

# ML\_Mini\_Project

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## Exploratory Data Analysis

First we must download our data into our R session

```
#save the input data file into project directory and save pathname
fn.data<="/Users/gregoryjordan/Downloads/WisconsinCancer.csv"

#read the csv file in, assign row names to first column, and save in data frame variable

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

examine the data

```
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			

remove the first column (diagnosis) from wisc.df because that is the answer and we do not need it

```
#use -1 to remove the first column
wisc.data<-wisc.df[,-1]
```

create a diagnosis vector

```
#save the diagnosis column in a new vector
#save as a factor
diagnosis <- as.factor(wisc.df[,1])
```

## Explore the Data

Q1. How many observations are in this dataset?

```
#number of rows = number of observations
nrow(wisc.data)
```

```
[1] 569
```

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

```
#filter where diagnosis == malignant
#then count number of observations (# of rows)
nrow(wisc.df[wisc.df$diagnosis=="M",])
```

```
[1] 212
```

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

```
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
```

```
#get indices of wisc.data column names that end in _mean
#get length of resultant vector to determine # of variables suffixed with _mean
length(grep(x=colnames(wisc.data),pattern="*_mean$"))
```

```
[1] 10
```

## Principal Component Analysis

determine if the data needs to be scaled (i.e. different units or significantly different variances)

```
#check column means and standard deviations
#colMeans function to get mean of columns
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

```

```

#remember apply function to apply a function over a vector
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

```

use `prcomp()` for PCA function

```

#perform pca on wisc.data
#the data$X column is full of nulls so let's remove it
#scale the units

wisc.pr <- prcomp(wisc.data[,-31],scale. = TRUE)

#look at the summary of the 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					

Q4. From your results, what proportion of the original variance is captured by the first principal components (PC1)?

*about 44% of the data*

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

*3 principal components (PC1:PC3)*

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

*7 principal components (PC1:PC7)*

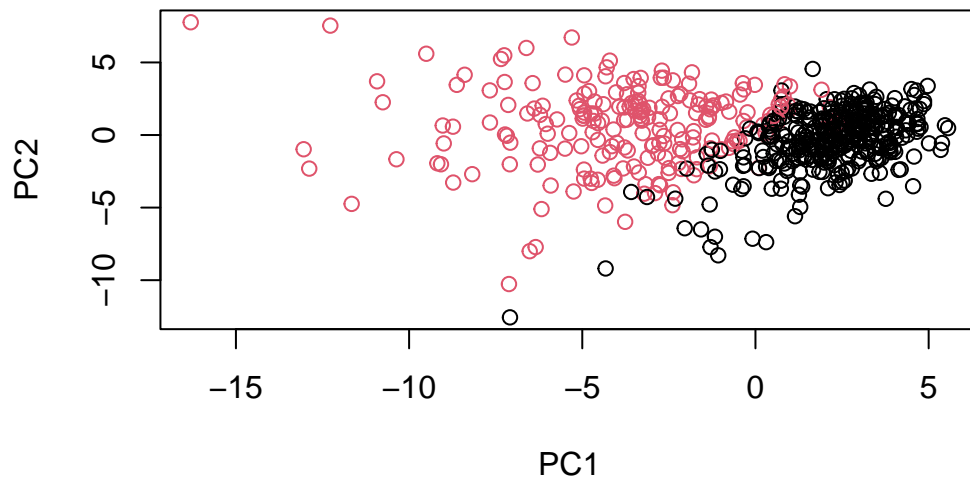
## Interpreting PCA Results

creat a biplot using the `biplot()` function

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

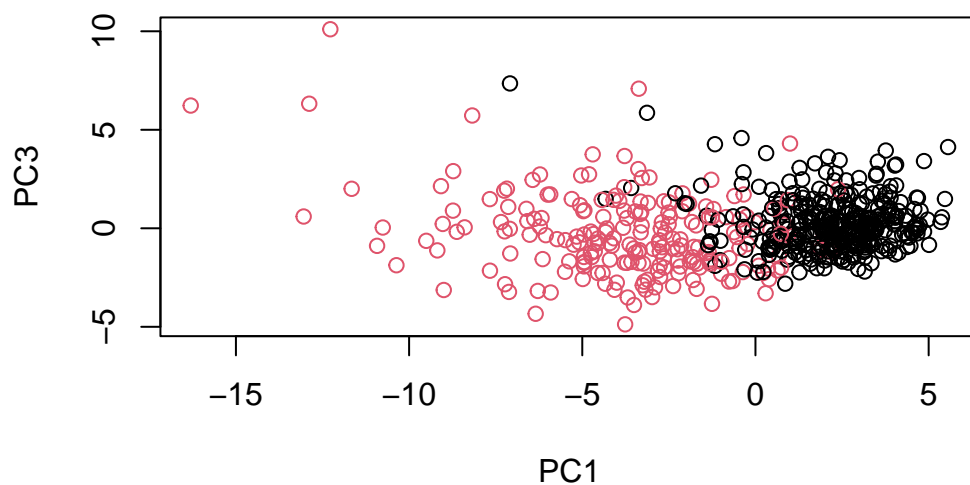






Q8. Generate a similar plot for principal components 1 and 3. What do you notice about these plots?

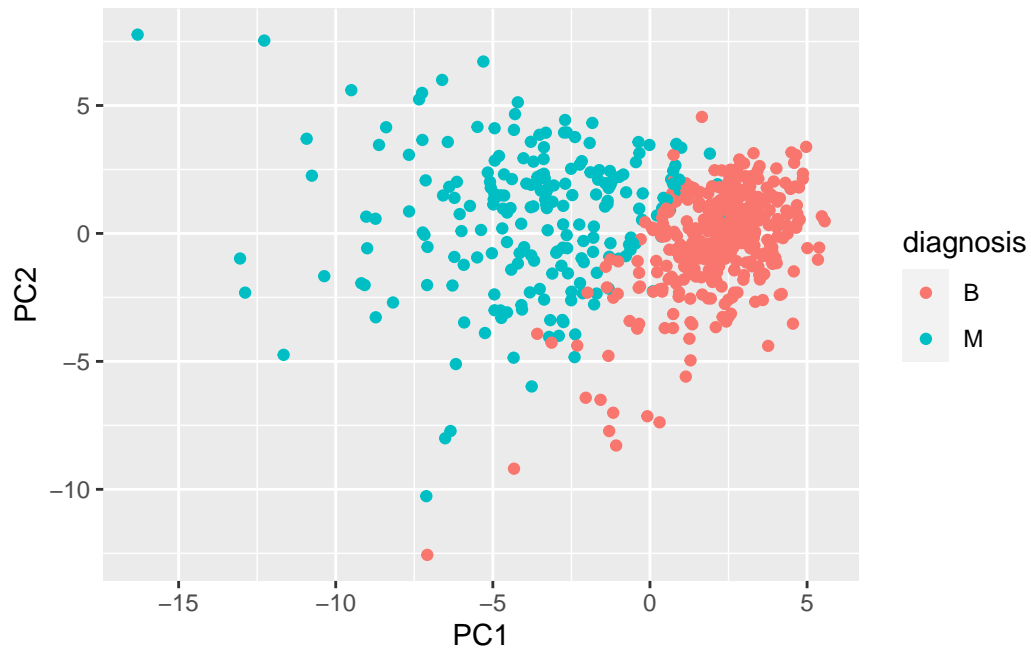
```
#scatterplot of PC1 vs PC3  
plot(wisc.pr$x[,1],wisc.pr$x[,3],col=diagnosis,xlab="PC1",ylab="PC3")
```



the plots look very similar, but the one with PC2 has a little more separation between the two populations because PC2 captures more of the variance

### Trying ggplot2

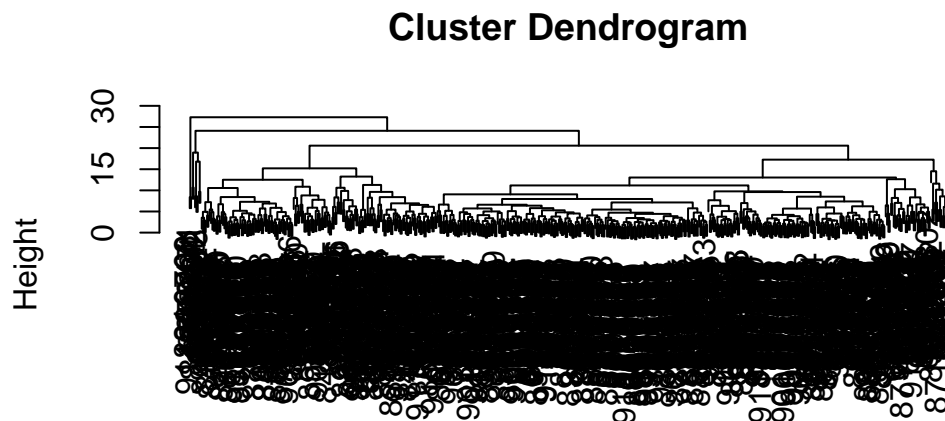
```
#load in ggplot2
library(ggplot2)
#creat a data frame
df<-as.data.frame(wisc.pr$x)
df$diagnosis<-diagnosis
#make a scatter plot
ggplot(df) + aes(PC1,PC2,col=diagnosis) + geom_point()
```



## Heirarchial Clustering of Data

```
#scale the data
data.scaled<-scale(wisc.data)
#get distance matrix
data.dist<-dist(data.scaled)
#heirarchial clustering
wisc.hclust<-hclust(data.dist)

#make a plot
wisc.plot<-plot(wisc.hclust)
```



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

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

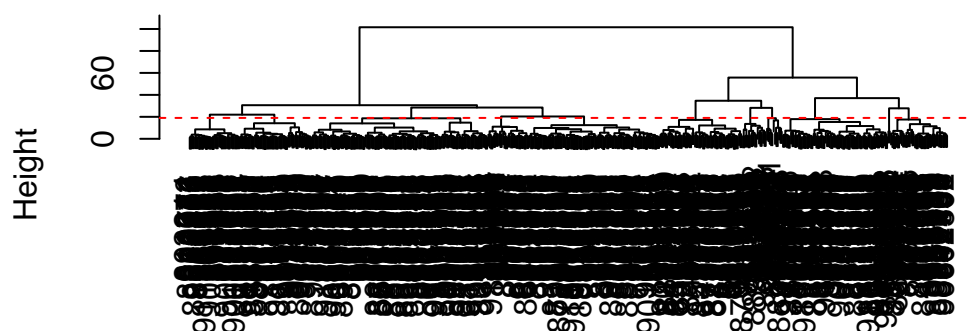
around 20 height

##Combining methods and clustering on PCA results

```
#combine clustering and PCA
wisc.pr.hclust <- hclust(dist(wisc.pr$x[,1:7]),method="ward.D2")

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

## Cluster Dendrogram



```
dist(wisc.pr$x[, 1:7])
hclust (*, "ward.D2")
```

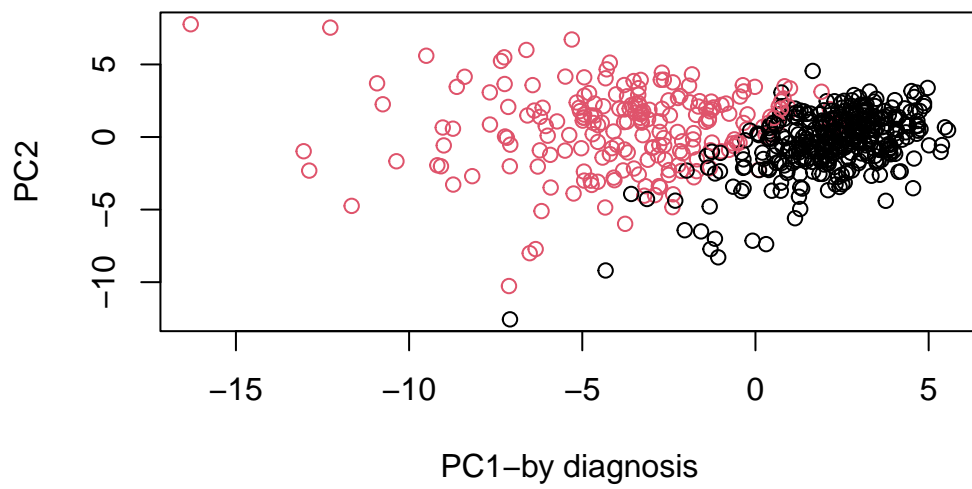
Q12. Which method gives your favorite results for the same data.dist dataset? Explain your reasoning.

I like ward.D2 because it works to minimize the variance within clusters which makes the cluster data more tight.

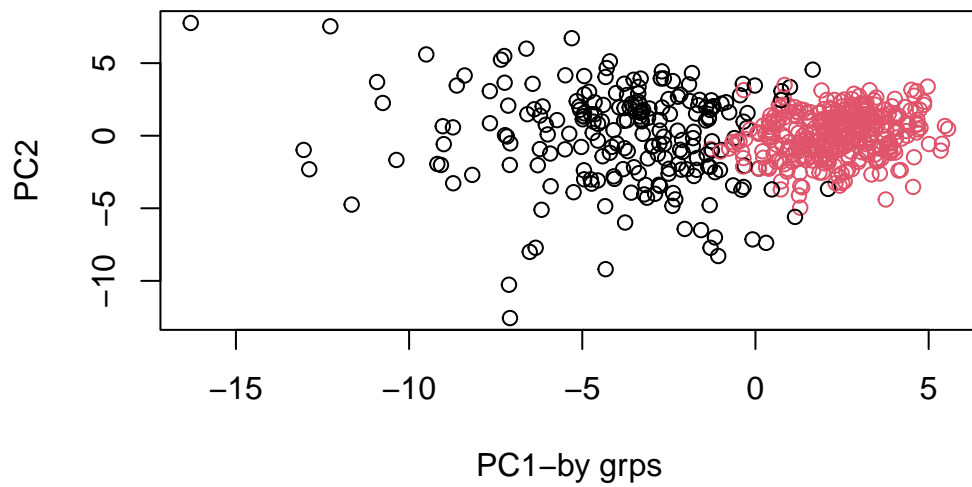
```
#cut it into groups
grps <- cutree(wisc.pr.hclust,k=2)
table(grps)
```

```
grps
 1  2
216 353
```

```
#make plots
plot(wisc.pr$x[,1:2], col=diagnosis, xlab="PC1-by diagnosis")
```



```
plot(wisc.pr$x[,1:2], col=grps, xlab="PC1-by grps")
```



```
g <- as.factor(grps)
g <- relevel(g,2)
plot(wisc.pr$x[,1:2], col=g)
```

