ISLR Lab

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Lab 8.3.1

[1]:
```
library(tree)
library(ISLR)
attach(Carseats)
```

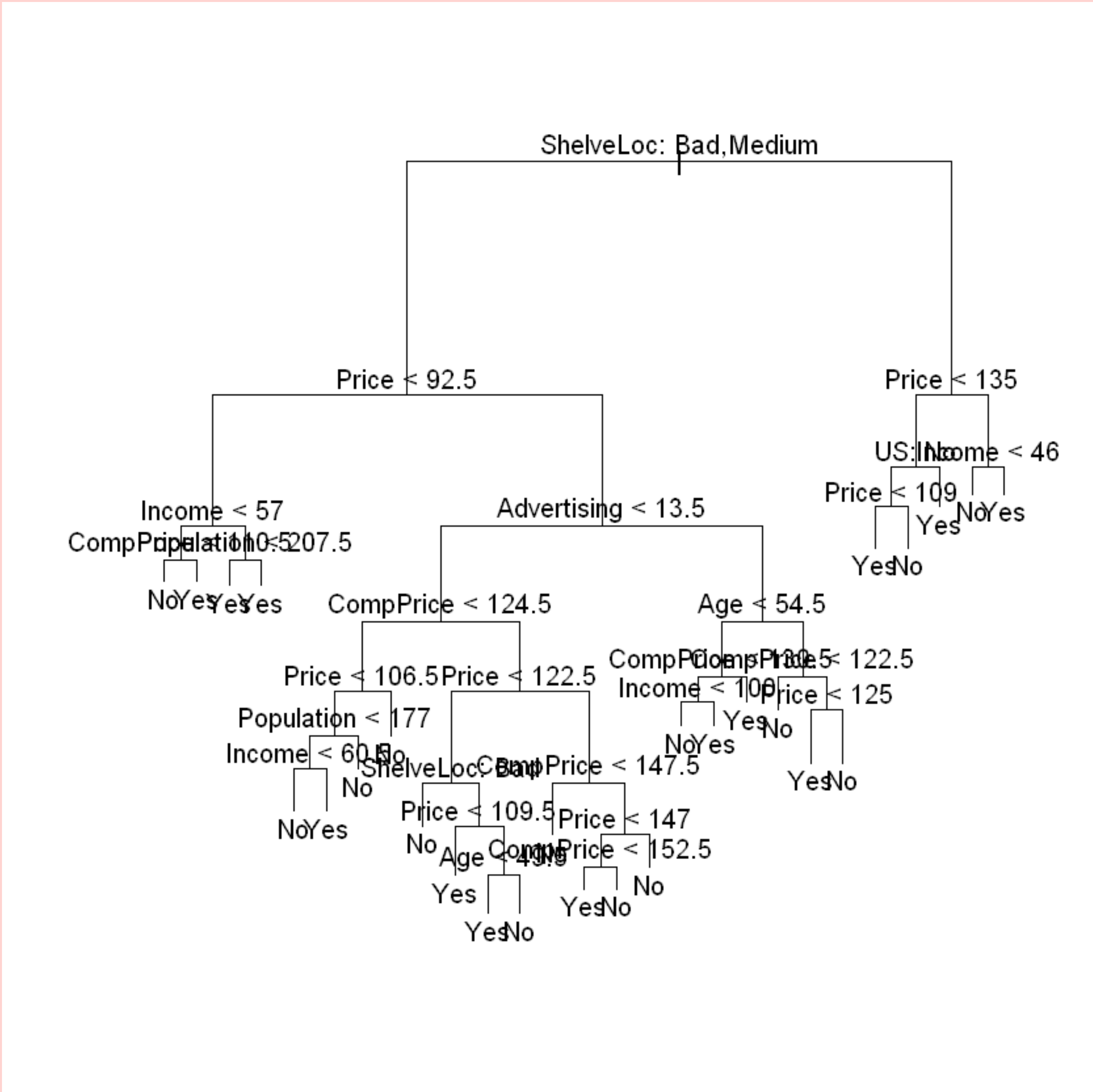
[2]:
```
High=factor(ifelse(Sales <=8,"No","Yes"))
Carseats =data.frame(Carseats ,High)
```

[3]:
```
tree.carseats =tree(High~.-Sales , Carseats )
```

[4]:
```
summary(tree.carseats )
```

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

[6]:
```
plot(tree.carseats )
text(tree.carseats ,pretty =0)
```



[7]:
```
print(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 ) *
```

[10]:
```
set.seed(2)
train=sample (1: nrow(Carseats ), 200)
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")
print(table(tree.pred ,High.test))
```

```
         High.test
tree.pred  No Yes
      No  104  33
      Yes  13  50
```

[11]:
```
 (86+57) /200
```

0.715

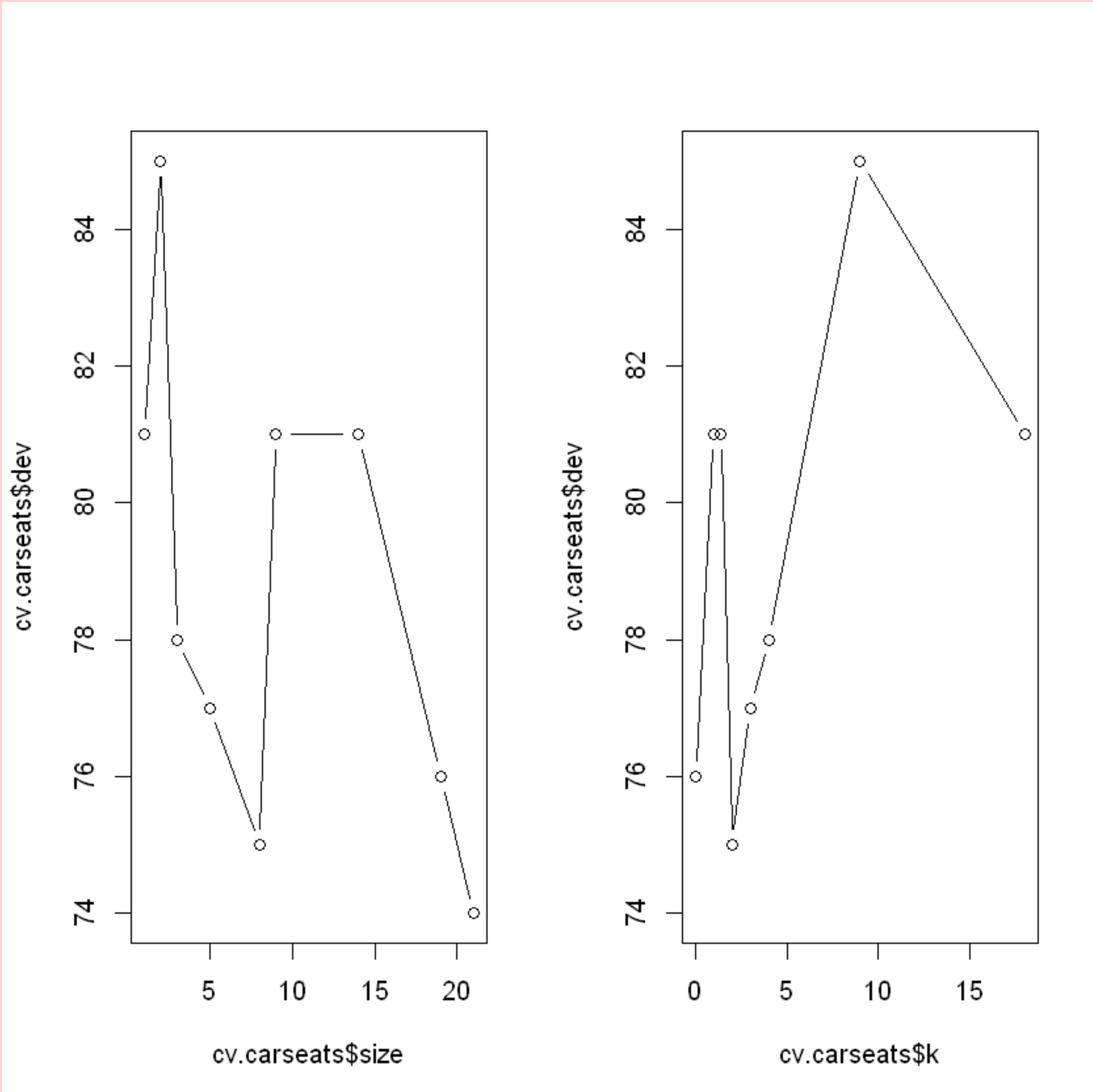
[12]:
```
set.seed(3)
cv.carseats =cv.tree(tree.carseats ,FUN=prune.misclass )
print(names(cv.carseats ))
```

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

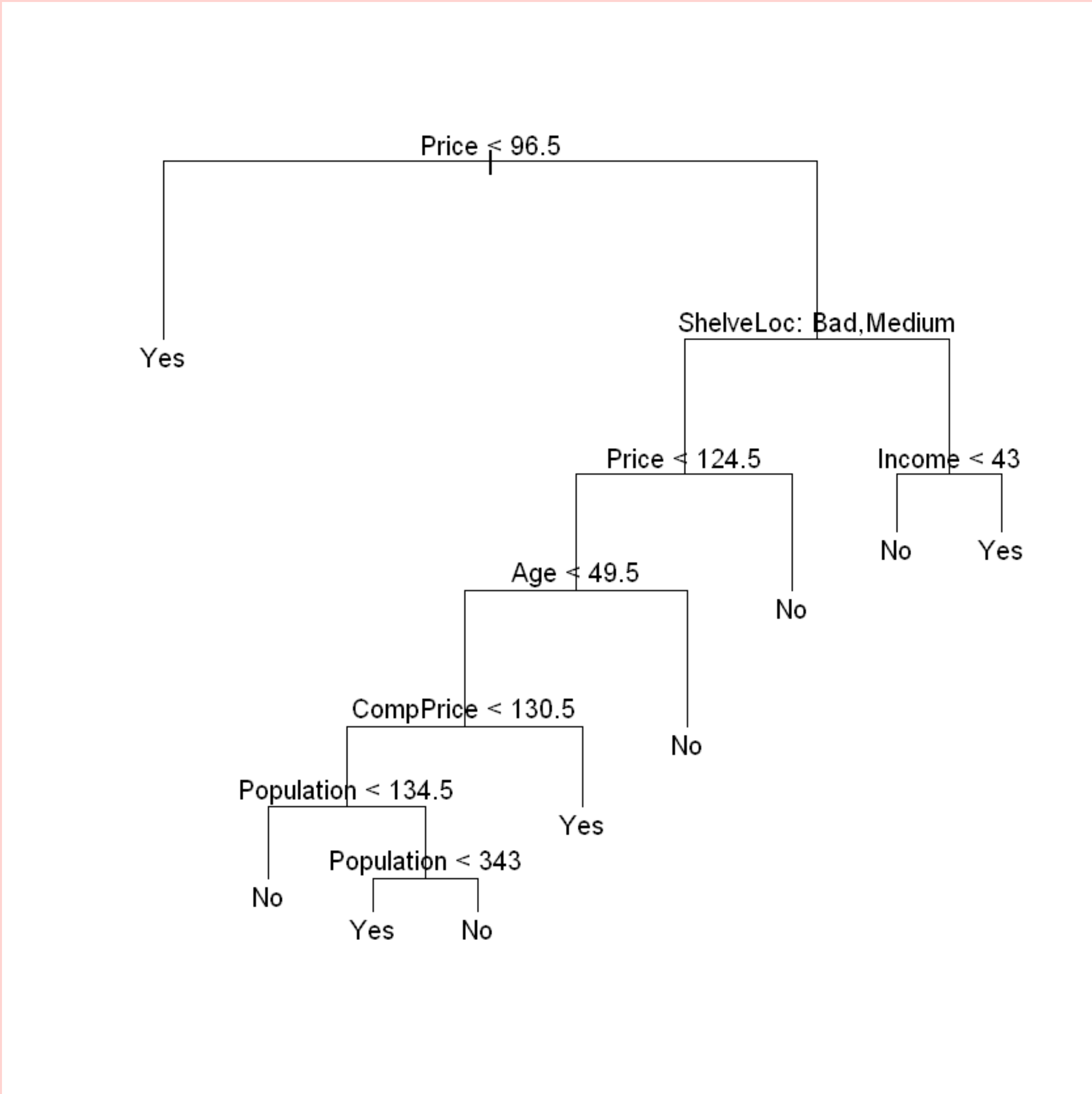
[13]:
```
print(cv.carseats)
```

```
$size
[1] 21 19 14  9  8  5  3  2  1

$dev
[1] 74 76 81 81 75 77 78 85 81

$k
[1] -Inf  0.0  1.0  1.4  2.0  3.0  4.0  9.0 18.0

$method
[1] "misclass"

attr(,"class")
[1] "prune"         "tree.sequence"
```

[14]:
```
par(mfrow=c(1,2))
plot(cv.carseats$size ,cv.carseats$dev ,type="b")
plot(cv.carseats$k ,cv.carseats$dev ,type="b")
```



[15]:
```
prune.carseats =prune.misclass(tree.carseats ,best=9)
plot(prune.carseats )
 text(prune.carseats ,pretty =0)
```



[17]:
```
tree.pred=predict(prune.carseats ,Carseats.test , type="class")
print(table(tree.pred ,High.test))
```

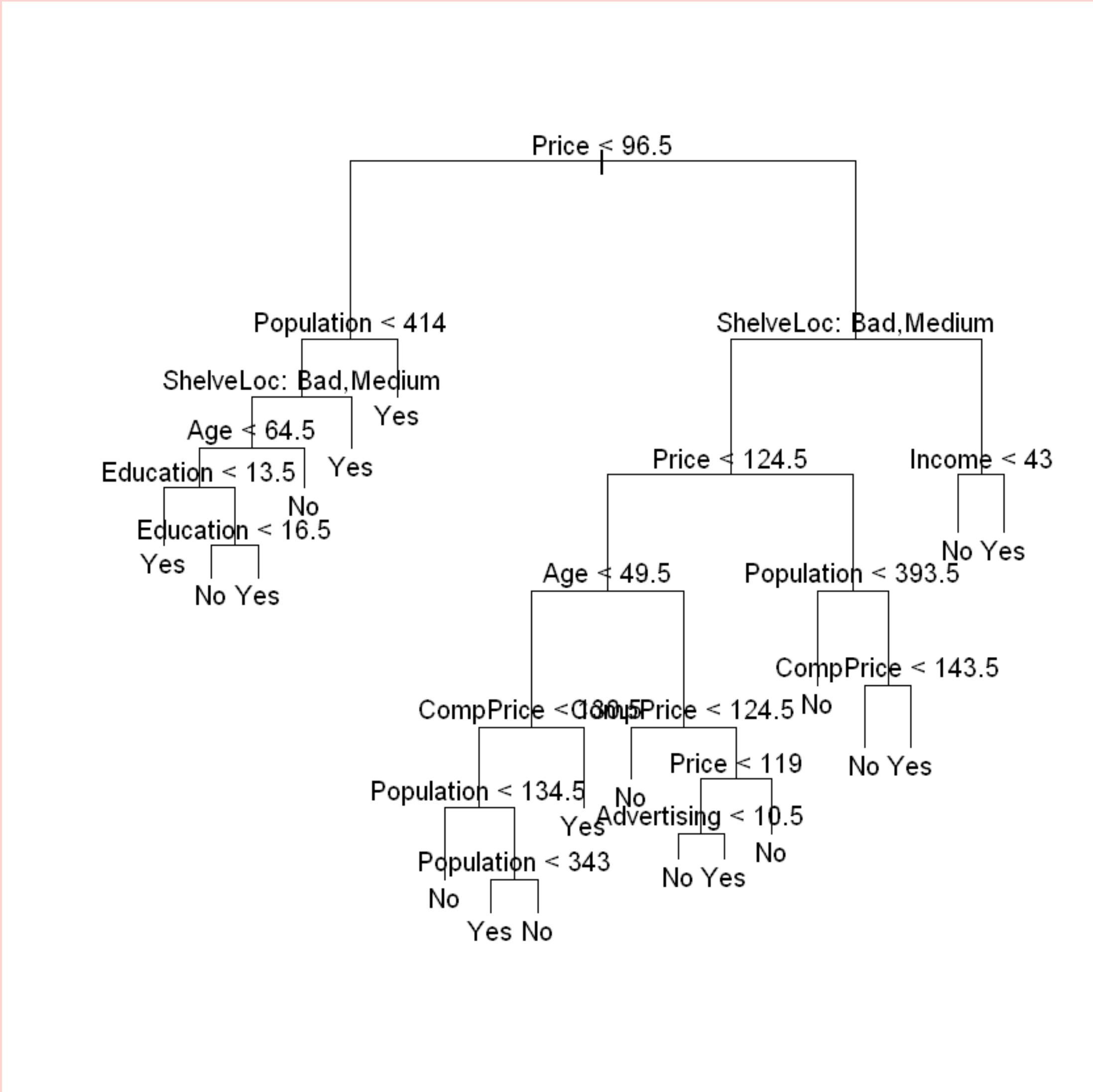
```
         High.test
tree.pred No  Yes
      No   97  25
      Yes  20  58
```

[18]:
```
 (94+60) /200
```

0.77

[22]:
```
prune.carseats =prune.misclass (tree.carseats ,best=15)
plot(prune.carseats )
```

```
text(prune.carseats ,pretty =0)
```



[23]:
```
tree.pred=predict(prune.carseats ,Carseats.test , type="class")
print(table(tree.pred ,High.test))
```

```
         High.test
tree.pred  No Yes
      No  102  30
      Yes  15  53
```

[24]:
```
(102 + 53)/200
```

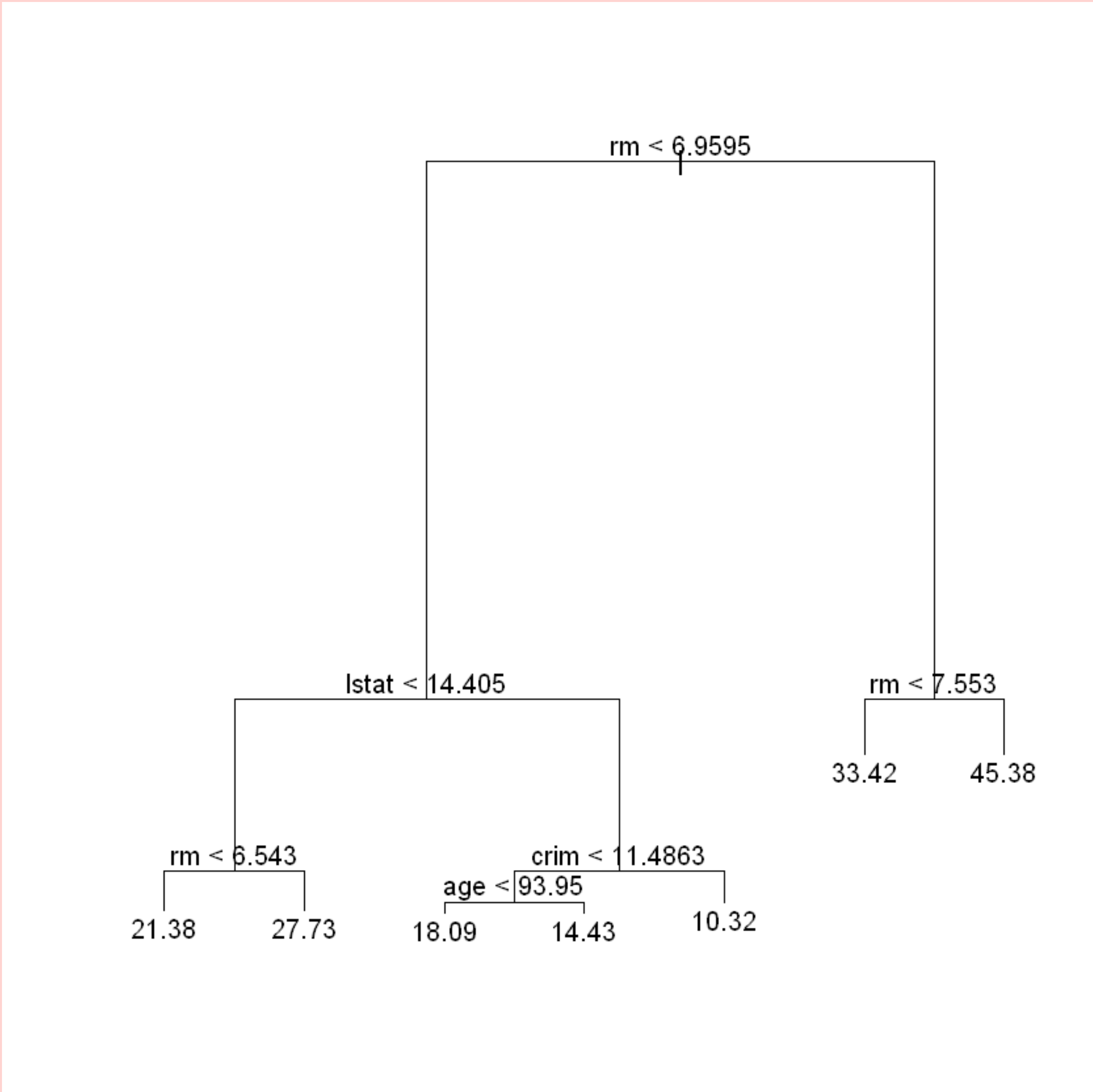
0.775

Lab 8.3.2

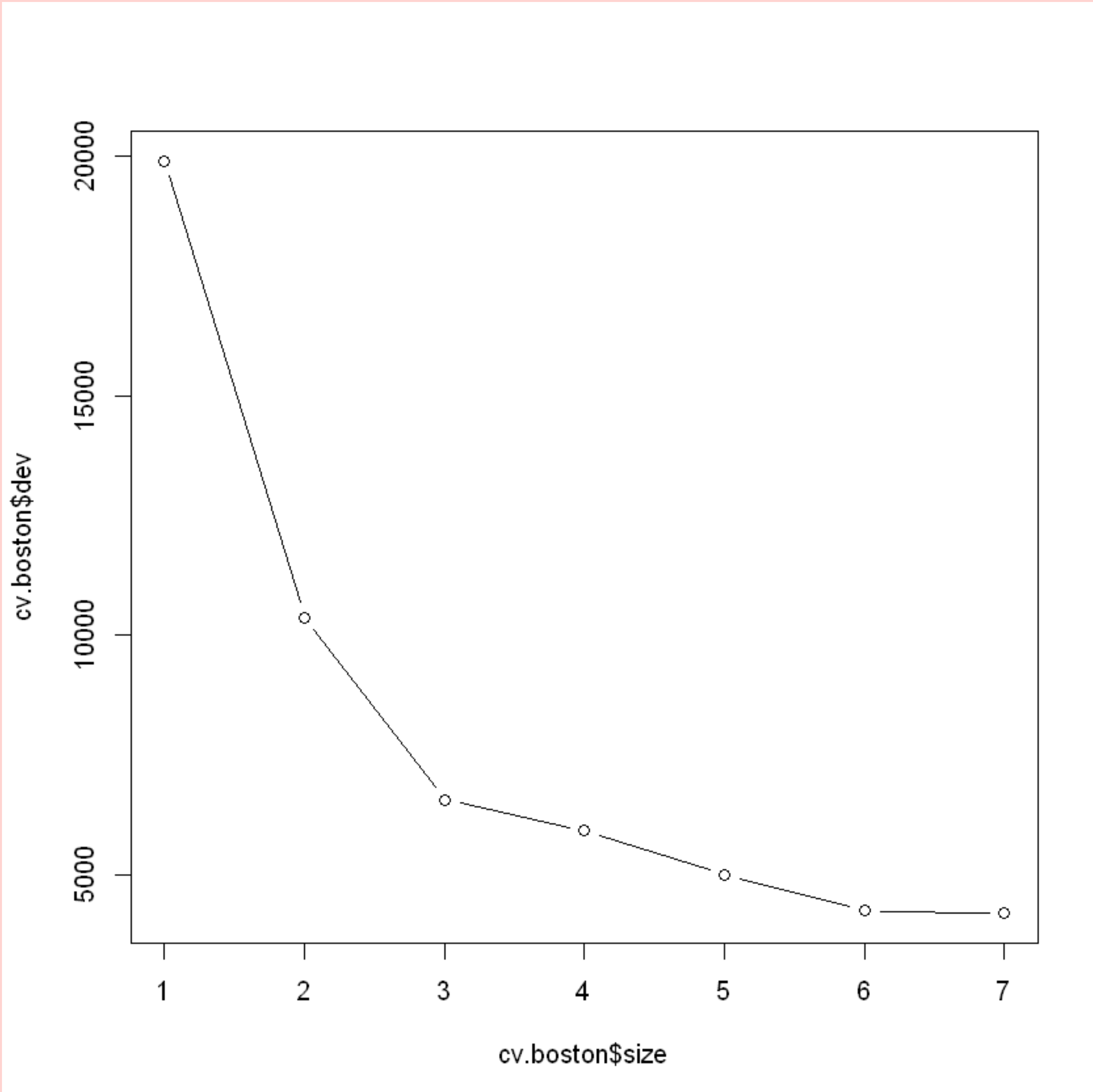
[26]:
```
library(MASS)
set.seed(1)
train = sample (1:nrow(Boston), nrow(Boston)/2)
tree.boston=tree(medv~.,Boston , subset=train)
summary(tree.boston)
```

```
Regression tree:
tree(formula = medv ~ ., data = Boston, subset = train)
Variables actually used in tree construction:
[1] "rm"    "lstat" "crim"  "age"
Number of terminal nodes:  7
Residual mean deviance:  10.38 = 2555 / 246
Distribution of residuals:
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-10.1800  -1.7770  -0.1775   0.0000   1.9230  16.5800
```

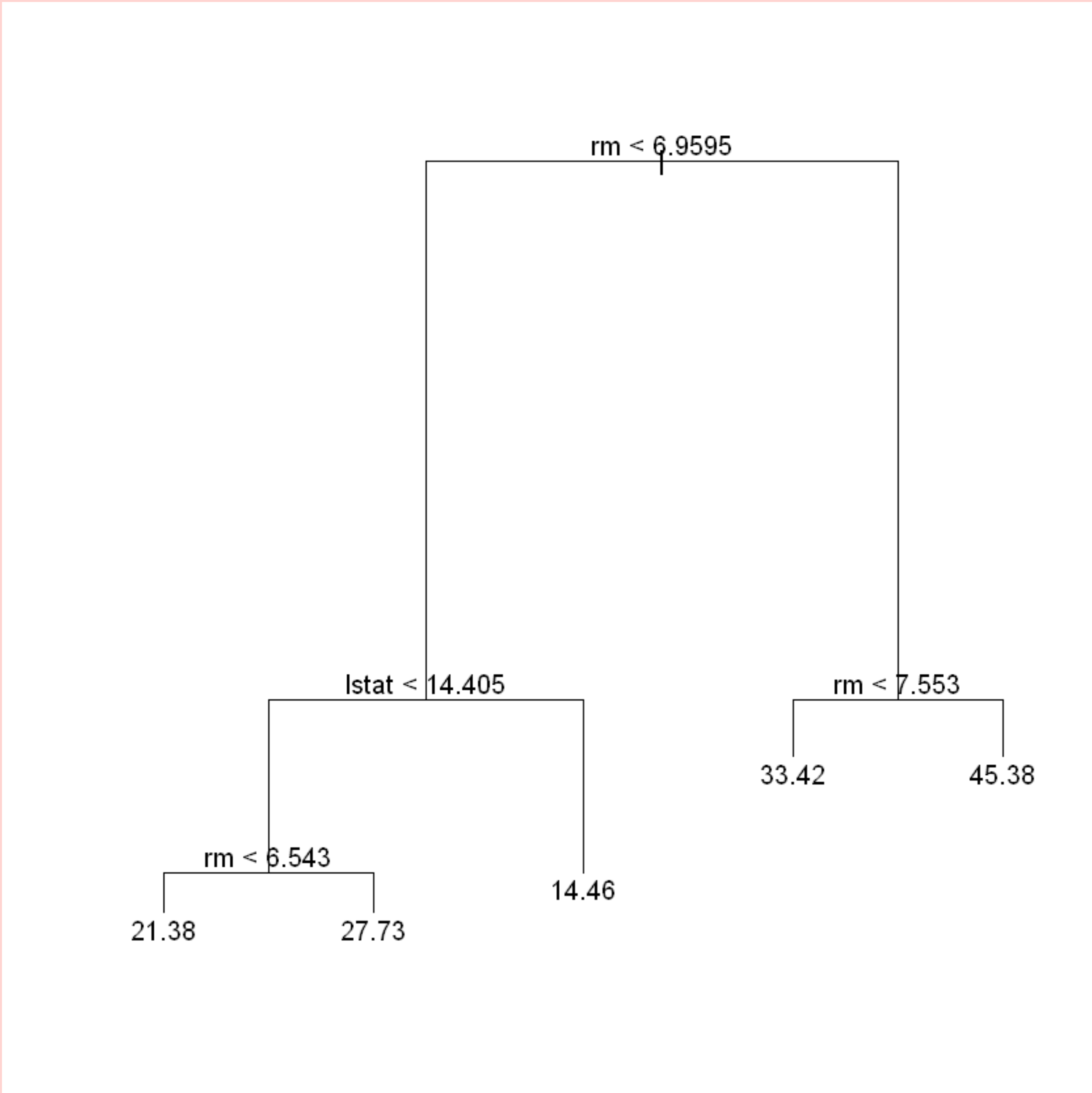
[28]:
```
plot(tree.boston)
 text(tree.boston , pretty =0)
```



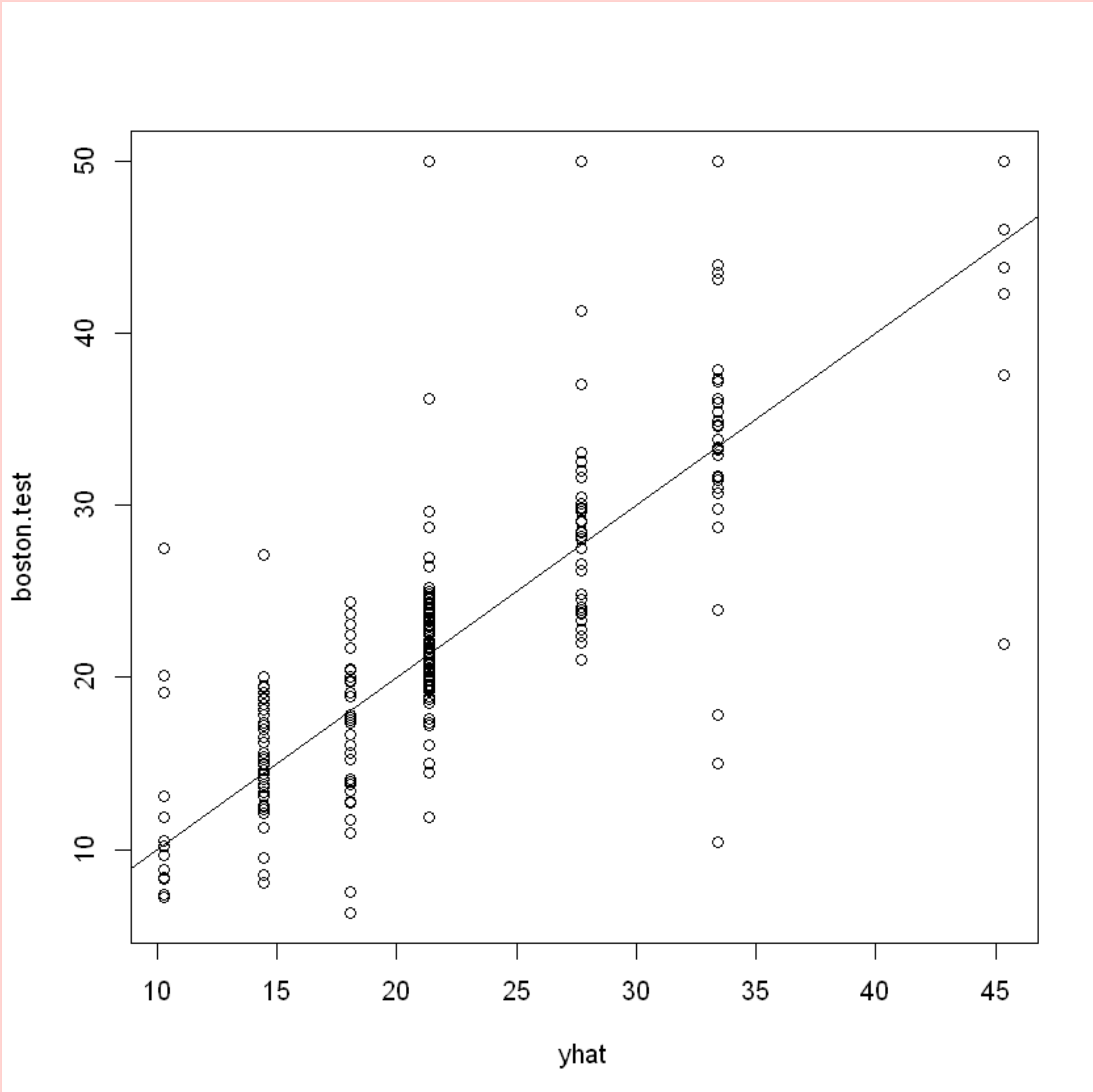
[30]:
```
cv.boston=cv.tree(tree.boston)
plot(cv.boston$size ,cv.boston$dev ,type='b')
```



[32]:
```
prune.boston=prune.tree(tree.boston ,best=5)
plot(prune.boston)
text(prune.boston , pretty =0)
```



[33]:
```
yhat=predict (tree.boston ,newdata=Boston[- train ,])
boston.test=Boston[-train ,"medv"]
 plot(yhat ,boston.test)
abline (0,1)
```



[34]:
```
mean((yhat -boston.test)^2)
```

35.2868818594623

[ ]: