Class 08

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Breast Cancer FNA data

```
wisc.df <- read.csv("WisconsinCancer.csv", row.names=1)
head(wisc.df)</pre>
```

	diagnosis rad	lius_mean	texture_mean	perimeter_mean	area_mea	n
842302	М	17.99	10.38	122.80	1001.	0
842517	М	20.57	17.77	132.90	1326.	0
84300903	М	19.69	21.25	130.00	1203.	0
84348301	М	11.42	20.38	77.58	386.	1
84358402	М	20.29	14.34	135.10	1297.	0
843786	M	12.45	15.70	82.57	477.	1
	smoothness_me	an compa	ctness_mean co	ncavity_mean c	oncave.po	ints_mean
842302	0.118	340	0.27760	0.3001		0.14710
842517	0.084	74	0.07864	0.0869		0.07017
84300903	0.109	060	0.15990	0.1974		0.12790
84348301	0.142	250	0.28390	0.2414		0.10520
84358402	0.100	30	0.13280	0.1980		0.10430
843786	0.127	'80	0.17000	0.1578		0.08089
	symmetry_mean	fractal	_dimension_mea	n radius_se te	xture_se	perimeter_se
842302	0.2419)	0.0787	1 1.0950	0.9053	8.589
842517	0.1812)	0.0566	7 0.5435	0.7339	3.398
84300903	0.2069)	0.0599	9 0.7456	0.7869	4.585
84348301	0.2597	•	0.0974	4 0.4956	1.1560	3.445
84358402	0.1809)	0.0588	3 0.7572	0.7813	5.438
843786	0.2087	•	0.0761	3 0.3345	0.8902	2.217
	area_se smoot	hness_se	compactness_s	e concavity_se	concave.	points_se
842302	153.40	0.006399	0.0490	4 0.05373		0.01587
842517	74.08	0.005225	0.0130	8 0.01860		0.01340

84300903	94.03	0.006150)	0.04006	0.03	3832	0.02058
84348301	27.23	0.009110)	0.07458	0.0	5661	0.01867
84358402	94.44	0.011490)	0.02461	0.0	5688	0.01885
843786	27.19	0.007510)	0.03345	0.03	3672	0.01137
	symmetry_se	fractal_d	limensi	on_se rad:	ius_worst	texture_worst	
842302	0.03003		0.0	006193	25.38	17.33	
842517	0.01389		0.0	03532	24.99	23.41	
84300903	0.02250		0.0	04571	23.57	25.53	
84348301	0.05963		0.0	09208	14.91	26.50	
84358402	0.01756		0.0	05115	22.54	16.67	
843786	0.02165		0.0	05082	15.47	23.75	
	perimeter_wor	rst area_	worst	smoothness	s_worst co	ompactness_wor	st
842302	184	.60 2	2019.0		0.1622	0.66	56
842517	158	.80 1	956.0		0.1238	0.18	66
84300903	152	.50 1	709.0		0.1444	0.42	45
84348301	98	. 87	567.7		0.2098	0.86	63
84358402	152	. 20 1	575.0		0.1374	0.20	50
843786	103	.40	741.6		0.1791	0.52	49
	concavity_wor	rst conca	ve.poi	nts_worst	symmetry	_worst	
842302	0.7	119		0.2654	(0.4601	
842517	0.24	416		0.1860	(0.2750	
84300903	0.4	504		0.2430	(0.3613	
84348301	0.68	369		0.2575	(0.6638	
84358402	0.40	000		0.1625	(0.2364	
843786	0.53	355		0.1741	(0.3985	
	fractal_dimen	nsion_wor	st				
842302		0.118	890				
842517		0.089	002				
84300903		0.087	'58				
84348301		0.173	800				
84358402		0.076	78				
843786		0.124	40				

Q1. How many rows/patients/subjects.

nrow(wisc.df)

[1] 569

Q2. How many M (cancer) B (healthy) patients

table(wisc.df\$diagnosis)

```
B M
357 212
```

Be sure to remove this diagnosis column from our data to analyze

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

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

```
length( grep("_mean", colnames(wisc.data)))
```

[1] 10

colMeans(wisc.data)

perimeter_mean	texture_mean	radius_mean
9.196903e+01	1.928965e+01	1.412729e+01
${\tt compactness_mean}$	${\tt smoothness_mean}$	area_mean
1.043410e-01	9.636028e-02	6.548891e+02
symmetry_mean	concave.points_mean	concavity_mean
1.811619e-01	4.891915e-02	8.879932e-02
texture_se	radius_se	fractal_dimension_mean
1.216853e+00	4.051721e-01	6.279761e-02
smoothness_se	area_se	perimeter_se
7.040979e-03	4.033708e+01	2.866059e+00
concave.points_se	concavity_se	${\tt compactness_se}$
1.179614e-02	3.189372e-02	2.547814e-02
radius_worst	${\tt fractal_dimension_se}$	symmetry_se
1.626919e+01	3.794904e-03	2.054230e-02
area_worst	perimeter_worst	texture_worst
8.805831e+02	1.072612e+02	2.567722e+01
concavity_worst	${\tt compactness_worst}$	smoothness_worst
2.721885e-01	2.542650e-01	1.323686e-01
${\tt fractal_dimension_worst}$	symmetry_worst	<pre>concave.points_worst</pre>
8.394582e-02	2.900756e-01	1.146062e-01

apply(wisc.data,2,sd)

perimeter_mean	texture_mean	radius_mean
2.429898e+01	4.301036e+00	3.524049e+00
compactness_mean	${\tt smoothness_mean}$	area_mean
5.281276e-02	1.406413e-02	3.519141e+02
symmetry_mean	concave.points_mean	concavity_mean
2.741428e-02	3.880284e-02	7.971981e-02
texture_se	radius_se	fractal_dimension_mean
5.516484e-01	2.773127e-01	7.060363e-03
smoothness_se	area_se	perimeter_se
3.002518e-03	4.549101e+01	2.021855e+00
concave.points_se	concavity_se	compactness_se
6.170285e-03	3.018606e-02	1.790818e-02
radius_worst	fractal_dimension_se	symmetry_se
4.833242e+00	2.646071e-03	8.266372e-03
area_worst	perimeter_worst	texture_worst
5.693570e+02	3.360254e+01	6.146258e+00
concavity_worst	compactness_worst	smoothness_worst
2.086243e-01	1.573365e-01	2.283243e-02
<pre>fractal_dimension_worst</pre>	symmetry_worst	concave.points_worst
1.806127e-02	6.186747e-02	6.573234e-02

Principal Component Analysis

We want to scale our data before PCA by setting the scale=Trueargument!

```
wisc.pr <- prcomp(wisc.data, scale=TRUE)
```

How much variance captured in each PC?

```
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
```

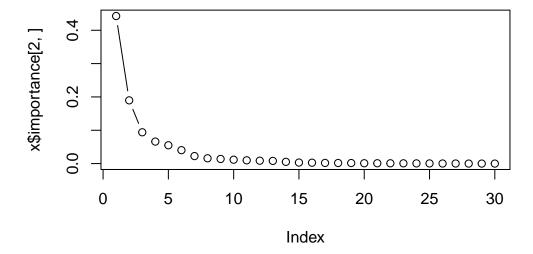
```
Proportion of Variance 0.01589 0.0139 0.01169 0.0098 0.00871 0.00805 0.00523
Cumulative Proportion 0.92598 0.9399 0.95157 0.9614 0.97007 0.97812 0.98335
                          PC15
                                  PC16
                                          PC17
                                                  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
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
```

How much variance captured in each PC?

```
x <- summary(wisc.pr)
x$importance</pre>
```

	PC1	PC2	PC3	PC4	PC5 PC6
Standard deviation	3.644394	2.385656 1	.678675 1.	407352 1.28	34029 1.098798
Proportion of Variance	0.442720	0.189710 0	.093930 0.	066020 0.09	54960 0.040250
Cumulative Proportion	0.442720	0.632430 0	.726360 0.	792390 0.84	17340 0.887590
	PC7	PC8	PC9	PC10	PC11
Standard deviation	0.8217178	0.6903746	0.6456739	0.5921938	0.5421399
Proportion of Variance	0.0225100	0.0158900	0.0139000	0.0116900	0.0098000
Cumulative Proportion	0.9101000	0.9259800	0.9398800	0.9515700	0.9613700
	PC12	PC13	PC14	PC15	PC16
Standard deviation	0.5110395	0.4912815	0.3962445	0.3068142	0.2826001
Proportion of Variance	0.0087100	0.0080500	0.0052300	0.0031400	0.0026600
Cumulative Proportion	0.9700700	0.9781200	0.9833500	0.9864900	0.9891500
	PC17	' PC18	PC19	PC20	PC21
Standard deviation	0.2437192	0.2293878	0.2224356	0.1765203	0.1731268
Proportion of Variance	0.0019800	0.0017500	0.0016500	0.0010400	0.0010000
Cumulative Proportion	0.9911300	0.9928800	0.9945300	0.9955700	0.9965700
	PC22	PC23	PC24	PC25	PC26
Standard deviation	0.1656484	0.1560155	0.1343689	0.1244238	0.0904303
Proportion of Variance	0.0009100	0.0008100	0.0006000	0.0005200	0.0002700
Cumulative Proportion	0.9974900	0.9983000	0.9989000	0.9994200	0.9996900
	PC2	27 PC2	8 PC	29 PO	C30
Standard deviation	0.0830690	3 0.039866	5 0.027364	27 0.011534	1 51

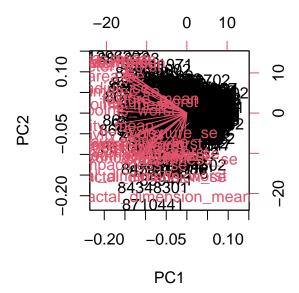
plot(x\$importance[2,], typ="b")



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

The plot is very difficult to understand because there are so many factors that are overlapping making the plot difficult to read.

biplot(wisc.pr)



attributes(wisc.pr)

\$names

[1] "sdev" "rotation" "center" "scale" "x"

\$class

[1] "prcomp"

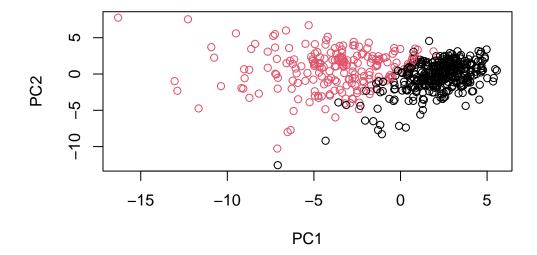
head(wisc.pr\$x)

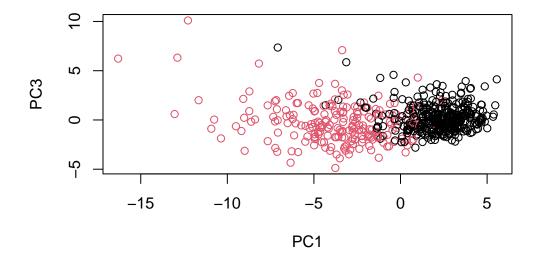
	PC1	PC2	PC3	PC4	PC5	PC	6
842302	-9.184755	-1.946870	-1.1221788	3.6305364	1.1940595	1.4101836	4
842517	-2.385703	3.764859	-0.5288274	1.1172808	-0.6212284	0.0286311	3
84300903	-5.728855	1.074229	-0.5512625	0.9112808	0.1769302	0.5409761	5
84348301	-7.116691	-10.266556	-3.2299475	0.1524129	2.9582754	3.0507375)
84358402	-3.931842	1.946359	1.3885450	2.9380542	-0.5462667	-1.2254164	1
843786	-2.378155	-3.946456	-2.9322967	0.9402096	1.0551135	-0.45064213	3
	PC	C7 I	PC8	PC9	PC10	PC11	PC12
842302	2.1574715	0.398056	698 - 0.15698	8023 -0.876	66305 -0.26	27243 -0.85	32593

```
842517
         0.01334635 -0.24077660 -0.71127897 1.1060218 -0.8124048 0.1577838
84300903 -0.66757908 -0.09728813 0.02404449 0.4538760 0.6050715 0.1242777
84348301 1.42865363 -1.05863376 -1.40420412 -1.1159933 1.1505012 1.0104267
84358402 -0.93538950 -0.63581661 -0.26357355 0.3773724 -0.6507870 -0.1104183
843786
         0.49001396 0.16529843 -0.13335576 -0.5299649 -0.1096698 0.0813699
              PC13
                           PC14
                                       PC15
                                                  PC16
                                                             PC17
842302
         0.10329677 -0.690196797 0.601264078 0.74446075 -0.26523740
842517
        -0.94269981 -0.652900844 -0.008966977 -0.64823831 -0.01719707
84300903 -0.41026561 0.016665095 -0.482994760 0.32482472 0.19075064
84348301 -0.93245070 -0.486988399 0.168699395 0.05132509 0.48220960
84358402 0.38760691 -0.538706543 -0.310046684 -0.15247165 0.13302526
843786
        -0.02625135 0.003133944 -0.178447576 -0.01270566 0.19671335
              PC18
                         PC19
                                    PC20
                                                PC21
                                                           PC22
842302
        -0.54907956 0.1336499 0.34526111 0.096430045 -0.06878939
842517
         0.31801756 -0.2473470 -0.11403274 -0.077259494 0.09449530
84300903 -0.08789759 -0.3922812 -0.20435242 0.310793246 0.06025601
84348301 -0.03584323 -0.0267241 -0.46432511 0.433811661
                                                      0.20308706
84358402 -0.01869779 0.4610302 0.06543782 -0.116442469
                                                      0.01763433
843786
        -0.29727706 -0.1297265 -0.07117453 -0.002400178
                                                      0.10108043
              PC23
                           PC24
                                       PC25
                                                   PC26
                                                              PC27
842302
         -0.21752666 -0.011280193 0.170360355 -0.041092627 0.18111081
842517
84300903 -0.07422581 -0.102671419 -0.171007656 0.004731249 0.04952586
84348301 -0.12399554 -0.153294780 -0.077427574 -0.274982822 0.18330078
84358402 0.13933105 0.005327110 -0.003059371 0.039219780 0.03213957
         0.03344819 -0.002837749 -0.122282765 -0.030272333 -0.08438081
843786
                PC28
                            PC29
                                          PC30
        842302
842517
         0.0325955021 -0.005682424 0.0018662342
84300903 0.0469844833 0.003143131 -0.0007498749
84348301 0.0424469831 -0.069233868 0.0199198881
84358402 -0.0347556386 0.005033481 -0.0211951203
843786
         0.0007296587 -0.019703996 -0.0034564331
```

My main PC results figure

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

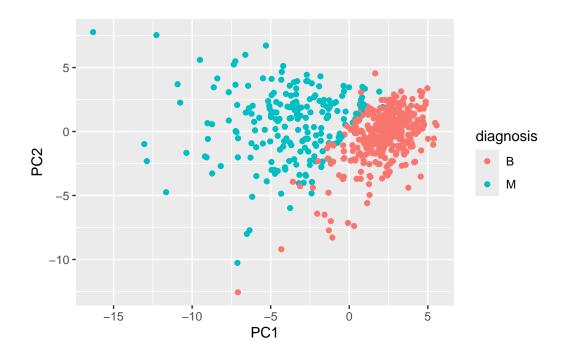




```
df <- as.data.frame(wisc.pr$x)
df$diagnosis <- diagnosis

library(ggplot2)

ggplot(df) +
   aes(PC1, PC2, col=diagnosis) +
   geom_point()</pre>
```



```
pr.var <- wisc.pr$sdev^2
head(pr.var)</pre>
```

[1] 13.281608 5.691355 2.817949 1.980640 1.648731 1.207357

Clustering

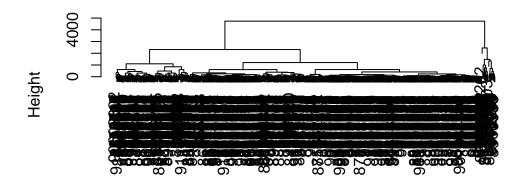
Try to cluster the wisc.data.

```
km <- kmeans(wisc.data, centers= 2)
table(km$cluster)</pre>
```

1 2 438 131

```
d <- dist (wisc.data)
hc <- hclust(d)
plot(hc)</pre>
```

Cluster Dendrogram



d hclust (*, "complete")

```
grps <- cutree(hc, k=3)
table(grps)</pre>
```

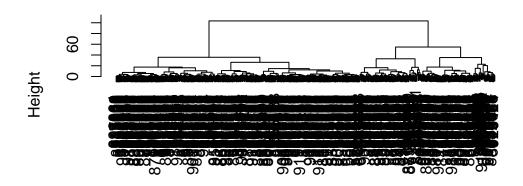
```
grps 1 2 3 549 19 1
```

Cluster in PC space

In other words use my PCA results as a baisis of clustering.

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

Cluster Dendrogram



d hclust (*, "ward.D2")

Cut this tree to yield 2 groups/clusters

```
grps <- cutree(hc, k=2)
table(grps)</pre>
```

grps 1 2 203 366

Compare to my expert M and B diagnosis

table(diagnosis)

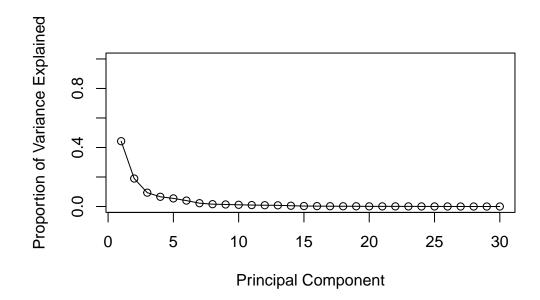
diagnosis B M 357 212

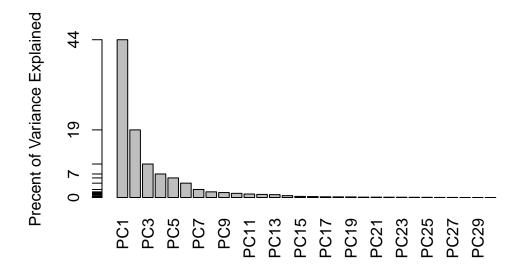
table(diagnosis, grps)

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

```
pve <- (wisc.pr$sdev^2) / sum(wisc.pr$sdev^2)

plot(pve, xlab = "Principal Component",
    ylab = "Proportion of Variance Explained",
    ylim = c(0, 1), type = "o")</pre>
```





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]

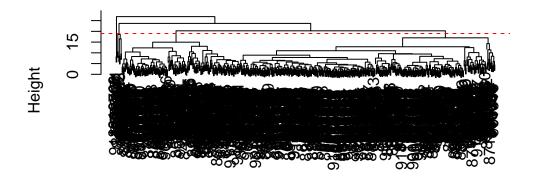
[1] -0.2608538

# 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")
plot(wisc.hclust)
abline(h = 19, col = "red", lty = 2)</pre>
```

Cluster Dendrogram



data.dist hclust (*, "complete")

```
wisc.hclust.clusters <- cutree(wisc.hclust, k = 4)</pre>
```

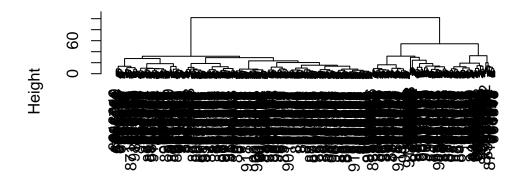
table(wisc.hclust.clusters, diagnosis)

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

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

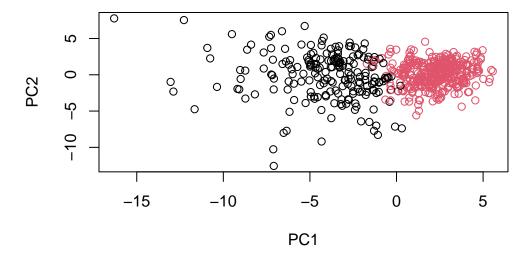
```
wisc.hclust <- hclust(data.dist, method = "ward.D2")
plot(wisc.hclust)</pre>
```

Cluster Dendrogram

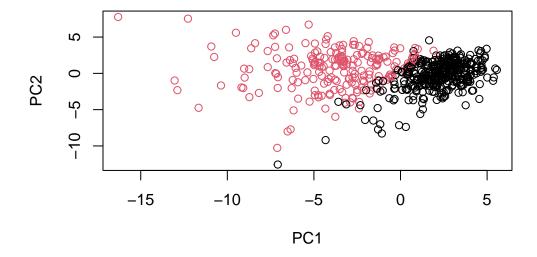


data.dist hclust (*, "ward.D2")

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



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



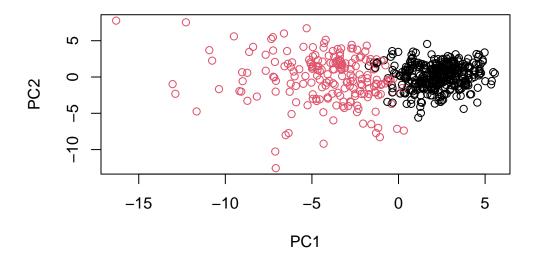
```
g <- as.factor(grps)
levels(g)</pre>
```

[1] "1" "2"

```
g <- relevel(g,2)
levels(g)</pre>
```

[1] "2" "1"

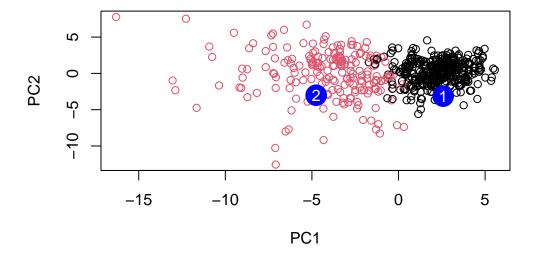
plot(wisc.pr\$x[,1:2], col=g)



```
url <- "https://tinyurl.com/new-samples-CSV"
new <- read.csv(url)
npc <- predict(wisc.pr, newdata=new)
npc</pre>
```

```
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?

Patient 2 should be prioritized because they have more malignant type cells.