Class 8: Mini-Project

Allen (A16897142)

Table of contents

Background

This mini-project explores unsupervised learning techniques applied to the Wisconsin Breast Cancer Diagnostic Data Set, which contains measurements of human breast mass cell nuclei. The project guides the user through exploratory data analysis, performing and interpreting Principal Component Analysis (PCA) to reduce the dimensionality of the data while retaining variance, and applying hierarchical clustering with different linkage methods. It also includes a section on K-means clustering for comparison. The ultimate goal is to combine PCA and clustering to better separate benign and malignant cell samples, evaluating the results using metrics like sensitivity and specificity, and finally demonstrating how to predict the classification of new samples using the developed PCA model.

Data Import

The data will be coming from the University of Wisconsin Medical Center

```r
url <- "https://bioboot.github.io/bimm143_S20/class-material/WisconsinCancer.csv"
wisc.df <- read.csv(url, 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
```

How many patients/samples are in this dataset?

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

```
[1] 569
```

How many of the observations have a malignant diagnosis?

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

```

  B   M 
357 212 
```

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

```
[1] 212
```

How many variables/features in the data are 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"
```

```
length(grep("mean",colnames(wisc.df),value=T))
```

```
[1] 10
```

There is a diagnosis column that represents the clinicians consensus that I want to exclude from any future analysis. We will first our data and then compare with the "diagnosis" later.

```
diagnosis <- as.factor(wisc.df$diagnosis)
head(diagnosis)
```

```
[1] M M M M M M
Levels: B M
```

No we will remove diagnosis from wisc.df

```
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
842302                   0.11890
842517                   0.08902
84300903                 0.08758
```

```
84348301                  0.17300
84358402                  0.07678
843786                    0.12440
```

Clustering

```r
kmeans(wisc.data,centers=2)
```

```
K-means clustering with 2 clusters of sizes 438, 131

Cluster means:
  radius_mean texture_mean perimeter_mean area_mean smoothness_mean
1    12.55630     18.57037       81.12347  496.0619       0.0948845
2    19.37992     21.69458      128.23130 1185.9298       0.1012946
  compactness_mean concavity_mean concave.points_mean symmetry_mean
1       0.09109982     0.06243776          0.03343254     0.1780580
2       0.14861298     0.17693947          0.10069878     0.1915397
  fractal_dimension_mean radius_se texture_se perimeter_se  area_se
1             0.06345402 0.3041909   1.215153     2.152881 23.78529
2             0.06060290 0.7428038   1.222538     5.250580 95.67817
  smoothness_se compactness_se concavity_se concave.points_se symmetry_se
1   0.007173263     0.02347469   0.02874551        0.01063632  0.02061358
2   0.006598687     0.03217669   0.04241977        0.01567398  0.02030397
  fractal_dimension_se radius_worst texture_worst perimeter_worst area_worst
1          0.003747503     14.04390      24.70954        91.93751   619.6479
2          0.003953389     23.70947      28.91267       158.49618  1753.0229
  smoothness_worst compactness_worst concavity_worst concave.points_worst
1        0.1299591         0.2233118       0.2192149           0.09132984
2        0.1404247         0.3577577       0.4493061           0.19243107
  symmetry_worst fractal_dimension_worst
1      0.2835537              0.08328194
2      0.3118817              0.08616550

Clustering vector:
   842302    842517  84300903  84348301  84358402    843786    844359  84458202
        2         2         2         1         2         1         2         1
   844981  84501001    845636  84610002    846226    846381  84667401  84799002
        1         1         1         2         2         1         1         1
   848406  84862001    849014   8510426   8510653   8510824   8511133    851509
        1         2         2         1         1         1         1         2
```

852552	852631	852763	852781	852973	853201	853401	853612
2	2	1	2	2	2	2	1
85382601	854002	854039	854253	854268	854941	855133	855138
2	2	2	2	1	1	1	1
855167	855563	855625	856106	85638502	857010	85713702	85715
1	1	2	1	1	2	1	1
857155	857156	857343	857373	857374	857392	857438	85759902
1	1	1	1	1	2	1	1
857637	857793	857810	858477	858970	858981	858986	859196
2	1	1	1	1	1	1	1
85922302	859283	859464	859465	859471	859487	859575	859711
1	1	1	1	1	1	2	1
859717	859983	8610175	8610404	8610629	8610637	8610862	8610908
2	1	1	2	1	2	2	1
861103	8611161	8611555	8611792	8612080	8612399	86135501	86135502
1	1	2	2	1	2	1	2
861597	861598	861648	861799	861853	862009	862028	86208
1	1	1	1	1	1	1	2
86211	862261	862485	862548	862717	862722	862965	862980
1	1	1	1	1	1	1	1
862989	863030	863031	863270	86355	864018	864033	86408
1	1	1	1	2	1	1	1
86409	864292	864496	864685	864726	864729	864877	865128
1	1	1	1	1	1	2	2
865137	86517	865423	865432	865468	86561	866083	866203
1	2	2	1	1	1	1	2
866458	866674	866714	8670	86730502	867387	867739	868202
1	2	1	1	1	1	2	1
868223	868682	868826	868871	868999	869104	869218	869224
1	1	1	1	1	2	1	1
869254	869476	869691	86973701	86973702	869931	871001501	871001502
1	1	1	1	1	1	1	1
8710441	87106	8711002	8711003	8711202	8711216	871122	871149
1	1	1	1	2	1	1	1
8711561	8711803	871201	8712064	8712289	8712291	87127	8712729
1	2	2	1	2	1	1	2
8712766	8712853	87139402	87163	87164	871641	871642	872113
2	1	1	1	1	1	1	1
872608	87281702	873357	873586	873592	873593	873701	873843
1	1	1	1	2	2	2	1
873885	874158	874217	874373	874662	874839	874858	875093
1	1	2	1	1	1	1	1
875099	875263	87556202	875878	875938	877159	877486	877500

1	1	1	1	1	2	2	1
877501	877989	878796	87880	87930	879523	879804	879830
1	2	2	1	1	1	1	2
8810158	8810436	881046502	8810528	8810703	881094802	8810955	8810987
1	1	2	1	2	1	1	1
8811523	8811779	8811842	88119002	8812816	8812818	8812844	8812877
1	1	2	2	1	1	1	1
8813129	88143502	88147101	88147102	88147202	881861	881972	88199202
1	1	1	1	1	1	2	1
88203002	88206102	882488	88249602	88299702	883263	883270	88330202
1	2	1	1	2	2	1	2
88350402	883539	883852	88411702	884180	884437	884448	884626
1	1	1	1	2	1	1	1
88466802	884689	884948	88518501	885429	8860702	886226	886452
1	1	2	1	2	2	2	1
88649001	886776	887181	88725602	887549	888264	888570	889403
2	1	2	1	2	2	2	1
889719	88995002	8910251	8910499	8910506	8910720	8910721	8910748
2	2	1	1	1	1	1	1
8910988	8910996	8911163	8911164	8911230	8911670	8911800	8911834
2	1	2	1	1	2	1	1
8912049	8912055	89122	8912280	8912284	8912521	8912909	8913
2	1	2	1	1	1	1	1
8913049	89143601	89143602	8915	891670	891703	891716	891923
1	1	1	1	1	1	1	1
891936	892189	892214	892399	892438	892604	89263202	892657
1	1	1	1	2	1	2	1
89296	893061	89344	89346	893526	893548	893783	89382601
1	1	1	1	1	1	1	1
89382602	893988	894047	894089	894090	894326	894329	894335
1	1	1	1	1	2	1	1
894604	894618	894855	895100	89511501	89511502	89524	895299
1	2	1	2	1	1	1	1
8953902	895633	896839	896864	897132	897137	897374	89742801
1	1	1	1	1	1	1	2
897604	897630	897880	89812	89813	898143	89827	898431
1	2	1	2	1	1	1	2
89864002	898677	898678	89869	898690	899147	899187	899667
1	1	1	1	1	1	1	1
899987	9010018	901011	9010258	9010259	901028	9010333	901034301
2	1	1	1	1	1	1	1
901034302	901041	9010598	9010872	9010877	901088	9011494	9011495
1	1	1	1	1	2	2	1

9011971	9012000	9012315	9012568	9012795	901288	9013005	901303
2	2	1	1	2	2	1	1
901315	9013579	9013594	9013838	901549	901836	90250	90251
1	1	1	1	1	1	1	1
902727	90291	902975	902976	903011	90312	90317302	903483
1	1	1	1	1	2	1	1
903507	903516	903554	903811	90401601	90401602	904302	904357
2	2	1	1	1	1	1	1
90439701	904647	904689	9047	904969	904971	905189	905190
2	1	1	1	1	1	1	1
90524101	905501	905502	905520	905539	905557	905680	905686
2	1	1	1	1	1	1	1
905978	90602302	906024	906290	906539	906564	906616	906878
1	2	1	1	1	1	1	1
907145	907367	907409	90745	90769601	90769602	907914	907915
1	1	1	1	1	1	1	1
908194	908445	908469	908489	908916	909220	909231	909410
2	2	1	1	1	1	1	1
909411	909445	90944601	909777	9110127	9110720	9110732	9110944
1	2	1	1	2	1	2	1
911150	911157302	9111596	9111805	9111843	911201	911202	9112085
1	2	1	2	1	1	1	1
9112366	9112367	9112594	9112712	911296201	911296202	9113156	911320501
1	1	1	1	2	2	1	1
911320502	9113239	9113455	9113514	9113538	911366	9113778	9113816
1	1	1	1	2	1	1	1
911384	9113846	911391	911408	911654	911673	911685	911916
1	1	1	1	1	1	1	1
912193	91227	912519	912558	912600	913063	913102	913505
1	1	1	1	1	1	1	2
913512	913535	91376701	91376702	914062	914101	914102	914333
1	1	1	2	2	1	1	1
914366	914580	914769	91485	914862	91504	91505	915143
1	1	2	2	1	1	1	2
915186	915276	91544001	91544002	915452	915460	91550	915664
1	1	1	1	1	1	1	1
915691	915940	91594602	916221	916799	916838	917062	917080
1	1	1	1	2	2	1	1
917092	91762702	91789	917896	917897	91805	91813701	91813702
1	2	1	1	1	1	1	1
918192	918465	91858	91903901	91903902	91930402	919537	919555
1	1	1	1	1	2	1	2
91979701	919812	921092	921362	921385	921386	921644	922296

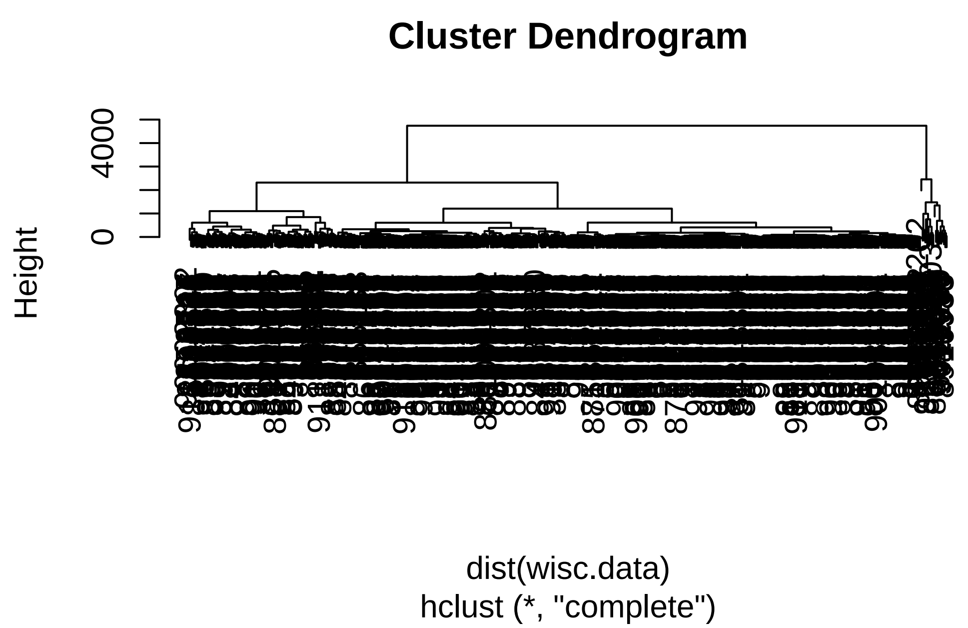
```
       1        1        1        1        1        1        1        1
  922297   922576   922577   922840   923169   923465   923748   923780
       1        1        1        1        1        1        1        1
  924084   924342   924632   924934   924964   925236   925277   925291
       1        1        1        1        1        1        1        1
  925292   925311   925622   926125   926424   926682   926954   927241
       1        1        1        2        2        2        1        2
   92751
       1

Within cluster sum of squares by cluster:
[1] 28559677 49383423
 (between_SS / total_SS =  69.6 %)

Available components:

[1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
[6] "betweenss"    "size"         "iter"         "ifault"
```

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



Clusters can be extracted from the dendrogram above with the function `cutree()`

```r
grps <- cutree(hc,k=2)
```

How many individuals in each cluster

```r
table(grps)
```

```
grps
  1   2
549  20
```

```r
table (diagnosis)
```

```
diagnosis
  B   M
357 212
```

Now we can use a cross-table that compares the clusters of `grps` with `diagnosis` to see if there are any similarities (are the 20 in `grps` malignant or not)

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

```
         grps
diagnosis   1   2
        B 357   0
        M 192  20
```

Principal Component Analysis

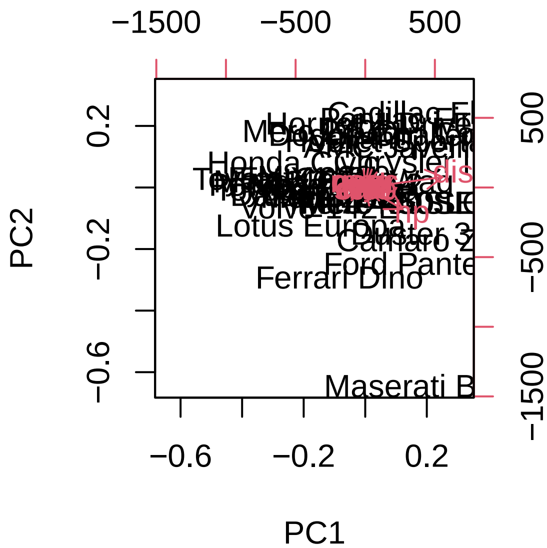
The main function for PCA in base R is `prcomp()` and has a default input parameter of `scale=FALSE`.

```r
head(mtcars)
```

```
                   mpg cyl disp  hp drat    wt  qsec vs am gear carb
Mazda RX4         21.0   6  160 110 3.90 2.620 16.46  0  1    4    4
Mazda RX4 Wag     21.0   6  160 110 3.90 2.875 17.02  0  1    4    4
Datsun 710        22.8   4  108  93 3.85 2.320 18.61  1  1    4    1
Hornet 4 Drive    21.4   6  258 110 3.08 3.215 19.44  1  0    3    1
Hornet Sportabout 18.7   8  360 175 3.15 3.440 17.02  0  0    3    2
Valiant           18.1   6  225 105 2.76 3.460 20.22  1  0    3    1
```

A PCA can be done but it could be misleading:

```r
pc <- prcomp(mtcars)
biplot(pc)
```




```r
colMeans(mtcars)
```

```
       mpg        cyl       disp         hp       drat         wt       qsec 
 20.090625   6.187500 230.721875 146.687500   3.596563   3.217250  17.848750 
        vs         am       gear       carb 
  0.437500   0.406250   3.687500   2.812500 
```

```r
apply(mtcars,2,sd)
```

```
        mpg         cyl        disp          hp        drat          wt 
  6.0269481   1.7859216 123.9386938  68.5628685   0.5346787   0.9784574 
       qsec          vs          am        gear        carb 
  1.7869432   0.5040161   0.4989909   0.7378041   1.6152000 
```

Let's scale the data before we conduct PCA to get a better representation and analysis of the columns.

```r
mtscale <- scale(mtcars)
```

```r
round(colMeans(mtscale))
```

```
 mpg  cyl disp   hp drat   wt qsec   vs   am gear carb 
   0    0    0    0    0    0    0    0    0    0    0 
```

```r
apply(mtscale,2,sd)
```

```
 mpg  cyl disp   hp drat   wt qsec   vs   am gear carb 
   1    1    1    1    1    1    1    1    1    1    1 
```

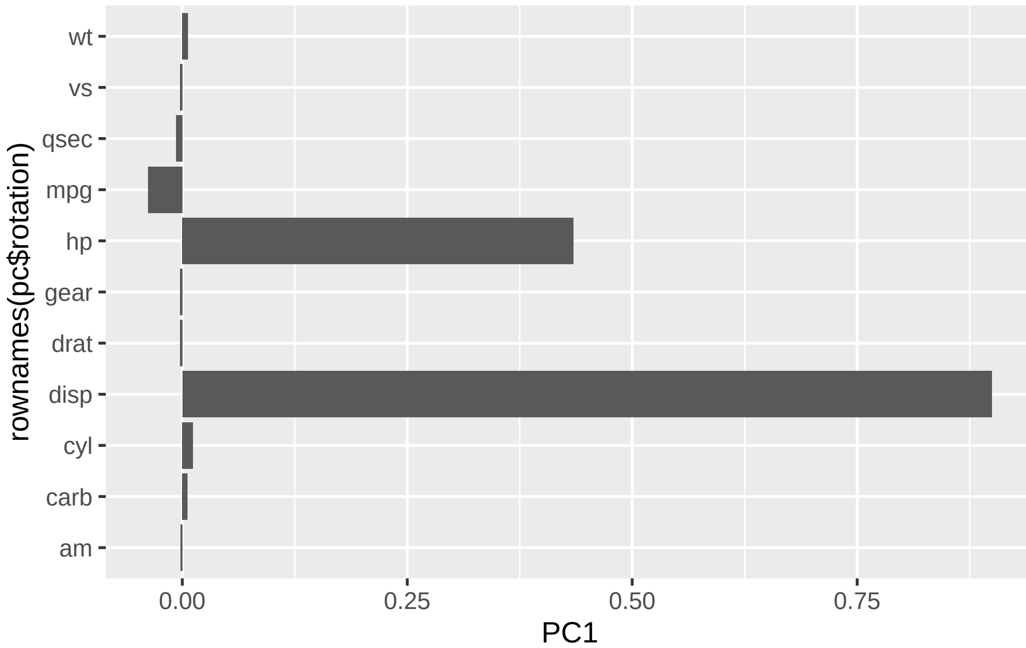
```r
pc.scale <- prcomp(mtscale)
```

We can look at the two main results figures from PCA - the "PC plot" (or score plot/PC1 vs PC2 plot). The "loadings plot" or how the original variables contribute to the new PC.

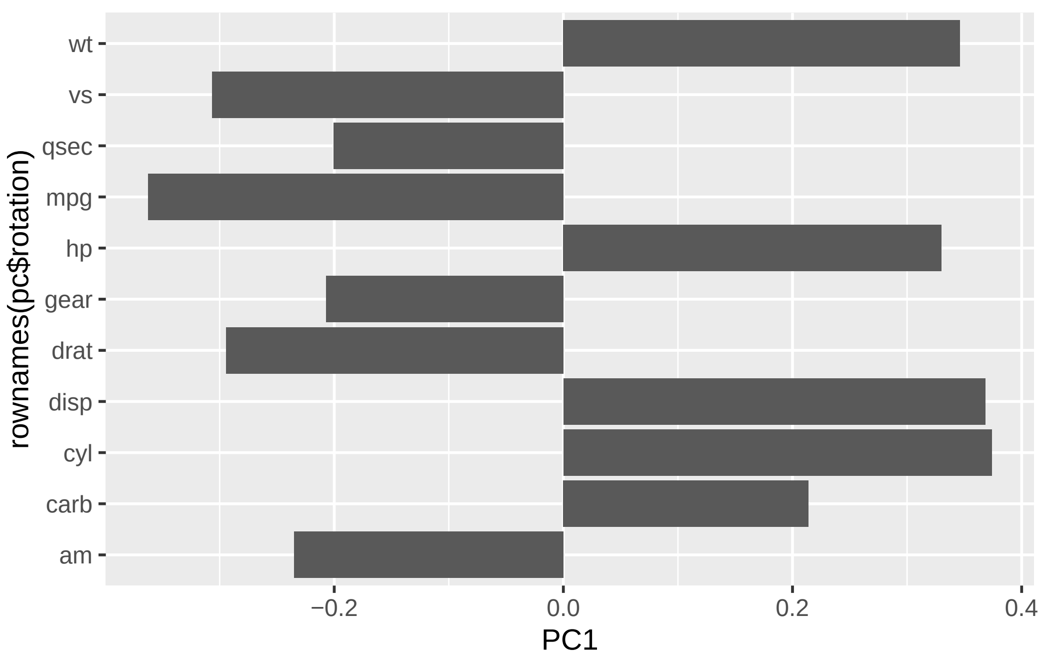
A loadings plot of the unscaled PCA results:

```r
library(ggplot2)

ggplot(pc$rotation)+
  aes(PC1,rownames(pc$rotation))+
  geom_col()
```



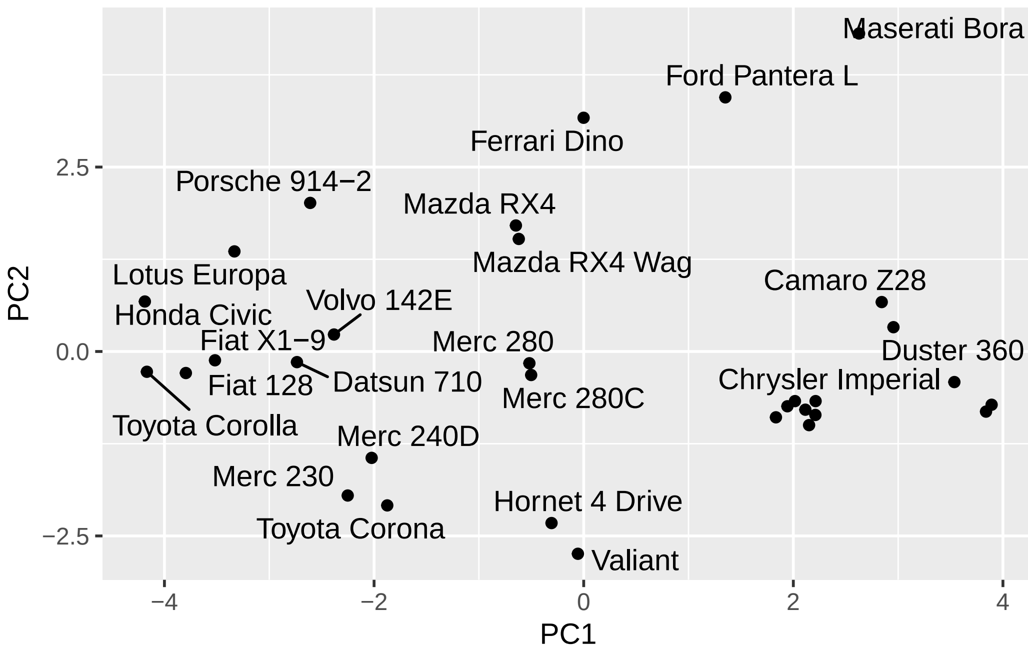

```r
ggplot(pc.scale$rotation)+
  aes(PC1,rownames(pc$rotation))+
  geom_col()
```



PC plot of scaled PCA results:

```
library(ggrepel)
ggplot(pc.scale$x)+
  aes(PC1,PC2,label=rownames(pc.scale$x))+
  geom_point()+
  geom_text_repel()
```

```
Warning: ggrepel: 9 unlabeled data points (too many overlaps). Consider
increasing max.overlaps
```



Remember that in general, we will set `scale=T` when we conudct PCAs.

PCA od wisc.data

Let's check out the SD and mean in `wisc.data`.

```
wisc.pc <- prcomp(wisc.data,scale=T)
```

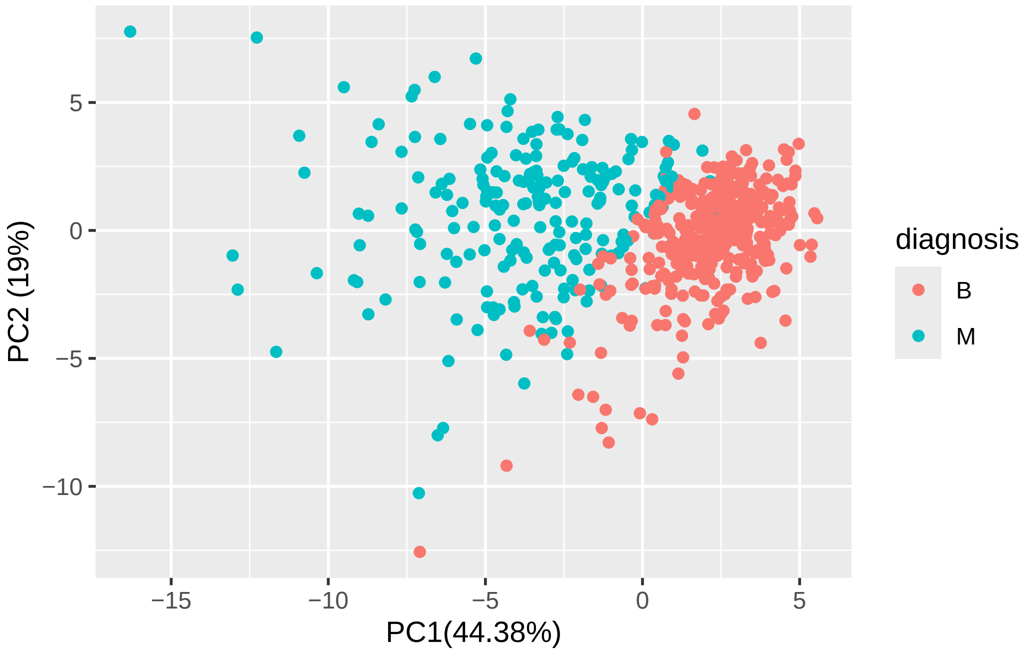
To see how well PCA is doing here in terms f capturing spread, we use `summary()` to help:

```r
summary(wisc.pc)
```

```
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
```

Let's make the PC1 vs PC2 figure:

```r
ggplot(wisc.pc$x)+
  aes(PC1,PC2, col=diagnosis)+
  geom_point()+
  xlab("PC1(44.38%)")+
  ylab("PC2 (19%)")
```



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

44.27% is captured by PC1

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

3 PCs are required to describe at least 70% of the original variance.

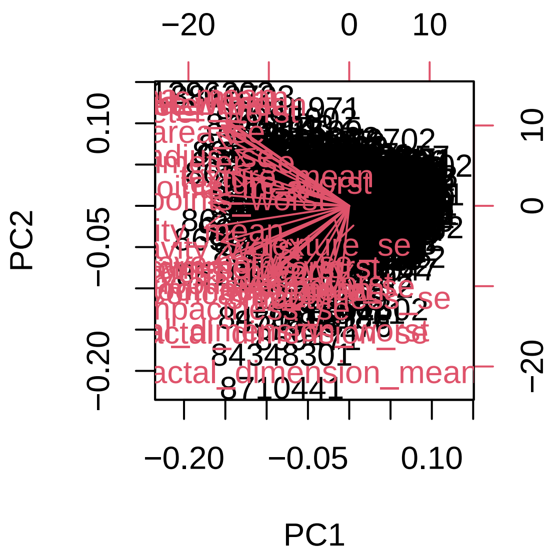
> Q6. How many principal components (PCs) are required to describe at least 90% of the original variance in the data?

7 PCs are required to describe at least 90% of the original variance.

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

The plot is very messy which makes it difficult to analyze and understand

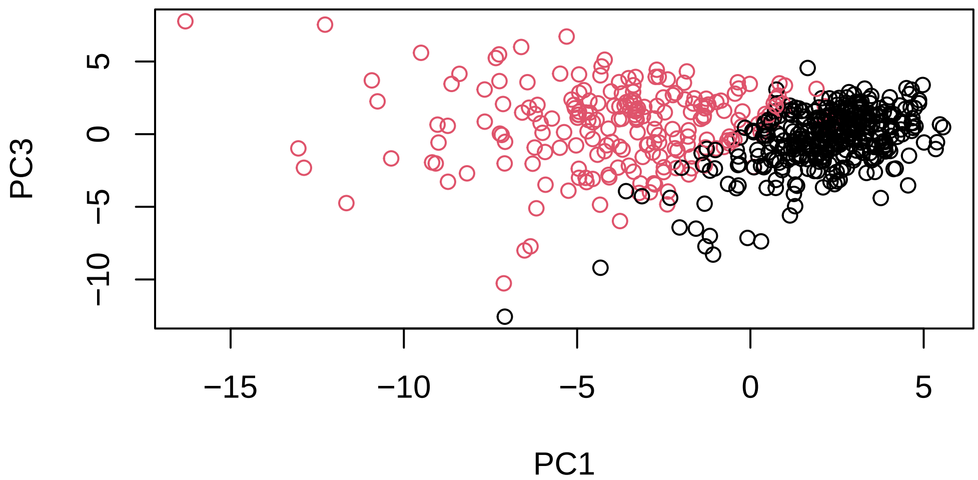
```r
biplot(wisc.pc)
```



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

Because PC2 caputures a greater amount of variance, there seems to be a better seperation of the diagnosis points in the plot. There was a mixture in the sepearation when you plotted PC3 instead of PC2.

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



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?

-0.26085376

```
wisc.pc$rotation[,1]
```

```
            radius_mean            texture_mean          perimeter_mean 
            -0.21890244             -0.10372458             -0.22753729 
              area_mean         smoothness_mean        compactness_mean 
            -0.22099499             -0.14258969             -0.23928535 
         concavity_mean     concave.points_mean           symmetry_mean 
            -0.25840048             -0.26085376             -0.13816696 
 fractal_dimension_mean               radius_se              texture_se 
            -0.06436335             -0.20597878             -0.01742803 
           perimeter_se                 area_se           smoothness_se 
            -0.21132592             -0.20286964             -0.01453145 
         compactness_se            concavity_se       concave.points_se 
            -0.17039345             -0.15358979             -0.18341740 
            symmetry_se    fractal_dimension_se            radius_worst 
            -0.04249842             -0.10256832             -0.22799663 
          texture_worst         perimeter_worst              area_worst 
            -0.10446933             -0.23663968             -0.22487053 
```

```
      smoothness_worst       compactness_worst         concavity_worst 
           -0.12795256             -0.21009588             -0.22876753 
  concave.points_worst          symmetry_worst fractal_dimension_worst 
           -0.25088597             -0.12290456             -0.13178394 
```

> Q10. What is the minimum number of principal components required to explain 80% of the variance of the data?

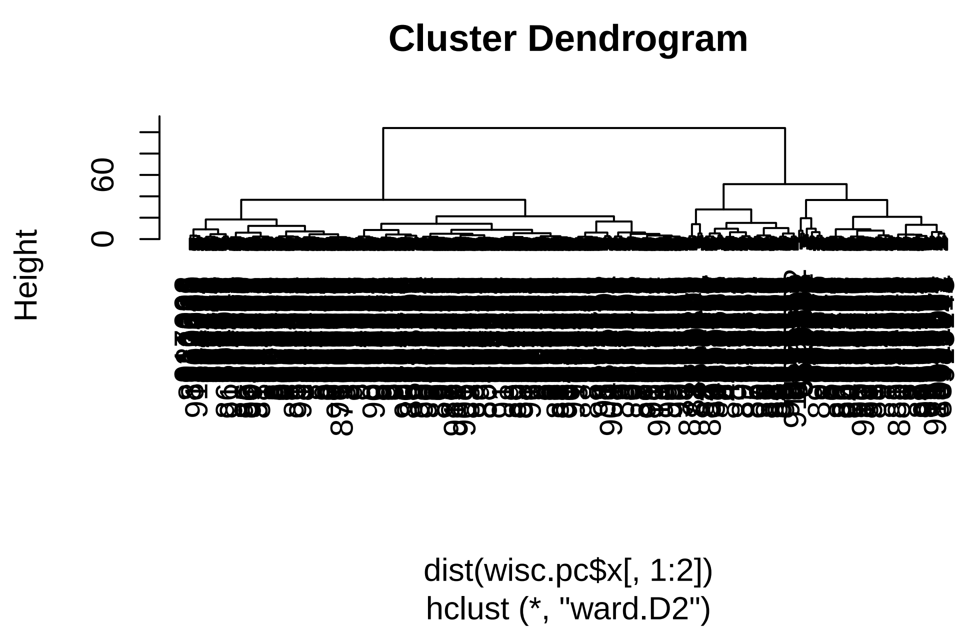
5 PCs required to explain 80% of the variance in the data.

Combining Methods

Using our PCA results, we can use them to help us with other analysis such as clustering.

Clustering on PCA results

```r
wisc.pc.hclust <- hclust(dist(wisc.pc$x[,1:2]),method="ward.D2")
plot(wisc.pc.hclust)
```



To cut our tree:

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

```
pc.grps
  1   2
195 374
```

And then to compare cluster groups to expert diagnosis:

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

```
         pc.grps
diagnosis   1   2
        B  18 339
        M 177  35
```

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

Better separation of the two diagnosis and can show which cases, and how many are "false positives" or "false negatives"

> Q16. 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.

They did really badly initially, but after PCA they were a lot better. The new PCA variables game a better seperation of Malignant vs Benign cases.

Prediction

> Q18. Which of these new patients should we prioritize for follow up based on your results?

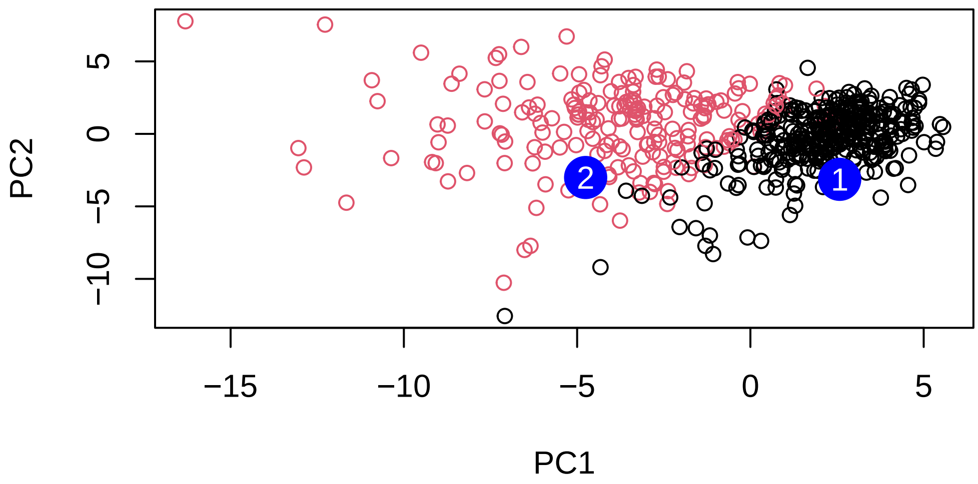
Based on the results below, I would prioritize patient 2 as they are in the malignant cases. They might have malignant cells you would want to check out.

Our PCA model will be used for an analysis of any data that is "unseen". In this cause it is data from UMich.

```r
#url <- "new_samples.csv"
url <- "https://tinyurl.com/new-samples-CSV"
new <- read.csv(url)
npc <- predict(wisc.pc, 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
```

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


PC2
PC1
5
0
−5
−10
−15
−10
−5
0
5
2
1