

Unsupervised Learning Mini-Project

```
# 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	X			
842302		0.11890	NA		
842517		0.08902	NA		
84300903		0.08758	NA		
84348301		0.17300	NA		
84358402		0.07678	NA		
843786		0.12440	NA		

```
# We can use -1 here to remove the first 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	X	
842302	0.11890	NA	
842517	0.08902	NA	
84300903	0.08758	NA	
84348301	0.17300	NA	
84358402	0.07678	NA	
843786	0.12440	NA	

```
# Create diagnosis vector for later
diagnosis <- as.vector(wisc.df$diagnosis)
head(diagnosis)
```

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

```
is.vector(diagnosis) == TRUE
```

```
[1] TRUE
```

Q1. How many observations are in this dataset?

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

```
[1] 569
```

569 observations.

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

```
sum(diagnosis == "B")
```

```
[1] 357
```

357 observations.

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

```
features <- as.vector(colnames(wisc.data))
sum(grepl("_mean", features))
```

[1] 10

10 features.

```
# 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	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
X		
NA		

```
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
X		
NA		

```
# Perform PCA on wisc.data by completing the following code
wisc.pr <- prcomp(wisc.data[,colnames(wisc.data) != "X"], 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)?

0.4427

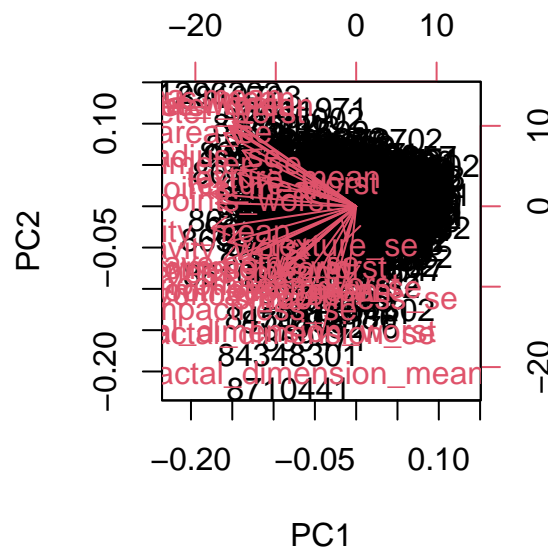
Q5. How many principal components (PCs) are required to describe at least 70% of the original variance in the data?

Three ("Cumulative Proportion" first exceeds 0.7 at PC3).

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

Three ("Cumulative Proportion" first exceeds 0.9 at PC7).

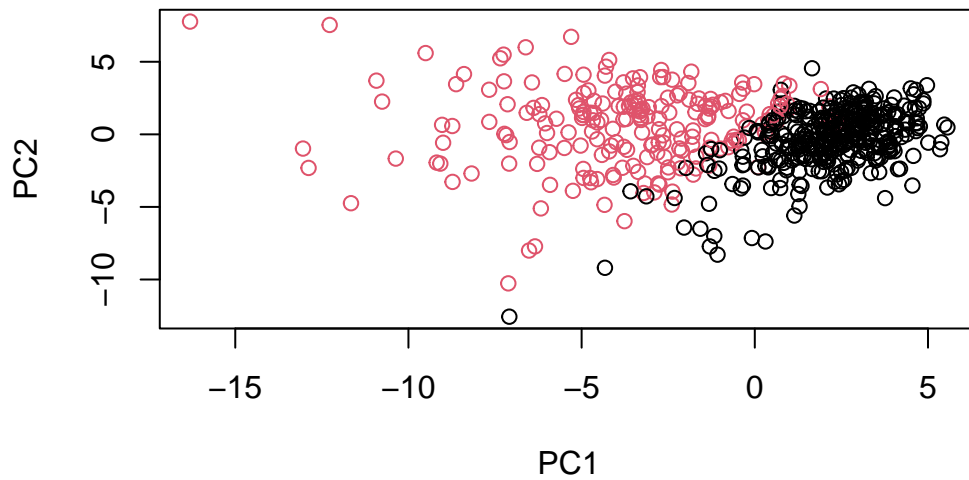
```
biplot(wisc.pr)
```



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

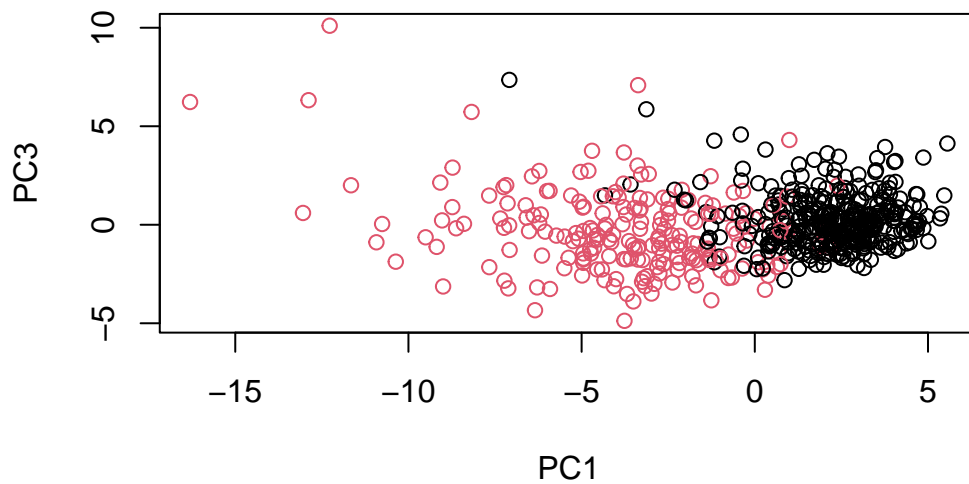
It is too crowded due to row names being plotted.

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



Q8

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



The variation along the vertical axis is less in PC3 than in PC2, because PC3 is less strong as a contributor.

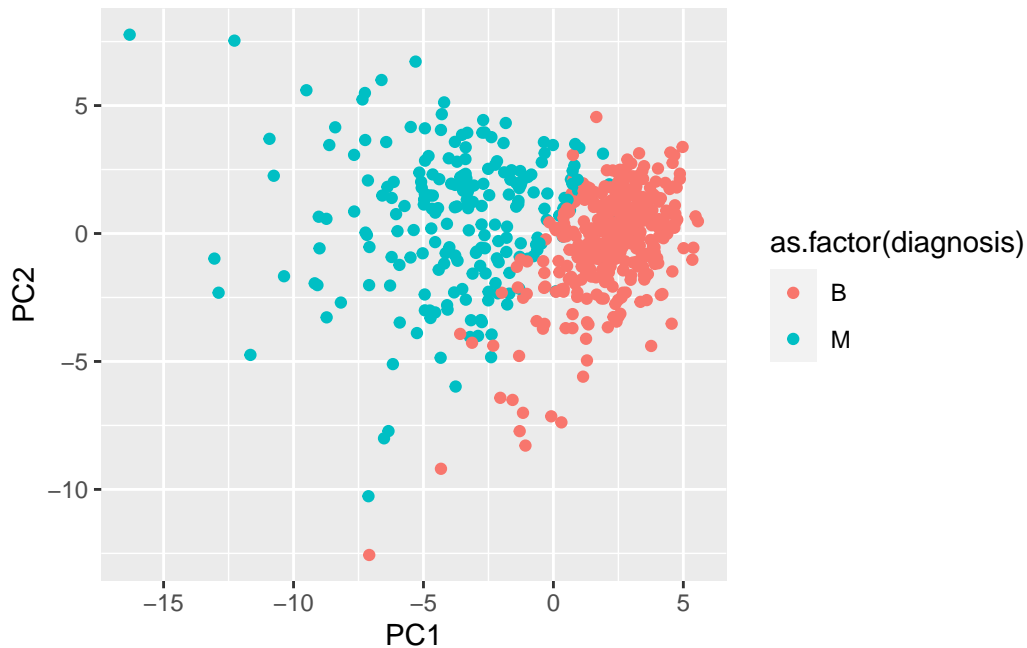
```
# Create a data.frame for ggplot
df <- as.data.frame(wisc.pr$x)
df$diagnosis <- diagnosis

# Load the ggplot2 package
```



```
library(ggplot2)

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

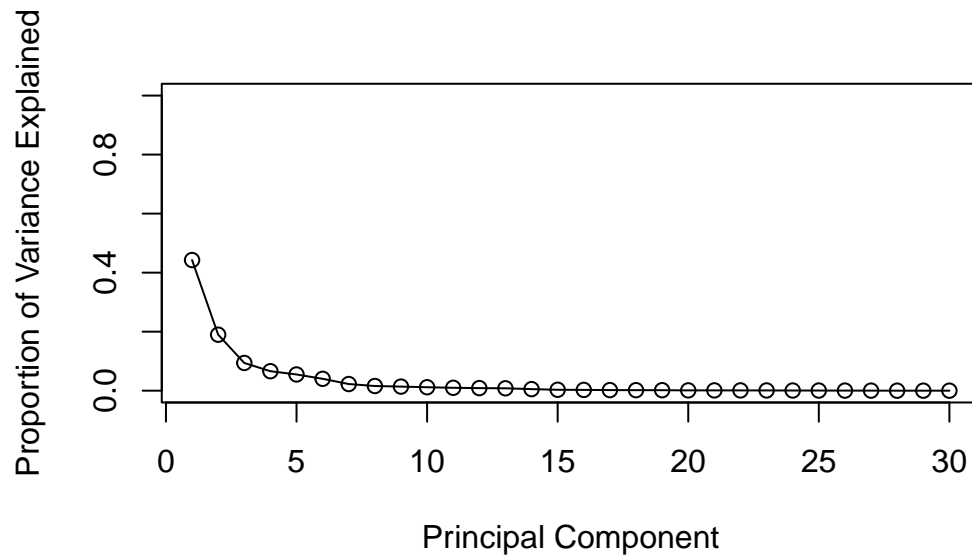


```
# Calculate variance of each component
pr.var <- wisc.pr$sdev^2
head(pr.var)
```

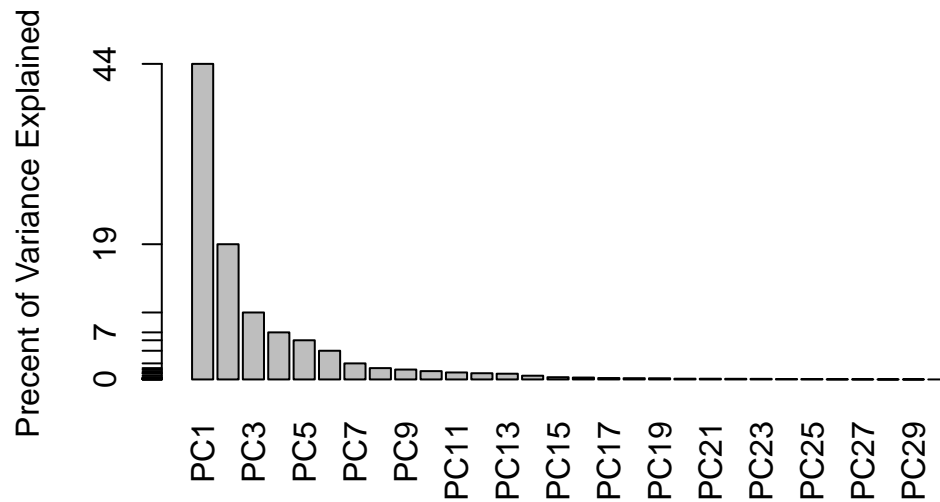
```
[1] 13.281608  5.691355  2.817949  1.980640  1.648731  1.207357
```

```
# Variance explained by each principal component: pve
pve <- wisc.pr$sdev^2 / sum(wisc.pr$sdev^2)

# Plot variance explained for each principal component
plot(pve, xlab = "Principal Component",
     ylab = "Proportion of Variance Explained",
     ylim = c(0, 1), type = "o")
```



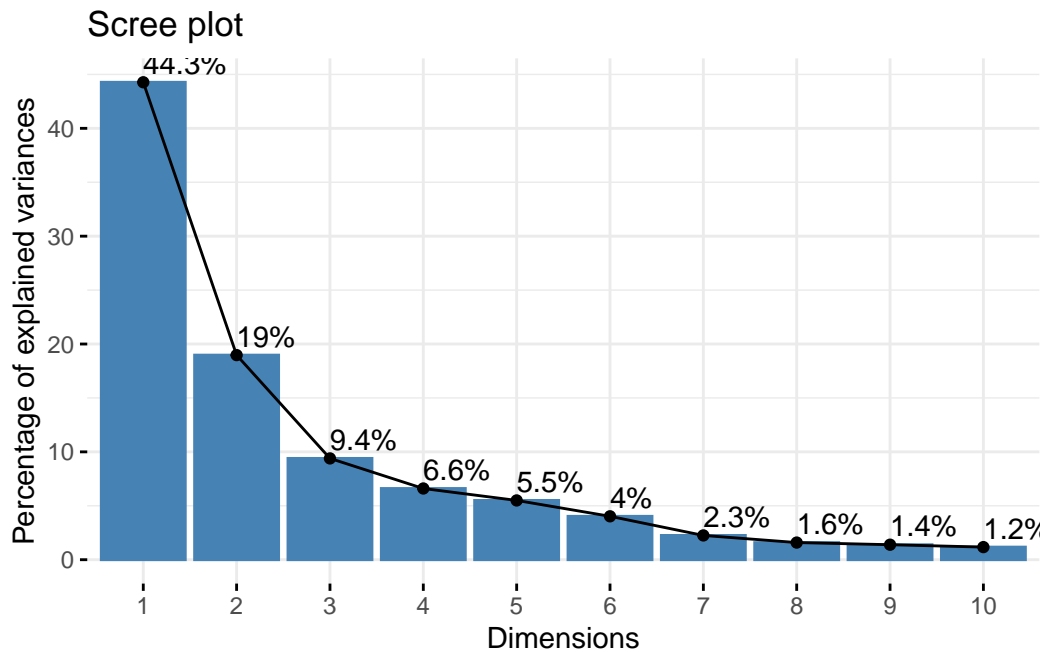
```
# Alternative scree plot of the same data, note data driven y-axis
barplot(pve, ylab = "Percent of Variance Explained",
        names.arg=paste0("PC",1:length(pve)), las=2, axes = FALSE)
axis(2, at=pve, labels=round(pve,2)*100 )
```



```
## 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)
```



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`? This tells us how much this original feature contributes to the first PC.

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

```
[1] -0.2608538
```

```
-0.2608538.
```

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

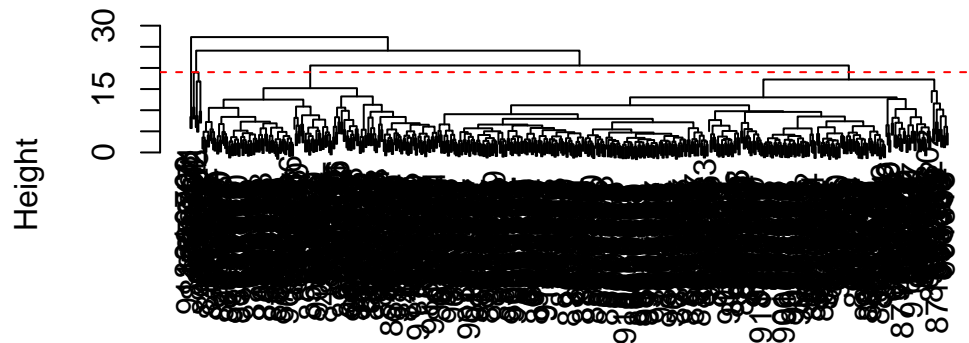
```
data.dist <- dist(data.scaled)
```

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

Q10. Using the `plot()` and `abline()` functions, what is the height at which the clustering model has 4 clusters?

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

Cluster Dendrogram



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

```
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

Q11. OPTIONAL: Can you find a better cluster vs diagnoses match by cutting into a different number of clusters between 2 and 10? How do you judge the quality of your result in each case?

Q12. Which method gives your favorite results for the same data.dist dataset? Explain your reasoning.

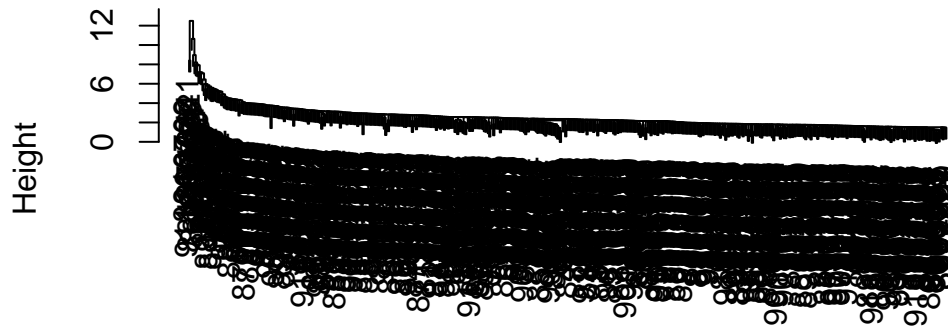
```

methods = c("single", "complete", "average", "ward.D2")

for (i in methods){
  hclust_data <- hclust(data.dist, method=i)
  plot(hclust_data)
}

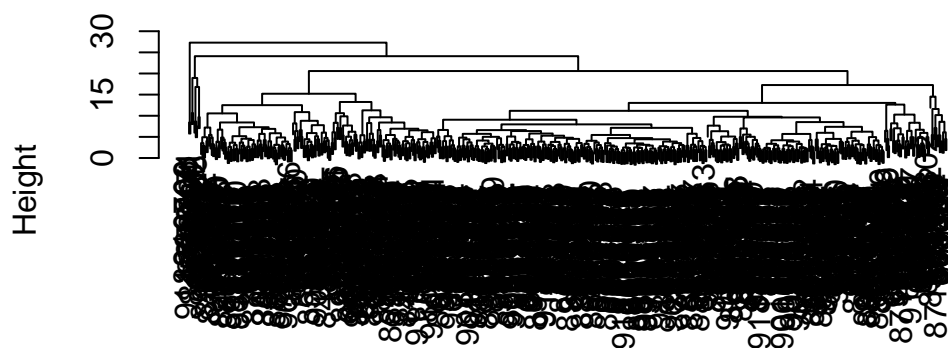
```

Cluster Dendrogram



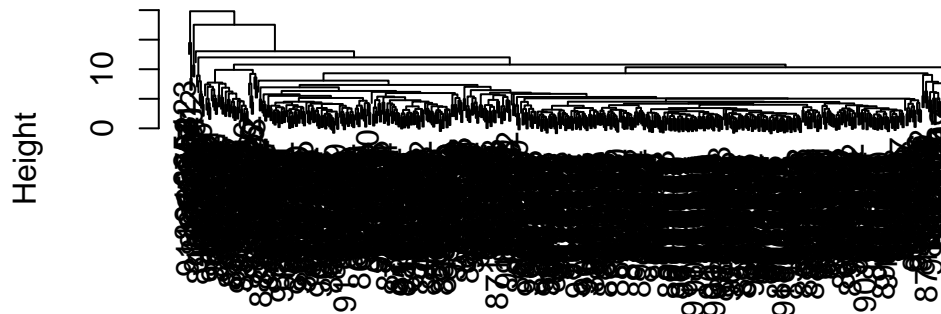
data.dist
hclust (*, "single")

Cluster Dendrogram



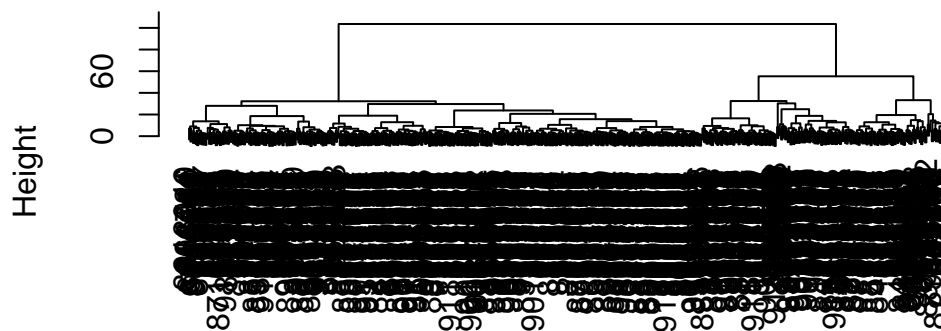
data.dist
hclust (*, "complete")

Cluster Dendrogram



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

Cluster Dendrogram



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

I prefer ward.D2, because it is able to categorize the data into two groups at the first clustering.

```
wisc.pr.hclust <- hclust(dist(wisc.pr$x[,1:7]), method="ward.D2")  
grps <- cutree(wisc.pr.hclust, k=2)
```

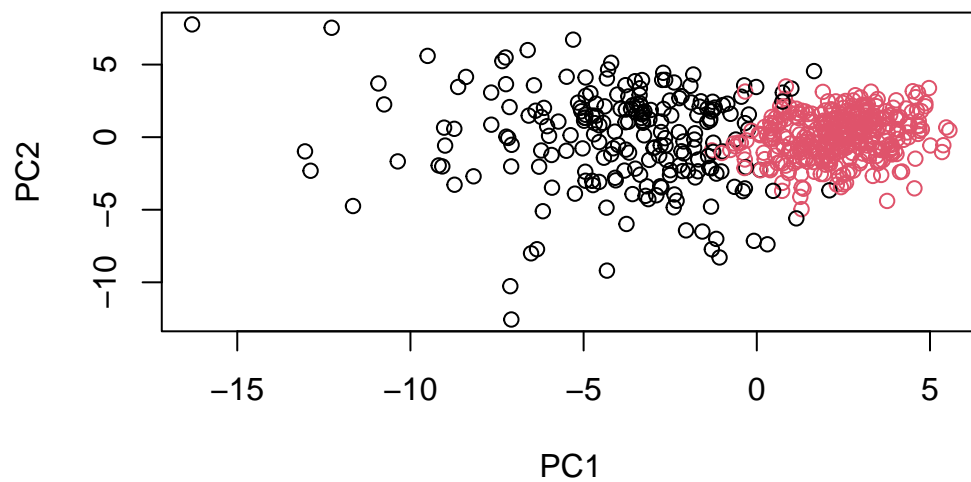
```
table(grps)
```

```
grps
  1  2
216 353
```

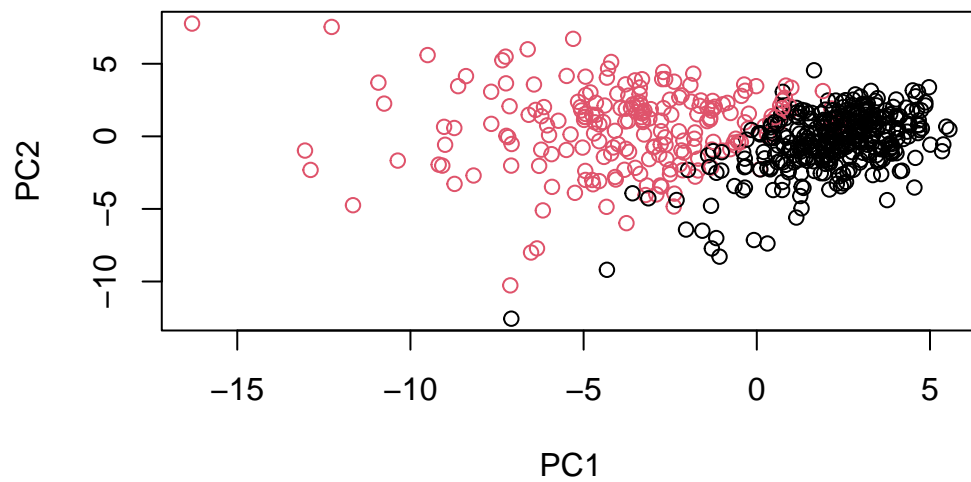
```
table(grps, diagnosis)
```

```
      diagnosis
grps   B     M
  1  28 188
  2 329  24
```

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



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



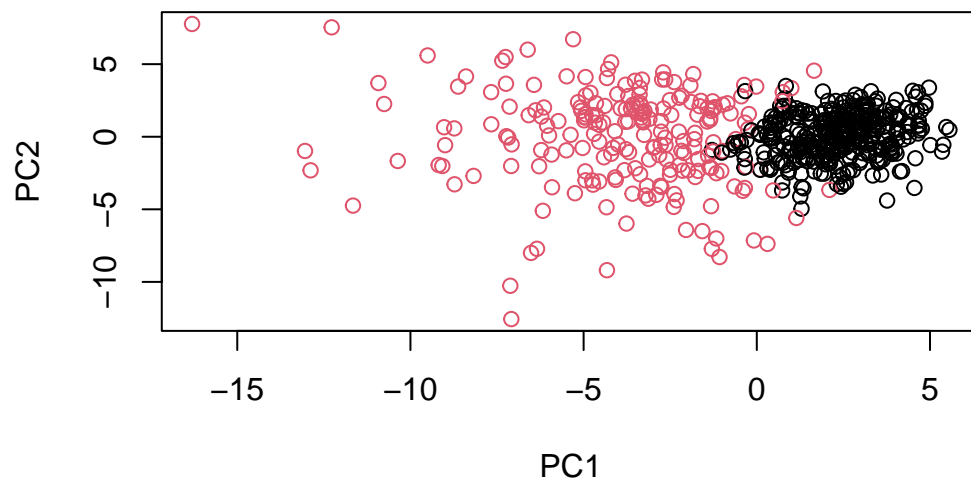
```
g <- as.factor(grps)
levels(g)
```

```
[1] "1" "2"
```

```
g <- relevel(g,2)
levels(g)
```

```
[1] "2" "1"
```

```
# Plot using our re-ordered factor
plot(wisc.pr$x[,1:2], col=g)
```




```
#library(rgl)
#plot3d(wisc.pr$x[,1:3], xlab="PC 1", ylab="PC 2", zlab="PC 3", cex=1.5, size=1, type="s",

## Use the distance along the first 7 PCs for clustering i.e. wisc.pr$x[, 1:7]
wisc.pr.hclust <- hclust(dist(wisc.pr$x[,1:7]), method="ward.D2")
wisc.pr.hclust.clusters <- cutree(wisc.pr.hclust, k=2)
```

Q13. How well does the newly created model with four clusters separate out the two diagnoses?

```
# Compare to actual diagnoses
table(wisc.pr.hclust.clusters, diagnosis)
```

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

It is able to separate the data into two groups (B and M) with as few as two rounds of clustering, which is a near-minimal number of clustering.

Q14. How well do the 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.

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

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

```
wisc.hclust.clusters_k2 <- cutree(wisc.hclust, k=2)
table(wisc.hclust.clusters_k2, diagnosis)
```

```

              diagnosis
wisc.hclust.clusters_k2  B  M
1 357 210
2  0  2

```

The model to which PCA analysis is applied is able to separate the data into two groups (B and M) with as few as two rounds of clustering, while the previous model takes four rounds of clustering. This suggests that the PCA-incorporated model is better at separating the two groups.

Q15. OPTIONAL: Which of your analysis procedures resulted in a clustering model with the best specificity? How about sensitivity?

```

#url <- "new_samples.csv"
url <- "https://tinyurl.com/new-samples-CSV"
new <- read.csv(url)
new

```

```

radius_mean texture_mean perimeter_mean area_mean smoothness_mean
1      8.598      20.98      54.66      221.8      0.1243
2     14.250      22.15      96.42     645.7      0.1049
compactness_mean concavity_mean concave.points_mean symmetry_mean
1      0.08963      0.0300      0.009259      0.1828
2      0.20080      0.2135      0.086530      0.1949
fractal_dimension_mean radius_se texture_se perimeter_se area_se
1      0.06757      0.3582      2.067      2.493     18.39
2      0.07292      0.7036      1.268      5.373     60.78
smoothness_se compactness_se concavity_se concave.points_se symmetry_se
1      0.011930      0.03162      0.03000      0.009259      0.03357
2      0.009407      0.07056      0.06899      0.018480      0.01700
fractal_dimension_se radius_worst texture_worst perimeter_worst area_worst
1      0.003048      9.565      27.04      62.06     273.9
2      0.006113     17.670      29.51     119.10    959.5
smoothness_worst compactness_worst concavity_worst concave.points_worst
1      0.1639      0.1698      0.09001      0.02778
2      0.1640      0.6247      0.69220      0.17850
symmetry_worst fractal_dimension_worst
1      0.2972      0.07712
2      0.2844      0.11320

```

```

npc <- predict(wisc.pr, newdata=new)
npc

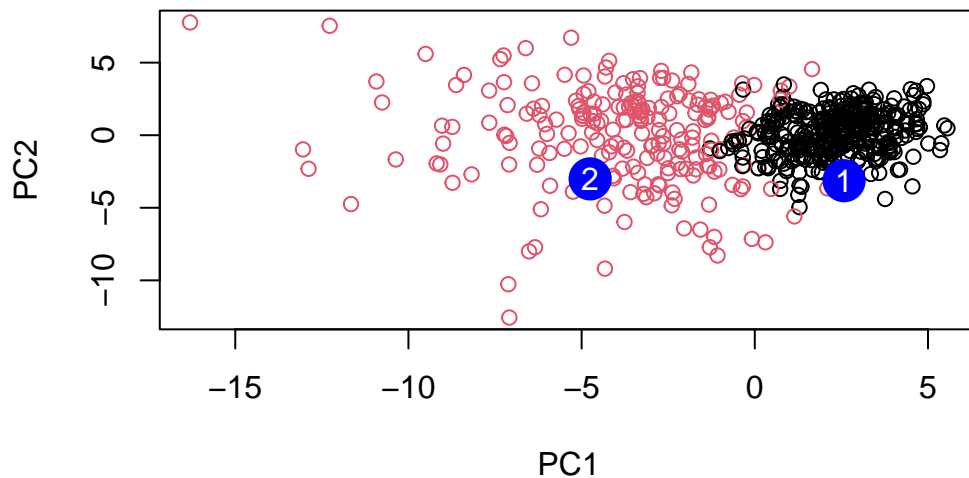
```

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
[1,]	2.576616	-3.135913	1.3990492	-0.7631950	2.781648	-0.8150185	-0.3959098
[2,]	-4.754928	-3.009033	-0.1660946	-0.6052952	-1.140698	-1.2189945	0.8193031
	PC8	PC9	PC10	PC11	PC12	PC13	PC14
[1,]	-0.2307350	0.1029569	-0.9272861	0.3411457	0.375921	0.1610764	1.187882
[2,]	-0.3307423	0.5281896	-0.4855301	0.7173233	-1.185917	0.5893856	0.303029
	PC15	PC16	PC17	PC18	PC19	PC20	
[1,]	0.3216974	-0.1743616	-0.07875393	-0.11207028	-0.08802955	-0.2495216	
[2,]	0.1299153	0.1448061	-0.40509706	0.06565549	0.25591230	-0.4289500	
	PC21	PC22	PC23	PC24	PC25	PC26	
[1,]	0.1228233	0.09358453	0.08347651	0.1223396	0.02124121	0.078884581	
[2,]	-0.1224776	0.01732146	0.06316631	-0.2338618	-0.20755948	-0.009833238	
	PC27	PC28	PC29	PC30			
[1,]	0.220199544	-0.02946023	-0.015620933	0.005269029			
[2,]	-0.001134152	0.09638361	0.002795349	-0.019015820			

```

plot(wisc.pr$x[,1:2], col=g)
points(npc[,1], npc[,2], col="blue", pch=16, cex=3)
text(npc[,1], npc[,2], c(1,2), col="white")

```



Q16. Which of these new patients should we prioritize for follow up based on your results?

1. Compared to 2, 1 is more closely located in the intersection of the black and red groups. So there is higher chance of patient 1 being categorized into incorrect groups (pseudo result).