

FML ASNMT 4

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```
##Load the libraries
library(factoextra)
```

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

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

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

```
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr      1.1.4      v readr      2.1.5
## v forcats    1.0.0      v stringr   1.5.1
## v lubridate  1.9.3      v tibble    3.2.1
## v purrr      1.0.2      v tidyr     1.3.1
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
library(ISLR)
library(NbClust)
library(cluster)
```

Import the data from csv file

```
Pharmaceuticaldata <- read.csv("/Users/chaithanayayennam/Downloads/Pharmaceuticals.csv")
View(Pharmaceuticaldata)
```

(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.

Create a new data frame 'R_data' by removing rows with missing values from 'Pharmaceutical'

```
R_data <- na.omit(Pharmaceuticaldata)
summary(R_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
##
##
##
```

Changing the data frame 'R_data's row names to the numbers in its first column Creating a new data frame 'Pharma_data' containing columns 3 to 11 from 'A' Presenting the rows of the 'Pharma_data' data frame

```
row.names(R_data) <- R_data[,1]

Pharma_data <- R_data[,3:11]

head(Pharma_data)
```

```
##      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
```

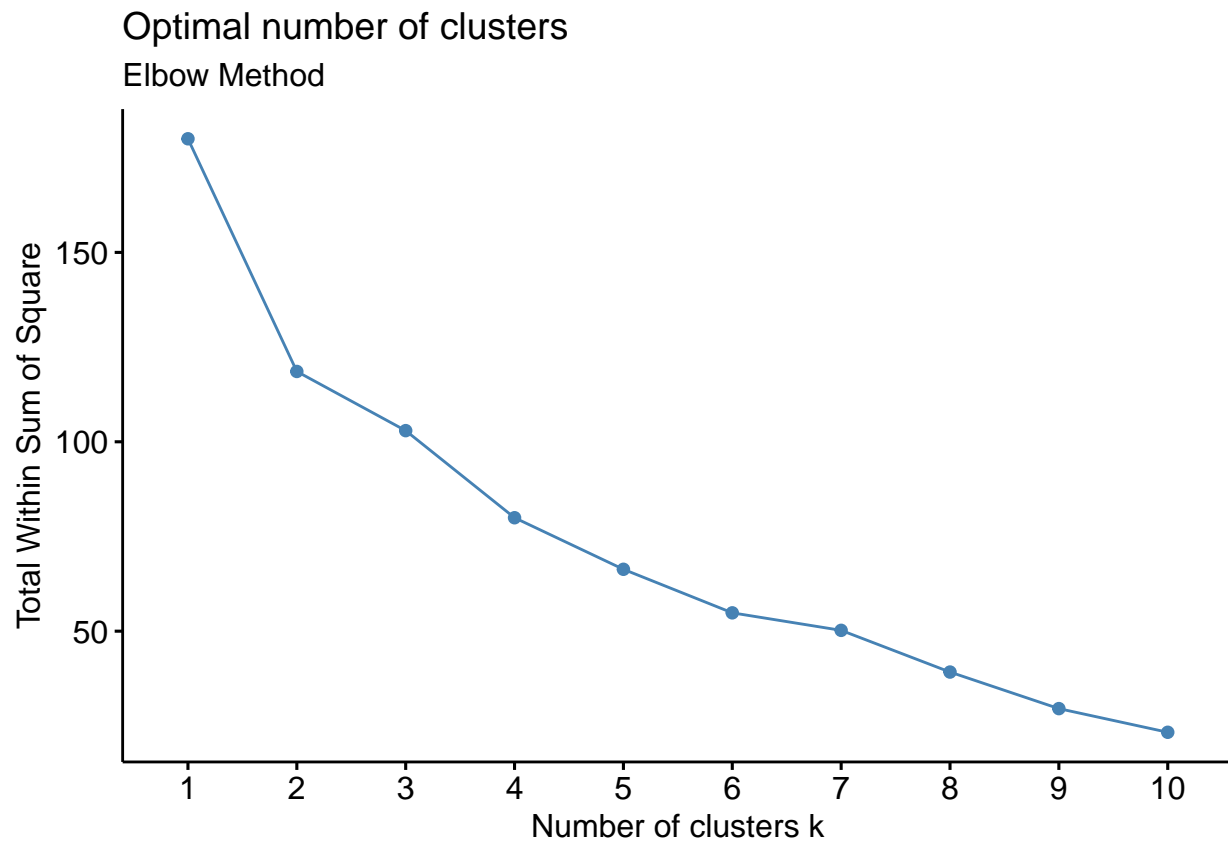
Normalizing variables by scaling the data in the 'Pharma_data' data frame. Presenting the rows of the 'Pharma_data' data frame

```
Chemist_data <- scale (Pharma_data)
```

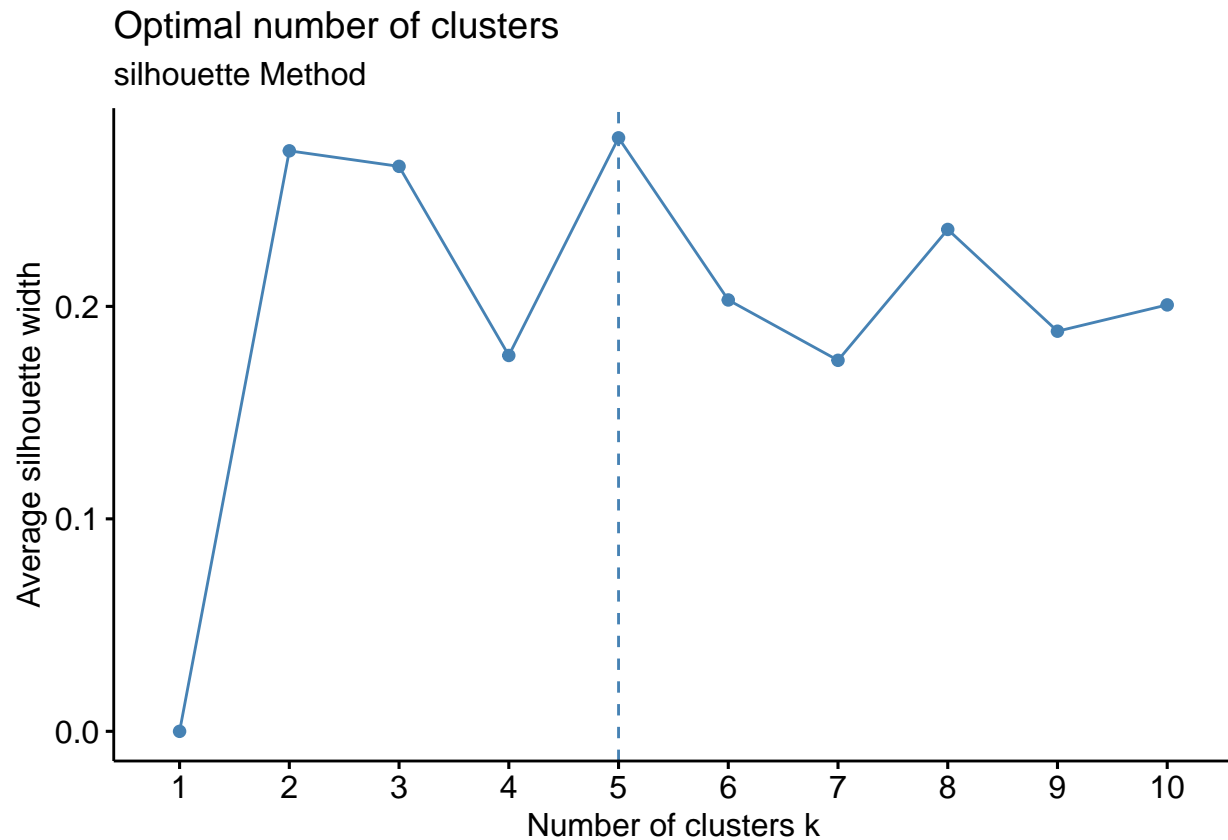
```
head(Chemist_data)
```

```
##      Market_Cap      Beta  PE_Ratio      ROE      ROA Asset_Turnover
## ABT  0.1840960 -0.80125356 -0.04671323  0.04009035  0.2416121  0.0000000
## 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
```

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



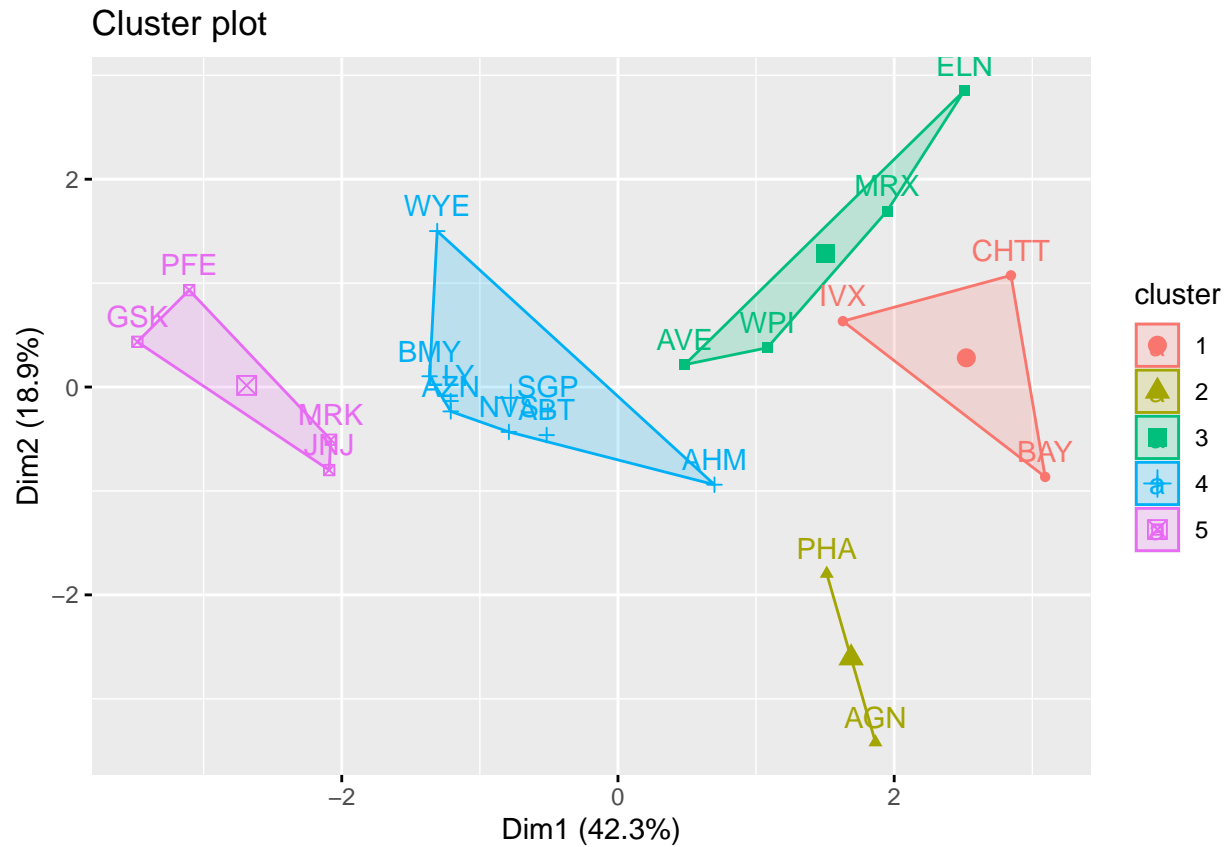
```
fviz_nbclust(Chemist_data, kmeans, method = "silhouette") + labs(subtitle = "silhouette Method")
```



```
#Set a seed for consistency
set.seed(64060)
#Subject 'Chemist' data to k-means clustering, with 5 clusters, with various initial configurations
k5_cluster_data <- kmeans(Chemist_data, centers = 5, nstart = 25)
#Present the cluster centers derived from the k-means clustering
k5_cluster_data$centers
```

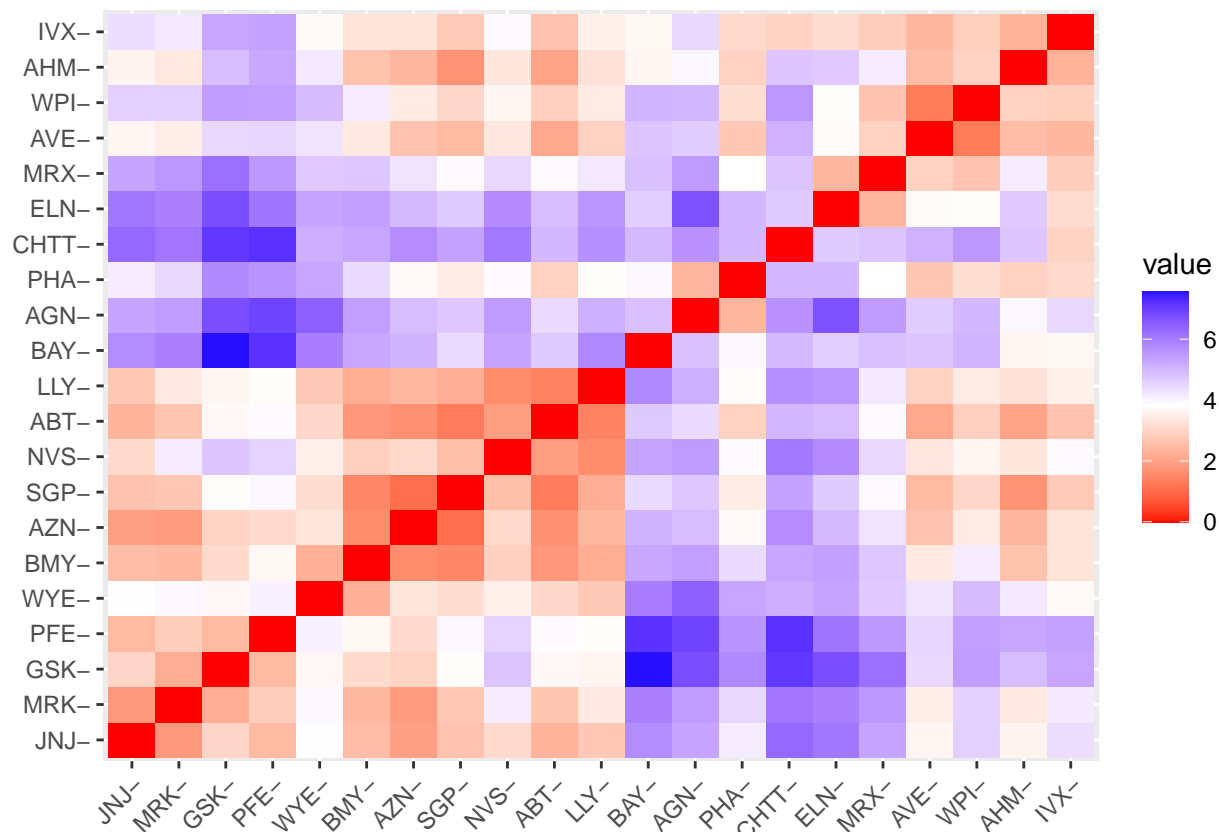
```
##      Market_Cap      Beta      PE_Ratio      ROE      ROA      Asset_Turnover
## 1 -0.87051511  1.3409869 -0.05284434 -0.6184015 -1.1928478   -0.4612656
## 2 -0.43925134 -0.4701800  2.70002464 -0.8349525 -0.9234951    0.2306328
## 3 -0.76022489  0.2796041 -0.47742380 -0.7438022 -0.8107428   -1.2684804
## 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  1.36644699 -0.6912914   -1.320000179
## 2 -0.14170336 -0.1168459   -1.416514761
## 3  0.06308085  1.5180158    -0.006893899
## 4 -0.27449312 -0.7041516     0.556954446
## 5 -0.46807818  0.4671788     0.591242521
```

```
fviz_cluster(k5_cluster_data, data = Chemist_data)
```



Computing the Euclidean distance matrix in the 'Chemist' dataset

```
distance <- dist(Chemist_data, method = "euclidean")
fviz_dist(distance)
```



Configuring the CRAN mirror to a specific location

```
options(repos = c(CRAN = "https://cran.rstudio.com/"))
```

```
result <- kmeans(Chemist_data, 5)
aggregate(Chemist_data, by = list(result$cluster), FUN=mean)
```

```
##   Group.1 Market_Cap      Beta  PE_Ratio      ROE      ROA
## 1      1  1.69558112 -0.1780563 -0.1984582  1.2349879  1.3503431
## 2      2 -0.66114002 -0.7233539 -0.3512251 -0.6736441 -0.5915022
## 3      3 -0.96247577  1.1949250 -0.3639982 -0.5200697 -0.9610792
## 4      4 -0.52462814  0.4451409  1.8498439 -1.0404550 -1.1865838
## 5      5  0.08926902 -0.4618336 -0.3208615  0.3260892  0.5396003
##   Asset_Turnover Leverage Rev_Growth Net_Profit_Margin
## 1  1.153164e+00 -0.4680782  0.4671788      0.5912425
## 2 -1.537552e-01 -0.4040831  0.6917224     -0.4005718
## 3 -1.153164e+00  1.4773718  0.7120120     -0.3688236
## 4  1.480297e-16 -0.3443544 -0.5769454     -1.6095439
## 5  6.589509e-02 -0.2559803 -0.7230135      0.7343816
```

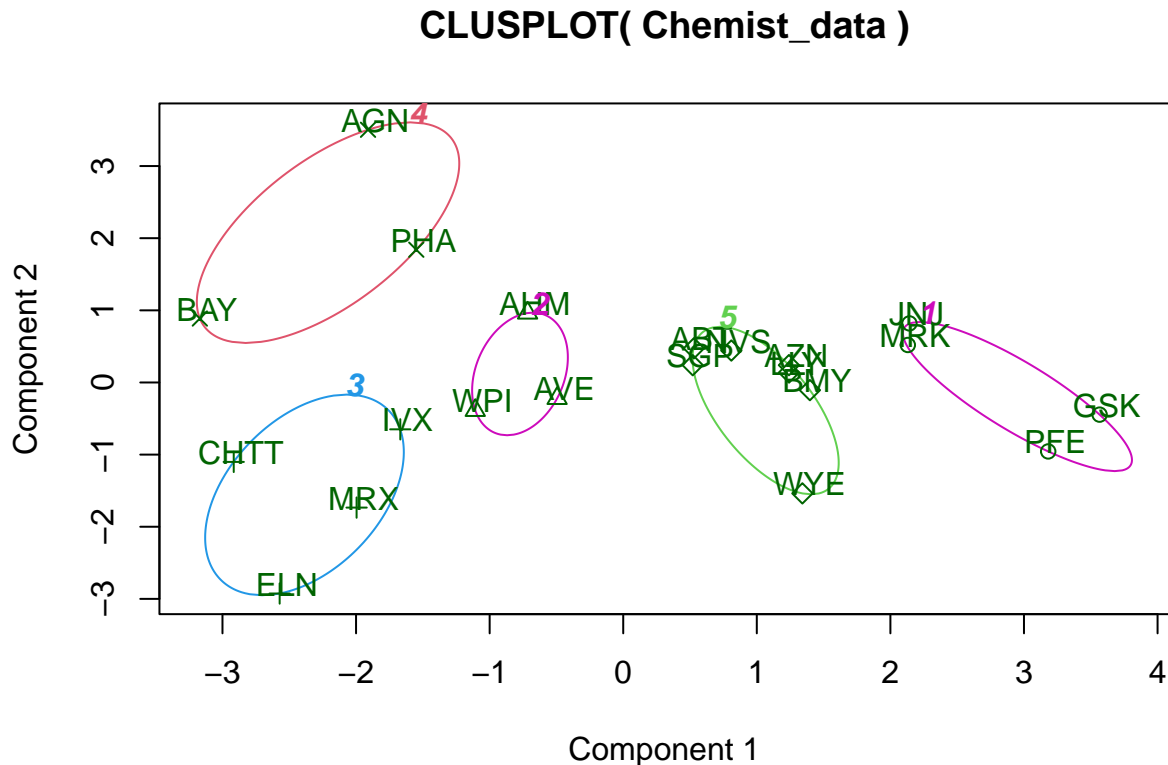
Creating a new data frame 'Chemist_1' by combining the original data 'Chemist_data' with the cluster assignments from 'result\$cluster'. Present the contents of the newly created data frame 'Chemist1'.

```
Chemist_1 <- data.frame(Chemist_data, result$cluster)
```

```
Chemist_1
```

##	Market_Cap	Beta	PE_Ratio	ROE	ROA	Asset_Turnover
## ABT	0.1840960	-0.80125356	-0.04671323	0.04009035	0.2416121	0.0000000
## 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
## BMY	-0.1078688	-0.10015669	-0.70887325	0.59693581	0.8617498	0.9225312
## CHTT	-0.9767669	1.26308721	0.03299122	-0.11237924	-1.1677918	-0.4612656
## ELN	-0.9704532	2.15893320	-1.34037772	-0.70899938	-1.0174553	-1.8450624
## LLY	0.2762415	-1.34655112	0.14948233	0.34502953	0.5610770	-0.4612656
## GSK	1.0999201	-0.68440408	-0.45749769	2.45971647	1.8389364	1.3837968
## IVX	-0.9393967	0.48409069	-0.34100657	-0.29136529	-0.6979905	-0.4612656
## JNJ	1.9841758	-0.25595600	0.18013789	0.18593083	1.0872544	0.9225312
## MRX	-0.9632863	0.87358895	0.19240011	-0.96753478	-0.9610792	-1.8450624
## MRK	1.2782387	-0.25595600	-0.40231769	0.98142435	0.8429577	1.8450624
## NVS	0.6654710	-1.30760129	-0.23677768	-0.52338423	0.1288598	-0.9225312
## PFE	2.4199899	0.48409069	-0.11415545	1.31287998	1.6322239	0.4612656
## PHA	-0.0240846	-0.48965495	1.90298017	-0.81506519	-0.9047030	-0.4612656
## SGP	-0.4018812	-0.06120687	-0.40231769	-0.21181593	0.5234929	0.4612656
## WPI	-0.9281345	-1.11285216	-0.43297324	-1.03382590	-0.6979905	-0.9225312
## WYE	-0.1614497	0.40619104	-0.75792214	1.92938746	0.5422849	-0.4612656
##	Leverage	Rev_Growth	Net_Profit_Margin	result.cluster		
## ABT	-0.21209793	-0.52776752	0.06168225	5		
## AGN	0.01828430	-0.38113909	-1.55366706	4		
## AHM	-0.40408312	-0.57211809	-0.68503583	2		
## AZN	-0.74965647	0.14744734	0.35122600	5		
## AVE	-0.31449003	1.21638667	-0.42597037	2		
## BAY	-0.74965647	-1.49714434	-1.99560225	4		
## BMY	-0.02011273	-0.96584257	0.74744375	5		
## CHTT	3.74279705	-0.63276071	-1.24888417	3		
## ELN	0.61983791	1.88617085	-0.36501379	3		
## LLY	-0.07130879	-0.64814764	1.17413980	5		
## GSK	-0.31449003	0.76926048	0.82363947	1		
## IVX	1.10620040	0.05603085	-0.71551412	3		
## JNJ	-0.62166634	-0.36213170	0.33598685	1		
## MRX	0.44065173	1.53860717	0.85411776	3		
## MRK	-0.39128411	0.36014907	-0.24310064	1		
## NVS	-0.67286239	-1.45369888	1.02174835	5		
## PFE	-0.54487226	1.10143723	1.44844440	1		
## PHA	-0.30169102	0.14744734	-1.27936246	4		
## SGP	-0.74965647	-0.43544591	0.29026942	5		
## WPI	-0.49367621	1.43089863	-0.09070919	2		
## WYE	0.68383297	-1.17763919	1.49416183	5		

```
clusplot(Chemist_data, result$cluster, color = TRUE, shade = FALSE, labels = 2, lines = 0)
```



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.

By looking at each cluster's average values for every numerical variable Cluster 1: BAY, CHTT, IVX Cluster 2: BMY, AZN, LLY, NVS, SGP, WYE, and ABT Cluster 3: ELN, MRX Cluster 4: MRK, PFE, GSK, and JNJ Cluster 5: AGN, AHM, WPI, PHA, and AVE

Cluster 1: This cluster has the lowest Market_Cap value, lowest ROE, ROA, leverage, Rev_Growth, and net profit margin. It also has the greatest beta and leverage values Cluster 2: This cluster has the lowest beta and the biggest net profit margin. Cluster 3: The highest Rev_Growth, lowest PE_Ratio, and lowest asset turnover are found in this cluster. Cluster 4: The highest Market_Cap, ROE, ROA, and Asset_Turnover are found in this cluster. Cluster 5: The PE_Ratio is greater in Cluster 5. . . . **(c): Is there a pattern in the clusters with respect to the numerical variables (10 to 12)? (those not used in forming the clusters)**

Regarding the Media suggestion variable, there seems to be a discernible pattern in the clusters. The majority of recommendations point to Cluster 1, which has the highest leverage and beta, as a Moderate Buy. The majority of the recommendations in Cluster 2, which has the highest net profit margin, are hold. A hold recommendation is made for Cluster 3, which has the lowest PE Ratio and lowest Asset Turnover. Market capitalization, return on equity, return on assets, and asset turnover are all highest in Cluster 4. It is equally advised to hold or purchase in moderation. With the highest PE_Ratio, Cluster 5 is highly suggested as an excellent investment option. This is because a high PE Ratio indicates that the business is expanding quickly. Regarding the variables, I observed a trend among the clusters (10 to 12). Most strongly linked to a Moderate Buy Recommendation are Clusters 1 and 4. It is advised that clusters 2, 3, and 4 be held. . . . **(d): Provide an appropriate name for each cluster using any or all of the variables in the dataset.**

Cluster 1 is a high-leverage and beta cluster that one should think about purchasing. Cluster 2: This cluster has a high hold or a high net profit margin.** Cluster 3: This cluster is appropriate for holding due to its

strong asset turnover and low PE ratio. Cluster 4: Suggested Purchase cluster Cluster 5: a high Buy cluster or a high PE Ratio cluster.