FML_Assignment_4

2024-03-14

Cluster Analysis of Pharmaceutical Firms

Introduction

In this analysis, we perform cluster analysis on a dataset containing information about pharmaceutical firms. We focus on using numerical variables (1 to 9) to cluster the 21 firms. 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, are justified.

```
#Importing Required Packages
library(readr)
#Importing Data Set
data <- read_csv("/Users/meghana/Downloads/Pharmaceuticals.csv")
```

```
## Rows: 21 Columns: 14
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (5): Symbol, Name, Median_Recommendation, Location, Exchange
## dbl (9): Market_Cap, Beta, PE_Ratio, ROE, ROA, Asset_Turnover, Leverage, Rev...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

Load necessary libraries

```
library("ggplot2")
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: lattice

## Loading required package: modeltools

## Loading required package: stats4
```

```r
library("cluster")
library("tidyverse")
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.4     v stringr   1.5.1
## v forcats   1.0.0     v tibble    3.2.1
## v lubridate 1.9.3     v tidyr     1.3.1
## 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
```

```r
#library("fvi_dist")
library("cluster")
```

```r
# Removing null values in data (data cleaning)
Pharma_data =  na.omit(data)
Pharma_data
```

Question(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.

```
## # A tibble: 21 x 14
##    Symbol Name     Market_Cap  Beta PE_Ratio   ROE   ROA Asset_Turnover Leverage
##    <chr>  <chr>         <dbl> <dbl>    <dbl> <dbl> <dbl>          <dbl>    <dbl>
##  1 ABT    Abbott ~      68.4   0.32     24.7  26.4  11.8            0.7     0.42
##  2 AGN    Allerga~       7.58  0.41     82.5  12.9   5.5            0.9     0.6
##  3 AHM    Amersha~       6.3   0.46     20.7  14.9   7.8            0.9     0.27
##  4 AZN    AstraZe~      67.6   0.52     21.5  27.4  15.4            0.9     0
##  5 AVE    Aventis       47.2   0.32     20.1  21.8   7.5            0.6     0.34
##  6 BAY    Bayer AG      16.9   1.11     27.9   3.9   1.4            0.6     0
##  7 BMY    Bristol~      51.3   0.5      13.9  34.8  15.1            0.9     0.57
##  8 CHTT   Chattem~       0.41  0.85     26    24.1   4.3            0.6     3.51
##  9 ELN    Elan Co~       0.78  1.08      3.6  15.1   5.1            0.3     1.07
## 10 LLY    Eli Lil~      73.8   0.18     27.9  31    13.5            0.6     0.53
## # i 11 more rows
## # i 5 more variables: Rev_Growth <dbl>, Net_Profit_Margin <dbl>,
## #   Median_Recommendation <chr>, Location <chr>, Exchange <chr>
```

```r
row.names <- Pharma_data[,1]
pharma_data1 <- Pharma_data[,3:11]#numerical variable from 3 to 11
head(pharma_data1)
```

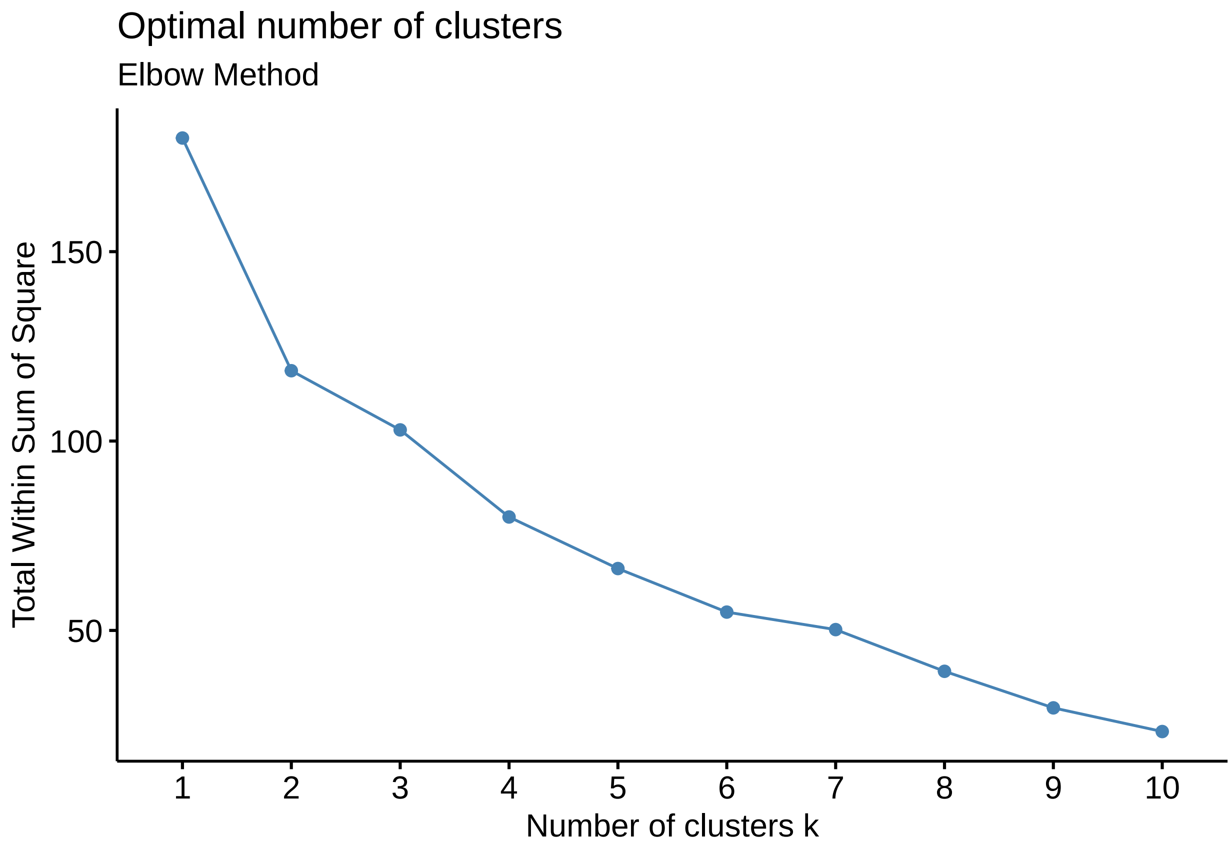
```
## # A tibble: 6 x 9
##   Market_Cap  Beta PE_Ratio   ROE   ROA Asset_Turnover Leverage Rev_Growth
```

```
##         <dbl> <dbl>    <dbl> <dbl> <dbl>          <dbl>    <dbl>      <dbl>
## 1      68.4   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     0.6        9.16
## 3       6.3   0.46     20.7  14.9   7.8             0.9     0.27       7.05
## 4      67.6   0.52     21.5  27.4  15.4             0.9     0          15
## 5      47.2   0.32     20.1  21.8   7.5             0.6     0.34      26.8
## 6      16.9   1.11     27.9   3.9   1.4             0.6     0         -3.17
## # i 1 more variable: Net_Profit_Margin <dbl>
```

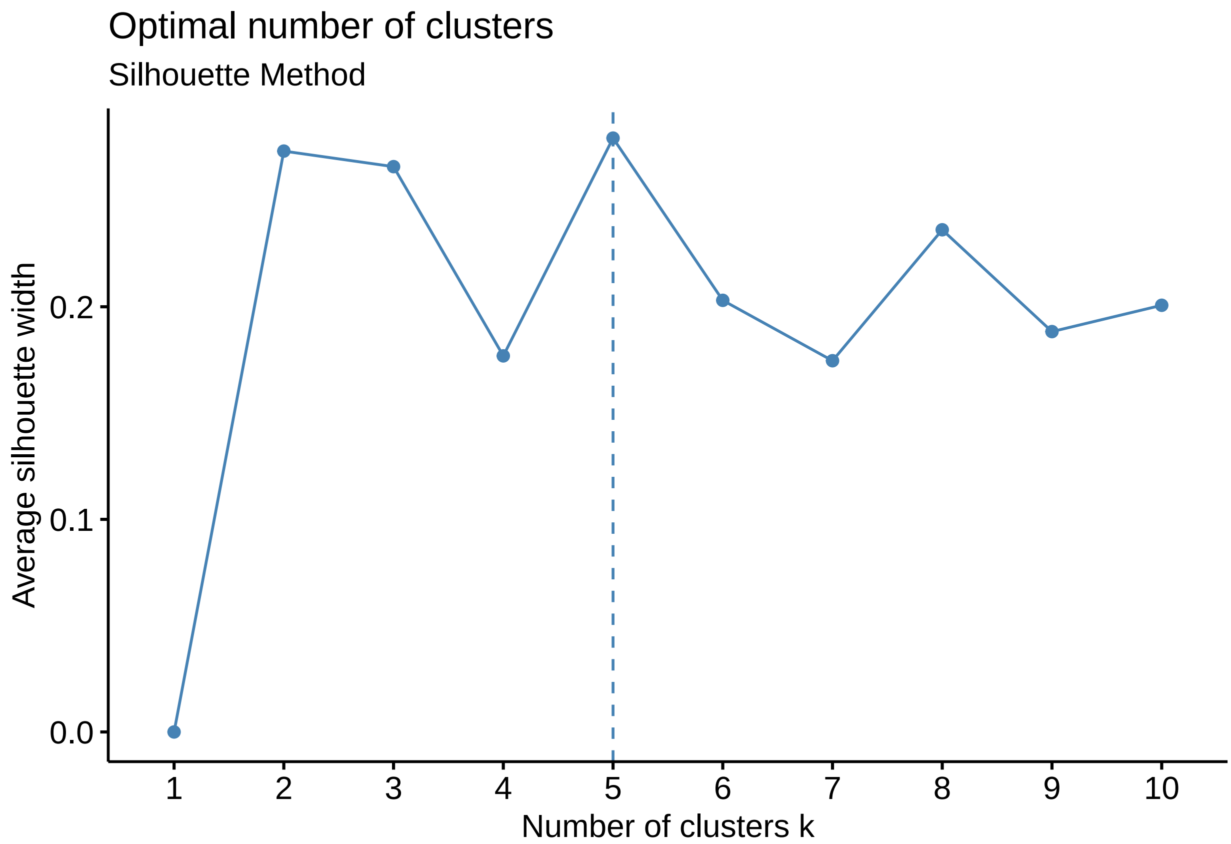
```r
pharma_data2 <- scale(pharma_data1)
head(pharma_data2)
```

```
##       Market_Cap        Beta    PE_Ratio         ROE        ROA Asset_Turnover
## [1,]  0.1840960 -0.80125356 -0.04671323  0.04009035  0.2416121  -5.121077e-16
## [2,] -0.8544181 -0.45070513  3.49706911 -0.85483986 -0.9422871   9.225312e-01
## [3,] -0.8762600 -0.25595600 -0.29195768 -0.72225761 -0.5100700   9.225312e-01
## [4,]  0.1702742 -0.02225704 -0.24290879  0.10638147  0.9181259   9.225312e-01
## [5,] -0.1790256 -0.80125356 -0.32874435 -0.26484883 -0.5664461  -4.612656e-01
## [6,] -0.6953818  2.27578267  0.14948233 -1.45146000 -1.7127612  -4.612656e-01
##        Leverage Rev_Growth Net_Profit_Margin
## [1,] -0.2120979 -0.5277675        0.06168225
## [2,]  0.0182843 -0.3811391       -1.55366706
## [3,] -0.4040831 -0.5721181       -0.68503583
## [4,] -0.7496565  0.1474473        0.35122600
## [5,] -0.3144900  1.2163867       -0.42597037
## [6,] -0.7496565 -1.4971443       -1.99560225
```

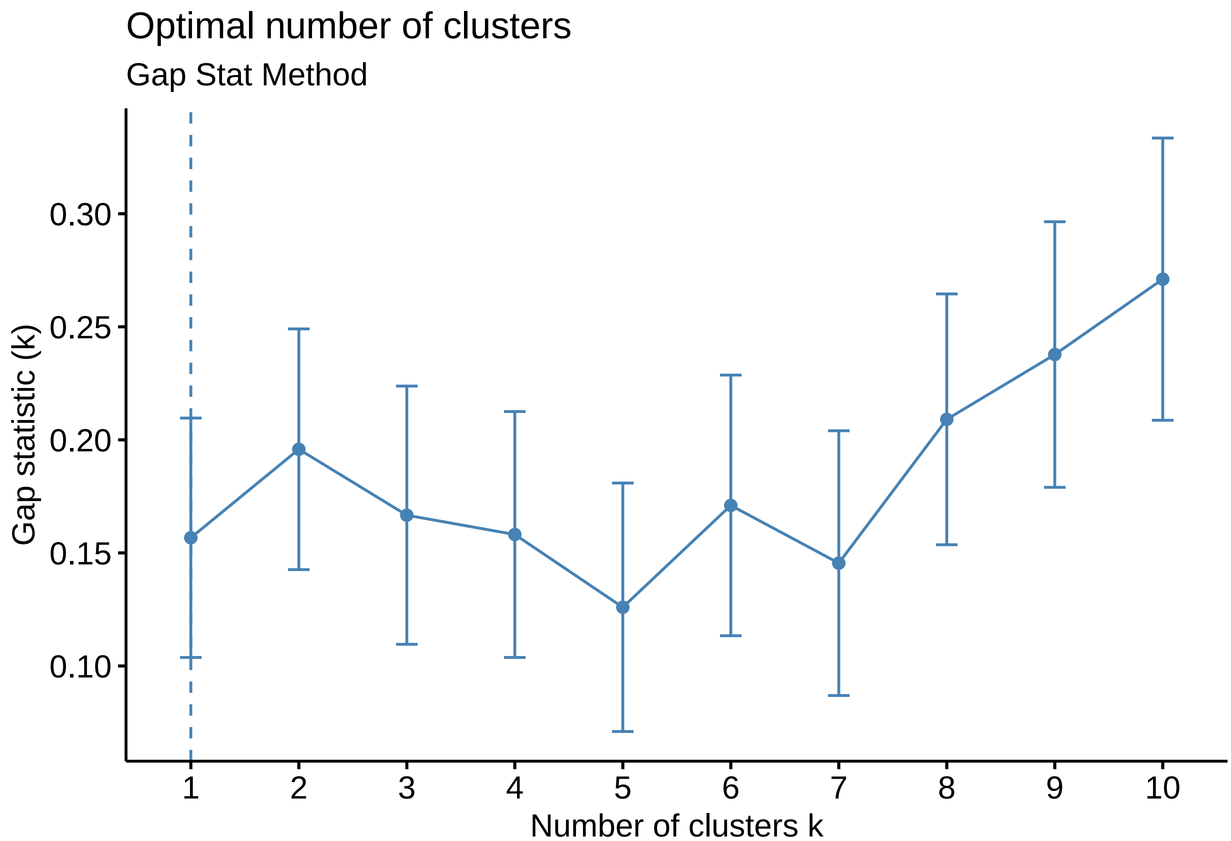
```r
#Determination of Number of Clusters
#We determine the optimal number of clusters using different methods such as the Elbow Method, Silhouet
fviz_nbclust(pharma_data2, kmeans, method = "wss") +labs(subtitle = "Elbow Method")
```




```
fviz_nbclust(pharma_data2, kmeans, method = "silhouette") + labs(subtitle = "Silhouette Method")
```



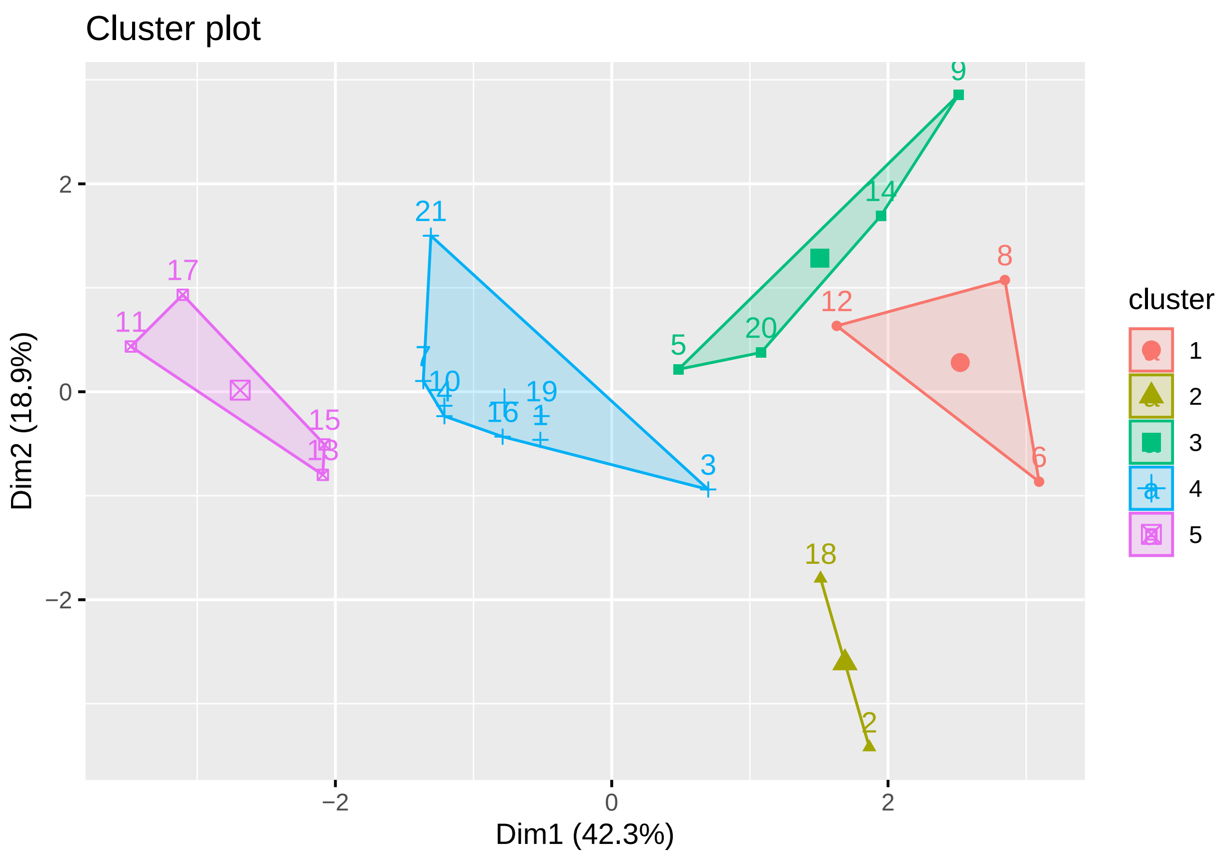

```
fviz_nbclust(pharma_data2, kmeans, method = "gap_stat") + labs(subtitle = "Gap Stat Method")
```




```r
set.seed(64060)
k_5 <- kmeans(pharma_data2, centers = 5, nstart = 25)
k_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
```

```r
fviz_cluster(k_5, data = pharma_data2)
```




```
k_5
```

```
## K-means clustering with 5 clusters of sizes 3, 2, 4, 8, 4
##
## Cluster means:
##    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
##
## Clustering vector:
##  [1] 4 2 4 4 3 1 4 1 3 4 5 1 5 3 5 4 5 2 4 3 4
##
## Within cluster sum of squares by cluster:
## [1] 15.595925  2.803505 12.791257 21.879320  9.284424
##  (between_SS / total_SS =  65.4 %)
##
## Available components:
```

```
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

```
Dist <- dist(pharma_data2, method = "euclidian")
#fvi_dist(Dist)
FITT <- kmeans(pharma_data2,5)
aggregate(pharma_data2,by = list(FITT$cluster), FUN = mean)
```

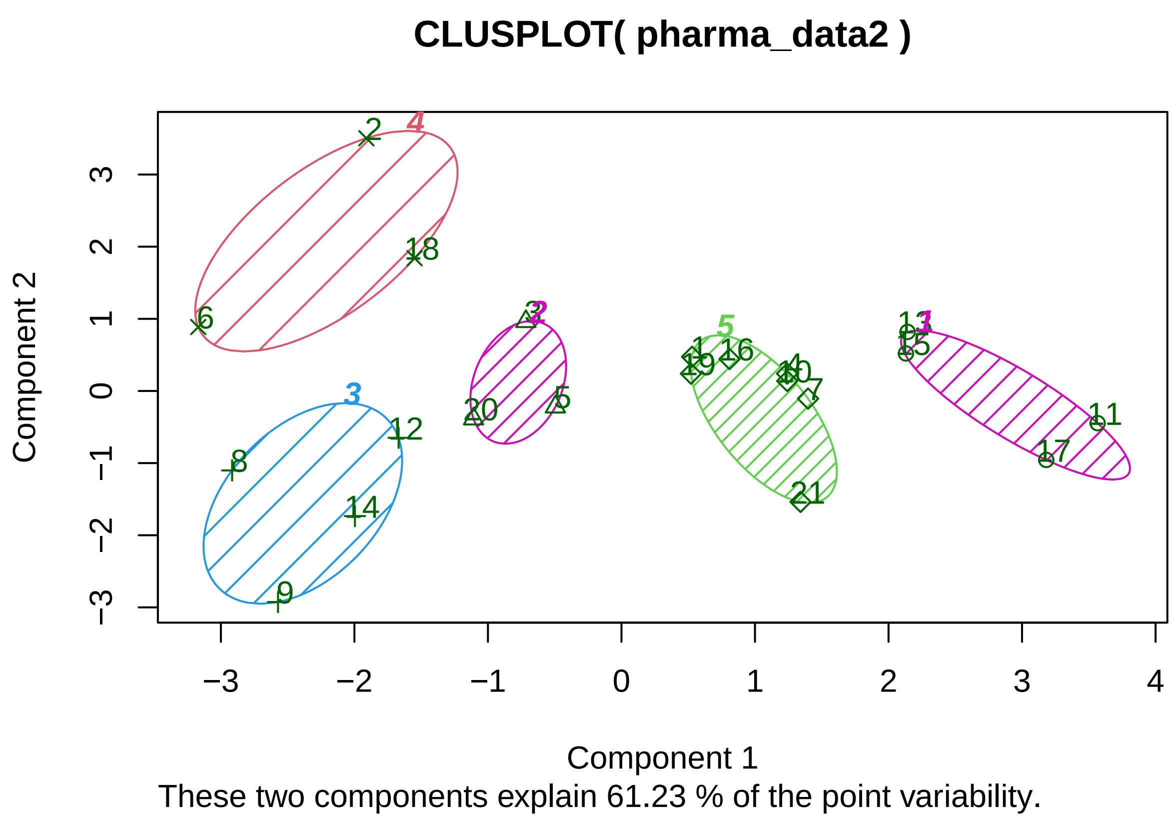
```
##   Group.1  Market_Cap       Beta   PE_Ratio        ROE        ROA
## 1       1  1.69558112 -0.1780563 -0.1984582  1.2349879  1.3503431
## 2       2 -0.66114002 -0.7233539 -0.3512251 -0.6736441 -0.5915022
## 3       3 -0.96247577  1.1949250 -0.3639982 -0.5200697 -0.9610792
## 4       4 -0.52462814  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  -3.330669e-16 -0.3443544 -0.5769454        -1.6095439
## 5   6.589509e-02 -0.2559803 -0.7230135         0.7343816
```

```
pharma_data3 <- data.frame(pharma_data2,FITT$cluster)
pharma_data3
```

```
##    Market_Cap        Beta    PE_Ratio         ROE        ROA Asset_Turnover
## 1   0.1840960 -0.80125356 -0.04671323  0.04009035  0.2416121  -5.121077e-16
## 2  -0.8544181 -0.45070513  3.49706911 -0.85483986 -0.9422871   9.225312e-01
## 3  -0.8762600 -0.25595600 -0.29195768 -0.72225761 -0.5100700   9.225312e-01
## 4   0.1702742 -0.02225704 -0.24290879  0.10638147  0.9181259   9.225312e-01
## 5  -0.1790256 -0.80125356 -0.32874435 -0.26484883 -0.5664461  -4.612656e-01
## 6  -0.6953818  2.27578267  0.14948233 -1.45146000 -1.7127612  -4.612656e-01
## 7  -0.1078688 -0.10015669 -0.70887325  0.59693581  0.8617498   9.225312e-01
## 8  -0.9767669  1.26308721  0.03299122 -0.11237924 -1.1677918  -4.612656e-01
## 9  -0.9704532  2.15893320 -1.34037772 -0.70899938 -1.0174553  -1.845062e+00
## 10  0.2762415 -1.34655112  0.14948233  0.34502953  0.5610770  -4.612656e-01
## 11  1.0999201 -0.68440408 -0.45749769  2.45971647  1.8389364   1.383797e+00
## 12 -0.9393967  0.48409069 -0.34100657 -0.29136529 -0.6979905  -4.612656e-01
## 13  1.9841758 -0.25595600  0.18013789  0.18593083  1.0872544   9.225312e-01
## 14 -0.9632863  0.87358895  0.19240011 -0.96753478 -0.9610792  -1.845062e+00
## 15  1.2782387 -0.25595600 -0.40231769  0.98142435  0.8429577   1.845062e+00
## 16  0.6654710 -1.30760129 -0.23677768 -0.52338423  0.1288598  -9.225312e-01
## 17  2.4199899  0.48409069 -0.11415545  1.31287998  1.6322239   4.612656e-01
## 18 -0.0240846 -0.48965495  1.90298017 -0.81506519 -0.9047030  -4.612656e-01
## 19 -0.4018812 -0.06120687 -0.40231769 -0.21181593  0.5234929   4.612656e-01
## 20 -0.9281345 -1.11285216 -0.43297324 -1.03382590 -0.6979905  -9.225312e-01
## 21 -0.1614497  0.40619104 -0.75792214  1.92938746  0.5422849  -4.612656e-01
##       Leverage  Rev_Growth Net_Profit_Margin FITT.cluster
## 1  -0.21209793 -0.52776752        0.06168225            5
## 2   0.01828430 -0.38113909       -1.55366706            4
## 3  -0.40408312 -0.57211809       -0.68503583            2
## 4  -0.74965647  0.14744734        0.35122600            5
## 5  -0.31449003  1.21638667       -0.42597037            2
```

```
## 6  -0.74965647 -1.49714434       -1.99560225           4
## 7  -0.02011273 -0.96584257        0.74744375           5
## 8   3.74279705 -0.63276071       -1.24888417           3
## 9   0.61983791  1.88617085       -0.36501379           3
## 10 -0.07130879 -0.64814764        1.17413980           5
## 11 -0.31449003  0.76926048        0.82363947           1
## 12  1.10620040  0.05603085       -0.71551412           3
## 13 -0.62166634 -0.36213170        0.33598685           1
## 14  0.44065173  1.53860717        0.85411776           3
## 15 -0.39128411  0.36014907       -0.24310064           1
## 16 -0.67286239 -1.45369888        1.02174835           5
## 17 -0.54487226  1.10143723        1.44844440           1
## 18 -0.30169102  0.14744734       -1.27936246           4
## 19 -0.74965647 -0.43544591        0.29026942           5
## 20 -0.49367621  1.43089863       -0.09070919           2
## 21  0.68383297 -1.17763919        1.49416183           5
```

```
clusplot(pharma_data2,FITT$cluster, color = TRUE, shade = TRUE,
 labels = 2,
 lines = 0)
```




```
aggregate(pharma_data2, by = list(FITT$cluster), FUN = mean)
```

Question(B) Interpret the clusters with respect to the numerical variables used in forming the clusters.

```
##   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  -3.330669e-16 -0.3443544 -0.5769454        -1.6095439
## 5   6.589509e-02 -0.2559803 -0.7230135         0.7343816
```

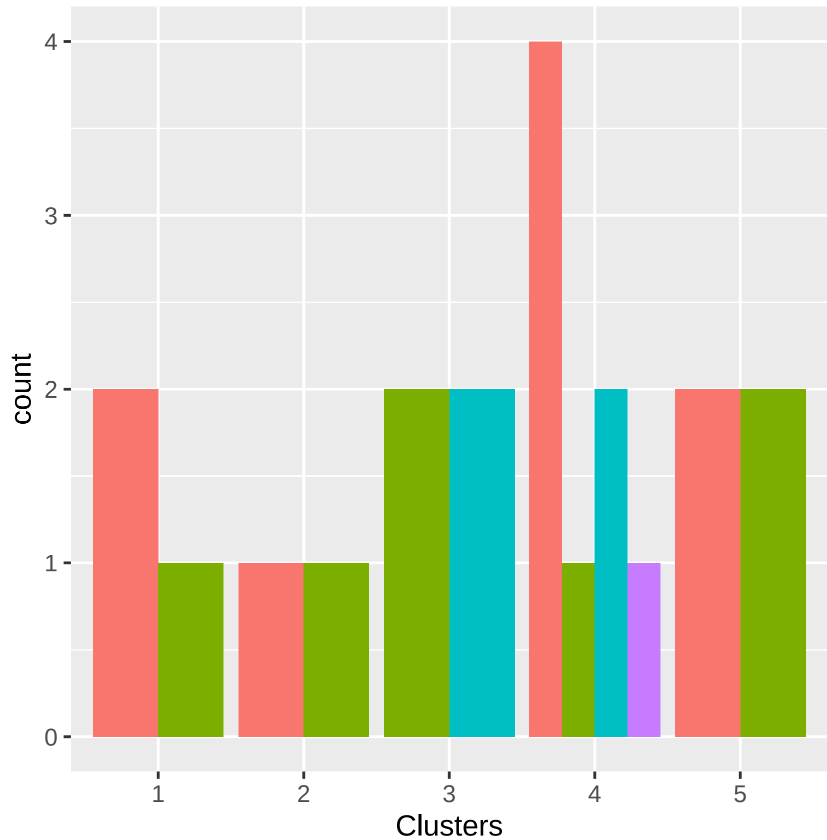
```r
Pharmacy <- data.frame(pharma_data2,k_5$cluster)
Pharmacy
```

```
##    Market_Cap        Beta    PE_Ratio         ROE        ROA Asset_Turnover
## 1   0.1840960 -0.80125356 -0.04671323  0.04009035  0.2416121  -5.121077e-16
## 2  -0.8544181 -0.45070513  3.49706911 -0.85483986 -0.9422871   9.225312e-01
## 3  -0.8762600 -0.25595600 -0.29195768 -0.72225761 -0.5100700   9.225312e-01
## 4   0.1702742 -0.02225704 -0.24290879  0.10638147  0.9181259   9.225312e-01
## 5  -0.1790256 -0.80125356 -0.32874435 -0.26484883 -0.5664461  -4.612656e-01
## 6  -0.6953818  2.27578267  0.14948233 -1.45146000 -1.7127612  -4.612656e-01
## 7  -0.1078688 -0.10015669 -0.70887325  0.59693581  0.8617498   9.225312e-01
## 8  -0.9767669  1.26308721  0.03299122 -0.11237924 -1.1677918  -4.612656e-01
## 9  -0.9704532  2.15893320 -1.34037772 -0.70899938 -1.0174553  -1.845062e+00
## 10  0.2762415 -1.34655112  0.14948233  0.34502953  0.5610770  -4.612656e-01
## 11  1.0999201 -0.68440408 -0.45749769  2.45971647  1.8389364   1.383797e+00
## 12 -0.9393967  0.48409069 -0.34100657 -0.29136529 -0.6979905  -4.612656e-01
## 13  1.9841758 -0.25595600  0.18013789  0.18593083  1.0872544   9.225312e-01
## 14 -0.9632863  0.87358895  0.19240011 -0.96753478 -0.9610792  -1.845062e+00
## 15  1.2782387 -0.25595600 -0.40231769  0.98142435  0.8429577   1.845062e+00
## 16  0.6654710 -1.30760129 -0.23677768 -0.52338423  0.1288598  -9.225312e-01
## 17  2.4199899  0.48409069 -0.11415545  1.31287998  1.6322239   4.612656e-01
## 18 -0.0240846 -0.48965495  1.90298017 -0.81506519 -0.9047030  -4.612656e-01
## 19 -0.4018812 -0.06120687 -0.40231769 -0.21181593  0.5234929   4.612656e-01
## 20 -0.9281345 -1.11285216 -0.43297324 -1.03382590 -0.6979905  -9.225312e-01
## 21 -0.1614497  0.40619104 -0.75792214  1.92938746  0.5422849  -4.612656e-01
##        Leverage  Rev_Growth Net_Profit_Margin k_5.cluster
## 1  -0.21209793 -0.52776752        0.06168225           4
## 2   0.01828430 -0.38113909       -1.55366706           2
## 3  -0.40408312 -0.57211809       -0.68503583           4
## 4  -0.74965647  0.14744734        0.35122600           4
## 5  -0.31449003  1.21638667       -0.42597037           3
## 6  -0.74965647 -1.49714434       -1.99560225           1
## 7  -0.02011273 -0.96584257        0.74744375           4
## 8   3.74279705 -0.63276071       -1.24888417           1
## 9   0.61983791  1.88617085       -0.36501379           3
## 10 -0.07130879 -0.64814764        1.17413980           4
## 11 -0.31449003  0.76926048        0.82363947           5
## 12  1.10620040  0.05603085       -0.71551412           1
```

```
## 13 -0.62166634 -0.36213170        0.33598685          5
## 14  0.44065173  1.53860717        0.85411776          3
## 15 -0.39128411  0.36014907       -0.24310064          5
## 16 -0.67286239 -1.45369888        1.02174835          4
## 17 -0.54487226  1.10143723        1.44844440          5
## 18 -0.30169102  0.14744734       -1.27936246          2
## 19 -0.74965647 -0.43544591        0.29026942          4
## 20 -0.49367621  1.43089863       -0.09070919          3
## 21  0.68383297 -1.17763919        1.49416183          4
```

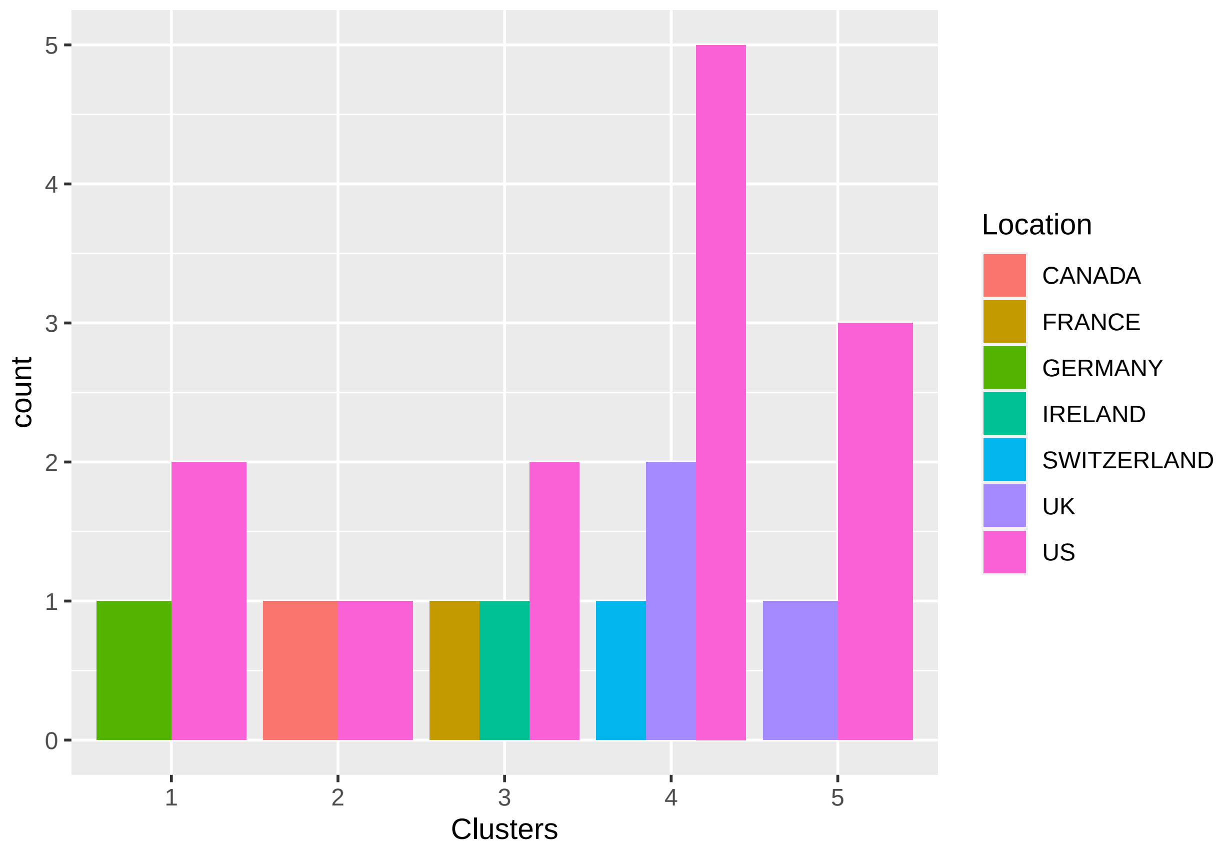
```r
Pharma <- data[12:14] %>% mutate(Clusters=k_5$cluster)
ggplot(Pharma, mapping = aes(factor(Clusters), fill =Median_Recommendation))+geom_bar(position='dodge')+
```

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

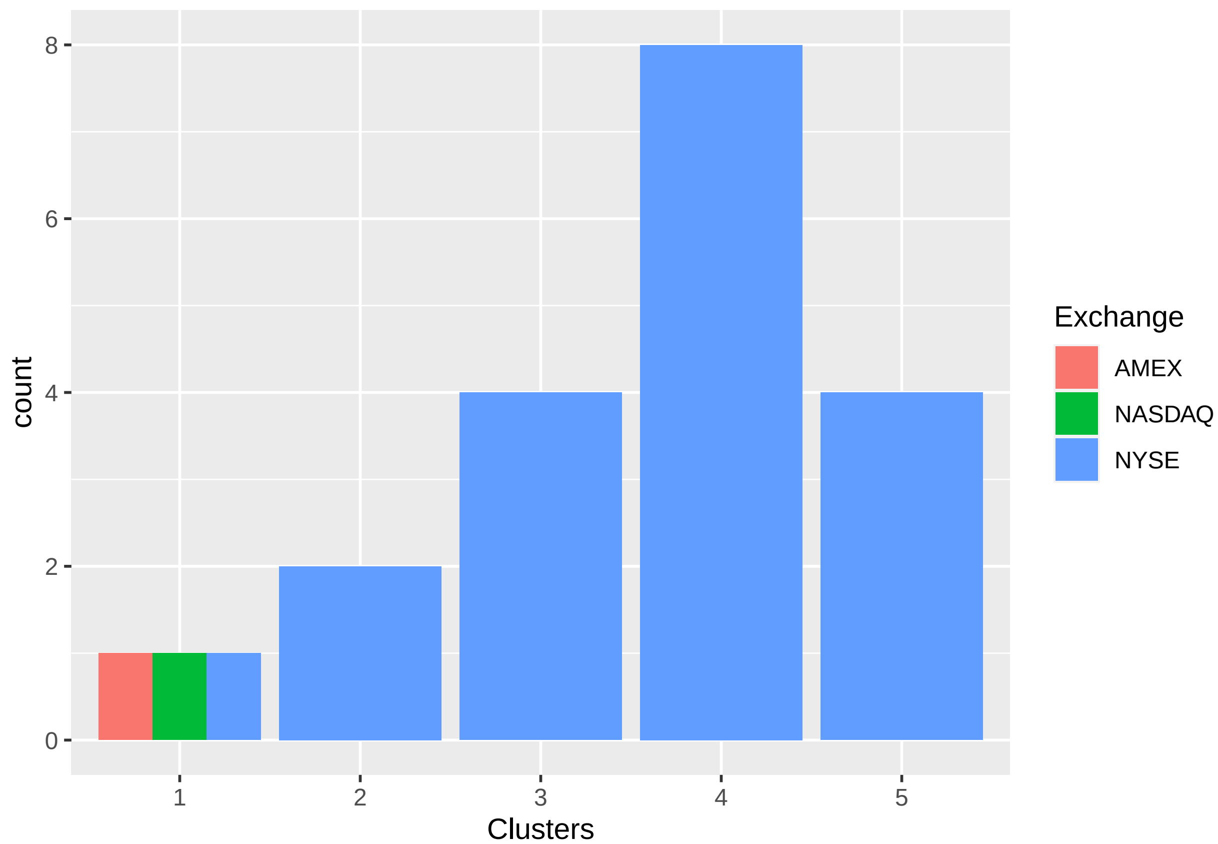


12)? (those not used in forming the clusters)

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




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



Interpretation :

We can see a minor pattern in the clusters from the graphs above

The cluster 1 has distinct Hold and Moderate Buy medians, as well as a different count from the US and Germany, but the businesses are evenly dispersed on the AMEX,NASDAQ and NYSE.

Hold and Moderate buy medians are similarly distributed in Cluster 2

the United States and Canada are listed on the NYSE.

Cluster 3 has similar Moderate Buy and Sell medians, but a different count from Cluster.

France, Ireland, and the United States are all listed on the NYSE

Cluster 4 offers Hold, Moderate Buy, Moderate Sell, and Strong Buy options.

The median for the hold is the highest. They are from the United States, the United Kingdom, and Switzerland, and they are listed in NYSE

Cluster 5 has the same hold and mdoerate purchase medians and is spread in

countries UK and US and is also listed in NYSE

```
#Naming clusters
#After performing cluster analysis on the pharmaceutical firms dataset,Assigning  descriptive names to

#Cluster 1 :- Buy Cluster
#Cluster 2 :- Sceptical Cluster
#Cluster 3 :- Moderate Buy Cluster
#Cluster 4 :- Hold Cluster
#Cluster 5 :- High Hold Cluster
```

Question(D) Provide an appropriate name for each cluster using any or all of the variables in the dataset.