

Assignment- 4 - CLUSTERING

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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)
```

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

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

```
## -- 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
```

At present, choose columns 3 through 11 and enter the information into 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
```

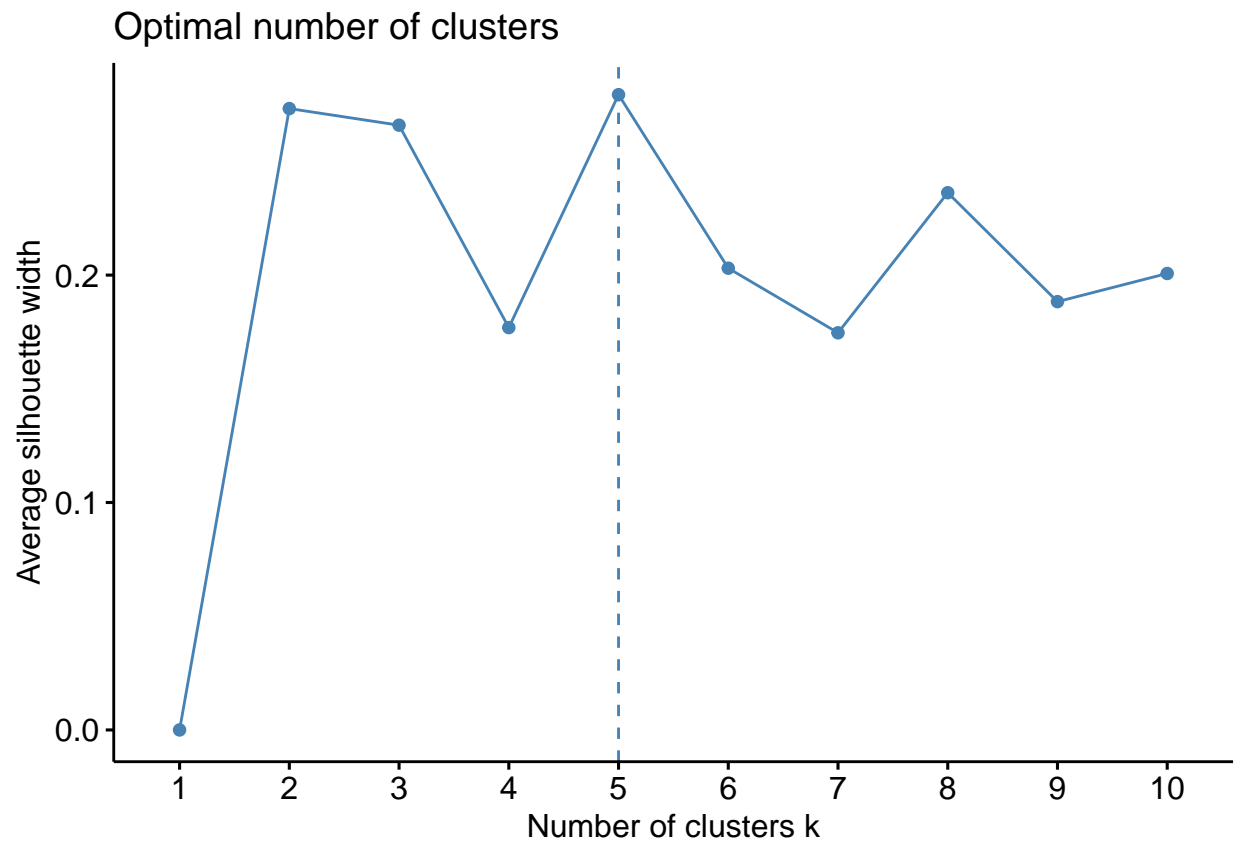
```
## 6      16.90 1.11      27.9 3.9 1.4      0.6      0.00      -3.17
## Net_Profit_Margin
## 1      16.1
## 2      5.5
## 3      11.2
## 4      18.0
## 5      12.9
## 6      2.6
```

```
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
```

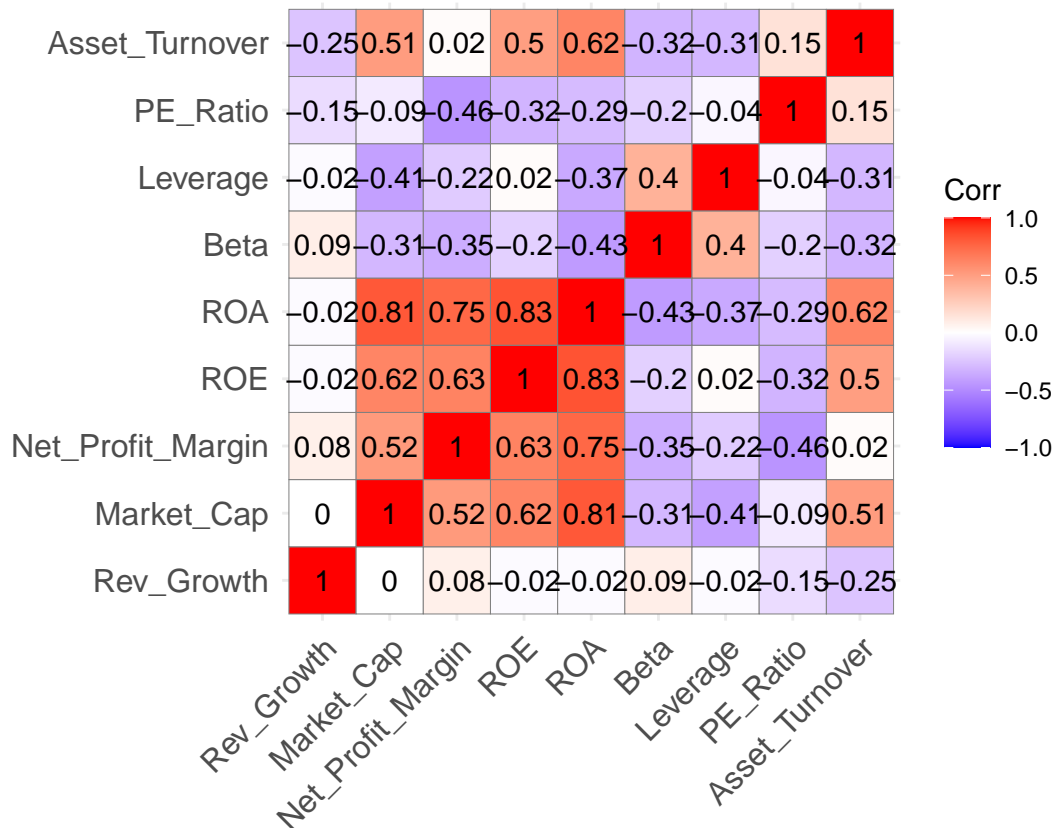
The various weights assigned to each variable along the rows will be used to scale the data in `pharma1` and the `pharma` updated data frame. calculating the distance between the rows of data and displaying the distance matrix using the `get_dist(distance)` and `fviz_dist(distance)` functions of the `factoextra` package

```
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")
```



Make a correlation matrix and print it to examine the relationship between the important variables.

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

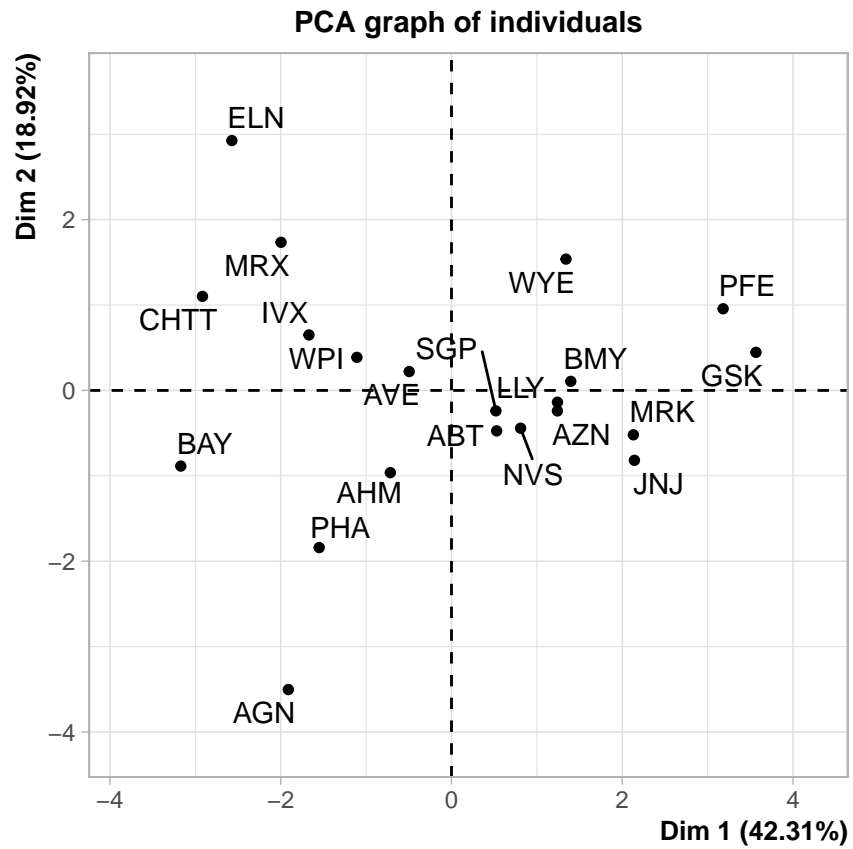


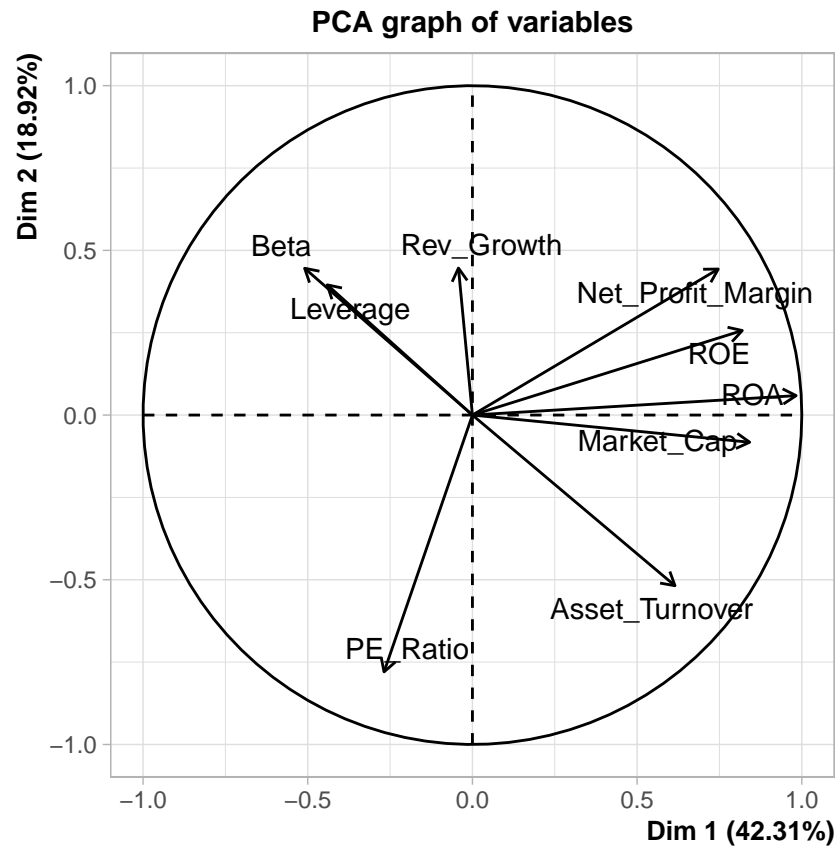
The Correlation Matrix shows that the ROA, ROE, Net Profit Margin, and Market Cap are all high

Principal component analysis will be used to figure out the relative importance of each of the key variables in the data collection.

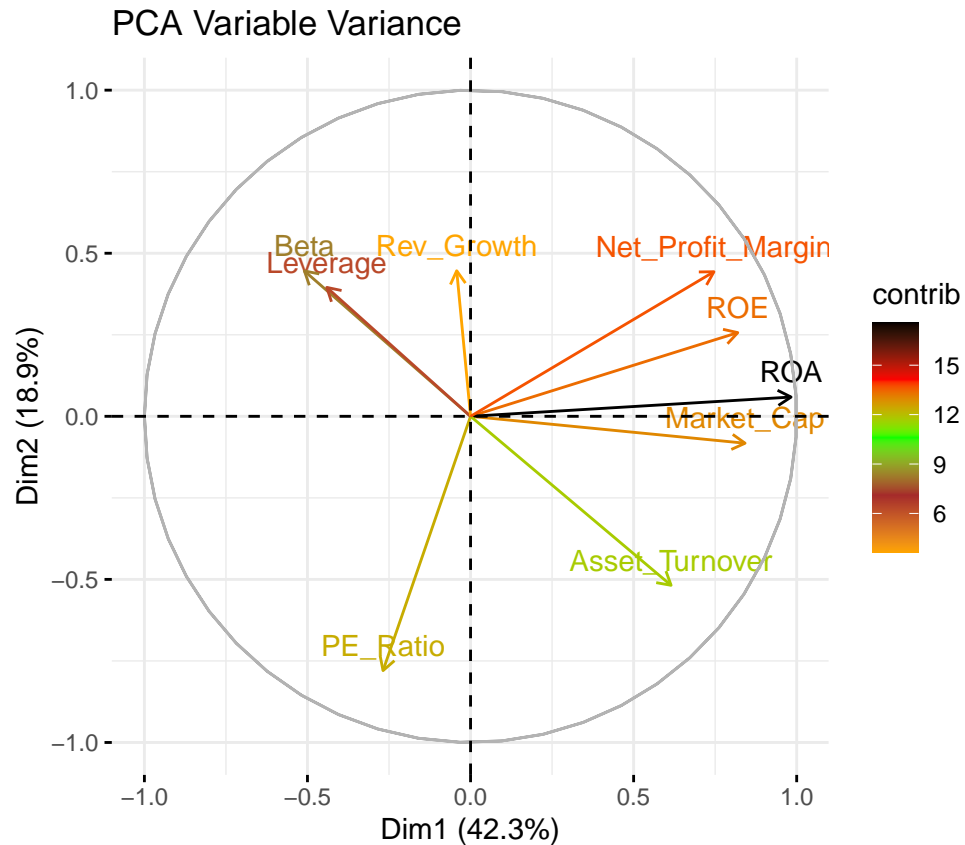
Assuming the optimal cluster size is 5

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





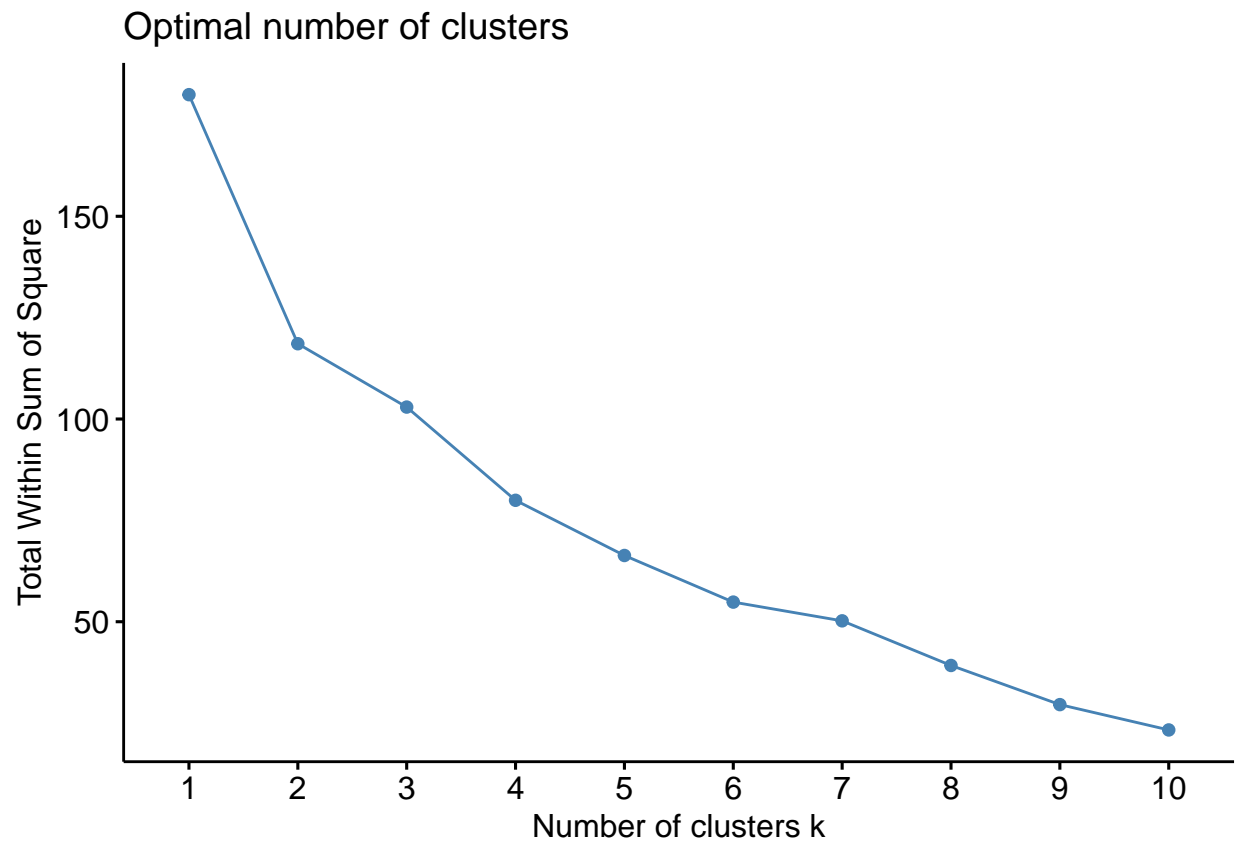
```
var <- get_pca_var(pca)
fviz_pca_var(pca, col.var="contrib",
             gradient.cols = c("orange","brown","green","red","black"),ggrepel = TRUE ) + labs( title =
```



We can assume from PCA Variable Variance that ROA, ROE, Net Profit Margin, Market Cap, and Asset Turnover contribute more than 61% to the two PCA components/dimensions, using the elbow technique to figure out the optimal customer base changeables.

```
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

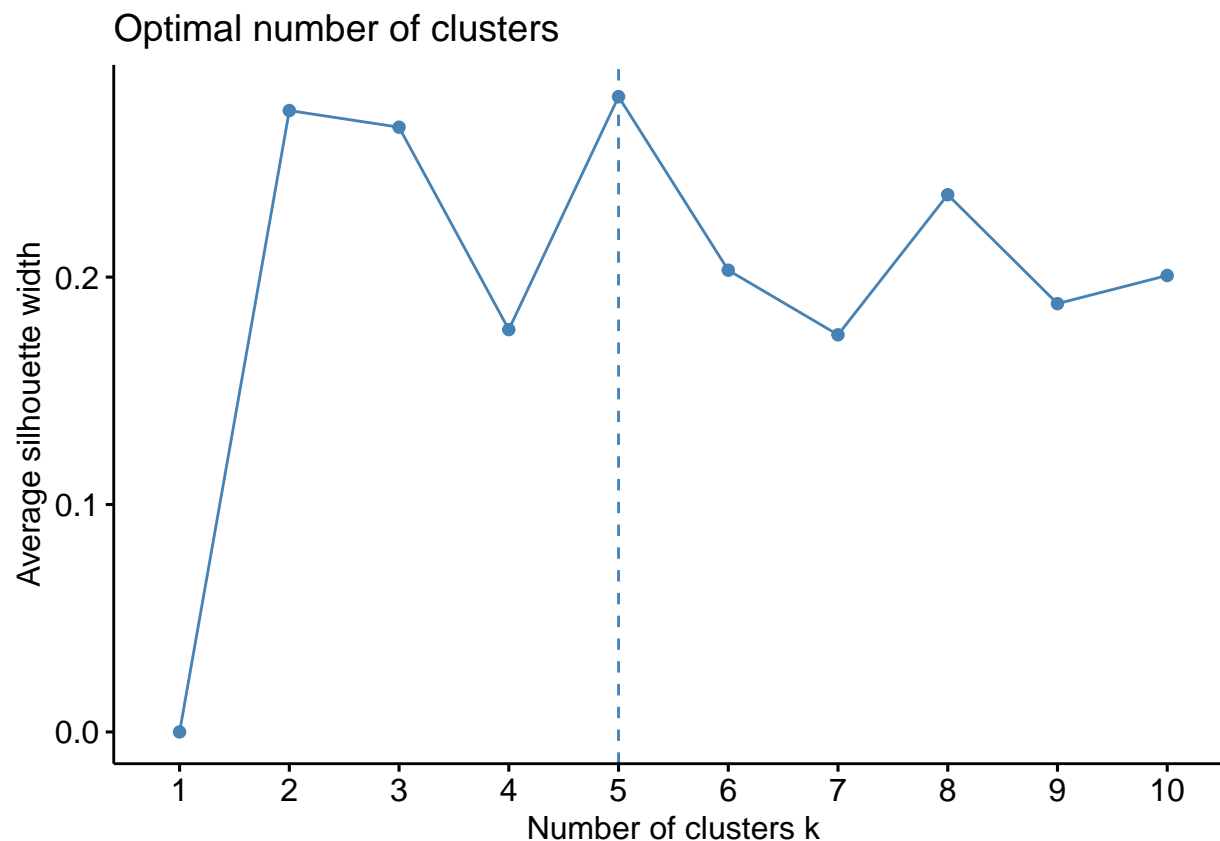
```
## [1] 180.00000 118.56934 95.99420 79.21748 65.61035 52.67476 47.66961
## [8] 41.12605 31.81763 31.57252
```

The optimal cluster is at number 5 just as expected

Determining the optimal cluster size.

Silhouette*

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



This indicates that the ideal number of clusters is five. forming five clusters with the k-means algorithm.

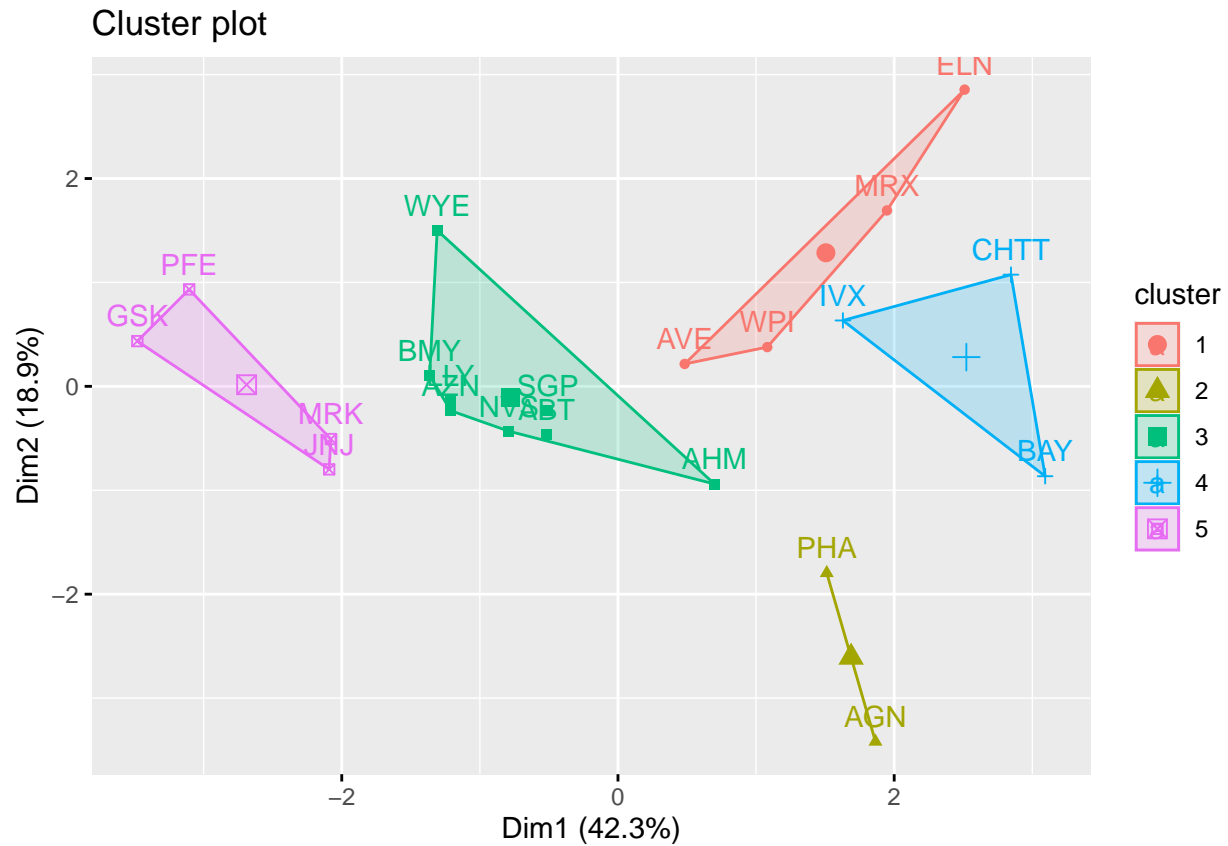
```
set.seed(1)
k5 <- kmeans(norm_data, centers = 5, nstart = 31) # k = 5, number of restarts = 31
k5$centers
```

```
##      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 Kmeans Clustering is applied.

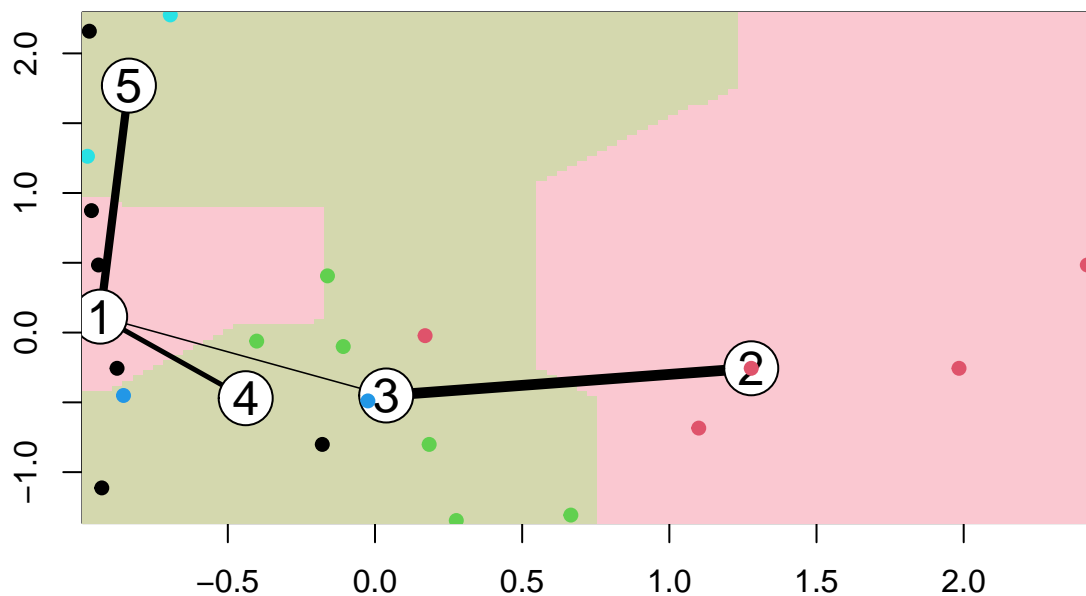
```
## kcca object of family 'kmedians'
##
## call:
## kcca(x = norm_data, k = 5, family = kccaFamily("kmedians"))
##
## cluster sizes:
##
## 1 2 3 4 5
## 6 5 6 2 2
```

```
#####Utilizing the predict function
```

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

```
##          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)
```



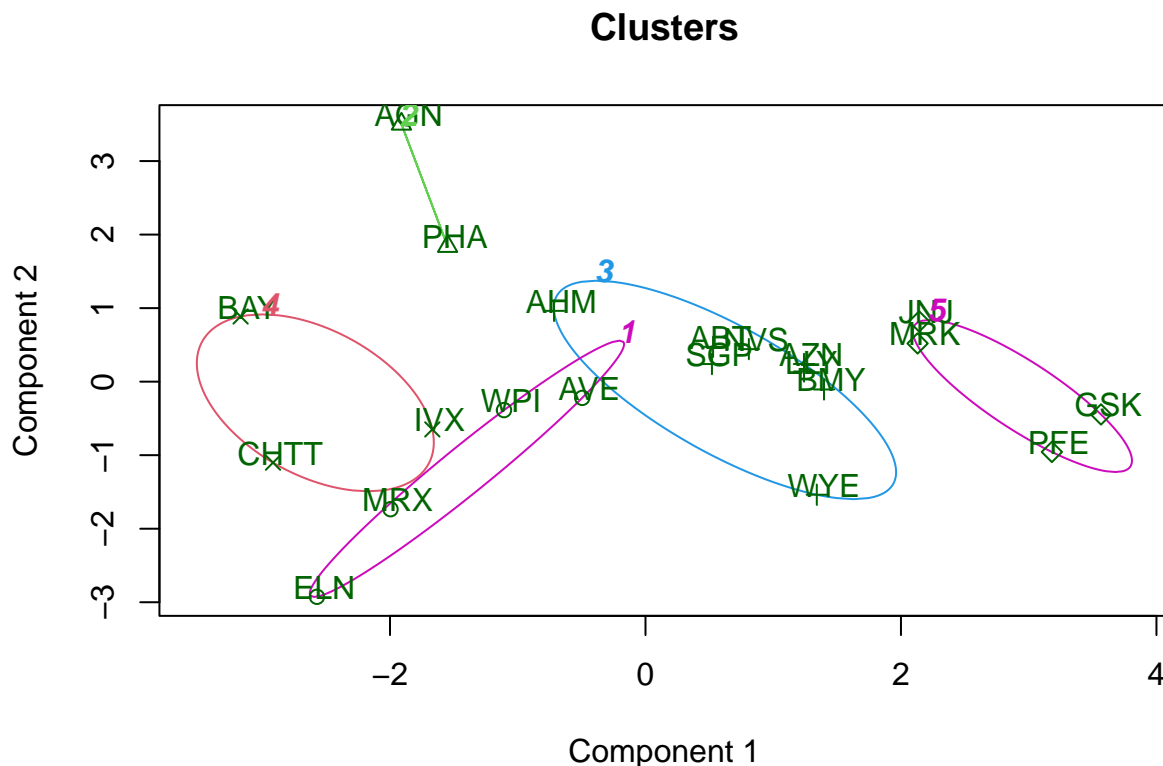
2. Interpret the clusters with respect to the numerical variables used in forming the clusters Using Kmeans method to calculate Mean.

```
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 divided into several clusters, which include:

**** Cluster 1: MRX,ELN, AVE and WPI ****

**** Cluster 2: PHA+ and AGN ****

**** Cluster 3: AHM,WYE,BMY,AZN, LLY, ABT, NVS and SGP ****

**** Cluster 4: BAY, CHTT and IVX ****

**** Cluster 5: JNJ, MRK, PFE and GSK ****

The following can be obtained from the cluster variable means:

**** Cluster 1 has the fastest sales growth, the lowest PE ratio, and the best net profit margin. It can be purchased or held in reserve.****

**** Cluster 2 PE ratio is extremely high.****

**** Cluster 3 has a moderate risk.****

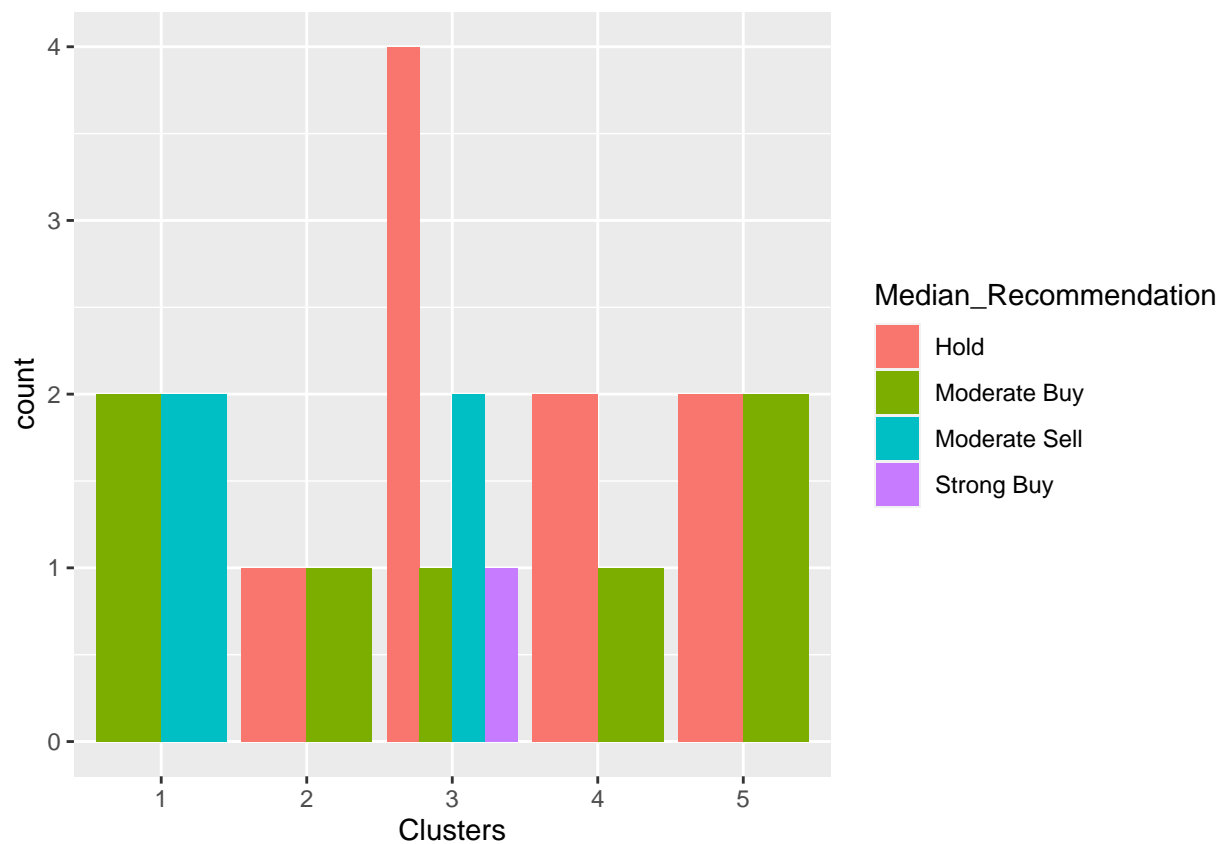
**** Cluster 4 It has a great PE ratio, but because of its weak Net Profit margin, high leverage, and high risk, it is an exceptionally risky stock to purchase. Revenue growth is likewise extremely low.****

** Cluster 5 possesses high market capitalization, return on investment (ROI), return on assets(ROA), (ROA) return on asset turnover, and (ROA) return on net profit margin. A low price-to-earnings ratio suggests that the business is appropriately valued and can be purchased and held. An 18.5% increase in revenue is also beneficial.**

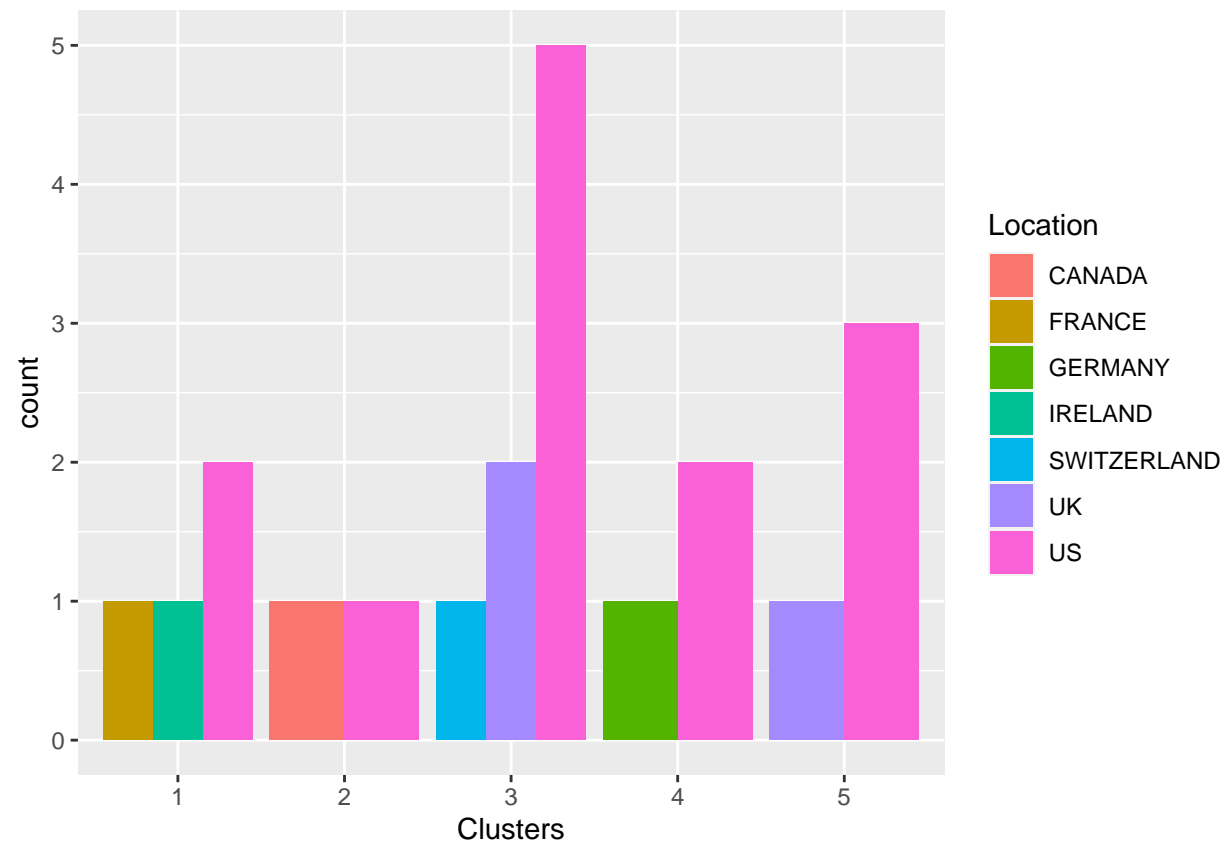
2B In relation to the numerical variables (10 to 12), are there any patterns in the clusters?

By comparing clusters to the variables, we may observe patterns.

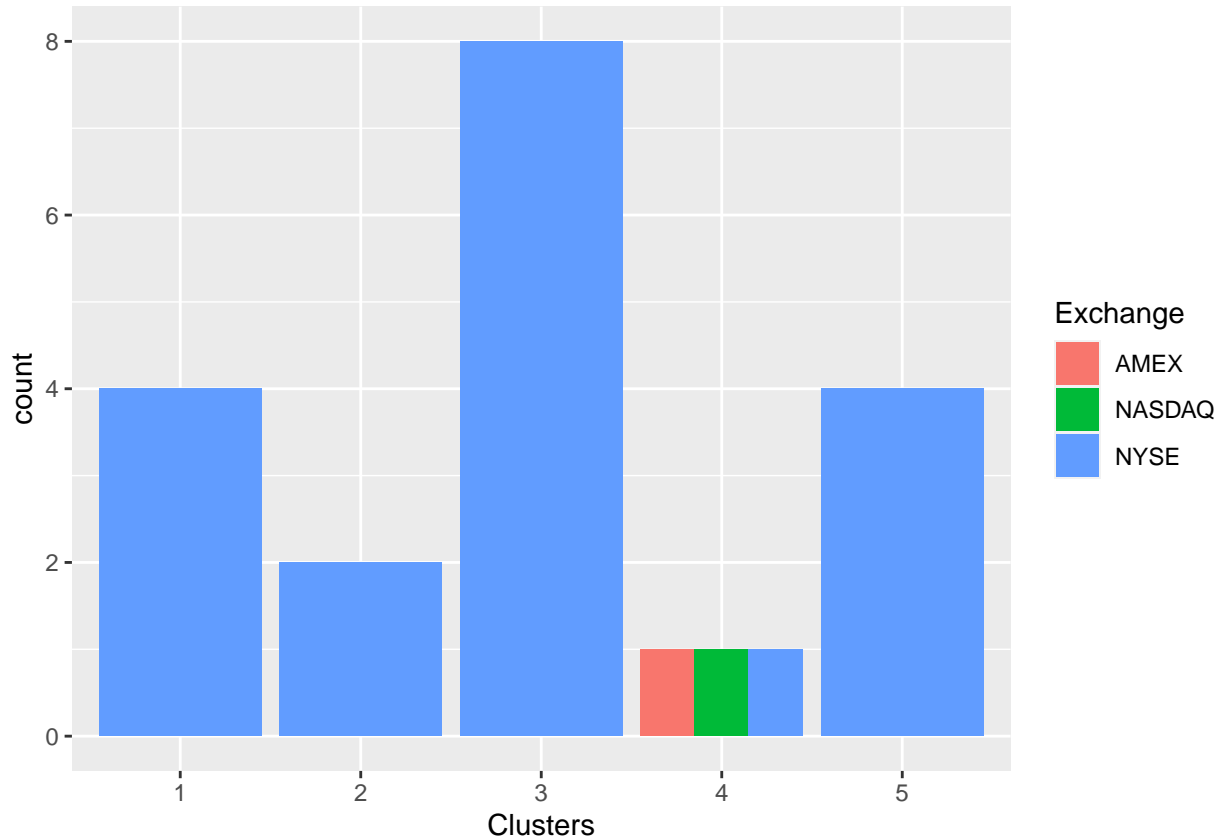
```
Info_2 <- pharma[12:14] %>% mutate(Clusters=k5$cluster)
ggplot(Info_2, mapping = aes(factor(Clusters), fill =Median_Recommendation))+geom_bar(position='dodge')
```



```
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 grouped together, The median recommendations indicate a pattern.

Other than the fact that most of the clusters/companies are based in the United States and are listed on

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

Market Cap, Beta, PE Ratio, ROE, ROA and Asset Turnover are the factors that I have taken into consideration when naming the clusters. and with that information, I have defined the Clusters.

Cluster 1: Profitable Giants

Significant market capitalization, low beta, low PE ratio, strong ROE, ROA, and asset turnover are indicators of this. These organizations stand for strong, successful leaders in the business sector.

Cluster 2: High Beta, High Risk Players

Cluster 2 represents businesses with higher risk levels and is identified by heightened Beta and PE Ratio. Due to potential overvaluation and increasing market sensitivity, investors should proceed with caution.

Cluster 3: Balanced Performers

Cluster 3 represents the businesses in a moderate-risk category by balancing the Market Cap, Beta and PE Ratio. These well-balanced performers represents both the potential and stability.

Cluster 4: High Risk, Low Efficiency

Entities in the Cluster 4 experience very high risk despite having a great PE Ratio; low efficiency is illustrated by low ROE, ROA and asset turnover. This cluster is thought to be less effective and high-risk.

Cluster 5: Efficient Powerhouses

Cluster 5 presents businesses with a gently valued PE Ratio along with strong efficiency measures, such as high ROE, ROA, and asset turnover. These effective powerhouses are essential for acquisition and as well as retention.