Class 8: PCA Mini project

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For example:

```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 
```

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

```
                            mpg        cyl        disp          hp        drat
Mazda RX4            0.15088482 -0.1049878 -0.57061982 -0.53509284  0.56751369
Mazda RX4 Wag        0.15088482 -0.1049878 -0.57061982 -0.53509284  0.56751369
Datsun 710           0.44954345 -1.2248578 -0.99018209 -0.78304046  0.47399959
Hornet 4 Drive       0.21725341 -0.1049878  0.22009369 -0.53509284 -0.96611753
Hornet Sportabout   -0.23073453  1.0148821  1.04308123  0.41294217 -0.83519779
Valiant             -0.33028740 -0.1049878 -0.04616698 -0.60801861 -1.56460776
Duster 360          -0.96078893  1.0148821  1.04308123  1.43390296 -0.72298087
Merc 240D            0.71501778 -1.2248578 -0.67793094 -1.23518023  0.17475447
```

Merc 230	0.44954345	-1.2248578	-0.72553512	-0.75387015	0.60491932
Merc 280	-0.14777380	-0.1049878	-0.50929918	-0.34548584	0.60491932
Merc 280C	-0.38006384	-0.1049878	-0.50929918	-0.34548584	0.60491932
Merc 450SE	-0.61235388	1.0148821	0.36371309	0.48586794	-0.98482035
Merc 450SL	-0.46302456	1.0148821	0.36371309	0.48586794	-0.98482035
Merc 450SLC	-0.81145962	1.0148821	0.36371309	0.48586794	-0.98482035
Cadillac Fleetwood	-1.60788262	1.0148821	1.94675381	0.85049680	-1.24665983
Lincoln Continental	-1.60788262	1.0148821	1.84993175	0.99634834	-1.11574009
Chrysler Imperial	-0.89442035	1.0148821	1.68856165	1.21512565	-0.68557523
Fiat 128	2.04238943	-1.2248578	-1.22658929	-1.17683962	0.90416444
Honda Civic	1.71054652	-1.2248578	-1.25079481	-1.38103178	2.49390411
Toyota Corolla	2.29127162	-1.2248578	-1.28790993	-1.19142477	1.16600392
Toyota Corona	0.23384555	-1.2248578	-0.89255318	-0.72469984	0.19345729
Dodge Challenger	-0.76168319	1.0148821	0.70420401	0.04831332	-1.56460776
AMC Javelin	-0.81145962	1.0148821	0.59124494	0.04831332	-0.83519779
Camaro Z28	-1.12671039	1.0148821	0.96239618	1.43390296	0.24956575
Pontiac Firebird	-0.14777380	1.0148821	1.36582144	0.41294217	-0.96611753
Fiat X1-9	1.19619000	-1.2248578	-1.22416874	-1.17683962	0.90416444
Porsche 914-2	0.98049211	-1.2248578	-0.89093948	-0.81221077	1.55876313
Lotus Europa	1.71054652	-1.2248578	-1.09426581	-0.49133738	0.32437703
Ford Pantera L	-0.71190675	1.0148821	0.97046468	1.71102089	1.16600392
Ferrari Dino	-0.06481307	-0.1049878	-0.69164740	0.41294217	0.04383473
Maserati Bora	-0.84464392	1.0148821	0.56703942	2.74656682	-0.10578782
Volvo 142E	0.21725341	-1.2248578	-0.88529152	-0.54967799	0.96027290

	wt	qsec	vs	am	gear
Mazda RX4	-0.610399567	-0.77716515	-0.8680278	1.1899014	0.4235542
Mazda RX4 Wag	-0.349785269	-0.46378082	-0.8680278	1.1899014	0.4235542
Datsun 710	-0.917004624	0.42600682	1.1160357	1.1899014	0.4235542
Hornet 4 Drive	-0.002299538	0.89048716	1.1160357	-0.8141431	-0.9318192
Hornet Sportabout	0.227654255	-0.46378082	-0.8680278	-0.8141431	-0.9318192
Valiant	0.248094592	1.32698675	1.1160357	-0.8141431	-0.9318192
Duster 360	0.360516446	-1.12412636	-0.8680278	-0.8141431	-0.9318192
Merc 240D	-0.027849959	1.20387148	1.1160357	-0.8141431	0.4235542
Merc 230	-0.068730634	2.82675459	1.1160357	-0.8141431	0.4235542
Merc 280	0.227654255	0.25252621	1.1160357	-0.8141431	0.4235542
Merc 280C	0.227654255	0.58829513	1.1160357	-0.8141431	0.4235542
Merc 450SE	0.871524874	-0.25112717	-0.8680278	-0.8141431	-0.9318192
Merc 450SL	0.524039143	-0.13920420	-0.8680278	-0.8141431	-0.9318192
Merc 450SLC	0.575139986	0.08464175	-0.8680278	-0.8141431	-0.9318192
Cadillac Fleetwood	2.077504765	0.07344945	-0.8680278	-0.8141431	-0.9318192
Lincoln Continental	2.255335698	-0.01608893	-0.8680278	-0.8141431	-0.9318192
Chrysler Imperial	2.174596366	-0.23993487	-0.8680278	-0.8141431	-0.9318192
Fiat 128	-1.039646647	0.90727560	1.1160357	1.1899014	0.4235542

Honda Civic	-1.637526508	0.37564148	1.1160357	1.1899014	0.4235542
Toyota Corolla	-1.412682800	1.14790999	1.1160357	1.1899014	0.4235542
Toyota Corona	-0.768812180	1.20946763	1.1160357	-0.8141431	-0.9318192
Dodge Challenger	0.309415603	-0.54772305	-0.8680278	-0.8141431	-0.9318192
AMC Javelin	0.222544170	-0.30708866	-0.8680278	-0.8141431	-0.9318192
Camaro Z28	0.636460997	-1.36476075	-0.8680278	-0.8141431	-0.9318192
Pontiac Firebird	0.641571082	-0.44699237	-0.8680278	-0.8141431	-0.9318192
Fiat X1-9	-1.310481114	0.58829513	1.1160357	1.1899014	0.4235542
Porsche 914-2	-1.100967659	-0.64285758	-0.8680278	1.1899014	1.7789276
Lotus Europa	-1.741772228	-0.53093460	1.1160357	1.1899014	1.7789276
Ford Pantera L	-0.048290296	-1.87401028	-0.8680278	1.1899014	1.7789276
Ferrari Dino	-0.457097039	-1.31439542	-0.8680278	1.1899014	1.7789276
Maserati Bora	0.360516446	-1.81804880	-0.8680278	1.1899014	1.7789276
Volvo 142E	-0.446876870	0.42041067	1.1160357	1.1899014	0.4235542

	carb
Mazda RX4	0.7352031
Mazda RX4 Wag	0.7352031
Datsun 710	-1.1221521
Hornet 4 Drive	-1.1221521
Hornet Sportabout	-0.5030337
Valiant	-1.1221521
Duster 360	0.7352031
Merc 240D	-0.5030337
Merc 230	-0.5030337
Merc 280	0.7352031
Merc 280C	0.7352031
Merc 450SE	0.1160847
Merc 450SL	0.1160847
Merc 450SLC	0.1160847
Cadillac Fleetwood	0.7352031
Lincoln Continental	0.7352031
Chrysler Imperial	0.7352031
Fiat 128	-1.1221521
Honda Civic	-0.5030337
Toyota Corolla	-1.1221521
Toyota Corona	-1.1221521
Dodge Challenger	-0.5030337
AMC Javelin	-0.5030337
Camaro Z28	0.7352031
Pontiac Firebird	-0.5030337
Fiat X1-9	-1.1221521
Porsche 914-2	-0.5030337
Lotus Europa	-0.5030337

```
Ford Pantera L       0.7352031
Ferrari Dino         1.9734398
Maserati Bora        3.2116766
Volvo 142E          -0.5030337
attr(,"scaled:center")
       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
attr(,"scaled:scale")
        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
```

```
colMeans(x)
```

```
          mpg           cyl          disp            hp          drat
 7.112366e-17 -1.474515e-17 -9.085614e-17  1.040834e-17 -2.918672e-16
           wt          qsec            vs            am          gear
 4.682398e-17  5.299580e-16  6.938894e-18  4.510281e-17 -3.469447e-18
         carb
 3.165870e-17
```

```
round(colMeans(x))
```

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

Key point: It is usually always a good idea to scale your data before to PCA

Breast Cancer Bioposy Analysis

```
#save input data file into project directory
fna.data <- "WisconsinCancer.csv"

#use read.csv() to read the data and save it in 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
```

```r
# We can use -1 here to remove the first column diagnosis
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
```

```
# Create diagnosis vector for later
diagnosis <- wisc.df[,1]
```

Remove this first 'diagnosis' column from the dataset as I don;t want to pass this to PCA etc.

Exploratory data analysis

- **Q1**. How many observations are in this dataset?

31(diagnosis included)

```
ncol(wisc.df)
```

```
[1] 31
```

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

  212

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

```

  B   M 
357 212 
```

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

```
grep("_mean",colnames(wisc.df), value =1)
```

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

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
```

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

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

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

See what is in our PCA result object:

```r
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`

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

  In order to get <70% of the original variance in the data, the cumulative poportion have to be grater than 0.7, which means 3 PCs is required according to the summary().

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

  In order to get <90% of the original variance in the data, the cumulative poportion have to be grater than 0.9, which means 7 PCs is required according to the summary().

Interpreting PCA results

Main PC score plot, PC1 vs. PC2

```r
attributes(wisc.pr)
```

```
$names
[1] "sdev"     "rotation" "center"   "scale"    "x"

$class
[1] "prcomp"
```

```
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
```

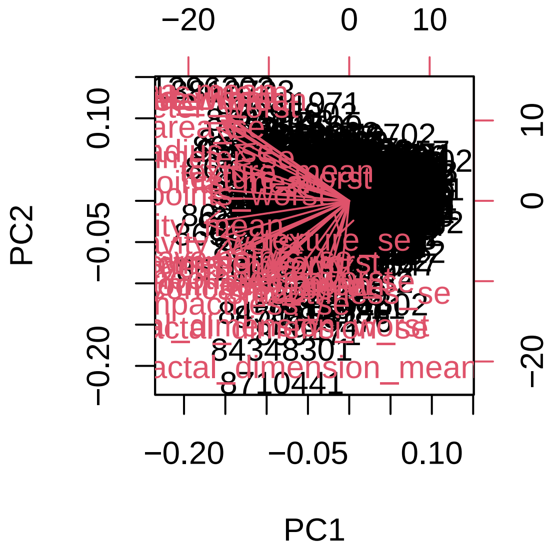
```
head(wisc.pr$x)
```

```
               PC1        PC2        PC3       PC4        PC5         PC6
842302   -9.184755  -1.946870 -1.1221788 3.6305364  1.1940595  1.41018364
842517   -2.385703   3.764859 -0.5288274 1.1172808 -0.6212284  0.02863116
84300903 -5.728855   1.074229 -0.5512625 0.9112808  0.1769302  0.54097615
84348301 -7.116691 -10.266556 -3.2299475 0.1524129  2.9582754  3.05073750
84358402 -3.931842   1.946359  1.3885450 2.9380542 -0.5462667 -1.22541641
843786   -2.378155  -3.946456 -2.9322967 0.9402096  1.0551135 -0.45064213
                 PC7         PC8         PC9       PC10       PC11       PC12
842302    2.15747152  0.39805698 -0.15698023 -0.8766305 -0.2627243 -0.8582593
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    0.08444429  0.175102213  0.150887294 -0.201326305 -0.25236294
842517   -0.21752666 -0.011280193  0.170360355 -0.041092627  0.18111081
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
843786    0.03344819 -0.002837749 -0.122282765 -0.030272333 -0.08438081
                  PC28         PC29          PC30
842302   -0.0338846387  0.045607590  0.0471277407
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
```

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

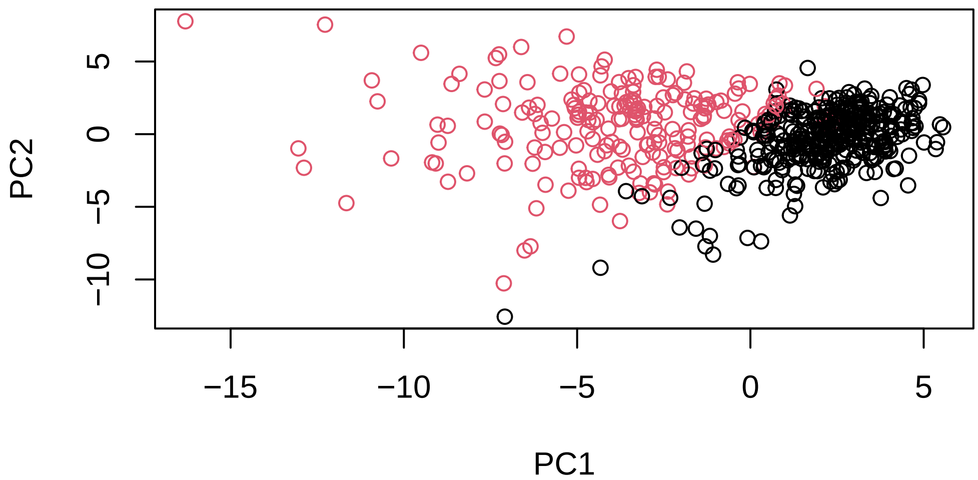
```r
biplot(wisc.pr)
```



The biplot was hard to understand as most of the data points are crowded together.

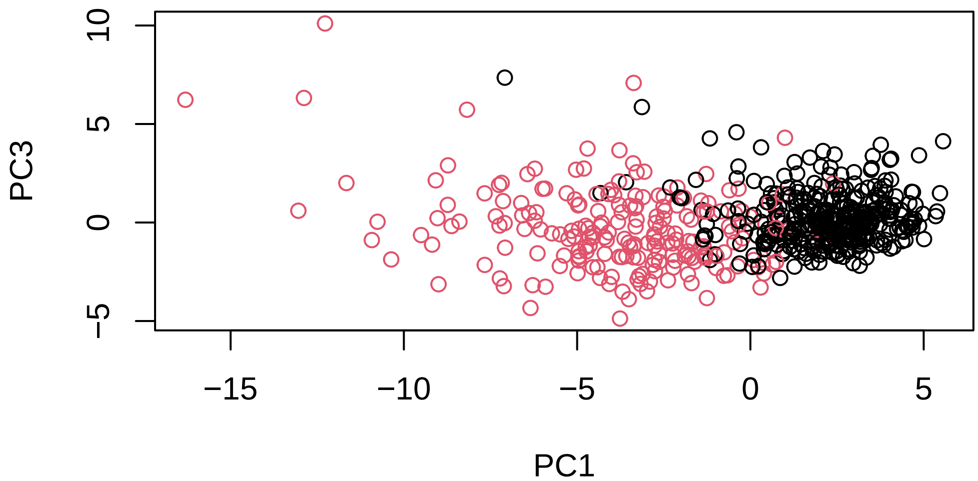
PCA plot

```r
plot(wisc.pr$x[,1], wisc.pr$x[,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")
```

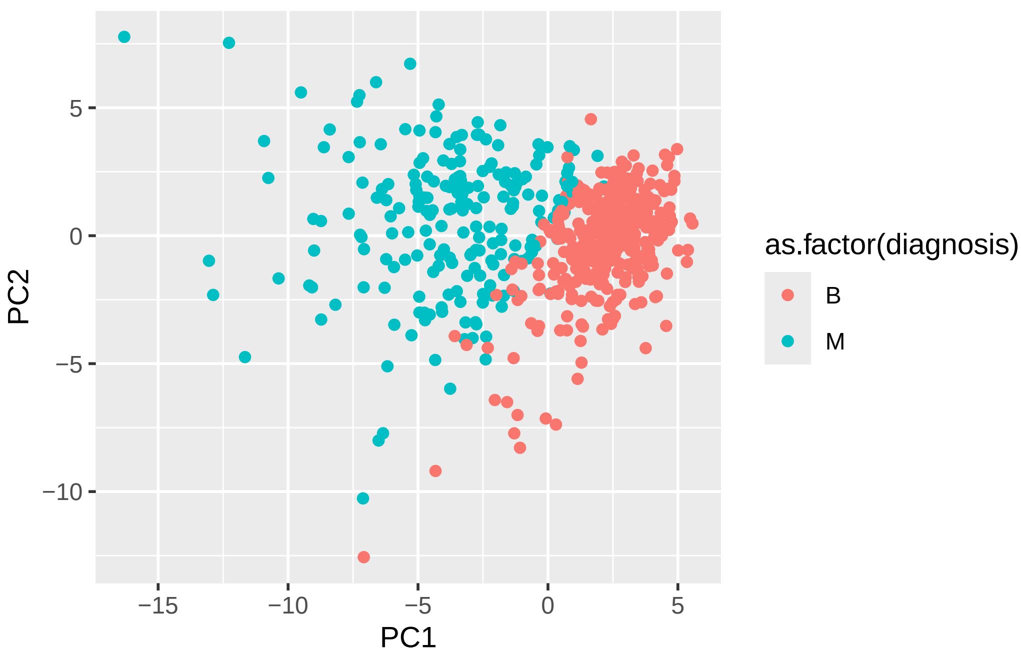


```
# Create a data.frame for ggplot
df <- as.data.frame(wisc.pr$x)
df$diagnosis <- diagnosis

# Load the ggplot2 package
library(ggplot2)
```

```
Warning: package 'ggplot2' was built under R version 4.3.3
```

```
# Make a scatter plot colored by diagnosis
ggplot(df) +
  aes(PC1, PC2, col= as.factor(diagnosis)) +
  geom_point()+
  labs(x="PC1", y="PC2")
```



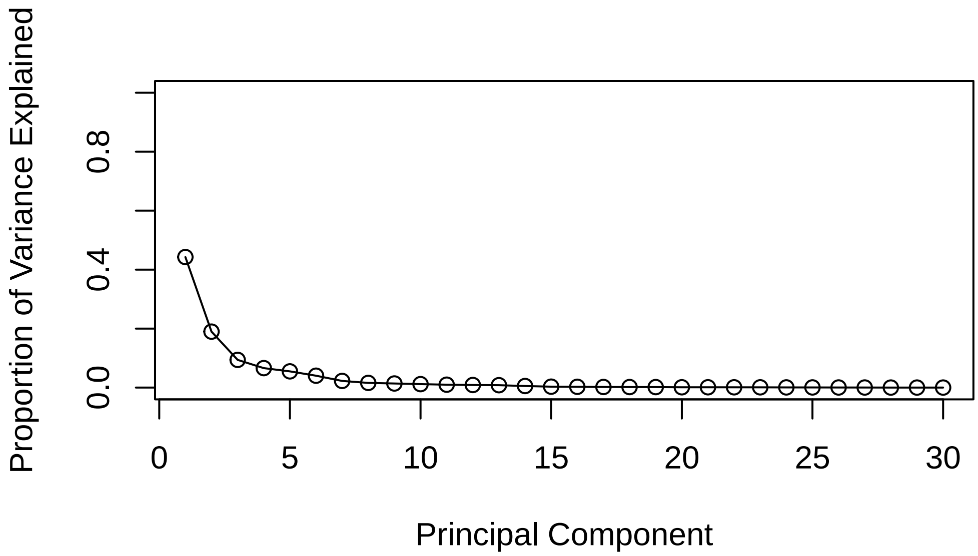
Variance explained

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

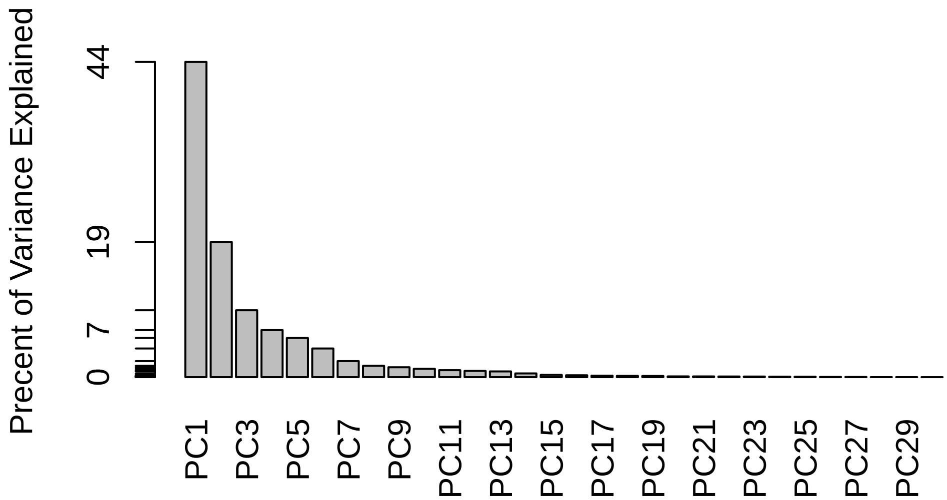
```
[1] 13.281608  5.691355  2.817949  1.980640  1.648731  1.207357
```

```r
# Variance explained by each principal component: pve
pve <- pr.var/sum(pr.var)

# Plot variance explained for each principal component
plot(pve, xlab = "Principal Component",
     ylab = "Proportion of Variance Explained",
     ylim = c(0, 1), type = "o")
```




```r
# 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 )
```

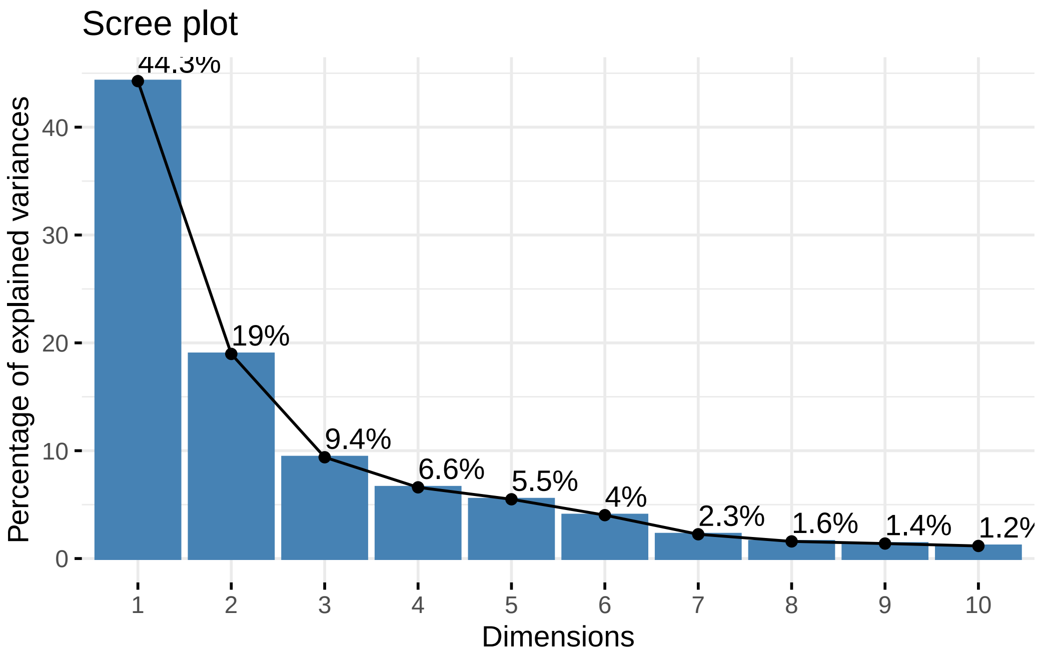



```
## ggplot based graph
#install.packages("factoextra")
library(factoextra)
```

```
Warning: package 'factoextra' was built under R version 4.3.3

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?

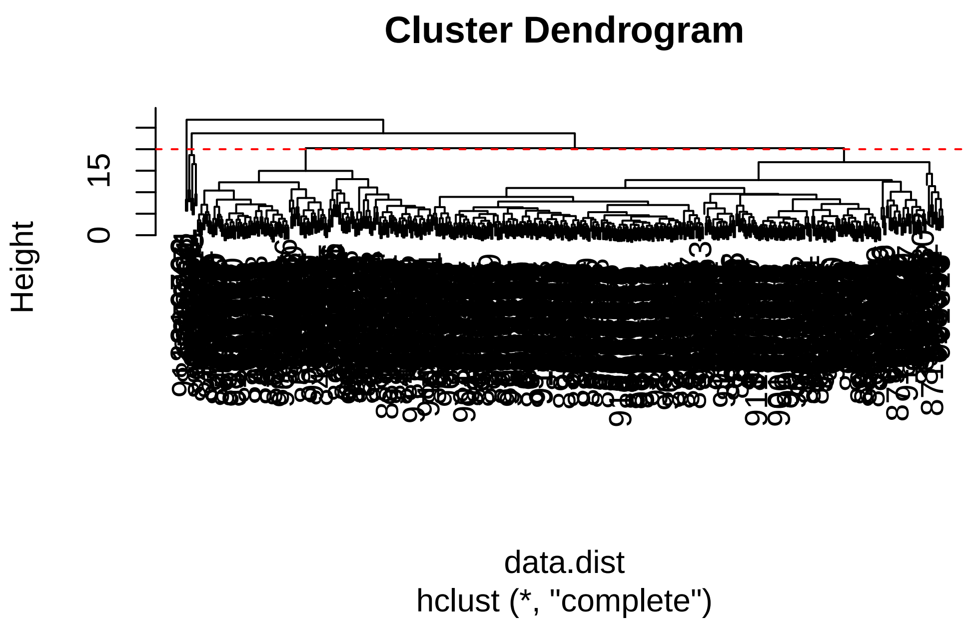
  5 PCs

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")
```

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

```r
plot(wisc.hclust)
abline(h=20, col="red", lty=2)
```



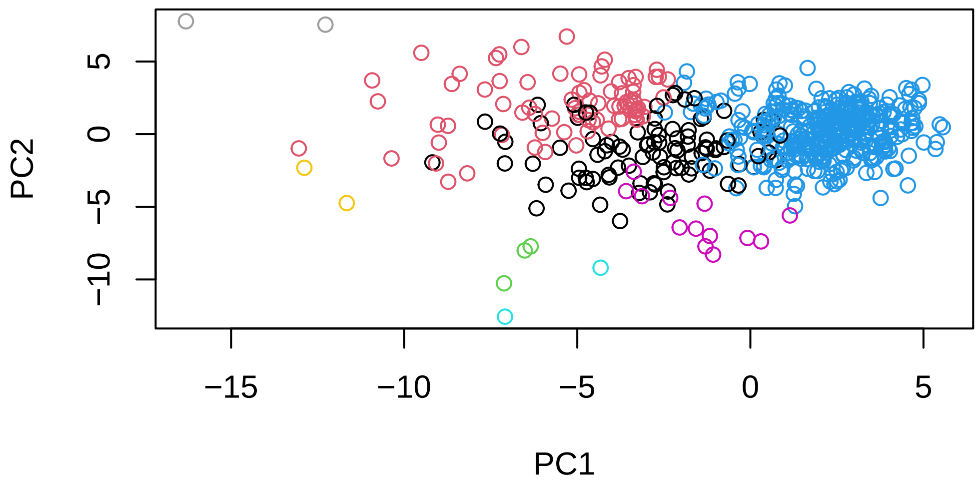
table(wisc.hclust.clusters, diagnosis)

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

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

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

```r
wisc.hclust.clusters <- cutree(wisc.hclust, k=8)
plot( wisc.pr$x[,1:2] , col = wisc.hclust.clusters,
xlab = "PC1", ylab = "PC2")
```



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

```
wisc.hclust_complete <- hclust(data.dist, method = "complete")
wisc.hclust_single <- hclust(data.dist, method = "single")
wisc.hclust_avg <- hclust(data.dist, method = "average")
wisc.hclust_ward <- hclust(data.dist, method = "ward.D2")
```

```
wisc.hclust.clusters <- cutree(wisc.hclust_complete, k=4)
table(wisc.hclust.clusters, diagnosis)
```

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

```
wisc.hclust.clusters <- cutree(wisc.hclust_single, k=4)
table(wisc.hclust.clusters, diagnosis)
```

```
                    diagnosis
wisc.hclust.clusters   B   M
                   1 356 209
```

```
                     2   1   0
                     3   0   2
                     4   0   1
```

```
wisc.hclust.clusters <- cutree(wisc.hclust_avg, k=4)
table(wisc.hclust.clusters, diagnosis)
```

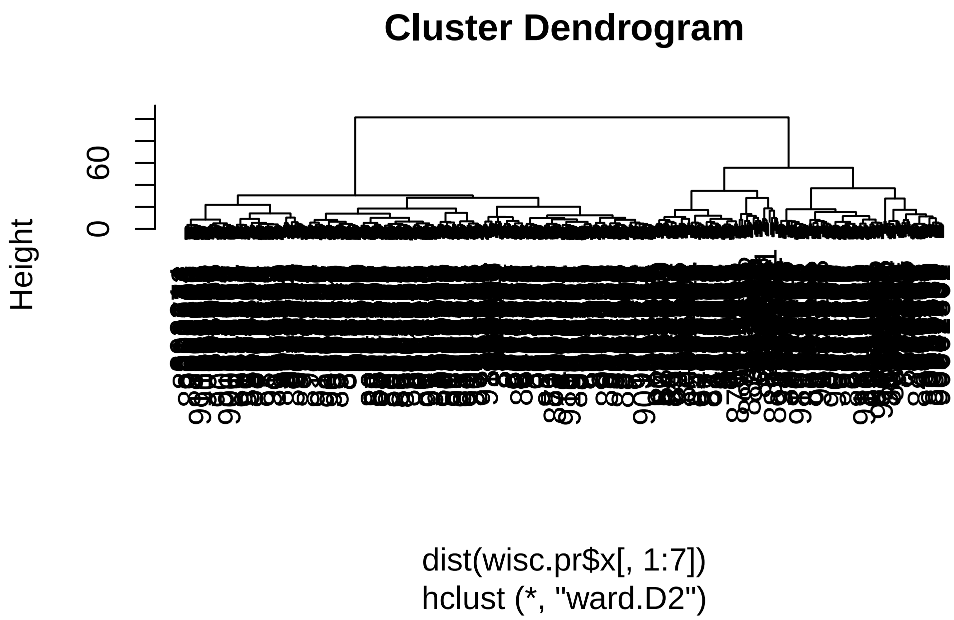
```
                    diagnosis
wisc.hclust.clusters   B   M
                   1 355 209
                   2   2   0
                   3   0   1
                   4   0   2
```

```
wisc.hclust.clusters <- cutree(wisc.hclust_ward, k=4)
table(wisc.hclust.clusters, diagnosis)
```

```
                    diagnosis
wisc.hclust.clusters   B   M
                   1   0 115
                   2   6  48
                   3 337  48
                   4  14   1
```

I like the ward.D2 method because I think it distributes the clusters in the most average way, which ensures each cluster would have enough data points.

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




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

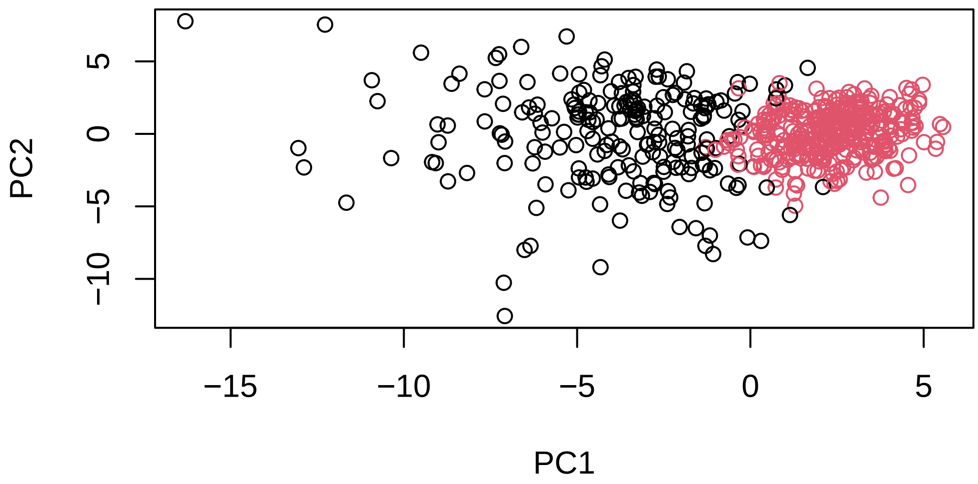
```
grps
  1   2
216 353
```

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

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

-

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



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

```
wisc.pr.hclust.clusters <- cutree(wisc.pr.hclust, k=2)
# Compare to actual diagnoses
table(wisc.pr.hclust.clusters, diagnosis)
```

```
                       diagnosis
wisc.pr.hclust.clusters   B   M
                      1  28 188
                      2 329  24
```

- **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.

```
wisc.km <- kmeans(wisc.data, centers= 2, nstart= 20)

table(wisc.km$cluster, diagnosis)
```

```
   diagnosis
      B   M
  1 356  82
  2   1 130
```

```
table(cutree(wisc.hclust, k=4), diagnosis)
```

```
   diagnosis
      B   M
  1  12 165
  2   2   5
  3 343  40
  4   0   2
```

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

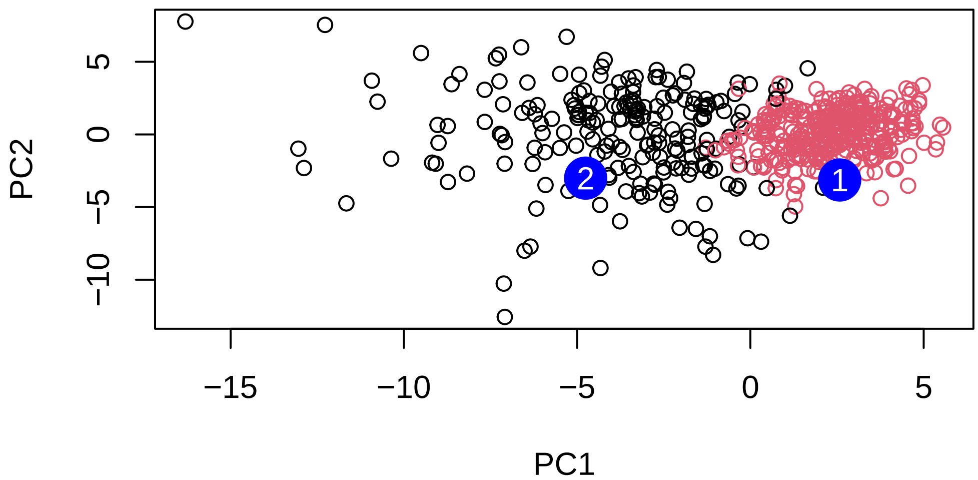
Specificity: Hierarchical clustering

Sensitivity: Kmean

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



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

  Patient 1