Class 8 Mini Project

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Preparing the data

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

Omit the first column and move it to a diagnosis vector

```
wisc.data <- wisc.df[,-1]
diagnosis <- as.factor(wisc.df$diagnosis)
```

Exploratory Data Analysis

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

```
[1] 569  30
```

Question 1: How many observations are in this dataset?

569 Rows so 569 Observations

Question 2: How many of the observations have a malignant diagnosis?

```r
sum(wisc.df$diagnosis == "M")
```

```
[1] 212
```

212 of the observations ahve a malignant diagnosis

Question 3: How many variables/features in the data set are suffixed with _mean

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

```
[1] 10
```

10 variables/features in the data set are suffixed with _mean

Principal Component Analysis

Performing PCA

```r
#Check column means and standard deviation
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
```

```r
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
```

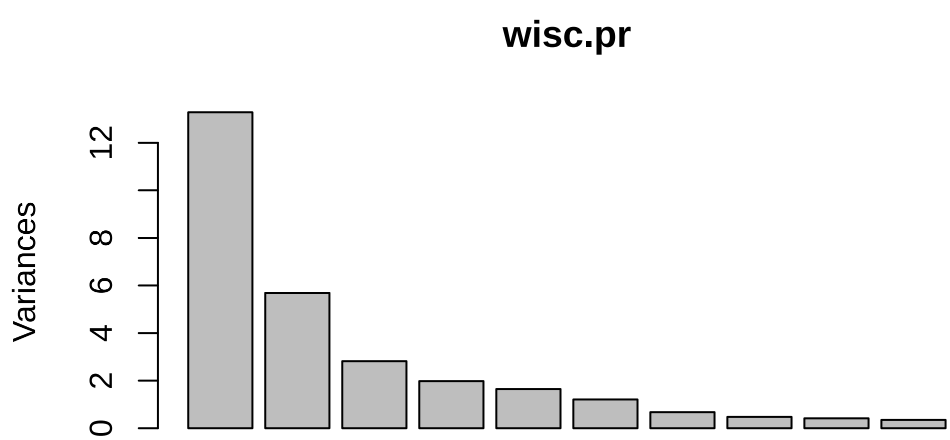
```r
#Perform PCA on wisc.data
wisc.pr <- prcomp( wisc.data, scale = TRUE )
```

```r
#Look at summary of results
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
```

```
plot(wisc.pr)
```



Question 4: From your results, what proportion of the original variance captured by the first principal components (PC1)?

From my results, the proportion of the original variance by the PC1 is 0.4427

Question 5: How many principal components (PCs) are required to describe at least 70% of the original variance in this data?

3 -> PC1, PC2, and PC3

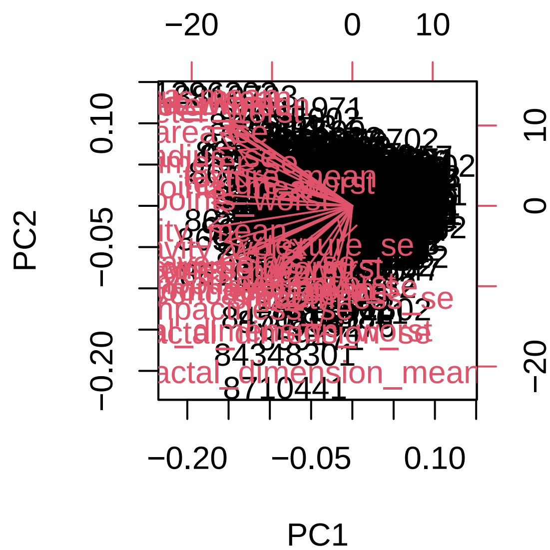
Question 6: How many principal components (PCs) are required to describe at least 90% of the original variance in this data?

7 -> PC1, PC2, PC3, PC4, PC5, PC6, PC7

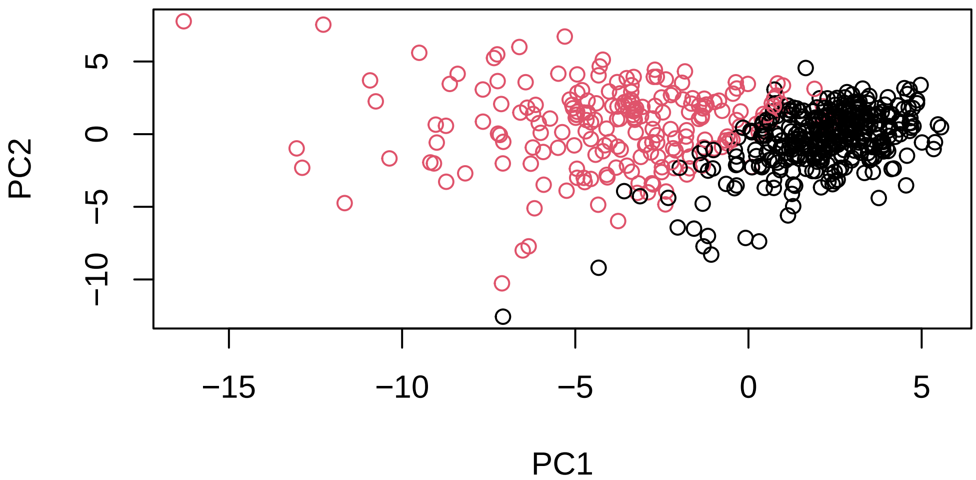
Question 7: What stands out to you about this plot? Is it easy or difficult to understand? Why?

What stands out to me about this plot is that each point on the plot is labeled by the row name which makes it really hard to distinguish the difference between points as the names just overlap onto each other causing a huge black uneven circle on the plot.

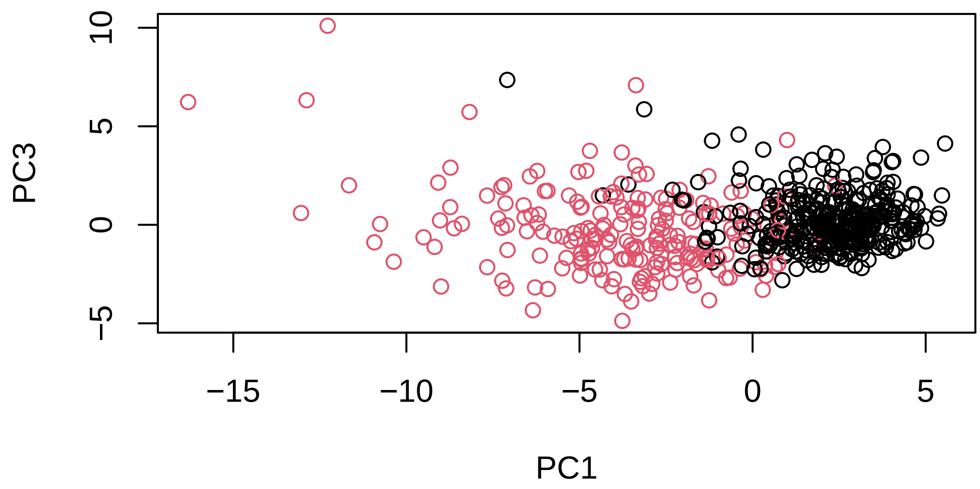
```
biplot(wisc.pr)
```




```
# Scatter plot Observations by components 1 and 2
plot( wisc.pr$x[,1], wisc.pr$x[,2], col = diagnosis,
     xlab = "PC1", ylab = "PC2")
```




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



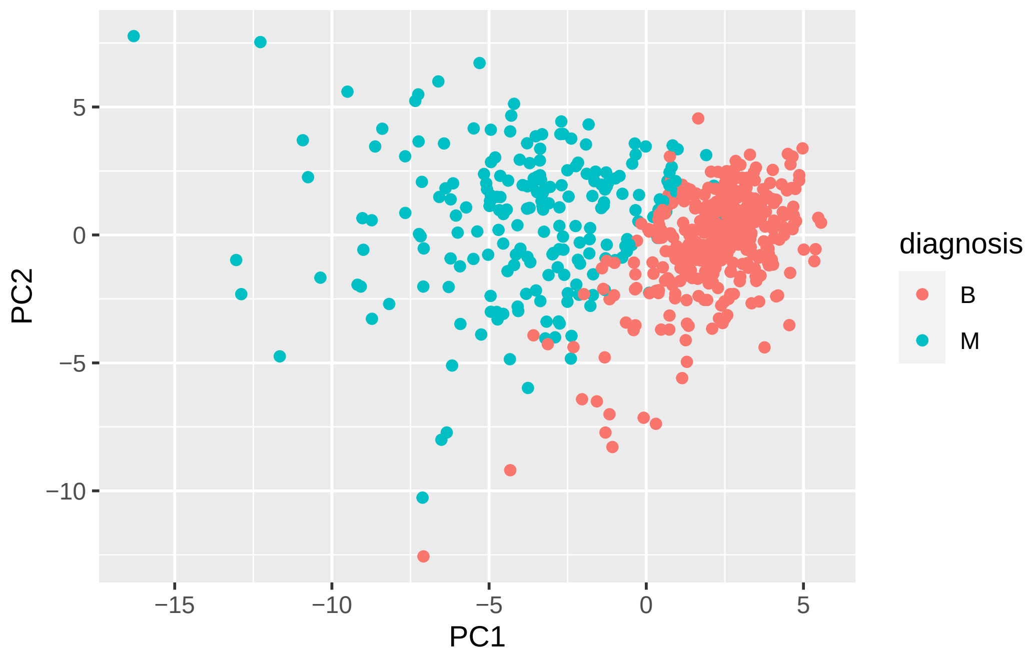
Question 8: Generate a similar plot for principal components 1 and 3. What do you notice about these plots?

The first plot between PC1 & PC2 has a more observant separation while the second plot between PC1 & PC3 has more data points overlapping

```
# Create a data.frame for ggplot
df <- as.data.frame(wisc.pr$x)
df$diagnosis <- diagnosis

# Load the ggplot 2 package
library(ggplot2)

#Make a scatter plot colored by diagnosis
ggplot(df) +
  aes(PC1, PC2, col = diagnosis) +
  geom_point()
```



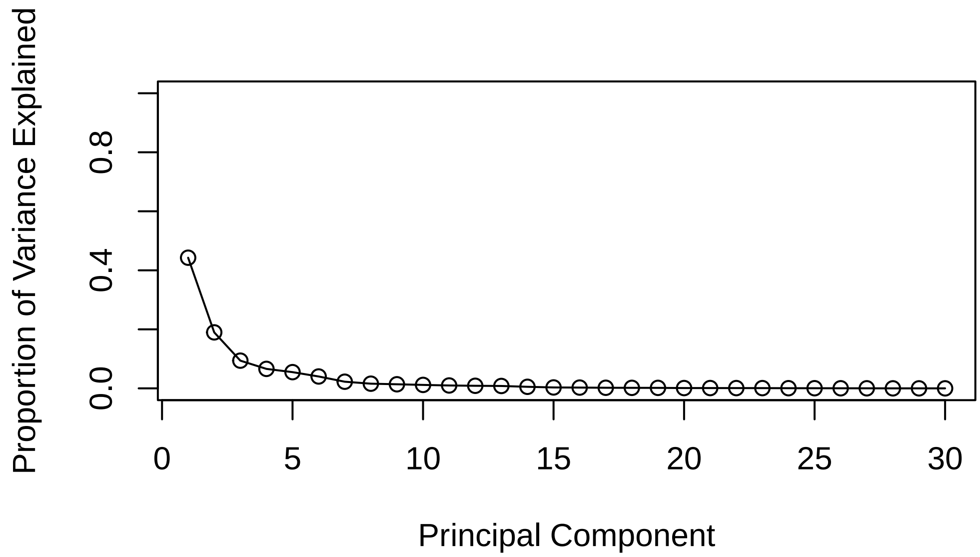
Variance Explained

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

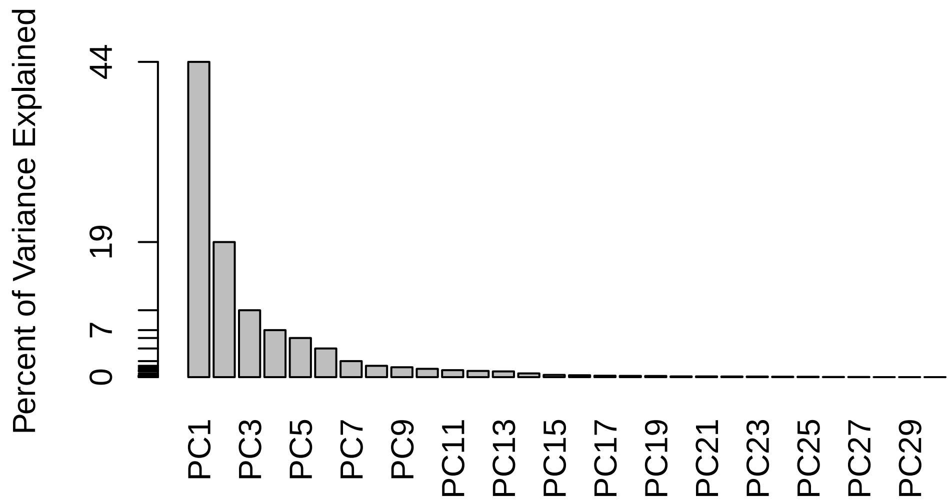
```
[1] 13.281608  5.691355  2.817949  1.980640  1.648731  1.207357
```

```
#Variance explained by each principal componenet: 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")
```



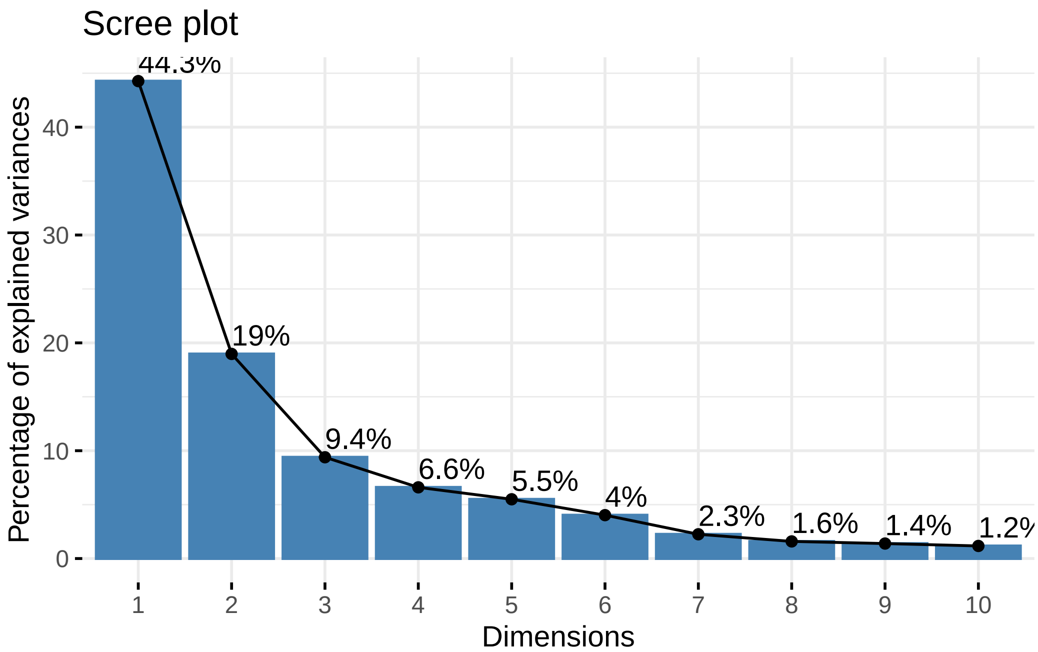

```
#Alternative scree plot of the same data, note data driven y-axis
barplot(pve, ylab = "Percent of Variance Explained",
        names.arg=paste0("PC", 1:length(pve)), las=2, axes = FALSE)
axis(2, at=pve, labels=round(pve,2)*100)
```




```
##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)
```



Question 10: What is the minimum number of principal components required to explain 80% of the variance of the data?

The minimum number of PC to explain 80% of the variance of the data is 5 (PC1-5)

Hierarchical Clustering

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

Combining Methods

Clustering on PCA Results

Question 15: How well does the newly created model with four clusters separate out the two diagnoses?

It seperates out the two diagnoses fairy well as the newly created model with four clusters is more easily to observe

Question 16: How well do the k-means and hierarchical clustering models you created in previous sections (i.e. before PCA) do in terms of separating the diagnoses? Again, use the table() function to compare the output of each model (wisc.km$cluster and wisc.hclust.clusters) with the vector containing the actual diagnoses.

In terms of separating the diagnoses, the k-means and hierarchical clustering models I created don't do that well compared to the newest models I've created

Question 17: Which of your analysis procedures resulted in a clustering model with the best specificity? How about sensitivity?

The analysis procedure which resulted in the best specificity is the hierarchical clustering model. The one with the best sensitivity is the PCA analysis

Question 18: Which of these new patients should we prioritize for follow up based on your results?

Patient 2 “‘