class08

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Today Mini-project we will explore a complete analysis using the unsupervised learning techniques covered in class (clustering and PCA for now)

```
# 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
```

```
#Data Frame We are Going to Work With
#Removing M / B column (which tells us the cancer we are working with)
wisc.data <- wisc.df[,-1]

diagnosis <- as.factor(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
```

Q1. How many observations are in this dataset? Answer: 569 observations

```
dim(wisc.data)
```

```
[1] 569  30
```

Q2. How many of the observations have a malignant diagnosis? Answer: 212 malignant diagnosis

```
table (diagnosis, exclude = "B")
```

```
diagnosis
  M
212
```

Q3. How many varaibles/features in the data are suffixed with _mean? Answer: 10 variable / features are suffixed with _mean

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

```
[1] 10
```

```
#Check column means and start 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
```

```
wisc.pr <- prcomp (wisc.data, scale = TRUE)
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) Answer: 44.27%

```
s <- summary(wisc.pr)
s$importance ["Proportion of Variance","PC1"]
```

```
[1] 0.44272
```

Q5. How many principal components (PCs) are required to describe at least 70% of the original variance in the data? Answer: 3PCs capture 72%

```
s$importance [3, ]
```

```
    PC1     PC2     PC3     PC4     PC5     PC6     PC7     PC8     PC9    PC10
0.44272 0.63243 0.72636 0.79239 0.84734 0.88759 0.91010 0.92598 0.93988 0.95157
   PC11    PC12    PC13    PC14    PC15    PC16    PC17    PC18    PC19    PC20
0.96137 0.97007 0.97812 0.98335 0.98649 0.98915 0.99113 0.99288 0.99453 0.99557
   PC21    PC22    PC23    PC24    PC25    PC26    PC27    PC28    PC29    PC30
0.99657 0.99749 0.99830 0.99890 0.99942 0.99969 0.99992 0.99997 1.00000 1.00000
```

Q6. How many principal componenets (PCs) are required to describe at least 90% of the original variance in the data Q6. Answer: 7 PCs

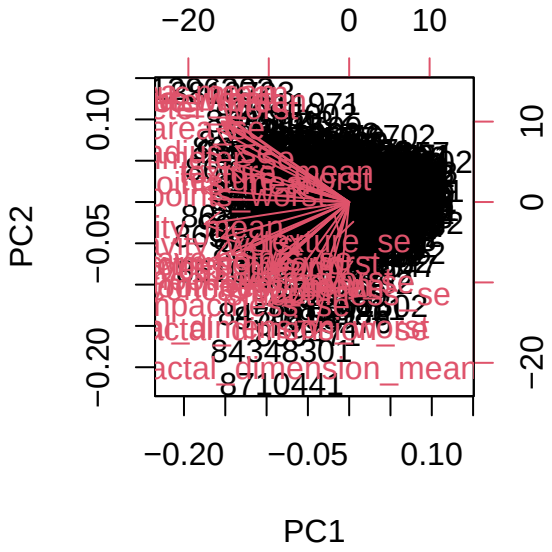
```
s$importance[3,]
```

```
    PC1     PC2     PC3     PC4     PC5     PC6     PC7     PC8     PC9    PC10
0.44272 0.63243 0.72636 0.79239 0.84734 0.88759 0.91010 0.92598 0.93988 0.95157
   PC11    PC12    PC13    PC14    PC15    PC16    PC17    PC18    PC19    PC20
0.96137 0.97007 0.97812 0.98335 0.98649 0.98915 0.99113 0.99288 0.99453 0.99557
   PC21    PC22    PC23    PC24    PC25    PC26    PC27    PC28    PC29    PC30
0.99657 0.99749 0.99830 0.99890 0.99942 0.99969 0.99992 0.99997 1.00000 1.00000
```

We need to make our plot of PC1 vs PC2 (a.k.a score plot, PC-plot, etc.) The main resuult of PCA

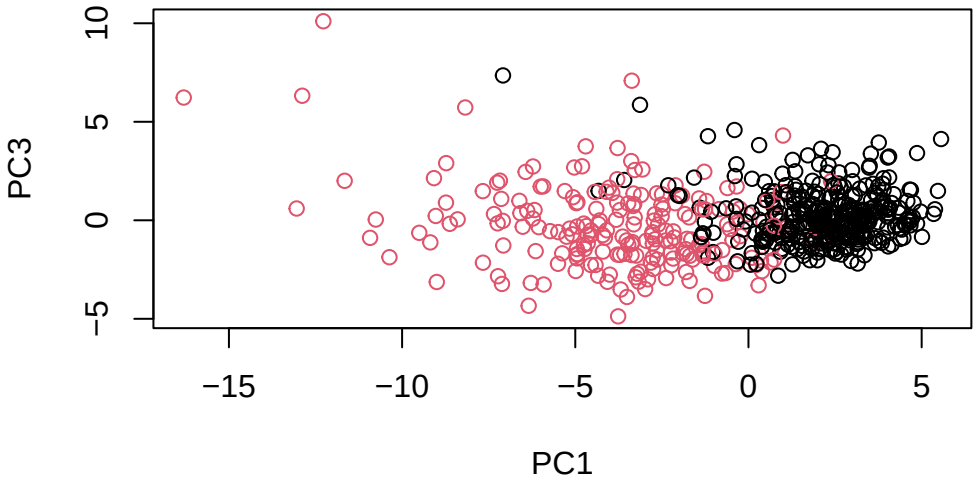
Q7. What stands out to you about this plot? Is it easy or difficult to understand? Why? Q7. Answers: The plot is difficult to understand. Its just a blob of data points

```
#? Concentration scatter plot>
biplot(wisc.pr)
```



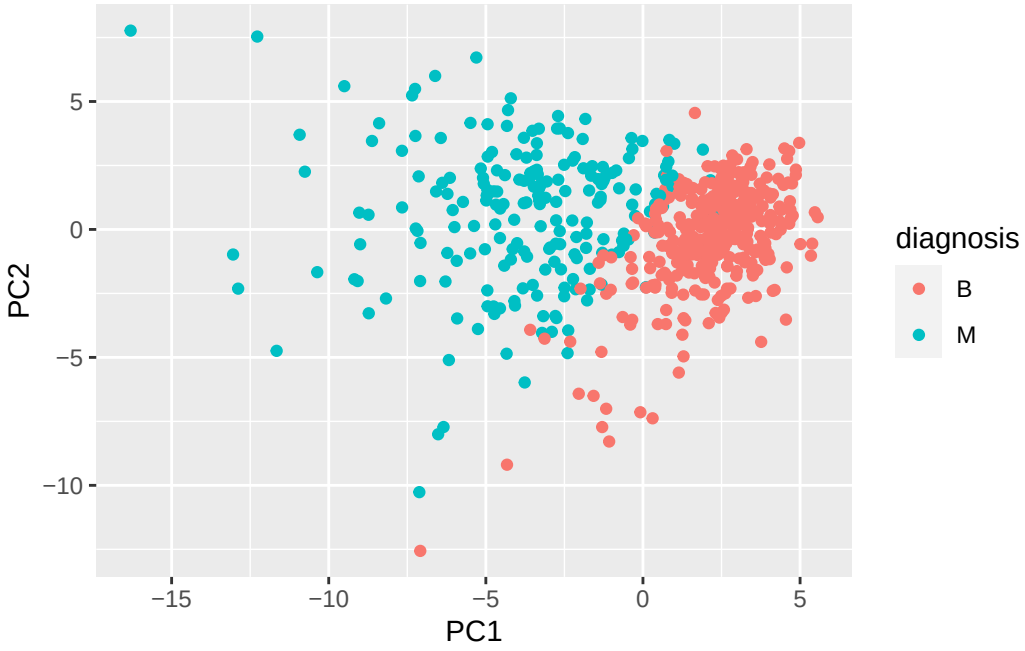
Q8. Generate a similar plot for principal componenets 1 and 3. What do you notice about these plots? Q8. Answer: The plots in this graph is more spread out / easier to read. The distinction of the two points is a lot easier to see.

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




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

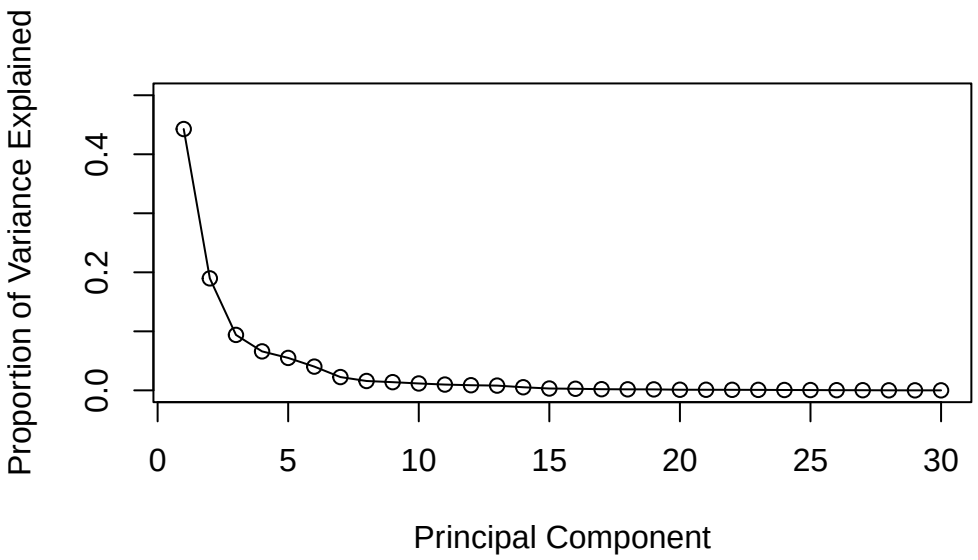



```
#Calculated variance of each component
pr.var <-  wisc.pr$sdev^2
head(pr.var)
```

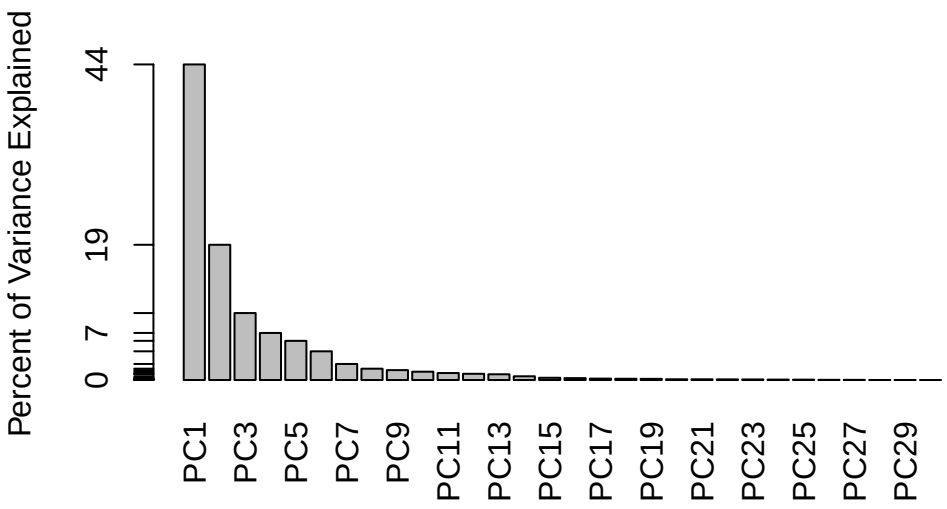
```
[1] 13.281608  5.691355  2.817949  1.980640  1.648731  1.207357
```

```
#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 =
```




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

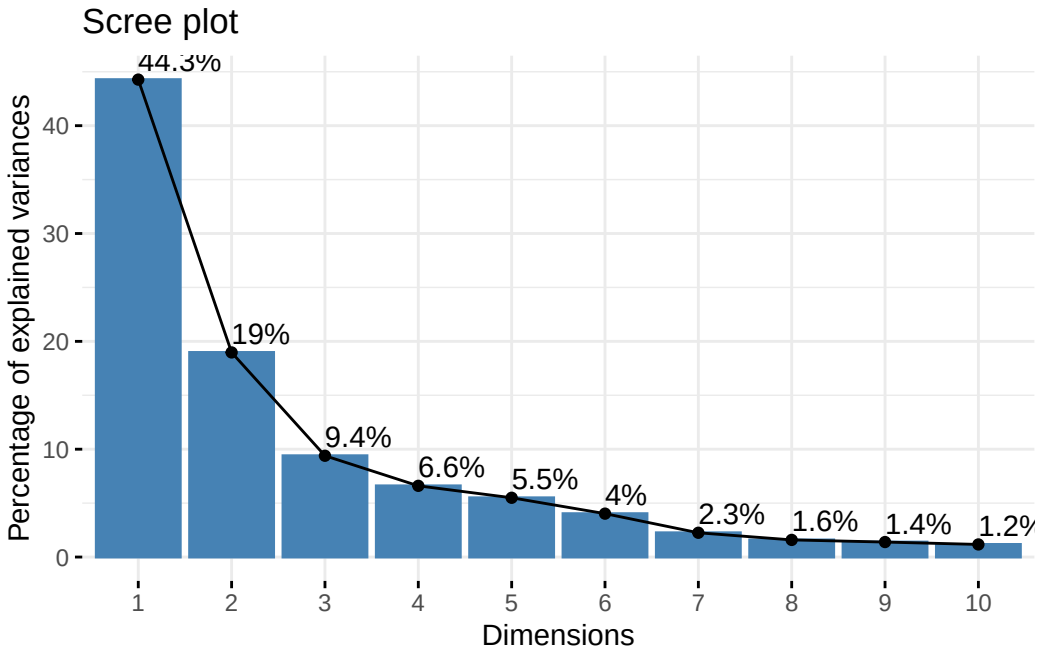


OPTION Graph!

```
## 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?

Q9. Answer: -0.26085376

```
#,1 focused on PC1
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
```

Q10: What is the minimum number of principal components required to explain 80% of the variance of the data? Q10. Answer: 5 PC

```
s$importance[3,]
```

```
    PC1     PC2     PC3     PC4     PC5     PC6     PC7     PC8     PC9    PC10
0.44272 0.63243 0.72636 0.79239 0.84734 0.88759 0.91010 0.92598 0.93988 0.95157
   PC11    PC12    PC13    PC14    PC15    PC16    PC17    PC18    PC19    PC20
0.96137 0.97007 0.97812 0.98335 0.98649 0.98915 0.99113 0.99288 0.99453 0.99557
   PC21    PC22    PC23    PC24    PC25    PC26    PC27    PC28    PC29    PC30
0.99657 0.99749 0.99830 0.99890 0.99942 0.99969 0.99992 0.99997 1.00000 1.00000
```

There is a commplicated mix of variables that go toegheter to make up PC1 - i.e. there are many of the original viarables that together contribute highly to PC1.

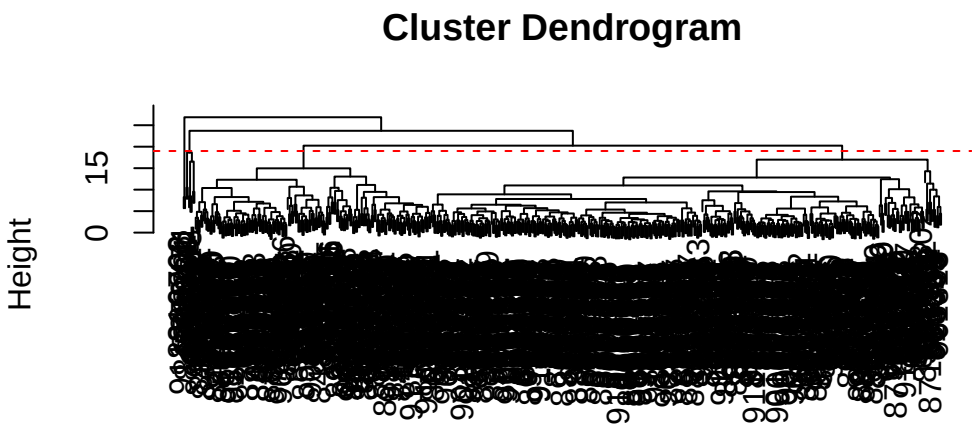
#3 Heirarchical Clustering

The goal of this section is to do hierarchical clustering original data. Firt we will scale the data, then distance matrix.

Q11. Using the plot() and abline() functions, what is the height at which the clustering model has 4 clusters? Q11. ANSWER: Around 19

```
#setting variables
data.scaled <- scale(wisc.data)
data.dist <- dist(data.scaled)
wisc.hclust <- hclust(data.dist, method =)

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



Cut this tree to yield cluster memberhsip vector with `cutree()` function

Q12. Can you find a better cluster vs diagnoses match by cutting into a different number of clusters between 2 and 10? Answer: No, I can't maybe there is a better method, but at my current ability i cant. 4 looks pretty good out of all of them. It divides the cluster nicely to our desired result / goal we are going for.

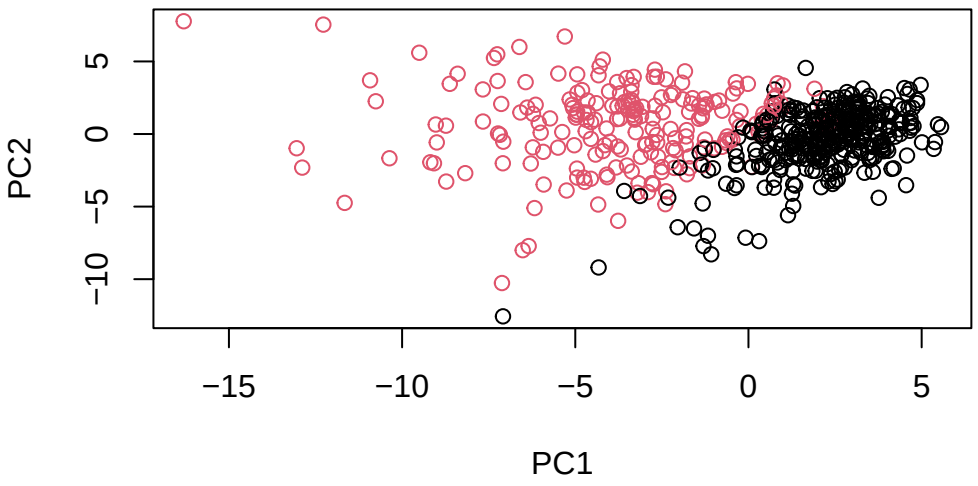
```
wisc.hclust.clusters <- cutree (wisc.hclust, k =4 )

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

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

```
#Forms a cross table, so you can read data points cleanly
#Code is not rendering since the variable wisc.pr.hclust was used later. As a result, im g

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




```
#Cluster the PCA results
d <-  dist (wisc.pr$x[,1:3])

wisc.pr.hclust <- hclust(d, method = "ward.D2")

grps <- cutree(wisc.pr.hclust, k=2)

table(grps)
```

```
grps
  1   2
203 366
```

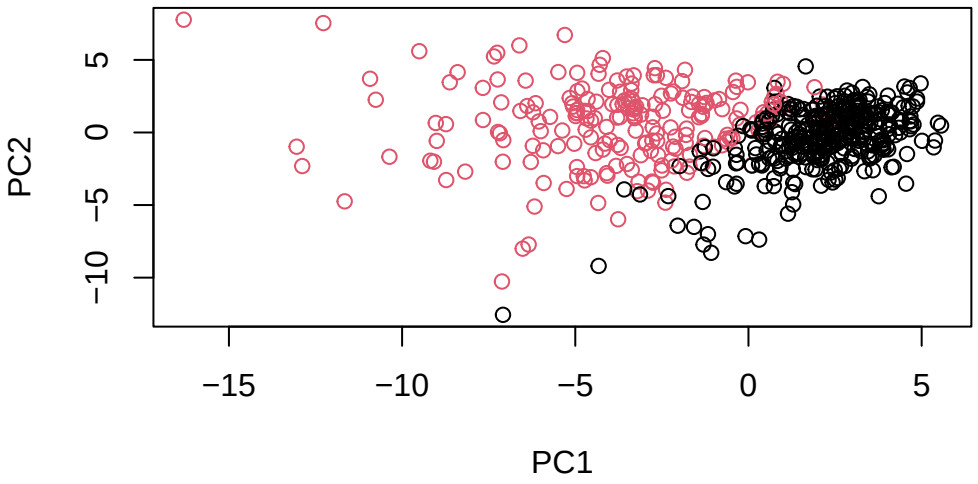
```
table(grps, diagnosis)
```

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

Q13. Which method gives your favorite results for the same data.dist dataset? Explain your reasoning. Answer: To be honest, I can't really tell the between the 4 methods. Maybe it is our dataset, but it look the same. As a result, I would probably go with complete since I'll remember complete rather than the other 4 methods.

#Combine Methods PCA

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

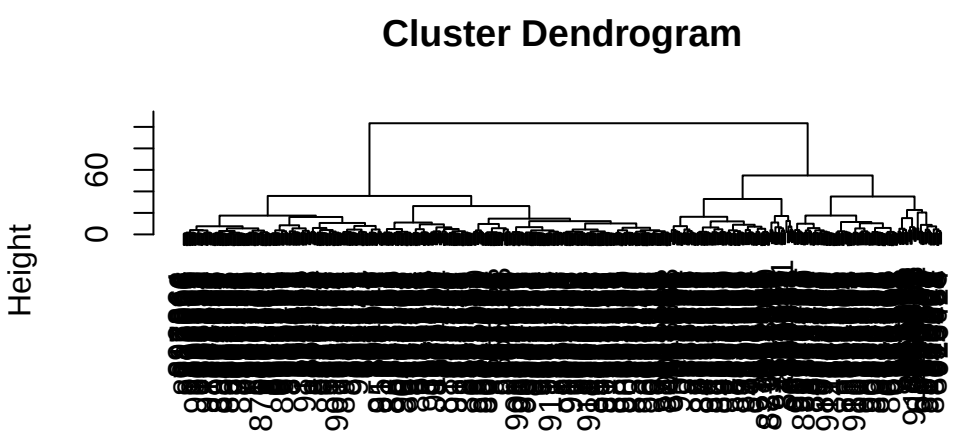



```
#Cluster the PCA results
d <-  dist (wisc.pr$x[,1:3])

wisc.pr.hclust <- hclust(d, method = "ward.D2")
```

An my tree result figure

```
#Cleaner Tree
plot (wisc.pr.hclust)
```




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

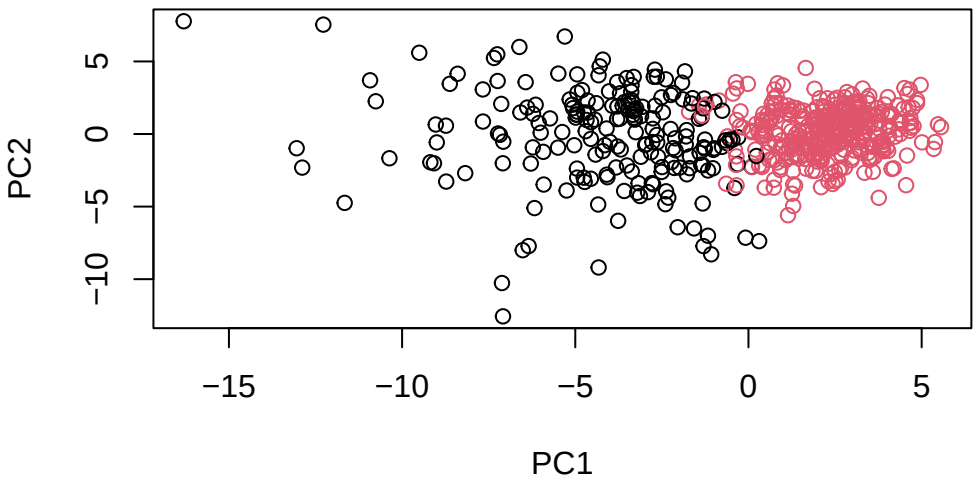
```
grps <- cutree(wisc.pr.hclust, k=2)
table(grps)
```

```
grps
  1   2
203 366
```

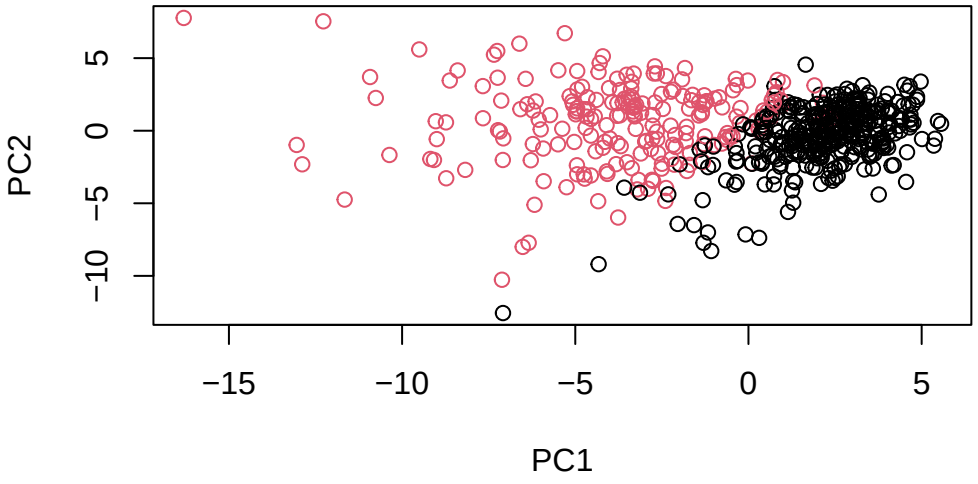
```
table (grps, diagnosis)
```

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

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




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



Q15. How well does the newly created model with four clusters separate out the two diagnoses? Answer: it separates the model really nicely. Cleaner to see the observation numbers. Easier way to see TN, TP, FN , FP, so this cluster is good.

```
#For the Hclust, you need to put in the distance function. REMMEMBER THAT
wisc.pr.hclust <- hclust( dist(wisc.pr$x[,1:7]), method="ward.D2")

wisc.pr.hclust.clusters <- cutree(wisc.pr.hclust, k=2)

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

```
                     diagnosis
wisc.pr.hclust.clusters   B   M
                      1  28 188
                      2 329  24
```