Class 8 mini project

Destiny (A16340362)

```
# Save your input data file into your Project directory

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

Now we'll store the diagnostics column for later and exclude it from the data set that I will actually do things with that I will call `wisc.data`

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

> Q1. How many observations are in this dataset?

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

```
[1] 569
```

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

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

```

  B   M 
357 212 
```

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

```
x <- colnames(wisc.df)
 grep("_mean", x, fixed = TRUE)
```

```
 [1]  2  3  4  5  6  7  8  9 10 11
```

```r
length(grep("_mean", x, fixed = TRUE))
```

```
[1] 10
```

Principal Component Analysis

We need to sclae our input data before PCA as some of the columns are measured in terms of very different unites with different means and different variances. The upshot here is that we set `scale-TRUE` to agrument `prcomp()` Scaling basicaly helps to normalize the data since each piece of the data is scaled extremly different

```r
# 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 
```

```r
apply(wisc.data,2,sd)
```

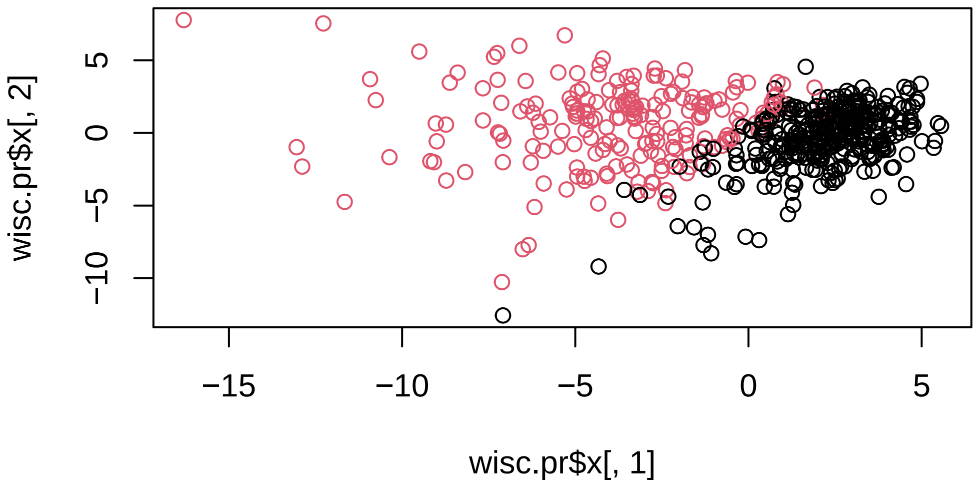
```
            radius_mean            texture_mean          perimeter_mean
           3.524049e+00            4.301036e+00            2.429898e+01
              area_mean         smoothness_mean        compactness_mean
           3.519141e+02            1.406413e-02            5.281276e-02
         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 on wisc.data by completing the following code
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
```

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



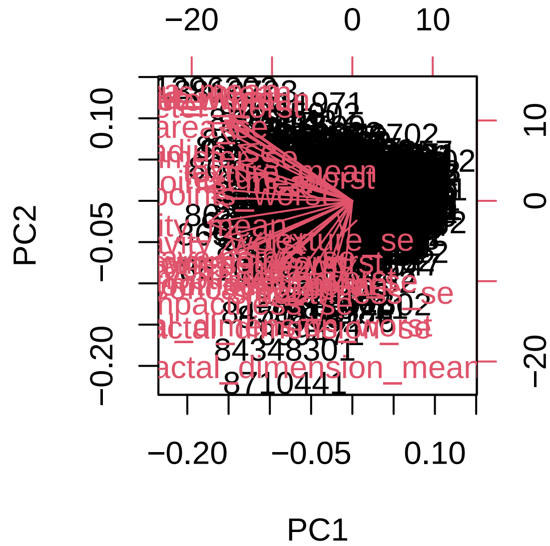
Q4. From your results, what proportion of the original variance is captured by the first principal components (PC1)? 0.4427

Q5. How many principal components (PCs) are required to describe at least 70% of the original variance in the data? PC1 through PC3 so need 3 componets

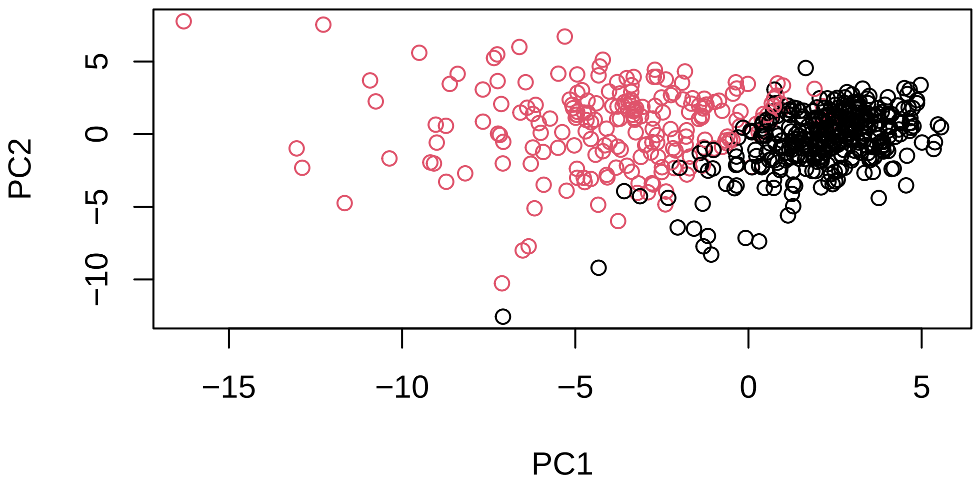
Q6. How many principal components (PCs) are required to describe at least 90% of the original variance in the data? PC 1 through PC 7 so need at least 7 components

Q7. What stands out to you about this plot? Is it easy or difficult to understand? Why? This plot is extremly clumped together and difficult to read and understand since the data isn't spread out.

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

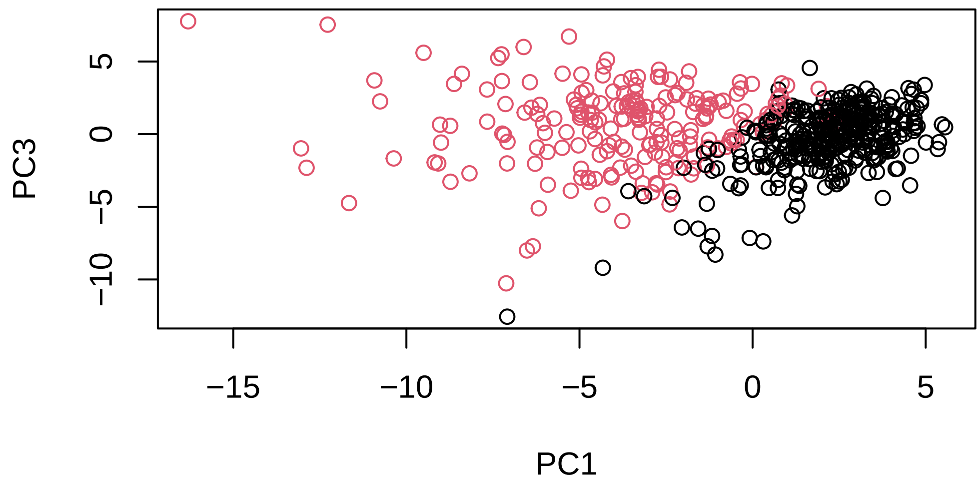



```r
# Scatter plot observations by components 1 and 2
plot( wisc.pr$x , col = diagnosis ,
     xlab = "PC1", ylab = "PC2")
```



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

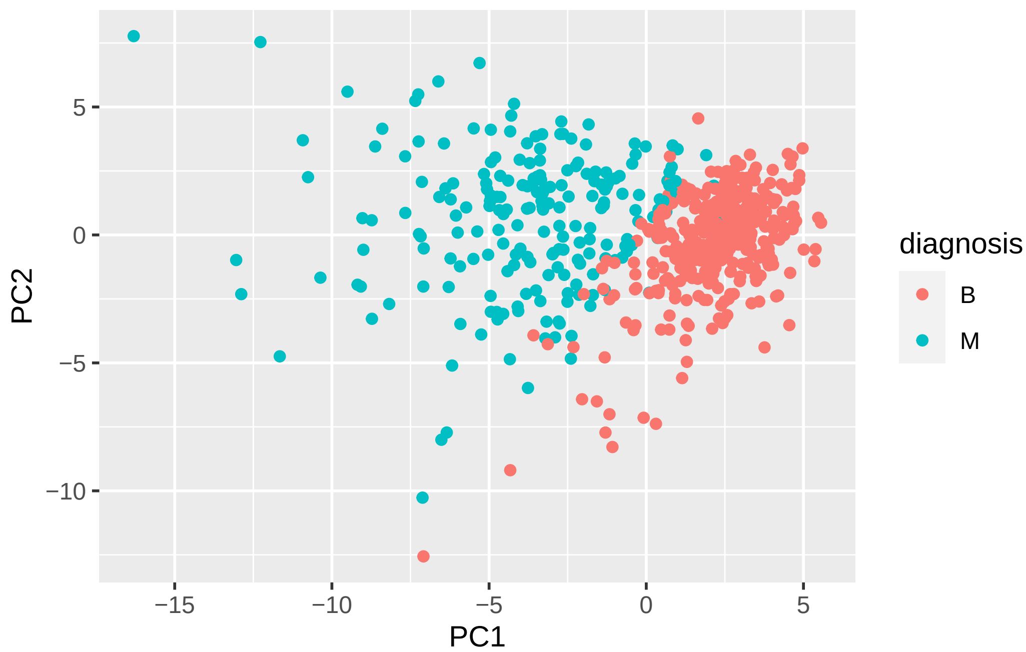
```
# Repeat for components 1 and 3
plot(wisc.pr$x[, 1:2 ],  col = diagnosis,
     xlab = "PC1", ylab = "PC3")
```




```
# 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()
```

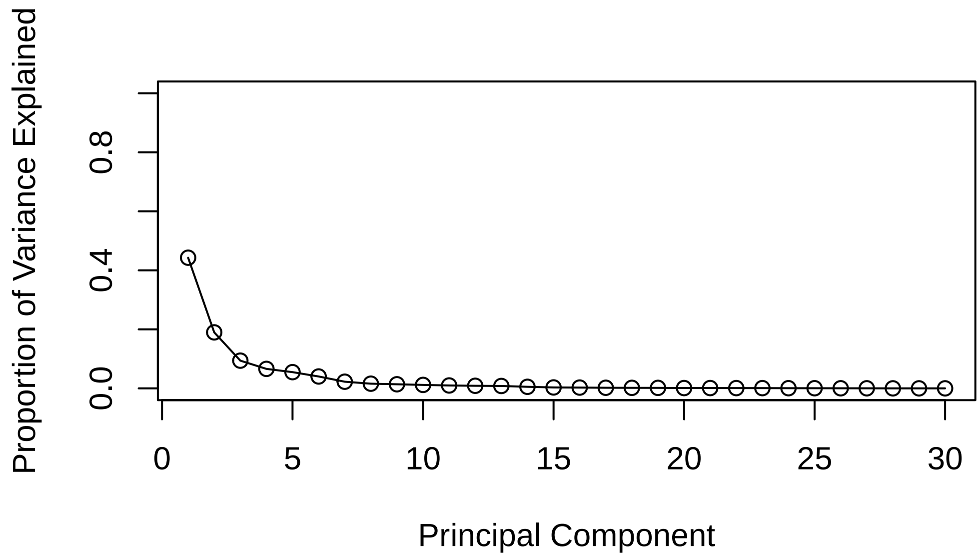



```r
# Calculate variance of each component
pr.var <- wisc.pr$sdev^2
head(pr.var)
```

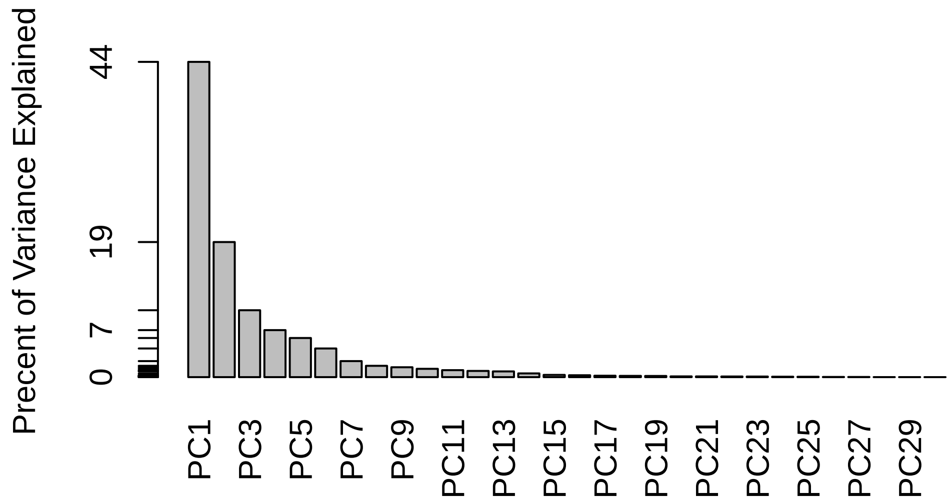
```
[1] 13.281608  5.691355  2.817949  1.980640  1.648731  1.207357
```

```r
# 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 )
```



##Communicating PCA results >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["concave.points_mean",1]
```

```
[1] -0.2608538
```

> Q10. What is the minimum number of principal components required to explain 80% of the variance of the data? It would need 5 PC

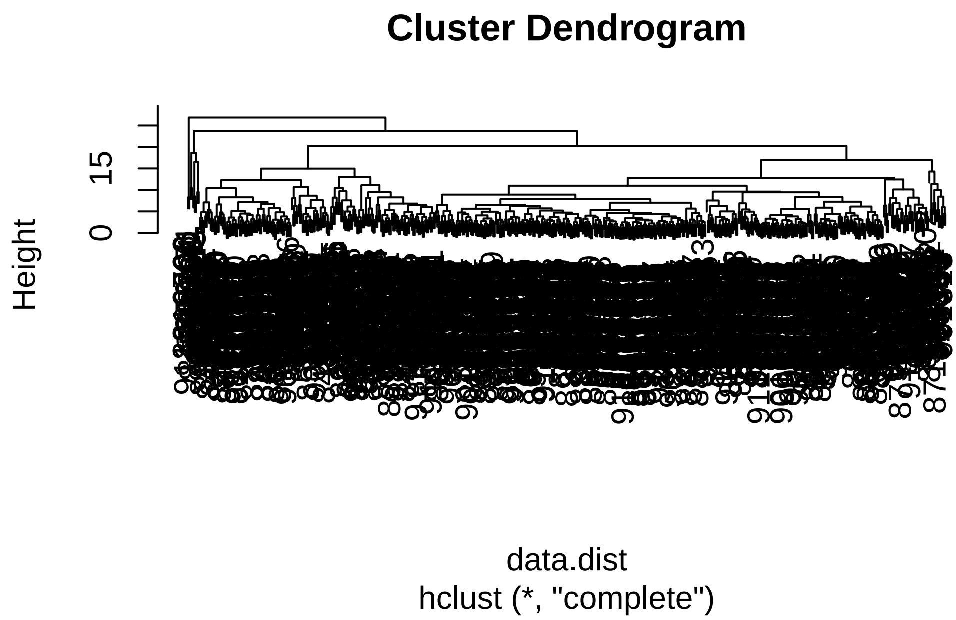
##Heirachical clustering

Can we just use custering on the orginal data and get some insgiht into M vs B

It's rather diffuclt, this "tree" look like a hot mess

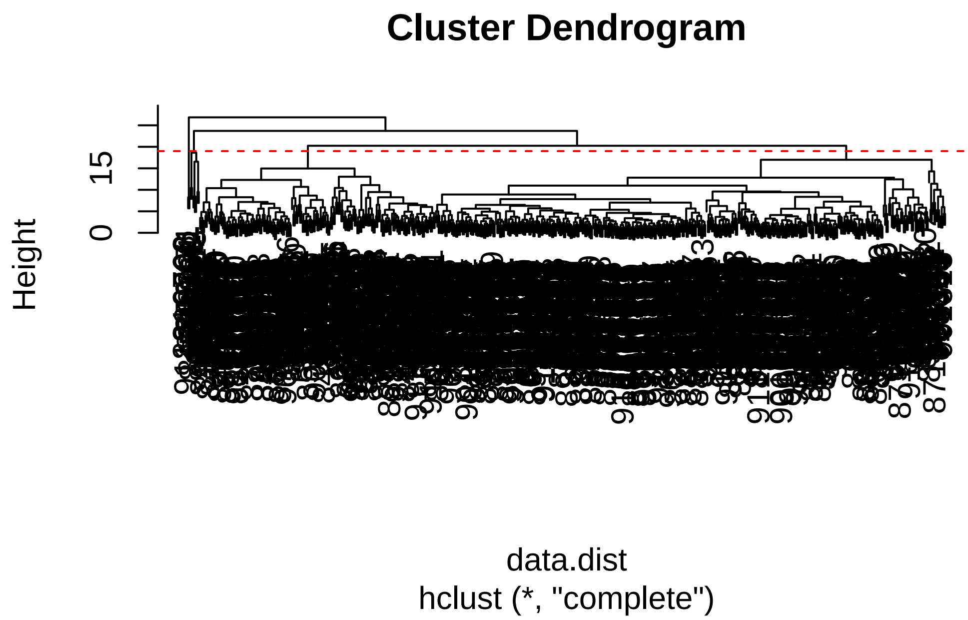
```
#distance matrix needed for hclust
data.dist <- dist(scale(wisc.data))

wisc.hclust <- hclust(data.dist)
plot(wisc.hclust)
```



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

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




```
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
```

> Q12. Can you find a better cluster vs diagnoses match by cutting into a different number of clusters between 2 and 10?

The better matches for the cuttung into the number of clusters is at lower numbers since the B and M clusters tend to be grouped or clustered more together, whereas with cutting into 4 clusters it's more spread out and not clumped together

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

```
                    diagnosis
```

```
wisc.hclust.clusters   B   M
                   1 357 210
                   2   0   2
```

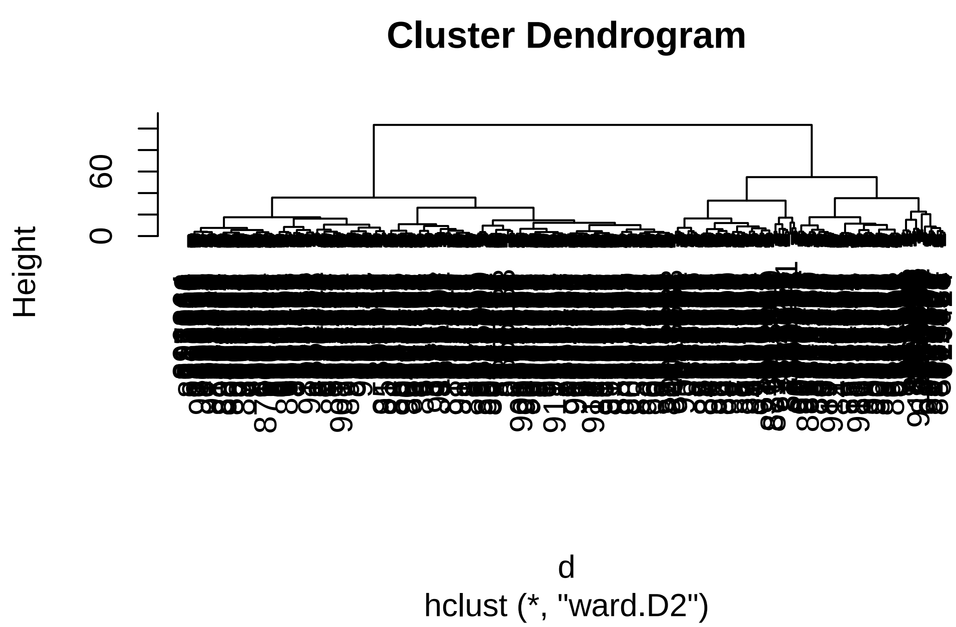
> Q13. Which method gives your favorite results for the same data.dist dataset? Explain your reasoning.

Using ward.D2 gives the best results with that dataset because minimizes the amount of variance between the clusters so things look a bit more neat and organized.

```
method="ward.D2"
```

##Combine 5 This approach will take not the orignal data, but out PCA results and work with them

```
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
```

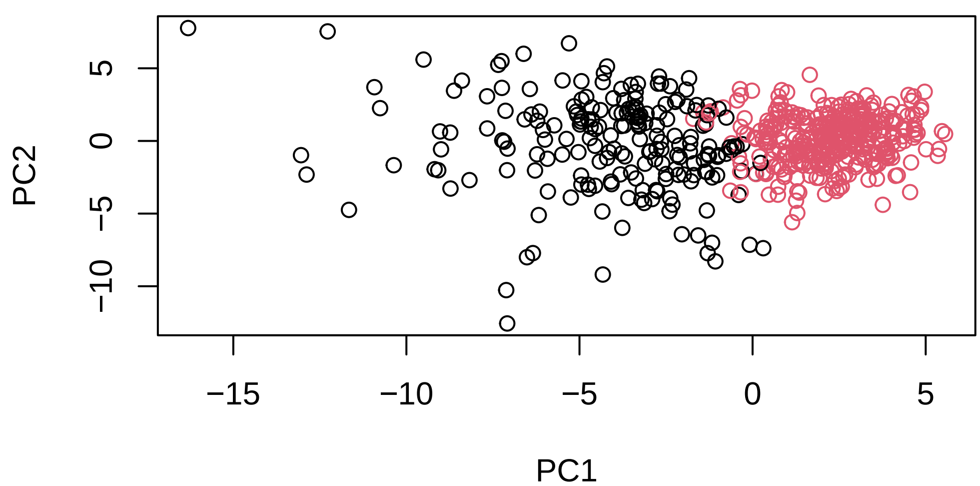
```
   842302    842517  84300903  84348301  84358402    843786    844359  84458202 
        1         1         1         1         1         1         1         1 
   844981  84501001    845636  84610002    846226    846381  84667401  84799002 
        1         1         2         1         1         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[,1:2], col=grps)
```



Q15. How well does the newly created model with four clusters separate out the two diagnoses?

The newly created model is pretty good with the separation of the two diagnosis because the way the B and M are split in a pretty even manner.

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

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