MBA Starting Salaries

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Read the data

```
mba.df <- read.csv(paste("MBA Starting Salaries Data.csv", sep=""))
View(mba.df)
```

Attach the dataframe

```
attach(mba.df)
```

Summarize the data

```
summary(mba.df)
```

```
##      age            sex          gmat_tot       gmat_qpc
##  Min.   :22.00   Min.   :1.000   Min.   :450.0   Min.   :28.00
##  1st Qu.:25.00   1st Qu.:1.000   1st Qu.:580.0   1st Qu.:72.00
##  Median :27.00   Median :1.000   Median :620.0   Median :83.00
##  Mean   :27.36   Mean   :1.248   Mean   :619.5   Mean   :80.64
##  3rd Qu.:29.00   3rd Qu.:1.000   3rd Qu.:660.0   3rd Qu.:93.00
##  Max.   :48.00   Max.   :2.000   Max.   :790.0   Max.   :99.00
##    gmat_vpc        gmat_tpc        s_avg          f_avg
##  Min.   :16.00   Min.   : 0.0   Min.   :2.000   Min.   :0.000
##  1st Qu.:71.00   1st Qu.:78.0   1st Qu.:2.708   1st Qu.:2.750
##  Median :81.00   Median :87.0   Median :3.000   Median :3.000
##  Mean   :78.32   Mean   :84.2   Mean   :3.025   Mean   :3.062
##  3rd Qu.:91.00   3rd Qu.:94.0   3rd Qu.:3.300   3rd Qu.:3.250
##  Max.   :99.00   Max.   :99.0   Max.   :4.000   Max.   :4.000
##    quarter        work_yrs        frstlang        salary
##  Min.   :1.000   Min.   : 0.000   Min.   :1.000   Min.   :     0
##  1st Qu.:1.250   1st Qu.: 2.000   1st Qu.:1.000   1st Qu.:     0
##  Median :2.000   Median : 3.000   Median :1.000   Median :   999
##  Mean   :2.478   Mean   : 3.872   Mean   :1.117   Mean   : 39026
##  3rd Qu.:3.000   3rd Qu.: 4.000   3rd Qu.:1.000   3rd Qu.: 97000
##  Max.   :4.000   Max.   :22.000   Max.   :2.000   Max.   :220000
##     satis
##  Min.   :  1.0
##  1st Qu.:  5.0
##  Median :  6.0
##  Mean   :172.2
##  3rd Qu.:  7.0
##  Max.   :998.0
```

```
library(psych)
describe(mba.df)
```

```
##         vars   n     mean       sd median  trimmed     mad min    max
## age        1 274    27.36     3.71     27    26.76    2.97  22     48
## sex        2 274     1.25     0.43      1     1.19    0.00   1      2
## gmat_tot    3 274   619.45    57.54    620   618.86   59.30 450    790
## gmat_qpc    4 274    80.64    14.87     83    82.31   14.83  28     99
## gmat_vpc    5 274    78.32    16.86     81    80.33   14.83  16     99
## gmat_tpc    6 274    84.20    14.02     87    86.12   11.86   0     99
## s_avg       7 274     3.03     0.38      3     3.03    0.44   2      4
## f_avg       8 274     3.06     0.53      3     3.09    0.37   0      4
## quarter     9 274     2.48     1.11      2     2.47    1.48   1      4
## work_yrs   10 274     3.87     3.23      3     3.29    1.48   0     22
## frstlang   11 274     1.12     0.32      1     1.02    0.00   1      2
## salary     12 274 39025.69 50951.56    999 33607.86 1481.12   0 220000
## satis      13 274   172.18   371.61      6    91.50    1.48   1    998
##         range  skew kurtosis      se
## age        26  2.16     6.45    0.22
## sex         1  1.16    -0.66    0.03
## gmat_tot    340 -0.01     0.06    3.48
## gmat_qpc     71 -0.92     0.30    0.90
## gmat_vpc     83 -1.04     0.74    1.02
## gmat_tpc     99 -2.28     9.02    0.85
## s_avg        2 -0.06    -0.38    0.02
## f_avg        4 -2.08    10.85    0.03
## quarter      3  0.02    -1.35    0.07
## work_yrs     22  2.78     9.80    0.20
## frstlang     1  2.37     3.65    0.02
## salary   220000  0.70    -1.05 3078.10
## satis       997  1.77     1.13   22.45
```

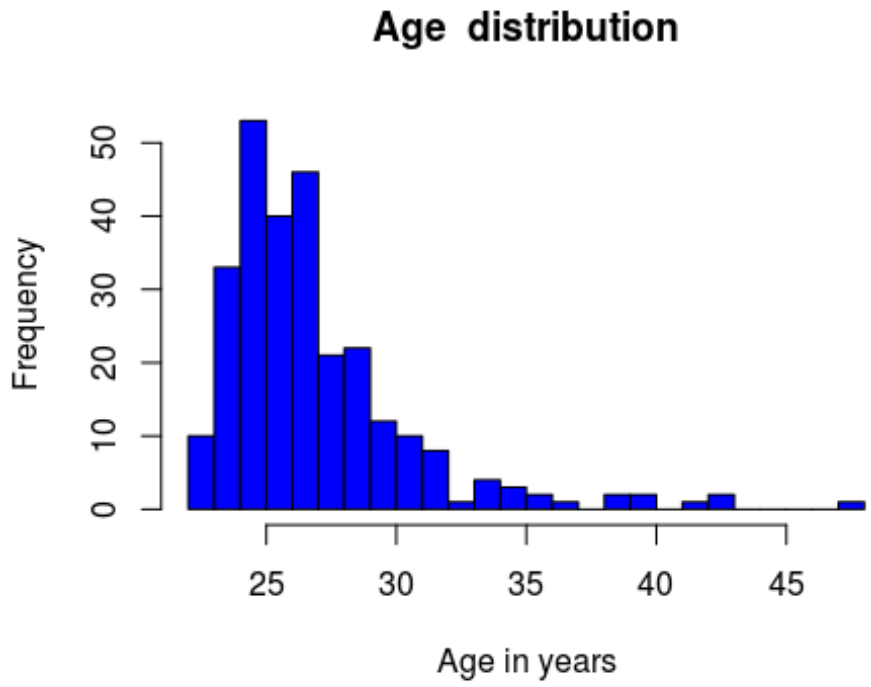
Data Types

```
str(mba.df)
```

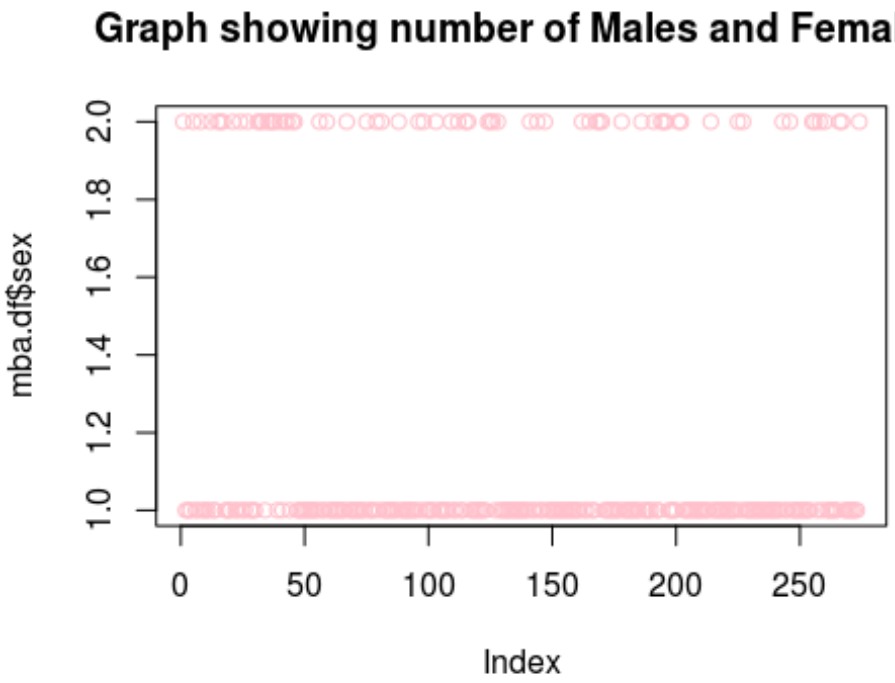
```
## 'data.frame':    274 obs. of  13 variables:
##  $ age     : int  23 24 24 24 24 24 25 25 25 25 ...
##  $ sex     : int  2 1 1 1 2 1 1 2 1 1 ...
##  $ gmat_tot: int  620 610 670 570 710 640 610 650 630 680 ...
##  $ gmat_qpc: int  77 90 99 56 93 82 89 88 79 99 ...
##  $ gmat_vpc: int  87 71 78 81 98 89 74 89 91 81 ...
##  $ gmat_tpc: int  87 87 95 75 98 91 87 92 89 96 ...
##  $ s_avg   : num  3.4 3.5 3.3 3.3 3.6 3.9 3.4 3.3 3.3 3.45 ...
##  $ f_avg   : num  3 4 3.25 2.67 3.75 3.75 3.5 3.75 3.25 3.67 ...
##  $ quarter : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ work_yrs: int  2 2 2 1 2 2 2 2 2 2 ...
##  $ frstlang: int  1 1 1 1 1 1 1 1 2 1 ...
##  $ salary  : int  0 0 0 0 999 0 0 0 999 998 ...
##  $ satis   : int  7 6 6 7 5 6 5 6 4 998 ...
```

Visualization

```
hist(mba.df$age, breaks=20,col="blue",xlab="Age in years", main="Age distribution")
```

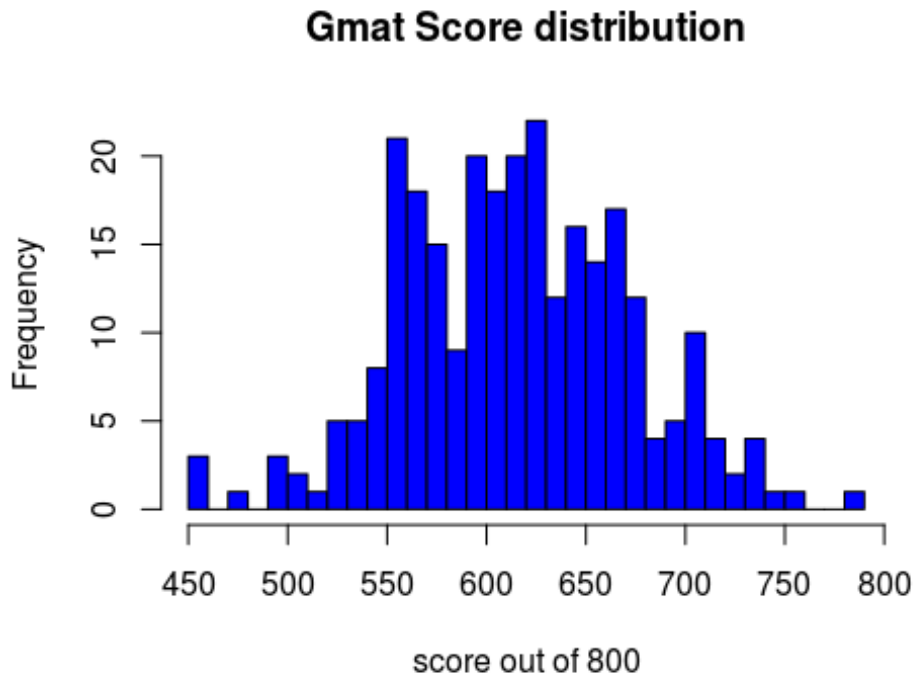



```
plot(mba.df$sex,main = "Graph showing number of Males and Females",col="pink")
```

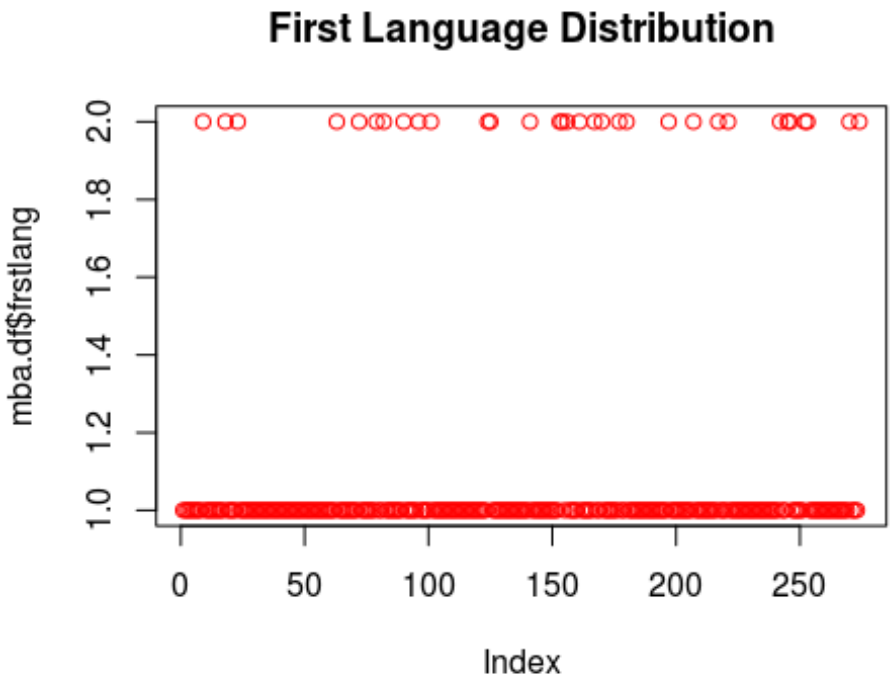



```
hist(mba.df$work_yrs, breaks=20,col="blue",xlab="Work Experience in
years", main="Work experience distribution")
```

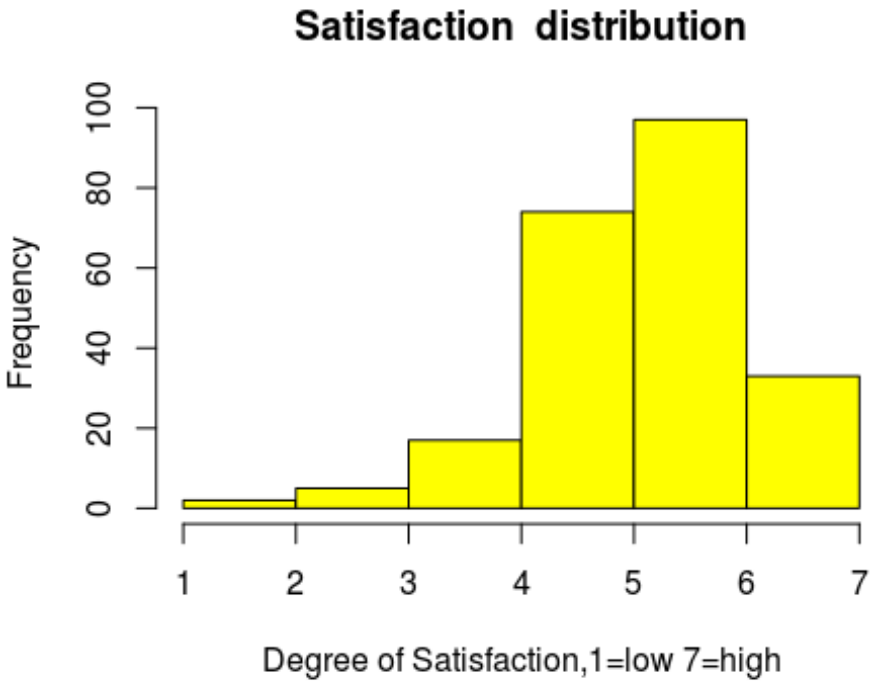
```
hist(mba.df$gmat_tot, breaks=40,col="blue",xlab="score out of 800",
main="Gmat Score distribution")
```



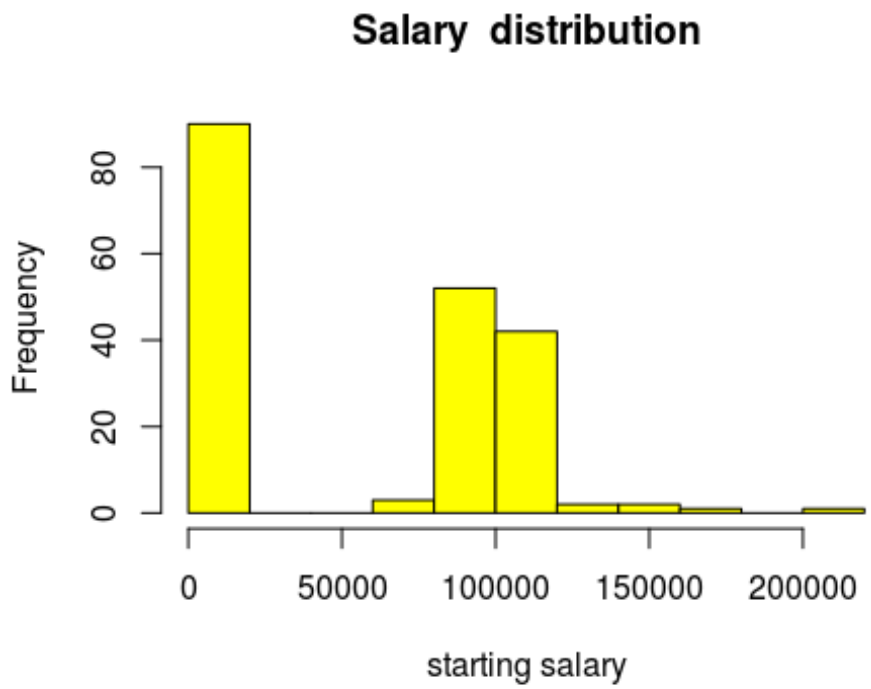

```
plot(mba.df$frstlang,main = "First Language Distribution",col="red")
```




```
newdata <- mba.df[ which(mba.df$satis<='7'), ]
hist(newdata$satis, breaks=5,col="yellow",xlab="Degree of
Satisfaction,1=low 7=high", main="Satisfaction  distribution")
```



```
newdata1 <- mba.df[ which(mba.df$salary !="998" & mba.df$salary !
="999"), ]
hist(newdata1$salary, breaks=10,col="yellow",xlab="starting salary",
main="Salary  distribution")
```




```
aggregate(cbind(salary, work_yrs, age) ~ sex, data = mba.df, mean)   #
Effect of gender on salary

##   sex   salary work_yrs      age
## 1   1 37013.62 3.893204 27.41748
## 2   2 45121.07 3.808824 27.17647

boxplot(salary ~ sex ,data=mba.df,col = c("magenta","green"), main="Effect
of Gender on Salary", ylab="Gender", xlab="Starting Salary")
```


```
aggregate(cbind(salary, work_yrs) ~ age, data = mba.df, mean)    # Effect of age on Salary
```

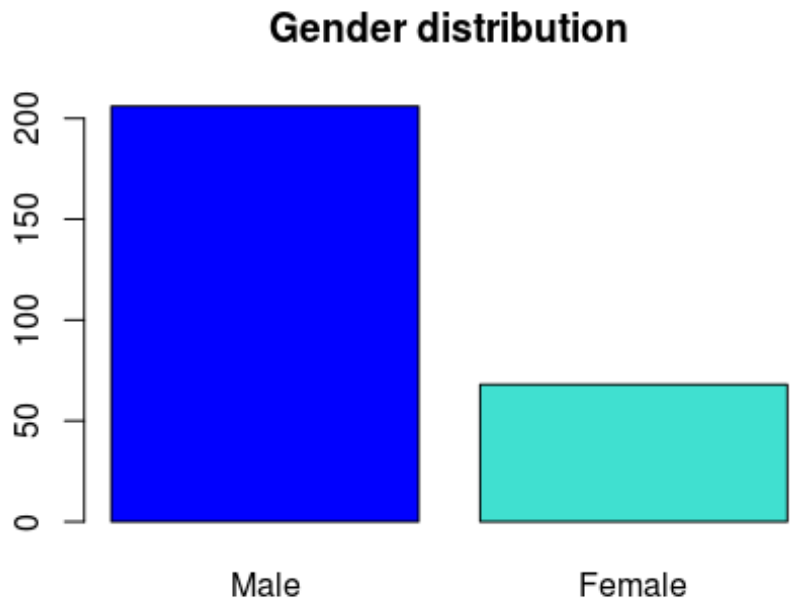
```
##    age   salary  work_yrs
## 1   22  42500.00  1.000000
## 2   23  57282.00  1.750000
## 3   24  49342.24  1.727273
## 4   25  43395.55  2.264151
## 5   26  35982.07  2.875000
## 6   27  31499.37  3.130435
## 7   28  39809.00  4.666667
## 8   29  28067.95  4.500000
## 9   30  55291.25  5.583333
## 10  31  40599.40  5.800000
## 11  32  13662.25  5.625000
## 12  33 118000.00 10.000000
## 13  34  26250.00 11.500000
## 14  35      0.00  9.333333
## 15  36      0.00 12.500000
## 16  37      0.00  9.000000
## 17  39  56000.00 10.500000
## 18  40 183000.00 15.000000
## 19  42      0.00 13.000000
## 20  43      0.00 19.000000
## 21  48      0.00 22.000000
```

```r
aggregate(cbind(salary, work_yrs) ~ satis , data = mba.df, mean)   # Effect of Salary on the Satisfaction level
```

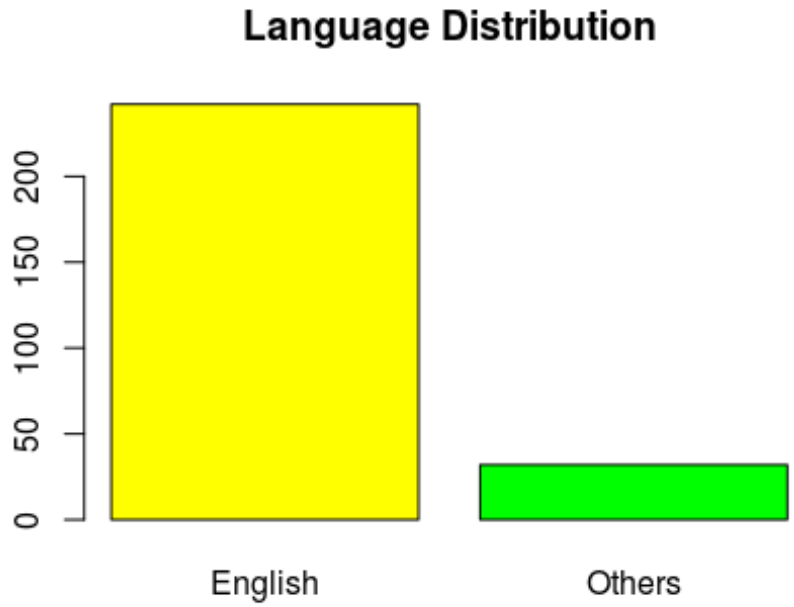
```
##   satis    salary work_yrs
## 1     1   999.000 3.000000
## 2     2   999.000 2.000000
## 3     3 19799.200 4.200000
## 4     4  6293.412 2.941176
## 5     5 40476.311 4.243243
## 6     6 54383.536 4.185567
## 7     7 65718.152 3.727273
## 8   998   998.000 3.086957
```

```r
boxplot(salary ~ work_yrs ,data=mba.df, main="Effect of Work Experience on Salary", xlab="Work Experience", ylab="Starting Salary",col=c("red","orangered","yellow2","green3","skyblue","blue2"))
```


```r
mba.df$sex=factor(mba.df$sex, levels=c(1,2), labels=c("Male","Female"))
plot(mba.df$sex,col = c("blue","turquoise"),main = "Gender distribution")
```



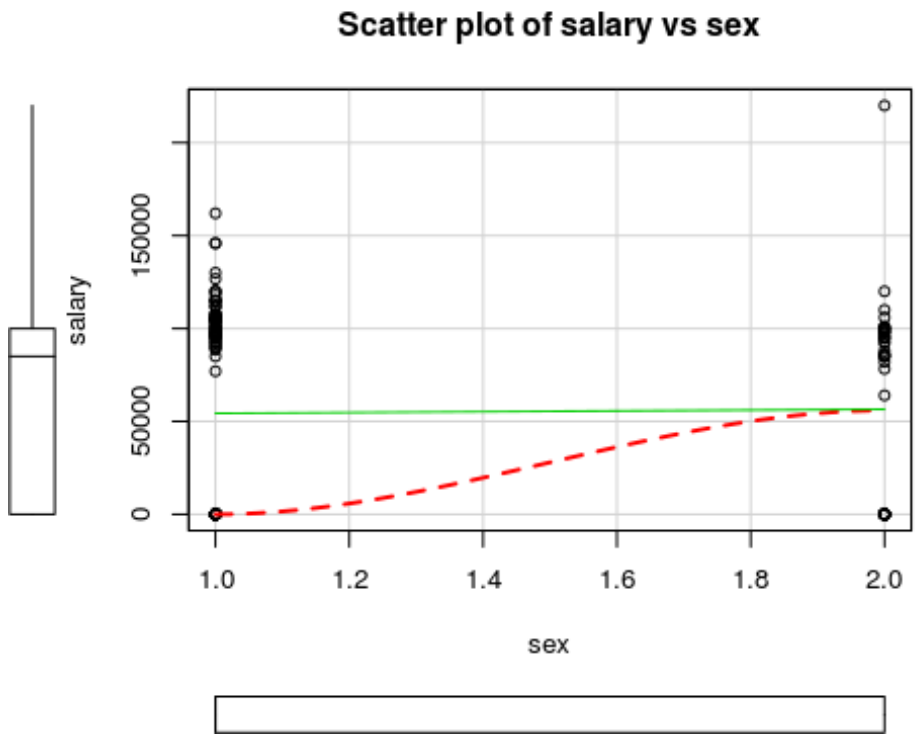

```
mba.df$frstlang = factor(mba.df$frstlang, levels=c(1,2),
labels=c("English","Others"))
plot(mba.df$frstlang,col=c("yellow","green"),main = "Language Distribution")
```



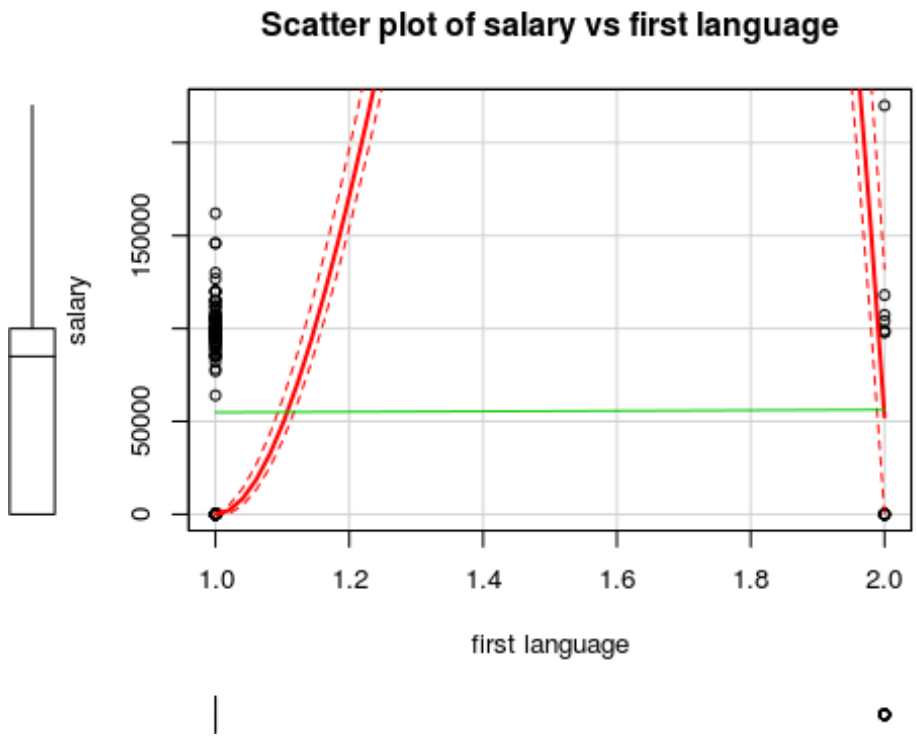
Scatter Plots

```
library(car)

##
## Attaching package: 'car'

## The following object is masked from 'package:psych':
##
##     logit

scatterplot(salary ~age, data=newdata1,
          spread=FALSE, smoother.args=list(lty=2),
          main="Scatter plot of salary vs age",
          xlab="age",
          ylab="salary")
```

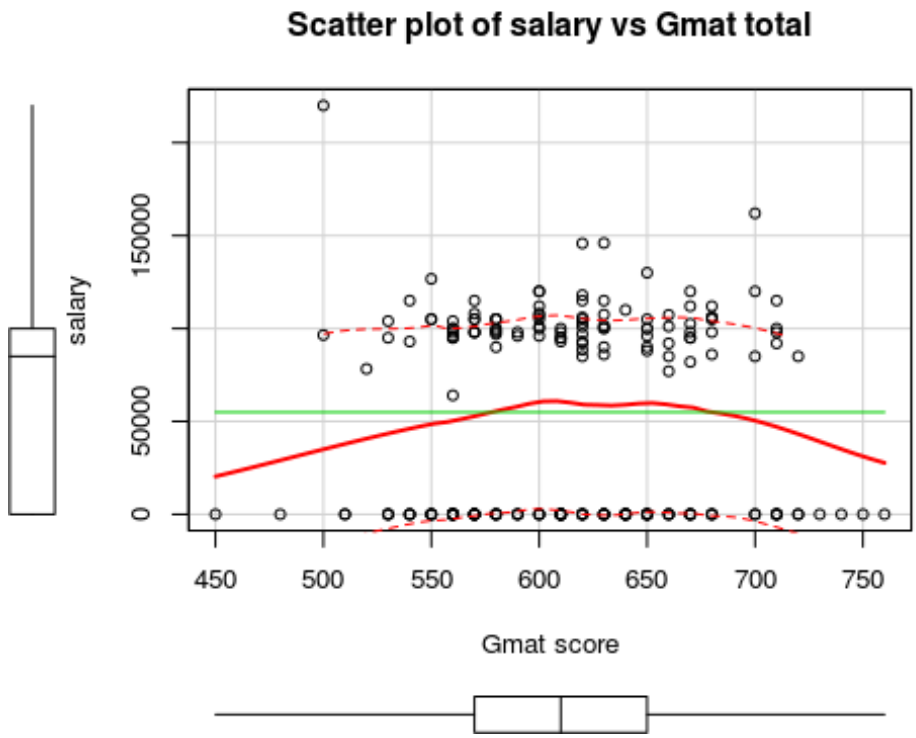

```
scatterplot(salary ~sex,     data=newdata1,
          spread=FALSE, smoother.args=list(lty=2),
          main="Scatter plot of salary vs sex",
          xlab="sex",
          ylab="salary")
```




```
scatterplot(salary ~frstlang,     data=newdata1,
          main="Scatter plot of salary vs first language",
          xlab="first language",
          ylab="salary")
```

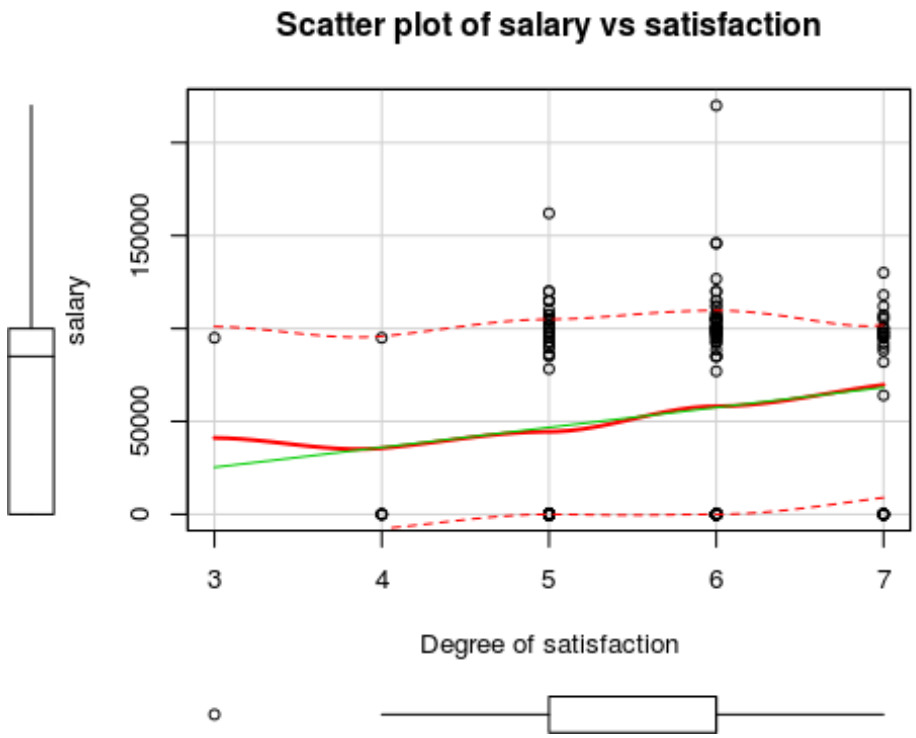



```
scatterplot(salary ~gmat_tot,     data=newdata1,
          main="Scatter plot of salary vs Gmat total",
          xlab="Gmat score",
          ylab="salary")
```



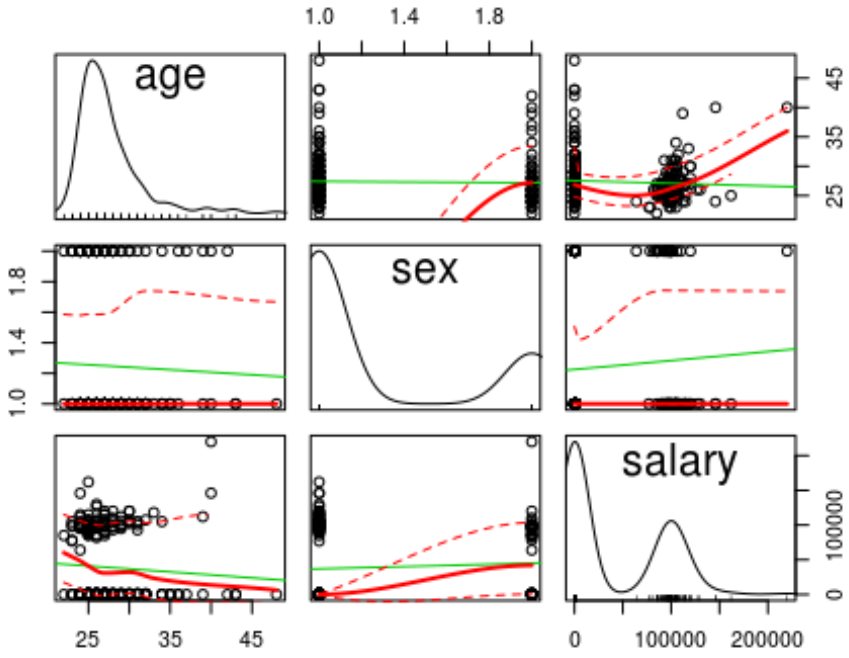

```
scatterplot(salary ~work_yrs,     data=newdata1,
          main="Scatter plot of salary vs Work exp.",
          xlab="Work experience in years",
          ylab="salary")
```


```
scatterplot(salary ~satis,    data=newdata1,
          main="Scatter plot of salary vs satisfaction",
          xlab="Degree of satisfaction",
          ylab="salary")
```

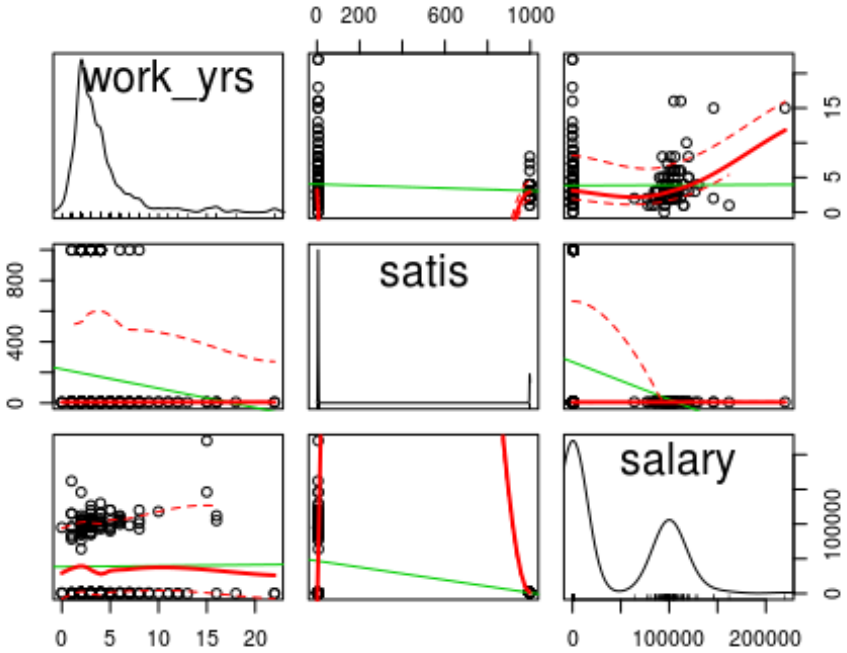


Scatterplot Matrix

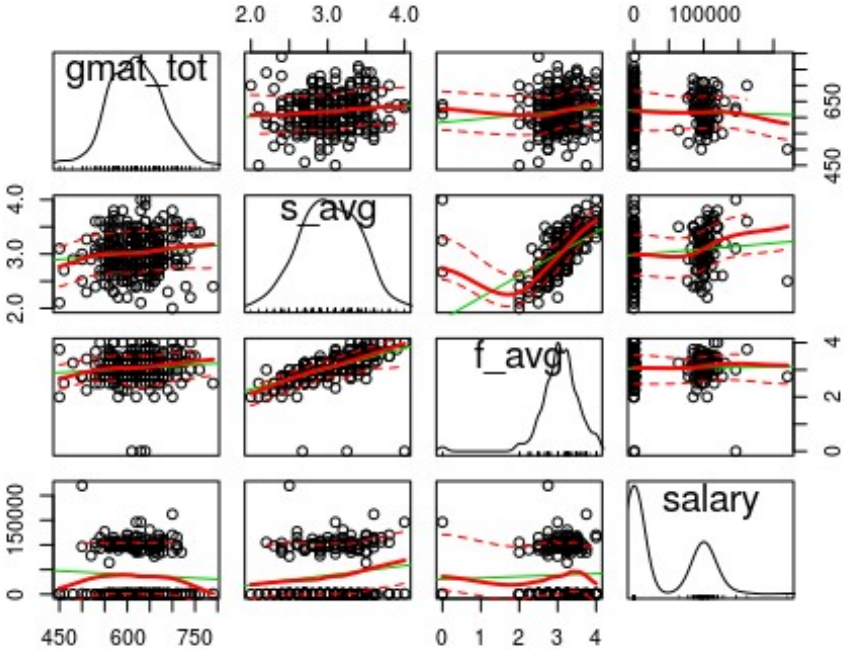
```
scatterplotMatrix(~age+sex+salary, data=mba.df)
```



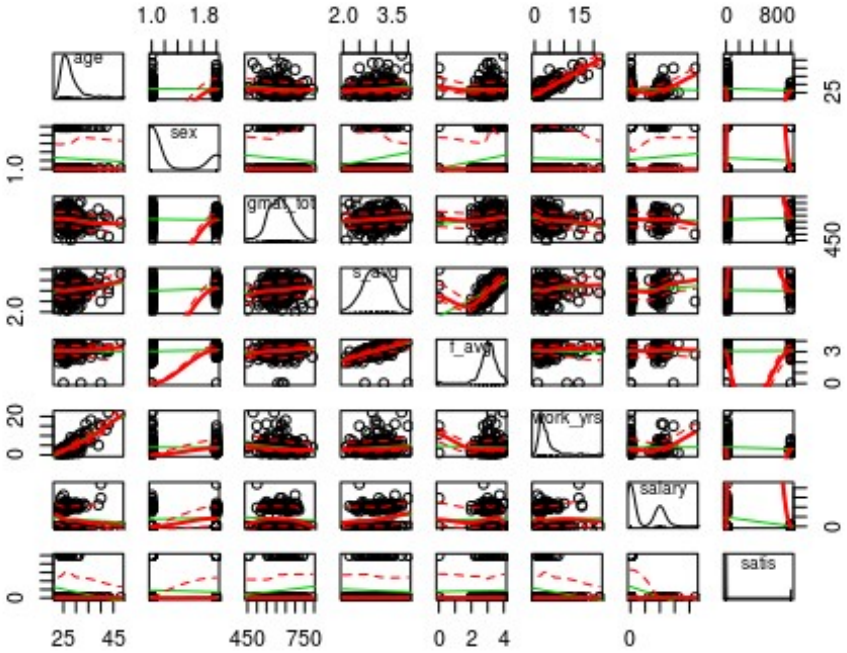
```
scatterplotMatrix(~work_yrs+satis+salary, data=mba.df)
```




```
scatterplotMatrix(~gmat_tot+s_avg+f_avg+salary, data=mba.df)
```

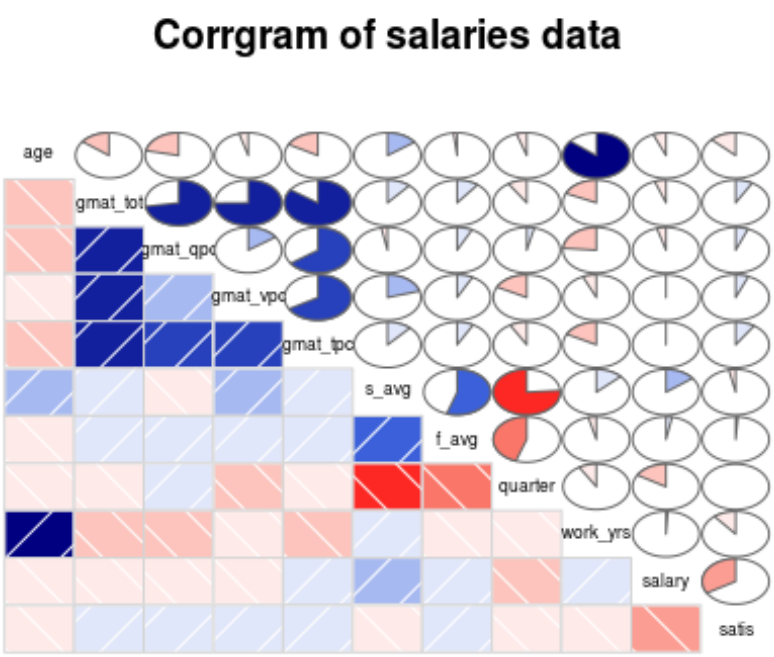


```
scatterplotMatrix(~age+sex+gmat_tot+s_avg+f_avg+work_yrs+salary+satis
, data=mba.df)
```



Corrgram

```
library(corrgram)
corrgram(mba.df, order=FALSE,
        lower.panel=panel.shade,
        upper.panel=panel.pie,
        text.panel=panel.txt,
        main="Corrgram of salaries data")
```



Correlation Matrix

```
correlationmatrix <- cor(mba.df[,c(3:10,12,13)])
round(correlationmatrix,digits = 2)
```

```
##            gmat_tot gmat_qpc gmat_vpc gmat_tpc s_avg f_avg quarter
work_yrs
## gmat_tot     1.00     0.72     0.75     0.85  0.11  0.10   -0.09    -0.18
## gmat_qpc     0.72     1.00     0.15     0.65 -0.03  0.07    0.04    -0.24
## gmat_vpc     0.75     0.15     1.00     0.67  0.20  0.08   -0.17    -0.07
## gmat_tpc     0.85     0.65     0.67     1.00  0.12  0.08   -0.08    -0.17
## s_avg        0.11    -0.03     0.20     0.12  1.00  0.55   -0.76     0.13
## f_avg        0.10     0.07     0.08     0.08  0.55  1.00   -0.45    -0.04
## quarter     -0.09     0.04    -0.17    -0.08 -0.76 -0.45    1.00    -0.09
## work_yrs    -0.18    -0.24    -0.07    -0.17  0.13 -0.04   -0.09     1.00
## salary      -0.05    -0.04    -0.01     0.00  0.15  0.03   -0.16     0.01
## satis        0.08     0.06     0.06     0.09 -0.03  0.01    0.00    -0.11
##              salary satis
## gmat_tot  -0.05  0.08
## gmat_qpc  -0.04  0.06
## gmat_vpc  -0.01  0.06
## gmat_tpc   0.00  0.09
## s_avg      0.15 -0.03
## f_avg      0.03  0.01
## quarter   -0.16  0.00
## work_yrs   0.01 -0.11
```

```
## salary     1.00 -0.34
## satis     -0.34  1.00
```

Variance- Covariance Matrix

```
VarianceCovariancematrix <- var(mba.df[,1:13])

## Warning in var(mba.df[, 1:13]): NAs introduced by coercion

round(VarianceCovariancematrix, 2)

##             age sex   gmat_tot  gmat_qpc gmat_vpc gmat_tpc   s_avg
## age        13.77  NA    -31.16    -11.93    -2.76    -8.84    0.21
## sex           NA  NA        NA        NA       NA       NA      NA
## gmat_tot   -31.16  NA   3310.69    620.02   726.00   683.99    2.48
## gmat_qpc   -11.93  NA    620.02    221.07    38.15   135.80   -0.17
## gmat_vpc    -2.76  NA    726.00     38.15   284.25   157.49    1.31
## gmat_tpc    -8.84  NA    683.99    135.80   157.49   196.61    0.63
## s_avg        0.21  NA      2.48     -0.17     1.31     0.63    0.15
## f_avg       -0.03  NA      3.15      0.58     0.67     0.59    0.11
## quarter     -0.20  NA     -5.89      0.60    -3.27    -1.29   -0.32
## work_yrs    10.29  NA    -33.92    -11.37    -3.62    -7.86    0.16
## frstlang       NA  NA        NA        NA       NA       NA      NA
## salary   -11830.42  NA -161159.99 -33358.23 -5273.85  3522.75 2831.60
## satis      -176.35  NA   1765.26    334.84   392.36   484.25   -4.63
##             f_avg  quarter work_yrs frstlang       salary       satis
## age         -0.03    -0.20    10.29       NA    -11830.42    -176.35
## sex            NA       NA       NA       NA           NA         NA
## gmat_tot     3.15    -5.89   -33.92       NA   -161159.99     1765.26
## gmat_qpc     0.58     0.60   -11.37       NA    -33358.23      334.84
## gmat_vpc     0.67    -3.27    -3.62       NA     -5273.85      392.36
## gmat_tpc     0.59    -1.29    -7.86       NA      3522.75      484.25
## s_avg        0.11    -0.32     0.16       NA      2831.60       -4.63
## f_avg        0.28    -0.26    -0.07       NA       787.66        2.13
## quarter     -0.26     1.23    -0.31       NA     -9296.21       -0.01
## work_yrs    -0.07    -0.31    10.45       NA      1486.15     -131.24
## frstlang       NA       NA       NA       NA           NA         NA
## salary     787.66 -9296.21  1486.15       NA 2596061571.52 -6347115.38
## satis        2.13    -0.01  -131.24       NA   -6347115.38   138097.38
```

Dataframe of those who were placed

```
placed.df <- mba.df[ which(mba.df$salary !="998" & mba.df$salary !="999"
& mba.df$salary!="0"), ]
head(placed.df)

##    age    sex gmat_tot gmat_qpc gmat_vpc gmat_tpc s_avg f_avg quarter
## 35  22 Female      660       90       92       94   3.5  3.75       1
## 36  27 Female      700       94       98       98   3.3  3.25       1
## 37  25 Female      680       87       96       96   3.5  2.67       1
```

```
## 38  25 Female     650      82      91      93   3.4  3.25      1
## 39  27   Male     710      96      96      98   3.3  3.50      1
## 40  28 Female     620      52      98      87   3.4  3.75      1
##    work_yrs frstlang salary satis
## 35       1  English  85000     5
## 36       2  English  85000     6
## 37       2  English  86000     5
## 38       3  English  88000     7
## 39       2  English  92000     6
## 40       5  English  93000     5
```

Contingency tables showing the affect of various factors on the starting salary

```
t1 <- xtabs(~salary+sex,data=placed.df)
t1
```

```
##        sex
## salary   Male Female
##   64000    0      1
##   77000    1      0
##   78256    0      1
##   82000    0      1
##   85000    1      3
##   86000    0      2
##   88000    0      1
##   88500    1      0
##   90000    3      0
##   92000    2      1
##   93000    2      1
##   95000    4      3
##   96000    3      1
##   96500    1      0
##   97000    2      0
##   98000    6      4
##   99000    0      1
##   100000   4      5
##   100400   1      0
##   101000   0      2
##   101100   1      0
##   101600   1      0
##   102500   1      0
##   103000   1      0
##   104000   2      0
##   105000  11      0
##   106000   2      1
##   107000   1      0
##   107300   1      0
##   107500   1      0
##   108000   2      0
```

```
##  110000   0    1
##  112000   3    0
##  115000   5    0
##  118000   1    0
##  120000   3    1
##  126710   1    0
##  130000   1    0
##  145800   1    0
##  146000   1    0
##  162000   1    0
##  220000   0    1
```

From this table it is evident that mostly men have higher starting salaries compared to women.

```
t2 <- xtabs(~salary+work_yrs,data=placed.df)
t2
```

```
##        work_yrs
## salary   0 1 2 3 4 5 6 7 8 10 15 16
##  64000  0 0 1 0 0 0 0 0 0  0  0  0
##  77000  0 0 1 0 0 0 0 0 0  0  0  0
##  78256  0 1 0 0 0 0 0 0 0  0  0  0
##  82000  0 1 0 0 0 0 0 0 0  0  0  0
##  85000  0 1 2 1 0 0 0 0 0  0  0  0
##  86000  0 0 1 1 0 0 0 0 0  0  0  0
##  88000  0 0 0 1 0 0 0 0 0  0  0  0
##  88500  0 0 0 1 0 0 0 0 0  0  0  0
##  90000  0 0 2 0 0 1 0 0 0  0  0  0
##  92000  0 0 3 0 0 0 0 0 0  0  0  0
##  93000  0 0 0 0 1 1 0 0 1  0  0  0
##  95000  1 1 2 2 0 1 0 0 0  0  0  0
##  96000  0 1 2 0 1 0 0 0 0  0  0  0
##  96500  0 0 1 0 0 0 0 0 0  0  0  0
##  97000  0 0 0 1 1 0 0 0 0  0  0  0
##  98000  0 0 7 1 1 0 0 1 0  0  0  0
##  99000  0 0 0 0 0 1 0 0 0  0  0  0
##  100000 0 0 6 1 1 0 1 0 0  0  0  0
##  100400 0 0 0 1 0 0 0 0 0  0  0  0
##  101000 0 0 2 0 0 0 0 0 0  0  0  0
##  101100 0 0 0 0 0 0 0 0 1  0  0  0
##  101600 0 0 0 1 0 0 0 0 0  0  0  0
##  102500 0 0 0 0 0 0 1 0 0  0  0  0
##  103000 0 0 0 1 0 0 0 0 0  0  0  0
##  104000 0 0 0 0 2 0 0 0 0  0  0  0
##  105000 0 0 4 4 0 1 1 0 0  0  0  1
##  106000 0 0 0 0 0 0 2 0 1  0  0  0
##  107000 0 0 1 0 0 0 0 0 0  0  0  0
##  107300 0 0 1 0 0 0 0 0 0  0  0  0
##  107500 0 0 0 1 0 0 0 0 0  0  0  0
##  108000 0 0 0 1 1 0 0 0 0  0  0  0
```

```
##   110000 0 0 0 0 0 0 1 0 0  0  0  0
##   112000 0 0 1 0 0 0 1 0 0  0  0  1
##   115000 0 2 0 1 2 0 0 0 0  0  0  0
##   118000 0 0 0 0 0 0 0 0 0  1  0  0
##   120000 0 0 0 1 0 2 0 0 1  0  0  0
##   126710 0 0 0 1 0 0 0 0 0  0  0  0
##   130000 0 0 0 0 1 0 0 0 0  0  0  0
##   145800 0 0 1 0 0 0 0 0 0  0  0  0
##   146000 0 0 0 0 0 0 0 0 0  0  1  0
##   162000 0 1 0 0 0 0 0 0 0  0  0  0
##   220000 0 0 0 0 0 0 0 0 0  0  1  0
```

From the above table it is evident that a minimum of 2 years of work experience is necessary for a good salary.

```
t3 <- xtabs(~salary+gmat_tot,data=placed.df)
t3
```

```
##        gmat_tot
## salary   500 520 530 540 550 560 570 580 590 600 610 620 630 640 650
660
##   64000   0   0   0   0   0   1   0   0   0   0   0   0   0   0   0   0
##   77000   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   1
##   78256   0   1   0   0   0   0   0   0   0   0   0   0   0   0   0   0
##   82000   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
##   85000   0   0   0   0   0   0   0   0   0   0   0   1   0   0   0   1
##   86000   0   0   0   0   0   0   0   0   0   0   0   0   1   0   0   0
##   88000   0   0   0   0   0   0   0   0   0   0   0   0   0   0   1   0
##   88500   0   0   0   0   0   0   0   0   0   0   0   1   0   0   0   0
##   90000   0   0   0   0   0   0   0   1   0   0   0   0   1   0   1   0
##   92000   0   0   0   0   0   0   0   0   0   0   0   1   0   0   0   1
##   93000   0   0   0   1   0   0   0   0   0   0   1   1   0   0   0   0
##   95000   0   0   1   0   0   2   0   0   0   0   2   0   0   0   0   0
##   96000   0   0   0   0   0   1   0   0   1   1   0   0   0   0   1   0
##   96500   1   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
##   97000   0   0   0   0   0   0   0   1   0   0   0   1   0   0   0   0
##   98000   0   0   0   0   0   1   3   1   1   0   1   0   0   0   0   0
##   99000   0   0   0   0   0   0   0   1   0   0   0   0   0   0   0   0
##   100000  0   0   0   0   0   2   0   1   0   1   1   0   1   0   2   0
##   100400  0   0   0   0   0   0   0   0   0   0   0   0   1   0   0   0
##   101000  0   0   0   0   0   0   0   0   0   1   0   1   0   0   0   0
##   101100  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   1
##   101600  0   0   0   0   0   0   0   0   0   0   0   0   1   0   0   0
##   102500  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
##   103000  0   0   0   0   0   0   0   0   0   0   0   1   0   0   0   0
##   104000  0   0   1   0   0   1   0   0   0   0   0   0   0   0   0   0
##   105000  0   0   0   0   2   0   2   3   0   1   0   1   0   0   1   0
##   106000  0   0   0   0   0   0   0   0   0   0   0   1   0   0   0   0
##   107000  0   0   0   0   0   0   0   0   0   1   0   0   0   0   0   0
##   107300  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   1
##   107500  0   0   0   0   0   0   0   0   0   0   0   0   1   0   0   0
```

```
##  108000  0  0  0  0  0  0  1  0  0  1  0  0  0  0  0  0
##  110000  0  0  0  0  0  0  0  0  0  0  0  0  0  1  0  0
##  112000  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0  0
##  115000  0  0  0  1  0  0  1  0  0  0  0  1  1  0  0  0
##  118000  0  0  0  0  0  0  0  0  0  0  0  1  0  0  0  0
##  120000  0  0  0  0  0  0  0  0  0  2  0  0  0  0  0  0
##  126710  0  0  0  0  1  0  0  0  0  0  0  0  0  0  0  0
##  130000  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1  0
##  145800  0  0  0  0  0  0  0  0  0  0  0  1  0  0  0  0
##  146000  0  0  0  0  0  0  0  0  0  0  0  0  1  0  0  0
##  162000  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##  220000  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##       gmat_tot
## salary   670 680 700 710 720
##  64000   0  0  0  0  0
##  77000   0  0  0  0  0
##  78256   0  0  0  0  0
##  82000   1  0  0  0  0
##  85000   0  0  1  0  1
##  86000   0  1  0  0  0
##  88000   0  0  0  0  0
##  88500   0  0  0  0  0
##  90000   0  0  0  0  0
##  92000   0  0  0  1  0
##  93000   0  0  0  0  0
##  95000   2  0  0  0  0
##  96000   0  0  0  0  0
##  96500   0  0  0  0  0
##  97000   0  0  0  0  0
##  98000   1  1  0  1  0
##  99000   0  0  0  0  0
##  100000  0  0  0  1  0
##  100400  0  0  0  0  0
##  101000  0  0  0  0  0
##  101100  0  0  0  0  0
##  101600  0  0  0  0  0
##  102500  1  0  0  0  0
##  103000  0  0  0  0  0
##  104000  0  0  0  0  0
##  105000  0  1  0  0  0
##  106000  0  2  0  0  0
##  107000  0  0  0  0  0
##  107300  0  0  0  0  0
##  107500  0  0  0  0  0
##  108000  0  0  0  0  0
##  110000  0  0  0  0  0
##  112000  1  1  0  0  0
##  115000  0  0  0  1  0
##  118000  0  0  0  0  0
##  120000  1  0  1  0  0
```

```
##  126710  0  0  0  0  0
##  130000  0  0  0  0  0
##  145800  0  0  0  0  0
##  146000  0  0  0  0  0
##  162000  0  0  1  0  0
##  220000  0  0  0  0  0
```

Generally, people with high Gmat Score also have high salaries.

```
t4 <-xtabs(~salary+frstlang,data=placed.df)
t4
```

```
##        frstlang
## salary   English Others
##  64000       1      0
##  77000       1      0
##  78256       1      0
##  82000       1      0
##  85000       4      0
##  86000       2      0
##  88000       1      0
##  88500       1      0
##  90000       3      0
##  92000       3      0
##  93000       3      0
##  95000       7      0
##  96000       4      0
##  96500       1      0
##  97000       2      0
##  98000       8      2
##  99000       0      1
##  100000      9      0
##  100400      1      0
##  101000      2      0
##  101100      1      0
##  101600      1      0
##  102500      1      0
##  103000      1      0
##  104000      1      1
##  105000     11      0
##  106000      3      0
##  107000      1      0
##  107300      0      1
##  107500      1      0
##  108000      2      0
##  110000      1      0
##  112000      3      0
##  115000      5      0
##  118000      0      1
##  120000      4      0
##  126710      1      0
```

```
##   130000      1     0
##   145800      1     0
##   146000      1     0
##   162000      1     0
##   220000      0     1
```

Employees with English as first language are mostly preferred and are given higher salaries compared to those who don’t have English as their first language.

Chi-squared test

```
chisq.test(placed.df$age,placed.df$salary)
```

```
## Warning in chisq.test(placed.df$age, placed.df$salary): Chi-squared
## approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  placed.df$age and placed.df$salary
## X-squared = 717.62, df = 574, p-value = 3.929e-05
```

```
chisq.test(placed.df$sex,placed.df$salary)
```

```
## Warning in chisq.test(placed.df$sex, placed.df$salary): Chi-squared
## approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  placed.df$sex and placed.df$salary
## X-squared = 52.681, df = 41, p-value = 0.1045
```

```
chisq.test(placed.df$gmat_tot,placed.df$salary)
```

```
## Warning in chisq.test(placed.df$gmat_tot, placed.df$salary): Chi-squared
## approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  placed.df$gmat_tot and placed.df$salary
## X-squared = 927.24, df = 820, p-value = 0.005279
```

```
chisq.test(placed.df$s_avg,placed.df$salary)
```

```
## Warning in chisq.test(placed.df$s_avg, placed.df$salary): Chi-squared
## approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
```

```
## data:  placed.df$s_avg and placed.df$salary
## X-squared = 792.97, df = 861, p-value = 0.9524

chisq.test(placed.df$f_avg,placed.df$salary)

## Warning in chisq.test(placed.df$f_avg, placed.df$salary): Chi-squared
## approximation may be incorrect

##
##  Pearson's Chi-squared test
##
## data:  placed.df$f_avg and placed.df$salary
## X-squared = 596.28, df = 574, p-value = 0.2518

chisq.test(placed.df$work_yrs,placed.df$salary)

## Warning in chisq.test(placed.df$work_yrs, placed.df$salary): Chi-squared
## approximation may be incorrect

##
##  Pearson's Chi-squared test
##
## data:  placed.df$work_yrs and placed.df$salary
## X-squared = 535.23, df = 451, p-value = 0.003809

chisq.test(placed.df$frstlang,placed.df$salary)

## Warning in chisq.test(placed.df$frstlang, placed.df$salary): Chi-squared
## approximation may be incorrect

##
##  Pearson's Chi-squared test
##
## data:  placed.df$frstlang and placed.df$salary
## X-squared = 69.847, df = 41, p-value = 0.003296
```

The results of the Chi-Squared tests tell us that age, GMAT percentiles, work experience and first language are factors that are statistically significant for starting salary ($p < 0.05$), whereas gender, average GPA for Spring and Fall semesters and quartile ranking with degree are not statistically significant for salary ($p > 0.05$).

T-test

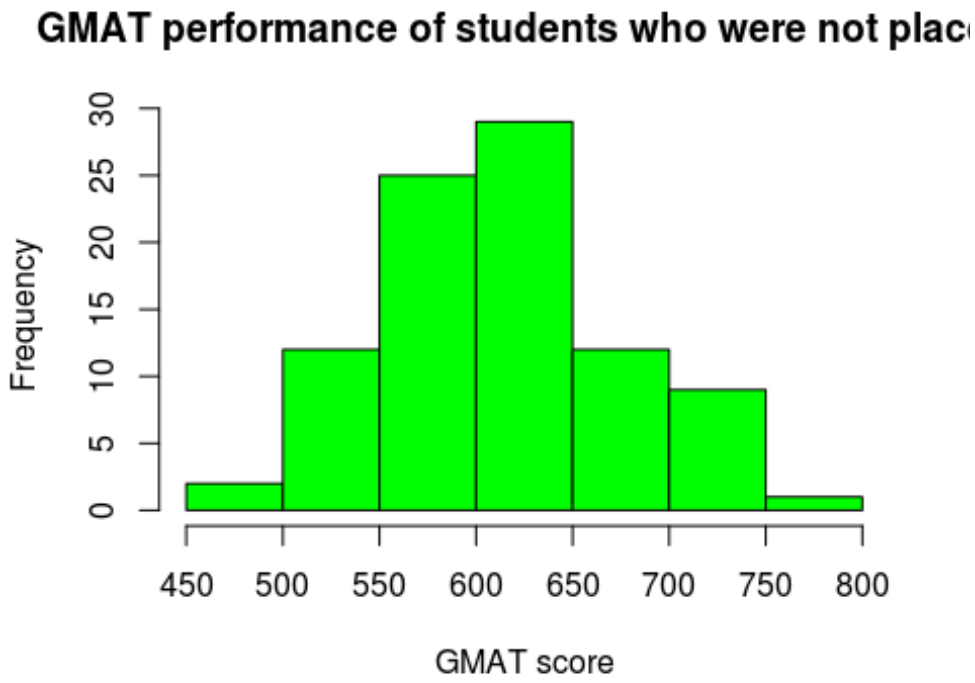
```
log.transformed.salary=log(placed.df$salary)
t.test(log.transformed.salary~ placed.df$sex, var.equal = TRUE)

##
##  Two Sample t-test
##
## data:  log.transformed.salary by placed.df$sex
## t = 2.4552, df = 101, p-value = 0.01579
## alternative hypothesis: true difference in means is not equal to 0
```

```
## 95 percent confidence interval:
##  0.01470674 0.13847594
## sample estimates:
##   mean in group Male mean in group Female
##            11.55390            11.47731
```

This T-test shows that there is a significant difference in salaries of men and women.

Dataset consisting of people who were not placed

```
notPlaced.df <- mba.df[ which(mba.df$salary !="998" & mba.df$salary !
="999" & mba.df$salary==0), ]
head(notPlaced.df)

##   age    sex gmat_tot gmat_qpc gmat_vpc gmat_tpc s_avg f_avg quarter
## 1  23 Female      620       77       87       87   3.4  3.00       1
## 2  24   Male      610       90       71       87   3.5  4.00       1
## 3  24   Male      670       99       78       95   3.3  3.25       1
## 4  24   Male      570       56       81       75   3.3  2.67       1
## 6  24   Male      640       82       89       91   3.9  3.75       1
## 7  25   Male      610       89       74       87   3.4  3.50       1
##   work_yrs frstlang salary satis
## 1        2  English      0     7
## 2        2  English      0     6
## 3        2  English      0     6
## 4        1  English      0     7
## 6        2  English      0     6
## 7        2  English      0     5

hist(notPlaced.df$gmat_tot,
    main = "GMAT performance of students who were not placed",
    xlab="GMAT score",
    breaks=10,
    col = "green")
```



GMAT score is distributed between 550-650 for unplaced students while it is more scattered amongst those who do have a job.

```
chisq.test(notPlaced.df$work_yrs,notPlaced.df$satis)
```

```
## Warning in chisq.test(notPlaced.df$work_yrs, notPlaced.df$satis): Chi-
## squared approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  notPlaced.df$work_yrs and notPlaced.df$satis
## X-squared = 44.974, df = 48, p-value = 0.5976
```

This shows that the unplaced students with work experience are satisfied with the MBA program.

Regression Analysis

Preparing for regression analysis

```
mba.df$sex[mba.df$sex == 1] <- 'Male'
mba.df$sex[mba.df$sex == 2] <- 'Female'
mba.df$sex <- factor(mba.df$sex)
mba.df$frstlang[mba.df$frstlang == 1] <- 'English'
mba.df$frstlang[mba.df$frstlang == 2] <- 'Other'
```

```
## Warning in `[<-.factor`(`*tmp*`, mba.df$frstlang == 2, value =
## structure(c(1L, : invalid factor level, NA generated
```

```
mba.df$frstlang <- factor(mba.df$frstlang)
```

Model 1

```
fit1 <- lm(salary ~ gmat_tot + gmat_vpc + gmat_qpc + gmat_tpc ,
data=placed.df)
summary(fit1)
```

```
##
## Call:
## lm(formula = salary ~ gmat_tot + gmat_vpc + gmat_qpc + gmat_tpc,
##     data = placed.df)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -40370  -8250  -2164   5253 100097
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 109539.54   48054.24   2.279   0.0248 *
## gmat_tot        55.01     181.71   0.303   0.7627
## gmat_vpc       546.10     543.85   1.004   0.3178
## gmat_qpc       718.40     541.90   1.326   0.1880
## gmat_tpc     -1663.16     801.57  -2.075   0.0406 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 17670 on 98 degrees of freedom
## Multiple R-squared:  0.06089,    Adjusted R-squared:  0.02256
## F-statistic: 1.589 on 4 and 98 DF,  p-value: 0.1834
```

Gmat_tpc is a significant variable in model 1 The multiple R squared value indicates that the model accounts for 6% of the variance in the variables The residual error (17670) can be thought of as the average error in predicting salary using the various gmat data available.

Model 2

```
fit2 <- lm(salary ~ frstlang + satis + work_yrs , data=placed.df)
summary(fit2)
```

```
##
## Call:
## lm(formula = salary ~ frstlang + satis + work_yrs, data = placed.df)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -31764  -9640   -604   4816  76193
##
## Coefficients:
```

```
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)    104142.2    11899.4   8.752 5.73e-14 ***
## frstlangOthers  13541.5     6305.7   2.147   0.0342 *
## satis          -1913.1     2000.0  -0.957   0.3411
## work_yrs        2506.8      528.6   4.742 7.11e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 15740 on 99 degrees of freedom
## Multiple R-squared:  0.2466, Adjusted R-squared:  0.2237
## F-statistic:  10.8 on 3 and 99 DF,  p-value: 3.354e-06
```

work_yrs and frstlang are significant variables in model 2 The multiple R squared value indicates that the model accounts for 24.66% of the variance in the variables The residual error(15740) can be thought of as the average error in predicting salary using work experience, job satisfaction and first language.

Model 3

```
fit3 <- lm(salary ~  s_avg + f_avg , data=placed.df)
summary(fit3)

##
## Call:
## lm(formula = salary ~ s_avg + f_avg, data = placed.df)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -41509  -7388  -1723   3119 119810
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)    97277      15352   6.336  6.8e-09 ***
## s_avg           8781       5171   1.698   0.0926 .
## f_avg          -6924       4013  -1.725   0.0875 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 17690 on 100 degrees of freedom
## Multiple R-squared:  0.03896,    Adjusted R-squared:  0.01974
## F-statistic: 2.027 on 2 and 100 DF,  p-value: 0.1371
```

We can see that model 2 is better than model 1 and model 3, with a higher R-squared value.

```
# beta coefficients
fit2$coefficients

##    (Intercept) frstlangOthers         satis      work_yrs
##     104142.167      13541.466      -1913.088       2506.764
```

```
# confidence intervals
confint(fit2)
```

```
##                 2.5 %     97.5 %
## (Intercept)    80531.137 127753.197
## frstlangOthers  1029.606  26053.326
## satis         -5881.593   2055.418
## work_yrs       1457.812   3555.716
```

Visualizing the beta coefficients

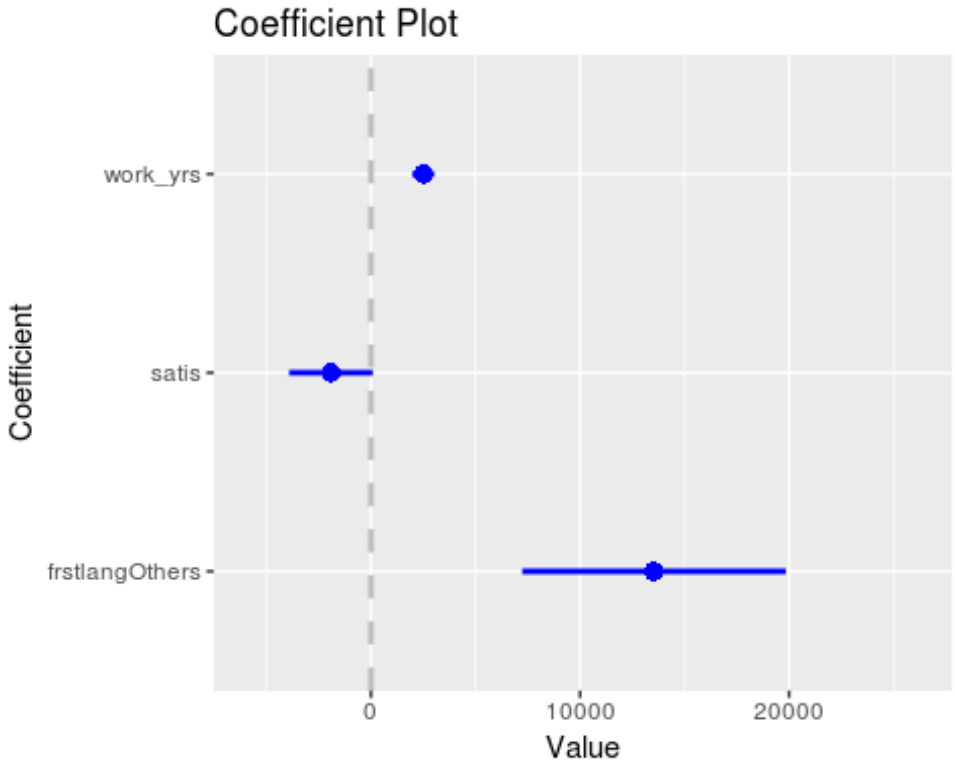
```
library(coefplot)
```

```
## Loading required package: ggplot2
```

```
##
## Attaching package: 'ggplot2'
```

```
## The following objects are masked from 'package:psych':
##
##     %+%, alpha
```

```
library(ggplot2)
coefplot(fit2, predictors=c("work_yrs", "frstlang", "satis"))
```



Executive Summary

- The starting salary of the Mba program of any individual student depends critically on the first language of the student and the

degree of satisfaction estimated through various boxplots and the scatterplots.

- Even from the corrogram and the correlation matrices , it is quite clear that the starting salaries are strongly correlated with the first language.
- From the chi- squared tests and the t-tests between the people who got a job and those who did not get a job , it can be analysed that there is a significant relationship between the starting salaries , degree of satisfaction of the MBA program and the first language of the people.
- The Regression model ,i.e. the best fit model , here the second model helps us in concluding that the salary has more or less a significant effect from work years experience, first language and satisfaction degree.