Report

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1. Introduction

Problem Statement:

Customer Personality Analysis is a detailed analysis of a company's ideal customers. It helps a business to better understand its customers and makes it easier for them to modify products according to the specific needs, behaviors and concerns of different types of customers. Customer personality analysis helps a business to modify its product based on its target customers from different types of customer segments. For example, instead of spending money to market a new product to every customer in the company's database, a company can analyze which customer segment is most likely to buy the product and then market the product only on that particular segment.

The crux of analyzing customer personalities lies in uncovering the responses to queries such as:

1. What individuals express about your product: this sheds light on the customers' perceptions and feelings about the item.
2. What individuals engage in: this uncovers the actual behaviors of people concerning your product, as opposed to their stated opinions.

Data description:

The marketing dataset comprises 2,240 rows and 29 columns, encapsulating essential attributes across product, people, promotion, and place domains. Product attributes include unique identifiers, product categories, features and prices . People attributes encompass customer identifiers, demographic details like age, gender, income, education, alongside preferences and segmentation data.

Total Observations : 2240 Null Observations : 24 Final Dataset : 2216

Source of the data:

https://www.kaggle.com/datasets/imakash3011/customer-personality-analysis

The Data:

THe datset contains 29 features, ID, Year_Birth, Education, Marital_Status, Income, Kidhome, Teenhome, Dt_Customer,Recency, MntWines, MntFruits, MntMeatProducts, MntFishProducts etc.

People:

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

Products:

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

Promotion:

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

Place:

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

2.Data Analysis

Our initial data exploration will involve analyzing each column of the dataset to understand its characteristics. We will utilize R's summary function to obtain a statistical overview of each variable.

```
corrplot 0.92 loaded
```

```
-- Attaching core tidyverse packages ----------------------- tidyverse 2.0.0 --
v dplyr     1.1.3     v readr     2.1.5
v forcats   1.0.0     v stringr   1.5.0
v lubridate 1.9.3     v tibble    3.2.1
v purrr     1.0.2     v tidyr     1.3.0
-- Conflicts ------------------------------------------ tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to beco
Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa

Loading required package: lattice


Attaching package: 'caret'


The following object is masked from 'package:purrr':

    lift
```

```r
head(data)
```

```
  X   ID Year_Birth  Education Marital_Status Income Kidhome Teenhome
1 1 5524       1957 Graduation         Single  58138       0        0
2 2 2174       1954 Graduation         Single  46344       1        1
3 3 4141       1965 Graduation       Together  71613       0        0
4 4 6182       1984 Graduation       Together  26646       1        0
5 5 5324       1981        PhD        Married  58293       1        0
6 6 7446       1967     Master       Together  62513       0        1
  Dt_Customer Recency MntWines MntFruits MntMeatProducts MntFishProducts
1  2012-09-04      58      635        88             546             172
2  2014-03-08      38       11         1               6               2
3  2013-08-21      26      426        49             127             111
4  2014-02-10      26       11         4              20              10
5  2014-01-19      94      173        43             118              46
6  2013-09-09      16      520        42              98               0
  MntSweetProducts MntGoldProds NumDealsPurchases NumWebPurchases
1               88           88                 3               8
2                1            6                 2               1
3               21           42                 1               8
4                3            5                 2               2
```

```
5               27           15                5               5
6               42           14                2               6
  NumCatalogPurchases NumStorePurchases NumWebVisitsMonth AcceptedCmp3
1                  10                 4                 7            0
2                   1                 2                 5            0
3                   2                10                 4            0
4                   0                 4                 6            0
5                   3                 6                 5            0
6                   4                10                 6            0
  AcceptedCmp4 AcceptedCmp5 AcceptedCmp1 AcceptedCmp2 Complain Z_CostContact
1            0            0            0            0        0             3
2            0            0            0            0        0             3
3            0            0            0            0        0             3
4            0            0            0            0        0             3
5            0            0            0            0        0             3
6            0            0            0            0        0             3
  Z_Revenue Response
1        11        1
2        11        0
3        11        0
4        11        0
5        11        0
6        11        0
```

```
dim(data)
```

```
[1] 2216   30
```

```
summary(data)
```

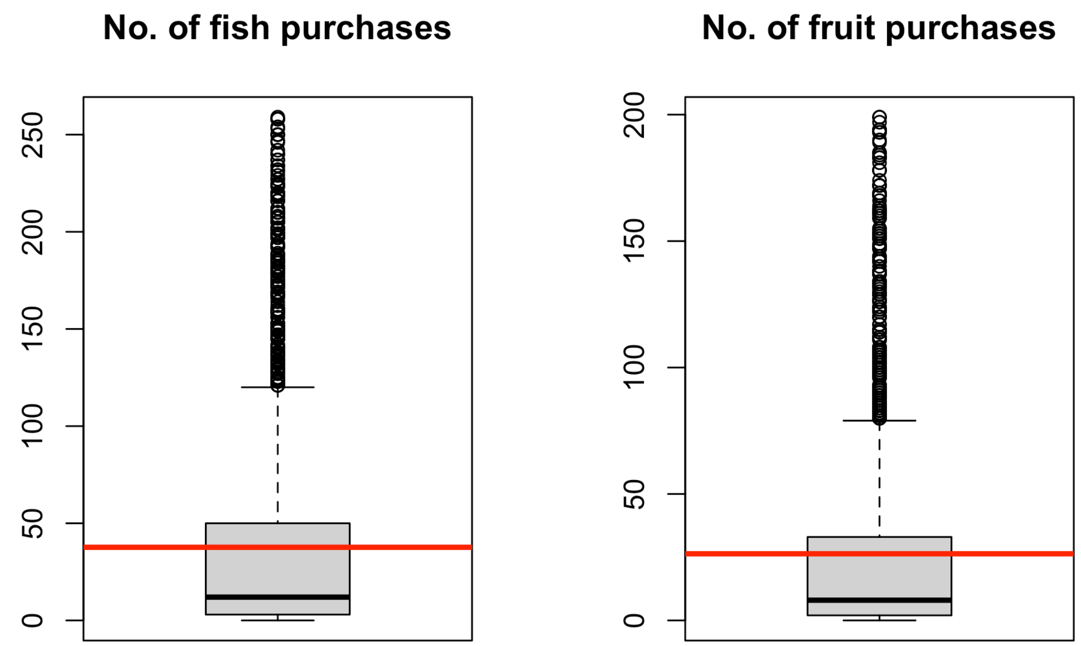
```
       X                ID          Year_Birth    Education        
 Min.   :   1.0   Min.   :    0   Min.   :1893   Length:2216       
 1st Qu.: 554.8   1st Qu.: 2815   1st Qu.:1959   Class :character  
 Median :1108.5   Median : 5458   Median :1970   Mode  :character  
 Mean   :1108.5   Mean   : 5588   Mean   :1969                     
 3rd Qu.:1662.2   3rd Qu.: 8422   3rd Qu.:1977                     
 Max.   :2216.0   Max.   :11191   Max.   :1996                     
 Marital_Status         Income         Kidhome          Teenhome     
 Length:2216        Min.   :  1730   Min.   :0.0000   Min.   :0.0000  
 Class :character   1st Qu.: 35303   1st Qu.:0.0000   1st Qu.:0.0000  
 Mode  :character   Median : 51382   Median :0.0000   Median :0.0000  
```

```
                   Mean   : 52247   Mean   :0.4418   Mean   :0.5054
                   3rd Qu.: 68522   3rd Qu.:1.0000   3rd Qu.:1.0000
                   Max.   :666666   Max.   :2.0000   Max.   :2.0000
Dt_Customer           Recency         MntWines        MntFruits
Length:2216        Min.   : 0.00   Min.   :   0.0   Min.   :  0.00
Class :character   1st Qu.:24.00   1st Qu.:  24.0   1st Qu.:  2.00
Mode  :character   Median :49.00   Median : 174.5   Median :  8.00
                   Mean   :49.01   Mean   : 305.1   Mean   : 26.36
                   3rd Qu.:74.00   3rd Qu.: 505.0   3rd Qu.: 33.00
                   Max.   :99.00   Max.   :1493.0   Max.   :199.00
MntMeatProducts  MntFishProducts  MntSweetProducts  MntGoldProds
Min.   :   0.0   Min.   :  0.00   Min.   :  0.00   Min.   :  0.00
1st Qu.:  16.0   1st Qu.:  3.00   1st Qu.:  1.00   1st Qu.:  9.00
Median :  68.0   Median : 12.00   Median :  8.00   Median : 24.50
Mean   : 167.0   Mean   : 37.64   Mean   : 27.03   Mean   : 43.97
3rd Qu.: 232.2   3rd Qu.: 50.00   3rd Qu.: 33.00   3rd Qu.: 56.00
Max.   :1725.0   Max.   :259.00   Max.   :262.00   Max.   :321.00
NumDealsPurchases NumWebPurchases  NumCatalogPurchases NumStorePurchases
Min.   : 0.000    Min.   : 0.000   Min.   : 0.000      Min.   : 0.000
1st Qu.: 1.000    1st Qu.: 2.000   1st Qu.: 0.000      1st Qu.: 3.000
Median : 2.000    Median : 4.000   Median : 2.000      Median : 5.000
Mean   : 2.324    Mean   : 4.085   Mean   : 2.671      Mean   : 5.801
3rd Qu.: 3.000    3rd Qu.: 6.000   3rd Qu.: 4.000      3rd Qu.: 8.000
Max.   :15.000    Max.   :27.000   Max.   :28.000      Max.   :13.000
NumWebVisitsMonth  AcceptedCmp3      AcceptedCmp4      AcceptedCmp5
Min.   : 0.000    Min.   :0.00000   Min.   :0.00000   Min.   :0.0000
1st Qu.: 3.000    1st Qu.:0.00000   1st Qu.:0.00000   1st Qu.:0.0000
Median : 6.000    Median :0.00000   Median :0.00000   Median :0.0000
Mean   : 5.319    Mean   :0.07356   Mean   :0.07401   Mean   :0.0731
3rd Qu.: 7.000    3rd Qu.:0.00000   3rd Qu.:0.00000   3rd Qu.:0.0000
Max.   :20.000    Max.   :1.00000   Max.   :1.00000   Max.   :1.0000
 AcceptedCmp1      AcceptedCmp2        Complain         Z_CostContact
Min.   :0.00000   Min.   :0.00000   Min.   :0.000000   Min.   :3
1st Qu.:0.00000   1st Qu.:0.00000   1st Qu.:0.000000   1st Qu.:3
Median :0.00000   Median :0.00000   Median :0.000000   Median :3
Mean   :0.06408   Mean   :0.01354   Mean   :0.009477   Mean   :3
3rd Qu.:0.00000   3rd Qu.:0.00000   3rd Qu.:0.000000   3rd Qu.:3
Max.   :1.00000   Max.   :1.00000   Max.   :1.000000   Max.   :3
  Z_Revenue     Response
Min.   :11   Min.   :0.0000
1st Qu.:11   1st Qu.:0.0000
Median :11   Median :0.0000
```

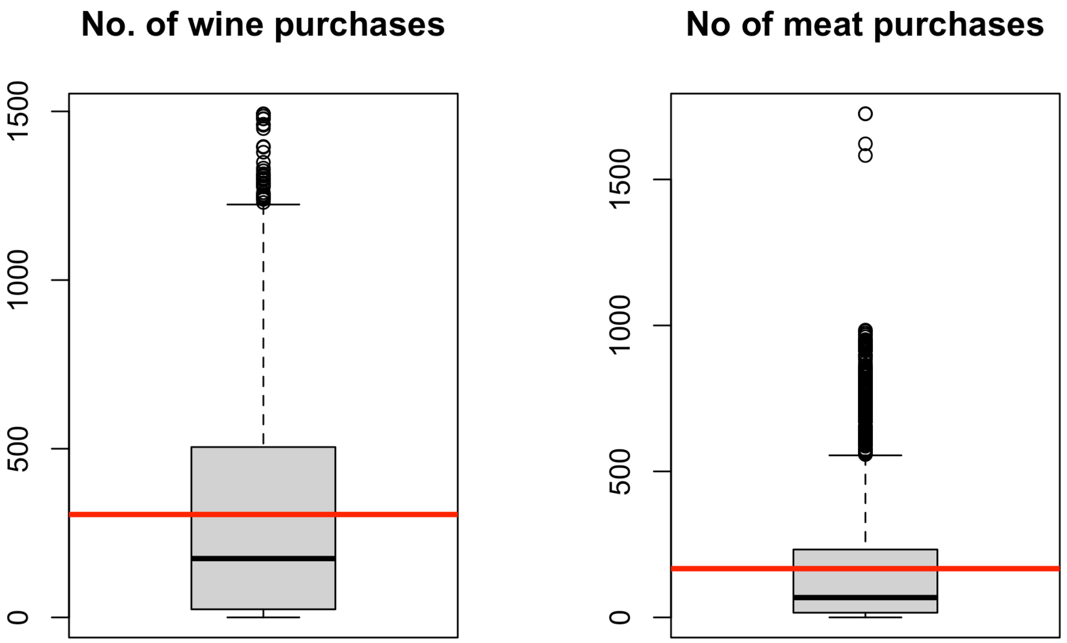
```
 Mean   :11   Mean   :0.1503
 3rd Qu.:11   3rd Qu.:0.0000
 Max.   :11   Max.   :1.0000
```

2.1 Food Item Analysis

This section delves into the exploration of four food item categories in our dataset: wine, meat, fish, and fruit. We focus on identifying outliers and data distribution within these categories using boxplots.



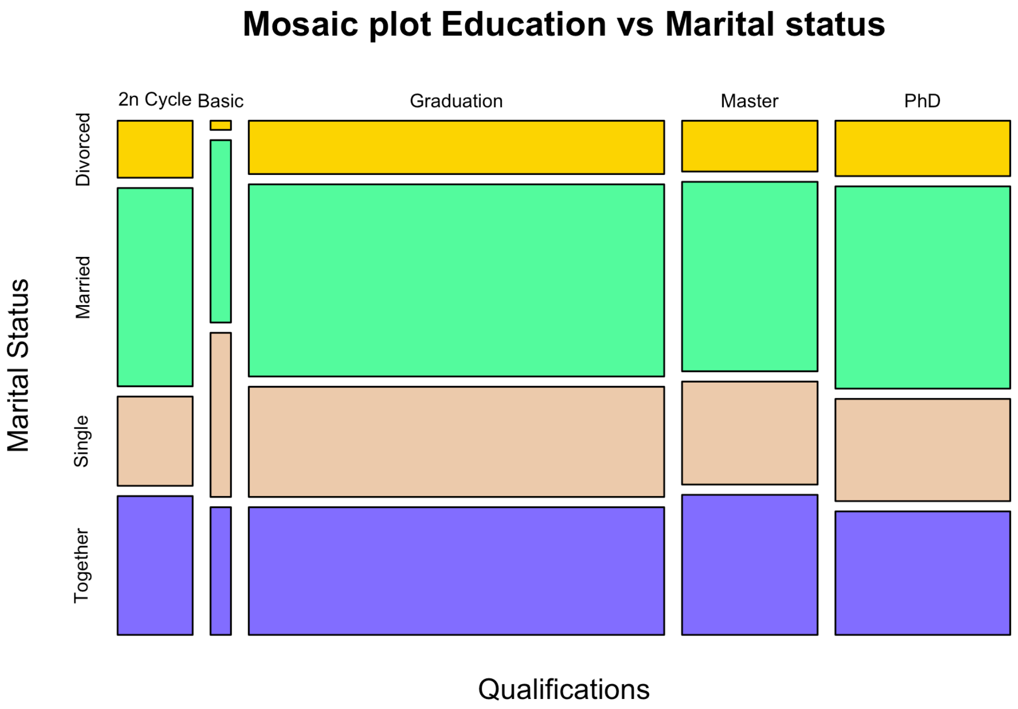
Our analysis revealed a significant presence of outliers in all four food item categories based on the boxplots. The boxes within the plots represent the interquartile range (IQR), encompassing the middle 50% of the data. Values falling outside the whiskers extending from the boxes are considered potential outliers. **We have made a horizontal red line along mean and which clearly shows that our mean and median differ from each other quite a bit in each food items.**



2.2 Mosaic Plots and Our Data

In this case, the mosaic plot will depict the proportion of individuals within each education level category (e.g. 2nd cycle, basic, graduation, masters, PhD) segmented by their marital status (e.g., married, single, together, divorced). The size of each rectangle will visually represent the percentage of people in that specific education level and marital status combination.

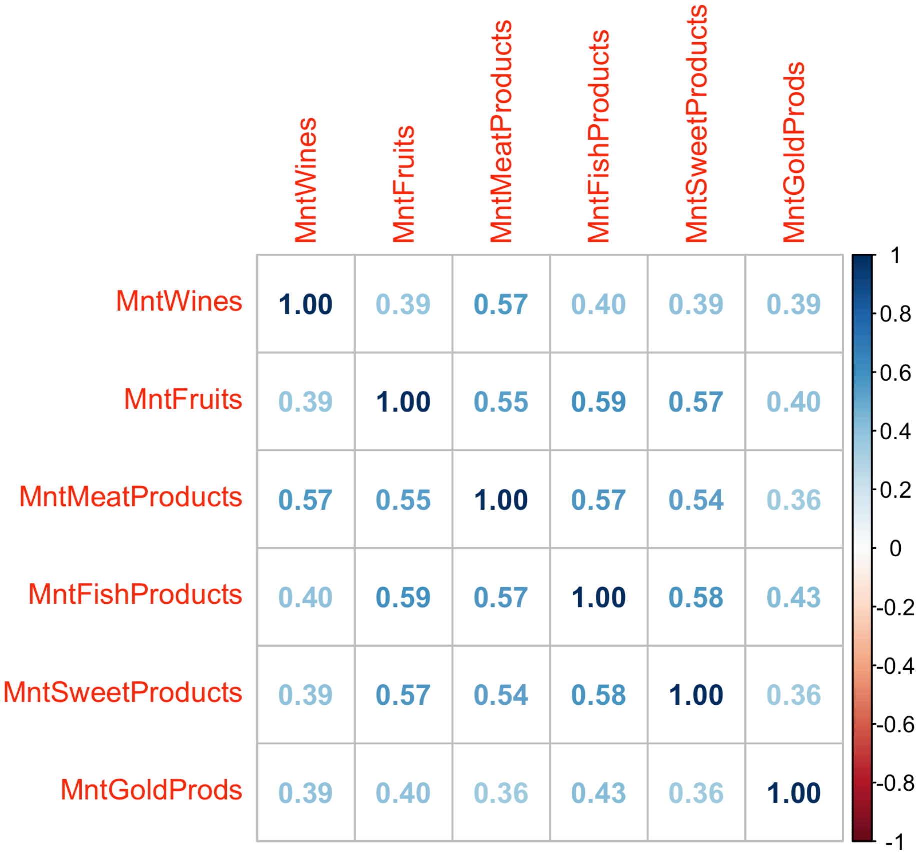
```
             Absurd Alone Divorced Married Single Together Widow YOLO
  2n Cycle        0     0       23      80     36       56     5    0
  Basic           0     0        1      20     18       14     1    0
  Graduation      1     1      119     429    246      285    35    0
  Master          1     1       37     138     75      102    11    0
  PhD             0     1       52     190     96      116    24    2
```


Mosaic plot Education vs Marital status
2n Cycle
Basic
Graduation
Master
PhD
Divorced
Married
Single
Together
Marital Status
Qualifications

2.3 Correlation Plot

2.3.1 Plot 1: Correlations Between All Products

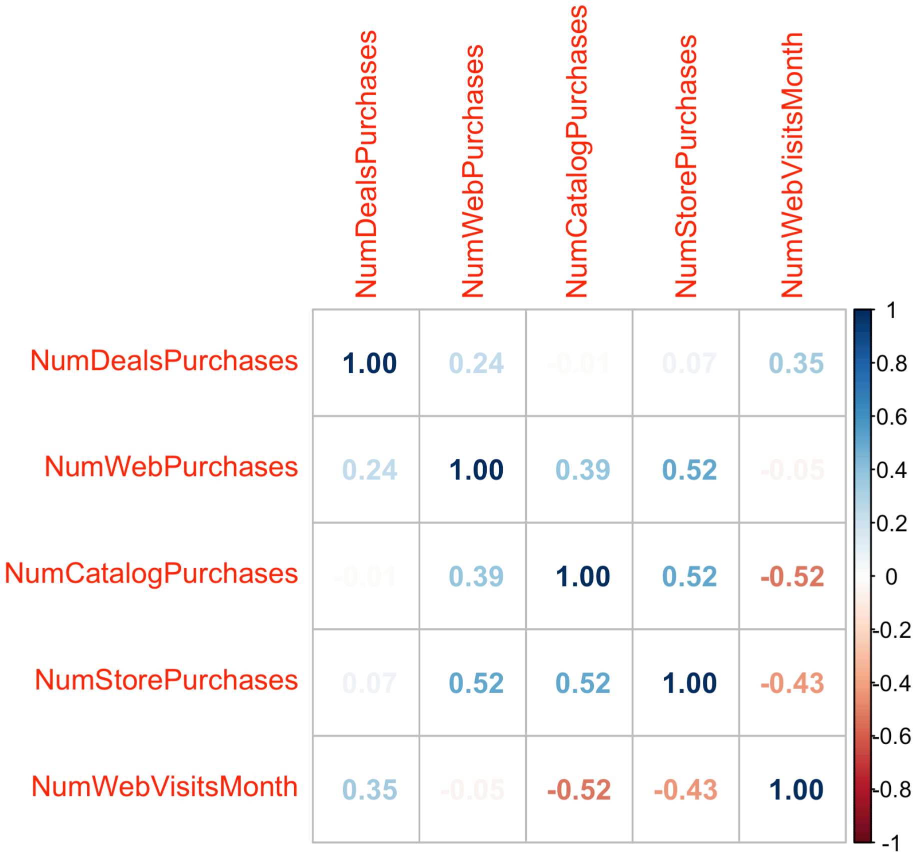
This correlation plot reveals a positive correlation (likely depicted by blue color) between all the products, including seats, fruits, wine, meat, fish, and gold. Positive correlation signifies that when the value of one product increases, the values of other products tend to increase as well, and vice versa.



	MntWines	MntFruits	MntMeatProducts	MntFishProducts	MntSweetProducts	MntGoldProds
MntWines	1.00	0.39	0.57	0.40	0.39	0.39
MntFruits	0.39	1.00	0.55	0.59	0.57	0.40
MntMeatProducts	0.57	0.55	1.00	0.57	0.54	0.36
MntFishProducts	0.40	0.59	0.57	1.00	0.58	0.43
MntSweetProducts	0.39	0.57	0.54	0.58	1.00	0.36
MntGoldProds	0.39	0.40	0.36	0.43	0.36	1.00

2.3.2 Plot 2: Correlations Between Purchase Sources

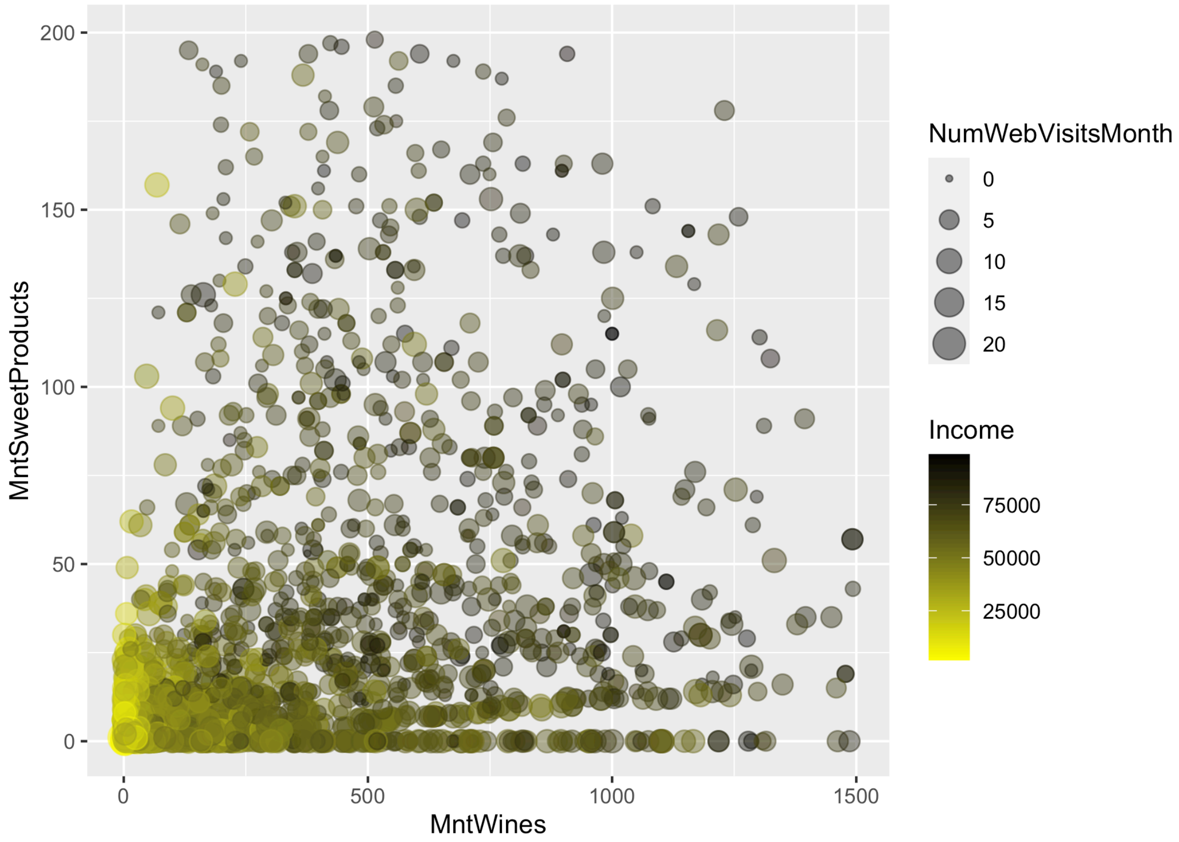
This correlation plot examines the relationship between purchase sources, such as web, catalog, store, and potentially others. **We can see a negative correlation between the Number of web visits and (Number of store and catalog purchases) and we can infer from it that tech savvy people prefer less to go physically to stores**



	NumDealsPurchases	NumWebPurchases	NumCatalogPurchases	NumStorePurchases	NumWebVisitsMonth
NumDealsPurchases	1.00	0.24	-0.01	0.07	0.35
NumWebPurchases	0.24	1.00	0.39	0.52	-0.05
NumCatalogPurchases	-0.01	0.39	1.00	0.52	-0.52
NumStorePurchases	0.07	0.52	0.52	1.00	-0.43
NumWebVisitsMonth	0.35	-0.05	-0.52	-0.43	1.00

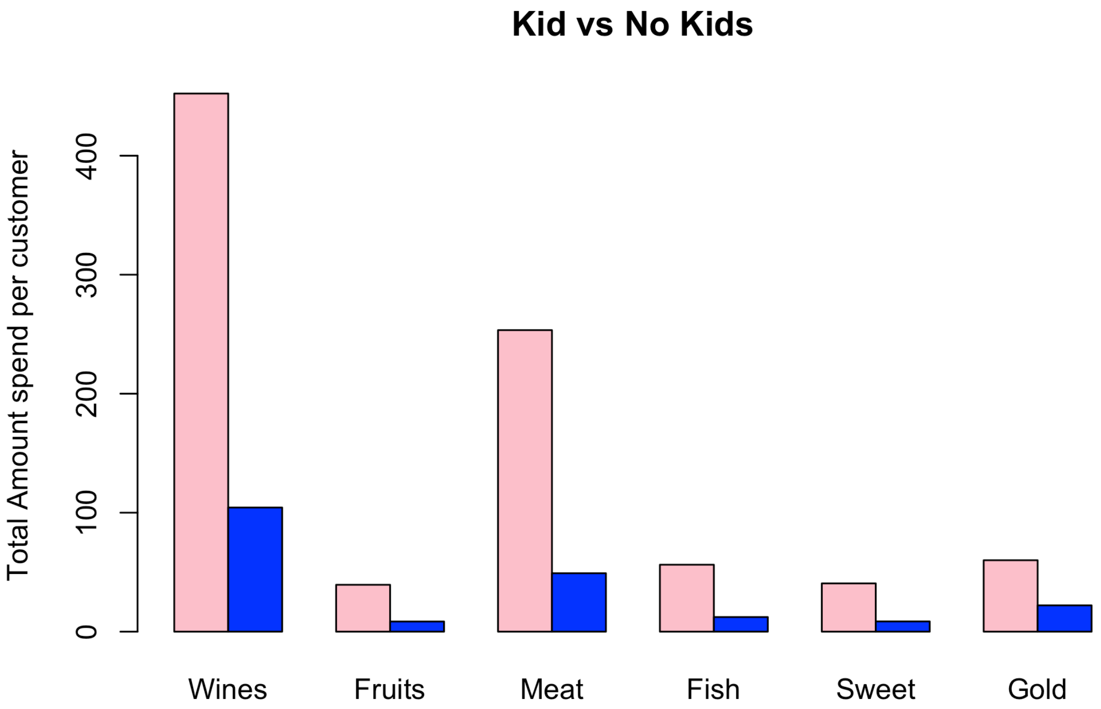
2.4 Scatter plot between premium products

Another analysis is using scatter plot where we can see that the buyers of the premium products of company like sweets and Wines have more income (Black color). And people with less income(Yellow color) didn't buy these products.



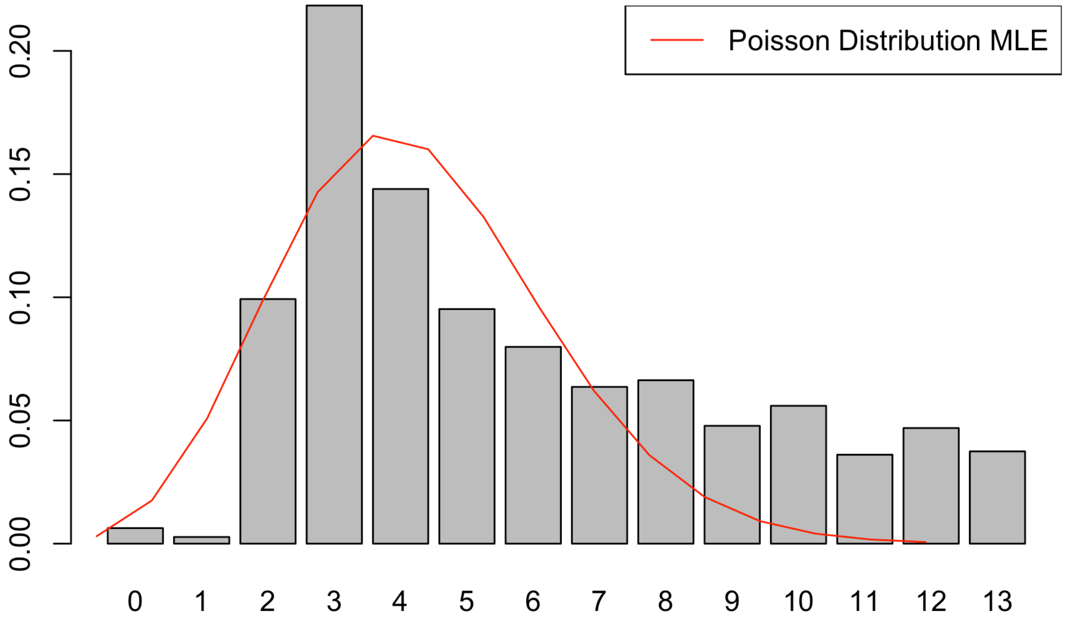
2.5 Amount spend on products (Kid vs No Kid)

his analysis show the total expenditure per customer for different products and with category kid vs no kid. It can be clearly seen that customer who have kids at their home spend more in every product category.

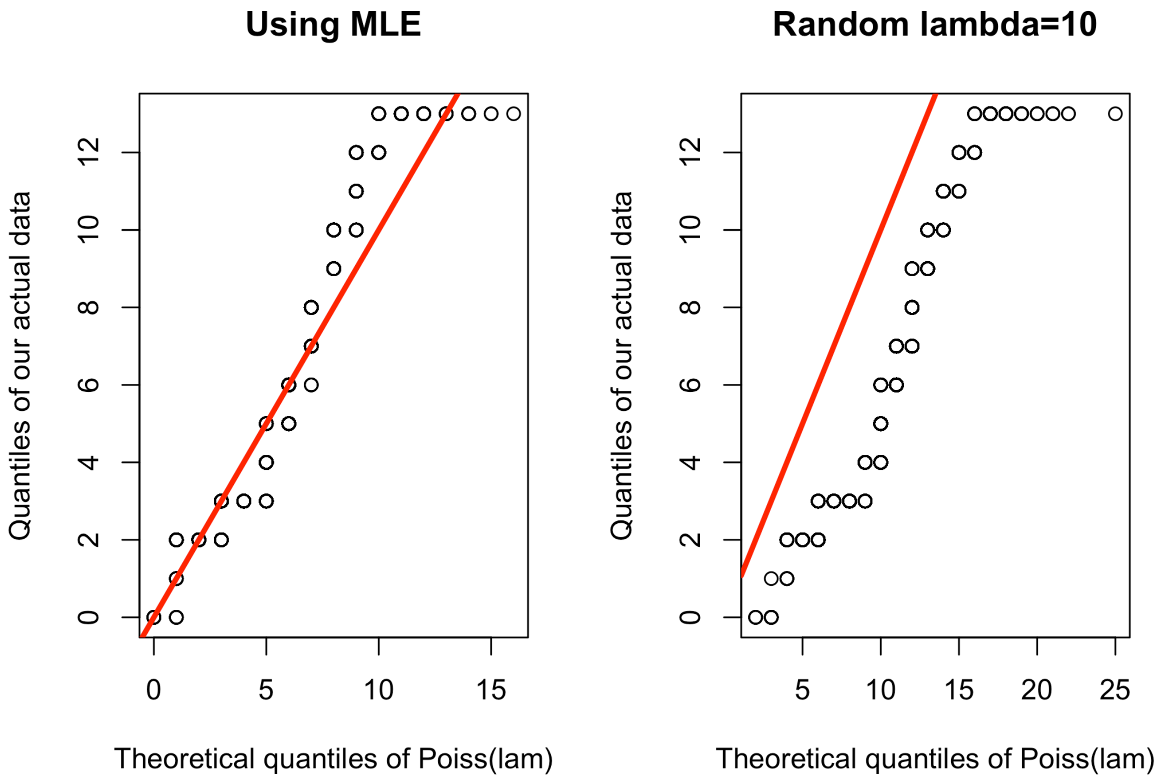


3. Maximum Likelihood Estimator

Now we tried to estimate our one of the variable NumStorePurchases using MLE. First we saw it's frequency shape using a histogram. And since it's a discrete variable. We assumed that they follow poisson distribution which is a good guess. Then using the optim function we found the best value of lambda. Below bar plot shows the density of our columns and red line shows our MLE.



We can check the quality of our estimator using the qqplots. Below we have plotted a QQplot of our data wrt data from MLE. And we can see that mostly points lie on the unit slope line from which we can infer that they are similar in distribution. Whereas when we take the parameter of our distribution randomly let's say 10 then the points doesn't lie on the unit slope line



4. Principal Component Analysis

The data we have was high dimensional data with multiple columns which led to difficulty in organizing and analyzing the various components. We thus used PCA to reduce the dimensionalty of our data.

First step was to clean and filter out the data which was not required. We removed the categorical variables as they were increasing the complexity of the data. Further, we removed the columns with zero variance and the rows with missing values. Following is the head of the cleaned data:

```
  X   ID Year_Birth Income Kidhome Teenhome Recency MntWines MntFruits
1 1 5524       1957  58138       0        0      58      635        88
2 2 2174       1954  46344       1        1      38       11         1
3 3 4141       1965  71613       0        0      26      426        49
4 4 6182       1984  26646       1        0      26       11         4
5 5 5324       1981  58293       1        0      94      173        43
  MntMeatProducts MntFishProducts MntSweetProducts MntGoldProds
1             546             172               88           88
2               6               2                1            6
3             127             111               21           42
```

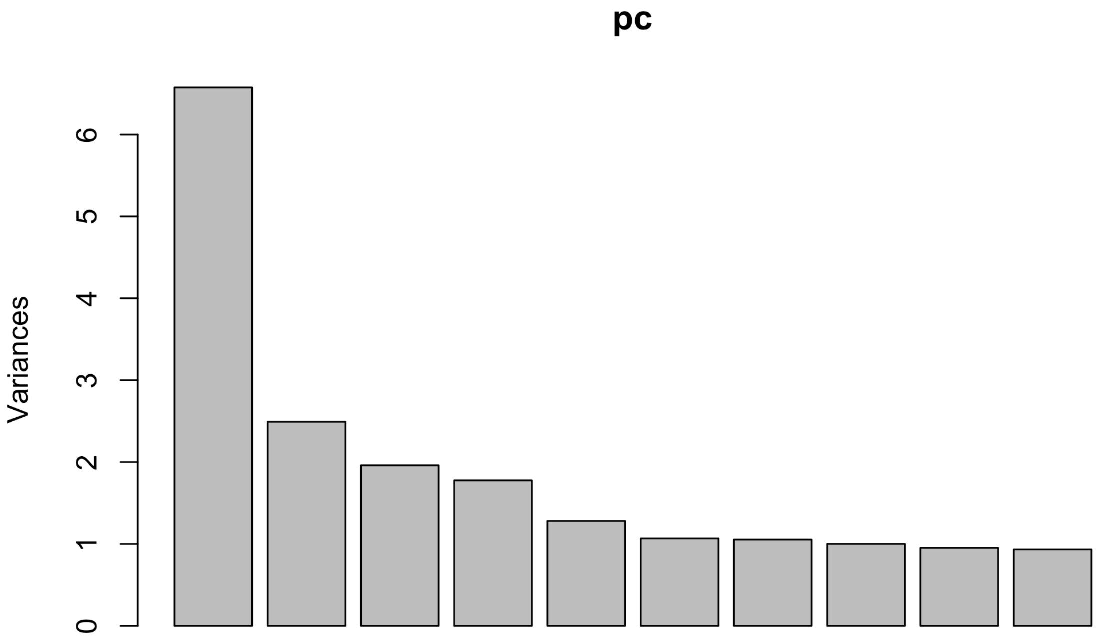
```
4              20              10                3            5
5             118              46               27           15
  NumDealsPurchases NumWebPurchases NumCatalogPurchases NumStorePurchases
1                 3               8                  10                 4
2                 2               1                   1                 2
3                 1               8                   2                10
4                 2               2                   0                 4
5                 5               5                   3                 6
  NumWebVisitsMonth AcceptedCmp3 AcceptedCmp4 AcceptedCmp5 AcceptedCmp1
1                 7            0            0            0            0
2                 5            0            0            0            0
3                 4            0            0            0            0
4                 6            0            0            0            0
5                 5            0            0            0            0
  AcceptedCmp2 Complain Response age_at_enroll days_customer_for
1            0        0        1            55               663
2            0        0        0            60               113
3            0        0        0            48               312
4            0        0        0            30               139
5            0        0        0            33               161
```

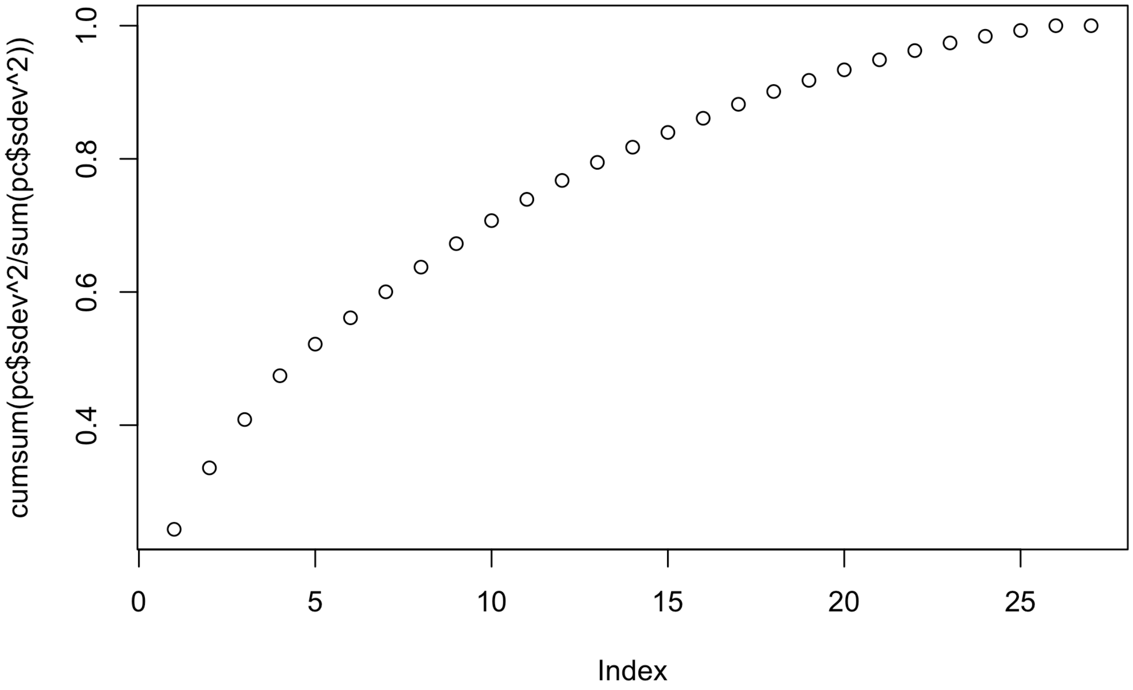
As we can see, there are 27 columns even after cleaning the data, which shows the high dimensionalty.

Then, we performed PCA which gave the following result:

```
Importance of components:
                          PC1     PC2    PC3     PC4     PC5     PC6     PC7
Standard deviation     2.5643 1.57840 1.4001 1.33304 1.13183 1.03342 1.02668
Proportion of Variance 0.2435 0.09227 0.0726 0.06582 0.04745 0.03955 0.03904
Cumulative Proportion  0.2435 0.33581 0.4084 0.47423 0.52168 0.56123 0.60027
                           PC8     PC9    PC10    PC11   PC12    PC13    PC14
Standard deviation     1.00059 0.97605 0.96592 0.92873 0.8757 0.85637 0.78433
Proportion of Variance 0.03708 0.03528 0.03456 0.03195 0.0284 0.02716 0.02278
Cumulative Proportion  0.63735 0.67263 0.70719 0.73914 0.7675 0.79470 0.81749
                          PC15    PC16    PC17    PC18    PC19    PC20    PC21
Standard deviation     0.77386 0.75817 0.75284 0.71983 0.67202 0.65333 0.63793
Proportion of Variance 0.02218 0.02129 0.02099 0.01919 0.01673 0.01581 0.01507
Cumulative Proportion  0.83967 0.86096 0.88195 0.90114 0.91786 0.93367 0.94875
                          PC22    PC23    PC24    PC25   PC26    PC27
Standard deviation     0.61110 0.55780 0.51989 0.48397 0.4410 0.01660
Proportion of Variance 0.01383 0.01152 0.01001 0.00867 0.0072 0.00001
Cumulative Proportion  0.96258 0.97410 0.98411 0.99279 1.0000 1.00000
```

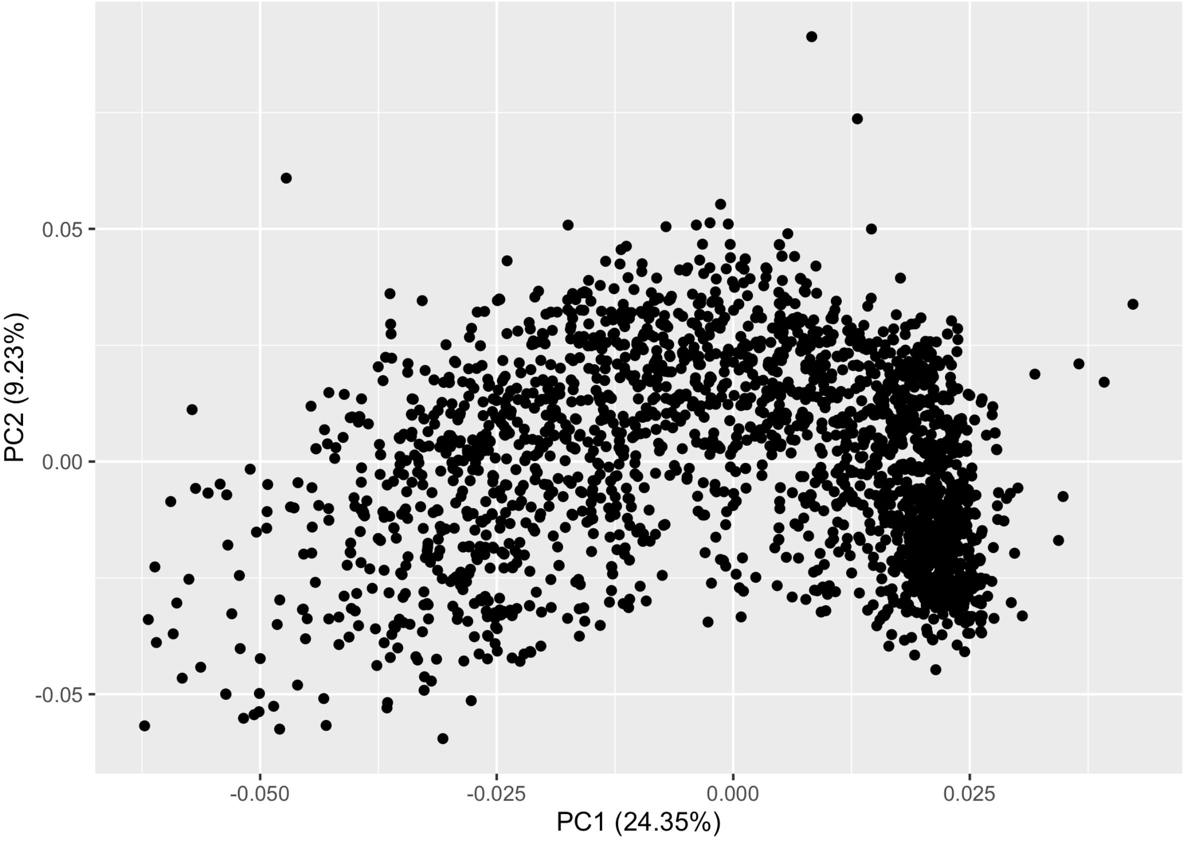
Below is the plot of the PCA analysis and the cumulative variance of the components:





Thus, around 13 components are able to explain 80% variability in the data.

Below is a plot of the relationship between the first two components after PCA.

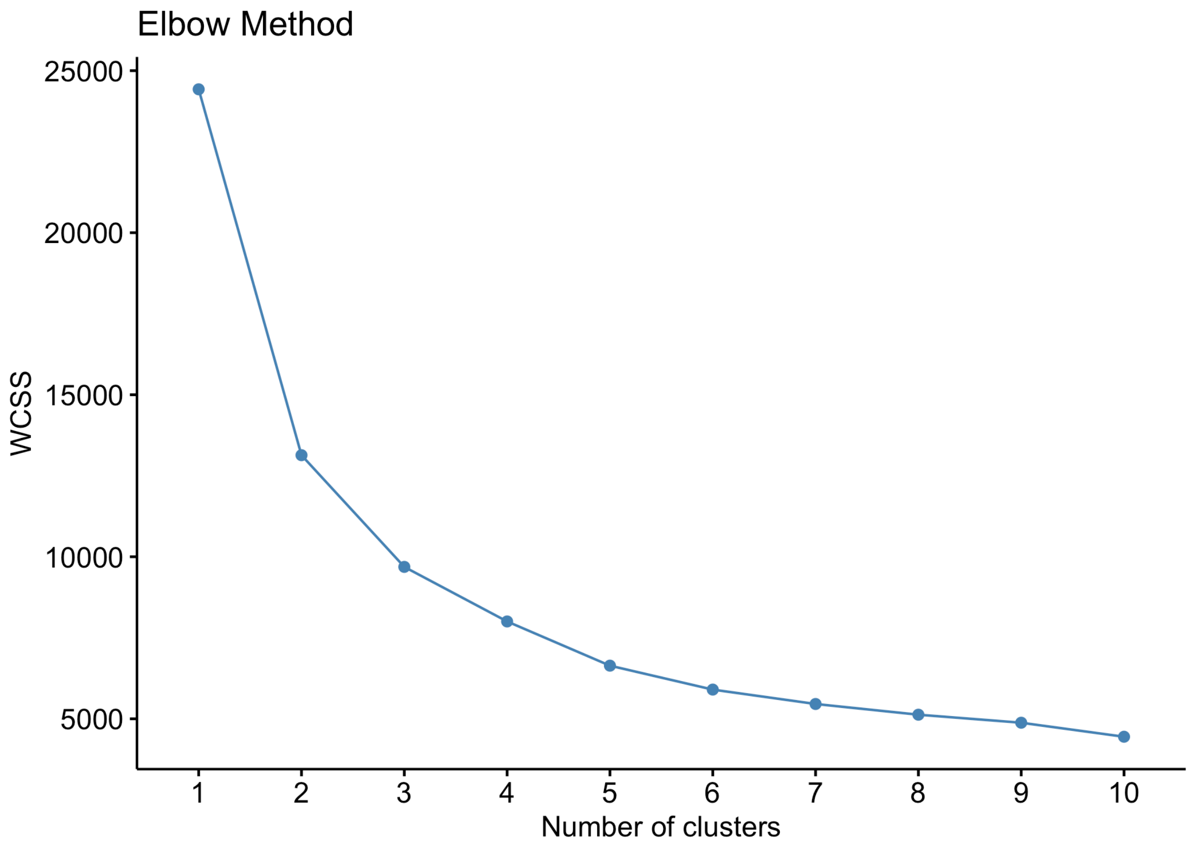


Thus, with the help of PCA we can reduce the data with 27 columns to upto 13 columns and still explain 80% variability in the data.

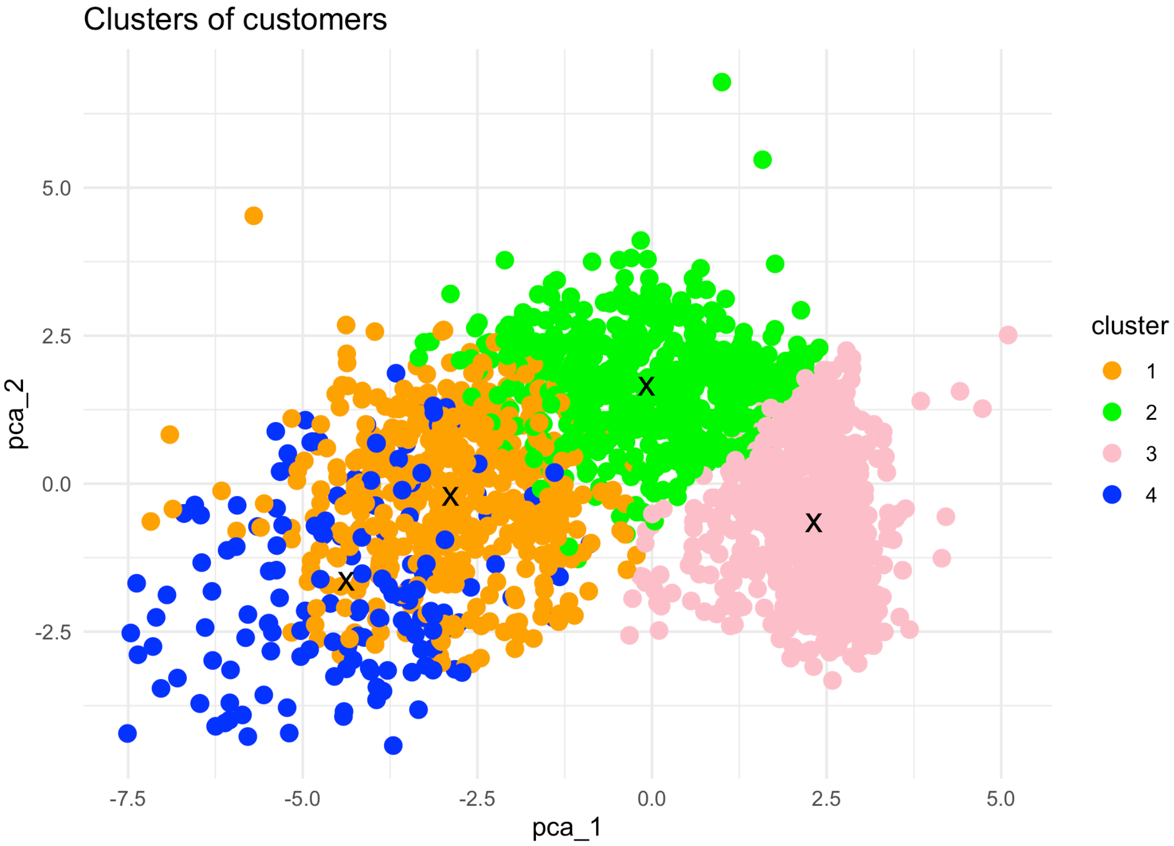
5. K-Means Clustering

After reducing the dimensionality, we moved on to clustering of the data to segment the customers according to their spending behaviors. For clustering, we considered the first 3 components from the PCA reduction.

We first applied the elbow method to find the optimum number of clusters



As is evident from the graph, the optimal number of clusters is 4, as after that there is not a significant reduction in the WCSS even when we increase the number of clusters.



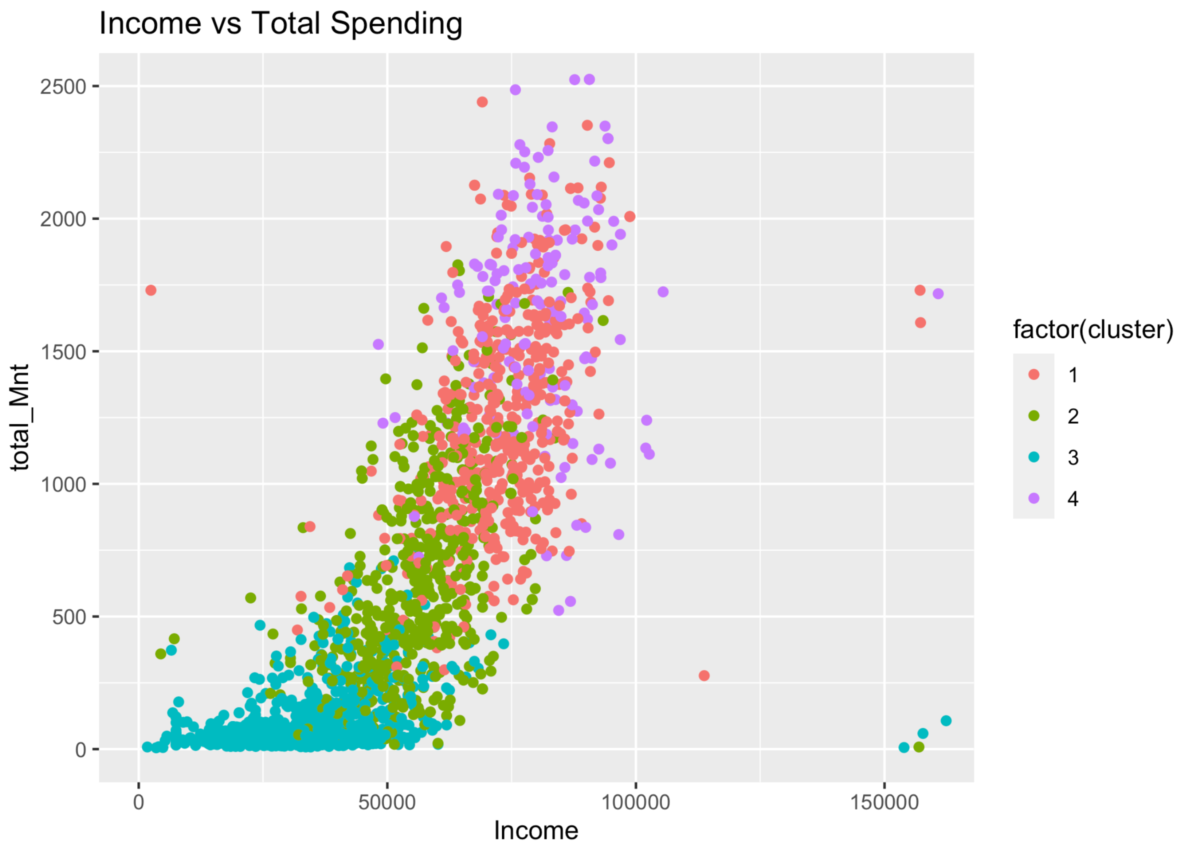
The figure above represents the different clusters of customers based and their relationship with the first and second PCA components.

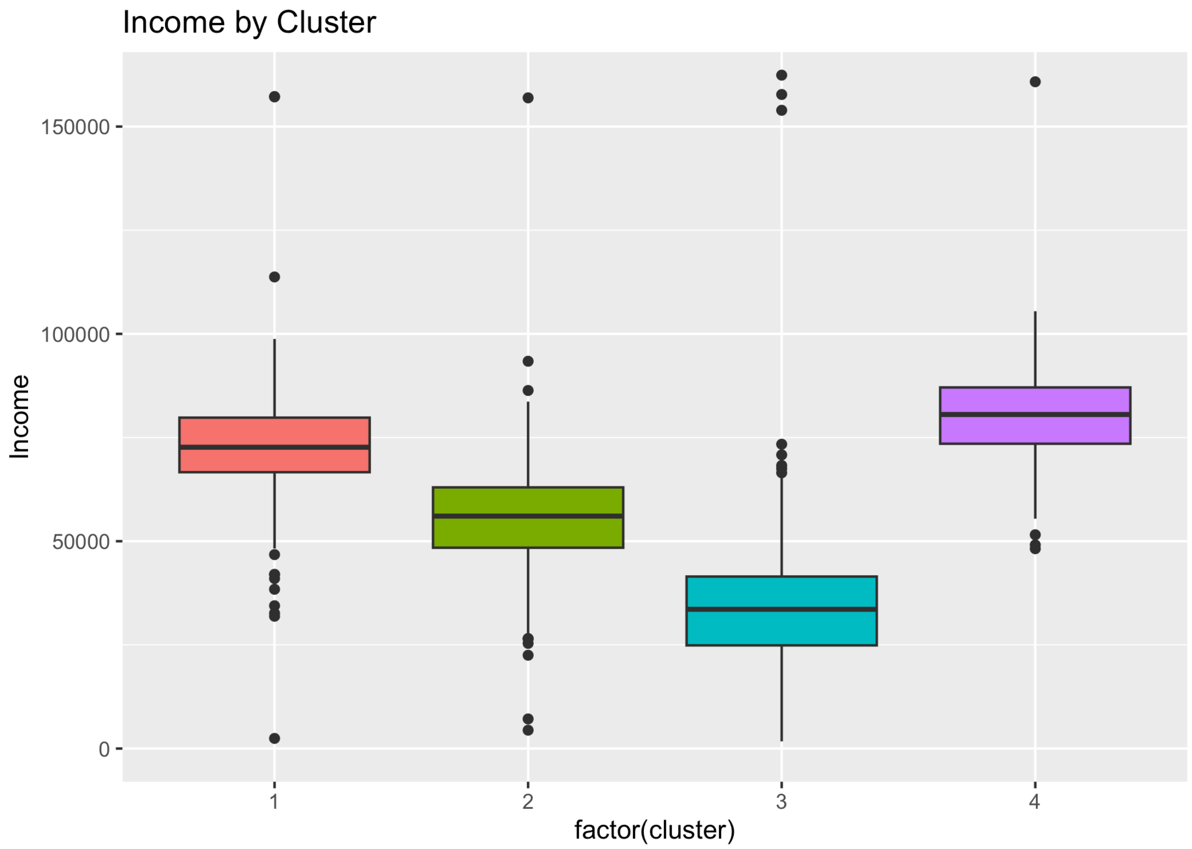
Below we have a summary of the different characteristics of all the different clusters:

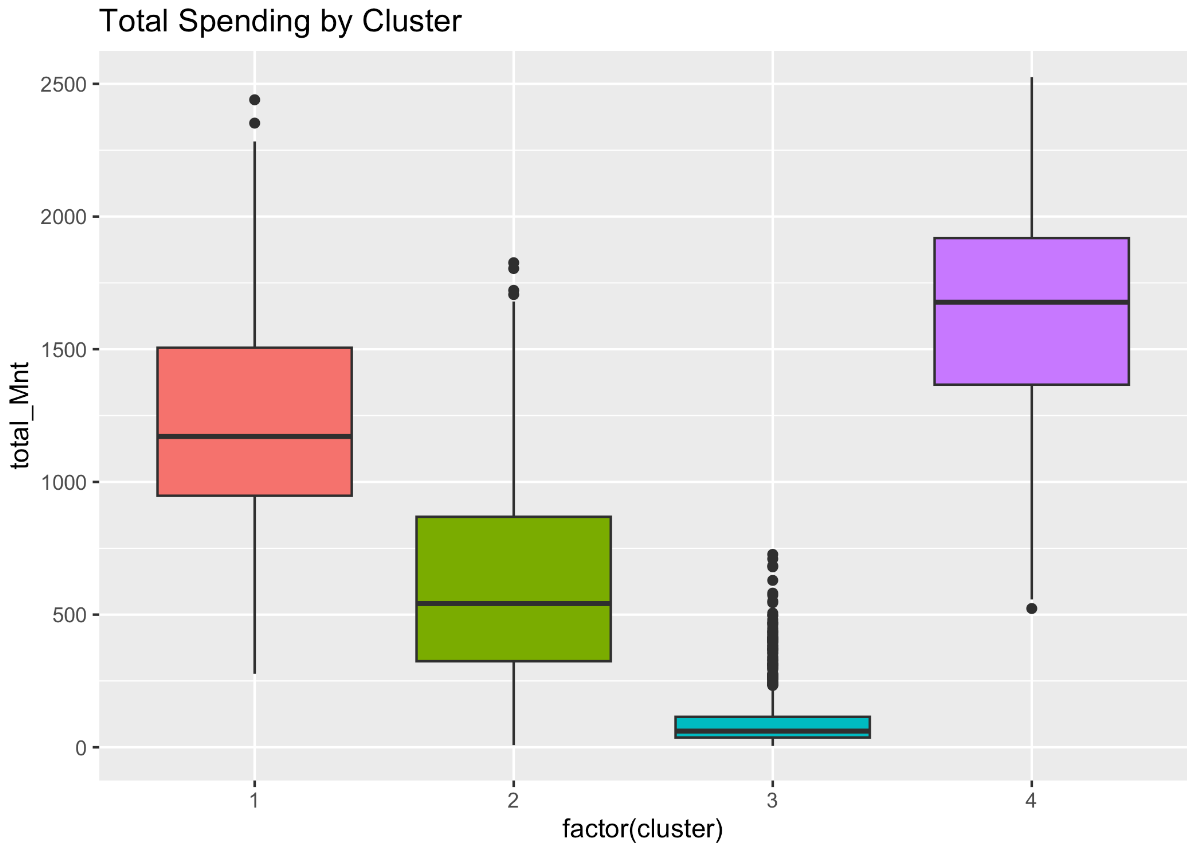
```
                           V1          V2          V3          V4
cluster                     1           2           3           4
Income               72832.08    55567.16    33837.31    80414.98
num_children        0.3299595   1.2112211   1.2286617   0.2108434
Kidhome            0.04858300  0.24752475  0.83667018  0.06024096
Teenhome            0.2813765   0.9636964   0.3919916   0.1506024
num_total_purchases  23.78138    24.80033    14.55427    25.04217
total_Mnt           1228.2146    614.9373    100.0875   1631.5904
```

5.1 Inference on the basis 0f Clusters

5.1.1 Plot 1: Income and Spending Patterns







As is evident by the plots:

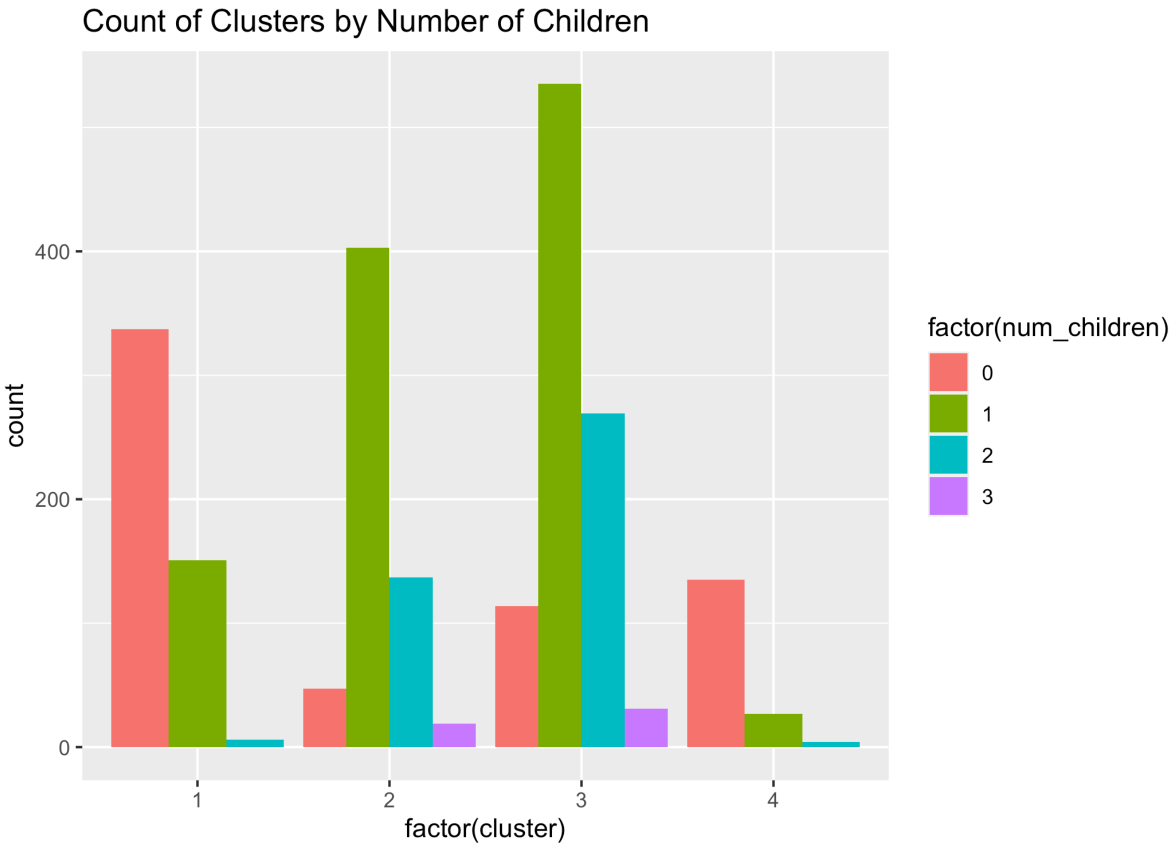
Cluster 1: This cluster is characterised by high income and high spending pattern customers. Their spending ranges from 1000 - 1500 units.

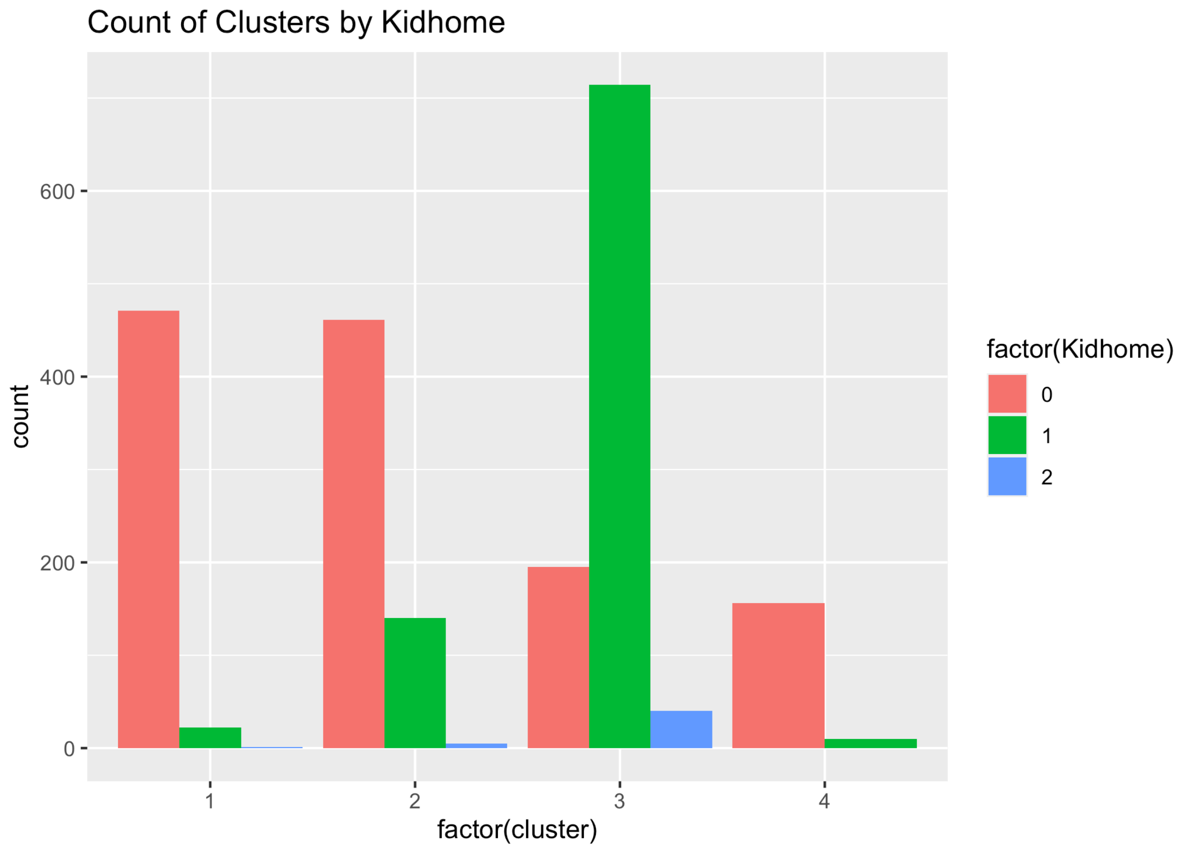
Cluster 2: This cluster is characterized by middle income and middle spending pattern customers. They also have a high variability in spending ranging from around 250 - 800 units.

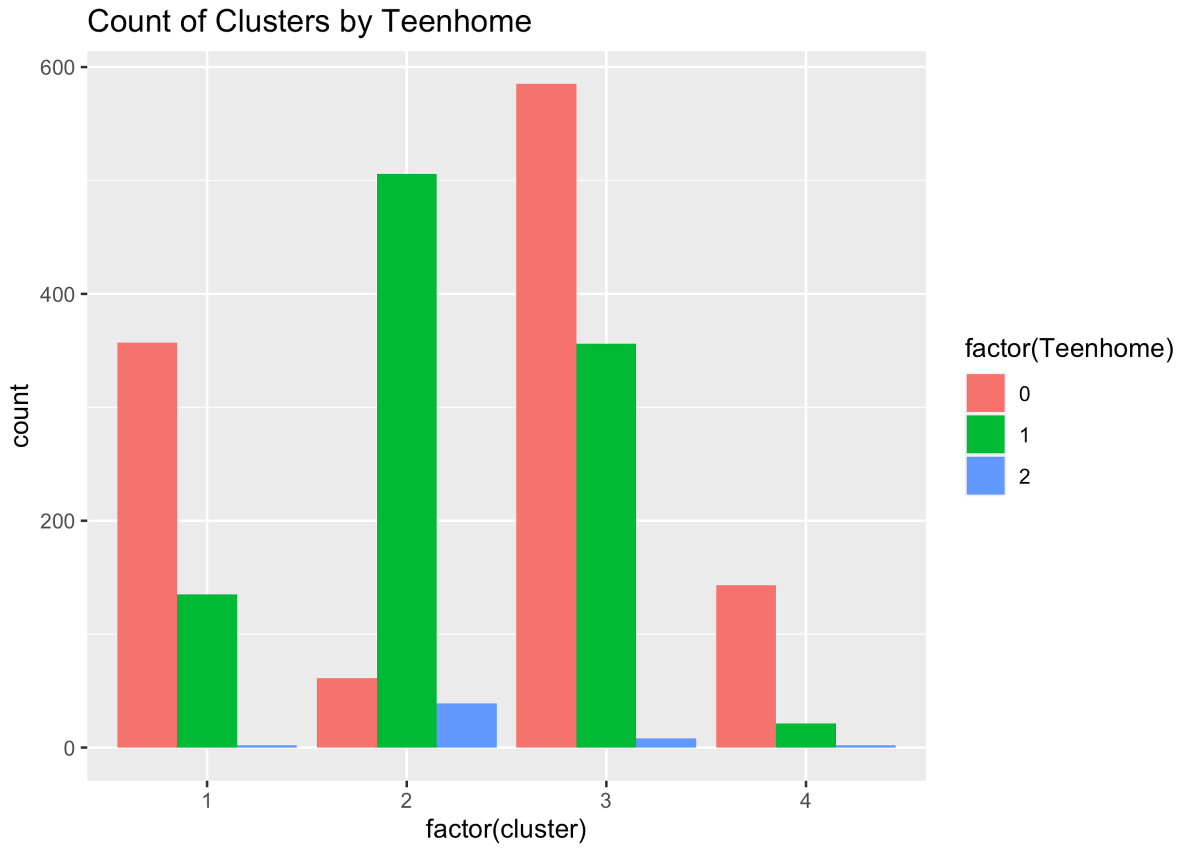
Cluster 3: This cluster contains customers with low income and low spending patterns. They have small variability in spending ranging from just around 10 - 100 units.

Cluster 4: This cluster is characterized by customers with highest income and highest spending patterns. They also have a large variability in spending patterns ranging from around 1400 - 1900 units.

5.1.2 Plot 2: Number of Children







Our analysis reveals distinct clusters based on income, spending habits, and the presence of children within each group:

Cluster 4: Characterized by highest income and high spending, with fewer children on average (0.13), predominantly having one child.

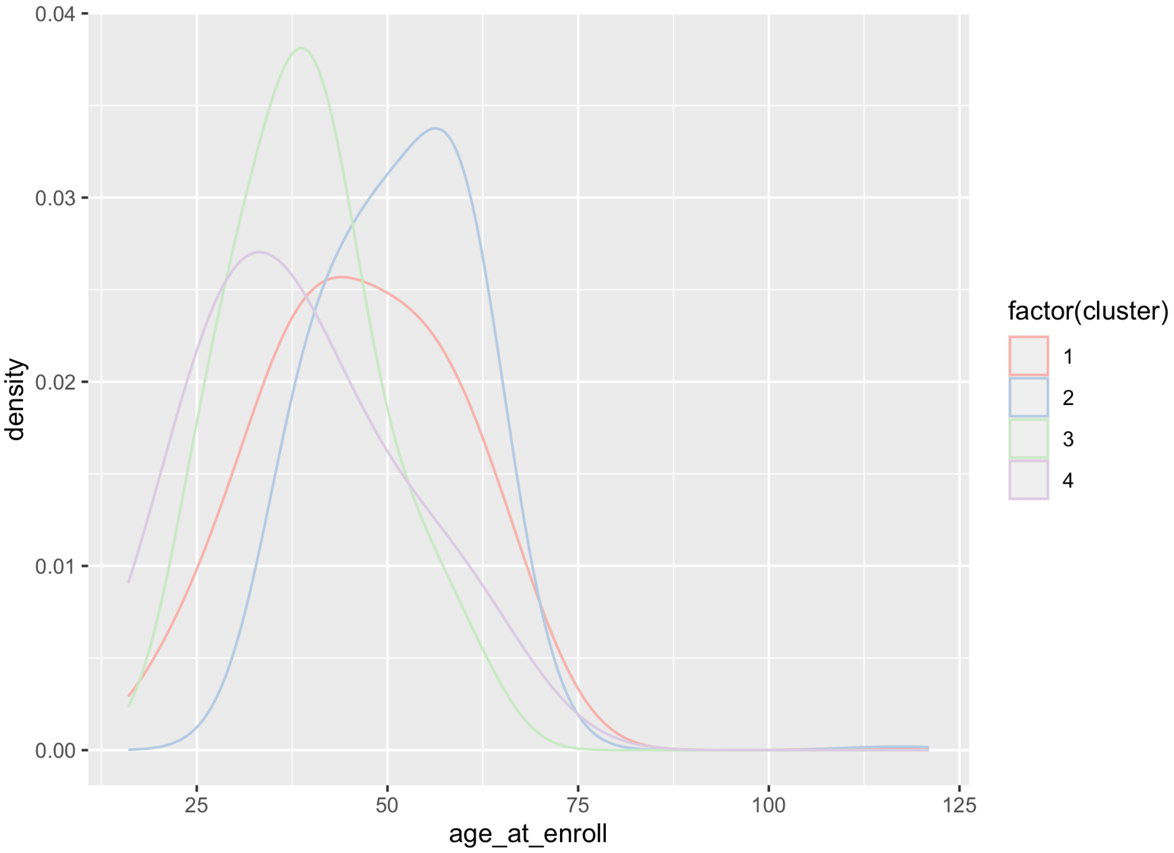
Cluster 1: Represents high-income individuals with moderate spending patterns. This group averages 1.16 children, with a higher proportion of teenagers (0.95) than younger children (0.21).

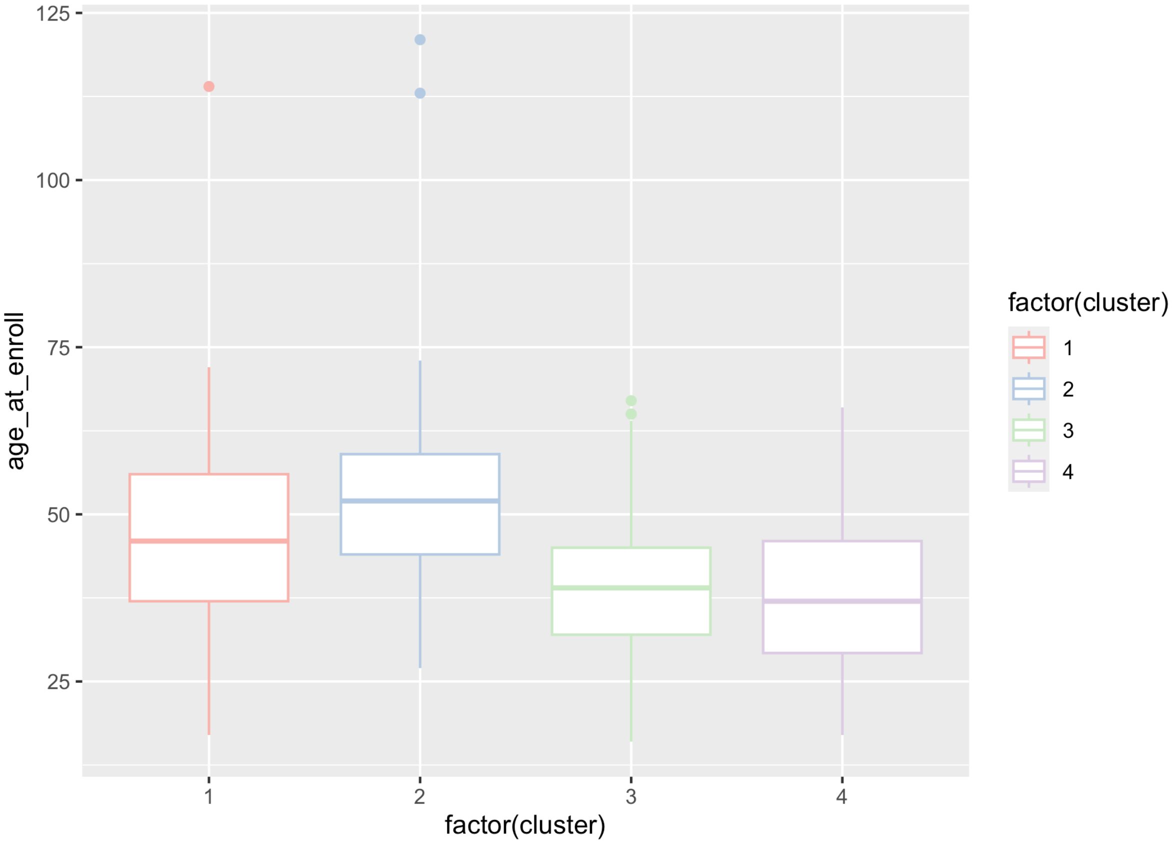
Cluster 2: Comprises individuals with middle income and spending, yet the highest number of children overall. With an average of 1.73 children, this group primarily consists of teenagers (1.02) with fewer younger children (0.71).

Cluster 3: Exhibits the lowest income and spending levels, with a moderate number of children (0.81). Notably, most children in this group are teenagers.

Understanding these clusters aids in tailoring marketing strategies and product offerings to better meet the diverse needs of customers across income levels and family demographics.

5.1.3 Plot 3: Age Analysis

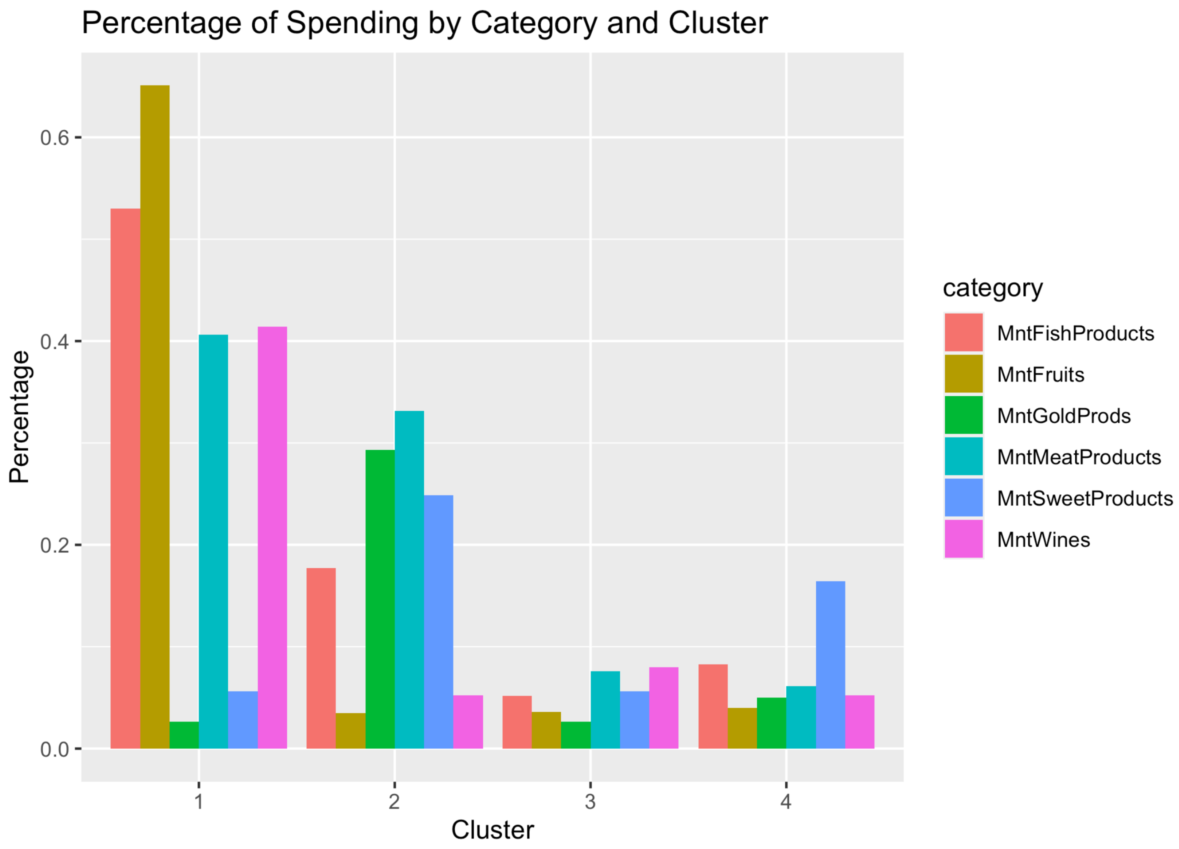




The analysis of customer behavior reveals a distinct pattern in income distribution across age groups. Notably, the youngest age group dominates the highest income bracket, alongside a noteworthy alignment with the lowest income group, which shares a similar average age profile. Conversely, individuals aged 50-55 predominantly occupy the middle income bracket, indicating a peak in earning capacity and career progression for this demographic segment. The concentration of mid-life earners within the middle income group suggests a stable income level corresponding to accrued experience and expertise. Additionally, the high income group's average age around 50 signifies sustained financial success and stability extending into mid-life stages.

These findings underscore the interplay between age, career trajectory, and economic status, offering valuable insights for targeted marketing strategies and tailored services to cater to diverse customer segments effectively.

5.1.4 Plot 4: Spending Pattern on different Products



For food category, we can see that:

The clusters spend on the category pretty much follows their overall spend. Cluster 1 spends the most on food, followed by cluster 2, cluster 3 and cluster 0.

All clusters spend more than wines, followed by meat products.

Cluster 3 and cluster 1 spend significantly more (over half of their total spend) on wine compared to other categories, then around 20% on meat products

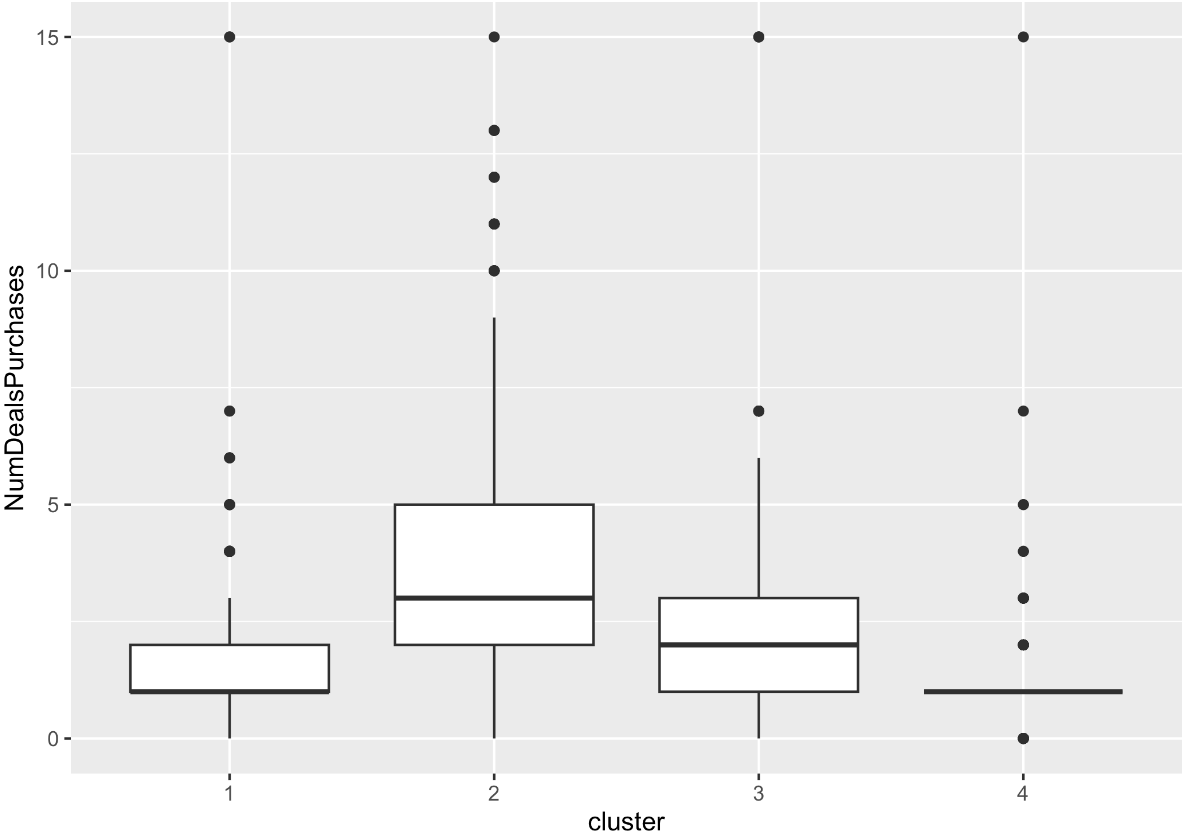
Cluster 4 spend more balanced than other clusters, this cluster spend more on gold than any other clusters. Interestingly, this cluster and cluster 0 are both lower income and lower spend clusters, but they spend more on gold than other clusters.

Cluster 2 spend around 45% on wine and 35% on meat products, they spend more than meat than other clusters

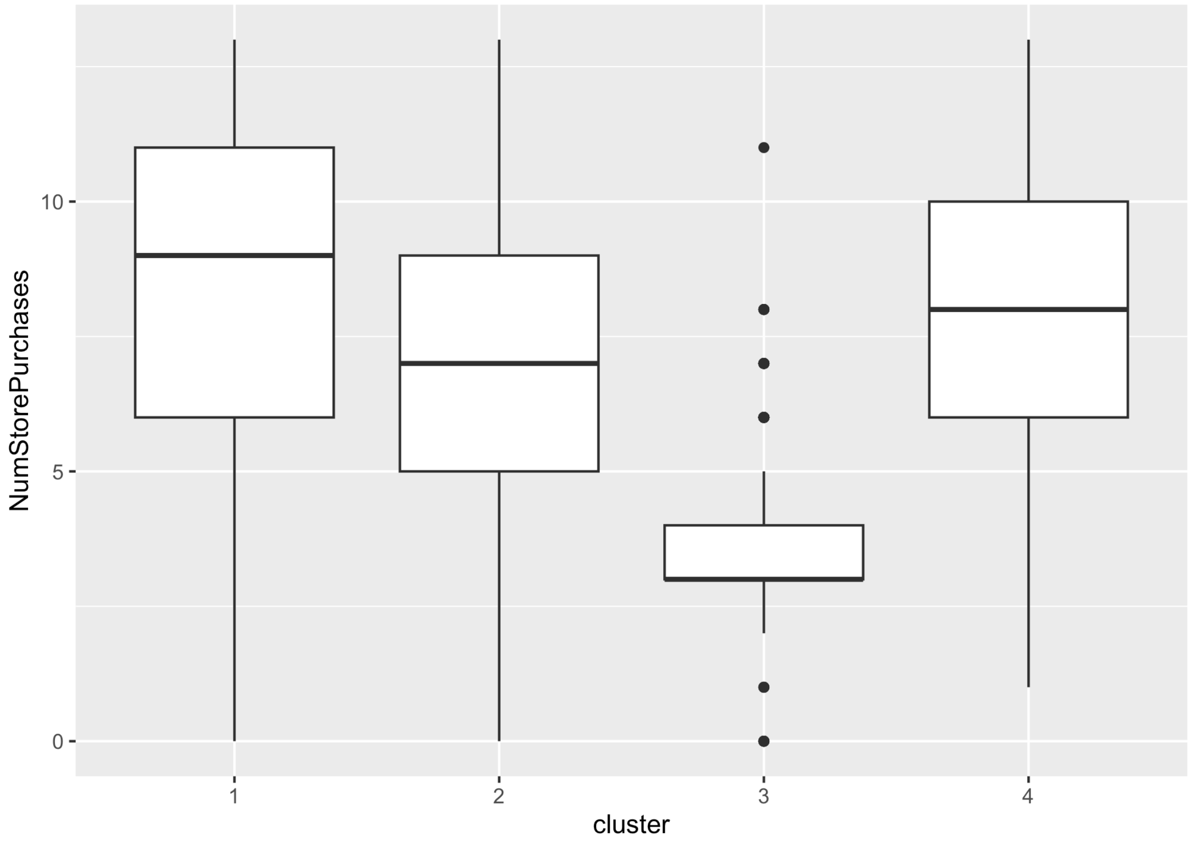
5.1.5 Plot 5: Purchase Preferences

```
  cluster NumDealsPurchases AcceptedCmp1 AcceptedCmp2 AcceptedCmp3 AcceptedCmp4
1       1               752           34            0           15           19
2       2              2200           14            6           35           82
```

```
3        3                1980            1            2            76            2
4        4                 213           93           22            37           61
  AcceptedCmp5 Response
1           42       50
2            5       73
3            0       86
4          115      124
```



Our analysis indicates that middle-income customers demonstrate the highest inclination towards purchasing discounted products, followed by the lowest income group. Conversely, the highest and high income brackets show less interest in discounted deals. This suggests that discount promotions should primarily target low-income customers to optimize sales opportunities.

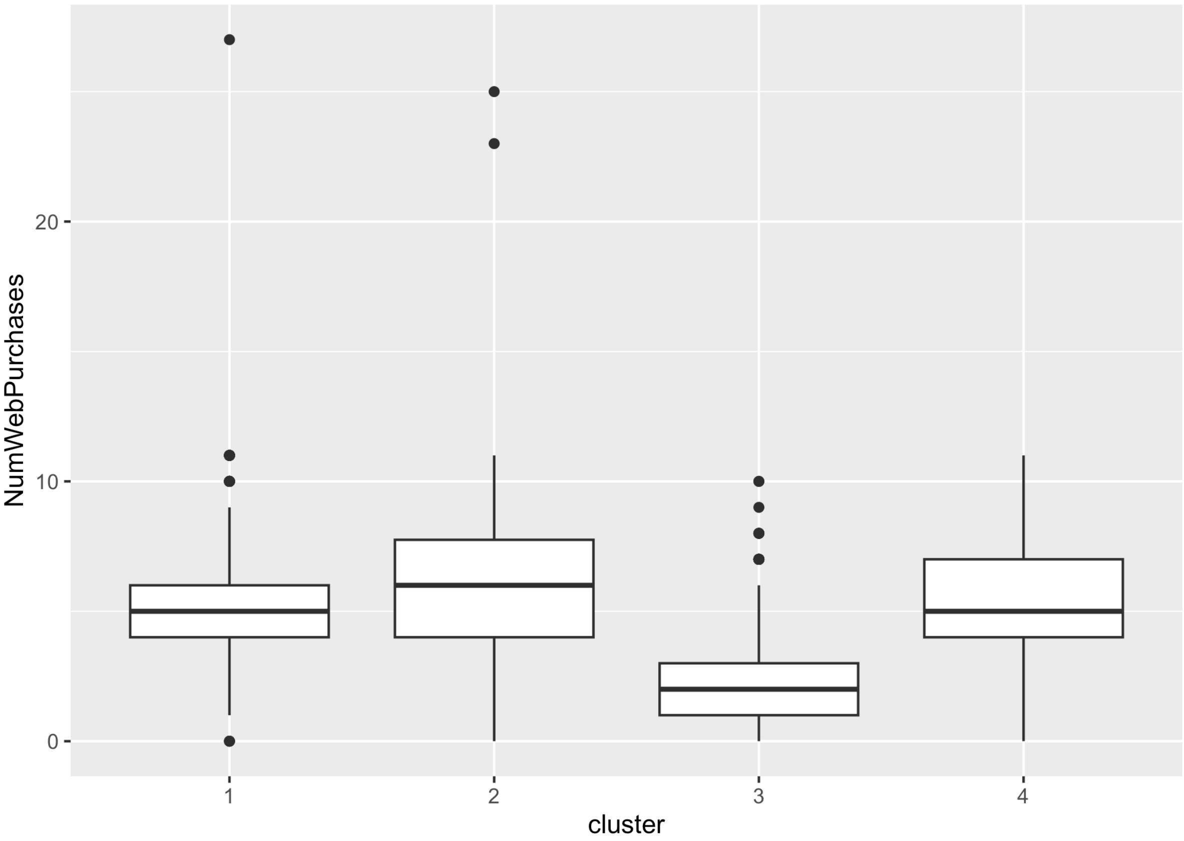


This analysis reveals significant disparities in store purchase behavior across different income clusters:

High-Income Cluster: Exhibits the highest frequency of store purchases, indicating a strong preference for in-store shopping among affluent customers.

Highest and Middle Income Customers: Display similar levels of store purchases, suggesting that these income groups also favor traditional brick-and-mortar retail experiences.

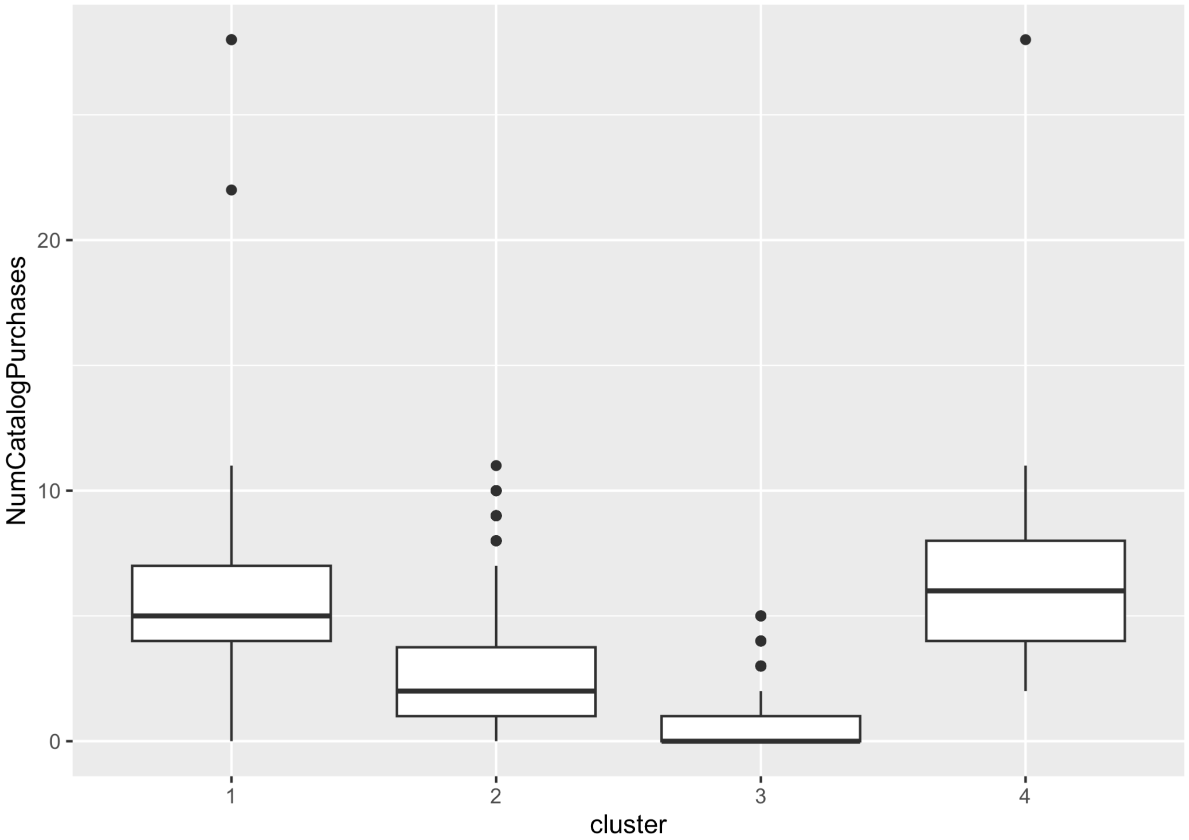
Low-Income Customers: Shows the least preference for store purchases, indicating a potential inclination towards alternative shopping channels or consumption patterns.



Lowest Income Cluster (Cluster 3): Displays the lowest frequency of web purchases, indicating limited engagement with online shopping platforms among individuals in this income bracket.

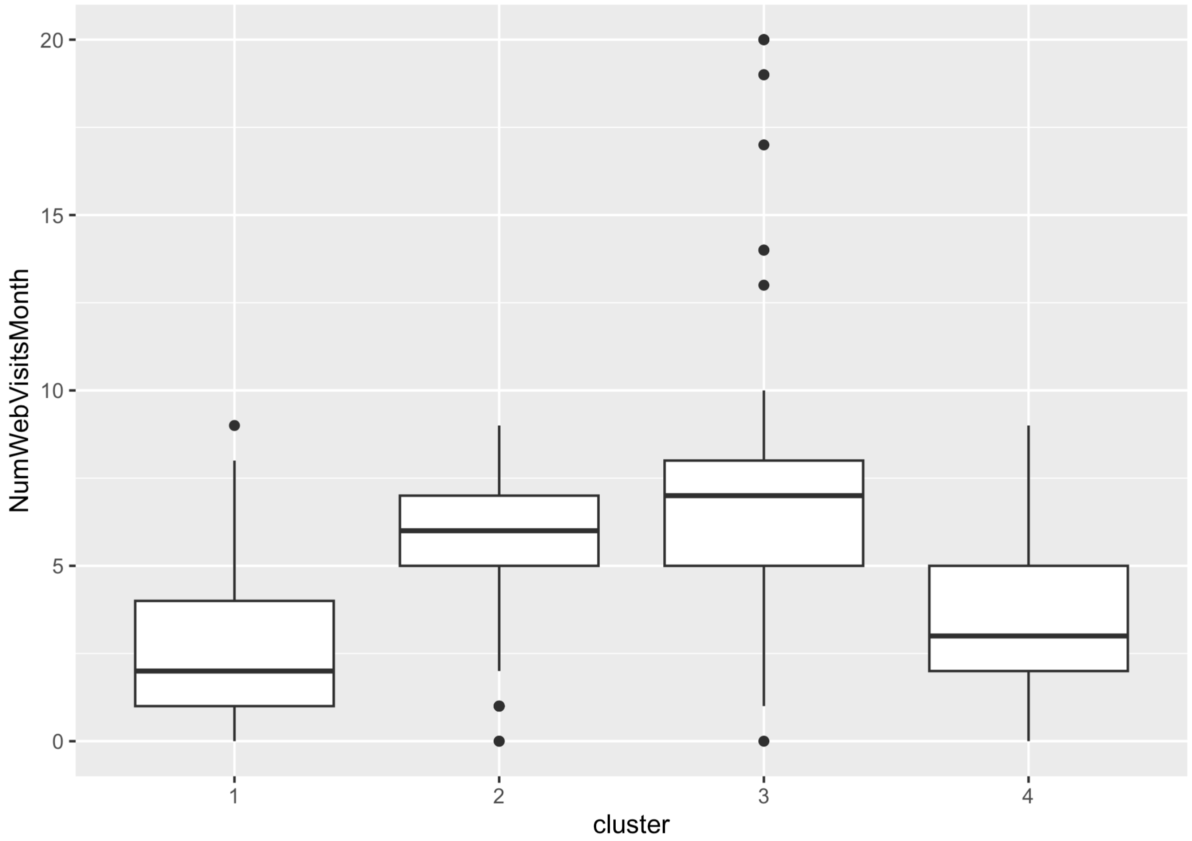
Middle-Income Cluster: Shows the highest level of web purchases, suggesting a significant reliance on online channels for shopping among this demographic.

High and Highest-Income Clusters (Clusters 1 and 4): Exhibit similar levels of web purchases, indicating comparable engagement with online shopping platforms among these customers.



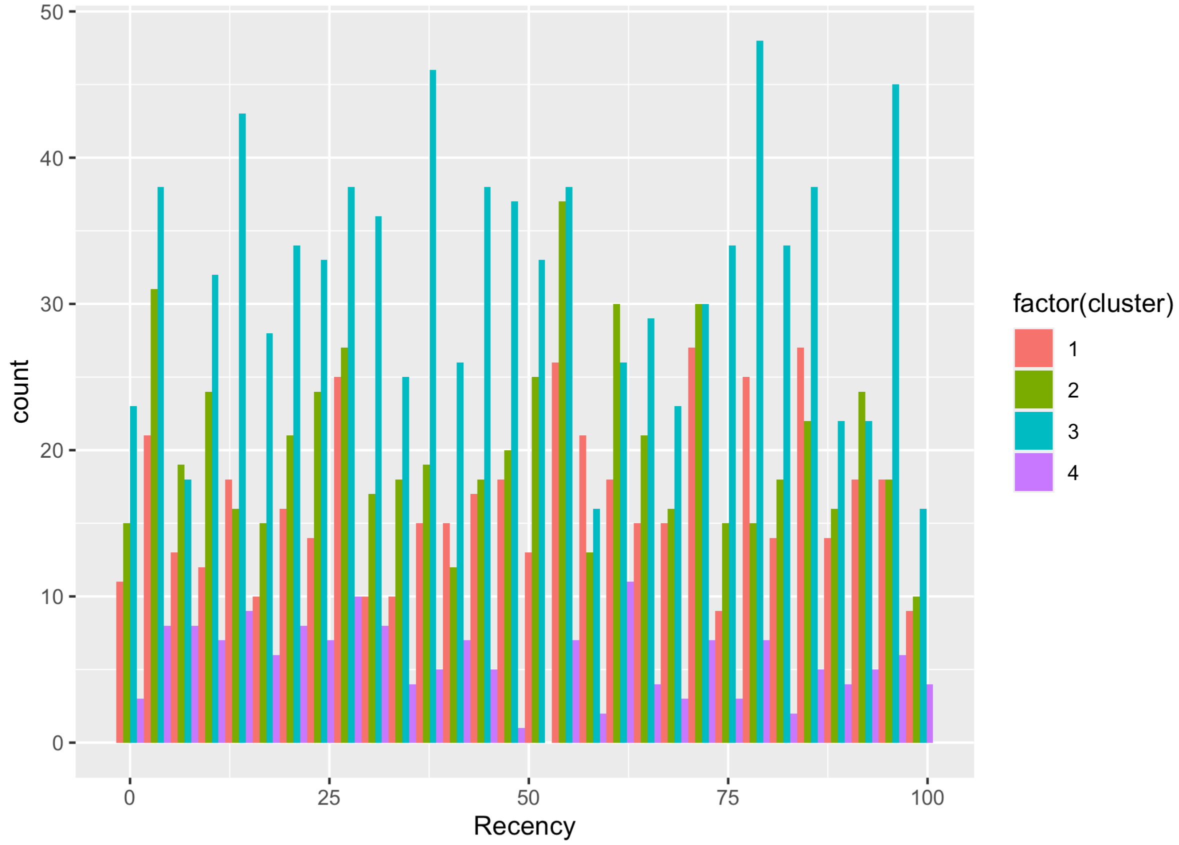
Catalog purchases are most prevalent among highest-income customers followed by high income customers, indicating a strong preference for this shopping channel. Conversely, individuals in the lowest income bracket show minimal engagement with catalogs and middle income bracket also does not seem to prefer the catalog purchases much but definitely they prefer it more than the lowest income group of customers.

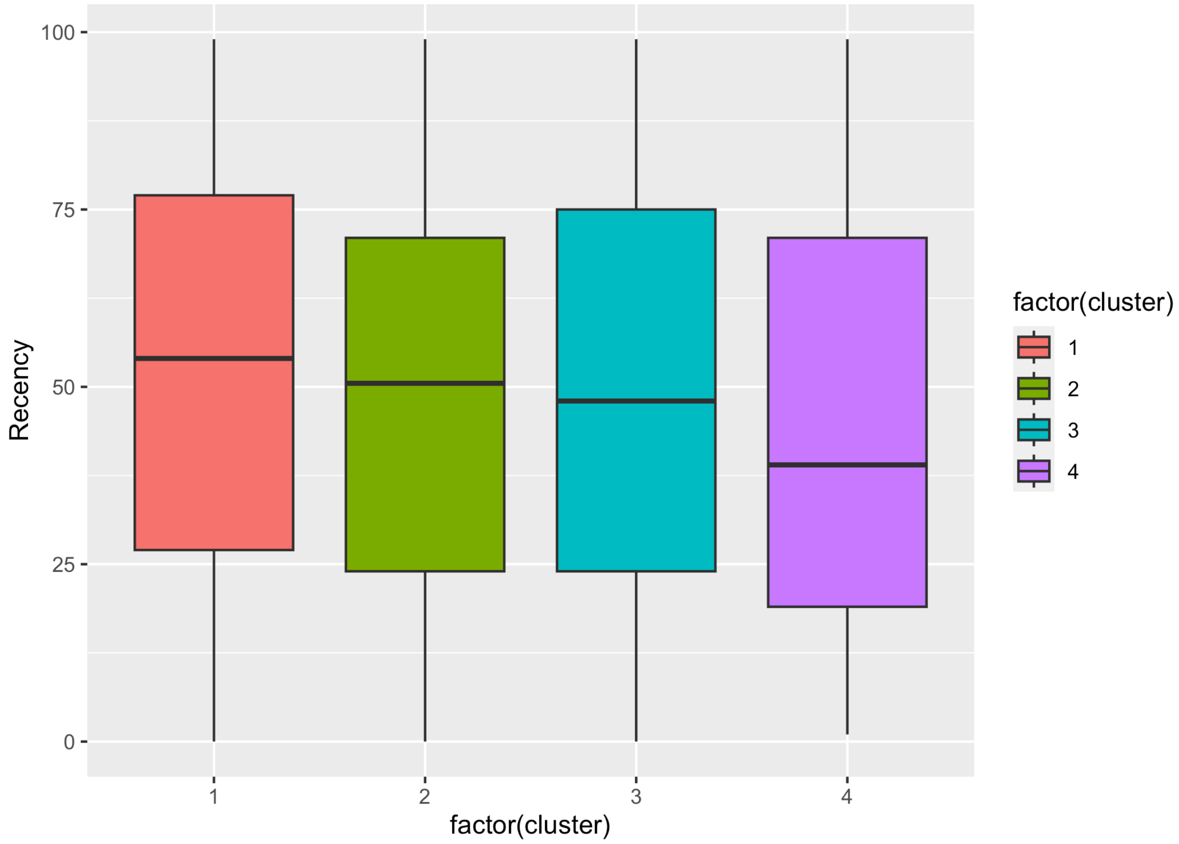
```
  cluster NumWebVisitsMonth
1       1              1411
2       2              3530
3       3              6253
4       4               587
```



Web visits are most frequent among the lowest income group, but their conversion to purchases is the lowest. Conversely, high and highest-income individuals visit the web less frequently but exhibit higher purchase conversion rates. This suggests a more purposeful and efficient online shopping behavior among high income segments.

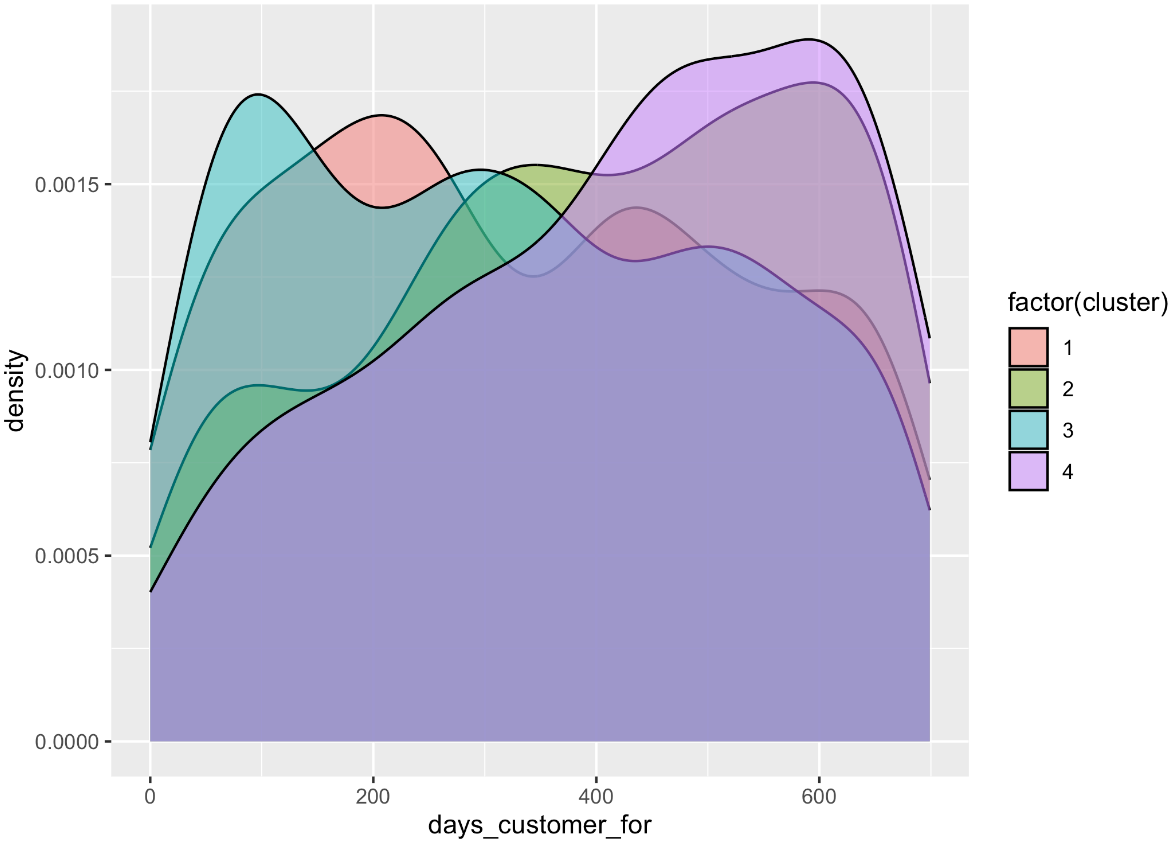
5.1.6 Plot 6: Recency Analysis

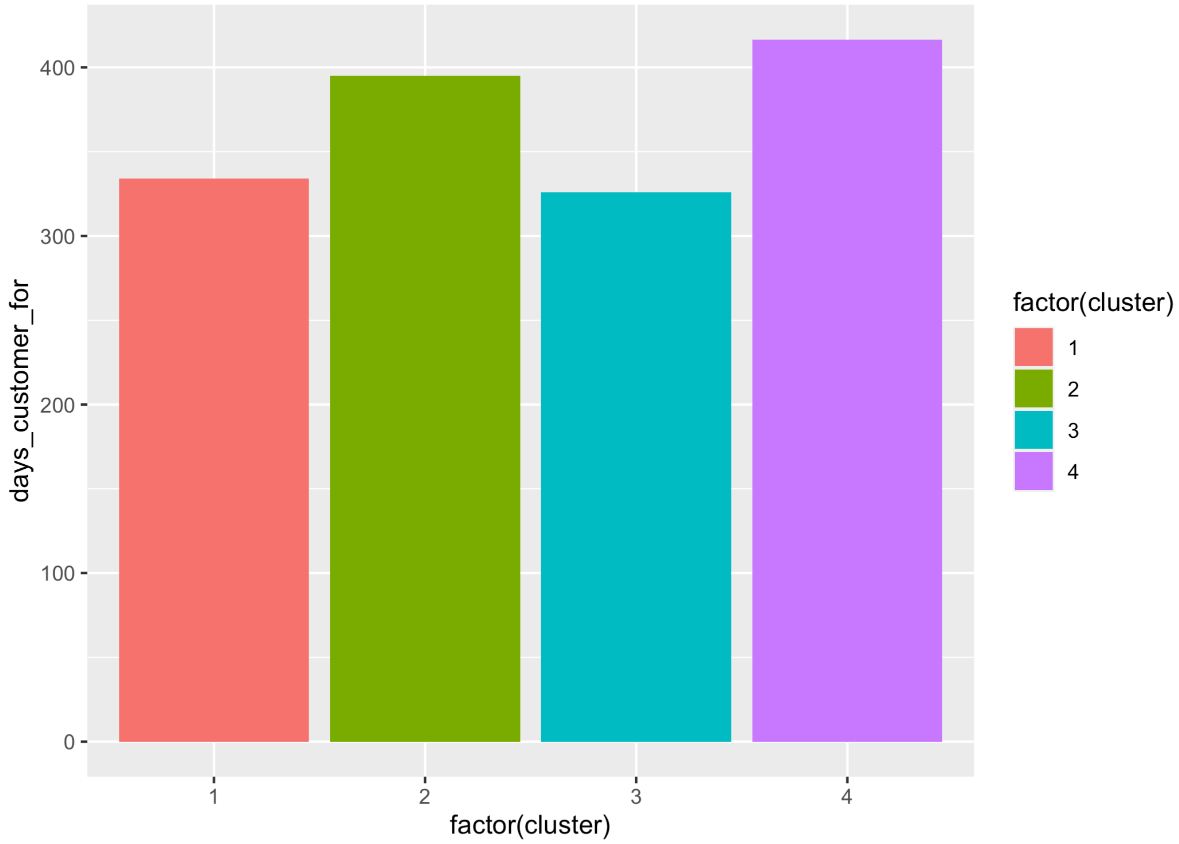




Recency analysis reveals the highest-income group with the least recent engagements, contrasting with the high-income group, which exhibits the highest recency. Interestingly, the low and middle income clusters show recency levels akin to the high-income group, despite their lower income status. These findings emphasize the need for tailored engagement strategies across income segments to optimize customer retention and satisfaction.

5.1.7 Plot 7: Retention Analysis





Customer retention rates vary across income groups, with highest-income individuals showing the highest retention, followed closely by middle-income customers. Interestingly, both high and lowest income groups exhibit similar, lower retention rates, indicating a propensity for changing preferences among these demographics. Tailored strategies are crucial to enhance loyalty across diverse income segments and maximize long-term customer value.

5.2 Conclusion

After conducting data analysis and clustering using K-means, four distinct customer segments emerged with unique characteristics and spending behaviors:

Cluster 4 - Highest Affluent and Highest Spender:

Family Portrait: Typically childless or with only one child; diverse age distribution. Spending Behavior: Prefers in-store and catalog shopping over online; shows a preference for wine and meat products; less inclined towards discounted items and prefer traditional shopping channels.

Cluster 1 - High Income and High Spend:

Family Portrait: More likely to have children, especially teenagers. Spending Behavior: Displays a strong affinity for wine purchases and discounts; exhibits higher online spending compared to other clusters showing a balance between online and offline shopping preferences.

Cluster 2 - Middle Income, Middle Spend:

Family Portrait: Likely to have both young children and teenagers. Spending Behavior: Despite low income, allocates a significant portion of spending to wine; also shows interest in gold products.

Cluster 3 - Low Income, Low Spend:

Family Portrait: Skews towards families with more young children than teenagers; relatively younger demographic. Spending Behavior: Balanced spending across categories; displays a preference for gold products despite limited overall spending; frequent website visits with low purchase conversion rates. Our analysis illustrates the challenges faced by lower-income families, highlighting their limited spending capacity despite preferences for certain product categories.

Understanding these distinct segments allows businesses to tailor marketing strategies and product offerings to better meet the needs and preferences of each customer group, ultimately enhancing customer satisfaction and engagement.

6. Linear Regression

The objective of this analysis is to explore the relationship between amount spent by people on different goods and several marketing and customer-related variables. The dataset used for the analysis contains information on sales, marketing campaign outcomes, customer demographics, and purchasing behavior. By building a linear regression model, we aim to identify the key predictors that influence sales and develop insights for optimizing marketing strategies and improving sales performance.

6.1 Methodology

The linear regression analysis follows a standard methodology, including data preprocessing, model building, and evaluation. Predictor variables were selected based on their relevance to sales and underwent scaling to ensure comparability. The dataset was split into training and testing sets using a 80-20 train-test split. A multiple linear regression model was fitted to the training data using ordinary least squares estimation. Model evaluation was performed using MSE and R-squared metrics on the testing set to assess predictive performance.

6.2 Feature Selection

```
                      Estimate Std. Error     t value      Pr(>|t|)
(Intercept)       -0.006621582 0.01220148  -0.5426869  5.874138e-01
Year_Birth        -0.003870839 0.01249941  -0.3096817  7.568395e-01
```

```
Income             0.209170838 0.01599842  13.0744683  2.349507e-37
Recency            0.024124390 0.01223271   1.9721219  4.875142e-02
NumWebVisitsMonth -0.103205776 0.01545830  -6.6763990  3.268796e-11
num_purchase       0.538368148 0.01476666  36.4583511 1.762826e-217
num_child         -0.252504193 0.01380095 -18.2961459  1.285949e-68
```

According to the p-value, insignificant predictors were dropped, including Year_Birth and Recency.

6.3 Results

```
                    Estimate Std. Error     t value      Pr(>|t|)
(Intercept)       -0.00683779 0.01220778  -0.5601176  5.754702e-01
Income             0.20906559 0.01597905  13.0837319  2.093654e-37
NumWebVisitsMonth -0.10450689 0.01537199  -6.7985283  1.440362e-11
num_purchase       0.53932074 0.01466609  36.7733229 2.175863e-220
num_child         -0.25112758 0.01359496 -18.4721115  8.317371e-70
```

The coefficients of the linear regression model are presented in Table 2. Significant predictors of sales include Income, Number of Web visits,Total number of purchases and number of kids, indicating their impact on sales performance.

6.4 Model Performance

```
[1] "Mean Squared Error: 0.273817801590123"
```

```
[1] "R-squared: 0.749229550492728"
```

Mean Squared Error (MSE): The MSE of the model on the testing set is 0.273, indicating that the model's predictions are generally close to the actual values of the target variable.

R-squared (R^2): The R-squared value of the model is 0.75, suggesting that the model explains a substantial portion of the variability in the target variable, but there is still some

6.5 Conclusion

The linear regression analysis conducted on the marketing data yielded insightful findings regarding the relationship between the predictor variables and the amount spent on products. The obtained R-squared value of 0.7492 indicates that approximately 74.92% of the variability in the amount spent can be explained by the selected predictor variables. This suggests that the model captures a substantial portion of the underlying patterns and trends in the data.

Furthermore, the Mean Squared Error (MSE) value of 0.2738 suggests that the model's predictions are generally close to the actual values of the target variable. Although there is some variability remaining unexplained by the model, the relatively low MSE indicates that the model performs well in terms of predicting the amount spent on products.

In summary, while the linear regression model explains a significant portion of the variability in the amount spent and provides accurate predictions, there may still be additional factors influencing purchasing behavior that are not captured by the selected predictor variables. Further refinement of the model or consideration of additional variables may enhance its predictive accuracy and provide deeper insights into consumer behavior and marketing strategies.

7. Hypothesis Testing

7.1 Test 1

In our first testing let Null hypothesis be - Mean of the income of people who have opted for higher studies is same as to those who have not.

```
    Two Sample t-test

data:  graduation.data and higherstudies.data.income
t = -1.773, df = 1960, p-value = 0.07638
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -4280.3840   215.7034
sample estimates:
mean of x mean of y
 52720.37  54752.71
```

Based on the p-value (0.0764) being slightly higher than 0.05, we *fail to reject the null hypothesis* at the 95% confidence level. This implies that the observed difference in mean income (-1.773) between the graduation and higher studies groups might be due to chance and not a true population difference.

7.2 Test 2

In our second test our **Null hypothesis is- The proportion of customers who accept the offer is the same for both graduation and Master's degree holders.** This essentially suggests that education level (graduation vs. Master's) has no influence on a customer's decision to accept the offer.

Alternative Hypothesis (H): The proportion of customers who accept the offer differs between graduation and Master's degree holders.

```
            Response
Education      0   1
  Graduation 964 152
  Master     309  56


    2-sample test for equality of proportions without continuity correction

data:  c(964, 309) out of c(1116, 365)
X-squared = 0.6759, df = 1, p-value = 0.411
alternative hypothesis: two.sided
95 percent confidence interval:
 -0.02487068  0.05931856
sample estimates:
   prop 1    prop 2
0.8637993 0.8465753
```

In this case, with a p-value of 0.411, we fail to reject the null hypothesis, indicating that the observed difference in offer acceptance proportions might be due to chance and not a true difference between the education groups.

8. Acknowledgement

We are especially grateful to our professor, Shubhajit Dutta, for providing us with the valuable opportunity to undertake this project. The experience has been instrumental in conducting extensive research and has significantly broadened our understanding of the subject matter.