

# Assignment 4 FML

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#Importing the Dataset

```
Pharmaceuticals <- read.csv("C:/Users/ADMIN/Downloads/Pharmaceuticals.csv")
summary(Pharmaceuticals)
```

##	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				
##					
##					
##					

```
str(Pharmaceuticals)
```

```
## 'data.frame':    21 obs. of  14 variables:
## $ Symbol          : chr  "ABT" "AGN" "AHM" "AZN" ...
## $ Name            : chr  "Abbott Laboratories" "Allergan, Inc." "Amersham plc" "AstraZeneca PLC" ...
## $ Market_Cap      : num  68.44 7.58 6.3 67.63 47.16 ...
## $ Beta            : num  0.32 0.41 0.46 0.52 0.32 1.11 0.5 0.85 1.08 0.18 ...
## $ PE_Ratio        : num  24.7 82.5 20.7 21.5 20.1 27.9 13.9 26 3.6 27.9 ...
## $ ROE             : num  26.4 12.9 14.9 27.4 21.8 3.9 34.8 24.1 15.1 31 ...
## $ ROA             : num  11.8 5.5 7.8 15.4 7.5 1.4 15.1 4.3 5.1 13.5 ...
## $ Asset_Turnover   : num  0.7 0.9 0.9 0.9 0.6 0.6 0.9 0.6 0.3 0.6 ...
## $ Leverage        : num  0.42 0.6 0.27 0 0.34 0 0.57 3.51 1.07 0.53 ...
## $ Rev_Growth       : num  7.54 9.16 7.05 15 26.81 ...
## $ Net_Profit_Margin : num  16.1 5.5 11.2 18 12.9 2.6 20.6 7.5 13.3 23.4 ...
## $ Median_Recommendation: chr  "Moderate Buy" "Moderate Buy" "Strong Buy" "Moderate Sell"
## ...
## $ Location         : chr  "US" "CANADA" "UK" "UK" ...
## $ Exchange         : chr  "NYSE" "NYSE" "NYSE" "NYSE" ...
```

```
library(readr)
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(caret)
```

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

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

```
library(tidyverse)
```

```
## — Attaching core tidyverse packages ————— tidyverse 2.0.0 —
## ✓ forcats   1.0.0   ✓ stringr   1.5.0
## ✓ lubridate 1.9.2   ✓ tibble    3.1.8
## ✓ purrr     1.0.1   ✓ tidyr     1.3.0
```

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

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

```
##
## Attaching package: 'gridExtra'
##
## The following object is masked from 'package:dplyr':
##
## combine
```

```
library(ggrepel)
library(factoextra)
```

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

```
library(flexclust)
```

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

```
library(ggcorrplot)
library(FactoMineR)
```

#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.

#Removing the Null Values in the dataset and selecting the Numercial variables.

```
colSums(is.na(Pharmaceuticals))
```

```
##          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
```

```
row.names(Pharmaceuticals)<- Pharmaceuticals[,1]
Pharmaceuticals_data_num<- Pharmaceuticals[, 3:11]
head(Pharmaceuticals_data_num)
```

```
##      Market_Cap Beta PE_Ratio  ROE  ROA Asset_Turnover Leverage Rev_Growth
## ABT      68.44 0.32   24.7 26.4 11.8           0.7    0.42      7.54
## AGN      7.58 0.41   82.5 12.9 5.5           0.9    0.60      9.16
## AHM      6.30 0.46   20.7 14.9 7.8           0.9    0.27      7.05
## AZN      67.63 0.52   21.5 27.4 15.4          0.9    0.00     15.00
## AVE      47.16 0.32   20.1 21.8 7.5           0.6    0.34     26.81
## BAY      16.90 1.11   27.9 3.9 1.4           0.6    0.00     -3.17
##      Net_Profit_Margin
## ABT              16.1
## AGN              5.5
## AHM             11.2
## AZN             18.0
## AVE             12.9
## BAY              2.6
```

## Scaling and Normalisation the dataset.

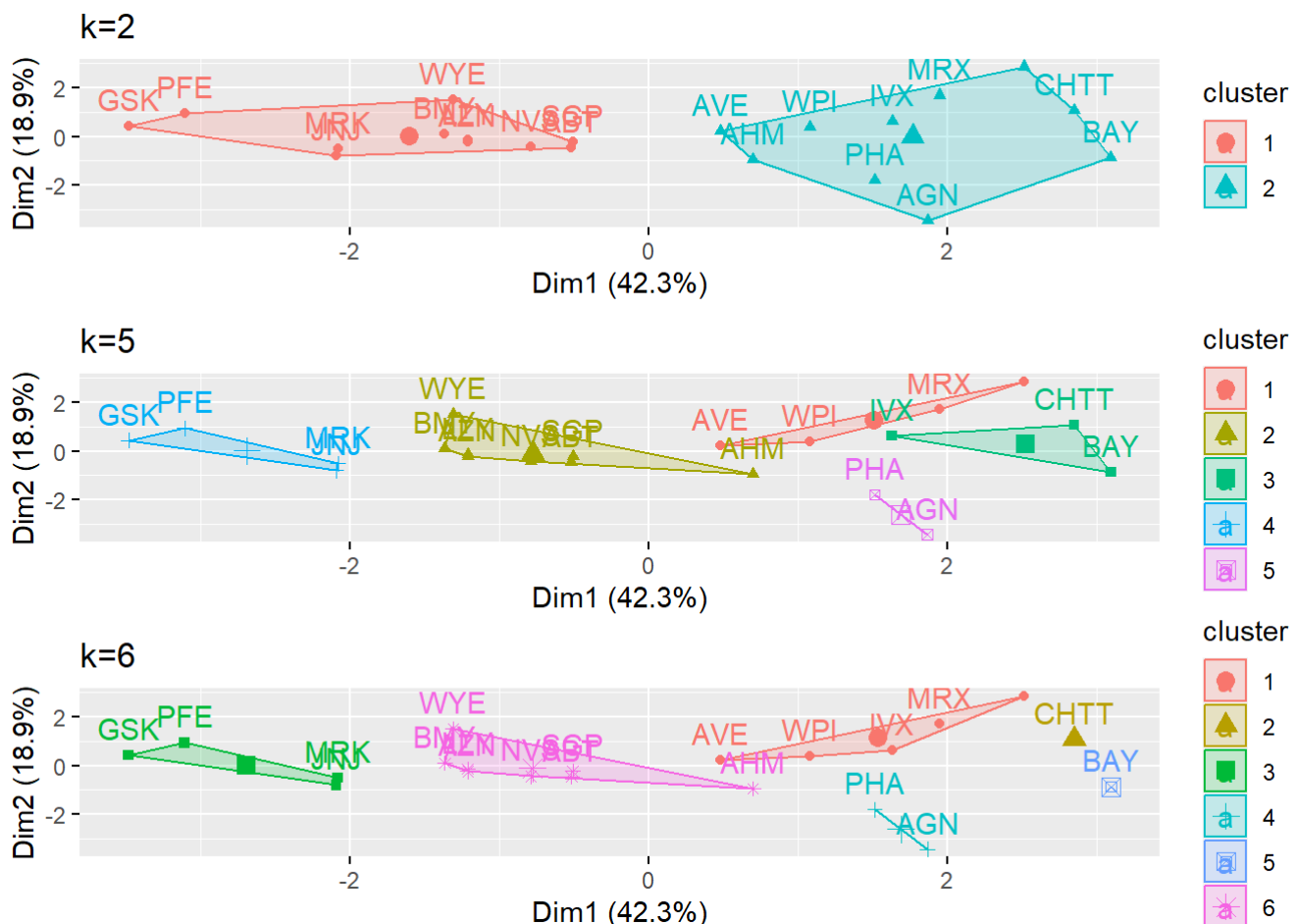
```
Pharmaceuticals_scale <- scale(Pharmaceuticals_data_num)
head(Pharmaceuticals_scale)
```

```
##      Market_Cap      Beta      PE_Ratio      ROE      ROA Asset_Turnover
## ABT  0.1840960 -0.80125356 -0.04671323  0.04009035  0.2416121  0.00000000
## AGN -0.8544181 -0.45070513  3.49706911 -0.85483986 -0.9422871  0.9225312
## AHM -0.8762600 -0.25595600 -0.29195768 -0.72225761 -0.5100700  0.9225312
## AZN  0.1702742 -0.02225704 -0.24290879  0.10638147  0.9181259  0.9225312
## AVE -0.1790256 -0.80125356 -0.32874435 -0.26484883 -0.5664461 -0.4612656
## BAY -0.6953818  2.27578267  0.14948233 -1.45146000 -1.7127612 -0.4612656
##      Leverage Rev_Growth Net_Profit_Margin
## ABT -0.2120979 -0.5277675      0.06168225
## AGN  0.0182843 -0.3811391     -1.55366706
## AHM -0.4040831 -0.5721181     -0.68503583
## AZN -0.7496565  0.1474473      0.35122600
## AVE -0.3144900  1.2163867     -0.42597037
## BAY -0.7496565 -1.4971443     -1.99560225
```

```
normal_data <- as.data.frame(scale(Pharmaceuticals_data_num))
```

# Computing K-means clustering for different centers and Using multiple values of K and examine the differences in results

```
kmeans_1 <- kmeans(Pharmaceuticals_scale, centers = 2, nstart = 30)
kmeans_2<- kmeans(Pharmaceuticals_scale, centers = 5, nstart = 30)
kmeans_3<- kmeans(Pharmaceuticals_scale, centers = 6, nstart = 30)
Plot_1<-fviz_cluster(kmeans_1, data = Pharmaceuticals_scale)+ggtitle("k=2")
plot_2<-fviz_cluster(kmeans_2, data = Pharmaceuticals_scale)+ggtitle("k=5")
plot_3<-fviz_cluster(kmeans_3, data = Pharmaceuticals_scale)+ggtitle("k=6")
grid.arrange(Plot_1,plot_2,plot_3, nrow = 3)
```

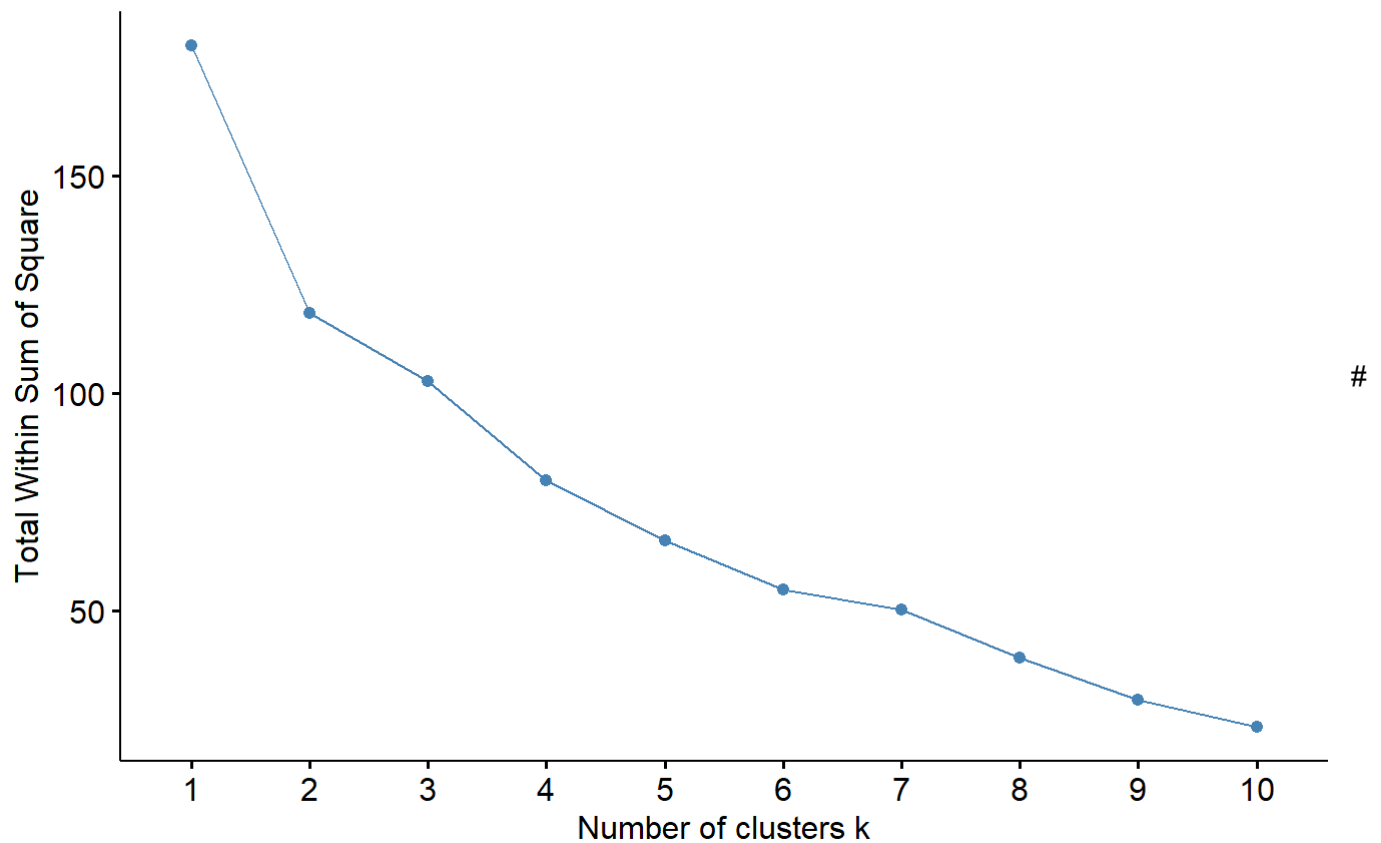


#so the recommended number of clusters is k=2 i.e plot2 # Estimating the number of clusters

```
fviz_nbclust(normal_data, FUNcluster = kmeans, method = "wss") + labs(subtitle = "Elbow Method")
```

## Optimal number of clusters

### Elbow Method

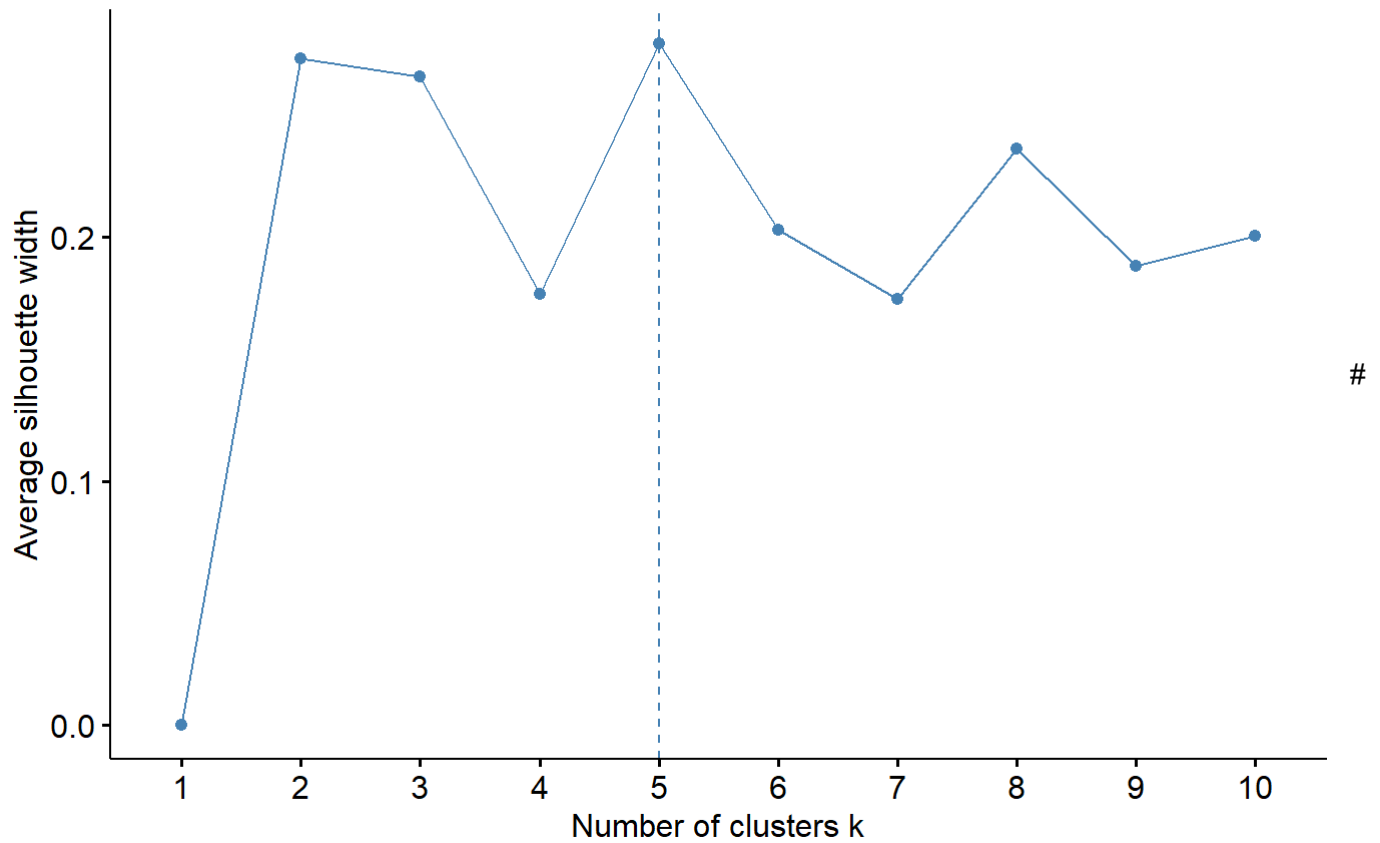


Silhouette Method is used in scaling the data to determine the number of clusters

```
fviz_nbclust(normal_data,FUNcluster = kmeans,method = "silhouette")+labs(subtitle="Silhouette Method")
```

## Optimal number of clusters

### Silhouette Method



Final analysis and Extracting results using 5 clusters and Visualize the results

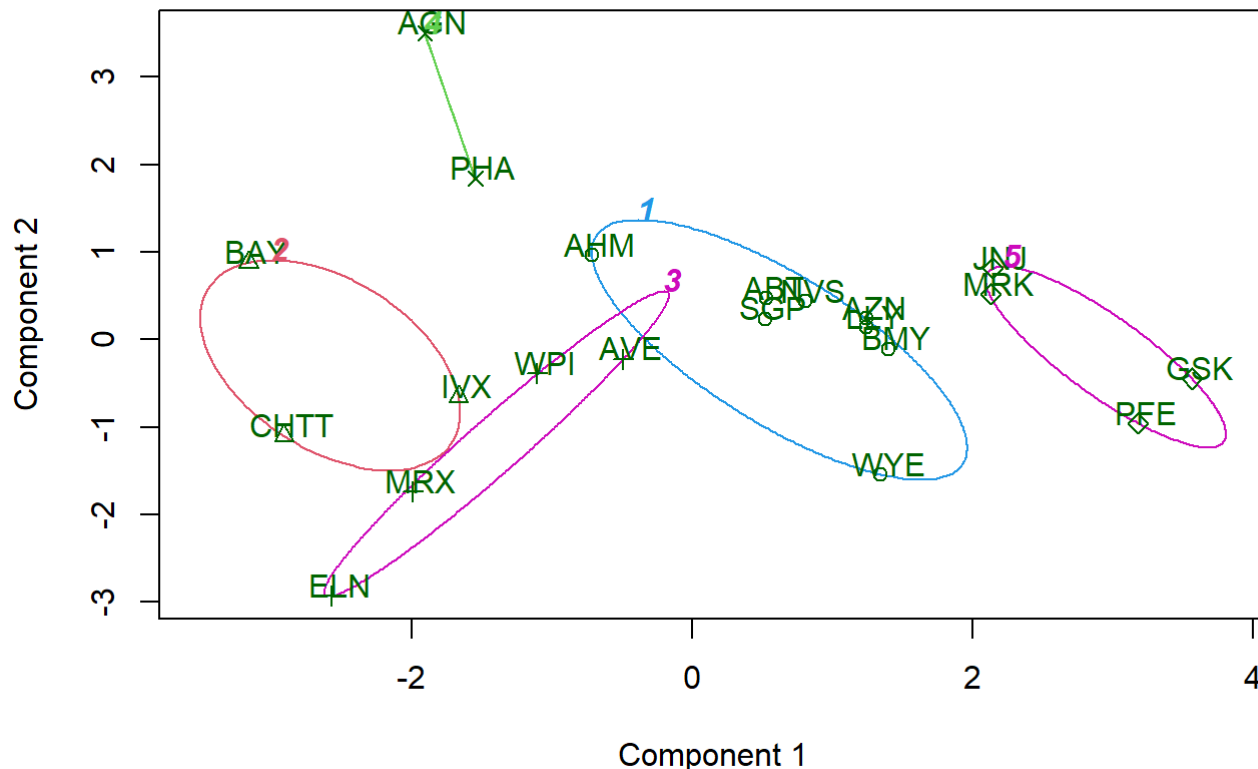
```
set.seed(300)
final_Cluster<- kmeans(Pharmaceuticals_scale, 5, nstart = 25)
print(final_Cluster)
```

```
## K-means clustering with 5 clusters of sizes 8, 3, 4, 2, 4
##
## Cluster means:
##   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 -0.76022489  0.2796041 -0.47742380 -0.7438022 -0.8107428   -1.2684804
## 4 -0.43925134 -0.4701800  2.70002464 -0.8349525 -0.9234951    0.2306328
## 5  1.69558112 -0.1780563 -0.19845823  1.2349879  1.3503431    1.1531640
##   Leverage Rev_Growth Net_Profit_Margin
## 1 -0.27449312 -0.7041516      0.556954446
## 2  1.36644699 -0.6912914     -1.320000179
## 3  0.06308085  1.5180158     -0.006893899
## 4 -0.14170336 -0.1168459     -1.416514761
## 5 -0.46807818  0.4671788      0.591242521
##
## Clustering vector:
##  ABT  AGN  AHM  AZN  AVE  BAY  BMY  CHTT  ELN  LLY  GSK  IVX  JNJ  MRX  MRK  NVS
##   1   4   1   1   3   2   1   2   3   1   5   2   5   3   5   1
##  PFE  PHA  SGP  WPI  WYE
##   5   4   1   3   1
##
## Within cluster sum of squares by cluster:
## [1] 21.879320 15.595925 12.791257  2.803505  9.284424
## (between_SS / total_SS =  65.4 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

```
clusplot(Pharmaceuticals_scale,final_Cluster$cluster, color = TRUE, labels = 2,lines = 0)
```



## CLUSPLOT( Pharmaceuticals\_scale )



These two components explain 61.23 % of the point variability.

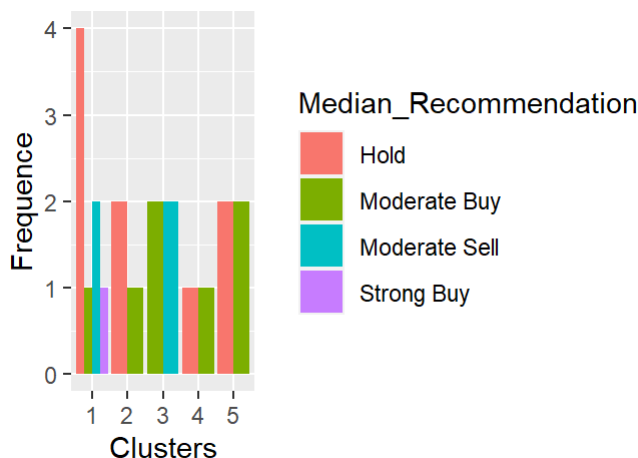
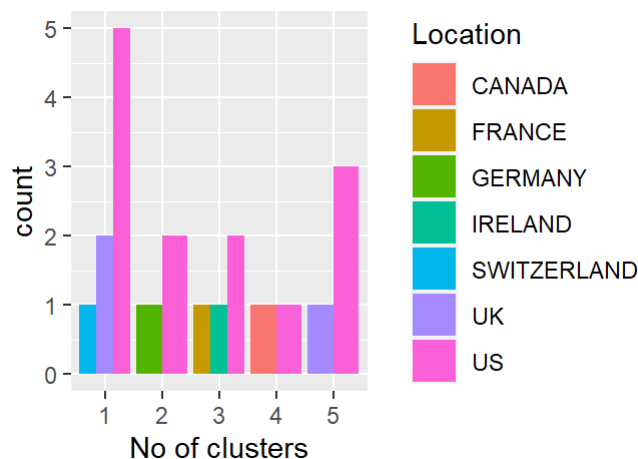
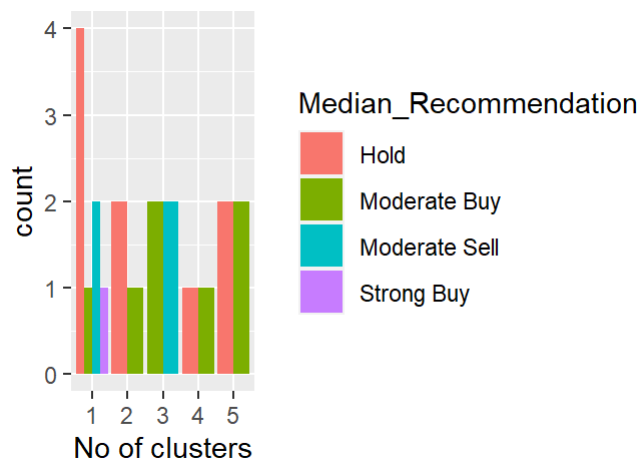
#B Interpret the clusters with respect to the numerical variables used in forming the clusters. #Cluster 1 - AHM,SGP,WYE,BMY,AZN, ABT, NVS, LLY ( lowest Market\_Cap,lowest Beta,lowest PE\_Ratio,highest Leverage,highest Rev\_Growth.) #Cluster 2 - BAY, CHTT, IVX (lowest Rev\_Growth,highest Beta and leverage,lowest Net\_Profit\_Margin) #Cluster 3 - WPI, MRX,ELN,AVE (lowest PE\_Ratio,highest ROE,lowest ROA,lowest Net\_Profit\_Margin, highest Rev\_Growth) #Cluster 4 - AGN, PHA (lowest Beta,lowest Asset\_Turnover, Highest PE Ratio) #Cluster 5 - JNJ, MRK, PFE,GSK (Highest Market\_Cap,ROE, ROA,Asset\_Turnover Ratio and lowest Beta/PE Ratio)

```
Pharmaceuticals_Cluster <- Pharmaceuticals[,c(12,13,14)]%>% mutate(clusters = final_Cluster$cluster)%>% arrange(clusters, ascending = TRUE)
Pharmaceuticals_Cluster
```

##	Median_Recommendation	Location	Exchange	clusters
## ABT	Moderate Buy	US	NYSE	1
## AHM	Strong Buy	UK	NYSE	1
## AZN	Moderate Sell	UK	NYSE	1
## BMY	Moderate Sell	US	NYSE	1
## LLY	Hold	US	NYSE	1
## NVS	Hold	SWITZERLAND	NYSE	1
## SGP	Hold	US	NYSE	1
## WYE	Hold	US	NYSE	1
## BAY	Hold	GERMANY	NYSE	2
## CHTT	Moderate Buy	US	NASDAQ	2
## IVX	Hold	US	AMEX	2
## AVE	Moderate Buy	FRANCE	NYSE	3
## ELN	Moderate Sell	IRELAND	NYSE	3
## MRX	Moderate Buy	US	NYSE	3
## WPI	Moderate Sell	US	NYSE	3
## AGN	Moderate Buy	CANADA	NYSE	4
## PHA	Hold	US	NYSE	4
## GSK	Hold	UK	NYSE	5
## JNJ	Moderate Buy	US	NYSE	5
## MRK	Hold	US	NYSE	5
## PFE	Moderate Buy	US	NYSE	5

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

```
plot1<-ggplot(Pharmaceuticals_Cluster, mapping = aes(factor(clusters), fill=Median_Recommendation))+geom_bar(position = 'dodge')+labs(x = 'No of clusters')
plot2<- ggplot(Pharmaceuticals_Cluster, mapping = aes(factor(clusters), fill = Location))+geom_bar(position = 'dodge')+labs(x = 'No of clusters')
plot3<- ggplot(Pharmaceuticals_Cluster, mapping = aes(factor(clusters), fill = Exchange))+geom_bar(position = 'dodge')+labs(x = 'No of clusters')
plot4<- ggplot(Pharmaceuticals_Cluster, mapping = aes(factor(clusters), fill=Median_Recommendation)) + geom_bar(position = 'dodge') + labs(x='Clusters', y='Frequency')
grid.arrange(plot1, plot2, plot3, plot4)
```



#AS per the graph

#Cluster 1 :The Hold median is the highest in this cluster , which also contains separate Hold, Moderate Buy, Moderate Sell, and Strong Buy medians. They are listed on the NYSE and come from the US, UK, and Switzerland.

#Cluster 2: Although the firms are evenly divided throughout AMEX, NASDAQ, and NYSE, has a distinct Hold and Moderate Buy median, as well as a different count between the US and Germany.

#Cluster 3: listed on the NYSE, has separate counts for France, Ireland, and the US, and has equal moderate buy and sell medians.

#Cluster 4: dispersed throughout the US and UK, as well as being listed in, has the identical hold and moderate buy medians

#Cluster 5: #solely listed on the NYSE, equally dispersed in the US and Canada, with Hold and Moderate Buy medians.