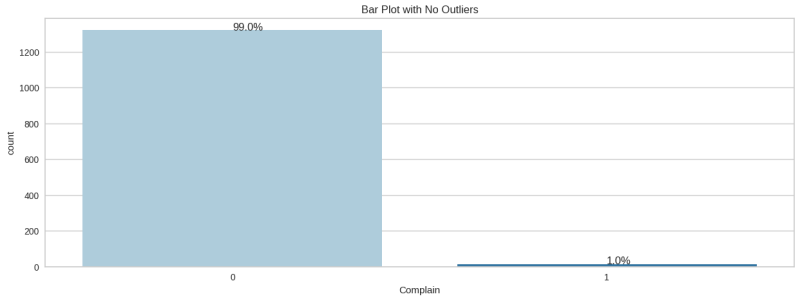


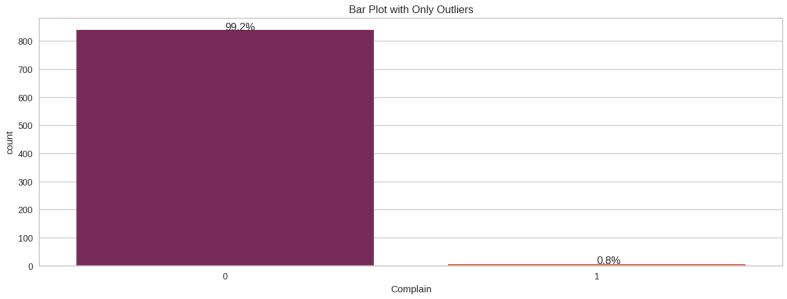




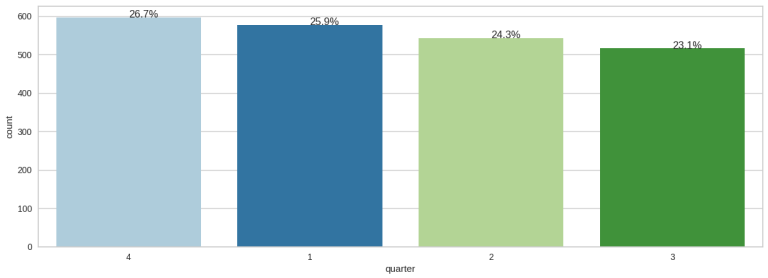
Bar plot for ‘Complain'

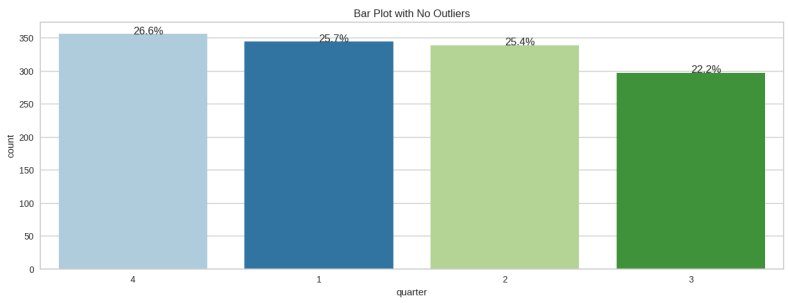


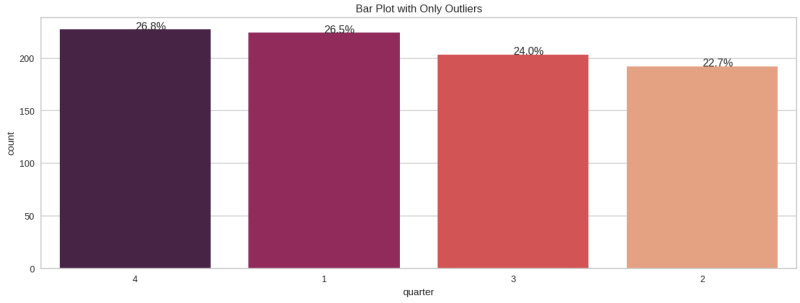


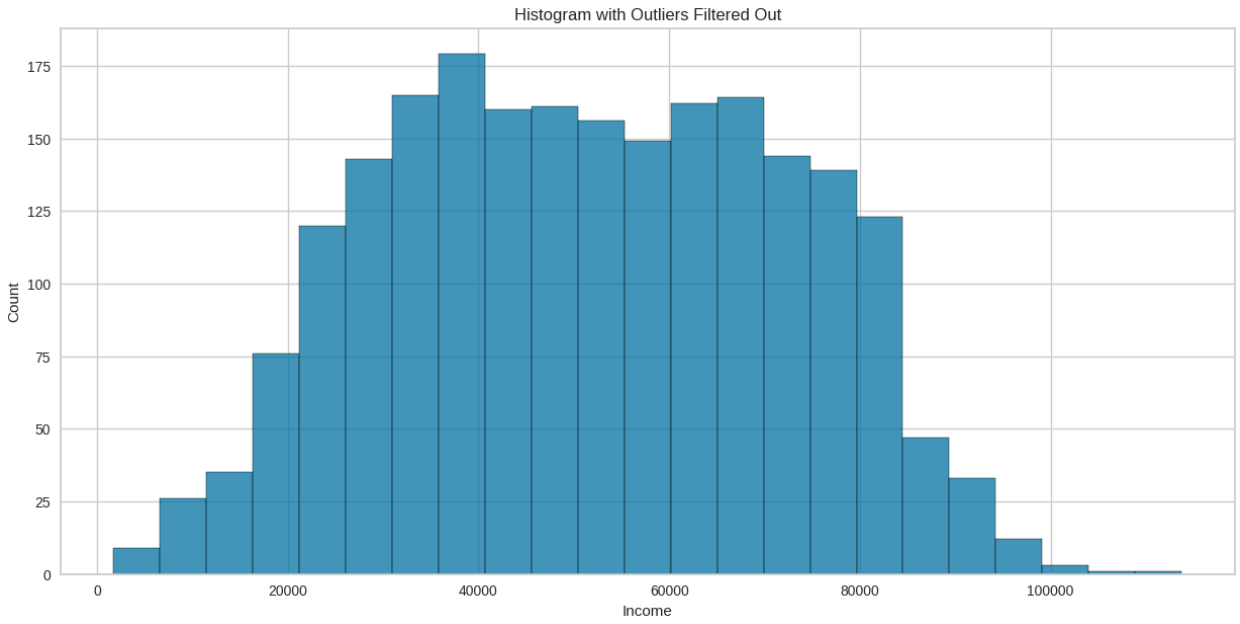


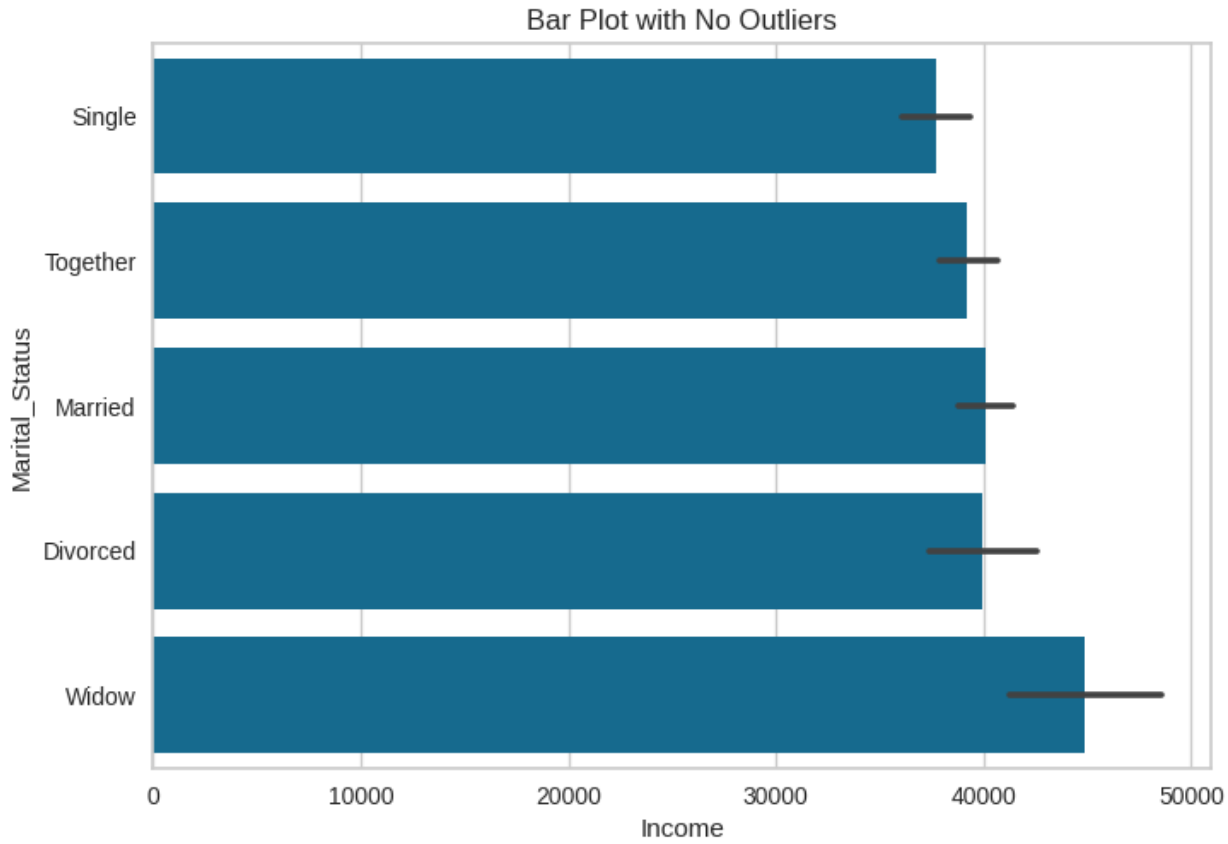
Bar plot for 'Dt_Customer by quarter’

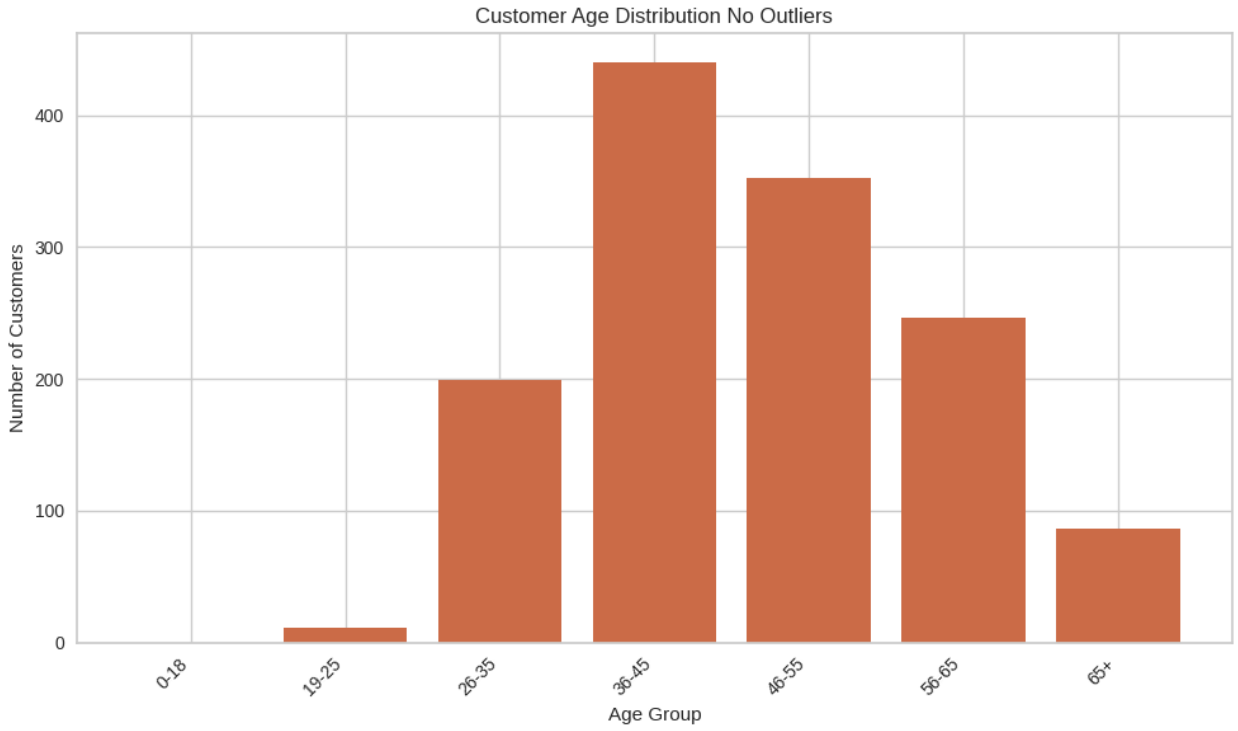




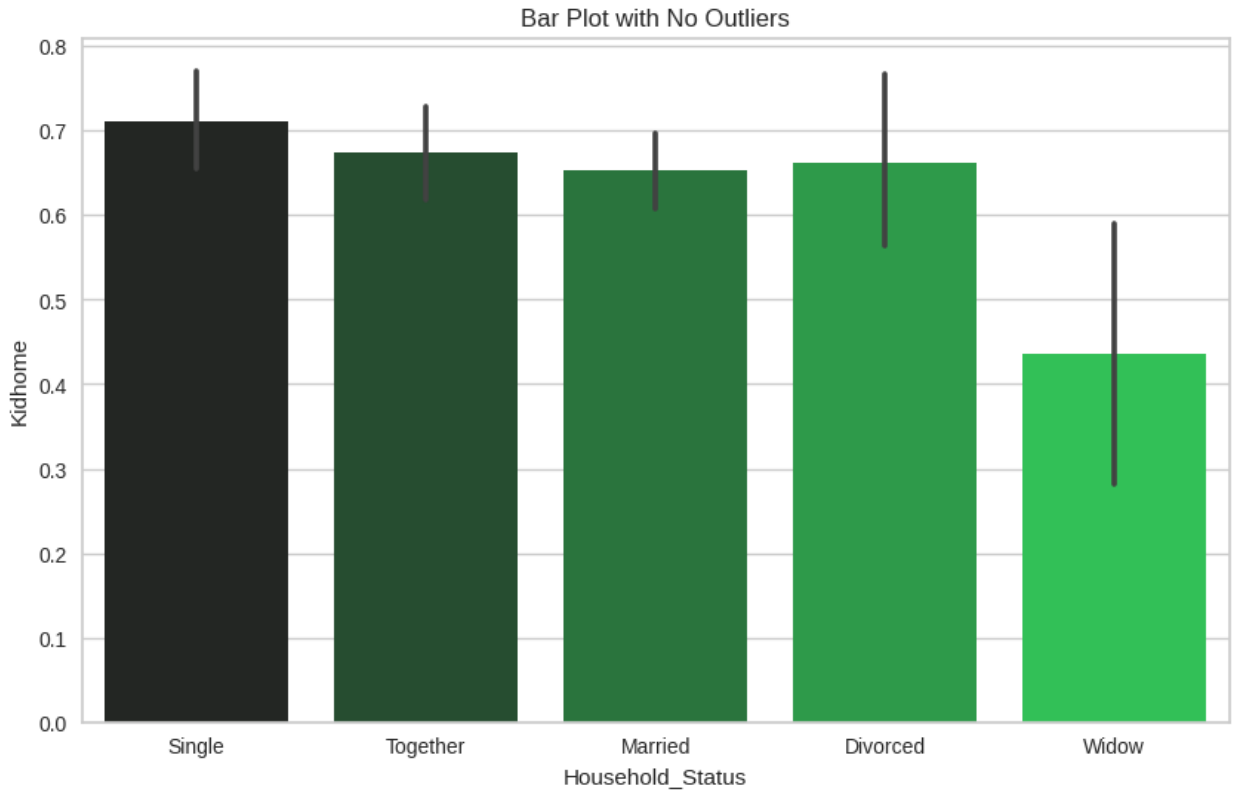


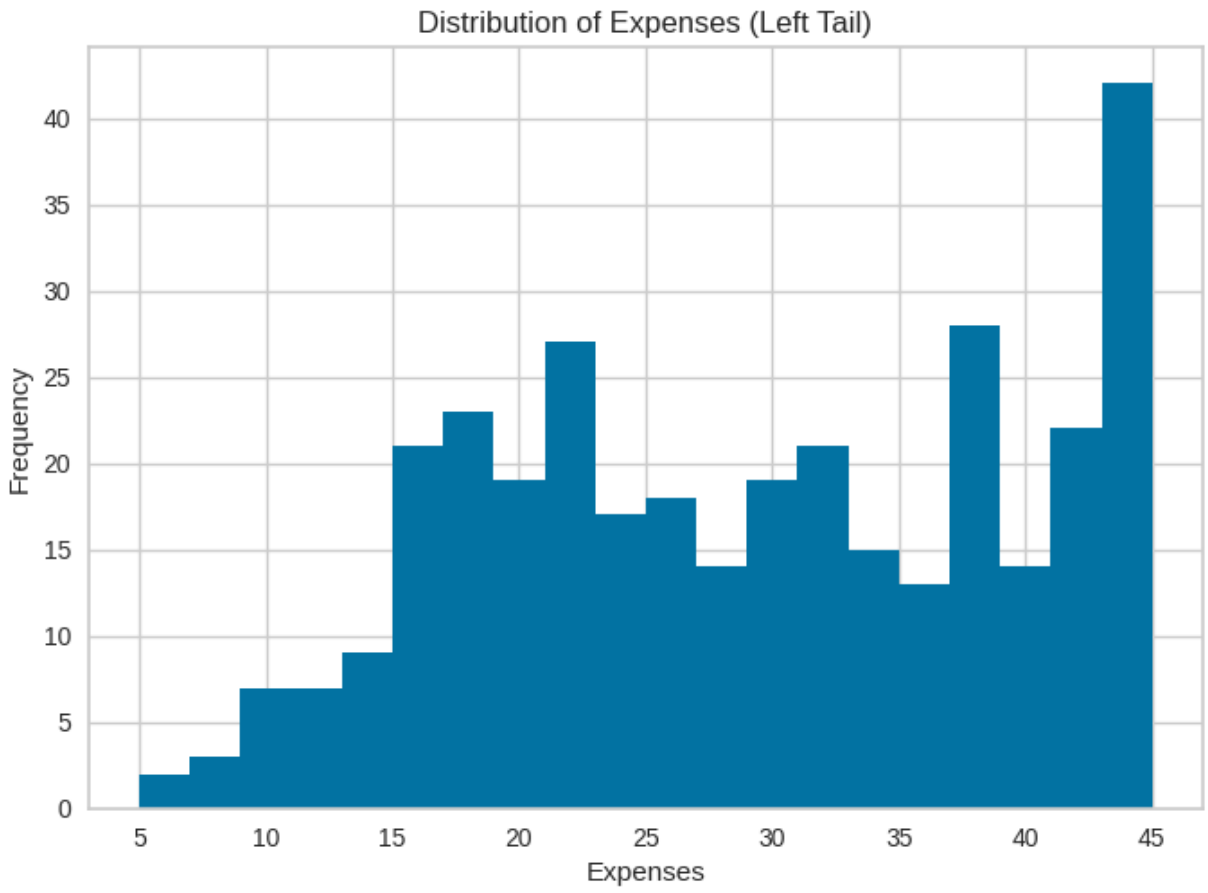

Histogram with Outliers Filtered Out
Count
Income
0
25
50
75
100
125
150
175
0
20000
40000
60000
80000
100000

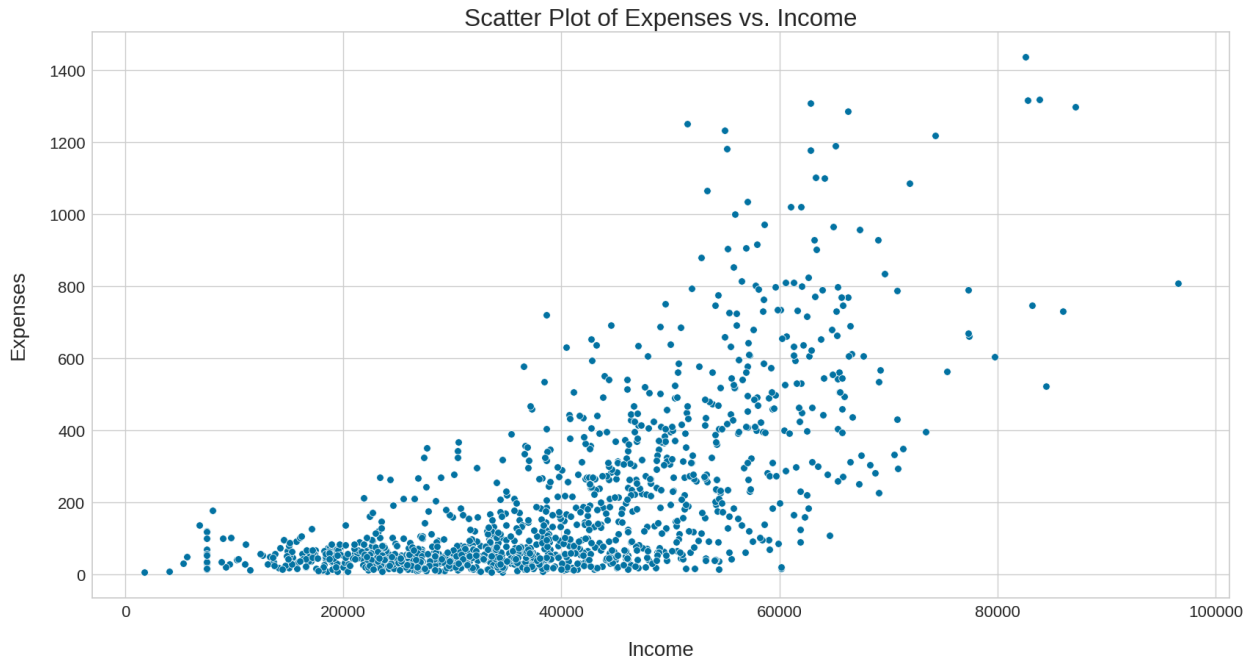

Bar Plot with No Outliers
Marital_Status
Single
Together
Married
Divorced
Widow
0
10000
20000
30000
40000
50000
Income

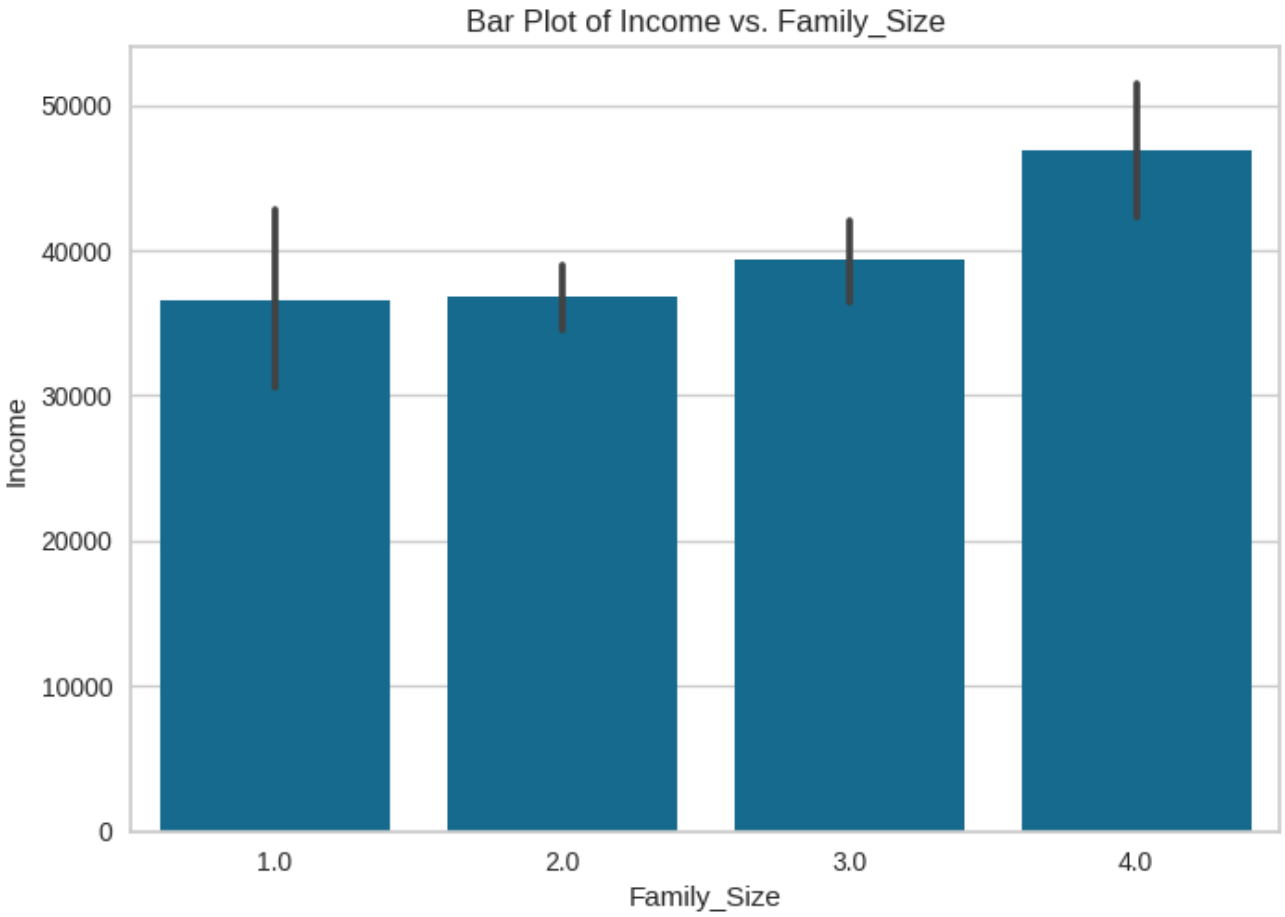

Customer Age Distribution No Outliers
Number of Customers
0
100
200
300
400
0-18
19-25
26-35
36-45
46-55
56-65
65+
Age Group


Customer Age Distribution Only Outliers
Number of Customers
0
50
100
150
200
0-18
19-24
25-34
35-44
45-54
55-64
65+
Age Group


Bar Plot with No Outliers
Kidhome
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Single
Together
Married
Divorced
Widow
Household_Status


Distribution of Expenses (Left Tail)
Frequency
0
5
10
15
20
25
30
35
40
5
10
15
20
25
30
35
40
45
Expenses


Scatter Plot of Expenses vs. Income
Expenses
Income
0
200
400
600
800
1000
1200
1400
0
20000
40000
60000
80000
100000


Bar Plot of Income vs. Family_Size
Income
Family_Size
0
10000
20000
30000
40000
50000
1.0
2.0
3.0
4.0

`data_no_outliers`

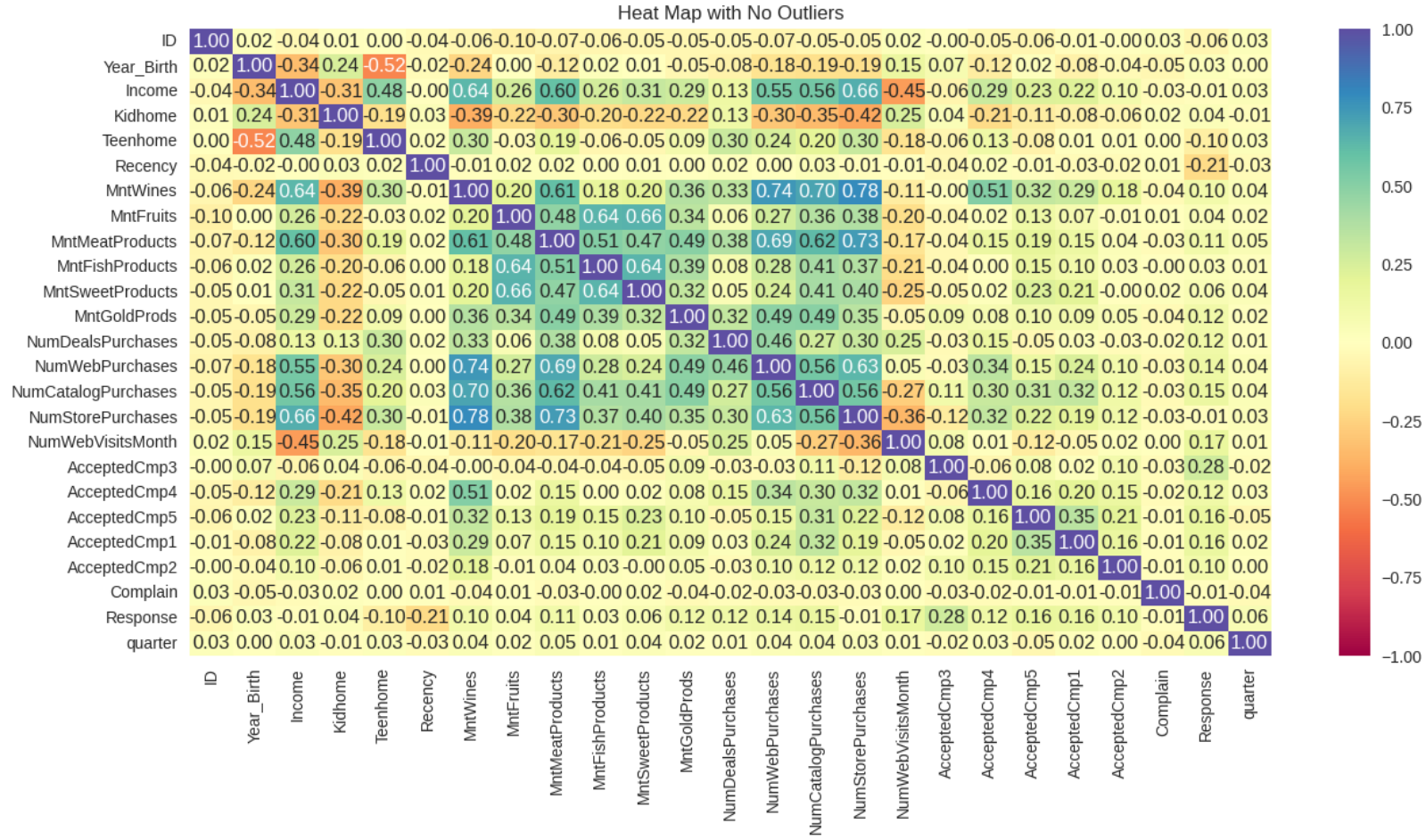
#	Column	Count	Non-Null	Dtype
0	ID	1336	non-null	int64
1	Year_Birth	1336	non-null	int64
2	Education	1336	non-null	object
3	Marital_Status	1336	non-null	object
4	Income	1321	non-null	float64
5	Kidhome	1336	non-null	int64
6	Teenhome	1336	non-null	int64
7	Dt_Customer	1336	non-null	datetime64[ns]
8	Recency	1336	non-null	int64
9	MntWines	1336	non-null	int64
10	MntFruits	1336	non-null	int64
11	MntMeatProducts	1336	non-null	int64
12	MntFishProducts	1336	non-null	int64
13	MntSweetProducts	1336	non-null	int64
14	MntGoldProds	1336	non-null	int64
15	NumDealsPurchases	1336	non-null	int64
16	NumWebPurchases	1336	non-null	int64
17	NumCatalogPurchas	1336	non-null	int64
18	NumStorePurchases	1336	non-null	int64
19	NumWebVisitsMont	1336	non-null	int64
20	AcceptedCmp3	1336	non-null	int64
21	AcceptedCmp4	1336	non-null	int64
22	AcceptedCmp5	1336	non-null	int64
23	AcceptedCmp1	1336	non-null	int64
24	AcceptedCmp2	1336	non-null	int64
25	Complain	1336	non-null	int64
26	Response	1336	non-null	int64
27	quarter	1336	non-null	int32

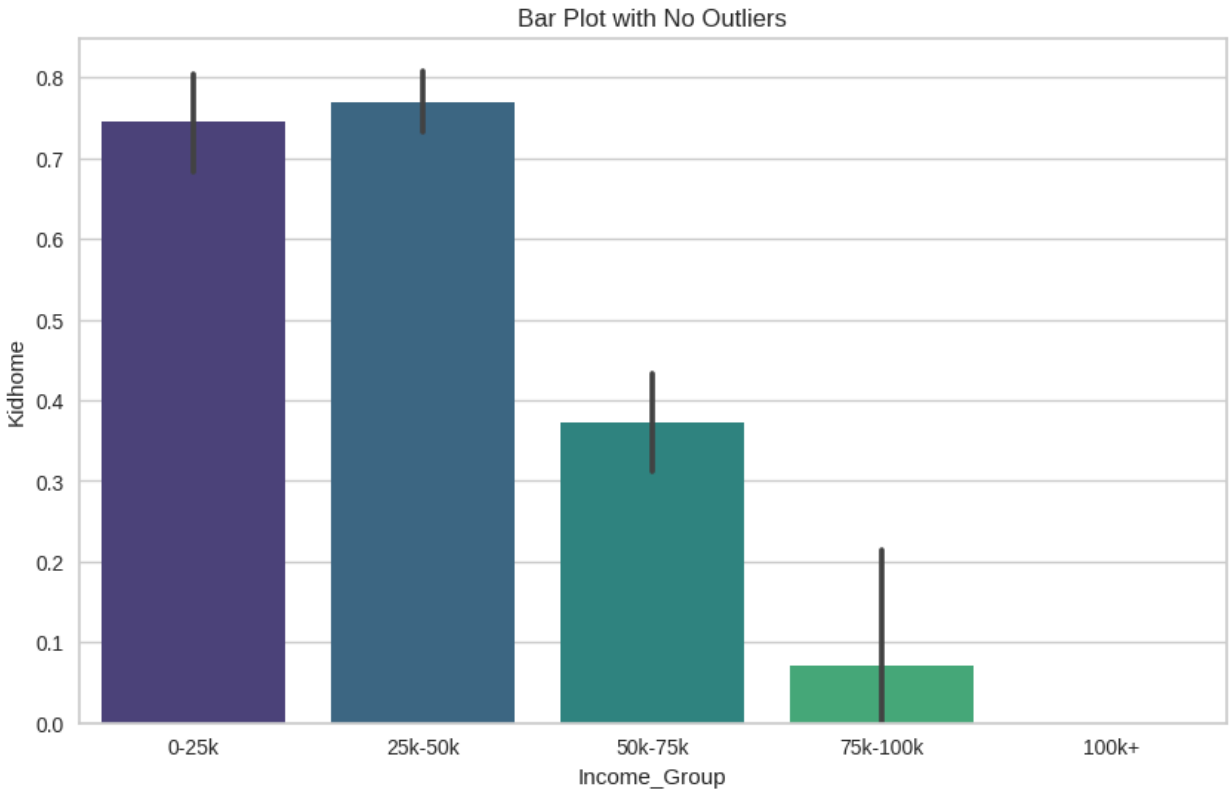
dtypes: datetime64[ns](1), float64(1), int32(1), int64(23), object(2)

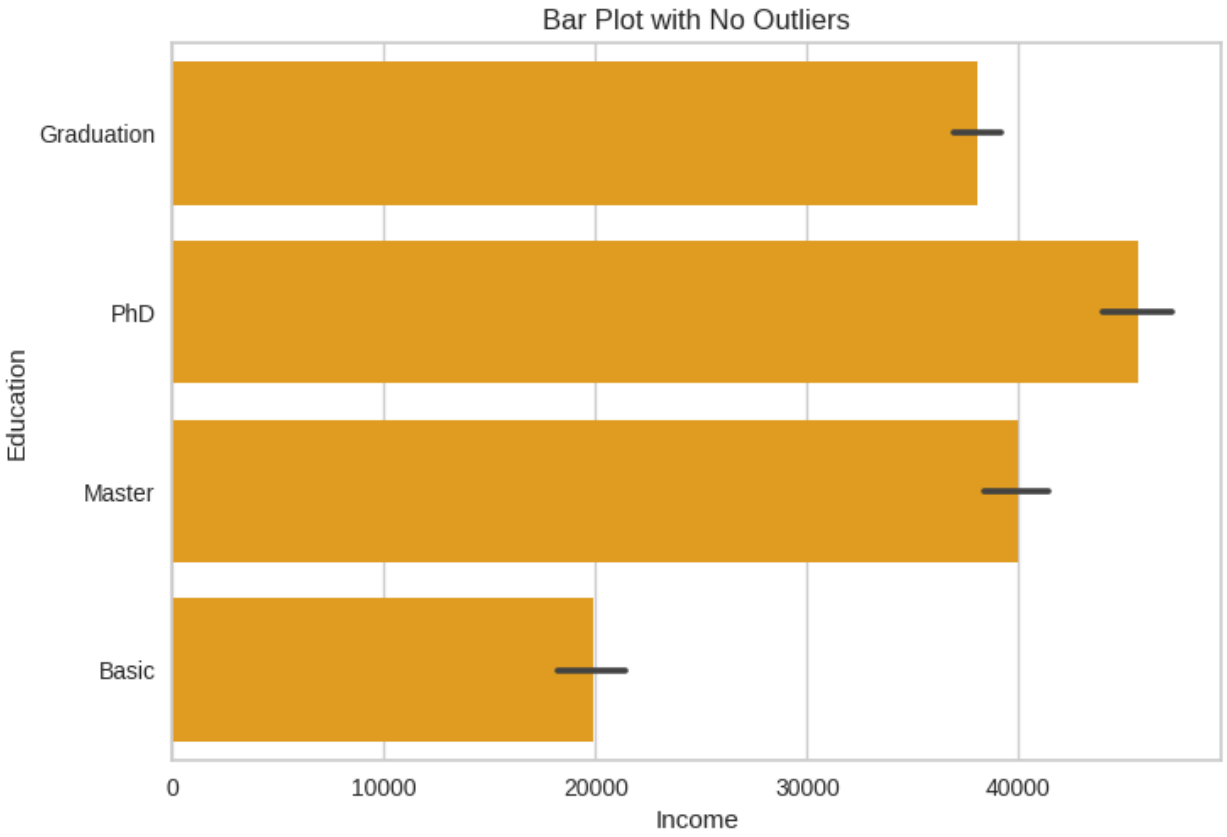
`data_only_outliers`

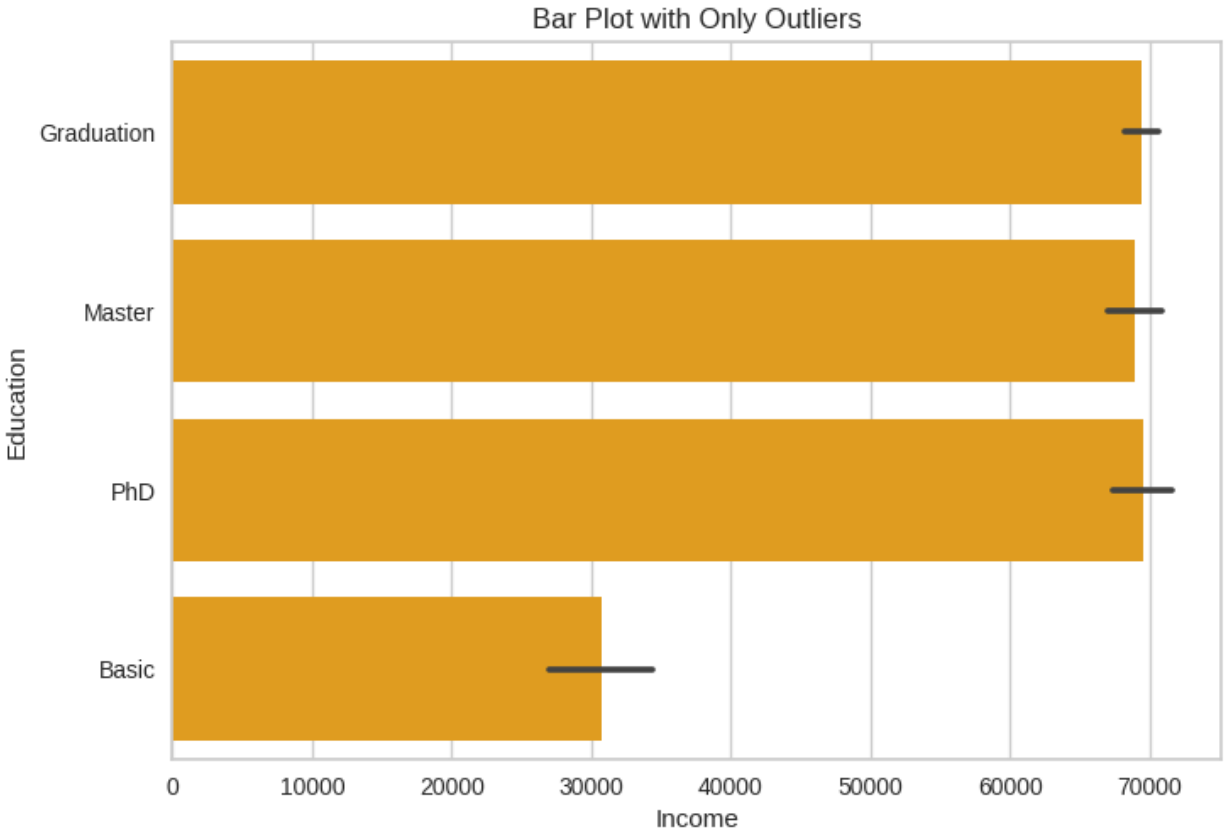
#	Column	Count	Non-Null	Dtype
0	ID	846	non-null	int64
1	Year_Birth	846	non-null	int64
2	Education	846	non-null	object
3	Marital_Status	846	non-null	object
4	Income	837	non-null	float64
5	Kidhome	846	non-null	int64
6	Teenhome	846	non-null	int64
7	Dt_Customer	846	non-null	datetime64[ns]
8	Recency	846	non-null	int64
9	MntWines	846	non-null	int64
10	MntFruits	846	non-null	int64
11	MntMeatProducts	846	non-null	int64
12	MntFishProducts	846	non-null	int64
13	MntSweetProducts	846	non-null	int64
14	MntGoldProds	846	non-null	int64
15	NumDealsPurchases	846	non-null	int64
16	NumWebPurchases	846	non-null	int64
17	NumCatalogPurchas	846	non-null	int64
18	NumStorePurchases	846	non-null	int64
19	NumWebVisitsMont	846	non-null	int64
20	AcceptedCmp3	846	non-null	int64
21	AcceptedCmp4	846	non-null	int64
22	AcceptedCmp5	846	non-null	int64
23	AcceptedCmp1	846	non-null	int64
24	AcceptedCmp2	846	non-null	int64
25	Complain	846	non-null	int64
26	Response	846	non-null	int64
27	quarter	846	non-null	int32

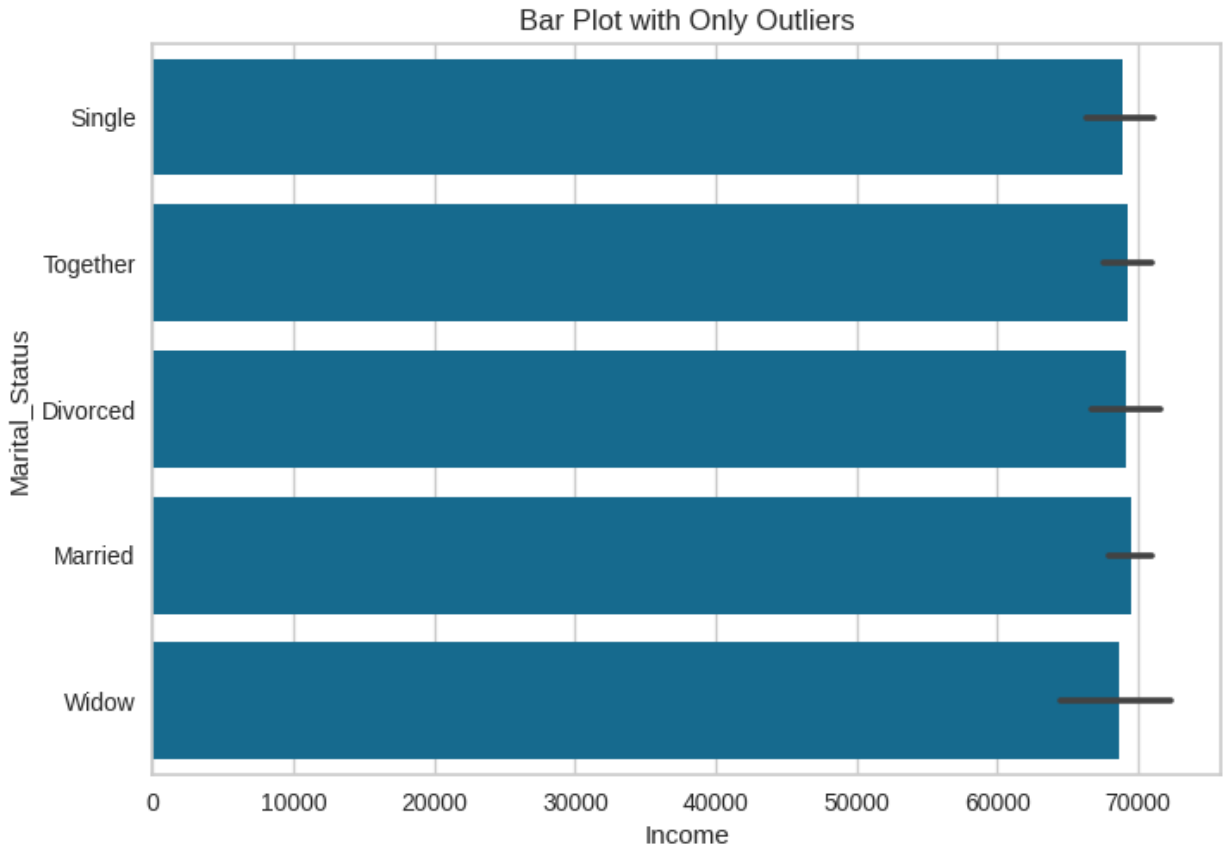
dtypes: datetime64[ns](1), float64(1), int32(1), int64(23), object(2)

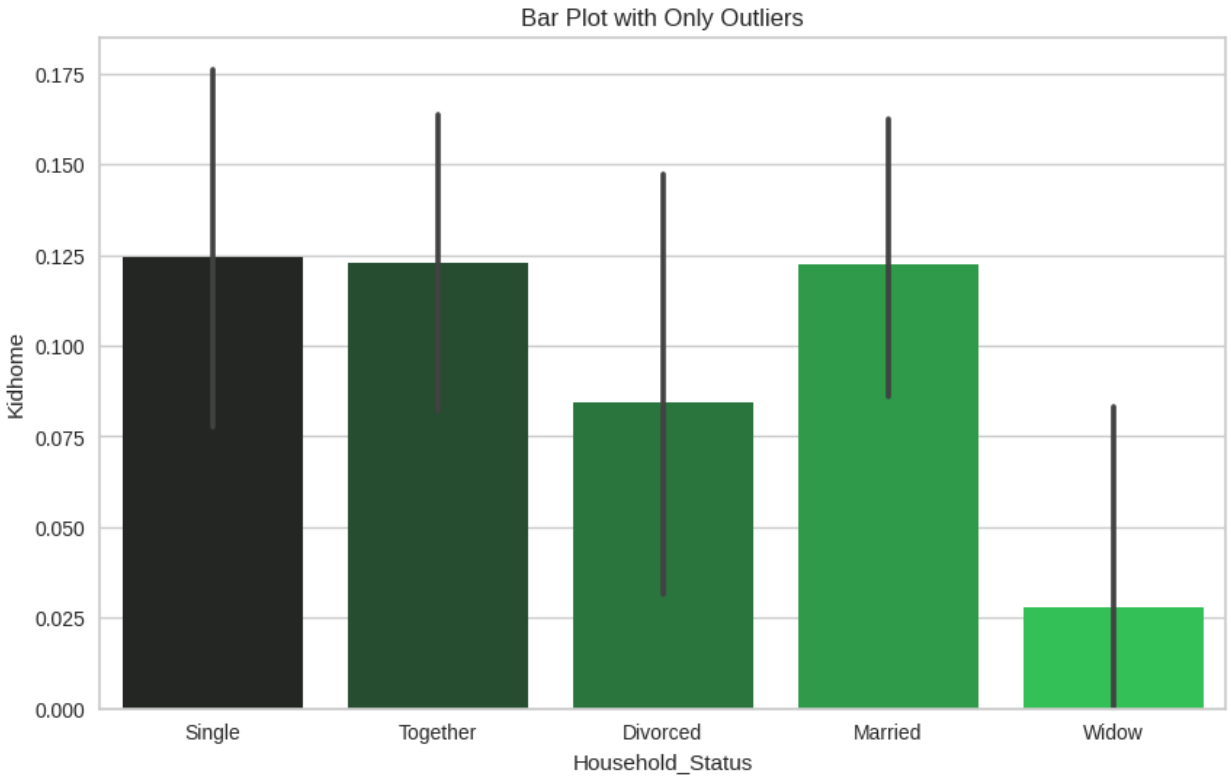

Heat Map with No Outliers
ID 1.00 0.02 -0.04 0.01 0.00 -0.04 -0.06 -0.10 -0.07 -0.06 -0.05 -0.05 -0.05 -0.07 -0.05 -0.05 0.02 -0.00 -0.05 -0.06 -0.01 -0.00 0.03 -0.06 0.03
Year_Birth 0.02 1.00 -0.34 0.24 -0.52 -0.02 -0.24 0.00 -0.12 0.02 0.01 -0.05 -0.08 -0.18 -0.19 -0.19 0.15 0.07 -0.12 0.02 -0.08 -0.04 -0.05 0.03 0.00
Income -0.04 -0.34 1.00 -0.31 0.48 -0.00 0.64 0.26 0.60 0.26 0.31 0.29 0.13 0.55 0.56 0.66 -0.45 -0.06 0.29 0.23 0.22 0.10 -0.03 -0.01 0.03
Kidhome 0.01 0.24 -0.31 1.00 -0.19 0.03 -0.39 -0.22 -0.30 -0.20 -0.22 -0.22 0.13 -0.30 -0.35 -0.42 0.25 0.04 -0.21 -0.11 -0.08 -0.06 0.02 0.04 -0.01
Teenhome 0.00 -0.52 0.48 -0.19 1.00 0.02 0.30 -0.03 0.19 -0.06 -0.05 0.09 0.30 0.24 0.20 0.30 -0.18 -0.06 0.13 -0.08 0.01 0.01 0.00 -0.10 0.03
Recency -0.04 -0.02 -0.00 0.03 0.02 1.00 -0.01 0.02 0.02 0.00 0.01 0.00 0.02 0.00 0.03 -0.01 -0.01 -0.04 0.02 -0.01 -0.03 -0.02 0.01 -0.21 -0.03
MntWines -0.06 -0.24 0.64 -0.39 0.30 -0.01 1.00 0.20 0.61 0.18 0.20 0.36 0.33 0.74 0.70 0.78 -0.11 -0.00 0.51 0.32 0.29 0.18 -0.04 0.10 0.04
MntFruits -0.10 0.00 0.26 -0.22 -0.03 0.02 0.20 1.00 0.48 0.64 0.66 0.34 0.06 0.27 0.36 0.38 -0.20 -0.04 0.02 0.13 0.07 -0.01 0.01 0.04 0.02
MntMeatProducts -0.07 -0.12 0.60 -0.30 0.19 0.02 0.61 0.48 1.00 0.51 0.47 0.49 0.38 0.69 0.62 0.73 -0.17 -0.04 0.15 0.19 0.15 0.04 -0.03 0.11 0.05
MntFishProducts -0.06 0.02 0.26 -0.20 -0.06 0.00 0.18 0.64 0.51 1.00 0.64 0.39 0.08 0.28 0.41 0.37 -0.21 -0.04 0.00 0.15 0.10 0.03 -0.00 0.03 0.01
MntSweetProducts -0.05 0.01 0.31 -0.22 -0.05 0.01 0.20 0.66 0.47 0.64 1.00 0.32 0.05 0.24 0.41 0.40 -0.25 -0.05 0.02 0.23 0.21 -0.00 0.02 0.06 0.04
MntGoldProds -0.05 -0.05 0.29 -0.22 0.09 0.00 0.36 0.34 0.49 0.39 0.32 1.00 0.32 0.49 0.49 0.35 -0.05 0.09 0.08 0.10 0.09 0.05 -0.04 0.12 0.02
NumDealsPurchases -0.05 -0.08 0.13 0.13 0.30 0.02 0.33 0.06 0.38 0.08 0.05 0.32 1.00 0.46 0.27 0.30 0.25 -0.03 0.15 -0.05 0.03 -0.03 -0.02 0.12 0.01
NumWebPurchases -0.07 -0.18 0.55 -0.30 0.24 0.00 0.74 0.27 0.69 0.28 0.24 0.49 0.46 1.00 0.56 0.63 0.05 -0.03 0.34 0.15 0.24 0.10 -0.03 0.14 0.04
NumCatalogPurchases -0.05 -0.19 0.56 -0.35 0.20 0.03 0.70 0.36 0.62 0.41 0.41 0.49 0.27 0.56 1.00 0.56 -0.27 0.11 0.30 0.31 0.32 0.12 -0.03 0.15 0.04
NumStorePurchases -0.05 -0.19 0.66 -0.42 0.30 -0.01 0.78 0.38 0.73 0.37 0.40 0.35 0.30 0.63 0.56 1.00 -0.36 -0.12 0.32 0.22 0.19 0.12 -0.03 -0.01 0.03
NumWebVisitsMonth 0.02 0.15 -0.45 0.25 -0.18 -0.01 -0.11 -0.20 -0.17 -0.21 -0.25 -0.05 0.25 0.05 -0.27 -0.36 1.00 0.08 0.01 -0.12 -0.05 0.02 0.00 0.17 0.01
AcceptedCmp3 -0.00 0.07 -0.06 0.04 -0.06 -0.04 -0.00 -0.04 -0.04 -0.04 -0.05 0.09 -0.03 -0.03 0.11 -0.12 0.08 1.00 -0.06 0.08 0.02 0.10 -0.03 0.28 -0.02
AcceptedCmp4 -0.05 -0.12 0.29 -0.21 0.13 0.02 0.51 0.02 0.15 0.00 0.02 0.08 0.15 0.34 0.30 0.32 0.01 -0.06 1.00 0.16 0.20 0.15 -0.02 0.12 0.03
AcceptedCmp5 -0.06 0.02 0.23 -0.11 -0.08 -0.01 0.32 0.13 0.19 0.15 0.23 0.10 -0.05 0.15 0.31 0.22 -0.12 0.08 0.16 1.00 0.35 0.21 -0.01 0.16 -0.05
AcceptedCmp1 -0.01 -0.08 0.22 -0.08 0.01 -0.03 0.29 0.07 0.15 0.10 0.21 0.09 0.03 0.24 0.32 0.19 -0.05 0.02 0.20 0.35 1.00 0.16 -0.01 0.16 0.02
AcceptedCmp2 -0.00 -0.04 0.10 -0.06 0.01 -0.02 0.18 -0.01 0.04 0.03 -0.00 0.05 -0.03 0.10 0.12 0.12 0.02 0.10 0.15 0.21 0.16 1.00 -0.01 0.10 0.00
Complain 0.03 -0.05 -0.03 0.02 0.00 0.01 -0.04 0.01 -0.03 -0.00 0.02 -0.04 -0.02 -0.03 -0.03 -0.03 0.00 -0.03 -0.02 -0.01 -0.01 -0.01 1.00 -0.01 -0.04
Response -0.06 0.03 -0.01 0.04 -0.10 -0.21 0.10 0.04 0.11 0.03 0.06 0.12 0.12 0.14 0.15 -0.01 0.17 0.28 0.12 0.16 0.16 0.10 -0.01 1.00 0.06
quarter 0.03 0.00 0.03 -0.01 0.03 -0.03 0.04 0.02 0.05 0.01 0.04 0.02 0.01 0.04 0.04 0.03 0.01 -0.02 0.03 -0.05 0.02 0.00 -0.04 0.06 1.00
ID Year_Birth Income Kidhome Teenhome Recency MntWines MntFruits MntMeatProducts MntFishProducts MntSweetProducts MntGoldProds NumDealsPurchases NumWebPurchases NumCatalogPurchases NumStorePurchases NumWebVisitsMonth AcceptedCmp3 AcceptedCmp4 AcceptedCmp5 AcceptedCmp1 AcceptedCmp2 Complain Response quarter
1.00 0.75 0.50 0.25 0.00 −0.25 −0.50 −0.75 −1.00


Bar Plot with No Outliers
Kidhome
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8
0-25k 25k-50k 50k-75k 75k-100k 100k+
Income_Group


Bar Plot with No Outliers
Graduation
PhD
Master
Basic
Education
0
10000
20000
30000
40000
Income

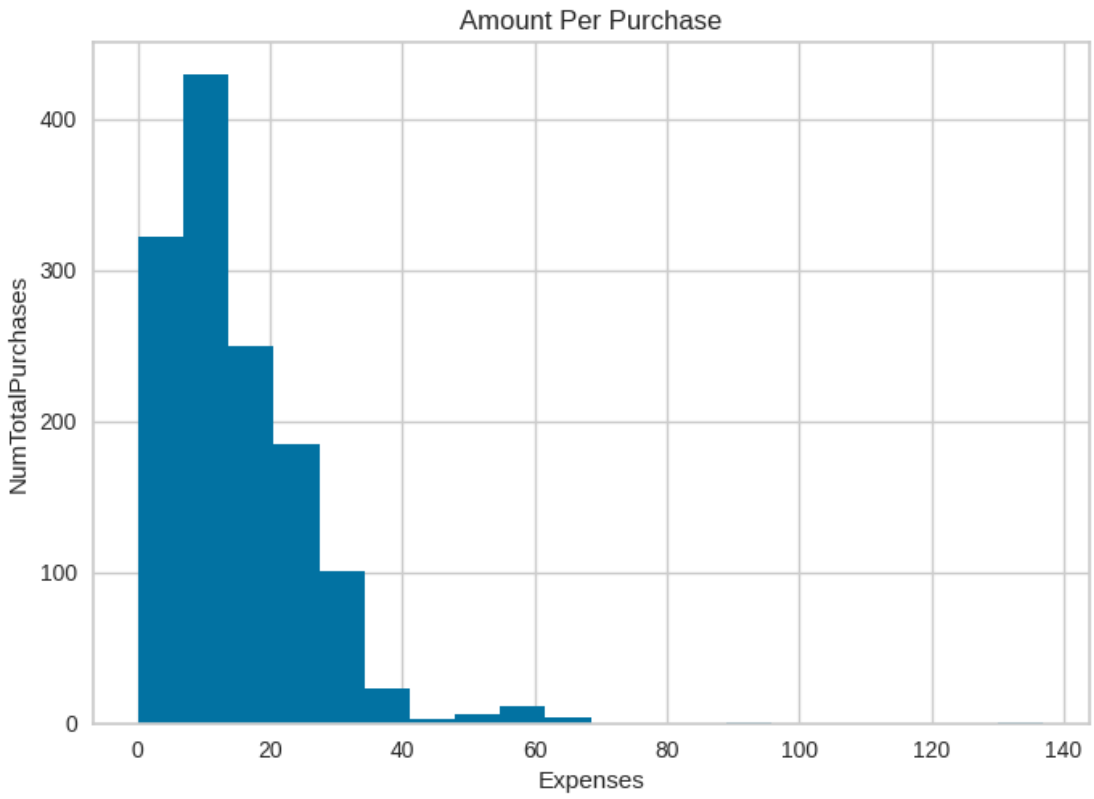

Bar Plot with Only Outliers
Graduation
Master
PhD
Basic
Education
0
10000
20000
30000
40000
50000
60000
70000
Income


Bar Plot with Only Outliers
Single
Together
Divorced
Married
Widow
Marital_Status
0
10000
20000
30000
40000
50000
60000
70000
Income

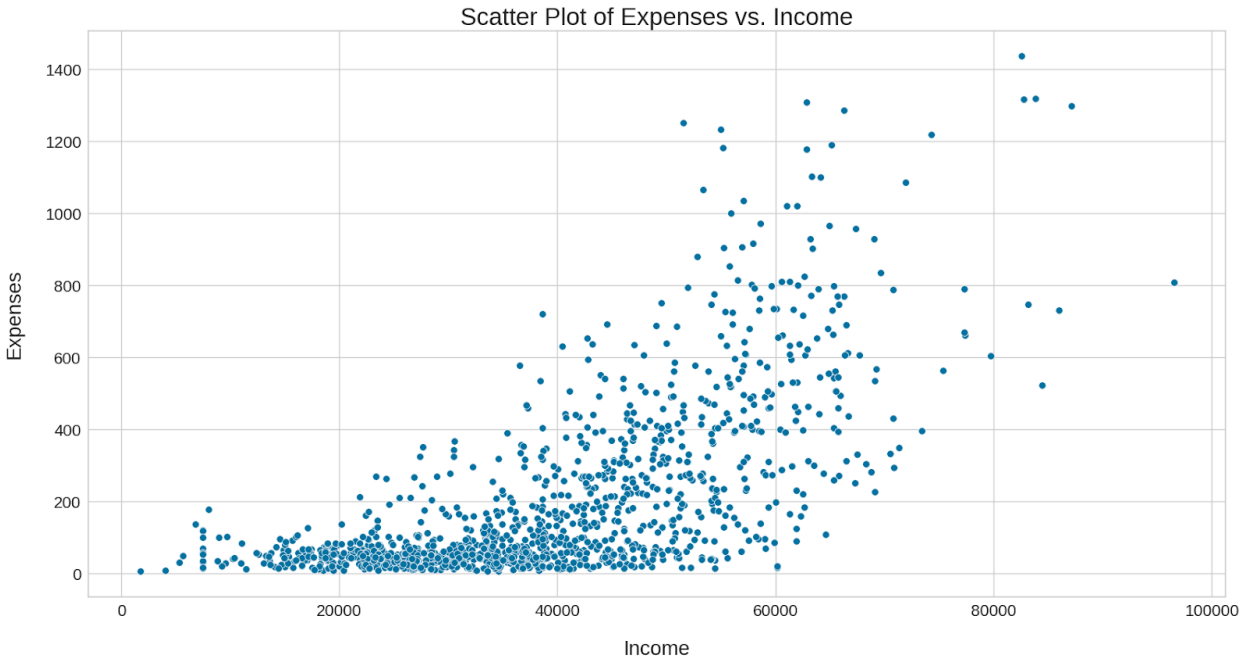

Bar Plot with Only Outliers
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
Kidhome
Single
Together
Divorced
Married
Widow
Household_Status

A summary of days with the company:

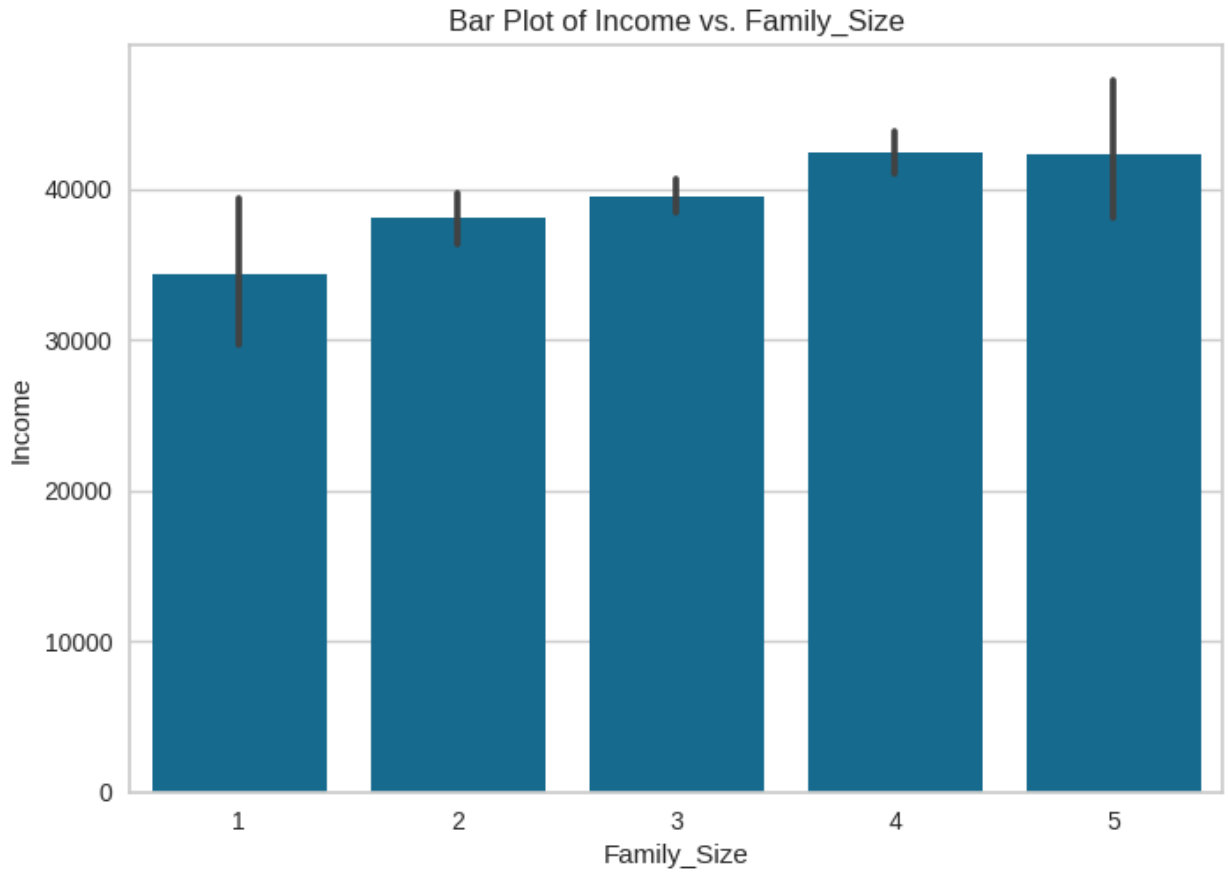
	Dt_Customer	DaysWithCompany
count	1336	1336.000000
mean	2013-08-03 13:10:03.592814336	515.451347
min	2012-01-08 00:00:00	26.000000
25%	2013-02-13 00:00:00	338.000000
50%	2013-08-07 00:00:00	512.000000
75%	2014-01-28 00:00:00	687.000000
90%	2014-05-25 12:00:00	827.000000
95%	2014-08-03 06:00:00	875.250000
99%	2014-12-01 00:00:00	1027.300000
max	2014-12-06 00:00:00	1089.000000
std	NaN	231.922648

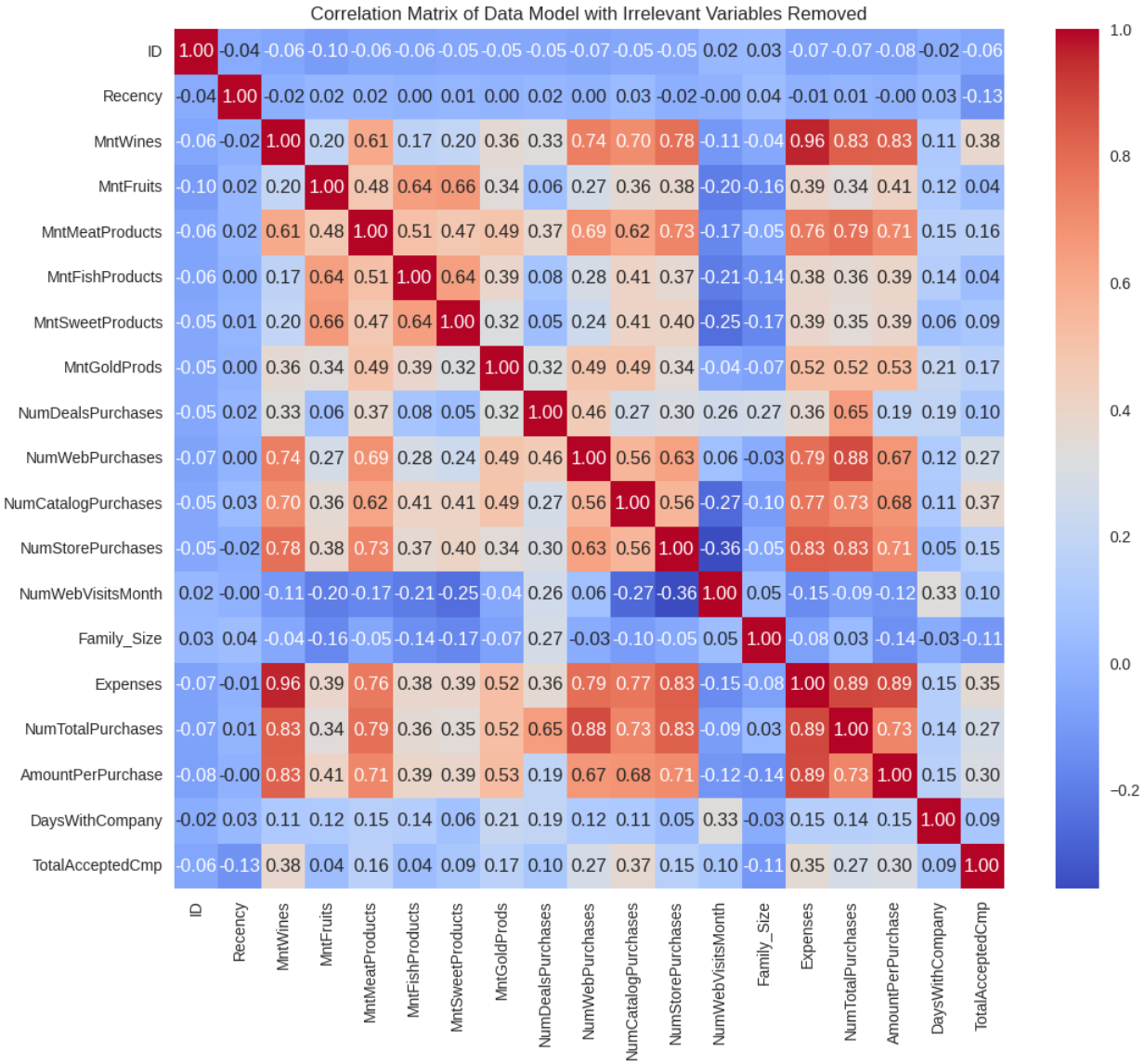


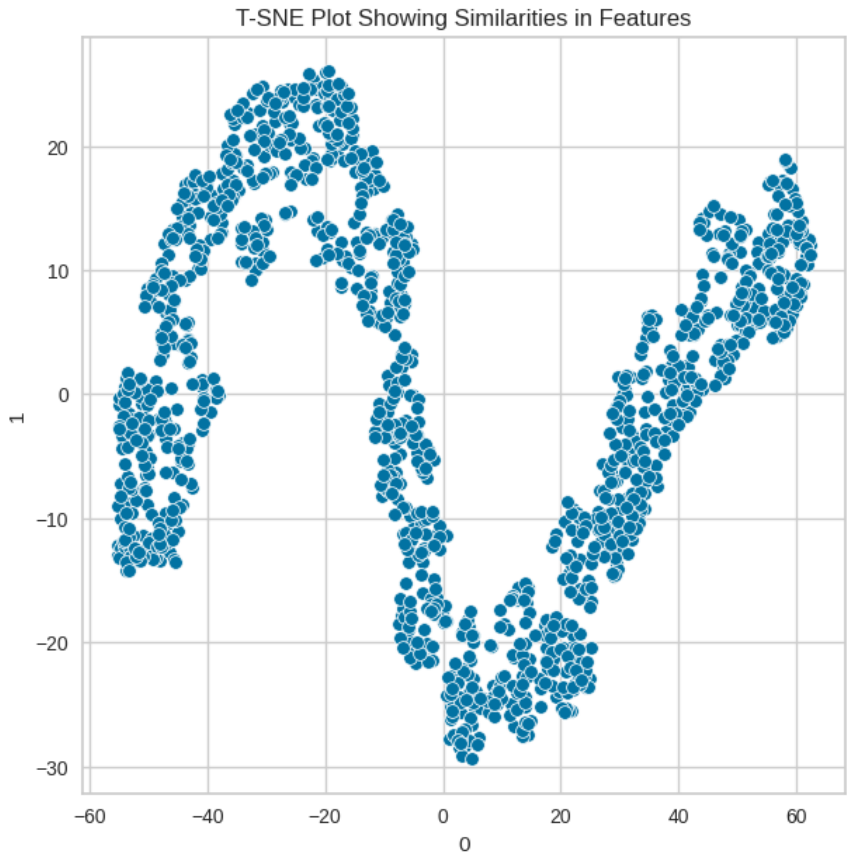
Income Vs Expenses

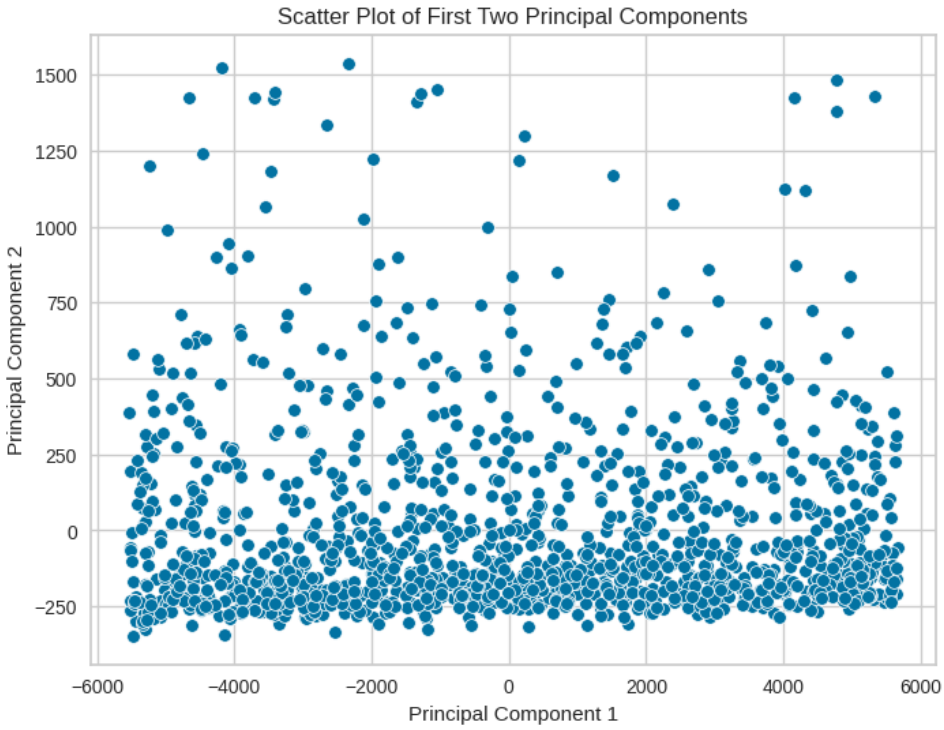


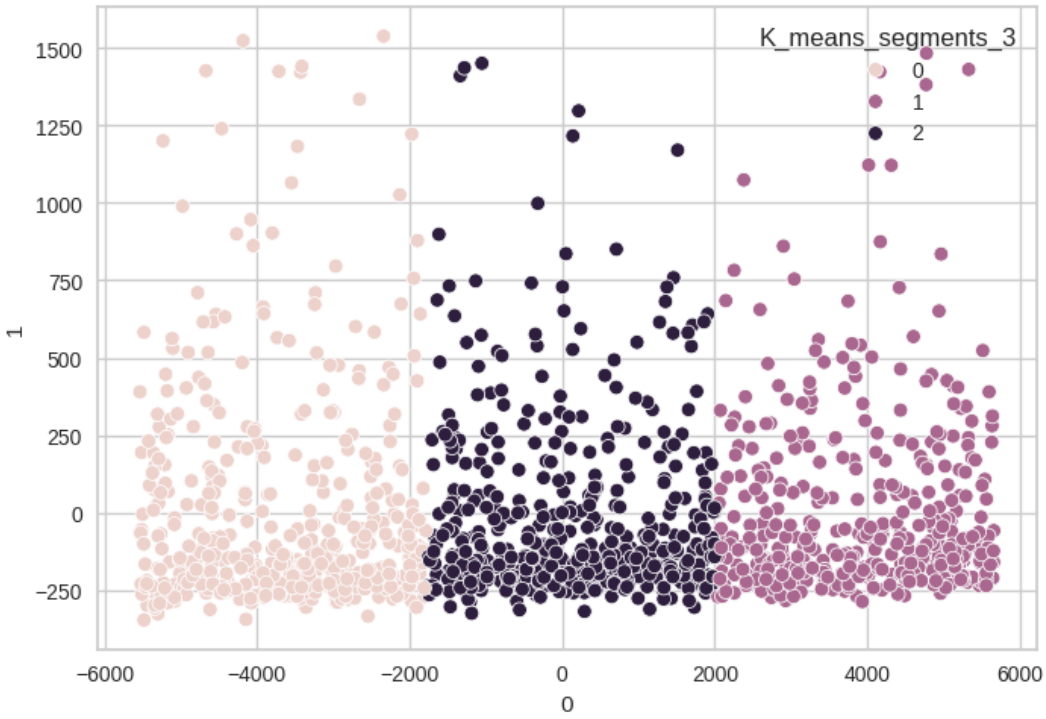
Family Size Vs Income




Correlation Matrix of Data Model with Irrelevant Variables Removed
ID 1.00 -0.04 -0.06 -0.10 -0.06 -0.06 -0.05 -0.05 -0.05 -0.07 -0.05 -0.05 0.02 0.03 -0.07 -0.07 -0.08 -0.02 -0.06
Recency -0.04 1.00 -0.02 0.02 0.02 0.00 0.01 0.00 0.02 0.00 0.03 -0.02 -0.00 0.04 -0.01 0.01 -0.00 0.03 -0.13
MntWines -0.06 -0.02 1.00 0.20 0.61 0.17 0.20 0.36 0.33 0.74 0.70 0.78 -0.11 -0.04 0.96 0.83 0.83 0.11 0.38
MntFruits -0.10 0.02 0.20 1.00 0.48 0.64 0.66 0.34 0.06 0.27 0.36 0.38 -0.20 -0.16 0.39 0.34 0.41 0.12 0.04
MntMeatProducts -0.06 0.02 0.61 0.48 1.00 0.51 0.47 0.49 0.37 0.69 0.62 0.73 -0.17 -0.05 0.76 0.79 0.71 0.15 0.16
MntFishProducts -0.06 0.00 0.17 0.64 0.51 1.00 0.64 0.39 0.08 0.28 0.41 0.37 -0.21 -0.14 0.38 0.36 0.39 0.14 0.04
MntSweetProducts -0.05 0.01 0.20 0.66 0.47 0.64 1.00 0.32 0.05 0.24 0.41 0.40 -0.25 -0.17 0.39 0.35 0.39 0.06 0.09
MntGoldProds -0.05 0.00 0.36 0.34 0.49 0.39 0.32 1.00 0.32 0.49 0.49 0.34 -0.04 -0.07 0.52 0.52 0.53 0.21 0.17
NumDealsPurchases -0.05 0.02 0.33 0.06 0.37 0.08 0.05 0.32 1.00 0.46 0.27 0.30 0.26 0.27 0.36 0.65 0.19 0.19 0.10
NumWebPurchases -0.07 0.00 0.74 0.27 0.69 0.28 0.24 0.49 0.46 1.00 0.56 0.63 0.06 -0.03 0.79 0.88 0.67 0.12 0.27
NumCatalogPurchases -0.05 0.03 0.70 0.36 0.62 0.41 0.41 0.49 0.27 0.56 1.00 0.56 -0.27 -0.10 0.77 0.73 0.68 0.11 0.37
NumStorePurchases -0.05 -0.02 0.78 0.38 0.73 0.37 0.40 0.34 0.30 0.63 0.56 1.00 -0.36 -0.05 0.83 0.83 0.71 0.05 0.15
NumWebVisitsMonth 0.02 -0.00 -0.11 -0.20 -0.17 -0.21 -0.25 -0.04 0.26 0.06 -0.27 -0.36 1.00 0.05 -0.15 -0.09 -0.12 0.33 0.10
Family_Size 0.03 0.04 -0.04 -0.16 -0.05 -0.14 -0.17 -0.07 0.27 -0.03 -0.10 -0.05 0.05 1.00 -0.08 0.03 -0.14 -0.03 -0.11
Expenses -0.07 -0.01 0.96 0.39 0.76 0.38 0.39 0.52 0.36 0.79 0.77 0.83 -0.15 -0.08 1.00 0.89 0.89 0.15 0.35
NumTotalPurchases -0.07 0.01 0.83 0.34 0.79 0.36 0.35 0.52 0.65 0.88 0.73 0.83 -0.09 0.03 0.89 1.00 0.73 0.14 0.27
AmountPerPurchase -0.08 -0.00 0.83 0.41 0.71 0.39 0.39 0.53 0.19 0.67 0.68 0.71 -0.12 -0.14 0.89 0.73 1.00 0.15 0.30
DaysWithCompany -0.02 0.03 0.11 0.12 0.15 0.14 0.06 0.21 0.19 0.12 0.11 0.05 0.33 -0.03 0.15 0.14 0.15 1.00 0.09
TotalAcceptedCmp -0.06 -0.13 0.38 0.04 0.16 0.04 0.09 0.17 0.10 0.27 0.37 0.15 0.10 -0.11 0.35 0.27 0.30 0.09 1.00
ID
Recency
MntWines
MntFruits
MntMeatProducts
MntFishProducts
MntSweetProducts
MntGoldProds
NumDealsPurchases
NumWebPurchases
NumCatalogPurchases
NumStorePurchases
NumWebVisitsMonth
Family_Size
Expenses
NumTotalPurchases
AmountPerPurchase
DaysWithCompany
TotalAcceptedCmp
1.0
0.8
0.6
0.4
0.2
0.0
−0.2


T-SNE Plot Showing Similarities in Features
20
10
0
−10
−20
−30
1
−60
−40
−20
0
20
40
60
0


Scatter Plot of First Two Principal Components
1500
1250
1000
750
500
250
0
−250
Principal Component 2
−6000
−4000
−2000
0
2000
4000
6000
Principal Component 1



	Characteristic Summary
0	Cluster 0: Characterized by high 1, 2, 0
1	Cluster 1: Characterized by high 1, 0, 2
2	Cluster 2: Characterized by high 0, 2, 1
3	Cluster 3: Characterized by high 2, 0, 1
4	Cluster 4: Characterized by high 2, 1, 0
5	Cluster 5: Characterized by high 2, 1, 0
6	Cluster 6: Characterized by high 1, 0, 2
7	Cluster 7: Characterized by high 2, 1, 0
8	Cluster 8: Characterized by high 0, 1, 2
9	Cluster 9: Characterized by high 2, 1, 0
10	Cluster 10: Characterized by high 2, 0, 1
11	Cluster 11: Characterized by high 0, 1, 2
12	Cluster 12: Characterized by high 2, 1, 0
13	Cluster 13: Characterized by high 0, 2, 1
14	Cluster 14: Characterized by high 0, 1, 2
15	Cluster 15: Characterized by high 2, 1, 0
16	Cluster 16: Characterized by high 1, 0, 2
17	Cluster 17: Characterized by high 2, 0, 1
18	Cluster 18: Characterized by high 2, 1,