FML ASSIGNMENT - 4

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```r
#install.packages("factoextra")
#install.packages("cowplot")
#install.packages("flexclust")
#install.packages("cluster")
#install.packages("NbClust")
```

```r
#Loading required packages.
library(factoextra)
```

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

## Loading required package: ggplot2

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

```r
library(cowplot)
```

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

```r
library(caret)
```

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

## Loading required package: lattice
```

```r
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(ggplot2)
library(tidyverse)
```

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

## Warning: package 'tidyr' was built under R version 4.3.2

## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v forcats   1.0.0     v stringr   1.5.0
## v lubridate 1.9.3     v tibble    3.2.1
## v purrr     1.0.2     v tidyr     1.3.0
## v readr     2.1.4

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter()    masks stats::filter()
## x dplyr::lag()       masks stats::lag()
## x purrr::lift()      masks caret::lift()
## x lubridate::stamp() masks cowplot::stamp()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```r
library(flexclust)
```

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

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

```r
library(cluster)
```

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

```r
library(NbClust)
```

```r
#Importing the dataset.
PharmaceuticalsData <- read.csv("C:/Users/saiha/OneDrive/Documents/R PROGRAMMING/Pharmaceuticals.csv")
```

```r
head(PharmaceuticalsData)
```

```
##   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
```

```r
colMeans(is.na(PharmaceuticalsData))
```

```
##                 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
```

```r
row.names(PharmaceuticalsData) <- PharmaceuticalsData[,2]
PharmaceuticalsData <- PharmaceuticalsData[,-2]
```

```r
#Summary of the dataset.
summary(PharmaceuticalsData)
```

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

```r
dim(PharmaceuticalsData)
```

```
## [1] 21 13
```

```r
colMeans(is.na(PharmaceuticalsData))
```

```
##                 Symbol            Market_Cap                  Beta
##                      0                     0                     0
##               PE_Ratio                   ROE                   ROA
##                      0                     0                     0
```

```
##        Asset_Turnover              Leverage            Rev_Growth
##                     0                     0                     0
##     Net_Profit_Margin Median_Recommendation              Location
##                     0                     0                     0
##              Exchange
##                     0
```

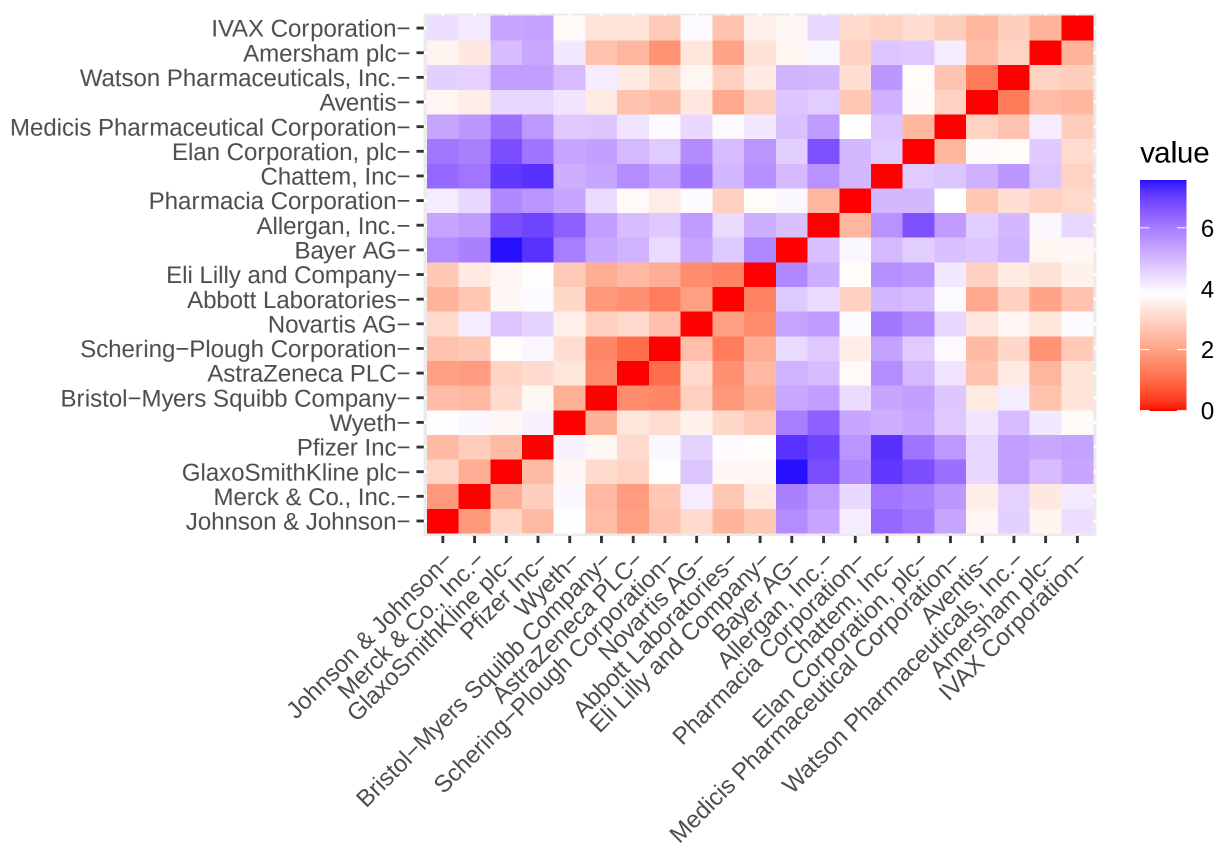
#a) Performing a cluster analysis involves making several decisions to ensure the process is meaningful and relevant to the underlying data structure. In the context of clustering 21 firms using only numerical variables (1 to 9).

```r
#In our analysis, we narrow our focus to a subset of the complete dataset, specifically emphasizing num
```

```r
#Excluding the variable "Symbol" and the final three categorical variables in the dataset.
PharmaceuticalsData1 <- PharmaceuticalsData[,-c(1,11:13)]
```

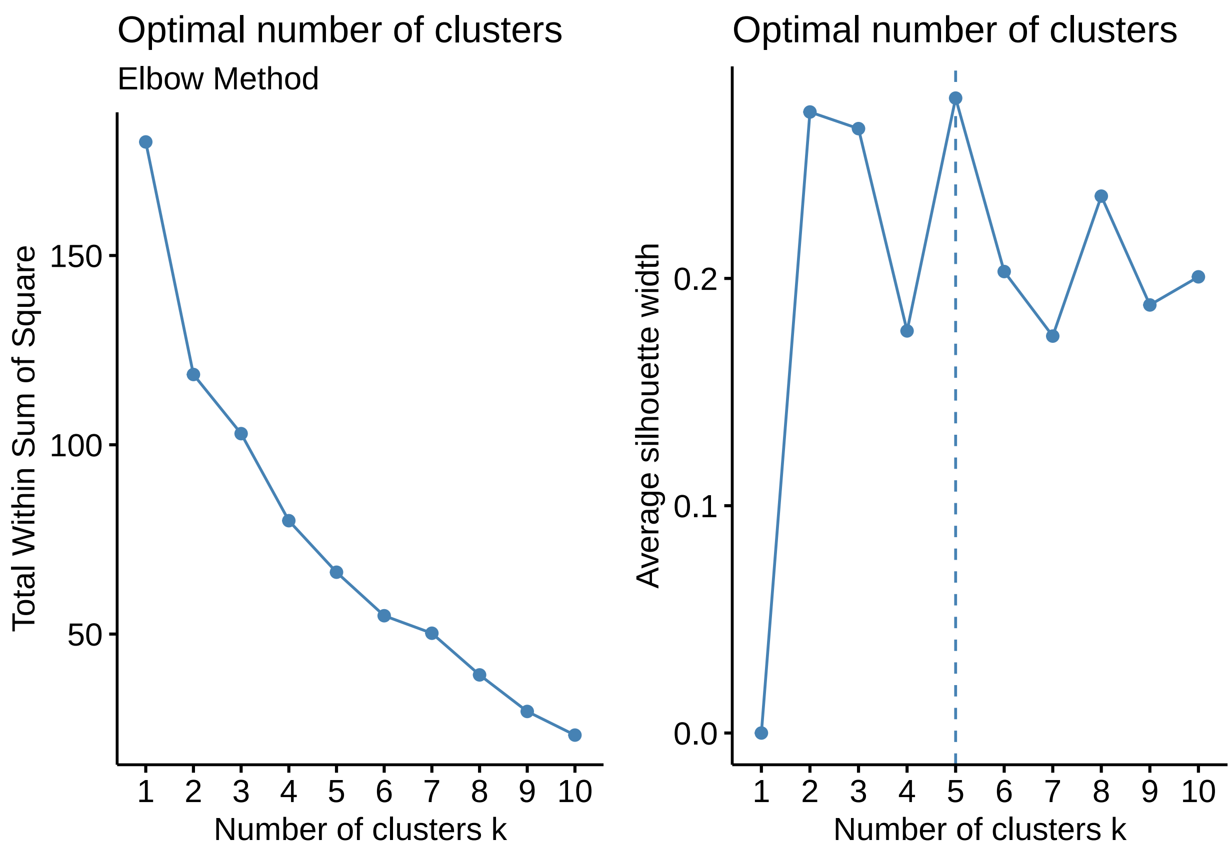
```r
#In this step, the dissimilarity between each observation is computed. To ensure accurate results, the
```

```r
#Normalising the data
norm.PharmaceuticalsData1 <- scale(PharmaceuticalsData1)

#Measuring and plotting the distance
dist <- get_dist(norm.PharmaceuticalsData1)
fviz_dist(dist)
```



```
#The graph shows that as we move along the diagonal, the color becomes less intense, reaching zero at t

#The Elbow chart and the Silhouette Method are helpful tools for figuring out how many clusters to use
```

```
Pharma_WSS <- fviz_nbclust(norm.PharmaceuticalsData1, kmeans, method = "wss") + labs(subtitle = "Elbow M
Pharma_Silho <- fviz_nbclust(norm.PharmaceuticalsData1, kmeans, method = "silhouette")
plot_grid(Pharma_WSS, Pharma_Silho) + labs(subtitle = "Silhouette Method")
```




```
#The elbow method suggests that the optimal number of clusters, k, is 2, based on the point where the l
```

```
#Using k-means method with k=5.
set.seed(123)
K_Means.PharmaceuticalsData.optimal <- kmeans(norm.PharmaceuticalsData1, centers = 5, nstart = 50)
K_Means.PharmaceuticalsData.optimal$centers
```

```
##     Market_Cap       Beta    PE_Ratio        ROE        ROA Asset_Turnover
## 1 -0.03142211 -0.4360989 -0.31724852  0.1950459  0.4083915      0.1729746
## 2 -0.87051511  1.3409869 -0.05284434 -0.6184015 -1.1928478     -0.4612656
## 3 -0.43925134 -0.4701800  2.70002464 -0.8349525 -0.9234951      0.2306328
## 4  1.69558112 -0.1780563 -0.19845823  1.2349879  1.3503431      1.1531640
## 5 -0.76022489  0.2796041 -0.47742380 -0.7438022 -0.8107428     -1.2684804
##      Leverage Rev_Growth Net_Profit_Margin
## 1 -0.27449312 -0.7041516       0.556954446
## 2  1.36644699 -0.6912914      -1.320000179
```

```
## 3 -0.14170336 -0.1168459      -1.416514761
## 4 -0.46807818  0.4671788       0.591242521
## 5  0.06308085  1.5180158      -0.006893899
```

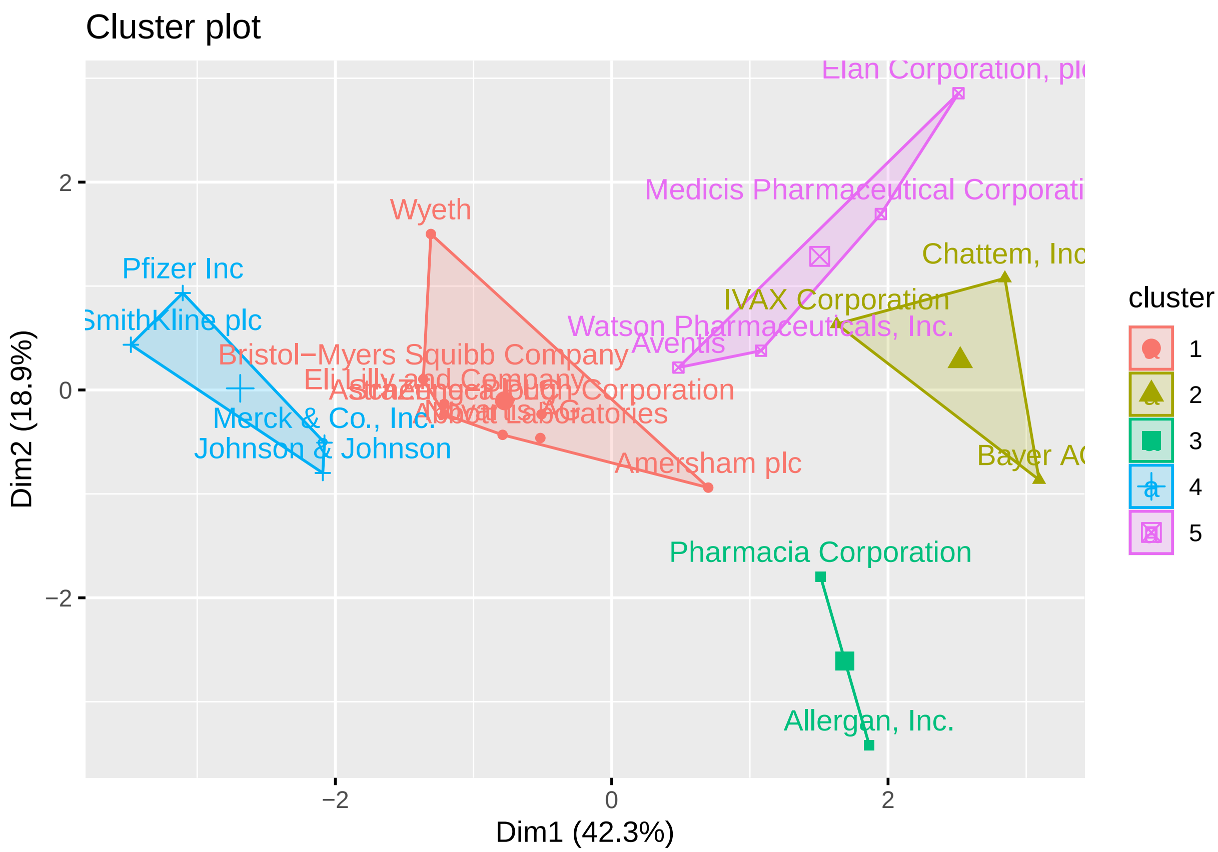
```
K_Means.PharmaceuticalsData.optimal$size
```

```
## [1] 8 3 2 4 4
```

```
K_Means.PharmaceuticalsData.optimal$withinss
```

```
## [1] 21.879320 15.595925  2.803505  9.284424 12.791257
```

```
fviz_cluster(K_Means.PharmaceuticalsData.optimal, data = norm.PharmaceuticalsData1)
```




```
#Using the data, we can categorize the firms into five clusters based on their distance from the centra
```

#b).Interpreting the clusters with respect to the numerical variables used in forming the clusters.

```
#I decided to rerun the model with only three clusters to gain a more comprehensive understanding of th
```

```
#Using k-means with k=3.
set.seed(123)
K_Means.PharmaceuticalsData <- kmeans(norm.PharmaceuticalsData1, centers = 3, nstart = 50)
K_Means.PharmaceuticalsData$centers
```

```
##   Market_Cap       Beta   PE_Ratio        ROE        ROA Asset_Turnover
## 1 -0.6125361  0.2698666  1.3143935 -0.9609057 -1.0174553      0.2306328
## 2  0.6733825 -0.3586419 -0.2763512  0.6565978  0.8344159      0.4612656
## 3 -0.8261772  0.4775991 -0.3696184 -0.5631589 -0.8514589     -0.9994088
##     Leverage Rev_Growth Net_Profit_Margin
## 1 -0.3592866 -0.5757385        -1.3784169
## 2 -0.3331068 -0.2902163         0.6823310
## 3  0.8502201  0.9158889        -0.3319956
```

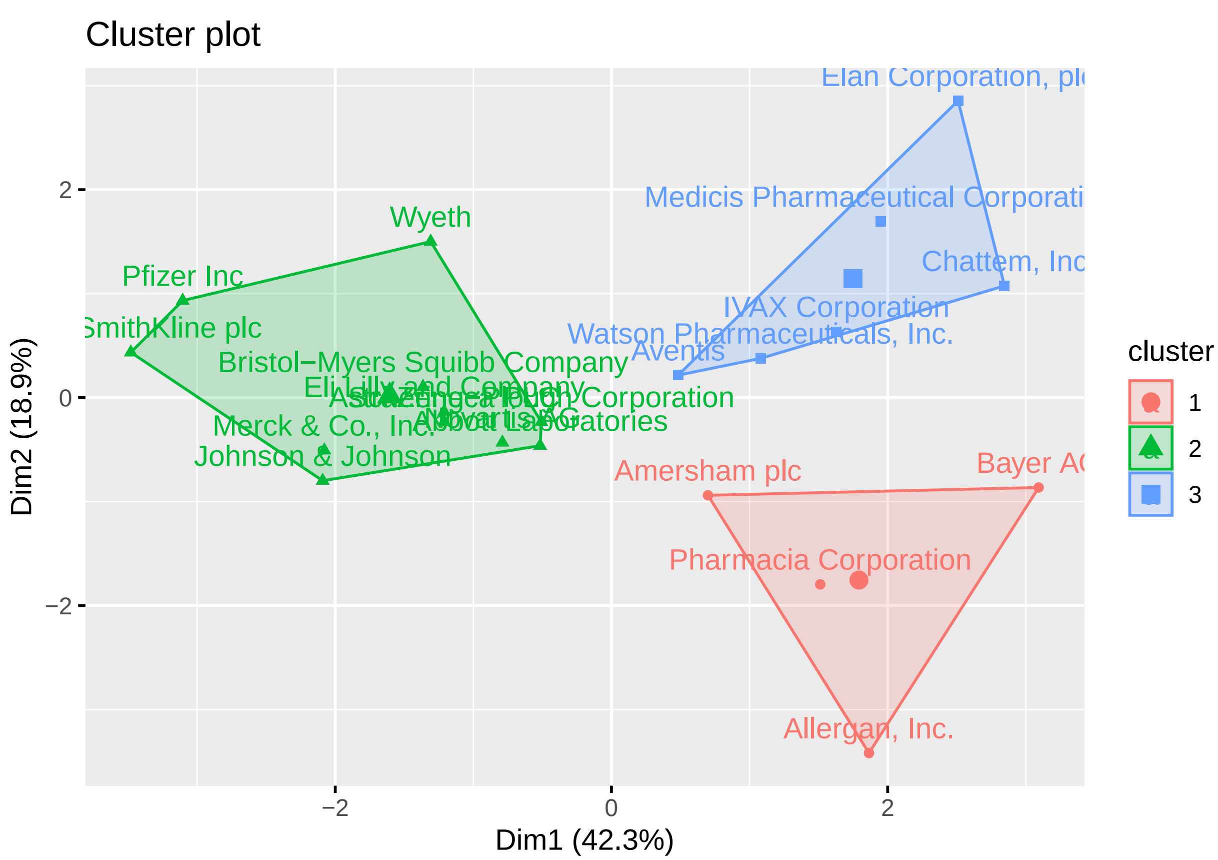
```
K_Means.PharmaceuticalsData$size
```

```
## [1]  4 11  6
```

```
K_Means.PharmaceuticalsData$withinss
```

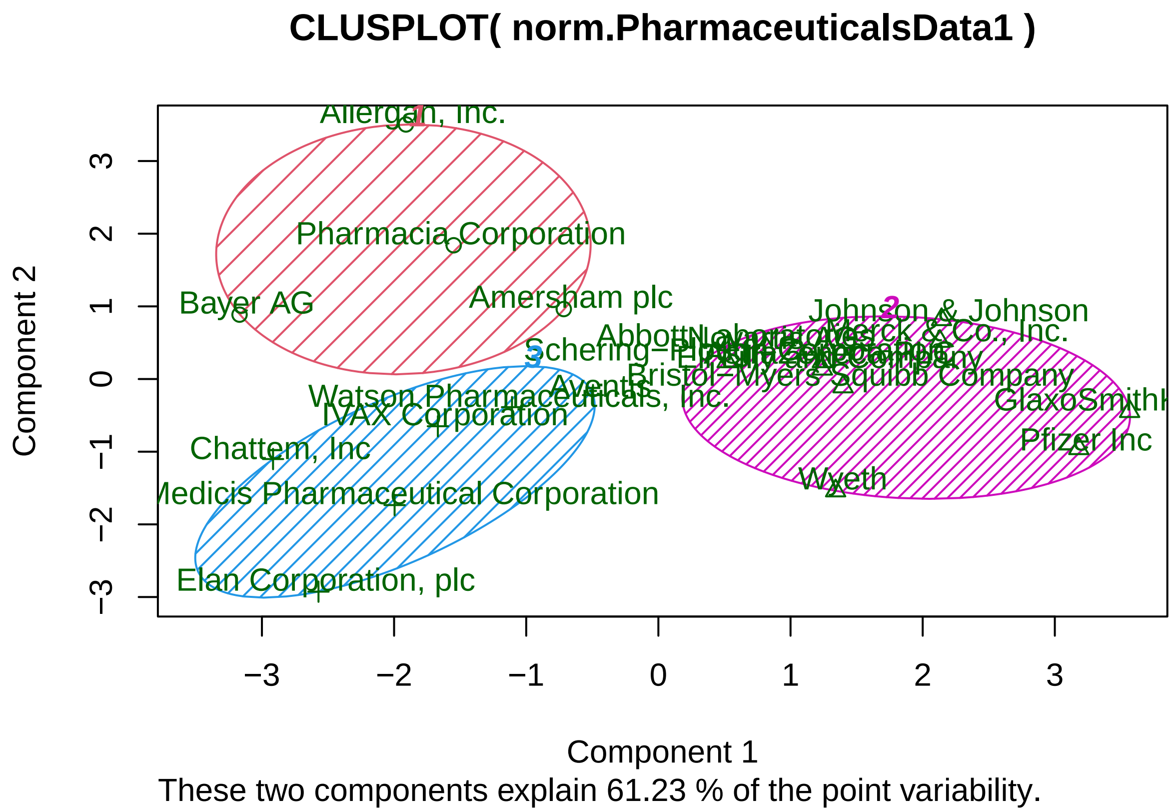
```
## [1] 20.54199 43.30886 32.14336
```

```
fviz_cluster(K_Means.PharmaceuticalsData, data = norm.PharmaceuticalsData1)
```




```
#The analysis has led to the identification and categorization of clusters. Specifically, there are fou
```

```
#To view the cluster plot-
clusplot(norm.PharmaceuticalsData1,K_Means.PharmaceuticalsData$cluster,color = TRUE,shade =TRUE, labels
```

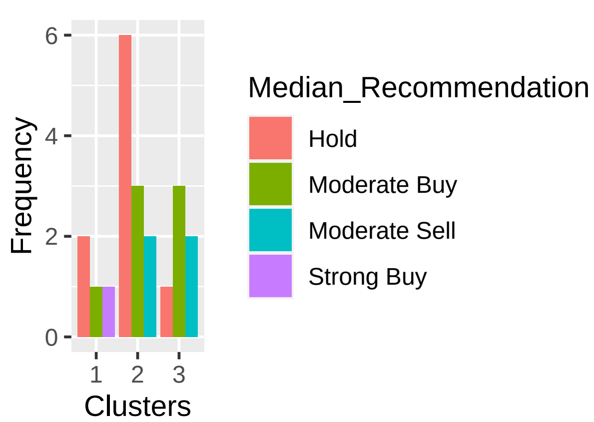


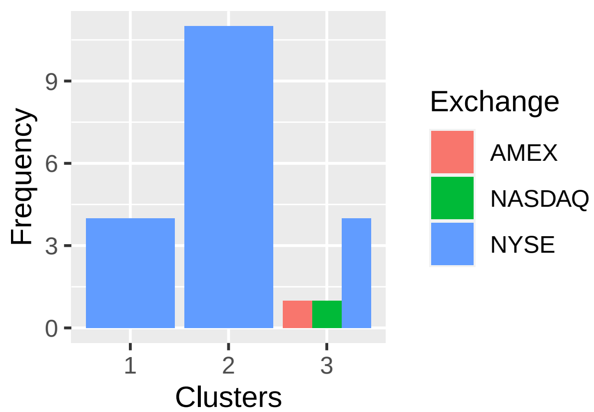
#c). Is there a pattern in the clusters with respect to the numerical variables (10 to 12)? (those not used in forming the clusters)

```
#To examine trends in the data, I opt to use bar charts to visually represent how firms are distributed
```

```
PharmaceuticalsData2 <-  PharmaceuticalsData %>% select(c(11,12,13)) %>%
    mutate(Cluster = K_Means.PharmaceuticalsData$cluster)
```

```
Median_Rec <- ggplot(PharmaceuticalsData2, mapping = aes(factor(Cluster), fill=Median_Recommendation)) +
  geom_bar(position = 'dodge') +
  labs(x='Clusters', y='Frequency')
Location <- ggplot(PharmaceuticalsData2, mapping = aes(factor(Cluster), fill=Location)) +
  geom_bar(position = 'dodge') +
  labs(x='Clusters', y='Frequency')
Exchange <- ggplot(PharmaceuticalsData2, mapping = aes(factor(Cluster), fill=Exchange)) +
  geom_bar(position = 'dodge') +
  labs(x='Clusters', y='Frequency')
plot_grid(Median_Rec, Location, Exchange)
```






```
#The chart clearly shows that most companies in cluster 3 are from the United States and all of them ha
```

#d). Assigning meaningful names to each cluster based on the characteristics of the firms can be accomplished by considering the distinctive features captured by the numerical variables. The labels should reflect the common traits shared by the firms within each cluster, making it easier to interpret and communicate the essence of each group.

#Ans).Cluster 1: These companies are termed as "overvalued international firms" because they operate globally, are listed on the NYSE, have low Net Profit Margins, and high Price/Earnings ratios. Despite their high market valuations, their current earnings may not justify such high stock prices. To sustain their stock value, they need to invest and increase earnings to meet investor expectations.

Cluster 2: This group is identified as a "growing and leveraged firm." They have "Moderate buy" evaluations, low asset turnover and Return on Assets (ROA), high leverage, and are expected to experience revenue growth. Although currently not very profitable and carrying significant debt, investors see potential in them and are willing to wait for future growth.

Cluster 3: These companies are characterized as "mature US firms" because they are based in the United States, listed on the NYSE, and have received "Hold" ratings. Their status suggests a stable and mature phase of development in the business.