

# Final Examination

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```
library(tidyverse)
```

```
## -- Attaching packages ----- tidyverse 1.2.1 --
```

```
## v ggplot2 3.2.1      v purrr   0.3.2
## v tibble  2.1.3      v dplyr   0.8.3
## v tidyr   1.0.0      v stringr 1.4.0
## v readr   1.3.1      v forcats 0.4.0
```

```
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()
```

```
#install.packages("factoextra")
library(factoextra)
```

```
## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
```

```
library(ISLR)
#install.packages("GGally")
library(GGally)
```

```
## Registered S3 method overwritten by 'GGally':
##   method from
##   +.gg      ggplot2
```

```
##
## Attaching package: 'GGally'
```

```
## The following object is masked from 'package:dplyr':
##
##   nasa
```

```
library(ggplot2)
set.seed(123)

MyData <- read_csv("BathSoap.csv")
```

```
## Parsed with column specification:  
## cols(  
##   .default = col_double()  
## )
```

```
## See spec(...) for full column specifications.
```

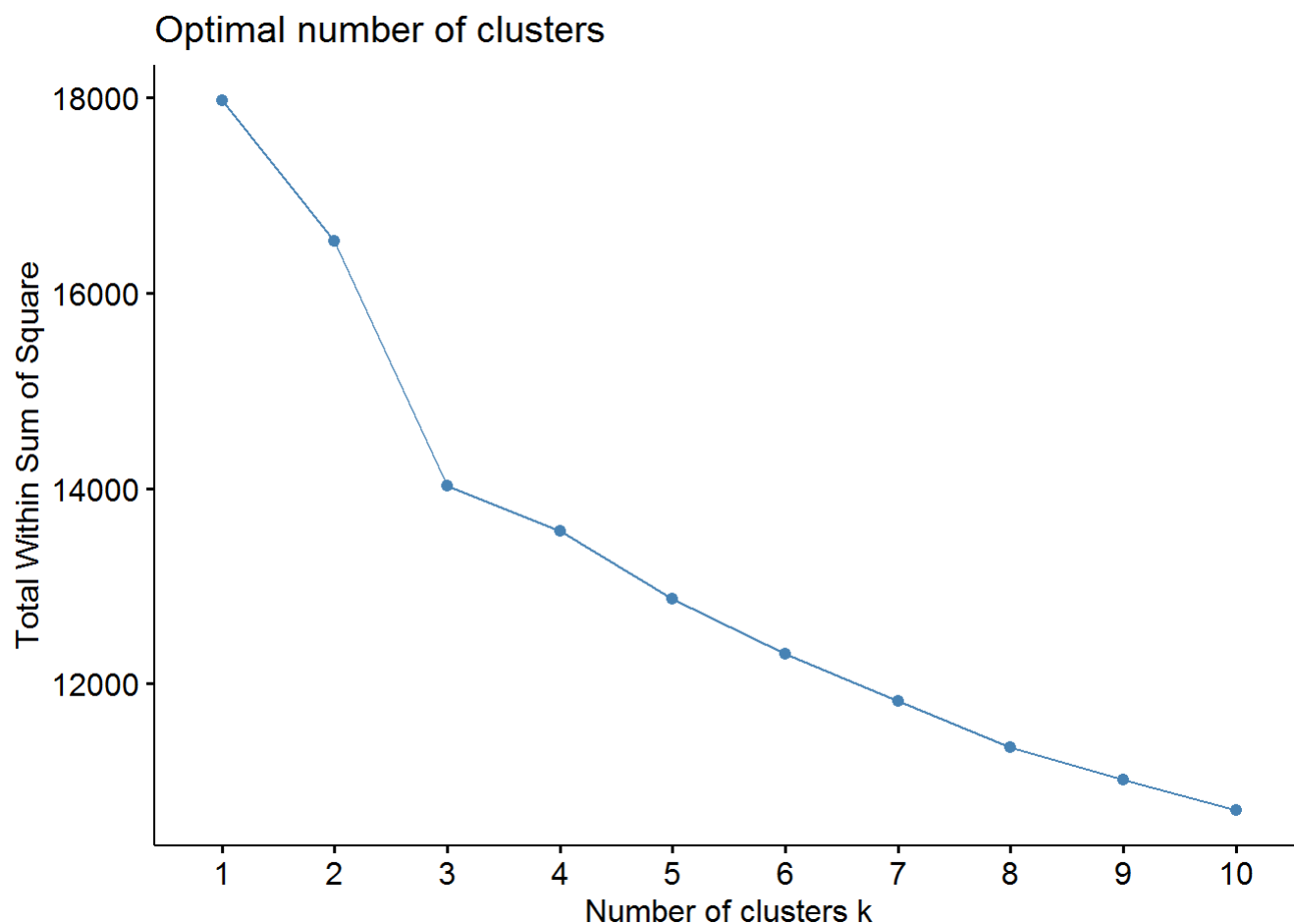
## Question 1:

Use k-means clustering to identify clusters of households based on:

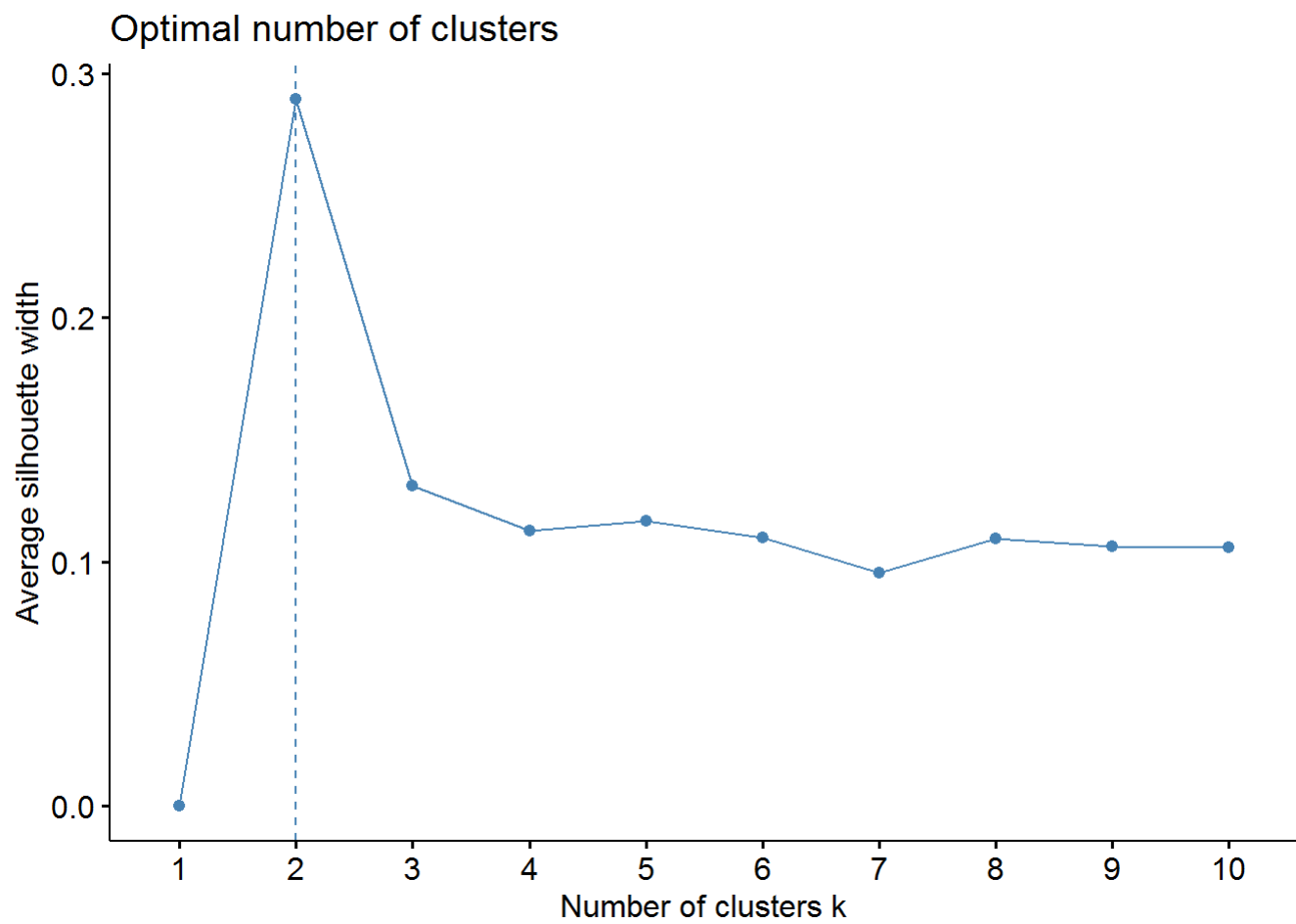
The variables that describe purchase behavior (including brand loyalty)

Demographics, Purchase summary over period, Purchase within promotion and Brandwise Purchase

```
MyData1 <- MyData[, c(2:31)]  
ScaleMyData1 <- scale(MyData1) #Scale the data  
fviz_nbclust(ScaleMyData1, kmeans, method = "wss") #Identify clusters using WSS method
```



```
fviz_nbclust(ScaleMyData1, kmeans, method = "silhouette") # Identify clusters using silhouette method
```



```
k3 <- kmeans(ScaleMyData1, centers = 3, nstart = 25) # Run Kmeans using K = 3  
k3$centers # Visualize the output
```

```

##          SEC          FEH          MT          SEX          AGE          EDU
## 1  0.7218197  0.4544365  0.4599949  0.3244124  0.03792137 -0.2867341
## 2 -0.3646327  0.1012115  0.1180836  0.3531570  0.09636472  0.5384551
## 3 -0.2628475 -1.8047556 -1.9043115 -2.6805048 -0.58631729 -1.8462679
##          HS          CHILD          CS Affluence Index No. of Brands
## 1  0.50750520 -0.2127780  0.2963992      -0.3536684      -0.3413481
## 2  0.07406281 -0.1697686  0.1990143      0.5056334      0.3502191
## 3 -1.82239236  1.4515254 -1.8362598      -1.4916636      -0.7567786
##  Brand Runs Total Volume No. of  Trans      Value Trans / Brand Runs
## 1 -0.4565524      0.6142065      -0.1235612  0.2198727      0.5280278
## 2  0.4408843      -0.1422375      0.3152275  0.0778873      -0.2354502
## 3 -0.8757394      -1.0564151      -1.2079004 -1.0165176      -0.3473341
##  Vol/Tran Avg. Price Pur Vol No Promo - % Pur Vol Promo 6 %
## 1  0.7409375 -0.7167817      0.34538215      -0.3470228
## 2 -0.4052208  0.3774845      -0.19594512      0.2391716
## 3 -0.1165205  0.1847084      -0.01935313      -0.1901672
##  Pur Vol Other Promo % Br. Cd. 57, 144 Br. Cd. 55 Br. Cd. 272 Br. Cd. 286
## 1      -0.12515999      0.07761540  0.5555646 -0.3208602  0.02436559
## 2      0.01602389      -0.05441557 -0.3686156  0.1610259  0.01348735
## 3      0.27950215      0.04710361  0.2336523  0.1220887 -0.13671365
##  Br. Cd. 24 Br. Cd. 481 Br. Cd. 352 Br. Cd. 5 Others 999
## 1 -0.22395100 -0.1461996  0.049425403 -0.1858712 -0.3318462
## 2  0.05007179  0.1192474  0.008171918  0.1449088  0.2259027
## 3  0.39406254 -0.1717272 -0.182233675 -0.1851377 -0.1679295

```

```
k3$size # size of each cluster
```

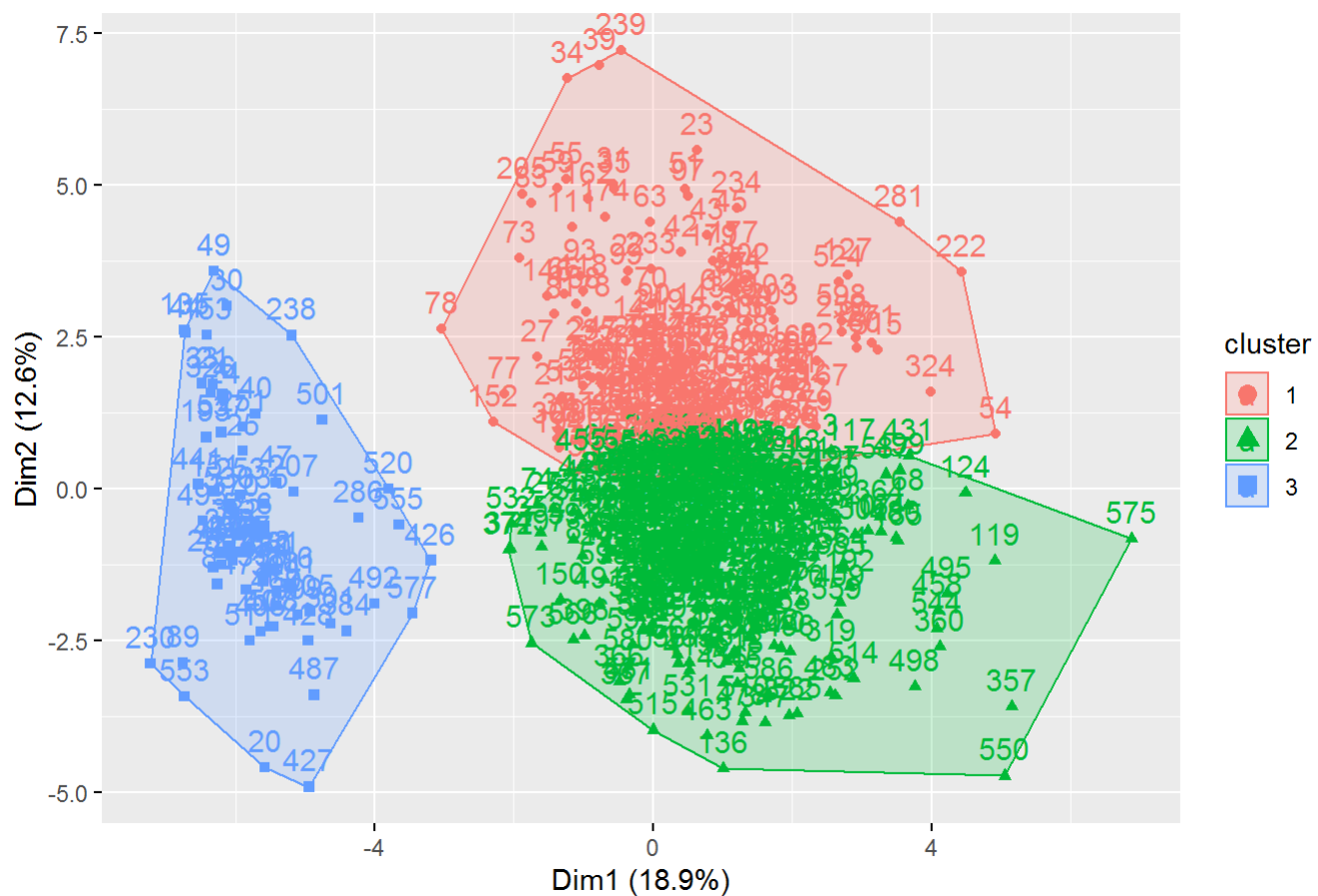
```
## [1] 195 337 68
```

```
k3$tot.withinss # Total within clusters sum of squares
```

```
## [1] 14021.43
```

```
fviz_cluster(k3, data = ScaleMyData1)
```

## Cluster plot



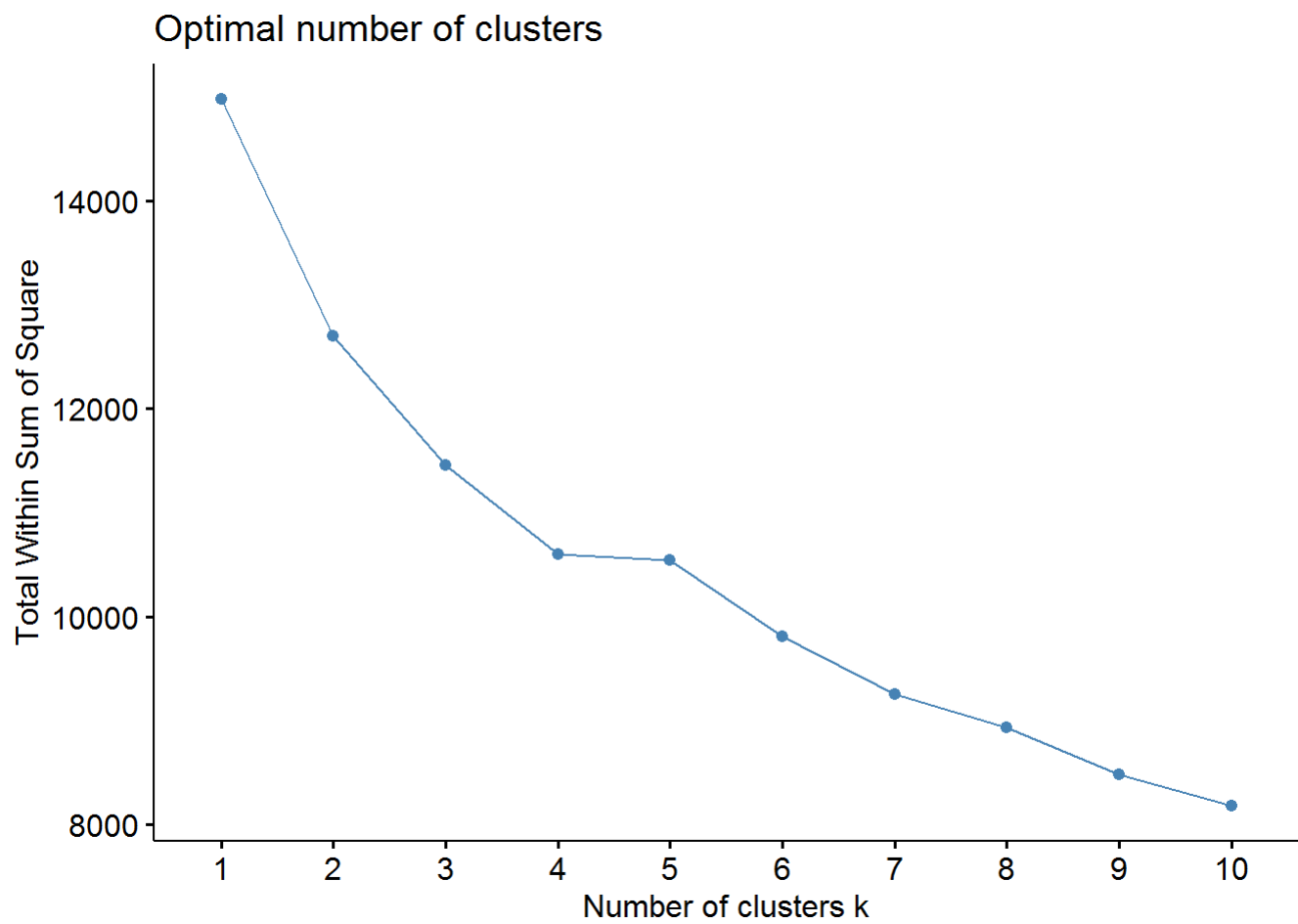
```
PBResult<-as.data.frame(cbind(1:nrow(k3$centers),k3$centers))
PBResult$V1<-as.factor(PBResult$V1)
PBResult # Characteristics of the cluster
```

```
##      V1      SEC      FEH      MT      SEX      AGE      EDU
## 1  1  0.7218197  0.4544365  0.4599949  0.3244124  0.03792137 -0.2867341
## 2  2 -0.3646327  0.1012115  0.1180836  0.3531570  0.09636472  0.5384551
## 3  3 -0.2628475 -1.8047556 -1.9043115 -2.6805048 -0.58631729 -1.8462679
##      HS      CHILD      CS Affluence Index No. of Brands
## 1  0.50750520 -0.2127780  0.2963992      -0.3536684      -0.3413481
## 2  0.07406281 -0.1697686  0.1990143      0.5056334      0.3502191
## 3 -1.82239236  1.4515254 -1.8362598      -1.4916636      -0.7567786
##      Brand Runs Total Volume No. of Trans      Value Trans / Brand Runs
## 1 -0.4565524      0.6142065      -0.1235612  0.2198727      0.5280278
## 2  0.4408843      -0.1422375      0.3152275  0.0778873      -0.2354502
## 3 -0.8757394      -1.0564151      -1.2079004 -1.0165176      -0.3473341
##      Vol/Tran Avg. Price Pur Vol No Promo - % Pur Vol Promo 6 %
## 1  0.7409375 -0.7167817      0.34538215      -0.3470228
## 2 -0.4052208  0.3774845      -0.19594512      0.2391716
## 3 -0.1165205  0.1847084      -0.01935313      -0.1901672
##      Pur Vol Other Promo % Br. Cd. 57, 144 Br. Cd. 55 Br. Cd. 272 Br. Cd. 286
## 1      -0.12515999      0.07761540  0.5555646 -0.3208602  0.02436559
## 2      0.01602389      -0.05441557 -0.3686156  0.1610259  0.01348735
## 3      0.27950215      0.04710361  0.2336523  0.1220887 -0.13671365
##      Br. Cd. 24 Br. Cd. 481 Br. Cd. 352 Br. Cd. 5 Others 999
## 1 -0.22395100 -0.1461996  0.049425403 -0.1858712 -0.3318462
## 2  0.05007179  0.1192474  0.008171918  0.1449088  0.2259027
## 3  0.39406254 -0.1717272 -0.182233675 -0.1851377 -0.1679295
```

The variables that describe the basis for purchase

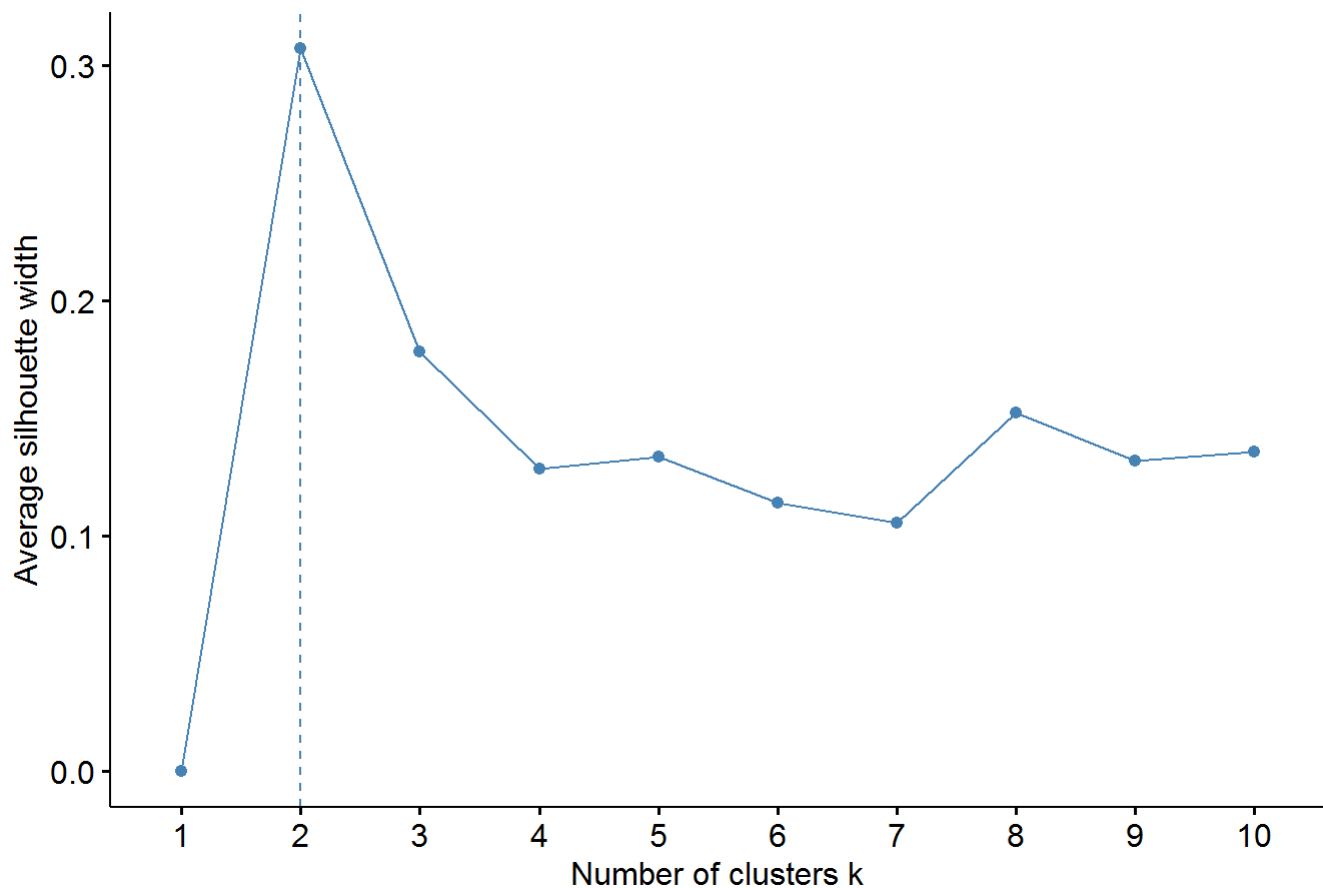
Demographics, Price Categorywise Purchase and Selling propositionwise Purchase

```
MyData2 <- MyData[, c(2:11,32:46)]
ScaleMyData2 <- scale(MyData2) #Scale the data
fviz_nbclust(ScaleMyData2, kmeans, method = "wss") #Identify clusters using WSS method
```



```
fviz_nbclust(ScaleMyData2, kmeans, method = "silhouette") # Identify clusters using silhouette method
```

## Optimal number of clusters



```
Price_k3 <- kmeans(ScaleMyData2, centers = 3, nstart = 25) # Run Kmeans using K = 3
Price_k3$centers # Visualize the output
```

```
##          SEC          FEH          MT          SEX          AGE          EDU
## 1  0.80431337  0.5112390  0.4308249  0.3153751 -0.1474532 -0.5220692
## 2 -0.08317815  0.1881746  0.2150118  0.3467491  0.1086392  0.3508464
## 3 -0.26284751 -1.8047556 -1.9043115 -2.6805048 -0.5863173 -1.8462679
##          HS          CHILD          CS Affluence Index  Pr Cat 1  Pr Cat 2
## 1  0.5191308 -0.1447613  0.3599313      -0.5764327 -0.76553768 -1.0752144
## 2  0.1895747 -0.1917109  0.2157370       0.3068905  0.06913496  0.2152032
## 3 -1.8223924  1.4515254 -1.8362598      -1.4916636  0.31834243 -0.3552774
##  Pr Cat 3  Pr Cat 4  PropCat 5  PropCat 6  PropCat 7  PropCat 8
## 1  2.1977250 -0.19848939 -0.9829177 -0.13034843 -0.45271296 -0.47637989
## 2 -0.3640164  0.05724436  0.1699837  0.03943746  0.08184361  0.05630924
## 3  0.2108060 -0.18459757 -0.1430625 -0.13376054 -0.09002704  0.10781946
##  PropCat 9  PropCat 10  PropCat 11  PropCat 12  PropCat 13  PropCat 14
## 1 -0.15655890 -0.25612705 -0.25644467 -0.16008000 -0.22913911  2.1959667
## 2  0.03843876  0.01637855  0.06697452 -0.01108779 -0.02112514 -0.3654695
## 3 -0.09999388  0.15238244 -0.19104563  0.24012000  0.37940521  0.2224889
##  PropCat 15
## 1 -0.11666791
## 2  0.05191261
## 3 -0.23260103
```



```
Price_k3$size # size of each cluster
```

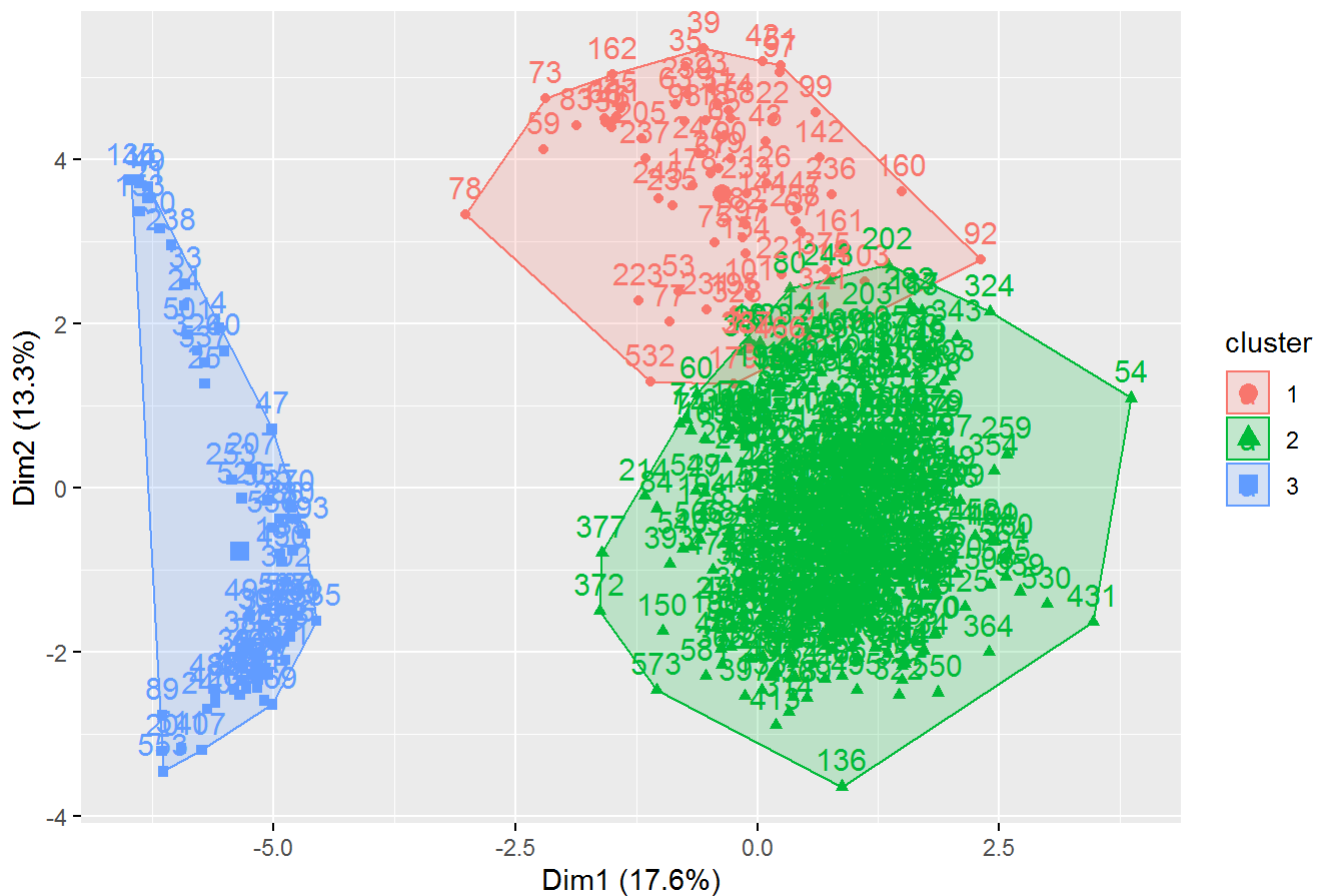
```
## [1] 70 462 68
```

```
Price_k3$tot.withinss # Total within clusters sum of squares
```

```
## [1] 11456.52
```

```
fviz_cluster(Price_k3, data = ScaleMyData2)
```

Cluster plot



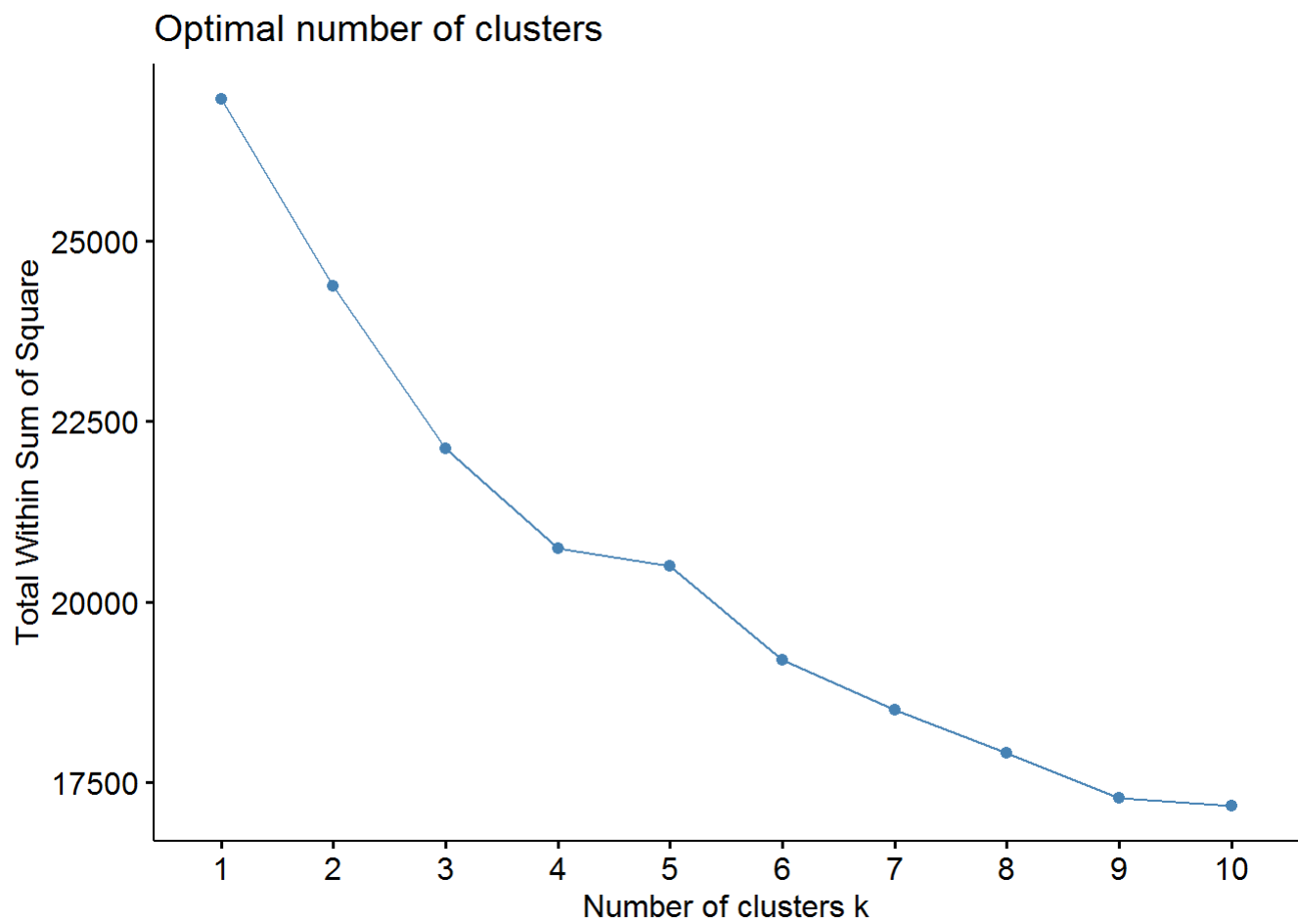
```
PriceResult<-as.data.frame(cbind(1:nrow(Price_k3$centers),Price_k3$centers))
PriceResult$V1<-as.factor(PriceResult$V1)
PriceResult #Characteristics of the clusters
```

```
##      V1      SEC      FEH      MT      SEX      AGE      EDU
## 1  1  0.80431337  0.5112390  0.4308249  0.3153751 -0.1474532 -0.5220692
## 2  2 -0.08317815  0.1881746  0.2150118  0.3467491  0.1086392  0.3508464
## 3  3 -0.26284751 -1.8047556 -1.9043115 -2.6805048 -0.5863173 -1.8462679
##      HS      CHILD      CS Affluence Index      Pr Cat 1      Pr Cat 2
## 1  0.5191308 -0.1447613  0.3599313      -0.5764327 -0.76553768 -1.0752144
## 2  0.1895747 -0.1917109  0.2157370      0.3068905  0.06913496  0.2152032
## 3 -1.8223924  1.4515254 -1.8362598      -1.4916636  0.31834243 -0.3552774
##      Pr Cat 3      Pr Cat 4      PropCat 5      PropCat 6      PropCat 7      PropCat 8
## 1  2.1977250 -0.19848939 -0.9829177 -0.13034843 -0.45271296 -0.47637989
## 2 -0.3640164  0.05724436  0.1699837  0.03943746  0.08184361  0.05630924
## 3  0.2108060 -0.18459757 -0.1430625 -0.13376054 -0.09002704  0.10781946
##      PropCat 9      PropCat 10      PropCat 11      PropCat 12      PropCat 13      PropCat 14
## 1 -0.15655890 -0.25612705 -0.25644467 -0.16008000 -0.22913911  2.1959667
## 2  0.03843876  0.01637855  0.06697452 -0.01108779 -0.02112514 -0.3654695
## 3 -0.09999388  0.15238244 -0.19104563  0.24012000  0.37940521  0.2224889
##      PropCat 15
## 1 -0.11666791
## 2  0.05191261
## 3 -0.23260103
```

The variables that describe both purchase behavior and basis of purchase

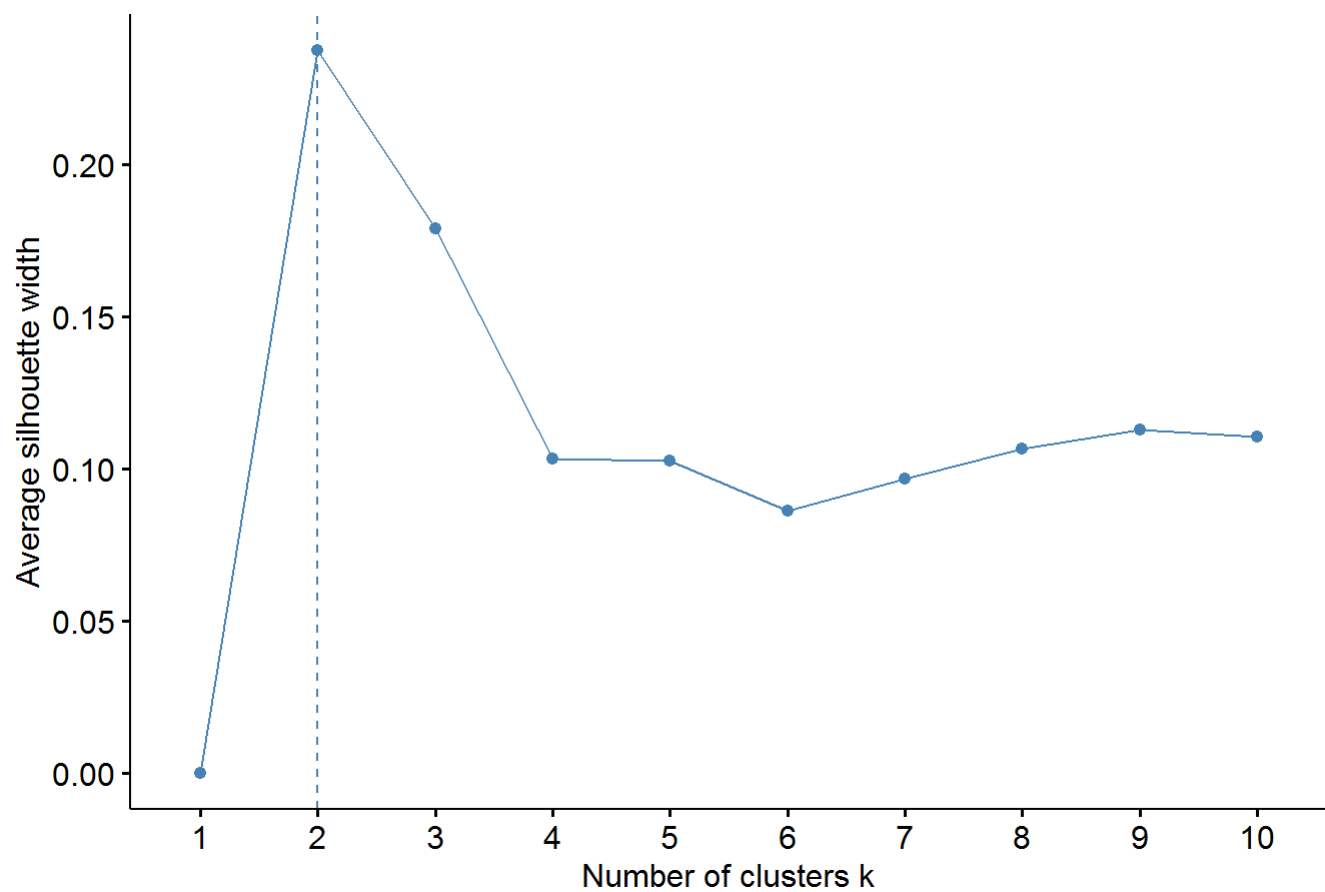
All variables used for both the above classifications

```
MyData3 <- MyData[, c(2:46)]
ScaleMyData3 <- scale(MyData3) #Scale the data
fviz_nbclust(ScaleMyData3, kmeans, method = "wss") #Identify clusters using WSS method
```



```
fviz_nbclust(ScaleMyData3, kmeans, method = "silhouette")
```

## Optimal number of clusters



```
PB_k3 <- kmeans(ScaleMyData3, centers = 3, nstart = 25) # Identify clusters using silhouette method
PB_k3$centers # Visualize the output
```

```

##          SEC          FEH          MT          SEX          AGE          EDU
## 1  0.88014090  0.2377594  0.1101796  0.006308169 -0.2815015 -0.7047173
## 2 -0.06707335  0.1995729  0.2302138  0.344808564  0.1052659  0.3364348
## 3 -0.43219025 -1.8047556 -1.9043115 -2.680504755 -0.5116665 -1.8462679
##          HS          CHILD          CS Affluence Index No. of Brands
## 1  0.2657999  0.05726429  0.1944064      -0.6869524      -0.4701671
## 2  0.1979348 -0.19518497  0.2096850      0.2882248      0.1563922
## 3 -1.8223924  1.45152536 -1.8362598      -1.4916636      -0.7039754
##  Brand Runs Total Volume No. of Trans      Value Trans / Brand Runs
## 1 -0.6945969  0.33468255      -0.2331075 -0.3940434      1.15384436
## 2  0.2038545  0.09322169      0.1877297  0.1844360      -0.09604714
## 3 -0.8291767 -1.08496568      -1.2034598 -1.0037930      -0.50366276
##  Vol/Tran Avg. Price Pur Vol No Promo - % Pur Vol Promo 6 %
## 1  0.59190625 -1.3441079      0.14045124      -0.39335180
## 2 -0.05603432  0.1375913      -0.02196560      0.07370602
## 3 -0.20592755  0.3873845      0.01835982      -0.14593002
##  Pur Vol Other Promo % Br. Cd. 57, 144 Br. Cd. 55 Br. Cd. 272 Br. Cd. 286
## 1      0.27677730      -0.65475853  2.4750858 -0.34652905 -0.22432733
## 2      -0.05893885      0.07423252 -0.3322173  0.02540135  0.04912537
## 3      0.15755366      0.13282102 -0.1019160  0.17796847 -0.13820817
##  Br. Cd. 24 Br. Cd. 481 Br. Cd. 352 Br. Cd. 5 Others 999 Pr Cat 1
## 1 -0.20268502 -0.24266621 -0.26277846 -0.15361212 -1.18135415 -0.80244172
## 2 -0.03196054  0.05425534  0.05869953  0.04440308  0.16348574  0.05157595
## 3  0.46712373 -0.15814439 -0.17084427 -0.17810255  0.01050197  0.46829067
##  Pr Cat 2 Pr Cat 3 Pr Cat 4 PropCat 5 PropCat 6 PropCat 7
## 1 -1.2608159  2.4929869 -0.25598885 -1.12011514 -0.24401644 -0.46330854
## 2  0.2054809 -0.3333984  0.05607884  0.15768600  0.04518157  0.07037197
## 3 -0.2291576 -0.1121263 -0.15786928 -0.01078491 -0.08632457 -0.04438654
##  PropCat 8 PropCat 9 PropCat 10 PropCat 11 PropCat 12 PropCat 13
## 1 -0.5021964 -0.18449435 -0.255562858 -0.25389703 -0.17278476 -0.22873159
## 2  0.0467883  0.03286223  0.009824713  0.05847556 -0.01310229 -0.02650603
## 3  0.1805590 -0.05520014  0.200328842 -0.17871700  0.28854389  0.45301047
##  PropCat 14 PropCat 15
## 1  2.4939655 -0.21355099
## 2 -0.3347382  0.05894921
## 3 -0.1027962 -0.22604282

```

```
PB_k3$size # size of each cluster
```

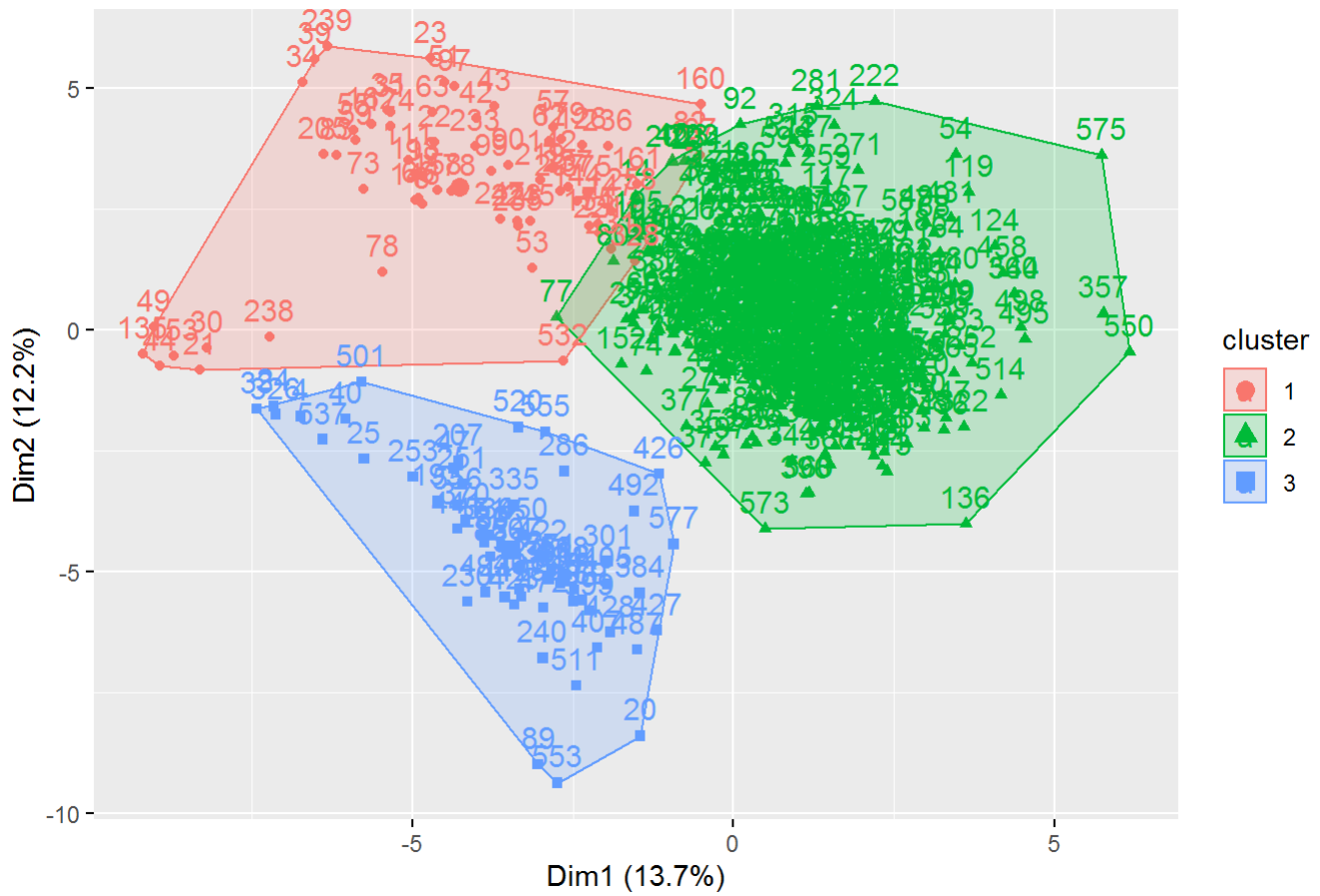
```
## [1] 66 473 61
```

```
PB_k3$tot.withinss # Total within clusters sum of squares
```

```
## [1] 22122.85
```

```
fviz_cluster(PB_k3, data = ScaleMyData3)
```

## Cluster plot



```
PBPRResult<-as.data.frame(cbind(1:nrow(PB_k3$centers),PB_k3$centers))
PBPRResult$V1<-as.factor(PBPRResult$V1)
PBPRResult #Characteristics of the clusters
```

```

##      V1          SEC          FEH          MT          SEX          AGE          EDU
## 1  1  0.88014090  0.2377594  0.1101796  0.006308169 -0.2815015 -0.7047173
## 2  2 -0.06707335  0.1995729  0.2302138  0.344808564  0.1052659  0.3364348
## 3  3 -0.43219025 -1.8047556 -1.9043115 -2.680504755 -0.5116665 -1.8462679
##      HS          CHILD          CS Affluence Index No. of Brands
## 1  0.2657999  0.05726429  0.1944064      -0.6869524      -0.4701671
## 2  0.1979348 -0.19518497  0.2096850      0.2882248      0.1563922
## 3 -1.8223924  1.45152536 -1.8362598      -1.4916636      -0.7039754
##      Brand Runs Total Volume No. of Trans      Value Trans / Brand Runs
## 1 -0.6945969  0.33468255      -0.2331075 -0.3940434      1.15384436
## 2  0.2038545  0.09322169      0.1877297  0.1844360      -0.09604714
## 3 -0.8291767 -1.08496568      -1.2034598 -1.0037930      -0.50366276
##      Vol/Tran Avg. Price Pur Vol No Promo - % Pur Vol Promo 6 %
## 1  0.59190625 -1.3441079      0.14045124      -0.39335180
## 2 -0.05603432  0.1375913      -0.02196560      0.07370602
## 3 -0.20592755  0.3873845      0.01835982      -0.14593002
##      Pur Vol Other Promo % Br. Cd. 57, 144 Br. Cd. 55 Br. Cd. 272 Br. Cd. 286
## 1      0.27677730      -0.65475853  2.4750858 -0.34652905 -0.22432733
## 2      -0.05893885      0.07423252 -0.3322173  0.02540135  0.04912537
## 3      0.15755366      0.13282102 -0.1019160  0.17796847 -0.13820817
##      Br. Cd. 24 Br. Cd. 481 Br. Cd. 352 Br. Cd. 5 Others 999 Pr Cat 1
## 1 -0.20268502 -0.24266621 -0.26277846 -0.15361212 -1.18135415 -0.80244172
## 2 -0.03196054  0.05425534  0.05869953  0.04440308  0.16348574  0.05157595
## 3  0.46712373 -0.15814439 -0.17084427 -0.17810255  0.01050197  0.46829067
##      Pr Cat 2 Pr Cat 3 Pr Cat 4 PropCat 5 PropCat 6 PropCat 7
## 1 -1.2608159  2.4929869 -0.25598885 -1.12011514 -0.24401644 -0.46330854
## 2  0.2054809 -0.3333984  0.05607884  0.15768600  0.04518157  0.07037197
## 3 -0.2291576 -0.1121263 -0.15786928 -0.01078491 -0.08632457 -0.04438654
##      PropCat 8 PropCat 9 PropCat 10 PropCat 11 PropCat 12 PropCat 13
## 1 -0.5021964 -0.18449435 -0.255562858 -0.25389703 -0.17278476 -0.22873159
## 2  0.0467883  0.03286223  0.009824713  0.05847556 -0.01310229 -0.02650603
## 3  0.1805590 -0.05520014  0.200328842 -0.17871700  0.28854389  0.45301047
##      PropCat 14 PropCat 15
## 1  2.4939655 -0.21355099
## 2 -0.3347382  0.05894921
## 3 -0.1027962 -0.22604282

```

## Question 2:

Select what you think is the best segmentation and comment on the characteristics (demographic, brand loyalty, and basis for purchase) of these clusters. (This information would be used to guide the development of advertising and promotional campaigns.)

## Comment:

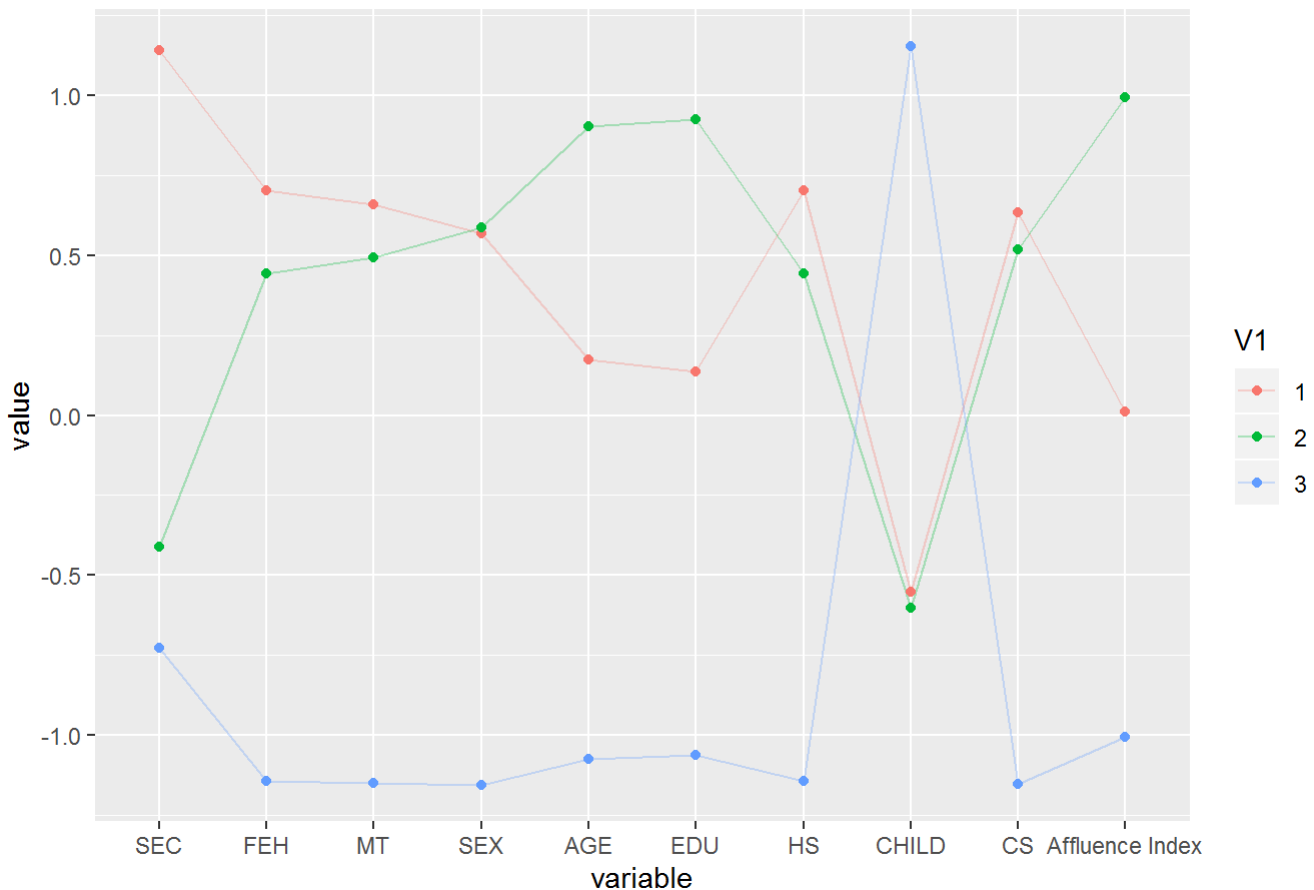
The best segmentation from all the above three classifications is either “The Variables that describe the Basis of Purchase” or “The variables that describe both purchase behavior and basis of purchase”.

But considering the Total within clusters sum of squares is smaller for “The Variables that describe the Basis of Purchase” when compared to the other, the best segmentation is “The Variables that describe the Basis of Purchase”

# Visual representation of characteristics of cluster for the best segmentation approach

```
ggparcoord(PriceResult,
  columns = 2:11, groupColumn = 1,
  showPoints = TRUE,
  title = "Characterisitcs of the cluster for Demographics",
  alphaLines = 0.3
)
```

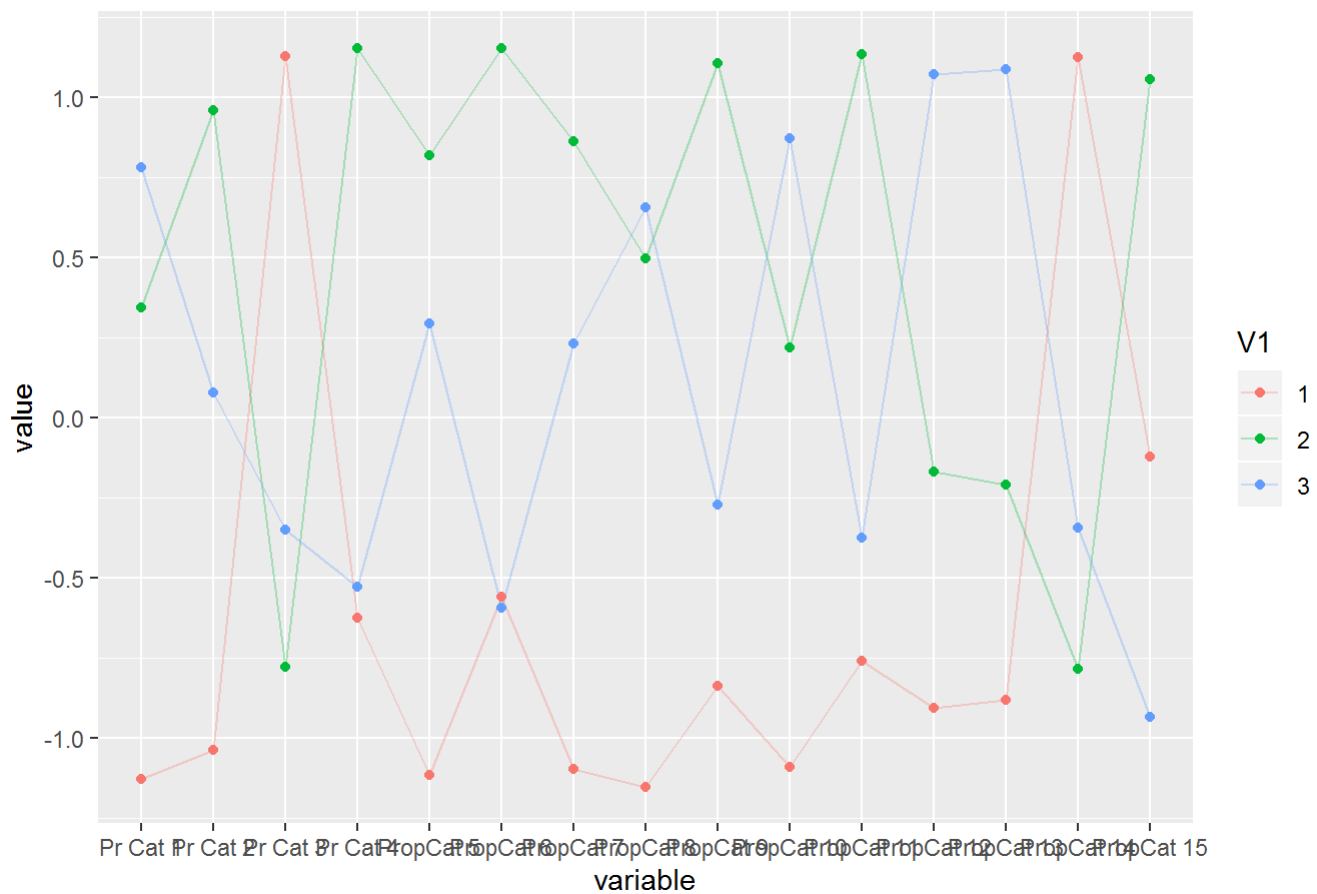
Characterisitcs of the cluster for Demographics



```
ggparcoord(PriceResult,
  columns = 12:26, groupColumn = 1,
  showPoints = TRUE,
  title = "Characterisitcs of the cluster on the Basis of Purchase",
  alphaLines = 0.3
)
```

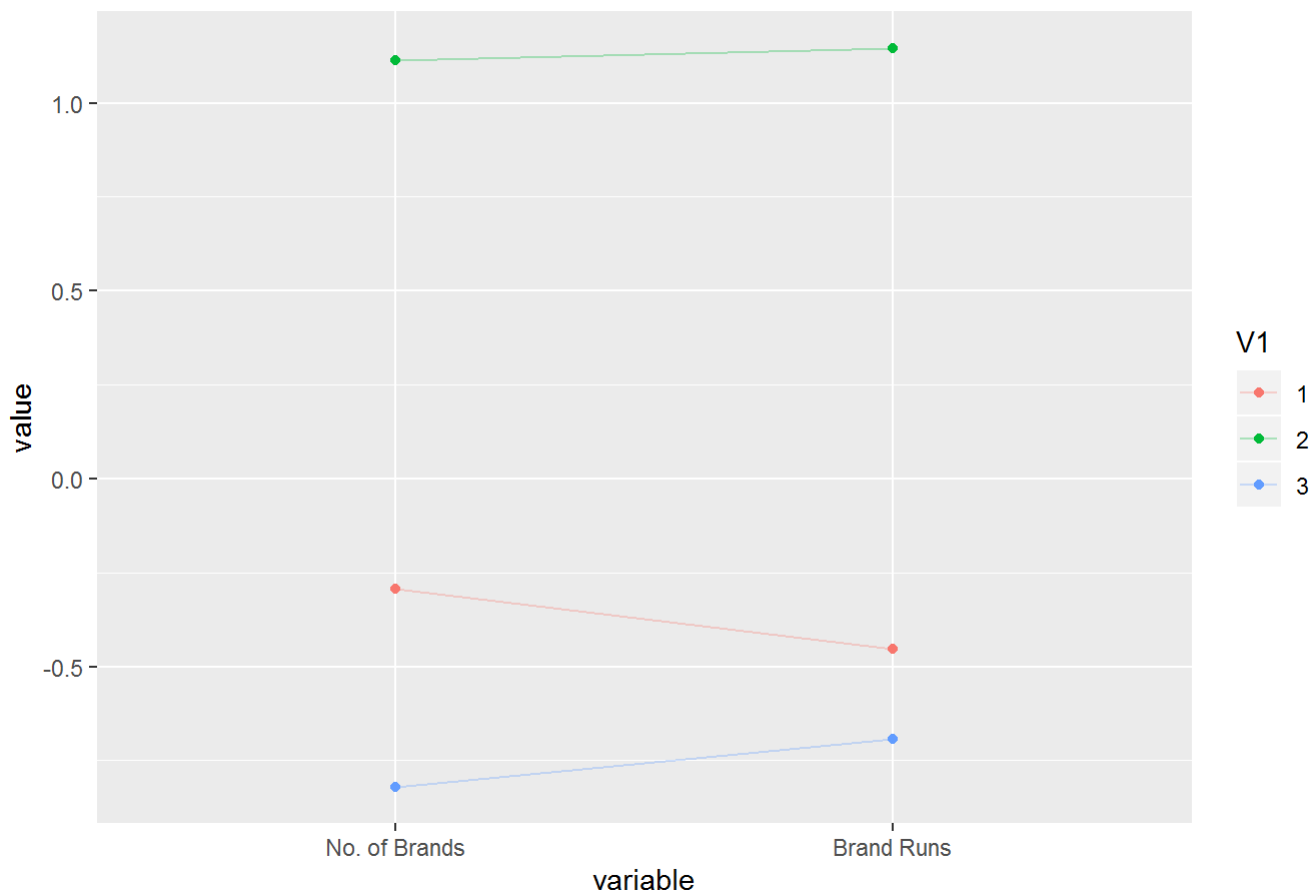


## Characterisitics of the cluster on the Basis of Purchase



```
ggparcoord(PBPRResult,
  columns = 12:13, groupColumn = 1,
  showPoints = TRUE,
  title = "Characterisitics of the cluster for brand Loyalty",
  alphaLines = 0.3
)
```

### Characterisitics of the cluster for brand Loyalty



## Comment:

Based on the above representation:

## Cluster 1:

Cluster 1 is demographically characterized by High socioeconomic class and more number of members in household. On the basis of purchase it is more influenced by Price category 3 and selling proposition category 14. It has low brand loyalty when compared to cluster 2.

## Cluster 2:

Cluster 2 is demographically characterized by Highly Educated, Age and more durability. On the basis of purchase it is more influenced by Price category 2 and most of the selling proposition categories. It has the highest brand loyalty when compared to other clusters.

## Cluster 3:

Cluster 3 is demographically characterized by low socioeconomic status and more number of children in household. On the basis of purchase it is more influenced by Price category 1 and the selling proposition categories 11 and 12. It has the lowest brand loyalty when compared to other clusters.

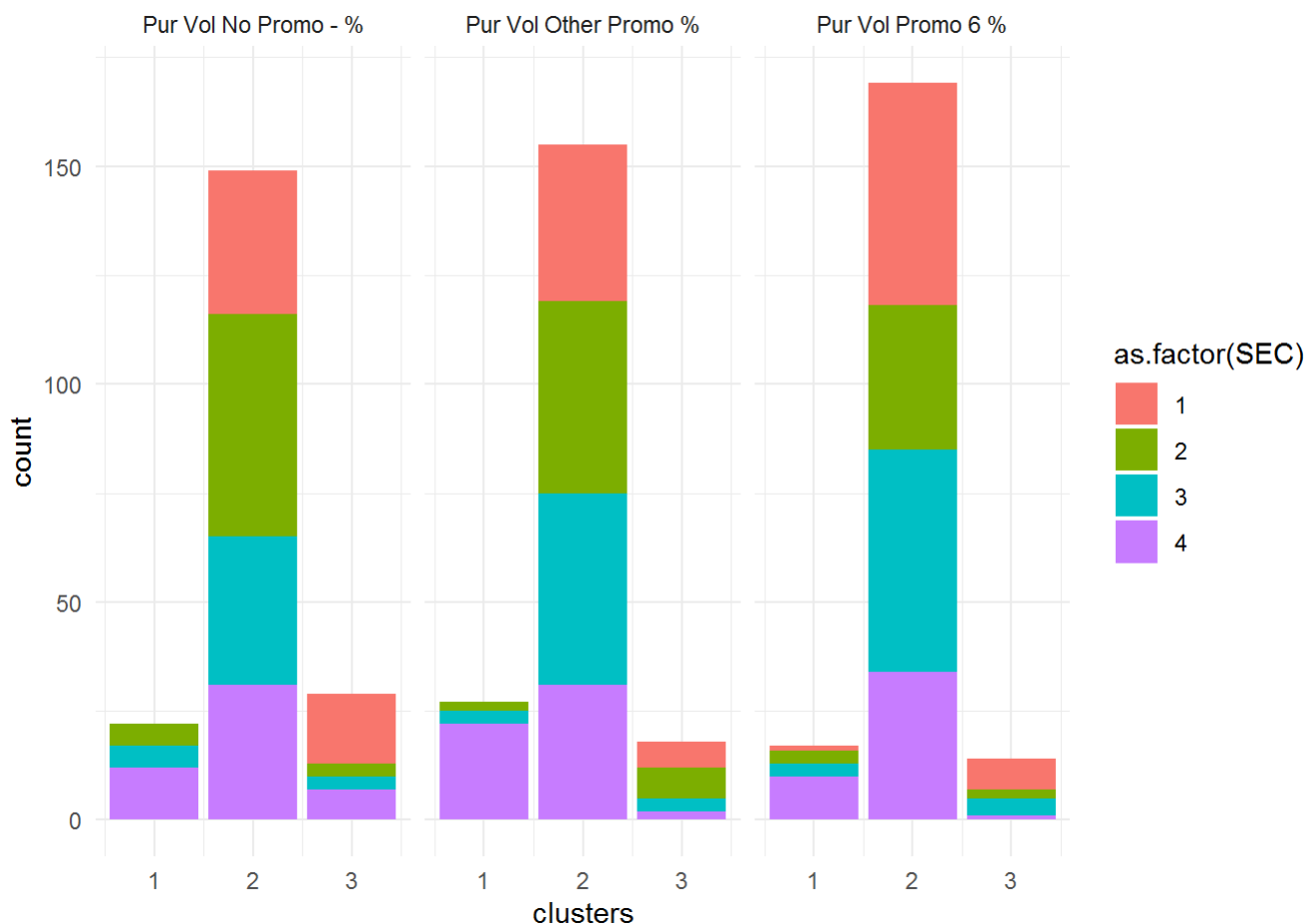
Cluster 2 is the most significant and best for any measure

## Question 3:

Develop a model that classifies the data into these segments. Since this information would most likely be used in targeting direct-mail promotions, it would be useful to select a market segment that would be defined as a success in the classification model.

## Comment:

```
MyData$clusters<-PB_k3$cluster
ggplot(MyData) +
  aes(x = clusters,fill=as.factor(SEC)) +
  geom_bar() +
  scale_fill_hue() +
  theme_minimal() +
  facet_wrap(vars(c("Pur Vol No Promo - %", "Pur Vol Promo 6 %", "Pur Vol Other Promo %")))
```



Based on the earlier findings,

## Cluster 1:

Cluster 1 is demographically characterized by High socioeconomic class and more number of members in household. But When compared to Cluster 2 this is less number. The cluster 1 has low brand loyalty when compared to cluster 2. Hence Cluster 1 targets mainly other Socioeconomic class people. But since brand loyalty

is less, marketing team will target the other socioeconomic class people by offering direct mail promotions.

## Cluster 2

Cluster 2 has a mix of all demographics, basis of purchase. It has high brand Loyalty when compared to the other two clusters.

## Cluster 3

Cluster 3 is demographically characterised by low socioeconomic class and lowest brand loyalty when compared to other clusters. Hence in cluster 3 the marketing team targets High Socioeconomic status class by offering direct mail promotions.