

Fundamentals Of Machine Learning- Assignment-4

Elmy Luka

2022-11-06

```
data_1 <- read.csv("~/Desktop/Pharmaceuticals.csv")
```

```
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 packages ----- tidyverse 1.3.2 --
```

```
## v tibble 3.1.8      v dplyr 1.0.10
## v tidyr  1.2.1      v stringr 1.4.1
## v readr  2.1.2      v forcats 0.5.2
## v purrr  0.3.4
```

```
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()
```

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

```
##Task 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.
```

```
P<- na.omit(data_1)
summary(P)
```

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

```
row.names(P) <- P[,1]
P_1 <- P[,3:11]
head(P_1)
```

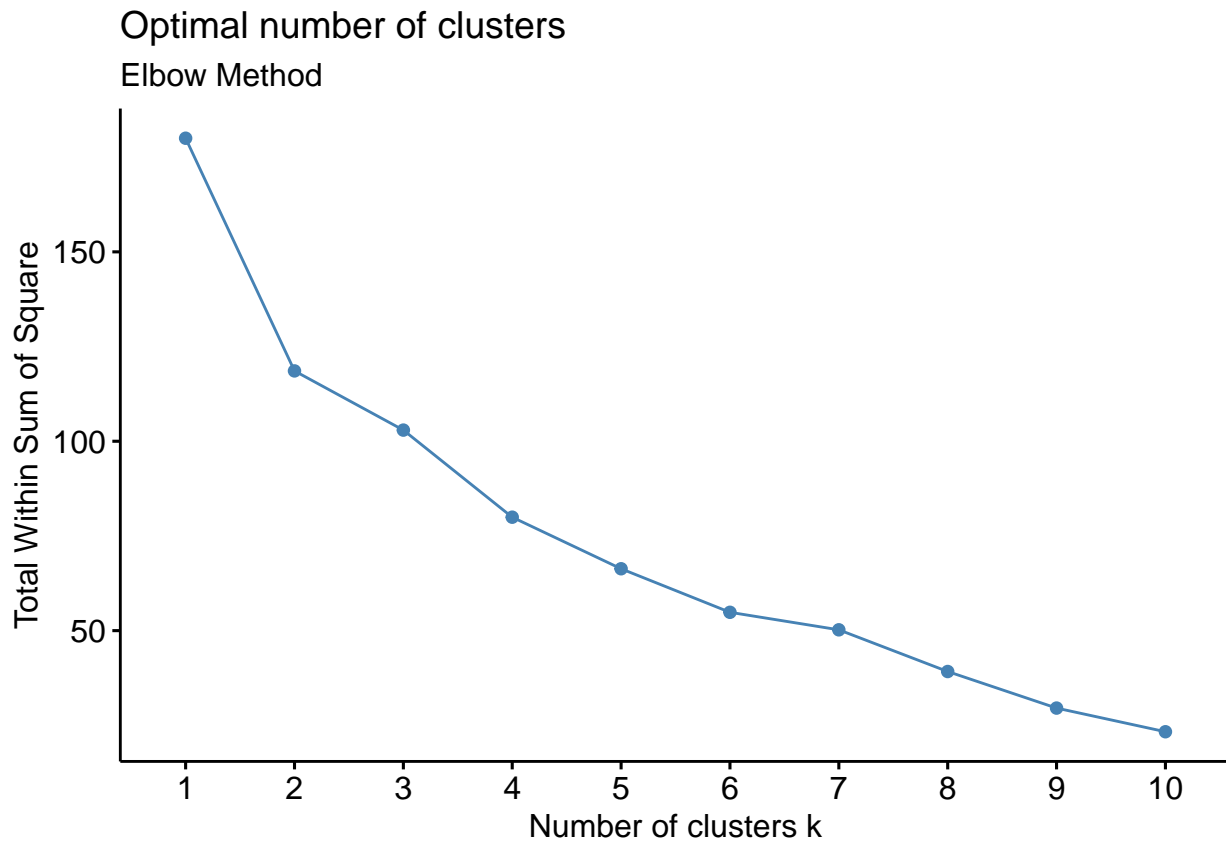
```
##      Market_Cap Beta PE_Ratio ROE ROA Asset_Turnover Leverage Rev_Growth
## ABT      68.44 0.32   24.7 26.4 11.8           0.7    0.42      7.54
## AGN      7.58 0.41   82.5 12.9 5.5           0.9    0.60      9.16
## AHM      6.30 0.46   20.7 14.9 7.8           0.9    0.27      7.05
## AZN     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
```

```
P_2 <- scale(P_1)
head(P_2)
```

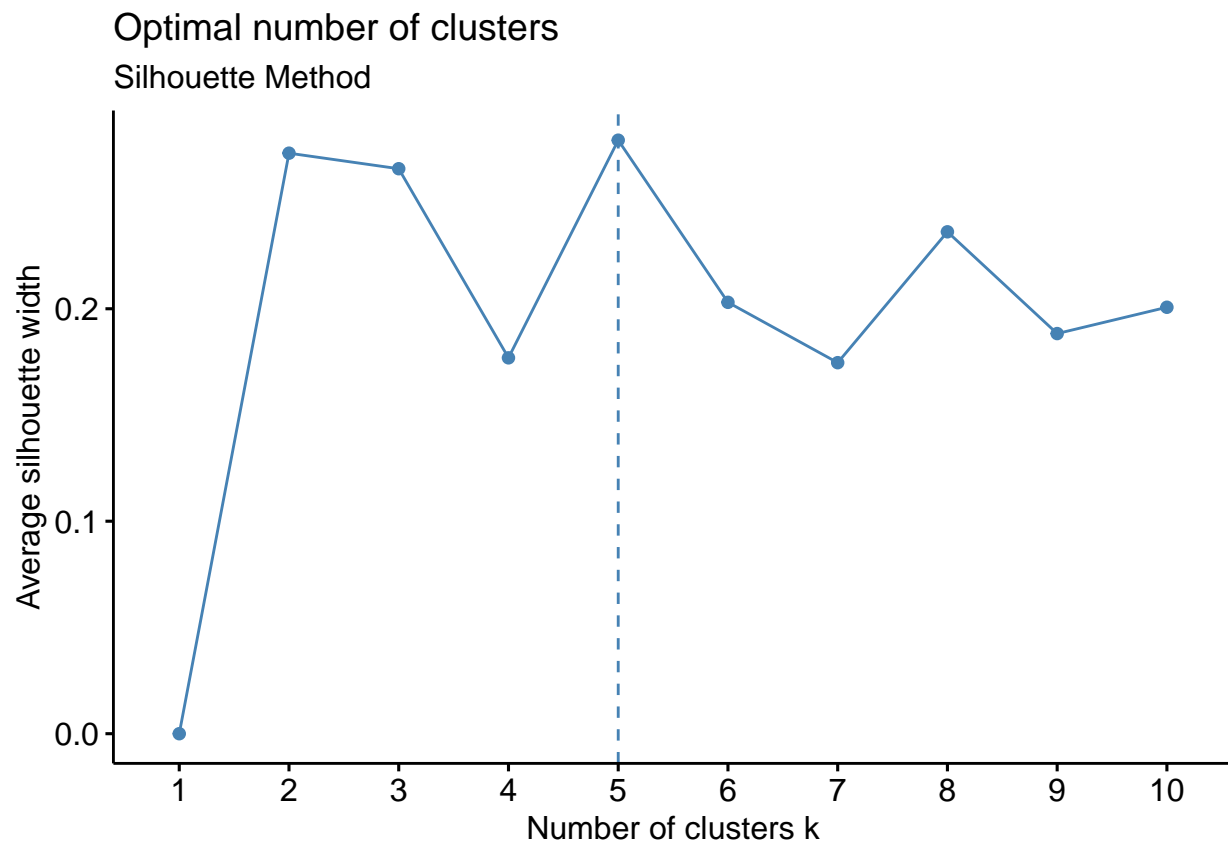
```
##      Market_Cap      Beta      PE_Ratio      ROE      ROA Asset_Turnover
## ABT  0.1840960 -0.80125356 -0.04671323  0.04009035  0.2416121  0.0000000
## AGN -0.8544181 -0.45070513  3.49706911 -0.85483986 -0.9422871  0.9225312
## AHM -0.8762600 -0.25595600 -0.29195768 -0.72225761 -0.5100700  0.9225312
## 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(P_2, kmeans, method = "wss") + labs(subtitle = "Elbow Method")
```



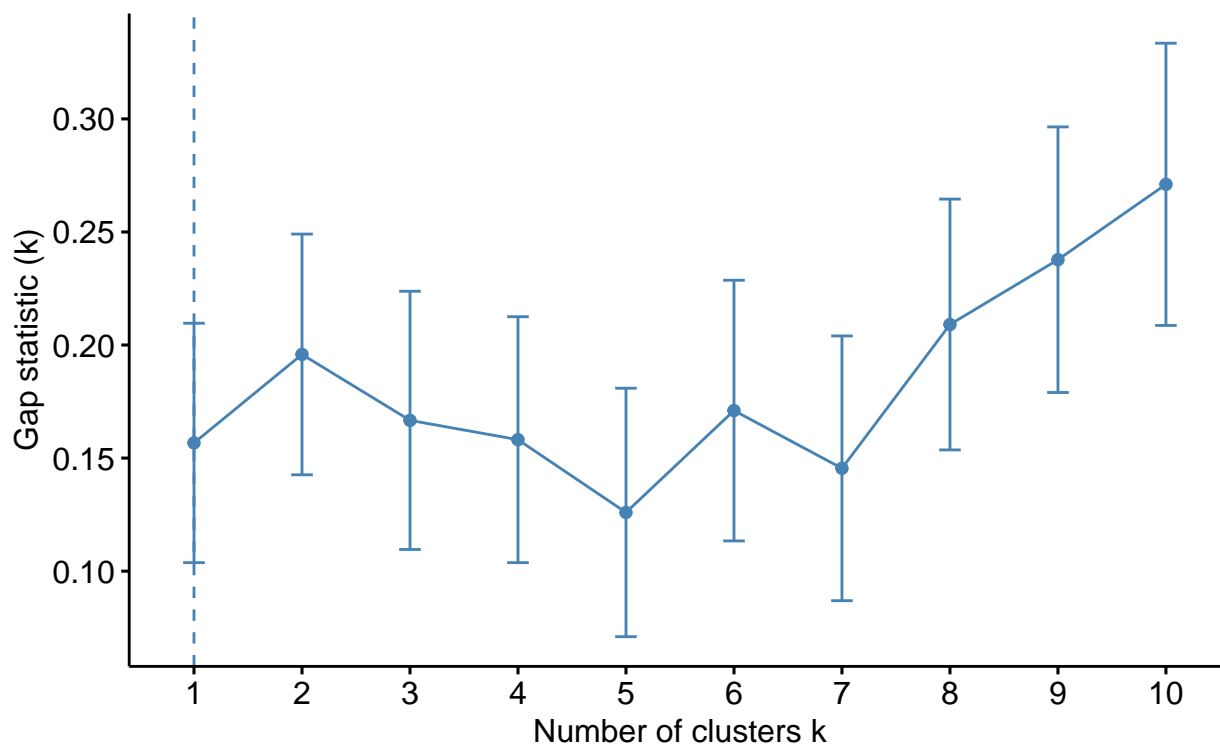
```
fviz_nbclust(P_2, kmeans, method = "silhouette") + labs(subtitle = "Silhouette Method")
```



```
fviz_nbclust(P_2, kmeans, method = "gap_stat") + labs(subtitle = "Gap Stat Method")
```

Optimal number of clusters

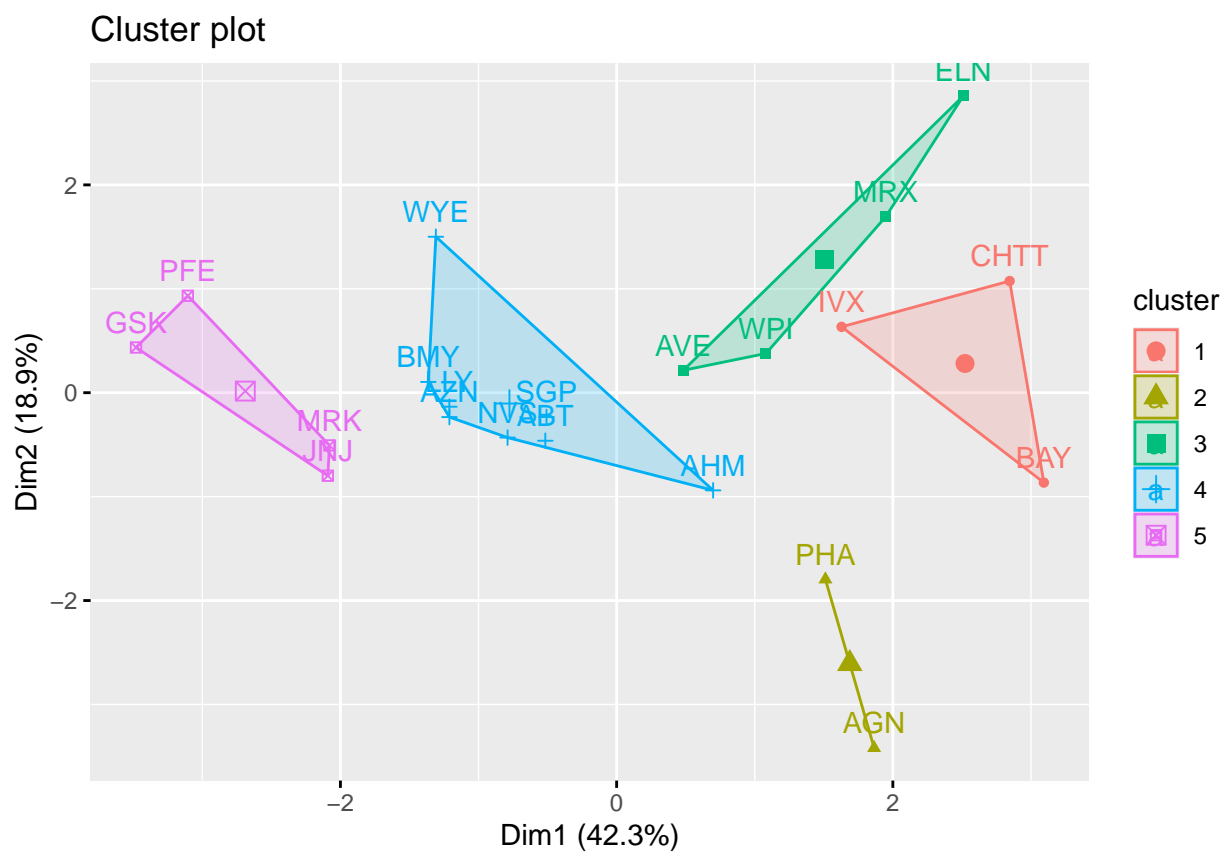
Gap Stat Method



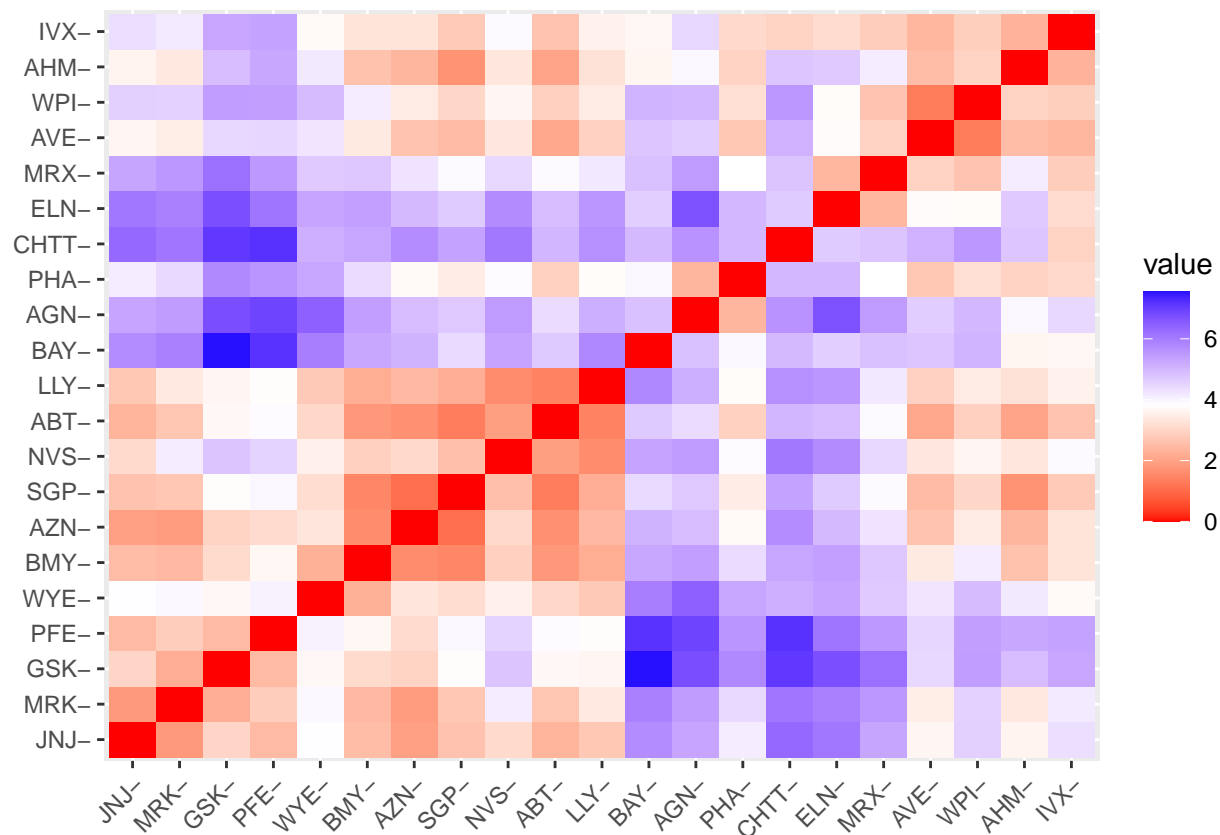
```
set.seed(64060)
k_value_5 <- kmeans(P_2, centers = 5, nstart = 25)
k_value_5$centers
```

```
##      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(k_value_5, data = P_2)
```



```
distance_1 <- dist(P_2, method = "euclidean")
fviz_dist(distance_1)
```



```
fit_1 <- kmeans(P_2, 5)
aggregate(P_2, by=list(fit_1$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
```

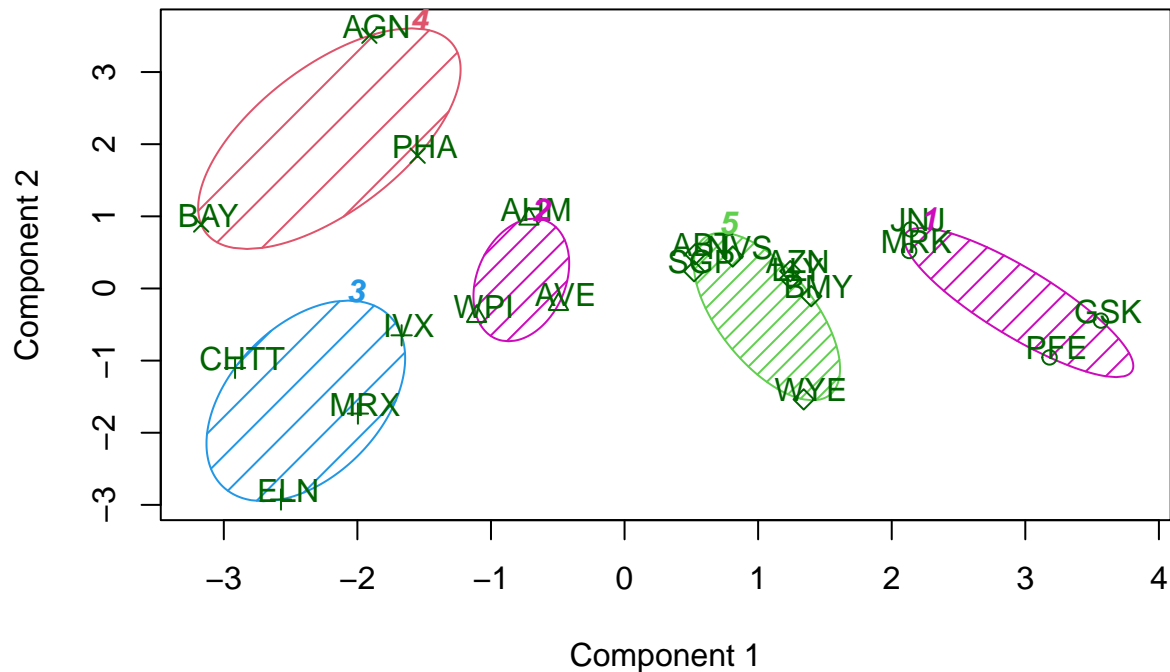
```
P_3 <- data.frame(P_2, fit_1$cluster)
P_3
```

```
##      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
```

##	BMJ	-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	fit_1.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		
##	BMJ	-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(P_2, fit_1$cluster, color = TRUE, shade = TRUE,
         labels = 2, lines = 0)
```


CLUSPLOT(P_2)



These two components explain 61.23 % of the point variability.

#Task 2

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

```
P_4 <- data.frame(P_2,k_value_5$cluster)
P_4
```

##	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	k_value_5	cluster	
## ABT	-0.21209793	-0.52776752	0.06168225			4
## AGN	0.01828430	-0.38113909	-1.55366706			2
## AHM	-0.40408312	-0.57211809	-0.68503583			4
## AZN	-0.74965647	0.14744734	0.35122600			4
## AVE	-0.31449003	1.21638667	-0.42597037			3
## BAY	-0.74965647	-1.49714434	-1.99560225			1
## BMY	-0.02011273	-0.96584257	0.74744375			4
## CHTT	3.74279705	-0.63276071	-1.24888417			1
## ELN	0.61983791	1.88617085	-0.36501379			3
## LLY	-0.07130879	-0.64814764	1.17413980			4
## GSK	-0.31449003	0.76926048	0.82363947			5
## IVX	1.10620040	0.05603085	-0.71551412			1
## JNJ	-0.62166634	-0.36213170	0.33598685			5
## MRX	0.44065173	1.53860717	0.85411776			3
## MRK	-0.39128411	0.36014907	-0.24310064			5
## NVS	-0.67286239	-1.45369888	1.02174835			4
## PFE	-0.54487226	1.10143723	1.44844440			5
## PHA	-0.30169102	0.14744734	-1.27936246			2
## SGP	-0.74965647	-0.43544591	0.29026942			4
## WPI	-0.49367621	1.43089863	-0.09070919			3
## WYE	0.68383297	-1.17763919	1.49416183			4

#Cluster-1

#JNJ,MRK,PFE,GSK belongs to this cluster.

#They have the highest Market Capitalization and the lowest Beta & Price/earnings ratio.

#Cluster 2

#AHM,WPI,AVE belongs to this cluster.

#They have the highest Estimated revenue growth

#and the lowest Price/earnings ratio & Asset Turnover ratio.

#Cluster 3

#CHTT,MRX,IVX,ELN belongs to this cluster.

#They have the highest Beta, Leverage & Asset turnover

#ratio and the lowest Net profit margin & Price/earnings ratio.

#Cluster 4

#AGN,BAY,PHA belongs to this cluster.

#They have the highest Profit/earnings ratio ad lowest

#Asset turnover ratio.

#Cluster 5

#ABT,SGP,NVS,AZN,BMY,WYE, LLY belongs to this cluster.

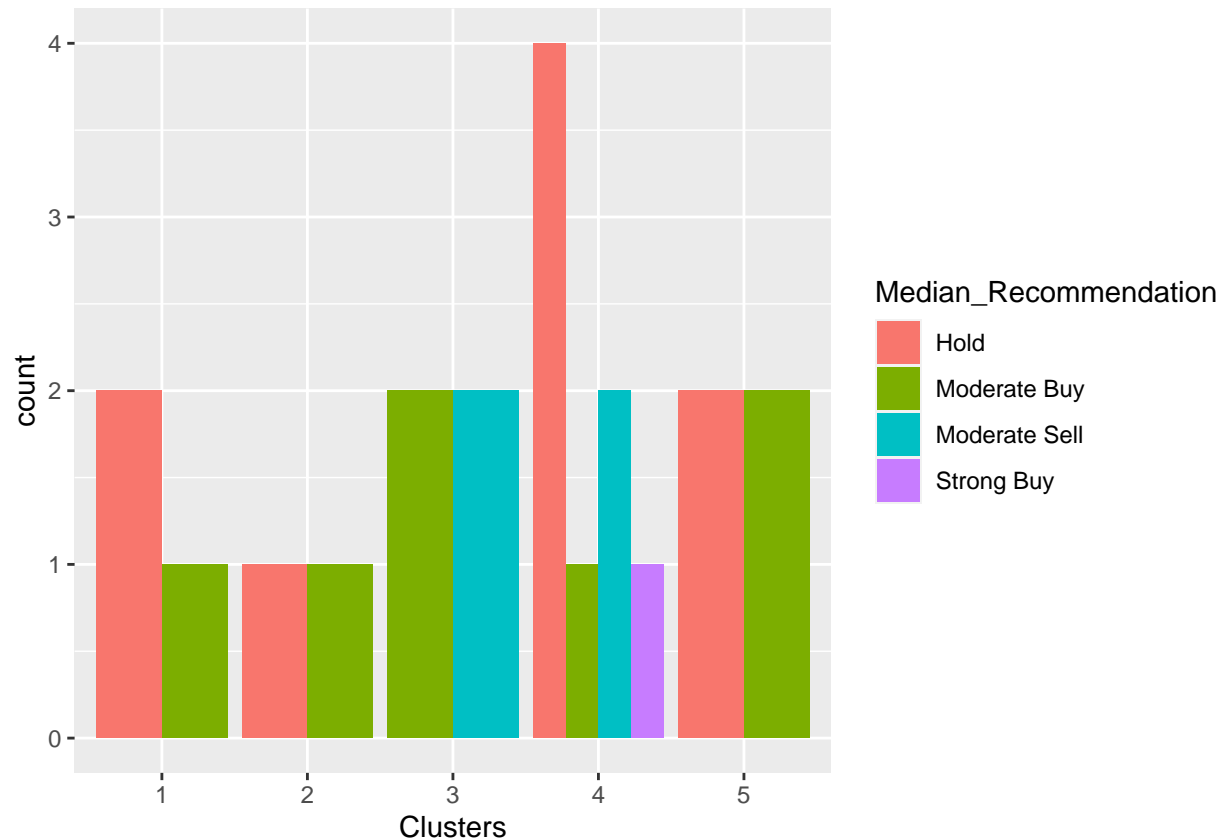
#They have the highest Net profit margin and lowest is

#the Leverage.

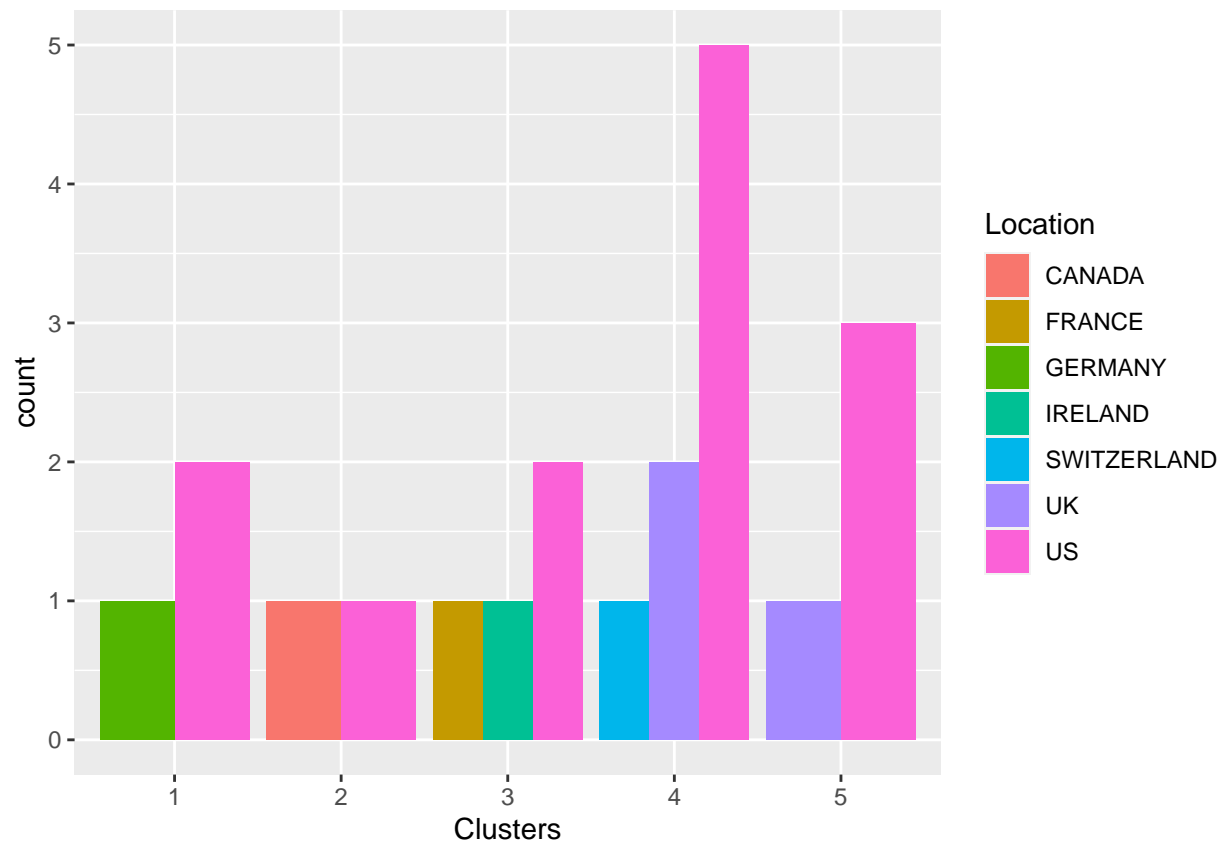
#Task 3

```
#Is there a pattern in the clusters with respect
#to the numerical variables (10 to 12)? #(those not
#used in forming the clusters)
```

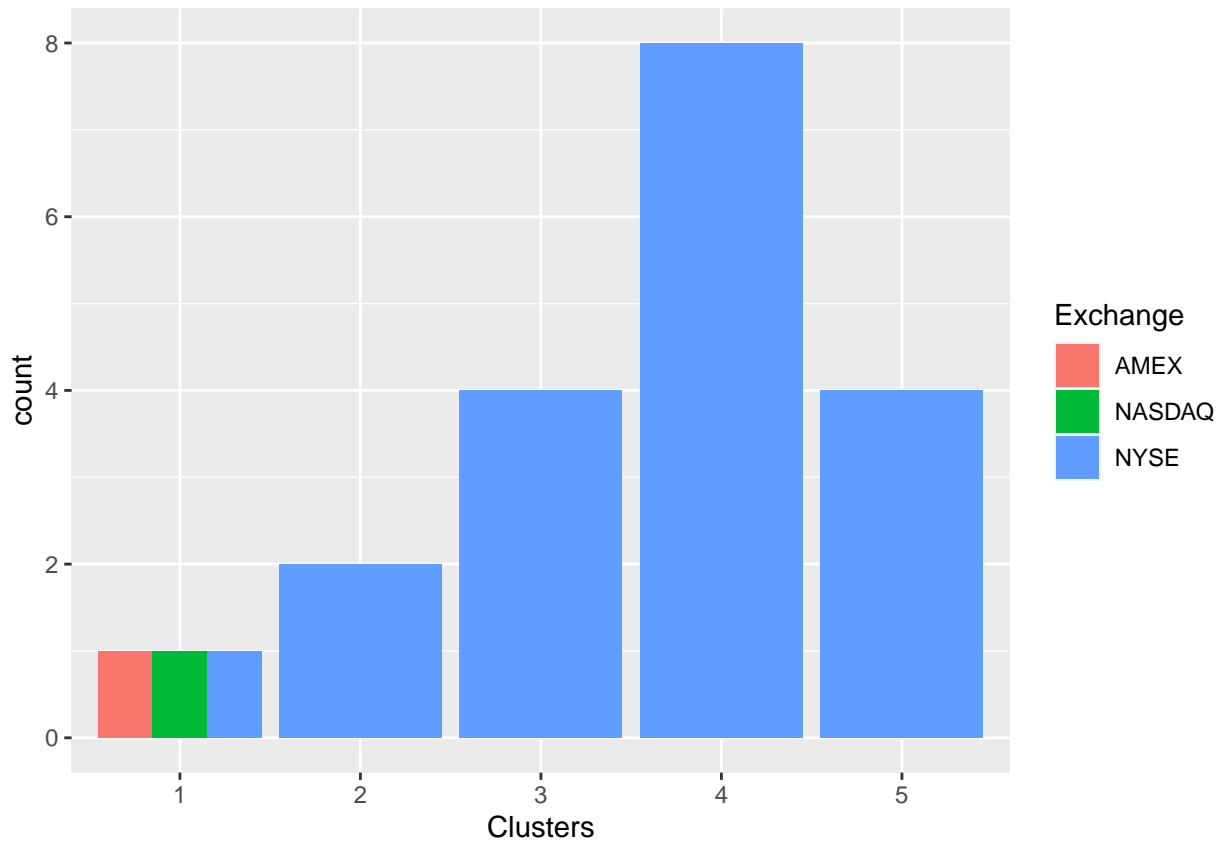
```
pharm <- data_1[12:14] %>%
  mutate(Clusters=k_value_5$cluster)
ggplot(pharm, mapping =
  aes(factor(Clusters), fill =Median_Recommendation)) +
  geom_bar(position='dodge')+labs(x = 'Clusters')
```



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



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



*#From the plotted graphs, a pattern has been
#observed among the clusters. The following statements
#are based on these observations:*

#Cluster 1

*#The companies are uniformly distributed throughout
#AMEX, NASDAQ, and NYSE while the Hold and Moderate
#Buy medians in cluster 1 are different from those in the
#US and Germany, respectively.*

#Cluster 2

*#This cluster is exclusively listed on the NYSE with
#an equal split between the US and Canada and it also has
#equal hold and moderate buy medians.*

#Cluster 3

*#Here the cluster has medians for moderate buys and sales
#that are equal, and the counts from those of France and Ireland
#are same while for the US it is different, and NYSE listing
#entirely covers this cluster.*

#Cluster 4

*#The Hold median in Cluster 4 is the highest, followed by
#Moderate Sell and then having Moderate Buy and Strong buy on
#the same level. They're from countries US, UK and Switzerland
#and they are listed in NYSE.*

*#Cluster 5
#This Cluster has the same hold and moderate buy medians
#and is distributed among the countries US and UK and also
#NYSE is listed here.*

#Task 4

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

*#Cluster 1- Highest Market Capitalization Cluster.
#Cluster 2- Highest Estimated Growth Cluster.
#Cluster 3- Highest Beta Cluster
#Cluster 4- Highest Profit/earnings ratio Cluster.
#Cluster 5- Highest Net profit margin Cluster.*