Customer Personality Analysis

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Purpose

Customer Personality Analysis is an essential tool for businesses aiming to understand and segment their customer base effectively. It involves a comprehensive examination of customers' preferences, behaviors, and demographic characteristics, which allows companies to tailor their products and marketing strategies to meet the specific needs of different customer segments. This approach not only enhances customer satisfaction but also optimizes marketing expenditures by targeting the most receptive audience.

In this analysis, K-Means and Association Rules will be used.

About the Data

```
## 'data.frame':    2240 obs. of  29 variables:
##  $ ID                 : int  5524 2174 4141 6182 5324 7446 965 6177 4855 5899 ...
##  $ Year_Birth         : int  1957 1954 1965 1984 1981 1967 1971 1985 1974 1950 ...
##  $ Education          : chr  "Graduation" "Graduation" "Graduation" "Graduation" ...
##  $ Marital_Status     : chr  "Single" "Single" "Together" "Together" ...
##  $ Income             : int  58138 46344 71613 26646 58293 62513 55635 33454 30351 5648 ...
##  $ Kidhome            : int  0 1 0 1 1 0 0 1 1 1 ...
##  $ Teenhome           : int  0 1 0 0 0 1 1 0 0 1 ...
##  $ Dt_Customer        : chr  "04-09-2012" "08-03-2014" "21-08-2013" "10-02-2014" ...
##  $ Recency            : int  58 38 26 26 94 16 34 32 19 68 ...
##  $ MntWines           : int  635 11 426 11 173 520 235 76 14 28 ...
##  $ MntFruits          : int  88 1 49 4 43 42 65 10 0 0 ...
##  $ MntMeatProducts    : int  546 6 127 20 118 98 164 56 24 6 ...
##  $ MntFishProducts    : int  172 2 111 10 46 0 50 3 3 1 ...
##  $ MntSweetProducts   : int  88 1 21 3 27 42 49 1 3 1 ...
##  $ MntGoldProds       : int  88 6 42 5 15 14 27 23 2 13 ...
##  $ NumDealsPurchases  : int  3 2 1 2 5 2 4 2 1 1 ...
##  $ NumWebPurchases    : int  8 1 8 2 5 6 7 4 3 1 ...
##  $ NumCatalogPurchases: int  10 1 2 0 3 4 3 0 0 0 ...
##  $ NumStorePurchases  : int  4 2 10 4 6 10 7 4 2 0 ...
##  $ NumWebVisitsMonth  : int  7 5 4 6 5 6 6 8 9 20 ...
##  $ AcceptedCmp3       : int  0 0 0 0 0 0 0 0 0 1 ...
##  $ AcceptedCmp4       : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ AcceptedCmp5       : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ AcceptedCmp1       : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ AcceptedCmp2       : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Complain           : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Z_CostContact      : int  3 3 3 3 3 3 3 3 3 3 ...
```

```
##  $ Z_Revenue          : int  11 11 11 11 11 11 11 11 11 11 ...
##  $ Response           : int  1 0 0 0 0 0 0 0 1 0 ...
```

Upon initially reviewing the data set, we can see that we need to address our features' data types. Below is an initial list of the features that need to be revised:

- Birth year should be transformed into an age feature and should be binned
- Education level should be factorized
- Marital status should be factorized
- Income should be numeric
- Dt_Customer should be transformed into a feature that describes how long a customer has been doing business with the company
- AcceptedCmp1-AcceptedCmp5 should be binary (yes accepted/no did not accept)
- Complain should be made binary (yes complain/ no did not complain)
- Response should be made binary (yes respond/ no did not respond)
- Kidhome and Teenhome should be factorized

After making these changes, redundancy within some of the features is apparent, listed below:

Additionally, some new features were created. Age was derived from Birth year and Customer Duration was derived from their Customer Date.

To see if there are missing values:

```
##                  ID           Education      Marital_Status              Income
##                   0                   0                   0                  24
##             Kidhome            Teenhome             Recency            MntWines
##                   0                   0                   0                   0
##           MntFruits     MntMeatProducts     MntFishProducts    MntSweetProducts
##                   0                   0                   0                   0
##        MntGoldProds   NumDealsPurchases     NumWebPurchases NumCatalogPurchases
##                   0                   0                   0                   0
##   NumStorePurchases   NumWebVisitsMonth        AcceptedCmp3        AcceptedCmp4
##                   0                   0                   0                   0
##        AcceptedCmp5        AcceptedCmp1        AcceptedCmp2            Complain
##                   0                   0                   0                   0
##       Z_CostContact           Z_Revenue            Response                 Age
##                   0                   0                   0                   0
##   Customer_Duration
##                   0
```

According to the R output above, there are 24 missing values in the Income feature. Due to having a large volume of observations, the 24 records containing missing data will be removed.

```
## `summarise()` has grouped output by 'key', 'total'. You can override using the
## `.groups` argument.
```


```
## [1] 0
```

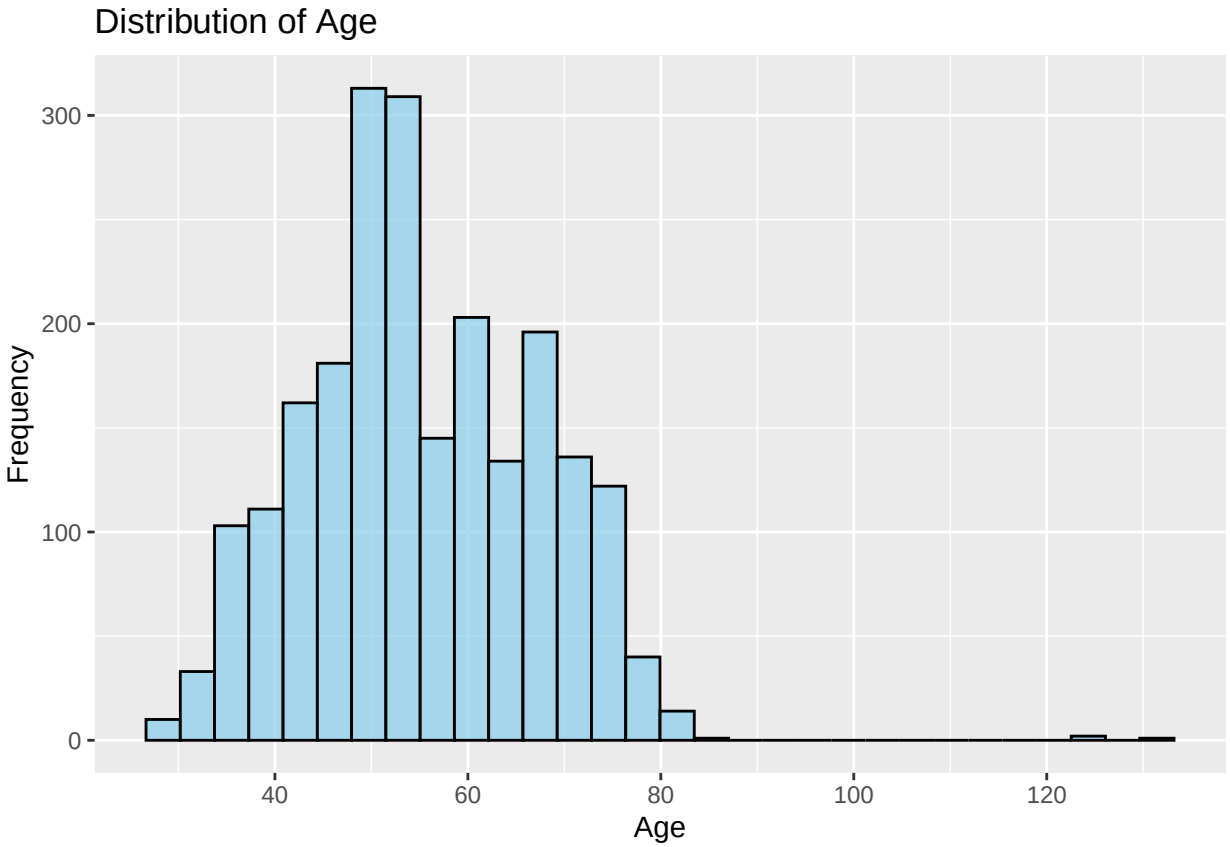
After removal of incomplete records, the total number of observations drops from 2240 to 2216.

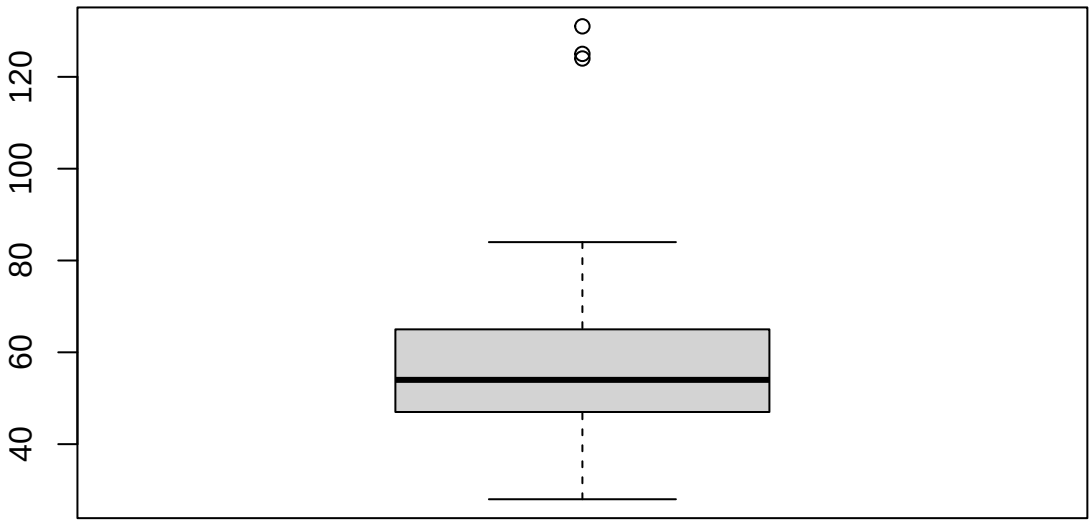
Exploratory Data Analysis

In order to accurately cluster, variables will be evaluated and records with outliers will be removed. Additionally, any oddities in categorical data will be removed. Lastly, all numeric data will be preprocessed for center and scaling to minimize the effects larger scales have on clustering algorithms.

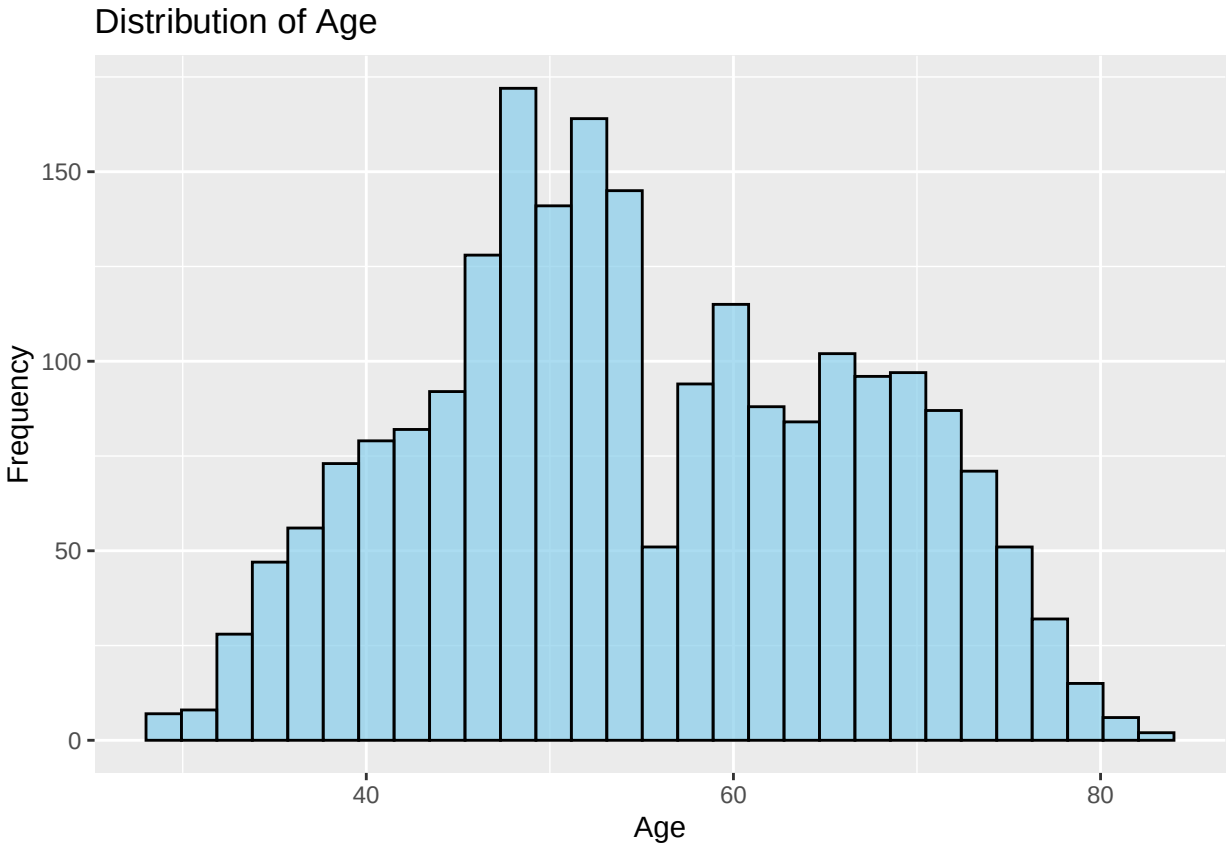
Age

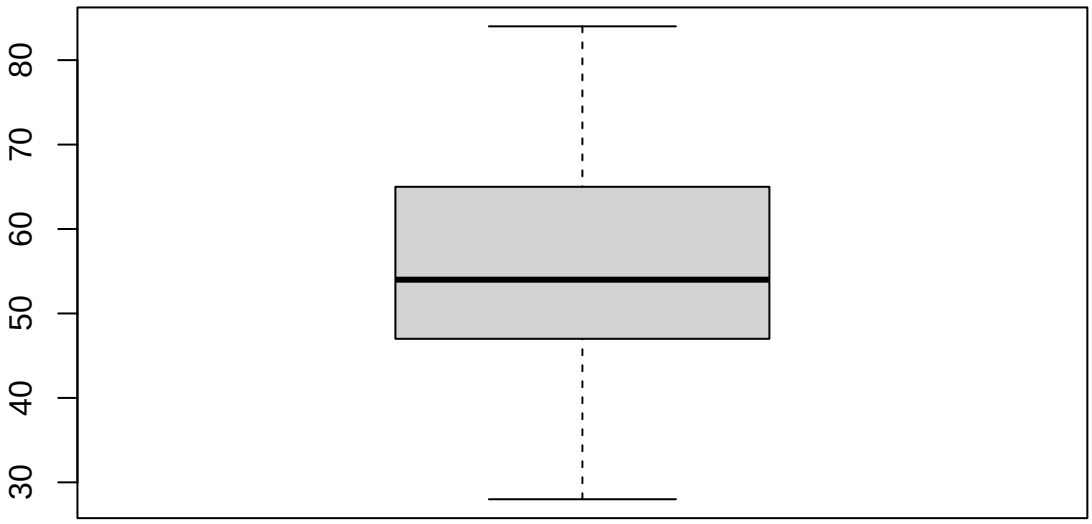
There seems to be a few outliers in our Age feature.


Distribution of Age
Frequency
300
200
100
0
40
60
80
100
120
Age



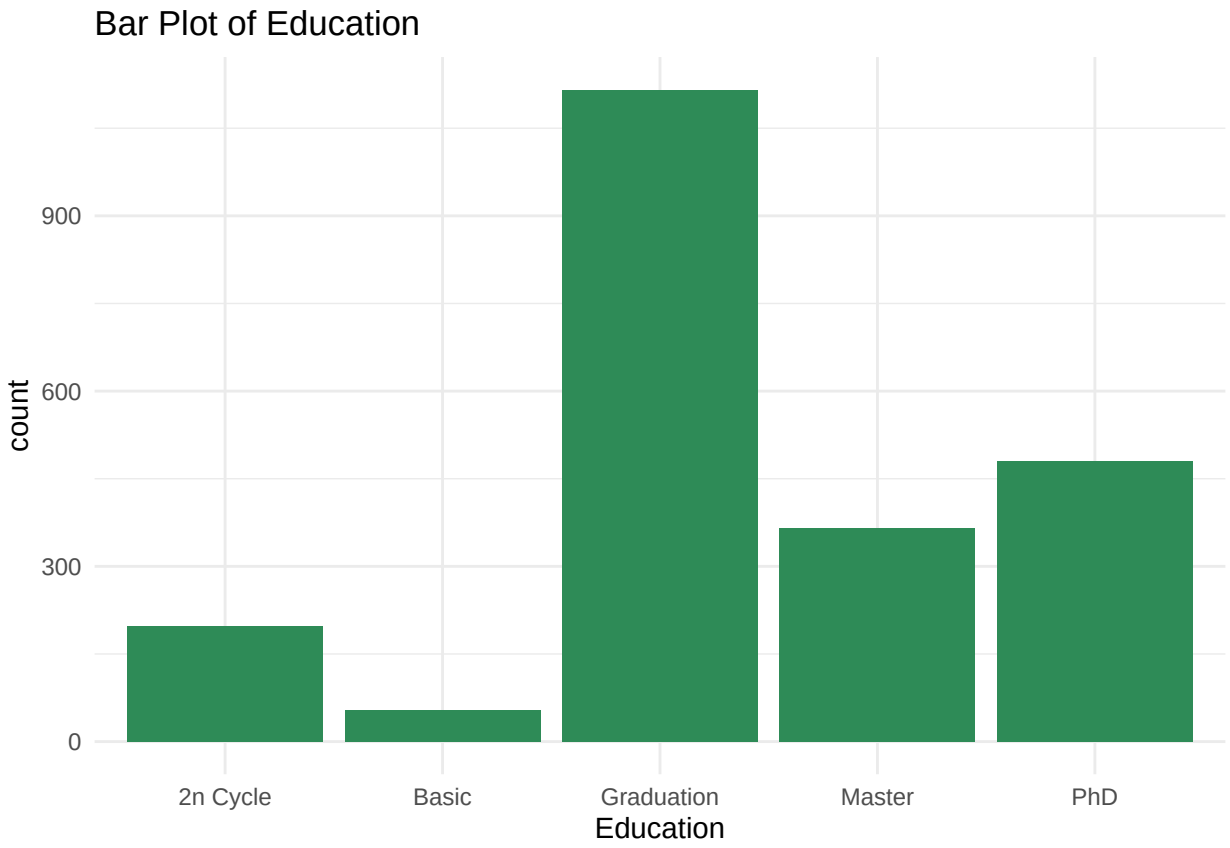
Re-run the histogram and the boxplot to visualize changes


Distribution of Age
Frequency
150
100
50
0
40
60
80
Age

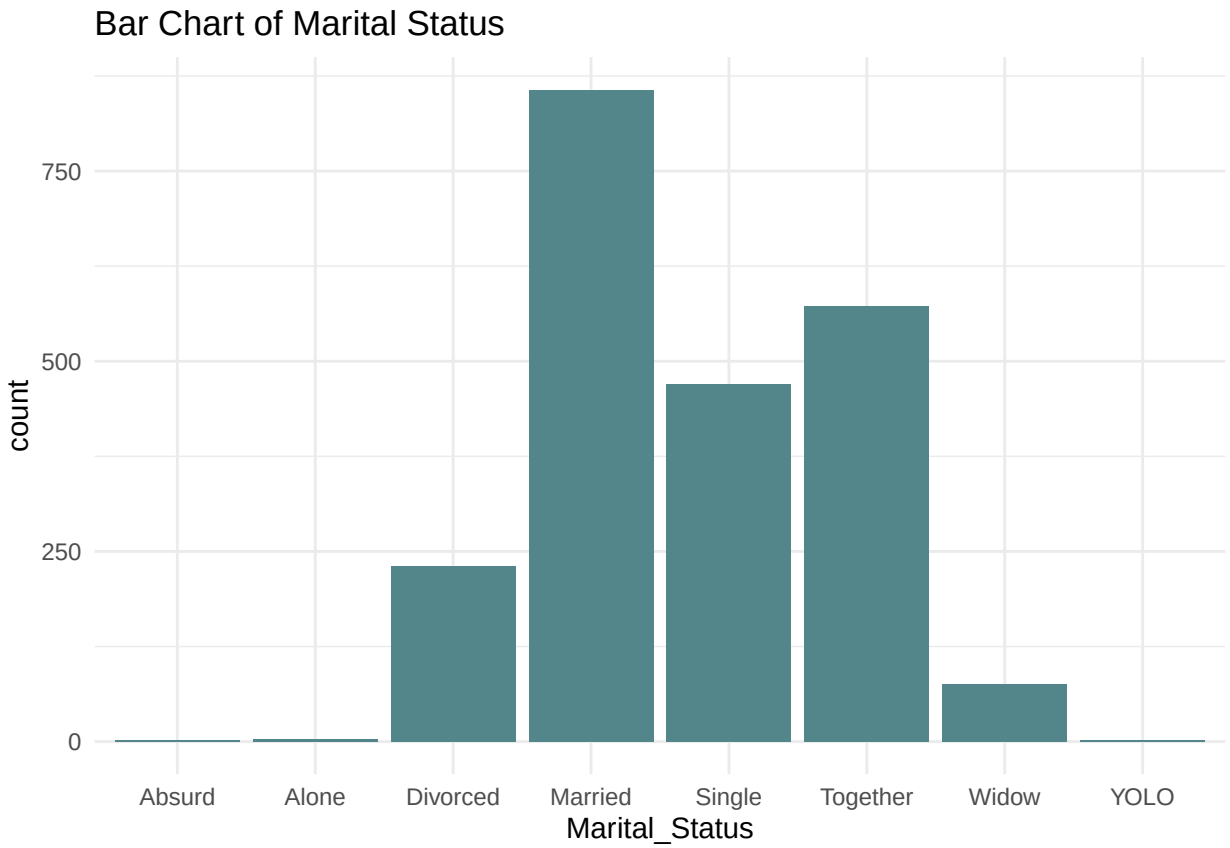


Age is now more normally distributed and the boxplot indicates that there are no more outliers.

Education


Bar Plot of Education
count
900
600
300
0
2n Cycle
Basic
Graduation
Master
PhD
Education

Marital Status



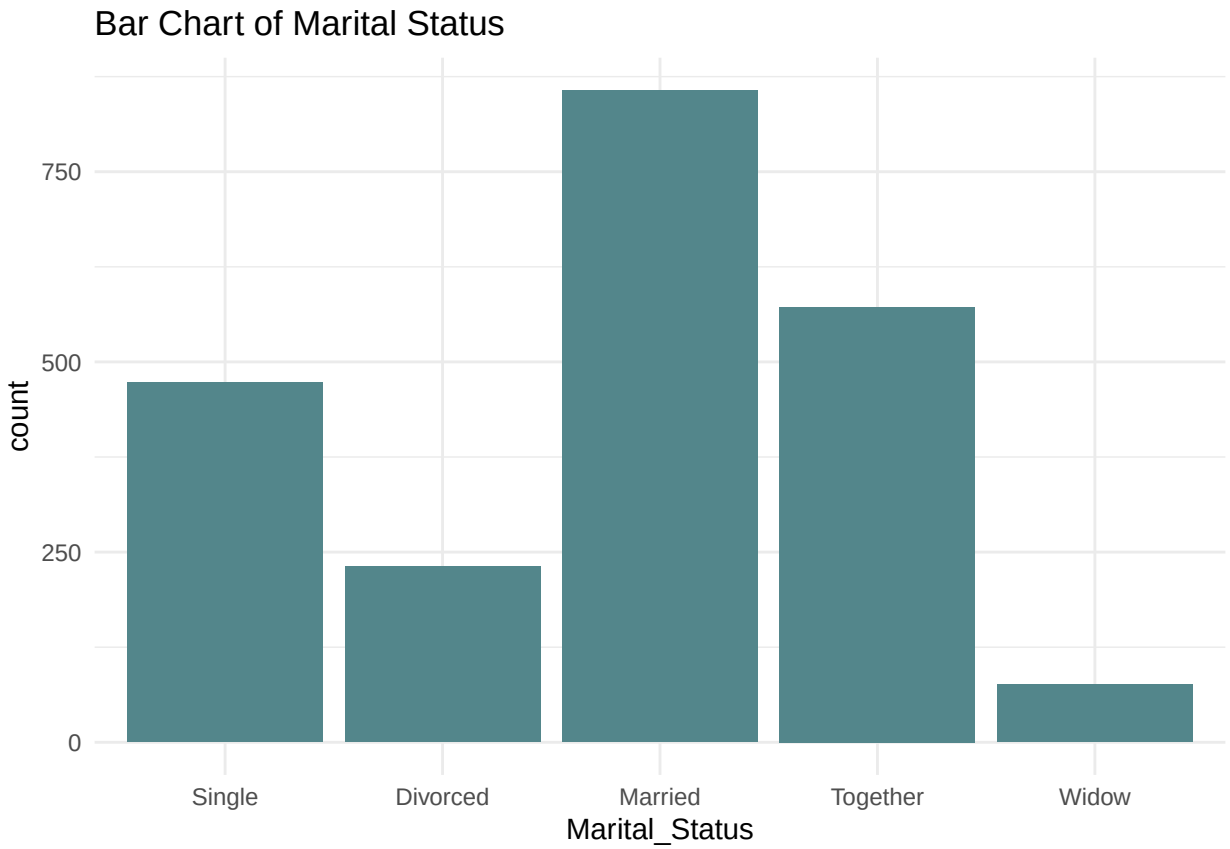
Alone and Single will be combined; Absurd and Yolo observations will be dropped from the data set.

```
## [1] "Absurd"   "Alone"    "Divorced" "Married"  "Single"   "Together" "Widow"
## [8] "YOLO"
```

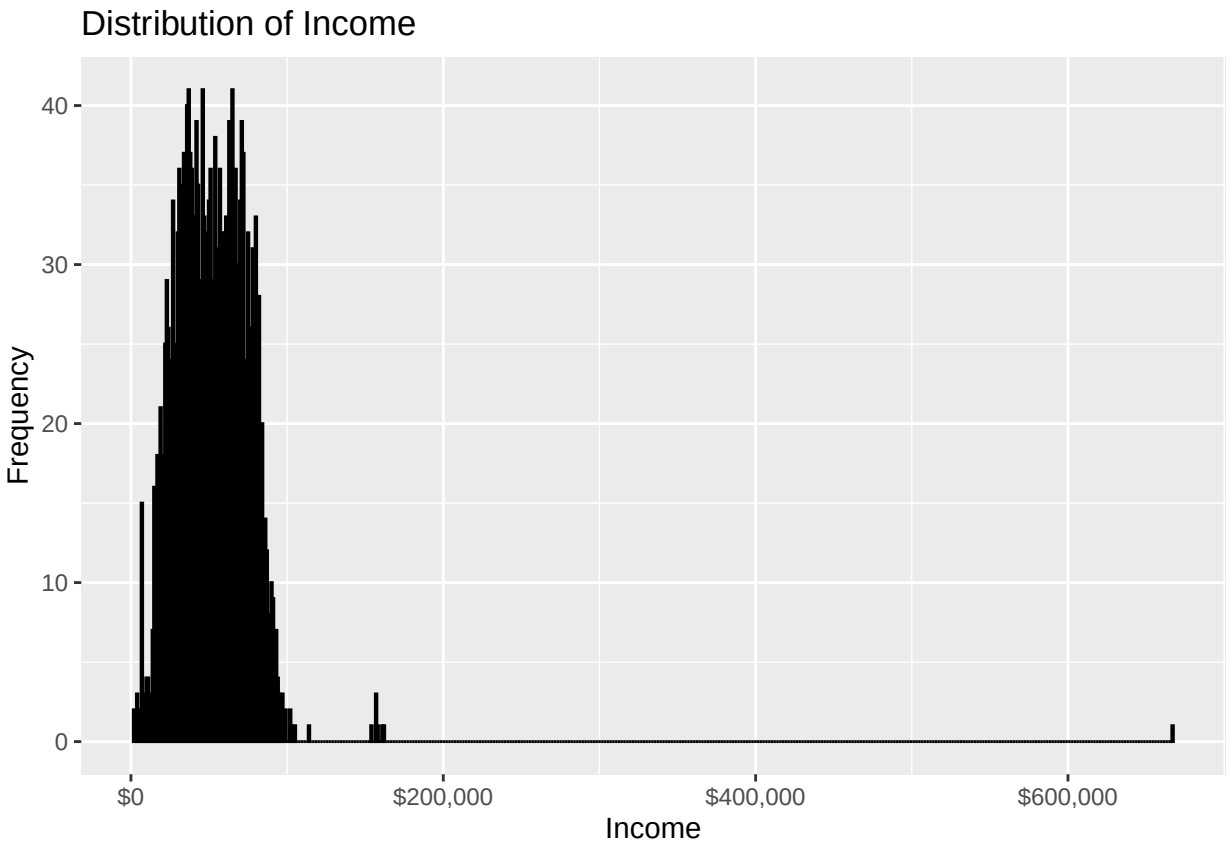
```
## [1] "Absurd"   "Single"   "Divorced" "Married"  "Together" "Widow"    "YOLO"
```

```
## [1] Single   Together Married  Divorced Widow
## Levels: Single Divorced Married Together Widow
```

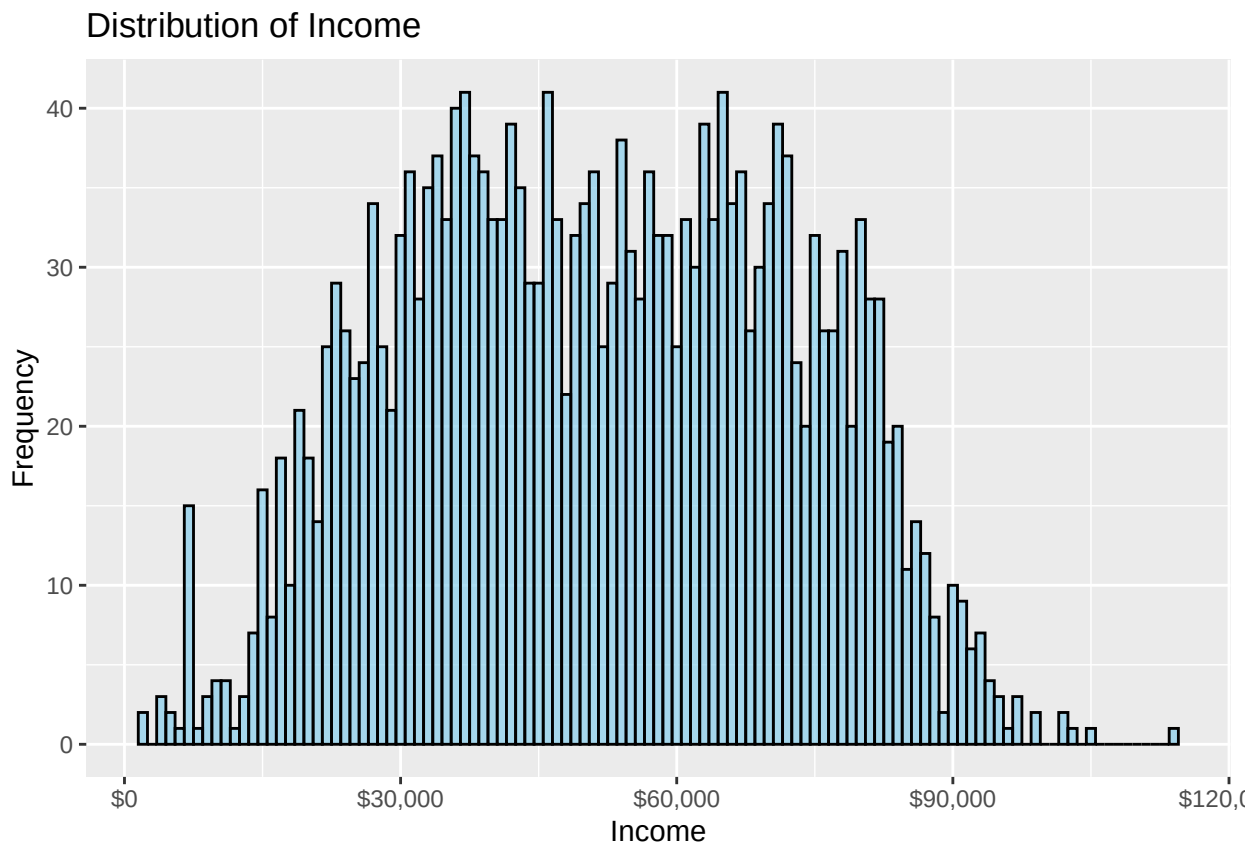
Re-run the plot for Marital Status.


Bar Chart of Marital Status
750
500
250
0
count
Single
Divorced
Married
Together
Widow
Marital_Status

Income



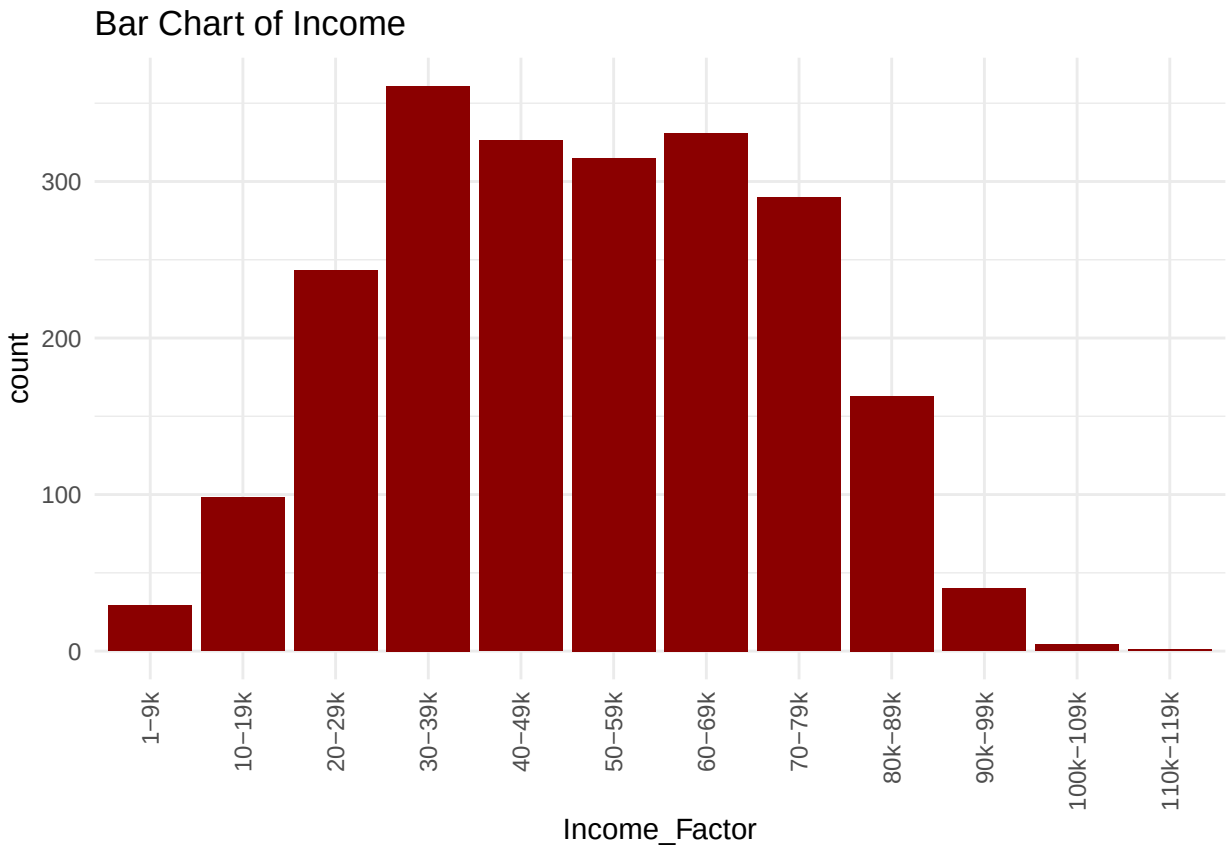
There seems to be outliers present in the Income feature. These outliers will be removed from the data set. Re-run the bar plot and the boxplot to visualize the changes.



Factorize the Income feature to preserve more descriptive bins for business use.

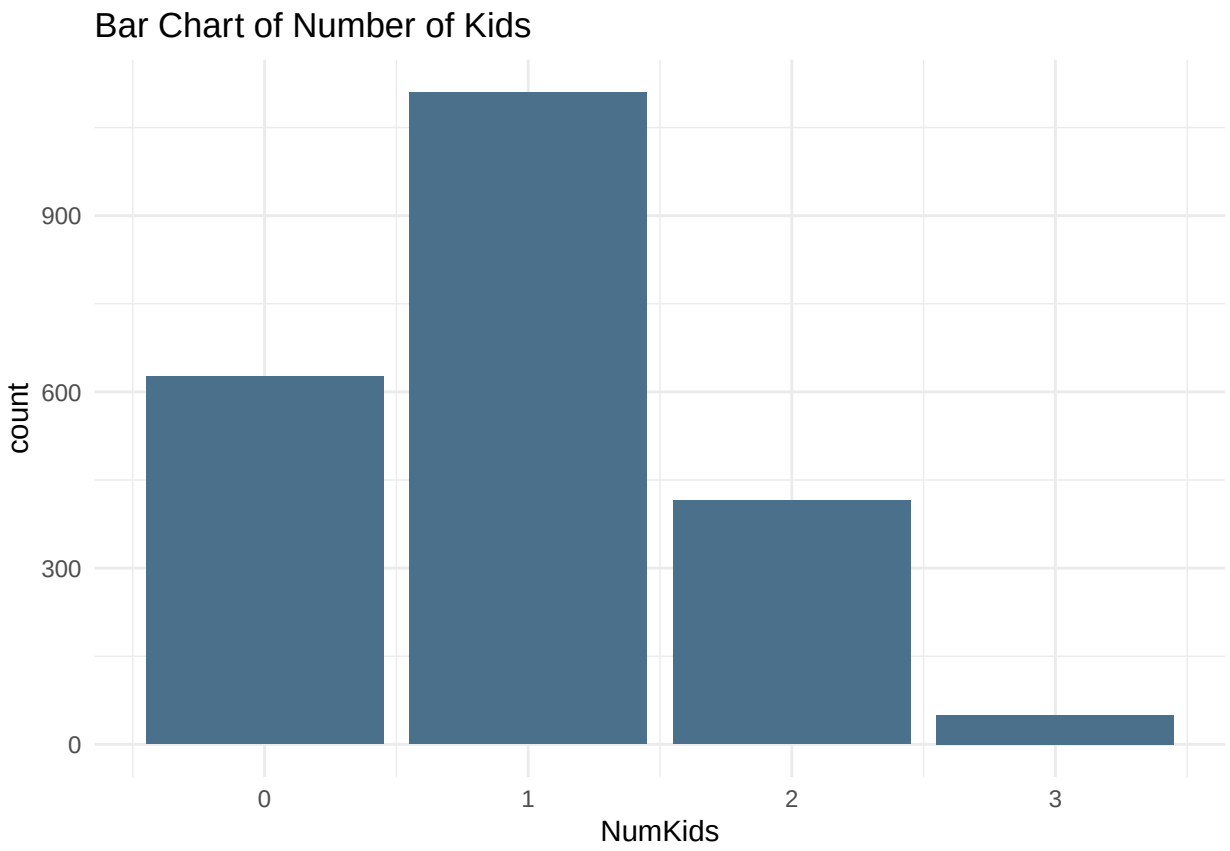
```
##  [1] "1-9k"      "10-19k"    "20-29k"    "30-39k"    "40-49k"    "50-59k"
##  [7] "60-69k"    "70-79k"    "80k-89k"   "90k-99k"   "100k-109k" "110k-119k"
```

Visualization of Income



Household Size

To reduce dimensionality in modeling, KidHome and TeenHome variables will be combined into a Number of Kids variable and then removed from the data set.



Creation of data subset by usable category

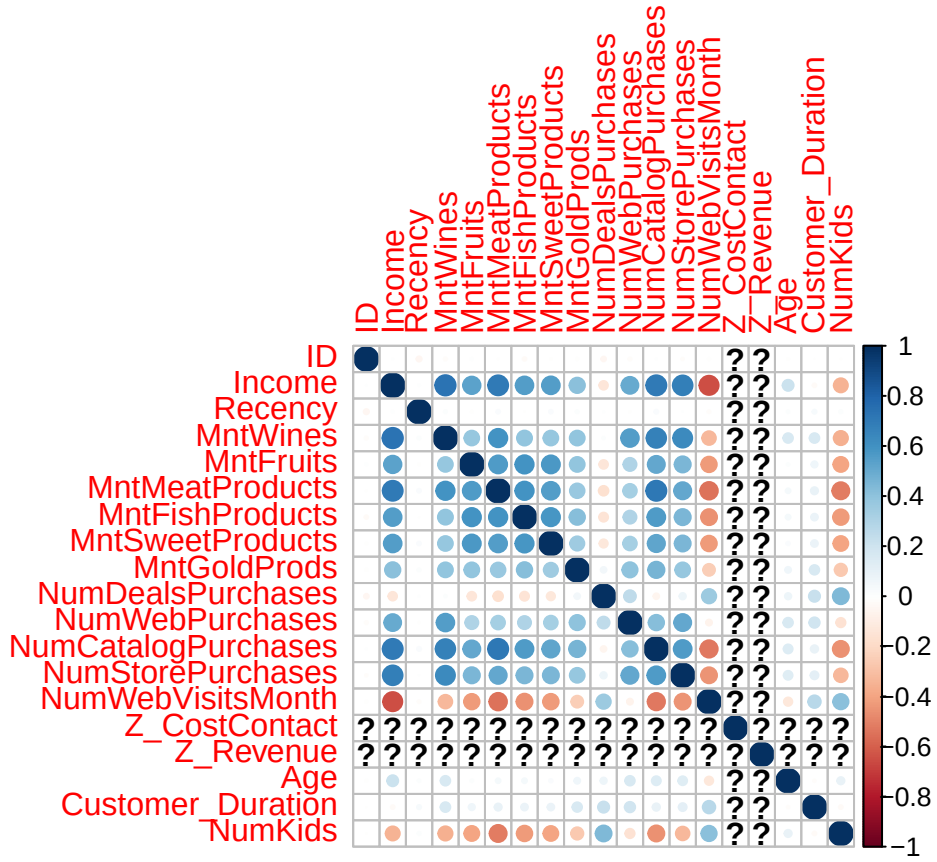
All variables will be subset into their respective domain and joined with product categories. Because the goal is to identify cluster personalities, product category subsets will be analyzed through people and promotional attributes.

```
people_attrs <- dt[, c("Age", "Education", "Marital_Status", "Income_Factor", "NumKids",
                       "Customer_Duration", "Recency", "Complain")]
product_attrs <- dt[, c("MntWines", "MntFruits", "MntMeatProducts",
                        "MntFishProducts", "MntSweetProducts", "MntGoldProds")]
promotion_attrs <- dt[, c("NumDealsPurchases", "AcceptedCmp1", "AcceptedCmp2",
                          "AcceptedCmp3", "AcceptedCmp4", "AcceptedCmp5", "Response")]
place_attrs <- dt[, c("NumWebPurchases", "NumCatalogPurchases", "NumStorePurchases")]
```

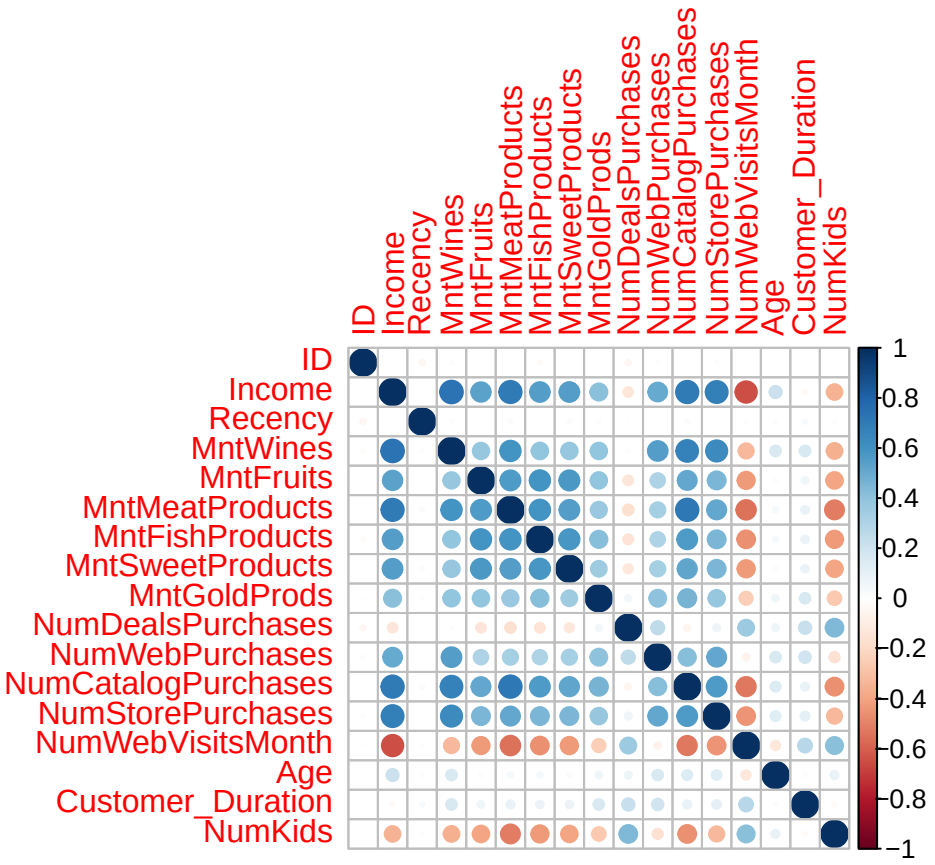
```
# wine data frame
Wine <- cbind(dt$MntWines, people_attrs, promotion_attrs)

# Food data frame
MntFood <- dt$MntFishProducts + dt$MntMeatProducts + dt$MntFruits
Food <- cbind(MntFood, people_attrs, promotion_attrs)

# Sweets data frame
Sweet <- cbind(dt$MntSweetProducts, people_attrs, promotion_attrs)
```

```
# Sweets dataf rame
Gold <- cbind(dt$MntGoldProds, people_attrs, promotion_attrs)
```

Correlation Plot



Z_Cost Contact and Z_-_Revenue have 0 variance and will be removed from the data set. In the correlation plot, there are several strong, positive correlations between income and the amount spent on Wines and Meat products, as well as store and catalog purchaes. Interestingly, there is a strong, negative relationship between income and number of web visits.



Modeling

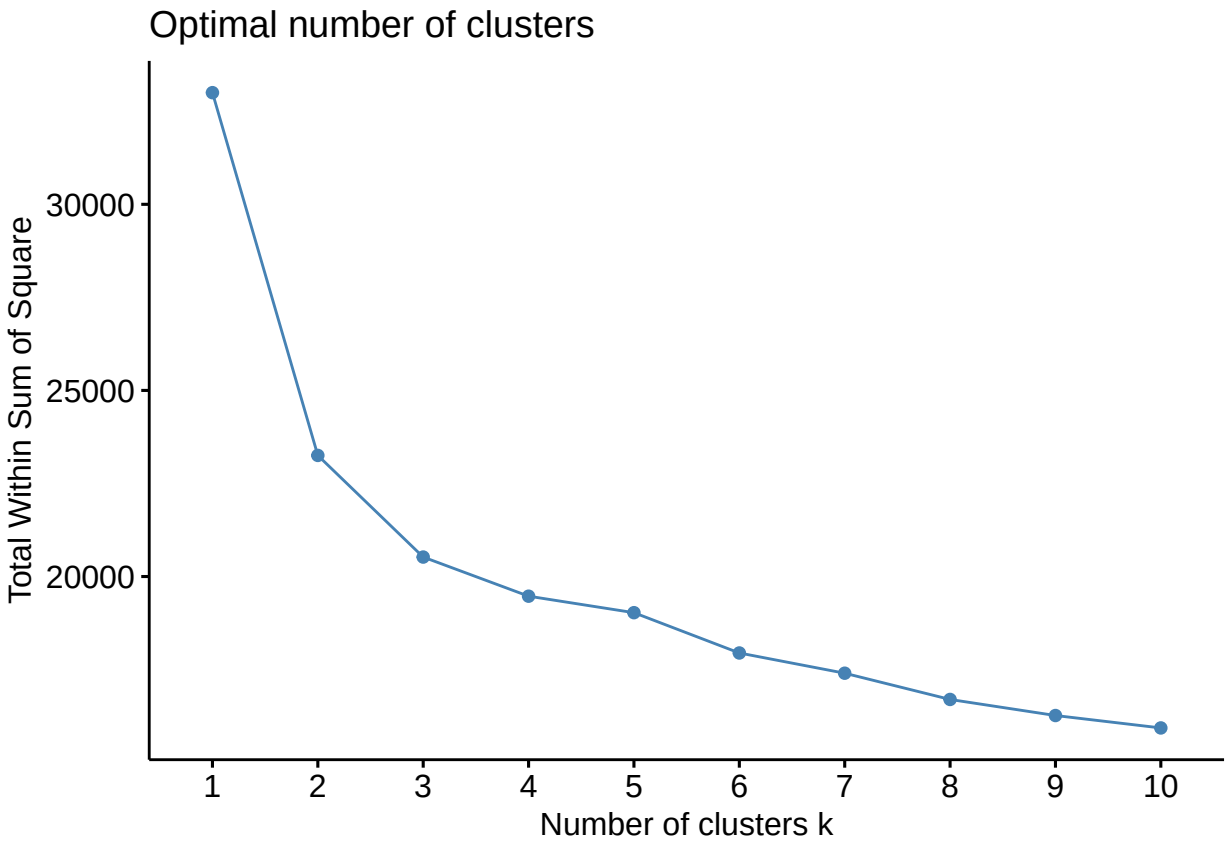
K-Means

K-Means is, simply put, an unsupervisored clustering algorithm that groups like data so that the difference within groups is minimized, and the difference between groups is maximized. In order to prepare for k-means clustering, and because the algorithm only works with numeric variables, the data frame will be pre-processed by centering and scaling the data. As a result, the clusters will be based on the following variables:

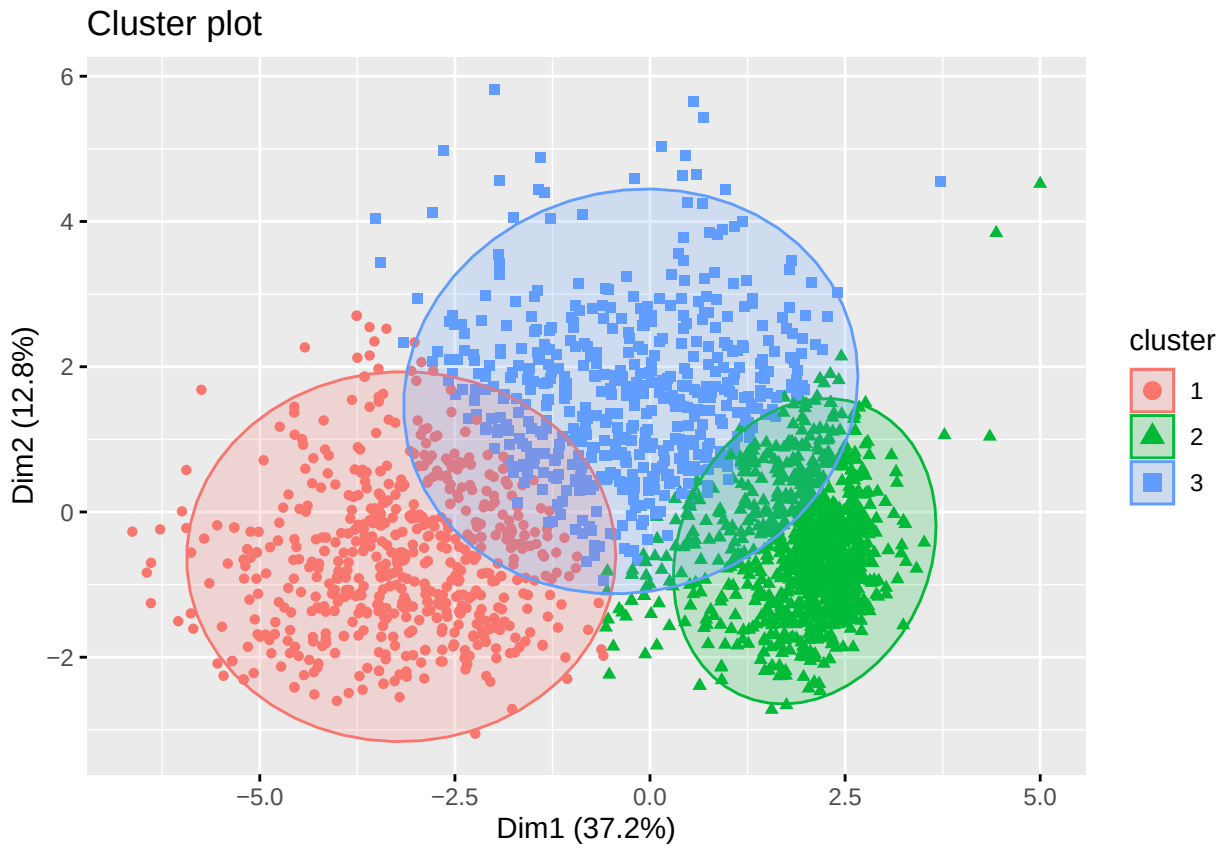
```
##  [1] "Income"              "Recency"             "MntWines"
##  [4] "MntFruits"           "MntMeatProducts"     "MntFishProducts"
##  [7] "MntSweetProducts"    "MntGoldProds"        "NumDealsPurchases"
## [10] "NumWebPurchases"     "NumCatalogPurchases" "NumStorePurchases"
## [13] "NumWebVisitsMonth"   "Age"                 "Customer_Duration"
## [16] "NumKids"
```

Elbow Plot

To determine the optimal number of clusters, the elbow plot will be used. The resulting optimal cluster value is 3.


Optimal number of clusters
Total Within Sum of Square
30000
25000
20000
1
2
3
4
5
6
7
8
9
10
Number of clusters k

Initial Cluster Visualization

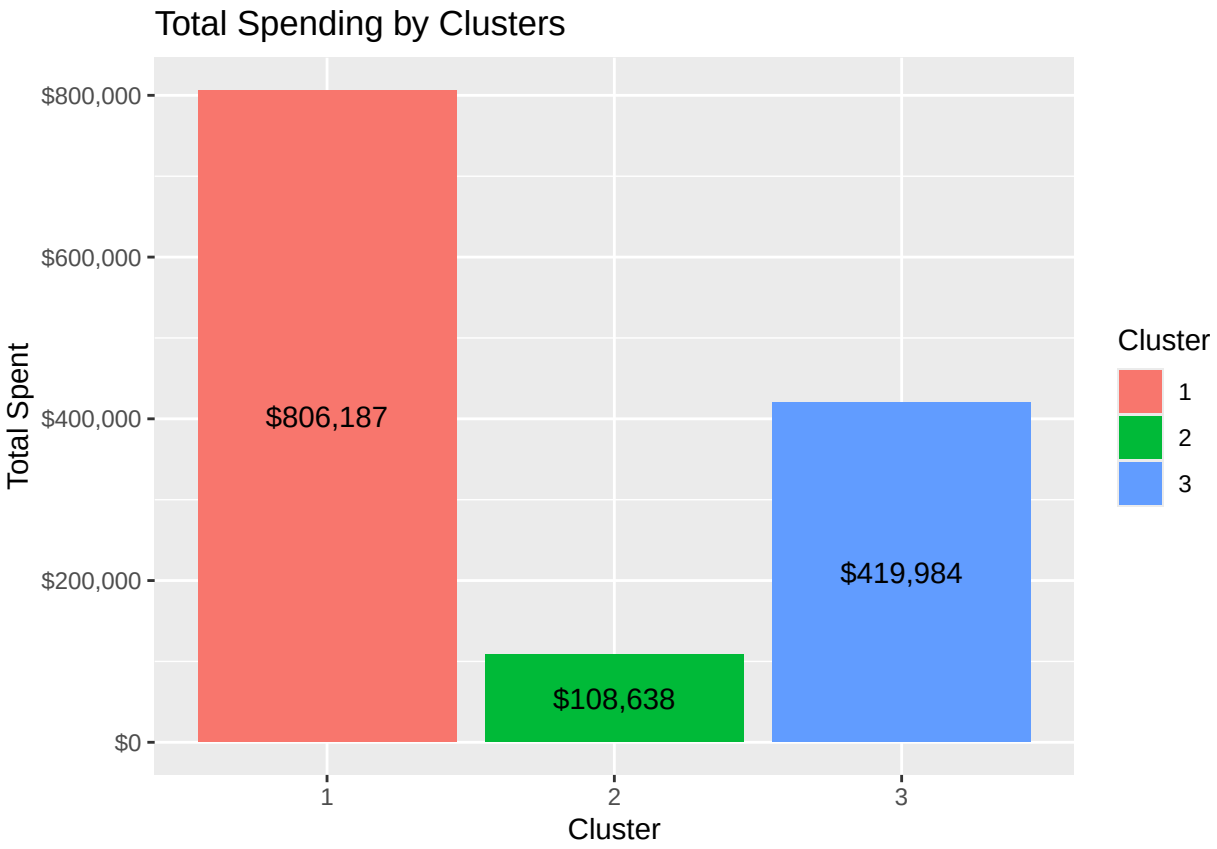


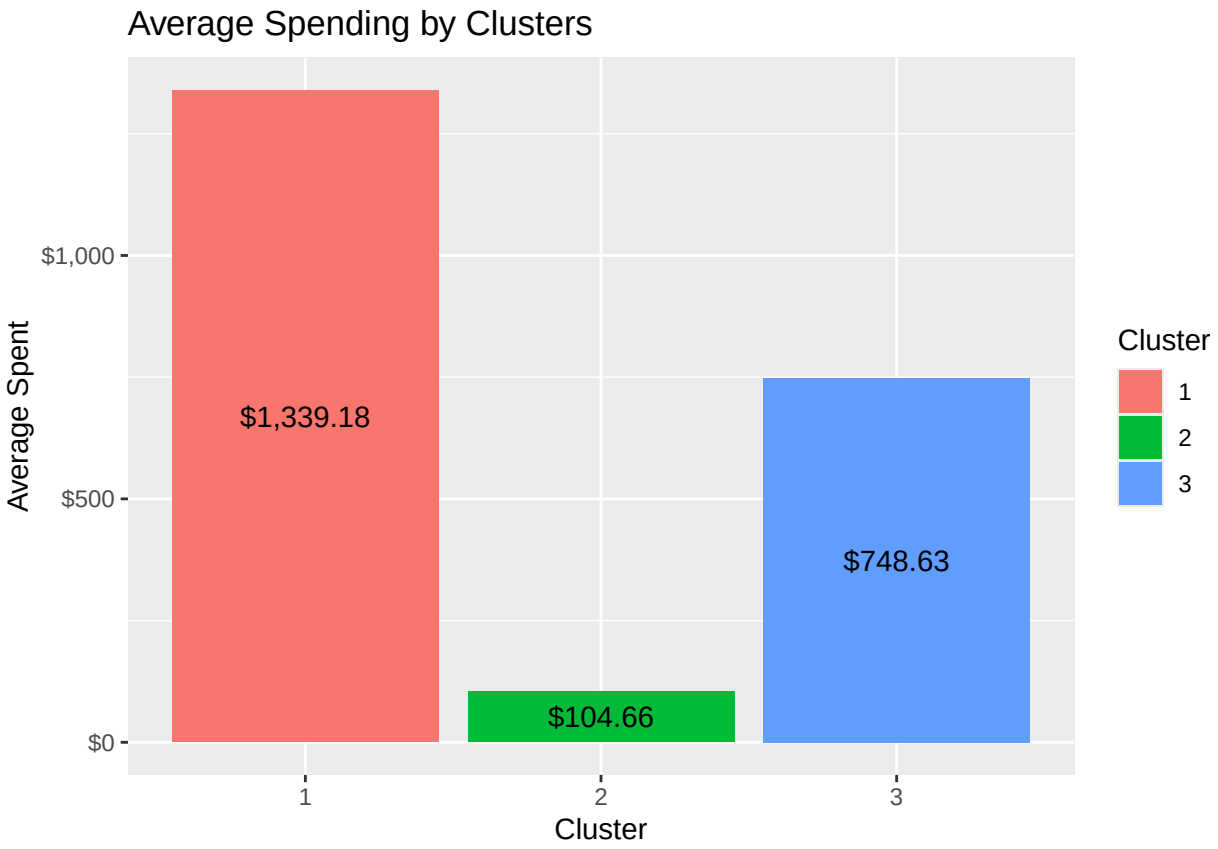
Exploration of Clusters

On initial inspection of clusters, cluster 2 has the most customers with 1038.

Exploring Amount Spent per Cluster

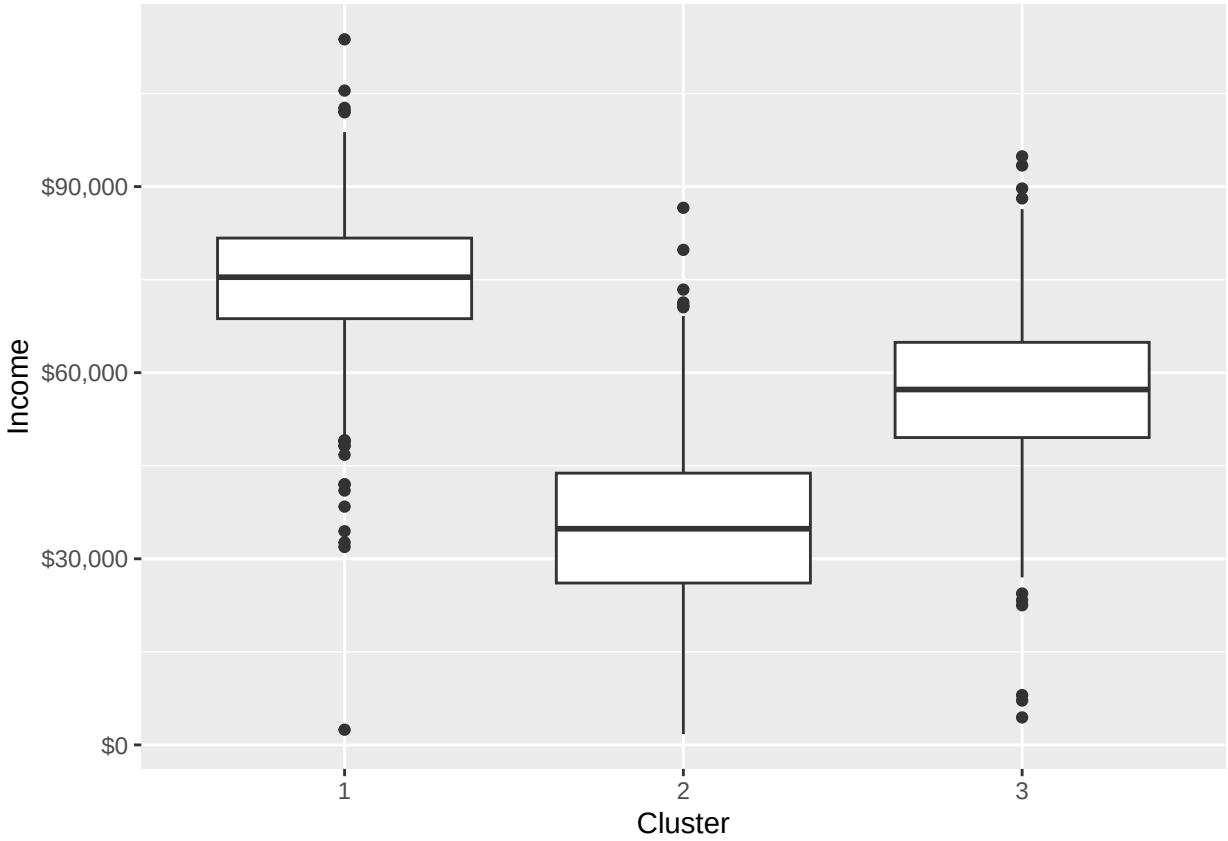
Despite it's size, Cluster 2 spend the least amount of money on products, where cluster 1 spend the overwhelming majority.


Total Spending by Clusters
$800,000
$600,000
$400,000
$200,000
$0
Total Spent
$806,187
$108,638
$419,984
1
2
3
Cluster
Cluster
1
2
3



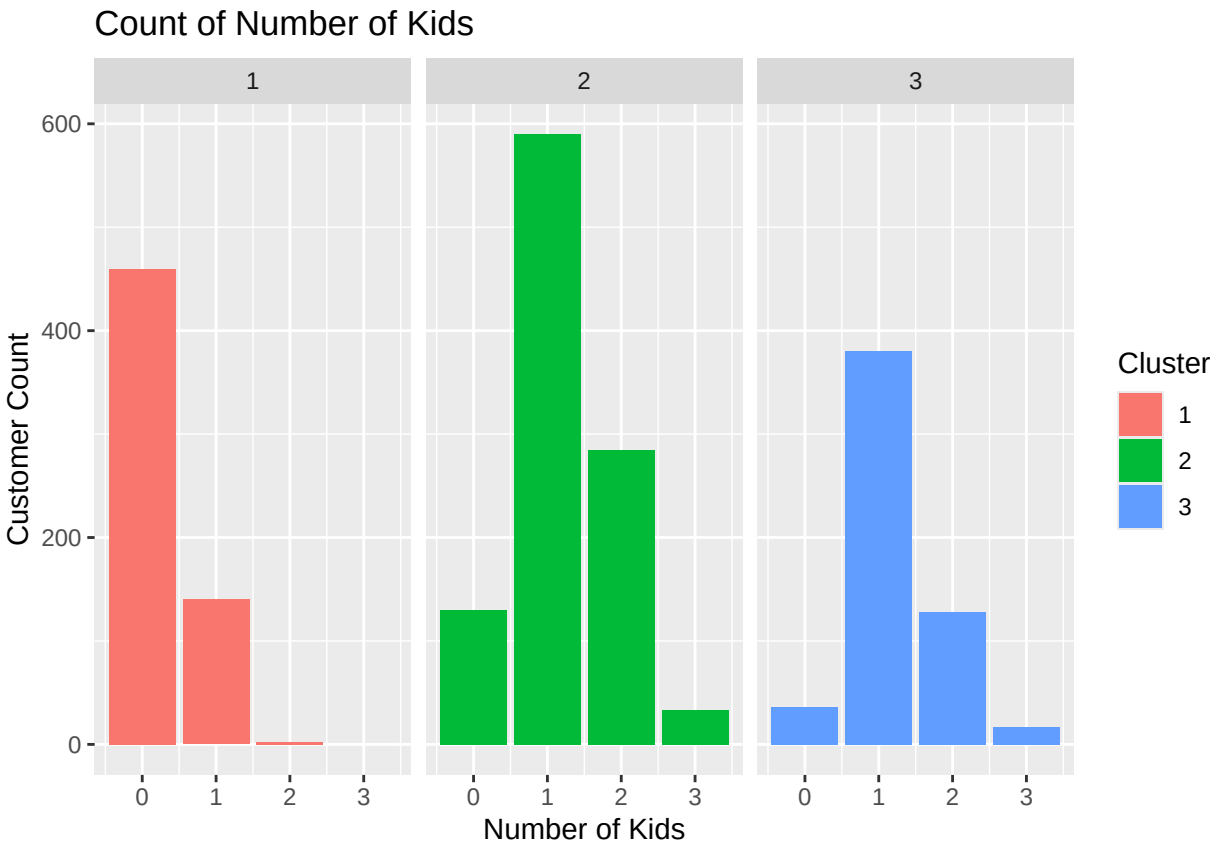
Income per Cluster

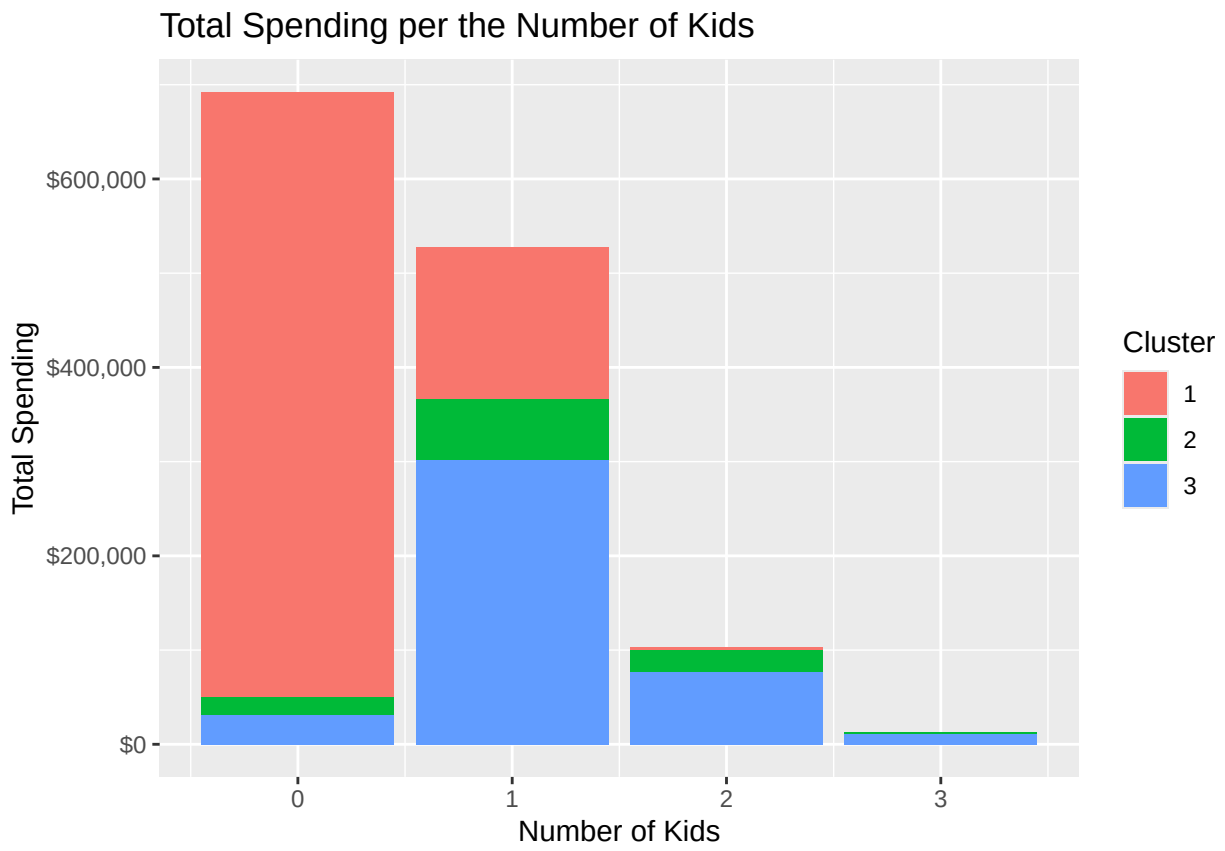
Cluster 1 has the high maximum and median income, where as cluster 2, the largest sized cluster, has the smallest. This could be an influential reason as to their limited spending habits, and why Cluster 1 has the highest spending and spending average.



Number of Kids and Spending

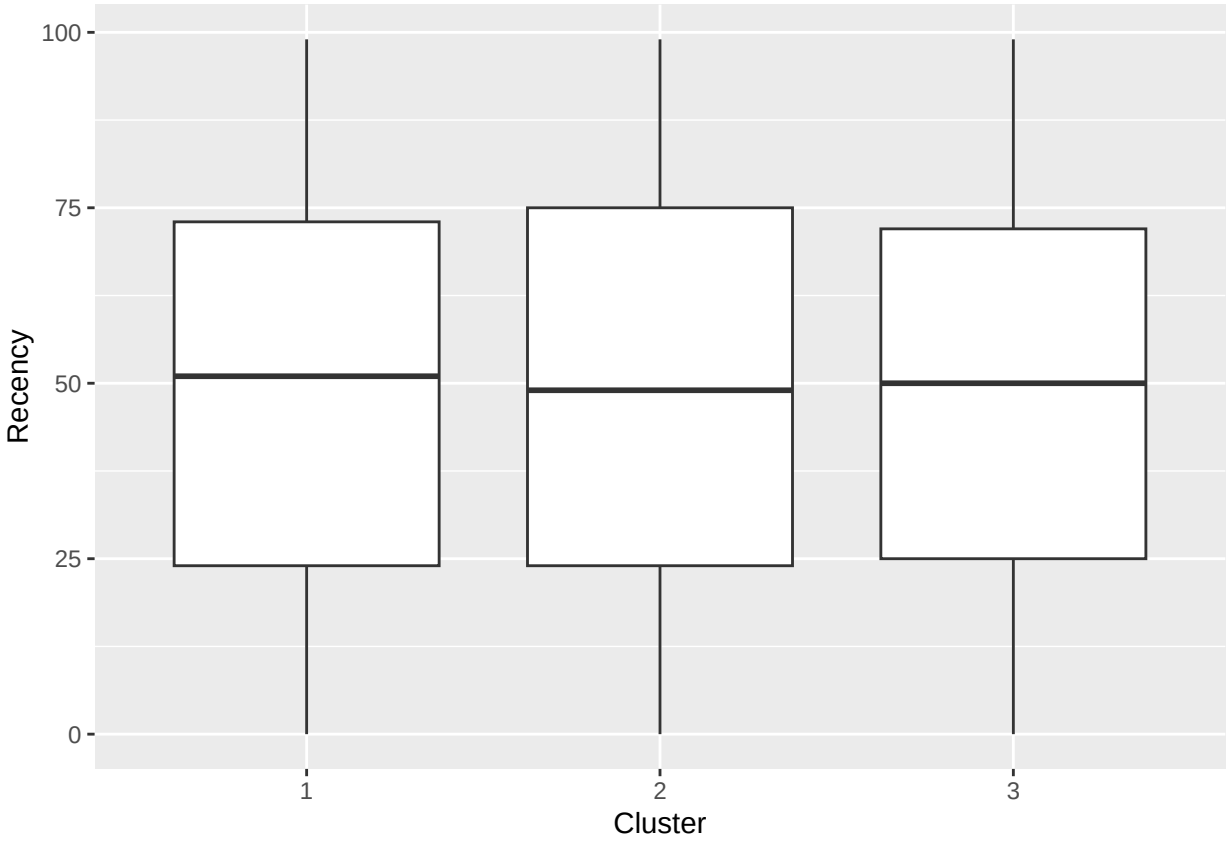
Furthering the income analysis above, by visualizing the number of kids alongside total spending, we can see that while clusters 2 and 3 have less income, they also have dependent as a financial concern, potentially limiting their spendable income and highlighting their price sensitivity.

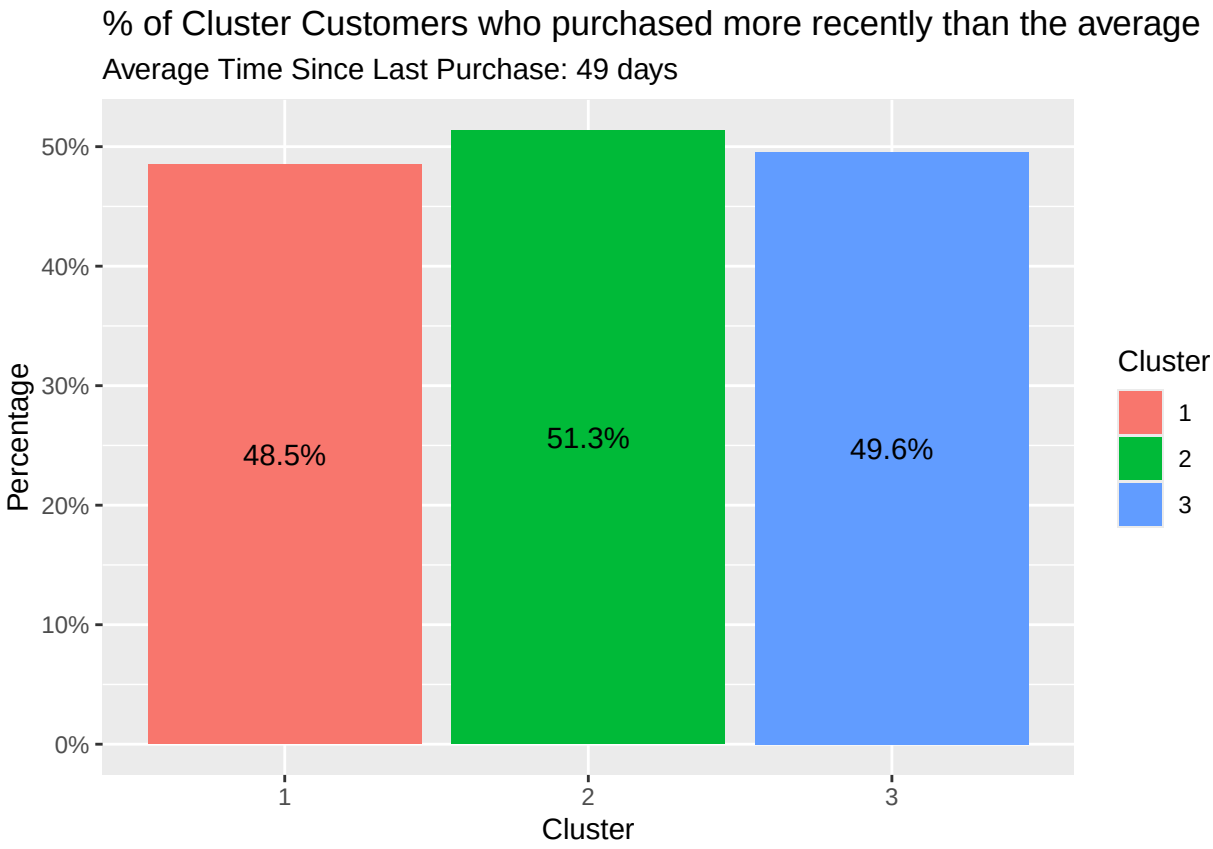

Count of Number of Kids
1
2
3
600
400
200
0
Customer Count
0
1
2
3
Number of Kids
Cluster
1
2
3

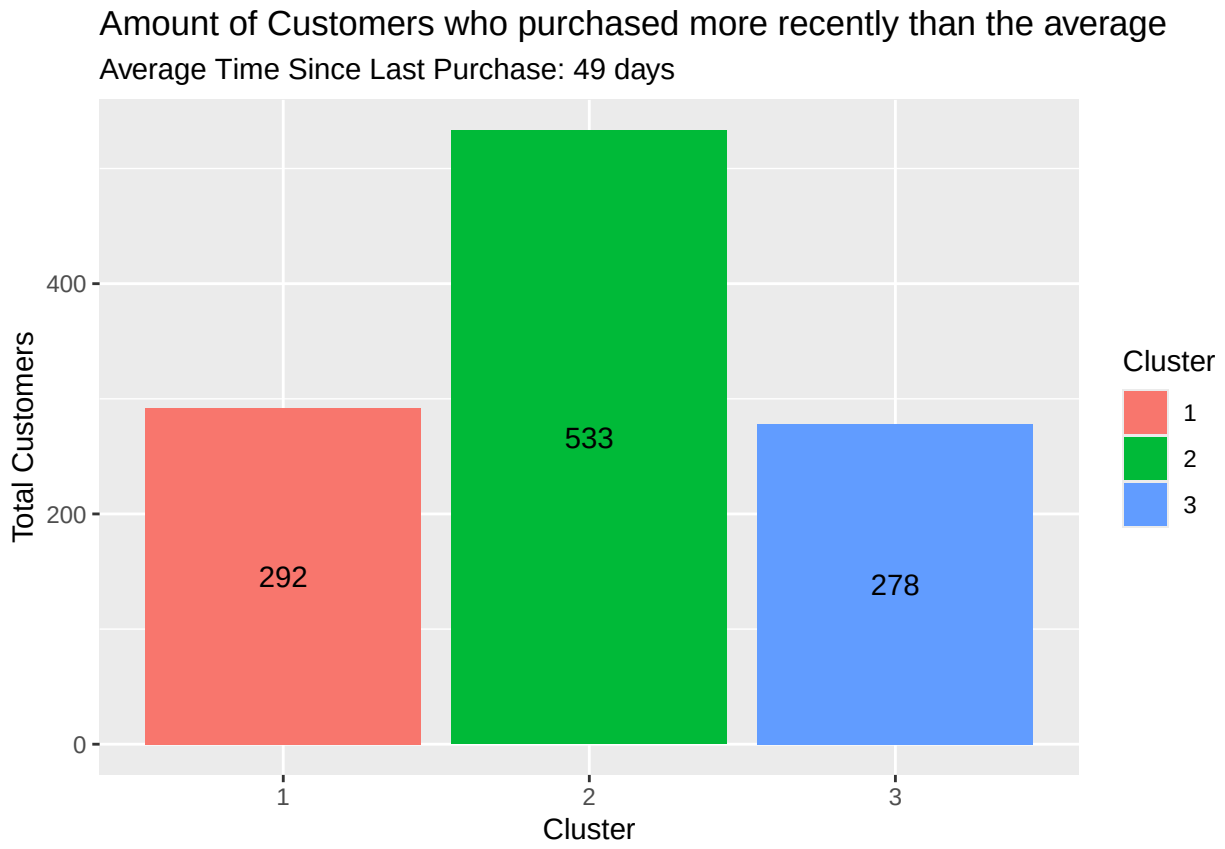


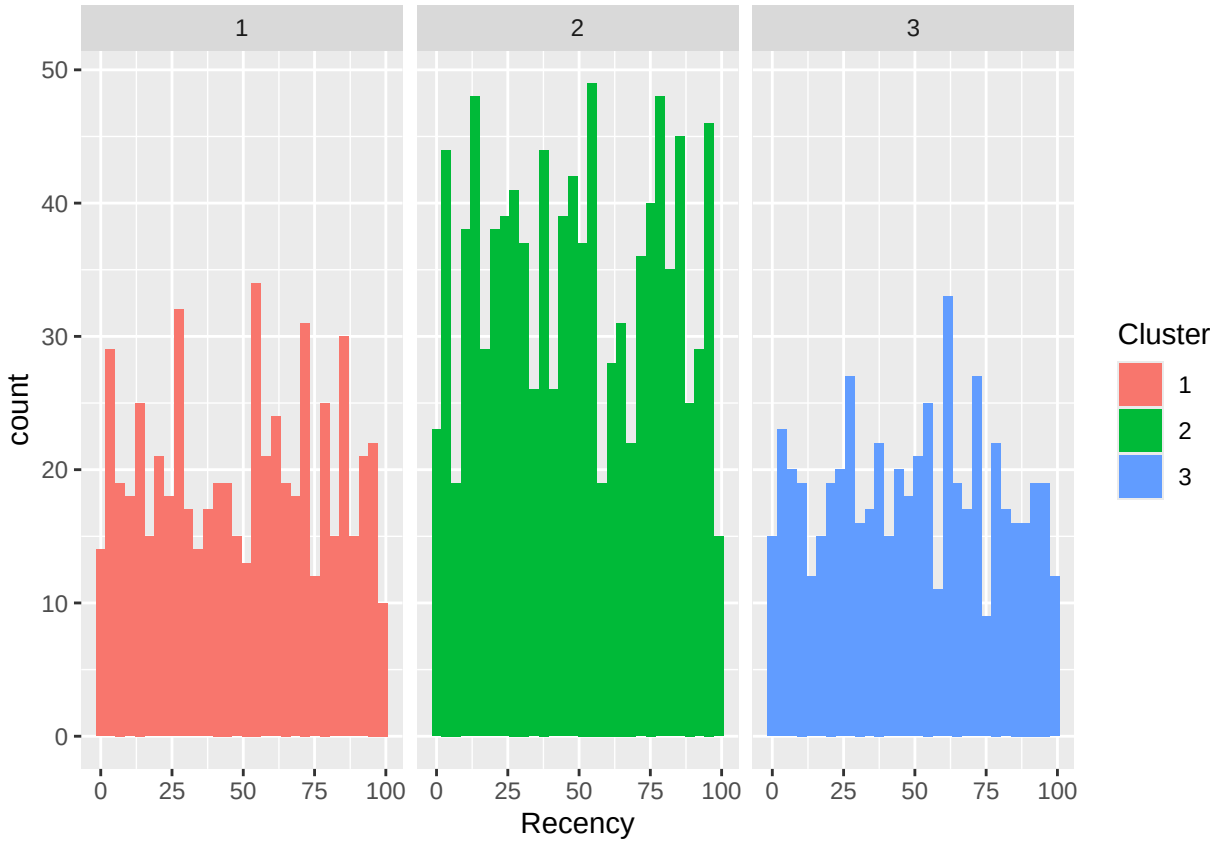
recency since Last Purchase

There are marginal differences in how recently customers of each cluster ordered. However, when comparing the cluster average to the average across all clusters, we can see that cluster 2 has more customers in it who have purchase more frequently than the average. Looking at the histogram faceted by Cluster, we can see Cluster 2 has a multi-modal distribution with peaks around the tails of values which is not as drastically present in cluster 1 and 3, which could be skewing the boxplot analysis. Accounting for size, this could indicate a shifting trend in more effective targeted advertisement subsequently increasing average spent per cluster average; however, Cluster 2 has the lowest median income which could be the overall limiting factor.


100
75
50
25
0
Recency
1
2
3
Cluster

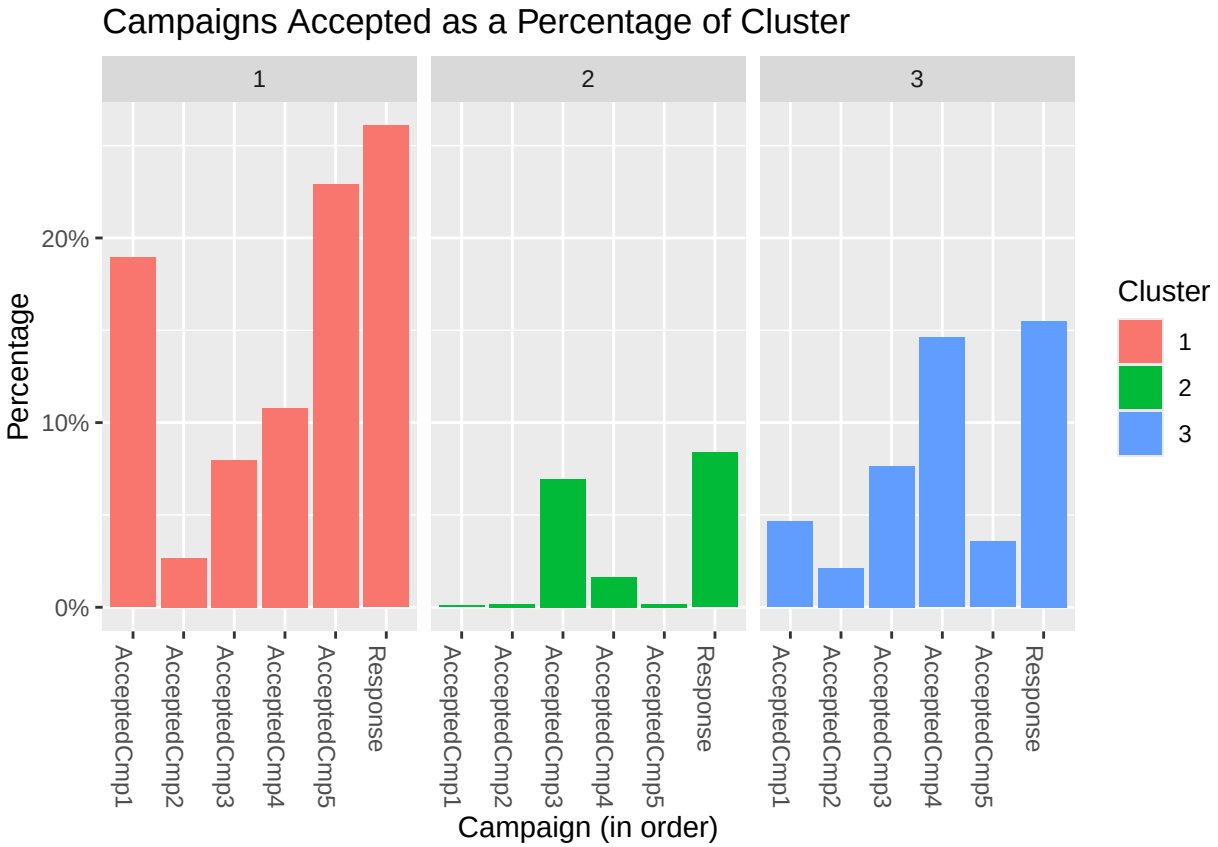

% of Cluster Customers who purchased more recently than the average
Average Time Since Last Purchase: 49 days
50%
40%
30%
20%
10%
0%
Percentage
48.5%
51.3%
49.6%
1
2
3
Cluster
Cluster
1
2
3


Amount of Customers who purchased more recently than the average
Average Time Since Last Purchase: 49 days
Total Customers
400
200
0
292
533
278
1
2
3
Cluster
Cluster
1
2
3



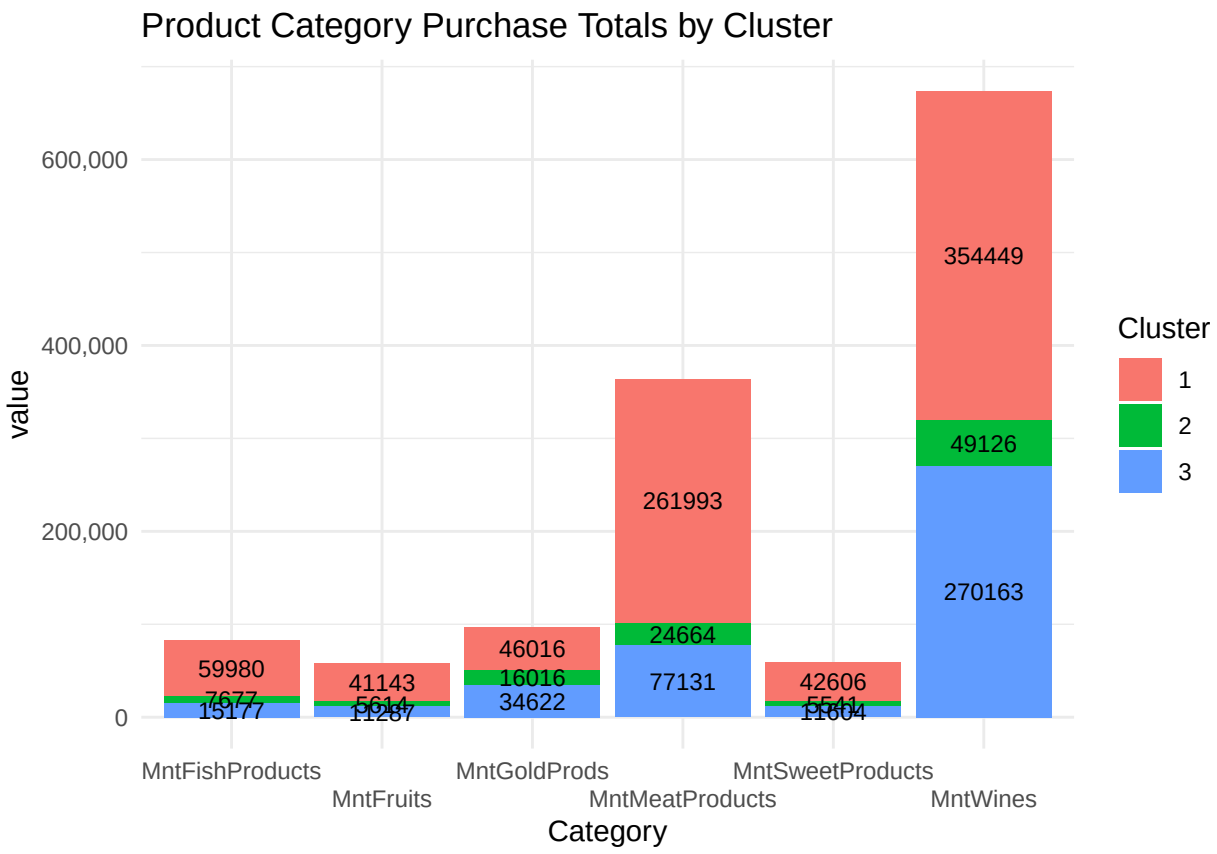
Responsiveness to Targeted Campaigns

Cluster 1 has been the most receptive to campaigns, with over 20% of the cluster accepting each of the last 2 campaigns. Cluster 2 has been largely non-responsive; accepting under 5% in 4 of the 6 campaigns. However, over 10% accepted the most recent campaign which, depending on timing, could explain the cluster's spike in recency since last purchase.



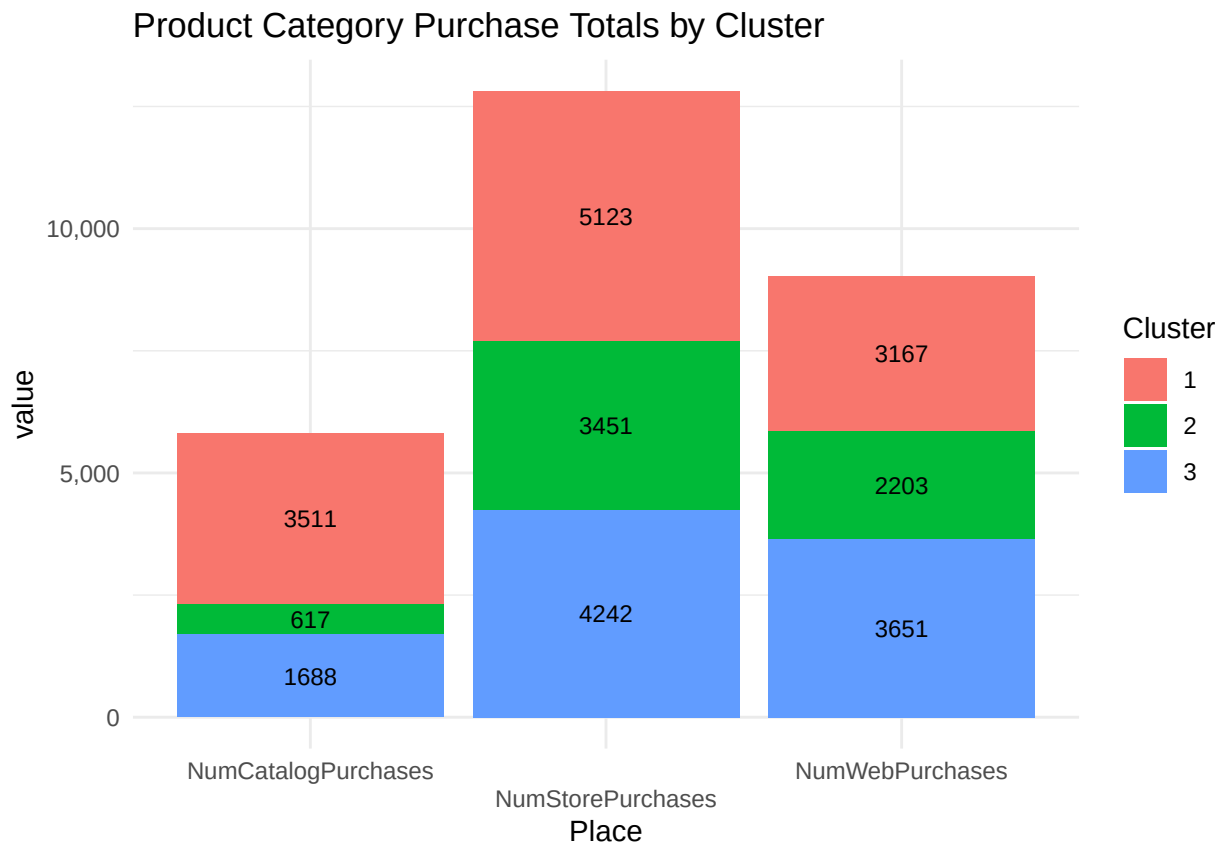
Product Category Purchase Totals by Cluster

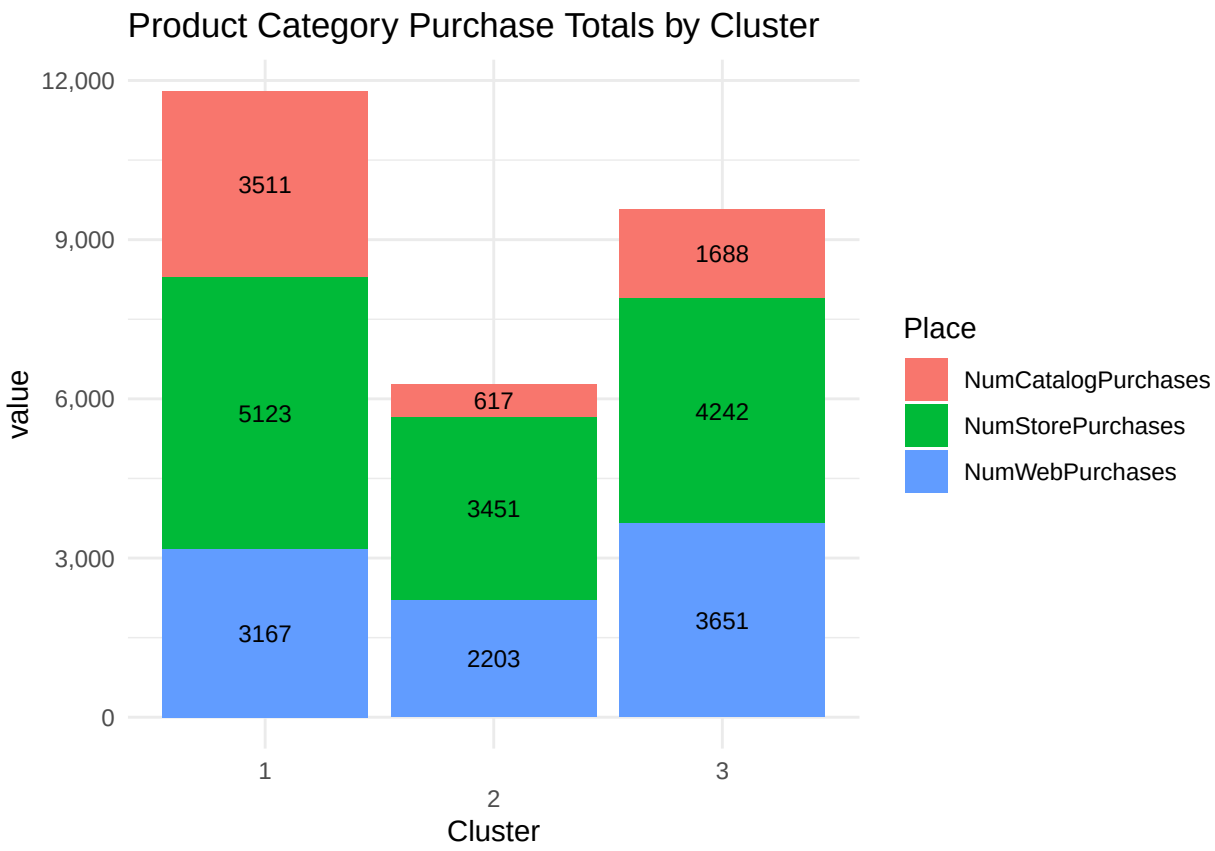
Wines and meat products account for the largest sum of sales, with clusters 1 and 3 accounting for the majority, respectively. Across all categories, Cluster 2, while being the largest cluster, purchases the least amount in all categories. By percentage, 75% of Cluster 2 customers purchased more luxurious products like Fish, Gold, and Sweets. This indicates a willingness to purchase the product but could be excluded from purchasing more based on their income. Respective to the cluster size, one way to boost total sales in these categories is to offer more price conscious offerings or targeted deals.

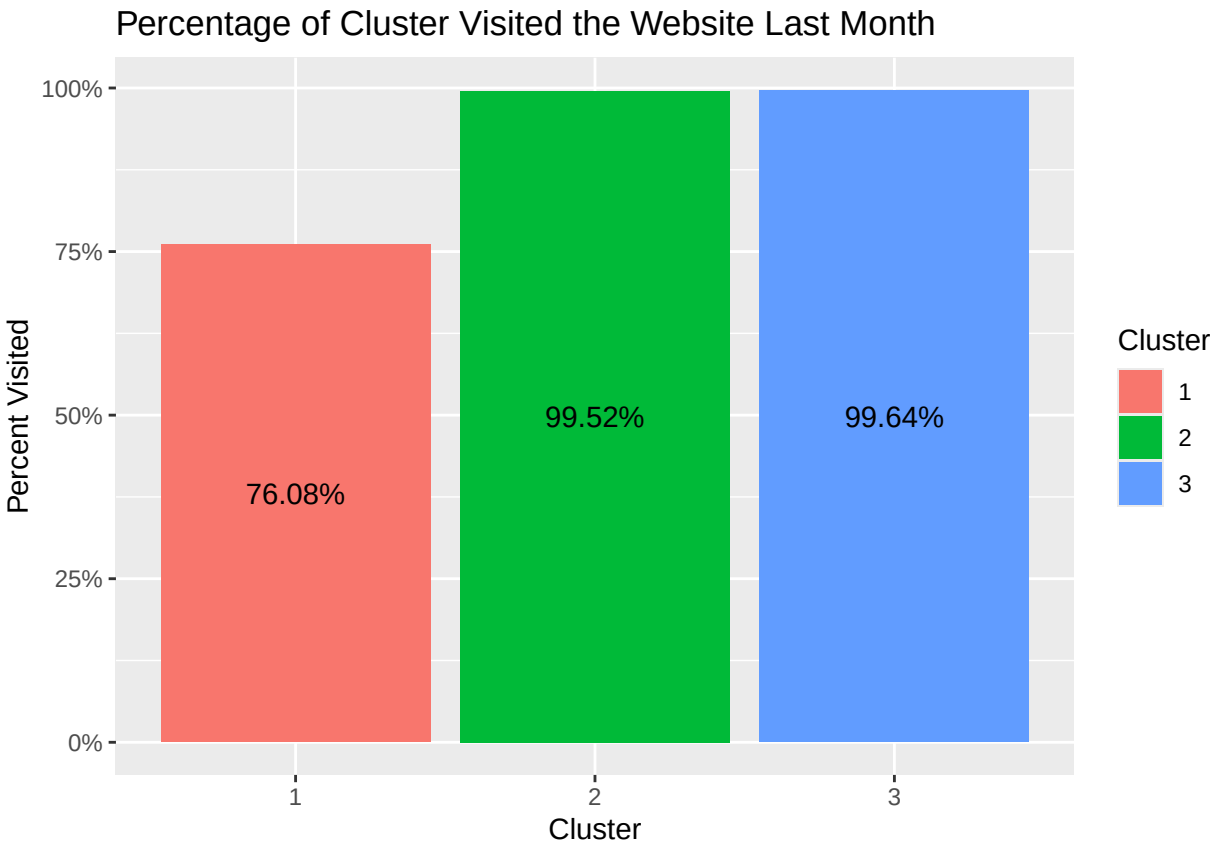

Product Category Purchase Totals by Cluster
600,000
400,000
200,000
0
value
59980
7677
15177
41143
5614
11287
46016
16016
34622
261993
24664
77131
42606
5541
11604
354449
49126
270163
MntFishProducts
MntFruits
MntGoldProds
MntMeatProducts
MntSweetProducts
MntWines
Category
Cluster
1
2
3

Place of Purchase per Customer

Store and Web purchases account for the most purchases, respectively. Additionally, this is the trend across all of the clusters with the exception of Cluster 1, who has more purchases through the catalog than the web. While there are no previous metrics to base this off of, almost 100% of cluster 2 visited the website in the last month. This is a good indication that they are not inactive customers. It is worth noting that almost 25% of cluster 1 has not visited the website in the last month. Their preference to the catalog over the web could suggest that the website is not showcasing the products cluster 1 is looking to purchase, in their preferred manner. Given this cluster is accounts for the most sales, a redesign of the website could be beneficial for sustaining their engagement. Alternatively, the catalog could be a way of keeping the company fresh in their minds in the event the cluster does not check promotional emails.

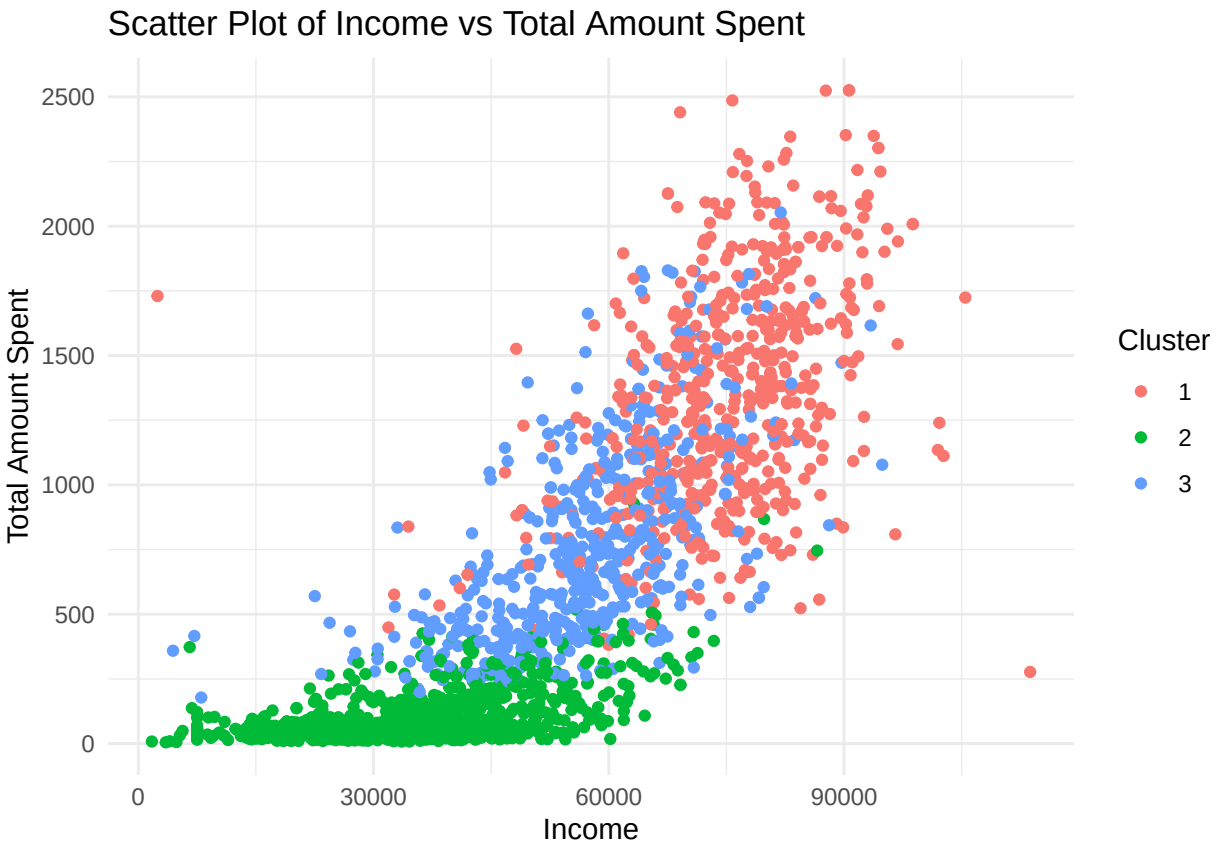

Product Category Purchase Totals by Cluster
value
10,000
5,000
0
5123
3451
3167
2203
3511
617
1688
4242
3651
NumCatalogPurchases
NumStorePurchases
NumWebPurchases
Place
Cluster
1
2
3

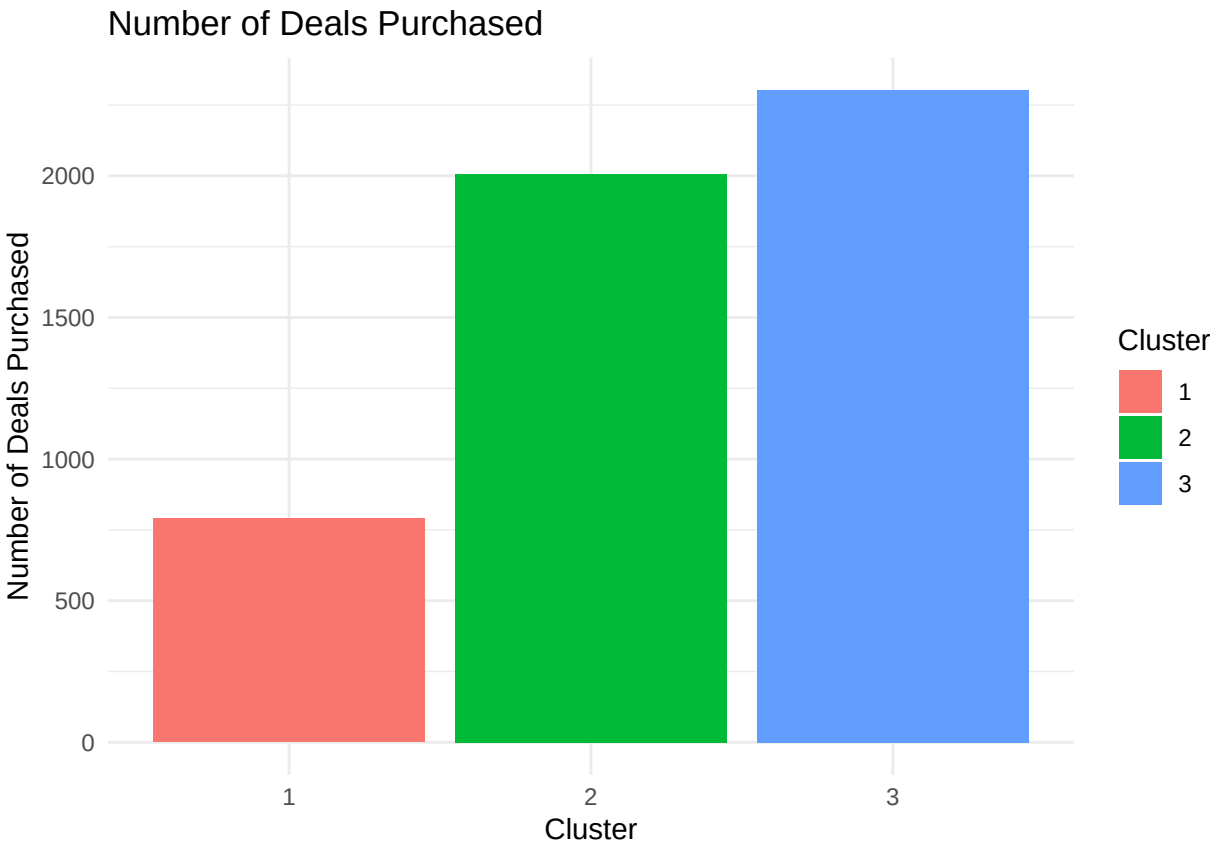

Product Category Purchase Totals by Cluster
12,000
9,000
6,000
3,000
0
value
3511
5123
3167
617
3451
2203
1688
4242
3651
1
2
3
Cluster
Place
NumCatalogPurchases
NumStorePurchases
NumWebPurchases

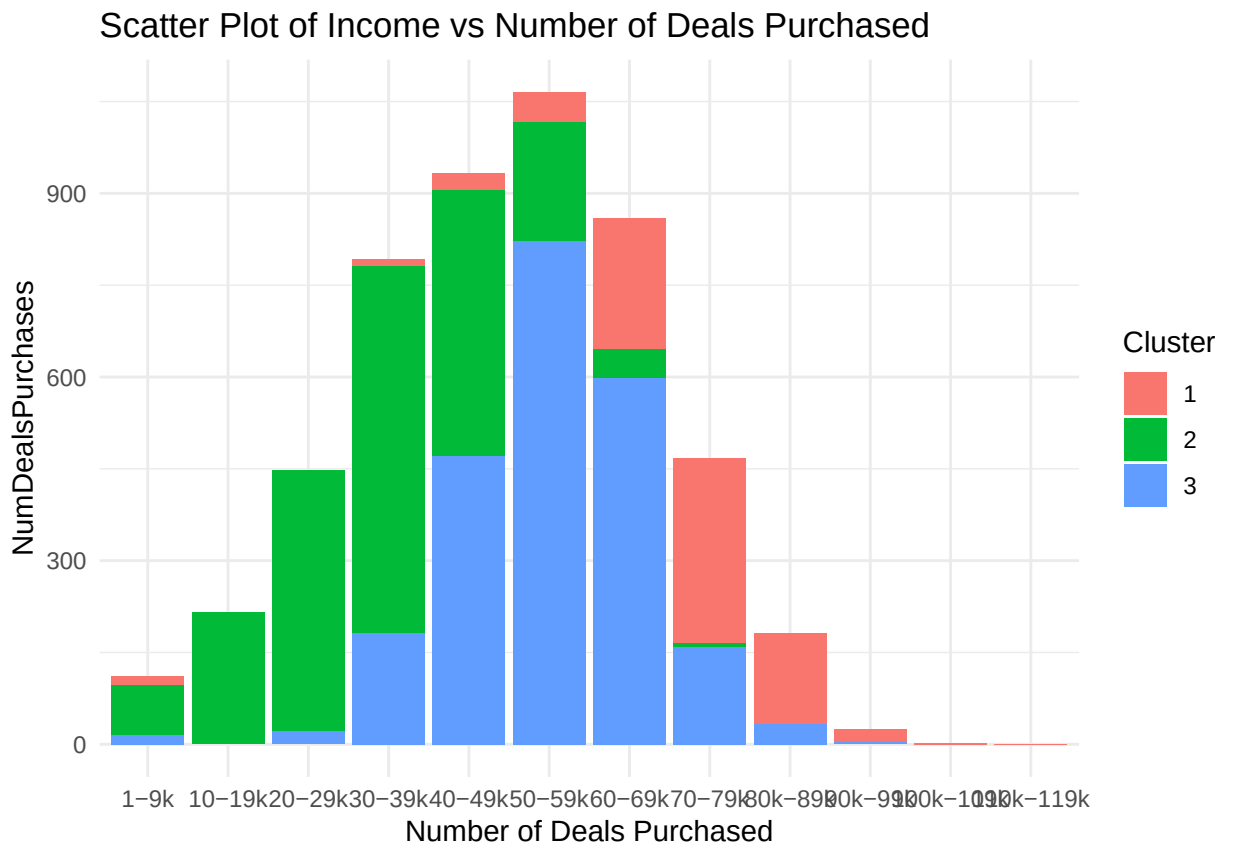


Total Spending and Deals Purchased

We can see a positive relationship between the amount spent and a customers income. Knowing income is not equally distributed across all clusters, we can see the highest earners in Cluster 1 do not purchases as many deals as clusters 2 and 3. As a stacked chart, we can see the parabolic relationship; where as deals increases as income increased until after around $59k, where as income increases, deals decreases. This indicates price sensitivity of the clusters and customer groups. Further data is needed for analysis on how the deals affects product category purchases in total, and within clusters.


Scatter Plot of Income vs Total Amount Spent
Total Amount Spent
2500
2000
1500
1000
500
0
0
30000
60000
90000
Income
Cluster
1
2
3


Number of Deals Purchased
Number of Deals Purchased
2000
1500
1000
500
0
1
2
3
Cluster
Cluster
1
2
3



Association Rules

Association Rules are a data mining technique to uncover hidden relationships between variables. High purchases for Food, Wine, Sweet, and Gold product categories will be mined based on "High" being calcualated as the top quartile in that spending category. The Apriori algorithm will be used in this analysis.

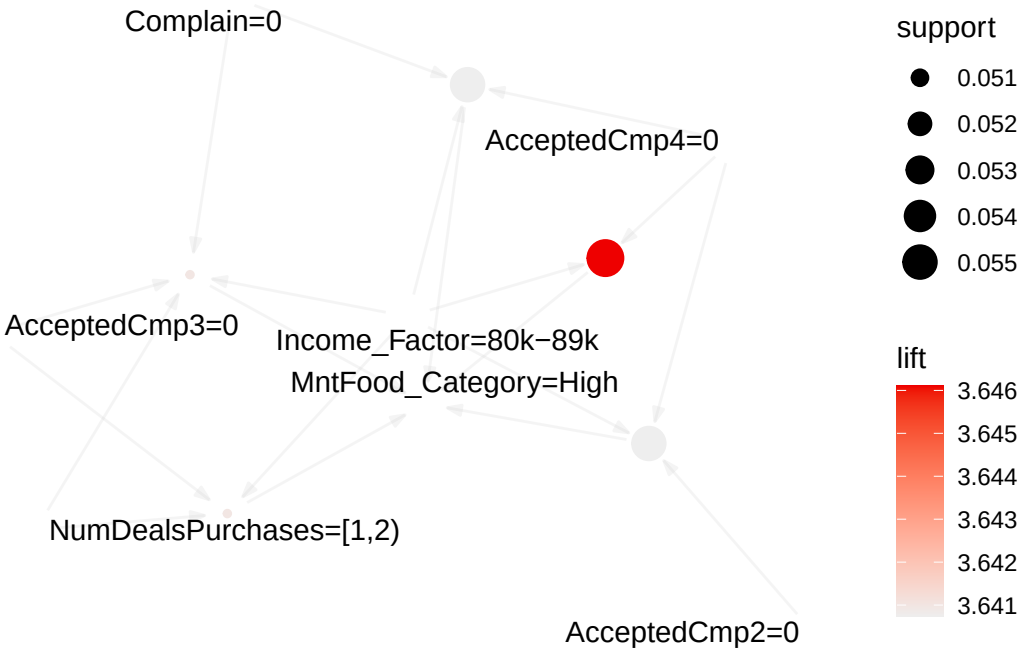
Food Association Rules

Looking at the first 5 rules, by lift, we can see that having an income of $80-89k is a common feature across the rules. Additionally worth noting, A high food spender would have purchased 1 deal and not accepted Campaigns 2, 3, or 4. This is an important discovery as it shows an ineffective target if that was the intent of the campaign.

```
##   0%  25%  50%  75% 100%
##    1   25   91  356 1727
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.8    0.1    1 none FALSE            TRUE       5    0.05      1
##  maxlen target  ext
##       5  rules TRUE
##
```

```
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 110
##
## set item appearances ...[1 item(s)] done [0.00s].
## set transactions ...[54 item(s), 2201 transaction(s)] done [0.00s].
## sorting and recoding items ... [44 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 5 done [0.02s].
## writing ... [80 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].

##     lhs                           rhs                        support confidence   coverage     lift c
## [1] {Income_Factor=80k-89k,
##      AcceptedCmp4=0}           => {MntFood_Category=High} 0.05588369  0.9111111 0.06133576 3.646101
## [2] {Income_Factor=80k-89k,
##      NumDealsPurchases=[1,2),
##      AcceptedCmp3=0}           => {MntFood_Category=High} 0.05043162  0.9098361 0.05542935 3.640999
## [3] {Income_Factor=80k-89k,
##      Complain=0,
##      NumDealsPurchases=[1,2),
##      AcceptedCmp3=0}           => {MntFood_Category=High} 0.05043162  0.9098361 0.05542935 3.640999
## [4] {Income_Factor=80k-89k,
##      AcceptedCmp2=0,
##      AcceptedCmp4=0}           => {MntFood_Category=High} 0.05497501  0.9097744 0.06042708 3.640752
## [5] {Income_Factor=80k-89k,
##      Complain=0,
##      AcceptedCmp4=0}           => {MntFood_Category=High} 0.05497501  0.9097744 0.06042708 3.640752
```



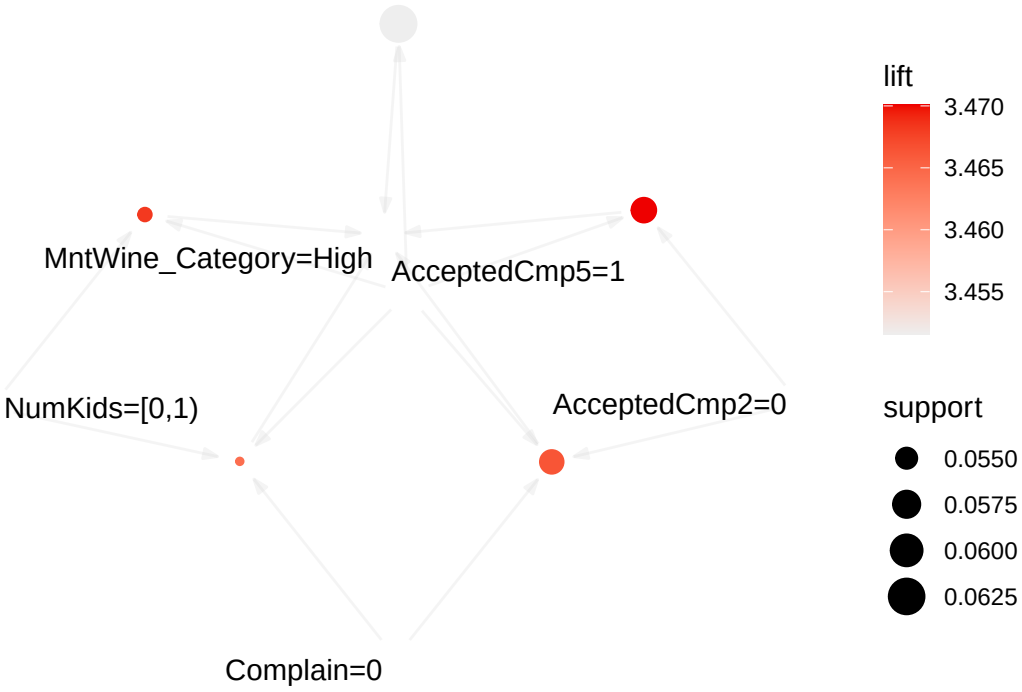
Wine Rules

To be a high spender in wine, the most common association across the first 5 rules (by lift), is that the customer would have accepted campaign 5. If the

```
##   0%  25%  50%  75% 100%
##    0   24  176  507 1493

## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.8    0.1    1 none FALSE            TRUE       5    0.05      1
##  maxlen target  ext
##       5  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 110
##
## set item appearances ...[1 item(s)] done [0.00s].
## set transactions ...[54 item(s), 2201 transaction(s)] done [0.00s].
## sorting and recoding items ... [44 item(s)] done [0.00s].
```

```
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 5 done [0.03s].
## writing ... [8 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

```
##     lhs                  rhs                        support confidence   coverage     lift count
## [1] {AcceptedCmp2=0,
##      AcceptedCmp5=1}  => {MntWine_Category=High} 0.05633803  0.8671329 0.06497047 3.470108   124
## [2] {NumKids=[0,1),
##      AcceptedCmp5=1}  => {MntWine_Category=High} 0.05315766  0.8666667 0.06133576 3.468242   117
## [3] {Complain=0,
##      AcceptedCmp2=0,
##      AcceptedCmp5=1}  => {MntWine_Category=High} 0.05588369  0.8661972 0.06451613 3.466364   123
## [4] {NumKids=[0,1),
##      Complain=0,
##      AcceptedCmp5=1}  => {MntWine_Category=High} 0.05270332  0.8656716 0.06088142 3.464261   116
## [5] {AcceptedCmp5=1}  => {MntWine_Category=High} 0.06269877  0.8625000 0.07269423 3.451568   138
```

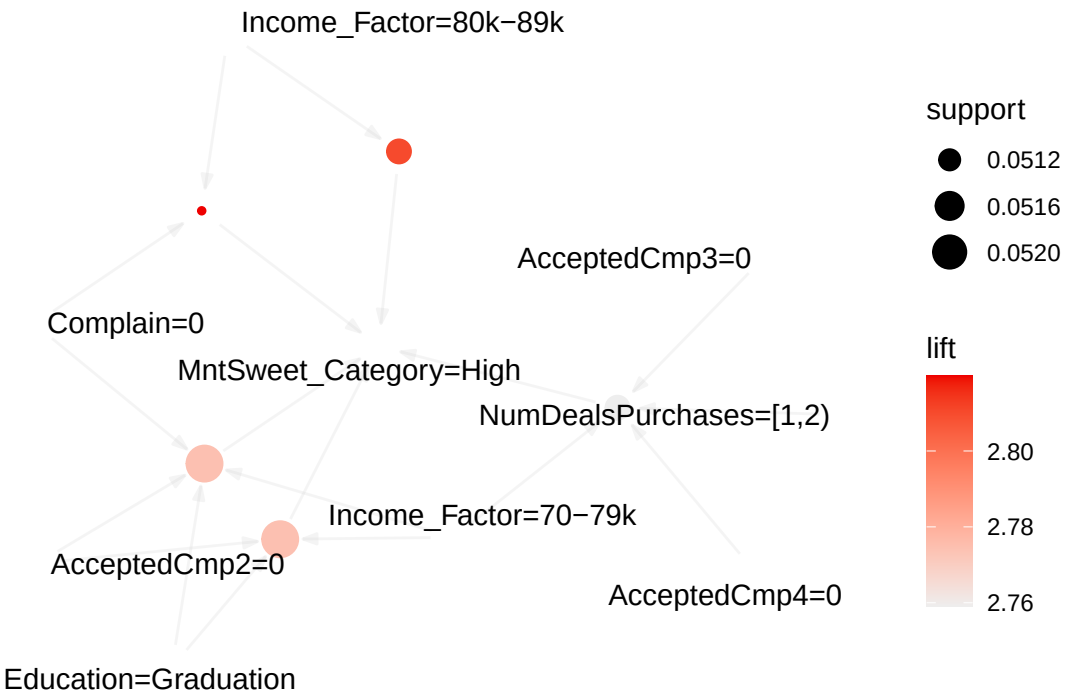


Sweet Rules

The most common association rules for Sweet are having an income between $70-89k. It is worth noting that, in these rules, we only have less than 70% confidence that they would lead to high spending in sweets.

```
##   0%  25%  50%  75% 100%
##    0    1    8   34  262
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.6    0.1    1 none FALSE            TRUE       5    0.05      1
##  maxlen target  ext
##       5  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 110
##
## set item appearances ...[1 item(s)] done [0.00s].
## set transactions ...[54 item(s), 2201 transaction(s)] done [0.00s].
## sorting and recoding items ... [44 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 5 done [0.02s].
## writing ... [81 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].

##     lhs                           rhs                         support confidence   coverage     lift
## [1] {Income_Factor=80k-89k,
##      Complain=0}               => {MntSweet_Category=High} 0.05088596  0.6956522 0.07314857 2.819761
## [2] {Income_Factor=80k-89k}    => {MntSweet_Category=High} 0.05134030  0.6932515 0.07405725 2.810031
## [3] {Education=Graduation,
##      Income_Factor=70-79k,
##      AcceptedCmp2=0}           => {MntSweet_Category=High} 0.05224898  0.6845238 0.07632894 2.774654
## [4] {Education=Graduation,
##      Income_Factor=70-79k,
##      Complain=0,
##      AcceptedCmp2=0}           => {MntSweet_Category=High} 0.05224898  0.6845238 0.07632894 2.774654
## [5] {Income_Factor=70-79k,
##      NumDealsPurchases=[1,2),
##      AcceptedCmp3=0,
##      AcceptedCmp4=0}           => {MntSweet_Category=High} 0.05134030  0.6807229 0.07542026 2.759247
```



Gold Rules

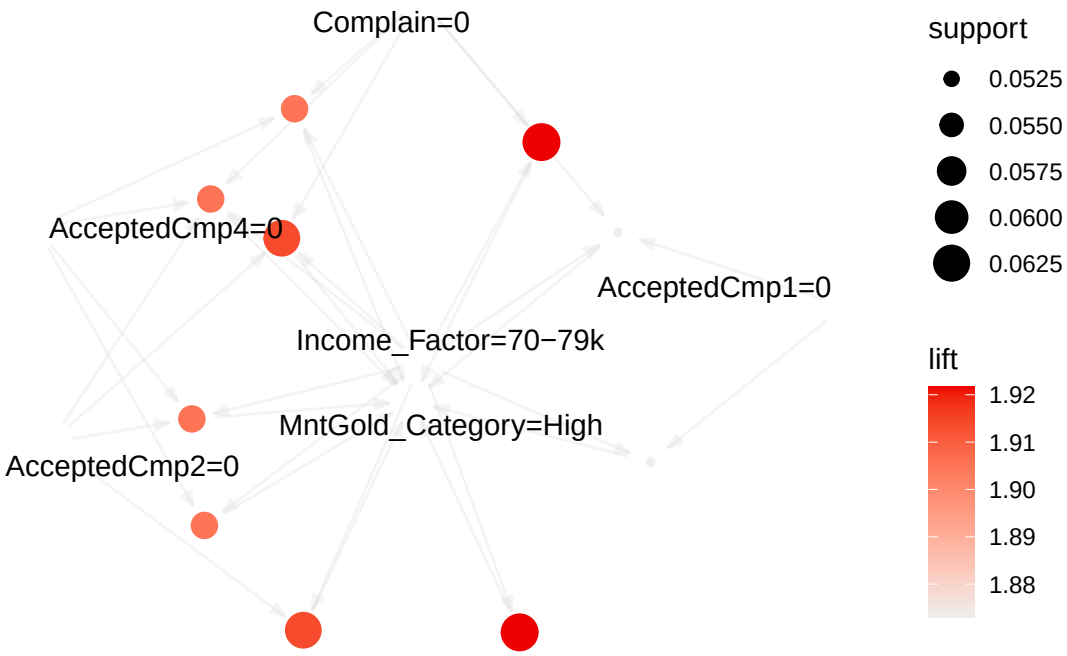
When sorting by lift, the most common association is that they have an income between $70-79k; however, much like with sweets, the confidence in these associations leading to high spenders in gold is below 50%.

```
##   0%  25%  50%  75% 100%
##    0    9   25   56  321
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.3    0.1    1 none FALSE            TRUE       5    0.05      1
##  maxlen target  ext
##       5  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 110
##
## set item appearances ...[1 item(s)] done [0.00s].
## set transactions ...[54 item(s), 2201 transaction(s)] done [0.00s].
## sorting and recoding items ... [44 item(s)] done [0.00s].
```

```
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 5 done [0.02s].
## writing ... [295 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

```
##     lhs                          rhs                          support confidence  coverage     lift coun
## [1] {Income_Factor=70-79k}    => {MntGold_Category=High} 0.06315311  0.4793103 0.1317583 1.921607   13
## [2] {Income_Factor=70-79k,
##      Complain=0}              => {MntGold_Category=High} 0.06315311  0.4793103 0.1317583 1.921607   13
## [3] {Income_Factor=70-79k,
##      AcceptedCmp2=0}          => {MntGold_Category=High} 0.06224443  0.4773519 0.1303953 1.913755   13
## [4] {Income_Factor=70-79k,
##      Complain=0,
##      AcceptedCmp2=0}          => {MntGold_Category=High} 0.06224443  0.4773519 0.1303953 1.913755   13
## [5] {Income_Factor=70-79k,
##      AcceptedCmp4=0}          => {MntGold_Category=High} 0.05633803  0.4750958 0.1185825 1.904710   12
```



Conclusion

Given the disparity of income and spending across clusters and product categories, a price sensitivity analysis should be conducted to determine how effective the item offerings are translating to sales. By the percentages, members of all clusters are purchasing products across all product categories; as such, the business should acknowledge the size of the clusters and the potential that they might not be offering products at the correct price point to entice the sales across their customer base. Additionally, deal purchases are highest around

the mean income; to further drive sales, promotional offerings need to be more directly targeted at the consumers with respect to their cluster and income. The high earners and spenders of Cluster 1 show to not be interacting with the web design despite each customer spending, on average, just over $1300. By redesigning the website to be more catering to their needs, the duration since their last purchase can be shortened and perhaps, increase in frequency as they would not be waiting on catalog mail before purchasing. Additionally, with the more price sensitive/income limited customers in clusters 2 and 3, we see the largest volume of deals purchased. A limited deal of a lower priced luxury item could be offered to spur sales from them. This maintains brand image and does not dilute quality, while maintaining an active customer base. Tailored campaigns focusing on essential products and cost-saving offers could better engage low-income customers, enhancing their loyalty and satisfaction.