

# MSDS 6372 Project 2

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## Data Set 1: Osteoporosis in Women

From Hosmer, Lemeshow, and Sturdivant (2013), Applied Logistic Regression, 3rd Edition. The Global Longitudinal Study of Osteoporosis in Women (GLOW) is an international study of osteoporosis in women aged 55 years and over. The major goals of the study are to examine prevention and treatment of fractures and distribution of risk factors among older women. Complete details on the study as well as a list of GLOW publications may be found at the Center for Outcomes Research web site, <http://www.outcomes-umassmed.org/glow>. There are over 60K observations in the original data set. This data set contains a sample of 500 of them. The link below is to a website with the data set and description of the variables. The data set in question is called “glow500”.

<https://www.umass.edu/statdata/statdata/data/glow/index.html> Note: If you choose this data set, you MAY NOT use the Hosmer, Lemeshow, and Sturdivant text to help you in your analysis. You may only use Chapter 1 in order to obtain a description of the data.

Of course if you don't have the book

<https://www.umass.edu/statdata/statdata/data/glow/glow.pdf> provides definitions to the variables.

The Global Longitudinal Study of Osteoporosis in Women (GLOW) (2005-2014) was a prospective cohort study of physician practices in the provision of prophylaxis and treatment against osteoporotic fractures. The goal of this research was to improve understanding of the risk and prevention of osteoporosis-related fractures among female residents of 10 countries who were 55 years of age and older. GLOW enrolled over 60,000 women through over 700 physicians in 10 countries, and conducted annual follow-up for up to 5 years through annual patient questionnaires.

## Setup:

### Data Import and Cleaning

Missing values were not detected in dataset. Special characters were removed from column headings. What we know/don't know about the sample (500): 1. We do not know if the subjects are distributed equally

around the world. We will assume that the same percentage from each region was selected for the sample in this dataset. 2. Based on the Sub\_ID(Subject ID), we can assume that the data is independent sample of participants. 3.

```
library(here)
```

```
## here() starts at D:/2018-stats2-project/stats2proj2
```

```
##
```

```
## Attaching package: 'here'
```

```
## The following object is masked from 'package:plyr':
```

```
##
```

```
##     here
```

```
glow_data_file <- here("data", "glow500.csv")
```

```
dataset <- read.csv(glow_data_file, sep=";", stringsAsFactors = TRUE, header=TRUE, na.strings=c(""))
```

```
#dataset <- read.csv("C:/Users/carol/OneDrive/Documents/MSDS6372/Proj2/glow500.csv", sep=";", stringsAs
```

```
# List rows of data that have missing values
```

```
Missing_values <- dataset[!complete.cases(dataset),]
```

```
# Create new dataset without missing data
```

```
dataset <- na.omit(dataset)
```

```
#remove FRACSCORE feature per professor Turner
```

```
drops <- c("FRACSCORE")
```

```
dataset <- dataset[, !(names(dataset) %in% drops)]
```

```
#Cleanup column names
```

```
colnames(dataset)[colnames(dataset)=="i.SUB_ID"] <- "SUB_ID"
```

## Grouping Variables as Continuous, Categorical, and ID

```
numericVar <- dataset[,5:8]
```

```
ID_var <- dataset[,c(1:3)]
```

```
set_noID <- dataset[4:14]
```

```
categoricalVar <- set_noID[, -c(2:5)]
```

## Create a vector of all categorical variables and run frequency 2X2s with Mosaic plots.

Chi-Square Test For the 2-way tables the chisq test independence will show if 2 categorical variables are related in some population. Null Hypothesis: The two categorical variables are independent. Alternative Hypothesis: The two categorical variables are dependent

Variable: PRIORFRAC 41% of subjects with Prior Fractures also had current Fractures but only make up 25% of the overall subjects in the sample that had prior fractures. The Chi-squared p-value favors overwhelmingly the alternative hypothesis that the PRIORFRAC variable is dependent on Fracture variable.

Variable: PREMENO 80% of the sample subjects are not in Pre-Menopausehad of which 24% had fractures. The same frequency of 25% Premenopausal women had fractures. The Chi-squared p-value favors the null hypothesis that the PREMENO variable is independent on Fracture variable.

Variable: MOMFRAC 13% of subjects have Mothers with a history of fractures. Out of those 13%, 36% of subjects also had fractures. The Chi-squared p-value favors the alternative hypothesis that the MOMFRAC variable is probably dependent on Fracture variable.

Variable: ARMASSIST 62% (312/500) subjects do not have Armassist of which 20% had fractures. Of those with Armassist, 33% had fractures. The Chi-squared p-value favors the alternative hypothesis that the ARMASSIST variable is most likely dependent on Fracture variable.

Variable: SMOKE In the dataset, 93% of subjects are non-smokers of which 26% had fractures. 7% of the subjects who were smokers of which 26% had no fractures. Although the subjects are not balance in smoker vs non-smoker category, the p-value for Chi-squared test shows .47 we favor the alternative hypothesis that the Smoke variable is dependent on the Fracture.

Variable: RATERISK Raterisk shows the frequency of subjects in each Raterisk level is between 29%-33%. This is pretty even in terms of how many subjects are within each Raterisk. For those that did have Fractures, their probability of a fracture increased with the level of Raterisk. This makes sense.

```
categoricalVarVec <- c("PRIORFRAC", "PREMENO", "MOMFRAC", "ARMASSIST", "SMOKE", "RATERISK")
for(categoricalVar in categoricalVarVec){
  CrossTable(dataset[,categoricalVar], dataset$FRACTURE, chisq = TRUE, expected = TRUE, dnn=c(categoricalVar, "FRACTURE"))
  mosaicplot(CrossTable(dataset[,categoricalVar], dataset$FRACTURE)$t, main=paste("FRACTURE vs", categoricalVar))
}
```

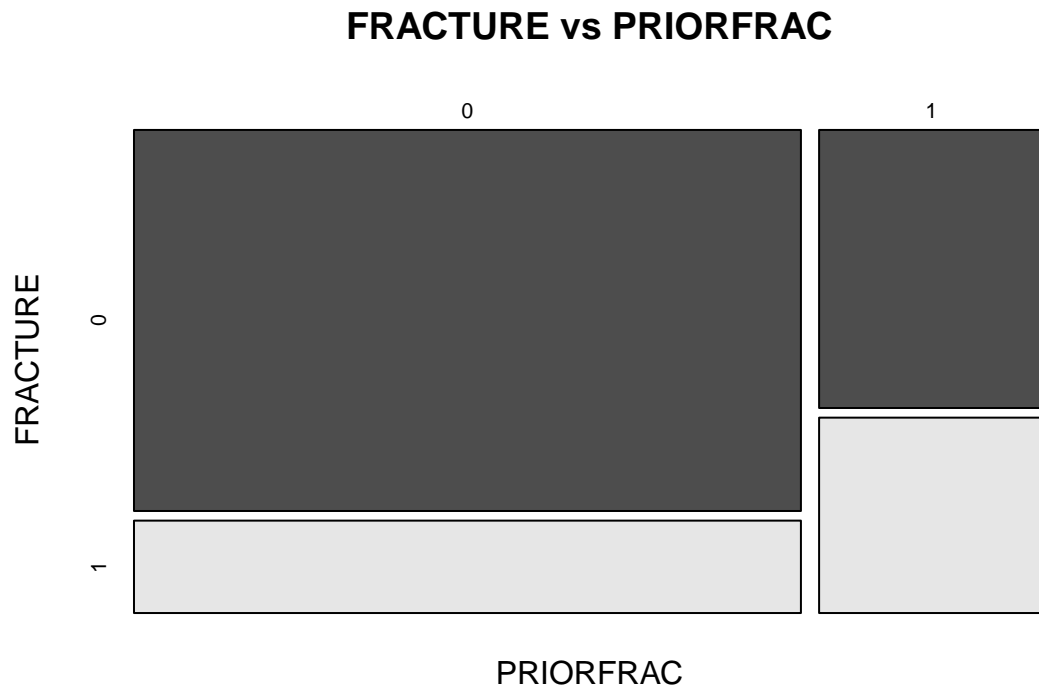
```
##
##
##      Cell Contents
## |-----|
## |                      N |
## |          Expected N |
## | Chi-square contribution |
## |      N / Row Total |
## |      N / Col Total |
## |      N / Table Total |
## |-----|
##
##
## Total Observations in Table:  500
##
##
##      | FRACTURE
## PRIORFRAC |      0 |      1 | Row Total |
## -----|-----|-----|-----|
##      0 |    301 |     73 |    374 |
##      | 280.500 |  93.500 |    |
##      |   1.498 |   4.495 |    |
##      |   0.805 |   0.195 |  0.748 |
##      |   0.803 |   0.584 |    |
##      |   0.602 |   0.146 |    |
## -----|-----|-----|-----|
##      1 |     74 |     52 |    126 |
##      |  94.500 |  31.500 |    |
##      |   4.447 |  13.341 |    |
```

```

##           |      0.587 |      0.413 |      0.252 |
##           |      0.197 |      0.416 |           |
##           |      0.148 |      0.104 |           |
## -----|-----|-----|-----|
## Column Total |      375 |      125 |      500 |
##           |      0.750 |      0.250 |           |
## -----|-----|-----|-----|
##
##
## Statistics for All Table Factors
##
##
## Pearson's Chi-squared test
## -----
## Chi^2 = 23.78123      d.f. = 1      p = 1.079299e-06
##
## Pearson's Chi-squared test with Yates' continuity correction
## -----
## Chi^2 = 22.63532      d.f. = 1      p = 1.958512e-06
##
##
##
## Cell Contents
## |-----|
## |              N |
## | Chi-square contribution |
## |      N / Row Total |
## |      N / Col Total |
## |      N / Table Total |
## |-----|
##
##
## Total Observations in Table: 500
##
##
##           | dataset$FRACTURE
## dataset[, categoricalVar] |      0 |      1 | Row Total |
## -----|-----|-----|-----|
##           0 |      301 |      73 |      374 |
##           |      1.498 |      4.495 |           |
##           |      0.805 |      0.195 |      0.748 |
##           |      0.803 |      0.584 |           |
##           |      0.602 |      0.146 |           |
## -----|-----|-----|-----|
##           1 |      74 |      52 |      126 |
##           |      4.447 |     13.341 |           |
##           |      0.587 |      0.413 |      0.252 |
##           |      0.197 |      0.416 |           |
##           |      0.148 |      0.104 |           |
## -----|-----|-----|-----|
##           Column Total |      375 |      125 |      500 |
##           |      0.750 |      0.250 |           |
## -----|-----|-----|-----|

```

##  
##



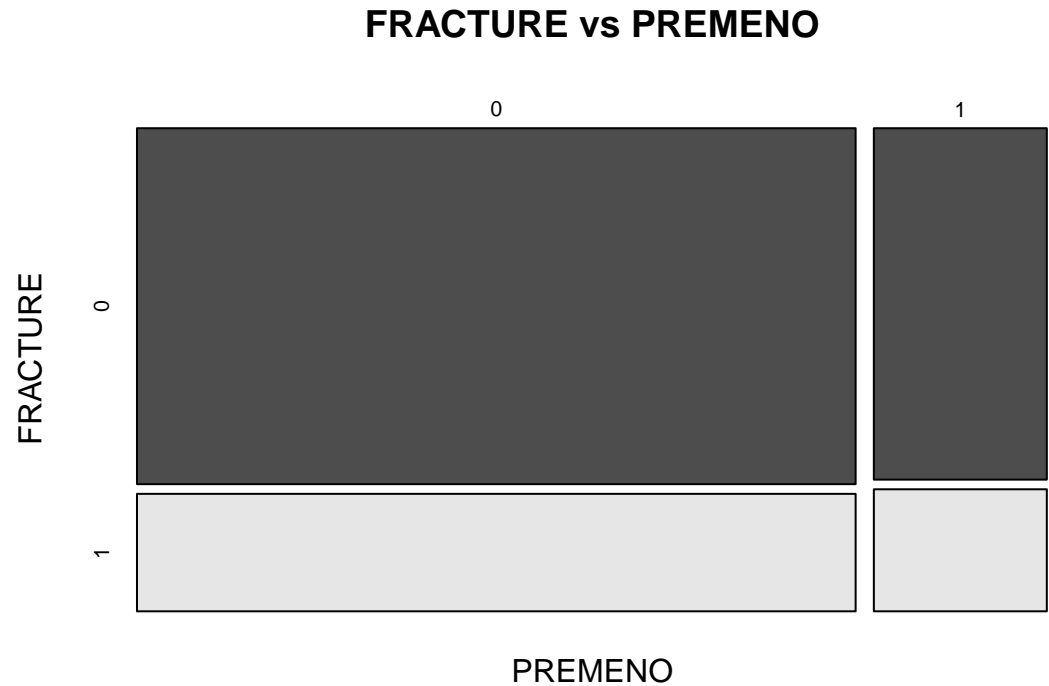
```
##
##
##      Cell Contents
## |-----|
## |              N |
## |      Expected N |
## | Chi-square contribution |
## |      N / Row Total |
## |      N / Col Total |
## |      N / Table Total |
## |-----|
##
##
## Total Observations in Table:  500
##
##
##      | FRACTURE
##      |
##      | 0 | 1 | Row Total |
## -----|-----|-----|
##      0 | 303 | 100 | 403 |
##      | 302.250 | 100.750 |
##      | 0.002 | 0.006 |
##      | 0.752 | 0.248 | 0.806 |
```

```

##          |      0.808 |      0.800 |          |
##          |      0.606 |      0.200 |          |
## -----|-----|-----|-----|
##          1 |         72 |         25 |         97 |
##          |      72.750 |      24.250 |          |
##          |      0.008 |      0.023 |          |
##          |      0.742 |      0.258 |      0.194 |
##          |      0.192 |      0.200 |          |
##          |      0.144 |      0.050 |          |
## -----|-----|-----|-----|
## Column Total |         375 |         125 |         500 |
##          |      0.750 |      0.250 |          |
## -----|-----|-----|-----|
##
##
## Statistics for All Table Factors
##
##
## Pearson's Chi-squared test
## -----
## Chi^2 =  0.038372      d.f. =  1      p =  0.844698
##
## Pearson's Chi-squared test with Yates' continuity correction
## -----
## Chi^2 =  0.004263556      d.f. =  1      p =  0.9479384
##
##
##
## Cell Contents
## |-----|
## |              N |
## | Chi-square contribution |
## |      N / Row Total |
## |      N / Col Total |
## |      N / Table Total |
## |-----|
##
##
## Total Observations in Table:  500
##
##
##          | dataset$FRACTURE
## dataset[, categoricalVar] |      0 |      1 | Row Total |
## -----|-----|-----|-----|
##          0 |      303 |      100 |      403 |
##          |      0.002 |      0.006 |          |
##          |      0.752 |      0.248 |      0.806 |
##          |      0.808 |      0.800 |          |
##          |      0.606 |      0.200 |          |
## -----|-----|-----|-----|
##          1 |      72 |      25 |      97 |
##          |      0.008 |      0.023 |          |
##          |      0.742 |      0.258 |      0.194 |

```

##		0.192	0.200	
##		0.144	0.050	
##				
##	Column Total	375	125	500
##		0.750	0.250	
##				
##				
##				



##	
##	
##	Cell Contents
##	-----
##	N
##	Expected N
##	Chi-square contribution
##	N / Row Total
##	N / Col Total
##	N / Table Total
##	-----
##	
##	
##	Total Observations in Table: 500
##	
##	
##	FRACTURE

```

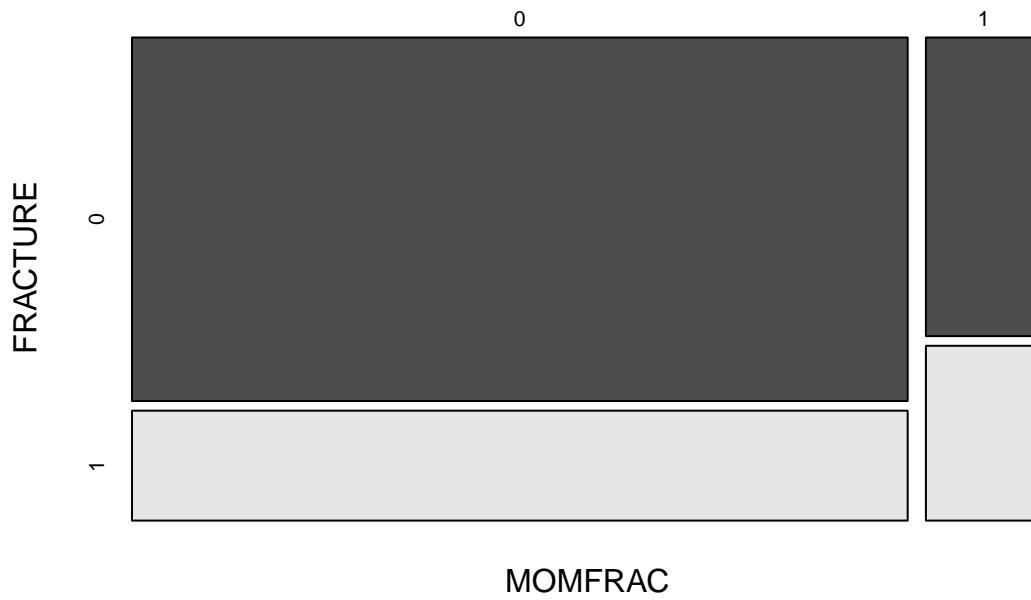
##      MOMFRAC |      0 |      1 | Row Total |
## -----|-----|-----|-----|
##           0 |      334 |      101 |      435 |
##           |    326.250 |    108.750 |      |
##           |      0.184 |      0.552 |      |
##           |      0.768 |      0.232 |    0.870 |
##           |      0.891 |      0.808 |      |
##           |      0.668 |      0.202 |      |
## -----|-----|-----|-----|
##           1 |       41 |       24 |       65 |
##           |    48.750 |    16.250 |      |
##           |      1.232 |      3.696 |      |
##           |      0.631 |      0.369 |    0.130 |
##           |      0.109 |      0.192 |      |
##           |      0.082 |      0.048 |      |
## -----|-----|-----|-----|
## Column Total |      375 |      125 |      500 |
##           |    0.750 |    0.250 |      |
## -----|-----|-----|-----|
##
##
## Statistics for All Table Factors
##
##
## Pearson's Chi-squared test
## -----
## Chi^2 =  5.664604      d.f. =  1      p =  0.01731063
##
## Pearson's Chi-squared test with Yates' continuity correction
## -----
## Chi^2 =  4.957265      d.f. =  1      p =  0.02598127
##
##
##
##      Cell Contents
## |-----|
## |              N |
## | Chi-square contribution |
## |      N / Row Total |
## |      N / Col Total |
## |      N / Table Total |
## |-----|
##
##
## Total Observations in Table:  500
##
##
##      | dataset$FRACTURE
## dataset[, categoricalVar] |      0 |      1 | Row Total |
## -----|-----|-----|-----|
##           0 |      334 |      101 |      435 |
##           |      0.184 |      0.552 |      |
##           |      0.768 |      0.232 |    0.870 |

```



##		0.891	0.808	
##		0.668	0.202	
##				
##	1	41	24	65
##		1.232	3.696	
##		0.631	0.369	0.130
##		0.109	0.192	
##		0.082	0.048	
##				
##	Column Total	375	125	500
##		0.750	0.250	
##				
##				
##				

## FRACTURE vs MOMFRAC



##	
##	
##	Cell Contents
##	-----
##	N
##	Expected N
##	Chi-square contribution
##	N / Row Total
##	N / Col Total
##	N / Table Total
##	-----

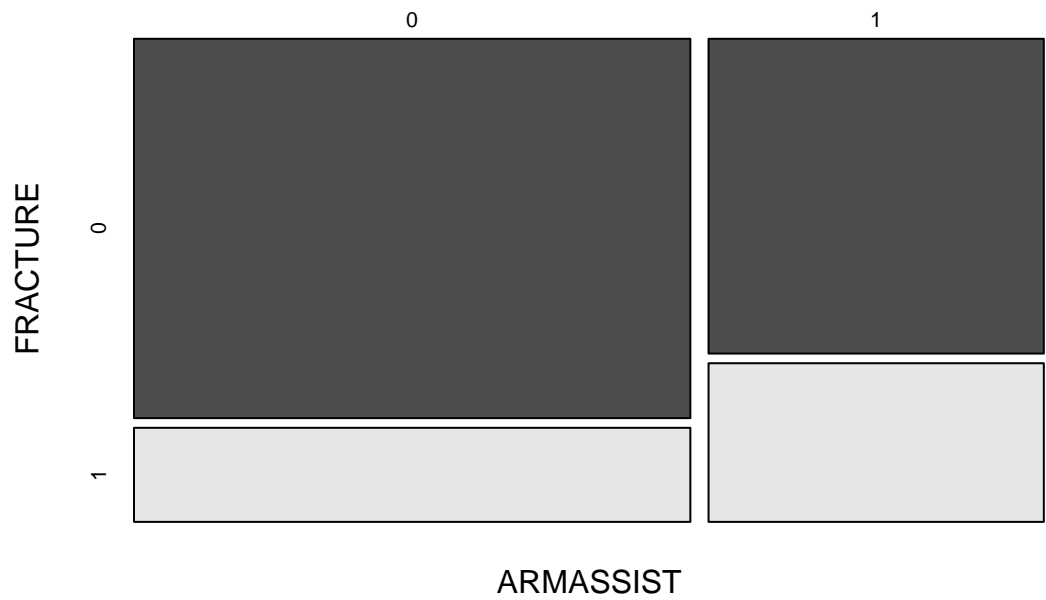
```

##
##
## Total Observations in Table:  500
##
##
##          | FRACTURE
##  ARMASSIST |          0 |          1 | Row Total |
##  -----|-----|-----|-----|
##          0 |          250 |          62 |          312 |
##          |        234.000 |        78.000 |          |
##          |         1.094 |         3.282 |          |
##          |         0.801 |         0.199 |        0.624 |
##          |         0.667 |         0.496 |          |
##          |         0.500 |         0.124 |          |
##  -----|-----|-----|-----|
##          1 |          125 |          63 |          188 |
##          |        141.000 |         47.000 |          |
##          |         1.816 |         5.447 |          |
##          |         0.665 |         0.335 |        0.376 |
##          |         0.333 |         0.504 |          |
##          |         0.250 |         0.126 |          |
##  -----|-----|-----|-----|
## Column Total |          375 |          125 |          500 |
##          |         0.750 |         0.250 |          |
##  -----|-----|-----|-----|
##
##
## Statistics for All Table Factors
##
##
## Pearson's Chi-squared test
## -----
## Chi^2 =  11.63848      d.f. =  1      p =  0.0006460138
##
## Pearson's Chi-squared test with Yates' continuity correction
## -----
## Chi^2 =  10.92244      d.f. =  1      p =  0.0009500637
##
##
##
## Cell Contents
## |-----|
## |                      N |
## | Chi-square contribution |
## |          N / Row Total |
## |          N / Col Total |
## |          N / Table Total |
## |-----|
##
##
## Total Observations in Table:  500
##
##

```

```
## dataset[, categoricalVar] | dataset$FRACTURE
## -----|-----|-----|
## 0 | 250 | 62 | 312 |
## 1.094 | 3.282 |
## 0.801 | 0.199 | 0.624 |
## 0.667 | 0.496 |
## 0.500 | 0.124 |
## -----|-----|-----|
## 1 | 125 | 63 | 188 |
## 1.816 | 5.447 |
## 0.665 | 0.335 | 0.376 |
## 0.333 | 0.504 |
## 0.250 | 0.126 |
## -----|-----|-----|
## Column Total | 375 | 125 | 500 |
## 0.750 | 0.250 |
## -----|-----|-----|
##
##
```

## FRACTURE vs ARMASSIST



```
##
##
## Cell Contents
## |-----|
## | N |
```

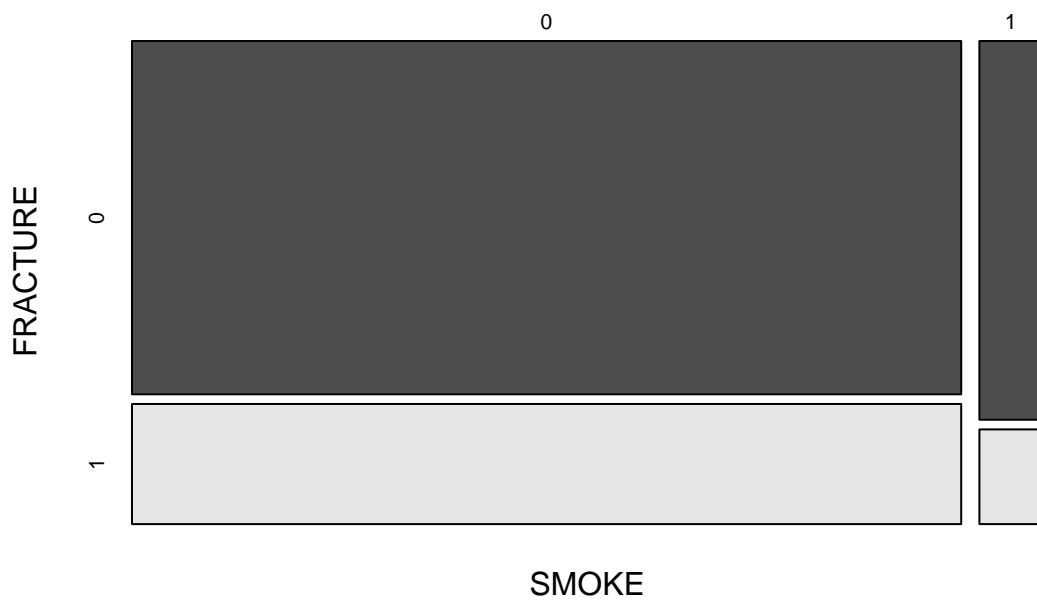
```

## |           Expected N |
## | Chi-square contribution |
## |           N / Row Total |
## |           N / Col Total |
## |           N / Table Total |
## |-----|
##
##
## Total Observations in Table:  500
##
##
##           | FRACTURE
##      SMOKE |           0 |           1 | Row Total |
## -----|-----|-----|-----|
##           0 |          347 |          118 |          465 |
##           |      348.750 |      116.250 |           |
##           |          0.009 |          0.026 |           |
##           |          0.746 |          0.254 |          0.930 |
##           |          0.925 |          0.944 |           |
##           |          0.694 |          0.236 |           |
## -----|-----|-----|-----|
##           1 |           28 |           7 |           35 |
##           |      26.250 |          8.750 |           |
##           |          0.117 |          0.350 |           |
##           |          0.800 |          0.200 |          0.070 |
##           |          0.075 |          0.056 |           |
##           |          0.056 |          0.014 |           |
## -----|-----|-----|-----|
## Column Total |          375 |          125 |          500 |
##           |          0.750 |          0.250 |           |
## -----|-----|-----|-----|
##
##
## Statistics for All Table Factors
##
##
## Pearson's Chi-squared test
## -----
## Chi^2 =  0.5017921      d.f. =  1      p =  0.4787137
##
## Pearson's Chi-squared test with Yates' continuity correction
## -----
## Chi^2 =  0.2560164      d.f. =  1      p =  0.6128703
##
##
##
##      Cell Contents
## -----|
## |           N |
## | Chi-square contribution |
## |           N / Row Total |
## |           N / Col Total |
## |           N / Table Total |

```

```
## |-----|
##
##
## Total Observations in Table:  500
##
##
##          | dataset$FRACTURE
## dataset[, categoricalVar] |          0 |          1 | Row Total |
## -----|-----|-----|-----|
##              0 |      347 |      118 |      465 |
##              |      0.009 |      0.026 |      |
##              |      0.746 |      0.254 |      0.930 |
##              |      0.925 |      0.944 |      |
##              |      0.694 |      0.236 |      |
## -----|-----|-----|-----|
##              1 |       28 |        7 |       35 |
##              |      0.117 |      0.350 |      |
##              |      0.800 |      0.200 |      0.070 |
##              |      0.075 |      0.056 |      |
##              |      0.056 |      0.014 |      |
## -----|-----|-----|-----|
##          Column Total |      375 |      125 |      500 |
##              |      0.750 |      0.250 |      |
## -----|-----|-----|-----|
##
##
```

## FRACTURE vs SMOKE



```

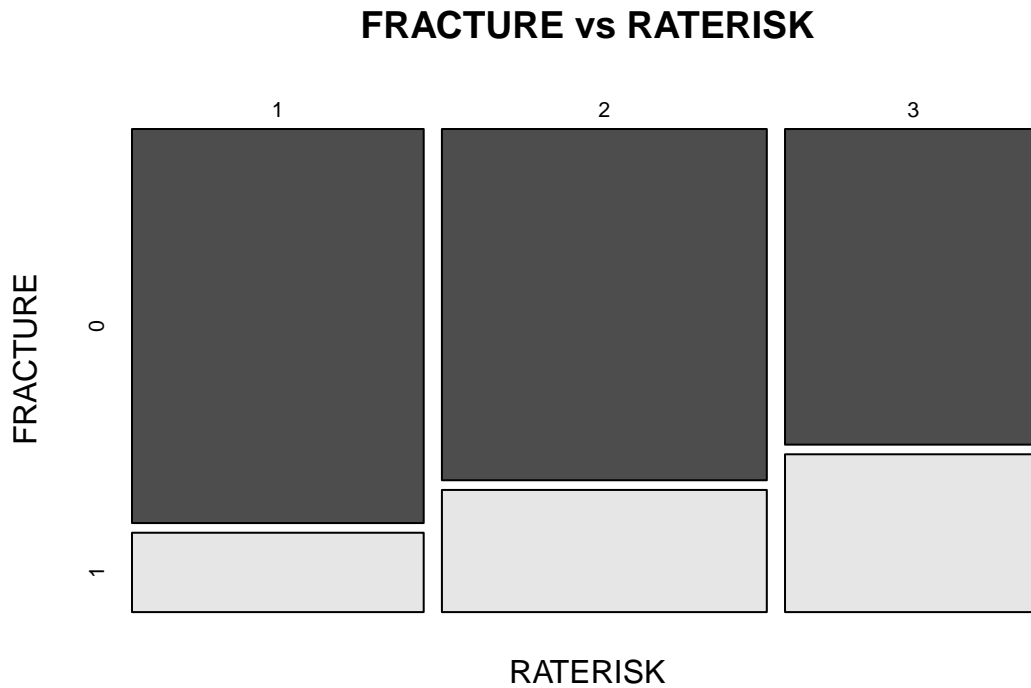
##
##
##   Cell Contents
## |-----|
## |              N |
## |      Expected N |
## | Chi-square contribution |
## |      N / Row Total |
## |      N / Col Total |
## |      N / Table Total |
## |-----|
##
##
## Total Observations in Table:  500
##
##
##           | FRACTURE
##   RATERISK |          0 |          1 | Row Total |
## |-----|-----|-----|-----|
##           1 |      139 |      28 |      167 |
##           |    125.250 |    41.750 |          |
##           |    1.509 |    4.528 |          |
##           |    0.832 |    0.168 |    0.334 |
##           |    0.371 |    0.224 |          |
##           |    0.278 |    0.056 |          |
## |-----|-----|-----|-----|
##           2 |      138 |      48 |      186 |
##           |    139.500 |    46.500 |          |
##           |    0.016 |    0.048 |          |
##           |    0.742 |    0.258 |    0.372 |
##           |    0.368 |    0.384 |          |
##           |    0.276 |    0.096 |          |
## |-----|-----|-----|-----|
##           3 |       98 |      49 |      147 |
##           |    110.250 |    36.750 |          |
##           |    1.361 |    4.083 |          |
##           |    0.667 |    0.333 |    0.294 |
##           |    0.261 |    0.392 |          |
##           |    0.196 |    0.098 |          |
## |-----|-----|-----|-----|
## Column Total |      375 |      125 |      500 |
##           |    0.750 |    0.250 |          |
## |-----|-----|-----|-----|
##
##
## Statistics for All Table Factors
##
##
## Pearson's Chi-squared test
## -----
## Chi^2 =  11.54688      d.f. =  2      p =  0.003109037
##
##
##

```

```

##
##
##   Cell Contents
## |-----|
## |               N |
## | Chi-square contribution |
## |       N / Row Total |
## |       N / Col Total |
## |       N / Table Total |
## |-----|
##
##
## Total Observations in Table:  500
##
##
##      | dataset$FRACTURE
## dataset[, categoricalVar] |      0 |      1 | Row Total |
## -----|-----|-----|-----|
##                1 |      139 |      28 |      167 |
##                |      1.509 |      4.528 |      |
##                |      0.832 |      0.168 |      0.334 |
##                |      0.371 |      0.224 |      |
##                |      0.278 |      0.056 |      |
## -----|-----|-----|-----|
##                2 |      138 |      48 |      186 |
##                |      0.016 |      0.048 |      |
##                |      0.742 |      0.258 |      0.372 |
##                |      0.368 |      0.384 |      |
##                |      0.276 |      0.096 |      |
## -----|-----|-----|-----|
##                3 |      98 |      49 |      147 |
##                |      1.361 |      4.083 |      |
##                |      0.667 |      0.333 |      0.294 |
##                |      0.261 |      0.392 |      |
##                |      0.196 |      0.098 |      |
## -----|-----|-----|-----|
##                Column Total |      375 |      125 |      500 |
##                |      0.750 |      0.250 |      |
## -----|-----|-----|-----|
##
##

```



## Exploratory Data Analysis

### Summary Tables

**Assumptions** This is a prospective study which means its a study over time of a group of similar individuals who differ with respect to certain factors under a study and how these factors affect rates of a certain outcome (Fracture vs No-Fracture) **Linearity** -

**Independence of errors** - Based on SUB\_ID(Subject ID) we confirm each record is an independent sample. **Multicollinearity** - Weight and BMI are highly correlated.

```
# display the first 20 rows
print(head(dataset, n=20))
```

##	SUB_ID	SITE_ID	PHY_ID	PRIORFRAC	AGE	WEIGHT	HEIGHT	BMI	PREMENO
## 1	1	1	14	0	62	70.3	158	28.16055	0
## 2	2	4	284	0	65	87.1	160	34.02344	0
## 3	3	6	305	1	88	50.8	157	20.60936	0
## 4	4	6	309	0	82	62.1	160	24.25781	0
## 5	5	1	37	0	61	68.0	152	29.43213	0
## 6	6	5	299	1	67	68.0	161	26.23356	0
## 7	7	5	302	0	84	50.8	150	22.57778	0
## 8	8	1	36	1	82	40.8	153	17.42919	0
## 9	9	1	8	1	86	62.6	156	25.72321	0



```
## 10      10      4    282      0 58   63.5   166 23.04398      0
## 11      11      6    315      0 67   67.6   153 28.87778      0
## 12      12      1     34      0 56  117.9   167 42.27473      0
## 13      13      6    315      0 59   67.1   162 25.56775      0
## 14      14      1     33      0 72   57.6   165 21.15702      0
## 15      15      1     23      0 64   61.2   160 23.90625      1
## 16      16      3    179      0 68   78.0   161 30.09143      0
## 17      17      4    284      0 67  105.7   165 38.82461      0
## 18      18      4    283      0 69   65.8   162 25.07240      0
## 19      19      3    179      1 78   81.6   162 31.09282      0
## 20      20      6    313      0 60   56.7   157 23.00296      0
##      MOMFRAC  ARMASSIST  SMOKE  RATERISK  FRACTURE
## 1          0          0      0          2          0
## 2          0          0      0          2          0
## 3          1          1      0          1          0
## 4          0          0      0          1          0
## 5          0          0      0          2          0
## 6          0          0      1          2          0
## 7          0          0      0          1          0
## 8          0          0      0          2          0
## 9          0          0      0          2          0
## 10         0          0      0          1          0
## 11         1          0      1          1          0
## 12         0          1      1          2          0
## 13         0          0      1          1          0
## 14         0          1      0          1          0
## 15         0          0      0          2          0
## 16         0          1      0          1          0
## 17         0          0      0          1          0
## 18         0          0      0          2          0
## 19         0          1      0          3          0
## 20         0          0      0          2          0
```

```
# display the dimensions of the dataset
print(dim(dataset))
```

```
## [1] 500 14
```

```
# list types for each attribute
print(sapply(dataset,class))
```

```
##      SUB_ID  SITE_ID  PHY_ID PRIORFRAC      AGE  WEIGHT  HEIGHT
## "integer" "integer" "integer" "integer" "integer" "numeric" "integer"
##      BMI  PREMENO  MOMFRAC ARMASSIST      SMOKE  RATERISK  FRACTURE
## "numeric" "integer" "integer" "integer" "integer" "integer" "integer"
```

```
# summarize the dataset
print(summary(set_noID))
```

```
##      PRIORFRAC      AGE      WEIGHT      HEIGHT
## Min.   :0.000  Min.   :55.00  Min.   : 39.90  Min.   :134.0
## 1st Qu.:0.000  1st Qu.:61.00  1st Qu.: 59.90  1st Qu.:157.0
```

```
## Median :0.000    Median :67.00    Median : 68.00    Median :161.5
## Mean   :0.252    Mean   :68.56    Mean   : 71.82    Mean   :161.4
## 3rd Qu.:1.000    3rd Qu.:76.00    3rd Qu.: 81.30    3rd Qu.:165.0
## Max.   :1.000    Max.   :90.00    Max.   :127.00    Max.   :199.0
##      BMI      PREMENO      MOMFRAC      ARMASSIST
## Min.   :14.88    Min.   :0.000    Min.   :0.00    Min.   :0.000
## 1st Qu.:23.27    1st Qu.:0.000    1st Qu.:0.00    1st Qu.:0.000
## Median :26.42    Median :0.000    Median :0.00    Median :0.000
## Mean   :27.55    Mean   :0.194    Mean   :0.13    Mean   :0.376
## 3rd Qu.:30.79    3rd Qu.:0.000    3rd Qu.:0.00    3rd Qu.:1.000
## Max.   :49.08    Max.   :1.000    Max.   :1.00    Max.   :1.000
##      SMOKE      RATERISK      FRACTURE
## Min.   :0.00    Min.   :1.00    Min.   :0.00
## 1st Qu.:0.00    1st Qu.:1.00    1st Qu.:0.00
## Median :0.00    Median :2.00    Median :0.00
## Mean   :0.07    Mean   :1.96    Mean   :0.25
## 3rd Qu.:0.00    3rd Qu.:3.00    3rd Qu.:0.25
## Max.   :1.00    Max.   :3.00    Max.   :1.00
```

```
# Standard Deviations for the non-categorical columns
std=sapply(set_noID,sd)
print('The standard deviations are:')
```

```
## [1] "The standard deviations are:"
```

```
print(std)
```

```
## PRIORFRAC      AGE      WEIGHT      HEIGHT      BMI      PREMENO
## 0.4345961  8.9895372 16.4359918  6.3554928  5.9739583  0.3958249
##      MOMFRAC  ARMASSIST      SMOKE      RATERISK      FRACTURE
## 0.3366402  0.4848651  0.2554025  0.7922470  0.4334464
```

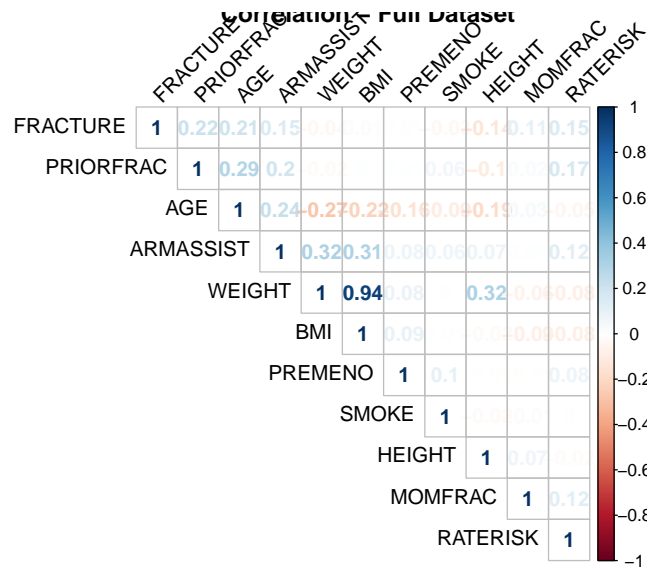
```
# Skewness
#The further the distribution of the skew value from zero,
# the larger the skew to the left (negative skew value) or right (positive skew value).
#library(e1071) # the library for skewness
library(e1071)

skew=sapply(set_noID[,c(1:11)], 2, skewness)
print(skew)
```

```
## PRIORFRAC      AGE      WEIGHT      HEIGHT      BMI      PREMENO
## 1.13900707 0.42737676 0.80951443 0.25181286 0.85717095 1.54304591
##      MOMFRAC  ARMASSIST      SMOKE      RATERISK      FRACTURE
## 2.19379594 0.51045948 3.36049899 0.07085255 1.15123817
```

```
# Correlations
library(corrplot)

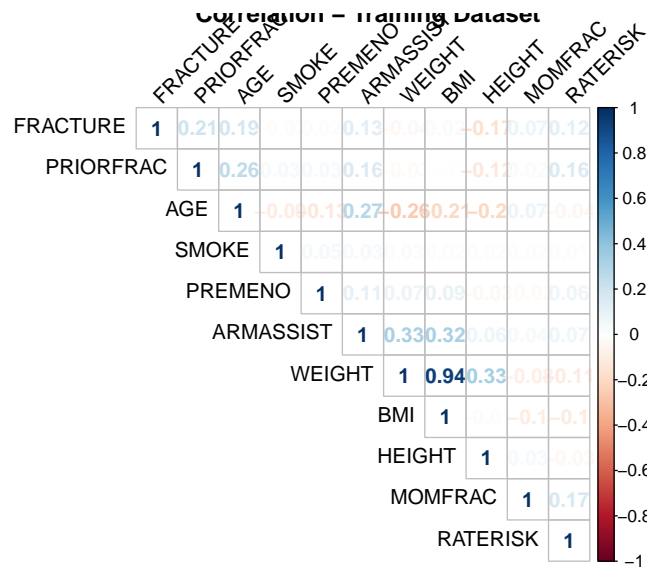
#Full dataset without ID columns
corrplot(cor(set_noID), method = "number", type = "upper", order = "hclust",
          tl.col = "black", tl.srt = 45,main="Correlation - Full Dataset")
```



```
#Training data set without ID columns
#split the data into training and validation sets
library(caret)
```

```
## Loading required package: lattice
```

```
set.seed(84)
validation_index = createDataPartition(dataset$FRACTURE, p=0.75, list=FALSE)
validationData = set_noID[-validation_index,]
trainingData = set_noID[validation_index,]
corrplot(cor(trainingData), method = "number", type = "upper", order = "hclust",
          tl.col = "black", tl.srt = 45, main="Correlation - Training Dataset")
```



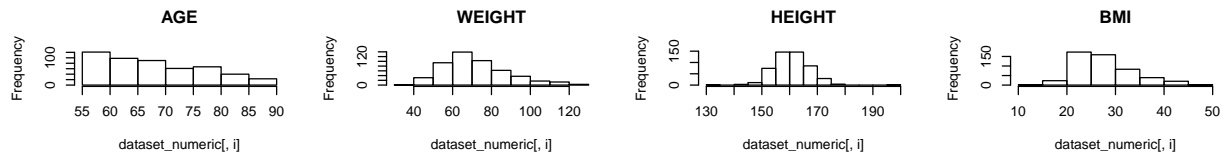
```
# Data visualizations
dataset_numeric = numericVar
```

```

#Histograms
par(mfrow=c(3,4)) # put four figures in a row (2*4)
for (i in 1:4) {
  hist(dataset_numeric[,i],main=names(dataset_numeric)[i])
}

#Density Plots
par(mfrow=c(3,4))

```

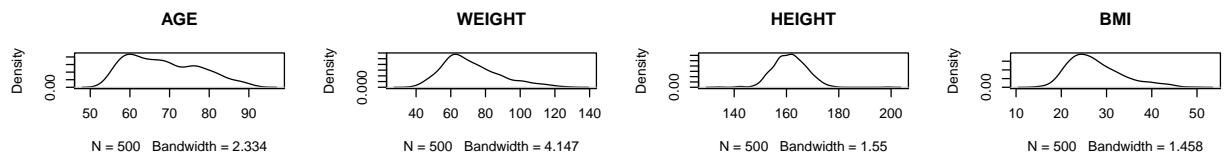


```

for(i in 1:4) {
  plot(density(dataset_numeric[,i]), main=names(dataset_numeric)[i])
}

#Box And Whisker Plots
par(mfrow=c(3,4))

```



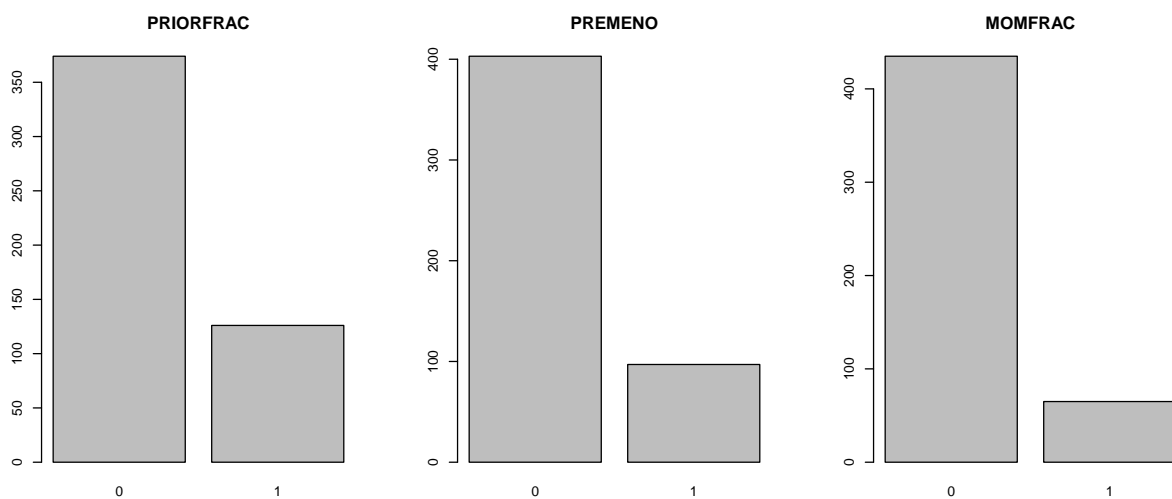
```
for(i in 1:4) {
  boxplot(dataset_numeric[,i], main=names(dataset_numeric)[i])
}
```

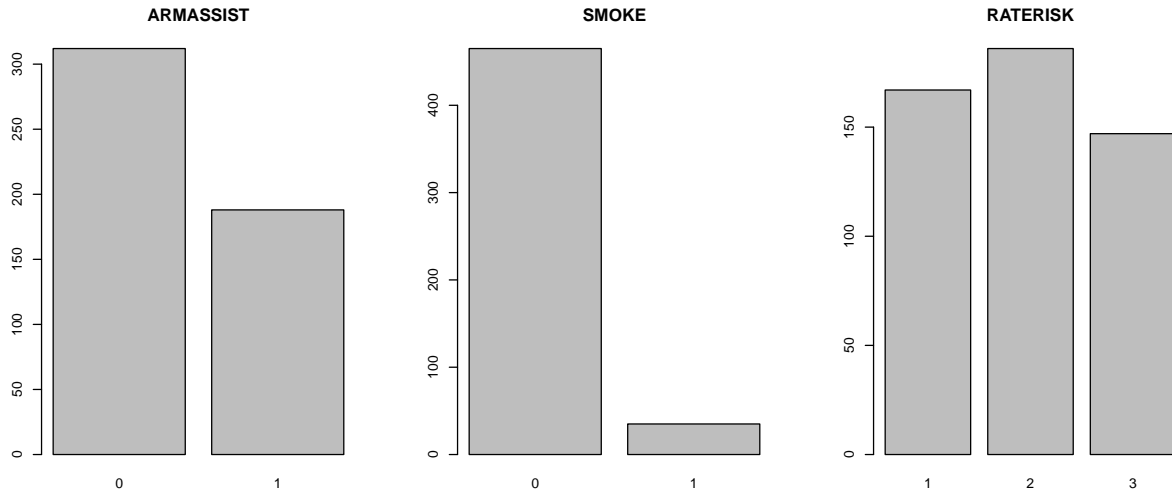
*#Barplots, which is used to count the accurances for categorical attributes*

```
dataset_categorical = set_noID[, -c(2:5)]
par(mfrow=c(1,3))
```



```
for(i in 1:7) {
  counts <- table(dataset_categorical[,i]) # get the count for each categorical value
  name <- names(dataset_categorical)[i]
  barplot(counts, main=name)
}
```

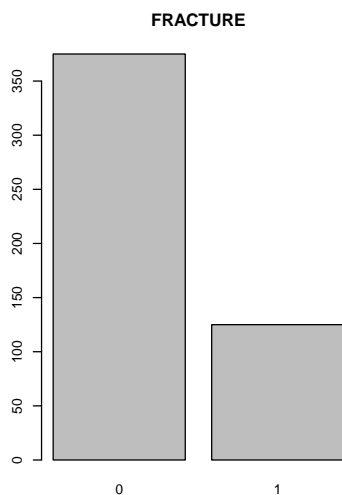




```
#Multivariate Visualization
library(corrplot) # for function corrplot()
correlations1=cor(dataset_numeric)
print(correlations1)
```

```
##          AGE      WEIGHT      HEIGHT      BMI
## AGE      1.0000000 -0.2715964 -0.19264861 -0.22125651
## WEIGHT  -0.2715964  1.0000000  0.31596915  0.93733603
## HEIGHT  -0.1926486  0.3159691  1.00000000 -0.02437689
## BMI      -0.2212565  0.9373360 -0.02437689  1.00000000
```

```
par(mfrow=c(1,1))
```

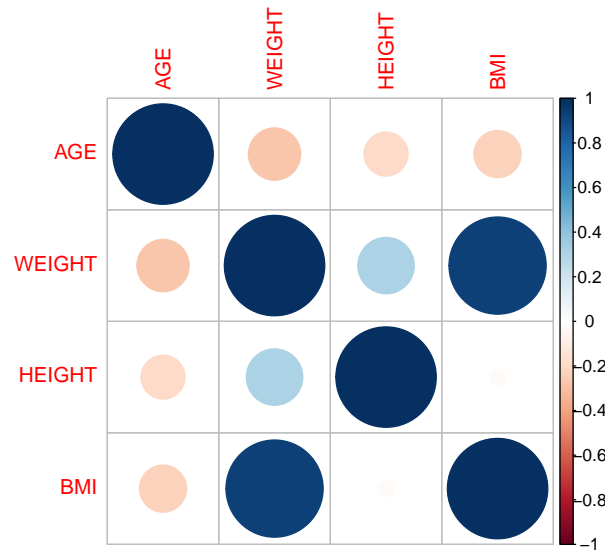


```
corrplot(correlations1, methods="circle")
```

```
## Warning in text.default(pos.xlabel[, 1], pos.xlabel[, 2], newcolnames, srt
## = tl.srt, : "methods" is not a graphical parameter
```

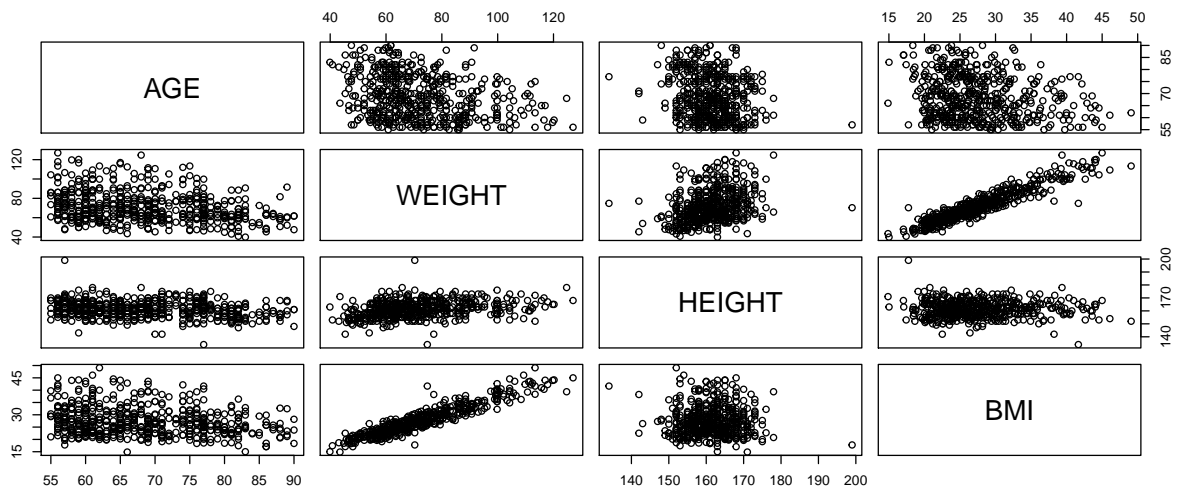
```
## Warning in text.default(pos.ylabel[, 1], pos.ylabel[, 2], newrownames, col
## = tl.col, : "methods" is not a graphical parameter
```

```
## Warning in title(title, ...): "methods" is not a graphical parameter
```



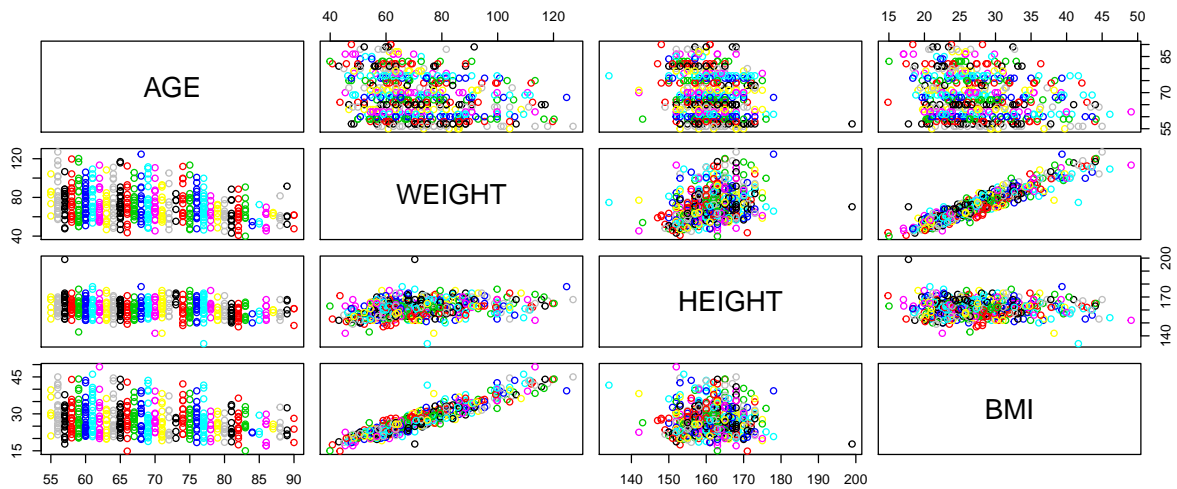
```
# pair-wise scatterplots of the numeric attributes
```

```
par(mfrow=c(1,1))
pairs(dataset_numeric)
```



```
#Scatterplot Matrix By Class (use different color to distinguish different class)
```

```
par(mfrow=c(1,1))
pairs(dataset_numeric, col=dataset[,5])
```



```
#Density By Class
library(caret)

# load the data
data(iris)

# density plots for each attribute by class value
x <- dataset_numeric
y <- dataset[,5]
scales <- list(x=list(relation="free"), y=list(relation="free"))
par(mfrow=c(1,1))
featurePlot(x=dataset_numeric, y=dataset[,5], plot="density", scales=scales)
```

```
## NULL
```

```
#Box And Whisker Plots By Class
featurePlot(x=dataset_numeric, y=dataset[,5], plot="box")
```

```
## NULL
```

## Logistic Regression

### Train / Test

Training set will be 70% of dataset and Test set will be remaining 30%

```
#smp_size <- floor(0.70 * nrow(dataset))
#set.seed(1234)
#train_ind <- sample(seq_len(nrow(dataset)), size=smp_size)
#test <- dataset[-train_ind,]
#train <- dataset[train_ind,]
```



```
# split the data into training and validation sets
library(caret)
set.seed(84)
validation_index = createDataPartition(dataset$FRACTURE, p=0.75, list=FALSE)
validationData = set_noID[-validation_index,]
trainingData = set_noID[validation_index,]

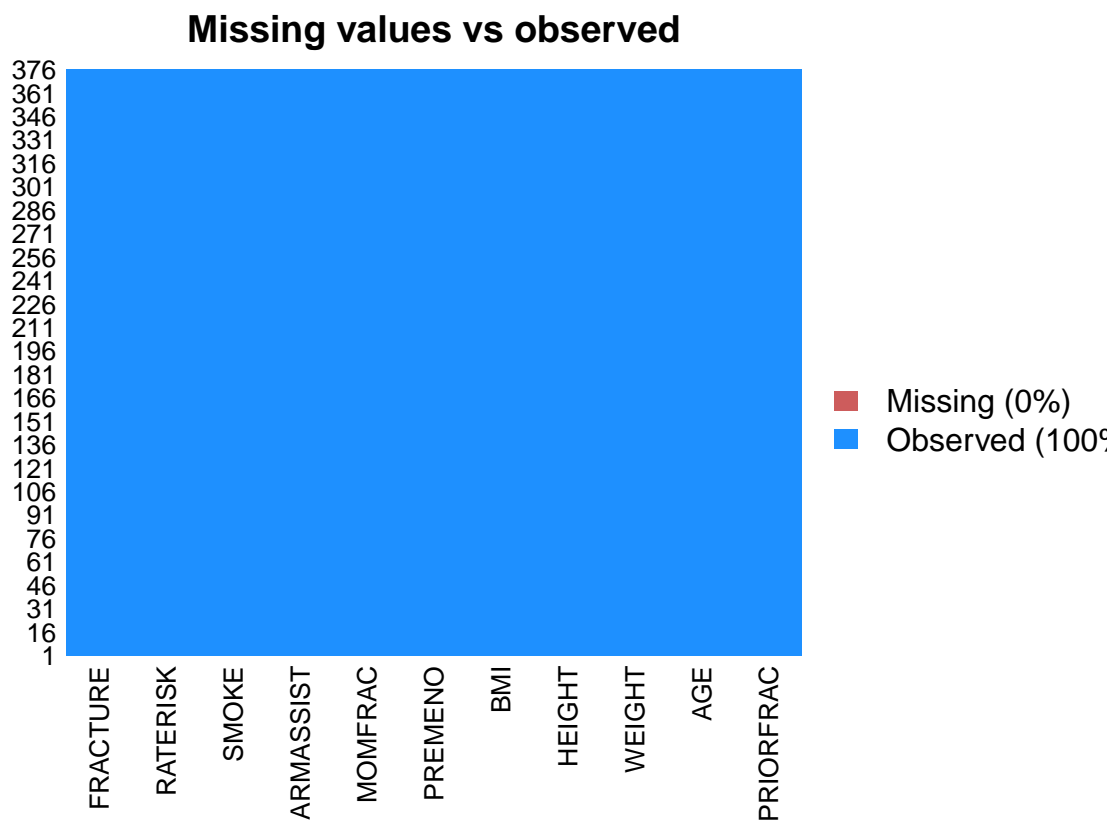
#check for Missing Data
sapply(trainingData,function(x) sum(is.na(x)))
```

```
## PRIORFRAC      AGE      WEIGHT      HEIGHT      BMI      PREMENO      MOMFRAC
##           0           0           0           0           0           0           0
## ARMASSIST      SMOKE      RATERISK      FRACTURE
##           0           0           0           0
```

```
sapply(trainingData, function(x) length(unique(x)))
```

```
## PRIORFRAC      AGE      WEIGHT      HEIGHT      BMI      PREMENO      MOMFRAC
##           2          36          120          33          318           2           2
## ARMASSIST      SMOKE      RATERISK      FRACTURE
##           2           2           3           2
```

```
missmap(trainingData, main = "Missing values vs observed") #library(Amelia)
```



```
##Build Model
```

Question of Interest? What are the odds of getting a fracture, given certain conditions?

```
set.seed(84)
model <- glm(FRACTURE~.,family = "binomial" (link='logit'), data=set_noID)
model
```

```
##
## Call:  glm(formula = FRACTURE ~ ., family = binomial(link = "logit"),
##       data = set_noID)
##
## Coefficients:
## (Intercept)  PRIORFRAC      AGE      WEIGHT      HEIGHT
## -16.03863    0.67285    0.03915   -0.12152    0.06564
##      BMI      PREMENO    MOMFRAC  ARMASSIST      SMOKE
##   0.33126    0.10438    0.63679    0.35875   -0.31360
##  RATERISK
##   0.37666
##
## Degrees of Freedom: 499 Total (i.e. Null);  489 Residual
## Null Deviance:      562.3
## Residual Deviance: 503.9      AIC: 525.9
```

```
summary(model)
```

```
##
## Call:
## glm(formula = FRACTURE ~ ., family = binomial(link = "logit"),
##      data = set_noID)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.6882  -0.7254  -0.5654  -0.0960   2.2111
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -16.03863   12.66515  -1.266  0.20538
## PRIORFRAC    0.67285    0.24967   2.695  0.00704 **
## AGE          0.03915    0.01471   2.662  0.00778 **
## WEIGHT      -0.12152    0.08658  -1.404  0.16044
## HEIGHT       0.06564    0.07815   0.840  0.40098
## BMI          0.33126    0.22326   1.484  0.13787
## PREMENO      0.10438    0.28486   0.366  0.71406
## MOMFRAC      0.63679    0.30767   2.070  0.03848 *
## ARMASSIST    0.35875    0.25615   1.401  0.16134
## SMOKE       -0.31360    0.46222  -0.678  0.49747
## RATERISK     0.37666    0.14896   2.529  0.01145 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 562.34  on 499  degrees of freedom
## Residual deviance: 503.87  on 489  degrees of freedom
```

```
## AIC: 525.87
##
## Number of Fisher Scoring iterations: 4
```

Interpretation of logistic regression model: Weight, height, BMI, Premeno, Armassist, and Smoke are not statistically significant variables. Priorfrac and Age are statistically significant variables and have the lowest p-value indicating a strong association with having a Fracture.

```
##glmnet
dat <- categoricalVar

#Get Training Set
dat.train <- trainingData

dat.train.x <- dat.train[,1:ncol(dat.train)]
dat.train.y <- dat.train$FRACTURE

dat.train.y <- as.factor(as.character(dat.train.y))

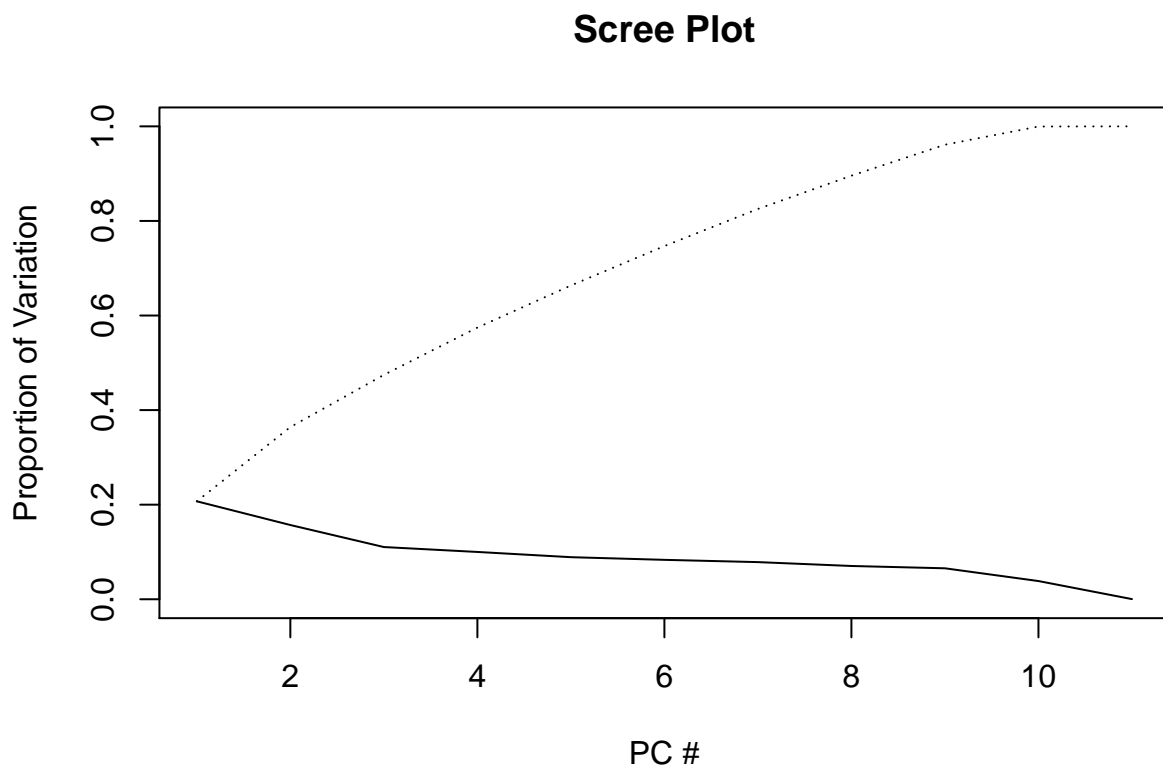
#PCA
pc.result<-prcomp(dat.train.x,scale.=TRUE)
pc.scores<-pc.result$x
pc.scores<-data.frame(pc.scores)
pc.scores$FRACTURE<-dat.train.y

PCA <- pc.result$rotation
PCA
```

```
##          PC1          PC2          PC3          PC4          PC5
## PRIORFRAC 0.07405715 -0.47973677 0.04196542 0.09391798 -0.13590836
## AGE       0.25108797 -0.44246880 -0.36503870 -0.23606187 -0.19052036
## WEIGHT    -0.64071593 -0.07386956 -0.01492425 -0.09380628 0.04511049
## HEIGHT    -0.22890271 0.24187107 0.22588400 -0.52730271 -0.16245665
## BMI       -0.59713909 -0.16251927 -0.09572198 0.09472088 0.11445051
## PREMENO   -0.11505234 -0.07693268 0.32458960 0.55307931 0.16142556
## MOMFRAC    0.11007196 -0.13173669 0.46323427 -0.46128883 0.06458940
## ARMASSIST -0.25734750 -0.47047462 -0.02257374 -0.19863859 -0.16959440
## SMOKE      -0.04972241 0.01391670 0.31483340 0.26442893 -0.86124378
## RATERISK   0.10918438 -0.20973926 0.61992312 -0.03166000 0.26572927
## FRACTURE   0.07750976 -0.44147408 0.02641809 0.10280064 0.17988806
##          PC6          PC7          PC8          PC9          PC10
## PRIORFRAC 0.009110347 -0.51653703 0.12726745 -0.65076852 -0.16932571
## AGE       0.245357588 0.13034942 0.07530809 0.08177107 0.65295027
## WEIGHT    -0.120183672 -0.03235101 0.02116421 -0.08190948 0.22942735
## HEIGHT    0.327444296 -0.34498645 -0.46918526 -0.08143823 0.14936479
## BMI       -0.245140543 0.09823153 0.18404370 -0.05154601 0.18874838
## PREMENO   0.622965173 0.25696963 -0.17636604 -0.16498653 0.17626188
## MOMFRAC   -0.148794845 0.59700737 0.10567492 -0.38334831 -0.04799385
## ARMASSIST 0.368115390 0.11545494 0.07410041 0.40014322 -0.57380527
## SMOKE     -0.230599843 0.09342985 -0.02981247 0.11155875 0.10632225
## RATERISK  -0.084062927 -0.37403086 0.29943887 0.43734477 0.24549790
## FRACTURE  -0.389848139 0.04558067 -0.76508915 0.12573228 -0.01463757
##          PC11
## PRIORFRAC -0.0073515954
```

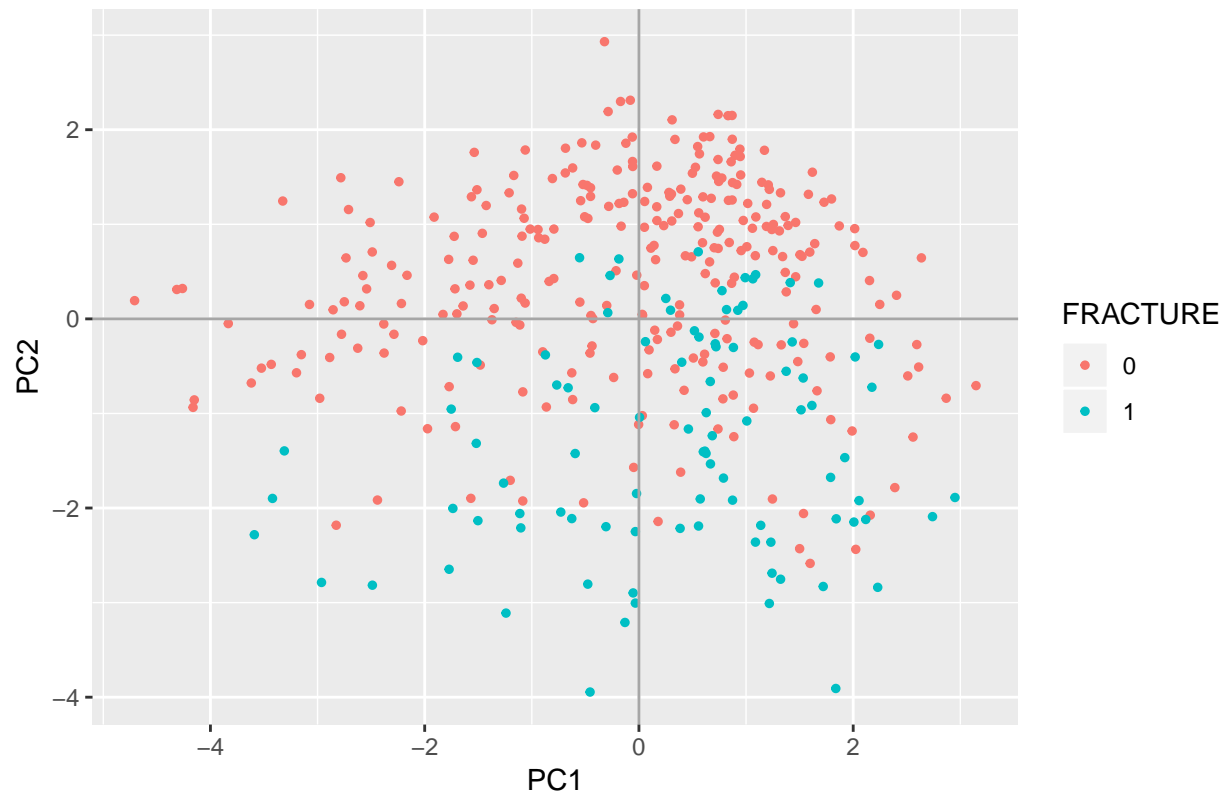
```
## AGE      -0.0025546320
## WEIGHT   0.7054674906
## HEIGHT   -0.2415073104
## BMI      -0.6662434928
## PREMENO  0.0042646791
## MOMFRAC  0.0004639497
## ARMASSIST -0.0001841958
## SMOKE    -0.0025392898
## RATERISK -0.0004029694
## FRACTURE 0.0048813762
```

```
#Scree plot
pc.eigen<-(pc.result$sdev)^2
pc.prop<-pc.eigen/sum(pc.eigen)
pc.cumprop<-cumsum(pc.prop)
plot(1:11,pc.prop,type="l",main="Scree Plot",ylim=c(0,1),xlab="PC #",ylab="Proportion of Variation")
lines(1:11,pc.cumprop,lty=3)
```



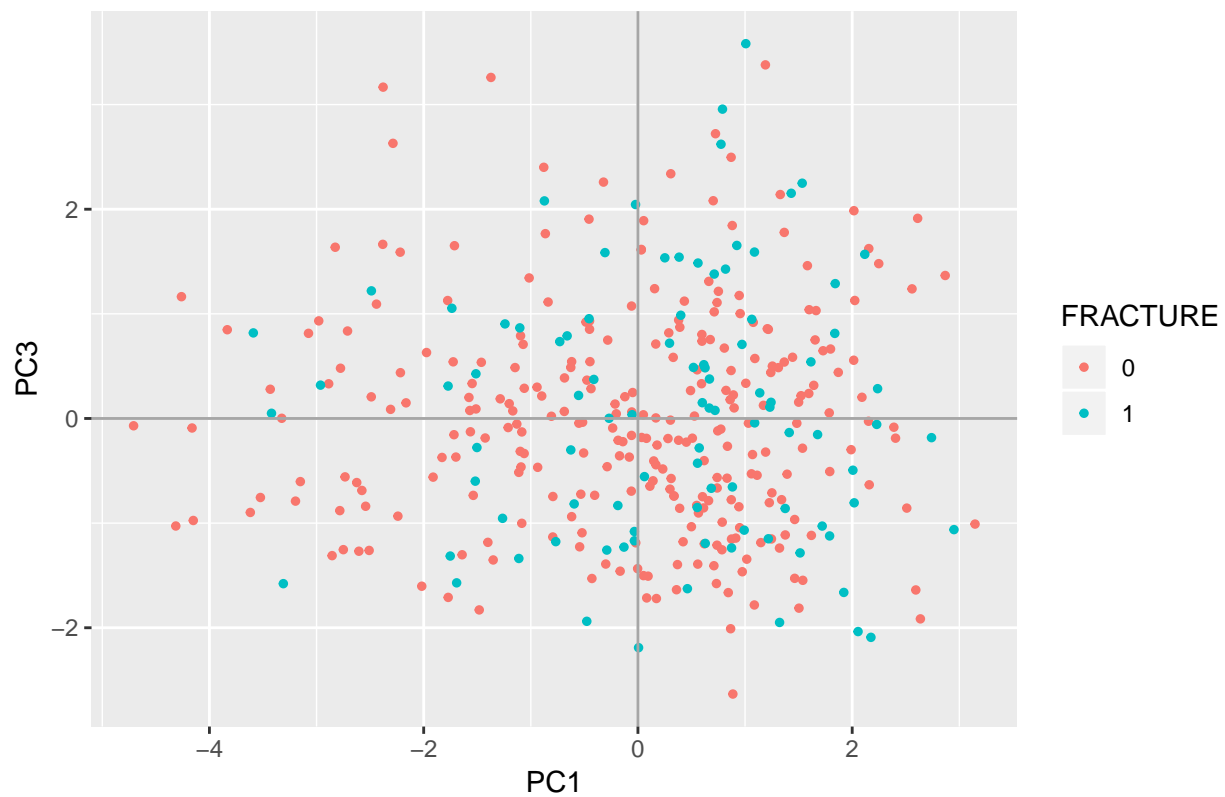
```
#Use ggplot2 to plot the first few pc's
ggplot(data = pc.scores, aes(x = PC1, y = PC2)) + geom_point(aes(col=FRACTURE), size=1) + geom_hline(yi
```

PCA plot of Osteo Study



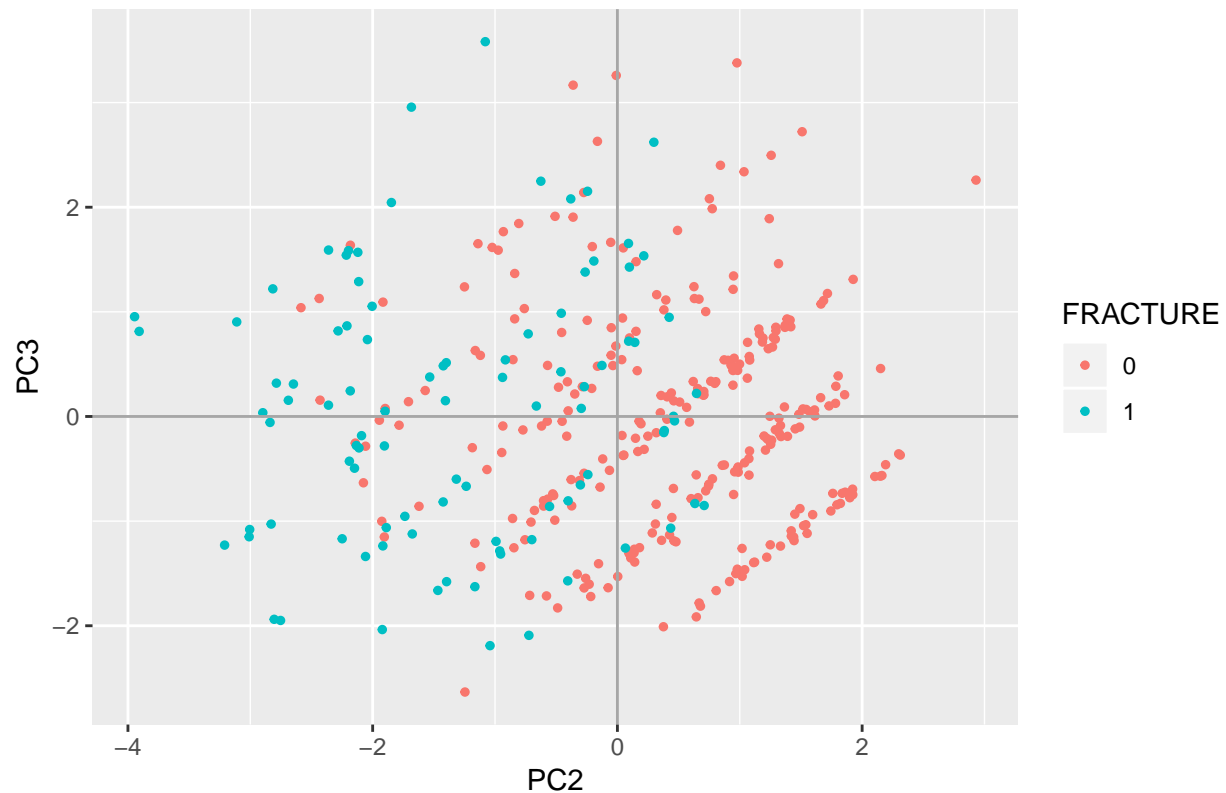
```
ggplot(data = pc.scores, aes(x = PC1, y = PC3)) + geom_point(aes(col=FRACTURE), size=1) + geom_hline(yi
```

PCA plot of Osteo Study



```
ggplot(data = pc.scores, aes(x = PC2, y = PC3)) + geom_point(aes(col=FRACTURE), size=1) + geom_hline(yi
```

PCA plot of Osteo Study

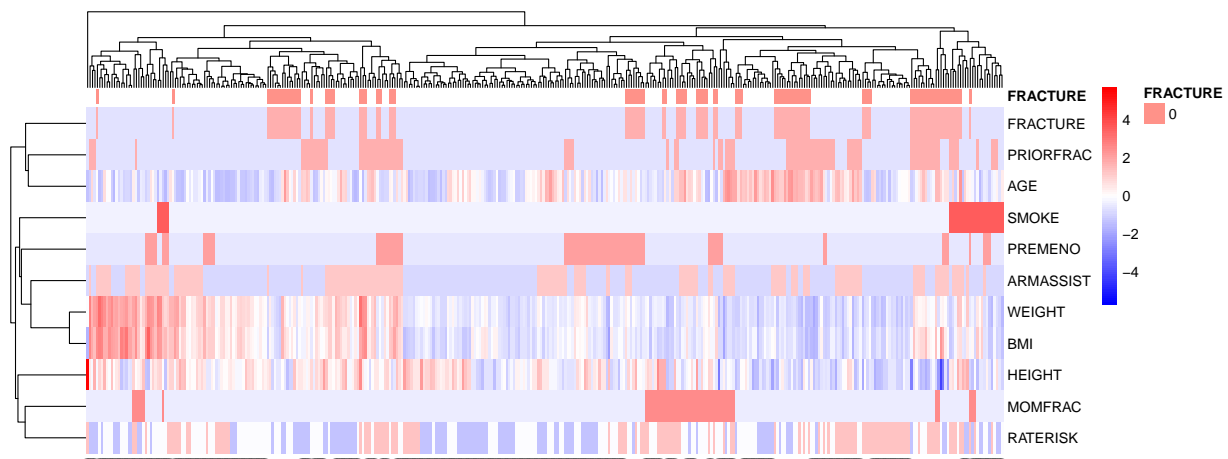


##Clustering

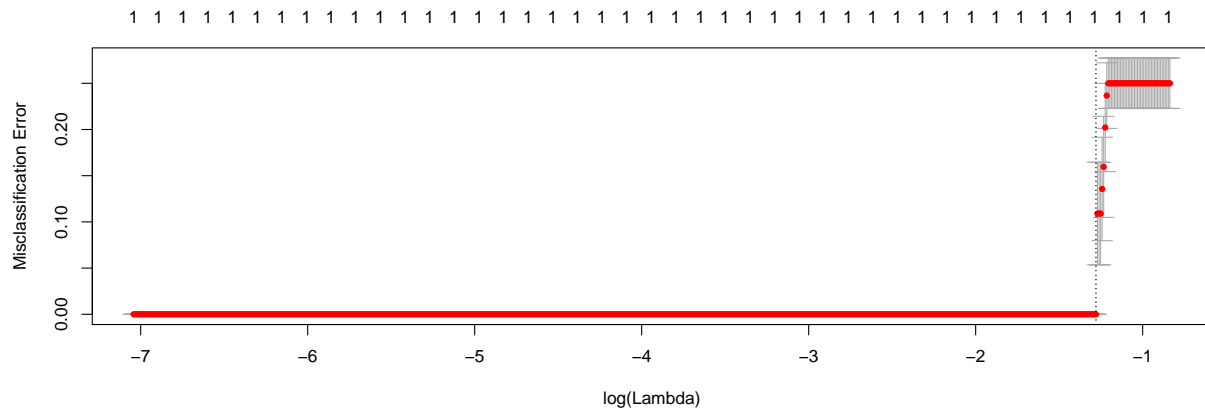
*#Lets look at a heatmap using hierarchical clustering to see if the  
#response naturally clusters out using the predictors*

*#Transposing the predictor matrix and giving the response categories its  
#row names.*

```
library(RColorBrewer)
x<-t(dat.train.x)
colnames(x)<-dat.train.y
pheatmap(x,annotation_col=data.frame(FRACTURE=dat.train.y),scale="row",legend=T,color=colorRampPalette(
```



```
##logistic regression
dat.train.x <- as.matrix(dat.train.x)
library(glmnet)
cvfit <- cv.glmnet(dat.train.x, dat.train.y, family = "binomial", type.measure = "class", nlambda = 100)
plot(cvfit)
```



```
coef(cvfit, s = "lambda.min")
```

```
## 12 x 1 sparse Matrix of class "dgCMatrix"
##              1
## (Intercept) -1.653758
## PRIORFRAC    .
## AGE          .
## WEIGHT       .
## HEIGHT       .
## BMI          .
## PREMENO      .
## MOMFRAC      .
## ARMASSIST    .
## SMOKE        .
## RATERISK     .
## FRACTURE     1.726571
```