Assignment 4

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Summary:

1. • Missing Values Check: checking the proportion of missing values in each column of our dataset.

• Normalization: Normalizing the data using the scale function. It’s essential for K-Means clustering to have variables on the same scale.

• Finding Optimal K: The optimal number of clusters using the Elbow method (wss) and Silhouette method. Where the optimal k value using the wss method is k = 2 and Silhouette method is k = 5

2.K-Means Clustering:

• K-Means clustering with k = 2 using the Within-Sum-of-Squares (WSS) method. The nstart parameter helps in running the algorithm multiple times with different initial centroids to avoid local minima. Within cluster sum of squares by clusters = 43.3, 75.2 & Between-Cluster Proportion(between_SS / total_SS) = 34.1 %

• K-Means clustering with k = 5 using the Silhouette method, providing a more nuanced understanding of the cluster structure. Similar to the WSS method, nstart is used to enhance the robustness of the results.Within cluster sum of squares by cluster: 12.79, 2.8, 15.595925, 21.879320, 9.284424 & Between-Cluster Proportion(between_SS / total_SS = 65.4 %)

Cluster Plot Visualizations:

• a cluster plot for K-Means results with k = 2, using the wss method forms 2 clusters of size 11 and 10.

• a cluster plot for K-Means results with k = 5, using the Silhouette method forms 5 clusters of size 3, 2, 8, 4 and 4.

median calculation:

WSS - One strong buy, seven moderate buys, nine holds, and four moderate sells make the total number of 21 recommendations. All four recommendations, including the opposite advice on buys and sells, are mixed together in Cluster 2. Only Hold Moderate, Buy Moderate & Sell Strong are found in cluster 1.

silhouette - One strong buy, seven moderate buys, nine holds, and four moderate sells make the total number of 21 recommendations. All four recommendations, including the opposite advice on buys and sells, are mixed together in Cluster 5. Only mod purchase and hold information can be found in Clusters 1, 2, and 3.Both a moderate buy and moderate sell recommendation are present for Cluster 4.

Loction:

WSS - Cluster 1 and Cluster 2 seems to have a pattern with respect to the location of the pharmaceutical firms. More than 50% of the firms across both the clusters have “US” as their location. This also states that US has firms which are both profitable to invest (Acceptable Profitability with Moderate Risk) as well as firms which don’t yield that good profits (Low Profitability with High Risk). But comparatively the better performing cluster i.e. Cluster 1 seems to have a greater ratio of companies based in US.

silhouette - In the silhouette clusters we get to see the see the similar level of pattern towards to the location as observed in the wss. Every cluster in here as more of it’s locations in “US” when compared to that with the other locations. But it seems interesting to observe that the best cluster which defines the domain with true sense i.e. Cluster 4 has a greater ratio of US companies with a lesser ratio of Non - US based companies.

exchange:

WSS - There are 21 companies overall, divided into 1 Amex, 1 Nasdaq, and 19 NYSE. Cluster 1 just has the NYSE. All three are in Cluster 2.

silhouette - There are 21 companies overall, divided into 1 Amex, 1 Nasdaq, and 19 NYSE. All three are in Cluster 3. clusters 1,2,4,5 all contains only NYSE.

3.

WSS –

1. Cluster1 - Acceptable Profitability with Moderate Risk
2. Cluster2 - Low Profitability with High Risk:

Silhouette-

1. Cluster1 - Emerging Group
2. Cluster2 - Overvalued and High-Risk Investment Group
3. Cluster3 - High-Risk Investment Group
4. Cluster4 - Promising Value opportunity Group
5. Cluster5 - Prime Investment with Slighter Risk Group

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

```
## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
## ✓ dplyr     1.1.3     ✓ readr     2.1.4
## ✓ forcats   1.0.0     ✓ stringr   1.5.0
## ✓ ggplot2   3.4.3     ✓ tibble    3.2.1
## ✓ lubridate 1.9.2     ✓ tidyr     1.3.0
## ✓ purrr     1.0.2
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## ✕ dplyr::filter() masks stats::filter()
## ✕ dplyr::lag()    masks stats::lag()
## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to be
come errors
```

```
library("factoextra")
```

```
## Warning: package 'factoextra' was built under R version 4.3.2
```

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

```
library("ggplot2")
library("dplyr")
library("esquisse")
```

#Loading and exploring the data

```
data <- read.csv("C:\\Users\\Siddhartha\\Desktop\\FMA\\Assignment 4\\Pharmaceuticals.csv")
head(data)
```

```
##   Symbol                Name Market_Cap Beta PE_Ratio  ROE  ROA Asset_Turnover
## 1    ABT Abbott Laboratories      68.44 0.32     24.7 26.4 11.8            0.7
## 2    AGN      Allergan, Inc.       7.58 0.41     82.5 12.9  5.5            0.9
## 3    AHM        Amersham plc       6.30 0.46     20.7 14.9  7.8            0.9
## 4    AZN     AstraZeneca PLC      67.63 0.52     21.5 27.4 15.4            0.9
## 5    AVE             Aventis      47.16 0.32     20.1 21.8  7.5            0.6
## 6    BAY            Bayer AG      16.90 1.11     27.9  3.9  1.4            0.6
##   Leverage Rev_Growth Net_Profit_Margin Median_Recommendation Location Exchange
## 1     0.42       7.54              16.1          Moderate Buy       US     NYSE
## 2     0.60       9.16               5.5          Moderate Buy   CANADA     NYSE
## 3     0.27       7.05              11.2            Strong Buy       UK     NYSE
## 4     0.00      15.00              18.0         Moderate Sell       UK     NYSE
## 5     0.34      26.81              12.9          Moderate Buy   FRANCE     NYSE
## 6     0.00      -3.17               2.6                  Hold  GERMANY     NYSE
```

```
summary(data)
```

```
##     Symbol              Name             Market_Cap          Beta
##  Length:21          Length:21          Min.   :  0.41   Min.   :0.1800
##  Class :character   Class :character   1st Qu.:  6.30   1st Qu.:0.3500
##  Mode  :character   Mode  :character   Median : 48.19   Median :0.4600
##                                        Mean   : 57.65   Mean   :0.5257
##                                        3rd Qu.: 73.84   3rd Qu.:0.6500
##                                        Max.   :199.47   Max.   :1.1100
##     PE_Ratio          ROE             ROA        Asset_Turnover    Leverage
##  Min.   : 3.60   Min.   : 3.9   Min.   : 1.40   Min.   :0.3    Min.   :0.0000
##  1st Qu.:18.90   1st Qu.:14.9   1st Qu.: 5.70   1st Qu.:0.6    1st Qu.:0.1600
##  Median :21.50   Median :22.6   Median :11.20   Median :0.6    Median :0.3400
##  Mean   :25.46   Mean   :25.8   Mean   :10.51   Mean   :0.7    Mean   :0.5857
##  3rd Qu.:27.90   3rd Qu.:31.0   3rd Qu.:15.00   3rd Qu.:0.9    3rd Qu.:0.6000
##  Max.   :82.50   Max.   :62.9   Max.   :20.30   Max.   :1.1    Max.   :3.5100
##    Rev_Growth    Net_Profit_Margin Median_Recommendation   Location
##  Min.   :-3.17   Min.   : 2.6      Length:21             Length:21
##  1st Qu.: 6.38   1st Qu.:11.2      Class :character      Class :character
##  Median : 9.37   Median :16.1      Mode  :character      Mode  :character
##  Mean   :13.37   Mean   :15.7
##  3rd Qu.:21.87   3rd Qu.:21.1
##  Max.   :34.21   Max.   :25.5
##    Exchange
##  Length:21
##  Class :character
##  Mode  :character
##
##
##
```

#1. Use only the numerical variables (1 to 9) to cluster the 21 firms. Justify the various choices made in conducting the cluster analysis, such as weights for different variables, the specific clustering algorithm(s) used, the number of clusters formed, and so on.

#Looking for na values

```
colMeans(is.na(data))
```

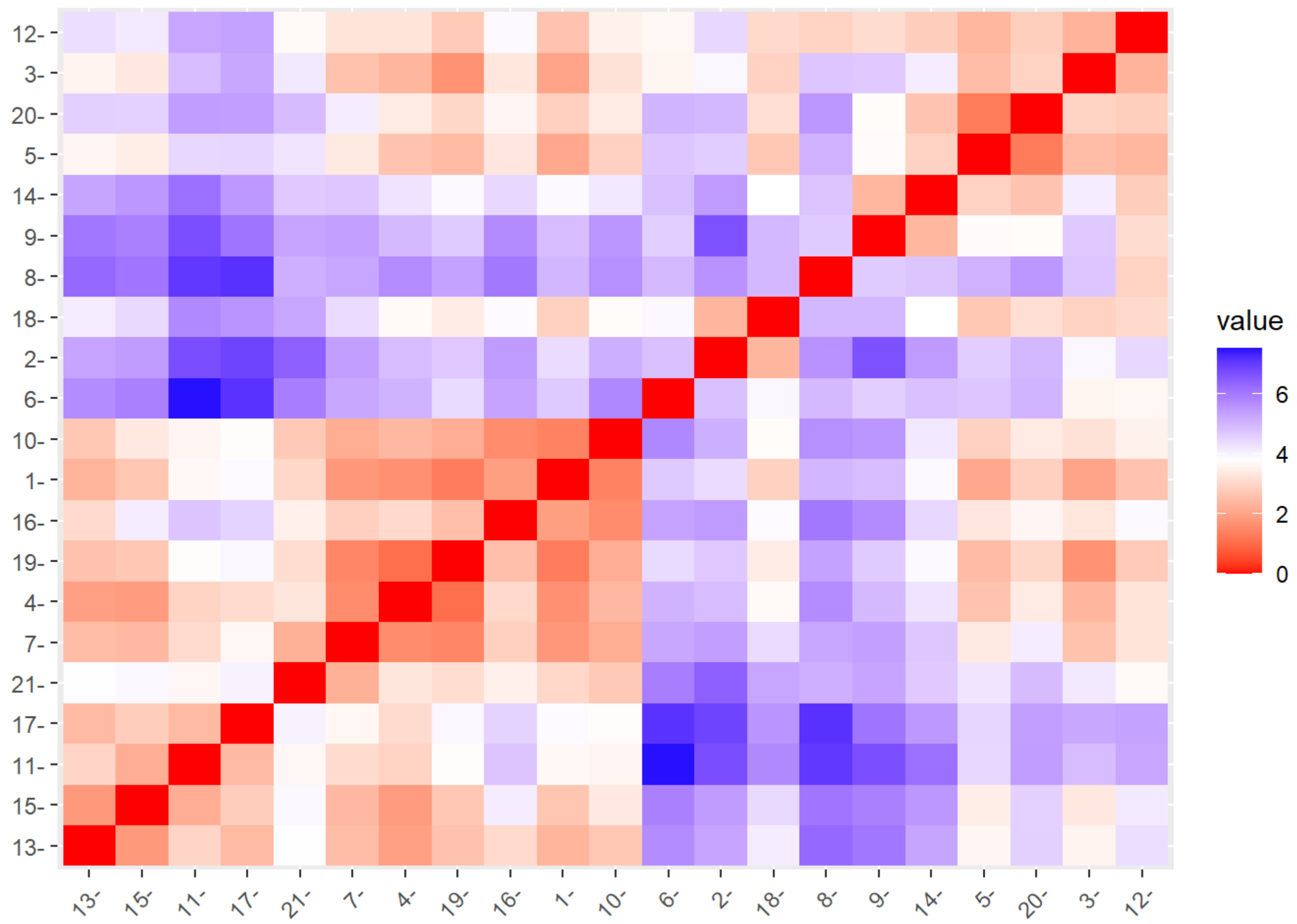
```
##                 Symbol                 Name              Market_Cap
##                      0                    0                       0
##                   Beta             PE_Ratio                     ROE
##                      0                    0                       0
##                    ROA       Asset_Turnover                Leverage
##                      0                    0                       0
##             Rev_Growth    Net_Profit_Margin Median_Recommendation
##                      0                    0                       0
##               Location             Exchange
##                      0                    0
```

#Performing z-score scaling Normalization

```
set.seed(123)
data.norm <- scale(data[,-c(1:2,12:14)])
```

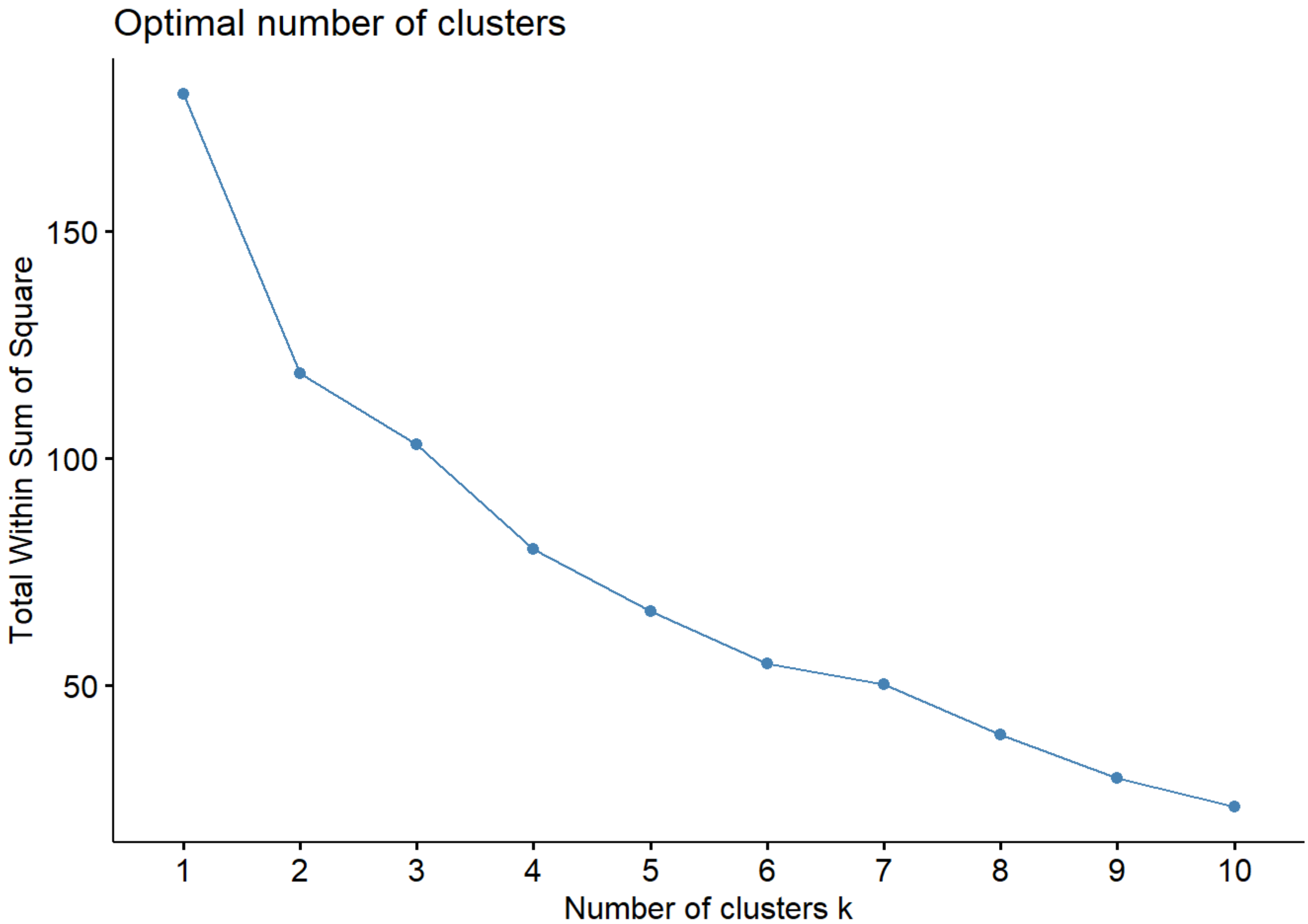
#visualizing the distance between rows of the distance matrix

```
Distance <- dist(data.norm, method = "euclidian")
fviz_dist(Distance)
```



Finding optimal K using wss method

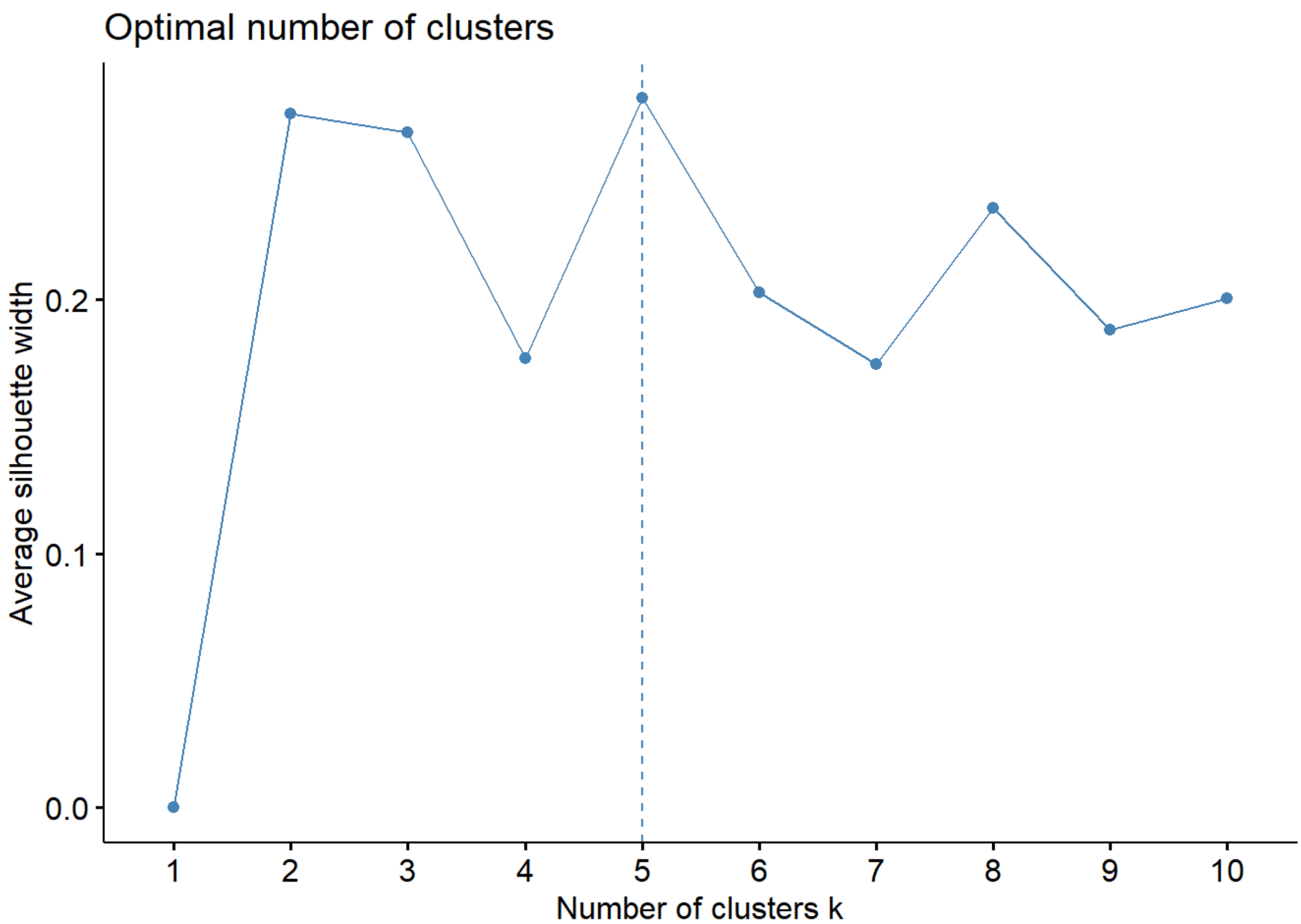
```
wss <- fviz_nbclust(data.norm,kmeans,method="wss")
wss
```



Here in this plot we can clearly see that the graph is forming an elbow shape at 2, The optimal number of clusters (k) determined through the Within-Sum-of-Squares (WSS) method is 2.

Finding optimal K using silhouette method

```
silhouette <- fviz_nbclust(data.norm,kmeans,method="silhouette")
silhouette
```



The optimal number of clusters (k) determined through the silhouette method is 5.

#2.1 Interpret the clusters with respect to the numerical variables used in forming the clusters.

#Formulation of clusters using K-Means with k = 2 (WSS)

```
wss_kmeans <- kmeans(data.norm,centers = 2,nstart=25)
wss_kmeans
```

```
## K-means clustering with 2 clusters of sizes 11, 10
##
## Cluster means:
##   Market_Cap       Beta   PE_Ratio        ROE        ROA Asset_Turnover
## 1  0.6733825 -0.3586419 -0.2763512  0.6565978  0.8344159      0.4612656
## 2 -0.7407208  0.3945061  0.3039863 -0.7222576 -0.9178575     -0.5073922
##     Leverage Rev_Growth Net_Profit_Margin
## 1 -0.3331068 -0.2902163         0.6823310
## 2  0.3664175  0.3192379        -0.7505641
##
## Clustering vector:
##  [1] 1 2 2 1 2 2 1 2 2 1 1 2 1 2 1 1 1 2 1 2 1
##
## Within cluster sum of squares by cluster:
## [1] 43.30886 75.26049
##  (between_SS / total_SS =  34.1 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

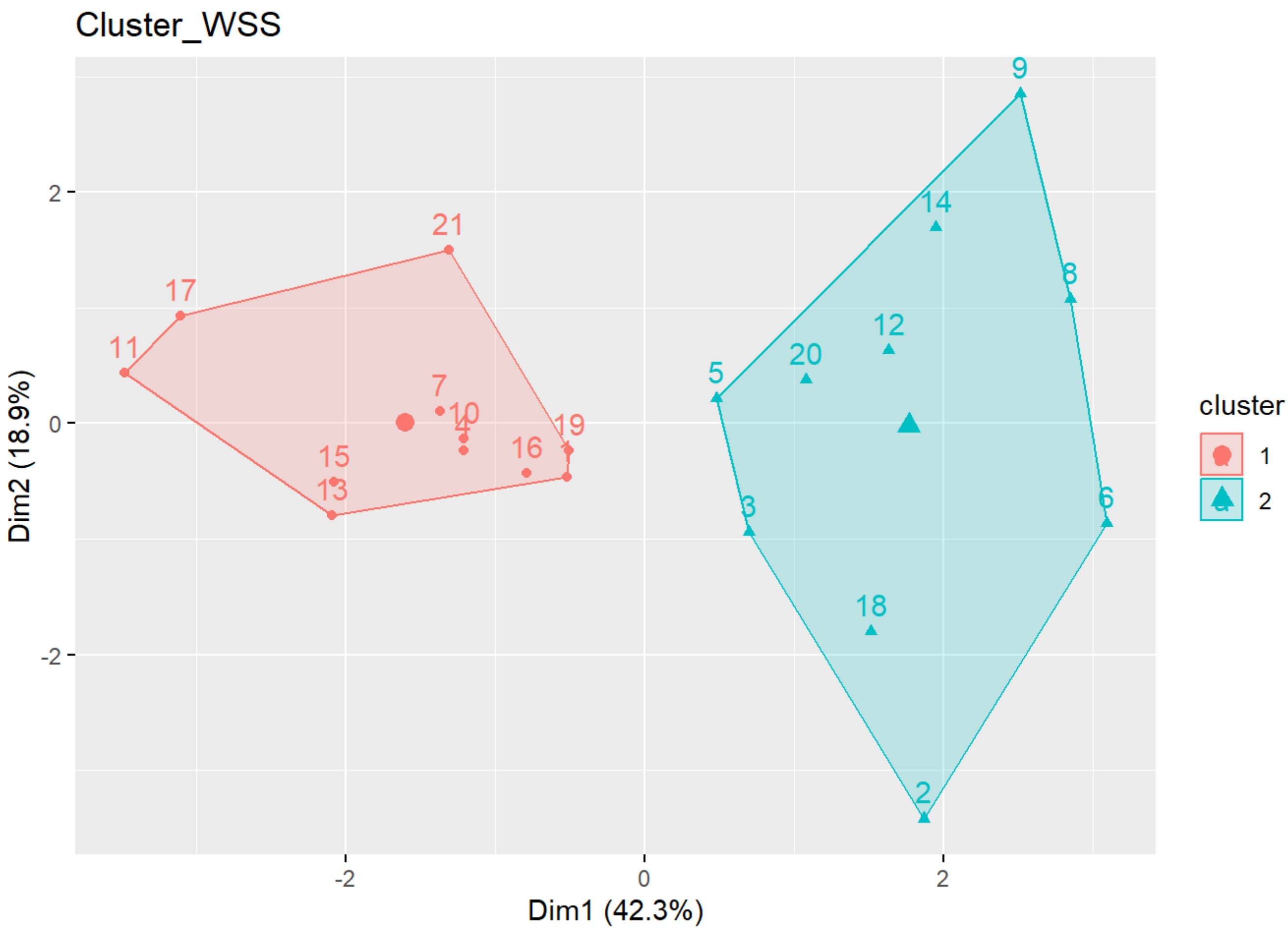
#Formulation of clusters using K-Means with k = 5 (Silhouette)

```
silhouette_kmeans <- kmeans(data.norm,centers=5,nstart=25)
silhouette_kmeans
```

```
## K-means clustering with 5 clusters of sizes 4, 2, 3, 8, 4
##
## Cluster means:
##    Market_Cap       Beta    PE_Ratio        ROE        ROA Asset_Turnover
## 1 -0.76022489  0.2796041 -0.47742380 -0.7438022 -0.8107428     -1.2684804
## 2 -0.43925134 -0.4701800  2.70002464 -0.8349525 -0.9234951      0.2306328
## 3 -0.87051511  1.3409869 -0.05284434 -0.6184015 -1.1928478     -0.4612656
## 4 -0.03142211 -0.4360989 -0.31724852  0.1950459  0.4083915      0.1729746
## 5  1.69558112 -0.1780563 -0.19845823  1.2349879  1.3503431      1.1531640
##      Leverage Rev_Growth Net_Profit_Margin
## 1  0.06308085  1.5180158      -0.006893899
## 2 -0.14170336 -0.1168459      -1.416514761
## 3  1.36644699 -0.6912914      -1.320000179
## 4 -0.27449312 -0.7041516       0.556954446
## 5 -0.46807818  0.4671788       0.591242521
##
## Clustering vector:
##  [1] 4 2 4 4 1 3 4 3 1 4 5 3 5 1 5 4 5 2 4 1 4
##
## Within cluster sum of squares by cluster:
## [1] 12.791257  2.803505 15.595925 21.879320  9.284424
##  (between_SS / total_SS =  65.4 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

#Cluster Plot Visualizations for k=2 (WSS)

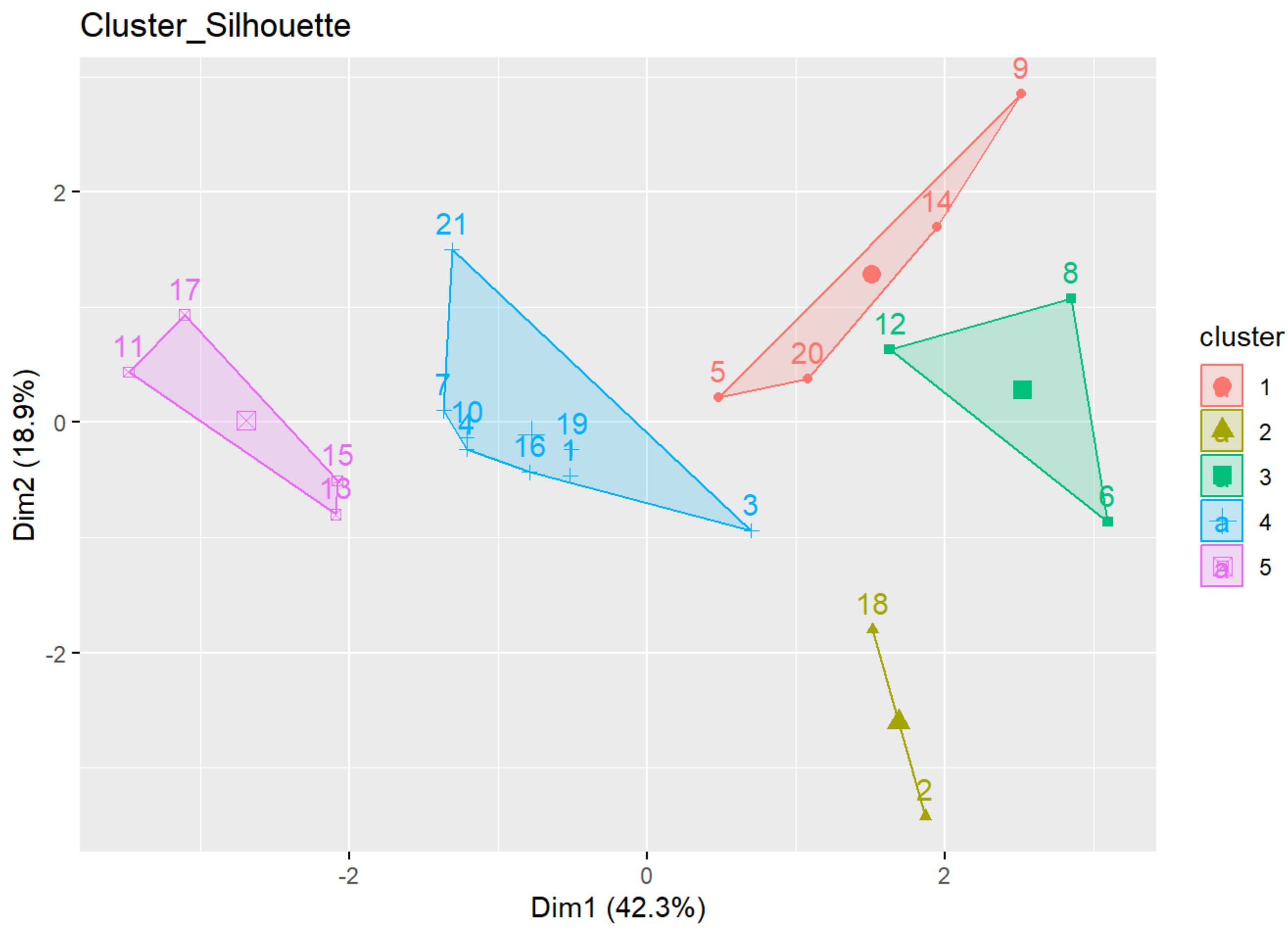
```
fviz_cluster(wss_kmeans,data[,-c(1:2,12:15)],main="Cluster_WSS")
```



By employing the WSS Method we get 2 clusters of size 11 and 10.

#Cluster Plot Visualizations for k=5 (Silhouette)

```
fviz_cluster(silhouette_kmeans,data[,-c(1:2,12:15)],main="Cluster_Silhouette")
```



By employing the Silhouette Method we get 5 clusters of size 3, 2, 8, 4 and 4.

#2.2 Is there a pattern in the clusters with respect to the numerical variables (10 to 12)? (those not used in forming the clusters)

#Binding the cluster assignment to the original data frame for analysis

```
clusters_wss <- wss_kmeans$cluster
clusters_silhouette <- silhouette_kmeans$cluster

data.1 <- cbind(data,clusters_wss)
data.2 <- cbind(data,clusters_silhouette)
```

#Aggregating the clusters to interpret the attributes - WSS

```
int_wss <- aggregate(data.1[,-c(1:2,12:14)],by=list(data.1$clusters_wss),FUN="median")
print(int_wss[,-1])
```

```
##   Market_Cap  Beta PE_Ratio  ROE  ROA Asset_Turnover Leverage Rev_Growth
## 1      73.84 0.460    21.50 31.0 15.0            0.8    0.280      8.560
## 2       4.78 0.555    23.35 14.2  5.6            0.6    0.475     14.495
##   Net_Profit_Margin clusters_wss
## 1              20.6            1
## 2              11.1            2
```

#Aggregating the clusters to interpret the attributes - Silhouette

```
int_silhouette <- aggregate(data.2[,-c(1:2,12:14)],by=list(data.2$clusters_silhouette),FUN="m
edian")
print(int_silhouette[,-1])
```

```
##   Market_Cap  Beta PE_Ratio   ROE   ROA Asset_Turnover Leverage Rev_Growth
## 1      2.230 0.535    19.25 13.15  6.10           0.40    0.635     29.775
## 2     31.910 0.405    69.50 13.20  5.60           0.75    0.475     12.080
## 3      2.600 0.850    26.00 21.40  4.30           0.60    1.450      6.380
## 4     59.480 0.480    21.10 26.90 13.35           0.75    0.345      6.630
## 5    153.245 0.460    21.25 43.10 17.75           0.95    0.220     19.610
##   Net_Profit_Margin clusters_silhouette
## 1              14.2                   1
## 2               6.4                   2
## 3               7.5                   3
## 4              19.3                   4
## 5              19.5                   5
```

#median calculation - WSS

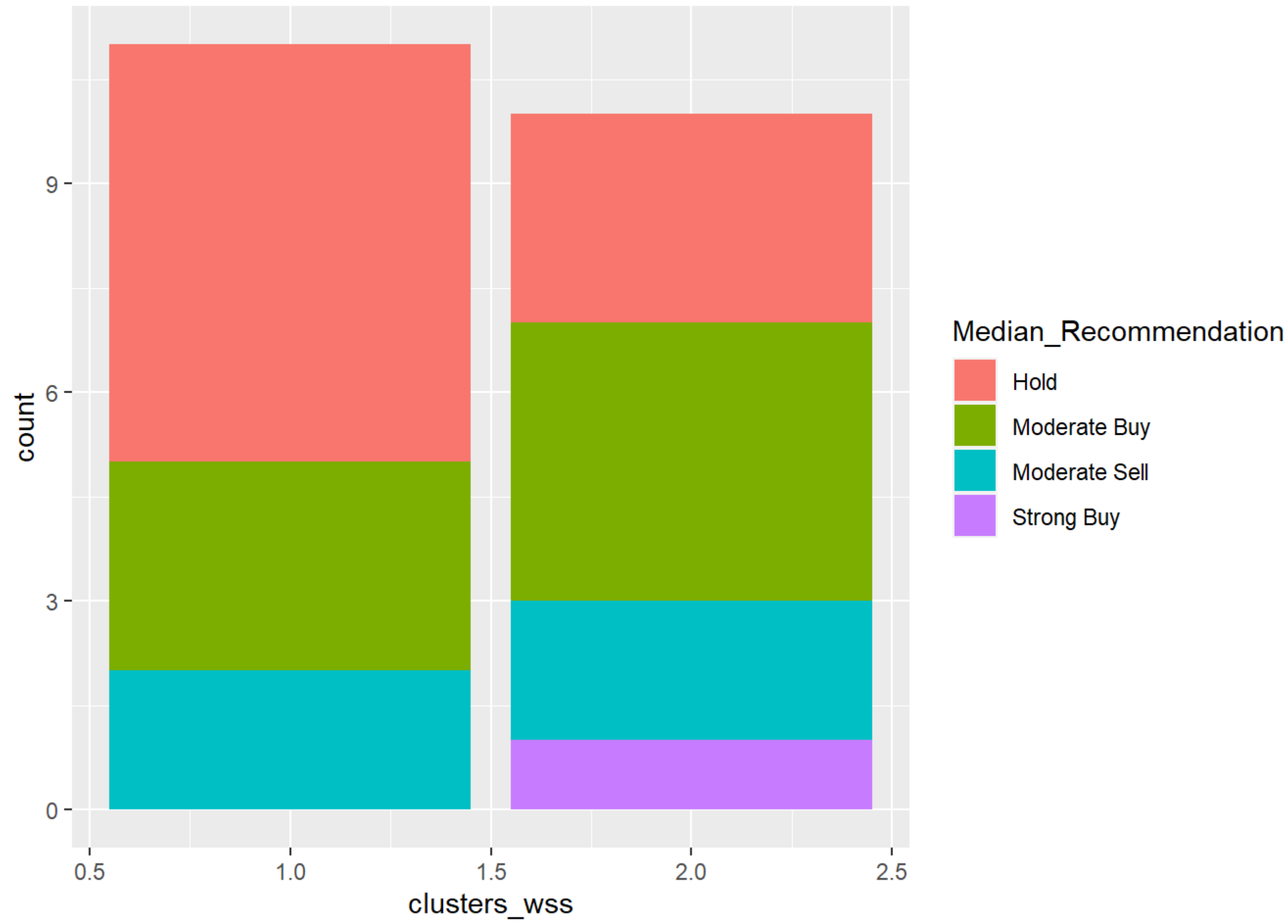
```
recommend_table1 <- table(data.1$cluster, data.1$Median_Recommendation)
names(dimnames(recommend_table1)) <- c("Cluster", "Recommendation")
recommend_table1 <- addmargins(recommend_table1)
recommend_table1
```

```
##        Recommendation
## Cluster Hold Moderate Buy Moderate Sell Strong Buy Sum
##     1      6            3             2          0  11
##     2      3            4             2          1  10
##     Sum    9            7             4          1  21
```

One strong buy, seven moderate buys, nine holds, and four moderate sells make the total number of 21 recommendations. All four recommendations, including the opposite advice on buys and sells, are mixed together in Cluster 2. Only Hold Moderate, Buy Moderate & Sell Strong are found in cluster 1.

#Plot Visualizations for median calculation - WSS

```
ggplot(data.1,aes(x=clusters_wss,fill=Median_Recommendation)) + geom_bar()
```



#median calculation - Silhouette

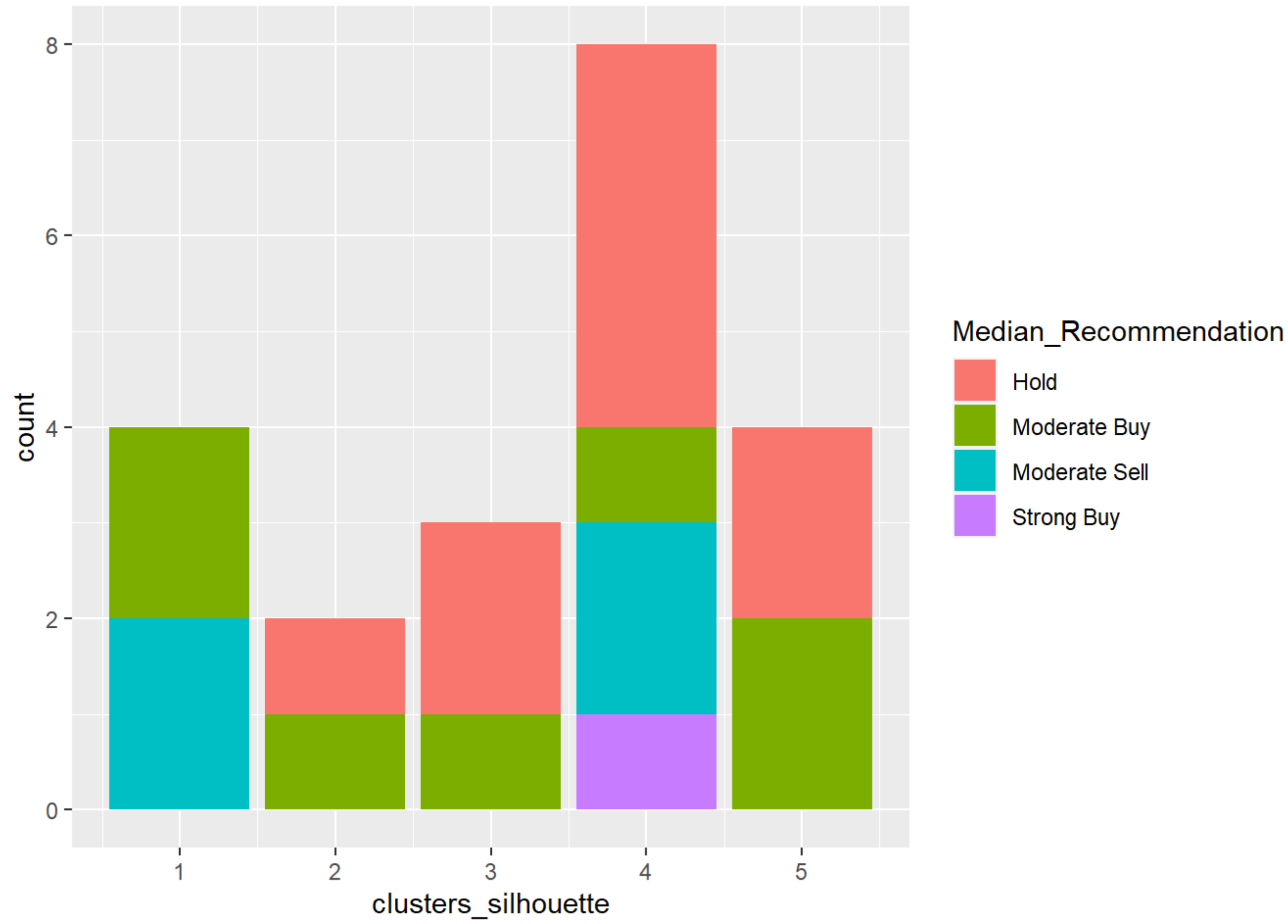
```
recommend_table2 <- table(data.2$cluster, data.2$Median_Recommendation)
names(dimnames(recommend_table2)) <- c("Cluster", "Recommendation")
recommend_table2 <- addmargins(recommend_table2)
recommend_table2
```

```
##        Recommendation
## Cluster Hold Moderate Buy Moderate Sell Strong Buy Sum
##     1      0            2             2          0   4
##     2      1            1             0          0   2
##     3      2            1             0          0   3
##     4      4            1             2          1   8
##     5      2            2             0          0   4
##     Sum    9            7             4          1  21
```

One strong buy, seven moderate buys, nine holds, and four moderate sells make the total number of 21 recommendations. All four recommendations, including the opposite advice on buys and sells, are mixed together in Cluster 5. Only mod purchase and hold information can be found in Clusters 1, 2, and 3.Both a moderate buy and moderate sell recommendation are present for Cluster 4.

#Plot Visualizations for median calculation - Silhouette

```
ggplot(data.2,aes(x=clusters_silhouette,fill=Median_Recommendation)) + geom_bar()
```



#Location of firm headquarter's breakdown of clusters based on the mergeddata - wss

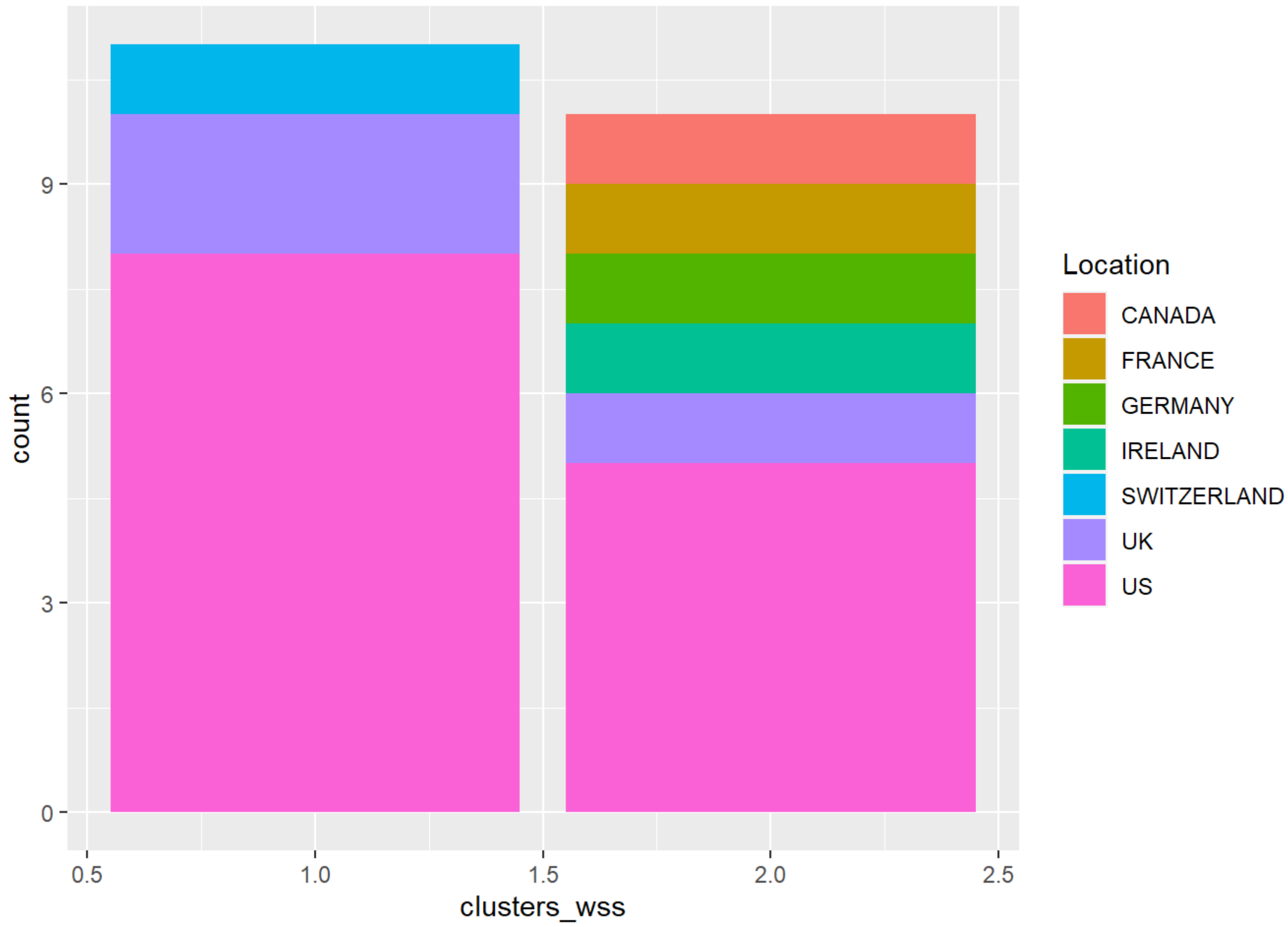
```
location_table <- table(data.1$cluster, data.1$Location)
names(dimnames(location_table)) <- c("Cluster", "Location")
location_table <- addmargins(location_table)
location_table
```

```
##        Location
## Cluster CANADA FRANCE GERMANY IRELAND SWITZERLAND UK  US  Sum
##     1        0      0       0       0           1  2   8   11
##     2        1      1       1       1           0  1   5   10
##     Sum      1      1       1       1           1  3  13   21
```

There are 21 firms in all, with 13 in the US, 3 in the UK, and 1 each in Canada, France, Germany, Ireland, and Switzerland. US, UK, and Switzerland are all featured in Cluster 2.Switzerland, Uk And Us are in Cluster 1. Expect Switzerland Remaining All Countries are in Cluster 2.

#Plot Visualizations for Loction - wss

```
ggplot(data.1,aes(x=clusters_wss,fill=Location)) + geom_bar()
```



Cluster 1 and Cluster 2 seems to have a pattern with respect to the location of the pharmaceutical firms. More than 50% of the firms across both the clusters have “US” as their location. This also states that US has firms which are both profitable to invest (Acceptable Profitability with Moderate Risk) as well as firms which don’t yield that good profits (Low Profitability with High Risk). But comparatively the better performing cluster i.e. Cluster 1 seems to have a greater ratio of companies based in US.

#Location of firm headquarter’s breakdown of clusters based on the mergeddata - Silhouette

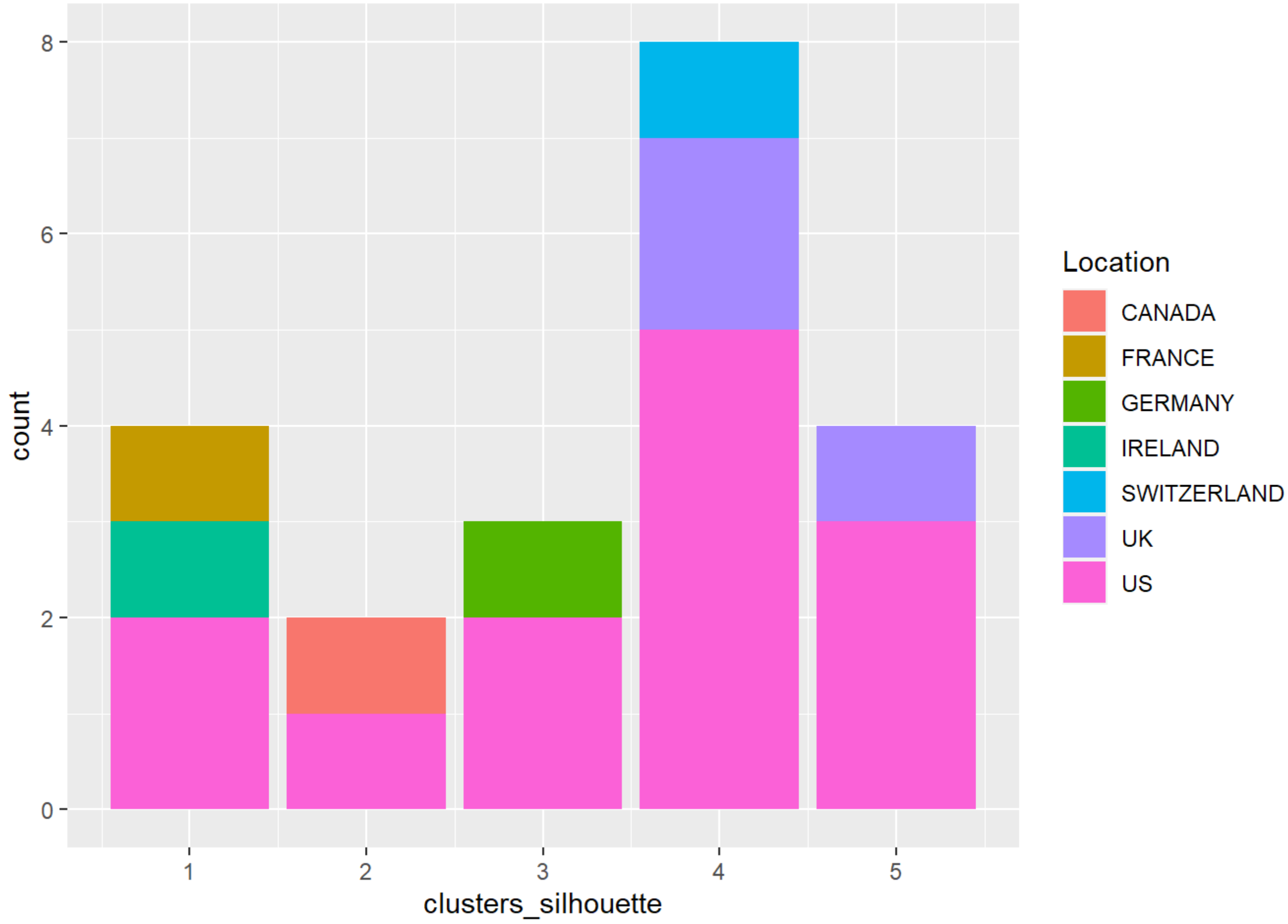
```
location_table <- table(data.2$cluster, data.2$Location)
names(dimnames(location_table)) <- c("Cluster", "Location")
location_table <- addmargins(location_table)
location_table
```

```
##        Location
## Cluster CANADA FRANCE GERMANY IRELAND SWITZERLAND UK US Sum
##     1        0      1       0       1           0  0  2   4
##     2        1      0       0       0           0  0  1   2
##     3        0      0       1       0           0  0  2   3
##     4        0      0       0       0           1  2  5   8
##     5        0      0       0       0           0  1  3   4
##     Sum      1      1       1       1           1  3 13  21
```

There are 21 firms in all, with 13 in the US, 3 in the UK, and 1 each in Canada, France, Germany, Ireland, and Switzerland. US, UK, and Switzerland are all featured in Cluster 5. Germany and the US are in Cluster 2. US and Canada are in Cluster 1. US and Britain are in Cluster 3. The US, France, and Ireland make up Cluster 4.

#Plot Visualizations for Loction - silhouette

```
ggplot(data.2,aes(x=clusters_silhouette,fill=Location)) + geom_bar()
```



In the silhouette clusters we get to see the see the similar level of pattern towards to the location as observed in the wss. Every cluster in here as more of it’s locations in “US” when compared to that with the other locations. But it seems interesting to observe that the best cluster which defines the domain with true sense i.e. Cluster 4 has a greater ratio of US companies with a lesser ratio of Non - US based companies.

*Note: The patterns therefore obtained in each of the clustering methods are generic, this is mostly because of the less amount of data which didn’t give any further scope to visualize the categorical attributes.

#summarizing the stock exchange values for each cluster - wss

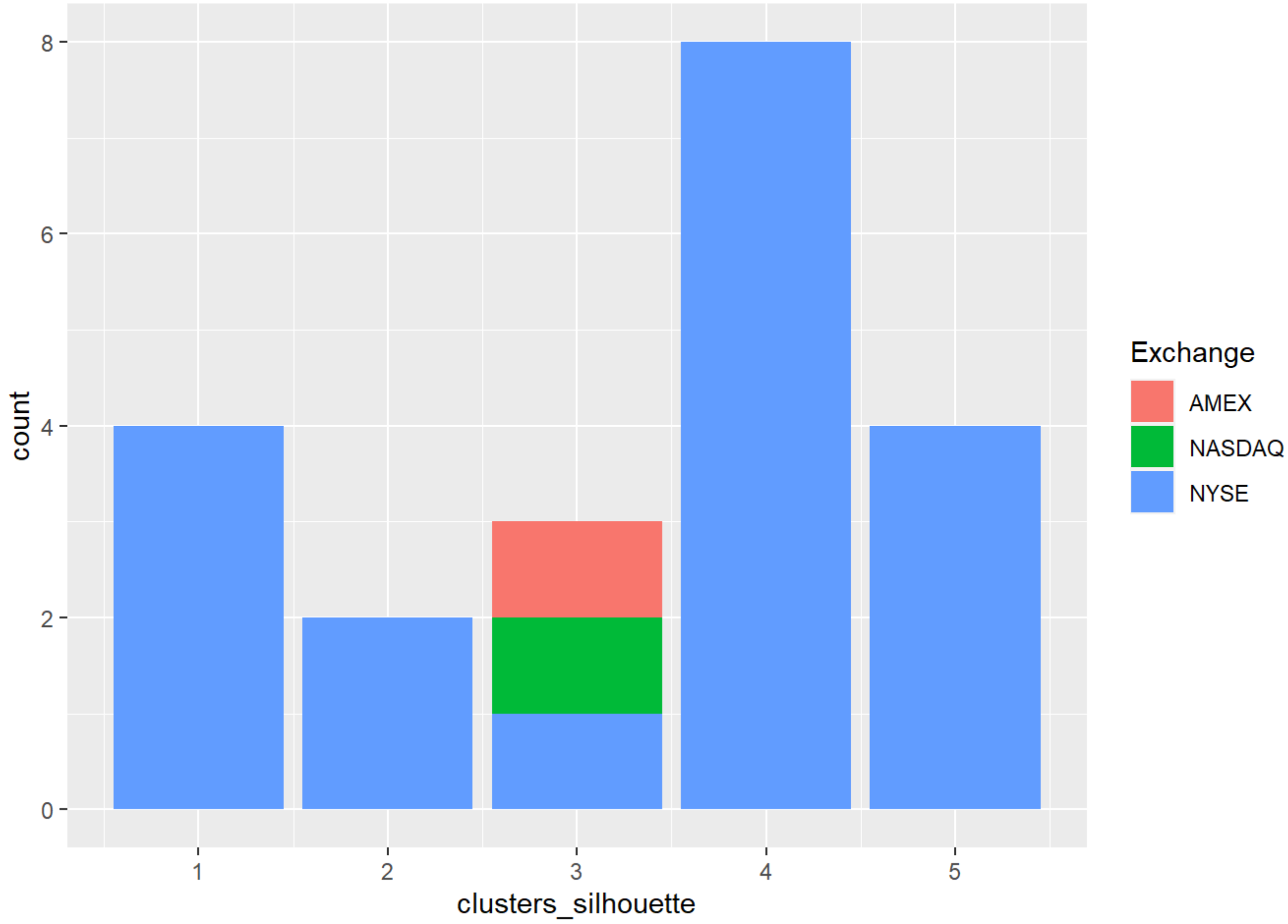
```
exchange_table <- table(data.1$cluster, data.1$Exchange)
names(dimnames(exchange_table)) <- c("Cluster", "Exchange")
exchange_table <- addmargins(exchange_table)
exchange_table
```

```
##        Exchange
## Cluster AMEX NASDAQ NYSE Sum
##     1      0      0   11  11
##     2      1      1    8  10
##     Sum    1      1   19  21
```

There are 21 companies overall, divided into 1 Amex, 1 Nasdaq, and 19 NYSE. Cluster 1 just has the NYSE. All three are in Cluster 2.

#Plot Visualizations for Exchange - wss

```
ggplot(data.1,aes(x=clusters_silhouette,fill=Exchange)) + geom_bar()
```



#summarizing the stock exchange values for each cluster - silhouette

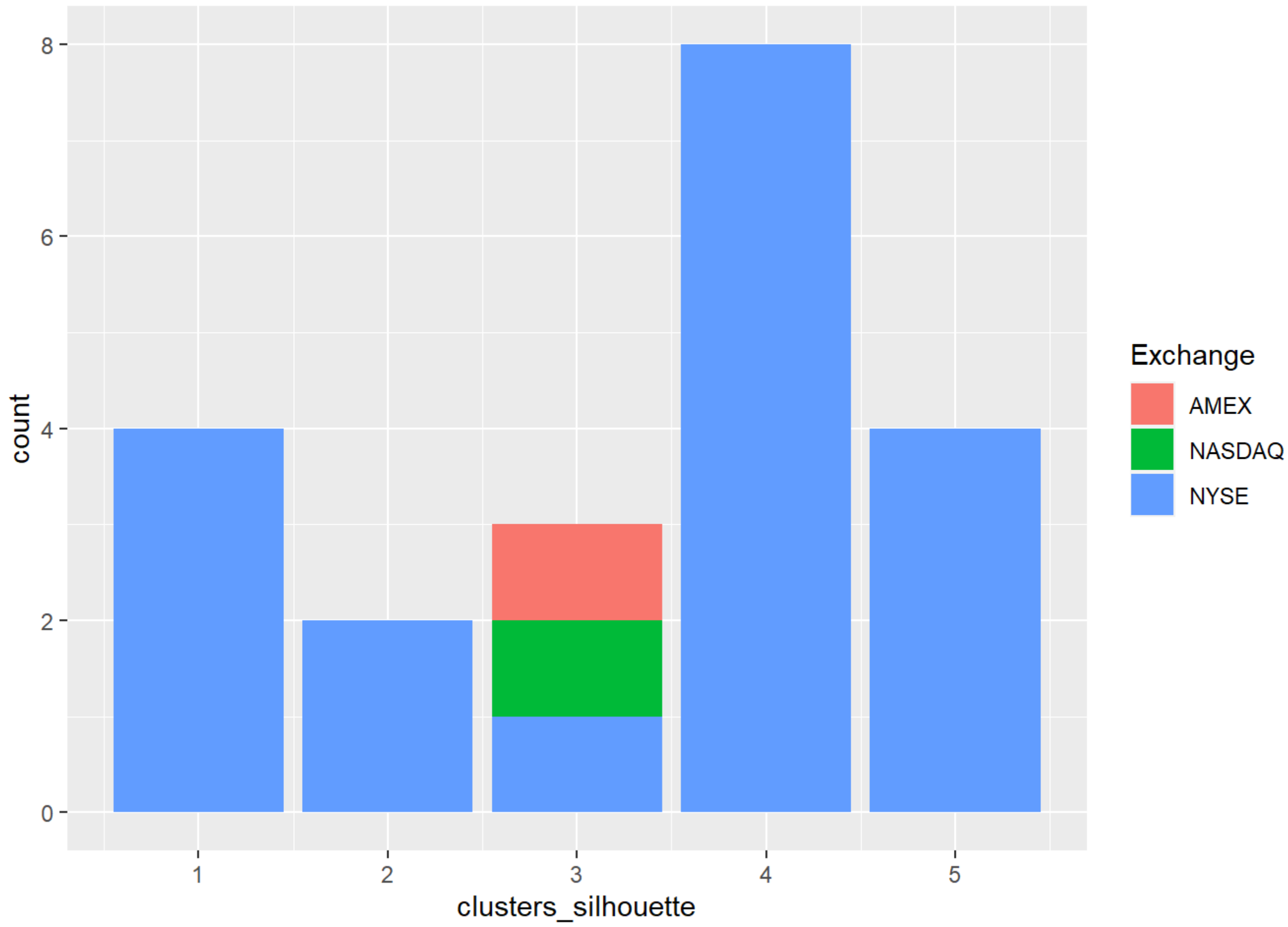
```
exchange_table <- table(data.2$cluster, data.2$Exchange)
names(dimnames(exchange_table)) <- c("Cluster", "Exchange")
exchange_table <- addmargins(exchange_table)
exchange_table
```

```
##         Exchange
## Cluster AMEX NASDAQ NYSE Sum
##     1      0      0    4   4
##     2      0      0    2   2
##     3      1      1    1   3
##     4      0      0    8   8
##     5      0      0    4   4
##     Sum    1      1   19  21
```

There are 21 companies overall, divided into 1 Amex, 1 Nasdaq, and 19 NYSE. All three are in Cluster 3. clusters 1,2,4,5 all contains only NYSE.

#Plot Visualizations for Exchange - silhouette

```
ggplot(data.2,aes(x=clusters_silhouette,fill=Exchange)) + geom_bar()
```



#3. Provide an appropriate name for each cluster using any or all of the variables in the dataset.

Interpretation:(WSS)

Note: The interpretation is exclusively based on the financial attributes of the specified firms in each of the clusters; the interpretation obtained would therefore assist a person in making a decision about which of the two clusters to invest in order to benefit.

A. Acceptable Profitability with Moderate Risk:

Because of the high possibility of success, the first cluster acquired here is an excellent investment. The criteria "Market Capital", ROE - Return on Expenditure, ROA - Return on Assets, Asset Turnover, and Net Profit Margin are used to measure success here. The capital value in this cluster is 73.84, ROE, which lets us know the returns on the money we put in as investment, is high (31), and ROA, which is the returns a corporation expects to earn on the money they invest in assets, is also high (15). Similarly, asset turnover and net profit are also high.The PE Ratio is less with that of the second cluster indicating that the company is properly valued without any disparity in it's share prices.

The level of risk in this investment is low which is called out by the "Beta" value, generally beta value should be lower than 1 in this case it is 0.46 which refers that the variability in these firms would be moderate not having enough of fluctuations.Also the "Leverage" value, which refers to a firm having borrowed capital for an investment should be as less as possible because market is always unpredictable and there would be possibilities of a firm loosing the money which they have borrowed for an investment expecting profits in return. Here the leverage value is 0.28 which is comparatively less to the second cluster. "With a good investment there should be very little chance of losing the total amount invested" and the group of firms in this cluster are expressing higher success rate when compared to that with the second cluster.

B. Low Profitability with High Risk:

Here, the second cluster has poor performance metrics when compared to the first cluster; the market capital is very low, at 4.78, compared to 73.84 in the first cluster, indicating that the firms listed in this cluster have a lower market share. Return on Expenditure (ROE), Return on Assets (ROA), Asset Turnover, and Net Profit Margin are all lower. The amount of risk indicated by the Beta and Leverage values is high in these firms, implying that there is considerable variability and borrowing in these enterprises in comparison to the first cluster.

Interpretation:(silhouette)

A. Emerging Group

The First Cluster is stammering when it comes to providing returns on the expenditure which is basically the value which any investor would seek as a return over investment. External borrowings are high as well including good amount of variability in the firms (beta). It also has least capital value across all the groups and shockingly it is amusing to see that the revenue across these firms are highest as well. This might be possibly because the firms might have originated recently and are stabilizing to start their journey in the market.

B. Overvalued and High-Risk Investment Group

The Second Cluster seems to have a lot of variability in it’s PE Ratio which is the share price to the company value stating that it is likely overvalued. The beta and leverage values are also high stating that there is subsequent risk involved in this group. This cannot be a good choice for a better investment.

C. High-Risk Investment Group

The Third Cluster is a highly fluctuative cluster with higher beta (variability in the firm) and leverage (outside borrowings) values indicating that there is high sense of risk in these firms. Also, the market capital & net profit margin are less making it less suitable for any possible investments.

D. Promising Value opportunity Group

Forth Cluster can be considered as a set of firms with feasible market capital which are properly valued (PE Ratio) with middling risk involved (Beta and Leverage). It also has better returns over the expenditure and assets with a lucrative tendency.It can be a possible source of investment although the capital value is less when distinguished with the fourth cluster, there might be chances of the valuation to change/rise in the future.

E. Prime Investment with Slighter Risk Group

The Fith Cluster is a good source of investment for any discrete individual who want to set a beneficial pitch for him/her. Here in this cluster as we see when compared to other firms across various clusters, the fourth cluster is having the “Highest Market Capital” of “153.245”, “Lofty ROE - Return on Expenditure of”43.10” & ROA - Return on Assets of “17.75”, “Sky-Spiking Asset Turnover” of “0.95” and “Net Profit Margin” of “19.5”. It also has a “decent beta value” - indicating that the variance would be less and no much of risk would be involved and not only that it has “less leverage value” - which refers stating that the borrowed capital for future investments is small. PE Ratio is less indicating that the price to earnings ratio (share price to company value) is manageable indicating that the company is properly valued. If anyone wants to invest in a company which has a higher capital ratio and moderate risk with fewer liabilities then the firms which are part of this cluster make the best choice.

Conclusion:

Any investment may be classified into three types based on three criteria: safety, income, and capital growth. Every investor must select an acceptable combination of these three elements.

Investment is always constrained by the “profit to loss ratio”; every given individual would want to maximize their profit while incurring the least amount of loss or incurring no loss at all. In this case, the cluster titled “Prime Investment with Slighter Risk” from the supplied data set demonstrates all such features. Based on the research and interpretation, I believe this is the ideal cluster to select for an investment since there is less danger and more earnings.

Note: the reason for selecting a cluster from the silhouette approach is that it aids in better defining the domain, which can be utilized by anybody to make an advantageous conclusion regarding their investment selections.