

## class8: Mini Project

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#Unsupervised Learning Analysis of Human Breast Cancer Cells

##Exploratory data analysis

###Read the data into R using read.csv()

```
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
```

```
### Remove diagnosis column
```

```
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
```

### Save diagnosis column as a new vector

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

```
## [1] M M M M M M
## Levels: B M
```

Q1. How many observations are in this dataset?

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

```
## [1] 569
```

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

```
sum(grepl("M", diagnosis))
```

```
## [1] 212
```

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

```
sum(grepl("_mean", names(wisc.data)))
```

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

```
##Principal Component Analysis
```

```
##Performing PCA
```

```
###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

```
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
```

###Perform PCA

```
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)?

44.27%

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

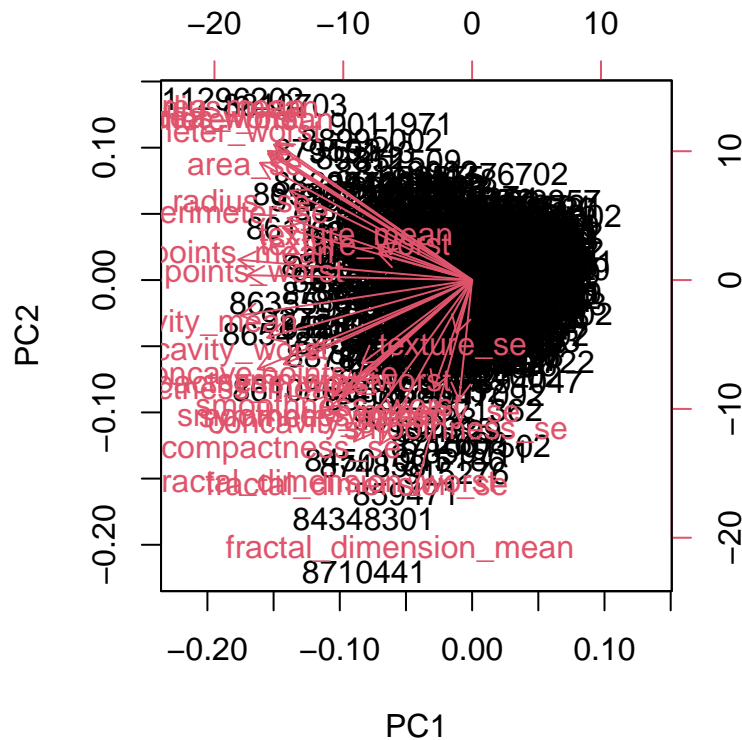
3 principal components (PC3)

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

7 principal components (PC7)

###Creating a Biplot `biplot()` of `wisc.pr` function

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

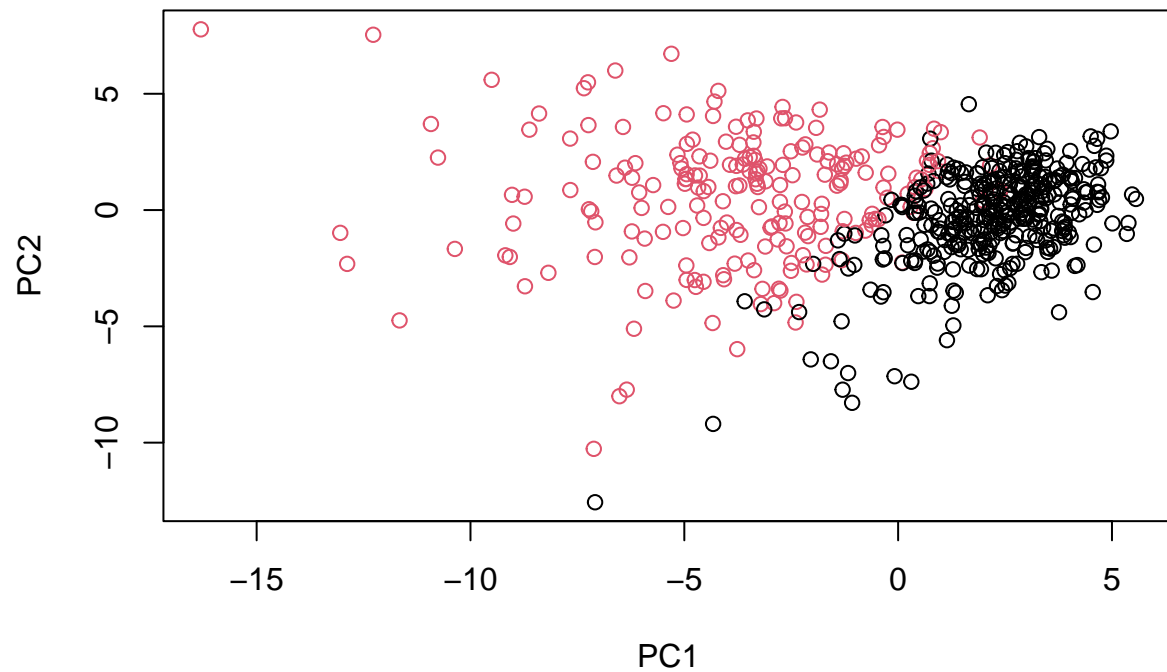


Q7. What stands out to you about this plot? Is it easy or difficult to understand? Why?

This plot is difficult to understand since everything is all bunched together and it is hard to read or look at data in the plot.

Now I will make result: “PCA Plot” (a.k.a. “score plot PC1 vs PC2 plot)

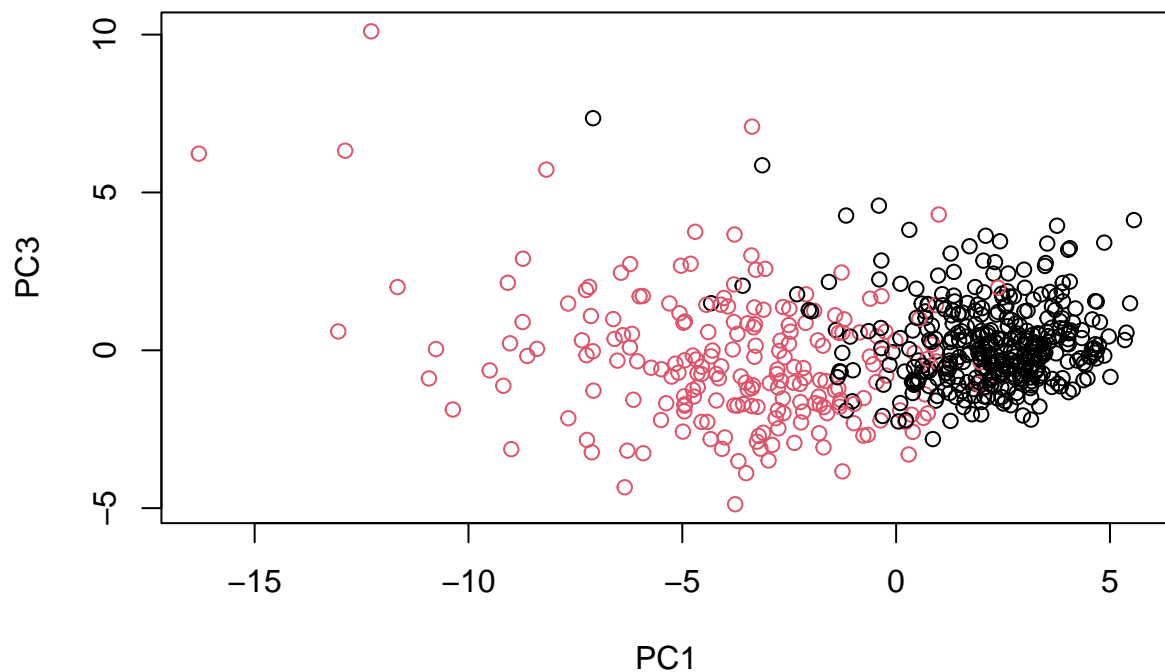
```
plot(wisc.pr$x[,1:2], col=diagnosis, xlab = "PC1", ylab = "PC2")
```



Now I will do the same to compare PC1 and PC3

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

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



### Attempt with ggplot function

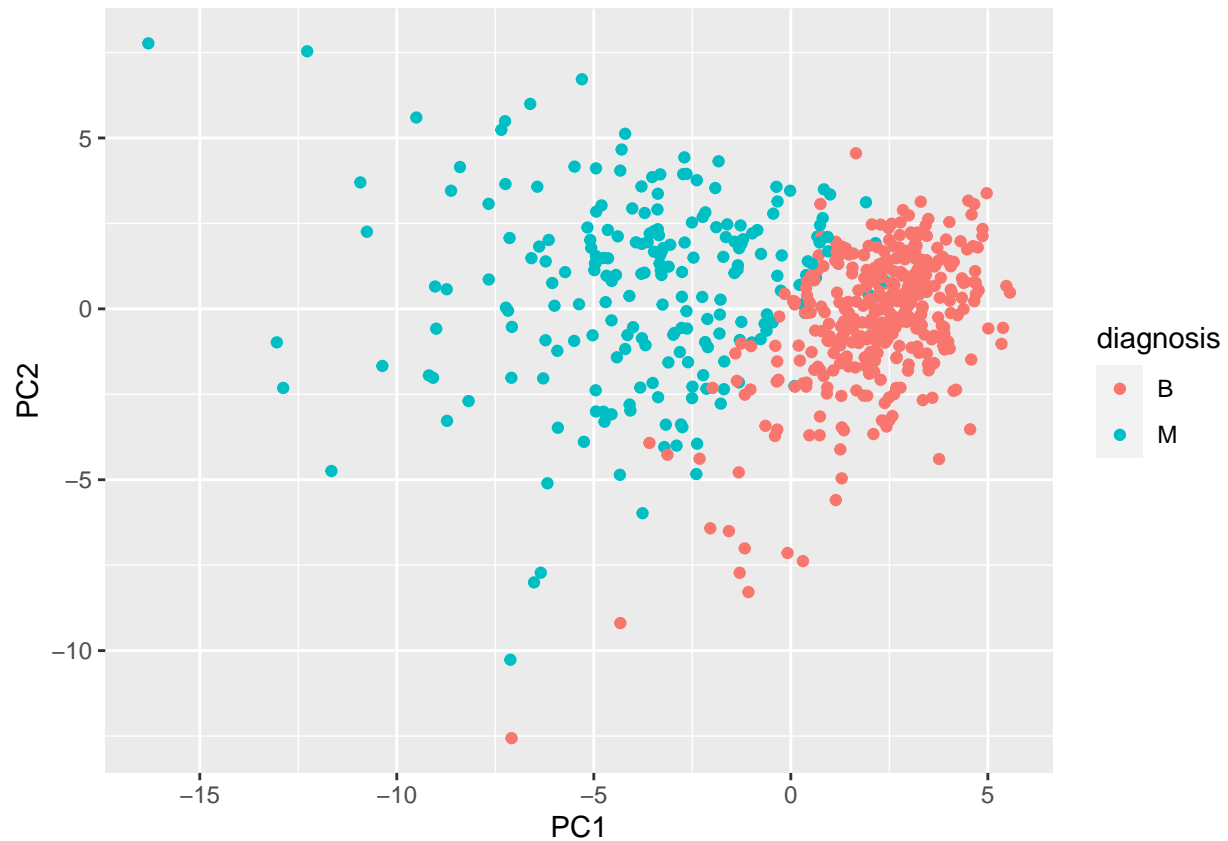
```
#create dataframe with ggplot  
df <- as.data.frame(wisc.pr$x)  
df$diagnosis <- diagnosis
```

```
#load ggplot2 package  
library(ggplot2)
```

```
## Warning in register(): Can't find generic 'scale_type' in package ggplot2 to  
## register S3 method.
```

```
#make a scatterplot colored by diagnosis  
ggplot(df) +  
  aes(PC1, PC2, col=diagnosis) +  
  geom_point()
```





```
### Variance Explained
```

```
### Scree Plot Attempt
```

```
# calculate variance of each component
```

```
pr.var <- wisc.pr$sdev^2
```

```
head(pr.var)
```

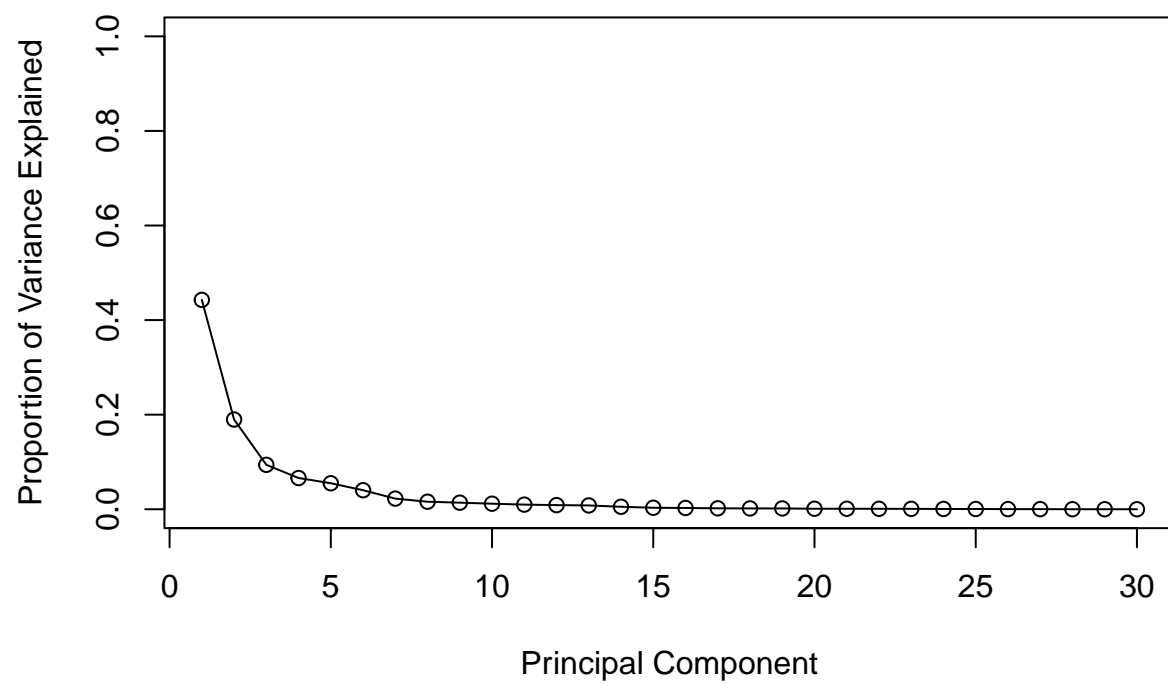
```
## [1] 13.281608  5.691355  2.817949  1.980640  1.648731  1.207357
```

```
# Variance explained by each principal component: pve
```

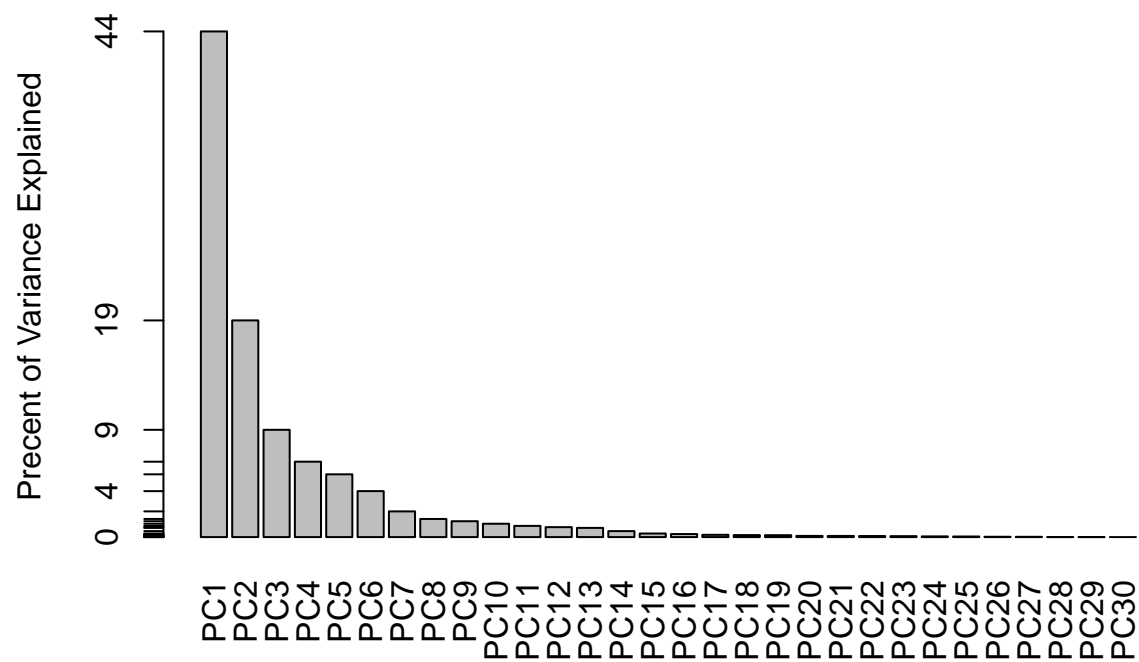
```
pve <- pr.var/ sum(pr.var)
```

```
# 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 )
```

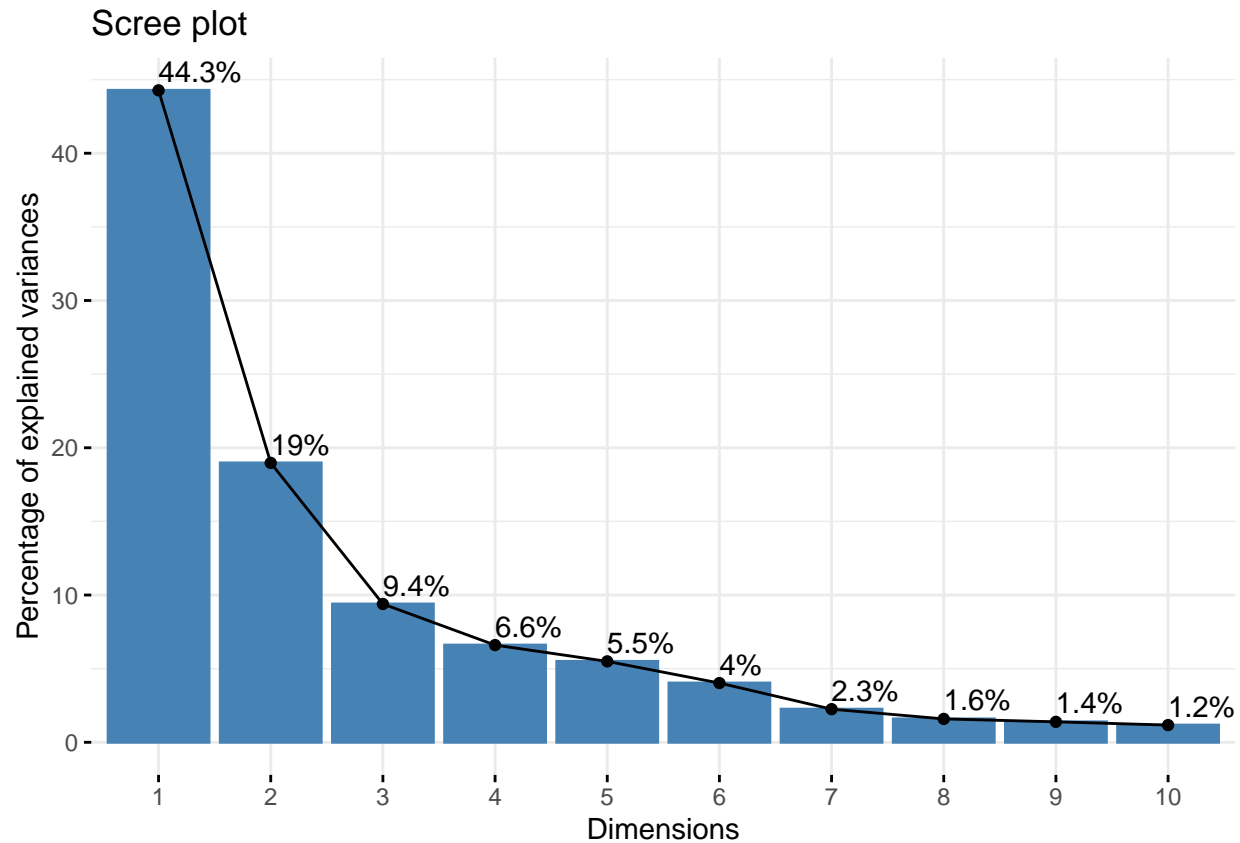


###Optional ggplot graph exploration

```
## 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)
```



##Communicating PCA

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`?

```
grep("concave.points_mean", names(wisc.pr$rotation[,1]))
```

```
## [1] 8
```

```
wisc.pr$rotation[8,1]
```

```
## [1] -0.2608538
```

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

```
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
```

Minimum is PC5 to explain 80% of variance of data

##Hierarchical Clustering

First we scale the data

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

Calculate (Euclidean) distances between all pairs of observations

```
data.dist <- dist(data.scaled)
head(data.dist)
```

```
## [1] 10.309426  6.771675 10.463467  8.663413  8.402233  9.843286
```

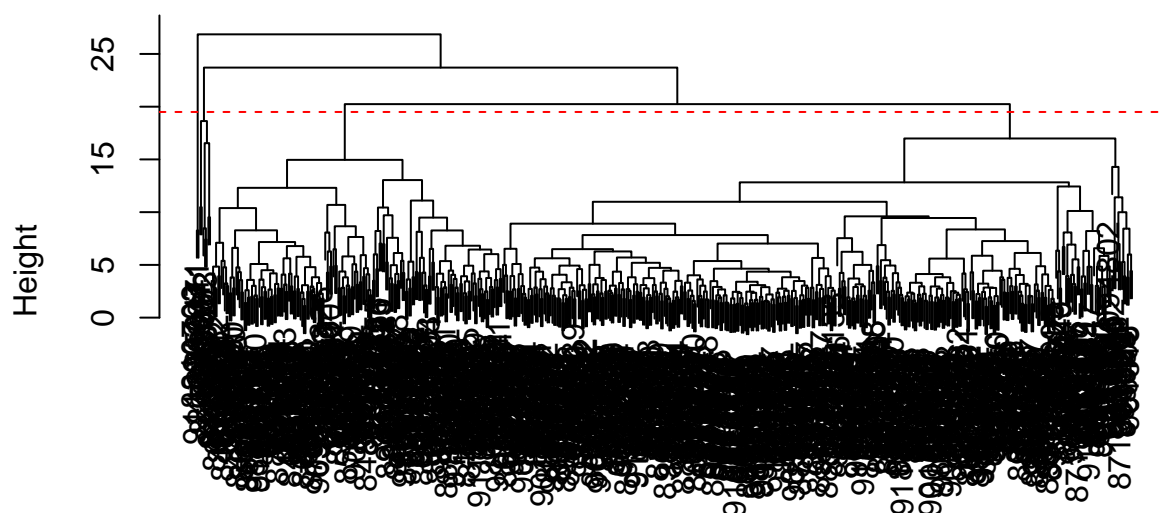
```
wisc.hclust <- hclust(data.dist, method= "complete")
```

###Result of Heirarchical clustering

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

```
plot(wisc.hclust)
abline(h=19.5, col="red", lty=2)
```

## Cluster Dendrogram



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

###Selecting number of Clusters

```
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
```

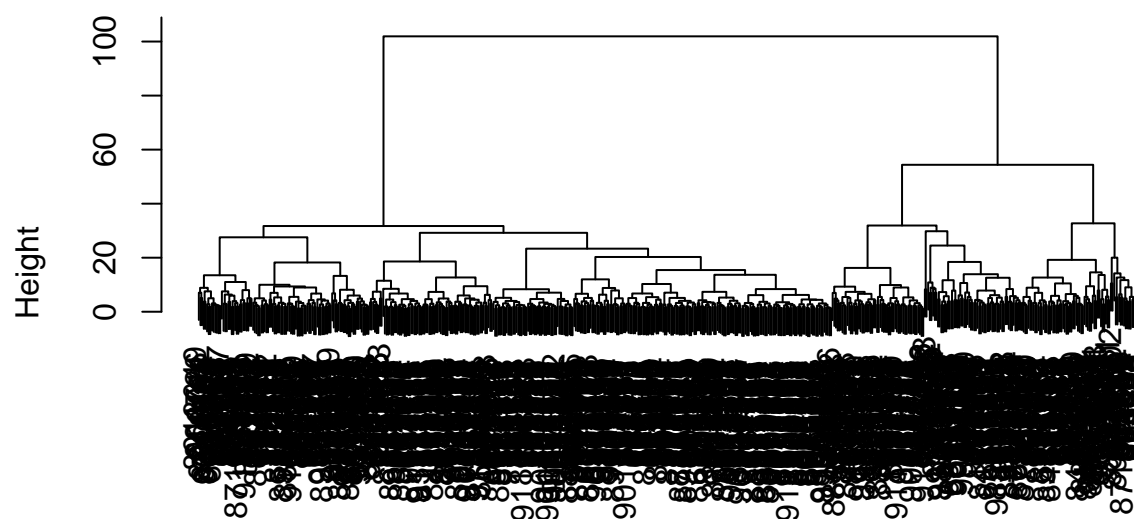
###Using different methods

Q13. Which method gives your favorite results for the same data.dist dataset? Explain your reasoning.

I chose “ward.D2” because it makes it easier for me to see the different groups and its a little easier to distinguish between possible clusters.

```
plot(hclust(data.dist, method= "ward.D2"))
```

## Cluster Dendrogram

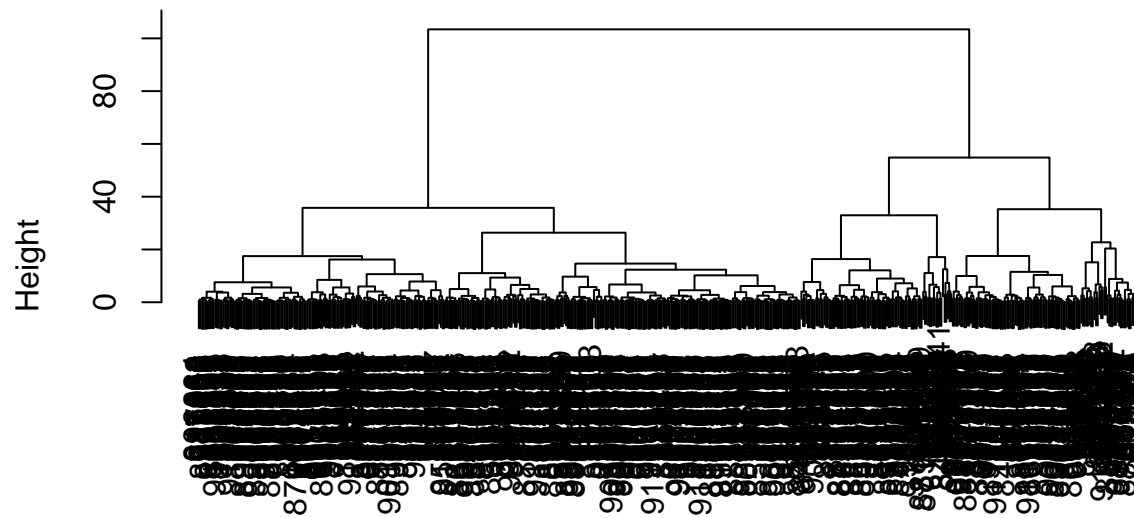


```
data.dist  
hclust (*, "ward.D2")
```

```
##Combining Methods
```

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

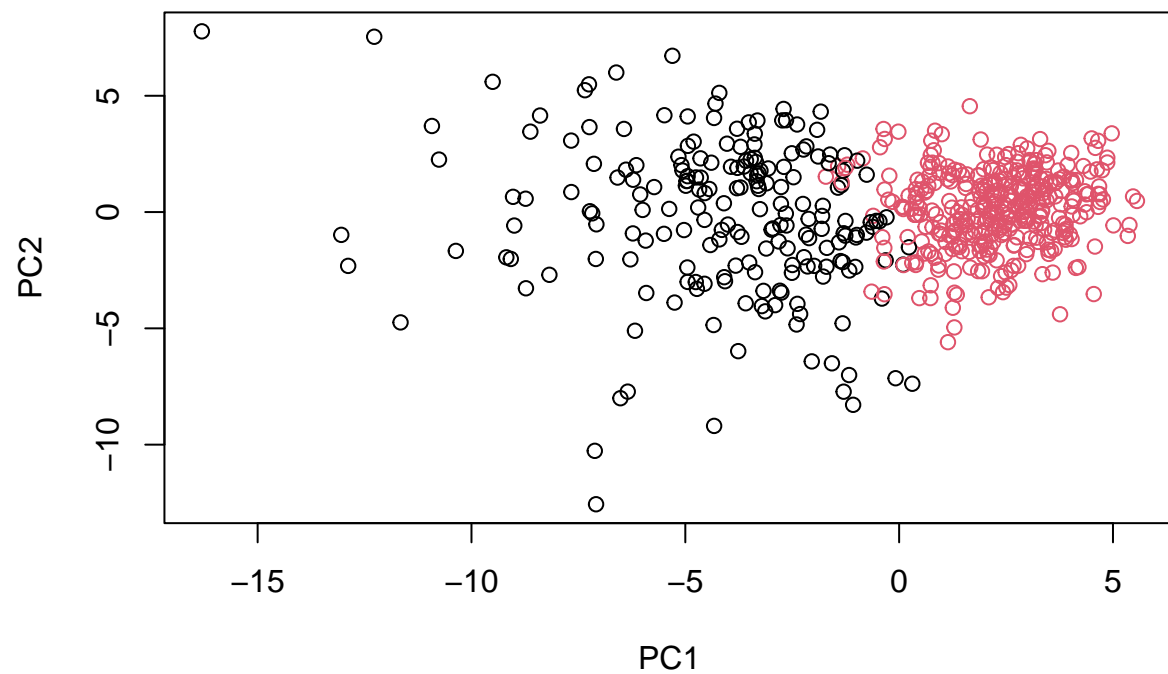
## Cluster Dendrogram



pcdist  
hclust (\*, "ward.D2")

```
grps <- cutree(wisc.pr.hclust, k=2)  
plot(wisc.pr$x[,1:2], col=grps)
```





```
table(diagnosis)
```

```
## diagnosis
##   B   M
## 357 212
```

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

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