# FML ASSIGNMENT 4

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```
# The necessary packages are loaded
library(caret)
```

```
## Loading required package: ggplot2
```

```
## Loading required package: lattice
```

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

```
## Warning: package 'factoextra' was built under R version 4.3.3
```

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

```
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
```

```
library(ggplot2)
```

```
library(tidyverse)
```

```
## Warning: package 'tidyverse' was built under R version 4.3.3
```

```
## Warning: package 'readr' was built under R version 4.3.3
```

```
## Warning: package 'forcats' was built under R version 4.3.3
```

```
## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
## ✓ forcats   1.0.0     ✓ stringr   1.5.1
## ✓ lubridate 1.9.3     ✓ tibble    3.2.1
## ✓ purrr     1.0.2     ✓ tidyr     1.3.1
## ✓ readr     2.1.5
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## ✖ dplyr::filter() masks stats::filter()
## ✖ dplyr::lag()    masks stats::lag()
## ✖ purrr::lift()   masks caret::lift()
## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom
e errors
```

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

```
## Warning: package 'cowplot' was built under R version 4.3.3
```

```
##
## Attaching package: 'cowplot'
```

```
## The following object is masked from 'package:lubridate':
##
##     stamp
```

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

```
## Warning: package 'flexclust' was built under R version 4.3.3
```

```
## Loading required package: grid
```

```
## Loading required package: modeltools
```

```
## Loading required package: stats4
```

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

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

```
# It imports the "Pharmaceuticals" dataset from the specified file path
Pharmacy <- read.csv("C:/Users/eshwa/Documents/Fundamentals of Machine Learning/ASSN 4/Pharmaceu
ticals.csv")
```

```
# The "Pharmacy" dataset will be viewed
view(Pharmacy)
```

```
#  It displays the first few rows of the "Pharmacy" dataset
head(Pharmacy)
```

```
##   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
```

```
# It displays the summary statistics for the "Pharmacy" dataset
summary(Pharmacy)
```

```
##     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
##
##
##
```

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

# Calculates the column wise mean of missing values in the "Pharmacy" dataset
colMeans(is.na(Pharmacy))
```

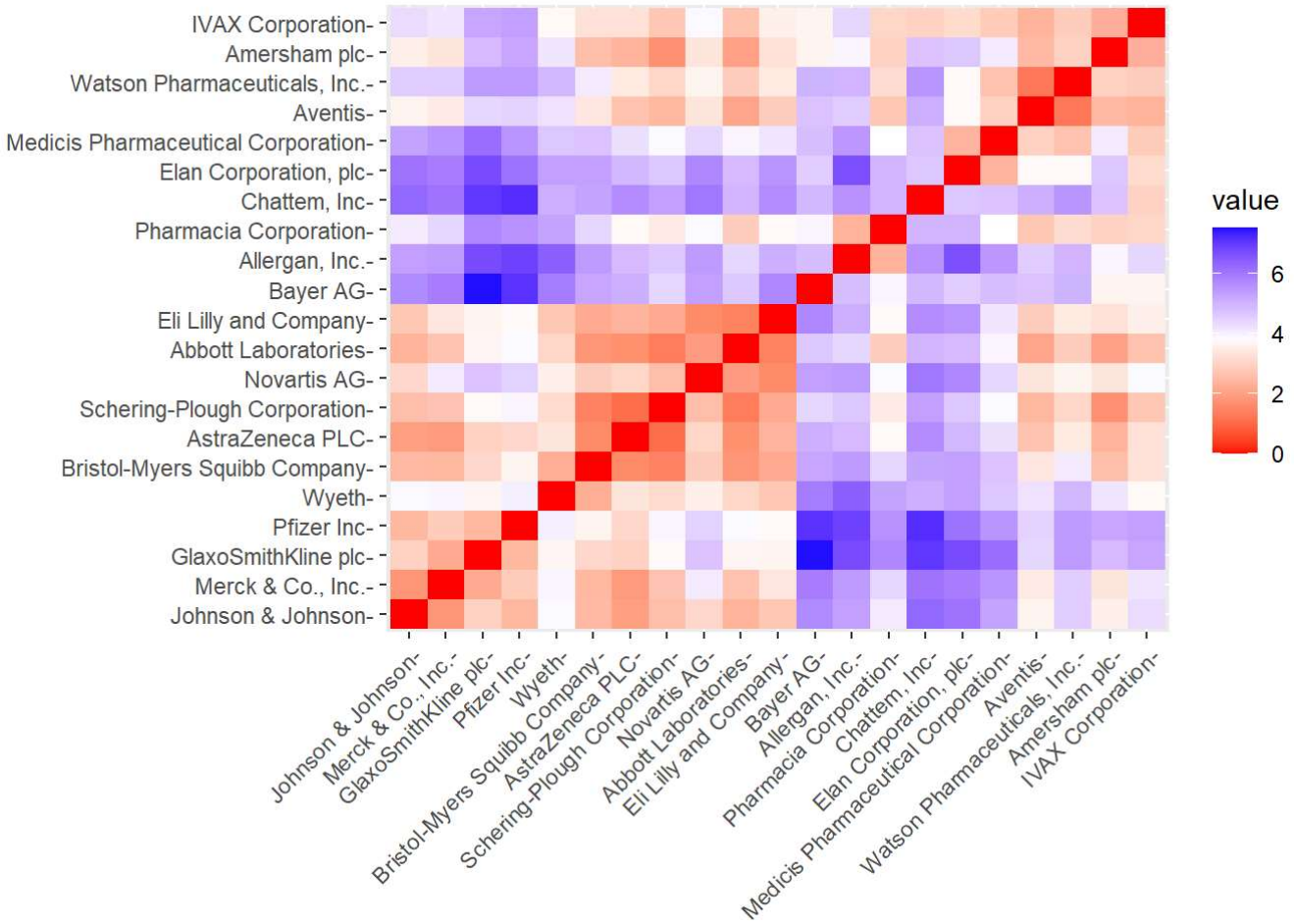
```
##               Symbol                 Name           Market_Cap
##                    0                    0                    0
##                 Beta             PE_Ratio                  ROE
##                    0                    0                    0
##                  ROA        Asset_Turnover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

```
# Sets row names of "Pharmacy" to the values in the second column.
row.names(Pharmacy) <- Pharmacy[,2]
# Removes the second column from the "Pharmacy" dataset
Pharmacy <- Pharmacy[,-2]
#  Removes the first column and columns 11 to 13 from the updated "Pharmacy" dataset
Pharmacy.1 <- Pharmacy[,-c(1,11:13)]
```

```
# Checks the dimensions of the "Pharmacy" dataset
dim(Pharmacy)
```

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

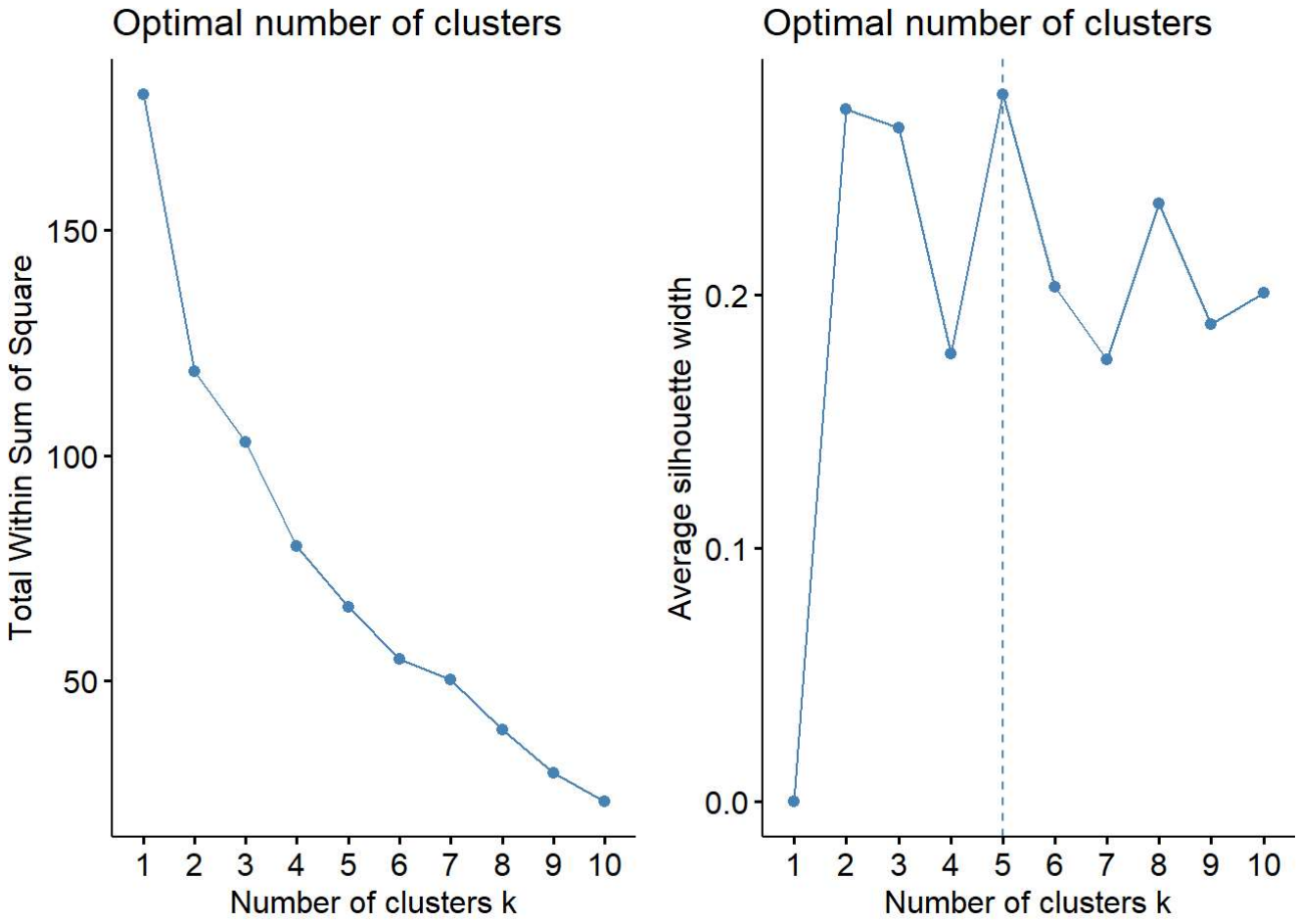
```
# Standardizes the columns of "Pharmacy.1" using the scale function
norm.Pharmacy.1 <- scale(Pharmacy.1)
# Calculates the distance matrix based on the standardized data
dist <- get_dist(norm.Pharmacy.1)
# Visualizes the distance matrix using function
fviz_dist(dist)
```



```
# The chart shows how the color intensity changes as we move across distances. As expected,the d
iagonal line representing the distance between two observations, has a value of zero.

# For finding the best K Value: The Elbow chart and the Silhouette Method are effective ways to
decide the number of clusters for a k-means model, especially when external factors don't guide
the decision. The Elbow chart shows how increasing the number of clusters decreases overall clus
ter diversity. On the other hand, the Silhouette Method evaluates how well an objects cluster al
igns with other clusters, helping us understand the cohesion within the clusters.
```

```
# Calculates Within Cluster Sum of Squares (WSS) for different numbers of clusters using the k-m
eans algorithm
WSS <- fviz_nbclust(norm.Pharmacy.1, kmeans, method = "wss")
# Calculates Silhouette scores for different numbers of clusters using the k-means algorithm
Sil <- fviz_nbclust(norm.Pharmacy.1, kmeans, method = "silhouette")
# Displays the plots of WSS and Silhouette scores
plot_grid(WSS, Sil)
```




```
# The charts indicate different optimal values for k, the Elbow Method suggests k=2, while the S
ilhouette Method produces k=5. Despite this, I have decided to use k=5 for the k-means method in
my analysis.
```

```
# Set the seed for reproducibility
# Performs k-means clustering on the normalized "Pharmacy.1" data with 5 centers
# Displays the cluster centers obtained from the k-means clustering
set.seed(123)
KMeans.Pharmacy.Opt <- kmeans(norm.Pharmacy.1, centers = 5, nstart = 50)
KMeans.Pharmacy.Opt$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
```

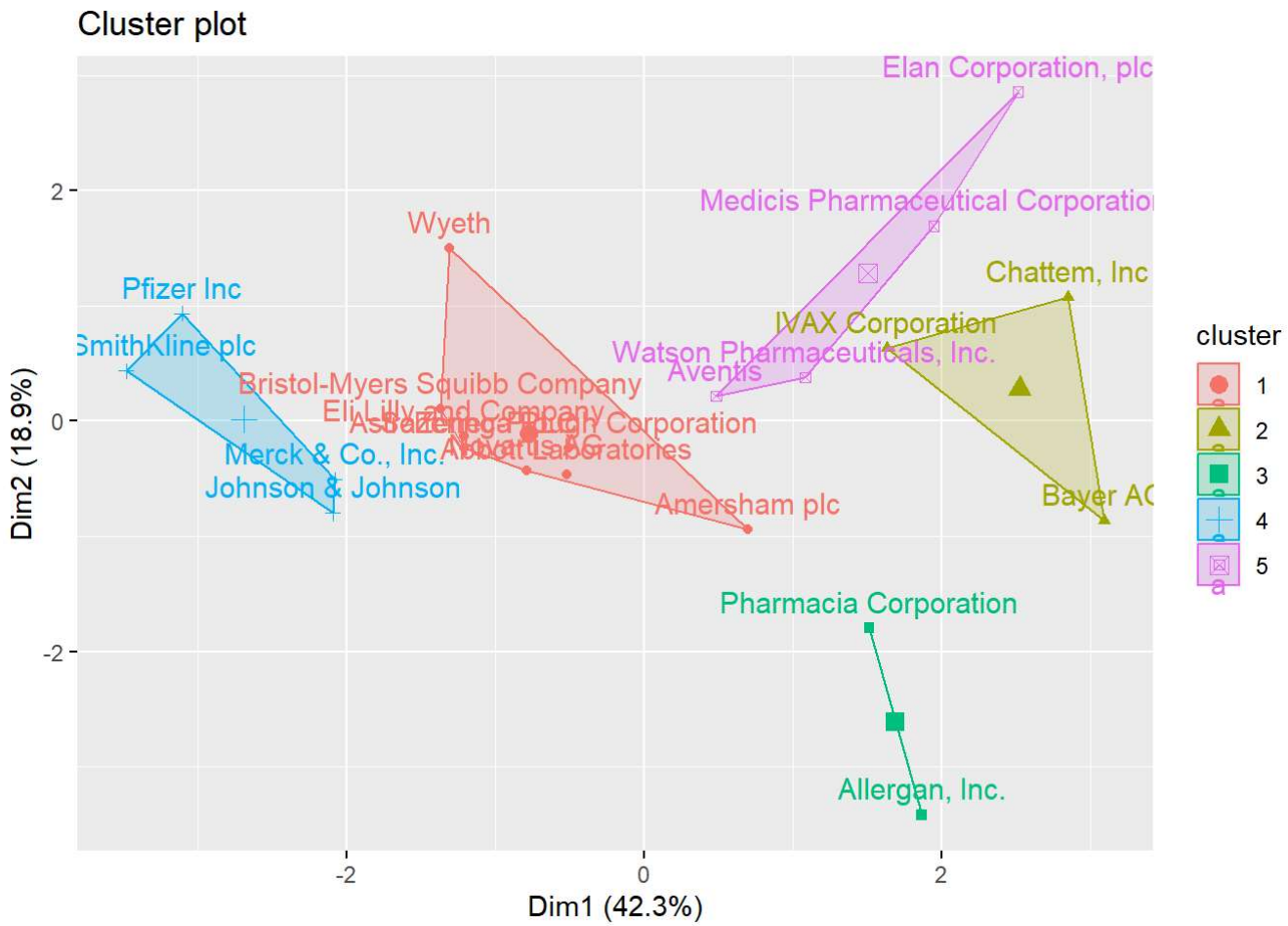
```
# Display the size of each cluster
KMeans.Pharmacy.Opt$size
```

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

```
# Display the within-cluster sum of squares
KMeans.Pharmacy.Opt$withinss
```

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

```
# Visualize the k-means clusters using a scatter plot
fviz_cluster(KMeans.Pharmacy.Opt, data = norm.Pharmacy.1)
```




```
# Using the dataset,we identified five clusters based on their proximity to core points. Cluster 4 stands out for its high Market Capital, while Cluster 2 is notable for its high Beta.
# On the other hand, Cluster 5 is characterized by a low Asset Turnover.Examining the size of each cluster, Cluster 1 has the most enterprises, while Cluster 3 consists of only two.
# The within-cluster sum of squared distances provides insights into data dispersion: Cluster 1 (21.9) is less homogeneous than Cluster 3 (2.8).Visualizing the algorithm's results allows us to see the distinct groups the data has been divided into.
```

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

# Set the seed for reproducibility
# Performs k-means clustering on the normalized "Pharmacy.1" data with 3 clusters
# Displays the cluster centers

set.seed(123)
KMeans.Pharmacy <- kmeans(norm.Pharmacy.1, centers = 3, nstart = 50)
KMeans.Pharmacy$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
```

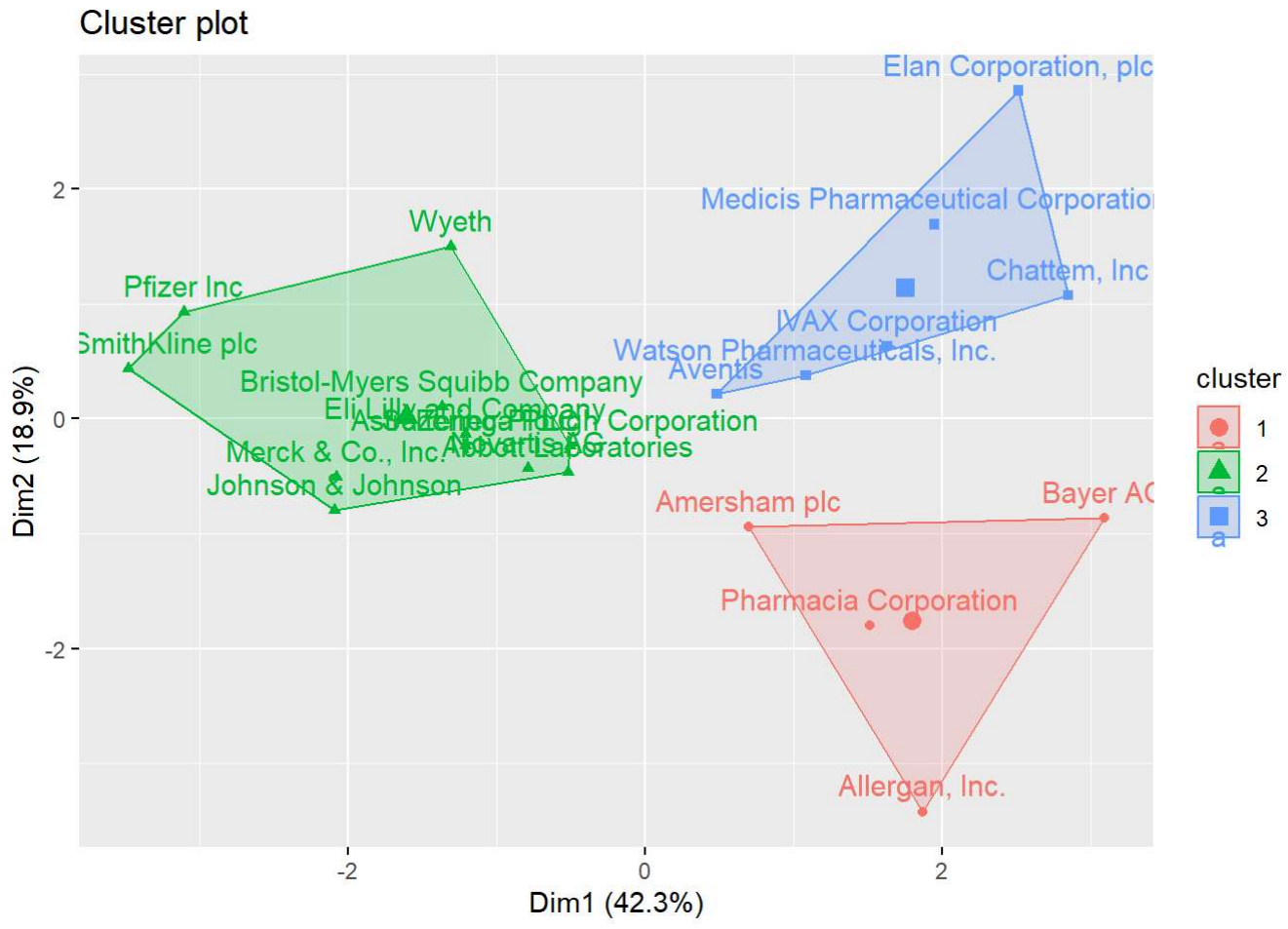
```
# Displays the sizes of each cluster obtained from the k-means clustering.
KMeans.Pharmacy$size
```

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

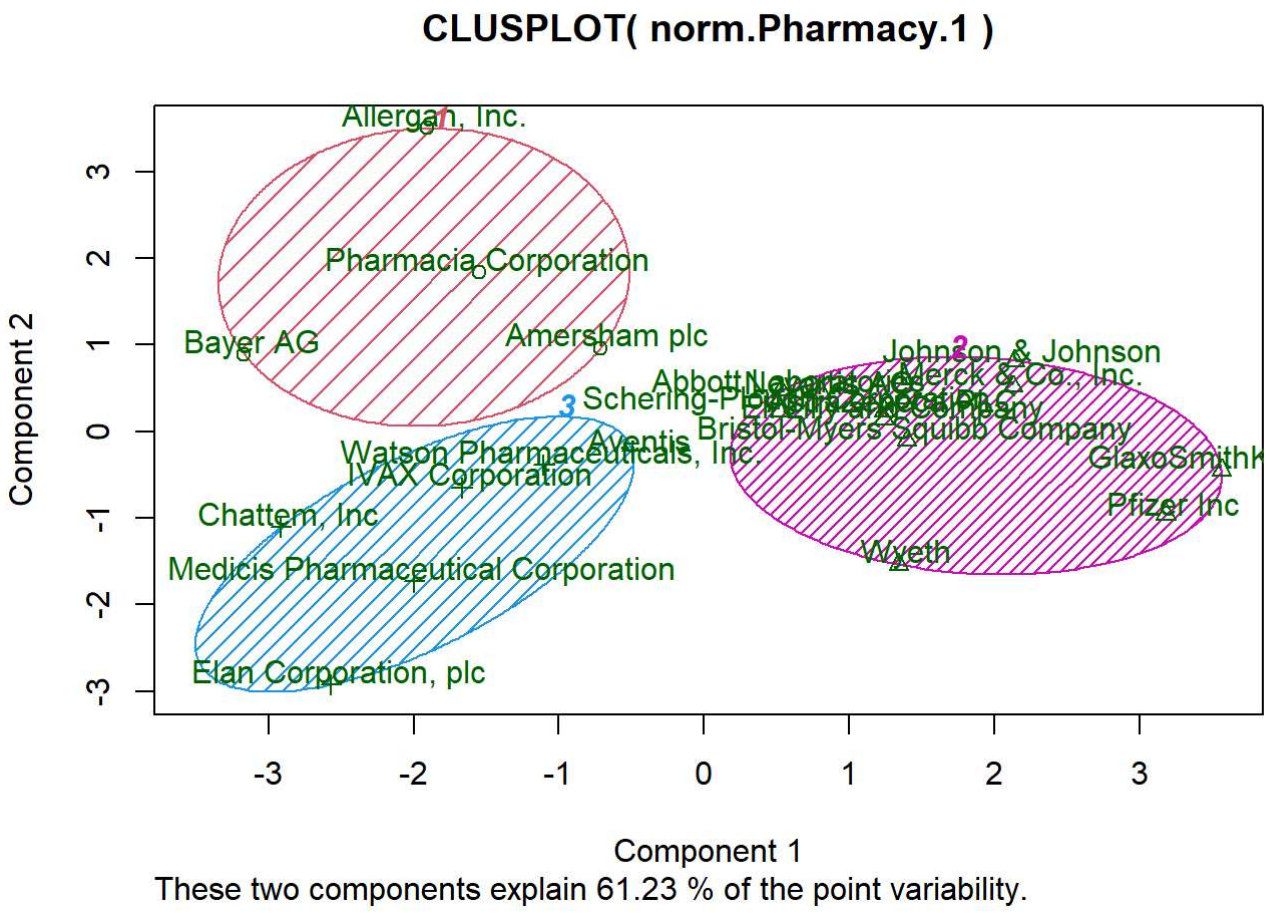
```
# Displays the within-cluster sum of squares for each cluster
KMeans.Pharmacy$withinss
```

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

```
# Visualize the k-means clusters using a scatter plot
fviz_cluster(KMeans.Pharmacy, data = norm.Pharmacy.1)
```



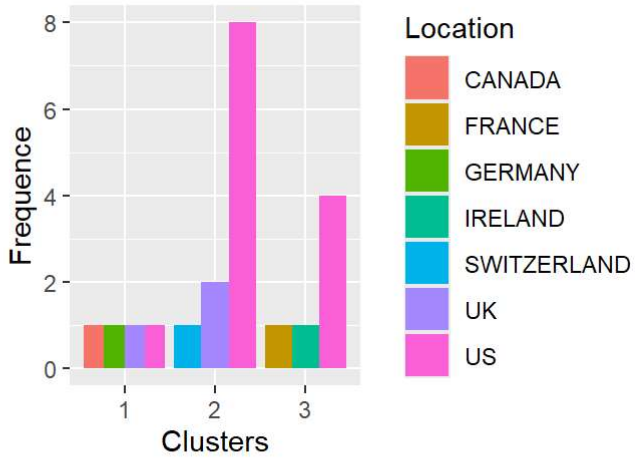
```
clusplot(norm.Pharmacy.1,KMeans.Pharmacy$cluster,color = TRUE,shade =TRUE, labels=2,lines=0)
```

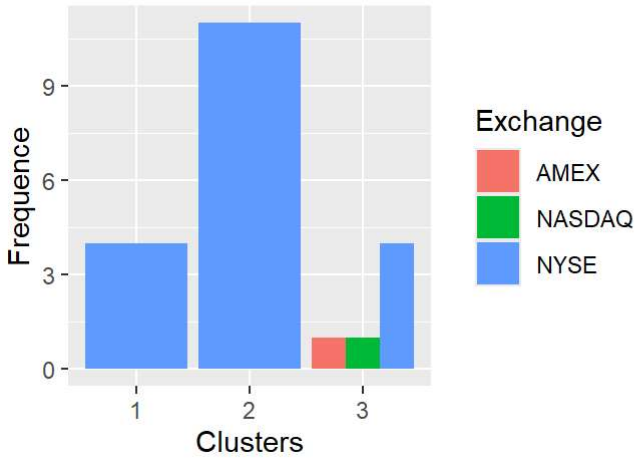



```
#c. Is there a pattern in the clusters with respect to the numerical variables (10 to 12)?

# To explore patterns in the data for the last three categorical variables—Median Recommendatio
n, Location, and Stock Exchange—I decided to use bar charts. These charts provide a visual repre
sentation of how firms are distributed among different clusters, allowing for a clearer understa
nding of trends in the data.

Pharmacy.2 <-  Pharmacy%>% select(c(11,12,13)) %>%
    mutate(Cluster = KMeans.Pharmacy$cluster)
Med_Recom <- ggplot(Pharmacy.2, mapping = aes(factor(Cluster), fill=Median_Recommendation)) +
  geom_bar(position = 'dodge') +
  labs(x='Clusters', y='Frequence')
Loc <- ggplot(Pharmacy.2, mapping = aes(factor(Cluster), fill=Location)) +
  geom_bar(position = 'dodge') +
  labs(x='Clusters', y='Frequence')
Ex <- ggplot(Pharmacy.2, mapping = aes(factor(Cluster), fill=Exchange)) +
  geom_bar(position = 'dodge') +
  labs(x='Clusters', y='Frequence')
plot_grid(Med_Recom, Loc, Ex)
```


```
# The chart makes it clear that most companies in cluster 3 are from the United States, and all of them suggest holding their shares.They're exclusively traded on the New York Stock Exchange. For cluster 2, we've selected stocks with a "Moderate Buy" recommendation, and only two companies are from different exchanges (AMEX and NASDAQ). Cluster 1 reveals that the four firms come from four different countries, yet all their stocks are traded on the NYSE.
```

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

#1) Cluster 1 - Global Giants: These companies are considered "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 value, it's not well-supported by their current earnings. To sustain their stock prices, they need to invest and increase earnings to meet investor expectations.
#2) Cluster 2 - Growth Prospects: This group is labeled as "growing and leveraged firms" due to "Moderate buy" evaluations, low asset turnover, low ROA, high leverage, and expected revenue growth.Even though they currently lack profitability and carry significant debt, investors see potential in their future growth, making them highly valued.
#3) Cluster 3 - Stable US Companies: Companies in this cluster are characterized as "mature US firms" since they are based in the US, listed on the NYSE, and have "Hold" ratings.They are considered stable and mature, indicating a more conservative investment approach compared to the other clusters.
```