# Lab Class 8: PCA Mini Project

Mariam Benny (A17103451)

It's important to consider scaling your data before analysis like PCA.

Example below:

```r
head(mtcars)
```

```
                   mpg cyl disp  hp drat    wt  qsec vs am gear carb
Mazda RX4         21.0   6  160 110 3.90 2.620 16.46  0  1    4    4
Mazda RX4 Wag     21.0   6  160 110 3.90 2.875 17.02  0  1    4    4
Datsun 710        22.8   4  108  93 3.85 2.320 18.61  1  1    4    1
Hornet 4 Drive    21.4   6  258 110 3.08 3.215 19.44  1  0    3    1
Hornet Sportabout 18.7   8  360 175 3.15 3.440 17.02  0  0    3    2
Valiant           18.1   6  225 105 2.76 3.460 20.22  1  0    3    1
```

```r
colMeans(mtcars)
```

```
       mpg        cyl       disp         hp       drat         wt       qsec 
 20.090625   6.187500 230.721875 146.687500   3.596563   3.217250  17.848750 
        vs         am       gear       carb 
  0.437500   0.406250   3.687500   2.812500 
```

```r
apply(mtcars, 2, sd)
```

```
        mpg         cyl        disp          hp        drat          wt 
  6.0269481   1.7859216 123.9386938  68.5628685   0.5346787   0.9784574 
       qsec          vs          am        gear        carb 
  1.7869432   0.5040161   0.4989909   0.7378041   1.6152000 
```

```r
x <- scale(mtcars)
head(x)
```

```
                         mpg        cyl        disp         hp       drat
Mazda RX4          0.1508848 -0.1049878 -0.57061982 -0.5350928  0.5675137
Mazda RX4 Wag      0.1508848 -0.1049878 -0.57061982 -0.5350928  0.5675137
Datsun 710         0.4495434 -1.2248578 -0.99018209 -0.7830405  0.4739996
Hornet 4 Drive     0.2172534 -0.1049878  0.22009369 -0.5350928 -0.9661175
Hornet Sportabout -0.2307345  1.0148821  1.04308123  0.4129422 -0.8351978
Valiant           -0.3302874 -0.1049878 -0.04616698 -0.6080186 -1.5646078
                            wt       qsec         vs         am       gear
Mazda RX4         -0.610399567 -0.7771651 -0.8680278  1.1899014  0.4235542
Mazda RX4 Wag     -0.349785269 -0.4637808 -0.8680278  1.1899014  0.4235542
Datsun 710        -0.917004624  0.4260068  1.1160357  1.1899014  0.4235542
Hornet 4 Drive    -0.002299538  0.8904872  1.1160357 -0.8141431 -0.9318192
Hornet Sportabout  0.227654255 -0.4637808 -0.8680278 -0.8141431 -0.9318192
Valiant            0.248094592  1.3269868  1.1160357 -0.8141431 -0.9318192
                        carb
Mazda RX4          0.7352031
Mazda RX4 Wag      0.7352031
Datsun 710        -1.1221521
Hornet 4 Drive    -1.1221521
Hornet Sportabout -0.5030337
Valiant           -1.1221521
```

```r
round(colMeans(x), 2)
```

```
 mpg  cyl disp   hp drat   wt qsec   vs   am gear carb 
   0    0    0    0    0    0    0    0    0    0    0 
```

Unsupervised Learning Analysis of Human Breast Cancer Cells

```r
fna.data <- "WisconsinCancer.csv"
wisc.df <- read.csv("WisconsinCancer.csv",
                      row.names=1)
head(wisc.df)
```

```
         diagnosis radius_mean texture_mean perimeter_mean area_mean
842302           M       17.99        10.38         122.80    1001.0
842517           M       20.57        17.77         132.90    1326.0
```

```
84300903         M       19.69        21.25         130.00    1203.0
84348301         M       11.42        20.38          77.58     386.1
84358402         M       20.29        14.34         135.10    1297.0
843786           M       12.45        15.70          82.57     477.1
         smoothness_mean compactness_mean concavity_mean concave.points_mean
842302           0.11840          0.27760         0.3001             0.14710
842517           0.08474          0.07864         0.0869             0.07017
84300903         0.10960          0.15990         0.1974             0.12790
84348301         0.14250          0.28390         0.2414             0.10520
84358402         0.10030          0.13280         0.1980             0.10430
843786           0.12780          0.17000         0.1578             0.08089
         symmetry_mean fractal_dimension_mean radius_se texture_se perimeter_se
842302          0.2419                0.07871    1.0950     0.9053        8.589
842517          0.1812                0.05667    0.5435     0.7339        3.398
84300903        0.2069                0.05999    0.7456     0.7869        4.585
84348301        0.2597                0.09744    0.4956     1.1560        3.445
84358402        0.1809                0.05883    0.7572     0.7813        5.438
843786          0.2087                0.07613    0.3345     0.8902        2.217
         area_se smoothness_se compactness_se concavity_se concave.points_se
842302    153.40      0.006399        0.04904      0.05373           0.01587
842517     74.08      0.005225        0.01308      0.01860           0.01340
84300903   94.03      0.006150        0.04006      0.03832           0.02058
84348301   27.23      0.009110        0.07458      0.05661           0.01867
84358402   94.44      0.011490        0.02461      0.05688           0.01885
843786     27.19      0.007510        0.03345      0.03672           0.01137
         symmetry_se fractal_dimension_se radius_worst texture_worst
842302       0.03003             0.006193        25.38         17.33
842517       0.01389             0.003532        24.99         23.41
84300903     0.02250             0.004571        23.57         25.53
84348301     0.05963             0.009208        14.91         26.50
84358402     0.01756             0.005115        22.54         16.67
843786       0.02165             0.005082        15.47         23.75
         perimeter_worst area_worst smoothness_worst compactness_worst
842302            184.60     2019.0           0.1622            0.6656
842517            158.80     1956.0           0.1238            0.1866
84300903          152.50     1709.0           0.1444            0.4245
84348301           98.87      567.7           0.2098            0.8663
84358402          152.20     1575.0           0.1374            0.2050
843786            103.40      741.6           0.1791            0.5249
         concavity_worst concave.points_worst symmetry_worst
842302            0.7119               0.2654         0.4601
842517            0.2416               0.1860         0.2750
84300903          0.4504               0.2430         0.3613
```

```
84348301          0.6869                 0.2575         0.6638
84358402          0.4000                 0.1625         0.2364
843786            0.5355                 0.1741         0.3985
         fractal_dimension_worst
842302                   0.11890
842517                   0.08902
84300903                 0.08758
84348301                 0.17300
84358402                 0.07678
843786                   0.12440
```

```
diagnosis <- wisc.df[,1]
table(diagnosis)
```

```
diagnosis
  B   M
357 212
```

We need to remove the first column as that is the expert diagnosis and we don't want it for our analysis.

```
# We can use -1 here to remove the first column
wisc.data <- wisc.df[,-1]
head(wisc.data)
```

```
         radius_mean texture_mean perimeter_mean area_mean smoothness_mean
842302         17.99        10.38         122.80    1001.0         0.11840
842517         20.57        17.77         132.90    1326.0         0.08474
84300903       19.69        21.25         130.00    1203.0         0.10960
84348301       11.42        20.38          77.58     386.1         0.14250
84358402       20.29        14.34         135.10    1297.0         0.10030
843786         12.45        15.70          82.57     477.1         0.12780
         compactness_mean concavity_mean concave.points_mean symmetry_mean
842302            0.27760         0.3001             0.14710        0.2419
842517            0.07864         0.0869             0.07017        0.1812
84300903          0.15990         0.1974             0.12790        0.2069
84348301          0.28390         0.2414             0.10520        0.2597
84358402          0.13280         0.1980             0.10430        0.1809
843786            0.17000         0.1578             0.08089        0.2087
         fractal_dimension_mean radius_se texture_se perimeter_se area_se
842302                  0.07871    1.0950     0.9053        8.589  153.40
```

| | | | | | |
|---|---|---|---|---|---|
| 842517 | 0.05667 | 0.5435 | 0.7339 | 3.398 | 74.08 |
| 84300903 | 0.05999 | 0.7456 | 0.7869 | 4.585 | 94.03 |
| 84348301 | 0.09744 | 0.4956 | 1.1560 | 3.445 | 27.23 |
| 84358402 | 0.05883 | 0.7572 | 0.7813 | 5.438 | 94.44 |
| 843786 | 0.07613 | 0.3345 | 0.8902 | 2.217 | 27.19 |

| | smoothness_se | compactness_se | concavity_se | concave.points_se |
|---|---|---|---|---|
| 842302 | 0.006399 | 0.04904 | 0.05373 | 0.01587 |
| 842517 | 0.005225 | 0.01308 | 0.01860 | 0.01340 |
| 84300903 | 0.006150 | 0.04006 | 0.03832 | 0.02058 |
| 84348301 | 0.009110 | 0.07458 | 0.05661 | 0.01867 |
| 84358402 | 0.011490 | 0.02461 | 0.05688 | 0.01885 |
| 843786 | 0.007510 | 0.03345 | 0.03672 | 0.01137 |

| | symmetry_se | fractal_dimension_se | radius_worst | texture_worst |
|---|---|---|---|---|
| 842302 | 0.03003 | 0.006193 | 25.38 | 17.33 |
| 842517 | 0.01389 | 0.003532 | 24.99 | 23.41 |
| 84300903 | 0.02250 | 0.004571 | 23.57 | 25.53 |
| 84348301 | 0.05963 | 0.009208 | 14.91 | 26.50 |
| 84358402 | 0.01756 | 0.005115 | 22.54 | 16.67 |
| 843786 | 0.02165 | 0.005082 | 15.47 | 23.75 |

| | perimeter_worst | area_worst | smoothness_worst | compactness_worst |
|---|---|---|---|---|
| 842302 | 184.60 | 2019.0 | 0.1622 | 0.6656 |
| 842517 | 158.80 | 1956.0 | 0.1238 | 0.1866 |
| 84300903 | 152.50 | 1709.0 | 0.1444 | 0.4245 |
| 84348301 | 98.87 | 567.7 | 0.2098 | 0.8663 |
| 84358402 | 152.20 | 1575.0 | 0.1374 | 0.2050 |
| 843786 | 103.40 | 741.6 | 0.1791 | 0.5249 |

| | concavity_worst | concave.points_worst | symmetry_worst |
|---|---|---|---|
| 842302 | 0.7119 | 0.2654 | 0.4601 |
| 842517 | 0.2416 | 0.1860 | 0.2750 |
| 84300903 | 0.4504 | 0.2430 | 0.3613 |
| 84348301 | 0.6869 | 0.2575 | 0.6638 |
| 84358402 | 0.4000 | 0.1625 | 0.2364 |
| 843786 | 0.5355 | 0.1741 | 0.3985 |

| | fractal_dimension_worst |
|---|---|
| 842302 | 0.11890 |
| 842517 | 0.08902 |
| 84300903 | 0.08758 |
| 84348301 | 0.17300 |
| 84358402 | 0.07678 |
| 843786 | 0.12440 |

```r
dim(wisc.df)
```

```
[1] 569  31
```

> Q1. How many observations are in this dataset?

There are 569 observations in this data set.

```r
nrow(wisc.df)
```

```
[1] 569
```

> Q2. How many of the observations have a malignant diagnosis?

212 observations have a malignant diagnosis.

```r
table(diagnosis)
```

```
diagnosis
  B   M 
357 212 
```

> Q3. How many variables/features in the data are suffixed with _mean?

10 features in the data are suffixed with _mean.

```r
length(grep("_mean", colnames(wisc.data)))
```

```
[1] 10
```

### PCA

```r
# Check column means and standard deviations
colMeans(wisc.data)
```

```
           radius_mean            texture_mean          perimeter_mean 
          1.412729e+01            1.928965e+01            9.196903e+01 
             area_mean         smoothness_mean        compactness_mean 
          6.548891e+02            9.636028e-02            1.043410e-01 
        concavity_mean     concave.points_mean           symmetry_mean 
```

```
           8.879932e-02            4.891915e-02            1.811619e-01
 fractal_dimension_mean               radius_se              texture_se
           6.279761e-02            4.051721e-01            1.216853e+00
           perimeter_se                 area_se           smoothness_se
           2.866059e+00            4.033708e+01            7.040979e-03
         compactness_se            concavity_se       concave.points_se
           2.547814e-02            3.189372e-02            1.179614e-02
            symmetry_se    fractal_dimension_se            radius_worst
           2.054230e-02            3.794904e-03            1.626919e+01
          texture_worst         perimeter_worst              area_worst
           2.567722e+01            1.072612e+02            8.805831e+02
       smoothness_worst       compactness_worst         concavity_worst
           1.323686e-01            2.542650e-01            2.721885e-01
   concave.points_worst          symmetry_worst fractal_dimension_worst
           1.146062e-01            2.900756e-01            8.394582e-02
```

```
apply(wisc.data,2,sd)
```

```
            radius_mean            texture_mean          perimeter_mean
           3.524049e+00            4.301036e+00            2.429898e+01
              area_mean         smoothness_mean        compactness_mean
           3.519141e+02            1.406413e-02            5.281276e-02
         concavity_mean     concave.points_mean           symmetry_mean
           7.971981e-02            3.880284e-02            2.741428e-02
 fractal_dimension_mean               radius_se              texture_se
           7.060363e-03            2.773127e-01            5.516484e-01
           perimeter_se                 area_se           smoothness_se
           2.021855e+00            4.549101e+01            3.002518e-03
         compactness_se            concavity_se       concave.points_se
           1.790818e-02            3.018606e-02            6.170285e-03
            symmetry_se    fractal_dimension_se            radius_worst
           8.266372e-03            2.646071e-03            4.833242e+00
          texture_worst         perimeter_worst              area_worst
           6.146258e+00            3.360254e+01            5.693570e+02
       smoothness_worst       compactness_worst         concavity_worst
           2.283243e-02            1.573365e-01            2.086243e-01
   concave.points_worst          symmetry_worst fractal_dimension_worst
           6.573234e-02            6.186747e-02            1.806127e-02
```

```
# Perform PCA on wisc.data by completing the following code
wisc.pr <- prcomp(wisc.data, scale=T)
summary(wisc.pr)
```

```
Importance of components:
                          PC1    PC2     PC3     PC4     PC5     PC6     PC7
Standard deviation     3.6444 2.3857 1.67867 1.40735 1.28403 1.09880 0.82172
Proportion of Variance 0.4427 0.1897 0.09393 0.06602 0.05496 0.04025 0.02251
Cumulative Proportion  0.4427 0.6324 0.72636 0.79239 0.84734 0.88759 0.91010
                           PC8    PC9    PC10   PC11    PC12    PC13    PC14
Standard deviation     0.69037 0.6457 0.59219 0.5421 0.51104 0.49128 0.39624
Proportion of Variance 0.01589 0.0139 0.01169 0.0098 0.00871 0.00805 0.00523
Cumulative Proportion  0.92598 0.9399 0.95157 0.9614 0.97007 0.97812 0.98335
                          PC15    PC16    PC17    PC18    PC19    PC20   PC21
Standard deviation     0.30681 0.28260 0.24372 0.22939 0.22244 0.17652 0.1731
Proportion of Variance 0.00314 0.00266 0.00198 0.00175 0.00165 0.00104 0.0010
Cumulative Proportion  0.98649 0.98915 0.99113 0.99288 0.99453 0.99557 0.9966
                          PC22    PC23   PC24    PC25    PC26    PC27    PC28
Standard deviation     0.16565 0.15602 0.1344 0.12442 0.09043 0.08307 0.03987
Proportion of Variance 0.00091 0.00081 0.0006 0.00052 0.00027 0.00023 0.00005
Cumulative Proportion  0.99749 0.99830 0.9989 0.99942 0.99969 0.99992 0.99997
                          PC29    PC30
Standard deviation     0.02736 0.01153
Proportion of Variance 0.00002 0.00000
Cumulative Proportion  1.00000 1.00000
```

> Q4. From your results, what proportion of the original variance is captured by the first principal components (PC1)?

44.27% of the original variance is captured by PC1.

> Q5. How many principal components (PCs) are required to describe at least 70% of the original variance in the data?

The first three PCs are required to describe at least 70% of the original variance. The cumulative proportion is 72%.

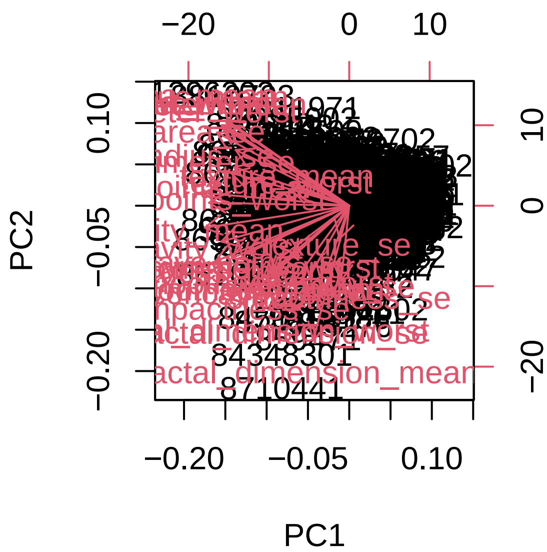
> Q6. How many principal components (PCs) are required to describe at least 90% of the original variance in the data?

The first seven PCs are required to describe at least 90% of the original variance. The cumulative proportion is 91%.

> Q7. What stands out to you about this plot? Is it easy or difficult to understand? Why?

This plot is sort of all over the place and hard to interpret, thus you can't understand the data from this single plot.

```r
biplot(wisc.pr)
```




Main “PC score Plot” and “PC1 vs PC2 plot”

```r
attributes(wisc.pr)
```

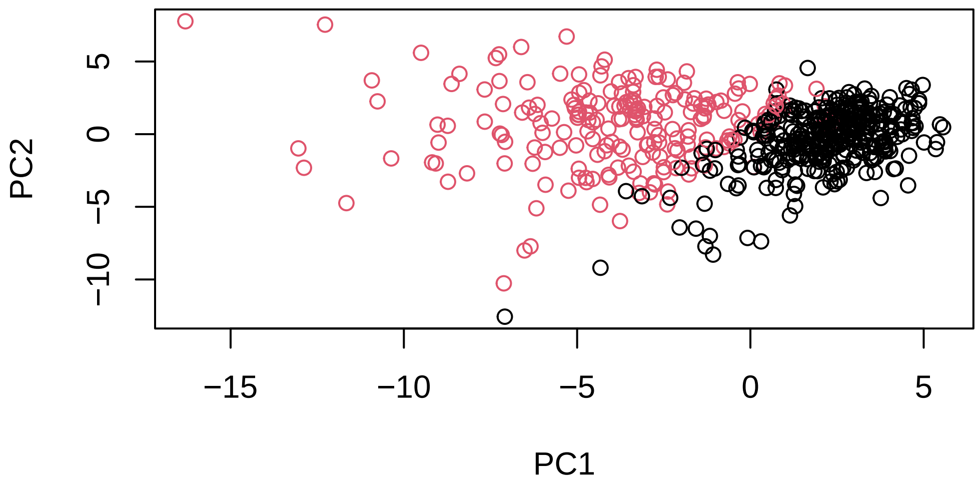
```
$names
[1] "sdev"     "rotation" "center"   "scale"    "x"

$class
[1] "prcomp"
```

```r
head(wisc.pr$x)
```

```
               PC1        PC2        PC3       PC4        PC5         PC6
842302   -9.184755  -1.946870 -1.1221788 3.6305364  1.1940595  1.41018364
842517   -2.385703   3.764859 -0.5288274 1.1172808 -0.6212284  0.02863116
84300903 -5.728855   1.074229 -0.5512625 0.9112808  0.1769302  0.54097615
84348301 -7.116691 -10.266556 -3.2299475 0.1524129  2.9582754  3.05073750
84358402 -3.931842   1.946359  1.3885450 2.9380542 -0.5462667 -1.22541641
843786   -2.378155  -3.946456 -2.9322967 0.9402096  1.0551135 -0.45064213
```

```
                PC7         PC8         PC9       PC10       PC11       PC12
842302    2.15747152  0.39805698 -0.15698023 -0.8766305 -0.2627243 -0.8582593
842517    0.01334635 -0.24077660 -0.71127897  1.1060218 -0.8124048  0.1577838
84300903 -0.66757908 -0.09728813  0.02404449  0.4538760  0.6050715  0.1242777
84348301  1.42865363 -1.05863376 -1.40420412 -1.1159933  1.1505012  1.0104267
84358402 -0.93538950 -0.63581661 -0.26357355  0.3773724 -0.6507870 -0.1104183
843786    0.49001396  0.16529843 -0.13335576 -0.5299649 -0.1096698  0.0813699
               PC13         PC14         PC15        PC16        PC17
842302    0.10329677 -0.690196797  0.601264078  0.74446075 -0.26523740
842517   -0.94269981 -0.652900844 -0.008966977 -0.64823831 -0.01719707
84300903 -0.41026561  0.016665095 -0.482994760  0.32482472  0.19075064
84348301 -0.93245070 -0.486988399  0.168699395  0.05132509  0.48220960
84358402  0.38760691 -0.538706543 -0.310046684 -0.15247165  0.13302526
843786   -0.02625135  0.003133944 -0.178447576 -0.01270566  0.19671335
               PC18       PC19        PC20         PC21        PC22
842302   -0.54907956  0.1336499  0.34526111  0.096430045 -0.06878939
842517    0.31801756 -0.2473470 -0.11403274 -0.077259494  0.09449530
84300903 -0.08789759 -0.3922812 -0.20435242  0.310793246  0.06025601
84348301 -0.03584323 -0.0267241 -0.46432511  0.433811661  0.20308706
84358402 -0.01869779  0.4610302  0.06543782 -0.116442469  0.01763433
843786   -0.29727706 -0.1297265 -0.07117453 -0.002400178  0.10108043
               PC23         PC24         PC25         PC26        PC27
842302    0.08444429  0.175102213  0.150887294 -0.201326305 -0.25236294
842517   -0.21752666 -0.011280193  0.170360355 -0.041092627  0.18111081
84300903 -0.07422581 -0.102671419 -0.171007656  0.004731249  0.04952586
84348301 -0.12399554 -0.153294780 -0.077427574 -0.274982822  0.18330078
84358402  0.13933105  0.005327110 -0.003059371  0.039219780  0.03213957
843786    0.03344819 -0.002837749 -0.122282765 -0.030272333 -0.08438081
                 PC28         PC29          PC30
842302   -0.0338846387  0.045607590  0.0471277407
842517    0.0325955021 -0.005682424  0.0018662342
84300903  0.0469844833  0.003143131 -0.0007498749
84348301  0.0424469831 -0.069233868  0.0199198881
84358402 -0.0347556386  0.005033481 -0.0211951203
843786    0.0007296587 -0.019703996 -0.0034564331
```

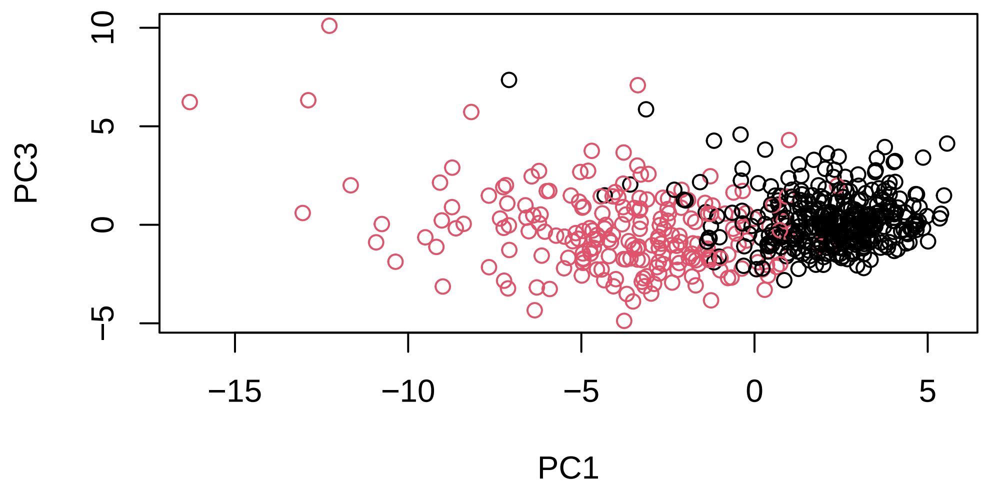
```
plot(wisc.pr$x[,1], wisc.pr$x[,2], col=as.factor(diagnosis), xlab = "PC1", ylab = "PC2")
```




Q8. Generate a similar plot for principal components 1 and 3. What do you notice about these plots?

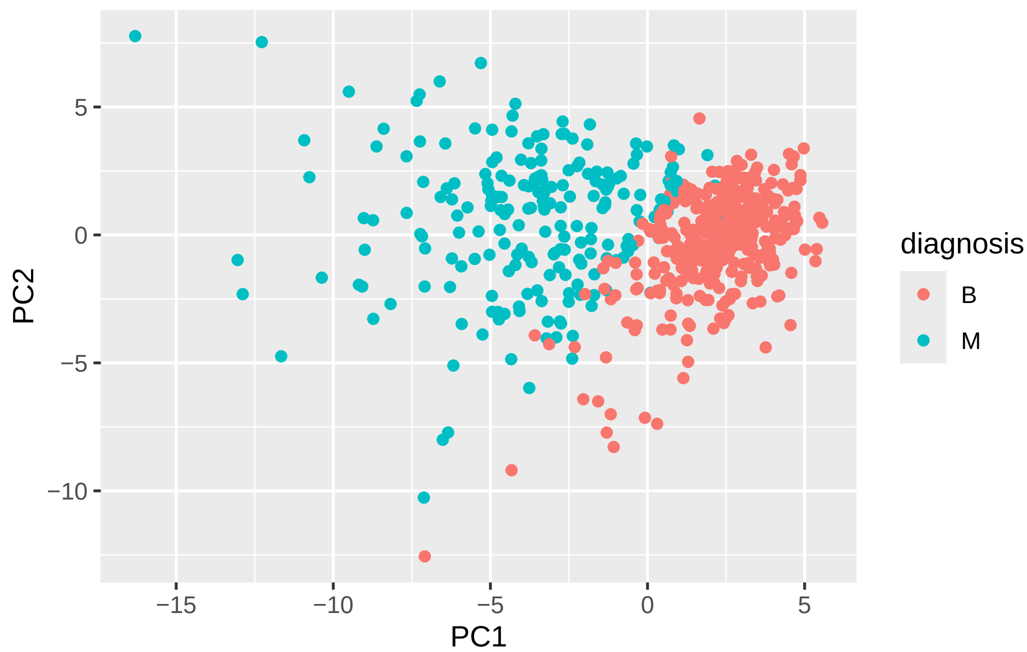
These plots have a clear separation between the malignant and benign pieces of data shown in red and black. The points are more closer together than in the ones in the previous plot.

```
plot(wisc.pr$x[,1], wisc.pr$x[,3],col =as.factor(diagnosis),
xlab = "PC1", ylab = "PC3")
```




```
library(ggplot2)
```

```
# Create a data.frame for ggplot
df <- as.data.frame(wisc.pr$x)
df$diagnosis <- diagnosis
# Load the ggplot2 package
library(ggplot2)
# Make a scatter plot colored by diagnosis
ggplot(df) +
aes(PC1, PC2, col=diagnosis) +
geom_point()
```

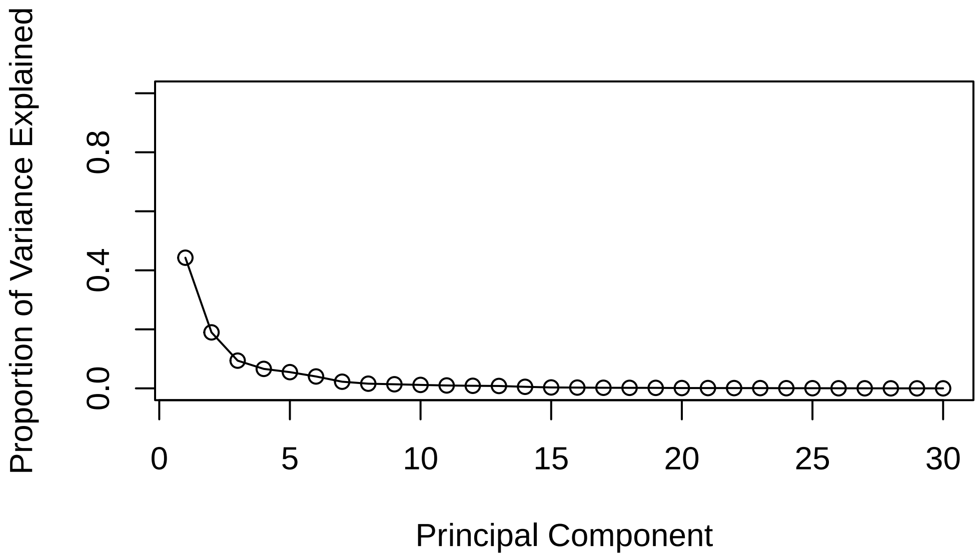



The Blue dots are malignant and the Red dots are benign.

```
# Calculate variance of each component
pr.var <- wisc.pr$sdev^2
head(pr.var)
```

```
[1] 13.281608  5.691355  2.817949  1.980640  1.648731  1.207357
```

```
# Variance explained by each principal component: pve
pve <- pr.var / sum(pr.var)
# Plot variance explained for each principal component
plot(pve, xlab = "Principal Component",
ylab = "Proportion of Variance Explained",
ylim = c(0, 1), type = "o")
```




> Q9. For the first principal component, what is the component of the loading vector (i.e. wisc.pr$rotation[,1]) for the feature concave.points_mean?

The first PC loading vector has a concave.points_mean value of -0.26, indicating the extent to which this variable influences the position in the first principal component.

```r
concave.points_mean <- wisc.pr$rotation[,1]
concave.points_mean
```

```
            radius_mean            texture_mean          perimeter_mean
            -0.21890244             -0.10372458             -0.22753729
              area_mean         smoothness_mean        compactness_mean
            -0.22099499             -0.14258969             -0.23928535
         concavity_mean     concave.points_mean           symmetry_mean
            -0.25840048             -0.26085376             -0.13816696
 fractal_dimension_mean               radius_se              texture_se
            -0.06436335             -0.20597878             -0.01742803
           perimeter_se                 area_se           smoothness_se
            -0.21132592             -0.20286964             -0.01453145
         compactness_se            concavity_se       concave.points_se
            -0.17039345             -0.15358979             -0.18341740
            symmetry_se    fractal_dimension_se            radius_worst
            -0.04249842             -0.10256832             -0.22799663
```

```
         texture_worst         perimeter_worst              area_worst 
           -0.10446933             -0.23663968             -0.22487053 
     smoothness_worst       compactness_worst         concavity_worst 
           -0.12795256             -0.21009588             -0.22876753 
  concave.points_worst          symmetry_worst fractal_dimension_worst 
           -0.25088597             -0.12290456             -0.13178394 
```

> Q10. What is the minimum number of principal components required to explain 80% of the variance of the data?

The minimum number of PCs required to explain 80% of variance is 5 which was derived from the data table we generated above. The cumulative variance is 84% at PC5.

```r
# Scale the wisc.data data using the "scale()" function
data.scaled <- scale(wisc.data)
```

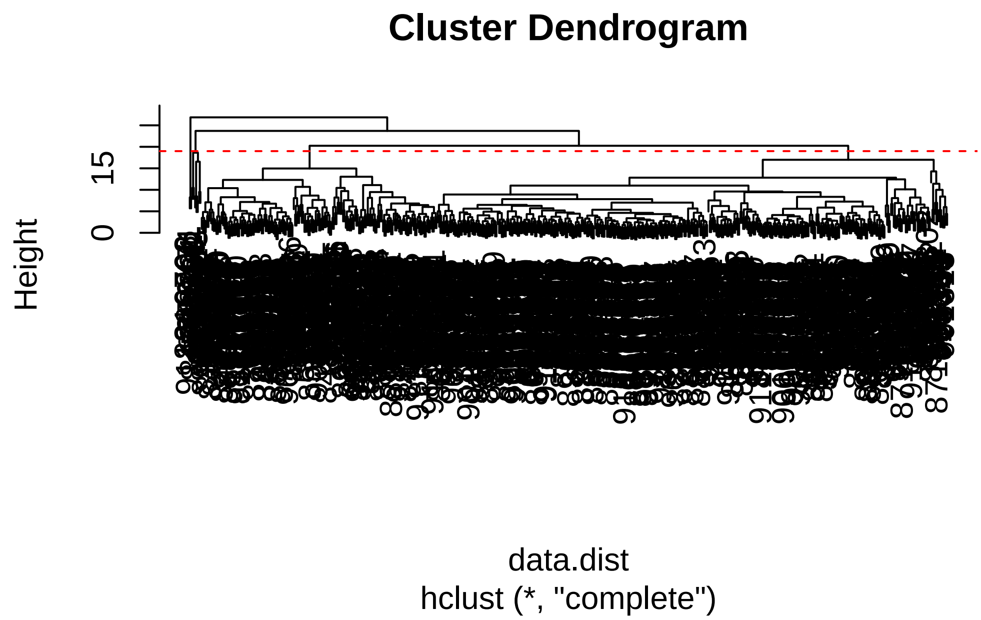
```r
data.dist <- dist(data.scaled)
```

```r
wisc.hclust <- hclust(data.dist, method = "complete")
```

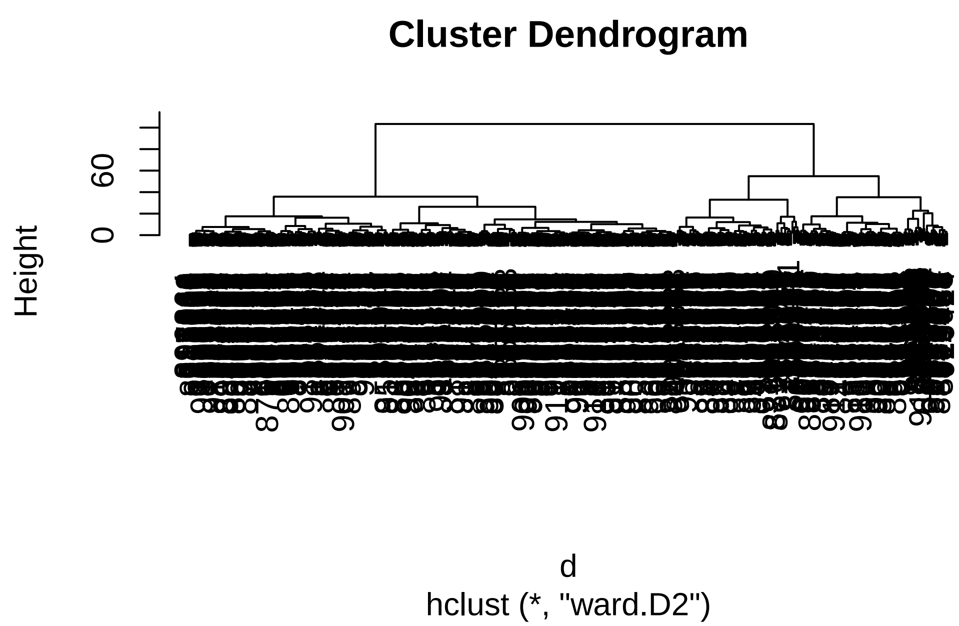
> Q11. Using the plot() and abline() functions, what is the height at which the clustering model has 4 clusters?

The height at which the clustering model has 4 clusters is at h=19.

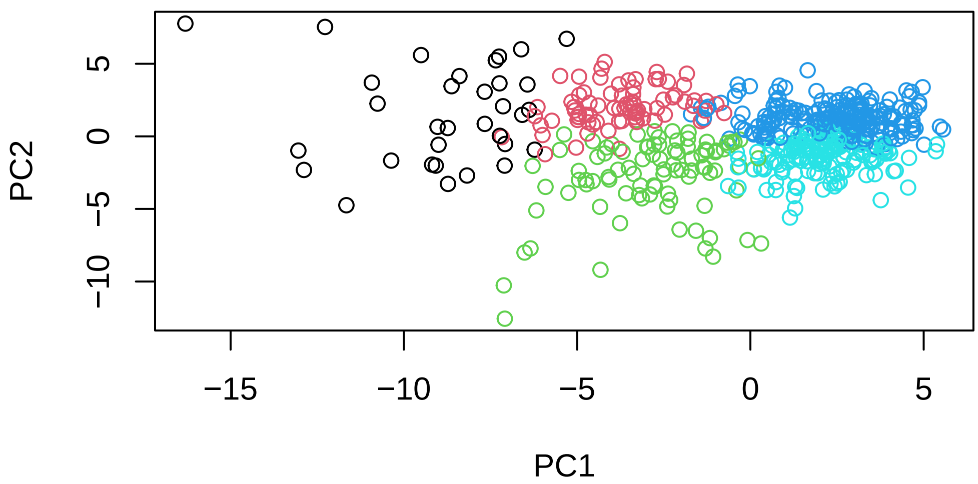
```r
plot(wisc.hclust)
abline(h=19, col="red", lty=2)
```




```r
d <- dist(wisc.pr$x[,1:3])
hc <- hclust(d, method="ward.D2")
plot(hc)
```



```r
grps <- cutree(hc, k=5)
plot(wisc.pr$x, col=grps)
```




```r
table(grps)
```

```
grps
  1   2   3   4   5 
 33  78  92 216 150 
```

```r
table(diagnosis, grps)
```

```
         grps
diagnosis   1   2   3   4   5
        B   0   0  24 184 149
        M  33  78  68  32   1
```

> Q12. Can you find a better cluster vs diagnoses match by cutting into a different number of clusters between 2 and 10?

By setting k=5, I observed an improved alignment between clusters and diagnoses in the graph, suggesting a better clustering match

```r
wisc.hclust.clusters <- cutree(wisc.hclust, k=4)
wisc.hclust.clusters
```

```
   842302    842517  84300903  84348301  84358402    843786    844359  84458202 
        1         1         1         2         1         1         1         1 
   844981  84501001    845636  84610002    846226    846381  84667401  84799002 
        1         2         3         1         1         3         1         1 
   848406  84862001    849014   8510426   8510653   8510824   8511133    851509 
        3         1         1         3         3         3         1         1 
   852552    852631    852763    852781    852973    853201    853401    853612 
        1         1         1         1         1         3         1         1 
 85382601    854002    854039    854253    854268    854941    855133    855138 
        1         1         1         1         1         3         3         1 
   855167    855563    855625    856106  85638502    857010  85713702     85715 
        3         1         1         1         1         1         3         1 
   857155    857156    857343    857373    857374    857392    857438  85759902 
        3         3         3         3         3         1         3         3 
   857637    857793    857810    858477    858970    858981    858986    859196 
        1         1         3         3         3         3         1         3 
 85922302    859283    859464    859465    859471    859487    859575    859711 
        1         1         3         3         2         3         1         3 
   859717    859983   8610175   8610404   8610629   8610637   8610862   8610908 
        1         1         3         3         3         1         2         3 
   861103   8611161   8611555   8611792   8612080   8612399  86135501  86135502 
        3         1         1         1         3         1         3         1 
   861597    861598    861648    861799    861853    862009    862028     86208 
        3         1         3         3         3         3         1         1 
    86211    862261    862485    862548    862717    862722    862965    862980 
        3         3         3         3         3         3         3         3 
   862989    863030    863031    863270     86355    864018    864033     86408 
        3         1         1         3         1         3         3         3 
    86409    864292    864496    864685    864726    864729    864877    865128 
        3         3         3         3         3         1         1         3 
   865137     86517    865423    865432    865468     86561    866083    866203 
        3         1         2         3         3         3         1         3 
   866458    866674    866714      8670  86730502    867387    867739    868202 
        1         1         3         1         1         3         1         3 
   868223    868682    868826    868871    868999    869104    869218    869224 
        3         3         1         3         3         3         3         3 
   869254    869476    869691  86973701  86973702    869931 871001501 871001502 
        3         3         1         3         3         3         3         3 
  8710441     87106   8711002   8711003   8711202   8711216    871122    871149 
```

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 2 | 3 | 3 | 3 | 1 | 3 | 3 | 3 |
| 8711561 | 8711803 | 871201 | 8712064 | 8712289 | 8712291 | 87127 | 8712729 |
| 3 | 1 | 1 | 3 | 1 | 3 | 3 | 3 |
| 8712766 | 8712853 | 87139402 | 87163 | 87164 | 871641 | 871642 | 872113 |
| 1 | 3 | 3 | 3 | 1 | 3 | 3 | 3 |
| 872608 | 87281702 | 873357 | 873586 | 873592 | 873593 | 873701 | 873843 |
| 3 | 1 | 3 | 3 | 1 | 1 | 1 | 3 |
| 873885 | 874158 | 874217 | 874373 | 874662 | 874839 | 874858 | 875093 |
| 1 | 3 | 3 | 3 | 3 | 3 | 2 | 3 |
| 875099 | 875263 | 87556202 | 875878 | 875938 | 877159 | 877486 | 877500 |
| 3 | 1 | 1 | 3 | 1 | 3 | 1 | 1 |
| 877501 | 877989 | 878796 | 87880 | 87930 | 879523 | 879804 | 879830 |
| 3 | 3 | 1 | 1 | 3 | 3 | 3 | 3 |
| 8810158 | 8810436 | 881046502 | 8810528 | 8810703 | 881094802 | 8810955 | 8810987 |
| 1 | 3 | 1 | 3 | 4 | 3 | 1 | 1 |
| 8811523 | 8811779 | 8811842 | 88119002 | 8812816 | 8812818 | 8812844 | 8812877 |
| 3 | 3 | 1 | 1 | 3 | 3 | 3 | 1 |
| 8813129 | 88143502 | 88147101 | 88147102 | 88147202 | 881861 | 881972 | 88199202 |
| 3 | 3 | 3 | 3 | 3 | 1 | 1 | 3 |
| 88203002 | 88206102 | 882488 | 88249602 | 88299702 | 883263 | 883270 | 88330202 |
| 3 | 1 | 3 | 3 | 1 | 1 | 3 | 1 |
| 88350402 | 883539 | 883852 | 88411702 | 884180 | 884437 | 884448 | 884626 |
| 3 | 3 | 3 | 3 | 1 | 3 | 3 | 3 |
| 88466802 | 884689 | 884948 | 88518501 | 885429 | 8860702 | 886226 | 886452 |
| 3 | 3 | 1 | 3 | 1 | 3 | 1 | 3 |
| 88649001 | 886776 | 887181 | 88725602 | 887549 | 888264 | 888570 | 889403 |
| 1 | 1 | 1 | 1 | 1 | 3 | 1 | 3 |
| 889719 | 88995002 | 8910251 | 8910499 | 8910506 | 8910720 | 8910721 | 8910748 |
| 1 | 1 | 3 | 3 | 3 | 3 | 3 | 3 |
| 8910988 | 8910996 | 8911163 | 8911164 | 8911230 | 8911670 | 8911800 | 8911834 |
| 1 | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
| 8912049 | 8912055 | 89122 | 8912280 | 8912284 | 8912521 | 8912909 | 8913 |
| 1 | 3 | 1 | 1 | 3 | 3 | 3 | 3 |
| 8913049 | 89143601 | 89143602 | 8915 | 891670 | 891703 | 891716 | 891923 |
| 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
| 891936 | 892189 | 892214 | 892399 | 892438 | 892604 | 89263202 | 892657 |
| 3 | 3 | 3 | 3 | 1 | 3 | 1 | 3 |
| 89296 | 893061 | 89344 | 89346 | 893526 | 893548 | 893783 | 89382601 |
| 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
| 89382602 | 893988 | 894047 | 894089 | 894090 | 894326 | 894329 | 894335 |
| 3 | 3 | 3 | 3 | 3 | 1 | 3 | 3 |
| 894604 | 894618 | 894855 | 895100 | 89511501 | 89511502 | 89524 | 895299 |
| 3 | 3 | 3 | 1 | 3 | 3 | 3 | 3 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 8953902 | 895633 | 896839 | 896864 | 897132 | 897137 | 897374 | 89742801 |
| 1 | 1 | 1 | 1 | 3 | 3 | 3 | 1 |
| 897604 | 897630 | 897880 | 89812 | 89813 | 898143 | 89827 | 898431 |
| 3 | 1 | 3 | 1 | 3 | 3 | 3 | 1 |
| 89864002 | 898677 | 898678 | 89869 | 898690 | 899147 | 899187 | 899667 |
| 3 | 3 | 3 | 3 | 3 | 3 | 3 | 1 |
| 899987 | 9010018 | 901011 | 9010258 | 9010259 | 901028 | 9010333 | 901034301 |
| 1 | 1 | 3 | 3 | 3 | 3 | 3 | 3 |
| 901034302 | 901041 | 9010598 | 9010872 | 9010877 | 901088 | 9011494 | 9011495 |
| 3 | 3 | 3 | 3 | 3 | 1 | 1 | 3 |
| 9011971 | 9012000 | 9012315 | 9012568 | 9012795 | 901288 | 9013005 | 901303 |
| 1 | 1 | 1 | 3 | 1 | 1 | 3 | 3 |
| 901315 | 9013579 | 9013594 | 9013838 | 901549 | 901836 | 90250 | 90251 |
| 3 | 3 | 3 | 1 | 3 | 3 | 3 | 3 |
| 902727 | 90291 | 902975 | 902976 | 903011 | 90312 | 90317302 | 903483 |
| 3 | 3 | 3 | 3 | 3 | 1 | 3 | 3 |
| 903507 | 903516 | 903554 | 903811 | 90401601 | 90401602 | 904302 | 904357 |
| 1 | 1 | 3 | 3 | 3 | 3 | 3 | 3 |
| 90439701 | 904647 | 904689 | 9047 | 904969 | 904971 | 905189 | 905190 |
| 1 | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
| 90524101 | 905501 | 905502 | 905520 | 905539 | 905557 | 905680 | 905686 |
| 1 | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
| 905978 | 90602302 | 906024 | 906290 | 906539 | 906564 | 906616 | 906878 |
| 3 | 1 | 3 | 3 | 3 | 1 | 3 | 3 |
| 907145 | 907367 | 907409 | 90745 | 90769601 | 90769602 | 907914 | 907915 |
| 3 | 3 | 3 | 3 | 3 | 3 | 1 | 3 |
| 908194 | 908445 | 908469 | 908489 | 908916 | 909220 | 909231 | 909410 |
| 1 | 1 | 3 | 1 | 3 | 3 | 3 | 3 |
| 909411 | 909445 | 90944601 | 909777 | 9110127 | 9110720 | 9110732 | 9110944 |
| 3 | 3 | 3 | 3 | 3 | 3 | 1 | 3 |
| 911150 | 911157302 | 9111596 | 9111805 | 9111843 | 911201 | 911202 | 9112085 |
| 3 | 1 | 3 | 1 | 3 | 3 | 3 | 3 |
| 9112366 | 9112367 | 9112594 | 9112712 | 911296201 | 911296202 | 9113156 | 911320501 |
| 3 | 3 | 3 | 3 | 1 | 4 | 3 | 3 |
| 911320502 | 9113239 | 9113455 | 9113514 | 9113538 | 911366 | 9113778 | 9113816 |
| 3 | 3 | 3 | 3 | 1 | 1 | 3 | 3 |
| 911384 | 9113846 | 911391 | 911408 | 911654 | 911673 | 911685 | 911916 |
| 3 | 3 | 3 | 3 | 3 | 3 | 3 | 1 |
| 912193 | 91227 | 912519 | 912558 | 912600 | 913063 | 913102 | 913505 |
| 3 | 3 | 3 | 3 | 3 | 3 | 3 | 1 |
| 913512 | 913535 | 91376701 | 91376702 | 914062 | 914101 | 914102 | 914333 |
| 3 | 3 | 3 | 3 | 1 | 3 | 3 | 3 |
| 914366 | 914580 | 914769 | 91485 | 914862 | 91504 | 91505 | 915143 |

```
       1          3          1          1          3          1          3          1
  915186     915276   91544001   91544002     915452     915460      91550     915664
       3          3          3          3          3          1          3          3
  915691     915940   91594602     916221     916799     916838     917062     917080
       1          3          3          3          1          1          3          3
  917092   91762702      91789     917896     917897      91805   91813701   91813702
       3          1          3          3          3          3          1          3
  918192     918465      91858   91903901   91903902   91930402     919537     919555
       3          3          3          3          3          1          3          1
91979701     919812     921092     921362     921385     921386     921644     922296
       3          1          3          3          3          1          3          3
  922297     922576     922577     922840     923169     923465     923748     923780
       3          3          3          3          3          3          3          3
  924084     924342     924632     924934     924964     925236     925277     925291
       3          3          3          3          3          3          3          3
  925292     925311     925622     926125     926424     926682     926954     927241
       3          3          1          1          1          1          3          1
   92751
       3
```

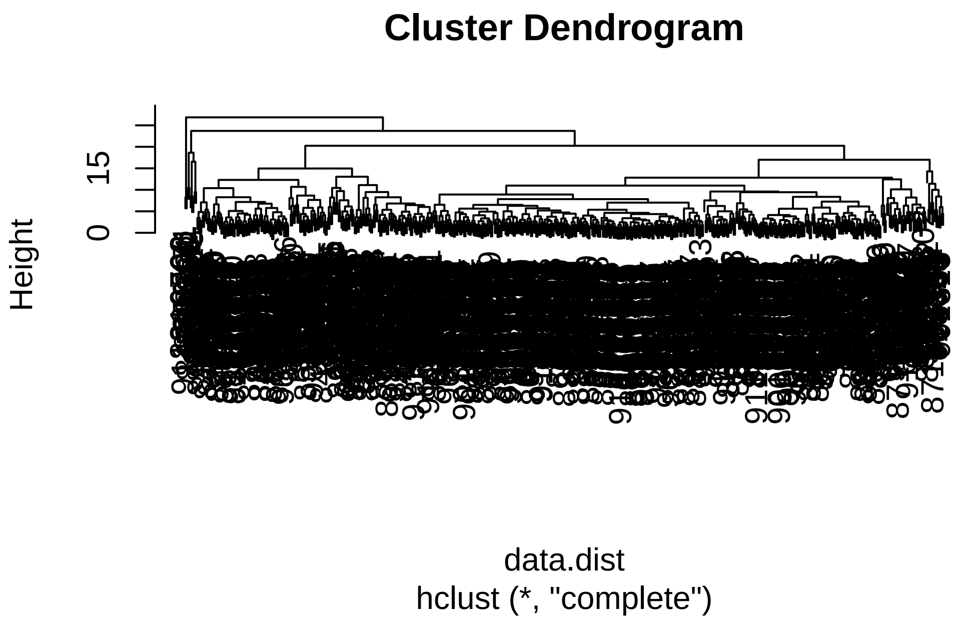
```r
table(wisc.hclust.clusters, diagnosis)
```

```
                    diagnosis
wisc.hclust.clusters   B   M
                   1  12 165
                   2   2   5
                   3 343  40
                   4   0   2
```

> Q13. Which method gives your favorite results for the same data.dist dataset? Explain your reasoning.

I like the "complete" method because it emphasizes connections among all observations in each cluster by considering the furthest distances within them. This approach offers a broad perspective on the most distinct values throughout the data, giving a clearer sense of group separation.

```r
hc.complete <- hclust(data.dist, method="complete")
plot(hc.complete)
```




```r
wisc.km <- kmeans(wisc.data, centers= 2, nstart= 20)
```

```r
table(wisc.km$cluster, diagnosis)
```

```
   diagnosis
      B   M
  1 356  82
  2   1 130
```

> Q14. How well does k-means separate the two diagnoses? How does it compare to your hclust results?

The k-means method divides the two diagnoses clearly into two groups, making it straightforward to interpret the sample data. This approach is more simple and better to interpret compared to the complex structure of the hclust data tables.