Wholesale customers clustering

Raheem Bukhsh

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Contents

1 Introduction:

This is 2nd project of capstone HarvardX for Data Science Professional Certificate. In this project we will analyze a dataset from UCI Machine Learning Repository. This data set contains information about clients of a wholesale distributor. It includes annual spending in monetary units (m.u) for different product categories.

1.1 Objective:

The objective of this project is to classify and cluster different segments of wholesale customers based on their spending prefrences.

1.2 Customer Segments:

Customer segmentation is an important application of unsupervised learning.
Customer segmentation/clustering is the process of dividing a braod customer base or business markets, normall consisting of existing and potential customers into sub-groups of consumers(Segments) based on type of shared characteristics. In dividing or segmenting makets, researchers typically look for common characteristics such as shared needs,common interests, similar lifestyles, alike spending patterns or even same demographic profiles. The overall aim of segmentation is to identify the *most profitable segments* with *growth potential*. Using clustering techniques, companies can identify the several segments of customers allowing them to target the potential user base.

1.3 Wholesale Customers Data Set:

Wholesale customers is a multivariate data set with 440 observations and 8 variables which are as follows:
1. Channel: customers Channel - Horeca (Hotel/Restaurant/Cafe) or Retail channel (Nominal)
2. Region: customers Region - Lisnon, Oporto or Other (Nominal)
3. Fresh: annual spending (m.u.) on fresh products (Continuous)
4. Milk: annual spending (m.u.) on milk products (Continuous)
5. Grocery: annual spending (m.u.)on grocery products (Continuous)
6. Frozen: annual spending (m.u.)on frozen products (Continuous)
7. Detergents_Paper: annual spending (m.u.) on detergents and paper products (Continuous)
8. Delicassen: annual spending (m.u.)on and delicatessen products (Continuous)

The data has been downladed from the url "$https : //archive.ics.uci.edu/ml/datasets/Wholesale + customers$"

2 Data Analysis:

First we upload the wholesale customers data set,

```
wholesale <- read.csv("C:\\Users\\Raheem\\Downloads\\Wholesale customers data.csv")
```

2.1 Data Exploration and Methods:

For data expolation upload the following packages and libraries.

```
library(tidyverse)
library(dplyr)
library(ggplot2)
```

2.1.1 Dimensions:

```
dim(wholesale)
```

```
## [1] 440   8
```

The wholesale customers dataset has 440 observations for 8 variables.

2.1.2 Variables:

```
glimpse(wholesale)
```

```
## Rows: 440
## Columns: 8
## $ Channel          <int> 2, 2, 2, 1, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 1, 2,...
## $ Region           <int> 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,...
## $ Fresh            <int> 12669, 7057, 6353, 13265, 22615, 9413, 12126, 7579...
## $ Milk             <int> 9656, 9810, 8808, 1196, 5410, 8259, 3199, 4956, 36...
## $ Grocery          <int> 7561, 9568, 7684, 4221, 7198, 5126, 6975, 9426, 61...
## $ Frozen           <int> 214, 1762, 2405, 6404, 3915, 666, 480, 1669, 425, ...
## $ Detergents_Paper <int> 2674, 3293, 3516, 507, 1777, 1795, 3140, 3321, 171...
## $ Delicassen       <int> 1338, 1776, 7844, 1788, 5185, 1451, 545, 2566, 750...
```

It shows that 2 variables channel and region are integers but categorical and can be classified as nominal integers.

2.1.3 Summary Statistics:

Summary statistics is useful insight for the continuous integers with details about Minimum, maximum, Mean, Median and Standard Deviation.

- **Summary of Wholesale Dataset:**

```
summary(wholesale)
```

```
##     Channel          Region          Fresh             Milk      
##  Min.   :1.000   Min.   :1.000   Min.   :     3   Min.   :   55  
##  1st Qu.:1.000   1st Qu.:2.000   1st Qu.:  3128   1st Qu.: 1533  
##  Median :1.000   Median :3.000   Median :  8504   Median : 3627  
##  Mean   :1.323   Mean   :2.543   Mean   : 12000   Mean   : 5796  
##  3rd Qu.:2.000   3rd Qu.:3.000   3rd Qu.: 16934   3rd Qu.: 7190  
##  Max.   :2.000   Max.   :3.000   Max.   :112151   Max.   :73498  
##     Grocery          Frozen        Detergents_Paper    Delicassen     
##  Min.   :    3   Min.   :   25.0   Min.   :    3.0   Min.   :    3.0  
##  1st Qu.: 2153   1st Qu.:  742.2   1st Qu.:  256.8   1st Qu.:  408.2  
##  Median : 4756   Median : 1526.0   Median :  816.5   Median :  965.5  
##  Mean   : 7951   Mean   : 3071.9   Mean   : 2881.5   Mean   : 1524.9  
##  3rd Qu.:10656   3rd Qu.: 3554.2   3rd Qu.: 3922.0   3rd Qu.: 1820.2  
##  Max.   :92780   Max.   :60869.0   Max.   :40827.0   Max.   :47943.0  
```

- **Standard deviation of variables:**

```
apply(wholesale, 2, sd)
```

```
##          Channel           Region            Fresh             Milk 
##     4.680516e-01     7.742724e-01     1.264733e+04     7.380377e+03 
##          Grocery           Frozen Detergents_Paper       Delicassen 
##     9.503163e+03     4.854673e+03     4.767854e+03     2.820106e+03 
```

Channel and Region are categorical variables thus their standard deviation can be ignored.

2.1.4 Channel and Region Insights:

- **Channel Distribution:**

```
table(wholesale$Channel)
```

```
##
##   1   2
## 298 142
```

1 is abbreviated for "HoReCa"(Hotel/Restaurant/Cafe) and 2 for "Retail" show the respective customers via each channel.

```
table(wholesale$Region)
```

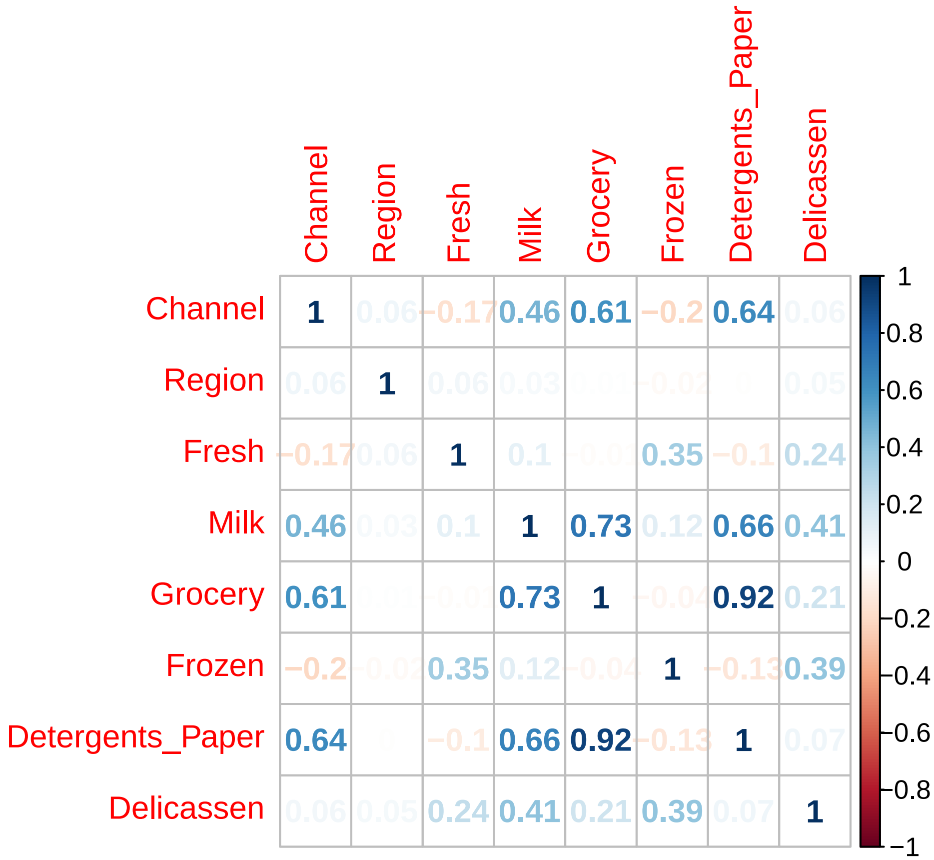
```
##
##   1   2   3
##  77  47 316
```

1 is abbreviation for "Lisbon", 2 for "Oporto" and 3 for "Other" regions.

2.1.5 Correlation between variables:

Let us further explore the dataset and check if any correlation exist between the variables.

```
library(corrplot)
ws_cor <- cor(wholesale)
corrplot(ws_cor, method = "number")
```



From the above correlation plot we can see that correlation exists between several variables but it is strongest between Detergent_Paper and Grocery.

2.2 Clustering Methods:

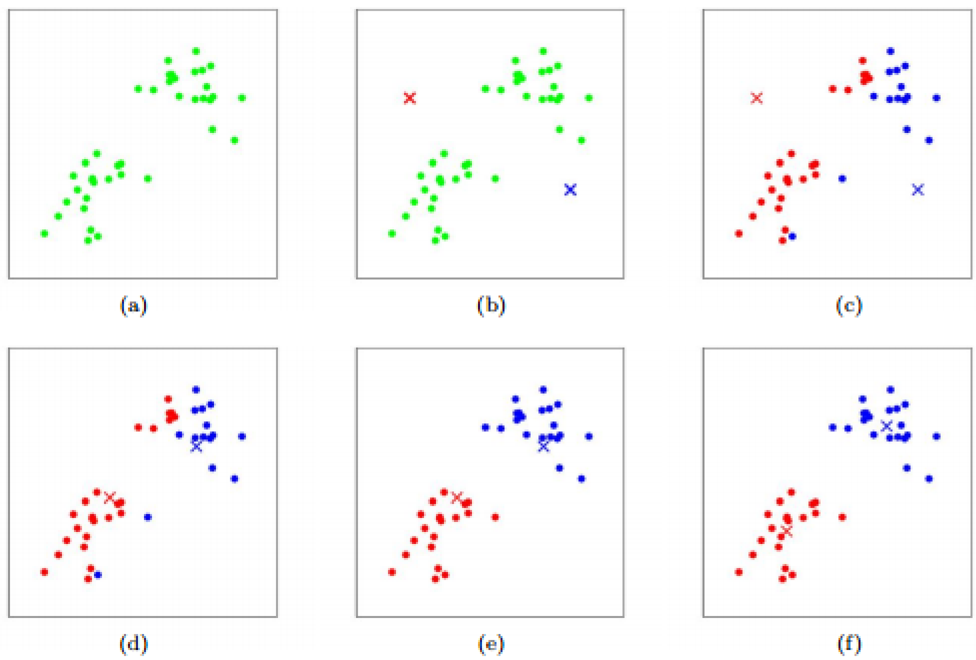
Clustering is the task of dividing the population or data points into a number of groups such that data points in the same groups are more similar to other data points in the same group than those in other groups. In simple words, the aim is to segregate groups with similar traits and assign them into clusters.

There are two widely used methods used for clustering purposes.

2.2.1 K Means Clustering:

K-Means is one of the most popular "clustering" algorithms. K-means stores k centroids that it uses to define clusters. A point is considered to be in a particular cluster if it is closer to that cluster's centroid than any other centroid.

K-Means finds the best centroids by alternating between (1) assigning data points to clusters based on the current centroids (2) chosing centroids (points which are the center of a cluster) based on the current assignment of data points to clusters.



K-means algorithm. Training examples are shown as dots, and cluster centroids are shown as crosses. (a) Original dataset. (b) Random initial cluster centroids. (c-f) Illustration of running two iterations of k-means. In each iteration, we assign each training example to the closest cluster centroid (shown by "painting" the training examples the same color as the cluster centroid to which is assigned); then we move each cluster centroid to the mean of the points assigned to it.

If the ith observation is in the kth cluster, then $i \in C_k$. The idea behind K-means clustering is that a *good* clustering is one for which the $within-cluster\ variation$ is as small as possible. The within-cluster variation for cluster C_k is a measure $W(Ck)$ of the amount by which the observations within a cluster differ from each other. Hence we want to solve the problem:

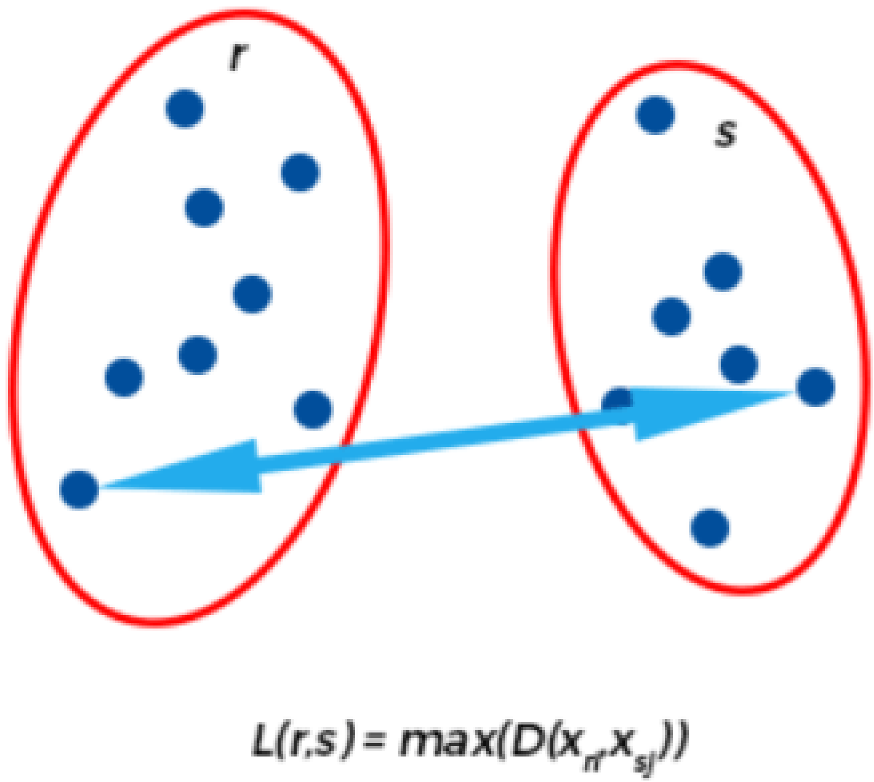
$minimize \ \{\sum_{K=1}^{K} W(C_k)\}$
$C1, ..., CK$

K Means Clustering algorithm works in five steps:
* Specify the desired number of clusters K.
* The algorithm selects k objects at random from the dataset. This object is the initial cluster or mean.
* The closest centroid obtains the assignment of a new observation. We base this assignment on the Euclidean Distance between object and the centroid.
* k clusters in the data points update the centroid through calculation of the new mean values present in all the data points of the cluster. The kth cluster's centroid has a length of p that contains means of all variables for observations in the k-th cluster. We denote the number of variables with p.
* Iterative minimization of the total within the sum of squares. Then through the iterative minimization of the total sum of the square, the assignment stop wavering when we achieve maximum iteration. The default value is 10 that the R software uses for the maximum iterations.

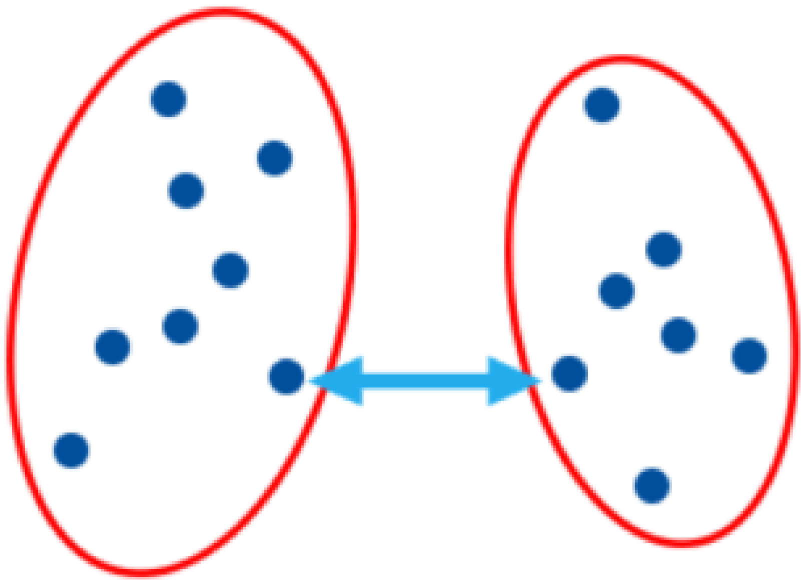
2.2.2 Hierarchical Clustering:

Hierarchical clustering, also known as hierarchical cluster analysis, is an algorithm that groups similar objects into groups called clusters. The endpoint is a set of clusters, where each cluster is distinct from each other cluster, and the objects within each cluster are broadly similar to each other.
Hierarchical clustering starts by treating each observation as a separate cluster. Then, it repeatedly executes the following two steps:

* Identify the two clusters that are closest together by measuring Euclidean distance. * Merge the two most similar clusters. This iterative process continues until all the clusters are merged together.
* **Computing hierarchical clustring:**
To compute the hierarchical clustering the distance matrix needs to be calculated using and put the data point to the correct cluster. There are different ways we can calculate the distance between the cluster, as given below:
1. **Complete Linkage:**
Maximum distance is calculated between clusters before merging.

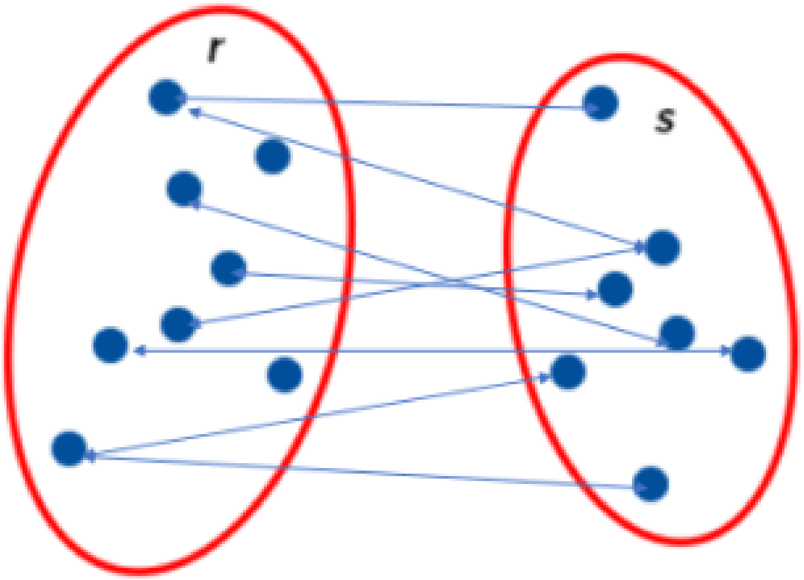


2. **Single Linkage:**
Minimum distance calculates between the clusters before merging.



$$L(r,s) = min(D(x_{ri}, x_{sj}))$$

3. **Average Linkage:**
   Calculates the average distance between clusters before merging.



$$L(r,s) = \frac{1}{n_r n_s} \sum_{i=1}^{n_r} \sum_{j=1}^{n_s} D(x_{ri}, x_{sj})$$

4. **Ward Linkage:**
   Instead of measuring the distance directly, it analyzes the variance of clusters. Ward's is said to be the most suitable method for quantitative variables. To implement this method, at each step find the pair of clusters that leads to minimum increase in total within-cluster variance after merging. This increase is a weighted squared distance between cluster centers.
   Ward's method says that the distance between two clusters, A and B, is how much the sum of squares will increase when we merge them:

$\Delta(A,B) = \sum_{i \in A \bigcup B} ||\overrightarrow{x_i} - \overrightarrow{m}_{A \bigcup B}||^2 - \sum_{i \in A} ||\overrightarrow{x_i} - \overrightarrow{m}_A||^2 - \sum_{i \in B} ||\overrightarrow{x_i} - \overrightarrow{m}_B||^2 = \frac{n_A n_B}{n_A + n_B} ||\overrightarrow{m}_A - \overrightarrow{m}_B||^2$
where $\overrightarrow{m}_j$ the center of cluster j, and n_j is the number of points in it. Δ is called the merging cost of combining the clusters A and B. With hierarchical clustering, the sum of squares starts out at zero (because every point is in its own cluster) and then grows as we merge clusters. Ward's method keeps this growth as small as possible.

3 Clustring Results and Analysis:

To apply the clustering model first we need to scale/standardize the data but here we have either the categorical variables channel and region in 1st and 2nd column and remaining 6 columns have the continuous numeric data (spending in $) therefore therefore no need to scale the data but just excluding the categorical variables for clustering is enough.

```
wholesale_sc <- as.matrix(scale(wholesale[3:8]))
head(wholesale_sc)
```

```
##             Fresh        Milk     Grocery     Frozen Detergents_Paper
## [1,]  0.05287300  0.52297247 -0.04106815 -0.5886970      -0.04351919
## [2,] -0.39085706  0.54383861  0.17012470 -0.2698290       0.08630859
## [3,] -0.44652098  0.40807319 -0.02812509 -0.1373793       0.13308016
## [4,]  0.09999758 -0.62331041 -0.39253008  0.6863630      -0.49802132
## [5,]  0.83928412 -0.05233688 -0.07926595  0.1736612      -0.23165413
## [6,] -0.20457266  0.33368675 -0.29729863 -0.4955909      -0.22787885
##        Delicassen
## [1,] -0.06626363
## [2,]  0.08904969
## [3,]  2.24074190
## [4,]  0.09330484
## [5,]  1.29786952
## [6,] -0.02619421
```

3.1 K Means Clustering:

- **Selecting the number of K's:**

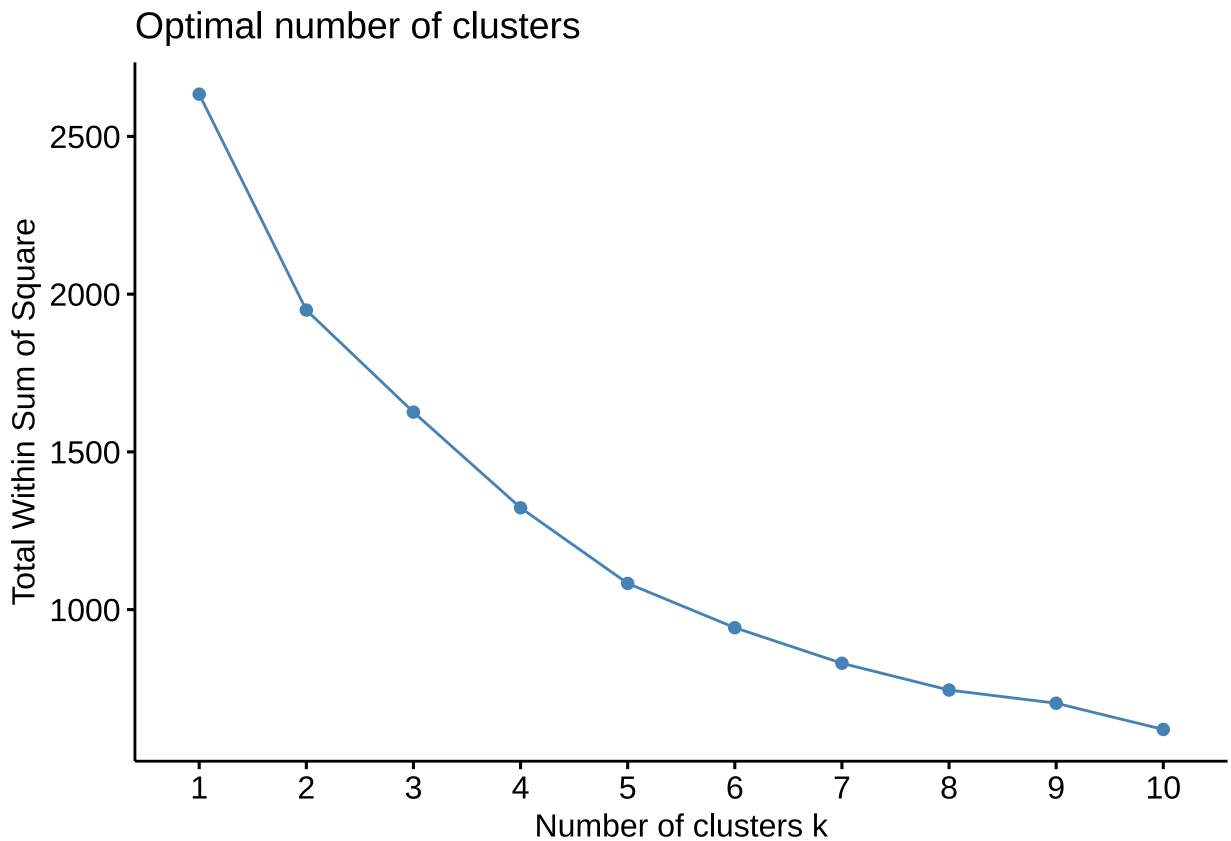
As discussed earlier first we need to find the optimal clusters,
There are three most popular methods to determine optimal clusters, which are:
* **Elbow Method**
* **Silhouette Method**
* **Gap Statistics**

Elbow Method:
We calculate the clustering algorithm for several values of k. This can be done by creating a variation within k from 1 to 10 clusters. We then calculate the total within cluster sum of square (wss). Then, we proceed to plot wss based on the number of k clusters. This plot denotes the appropriate number of clusters required in our model. In the plot, the location of a **bend** or **elbow** is the indication of the optimum number of clusters.
The process to compute the "Elbow method" has been wrapped up in a single function (fviz_nbclust):

```
library(factoextra)
library(cluster)
library(gridExtra)

set.seed(123)

fviz_nbclust(wholesale_sc , kmeans, method = "wss")
```



The elbow or bend is not sharp and any value among 2 or 5 can be selected and we select k = 5

Silhouette method:

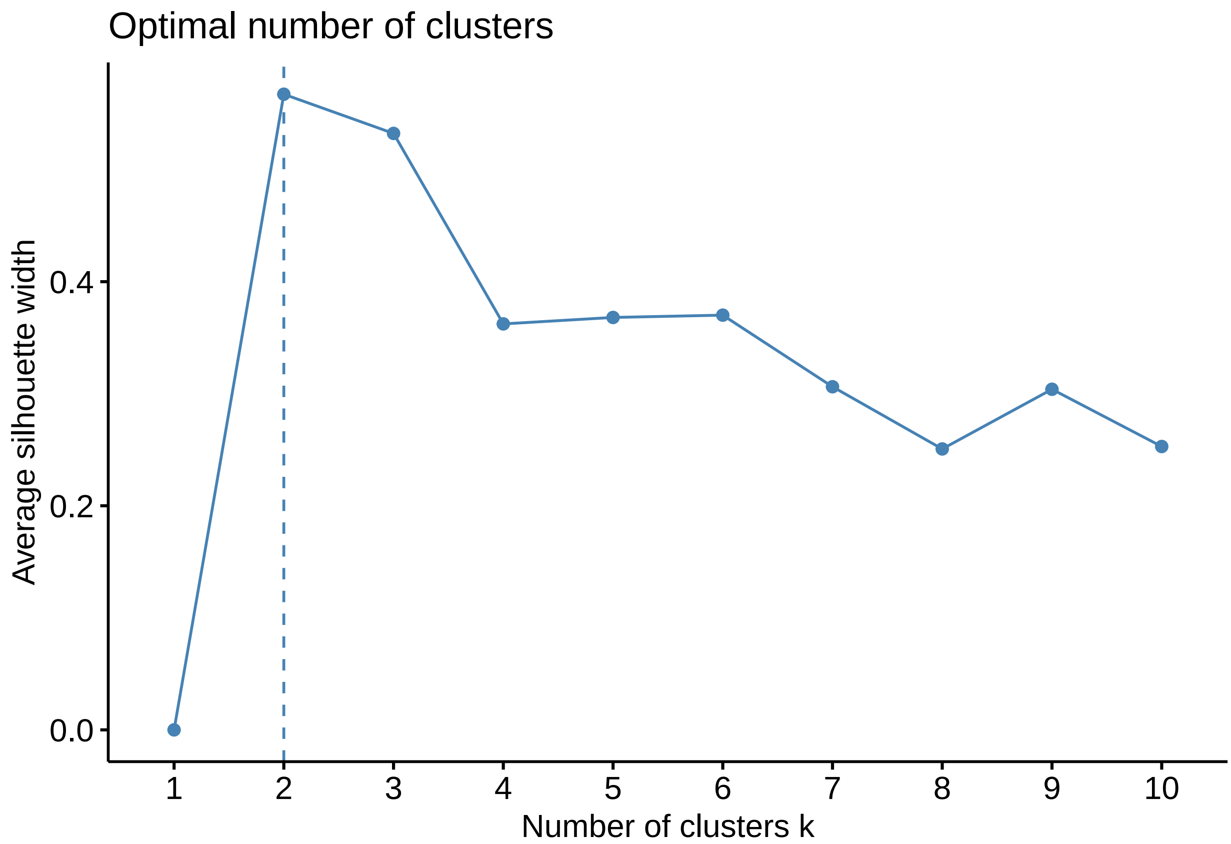
Silhouette refers to a method of interpretation and validation of consistency within clusters of data. The technique provides a succinct graphical representation of how well each object has been classified.

The silhouette value is a measure of how similar an object is to its own cluster (cohesion) compared to other clusters (separation). The silhouette ranges from -1 to $+1$, where a high value indicates that the object is well matched to its own cluster and poorly matched to neighboring clusters. If most objects have a high value, then the clustering configuration is appropriate. If many points have a low or negative value, then the clustering configuration may have too many or too few clusters.

The silhouette can be calculated with any distance metric, such as the Euclidean distance or the Manhattan distance. Just like elbow method, this process to compute the "average silhoutte method" has been wrapped up in a single function (fviz_nbclust):

```
set.seed(123)

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



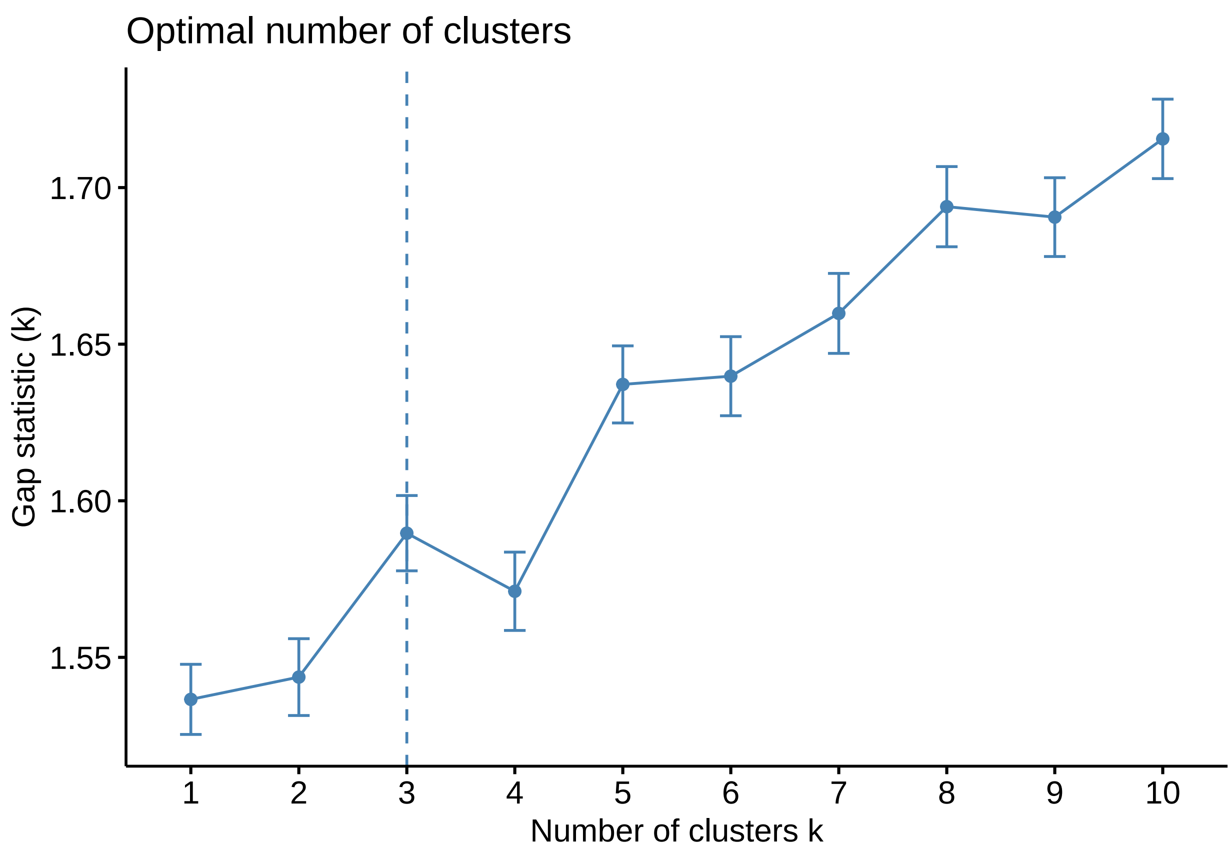
The optimal number of clusters defined by Silhouette method is 2.

Gap Statistics:

In 2001, researchers at Stanford University – R. Tibshirani, G.Walther and T. Hastie published the Gap Statistic Method. We can use this method to any of the clustering method like K-means, hierarchical clustering etc. Using the gap statistic, one can compare the total intracluster variation for different values of k along with their expected values under the null reference distribution of data. With the help of Monte Carlo simulations, one can produce the sample dataset. For each variable in the dataset, we can calculate the range between min(xi) and max (xj) through which we can produce values uniformly from interval lower bound to upper bound.
For computing the gap statistics method we can utilize the clusGap function for providing gap statistic as well as standard error for a given output.We can visualize the results with fviz_gap_stat which suggests the optimal number of clusters.

```
set.seed(123)
gap_stat_clust <- clusGap(wholesale_sc, FUN = kmeans, nstart = 25,K.max = 10, B = 50)
```

```
fviz_gap_stat(gap_stat_clust)
```

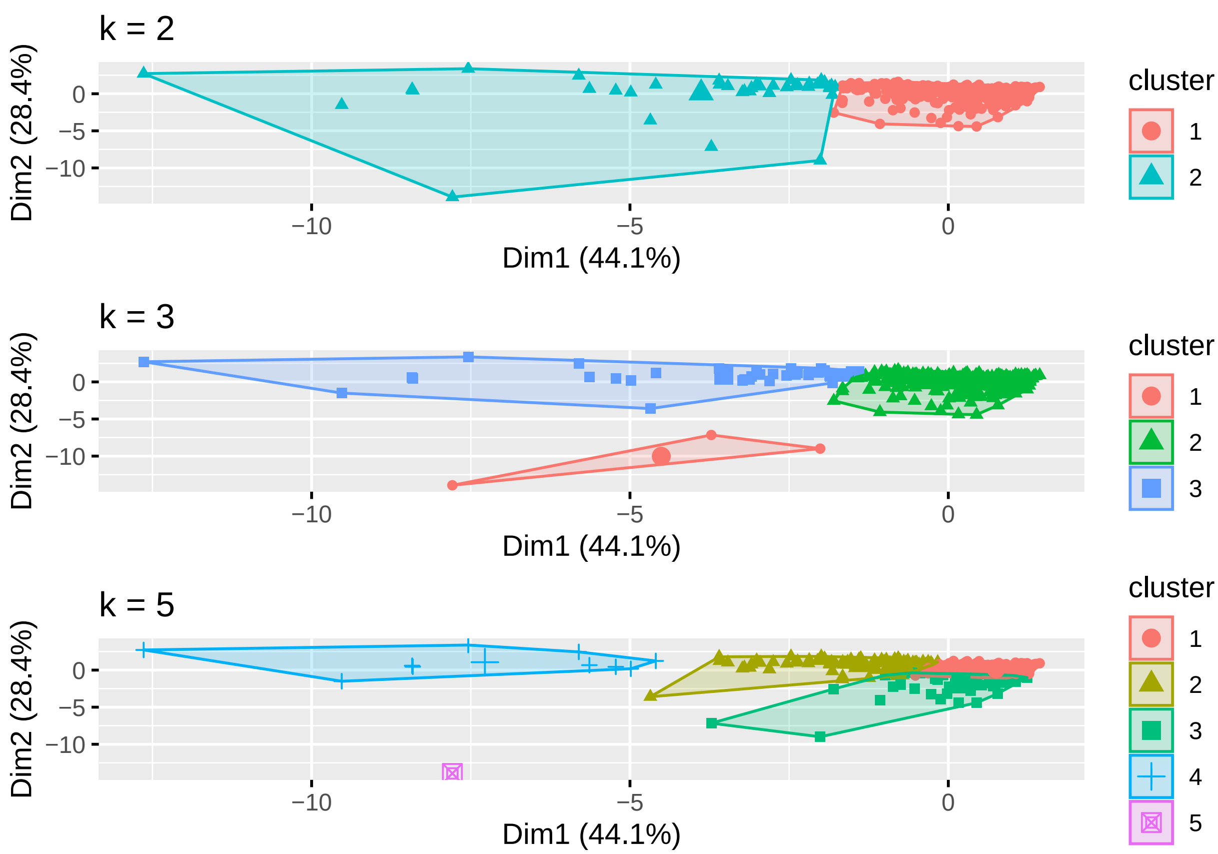


Gap statistic method shows that optimal number of clusters is 3.

- **Selecting Optimal Clusters:**
  While using the above estimates the optimal value of clusters has been 2,3 and 5. Now we have to select the most optimal number of K clusters. We can also view our results by using fviz_cluster. This provides a nice illustration of the clusters. If there are more than two dimensions (variables) fviz_cluster will perform principal component analysis (PCA) and plot the data points according to the first two principal components that explain the majority of the variance.

```
#Compute Kmeans for K=2, K=3 and K=5
k2 <- kmeans(wholesale_sc, centers = 2, nstart = 30)
k3 <- kmeans(wholesale_sc, centers = 3, nstart = 30)
k5 <- kmeans(wholesale_sc, centers = 5, nstart = 30)
#Use fviz_cluster() to compare the results
d1 <- fviz_cluster(k2, geom = "point", data = wholesale_sc) + ggtitle("k = 2")
d2 <- fviz_cluster(k3, geom = "point",  data = wholesale_sc) + ggtitle("k = 3")
d3 <- fviz_cluster(k5, geom = "point",  data = wholesale_sc) + ggtitle("k = 5")

grid.arrange(d1, d2, d3, nrow = 3)
```



From above diagram it is visible that when number of clusters is 2 and 3 it separates the data in to distinctive clusters as calculated by Silhoutte method and Gap statistic.
Now look in further detail clusters 2 and 3.

```r
print(k2)
```

```
## K-means clustering with 2 clusters of sizes 399, 41
##
## Cluster means:
##         Fresh       Milk    Grocery      Frozen Detergents_Paper Delicassen
## 1 -0.00542930 -0.2122882 -0.2302493 -0.03310806       -0.2320799 -0.0826124
## 2  0.05283636  2.0659269  2.2407190  0.32219794        2.2585338  0.8039597
##
## Clustering vector:
##   [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 1 1 1 2 1 1 1 1 1 1 1 1
##  [38] 1 1 1 1 1 1 2 1 2 2 2 1 2 1 1 1 1 1 1 2 1 1 1 1 2 1 1 1 2 1 1 1 1 1 1 1 1
##  [75] 1 1 1 2 1 1 1 1 1 1 1 2 2 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [112] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 1
## [149] 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 2 1 2 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 2 1 2 1
## [186] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 1 1 1 2 1 1 1 2 1 2 1 1 1 1 2 1 1 1 1 1
## [223] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1
## [260] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [297] 1 1 1 1 1 2 1 1 2 1 2 1 1 2 1 1 2 1 1 1 1 1 1 2 1 1 1 1 1 2 1 1 1 1 1 2 1
## [334] 2 1 1 1 1 1 1 1 1 1 2 1 1 1 1 1 2 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [371] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [408] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 1
```

```
##
## Within cluster sum of squares by cluster:
## [1] 982.9619 966.3860
##  (between_SS / total_SS =  26.0 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

```
print(k3)
```

```
## K-means clustering with 3 clusters of sizes 3, 393, 44
##
## Cluster means:
##          Fresh       Milk    Grocery      Frozen Detergents_Paper  Delicassen
## 1  3.840444845  3.2957757  0.9852919  7.20489292       -0.1527927  6.79967230
## 2  0.004950908 -0.2277887 -0.2542638 -0.02703683       -0.2486071 -0.08005229
## 3 -0.306069120  1.8098555  2.2038591 -0.24975466        2.2309315  0.25139852
##
## Clustering vector:
##   [1] 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 3 2 2 2 2 2 2 2 2
##  [38] 2 3 2 2 2 2 3 2 3 3 3 2 3 2 2 2 2 2 2 3 2 2 2 2 3 2 2 2 3 2 2 2 2 2 2 2 2
##  [75] 2 2 2 3 2 2 2 2 2 2 2 2 3 3 2 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2
## [112] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2
## [149] 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 3 2 3 2 2 2 2 2 3 2 3 2 2 2 2 2 2 2 2 1 2 1 2
## [186] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 3 2 2 2 3 2 2 2 3 2 3 2 2 2 2 3 2 2 2 2 2
## [223] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 2
## [260] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [297] 2 2 2 2 2 3 2 2 3 2 3 2 2 3 2 2 3 2 2 2 2 2 2 3 2 2 2 2 2 1 2 2 2 2 2 3 2
## [334] 3 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 3 2 3 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [371] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [408] 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2
##
## Within cluster sum of squares by cluster:
## [1] 214.5396 944.8291 441.0021
##  (between_SS / total_SS =  39.2 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

From the above details we can conclude that cluster size 3 is the most optimal number of clusters as it separates the highly variable observations in to distinctive groups. These clusters can include potentially high spending customers.

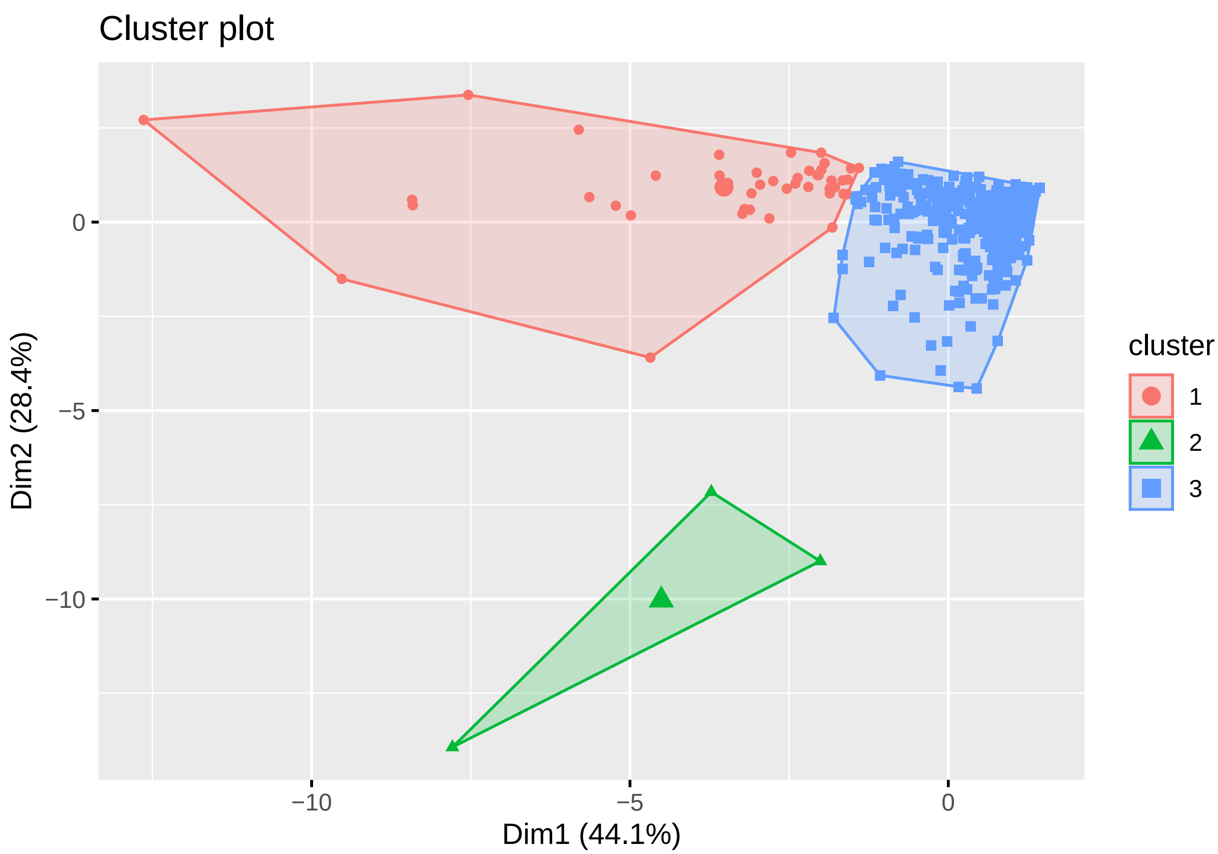
- **Clustering with K=3:**

```
# Compute K-Means Clustering with K =3
set.seed(123)
final_segments <- kmeans(wholesale_sc, centers = 3, nstart = 30)
print(final_segments)
```

```
## K-means clustering with 3 clusters of sizes 44, 3, 393
##
## Cluster means:
##          Fresh       Milk    Grocery      Frozen Detergents_Paper  Delicassen
## 1 -0.306069120  1.8098555  2.2038591 -0.24975466        2.2309315  0.25139852
## 2  3.840444845  3.2957757  0.9852919  7.20489292       -0.1527927  6.79967230
## 3  0.004950908 -0.2277887 -0.2542638 -0.02703683       -0.2486071 -0.08005229
##
## Clustering vector:
##   [1] 3 3 3 3 3 3 3 3 3 1 3 3 3 3 3 3 3 3 3 3 3 3 1 3 3 3 3 1 3 3 3 3 3 3 3 3 3
##  [38] 3 1 3 3 3 3 1 3 1 1 1 3 1 3 3 3 3 3 3 1 3 3 3 3 1 3 3 3 1 3 3 3 3 3 3 3 3
##  [75] 3 3 3 1 3 3 3 3 3 3 3 1 1 3 3 3 3 3 1 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 1 3
## [112] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 1 3 3
## [149] 3 3 3 3 3 3 3 1 3 3 3 3 3 3 3 1 3 1 3 3 3 3 3 1 3 1 3 3 3 3 3 3 3 2 3 2 3
## [186] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 1 1 3 3 3 1 3 3 3 1 3 1 3 3 3 3 1 3 3 3 3 3
## [223] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 1 3 3 3 3 3 3 3 3
## [260] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
## [297] 3 3 3 3 3 1 3 3 1 3 1 3 3 1 3 3 1 3 3 3 3 3 3 1 3 3 3 3 3 2 3 3 3 3 3 1 3
## [334] 1 3 3 3 3 3 3 3 3 3 1 3 3 3 3 3 1 3 1 3 1 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
## [371] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
## [408] 1 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 1 3 3
##
## Within cluster sum of squares by cluster:
## [1] 441.0021 214.5396 944.8291
##  (between_SS / total_SS =  39.2 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

Now visualize the final clustering when K=3

```r
#Visualize the final clusters
fviz_cluster(final_segments, geom = "point",  data = wholesale_sc)
```



Cluster plot
Dim2 (28.4%)
0
−5
−10
−10
−5
0
Dim1 (44.1%)
cluster
1
2
3