# STAT 702 - ASSIGNMENT-1

# Sumukh Sagar Manjunath

February 9, 2016

```
> library(MASS)
> head(Boston)
    crim zn indus chas
                                           dis rad tax ptratio black lstat medv
                         nox
                                rm age
1 0.00632 18 2.31
                     0 0.538 6.575 65.2 4.0900
                                                1 296
                                                          15.3 396.90 4.98 24.0
2 0.02731 0 7.07
                     0 0.469 6.421 78.9 4.9671
                                                 2 242
                                                          17.8 396.90
3 0.02729
         0 7.07
                     0 0.469 7.185 61.1 4.9671
                                                 2 242
                                                          17.8 392.83 4.03 34.7
4 0.03237
          0 2.18
                     0 0.458 6.998 45.8 6.0622
                                                 3 222
                                                          18.7 394.63
                                                                       2.94 33.4
5 0.06905
          0 2.18
                     0 0.458 7.147 54.2 6.0622
                                                 3 222
                                                          18.7 396.90
                                                                      5.33 36.2
                                                          18.7 394.12 5.21 28.7
6 0.02985 0 2.18
                     0 0.458 6.430 58.7 6.0622
                                                 3 222
> names(Boston)
[1] "crim"
[9] "rad"
              "zn"
                        "indus" "chas"
                                            "nox"
                                                      "rm"
                                                                "age"
                                                                          "dis"
                        "ptratio" "black"
                                            "lstat"
              "tax"
                                                      "medv"
```

1.a Size and Class of Dataset.

1.b Relationship between the predictors in the data set and per-capita crime rate.

```
> cor(Boston[2:length(Boston)],Boston$crim,method="pearson")
               [,1]
         -0.20046922
zn
indus
         0.40658341
chas
         -0.05589158
         0.42097171
        -0.21924670
         0.35273425
        -0.37967009
dis
         0.62550515
rad
         0.58276431
tax
        0.28994558
ptratio
        -0.38506394
black
         0.45562148
lstat
        -0.38830461
```

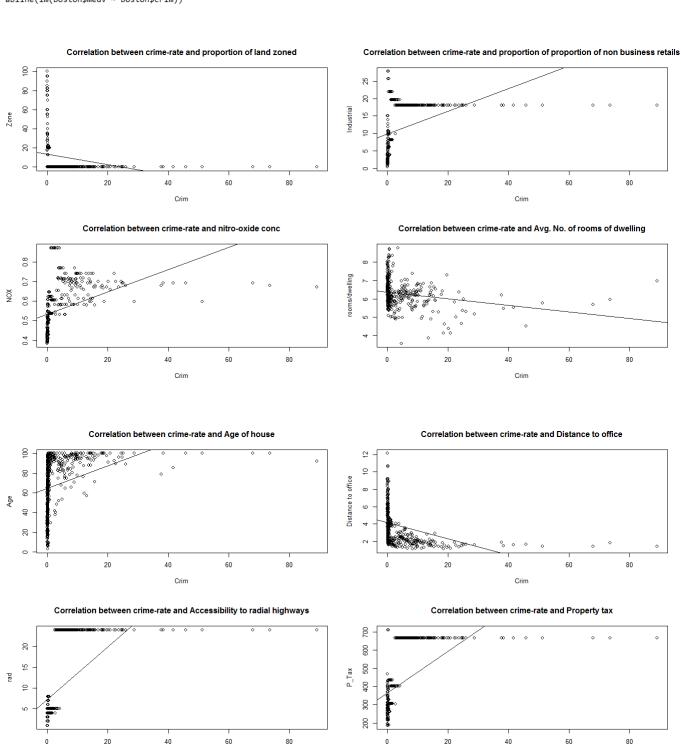
```
> # Function to retreive significant correlations
crim_cor = function()
  sig cnt = 1
  res_corr = c()
  p_{val} = c()
  ind_var_name = c()
  assoc = c()
  ind_var = Boston[,names(Boston)!="crim"]
  for(i in 1:length(Boston))
    if(cor.test(Boston[[i]],Boston\$crim,method="pearson")\$p.value < 0.05 \& names(Boston[i])!="crim")
      res_corr[sig_cnt] = cor(Boston[[i]],Boston$crim,method="pearson")
      ind_var_name[sig_cnt] = names(Boston[i])
p_val[sig_cnt] = cor.test(Boston[[i]],Boston$crim,method="pearson")$p.value
       if(res_corr[[sig_cnt]]<0)
      {
        assoc = c(assoc, "neg")
      else
        assoc = c(assoc, "pos")
      sig_cnt = sig_cnt + 1
    }
  names(res_corr) = ind_var_name
  res_corr = rbind(res_corr,p_val)
res_corr = rbind(res_corr,assoc)
  return (res_corr)
  # print(res_corr)
> a = crim_cor()
> a
                                   indus
                                                                               rm
"-0.219246702862514"
          "-0.200469219662547"
                                   "0.406583411406259"
res corr
                                                          "0.420971711392456"
                                                                                                         "0.352734250901364"
                                                                                                                                   "-0.379670086951024"
          "5.50647210767929e-06"
                                                                                "6.34670298468773e-07"
p_val
                                   "a"
                                                          "a"
                                                                                                         "4.44089209850063e-16" "8.51994876692635e-19"
          "neg"
assoc
                                   "pos
                                                         "pos'
                                                                                "neg"
                                                                                                         "pos"
                                                                                                                                   "neg"
                                                                                                                              medv
          rad
                                tax
                                                      ntratio
                                                                               black.
                                                                                                        1stat
                                                      "0.28994557927952"
                                                                                                                              "-0.388304608586812"
          "0.625505145262602"
                                "0.582764312032585"
                                                                                "-0.385063941994224"
                                                                                                        "0.455621479447946"
res corr
          "0"
                                "0"
                                                      "2.94293478475538e-11"
                                                                               "2.4872739737737e-19" "0"
                                                                                                                              "1.17398708219436e-19"
p_val
assoc
          "pos
                                "pos"
                                                      "pos"
                                                                                "neg"
                                                                                                        "pos'
                                                                                                                              "neg'
```

Here the Variable 'a' stores the predictor's r-value, p-value and their associations row wise.

## 1.c X-Y Plots for the significant correlations.

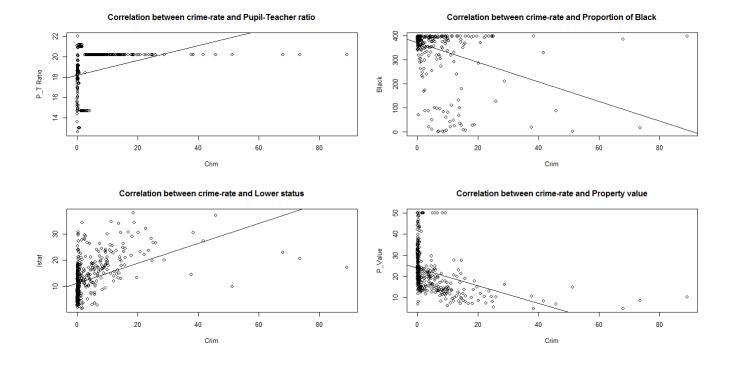
```
par(mfrow=c(2,2))
plot(Boston$crim,Boston$zn,main="Correlation between crime-rate and proportion of land zoned",xlab="Crim", ylab="Zone")
abline(lm(Boston$zn ~ Boston$crim))
plot(Boston$crim,Boston$indus,main="Correlation between crime-rate and proportion of non business retails",xlab="Crim", ylab="Industrial")
abline(lm(Boston$indus ~ Boston$crim))
\verb|plot(Boston\$crim,Boston\$nox,main="Correlation between crime-rate and nitro-oxide conc", \verb|xlab="Crim", ylab="NOX"|| \\
abline(lm(Boston$nox ~ Boston$crim))
plot(Boston$crim,Boston$rm,main="Correlation between crime-rate and Avg. No. of rooms of dwelling", ylab="Crim", ylab="rooms/dwelling")
abline(lm(Boston$rm ~ Boston$crim))
par(mfrow=c(2,2))
plot(Boston$crim,Boston$age,main="Correlation between crime-rate and Age of house",xlab="Crim", ylab="Age")
abline(lm(Boston$age ~ Boston$crim))
plot(Boston$crim,Boston$dis,main="Correlation between crime-rate and Distance to office",xlab="Crim", ylab="Distance to office")
abline(lm(Boston$dis ~ Boston$crim))
abline(lm(Boston$rad ~ Boston$crim))
plot(Boston$crim,Boston$tax,main="Correlation between crime-rate and Property tax",xlab="Crim", ylab="P_Tax")
abline(lm(Boston$tax ~ Boston$crim))
```

```
par(mfrow=c(2,2))
plot(Boston$crim,Boston$ptratio,main="Correlation between crime-rate and Pupil-Teacher ratio",xlab="Crim", ylab="P_T Ratio")
abline(lm(Boston$ptratio ~ Boston$crim))
plot(Boston$crim,Boston$black,main="Correlation between crime-rate and Proportion of Black",xlab="Crim", ylab="Black")
abline(lm(Boston$black ~ Boston$crim))
plot(Boston$crim,Boston$lstat,main="Correlation between crime-rate and Lower status",xlab="Crim", ylab="lstat")
abline(lm(Boston$lstat ~ Boston$crim))
plot(Boston$crim,Boston$medv,main="Correlation between crime-rate and Property value",xlab="Crim", ylab="P_Value")
abline(lm(Boston$medv ~ Boston$crim))
```



Crim

Crim



1.d Number of suburbs in this data set which bound the Charles River.

```
> with(Boston, subset(Boston, Boston$chas==1 ))
    crim zn indus chas    nox    rm    age
                                                      rad tax ptratio black 1stat medv
                         1 0.8710 5.403 100.0 1.3216
143 3.32105 0 19.58
                                                        5 403
                                                                  14.7 396.90 26.82 13.4
                           0.8710 5.012 88.0 1.6102
                                                        5 403
                                                                  14.7 343.28 12.12 15.3
153 1.12658
             0 19.58
155 1.41385
             0 19.58
                           0.8710 6.129
                                          96.0 1.7494
                                                          403
                                                                  14.7 321.02 15.12 17.0
156 3.53501
             0 19.58
                         1 0.8710 6.152
                                         82.6 1.7455
                                                        5 403
                                                                  14.7 88.01 15.02 15.6
                           0.6050 6.250
                                                        5 403
                                                                  14.7 338.92 5.50 27.0
161 1.27346
                                          92.6 1.7984
             0 19.58
163 1.83377
              0 19.58
                           0.6050 7.802
                                          98.2 2.0407
                                                          403
                                                                  14.7 389.61
                                                                              1.92 50.0
164 1.51902
             0 19.58
                         1 0.6050 8.375
                                          93.9 2.1620
                                                        5 403
                                                                  14.7 388.45
                                                                              3.32 50.0
209 0.13587
                           0.4890 6.064
                                                        4 277
             0 10.59
                                          59.1 4.2392
                                                                  18.6 381.32 14.66 24.4
210 0.43571
              0 10.59
                           0.4890 5.344 100.0 3.8750
                                                        4 277
                                                                  18.6 396.90 23.09 20.0
211 0.17446
             0 10.59
                           0.4890 5.960
                                         92.1 3.8771
                                                        4 277
                                                                  18.6 393.25 17.27 21.7
212 0.37578
             0 10.59
                           0.4890 5.404
                                          88.6 3.6650
                                                        4 277
                                                                  18.6 395.24 23.98 19.3
213 0.21719
             0 10.59
                           0.4890 5.807
                                          53.8 3.6526
                                                        4 277
                                                                  18.6 390.94 16.03 22.4
                         1 0.5500 5.888
                                                        5 276
217 0.04560
             0 13.89
                                          56.0 3.1121
                                                                  16.4 392.80 13.51 23.3
219 0.11069
             0 13.89
                           0.5500 5.951
                                          93.8 2.8893
                                                          276
                                                                  16.4 396.90 17.92 21.5
220 0.11425
             0 13.89
                           0.5500 6.373
                                          92.4 3.3633
                                                        5 276
                                                                  16.4 393.74 10.50 23.0
221 0.35809
                         1 0.5070 6.951
                                          88.5 2.8617
                                                        8 307
                                                                  17.4 391.70 9.71 26.7
             0 6.20
222 0.40771
                6.20
                           0.5070 6.164
                                          91.3 3.0480
                                                          307
                                                                  17.4 395.24 21.46 21.7
223 0.62356
             0
                6.20
                           0.5070 6.879
                                          77.7 3.2721
                                                        8 307
                                                                  17.4 390.39 9.93 27.5
235 0.44791
                           0.5070 6.726
                                          66.5 3.6519
                                                        8 307
                                                                  17.4 360.20 8.05 29.0
             0
                6.20
237 0.52058
                           0.5070 6.631
                                                          307
                                                                  17.4 388.45 9.54 25.1
                6.20
                                          76.5 4.1480
270 0.09065 20
                6.96
                           0.4640 5.920
0.4640 7.691
                                          61.5 3.9175
51.8 4.3665
                                                        3 223
                                                                  18.6 391.34 13.65 20.7
                                                        3 223
                                                                  18.6 390.77 6.58 35.2
274 0.22188 20
                6.96
275 0.05644 40
                6.41
                           0.4470 6.758
                                          32.9 4.0776
                                                          254
                                                                  17.6 396.90
                                                                               3.53 32.4
277 0.10469 40
                6.41
                           0.4470 7.267
                                          49.0 4.7872
                                                        4 254
                                                                  17.6 389.25 6.05 33.2
278 0.06127 40
                           0.4470 6.826
                                                        4 254
                6.41
                                          27.6 4.8628
                                                                  17.6 393.45
                                                                               4.16 33.1
283 0.06129 20
                3.33
                           0.4429 7.645
                                          49.7 5.2119
                                                        5 216
                                                                  14.9 377.07
                                                                               3.01 46.0
284 0.01501 90
                1.21
                           0.4010 7.923
                                          24.8 5.8850
                                                        1 198
                                                                  13.6 395.52 3.16 50.0 20.2 377.73 17.60 17.8
                           0.7700 6.212
                                          97.4 2.1222
                                                       24 666
357 8.98296
            0 18.10
358 3.84970
             0 18.10
                           0.7700 6.395
                                          91.0 2.5052
                                                       24 666
                                                                  20.2 391.34 13.27 21.7
359 5.20177
             0 18.10
                           0.7700 6.127
                                          83.4 2.7227
                                                       24 666
                                                                  20.2 395.43 11.48 22.7
                           0.7700 5.803
                                                                  20.2 353.04 14.64 16.8
364 4.22239
             0 18.10
                                          89.0 1.9047
                                                       24 666
365 3.47428
             0 18.10
                           0.7180 8.780
                                          82.9 1.9047
                                                       24 666
                                                                  20.2 354.55 5.29 21.9
370 5.66998
             0 18.10
                           0.6310 6.683
                                          96.8 1.3567
                                                       24 666
                                                                  20.2 375.33 3.73 50.0
                           0.6310 7.016
                                                                  20.2 392.05
                                                                               2.96 50.0
371 6.53876
             0 18.10
                                          97.5 1.2024
                                                       24 666
373 8.26725
            0 18.10
                         1 0.6680 5.875
                                         89.6 1.1296
                                                       24 666
                                                                  20.2 347.88
                                                                               8.88 50.0
> nrow(with(Boston, subset(Boston, Boston$chas==1 )))
[1] 35
```

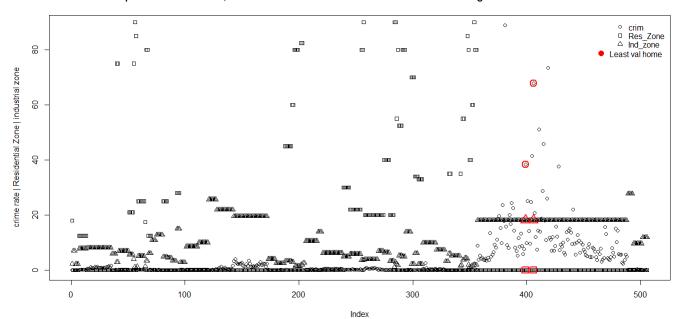
1.e Median pupil-teacher ratio among the towns in this data set.

```
> median(Boston$ptratio)
[1] 19.05
```

1.f Lowest median value of owner occupied homes and comparison of other predictors from this group with rest of the sample.

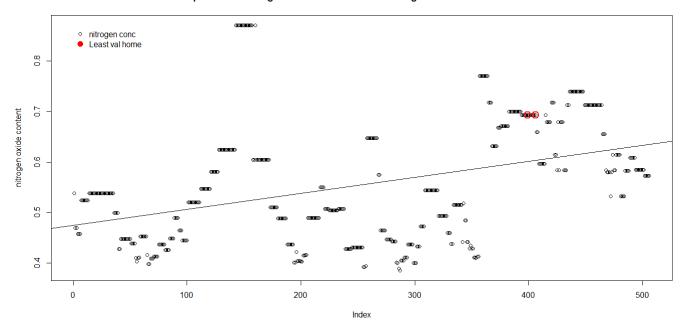
```
> Boston[Boston$medv == min(as.numeric(Boston$medv)),]
                         crim zn indus chas nox rm age dis rad tax ptratio black lstat medv
3518 0 18.1 0 0.693 5.453 100 1.4896 24 666 20.2 396.90 30.59 5
399 38.3518 0 18.1
406 67.9208 0 18.1
                                                                                         0 0.693 5.683 100 1.4254 24 666
                                                                                                                                                                                                                                  20.2 384.97 22.98
> plot(Boston$crim,ylab="crime rate | Residential Zone | industrial zone")
      points(rownames(Boston$medv) == min(as.numeric(Boston$medv)),]),Boston$crim[Boston$medv == min(as.numeric(Boston$medv))],col="#FF0000",lwd=2,cex=2) points(Boston$zn,lwd=1,cex=1,pch=22)
> points(rownames(Boston[Boston$medv == min(as.numeric(Boston$medv)),]),Boston$zn[Boston$medv == min(as.numeric(Boston$medv))],col="#FF0000",lwd=2,cex=2,pch=22)
> points(Poston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|Moston|
```

#### Comparision of crime rate, Residential zone and industrial zone of suburbs having least home value and others



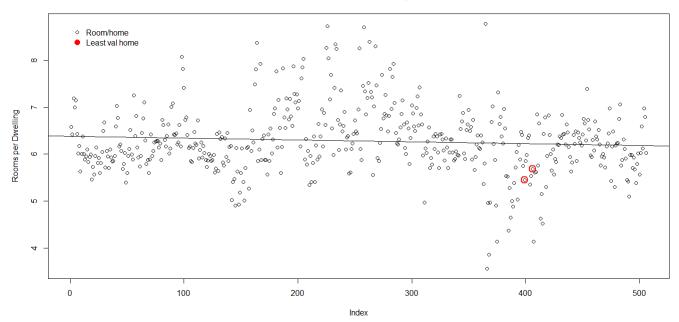
```
> plot(Boston$nox,ylab="nitrogen oxide content")
> points(rownames(Boston)$medv == min(as.numeric(Boston$medv)),]),Boston$nox[Boston$medv == min(as.numeric(Boston$medv))],col="#FF0000",lwd=2,cex=2) > legend('topleft',c("nitrogen conc"),pch=21,bty="n",x.intersp=0.3,y.intersp=0.3) > legend('topleft',c("Least val home"),pch=19,col="red",cex=1,bty='n',x.intersp=0.3,pt.cex = 1.5) > abline(lm(Boston$nox ~ as.numeric(rownames(Boston)))) > title("Comparision of Nitrogen Ox. Conc of suburbs having least home value with others")
```

## Comparision of Nitrogen Ox. Conc of suburbs having least home value with others



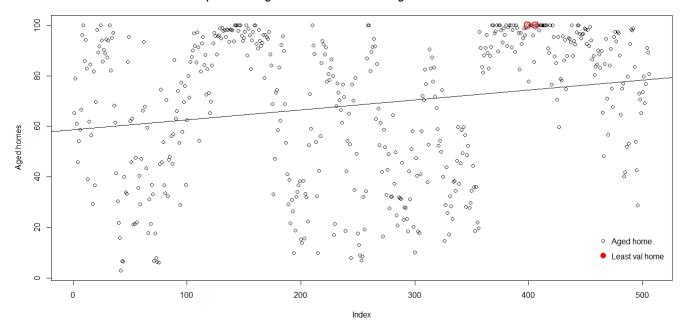
```
> plot(Boston$rm,ylab="Rooms per Dwelling")
> points(rownames(Boston[Boston$medv == min(as.numeric(Boston$medv)),]),Boston$rm[Boston$medv == min(as.numeric(Boston$medv))],col="#FF0000",lwd=2,cex=2)
> legend('topleft',c("Room/home"),pch=21,bty="n",x.intersp=0.3,y.intersp=0.3)
> legend('topleft',c("Least val home"),pch=19,col="red",cex=1,bty='n',x.intersp=0.3,pt.cex = 1.5)
> abline(lm(Boston$rm ~ as.numeric(rownames(Boston))))
> title("Comparision of rooms per home of suburbs having least home value with others")
```

#### Comparision of rooms per home of suburbs having least home value with others



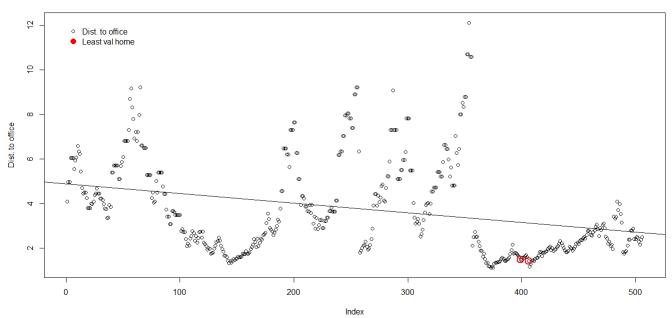
```
> plot(Boston$age,ylab="Aged homes")
> piot(poston)age, ylab= aged nomes )
> points(rownames(Boston)smedv == min(as.numeric(Boston)medv)),]),Boston\square[Boston\square]medv == min(as.numeric(Boston\square]medv))],col="#FF0000",lwd=2,cex=2)
> legend(x=440,y=22,c("Aged home"),pch=21,bty="n",x.intersp=0.3,y.intersp=0.3)
> legend(x=440,y=20,c("Least val home"),pch=19,col="red",cex=1,bty='n',x.intersp=0.3,pt.cex = 1.5)
> abline(lm(Boston\square)age ~ as.numeric(rownames(Boston)) ))
> title("Comparision of Aged Homes of suburbs having least home value with others")
```

## Comparision of Aged Homes of suburbs having least home value with others



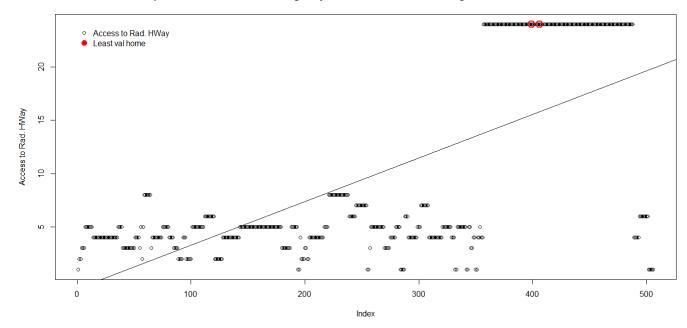
```
> plot(Boston$dis,ylab="Dist. to office")
> piot(NostonSpuis,yi80= UIST. TO Office )
> points(nonwames(Boston[BostonSmedv == min(as.numeric(BostonSmedv)),]),BostonSdis[BostonSmedv == min(as.numeric(BostonSmedv))],col="#FF0000",lwd=2,cex=2)
> legend('topleft',c("Dist. to office"),pch=21,bty="n",x.intersp=0.3,y.intersp=0.3)
> legend('topleft',c("Least val home"),pch=19,col="red",cex=1,bty='n',x.intersp=0.3,pt.cex = 1.5)
> abline(lm(BostonSdis ~ as.numeric(rownames(Boston))))
> title("Comparision of distance to office from home of suburbs having least home value with others")
```

## Comparision of distance to office from home of suburbs having least home value with others



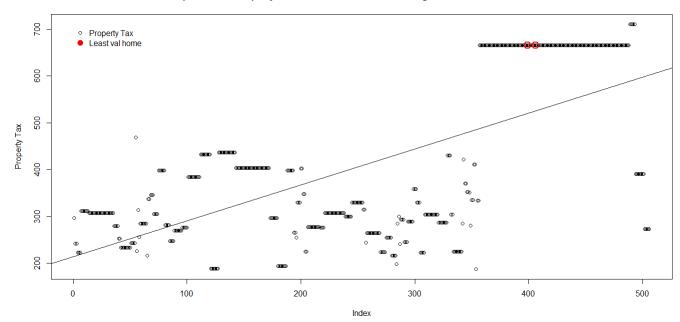
<sup>&</sup>gt; plot(Boston\$rad,ylab="Access to Rad. HWay")
> points(rownames(Boston\$medv == min(as.numeric(Boston\$medv)),]),Boston\$rad[Boston\$medv == min(as.numeric(Boston\$medv))],col="#FF0000",lwd=2,cex=2)
> legend('topleft',c("Access to Rad. HWay"),pch=21,bty="n",x.intersp=0.3,y.intersp=0.3)
> legend('topleft',c("Least val home"),pch=19,col="red",cex=1,bty='n',x.intersp=0.3,pt.cex = 1.5)
> abline(lm(Boston\$rad ~ as.numeric(rownames(Boston)) ))
> title("Comparision of Access to Radial HighWay from home of suburbs having least home value with others")

## Comparision of Access to Radial HighWay from home of suburbs having least home value with others



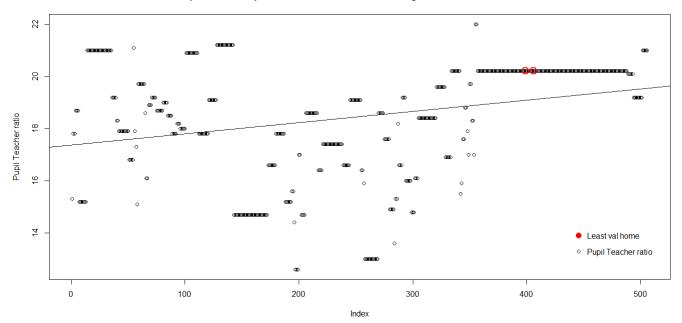
- > plot(Boston\$tax,ylab="Property Tax")
  > points(rownames(Boston[Boston\$medv == min(as.numeric(Boston\$medv)),]),Boston\$tax[Boston\$medv == min(as.numeric(Boston\$medv))],col="#FF0000",lwd=2,cex=2)
  > legend('topleft',c("Property Tax"),pch=21,bty="n",x.intersp=0.3,y.intersp=0.3)
  > legend('topleft',c("Least val home"),pch=19,col="red",cex=1,bty='n',x.intersp=0.3,pt.cex = 1.5)
  > abline(lm(Boston\$tax ~ as.numeric(rownames(Boston)) ))
  > title("Comparision of Property Tax of homes of suburbs having least home value with others")

## Comparision of Property Tax of homes of suburbs having least home value with others



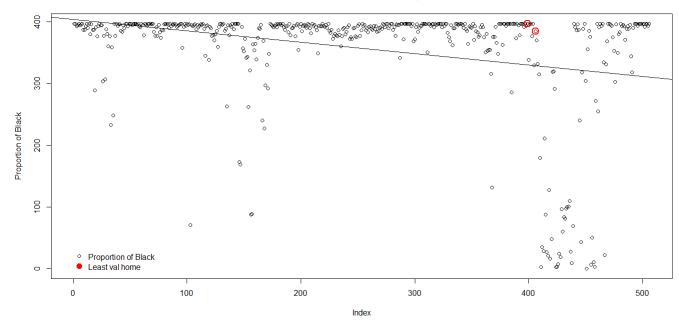
- > plot(Boston\$ptratio,ylab="Pupil Teacher ratio")
  > points(rownames(Boston[Boston\$medv == min(as.numeric(Boston\$medv)),]),Boston\$ptratio[Boston\$medv == min(as.numeric(Boston\$medv))],col="#FF0000",lwd=2,cex=2)
  > legend(x=420,y=15,c("Pupil Teacher ratio"),pch=21,bty="n",x.intersp=0.3,y.intersp=0.3)
  > legend(x=420,y=15,c("Least val home"),pch=19,col="red",cex=1,bty='n',x.intersp=0.3,pt.cex = 1.5)
  > abline(lm(Boston\$ptratio ~ as.numeric(rownames(Boston))))
  > title("Comparision of Pupil Teacher ratio of suburbs having least home value with others")

## Comparision of Pupil Teacher ratio of suburbs having least home value with others



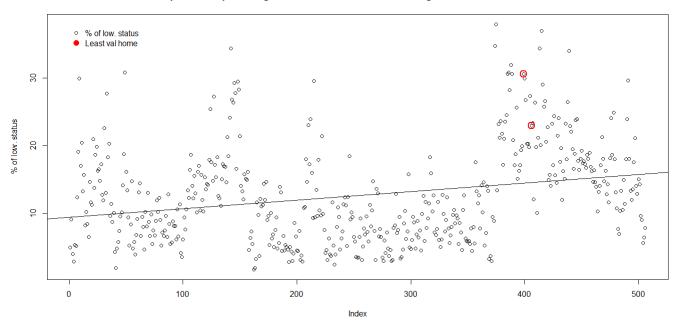
- > plot(Boston\$black,ylab="Proportion of Black")
  > points(rownames(Boston[Boston\$medv == min(as.numeric(Boston\$medv)),]),Boston\$black[Boston\$medv == min(as.numeric(Boston\$medv))],col="#FF0000",lwd=2,cex=2)
  > legend(x=-20,y=50,c("Proportion of Black"),pch=21,bty="n",x.intersp=0.3,y.intersp=0.3,pt.cex = 1.5)
  > legend(x=-20,y=50,c("Least val home"),pch=19,col="red",cex=1,bty='n',x.intersp=0.3,pt.cex = 1.5)
  > abline(lm(Boston\$black ~ as.numeric(rownames(Boston)) ))
  > title("Comparision of Proportion of Black in suburbs having least home value with others")

#### Comparision of Proportion of Black in suburbs having least home value with others



- > plot(Boston\$lstat,ylab="% of low. status")
  > points(rownames(Boston[Boston\$medv == min(as.numeric(Boston\$medv)),]),Boston\$lstat[Boston\$medv == min(as.numeric(Boston\$medv))],col="#FF0000",lwd=2,cex=2)
  > legend('topleft',c("% of low. status"),pch=21,bty="n",x.intersp=0.3,y.intersp=0.3)
  > legend('topleft',c("Least val home"),pch=19,col="n-ed",cex=1,bty='n',x.intersp=0.3,pt.cex = 1.5)
  > abline(lm(Boston\$lstat ~ as.numeric(rownames(Boston)) ))
  > title("Comparision of percentage of lower status in suburbs having least home value with others")

## Comparision of percentage of lower status in suburbs having least home value with others



Comparison/Characteristics of predictors :

- Higher Crime rates than other suburbs.
- No proportion of residential land zoned for lots over 25,000 sq.ft.
- Higher proportion of non-retail business acres per town.
- Very high proportion of owner-occupied units built prior to 1940 houses.
- High proportion of blacks by town.
- Very Low weighted mean of distances to five Boston employment centers.
- High percentage of lower status population.
- Above average level of nitrogen oxide concentration.
- Pupil-teacher ratio by town slightly higher than the mean.
- High index of accessibility to radial highways.
- Average number of rooms per dwelling is just below the average.
- High full-value property-tax rate per \$10,000.

 $1.\mathrm{e}$  Suburbs having average more than 7 and 8 rooms per dwelling.

```
> nrow(Boston[Boston$rm > 7,])
[1] 64
> nrow(Boston[Boston$rm > 8,])
[1] 13
```

Observations of characteristic of dwelling with more than 8 rooms:

- For Majority of the dwellings, the tract does not bound the Charles river.
- Percentage of the lowers status population is lower than the mean of sample population.
- Generally low crime rates.

10

- Mean of 'age' variable is slightly higher than that of the population. However median is very close to the sample population median. (Possible outlier with 'age'=8.4 whereas mean for the category being 71.53).
- Mean and median for 'medy' is more than twice for corresponding sample population values.

.

2.a Code for calculating Mahalanobi's distance.

```
> x = matrix(c(2,10,3,3,7,2),nrow=3)
> x
     [,1] [,2]
[1,]
      10
[2,]
[3,]
> y=matrix(c(1,3,5,15,8,16,4,3,7,2,2,4,33,7),ncol=2)
     [,1] [,2]
[1,]
[2,]
[3,]
        5
[4,]
       15
[5,]
       8
       16
[6,]
[7,]
> mean_x = matrix(c(mean(x[,1]),mean(x[,2])),nrow=2)
> mean_x
     [,1]
[1,]
[2,]
> mean_y = matrix(c(mean(y[,1]),mean(y[,2])),nrow=2)
> mean_y
[1,] 7.428571
[2,] 8.285714
\rightarrow x1=matrix(c(x[,1]-mean(x[,1]),c(x[,2]-mean(x[,2]))),ncol=2)
> x1
     [,1] [,2]
[1,]
      -3 -1
5 3
-2 -2
[2,]
[3,]
> y1=matrix(c(y[,1]-mean(y[,1]),c(y[,2]-mean(y[,2]))),ncol=2)
> y1
           [,1]
                      [,2]
[1,] -6.4285714 -5.285714
[2,] -4.4285714 -1.285714
[3,] -2.4285714 -6.285714
[4,] 7.5714286 -6.285714
[5,] 0.5714286 -4.285714
[6,] 8.5714286 24.714286
[7,] -3.4285714 -1.285714
> c1 = (1/nrow(x1))*(t(x1)%*%x1)
> c1
          [,1]
[1,] 12.666667 7.333333
[2,] 7.333333 4.666667
> c2 = (1/nrow(y1))*(t(y1)%*%y1)
> c2
         [,1]
[1,] 29.95918 31.59184
[2,] 31.59184 105.63265
> s = (nrow(x1)/(nrow(x1)+nrow(y1)))*c1 + (nrow(y1)/(nrow(x1)+nrow(y1)))*c2
[1,] 24.77143 24.31429
[2,] 24.31429 75.34286
> solve(s)
[,1] [,2]
[1,] 0.05908476 -0.01906755
[2,] -0.01906755 0.01942605
> Mahalanobis_dist = sqrt(t(mean_x - mean_y) %*% solve(s) %*% (mean_x - mean_y))
> Mahalanobis_dist
         [,1]
[1,] 0.555309
```

2.b Function that calculates Mahalanobi's distance.

```
Mahalanobis_dist = function(x,y)
       if(ncol(x)!=ncol(y))
       {
            print("ERROR! Number of columns in two matrices must be same!")
       mean_x = matrix(c(mean(x[,1]),mean(x[,2])),nrow=2)
        \begin{array}{ll} \text{mean} y = \text{matrix}(c(\text{mean}(y[,1]), \text{mean}(y[,2])), \text{nrow=2}) \\ x1 = \text{matrix}(c(x[,1]-\text{mean}(x[,1]), c(x[,2]-\text{mean}(x[,2]))), \text{ncol=2}) \end{array} 
       y1=matrix(c(y[,1]-mean(y[,1]),c(y[,2]-mean(y[,2]))),ncol=2)
       c1 = (1/nrow(x1))*(t(x1)%*%x1)
       c2 = (1/nrow(y1))*(t(y1)%*%y1)
       s = (nrow(x1)/(nrow(x1)+nrow(y1)))*c1 + (nrow(y1)/(nrow(x1)+nrow(y1)))*c2
       dist = sqrt(t(mean_x - mean_y) %*% solve(s) %*% (mean_x - mean_y))
       return(dist)
\rightarrow x= matrix(c(2,10,3,3,7,2),nrow=3)
      [,1] [,2]
[2,]
        10
               7
[3,]
> y=matrix(c(1,3,5,15,8,16,4,3,7,2,2,4,33,7),ncol=2)
      [,1] [,2]
[1,]
[2,]
[3,]
        15
         8
                4
        16
               33
          4
> Mahalanobis dist(x,y)
[1,] 0.555309
```

3 Difference between Artificial Intelligence, Machine Learning, Statistics, and Data Mining.

Though all of the four terms in discussion has many grounds overlapping each other, there are some significant differences among them. All are in way either related to each other or one form of the other.

Starting from Artificial Intelligence (AI), the goal of AI is simply to induce intelligence to machines, so that they are enabled to make independent decisions without human intervention. This is a very broad area and has given rise to many disciplines within itself like Natural Language Processing (NLP), Robotics, Computer vision, Reasoning etc. Machine Learning is one such discipline that has grown out of the need for pure AI.

Machine Learning tries to enable machines to make decisions on their own by feeding them with training data and using some generic algorithms. These algorithms can be employed to solve a variety of problems and are most of the time, if not always, are directly derived or inspired by classical statistics. One of the application of such algorithms are in Data Mining.

Data Mining uses algorithms or techniques that are mostly coined by Machine learning, and apply it to a specific domain/area of interest. Data mining has a very clear goal unlike Machine learning and tries to solve/understand a particular problem. Data Mining has been commonly used to leverage the data in hand and make predictions, draw inferences, reason associations, finding patterns etc. It has been branched out from the field of exploratory Statistics.

Lastly, Statistics is a branch of mathematics that concentrates on collection, analysis, interpretation, presentation and organization of the data. This is the oldest of the other three fields in discussion. Statistics can also be seen as a way to transform data into information or insights.