Class 8 mini-project

Matthew White

```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)
```

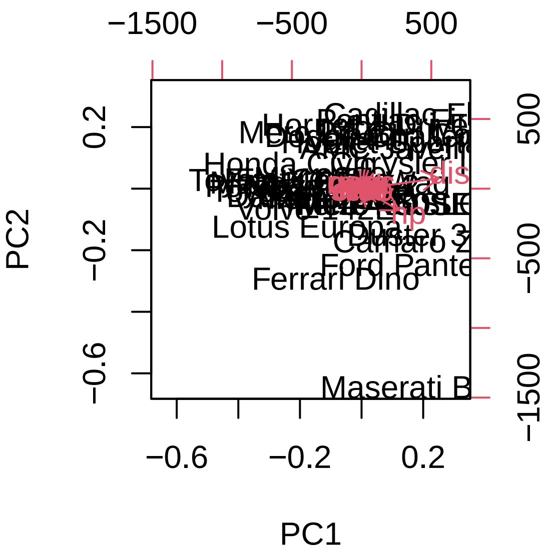
```
       mpg        cyl       disp         hp       drat         wt       qsec 
 20.090625   6.187500 230.721875 146.687500   3.596563   3.217250  17.848750 
        vs         am       gear       carb 
  0.437500   0.406250   3.687500   2.812500 
```

Let's look at "spread" via standard deviation `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)
```



Let’s try scaling this 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
```

```
mean(mtscale)
```

```
[1] -1.573867e-16
```

```
sd(mtscale)
```

```
[1] 0.9856521
```

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

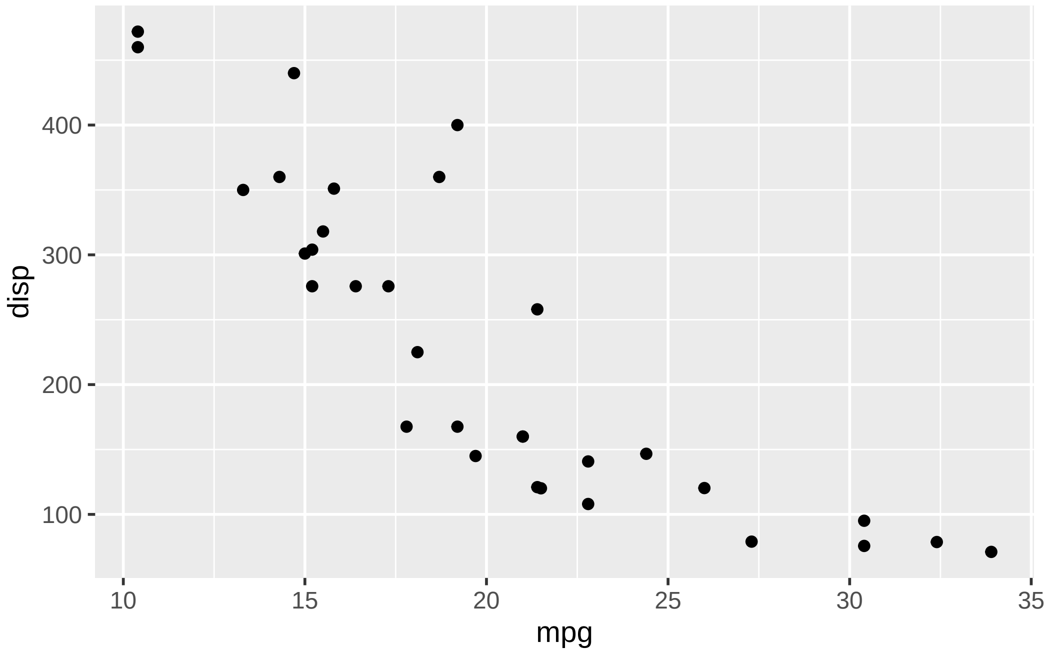
```
 mpg  cyl disp   hp drat   wt qsec   vs   am gear carb 
   0    0    0    0    0    0    0    0    0    0    0 
```

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

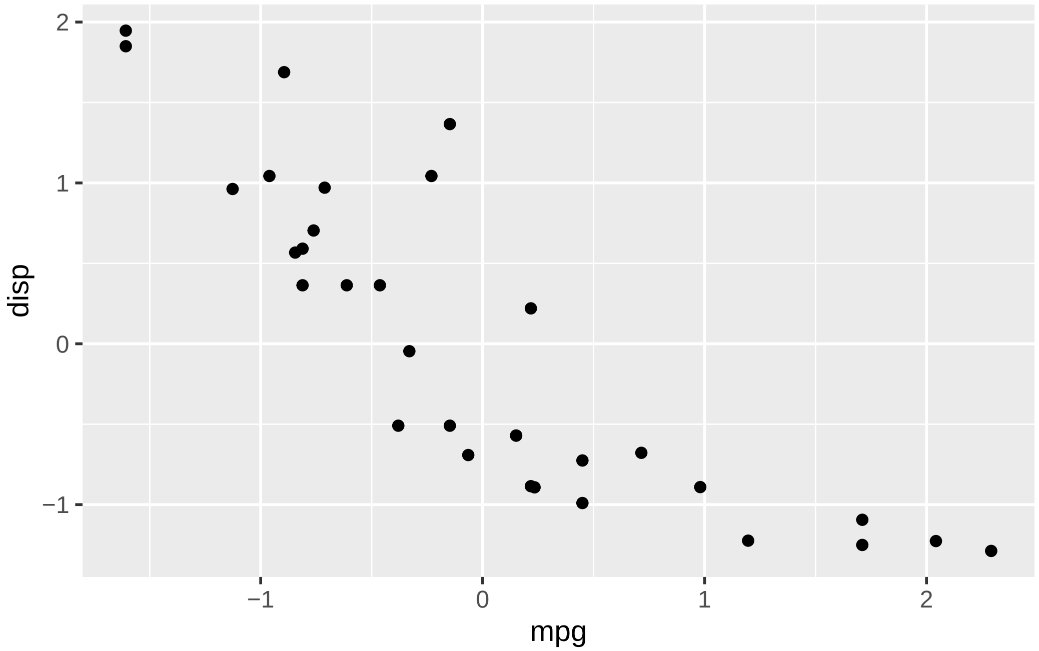
```
 mpg  cyl disp   hp drat   wt qsec   vs   am gear carb 
   1    1    1    1    1    1    1    1    1    1    1 
```

Let's plot

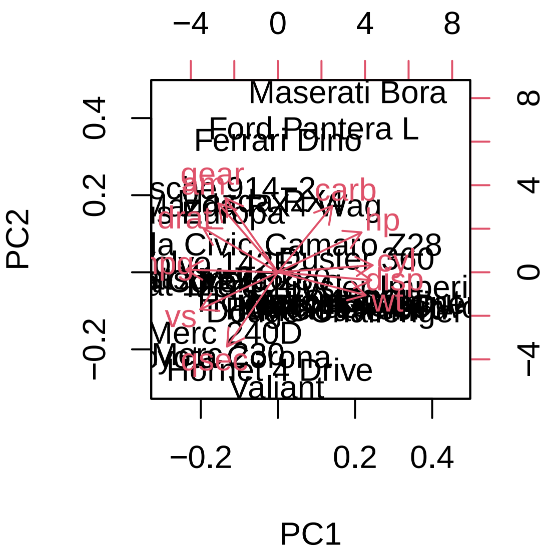
```
library(ggplot2)

# disp v mpg for og and for scale dataset
ggplot(mtcars) + aes(mpg, disp) + geom_point()
```



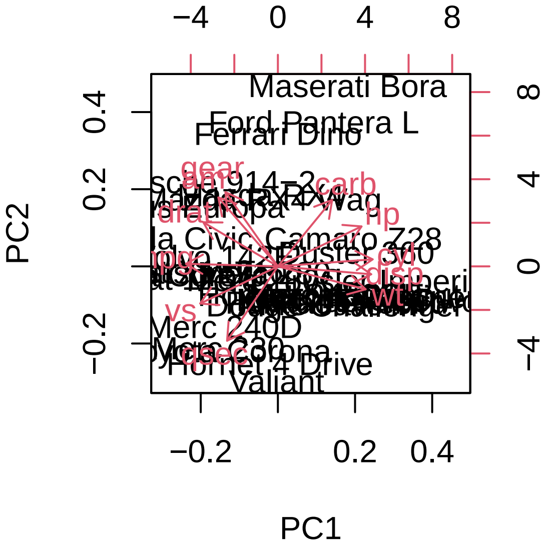
```
ggplot(mtscale, aes(mpg,disp)) + geom_point()
```



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



```
#can achieve same thing by setting scale argument to TRUE in prcomp() function on og dataset
pca3 <- prcomp(mtcars, scale = T)
biplot(pca3)
```



##Mini Project Start

```
#row.names=1 tells to use the 1st column as the row names
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
```

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

```
[1] 569  31
```

```r
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
```

```
diagnosis <- wisc.df$diagnosis
head(diagnosis)
```

```
[1] "M" "M" "M" "M" "M" "M"
```

```
#make diagnosis data a factor so that it is understood as a categorical and not a continuous
diagnosis_f <- as.factor(diagnosis)
diagnosis_f
```

```
  [1] M M M M M M M M M M M M M M M M M M M B B B M M M M M M M M M M M M M M M
 [38] B M M M M M M M M B M B B B B B M M B M M B B B B M B M M B B B B M B M M
 [75] B M B M M B B B M M B M M M B B B M B B M M B B B M M B B B B M B B M B B
[112] B B B B B B M M M B M M B B B M M B M B M M B M M B B M B B M B B B B M B
[149] B B B B B B B B M B B B B M M B M B B M M B B M M B B B B M B B M M M B M
[186] B M B B B M B B M M B M M M M B M M M B M B M B B M B M M M M B B M M B B
[223] B M B B B B B M M B B M B B M M B M B B B B M B B B B B M B M M M M M M M
[260] M M M M M M M B B B B B B M B M B B M B B M B M M B B B B B B B B B B B B
[297] B M B B M B M B B B B B B B B B B B B B B M B B B M B M B B B B M M M B B
```

```
[334] B B M B M B M B B B M B B B B B B B M M M B B B B B B B B B B B M M B M M
[371] M B M M B B B B B M B B B B B M B B B M B B M M B B B B B B M B B B B B B
[408] B M B B B B B M B B M B B B B B B B B B B B B M B M M B M B B B B B M B B
[445] M B M B B M B M B B B B B B B B M M B B B B B B M B B B B B B B B B B M B
[482] B B B B B B M B M B B M B B B B B M M B M B M B B B B B M B B M B M B M M
[519] B B B M B B B B B B B B B B B M B M M B B B B B B B B B B B B B B B B B B
[556] B B B B B B B M M M M M M B
Levels: B M
```

##Questions 1-3

```
#Q1 and Q2
dim(wisc.data)
```

```
[1] 569  30
```

```
table(diagnosis_f)
```

```
diagnosis_f
  B   M 
357 212 
```

```
#Q3, how many variables in the data are suffixed with _mean?
grep("_mean", colnames(wisc.data))
```

```
 [1]  1  2  3  4  5  6  7  8  9 10
```

```
grep("_mean", colnames(diagnosis_f))
```

```
integer(0)
```

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

```
[1] 10
```

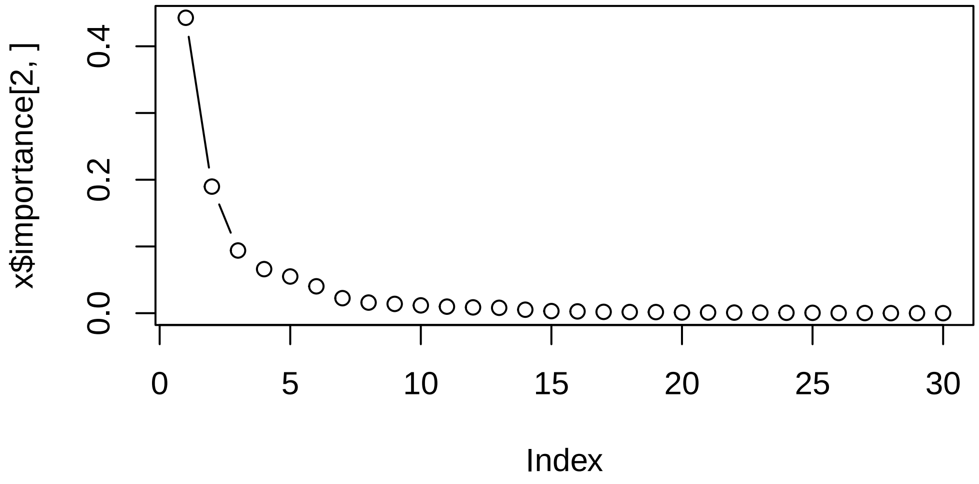
##PCA portion, Q4-6

Should scale our data in the PCA function!

```r
#colMeans(wisc.data)
#apply(wisc.data,2,sd)

wisc.pr <- prcomp(wisc.data, scale = T)
x <- summary(wisc.pr)
x
```

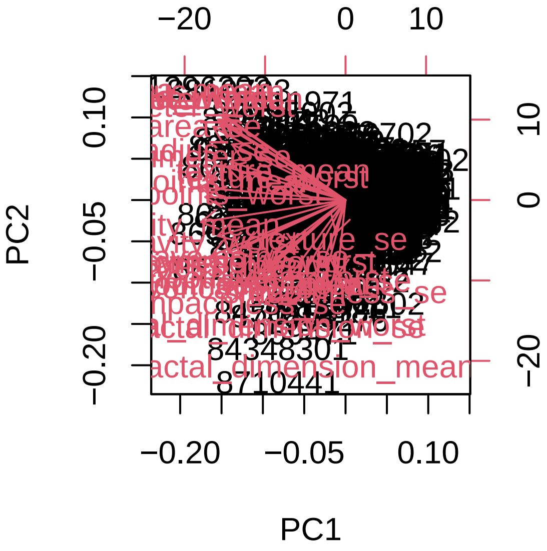
```
Importance of components:
                          PC1    PC2     PC3     PC4     PC5     PC6     PC7
Standard deviation     3.6444 2.3857 1.67867 1.40735 1.28403 1.09880 0.82172
Proportion of Variance 0.4427 0.1897 0.09393 0.06602 0.05496 0.04025 0.02251
Cumulative Proportion  0.4427 0.6324 0.72636 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
```

```r
##PCs are doing alright, but we still don't capture all variance in first couple PCs.

#Q4:  Captured 44% of variance in PC1
#Q5:  Require 3 PCs to capture at least 70% of og data variance
#Q6: Require 7 PCs to capture 90% variance

#can also plot this summary
plot(x$importance[2,], typ="b")
```



##Interpreting PCA results

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



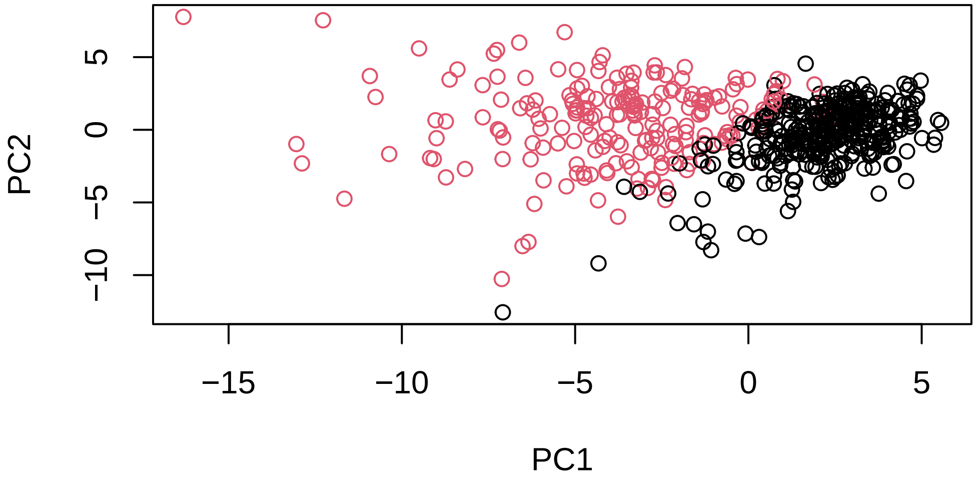
```
#Q7: plot looks pretty shite. overcrowded, can't visualize any labels or results.
```

```
#x is the coordinates of the patient on new PC plot. The value in each PC for each individual
head(wisc.pr$x)
```

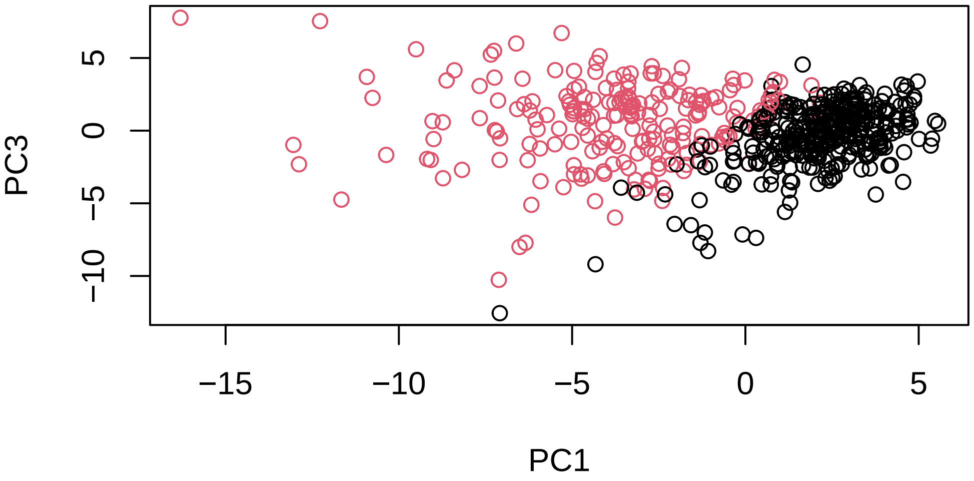
```
               PC1        PC2        PC3       PC4        PC5         PC6
842302   -9.184755  -1.946870 -1.1221788 3.6305364  1.1940595  1.41018364
842517   -2.385703   3.764859 -0.5288274 1.1172808 -0.6212284  0.02863116
84300903 -5.728855   1.074229 -0.5512625 0.9112808  0.1769302  0.54097615
84348301 -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
```

```
#colored by diagnosis to assess if there is any difference in malignant and benign samples.
plot(wisc.pr$x, col = diagnosis_f, xlab = "PC1", ylab = "PC2")
```

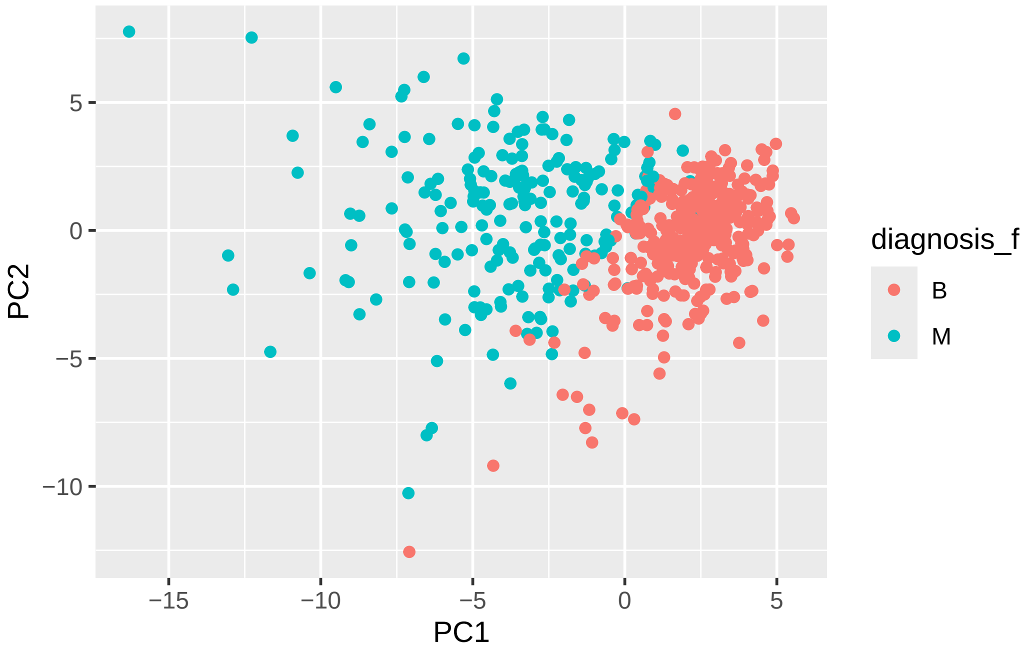


```
plot(wisc.pr$x[,1:3], col = diagnosis_f, xlab = "PC1", ylab = "PC3")
```



Now make a nicer ggplot version of the above

```
df <- as.data.frame(wisc.pr$x)

ggplot(df, aes(PC1, PC2, col = diagnosis_f)) + geom_point()
```



Now we can look at the proportion of variance explained by each principal component.

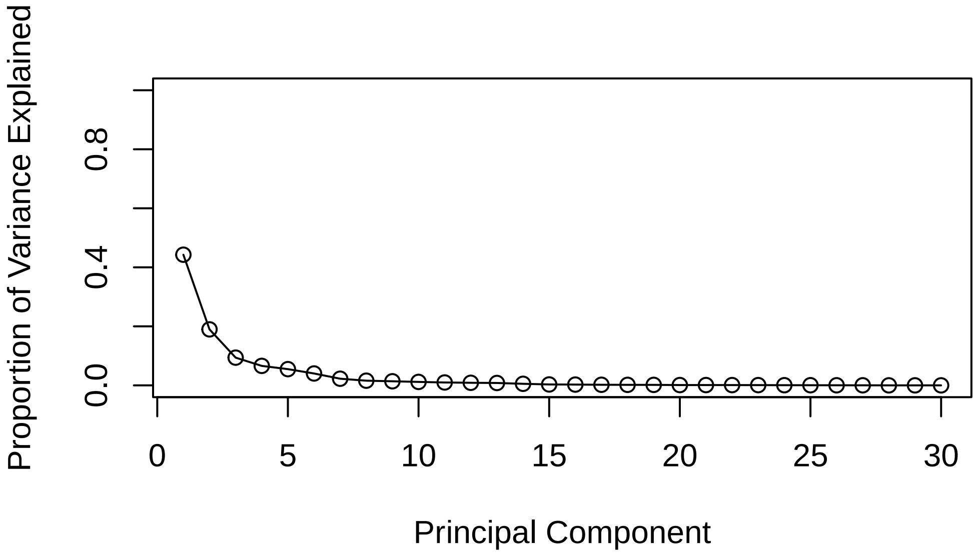
```
#Variance of each component
pr.var <- wisc.pr$sdev^2
head(pr.var)
```

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

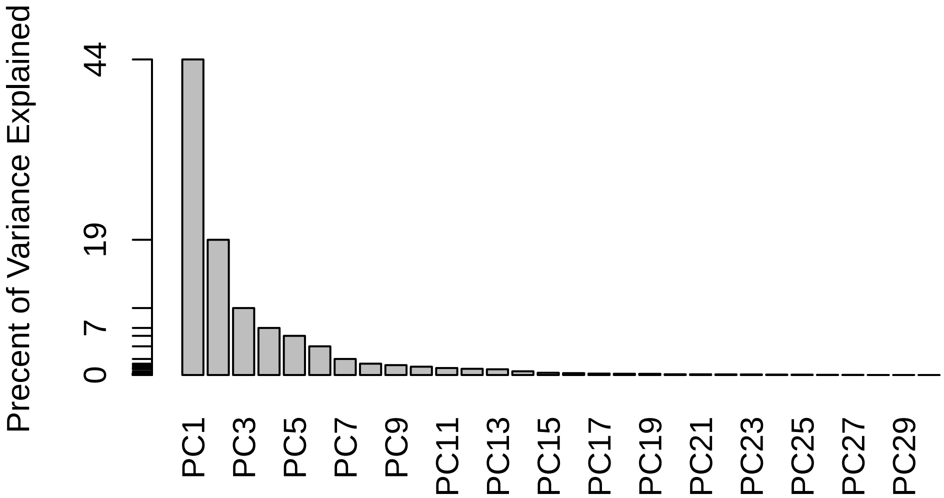
```
#variance explained by each principal component
pve <- pr.var/sum(pr.var)
head(pve)
```

```
[1] 0.44272026 0.18971182 0.09393163 0.06602135 0.05495768 0.04024522
```

```
plot(pve, xlab ="Principal Component", ylab = "Proportion of Variance Explained", ylim = c(0
```



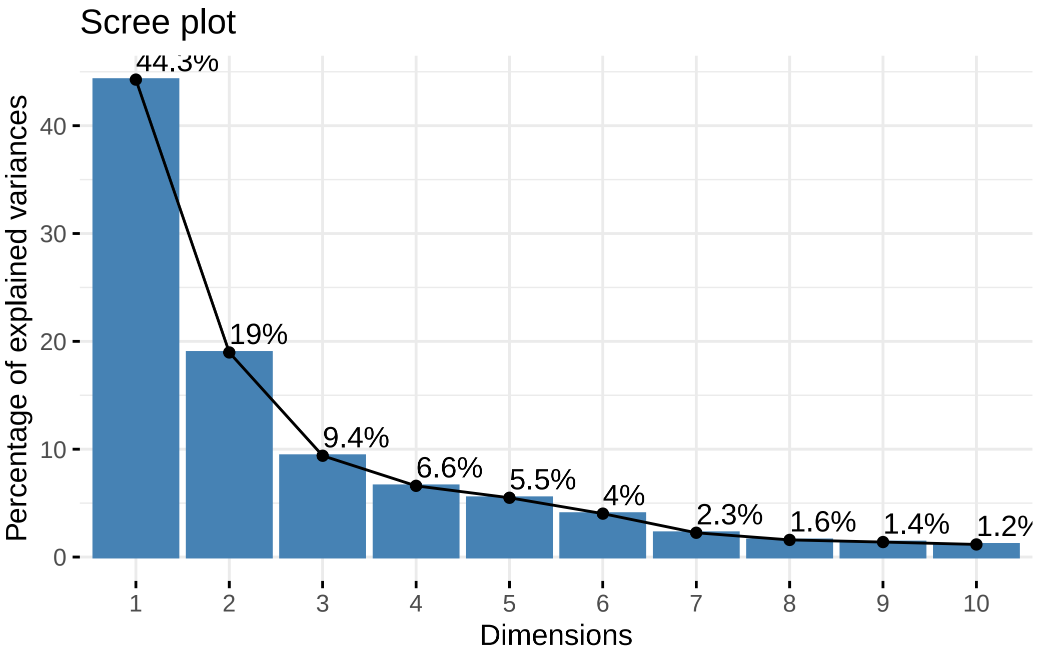
```
#scree plot of the same data
barplot(pve, ylab = "Precent of Variance Explained",
     names.arg=paste0("PC",1:length(pve)), las=2, axes = FALSE)
axis(2, at=pve, labels=round(pve,2)*100)
```



```
#factoextra makes prettier plot
library(factoextra)
```

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

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

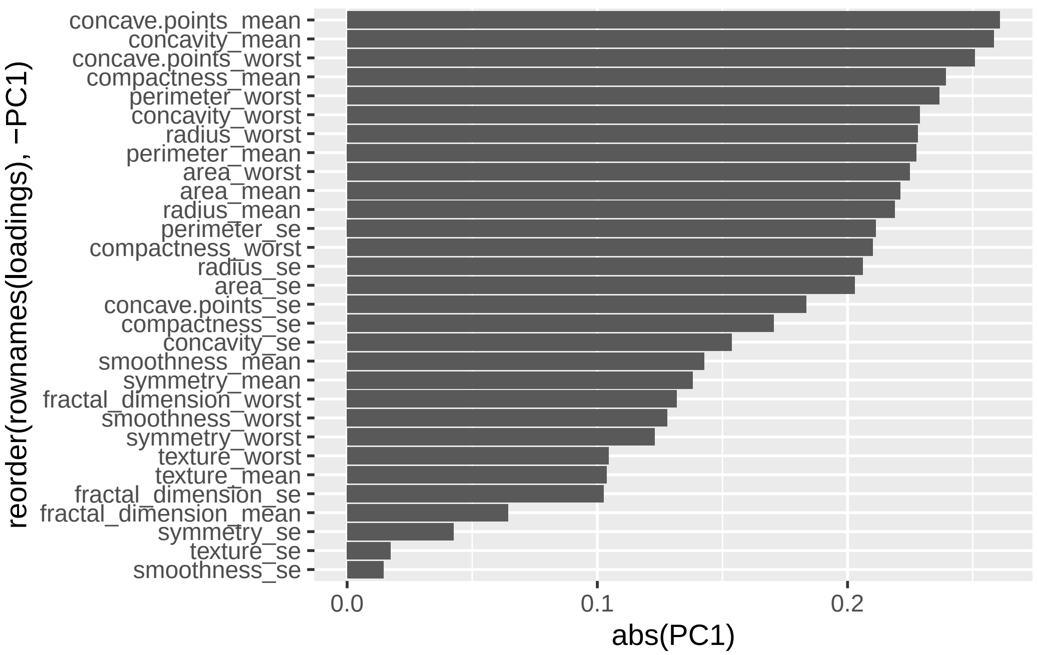


##Communicating PCA Results

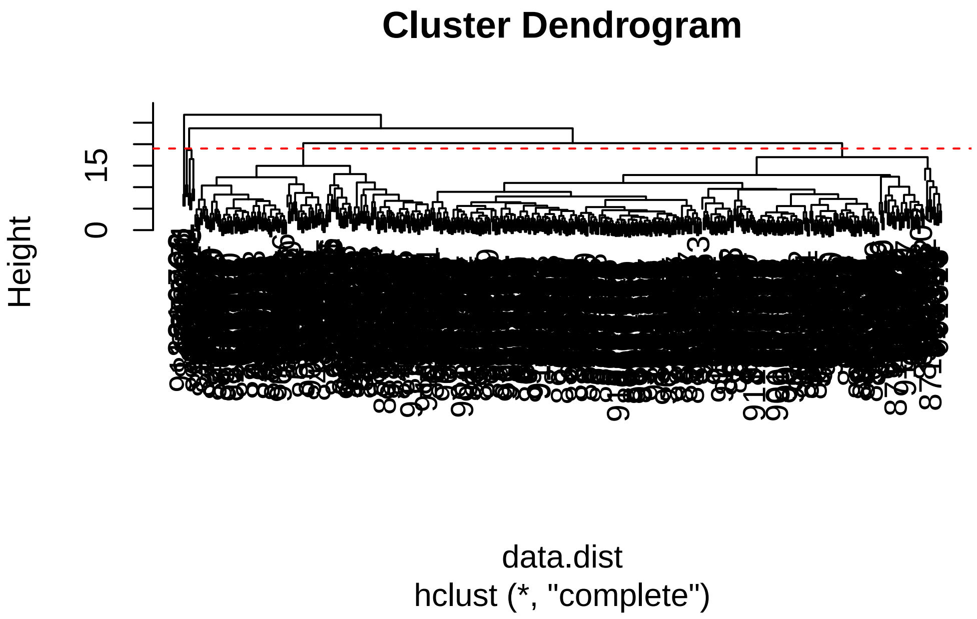
```
#NOW, we are seeing how to look at variation (rotation of PC) explained by each variable (he
wisc.pr$rotation["concave.points_mean", 1]
```

```
[1] -0.2608538
```

```
loadings <- wisc.pr$rotation
ggplot(loadings) + aes(abs(PC1), reorder(rownames(loadings), -PC1)) + geom_col()
```



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

#Q10
plot(wisc.hclust)
abline(h = 19, col = "red", lty = 2)
```



```
#or

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

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

```
#Q11
wisc.hclust.clusters <- cutree(wisc.hclust, k = 5)
table(wisc.hclust.clusters, diagnosis_f)
```

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

```
                    5    0    2
```

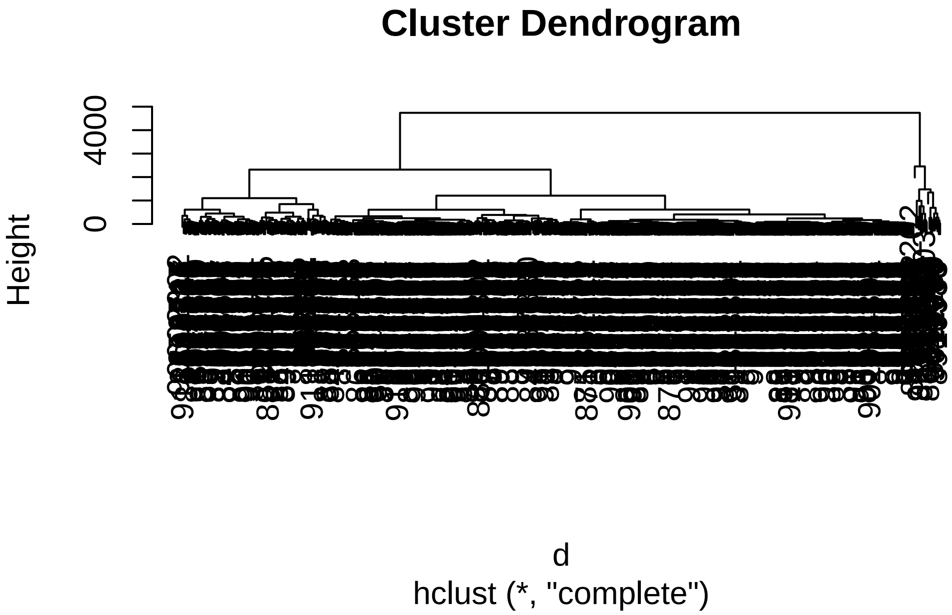
##K-means clustering

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

```

  1   2 
438 131 
```

##Hierarchical Clustering

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



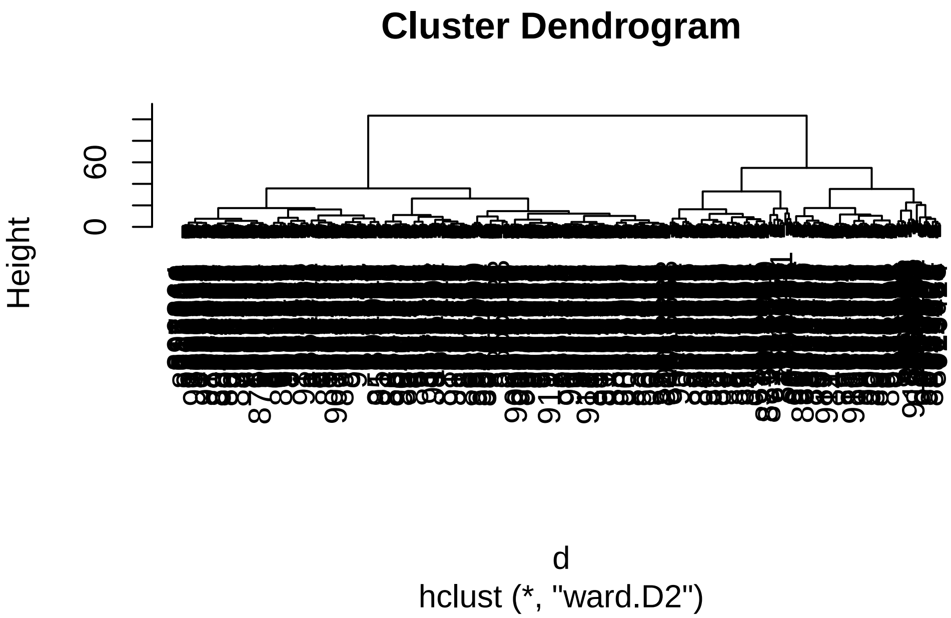
```
grps <- cutree(hc, k=3)
table(grps)
```

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

##Cluster in PC space

In other words, use my PCA results as the basis for clustering

```
#what is used to make older PCA plot
#wisc.pr$x

#make distance vector out of this in order to cluster hierarchically
d <- dist(wisc.pr$x[,1:3])
hc <- hclust(d, method = "ward.D2")
plot(hc)
```



```
#Cut this tree to yield 2 groups/clusters (the benign and malignant groups)

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

```
grps
```

```
  1   2
203 366
```

Compare to my expert M and B `diagnosis_f`

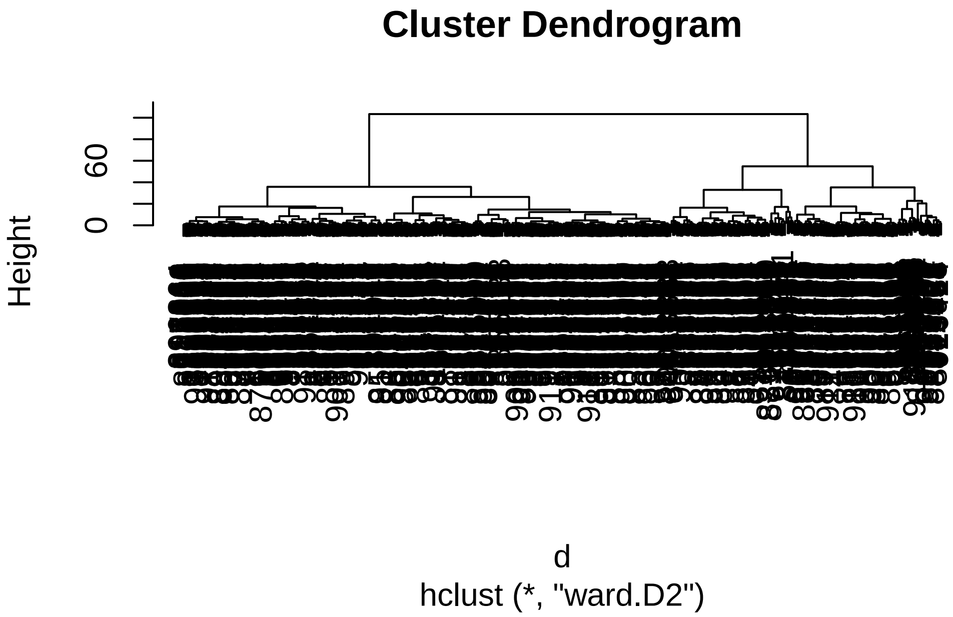
```
table(diagnosis_f)
```

```
diagnosis_f
  B   M
357 212
```

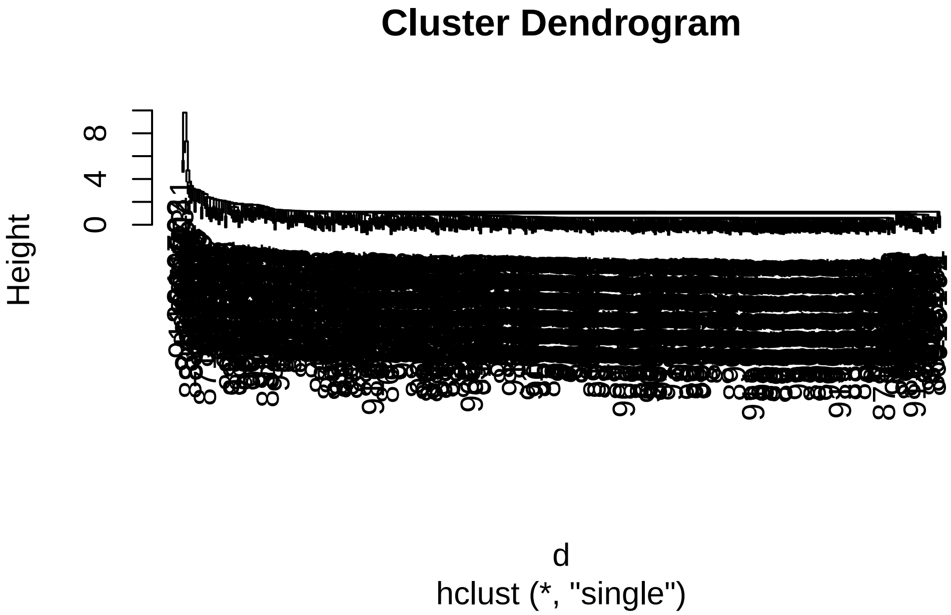
```
table(diagnosis_f, grps)
```

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

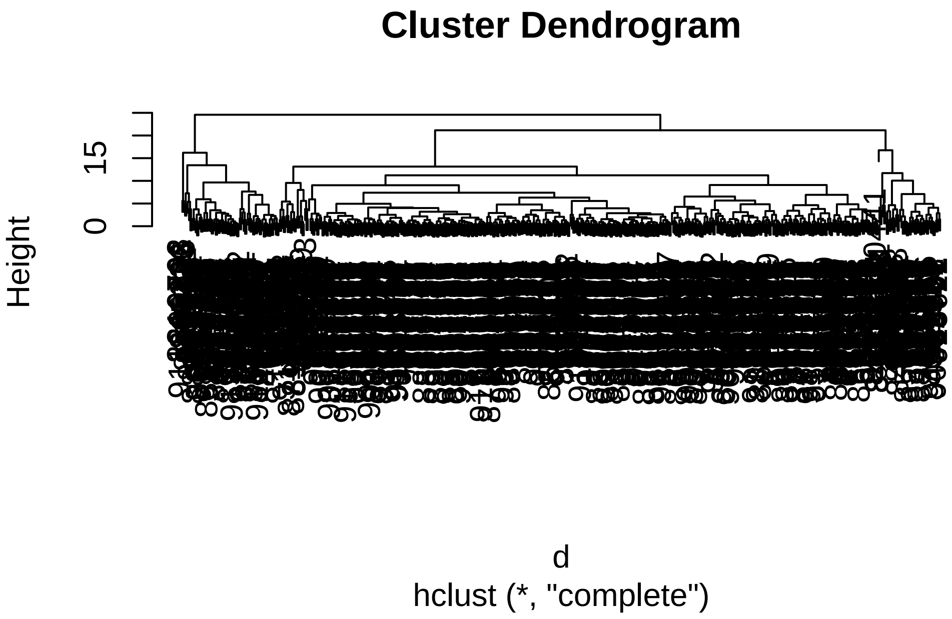
```
#Q12

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



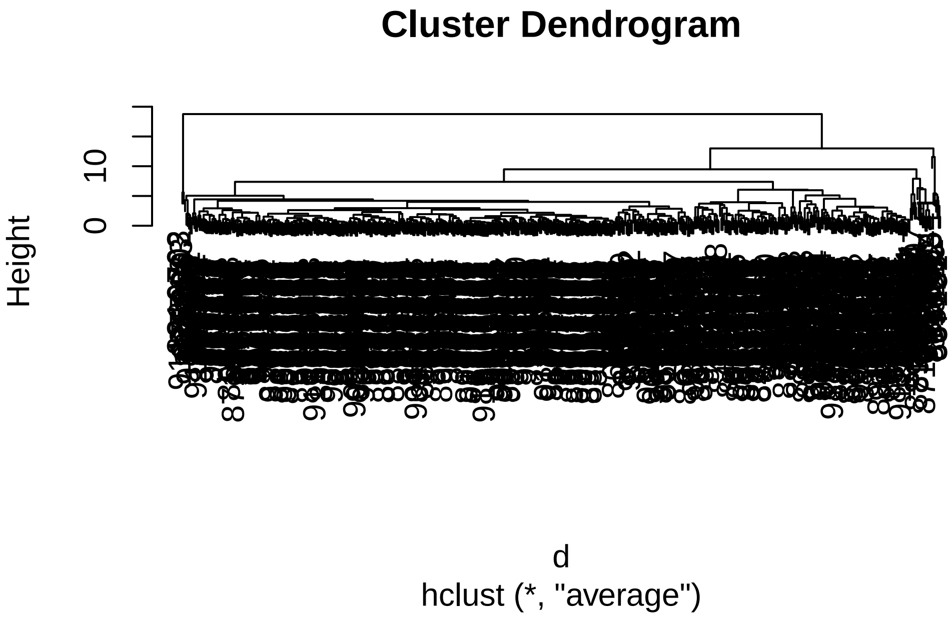
```
d <- dist(wisc.pr$x[,1:3])
hc <- hclust(d, method = "single")
plot(hc)
```



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



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



```
#The ward.D2 method produces the dendrogram with highest crossbars and most easy to see two r

#However, the complete method also lets us see that breaking into more clusters can provide a
```