class08 mini project

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```r
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
```

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

Q1. How many observations are in this dataset? There are 569 observations(rows) in this dataset.

```r
nrow(wisc.df)
```

```
[1] 569
```

Q2. How many of the observations have a malignant diagnosis? There are 212 Malignant diagnosis.

```r
table(wisc.df$diagnosis)
```

```

  B   M 
357 212 
```

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

```
[1] 212
```

> Q3. How many variables/features in the data are suffixed with _mean? There are 10 variables in the data suffixed with _mean.

```r
colnames(wisc.df)
```

```
 [1] "diagnosis"               "radius_mean"            
 [3] "texture_mean"            "perimeter_mean"         
 [5] "area_mean"               "smoothness_mean"        
 [7] "compactness_mean"        "concavity_mean"         
 [9] "concave.points_mean"     "symmetry_mean"          
[11] "fractal_dimension_mean"  "radius_se"              
[13] "texture_se"              "perimeter_se"           
[15] "area_se"                 "smoothness_se"          
[17] "compactness_se"          "concavity_se"           
[19] "concave.points_se"       "symmetry_se"            
[21] "fractal_dimension_se"    "radius_worst"           
[23] "texture_worst"           "perimeter_worst"        
[25] "area_worst"              "smoothness_worst"       
[27] "compactness_worst"       "concavity_worst"        
[29] "concave.points_worst"    "symmetry_worst"         
[31] "fractal_dimension_worst"
```

```r
grep("mean", colnames(wisc.df), value=TRUE)
```

```
 [1] "radius_mean"            "texture_mean"           "perimeter_mean"        
 [4] "area_mean"              "smoothness_mean"        "compactness_mean"      
 [7] "concavity_mean"         "concave.points_mean"    "symmetry_mean"         
[10] "fractal_dimension_mean"
```

```r
x <- colnames(wisc.df)
length( grep("mean", x))
```

```
[1] 10
```

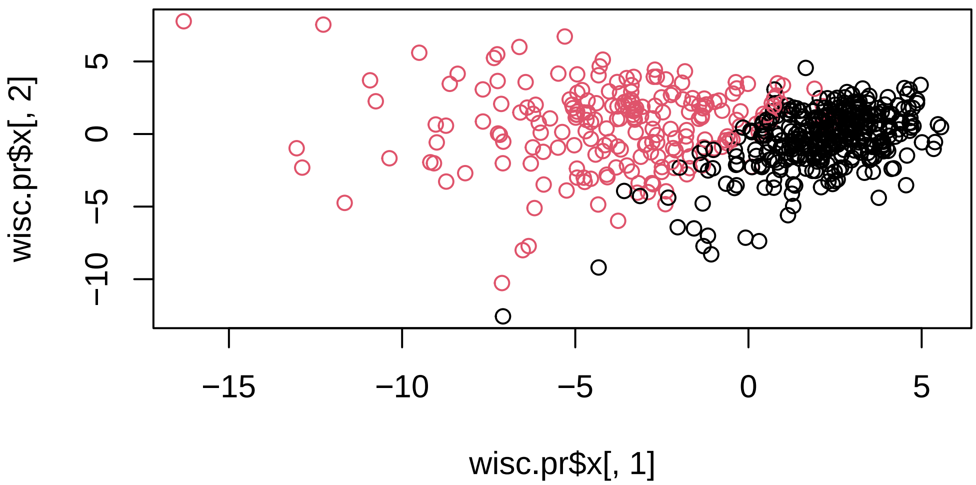
#Principal Component Analysis

We need to scale our input data before PCA as some of th ecolumns are measured in terms of very different units with different means and different variances. The upshot here is we set `scale=TRUE` argument to `prcomp()`.

```r
wisc.pr <- prcomp( wisc.data, scale=T )
summary(wisc.pr)
```

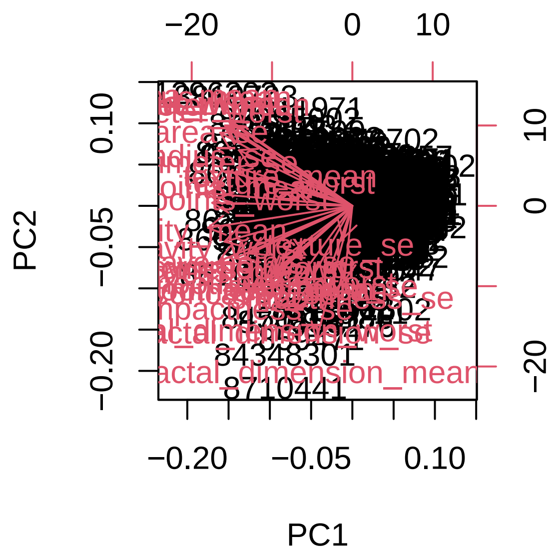
```
Importance of components:
                          PC1    PC2     PC3     PC4     PC5     PC6     PC7
Standard deviation     3.6444 2.3857 1.67867 1.40735 1.28403 1.09880 0.82172
Proportion of Variance 0.4427 0.1897 0.09393 0.06602 0.05496 0.04025 0.02251
Cumulative Proportion  0.4427 0.6324 0.72636 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
```

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



Q4. From your results, what proportion of the original variance is captured by the first principal components (PC1)? PC1 account for 44.27% of total variance or .4427. Q5. How many principal components (PCs) are required to describe at least 70% of the original variance in the data? PC1,PC2,PC3 Q6. How many principal components (PCs) are required to describe at least 90% of the original variance in the data? PC1,PC2, PC3, PC4, PC5, PC6, PC7

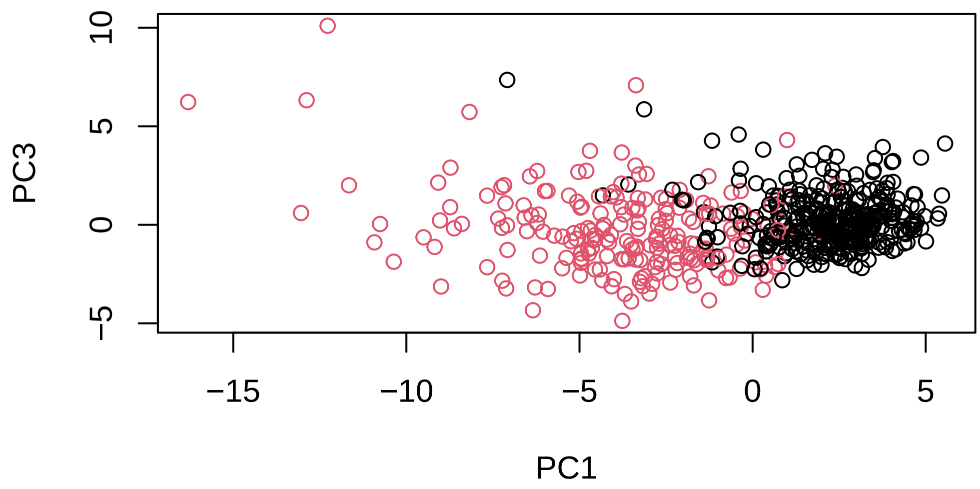
```
biplot(wisc.pr)
```



Q7. What stands out to you about this plot? Is it easy or difficult to understand? Why? This plot is very difficult to read and the variable names are overlapping and the color are also very overlapping it does not display meaningful information.

Q8. Generate a similar plot for principal components 1 and 3. What do you notice about these plots? This plot shows how PC1 captures a better variance between M and B tumors and the first plot is cleaner and shows the separate clusters more.

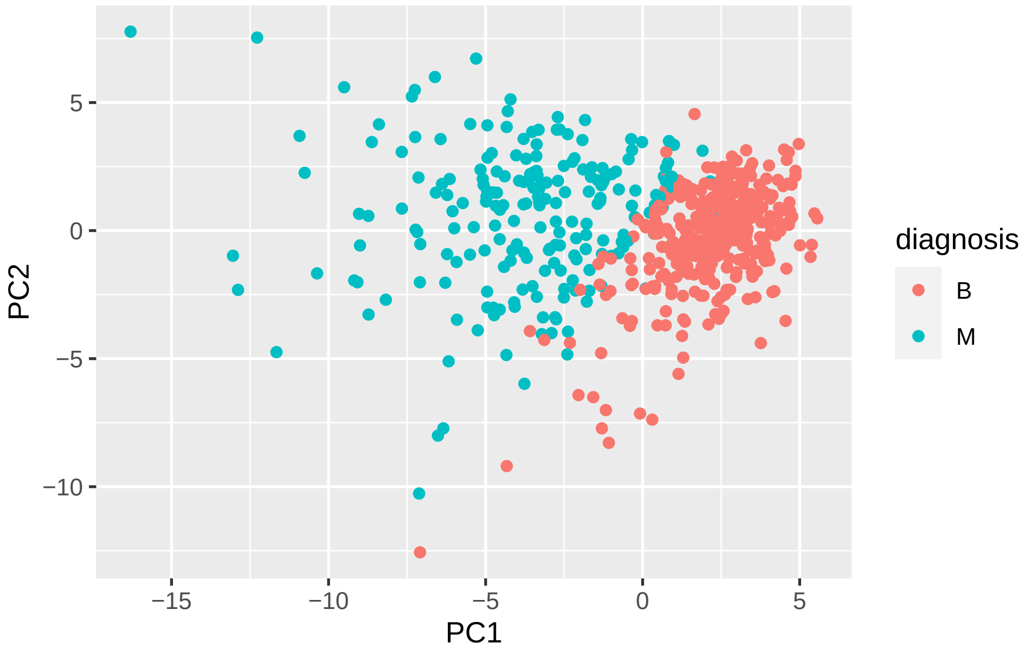
```
plot(wisc.pr$x[, 1], wisc.pr$x[, 3], col = diagnosis,
     xlab = "PC1", ylab = "PC3")
```




```r
# 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()
```

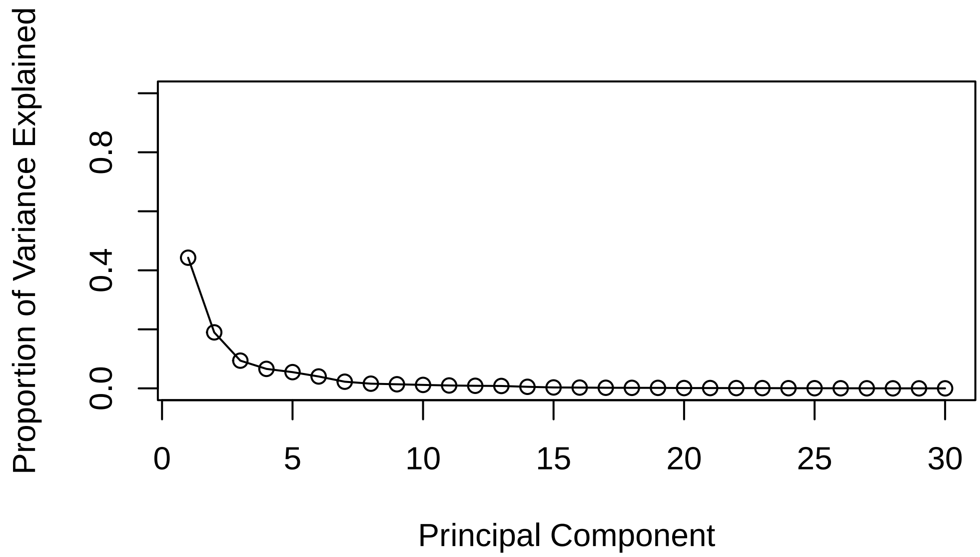



```
# Calculate variance of each component
pr.var <- wisc.pr$sdev^2
head(pr.var)
```

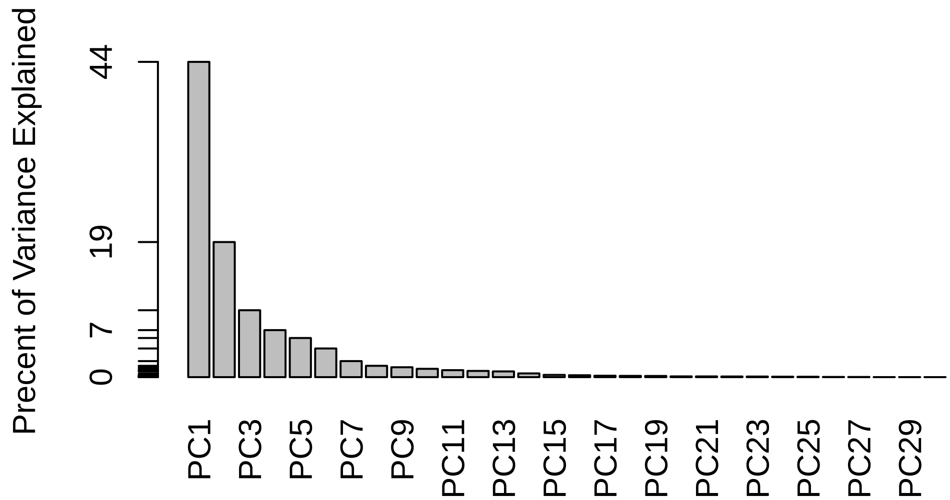
```
[1] 13.281608  5.691355  2.817949  1.980640  1.648731  1.207357
```

```
# 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")
```



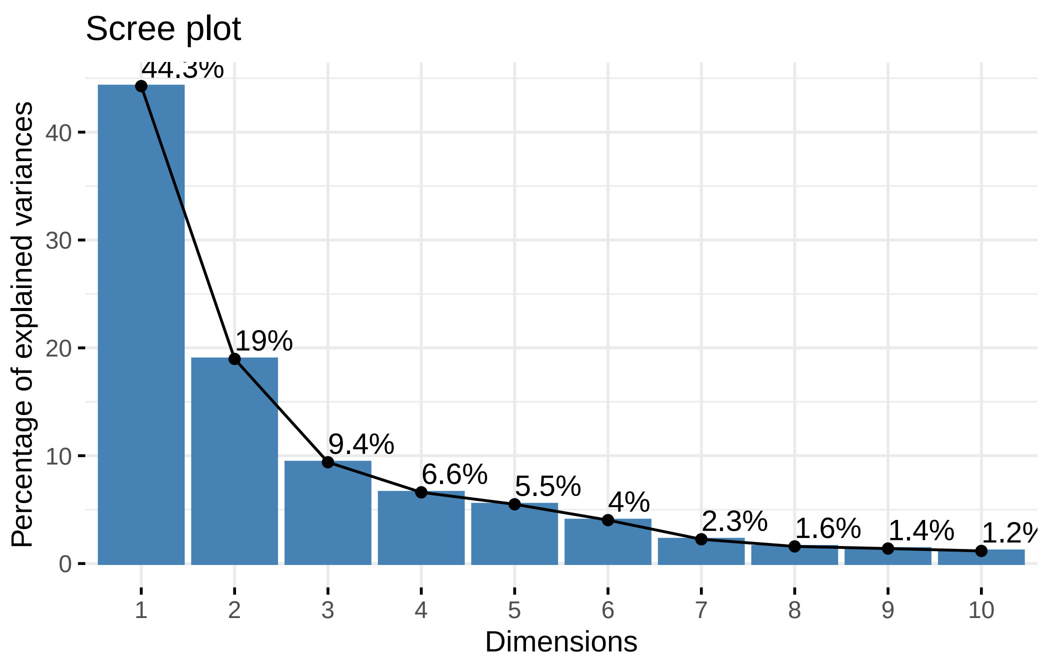

```
barplot(pve, ylab = "Precent of Variance Explained",
     names.arg=paste0("PC",1:length(pve)), las=2, axes = FALSE)
axis(2, at=pve, labels=round(pve,2)*100 )
```




```r
library(factoextra)
```

```
Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
```

```r
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?

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

```
concave.points_mean
         -0.2608538
```

Q10. What is the minimum number of principal components required to explain 80% of the variance of the data? PC1, PC2, PC3, PC4, PC5

##3 Hierarchical Clustering

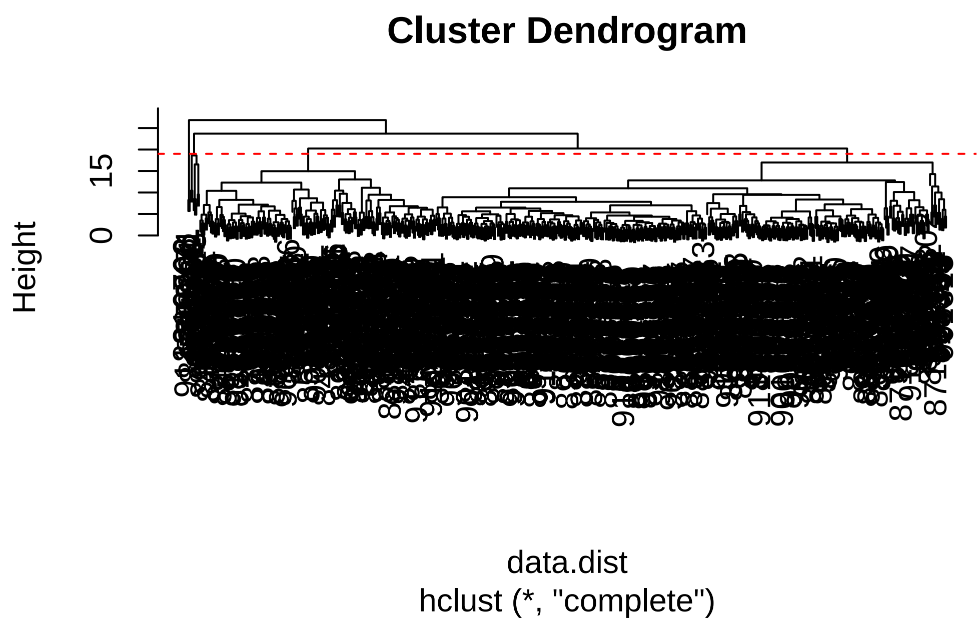
```
data.scaled <- scale(wisc.data)
```

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

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

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

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




```r
wisc.hclust.clusters <- cutree(wisc.hclust, k=4)
```

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

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

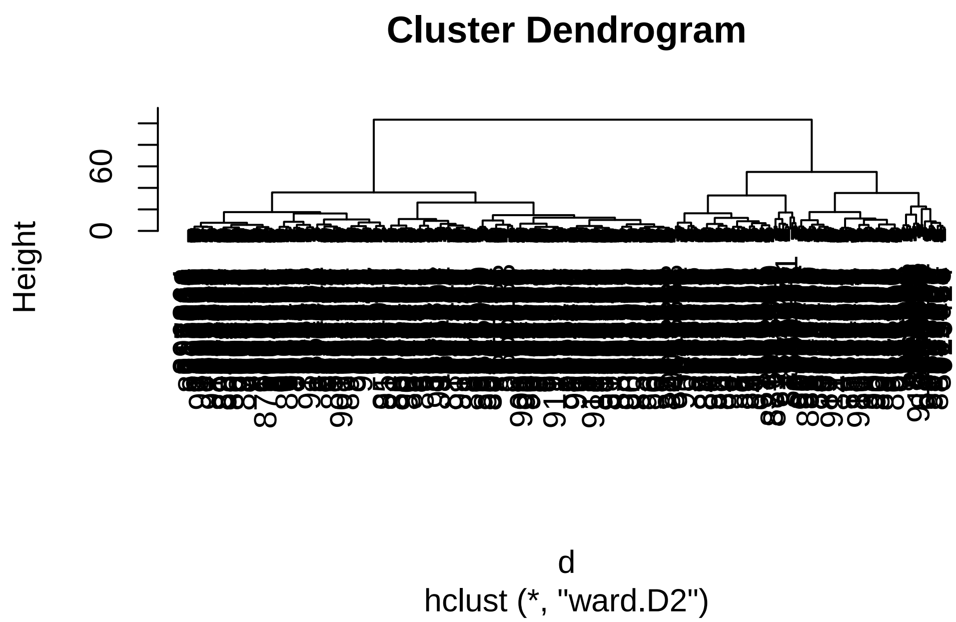
Q12. Can you find a better cluster vs diagnoses match by cutting into a different number of clusters between 2 and 10? 4 is the better cluster because it has the best number of clusters and gives the best/clear separation of B and M tumors.

Q13. Which method gives your favorite results for the same data.dist dataset? Explain your reasoning. My favorite is ward.D2 because it helps reduce the variance, and the clusters are made even, and groups data points that are alike.

##5 Combining Methods.

This approach will take not original data but our PCA results and work with them.

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



Generate 2 cluster groups from this hclust object.

```r
grps <- cutree(wisc.pr.hclust, k=2)
grps
```

```
  842302   842517 84300903 84348301 84358402   843786   844359 84458202 
       1        1        1        1        1        1        1        1 
  844981 84501001   845636 84610002   846226   846381 84667401 84799002 
       1        1        2        1        1        2        1        1 
  848406 84862001   849014  8510426  8510653  8510824  8511133   851509 
       2        1        1        2        2        2        1        1 
  852552   852631   852763   852781   852973   853201   853401   853612 
       1        1        1        1        1        2        1        1 
85382601   854002   854039   854253   854268   854941   855133   855138 
```

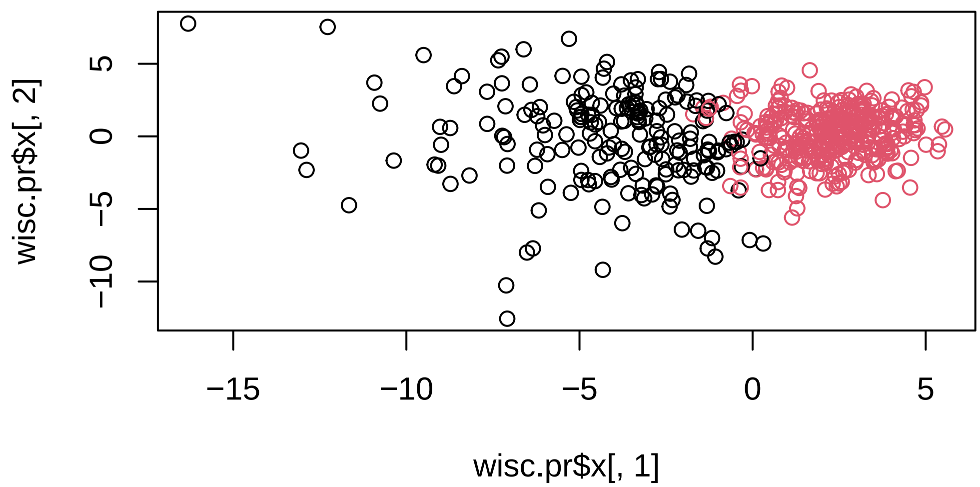
```
        1         1         1         1         1         2         2         1
   855167    855563    855625    856106  85638502    857010  85713702     85715
        2         1         1         1         2         1         2         1
   857155    857156    857343    857373    857374    857392    857438  85759902
        2         2         2         2         2         1         2         2
   857637    857793    857810    858477    858970    858981    858986    859196
        1         1         2         2         2         2         1         2
 85922302    859283    859464    859465    859471    859487    859575    859711
        1         1         2         2         1         2         1         1
   859717    859983   8610175   8610404   8610629   8610637   8610862   8610908
        1         2         2         2         2         1         1         2
   861103   8611161   8611555   8611792   8612080   8612399  86135501  86135502
        2         1         1         1         2         1         2         1
   861597    861598    861648    861799    861853    862009    862028     86208
        2         1         2         2         2         2         1         1
    86211    862261    862485    862548    862717    862722    862965    862980
        2         2         2         1         2         2         2         2
   862989    863030    863031    863270     86355    864018    864033     86408
        2         1         2         2         1         2         2         2
    86409    864292    864496    864685    864726    864729    864877    865128
        1         2         2         2         2         1         1         2
   865137     86517    865423    865432    865468     86561    866083    866203
        2         1         1         2         2         2         2         1
   866458    866674    866714      8670  86730502    867387    867739    868202
        1         1         2         1         1         2         1         2
   868223    868682    868826    868871    868999    869104    869218    869224
        2         2         1         2         2         2         2         2
   869254    869476    869691  86973701  86973702    869931 871001501 871001502
        2         2         1         2         2         2         2         1
  8710441     87106   8711002   8711003   8711202   8711216    871122    871149
        1         2         2         2         1         2         2         2
  8711561   8711803    871201   8712064   8712289   8712291     87127   8712729
        2         1         1         2         1         2         2         2
  8712766   8712853  87139402     87163     87164    871641    871642    872113
        1         2         2         2         1         2         2         2
   872608  87281702    873357    873586    873592    873593    873701    873843
        1         1         2         2         1         1         1         2
   873885    874158    874217    874373    874662    874839    874858    875093
        2         2         2         2         2         2         1         2
   875099    875263  87556202    875878    875938    877159    877486    877500
        2         1         1         2         1         1         1         1
   877501    877989    878796     87880     87930    879523    879804    879830
        2         1         1         1         2         2         2         2
```

8810158	8810436	881046502	8810528	8810703	881094802	8810955	8810987
1	2	1	2	1	1	1	1
8811523	8811779	8811842	88119002	8812816	8812818	8812844	8812877
2	2	1	1	2	2	2	1
8813129	88143502	88147101	88147102	88147202	881861	881972	88199202
2	2	2	2	2	1	1	2
88203002	88206102	882488	88249602	88299702	883263	883270	88330202
2	1	2	2	1	1	2	1
88350402	883539	883852	88411702	884180	884437	884448	884626
2	2	1	2	1	2	2	1
88466802	884689	884948	88518501	885429	8860702	886226	886452
2	2	1	2	1	1	1	1
88649001	886776	887181	88725602	887549	888264	888570	889403
1	1	1	1	1	2	1	2
889719	88995002	8910251	8910499	8910506	8910720	8910721	8910748
1	1	2	2	2	2	2	2
8910988	8910996	8911163	8911164	8911230	8911670	8911800	8911834
1	2	2	2	2	2	2	2
8912049	8912055	89122	8912280	8912284	8912521	8912909	8913
1	2	1	1	2	2	2	2
8913049	89143601	89143602	8915	891670	891703	891716	891923
1	2	1	2	2	2	2	2
891936	892189	892214	892399	892438	892604	89263202	892657
2	2	2	2	1	2	1	2
89296	893061	89344	89346	893526	893548	893783	89382601
2	2	2	2	2	2	2	2
89382602	893988	894047	894089	894090	894326	894329	894335
2	2	2	2	2	1	1	2
894604	894618	894855	895100	89511501	89511502	89524	895299
2	1	2	1	2	2	2	2
8953902	895633	896839	896864	897132	897137	897374	89742801
1	1	1	2	2	2	2	1
897604	897630	897880	89812	89813	898143	89827	898431
2	1	2	1	1	2	2	1
89864002	898677	898678	89869	898690	899147	899187	899667
2	2	2	2	2	2	2	1
899987	9010018	901011	9010258	9010259	901028	9010333	901034301
1	1	2	2	2	2	2	2
901034302	901041	9010598	9010872	9010877	901088	9011494	9011495
2	2	2	2	2	1	1	2
9011971	9012000	9012315	9012568	9012795	901288	9013005	901303
1	1	1	2	1	1	2	2
901315	9013579	9013594	9013838	901549	901836	90250	90251

1	2	2	1	2	2	2	2
902727	90291	902975	902976	903011	90312	90317302	903483
2	2	2	2	2	1	2	2
903507	903516	903554	903811	90401601	90401602	904302	904357
1	1	2	2	2	2	2	2
90439701	904647	904689	9047	904969	904971	905189	905190
1	2	2	2	2	2	2	2
90524101	905501	905502	905520	905539	905557	905680	905686
1	2	2	2	2	2	2	2
905978	90602302	906024	906290	906539	906564	906616	906878
2	1	2	2	2	1	2	2
907145	907367	907409	90745	90769601	90769602	907914	907915
2	2	2	2	2	2	1	2
908194	908445	908469	908489	908916	909220	909231	909410
1	1	2	1	2	2	2	2
909411	909445	90944601	909777	9110127	9110720	9110732	9110944
2	1	2	2	1	2	1	2
911150	911157302	9111596	9111805	9111843	911201	911202	9112085
2	1	2	1	2	2	2	2
9112366	9112367	9112594	9112712	911296201	911296202	9113156	911320501
2	2	2	2	1	1	2	2
911320502	9113239	9113455	9113514	9113538	911366	9113778	9113816
2	1	2	2	1	2	2	2
911384	9113846	911391	911408	911654	911673	911685	911916
2	2	2	2	2	2	2	1
912193	91227	912519	912558	912600	913063	913102	913505
2	2	2	2	2	1	2	1
913512	913535	91376701	91376702	914062	914101	914102	914333
2	2	2	2	1	2	2	2
914366	914580	914769	91485	914862	91504	91505	915143
1	2	1	1	2	1	2	1
915186	915276	91544001	91544002	915452	915460	91550	915664
1	1	2	2	2	1	2	2
915691	915940	91594602	916221	916799	916838	917062	917080
1	2	2	2	1	1	2	2
917092	91762702	91789	917896	917897	91805	91813701	91813702
2	1	2	2	2	2	2	2
918192	918465	91858	91903901	91903902	91930402	919537	919555
2	2	2	2	2	1	2	1
91979701	919812	921092	921362	921385	921386	921644	922296
1	2	2	2	2	1	2	2
922297	922576	922577	922840	923169	923465	923748	923780
2	2	2	2	2	2	2	2

```
 924084   924342   924632   924934   924964   925236   925277   925291
      2        2        2        2        2        2        2        2
 925292   925311   925622   926125   926424   926682   926954   927241
      2        2        1        1        1        1        2        1
  92751
      2
```

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




```
table(grps)
```

```
grps
  1   2
203 366
```

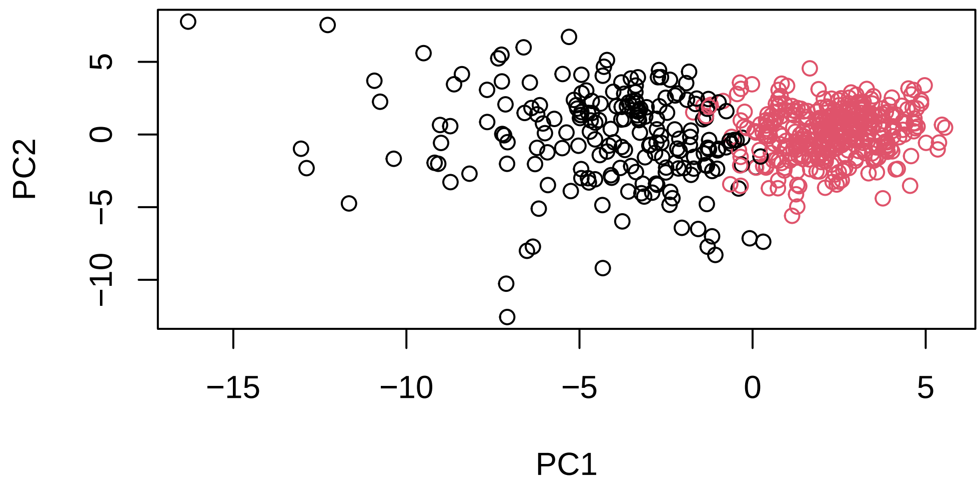
```
table(diagnosis)
```

```
diagnosis
  B   M
357 212
```

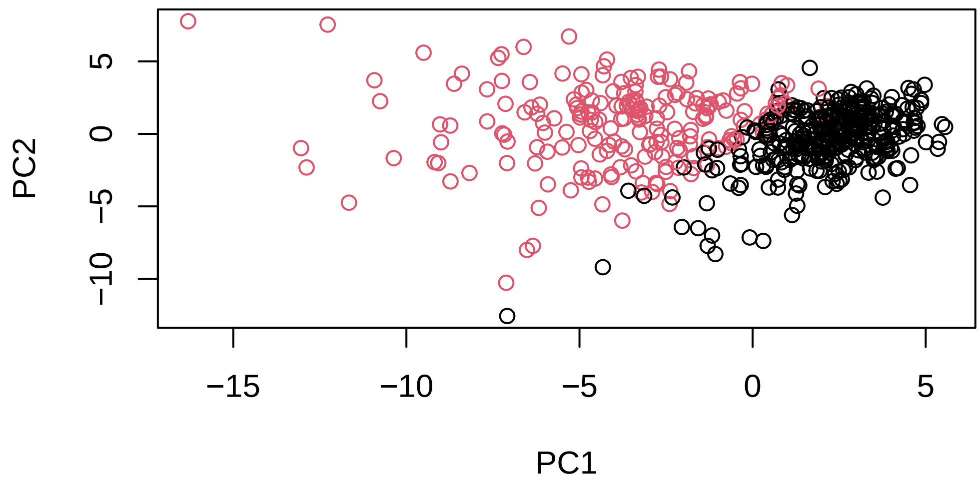
```r
table(diagnosis, grps)
```

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

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




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



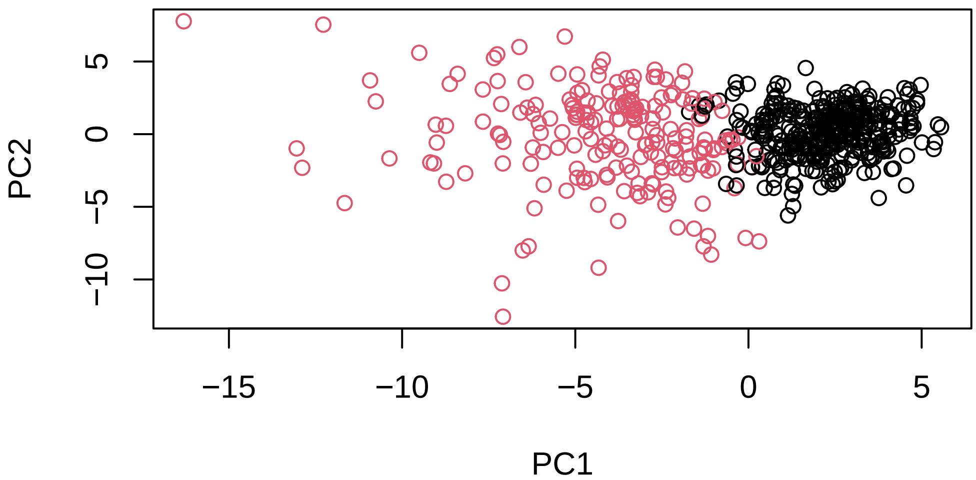

```
g <- as.factor(grps)
levels(g)
```

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

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

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

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




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

```
y <- wisc.pr.hclust.clusters <- cutree(wisc.pr.hclust, k=2)
```

Q15. How well does the newly created model with four clusters separate out the two diagnoses? It separates them out very well and it is organized and clear.

```
table(y, diagnosis)
```

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