

Assignment_4

Ganesh Reddy

2023-11-12

Loading the Required packages

```
library(flexclust)
```

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

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

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

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

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

```
library(cluster)
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr      1.1.3      v readr      2.1.4
## v forcats    1.0.0      v stringr   1.5.0
## v ggplot2    3.4.3      v tibble    3.2.1
## v lubridate  1.9.3      v tidyr     1.3.0
## v purrr      1.0.2
```

```
## -- 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(factoextra)
```

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

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

```
library(FactoMineR)
```

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

```
library(ggcorrplot)
```

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

1. 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.

Loading the data

```
pharma <- read.csv("Pharmaceuticals.csv")  
head(pharma)
```

##	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		

Choosing columns 3 to 11 now, and putting the information in variable Info 1

```
pharma1 <- pharma[3:11]  
head(pharma1)
```

##	Market_Cap	Beta	PE_Ratio	ROE	ROA	Asset_Turnover	Leverage	Rev_Growth
## 1	68.44	0.32	24.7	26.4	11.8	0.7	0.42	7.54
## 2	7.58	0.41	82.5	12.9	5.5	0.9	0.60	9.16
## 3	6.30	0.46	20.7	14.9	7.8	0.9	0.27	7.05
## 4	67.63	0.52	21.5	27.4	15.4	0.9	0.00	15.00
## 5	47.16	0.32	20.1	21.8	7.5	0.6	0.34	26.81
## 6	16.90	1.11	27.9	3.9	1.4	0.6	0.00	-3.17

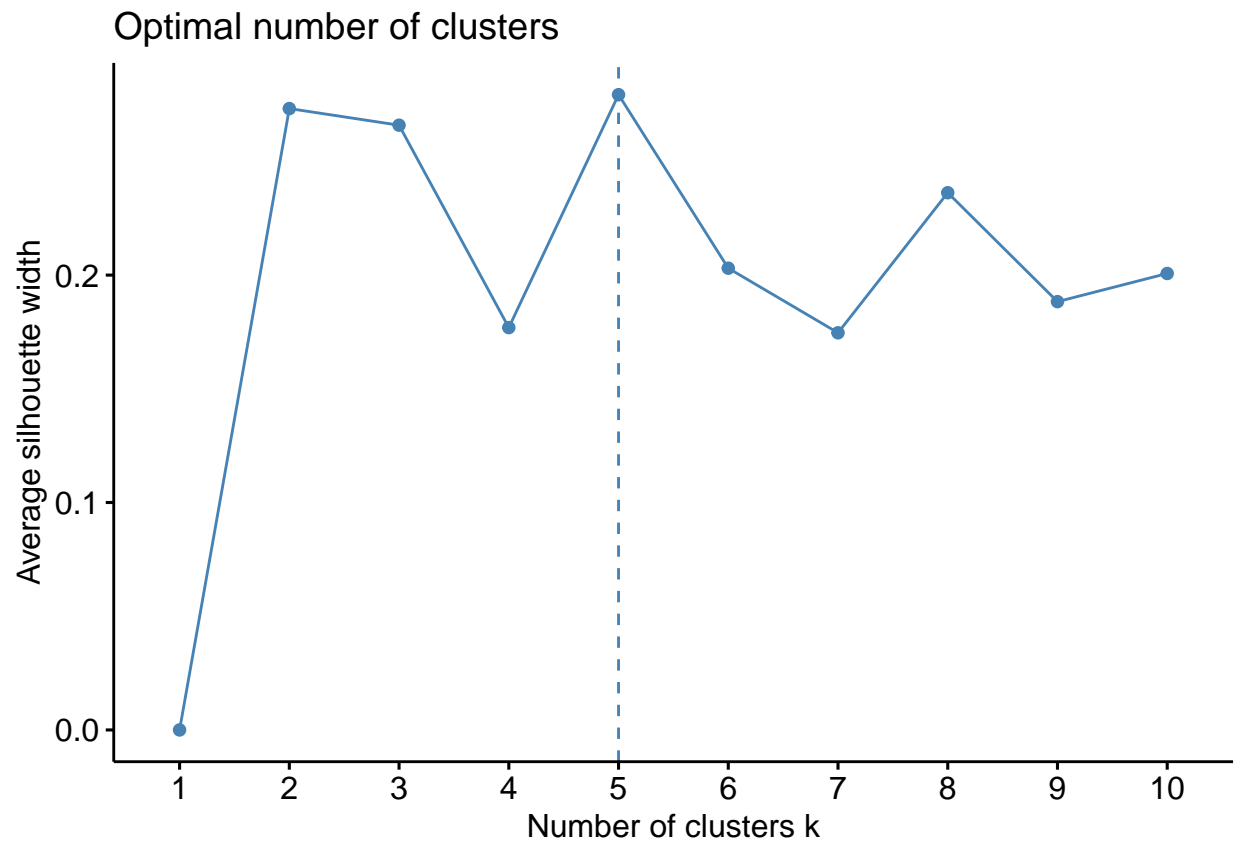
```
## Net_Profit_Margin
## 1          16.1
## 2           5.5
## 3          11.2
## 4          18.0
## 5          12.9
## 6           2.6
```

```
summary(pharma1)
```

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

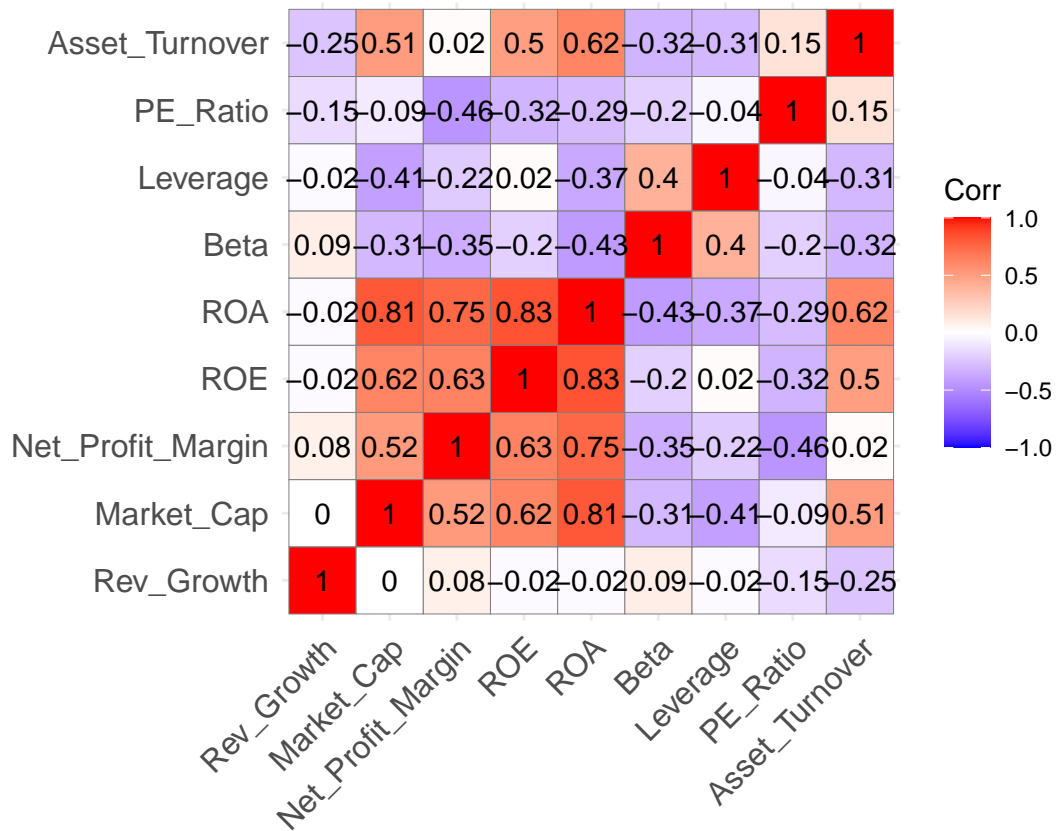
The data in `pharma1` and the `pharma` updated dataframe will be scaled according to the varying weights assigned to each variable along the rows. using the `factoextra` package's `get_dist` and `fviz_dist` functions to measure the distance between data rows and visualize the distance matrix

```
norm_data <- scale(pharma1)
row.names(norm_data) <- pharma[,1]
distance <- get_dist(norm_data)
corr <- cor(norm_data)
fviz_nbclust(norm_data, kmeans, method = "silhouette")
```



To check the correlation between key variables, create a correlation matrix and print

```
corr <- cor(norm_data)
ggcorrplot(corr, outline.color = "grey50", lab = TRUE, hc.order = TRUE, type = "full")
```

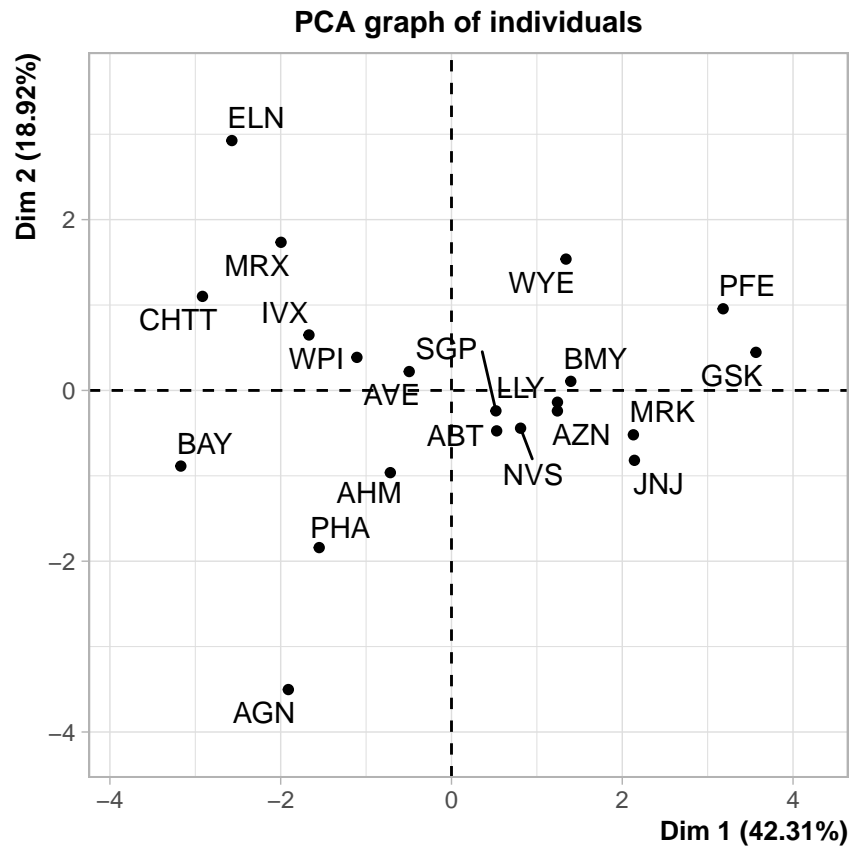


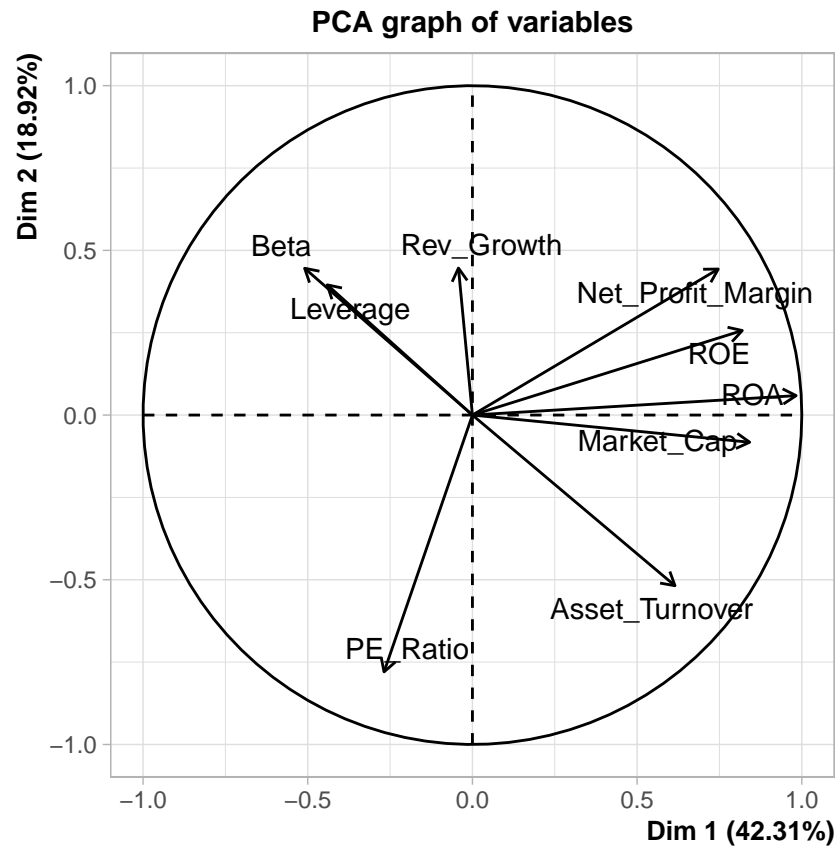
The ROA, ROE, Net Profit Margin, and Market Cap are all high, according to the Correlation Matrix

Finding out the relative importance of the primary variables in the data set will be done using principal component analysis.

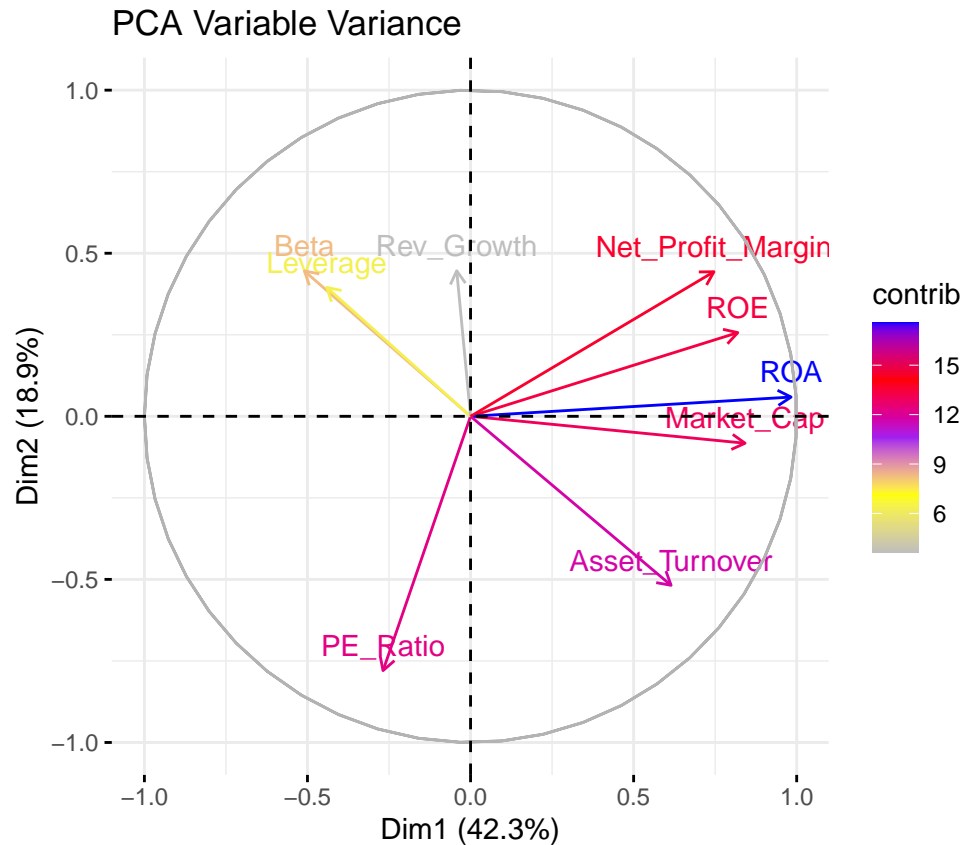
assuming the optimal cluster size is 5

```
pca <- PCA(norm_data)
```





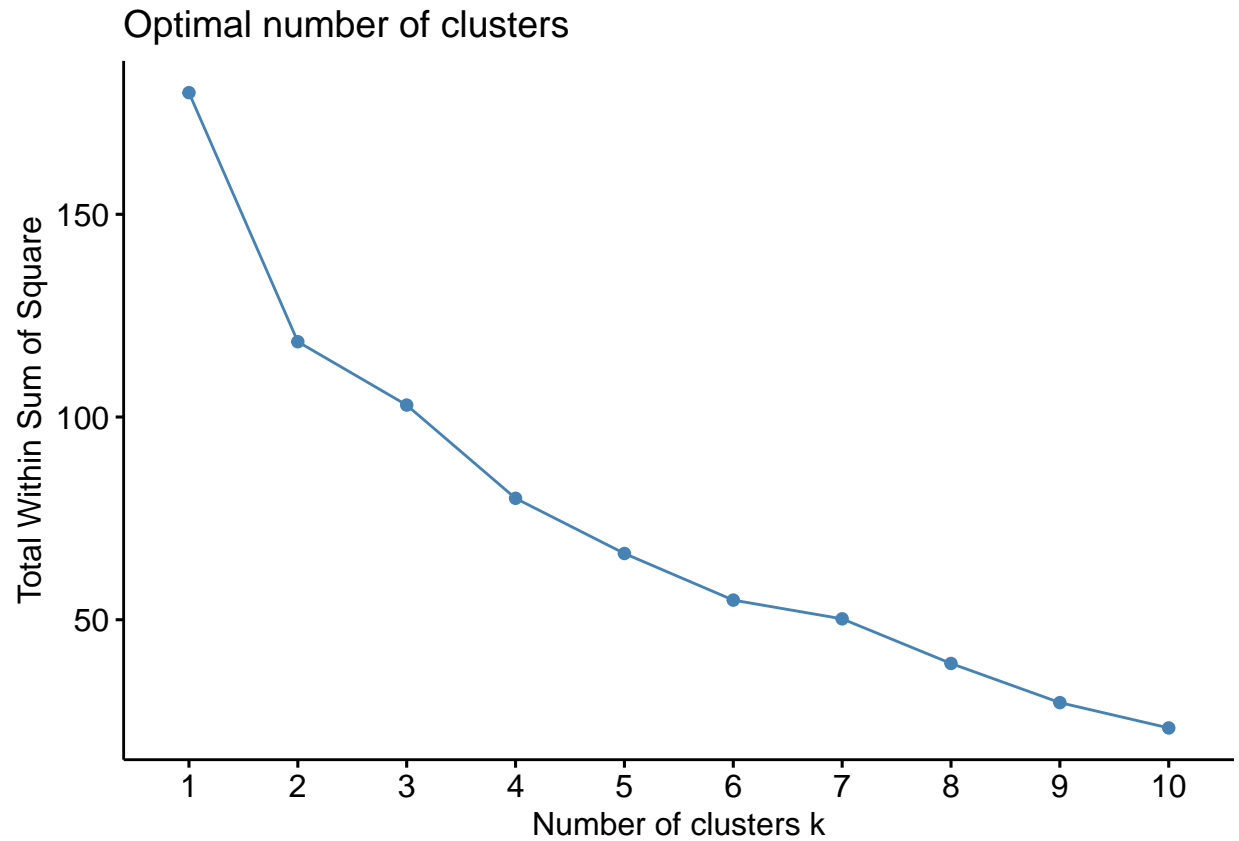
```
var <- get_pca_var(pca)
fviz_pca_var(pca, col.var="contrib",
             gradient.cols = c("grey","yellow","purple","red","blue"),ggrepel = TRUE ) + labs( title =
```



Using the elbow technique to discover the ideal number of customers, we can infer from PCA Variable Variance that ROA, ROE, Net Profit Margin, Market Cap, and Asset Turnover contribute over 61% to the two PCA components/dimensions Variables

```
set.seed(10)

wss <- vector()
for(i in 1:10) wss[i] <- sum(kmeans(norm_data,i)$withinss)
fviz_nbclust(norm_data, kmeans, method = "wss")
```

WSS

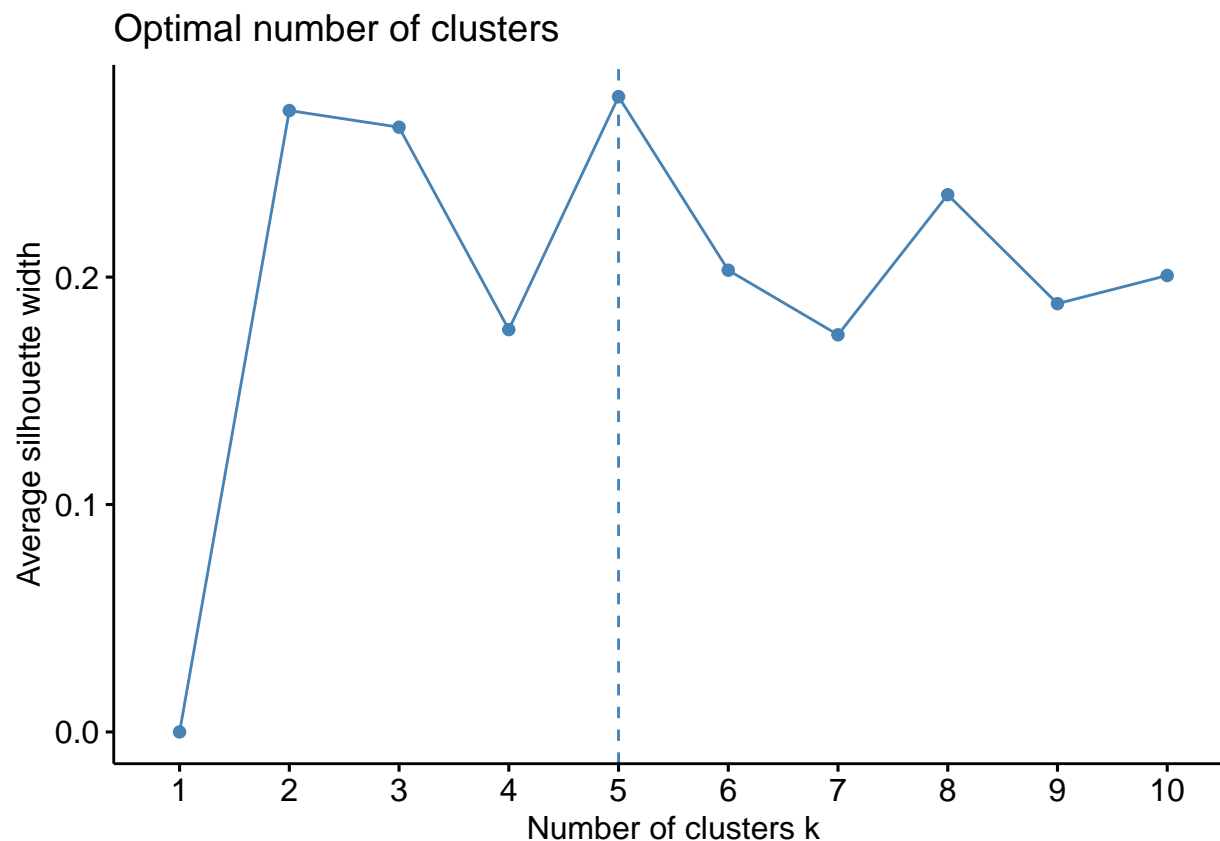
```
## [1] 180.00000 118.56934 95.99420 79.21748 65.61035 52.67476 47.66961
## [8] 41.12605 31.81763 31.57252
```

Exactly as predicted, the ideal cluster is at number 5.

Determining the optimal cluster size.

Silhouette*

```
fviz_nbclust(norm_data, kmeans, method = "silhouette")
```



This demonstrates that five clusters are the optimum number. Using the k-means method to create a 5 clu

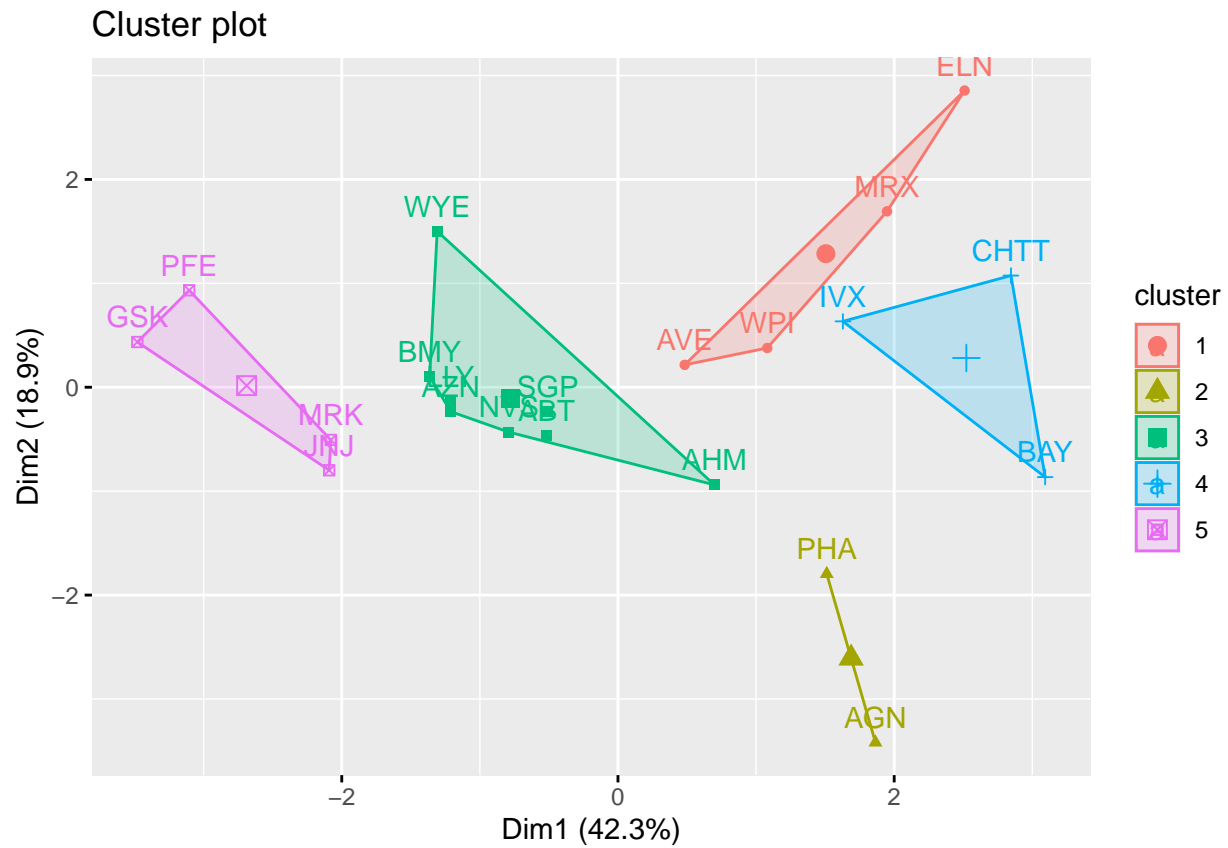
```
set.seed(1)
k5 <- kmeans(norm_data, centers = 5, nstart = 31) # k = 5, number of restarts = 31
k5$centers
```

```
##      Market_Cap      Beta    PE_Ratio      ROE      ROA Asset_Turnover
## 1 -0.76022489  0.2796041 -0.47742380 -0.7438022 -0.8107428  -1.2684804
## 2 -0.43925134 -0.4701800  2.70002464 -0.8349525 -0.9234951   0.2306328
## 3 -0.03142211 -0.4360989 -0.31724852  0.1950459  0.4083915   0.1729746
## 4 -0.87051511  1.3409869 -0.05284434 -0.6184015 -1.1928478  -0.4612656
## 5  1.69558112 -0.1780563 -0.19845823  1.2349879  1.3503431   1.1531640
##      Leverage Rev_Growth Net_Profit_Margin
## 1  0.06308085  1.5180158    -0.006893899
## 2 -0.14170336 -0.1168459    -1.416514761
## 3 -0.27449312 -0.7041516     0.556954446
## 4  1.36644699 -0.6912914    -1.320000179
## 5 -0.46807818  0.4671788     0.591242521
```

```
k5$size
```

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

```
fviz_cluster(k5, data = norm_data)
```



```
set.seed(15)
k51 = kcca(norm_data, k=5, kccaFamily("kmedians"))
k51
```

Manhattan Distance when using Kmeans Clustering.

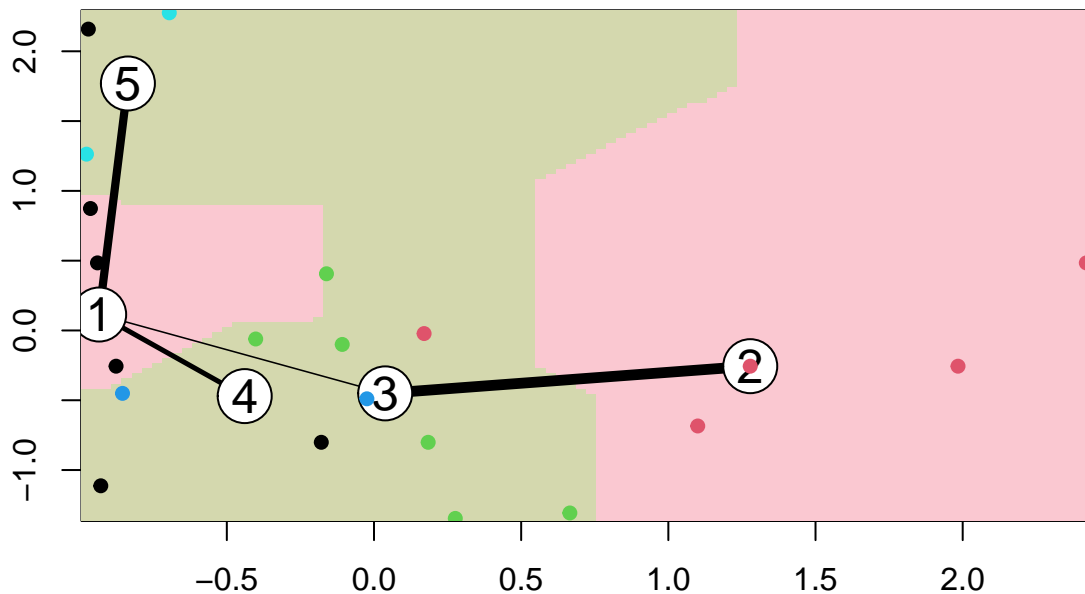
```
## kcca object of family 'kmedians'
##
## call:
## kcca(x = norm_data, k = 5, family = kccaFamily("kmedians"))
##
## cluster sizes:
##
## 1 2 3 4 5
## 6 5 6 2 2
```

```
clusters_index <- predict(k51)
dist(k51@centers)
```

Using predict function.

```
##          1          2          3          4
## 2 3.945545
## 3 3.168054 2.377053
## 4 3.724526 4.795056 4.301987
## 5 3.578425 5.494529 4.448919 4.043870
```

```
image(k51)
points(norm_data, col=clusters_index, pch=19, cex=0.9)
```



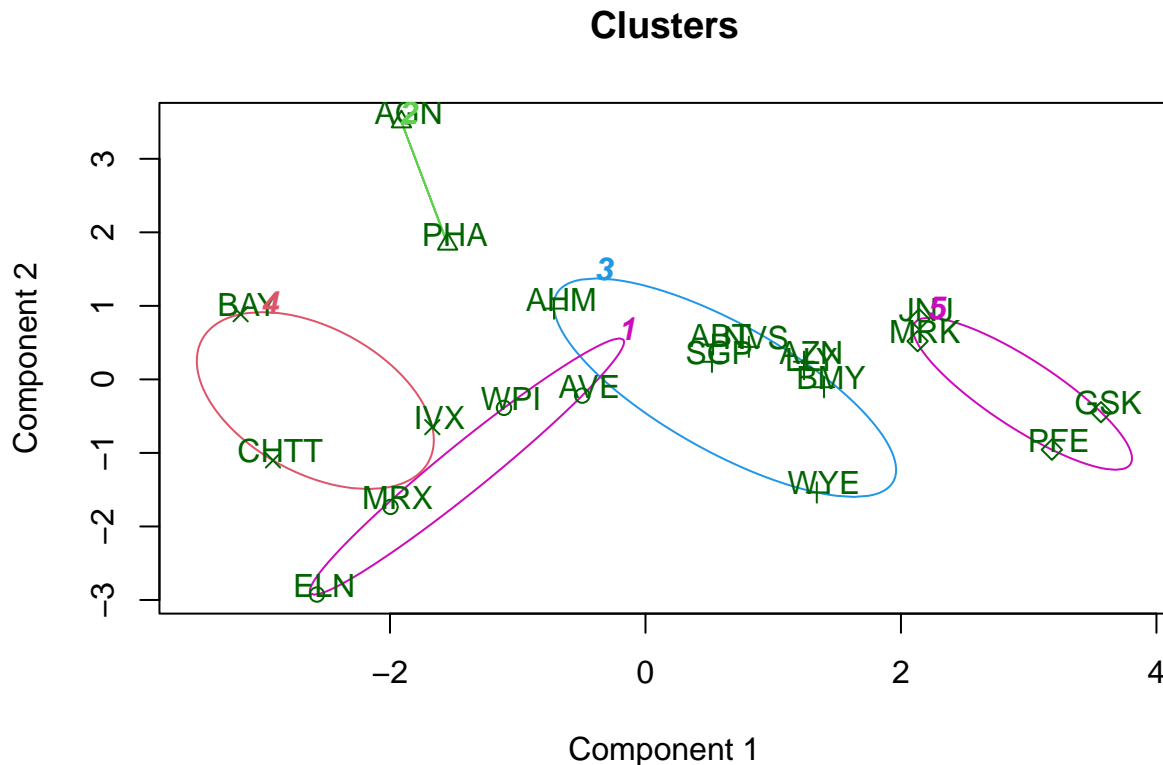
2. Interpret the clusters with respect to the numerical variables used in forming the clusters Using Kmeans method to calculate Mean.

```
pharma1 %>% mutate(Cluster = k5$cluster) %>% group_by(Cluster) %>% summarise_all("mean")
```

```
## # A tibble: 5 x 10
##   Cluster Market_Cap Beta PE_Ratio ROE ROA Asset_Turnover Leverage
##   <int>      <dbl> <dbl>   <dbl> <dbl> <dbl>      <dbl>      <dbl>
## 1     1      13.1  0.598   17.7  14.6  6.2        0.425      0.635
## 2     2      31.9  0.405   69.5  13.2  5.6        0.75       0.475
## 3     3      55.8  0.414   20.3  28.7 12.7        0.738      0.371
## 4     4       6.64  0.87    24.6  16.5  4.17       0.6       1.65
```

```
## 5      5      157.    0.48      22.2  44.4 17.7      0.95    0.22
## # i 2 more variables: Rev_Growth <dbl>, Net_Profit_Margin <dbl>
```

```
clusplot(norm_data,k5$cluster, main="Clusters",color = TRUE, labels = 2,lines = 0)
```



These two components explain 61.23 % of the point variability.

Companies are categorized into different clusters as follows:

- Cluster 1: ELN, MRX, WPI and AVE+
- Cluster 2: AGN and PHA+
- Cluster 3: AHM, WYE, BMY, AZN, LLY, ABT, NVS and SGP+
- Cluster 4: BAY, CHTT and IVX+
- Cluster 5: JNJ, MRK, PFE and GSK+

From the means of the cluster variables, it can be obtain as follow:

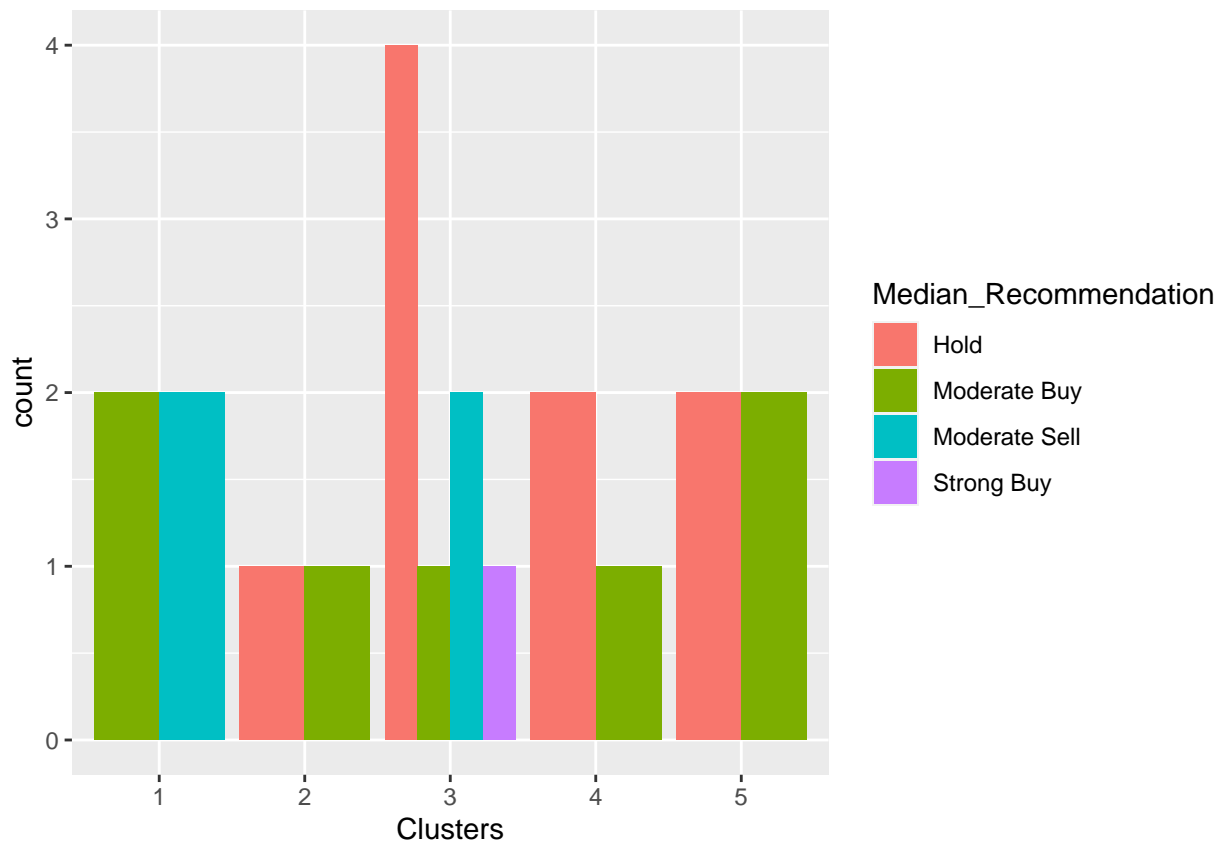
- Cluster 1 has the best Net Profit Margin, the lowest PE ratio, and the fastest sales growth. It can be bought or kept on hand as a reserve.+
- Cluster 2 PE ratio is very high.+
- Cluster 3 has a medium risk.+
- Cluster 4 Despite having an excellent PE ratio, it is incredibly risky to own due to its extremely high risk, extremely high leverage, and poor Net Profit margin. Also very low is revenue growth.+

- Cluster 5 has strong market capitalization, ROI, ROA, ROA on assets, ROA on turnover of assets, and ROA on net profit margin. A low PE ratio indicates that the stock price is moderately valued and may thus be bought and kept. Revenue growth of 18.5% is also favorable.+

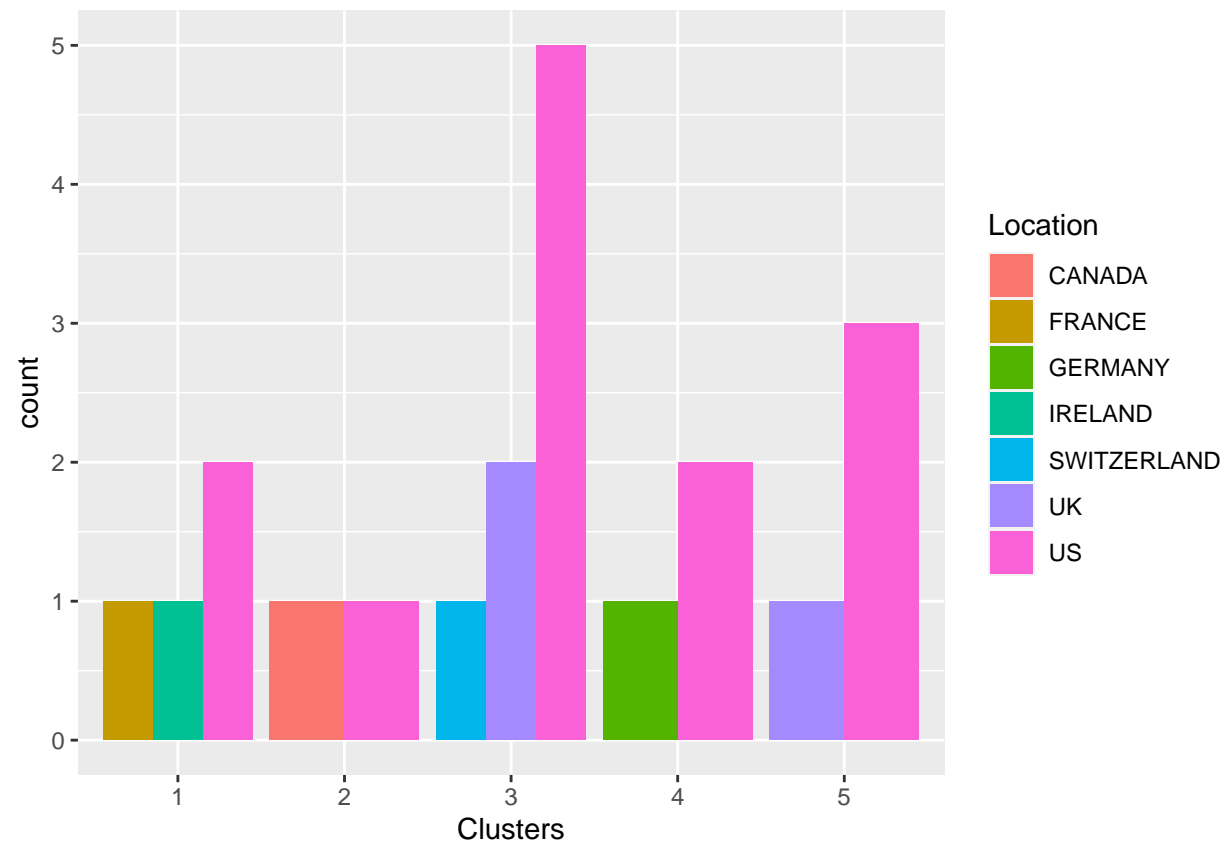
2B Is there a pattern in the clusters with respect to the numerical variables (10 to 12)?

We can examine patterns by visualizing clusters against the variables

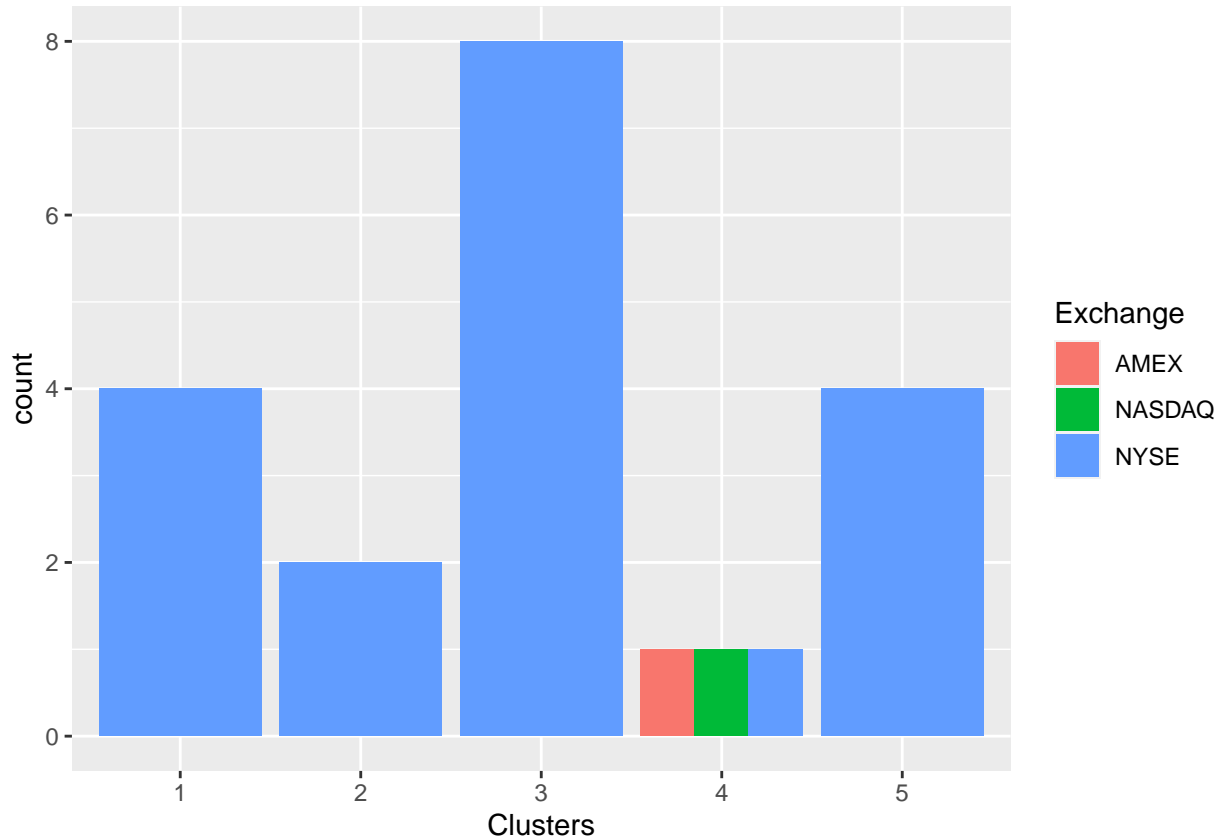
```
Info_2 <- pharma[12:14] %>% mutate(Clusters=k5$cluster)
ggplot(Info_2, mapping = aes(factor(Clusters), fill =Median_Recommendation))+geom_bar(position='dodge')
```



```
ggplot(Info_2, mapping = aes(factor(Clusters),fill = Location))+geom_bar(position = 'dodge')+labs(x = 'C
```



```
ggplot(Info_2, mapping = aes(factor(Clusters),fill = Exchange))+geom_bar(position = 'dodge')+labs(x = 'Clusters', y = 'count')
```



The variable in clusters, There is a trend in the median recommendations

There doesn't seem to be any discernable pattern among the clusters, locations, or exchanges other than

3. Provide an appropriate name for each cluster using any or all of the variables in the data set.

To Name for the clusters, Here I have consider Market_Cap, Beta, PE_Ratio, ROE, ROA, Asset_Turnover. and

Cluster 1: Profitable Giants

- Identified by substantial Market Cap, low Beta, low PE Ratio, high ROE, ROA, and Asset Turnover. These entities represent formidable, profitable giants in the market.+

Cluster 2: High Beta, High Risk Players

- Marked by elevated Beta and PE Ratio, Cluster 2 signifies entities with higher risk levels. Investors should exercise caution due to increased market sensitivity and potential overvaluation.+

Cluster 3: Balanced Performers

- Cluster 3 strikes a balance across Market Cap, Beta, and PE Ratio, representing entities in a moderate-risk category. These balanced performers exhibit stability and potential.+

Cluster 4: High Risk, Low Efficiency

- Despite a strong PE Ratio, entities in Cluster 4 face exceptionally high risk, with low efficiency indicated by poor ROE, ROA, and Asset Turnover. This cluster is deemed high-risk and less efficient. +

Cluster 5: Efficient Powerhouses

- Cluster 5 showcases entities with strong efficiency metrics, including high ROE, ROA, and Asset Turnover, paired with a moderately valued PE Ratio. These efficient powerhouses are attractive for both purchase and retention. +