class 8: PCA Mini Project

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Side_Note

```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
```

Let's look at the mean value of every column:

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

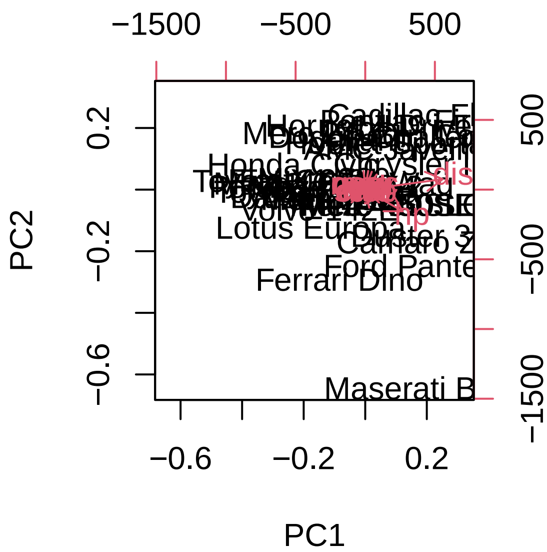
```
       mpg        cyl       disp         hp       drat         wt       qsec 
 20.090625   6.187500 230.721875 146.687500   3.596563   3.217250  17.848750 
        vs         am       gear       carb 
  0.437500   0.406250   3.687500   2.812500 
```

Lets look at "spread" via `sd()`

```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
pca <- prcomp(mtcars)
biplot(pca)
```



We could do this with PCA

Lets try scaling the data :

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

```
                          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
```

What is the mean of each "dimension"/column in mtscale?

```r
round(apply(mtscale, 2, mean), 3)
```

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

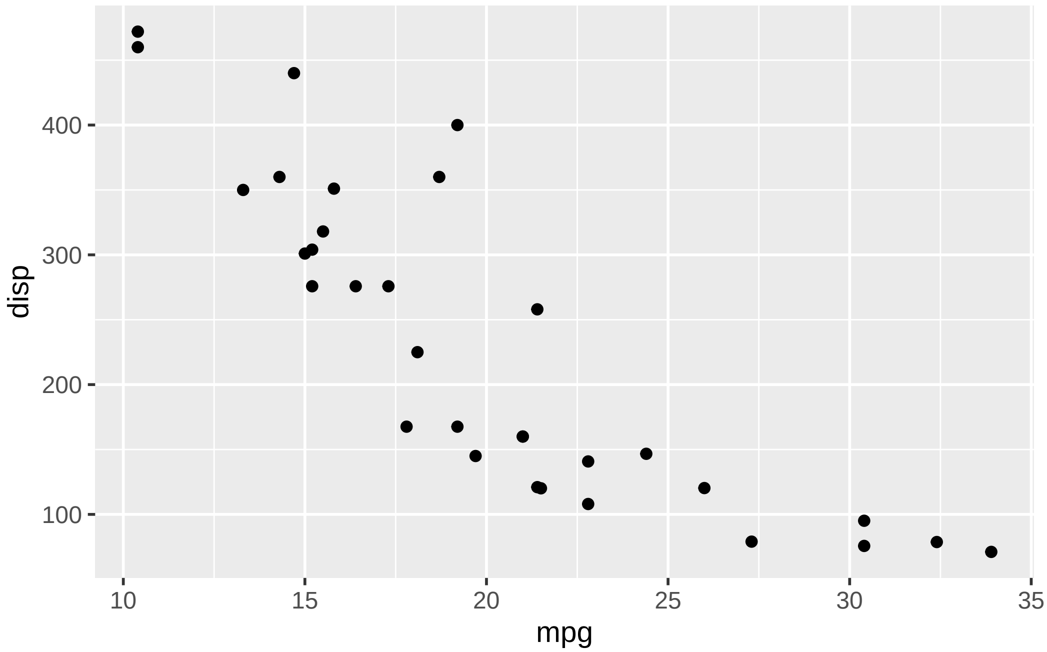
```r
round(apply(mtscale, 2, sd), 3)
```

```
 mpg  cyl disp   hp drat   wt qsec   vs   am gear carb
   1    1    1    1    1    1    1    1    1    1    1
```

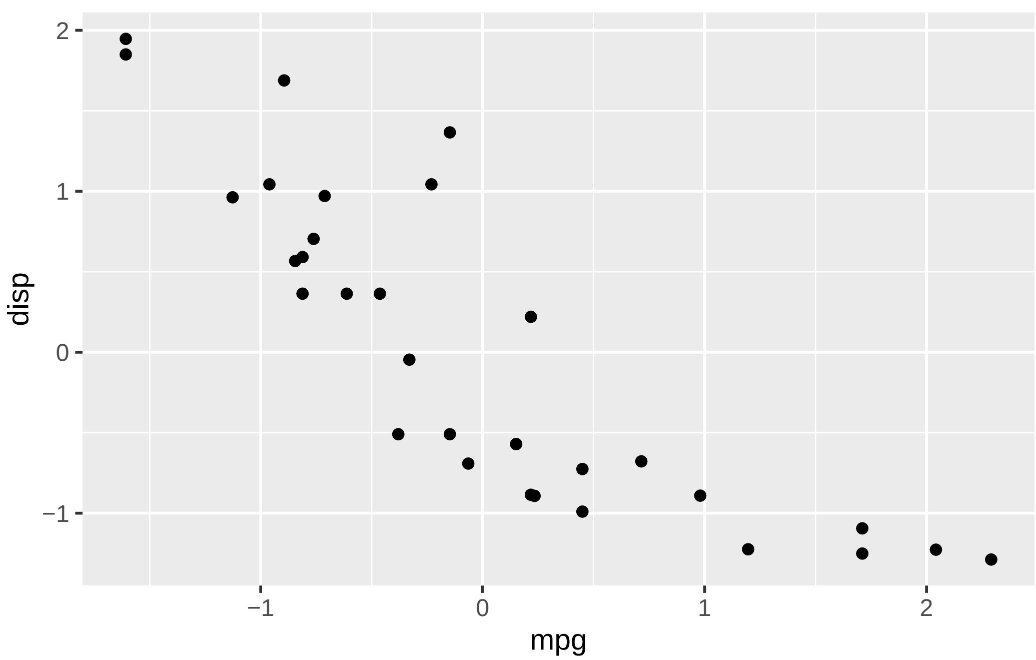
Let's plot `mpg` vs `disp` for both mtcars and after the scaled fata in `mtscale`

```r
library(ggplot2)

ggplot(mtcars) +
  aes(mpg, disp) +
  geom_point()
```



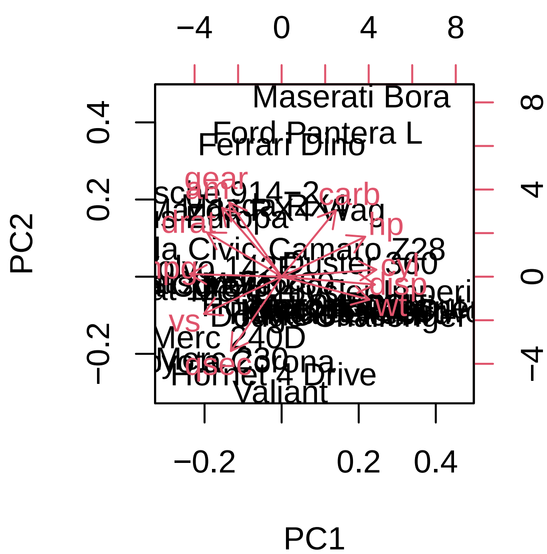

```r
ggplot(mtscale) +
  aes(mpg, disp) +
  geom_point()
```



They look exactly the same. They are just standard by 0

Doesn't change the data it just scales it.

```
pca2 <- prcomp(mtscale)
biplot(pca2)
```



#better representation of the data– it hasnt been scaled to the vector with the biggest frame.

##Breast Cancer FNA data

```
# Save your input data file into your Project directory
fna.data <- "WisconsinCancer.csv"
# Complete the following code to input the data and store as wisc.df
wisc.df <- read.csv(fna.data, 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
```

```
#remove the first column
wisc.data <- wisc.df[,-1]
```

```
# Create diagnosis vector for later
diagnosis <- as.factor(wisc.df$diagnosis)
```

Q1. How many observations= rows/patients/sibjects are in the data set?

```
nrow(wisc.data)
```

```
[1] 569
```

#there are 569 observations#

Q2. How many M (cancer) B (healthy) patients

```
table(wisc.df$diagnosis)
```

```

  B   M 
357 212 
```

#there are 357 healthy patients and 212 cancer patients

Be sure to remove this diagnosis column from our data to analyze

```
#remove the first column
wisc.data <- wisc.df[,-1]
# Create diagnosis vector for later

#factor is categorical
```

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

```
 columns <-colnames(wisc.data)

length(grep( "_mean",x=columns, value=T))
```

```
[1] 10
```

#there are 10 columns with "_mean"

##PCA

We want to scale out data before PCA by setting the `scale=TRUE`

```
wisc.pr <- prcomp(wisc.data, scale=TRUE)
# 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
```

How much variance captured in each PC

```r
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
```

```
# the total variance is not as high/moderate for PC's
```

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

#PC1 proportion of variance = 44.27%

> Q5. How many principal components (PCs) are required to describe at least 70% of the original variance in the data? #The first 3 PC1-3

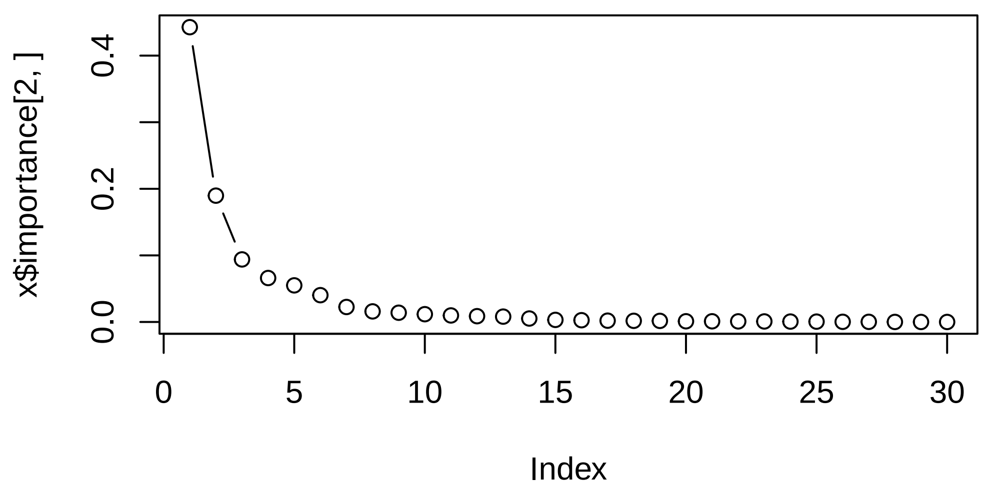
> Q6. How many principal components (PCs) are required to describe at least 90% of the original variance in the data? # the first 7 PC1-7

```
x <- summary(wisc.pr)
x$importance
```

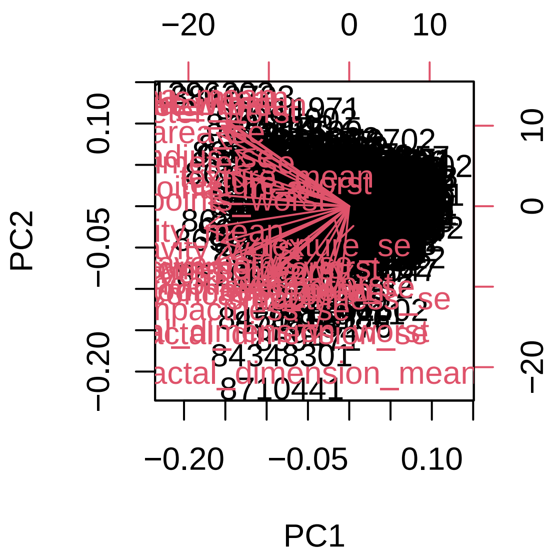
```
                            PC1      PC2      PC3      PC4      PC5      PC6
Standard deviation     3.644394 2.385656 1.678675 1.407352 1.284029 1.098798
Proportion of Variance 0.442720 0.189710 0.093930 0.066020 0.054960 0.040250
Cumulative Proportion  0.442720 0.632430 0.726360 0.792390 0.847340 0.887590
                             PC7       PC8       PC9      PC10      PC11
Standard deviation     0.8217178 0.6903746 0.6456739 0.5921938 0.5421399
Proportion of Variance 0.0225100 0.0158900 0.0139000 0.0116900 0.0098000
Cumulative Proportion  0.9101000 0.9259800 0.9398800 0.9515700 0.9613700
                            PC12      PC13      PC14      PC15      PC16
Standard deviation     0.5110395 0.4912815 0.3962445 0.3068142 0.2826001
Proportion of Variance 0.0087100 0.0080500 0.0052300 0.0031400 0.0026600
Cumulative Proportion  0.9700700 0.9781200 0.9833500 0.9864900 0.9891500
                            PC17      PC18      PC19      PC20      PC21
Standard deviation     0.2437192 0.2293878 0.2224356 0.1765203 0.1731268
Proportion of Variance 0.0019800 0.0017500 0.0016500 0.0010400 0.0010000
Cumulative Proportion  0.9911300 0.9928800 0.9945300 0.9955700 0.9965700
                            PC22      PC23      PC24      PC25      PC26
Standard deviation     0.1656484 0.1560155 0.1343689 0.1244238 0.0904303
Proportion of Variance 0.0009100 0.0008100 0.0006000 0.0005200 0.0002700
Cumulative Proportion  0.9974900 0.9983000 0.9989000 0.9994200 0.9996900
                             PC27       PC28       PC29       PC30
```

```
Standard deviation     0.08306903 0.0398665 0.02736427 0.01153451
Proportion of Variance 0.00023000 0.0000500 0.00002000 0.00000000
Cumulative Proportion  0.99992000 0.9999700 1.00000000 1.00000000
```

```
plot(x$importance[2,], typ="b")
```




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



Q7. What stands out to you about this plot? Is it easy or difficult to understand? Why? This plot has a lot of noise ande it is too hard to read and understand.

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

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

$class
[1] "prcomp"
```

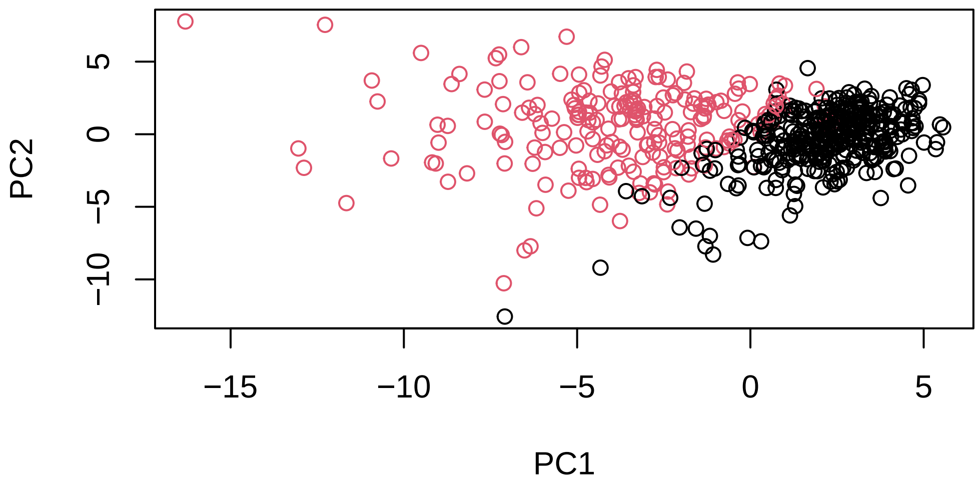
```r
head(wisc.pr$x)
```

```
               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
```

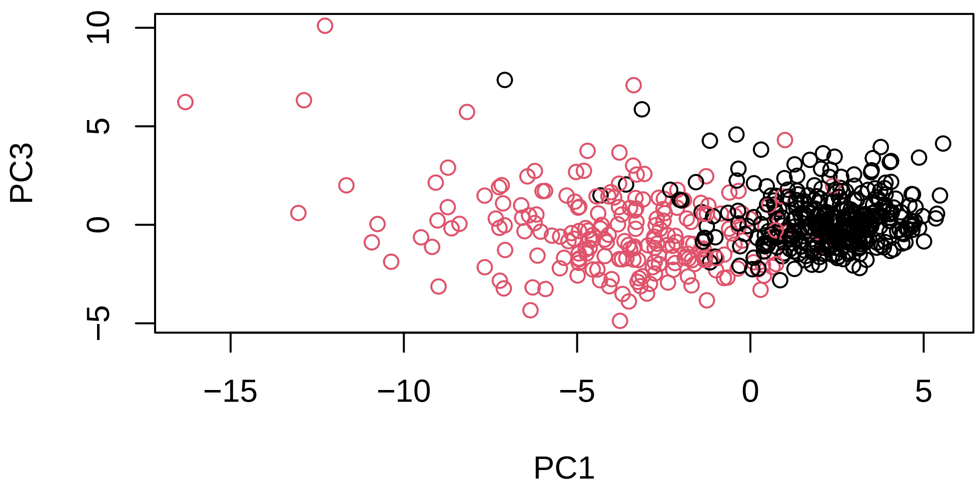
#My main PC result figure

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




```r
# each point represents a patient and the color represents whether its red malignant or black
```

```r
# Repeat for components 1 and 3
plot(wisc.pr$x[,1], wisc.pr$x[,3], col=diagnosis, xlab="PC1", ylab="PC3")
```



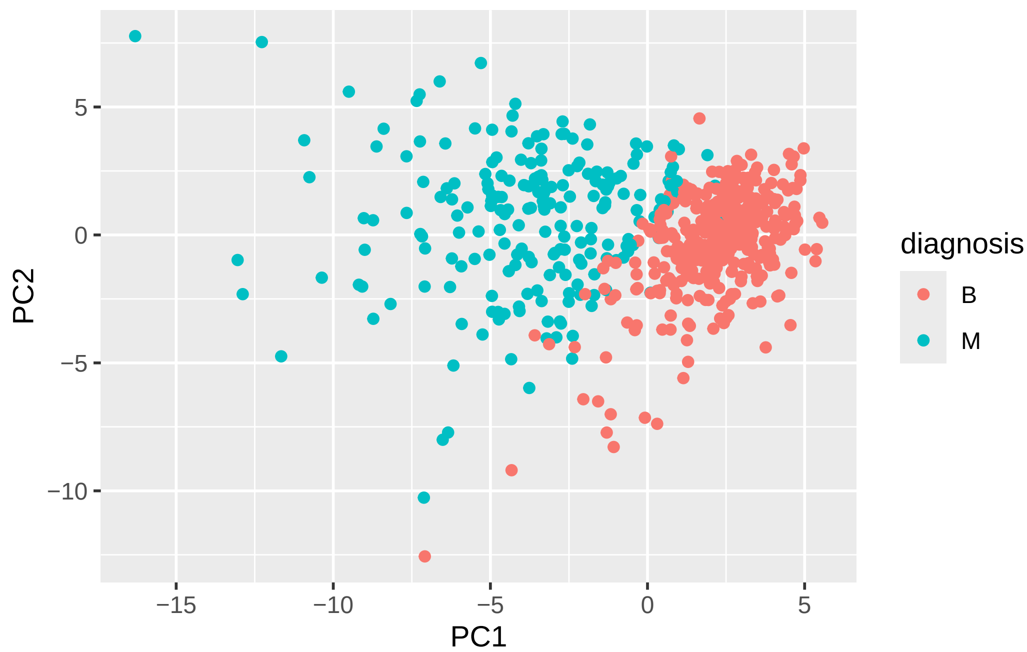
Q8. Generate a similar plot for principal components 1 and 3. What do you notice about these plots? There is more overlap between PC1 and PC2

Lets make a ggplot

```
# 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()
```



Its telling me that these benign samples have a greater difference than cancer samples

#each point represents a sample and all of the transcripts

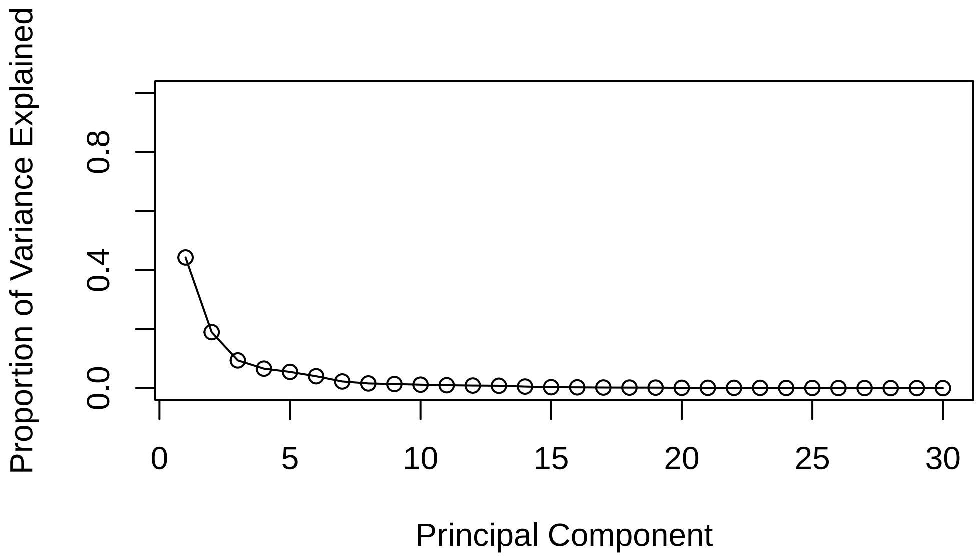
##Variance explained:

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

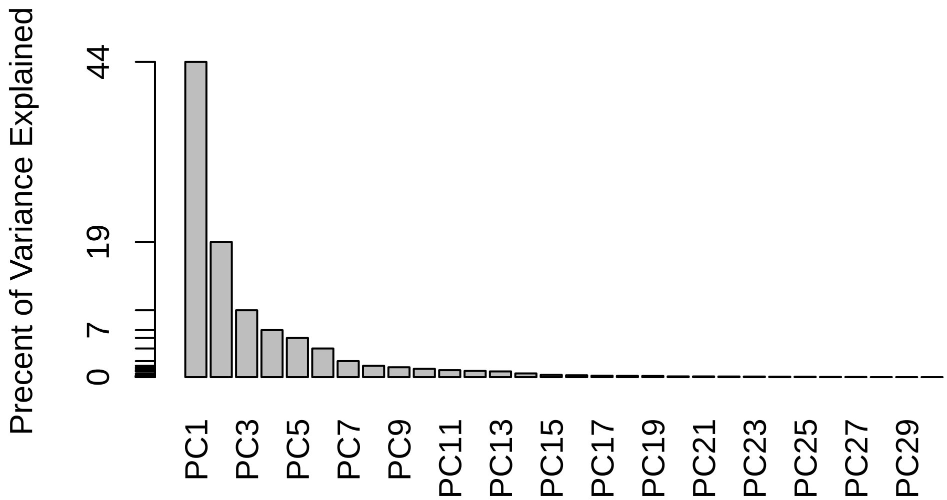
```
[1] 13.281608  5.691355  2.817949  1.980640  1.648731  1.207357
```

```
# 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")
```



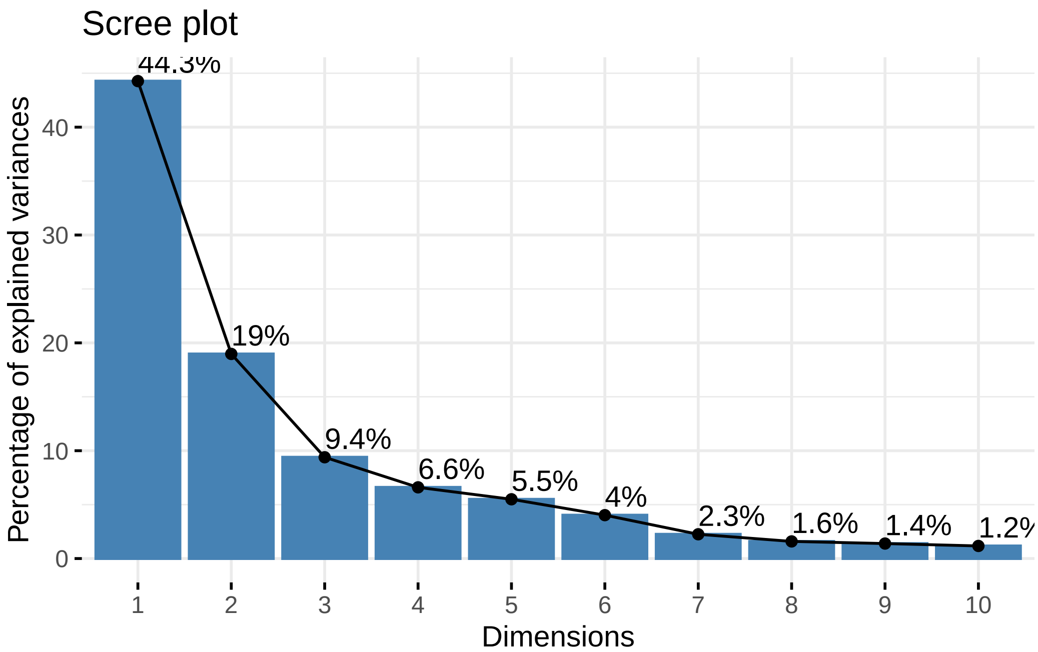

```
# Alternative scree plot of the same data, note data driven y-axis
barplot(pve, ylab = "Precent of Variance Explained",
     names.arg=paste0("PC",1:length(pve)), las=2, axes = FALSE)
axis(2, at=pve, labels=round(pve,2)*100 )
```




```
## ggplot based graph
#install.packages("factoextra")
library(factoextra)
```

```
Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
```

```
fviz_eig(wisc.pr, addlabels = TRUE)
```



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? #This tells us how much this original feature contributes to the first PC.

```
wisc.pr$rotation[,1]
```

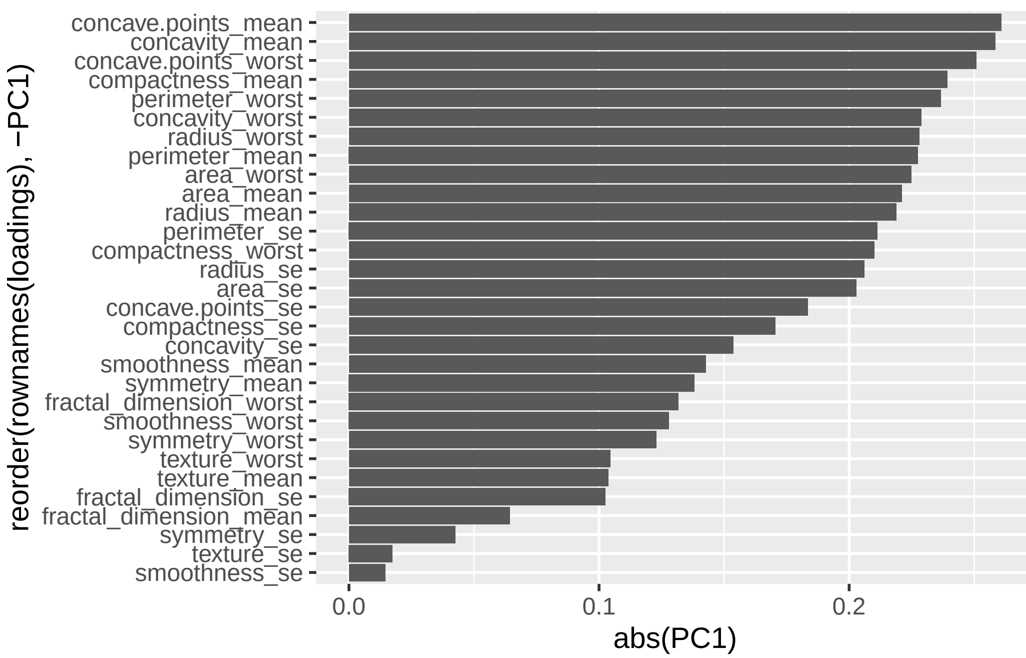
```
            radius_mean            texture_mean          perimeter_mean 
            -0.21890244             -0.10372458             -0.22753729 
              area_mean         smoothness_mean        compactness_mean 
            -0.22099499             -0.14258969             -0.23928535 
         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
```

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

```
concave.points_mean
         -0.2608538
```

```r
loadings <- wisc.pr$rotation
#this can allow us to see percent variations in PCAs
ggplot(loadings)+
  aes(abs(PC1), reorder(rownames(loadings), -PC1))+
  geom_col()
```



##Hierarchical clustering

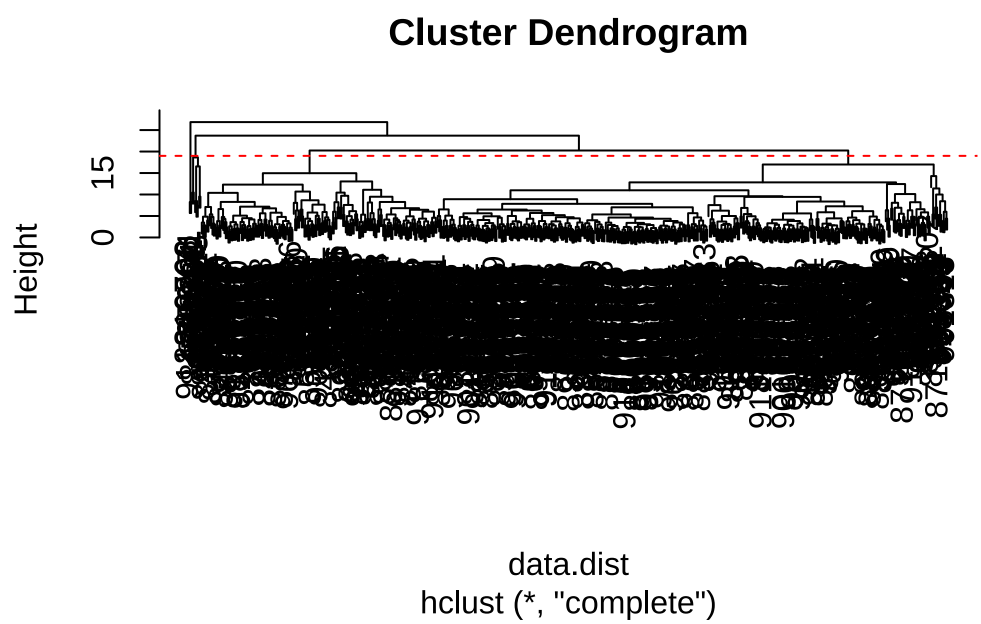
```r
# Scale the wisc.data data using the "scale()" function
data.scaled <- scale(wisc.data)
```

```r
data.dist <- dist(data.scaled, method="euclidean")
```

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

##results of hierarchical clustering

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




```r
#q11
```

##Selecting number of clusters

```r
wisc.hclust.clusters <-cutree(wisc.hclust, h=19)
table(wisc.hclust.clusters, diagnosis)
```

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

> Q11. OPTIONAL: Can you find a better cluster vs diagnoses match by cutting into a different number of clusters between 2 and 10? How do you judge the quality of your result in each case?

#This is pretty difficult to decipher between cutting into different clusters for each diagnosis because the more clusters the harder to determine the correct points vs clustering into might lead you to greater chance of false positives.

```
wisc.hclust.clusters <-cutree(wisc.hclust, k=2)
table(wisc.hclust.clusters, diagnosis)
```

```
                    diagnosis
wisc.hclust.clusters   B   M
                   1 357 210
                   2   0   2
```

Clustering

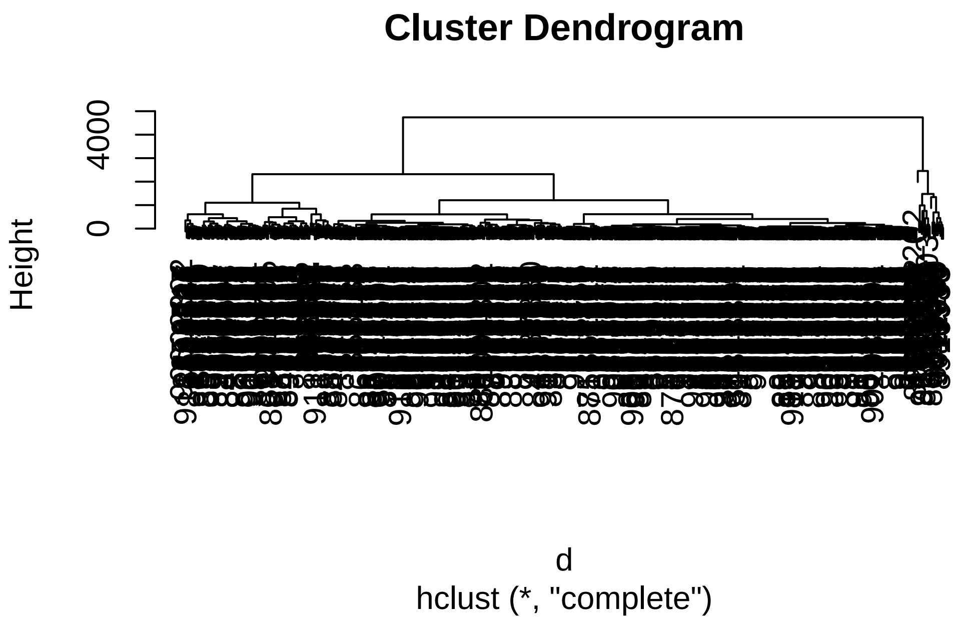
Try to cluster tje `wisc.data`

```
km <- kmeans(wisc.data, centers =2)
table(km$cluster)
```

```

  1   2 
438 131 
```

```
d <- dist(wisc.data)
hc <- hclust(d)
plot(hc)
```




```r
grps<- cutree(hc, k=3)
table(grps)
```

```
grps
  1   2   3 
549  19   1 
```

##Cluster in PC space

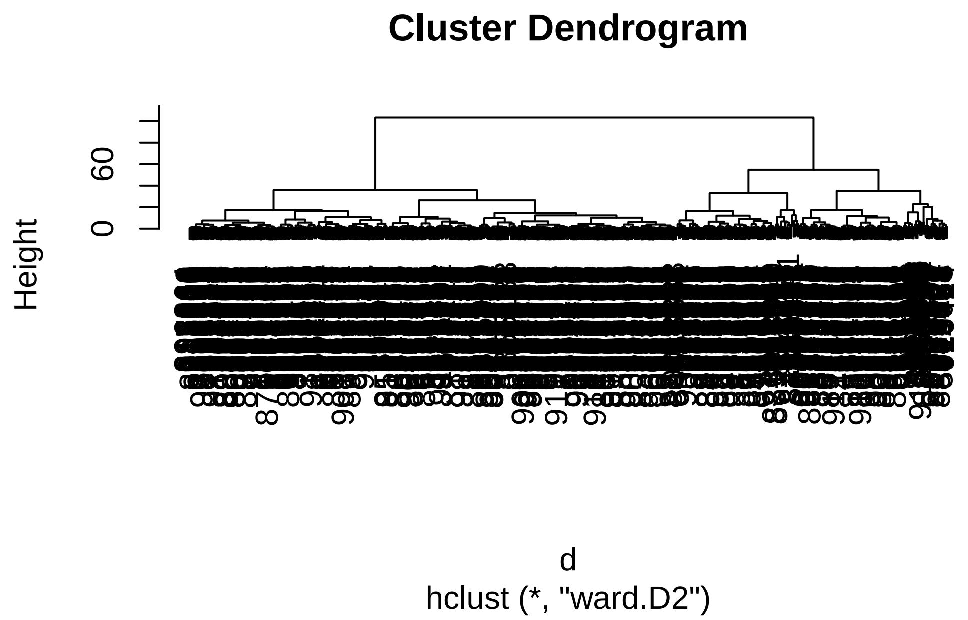
In other words use my PCA results as a basis of clustering

```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
```

```
##Q12
d <- dist(wisc.pr$x[,1:3])
hc <- hclust(d, method="ward.D2")
#claculates distance
plot(hc)
```



Q12. Which method gives your favorite results for the same data.dist dataset? Explain your reasoning. #The method that gives me the best results is using "ward.D2" because it considers each point distance between the centroids of the clusters being merged giving the best clustering method for PCA data.

```
grps <-cutree(hc, k=2)
table(grps)
```

```
grps
  1   2 
203 366 
```

Compare to my expert M and B `diagnosis`

```
table(diagnosis)
```

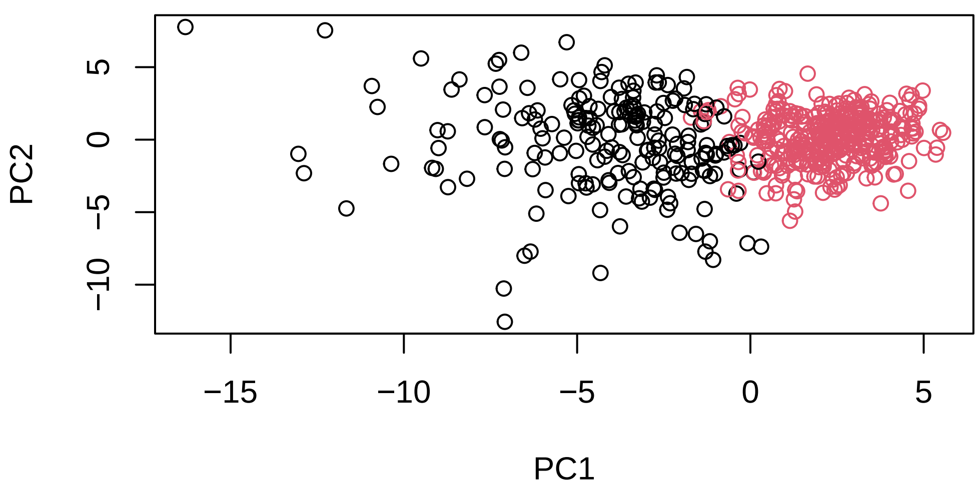
```
diagnosis
  B   M 
357 212 
```

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

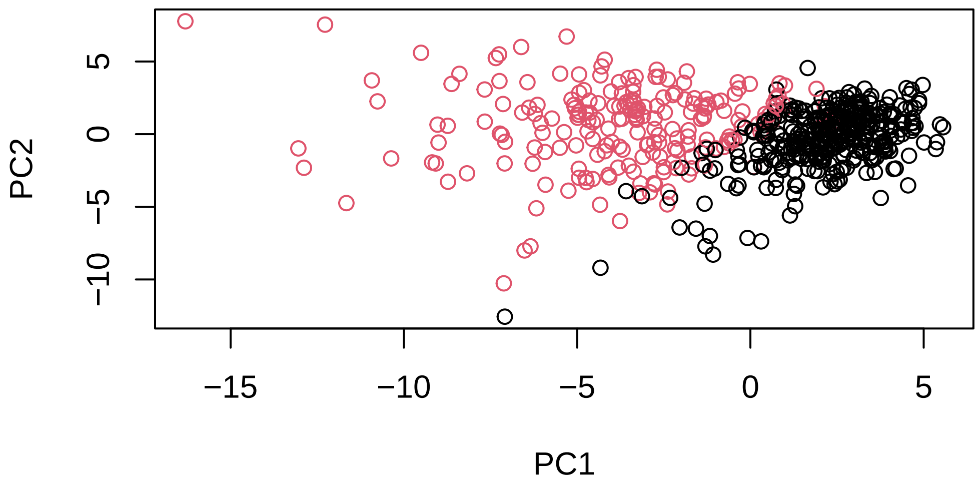
```
         grps
diagnosis   1   2
        B  24 333
        M 179  33
```

#we're getting 33 false pos for malignant and 24 false pos for benign # how can we be 100% sensitive ??

```r
plot(wisc.pr$x[,1:2], col=grps)
```




```r
plot(wisc.pr$x[,1:2],col=diagnosis)
```



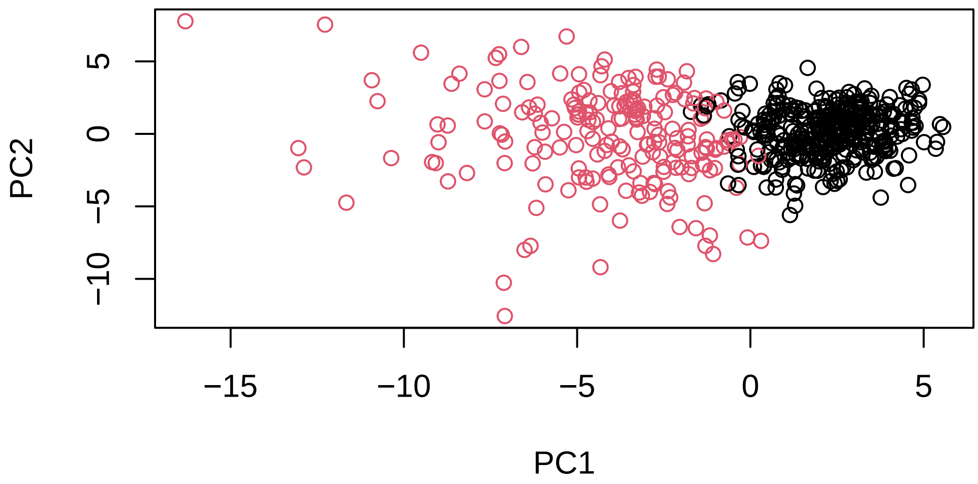

```
g <-as.factor(grps)
levels(g)
```

```
[1] "1" "2"
```

```
g <-relevel(g,2)
levels(g)
```

```
[1] "2" "1"
```

```
#plot using our re-ordered factor
plot(wisc.pr$x[,1:2], col=g)
```



##Let's make it 3D!!

```
#library(rgl)
#plot3d(wisc.pr$x[,1:3], xlab="PC 1", ylab="PC 2", zlab="PC 3", #cex=1.5, size=1, type="s", c
```