

# mini\_projects

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## Preparing the data

```
# Save your input data file into your Project directory
fna.data <- "WisconsinCancer.csv"

# Complete the following code to input the data and store as wisc.df
wisc.df <- read.csv(fna.data, 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
```

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

```
# Create diagnosis vector for later
diagnosis <- wisc.df$diagnosis
diagnosis
```

```
##      [1] "M" "M" "M" "M" "M" "M" "M" "M" "M" "M" "M" "M" "M" "M" "M" "M" "M"
##     [19] "M" "B" "B" "B" "M" "M" "M" "M" "M" "M" "M" "M" "M" "M" "M" "M" "M"
##     [37] "M" "B" "M" "M" "M" "M" "M" "M" "M" "M" "B" "M" "B" "B" "B" "B" "M"
##     [55] "M" "B" "M" "M" "B" "B" "B" "B" "M" "B" "M" "M" "B" "B" "B" "B" "M"
##     [73] "M" "M" "B" "M" "B" "M" "M" "B" "B" "B" "M" "M" "B" "M" "M" "M" "B"
##     [91] "B" "M" "B" "B" "M" "M" "B" "B" "B" "M" "M" "B" "B" "B" "B" "M" "B"
##    [109] "M" "B" "B" "B" "B" "B" "B" "B" "B" "M" "M" "M" "B" "M" "M" "B" "B"
##    [127] "M" "M" "B" "M" "B" "M" "M" "B" "M" "M" "B" "B" "M" "B" "B" "M" "B"
##    [145] "B" "B" "M" "B" "B" "B" "B" "B" "B" "B" "B" "B" "M" "B" "B" "B" "M"
##    [163] "M" "B" "M" "B" "B" "M" "M" "B" "B" "M" "M" "B" "B" "B" "B" "M" "B"
##    [181] "M" "M" "M" "B" "M" "B" "M" "B" "B" "B" "M" "B" "B" "M" "M" "B" "M"
##    [199] "M" "M" "B" "M" "M" "M" "B" "M" "B" "M" "B" "B" "M" "B" "M" "M" "M"
##    [217] "B" "B" "M" "M" "B" "B" "B" "M" "B" "B" "B" "B" "B" "M" "M" "B" "M"
##    [235] "B" "B" "M" "M" "B" "M" "B" "B" "B" "B" "M" "B" "B" "B" "B" "B" "M"
##    [253] "M" "M" "M" "M" "M" "M" "M" "M" "M" "M" "M" "M" "M" "M" "B" "B" "B"
##    [271] "B" "B" "M" "B" "M" "B" "B" "M" "B" "B" "M" "B" "M" "M" "B" "B" "B"
##    [289] "B" "B" "B" "B" "B" "B" "B" "B" "B" "M" "B" "B" "M" "B" "M" "B" "B"
##    [307] "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "M" "B" "B" "B" "M" "M"
##    [325] "B" "B" "B" "B" "M" "M" "M" "B" "B" "B" "B" "M" "B" "M" "B" "M" "B"
##    [343] "B" "M" "B" "B" "B" "B" "B" "B" "B" "M" "M" "M" "B" "B" "B" "B" "B"
```

```
## [361] "B" "B" "B" "B" "B" "M" "M" "B" "M" "M" "M" "B" "M" "M" "B" "B" "B" "B"
## [379] "B" "M" "B" "B" "B" "B" "B" "M" "B" "B" "B" "M" "B" "B" "M" "M" "B" "B"
## [397] "B" "B" "B" "B" "M" "B" "B" "B" "B" "B" "B" "B" "M" "B" "B" "B" "B" "B"
## [415] "M" "B" "B" "M" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "M" "B"
## [433] "M" "M" "B" "M" "B" "B" "B" "B" "B" "M" "B" "B" "M" "B" "M" "B" "B" "M"
## [451] "B" "M" "B" "B" "B" "B" "B" "B" "B" "B" "M" "M" "B" "B" "B" "B" "B" "B"
## [469] "M" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "M" "B" "B" "B" "B" "B" "B"
## [487] "B" "M" "B" "M" "B" "B" "M" "B" "B" "B" "B" "B" "M" "M" "B" "M" "B" "M"
## [505] "B" "B" "B" "B" "B" "M" "B" "B" "M" "B" "M" "B" "M" "M" "B" "B" "B" "M"
## [523] "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "M" "B" "M" "M" "B" "B" "B"
## [541] "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B"
## [559] "B" "B" "B" "B" "M" "M" "M" "M" "M" "M" "M" "B"
```

## Exploratory data analysis

Q1. How many observations are in this dataset?

```
dim(wisc.data)
```

```
## [1] 569 30
```

```
nrow(wisc.data)
```

```
## [1] 569
```

```
#there are 569 observations in the data set
```

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

```
#use the table function to count the number of benign and malignant diagnosis
table(diagnosis)
```

```
## diagnosis
##    B    M
## 357 212
```

```
#There are 212 malignant diagnosis
```

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

```
#Check the variables in the data
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"
```

```
#Use grep to create a vector that has a count of the column names with "_mean"
#Use length to count the vector created by grep
length(grep("_mean",colnames(wisc.df)))
```

```
## [1] 10
```

```
#there are 10 variables in the data that are suffixed with "_mean"
```

## Performing PCA

```
# 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
```

```
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 )
wisc.pr
```

```
## Standard deviations (1, ..., p=30):
```

```
## [1] 3.64439401 2.38565601 1.67867477 1.40735229 1.28402903 1.09879780
## [7] 0.82171778 0.69037464 0.64567392 0.59219377 0.54213992 0.51103950
## [13] 0.49128148 0.39624453 0.30681422 0.28260007 0.24371918 0.22938785
## [19] 0.22243559 0.17652026 0.17312681 0.16564843 0.15601550 0.13436892
## [25] 0.12442376 0.09043030 0.08306903 0.03986650 0.02736427 0.01153451
##
```

```
## Rotation (n x k) = (30 x 30):
```

```
##          PC1          PC2          PC3          PC4
## radius_mean          -0.21890244  0.233857132 -0.008531243  0.041408962
## texture_mean          -0.10372458  0.059706088  0.064549903 -0.603050001
## perimeter_mean          -0.22753729  0.215181361 -0.009314220  0.041983099
## area_mean          -0.22099499  0.231076711  0.028699526  0.053433795
## smoothness_mean          -0.14258969 -0.186113023 -0.104291904  0.159382765
## compactness_mean          -0.23928535 -0.151891610 -0.074091571  0.031794581
## concavity_mean          -0.25840048 -0.060165363  0.002733838  0.019122753
## concave.points_mean          -0.26085376  0.034767500 -0.025563541  0.065335944
## symmetry_mean          -0.13816696 -0.190348770 -0.040239936  0.067124984
## fractal_dimension_mean          -0.06436335 -0.366575471 -0.022574090  0.048586765
## radius_se          -0.20597878  0.105552152  0.268481387  0.097941242
## texture_se          -0.01742803 -0.089979682  0.374633665 -0.359855528
## perimeter_se          -0.21132592  0.089457234  0.266645367  0.088992415
## area_se          -0.20286964  0.152292628  0.216006528  0.108205039
## smoothness_se          -0.01453145 -0.204430453  0.308838979  0.044664180
## compactness_se          -0.17039345 -0.232715896  0.154779718 -0.027469363
## concavity_se          -0.15358979 -0.197207283  0.176463743  0.001316880
## concave.points_se          -0.18341740 -0.130321560  0.224657567  0.074067335
## symmetry_se          -0.04249842 -0.183848000  0.288584292  0.044073351
## fractal_dimension_se          -0.10256832 -0.280092027  0.211503764  0.015304750
## radius_worst          -0.22799663  0.219866379 -0.047506990  0.015417240
## texture_worst          -0.10446933  0.045467298 -0.042297823 -0.632807885
## perimeter_worst          -0.23663968  0.199878428 -0.048546508  0.013802794
```

## area_worst	-0.22487053	0.219351858	-0.011902318	0.025894749
## smoothness_worst	-0.12795256	-0.172304352	-0.259797613	0.017652216
## compactness_worst	-0.21009588	-0.143593173	-0.236075625	-0.091328415
## concavity_worst	-0.22876753	-0.097964114	-0.173057335	-0.073951180
## concave.points_worst	-0.25088597	0.008257235	-0.170344076	0.006006996
## symmetry_worst	-0.12290456	-0.141883349	-0.271312642	-0.036250695
## fractal_dimension_worst	-0.13178394	-0.275339469	-0.232791313	-0.077053470
##	PC5	PC6	PC7	PC8
## radius_mean	-0.037786354	0.0187407904	-0.1240883403	0.007452296
## texture_mean	0.049468850	-0.0321788366	0.0113995382	-0.130674825
## perimeter_mean	-0.037374663	0.0173084449	-0.1144770573	0.018687258
## area_mean	-0.010331251	-0.0018877480	-0.0516534275	-0.034673604
## smoothness_mean	0.365088528	-0.2863744966	-0.1406689928	0.288974575
## compactness_mean	-0.011703971	-0.0141309489	0.0309184960	0.151396350
## concavity_mean	-0.086375412	-0.0093441809	-0.1075204434	0.072827285
## concave.points_mean	0.043861025	-0.0520499505	-0.1504822142	0.152322414
## symmetry_mean	0.305941428	0.3564584607	-0.0938911345	0.231530989
## fractal_dimension_mean	0.044424360	-0.1194306679	0.2957600240	0.177121441
## radius_se	0.154456496	-0.0256032561	0.3124900373	-0.022539967
## texture_se	0.191650506	-0.0287473145	-0.0907553556	0.475413139
## perimeter_se	0.120990220	0.0018107150	0.3146403902	0.011896690
## area_se	0.127574432	-0.0428639079	0.3466790028	-0.085805135
## smoothness_se	0.232065676	-0.3429173935	-0.2440240556	-0.573410232
## compactness_se	-0.279968156	0.0691975186	0.0234635340	-0.117460157
## concavity_se	-0.353982091	0.0563432386	-0.2088237897	-0.060566501
## concave.points_se	-0.195548089	-0.0312244482	-0.3696459369	0.108319309
## symmetry_se	0.252868765	0.4902456426	-0.0803822539	-0.220149279
## fractal_dimension_se	-0.263297438	-0.0531952674	0.1913949726	-0.011168188
## radius_worst	0.004406592	-0.0002906849	-0.0097099360	-0.042619416
## texture_worst	0.092883400	-0.0500080613	0.0098707439	-0.036251636
## perimeter_worst	-0.007454151	0.0085009872	-0.0004457267	-0.030558534
## area_worst	0.027390903	-0.0251643821	0.0678316595	-0.079394246
## smoothness_worst	0.324435445	-0.3692553703	-0.1088308865	-0.205852191
## compactness_worst	-0.121804107	0.0477057929	0.1404729381	-0.084019659
## concavity_worst	-0.188518727	0.0283792555	-0.0604880561	-0.072467871
## concave.points_worst	-0.043332069	-0.0308734498	-0.1679666187	0.036170795
## symmetry_worst	0.244558663	0.4989267845	-0.0184906298	-0.228225053
## fractal_dimension_worst	-0.094423351	-0.0802235245	0.3746576261	-0.048360667
##	PC9	PC10	PC11	PC12
## radius_mean	-0.223109764	0.095486443	-0.04147149	0.051067457
## texture_mean	0.112699390	0.240934066	0.30224340	0.254896423
## perimeter_mean	-0.223739213	0.086385615	-0.01678264	0.038926106
## area_mean	-0.195586014	0.074956489	-0.11016964	0.065437508
## smoothness_mean	0.006424722	-0.069292681	0.13702184	0.316727211
## compactness_mean	-0.167841425	0.012936200	0.30800963	-0.104017044
## concavity_mean	0.040591006	-0.135602298	-0.12419024	0.065653480
## concave.points_mean	-0.111971106	0.008054528	0.07244603	0.042589267
## symmetry_mean	0.256040084	0.572069479	-0.16305408	-0.288865504
## fractal_dimension_mean	-0.123740789	0.081103207	0.03804827	0.236358988
## radius_se	0.249985002	-0.049547594	0.02535702	-0.016687915
## texture_se	-0.246645397	-0.289142742	-0.34494446	-0.306160423
## perimeter_se	0.227154024	-0.114508236	0.16731877	-0.101446828
## area_se	0.229160015	-0.091927889	-0.05161946	-0.017679218
## smoothness_se	-0.141924890	0.160884609	-0.08420621	-0.294710053

## compactness_se	-0.145322810	0.043504866	0.20688568	-0.263456509
## concavity_se	0.358107079	-0.141276243	-0.34951794	0.251146975
## concave.points_se	0.272519886	0.086240847	0.34237591	-0.006458751
## symmetry_se	-0.304077200	-0.316529830	0.18784404	0.320571348
## fractal_dimension_se	-0.213722716	0.367541918	-0.25062479	0.276165974
## radius_worst	-0.112141463	0.077361643	-0.10506733	0.039679665
## texture_worst	0.103341204	0.029550941	-0.01315727	0.079797450
## perimeter_worst	-0.109614364	0.050508334	-0.05107628	-0.008987738
## area_worst	-0.080732461	0.069921152	-0.18459894	0.048088657
## smoothness_worst	0.112315904	-0.128304659	-0.14389035	0.056514866
## compactness_worst	-0.100677822	-0.172133632	0.19742047	-0.371662503
## concavity_worst	0.161908621	-0.311638520	-0.18501676	-0.087034532
## concave.points_worst	0.060488462	-0.076648291	0.11777205	-0.068125354
## symmetry_worst	0.064637806	-0.029563075	-0.15756025	0.044033503
## fractal_dimension_worst	-0.134174175	0.012609579	-0.11828355	-0.034731693
##	PC13	PC14	PC15	PC16
## radius_mean	0.01196721	0.059506135	-0.051118775	-0.15058388
## texture_mean	0.20346133	-0.021560100	-0.107922421	-0.15784196
## perimeter_mean	0.04410950	0.048513812	-0.039902936	-0.11445396
## area_mean	0.06737574	0.010830829	0.013966907	-0.13244803
## smoothness_mean	0.04557360	0.445064860	-0.118143364	-0.20461325
## compactness_mean	0.22928130	0.008101057	0.230899962	0.17017837
## concavity_mean	0.38709081	-0.189358699	-0.128283732	0.26947021
## concave.points_mean	0.13213810	-0.244794768	-0.217099194	0.38046410
## symmetry_mean	0.18993367	0.030738856	-0.073961707	-0.16466159
## fractal_dimension_mean	0.10623908	-0.377078865	0.517975705	-0.04079279
## radius_se	-0.06819523	0.010347413	-0.110050711	0.05890572
## texture_se	-0.16822238	-0.010849347	0.032752721	-0.03450040
## perimeter_se	-0.03784399	-0.045523718	-0.008268089	0.02651665
## area_se	0.05606493	0.083570718	-0.046024366	0.04115323
## smoothness_se	0.15044143	-0.201152530	0.018559465	-0.05803906
## compactness_se	0.01004017	0.491755932	0.168209315	0.18983090
## concavity_se	0.15878319	0.134586924	0.250471408	-0.12542065
## concave.points_se	-0.49402674	-0.199666719	0.062079344	-0.19881035
## symmetry_se	0.01033274	-0.046864383	-0.113383199	-0.15771150
## fractal_dimension_se	-0.24045832	0.145652466	-0.353232211	0.26855388
## radius_worst	-0.13789053	0.023101281	0.166567074	-0.08156057
## texture_worst	-0.08014543	0.053430792	0.101115399	0.18555785
## perimeter_worst	-0.09696571	0.012219382	0.182755198	-0.05485705
## area_worst	-0.10116061	-0.006685465	0.314993600	-0.09065339
## smoothness_worst	-0.20513034	0.162235443	0.046125866	0.14555166
## compactness_worst	0.01227931	0.166470250	-0.049956014	-0.15373486
## concavity_worst	0.21798433	-0.066798931	-0.204835886	-0.21502195
## concave.points_worst	-0.25438749	-0.276418891	-0.169499607	0.17814174
## symmetry_worst	-0.25653491	0.005355574	0.139888394	0.25789401
## fractal_dimension_worst	-0.17281424	-0.212104110	-0.256173195	-0.40555649
##	PC17	PC18	PC19	PC20
## radius_mean	0.202924255	0.1467123385	0.22538466	-0.049698664
## texture_mean	-0.038706119	-0.0411029851	0.02978864	-0.244134993
## perimeter_mean	0.194821310	0.1583174548	0.23959528	-0.017665012
## area_mean	0.255705763	0.2661681046	-0.02732219	-0.090143762
## smoothness_mean	0.167929914	-0.3522268017	-0.16456584	0.017100960
## compactness_mean	-0.020307708	0.0077941384	0.28422236	0.488686329
## concavity_mean	-0.001598353	-0.0269681105	0.00226636	-0.033387086

## concave.points_mean	0.034509509	-0.0828277367	-0.15497236	-0.235407606
## symmetry_mean	-0.191737848	0.1733977905	-0.05881116	0.026069156
## fractal_dimension_mean	0.050225246	0.0878673570	-0.05815705	-0.175637222
## radius_se	-0.139396866	-0.2362165319	0.17588331	-0.090800503
## texture_se	0.043963016	-0.0098586620	0.03600985	-0.071659988
## perimeter_se	-0.024635639	-0.0259288003	0.36570154	-0.177250625
## area_se	0.334418173	0.3049069032	-0.41657231	0.274201148
## smoothness_se	0.139595006	-0.2312599432	-0.01326009	0.090061477
## compactness_se	-0.008246477	0.1004742346	-0.24244818	-0.461098220
## concavity_se	0.084616716	-0.0001954852	0.12638102	0.066946174
## concave.points_se	0.108132263	0.0460549116	-0.01216430	0.068868294
## symmetry_se	-0.274059129	0.1870147640	-0.08903929	0.107385289
## fractal_dimension_se	-0.122733398	-0.0598230982	0.08660084	0.222345297
## radius_worst	-0.240049982	-0.2161013526	0.01366130	-0.005626909
## texture_worst	0.069365185	0.0583984505	-0.07586693	0.300599798
## perimeter_worst	-0.234164147	-0.1885435919	0.09081325	0.011003858
## area_worst	-0.273399584	-0.1420648558	-0.41004720	0.060047387
## smoothness_worst	-0.278030197	0.5015516751	0.23451384	-0.129723903
## compactness_worst	-0.004037123	-0.0735745143	0.02020070	0.229280589
## concavity_worst	-0.191313419	-0.1039079796	-0.04578612	-0.046482792
## concave.points_worst	-0.075485316	0.0758138963	-0.26022962	0.033022340
## symmetry_worst	0.430658116	-0.2787138431	0.11725053	-0.116759236
## fractal_dimension_worst	0.159394300	0.0235647497	-0.01149448	-0.104991974
##	PC21	PC22	PC23	PC24
## radius_mean	-0.0685700057	-0.07292890	-0.0985526942	-0.18257944
## texture_mean	0.4483694667	-0.09480063	-0.0005549975	0.09878679
## perimeter_mean	-0.0697690429	-0.07516048	-0.0402447050	-0.11664888
## area_mean	-0.0184432785	-0.09756578	0.0077772734	0.06984834
## smoothness_mean	-0.1194917473	-0.06382295	-0.0206657211	0.06869742
## compactness_mean	0.1926213963	0.09807756	0.0523603957	-0.10413552
## concavity_mean	0.0055717533	0.18521200	0.3248703785	0.04474106
## concave.points_mean	-0.0094238187	0.31185243	-0.0514087968	0.08402770
## symmetry_mean	-0.0869384844	0.01840673	-0.0512005770	0.01933947
## fractal_dimension_mean	-0.0762718362	-0.28786888	-0.0846898562	-0.13326055
## radius_se	0.0863867747	0.15027468	-0.2641253170	-0.55870157
## texture_se	0.2170719674	-0.04845693	-0.0008738805	0.02426730
## perimeter_se	-0.3049501584	-0.15935280	0.0900742110	0.51675039
## area_se	0.1925877857	-0.06423262	0.0982150746	-0.02246072
## smoothness_se	-0.0720987261	-0.05054490	-0.0598177179	0.01563119
## compactness_se	-0.1403865724	0.04528769	0.0091038710	-0.12177779
## concavity_se	0.0630479298	0.20521269	-0.3875423290	0.18820504
## concave.points_se	0.0343753236	0.07254538	0.3517550738	-0.10966898
## symmetry_se	-0.0976995265	0.08465443	-0.0423628949	0.00322620
## fractal_dimension_se	0.0628432814	-0.24470508	0.0857810992	0.07519442
## radius_worst	0.0072938995	0.09629821	-0.0556767923	-0.15683037
## texture_worst	-0.5944401434	0.11111202	-0.0089228997	-0.11848460
## perimeter_worst	-0.0920235990	-0.01722163	0.0633448296	0.23711317
## area_worst	0.1467901315	0.09695982	0.1908896250	0.14406303
## smoothness_worst	0.1648492374	0.06825409	0.0936901494	-0.01099014
## compactness_worst	0.1813748671	-0.02967641	-0.1479209247	0.18674995
## concavity_worst	-0.1321005945	-0.46042619	0.2864331353	-0.28885257
## concave.points_worst	0.0008860815	-0.29984056	-0.5675277966	0.10734024
## symmetry_worst	0.1627085487	-0.09714484	0.1213434508	-0.01438181
## fractal_dimension_worst	-0.0923439434	0.46947115	0.0076253382	0.03782545



##	PC25	PC26	PC27	PC28
## radius_mean	-0.01922650	-0.129476396	-0.131526670	2.111940e-01
## texture_mean	0.08474593	-0.024556664	-0.017357309	-6.581146e-05
## perimeter_mean	0.02701541	-0.125255946	-0.115415423	8.433827e-02
## area_mean	-0.21004078	0.362727403	0.466612477	-2.725083e-01
## smoothness_mean	0.02895489	-0.037003686	0.069689923	1.479269e-03
## compactness_mean	0.39662323	0.262808474	0.097748705	-5.462767e-03
## concavity_mean	-0.09697732	-0.548876170	0.364808397	4.553864e-02
## concave.points_mean	-0.18645160	0.387643377	-0.454699351	-8.883097e-03
## symmetry_mean	-0.02458369	-0.016044038	-0.015164835	1.433026e-03
## fractal_dimension_mean	-0.20722186	-0.097404839	-0.101244946	-6.311687e-03
## radius_se	-0.17493043	0.049977080	0.212982901	-1.922239e-01
## texture_se	0.05698648	-0.011237242	-0.010092889	-5.622611e-03
## perimeter_se	0.07292764	0.103653282	0.041691553	2.631919e-01
## area_se	0.13185041	-0.155304589	-0.313358657	-4.206811e-02
## smoothness_se	0.03121070	-0.007717557	-0.009052154	9.792963e-03
## compactness_se	0.17316455	-0.049727632	0.046536088	-1.539555e-02
## concavity_se	0.01593998	0.091454968	-0.084224797	5.820978e-03
## concave.points_se	-0.12954655	-0.017941919	-0.011165509	-2.900930e-02
## symmetry_se	-0.01951493	-0.017267849	-0.019975983	-7.636526e-03
## fractal_dimension_se	-0.08417120	0.035488974	-0.012036564	1.975646e-02
## radius_worst	0.07070972	-0.197054744	-0.178666740	4.126396e-01
## texture_worst	-0.11818972	0.036469433	0.021410694	-3.902509e-04
## perimeter_worst	0.11803403	-0.244103670	-0.241031046	-7.286809e-01
## area_worst	-0.03828995	0.231359525	0.237162466	2.389603e-01
## smoothness_worst	-0.04796476	0.012602464	-0.040853568	-1.535248e-03
## compactness_worst	-0.62438494	-0.100463424	-0.070505414	4.869182e-02
## concavity_worst	0.11577034	0.266853781	-0.142905801	-1.764090e-02
## concave.points_worst	0.26319634	-0.133574507	0.230901389	2.247567e-02
## symmetry_worst	0.04529962	0.028184296	0.022790444	4.920481e-03
## fractal_dimension_worst	0.28013348	0.004520482	0.059985998	-2.356214e-02
##	PC29	PC30		
## radius_mean	2.114605e-01	0.7024140910		
## texture_mean	-1.053393e-02	0.0002736610		
## perimeter_mean	3.838261e-01	-0.6898969685		
## area_mean	-4.227949e-01	-0.0329473482		
## smoothness_mean	-3.434667e-03	-0.0048474577		
## compactness_mean	-4.101677e-02	0.0446741863		
## concavity_mean	-1.001479e-02	0.0251386661		
## concave.points_mean	-4.206949e-03	-0.0010772653		
## symmetry_mean	-7.569862e-03	-0.0012803794		
## fractal_dimension_mean	7.301433e-03	-0.0047556848		
## radius_se	1.184421e-01	-0.0087110937		
## texture_se	-8.776279e-03	-0.0010710392		
## perimeter_se	-6.100219e-03	0.0137293906		
## area_se	-8.592591e-02	0.0011053260		
## smoothness_se	1.776386e-03	-0.0016082109		
## compactness_se	3.158134e-03	0.0019156224		
## concavity_se	1.607852e-02	-0.0089265265		
## concave.points_se	-2.393779e-02	-0.0021601973		
## symmetry_se	-5.223292e-03	0.0003293898		
## fractal_dimension_se	-8.341912e-03	0.0017989568		
## radius_worst	-6.357249e-01	-0.1356430561		
## texture_worst	1.723549e-02	0.0010205360		

```
## perimeter_worst      2.292180e-02  0.0797438536
## area_worst           4.449359e-01  0.0397422838
## smoothness_worst     7.385492e-03  0.0045832773
## compactness_worst    3.566904e-06 -0.0128415624
## concavity_worst      -1.267572e-02  0.0004021392
## concave.points_worst  3.524045e-02 -0.0022884418
## symmetry_worst       1.340423e-02  0.0003954435
## fractal_dimension_worst 1.147766e-02  0.0018942925
```

```
# Look at summary of results
summary(wisc.pr)
```

```
## Importance of components:
##              PC1      PC2      PC3      PC4      PC5      PC6      PC7
## Standard deviation  3.6444  2.3857  1.67867  1.40735  1.28403  1.09880  0.82172
## Proportion of Variance 0.4427  0.1897  0.09393  0.06602  0.05496  0.04025  0.02251
## Cumulative Proportion 0.4427  0.6324  0.72636  0.79239  0.84734  0.88759  0.91010
##              PC8      PC9      PC10     PC11     PC12     PC13     PC14
## Standard deviation  0.69037  0.6457  0.59219  0.5421  0.51104  0.49128  0.39624
## Proportion of Variance 0.01589  0.0139  0.01169  0.0098  0.00871  0.00805  0.00523
## Cumulative Proportion 0.92598  0.9399  0.95157  0.9614  0.97007  0.97812  0.98335
##              PC15     PC16     PC17     PC18     PC19     PC20     PC21
## Standard deviation  0.30681  0.28260  0.24372  0.22939  0.22244  0.17652  0.1731
## Proportion of Variance 0.00314  0.00266  0.00198  0.00175  0.00165  0.00104  0.0010
## Cumulative Proportion 0.98649  0.98915  0.99113  0.99288  0.99453  0.99557  0.9966
##              PC22     PC23     PC24     PC25     PC26     PC27     PC28
## Standard deviation  0.16565  0.15602  0.1344  0.12442  0.09043  0.08307  0.03987
## Proportion of Variance 0.00091  0.00081  0.0006  0.00052  0.00027  0.00023  0.00005
## Cumulative Proportion 0.99749  0.99830  0.9989  0.99942  0.99969  0.99992  0.99997
##              PC29     PC30
## Standard deviation  0.02736  0.01153
## Proportion of Variance 0.00002  0.00000
## Cumulative Proportion 1.00000  1.00000
```

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

- 0.4427 of the original variance is captured by the first principal components (PC1)

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

- 3 components describe at least 70% of the original variance in the data

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

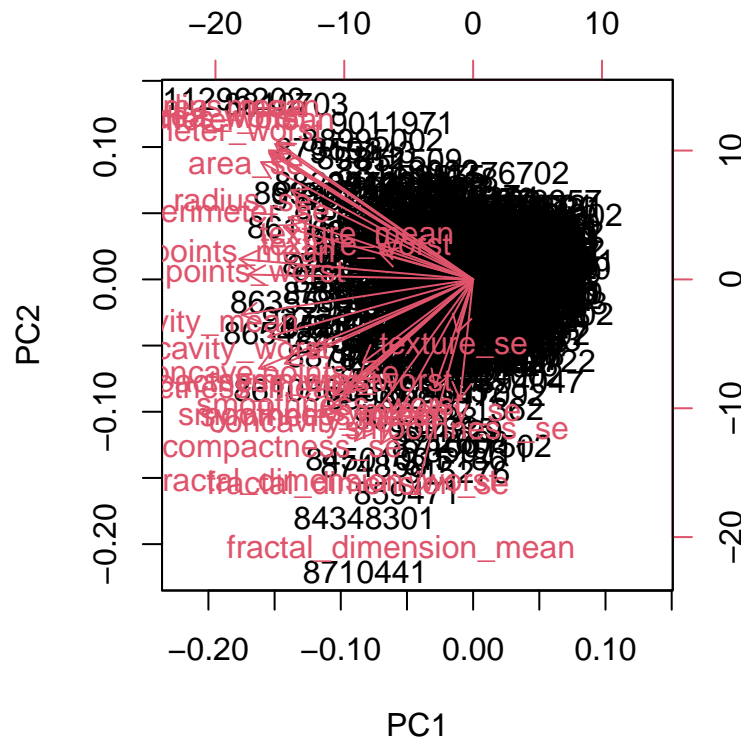
- 7 components describe at least 90% of the original variance in the data

## Interpreting PCA results

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

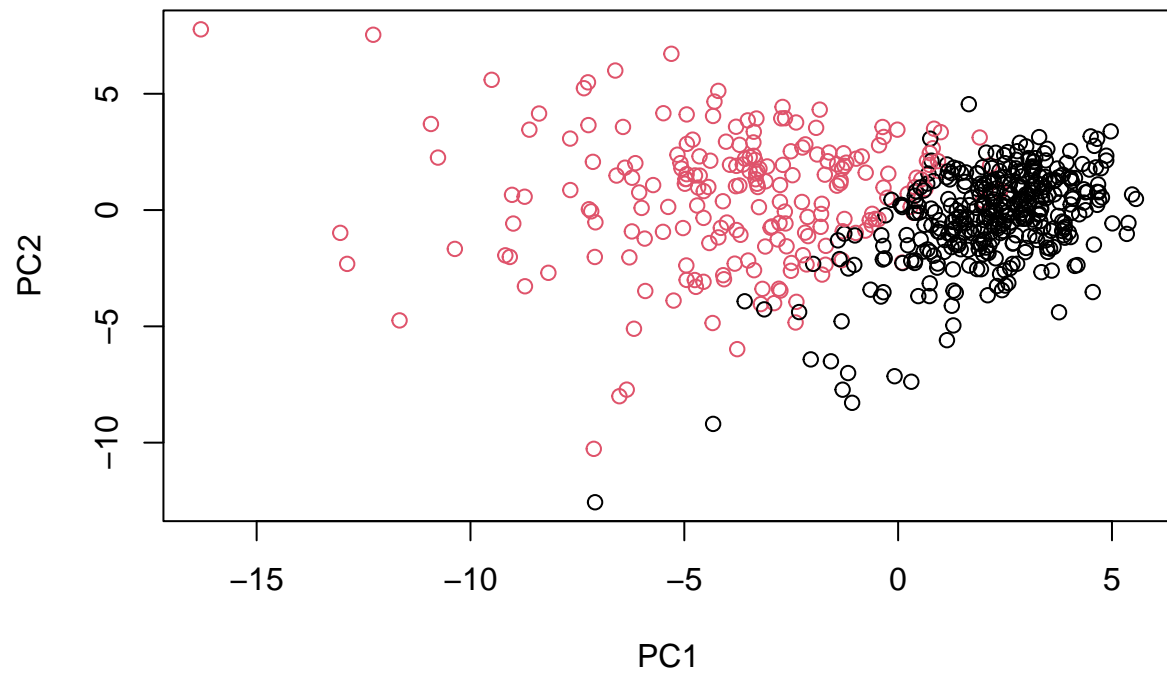
- This plot is messy and difficult to interpret because it uses rownames as the plotting character for biplots

```
#Create a biplot of the wisc.pr using the biplot() function
biplot(wisc.pr)
```



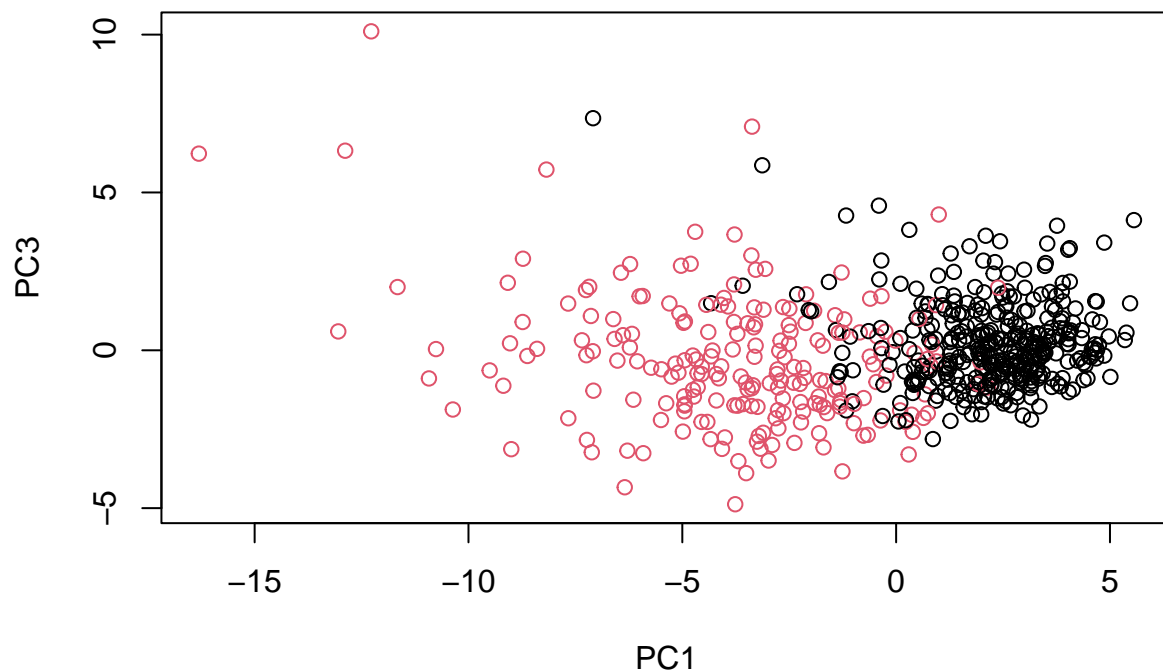
```
#Scatter plot observations by components 1 and 2
#we need to access the pca scores data using wisc.pr$x
#pc1 and pc2 are in [,1:2]
#use as.factor to make diagnosis a binary to differentiate colors

plot(wisc.pr$x[,1:2], col=as.factor(diagnosis), xlab = "PC1", ylab = "PC2")
```



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

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



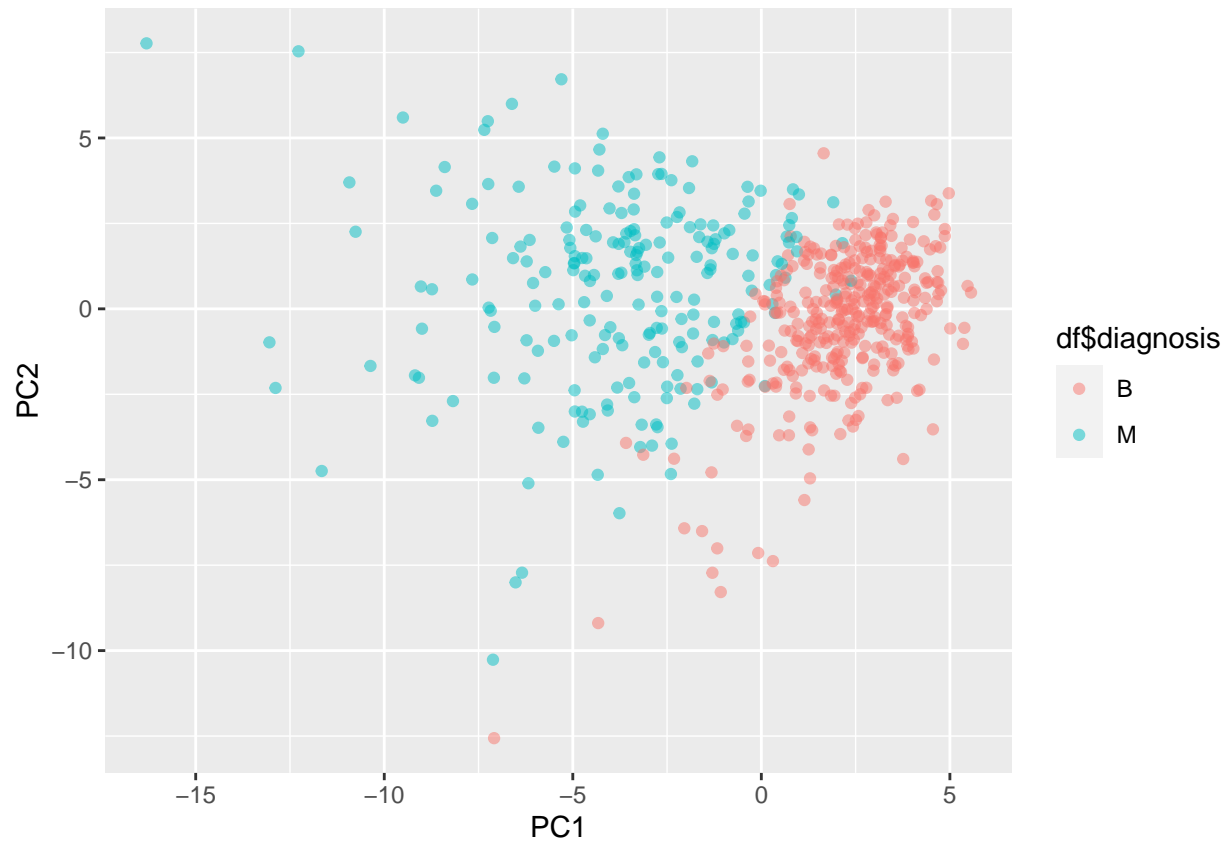
- the component 2 explains more variance in the original data than component 3. The first plot has a cleaner separation between the two subgroups.

```
# 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, color=df$diagnosis) +
  geom_point(alpha=0.5)
```

```
## Warning: Use of 'df$diagnosis' is discouraged. Use 'diagnosis' instead.
```



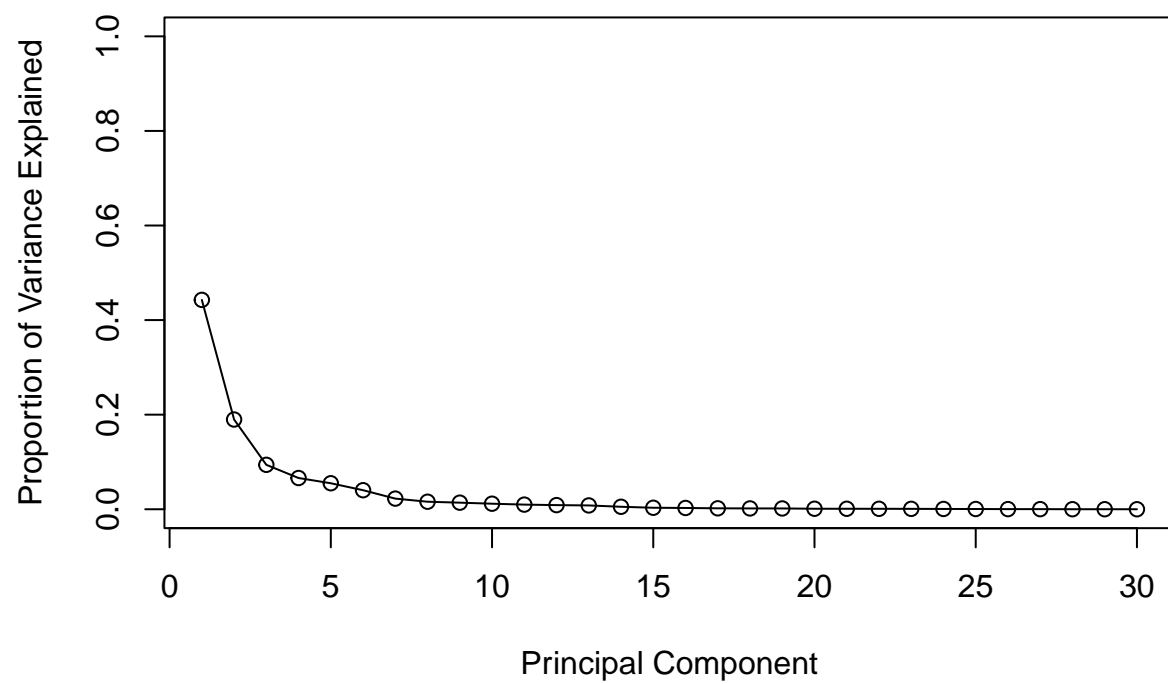
## Variance explained

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

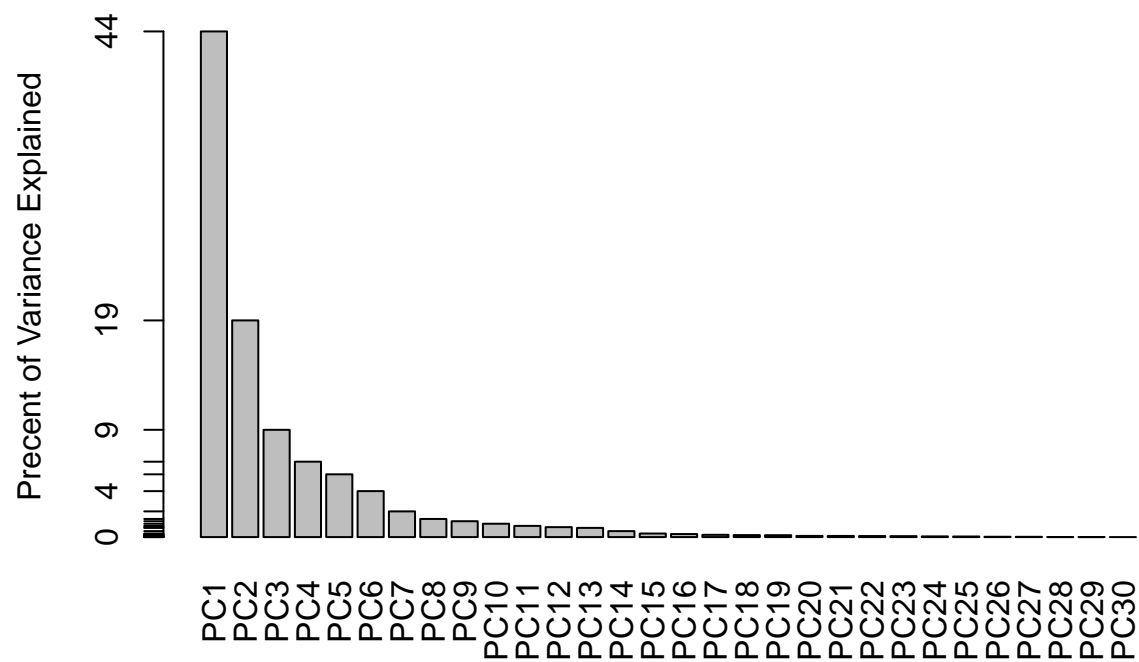
```
## [1] 13.281608  5.691355  2.817949  1.980640  1.648731  1.207357
```

```
# 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")
```



```
# 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 )
```

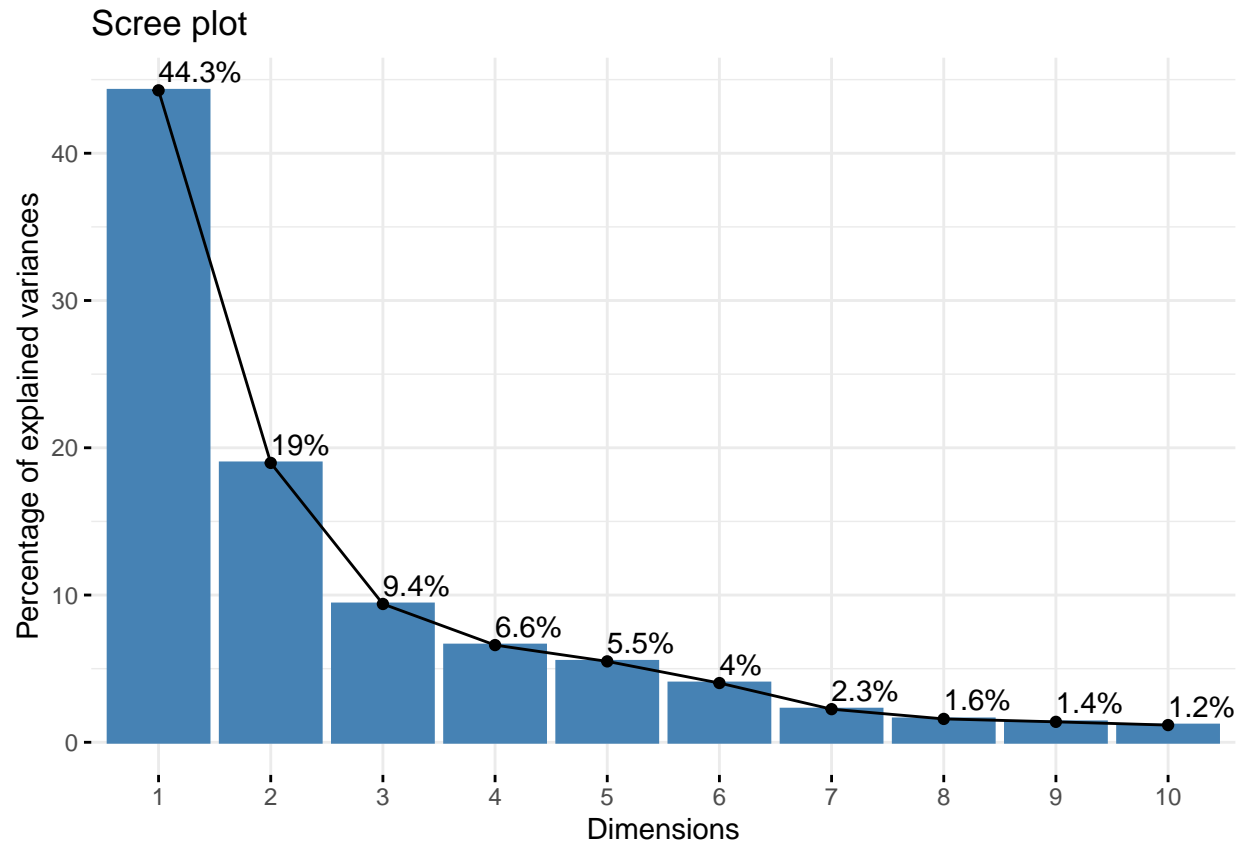


```
## ggplot based graph
#install.packages("factoextra")
library(factoextra)
```

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

```
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["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?

-5 principles

```
wisc.pr$center
```

```
##          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
```

```
##Hierarchical clustering
```

```
# Scale the wisc.data data using the "scale()" function
data.scaled <- scale(wisc.data)
```

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

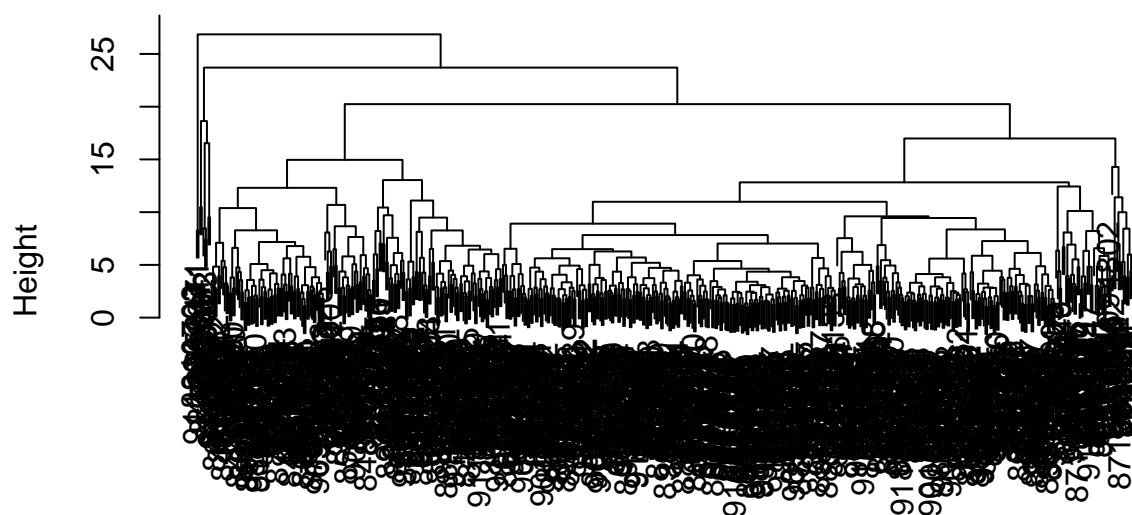
```
wisc.hclust <- hclust(data.dist, method="complete", members=NULL)
```

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

-height at 19

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

## Cluster Dendrogram



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

```
#library(rgl)
#plot3d(wisc.pr$x[,1:3], xlab="PC 1", ylab="PC 2", zlab="PC 3", cex=1.5, size=1, type="s", col=grps)
```

## Selecting number of clusters

```
#Use cutree() to cut the tree so that it has 4 clusters. Assign the output to the variable wisc.hclust.
wisc.hclust.clusters <- cutree(wisc.hclust, k=4)
```

```
#We can use the table() function to compare the cluster membership to the actual diagnoses.
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?

```
#cluster 2
wisc.hclust.clusters1 <- cutree(wisc.hclust, k=2)
table(wisc.hclust.clusters1, diagnosis)
```

```
##              diagnosis
## wisc.hclust.clusters1  B  M
##              1 357 210
##              2   0   2
```

```
#cluster 10
wisc.hclust.clusters2 <- cutree(wisc.hclust, k=10)
table(wisc.hclust.clusters2, diagnosis)
```

```
##              diagnosis
## wisc.hclust.clusters2  B  M
##              1  12 86
##              2   0 59
##              3   0  3
##              4 331 39
##              5   0 20
##              6   2  0
##              7  12  0
##              8   0  2
##              9   0  2
##             10   0  1
```

```
(357+164)/nrow(wisc.data)
```

```
## [1] 0.9156415
```

```
(201+6)/nrow(wisc.data)
```

```
## [1] 0.3637961
```

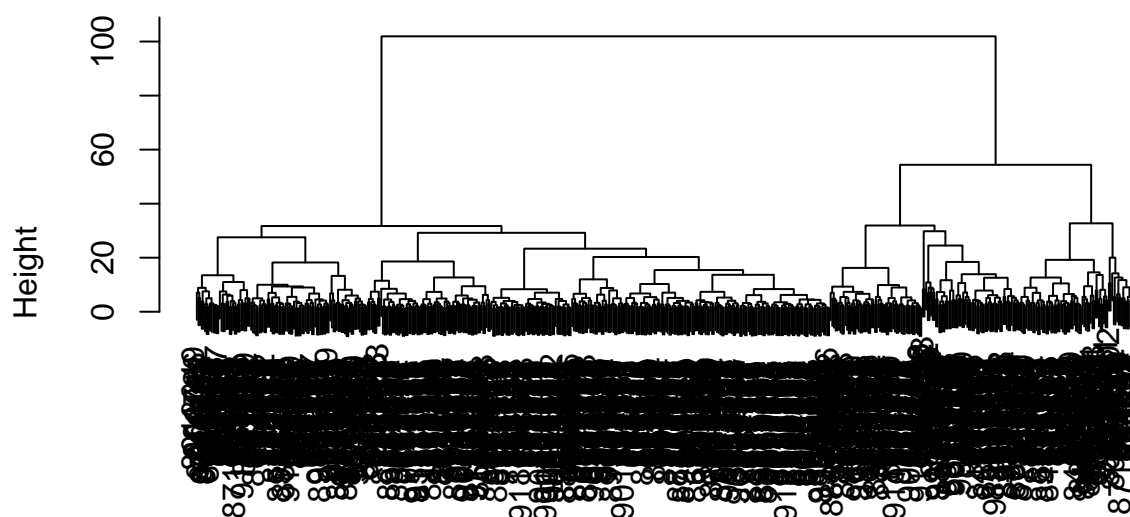
## Using different methods

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

- I like ward.D2 because it creates groups such that variance is minimized within clusters. It doesn't require squaring the Euclidean distances `dist()` are squared before inputting them to the `hclust()`

```
wisc.hclustx <- hclust(data.dist, method="ward.D2", members=NULL)
plot(wisc.hclustx)
```

## Cluster Dendrogram



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

## Combining methods

We take the results of our pca analysis and cluster in this space `wisc.pr$x`

```
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
```

```
wisc.pr$x[5,3]
```

```
## [1] 1.388545
```

```
hclust(dist(wisc.pr$x[,1:3]))
```

```
##
## Call:
## hclust(d = dist(wisc.pr$x[, 1:3]))
##
## Cluster method   : complete
## Distance         : euclidean
## Number of objects: 569
```

```
#Use the distance along the first 7 PCs for clustering
wisc.pr.hclust <- hclust(data.dist, method="ward.D2", members=NULL)
```

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

crops table compare of diagnosis and my cluster groups

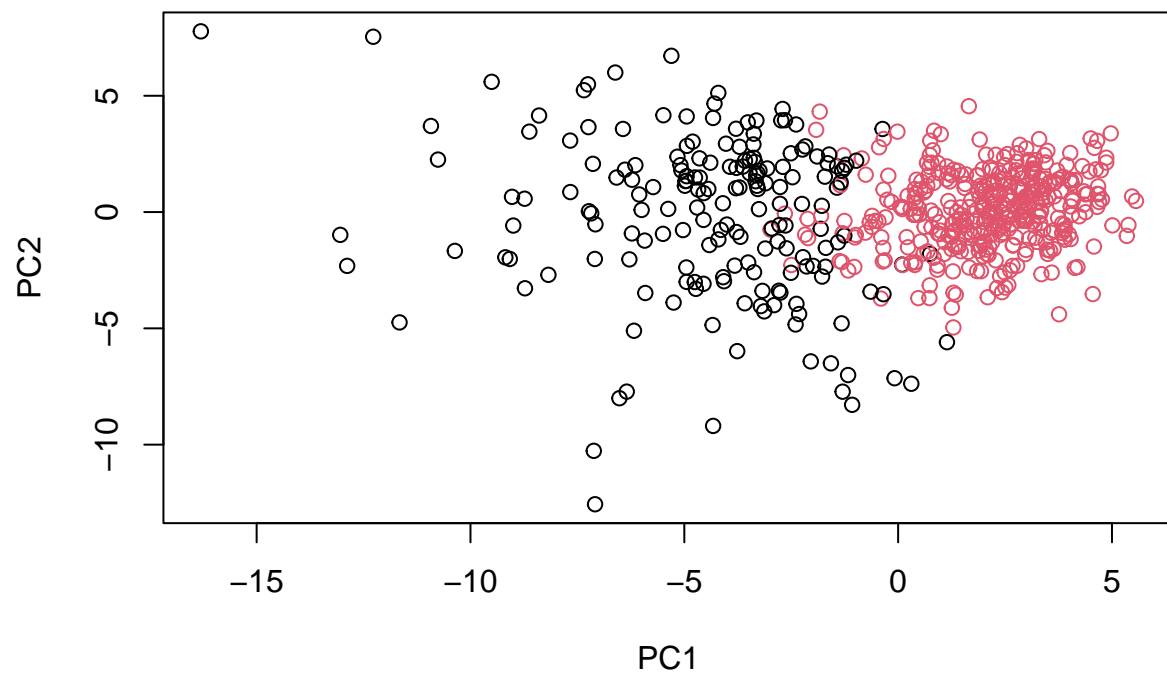
```
grps <- cutree(wisc.pr.hclust, k=2)
table(grps)
```

```
## grps
##   1   2
## 184 385
```

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

```
##           grps
## diagnosis  1   2
##           B  20 337
##           M 164  48
```

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



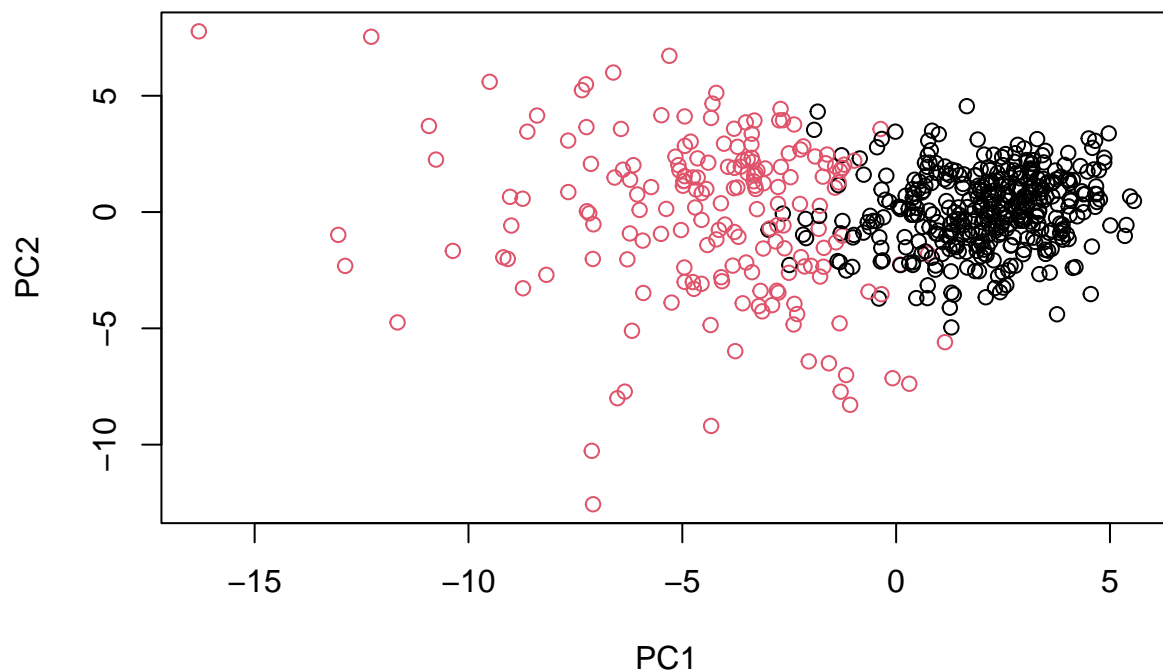
```
g <- as.factor(grps)
levels(g)
```

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

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

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

```
# Plot using our re-ordered factor
plot(wisc.pr$x[,1:2], col=g)
```



```
#install.packages("rgl")
library(rgl)
plot3d(wisc.pr$x[,1:3], xlab="PC 1", ylab="PC 2", zlab="PC 3", cex=1.5, size=1, type="s", col=grps)
```

## Sensitivity/ Specificity

```
#Use the distance along the first 7 PCs for clustering
wisc.pr.hclust <- hclust(data.dist, method="ward.D2", members=NULL)
```

```
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?

-the new model has 90.86% accuracy

```
# Compare to actual diagnoses
table(wisc.pr.hclust.clusters, diagnosis)
```

```
##              diagnosis
## wisc.pr.hclust.clusters  B  M
##              1  20 164
##              2 337  48
```



Q16. How well do the k-means and 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.

-using `wisc.km$cluster` K-means clustering works the best in separating diagnosis

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

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

**Accuracy** what proportion did we get correct if we call cluster 1 M and cluster 2B

```
(329+188)/nrow(wisc.data)
```

```
## [1] 0.9086116
```

```
(175+343)/nrow(wisc.data)
```

```
## [1] 0.9103691
```

```
(165+343)/nrow(wisc.data)
```

```
## [1] 0.8927944
```

**Sensitivity**

```
(188)/(188+28)
```

```
## [1] 0.8703704
```

```
(175)/(175+14)
```

```
## [1] 0.9259259
```

```
(165)/(165+12)
```

```
## [1] 0.9322034
```

**Specificity**

```
329/(329+24)
```

```
## [1] 0.9320113
```

```
343/(343+37)
```

```
## [1] 0.9026316
```

```
343/(343+40)
```

```
## [1] 0.8955614
```

Q17. Which of your analysis procedures resulted in a clustering model with the best specificity?  
How about sensitivity?

-specificity: wisc.pr.hclust.clusters -sensitivity: wisc.hclust.clusters

## Prediction

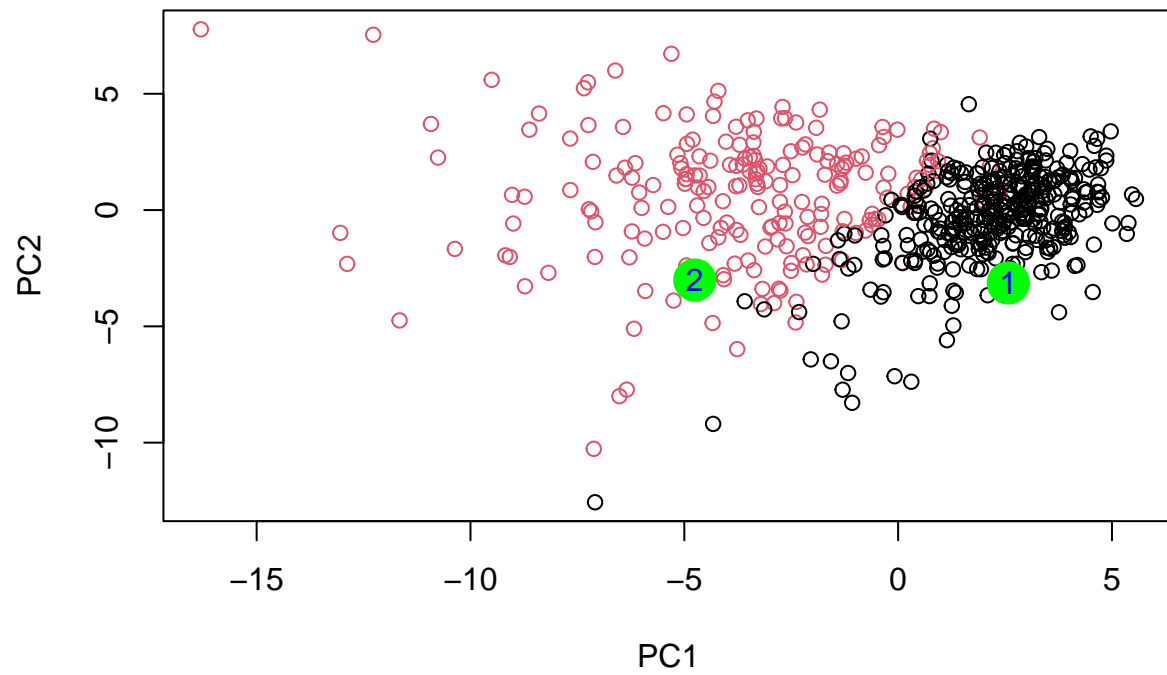
Here we read some new data and use PCA model to examine whether they most closely resemble M or B patients from our original dataset

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

Plot onto our PCA model

```
plot(wisc.pr$x[,1:2], col=as.factor(diagnosis))
points(npc[,1],npc[,2], col="green", pch=16, cex=3)
text(npc[,1],npc[,2], labels = c(1,2), col="blue")
```



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

-patient 2 id more malignant