Assignment_4

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2023-10-29

```
knitr::opts_chunk$set(echo = TRUE)
```

```
#install.packages("httr")
#install.packages("readr")
#install.packages("factoextra")
#install.packages("flexclust")
library(httr)
library(readr)
library(tidyverse)
```

```
## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.
0.0 ──
## ✔ dplyr     1.1.3     ✔ purrr     1.0.2
## ✔ forcats   1.0.0     ✔ stringr   1.5.0
## ✔ ggplot2   3.4.3     ✔ tibble    3.2.1
## ✔ lubridate 1.9.3     ✔ tidyr     1.3.0
## ── Conflicts ────────────────────────────────────────── tidyverse_conflict
s() ──
## ✖ 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 become errors
```

```
library(factoextra)
```

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

```
library(ISLR)
library(flexclust)
```

```
## Loading required package: grid
## Loading required package: lattice
## Loading required package: modeltools
## Loading required package: stats4
```

```
library(caret)
```

```
##
## Attaching package: 'caret'
##
## The following object is masked from 'package:purrr':
##
```

```
##     lift
##
## The following object is masked from 'package:httr':
##
##     progress
```

#Importing Data set

```r
#importing Data set and converting
getwd()

## [1] "C:/Users/durga/OneDrive/Documents"

pharma<-read.csv("C:/Users/durga/Downloads/Pharmaceuticals.csv")
#summarize the Data
#str(pharma)
head(pharma,10)

##    Symbol                        Name Market_Cap Beta PE_Ratio  ROE  ROA
## 1     ABT         Abbott Laboratories      68.44 0.32     24.7 26.4 11.8
## 2     AGN              Allergan, Inc.       7.58 0.41     82.5 12.9  5.5
## 3     AHM                Amersham plc       6.30 0.46     20.7 14.9  7.8
## 4     AZN             AstraZeneca PLC      67.63 0.52     21.5 27.4 15.4
## 5     AVE                     Aventis      47.16 0.32     20.1 21.8  7.5
## 6     BAY                    Bayer AG      16.90 1.11     27.9  3.9  1.4
## 7     BMY Bristol-Myers Squibb Company      51.33 0.50     13.9 34.8 15.1
## 8    CHTT                Chattem, Inc       0.41 0.85     26.0 24.1  4.3
## 9     ELN       Elan Corporation, plc       0.78 1.08      3.6 15.1  5.1
## 10    LLY         Eli Lilly and Company      73.84 0.18     27.9 31.0 13.5
##    Asset_Turnover Leverage Rev_Growth Net_Profit_Margin Median_Recommendat
ion
## 1             0.7     0.42       7.54              16.1           Moderate
Buy
## 2             0.9     0.60       9.16               5.5           Moderate
Buy
## 3             0.9     0.27       7.05              11.2             Strong
Buy
## 4             0.9     0.00      15.00              18.0         Moderate S
ell
## 5             0.6     0.34      26.81              12.9           Moderate
Buy
## 6             0.6     0.00      -3.17               2.6                  H
old
## 7             0.9     0.57       2.70              20.6         Moderate S
ell
## 8             0.6     3.51       6.38               7.5           Moderate
Buy
## 9             0.3     1.07      34.21              13.3         Moderate S
ell
## 10            0.6     0.53       6.21              23.4                  H
old
```

```
##    Location Exchange
## 1        US     NYSE
## 2    CANADA     NYSE
## 3        UK     NYSE
## 4        UK     NYSE
## 5    FRANCE     NYSE
## 6   GERMANY     NYSE
## 7        US     NYSE
## 8        US   NASDAQ
## 9   IRELAND     NYSE
## 10       US     NYSE
```

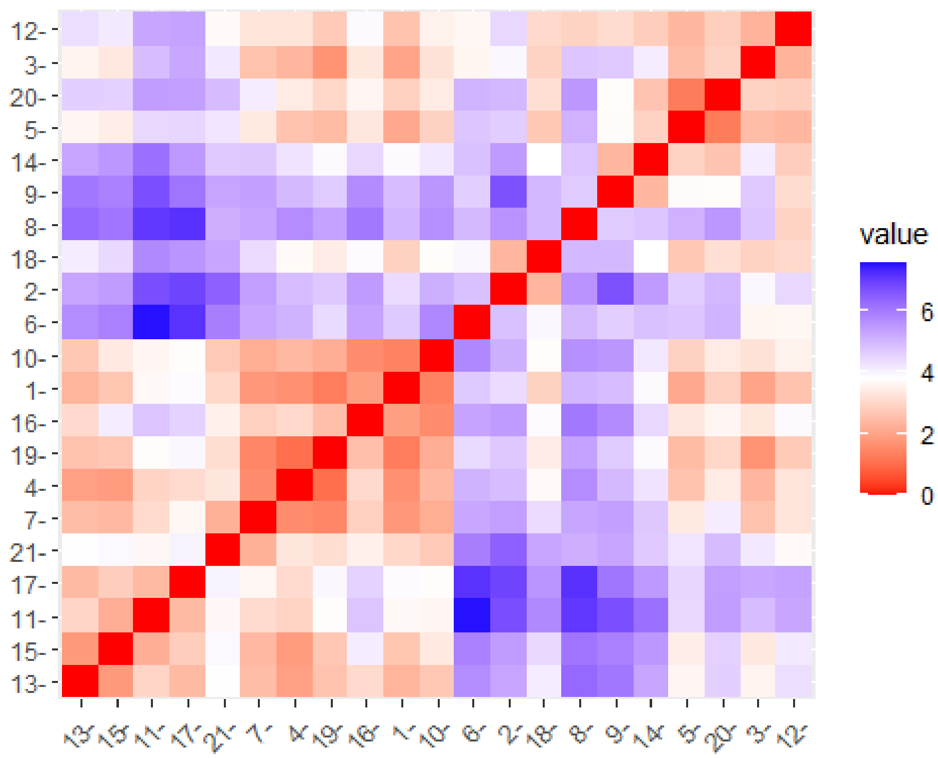
```
set.seed(23)
#Data frame  Z Score scaling
pharma_scaled <- scale(pharma[,3:11])
summary(pharma_scaled)
```

```
##    Market_Cap             Beta              PE_Ratio             ROE         
##  Min.   :-0.9768   Min.   :-1.3466   Min.   :-1.3404   Min.   :-1.4515  
##  1st Qu.:-0.8763   1st Qu.:-0.6844   1st Qu.:-0.4023   1st Qu.:-0.7223  
##  Median :-0.1614   Median :-0.2560   Median :-0.2429   Median :-0.2118  
##  Mean   : 0.0000   Mean   : 0.0000   Mean   : 0.0000   Mean   : 0.0000  
##  3rd Qu.: 0.2762   3rd Qu.: 0.4841   3rd Qu.: 0.1495   3rd Qu.: 0.3450  
##  Max.   : 2.4200   Max.   : 2.2758   Max.   : 3.4971   Max.   : 2.4597  
##       ROA           Asset_Turnover       Leverage           Rev_Growth     
##  Min.   :-1.7128   Min.   :-1.8451   Min.   :-0.74966   Min.   :-1.4971  
##  1st Qu.:-0.9047   1st Qu.:-0.4613   1st Qu.:-0.54487   1st Qu.:-0.6328  
##  Median : 0.1289   Median :-0.4613   Median :-0.31449   Median :-0.3621  
##  Mean   : 0.0000   Mean   : 0.0000   Mean   : 0.00000   Mean   : 0.0000  
##  3rd Qu.: 0.8430   3rd Qu.: 0.9225   3rd Qu.: 0.01828   3rd Qu.: 0.7693  
##  Max.   : 1.8389   Max.   : 1.8451   Max.   : 3.74280   Max.   : 1.8862  
##  Net_Profit_Margin 
##  Min.   :-1.99560  
##  1st Qu.:-0.68504  
##  Median : 0.06168  
##  Mean   : 0.00000  
##  3rd Qu.: 0.82364  
##  Max.   : 1.49416
```

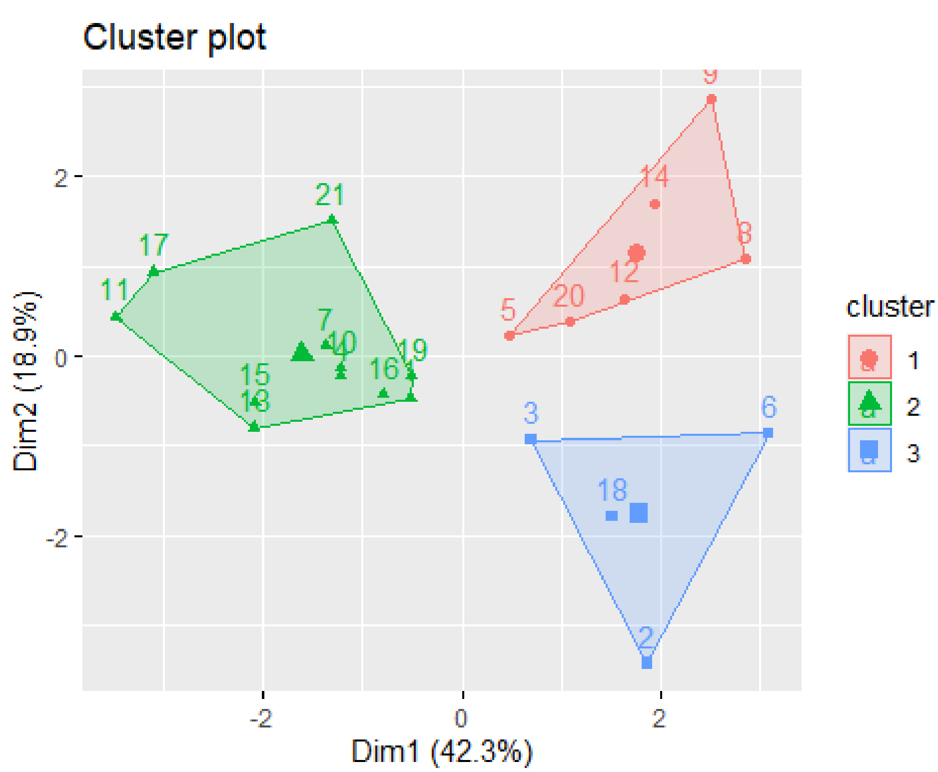
```
# Data Frame Range Scaling
pharma_range <- scale(pharma[,3:11])
```

a. 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.

```
set.seed(23)
dst_rows <- get_dist(pharma_scaled)
fviz_dist(dst_rows) #To visualize distance between matrix rows
```




```r
cluster1 <- kmeans(pharma_scaled, centers = 3, nstart = 15) # HEre taking K=3
& nstart=15
fviz_cluster(cluster1, data = pharma_scaled)
```

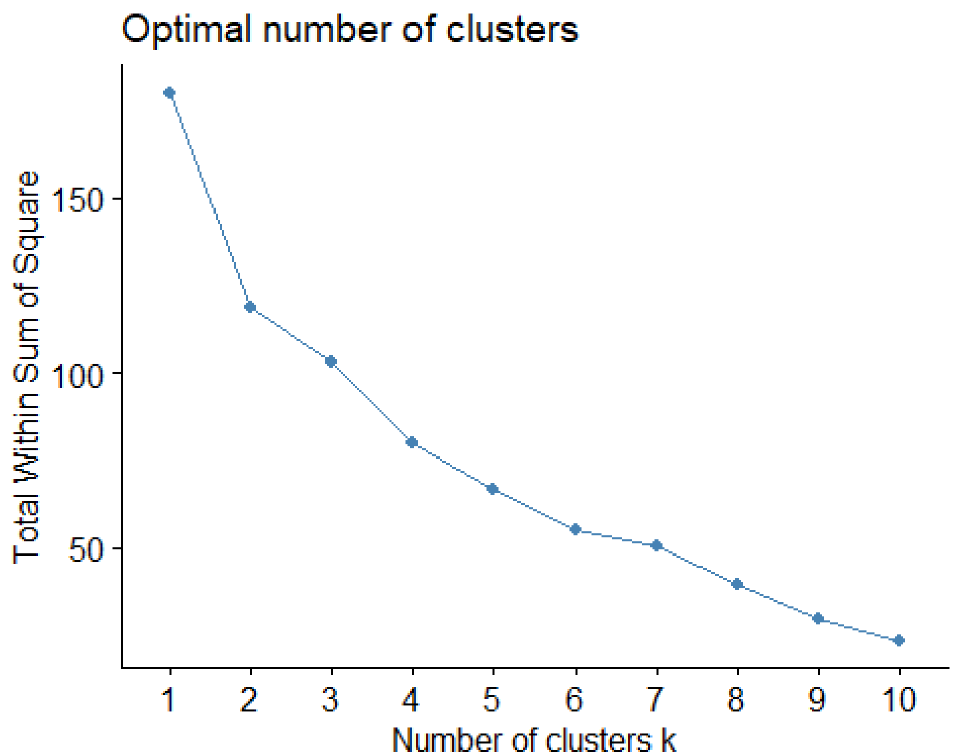


```r
print(cluster1)
```

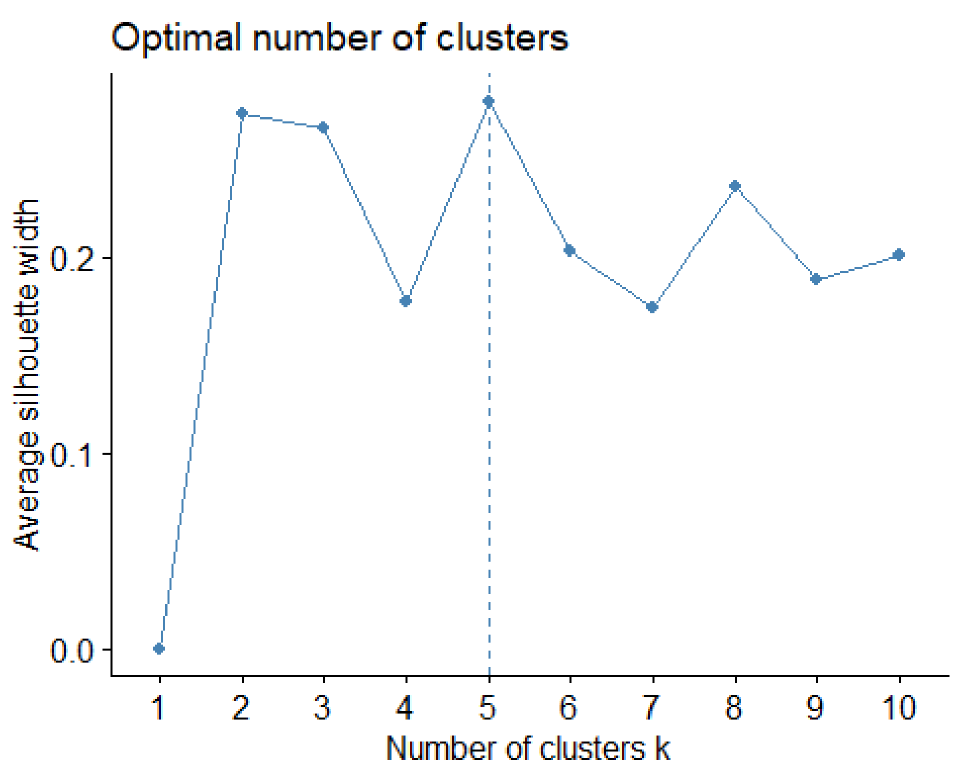
```
## K-means clustering with 3 clusters of sizes 6, 11, 4
## 
## Cluster means:
##   Market_Cap       Beta   PE_Ratio        ROE        ROA Asset_Turnover
## 1 -0.8261772  0.4775991 -0.3696184 -0.5631589 -0.8514589     -0.9994088
## 2  0.6733825 -0.3586419 -0.2763512  0.6565978  0.8344159      0.4612656
## 3 -0.6125361  0.2698666  1.3143935 -0.9609057 -1.0174553      0.2306328
##     Leverage Rev_Growth Net_Profit_Margin
## 1  0.8502201  0.9158889        -0.3319956
## 2 -0.3331068 -0.2902163         0.6823310
## 3 -0.3592866 -0.5757385        -1.3784169
## 
## Clustering vector:
##  [1] 2 3 3 2 1 3 2 1 1 2 2 1 2 1 2 2 2 3 2 1 2
## 
## Within cluster sum of squares by cluster:
## [1] 32.14336 43.30886 20.54199
##  (between_SS / total_SS =  46.7 %)
## 
## Available components:
## 
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withi
nss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

The k-means algorithm was used to divide the 21 enterprises into three groups with no variable weights. We chose k=3 since that is the optimal k indicated by the silhouette approach.

```r
fviz_nbclust(pharma_scaled, kmeans, method = "wss") # WSS method (ELBOW METHO
OD)
```




```r
fviz_nbclust(pharma_scaled, kmeans, method = "silhouette") #SILHOUETTE Method
(To find best K value)
```



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

I did not use the WSS approach since the graph did not show a distinct elbow and was extremely unclear. The graph does not indicate the elbow/knee position, and it flattens out more than once at k = 4 and 6, respectively, and I chose the silhouette approach since it is apparent to display the ideal cluster K = 5.

```
#let's look at the mean value from actual data by clusters
aggregate(pharma[3:11], by=list(cluster=cluster1$cluster), mean)
```

```
##   cluster Market_Cap      Beta PE_Ratio  ROE       ROA Asset_Turnover  Lev
erage
## 1       1    9.23500 0.6483333 19.43333 17.3  5.983333      0.4833333 1.25
00000
## 2       2   97.11364 0.4336364 20.95455 35.7 14.954545      0.8000000 0.32
54545
## 3       3   21.75500 0.5950000 46.90000 11.3  5.100000      0.7500000 0.30
50000
##   Rev_Growth Net_Profit_Margin
## 1   23.49000          13.51667
## 2   10.16455          20.17273
## 3    7.01000           6.65000
```

```
actual_data <- cbind(pharma, cluster = cluster1$cluster)
tibble(actual_data)
```

```
## # A tibble: 21 × 15
##    Symbol Name     Market_Cap  Beta PE_Ratio   ROE   ROA Asset_Turnover Le
verage
##    <chr>  <chr>         <dbl> <dbl>    <dbl> <dbl> <dbl>          <dbl>
<dbl>
##  1 ABT    Abbott …      68.4   0.32     24.7  26.4  11.8            0.7
0.42
##  2 AGN    Allerga…       7.58  0.41     82.5  12.9   5.5            0.9
0.6
##  3 AHM    Amersha…       6.3   0.46     20.7  14.9   7.8            0.9
0.27
##  4 AZN    AstraZe…      67.6   0.52     21.5  27.4  15.4            0.9
0
##  5 AVE    Aventis       47.2   0.32     20.1  21.8   7.5            0.6
0.34
##  6 BAY    Bayer AG      16.9   1.11     27.9   3.9   1.4            0.6
0
##  7 BMY    Bristol…      51.3   0.5      13.9  34.8  15.1            0.9
0.57
##  8 CHTT   Chattem…       0.41  0.85     26    24.1   4.3            0.6
3.51
##  9 ELN    Elan Co…       0.78  1.08      3.6  15.1   5.1            0.3
1.07
## 10 LLY    Eli Lil…      73.8   0.18     27.9  31    13.5            0.6
```

```
0.53
## # ℹ 11 more rows
## # ℹ 6 more variables: Rev_Growth <dbl>, Net_Profit_Margin <dbl>,
## #   Median_Recommendation <chr>, Location <chr>, Exchange <chr>, cluster <
int>

by(actual_data, factor(actual_data$cluster), summary)#intensive statistical c
luster analysis

## factor(actual_data$cluster): 1
##     Symbol               Name             Market_Cap          Beta       
##  Length:6           Length:6           Min.   : 0.410   Min.   :0.2400  
##  Class :character   Class :character   1st Qu.: 0.885   1st Qu.:0.4025  
##  Mode  :character   Mode  :character   Median : 1.900   Median :0.7000  
##                                        Mean   : 9.235   Mean   :0.6483  
##                                        3rd Qu.: 3.095   3rd Qu.:0.8250  
##                                        Max.   :47.160   Max.   :1.0800  
##     PE_Ratio          ROE             ROA        Asset_Turnover  
##  Min.   : 3.60   Min.   :10.20   Min.   :4.300   Min.   :0.3000  
##  1st Qu.:18.77   1st Qu.:12.18   1st Qu.:5.175   1st Qu.:0.3500  
##  Median :20.00   Median :18.25   Median :6.100   Median :0.5500  
##  Mean   :19.43   Mean   :17.30   Mean   :5.983   Mean   :0.4833  
##  3rd Qu.:24.52   3rd Qu.:21.70   3rd Qu.:6.800   3rd Qu.:0.6000  
##  Max.   :28.60   Max.   :24.10   Max.   :7.500   Max.   :0.6000  
##     Leverage        Rev_Growth    Net_Profit_Margin Median_Recommendation
##  Min.   :0.2000   Min.   : 6.38   Min.   : 7.50     Length:6           
##  1st Qu.:0.4875   1st Qu.:17.20   1st Qu.:11.47     Class :character   
##  Median :1.0000   Median :28.00   Median :13.10     Mode  :character   
##  Mean   :1.2500   Mean   :23.49   Mean   :13.52                        
##  3rd Qu.:1.3550   3rd Qu.:30.07   3rd Qu.:14.65                        
##  Max.   :3.5100   Max.   :34.21   Max.   :21.30                        
##    Location           Exchange            cluster 
##  Length:6           Length:6           Min.   :1  
##  Class :character   Class :character   1st Qu.:1  
##  Mode  :character   Mode  :character   Median :1  
##                                        Mean   :1  
##                                        3rd Qu.:1  
##                                        Max.   :1  
## ------------------------------------------------------------ 
## factor(actual_data$cluster): 2
##     Symbol               Name             Market_Cap          Beta       
##  Length:11          Length:11          Min.   : 34.10   Min.   :0.1800  
##  Class :character   Class :character   1st Qu.: 59.48   1st Qu.:0.3350  
##  Mode  :character   Mode  :character   Median : 73.84   Median :0.4600  
##                                        Mean   : 97.11   Mean   :0.4336  
##                                        3rd Qu.:127.33   3rd Qu.:0.5150  
##                                        Max.   :199.47   Max.   :0.6500  
##     PE_Ratio          ROE            ROA        Asset_Turnover    Leverage   
##  Min.   :13.10   Min.   :17.9   Min.   :11.20   Min.   :0.50   Min.   :0.0
000
```

```
##  1st Qu.:18.45   1st Qu.:26.9   1st Qu.:13.35   1st Qu.:0.65   1st Qu.:0.0
800
##  Median :21.50   Median :31.0   Median :15.00   Median :0.80   Median :0.2
800
##  Mean   :20.95   Mean   :35.7   Mean   :14.95   Mean   :0.80   Mean   :0.3
255
##  3rd Qu.:24.15   3rd Qu.:43.1   3rd Qu.:15.85   3rd Qu.:0.90   3rd Qu.:0.4
750
##  Max.   :28.40   Max.   :62.9   Max.   :20.30   Max.   :1.10   Max.   :1.1
200
##    Rev_Growth     Net_Profit_Margin Median_Recommendation   Location
##  Min.   :-2.690   Min.   :14.10     Length:11             Length:11
##  1st Qu.: 4.455   1st Qu.:17.75     Class :character      Class :character
##  Median : 8.560   Median :20.60     Mode  :character      Mode  :character
##  Mean   :10.165   Mean   :20.17
##  3rd Qu.:16.175   3rd Qu.:22.90
##  Max.   :25.540   Max.   :25.50
##    Exchange            cluster
##  Length:11          Min.   :2
##  Class :character   1st Qu.:2
##  Mode  :character   Median :2
##                     Mean   :2
##                     3rd Qu.:2
##                     Max.   :2
## ------------------------------------------------------------
## factor(actual_data$cluster): 3
##     Symbol              Name             Market_Cap         Beta
##  Length:4           Length:4           Min.   : 6.30   Min.   :0.4000
##  Class :character   Class :character   1st Qu.: 7.26   1st Qu.:0.4075
##  Mode  :character   Mode  :character   Median :12.24   Median :0.4350
##                                        Mean   :21.75   Mean   :0.5950
##                                        3rd Qu.:26.73   3rd Qu.:0.6225
##                                        Max.   :56.24   Max.   :1.1100
##     PE_Ratio         ROE              ROA         Asset_Turnover    Leverage
##  Min.   :20.7   Min.   : 3.90   Min.   :1.400   Min.   :0.60   Min.   :0.0
000
##  1st Qu.:26.1   1st Qu.:10.65   1st Qu.:4.475   1st Qu.:0.60   1st Qu.:0.2
025
##  Median :42.2   Median :13.20   Median :5.600   Median :0.75   Median :0.3
100
##  Mean   :46.9   Mean   :11.30   Mean   :5.100   Mean   :0.75   Mean   :0.3
050
##  3rd Qu.:63.0   3rd Qu.:13.85   3rd Qu.:6.225   3rd Qu.:0.90   3rd Qu.:0.4
125
##  Max.   :82.5   Max.   :14.90   Max.   :7.800   Max.   :0.90   Max.   :0.6
000
##    Rev_Growth     Net_Profit_Margin Median_Recommendation   Location
##  Min.   :-3.170   Min.   : 2.600    Length:4              Length:4
##  1st Qu.: 4.495   1st Qu.: 4.775    Class :character      Class :character
##  Median : 8.105   Median : 6.400    Mode  :character      Mode  :character
```

```
##  Mean   : 7.010   Mean   : 6.650
##  3rd Qu.:10.620   3rd Qu.: 8.275
##  Max.   :15.000   Max.   :11.200
##    Exchange            cluster
##  Length:4           Min.   :3
##  Class :character   1st Qu.:3
##  Mode  :character   Median :3
##                     Mean   :3
##                     3rd Qu.:3
##                     Max.   :3
```

Recommendations, Location and Exchange of cluster

```
#Cluster median recommendation
T_Recom <- table(actual_data$cluster, actual_data$Median_Recommendation)
names(dimnames(T_Recom)) <- c("Cluster", "Recommendation")
TR <- addmargins(T_Recom)
TR
```

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

The data do not show a clear link between clusterMedian Recommendation. There are 21 recommendations in total, with 1 strong buy, 7 moderate buys, 9 holds, and 4 moderate sells.

```
#Cluster-based location breakdown
T_Location <- table(actual_data$cluster, actual_data$Location)
names(dimnames(T_Location)) <- c("Cluster", "Location")
Tlocation <- addmargins(T_Location)
Tlocation
```

```
##        Location
## Cluster CANADA FRANCE GERMANY IRELAND SWITZERLAND UK US Sum
##     1        0      1       0       1           0  0  4   6
##     2        0      0       0       0           1  2  8  11
##     3        1      0       1       0           0  1  1   4
##     Sum      1      1       1       1           1  3 13  21
```

We cannot deduce any association between cluster Location from the findings. A total of 21 firms are divided into 13 in the United States, three in the United Kingdom, and one each in Canada, France, Germany, Ireland, and Switzerland.

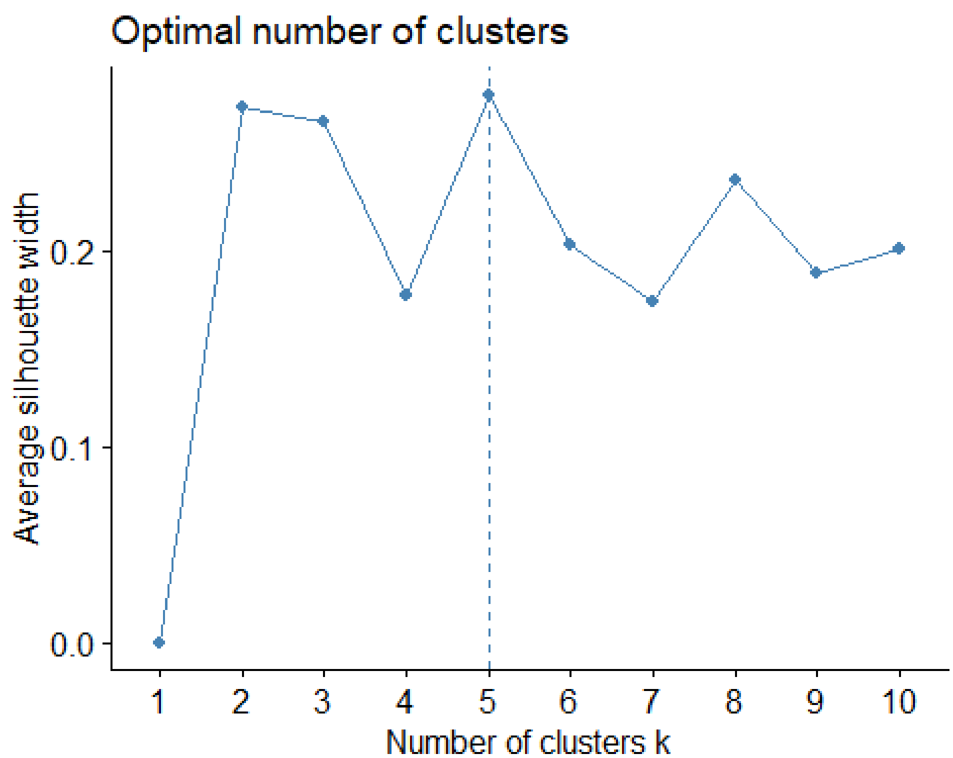
```
#Exchange breakdown by cluster
T_Exchange <- table(actual_data$cluster, actual_data$Exchange)
names(dimnames(T_Exchange)) <- c("Cluster", "Exchange")
```

```r
Texchange <- addmargins(T_Exchange)
Texchange

##        Exchange
## Cluster AMEX NASDAQ NYSE  Sum
##      1       1       1    4    6
##      2       0       0   11   11
##      3       0       0    4    4
##      Sum     1       1   19   21
```

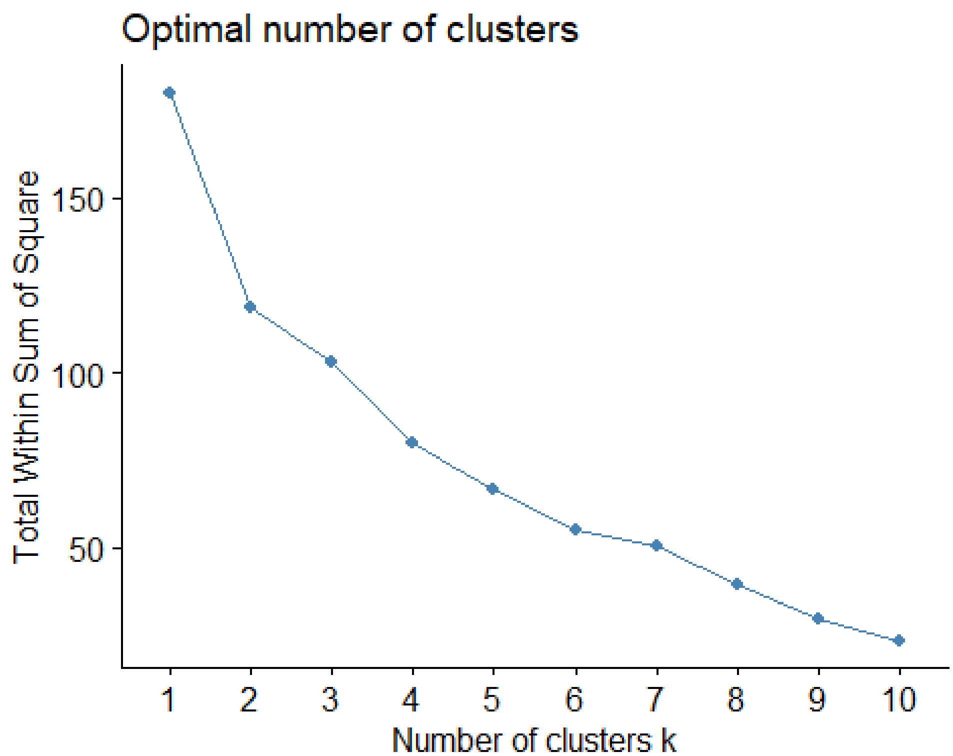
The results show that there is no link between clusterExchange. There are 21 corporations in all, divided into 1 Amex, 1 Nasdaq, and 19 NYSE.

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

```r
fviz_nbclust(pharma_range, FUN = kmeans, method = "silhouette")
```




```r
fviz_nbclust(pharma_range, kmeans, method = "wss")
```

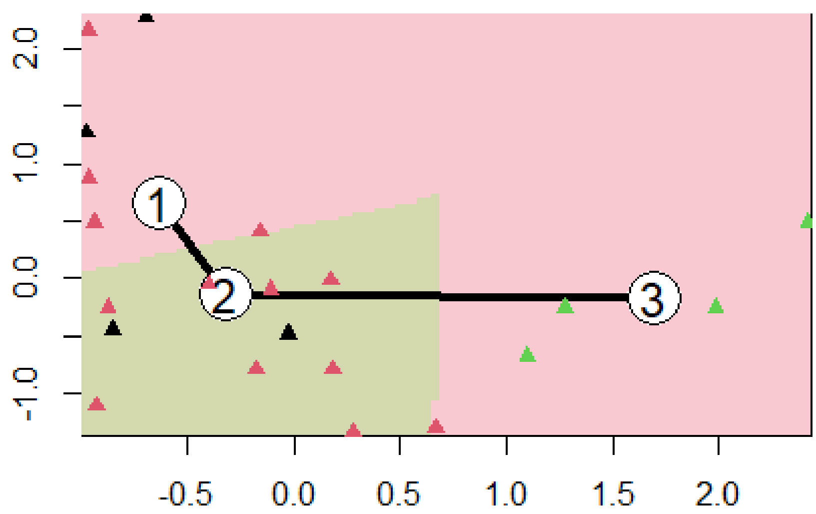


We also perform tests to determine the best k using range normalization. The ideal k is 2 from the silhouette and 6 from the elbow (not clear). We'll stick with z-score normalization data because the k from range normalization isn't as good.

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

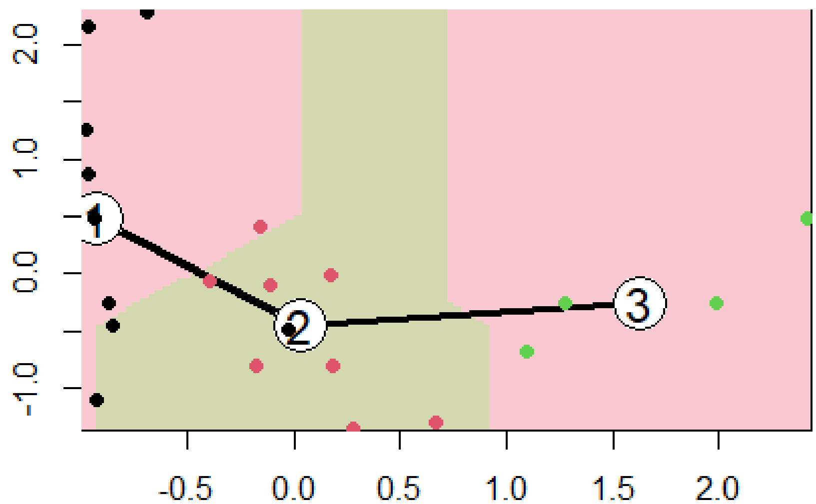
```
set.seed(11)
cluster2 = kcca(pharma_scaled, k=3, kccaFamily("kmeans"))
cluster2

## kcca object of family 'kmeans'
##
## call:
## kcca(x = pharma_scaled, k = 3, family = kccaFamily("kmeans"))
##
## cluster sizes:
##
##  1  2  3
##  4 13  4

clusters(cluster2)

##  [1] 2 1 2 2 2 1 2 1 2 2 3 2 3 2 3 2 3 1 2 2 2

#Apply the predict() function
clusters_index <- predict(cluster2)
```

```
image(cluster2)
points(pharma_scaled, col=clusters_index, pch=17, cex=1.0)
```



To run kmeans cluster on k =3, we use the kcca algorithm instead of kmeans from basic R.

```
set.seed(11)
cluster2 = kcca(pharma_scaled, k=3, kccaFamily("kmedians"))
cluster2

## kcca object of family 'kmedians'
##
## call:
## kcca(x = pharma_scaled, k = 3, family = kccaFamily("kmedians"))
##
## cluster sizes:
##
## 1 2 3
## 9 8 4

clusters(cluster2)

##  [1] 2 1 1 2 2 1 2 1 1 2 3 1 3 1 3 2 3 1 2 1 2

#Apply the predict() function
clusters_index <- predict(cluster2)
image(cluster2)
points(pharma_scaled, col=clusters_index, pch=16, cex=1.0)
```



a) Now that the clustering is complete, there are some insights we can pull from the output. Particularly, by using both the WSS and Silhouette methods, we could accurately determine that 5 clusters were needed as they both returned 5 as the optimum point.

b) we can make some general inferences about the clusters:

Cluster 1 had high ROE, ROA, Asset_Turnover, and Net_Profit_Margin, but low Market_Cap and Rev_Growth. Cluster 2 had very high Beta and Leverage, but very low Market_Cap, ROE, ROA, Net_Profit_Margins_, and Revenue Growth, which is likely why is is the furthest away from cluster 4. cluster 3 is the oddest of the bunch with only 2 members. This cluster has a VERY high PE_Ratio as well as a positive Asset_Turnover, but is low in every other category. While having low leverage,Beta, and PE_Ratio: cluster 4 held high Market_cap, ROE, ROA, Asset_Turnover, Revenue Growth, and Net_Profit_Margin which together set it apart from its closest neighbor, cluster 1. Cluster 5 has the a very high Rev_Growth and positive Beta and Leverage, while maintaining low numbers in the other categories.

c) Looking at the last three columns that were not used in the clustering, there seems to be no consistent patterns within the clusters. Between most points, you will find that while they both may have the same exchange, the location or recommendation would be different, or visa versa. Though generally speaking, almost all were in the NYSE exchange anyways.

d) Cluster 1: Medium Market_cap,ROE,ROA,Asset_Turnover,Leverage, Net_Profit_Margin, and Rev_Growth: “Medium”

Cluster 2: very high Beta and Leverage, very low ROA and Net_Profit_Margin: “High beta, low assets”

Cluster 3: Extreme PE_Ratio and low Net_Profit_Margin:“High Price Earnings ratio, but low new profits”

Cluster 4: highest Market_Cap, ROE, ROA, Asset_Turnover, and Net_Profit_Margin: “great asset management with small negatives”

Cluster 5: small positive Beta with highest Rev_Growth and slightly negative Net_profit_margin: “bad asset management with good growth”