Lab 8: PCA Mini Project

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It is important to consider scalling your data before analysis such as PCA.

For example:

```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
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 
```

Remove the first column `diagnosis` bc it is essentially the "answer" to the question which cell samples are malignant or benign.

```
# 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 dataset.

```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?

10features 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
```

```r
# 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 (cumulative proportion=72%).

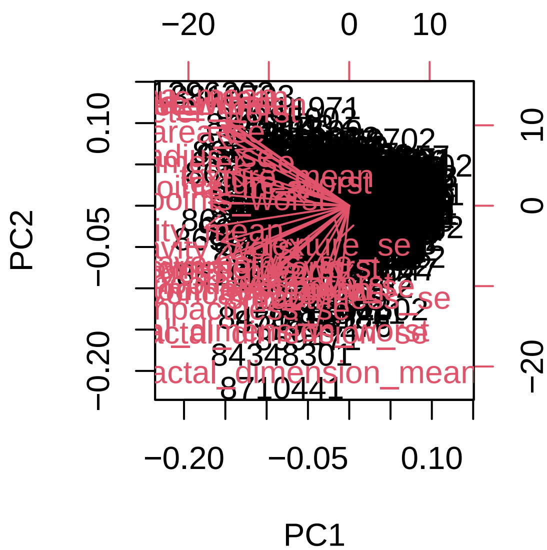
> Q6. How many principal components (PCs) are required to describe at least 90% of the original variance in the data?

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

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

This plot is very messy and hard to understand. Not much can be intrepreted from this plot alone.

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



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

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

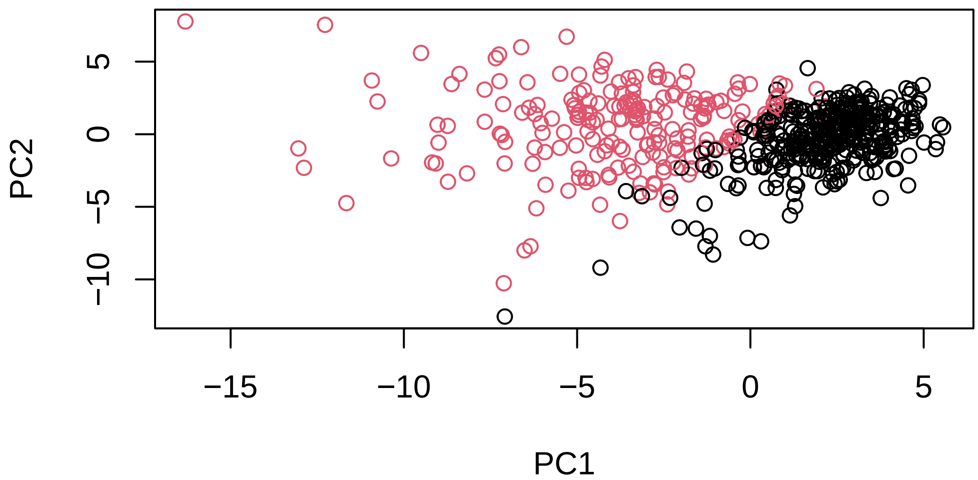
```
$names
[1] "sdev"     "rotation" "center"   "scale"    "x"

$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
```

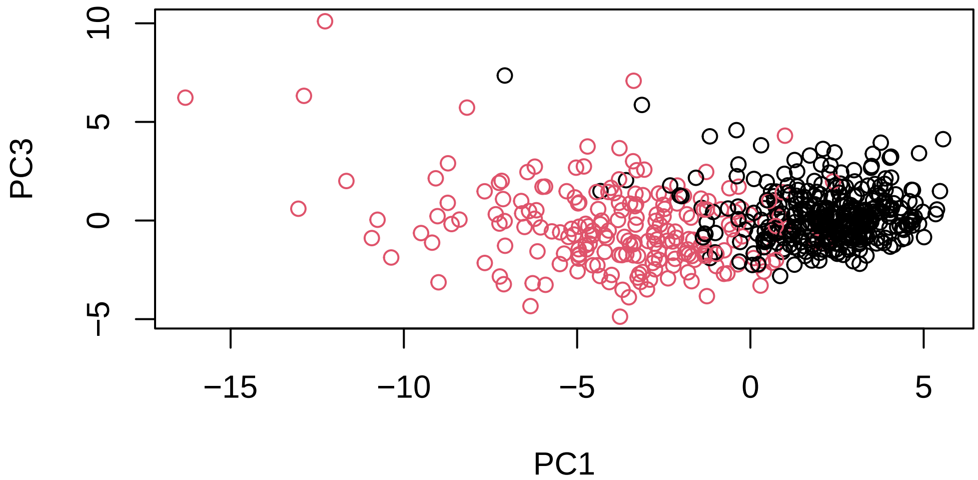
```
plot(wisc.pr$x[,1], wisc.pr$x[,2], col=as.factor(diagnosis), xlab = "PC1", ylab = "PC2")
```



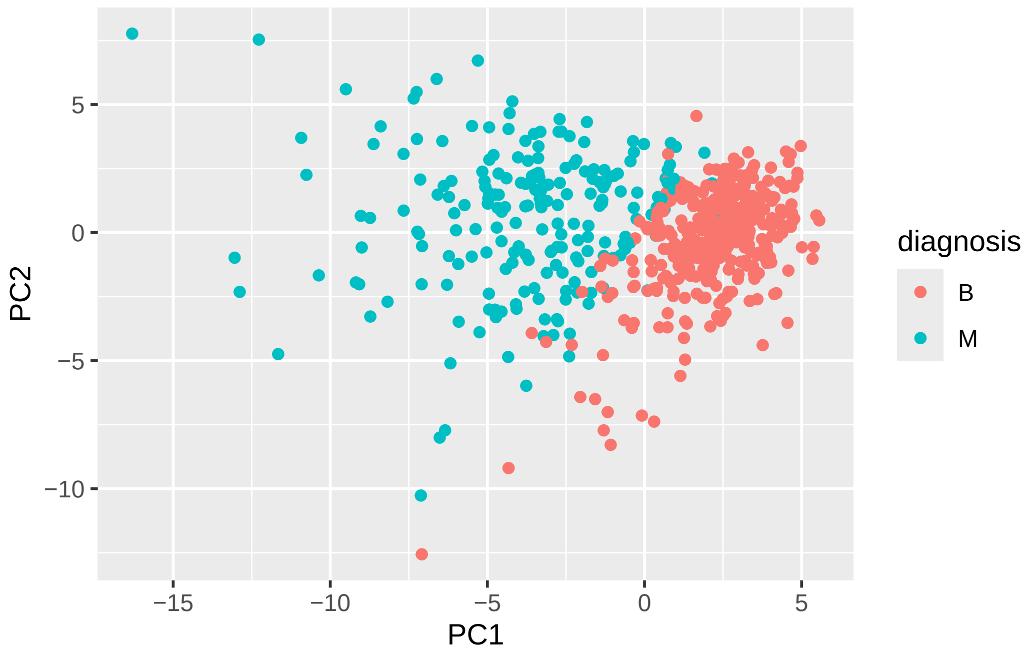
> Q8. Generate a similar plot for principal components 1 and 3. What do you notice about these plots?

These plots have a distinguishable separation between the malignant and benign observations seen in red and black. These points are slightly closer together than the ones in the previous plot.

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




```
# 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()
```

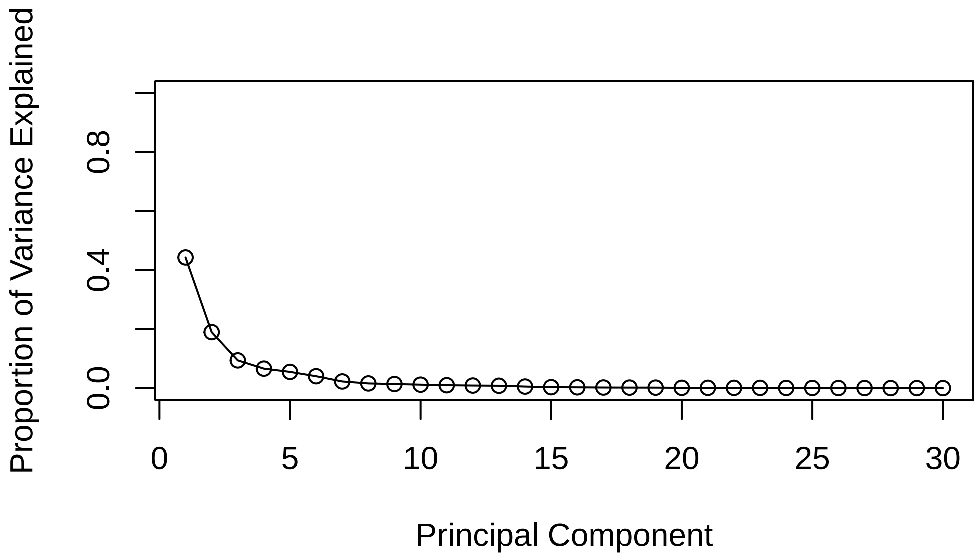


Blue = malignant , Red = benign

```
# 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 concave.points_mean for the first PC loading vector is -0.26. This loading vector explains how much this variable affects that position in the first PC.

```
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% os variance is 5 as seen from the data table we generated previously (cumulative variance=84% at PC5).

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

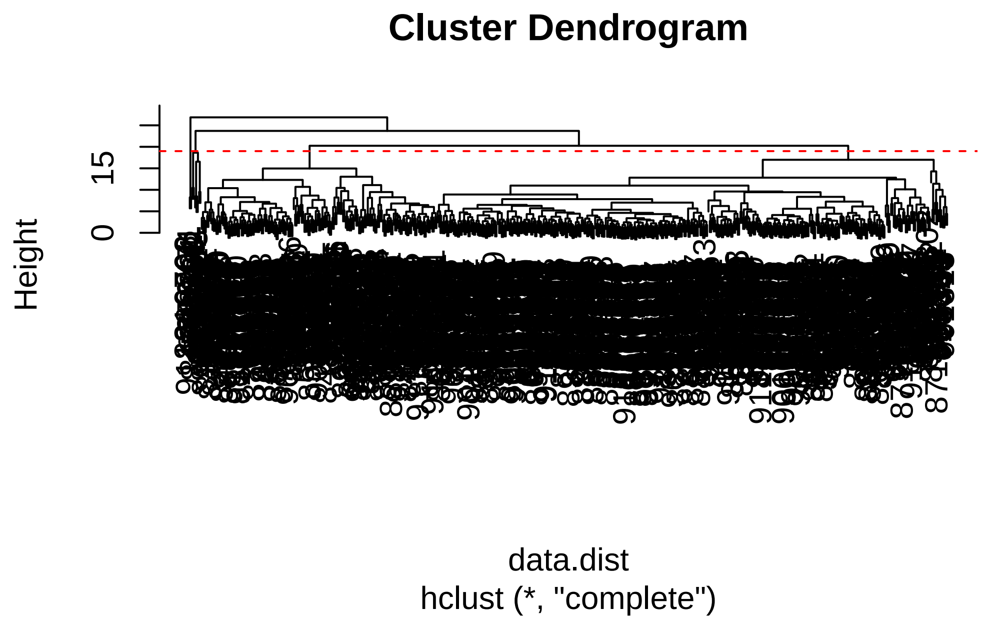
```r
data.dist <- dist(data.scaled)
```

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

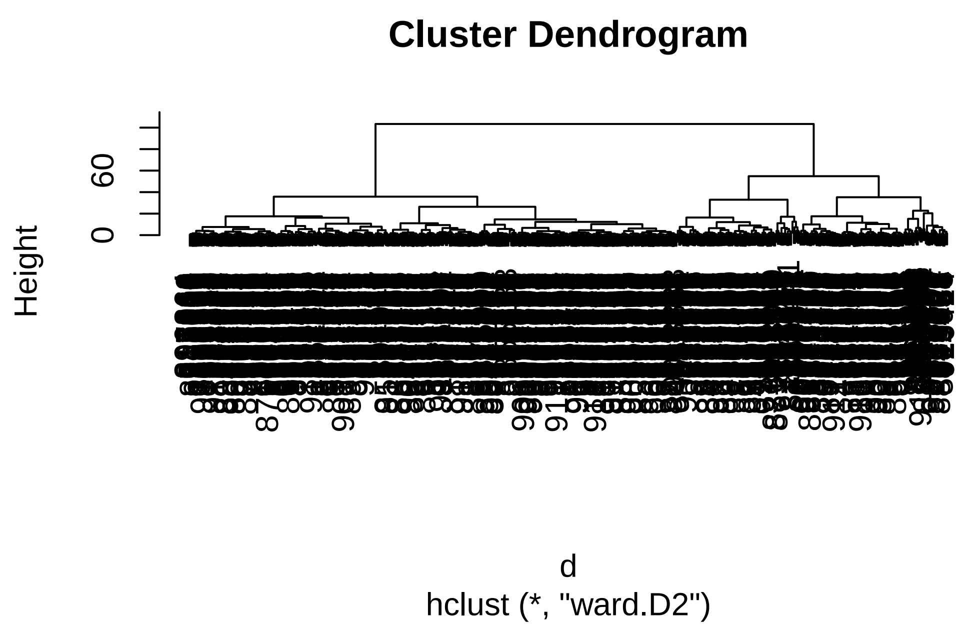
> Q11. Using the plot() and abline() functions, what is the height at which the clustering model has 4 clusters?

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)
```

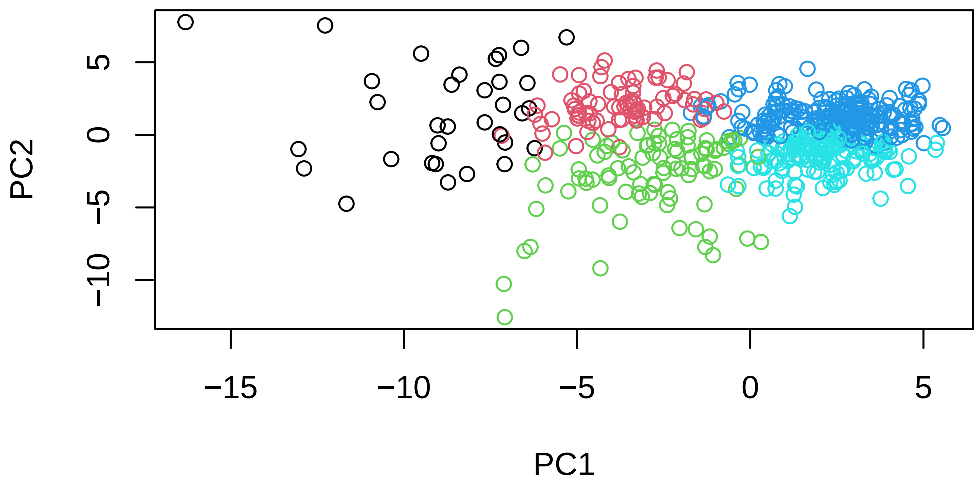


```r
d <- dist(wisc.pr$x[,1:3])
hc <- hclust(d, method="ward.D2")
plot(hc)
```



```r
grps <- cutree(hc, k=5)
```

```r
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?

I changed k into 5 and got what appears to be a better clustering of the data on the graph.

```
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
```

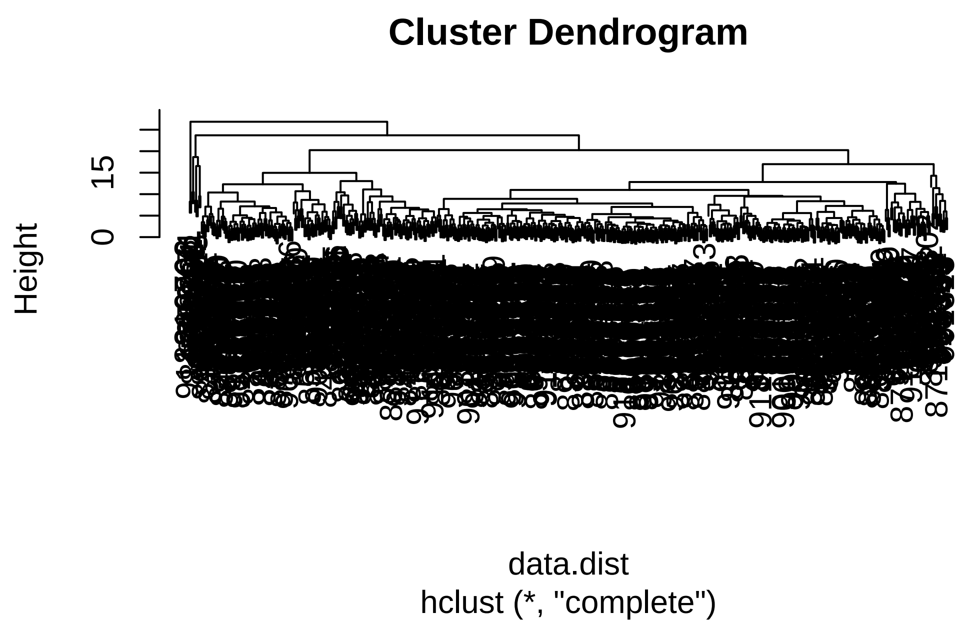
```
table(wisc.hclust.clusters, diagnosis)
```

```
                    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 prefer using the "complete" method as it shows the similarity between all observations in the cluster using the largest of similarities, it provides a comprehensive view of the greatest values throughout the entire data.

```
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 kmeans separates the 2 diagnoses very simply into 2 groups as seen above. It provides a much easier way to interpret the data of the sample than the hclust data tables.