CSE 574
Assign 2
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TASK 0 Preparation 10 points (state in your report the platform you use)
Soln:
Platform used:
R studio: version 1.1.419
Rmarkdown (was used for producing your report).
Library used:

```
library(randomForest)
library(MASS)
require(tree)
require(devtools)
require(ISLR)
require(MASS)
require(randomForest)
require(gbm)
library(caret)

attach ( Carseats )
```

TASK 1 Fitting Classification Trees
Soln:
The solution for this is in filename : assign2_part1.Rmd

```
require(tree)
require(devtools)
require(ISLR)
require(MASS)
require(randomForest)
library(gbm)
```

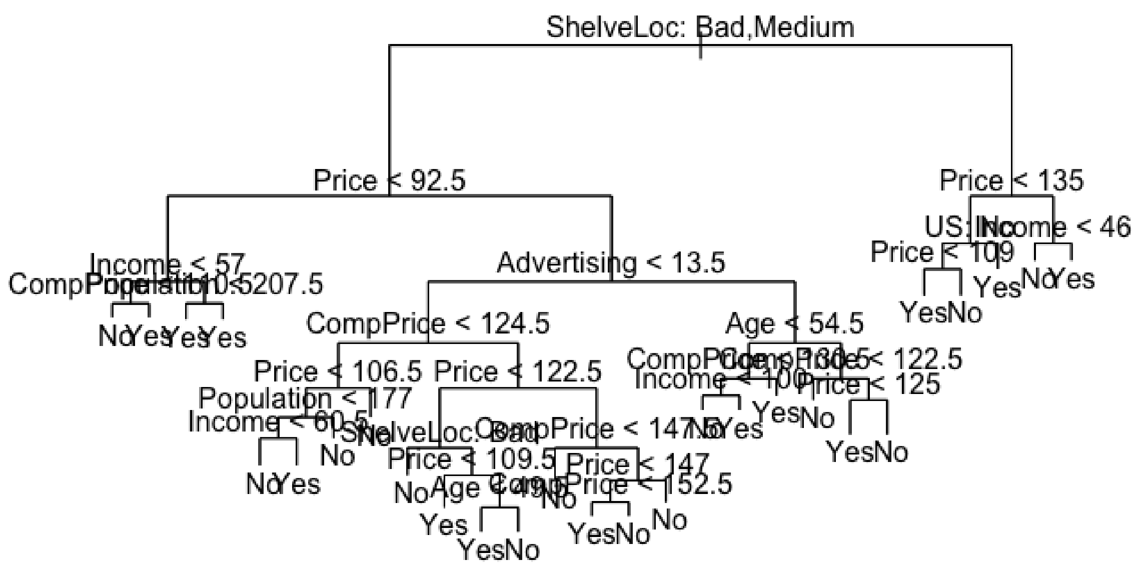
o/p:: Using classification trees to analyze the Carseats data set.Sales is a continuous variable, and so we begin by recoding it as a binary variable.

```
library (ISLR )
attach ( Carseats )
High= ifelse (Sales <=8 ," No"," Yes ")
Carseats = data.frame (Carseats , High)
tree.carseats =tree (High~.-Sales , Carseats )
summary (tree.carseats )
```

o/p::

Classification tree:
tree(formula = High ~ . - Sales, data = Carseats)
Variables actually used in tree construction:
[1] "ShelveLoc"   "Price"   "Income"   "CompPrice"   "Population" "Advertising" "Age"
[8] "US"
Number of terminal nodes: 27
Residual mean deviance: 0.4575 = 170.7 / 373
Misclassification error rate: 0.09 = 36 / 400

plot(tree.carseats)
text(tree.carseats ,pretty =0)




```
tree.carseats

## node), split, n, deviance, yval, (yprob)
##       * denotes terminal node
##
##   1) root 400 541.500  No ( 0.59000 0.41000 )
##     2) ShelveLoc: Bad,Medium 315 390.600  No ( 0.68889 0.31111 )
##       4) Price < 92.5 46  56.530  Yes  ( 0.30435 0.69565 )
##         8) Income < 57 10  12.220  No ( 0.70000 0.30000 )
##          16) CompPrice < 110.5 5   0.000  No ( 1.00000 0.00000 ) *
##          17) CompPrice > 110.5 5   6.730  Yes  ( 0.40000 0.60000 ) *
##         9) Income > 57 36  35.470  Yes  ( 0.19444 0.80556 )
```

```
##          18) Population < 207.5 16  21.170  Yes  ( 0.37500 0.62500 ) *
##          19) Population > 207.5 20   7.941  Yes  ( 0.05000 0.95000 ) *
##       5) Price > 92.5 269 299.800  No ( 0.75465 0.24535 )
##        10) Advertising < 13.5 224 213.200  No ( 0.81696 0.18304 )
##          20) CompPrice < 124.5 96  44.890  No ( 0.93750 0.06250 )
##            40) Price < 106.5 38  33.150  No ( 0.84211 0.15789 )
##              80) Population < 177 12  16.300  No ( 0.58333 0.41667 )
##               160) Income < 60.5 6   0.000  No ( 1.00000 0.00000 ) *
##               161) Income > 60.5 6   5.407  Yes  ( 0.16667 0.83333 ) *
##              81) Population > 177 26   8.477  No ( 0.96154 0.03846 ) *
##            41) Price > 106.5 58   0.000  No ( 1.00000 0.00000 ) *
##          21) CompPrice > 124.5 128 150.200  No ( 0.72656 0.27344 )
##            42) Price < 122.5 51  70.680  Yes  ( 0.49020 0.50980 )
##              84) ShelveLoc: Bad 11   6.702  No ( 0.90909 0.09091 ) *
##              85) ShelveLoc: Medium 40  52.930  Yes  ( 0.37500 0.62500 )
##               170) Price < 109.5 16   7.481  Yes  ( 0.06250 0.93750 ) *
##               171) Price > 109.5 24  32.600  No ( 0.58333 0.41667 )
##                 342) Age < 49.5 13  16.050  Yes  ( 0.30769 0.69231 ) *
##                 343) Age > 49.5 11   6.702  No ( 0.90909 0.09091 ) *
##            43) Price > 122.5 77  55.540  No ( 0.88312 0.11688 )
##              86) CompPrice < 147.5 58  17.400  No ( 0.96552 0.03448 ) *
##              87) CompPrice > 147.5 19  25.010  No ( 0.63158 0.36842 )
##               174) Price < 147 12  16.300  Yes  ( 0.41667 0.58333 )
##                 348) CompPrice < 152.5 7   5.742  Yes  ( 0.14286 0.85714 )
*
##                 349) CompPrice > 152.5 5   5.004  No ( 0.80000 0.20000 ) *
##               175) Price > 147 7   0.000  No ( 1.00000 0.00000 ) *
##        11) Advertising > 13.5 45  61.830  Yes  ( 0.44444 0.55556 )
##          22) Age < 54.5 25  25.020  Yes  ( 0.20000 0.80000 )
##            44) CompPrice < 130.5 14  18.250  Yes  ( 0.35714 0.64286 )
##              88) Income < 100 9  12.370  No ( 0.55556 0.44444 ) *
##              89) Income > 100 5   0.000  Yes  ( 0.00000 1.00000 ) *
##            45) CompPrice > 130.5 11   0.000  Yes  ( 0.00000 1.00000 ) *
##          23) Age > 54.5 20  22.490  No ( 0.75000 0.25000 )
##            46) CompPrice < 122.5 10   0.000  No ( 1.00000 0.00000 ) *
##            47) CompPrice > 122.5 10  13.860  No ( 0.50000 0.50000 )
##              94) Price < 125 5   0.000  Yes  ( 0.00000 1.00000 ) *
##              95) Price > 125 5   0.000  No ( 1.00000 0.00000 ) *
##     3) ShelveLoc: Good 85  90.330  Yes  ( 0.22353 0.77647 )
##       6) Price < 135 68  49.260  Yes  ( 0.11765 0.88235 )
##        12) US: No 17  22.070  Yes  ( 0.35294 0.64706 )
##          24) Price < 109 8   0.000  Yes  ( 0.00000 1.00000 ) *
##          25) Price > 109 9  11.460  No ( 0.66667 0.33333 ) *
##        13) US: Yes 51  16.880  Yes  ( 0.03922 0.96078 ) *
##       7) Price > 135 17  22.070  No ( 0.64706 0.35294 )
##        14) Income < 46 6   0.000  No ( 1.00000 0.00000 ) *
##        15) Income > 46 11  15.160  Yes  ( 0.45455 0.54545 ) *
```

```r
set.seed (2)
train = sample (1: nrow( Carseats ), 200)
```

```r
Carseats.test= Carseats [-train ,]
High.test=High[-train ]
tree.carseats =tree (High~.-Sales , Carseats , subset =train )
tree.pred = predict ( tree.carseats , Carseats.test ,type ="class")
table ( tree.pred ,High.test)
```

```
##          High.test
## tree.pred  No  Yes
##       No   86   27
##       Yes  30   57
```

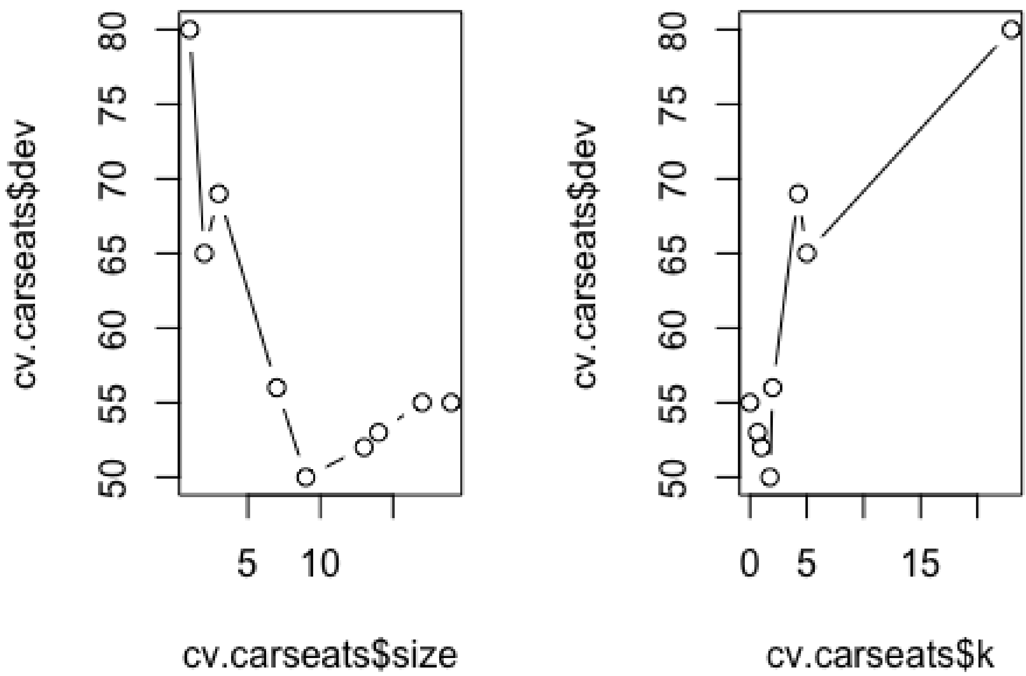
```r
set.seed (3)
cv.carseats =cv.tree(tree.carseats ,FUN = prune.misclass )
names (cv.carseats )
```

```
## [1] "size"   "dev"    "k"      "method"
```

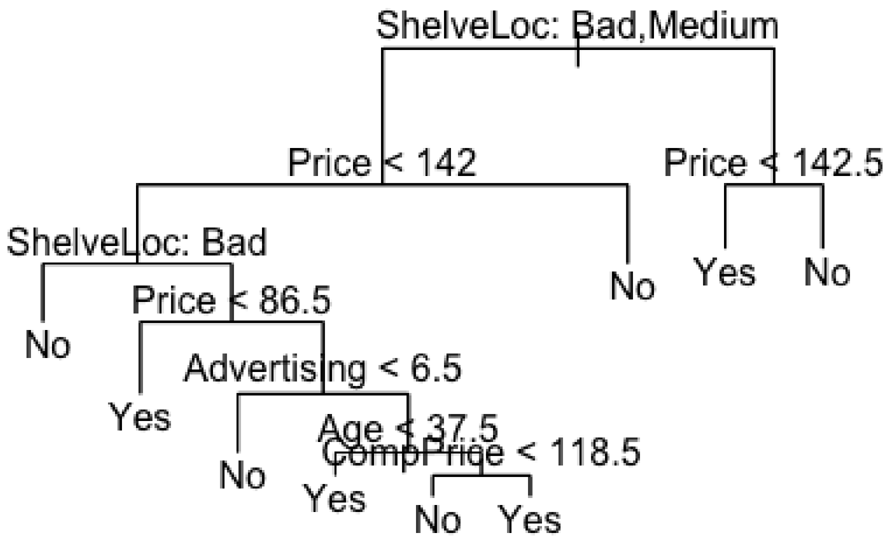
```r
cv.carseats
```

```
## $size
## [1] 19 17 14 13  9  7  3  2  1
##
## $dev
## [1] 55 55 53 52 50 56 69 65 80
##
## $k
## [1]       -Inf  0.0000000  0.6666667  1.0000000  1.7500000  2.0000000
## [7]  4.2500000  5.0000000 23.0000000
##
## $method
## [1] "misclass"
##
## attr(,"class")
## [1] "prune"         "tree.sequence"
```

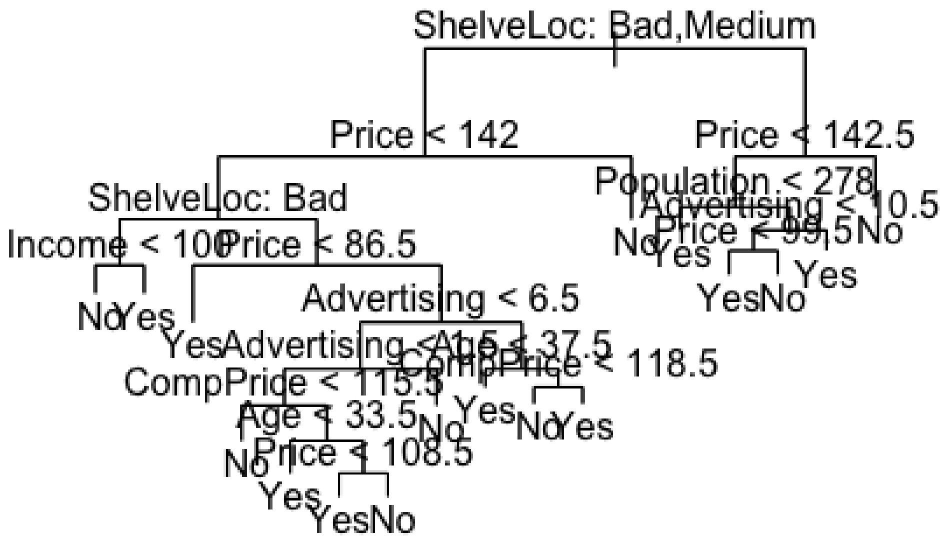
```r
par ( mfrow =c(1 ,2) )
plot(cv.carseats$size ,cv.carseats$dev , type ="b")
plot(cv.carseats$k ,cv.carseats$dev , type ="b")
```




```
prune.carseats = prune.misclass ( tree.carseats , best =9)
plot( prune.carseats )
text( prune.carseats , pretty =0)
```




```
tree.pred = predict ( prune.carseats , Carseats.test , type ="class")
table ( tree.pred ,High.test)

##           High.test
## tree.pred  No  Yes
##       No    94   24
##       Yes   22   60

prune.carseats = prune.misclass ( tree.carseats , best =15)
plot( prune.carseats )
text( prune.carseats , pretty =0)
```




```
tree.pred = predict ( prune.carseats , Carseats.test , type ="class")
table ( tree.pred ,High.test)
```

```
##           High.test
## tree.pred  No  Yes
##       No   86   22
##       Yes  30   62
```

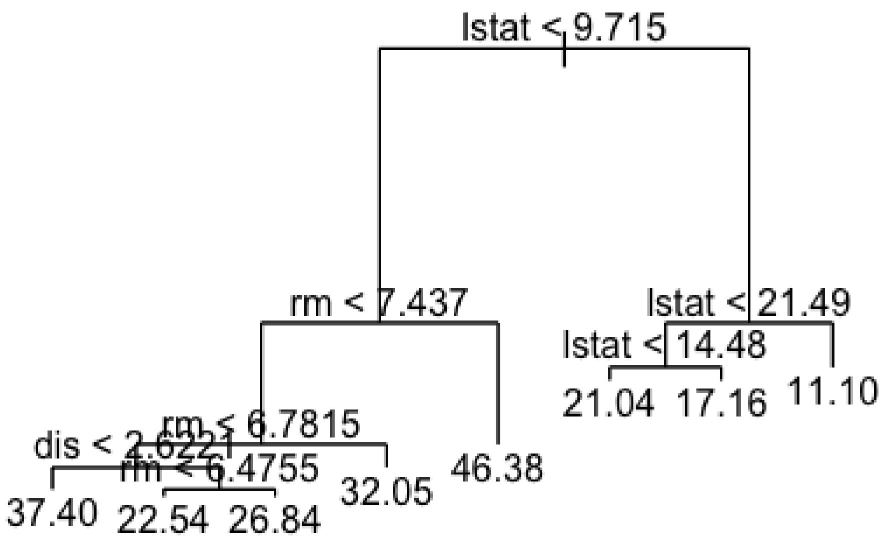
TASK 2 Fitting Classification Trees
Soln:
The solution for this is in filename : assign2_part2.Rmd

TASK 2 : Fitting Regression Trees 20 points

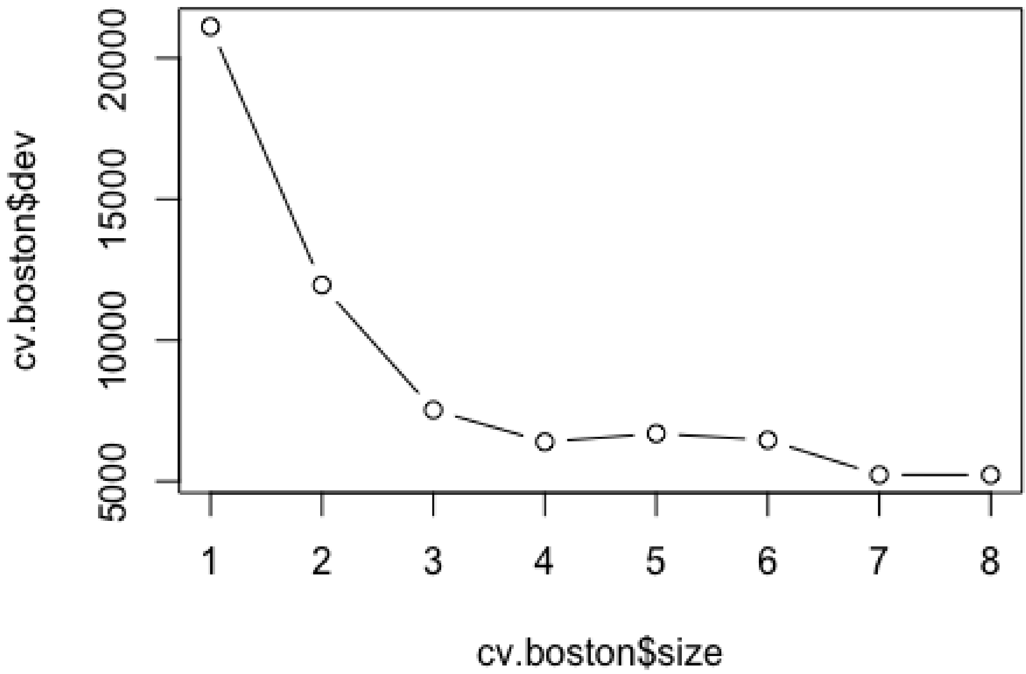
```
library (MASS)
require(tree)
```

```
## Loading required package: tree

## Warning: package 'tree' was built under R version 3.4.4
```

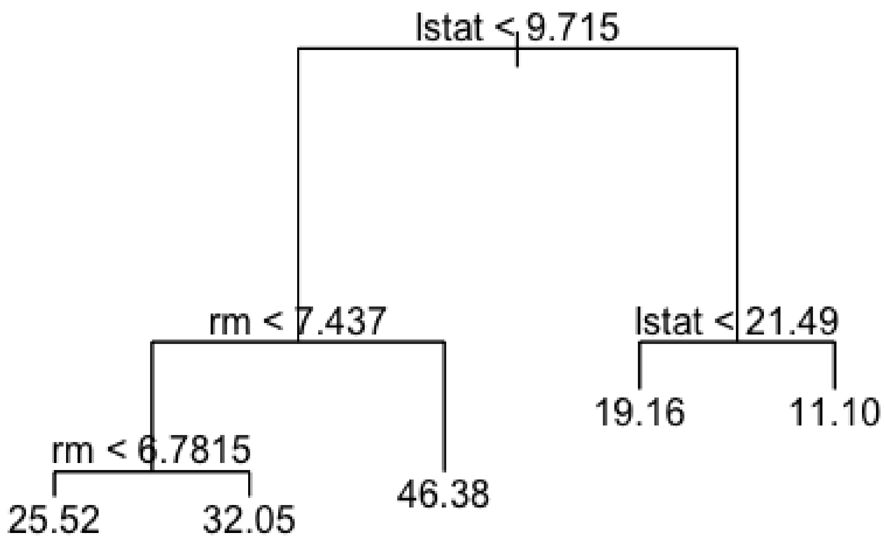
```r
require(devtools)

## Loading required package: devtools

require(ISLR)

## Loading required package: ISLR

require(MASS)
require(randomForest)

## Loading required package: randomForest

## Warning: package 'randomForest' was built under R version 3.4.4

## randomForest 4.6-14

## Type rfNews() to see new features/changes/bug fixes.

require(gbm)

## Loading required package: gbm

## Loading required package: survival

## Loading required package: lattice

## Loading required package: splines

## Loading required package: parallel

## Loaded gbm 2.1.3

set.seed (1)
train = sample (1: nrow ( Boston ), nrow( Boston )/2)
tree.boston = tree(medv~.,Boston , subset = train )
summary (tree.boston )

##
## Regression tree:
## tree(formula = medv ~ ., data = Boston, subset = train)
## Variables actually used in tree construction:
## [1] "lstat" "rm"    "dis"
## Number of terminal nodes:  8
## Residual mean deviance:  12.65 = 3099 / 245
## Distribution of residuals:
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## -14.10000  -2.04200  -0.05357   0.00000   1.96000  12.60000

plot(tree.boston )
text(tree.boston , pretty =0)
```



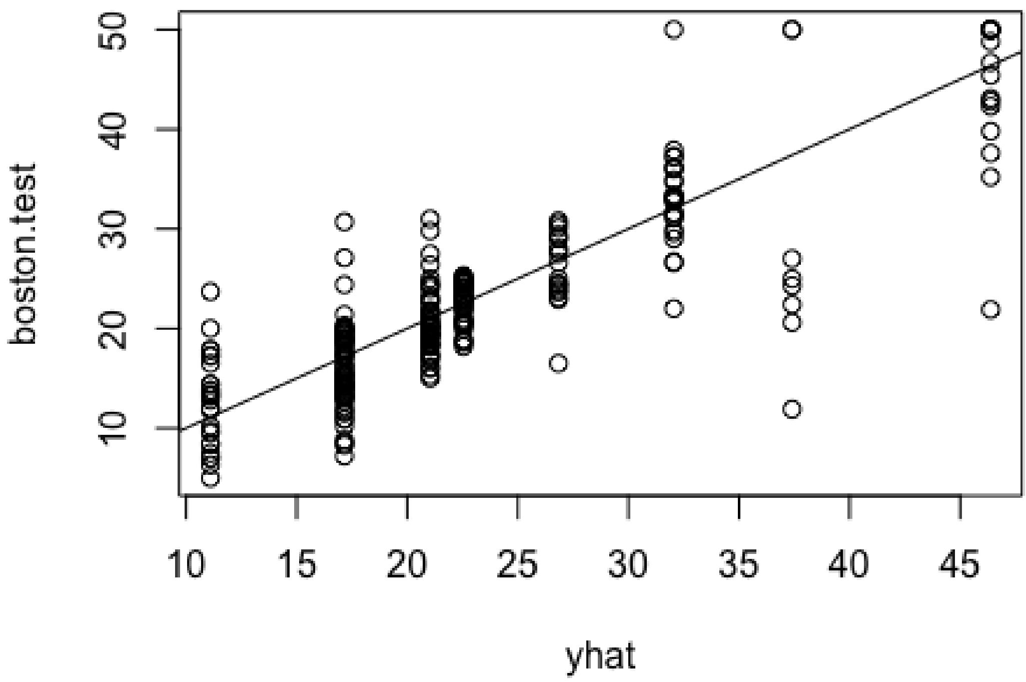

```
cv.boston =cv.tree( tree.boston )
plot(cv.boston$size ,cv.boston$dev ,type="b")
```




```
prune.boston =prune.tree( tree.boston, best =5)
plot( prune.boston )
text( prune.boston , pretty =0)
```




```
yhat= predict (tree.boston , newdata = Boston [-train ,])
boston.test= Boston [-train ,"medv"]
plot(yhat ,boston.test )
abline (0 ,1)
```




```
mean (( yhat - boston.test)^2)

## [1] 25.04559
```

TASK 3 Bagging and Random Forests
Soln:
The solution for this is in filename : assign2_part3.Rmd
library(randomForest)
library(MASS)
require(tree)
require(devtools)
require(ISLR)
require(MASS)
require(randomForest)
require(gbm)
library(caret)

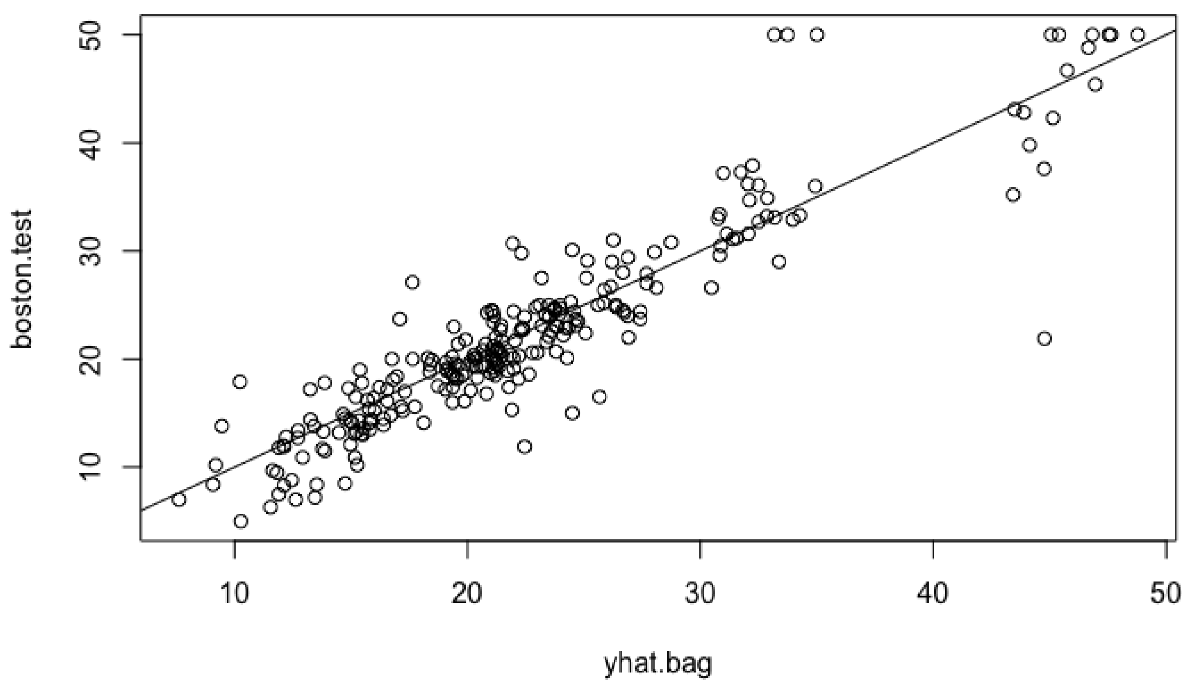
set.seed(1)

bag.boston = randomForest(medv~., data = Boston , subset = train, mtry =13, importance =TRUE)
bag.boston
o/p::

```
Call:
 randomForest(formula = medv ~ ., data = Boston, mtry = 13, importance = TRUE,      subset = train)
               Type of random forest: regression
                     Number of trees: 500
No. of variables tried at each split: 13

          Mean of squared residuals: 11.15723
                    % Var explained: 86.49
```

yhat.bag = predict (bag.boston , newdata = Boston [-train ,])
plot(yhat.bag , boston.test)
abline (0 ,1)
mean ((yhat.bag - boston.test)^2)

O/p::




```{r}
bag.boston = randomForest( medv~., data= Boston , subset =train ,mtry =13, ntree =25)
yhat.bag = predict (bag.boston , newdata = Boston [-train ,])
mean (( yhat.bag - boston.test)^2)
```

o/p:: [1] 13.94835

```{r}
```

```
set.seed (1)
rf.boston = randomForest(medv~., data=Boston , subset =train ,mtry =6, importance =TRUE)
yhat.rf = predict (rf.boston , newdata = Boston [-train ,])
mean ((yhat.rf - boston.test)^2)
```

o/p::

[1] 11.66454

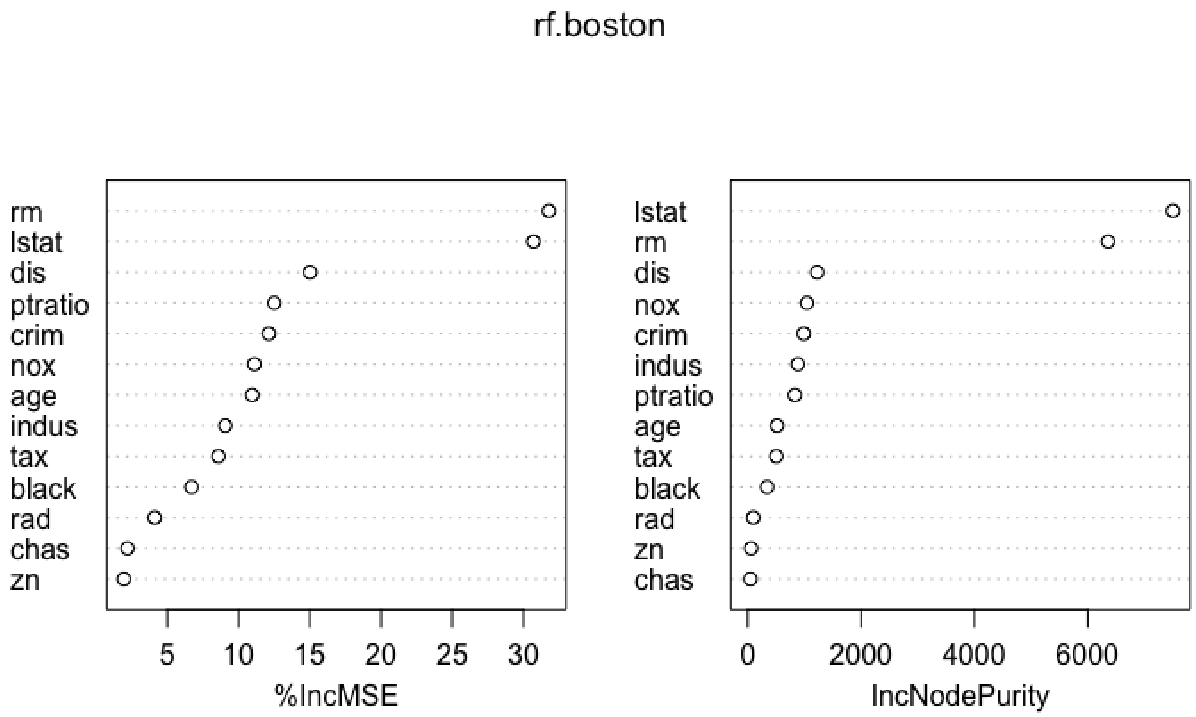
```{r}
importance (rf.boston )
```

o/p

	%IncMSE	IncNodePurity
crim	12.132320	986.50338
zn	1.955579	57.96945
indus	9.069302	882.78261
chas	2.210835	45.22941
nox	11.104823	1044.33776
rm	31.784033	6359.31971
age	10.962684	516.82969
dis	15.015236	1224.11605
rad	4.118011	95.94586
tax	8.587932	502.96719
ptratio	12.503896	830.77523
black	6.702609	341.30361
lstat	30.695224	7505.73936

```{r}
varImpPlot (rf.boston )
```

o/p::



TASK 4 Boosting

Soln:

The solution for this is in filename : assign2_part4.Rmd

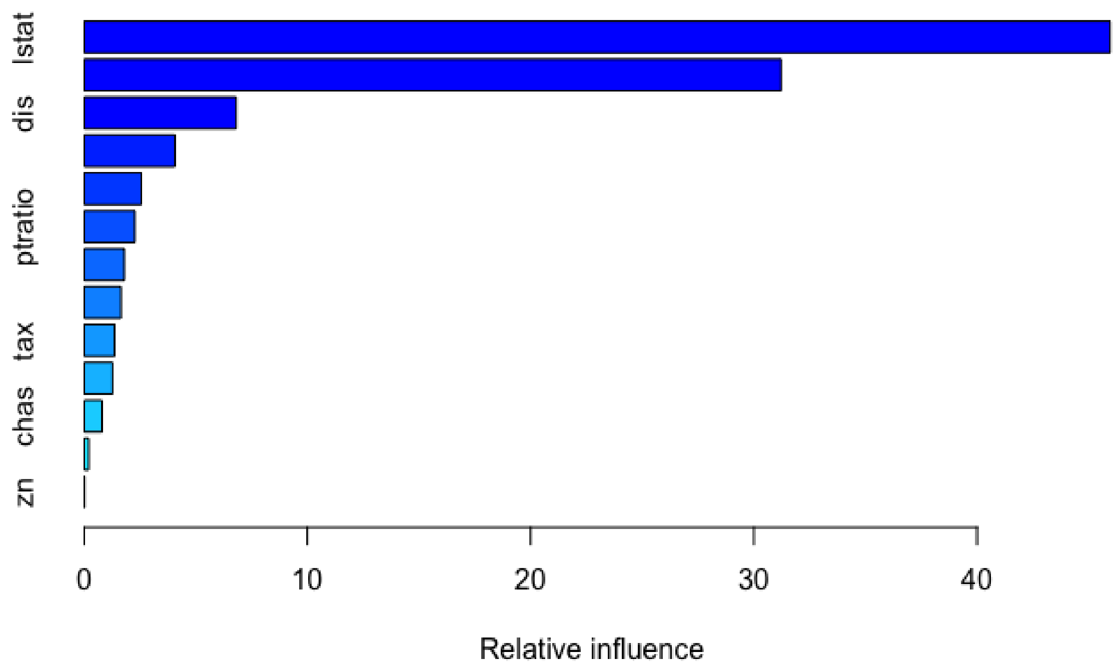
```
library (gbm )
library (MASS)
require(tree)
require(devtools)
require(ISLR)
require(MASS)
require(randomForest)
library(caret)
set.seed (1)
boost.boston=gbm(medv~.,data=Boston[train,],distribution="gaussian",n.trees=5000,interaction.depth=4)
summary(boost.boston)
```

o/p ::

	var <fctr>	rel.inf <dbl>
lstat	lstat	45.9627334
rm	rm	31.2238187
dis	dis	6.8087398
crim	crim	4.0743784
nox	nox	2.5605001
ptratio	ptratio	2.2748652

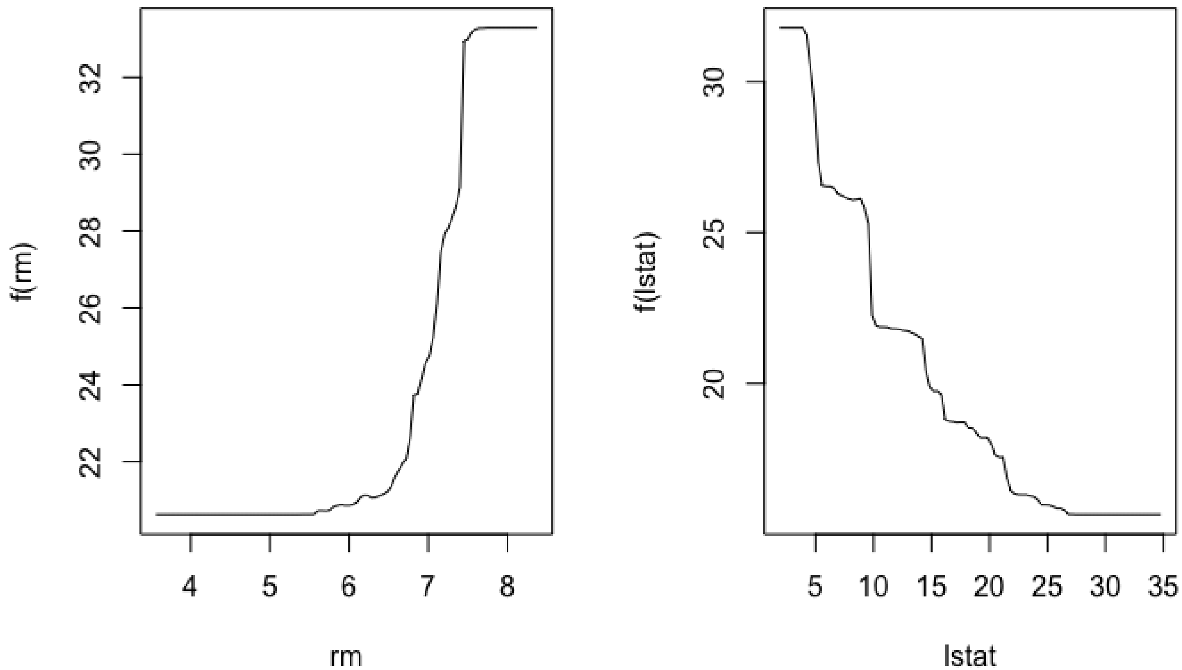
black	black	1.7971159
age	age	1.6488532
tax	tax	1.3595005
indus	indus	1.2705924
chas	chas	0.8014323
rad	rad	0.2026619
zn	zn	0.0148083

o/p2::




```
```{r}
par ( mfrow =c(1 ,2) )
plot( boost.boston ,i="rm")
plot( boost.boston ,i="lstat")
```
```

o/p::



```{r}
yhat.boost = predict (boost.boston , newdata = Boston [-train ,],n.trees =5000)
mean ((yhat.boost - boston.test)^2)
```
o/p:: [1] 11.84434

```{r}
boost.boston =gbm (medv~., data= Boston [train ,], distribution="gaussian",n.trees =5000 , interaction.depth=4, shrinkage =0.2 ,verbose =F)
yhat.boost = predict (boost.boston , newdata = Boston [-train ,],n.trees =5000)
mean((yhat.boost - boston.test)^2)
```
o/p:: [1] 11.51109

TASK 5 Summary
Report time required for homework, difficulties encountered, and collaborators
Soln:
Report Time: The project took 4 days to complete.
Difficulties encountered: Decision Trees being a new algorithm did present a few initial difficulties while understanding the concepts. However, the task became much simpler due to lucid explanation given in ISL book.

Collaborators: None