## Mini-project

Pham Vo

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

#Remove the first column as we will not use that for unsupervised analysis.
wisc.data <- wisc.df[,-1]</pre>
```

### Create diagnosis vector for later

```
diagnosis <- wisc.df[,1]</pre>
```

Q1. How many observations are in this dataset?

```
wisc.data <- wisc.df[,-1]
diagnosis <- wisc.df[,1]
ncol(wisc.data)</pre>
```

## [1] 31

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

```
wisc.data <- wisc.df[,-1]
diagnosis <- wisc.df[,1]
table(wisc.df$diagnosis)</pre>
```

## B M ## 357 212

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

```
wisc.data <- wisc.df[,-1]
diagnosis <- wisc.df[,1]
colvec <- colnames(wisc.data)
length(grep("_mean", colvec))</pre>
```

```
## [1] 10
```

##Performing PCA

# Check column means and standard deviations

#### colMeans(wisc.data)

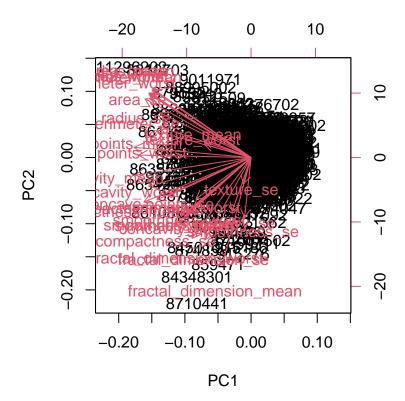
##	radius_mean	texture_mean	perimeter_mean
##	1.412729e+01	1.928965e+01	9.196903e+01
##	area_mean	${\tt smoothness\_mean}$	compactness_mean
##	6.548891e+02	9.636028e-02	1.043410e-01
##	${\tt concavity\_mean}$	concave.points_mean	symmetry_mean
##	8.879932e-02	4.891915e-02	1.811619e-01
##	fractal_dimension_mean	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	${\tt fractal\_dimension\_worst}$
##	1.146062e-01	2.900756e-01	8.394582e-02
##	X		
##	NA		

### apply(wisc.data,2,sd)

##	radius_mean	texture_mean	perimeter_mean
##	3.524049e+00	4.301036e+00	2.429898e+01
##	area_mean	${\tt smoothness\_mean}$	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	<pre>fractal_dimension_worst</pre>
##	6.573234e-02	6.186747e-02	1.806127e-02
##	X		
##	NA		

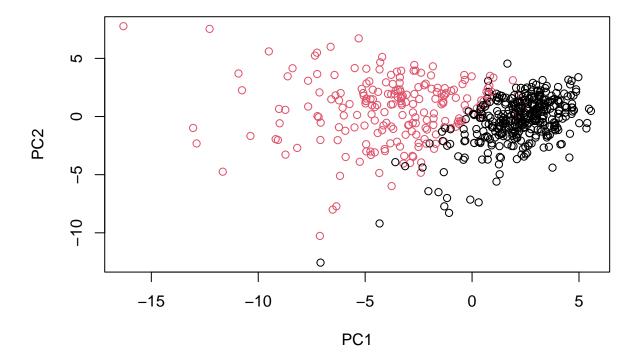
### Perform PCA on wisc.data by completing the following code

```
wisc.data <- wisc.df[,-1]</pre>
wisc.data1 <- na.omit(wisc.data)</pre>
diagnosis <- wisc.df[,1]</pre>
wisc.data.scaled.2 <- data.frame(t(na.omit(t(wisc.data))))</pre>
wisc.pr <- prcomp(wisc.data.scaled.2, scale=TRUE)</pre>
summary(wisc.pr)
## Importance of components:
                              PC1
                                      PC2
                                                               PC5
##
                                              PC3
                                                       PC4
                                                                        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
##
                                              PC10
                                                      PC11
                                                              PC12
                               PC8
                                       PC9
                                                                       PC13
## 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
## 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
## Standard deviation
                           0.16565 0.15602 0.1344 0.12442 0.09043 0.08307 0.03987
## Proportion of Variance 0.00091 0.00081 0.0006 0.00052 0.00027 0.00023 0.00005
## Cumulative Proportion 0.99749 0.99830 0.9989 0.99942 0.99969 0.99992 0.99997
                              PC29
                                       PC30
## Standard deviation
                           0.02736 0.01153
## Proportion of Variance 0.00002 0.00000
## Cumulative Proportion 1.00000 1.00000
     Q4. From your results, what proportion of the original variance is captured by the first principal
     components (PC1)?
44.27\%
     Q5. How many principal components (PCs) are required to describe at least 70% of the original
     variance in the data?
3 PCs
     Q6. How many principal components (PCs) are required to describe at least 90% of the original
     variance in the data?
7 PCs
#Plot pca
biplot(wisc.pr)
```



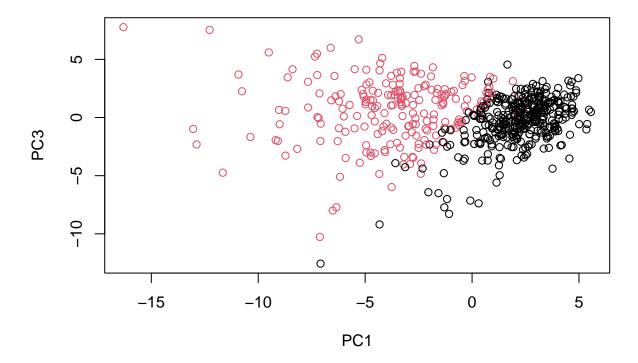
# Scatter plot observations by components ${\bf 1}$ and ${\bf 2}$

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



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

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



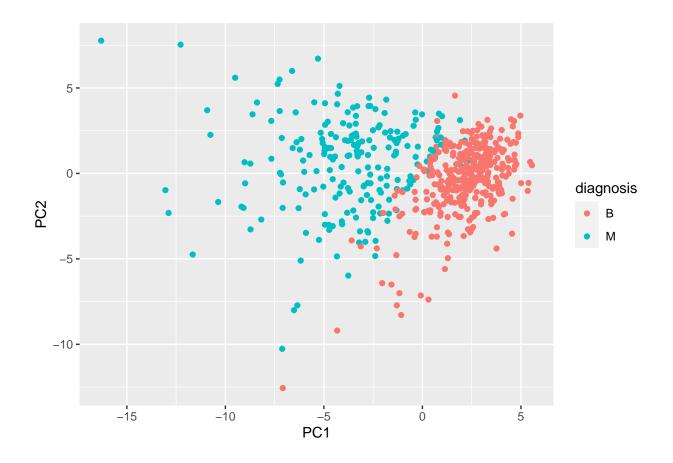
The first plot shows a better separation between the two groups.

Plot using ggplot2 package

```
# 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()</pre>
```



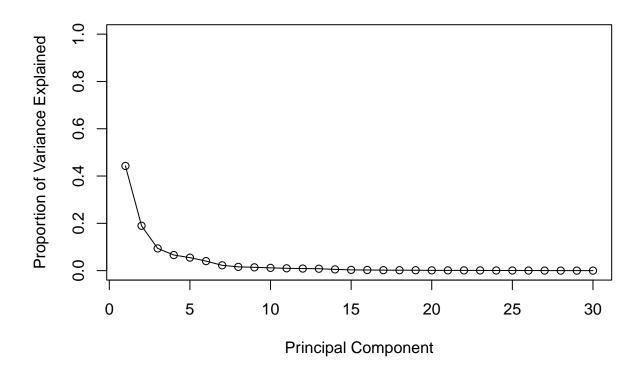
### Variance explained

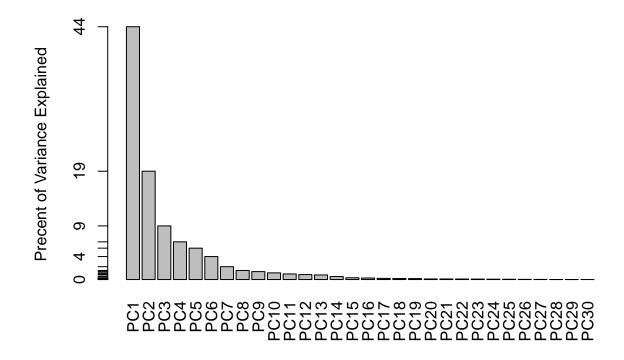
```
# Calculate variance of each component
pr.var <- wisc.pr$sdev^2
head(pr.var)

## [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")</pre>
```





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?

#### -0.2608538

```
loading_scores <- wisc.pr$rotation[,1]
loading_scores["concave.points_mean"]</pre>
```

```
## concave.points_mean
## -0.2608538
```

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

5 PCs.

### Hierarchical clustering

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

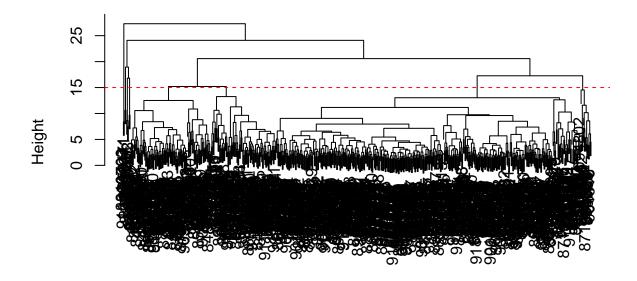
```
# Scale the wisc.data data using the "scale()" function
data.scaled <- scale(wisc.data)

#Calculate the (Euclidean) distances between all pairs of observations in the new scaled dataset and as
data.dist <- dist(data.scaled)

#Create a hierarchical clustering model using complete linkage. Manually specify the method argument to
wisc.hclust <- hclust(data.dist, method="complete")

#Using the plot() and abline() functions, what is the height at which the clustering model has 4 cluste
plot(wisc.hclust)
abline(h=15, col="red", lty=2)</pre>
```

### **Cluster Dendrogram**



data.dist hclust (\*, "complete")

### Selecting number of clusters

```
wisc.hclust.clusters <- cutree(wisc.hclust, k=4)
#We can use the table() function to compare the cluster membership to the actual diagnoses.
table(wisc.hclust.clusters, diagnosis)</pre>
```

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

```
tinytex::install_tinytex()
```

## The directory /usr/local/bin is not writable. I recommend that you make it writable. See https://git