k means clustering

Sai Sree Pulimamidi

2022-11-06

```
library(readr)
Pharmaceuticals <- read_csv("C:/users/91773/Desktop/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.

View(Pharmaceuticals)
```

installing 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

library(cluster)
library(tidyverse)

## ── Attaching packages
## ───────────────────────────────────────
## tidyverse 1.3.2 ──

## ✔ tibble  3.1.8      ✔ dplyr   1.0.10
## ✔ tidyr   1.2.1      ✔ stringr 1.4.1
```

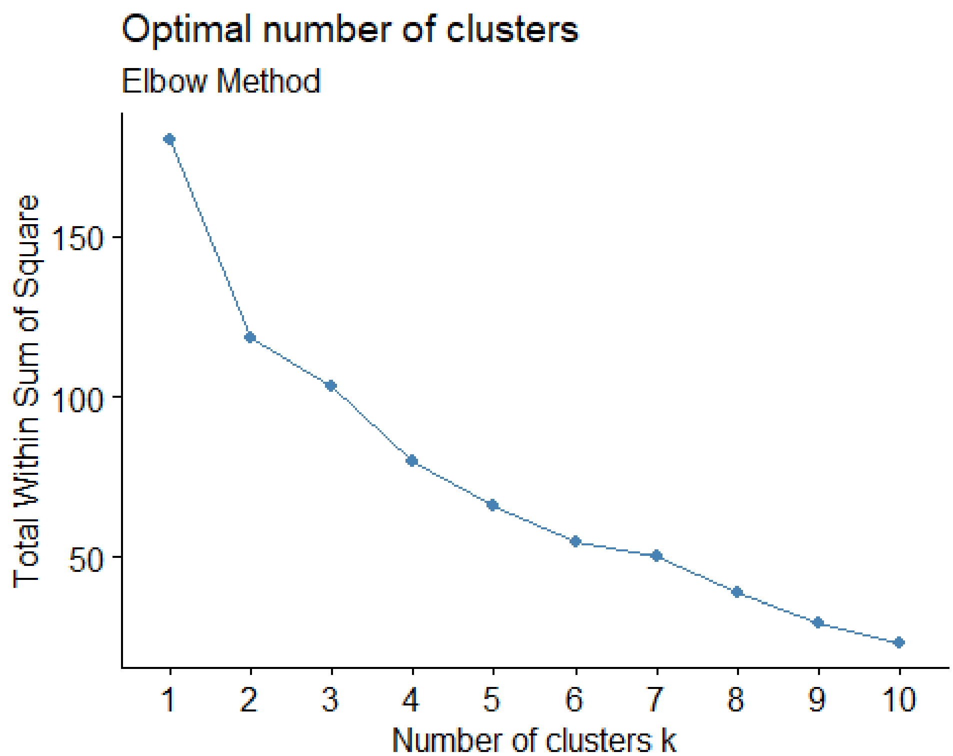
```
## ✓ purrr   0.3.5      ✓ forcats 0.5.2
## ── Conflicts ──────────────────────────────────────────
tidyverse_conflicts() ──
## ✖ dplyr::filter() masks stats::filter()
## ✖ dplyr::lag()    masks stats::lag()

summary(Pharmaceuticals)

##     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
##
##
##

#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 the algorithm(s) used,number of clusters formed, and so on.
R <- na.omit(Pharmaceuticals)
R
```

```
## # A tibble: 21 × 14
##    Symbol Name          Marke…¹  Beta PE_Ra…²   ROE   ROA Asset…³ Lever…⁴
Rev_G…⁵
##    <chr>  <chr>           <dbl> <dbl>   <dbl> <dbl> <dbl>   <dbl>   <dbl>
<dbl>
##  1 ABT    Abbott Labo…   68.4   0.32    24.7  26.4  11.8     0.7    0.42
7.54
##  2 AGN    Allergan, I…    7.58  0.41    82.5  12.9   5.5     0.9    0.6
9.16
##  3 AHM    Amersham plc    6.3   0.46    20.7  14.9   7.8     0.9    0.27
7.05
##  4 AZN    AstraZeneca…   67.6   0.52    21.5  27.4  15.4     0.9    0
15
##  5 AVE    Aventis        47.2   0.32    20.1  21.8   7.5     0.6    0.34
26.8
##  6 BAY    Bayer AG       16.9   1.11    27.9   3.9   1.4     0.6    0
-3.17
##  7 BMY    Bristol-Mye…   51.3   0.5     13.9  34.8  15.1     0.9    0.57
2.7
##  8 CHTT   Chattem, Inc    0.41  0.85    26    24.1   4.3     0.6    3.51
6.38
##  9 ELN    Elan Corpor…    0.78  1.08     3.6  15.1   5.1     0.3    1.07
34.2
## 10 LLY    Eli Lilly a…   73.8   0.18    27.9  31    13.5     0.6    0.53
6.21
## # … with 11 more rows, 4 more variables: Net_Profit_Margin <dbl>,
## #   Median_Recommendation <chr>, Location <chr>, Exchange <chr>, and
## #   abbreviated variable names ¹Market_Cap, ²PE_Ratio, ³Asset_Turnover,
## #   ⁴Leverage, ⁵Rev_Growth
```

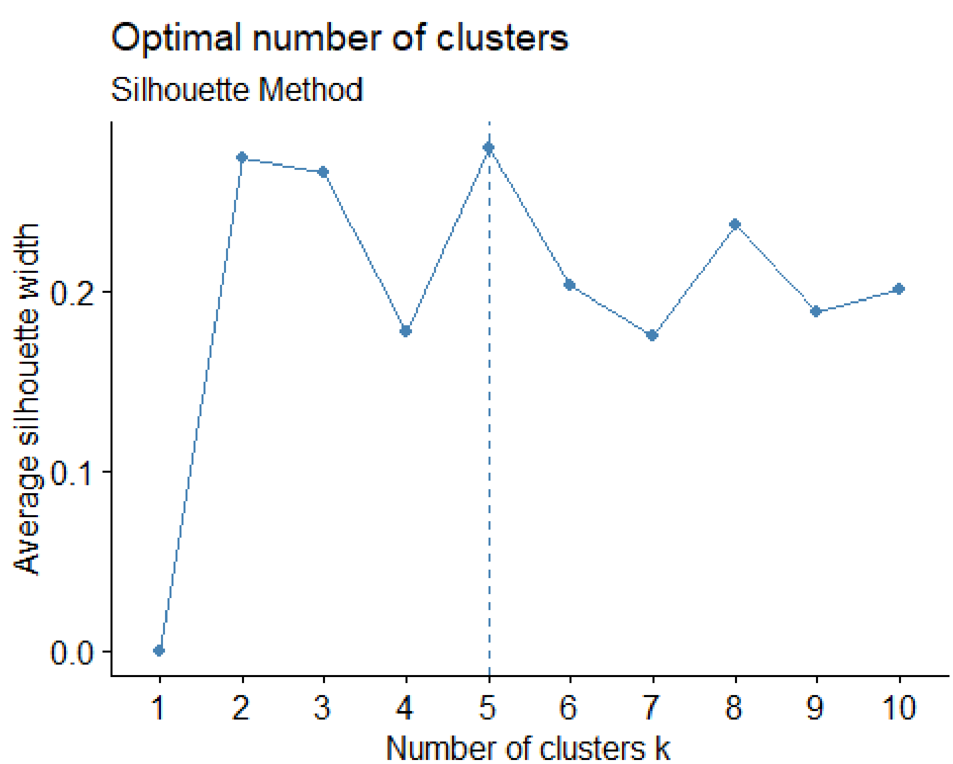
```
row.names <- R[,1]
Pharmaceuticals1 <-  R[,3:11]
head(Pharmaceuticals1)
```

```
## # A tibble: 6 × 9
##   Market_Cap  Beta PE_Ratio   ROE   ROA Asset_Turnover Leverage Rev_Gr…¹
Net_P…²
##        <dbl> <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
16.1
## 2       7.58  0.41     82.5  12.9   5.5            0.9     0.6      9.16
5.5
## 3       6.3   0.46     20.7  14.9   7.8            0.9     0.27     7.05
11.2
## 4      67.6   0.52     21.5  27.4  15.4            0.9     0       15
18
## 5      47.2   0.32     20.1  21.8   7.5            0.6     0.34    26.8
12.9
## 6      16.9   1.11     27.9   3.9   1.4            0.6     0       -3.17
```

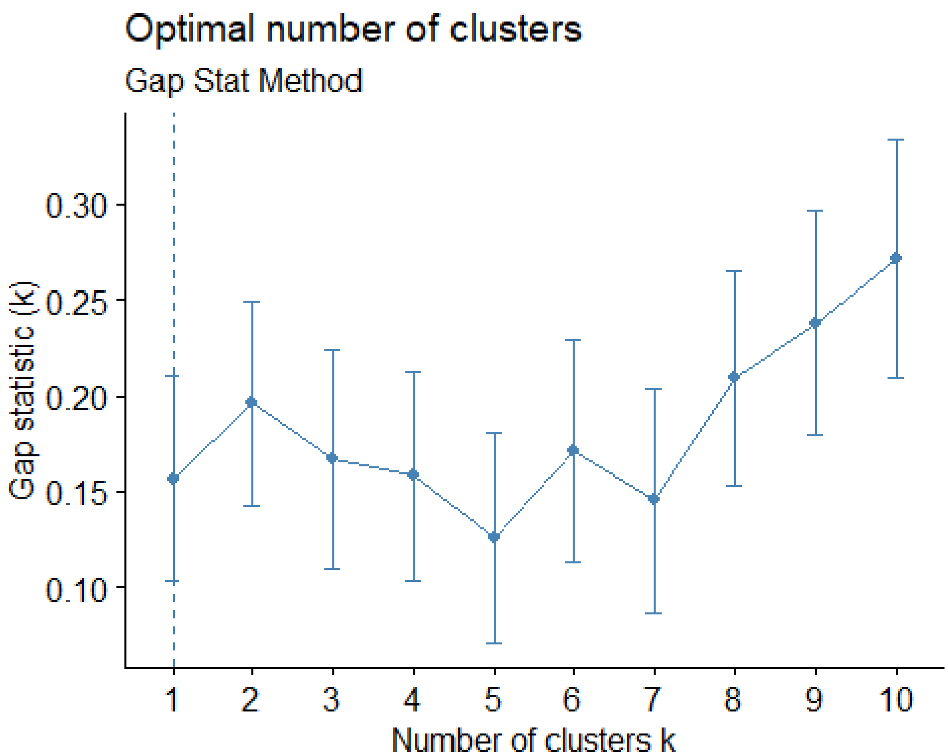
```
2.6
## # … with abbreviated variable names ¹Rev_Growth, ²Net_Profit_Margin

Pharmaceuticals2 <- scale(Pharmaceuticals1)
head(Pharmaceuticals2)

##       Market_Cap        Beta    PE_Ratio         ROE        ROA
Asset_Turnover
## [1,]  0.1840960 -0.80125356 -0.04671323  0.04009035  0.2416121
0.0000000
## [2,] -0.8544181 -0.45070513  3.49706911 -0.85483986 -0.9422871
0.9225312
## [3,] -0.8762600 -0.25595600 -0.29195768 -0.72225761 -0.5100700
0.9225312
## [4,]  0.1702742 -0.02225704 -0.24290879  0.10638147  0.9181259
0.9225312
## [5,] -0.1790256 -0.80125356 -0.32874435 -0.26484883 -0.5664461     -
0.4612656
## [6,] -0.6953818  2.27578267  0.14948233 -1.45146000 -1.7127612     -
0.4612656
##        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

fviz_nbclust(Pharmaceuticals2, kmeans, method = "wss") +
  labs(subtitle = "Elbow Method")
```



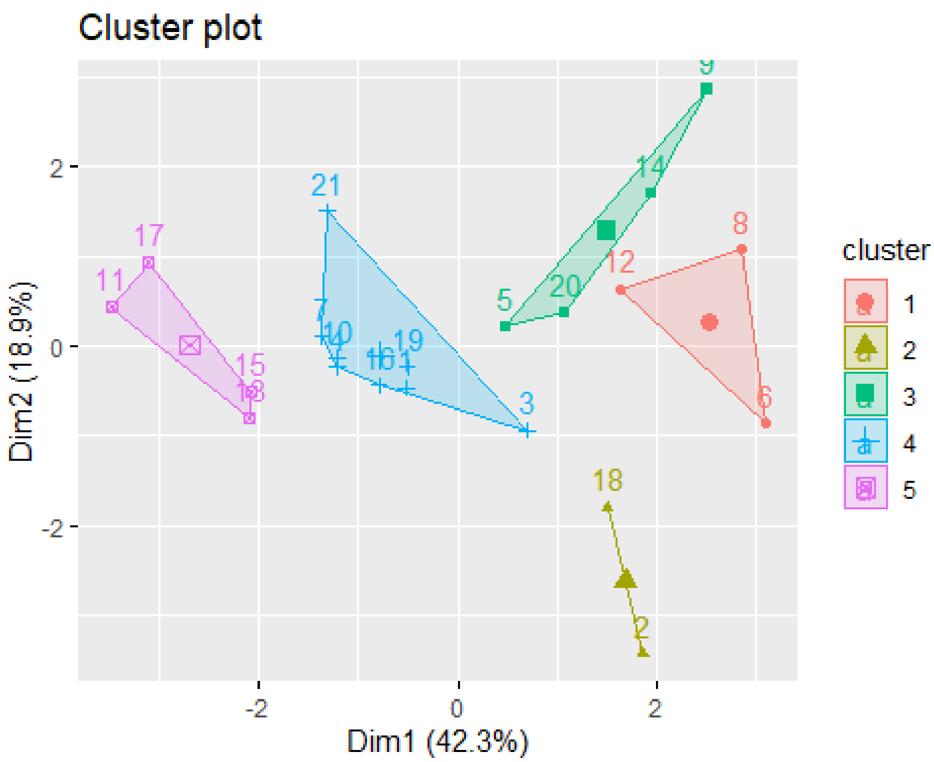

```
fviz_nbclust(Pharmaceuticals2, kmeans, method = "silhouette") + labs(subtitle
= "Silhouette Method")
```



```
fviz_nbclust(Pharmaceuticals2, kmeans, method = "gap_stat") + labs(subtitle =
"Gap Stat Method")
```




```
set.seed(64060)
k5 <- kmeans(Pharmaceuticals2, centers = 5, nstart = 25)
k5 $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, data = Pharmaceuticals2)
```




```
k5

## 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"
```

```
Fitting <- kmeans(Pharmaceuticals2,5)
aggregate(Pharmaceuticals2,by = list(Fitting$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
```

```
Pharmaceuticals3 <- data.frame(Pharmaceuticals2,Fitting$cluster)
Pharmaceuticals3
```

```
##    Market_Cap        Beta    PE_Ratio         ROE        ROA
Asset_Turnover
## 1   0.1840960 -0.80125356 -0.04671323  0.04009035  0.2416121
0.0000000
## 2  -0.8544181 -0.45070513  3.49706911 -0.85483986 -0.9422871
0.9225312
## 3  -0.8762600 -0.25595600 -0.29195768 -0.72225761 -0.5100700
0.9225312
## 4   0.1702742 -0.02225704 -0.24290879  0.10638147  0.9181259
0.9225312
## 5  -0.1790256 -0.80125356 -0.32874435 -0.26484883 -0.5664461     -
0.4612656
## 6  -0.6953818  2.27578267  0.14948233 -1.45146000 -1.7127612     -
0.4612656
## 7  -0.1078688 -0.10015669 -0.70887325  0.59693581  0.8617498
0.9225312
## 8  -0.9767669  1.26308721  0.03299122 -0.11237924 -1.1677918     -
0.4612656
## 9  -0.9704532  2.15893320 -1.34037772 -0.70899938 -1.0174553     -
1.8450624
## 10  0.2762415 -1.34655112  0.14948233  0.34502953  0.5610770     -
0.4612656
## 11  1.0999201 -0.68440408 -0.45749769  2.45971647  1.8389364
1.3837968
## 12 -0.9393967  0.48409069 -0.34100657 -0.29136529 -0.6979905     -
0.4612656
## 13  1.9841758 -0.25595600  0.18013789  0.18593083  1.0872544
0.9225312
```

```
## 14 -0.9632863  0.87358895  0.19240011 -0.96753478 -0.9610792     -
1.8450624
## 15  1.2782387 -0.25595600 -0.40231769  0.98142435  0.8429577
1.8450624
## 16  0.6654710 -1.30760129 -0.23677768 -0.52338423  0.1288598     -
0.9225312
## 17  2.4199899  0.48409069 -0.11415545  1.31287998  1.6322239
0.4612656
## 18 -0.0240846 -0.48965495  1.90298017 -0.81506519 -0.9047030     -
0.4612656
## 19 -0.4018812 -0.06120687 -0.40231769 -0.21181593  0.5234929
0.4612656
## 20 -0.9281345 -1.11285216 -0.43297324 -1.03382590 -0.6979905     -
0.9225312
## 21 -0.1614497  0.40619104 -0.75792214  1.92938746  0.5422849     -
0.4612656
##       Leverage  Rev_Growth Net_Profit_Margin Fitting.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
```

```r
#Task 2

#using cluster formation to interpret the clusters in relation to the
numerical variables.

aggregate(Pharmaceuticals2, by = list(Fitting$cluster), FUN = mean)
```

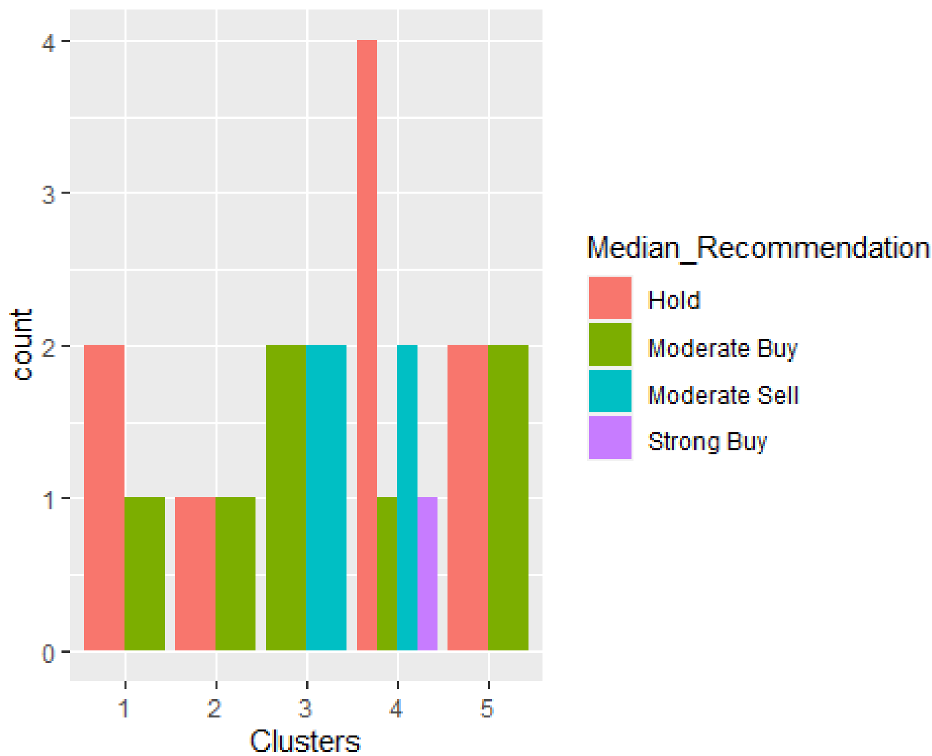
```
##   Group.1  Market_Cap       Beta   PE_Ratio        ROE        ROA
## 1       1  1.69558112 -0.1780563 -0.1984582  1.2349879  1.3503431
## 2       2 -0.66114002 -0.7233539 -0.3512251 -0.6736441 -0.5915022
## 3       3 -0.96247577  1.1949250 -0.3639982 -0.5200697 -0.9610792
```

```
## 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
```

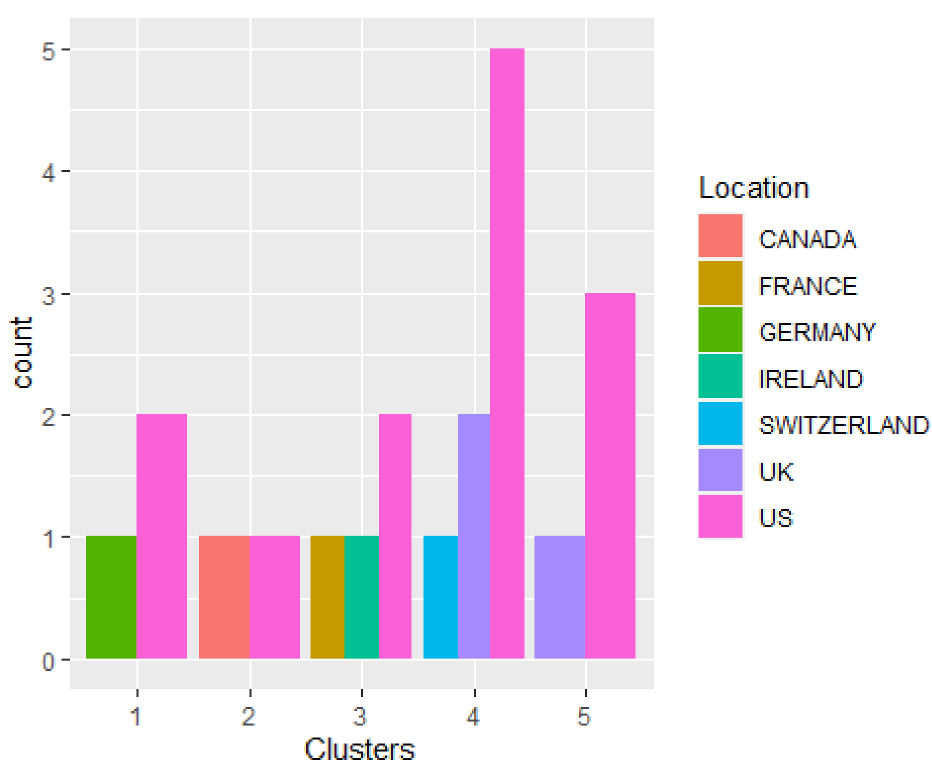
```
Pharmacy <- data.frame(Pharmaceuticals2,k5$cluster)
Pharmacy
```

```
##    Market_Cap        Beta    PE_Ratio         ROE        ROA
Asset_Turnover
## 1   0.1840960 -0.80125356 -0.04671323  0.04009035  0.2416121
0.0000000
## 2  -0.8544181 -0.45070513  3.49706911 -0.85483986 -0.9422871
0.9225312
## 3  -0.8762600 -0.25595600 -0.29195768 -0.72225761 -0.5100700
0.9225312
## 4   0.1702742 -0.02225704 -0.24290879  0.10638147  0.9181259
0.9225312
## 5  -0.1790256 -0.80125356 -0.32874435 -0.26484883 -0.5664461     -
0.4612656
## 6  -0.6953818  2.27578267  0.14948233 -1.45146000 -1.7127612     -
0.4612656
## 7  -0.1078688 -0.10015669 -0.70887325  0.59693581  0.8617498
0.9225312
## 8  -0.9767669  1.26308721  0.03299122 -0.11237924 -1.1677918     -
0.4612656
## 9  -0.9704532  2.15893320 -1.34037772 -0.70899938 -1.0174553     -
1.8450624
## 10  0.2762415 -1.34655112  0.14948233  0.34502953  0.5610770     -
0.4612656
## 11  1.0999201 -0.68440408 -0.45749769  2.45971647  1.8389364
1.3837968
## 12 -0.9393967  0.48409069 -0.34100657 -0.29136529 -0.6979905     -
0.4612656
## 13  1.9841758 -0.25595600  0.18013789  0.18593083  1.0872544
0.9225312
## 14 -0.9632863  0.87358895  0.19240011 -0.96753478 -0.9610792     -
1.8450624
## 15  1.2782387 -0.25595600 -0.40231769  0.98142435  0.8429577
1.8450624
## 16  0.6654710 -1.30760129 -0.23677768 -0.52338423  0.1288598     -
0.9225312
## 17  2.4199899  0.48409069 -0.11415545  1.31287998  1.6322239
0.4612656
## 18 -0.0240846 -0.48965495  1.90298017 -0.81506519 -0.9047030     -
0.4612656
```

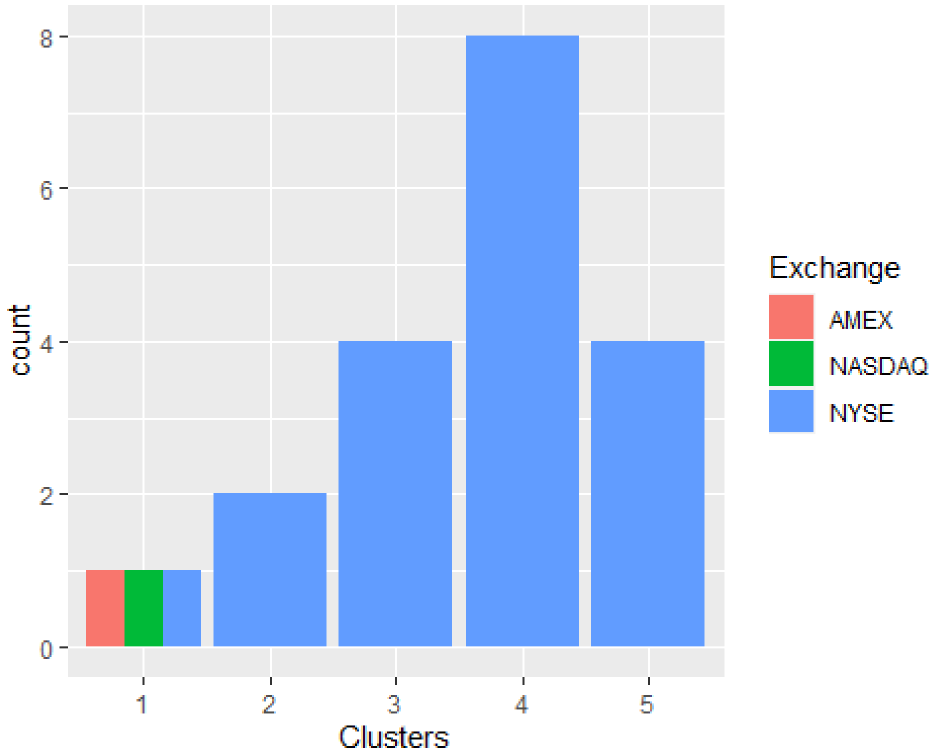
```
## 19 -0.4018812 -0.06120687 -0.40231769 -0.21181593  0.5234929
0.4612656
## 20 -0.9281345 -1.11285216 -0.43297324 -1.03382590 -0.6979905     -
0.9225312
## 21 -0.1614497  0.40619104 -0.75792214  1.92938746  0.5422849     -
0.4612656
##       Leverage  Rev_Growth Net_Profit_Margin k5.cluster
## 1  -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

#CLuster 1:- JNJ, MRK, GSK, PFE
#Cluster 1: Highest Market_Cap and lowest Beta/PE Ratio
#Cluster 2:- AHM, WPI, AVE
#Cluster 2: Highest Revenue Growth and lowest PE/Asset Turnover Ratio
#Cluster 3:- CHTT, IVX, MRX, ELN
#Cluster 3: Highest Beta/leverage/Asset Turnover Ratio and lowest
#Net_Profit_Margin, PE ratio and Market#Cluster
#Cluster 4:- AGN,BAY, PHA
#Cluster 4: Highest PE ratio and lowest Leverage/Asset_Turnover
#Cluster 5:- ABT, WYE, AZN, SGP, BMY, NVS, LLY
#Cluster 5: Highest Net_Proft_Margin and lowest Leverage

#Task3
#Is there a pattern in the clusters with respect to the numerical
#variables (10 to 12)? (those \n #not used in forming the clusters)
RD <- Pharmaceuticals[12:14] %>% mutate(Clusters=k5$cluster)
ggplot(RD, mapping = aes(factor(Clusters), fill
=Median_Recommendation))+geom_bar(position='dodge')+labs(x ='Clusters')
```




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



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




```
#The above graphs indicates that there is a slim pattern in the clusters.

#In Cluster 1,the firms are evenly distributed among AMEX,NASDAQ, and NYSE
despite the fact that cluster 1 has a different Hold and Moderate Buy median,
a different count from the US and Germany, and a distinct nation count.

#In Cluster 2,The medians for the cluster 2 are equally split between "Hold"
and "Moderate Buy," and it is solely listed on the NYSE.

#In Cluster 3,the Moderate Buy and Sell medians for the NYSE-listed are
equal, and it has a separate count for France, Ireland, and the US.

#In Cluster 4, the Hold median is the highest, followed by the Moderate Buy
and Strong Buy medians, and the Hold median. They are listed on the NYSE and
are from the US, the UK, and Switzerland.

#The Cluster 5 is distributed throughout the US and the UK, it is listed on
the NYSE, and it has the same hold and mild buy medians.

#TASK 4
#Provide an appropriate name for each cluster using any or all of the
variables in the dataset.
```

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