Intro to ML : Take Home Assignment

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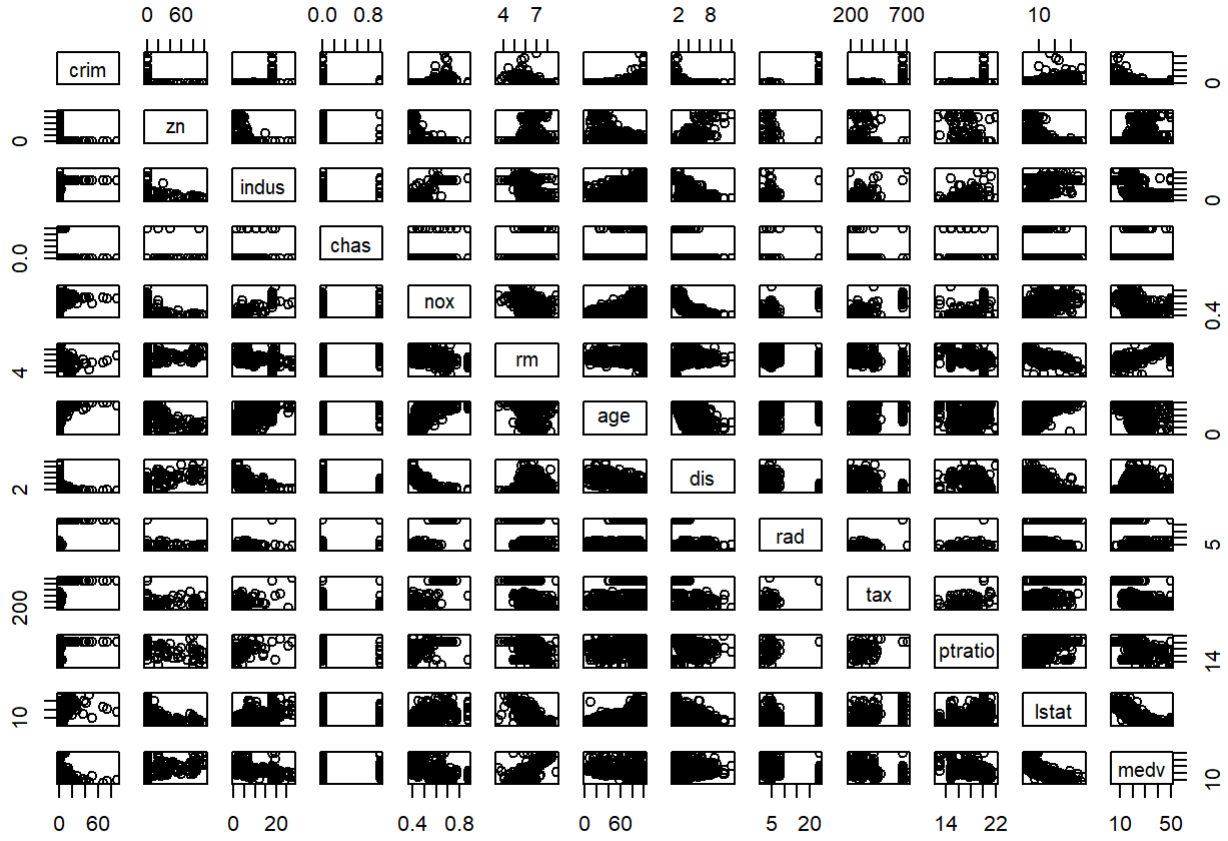
Chapter 2

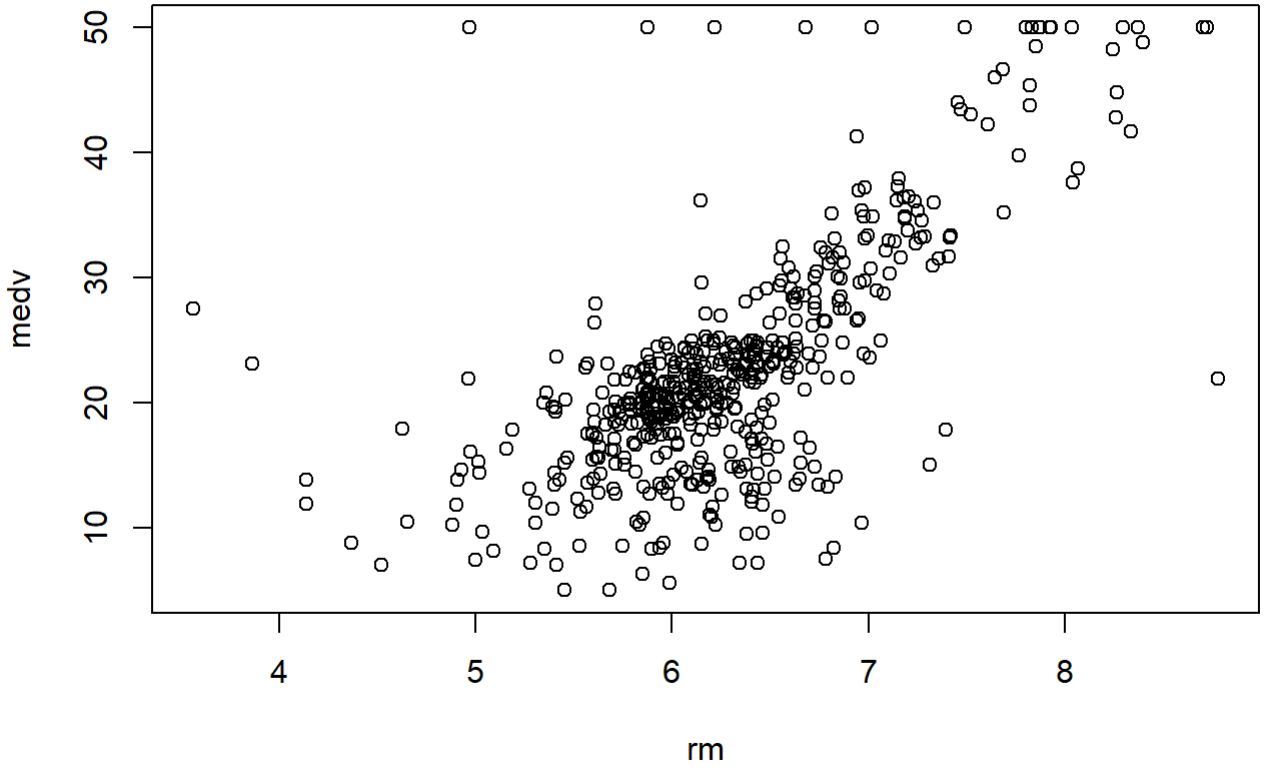
Question 10

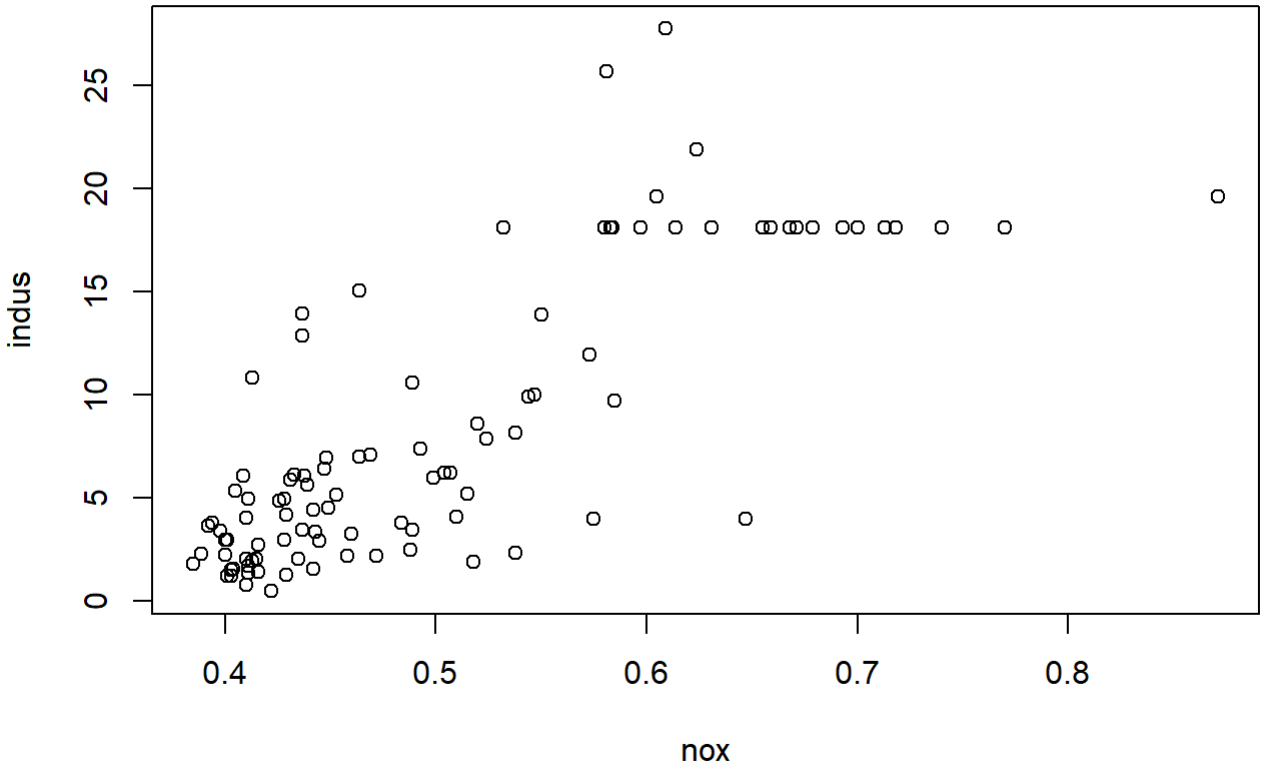
Load the Boston data set. How many rows are in this data set? How many columns? What do the rows and columns represent?

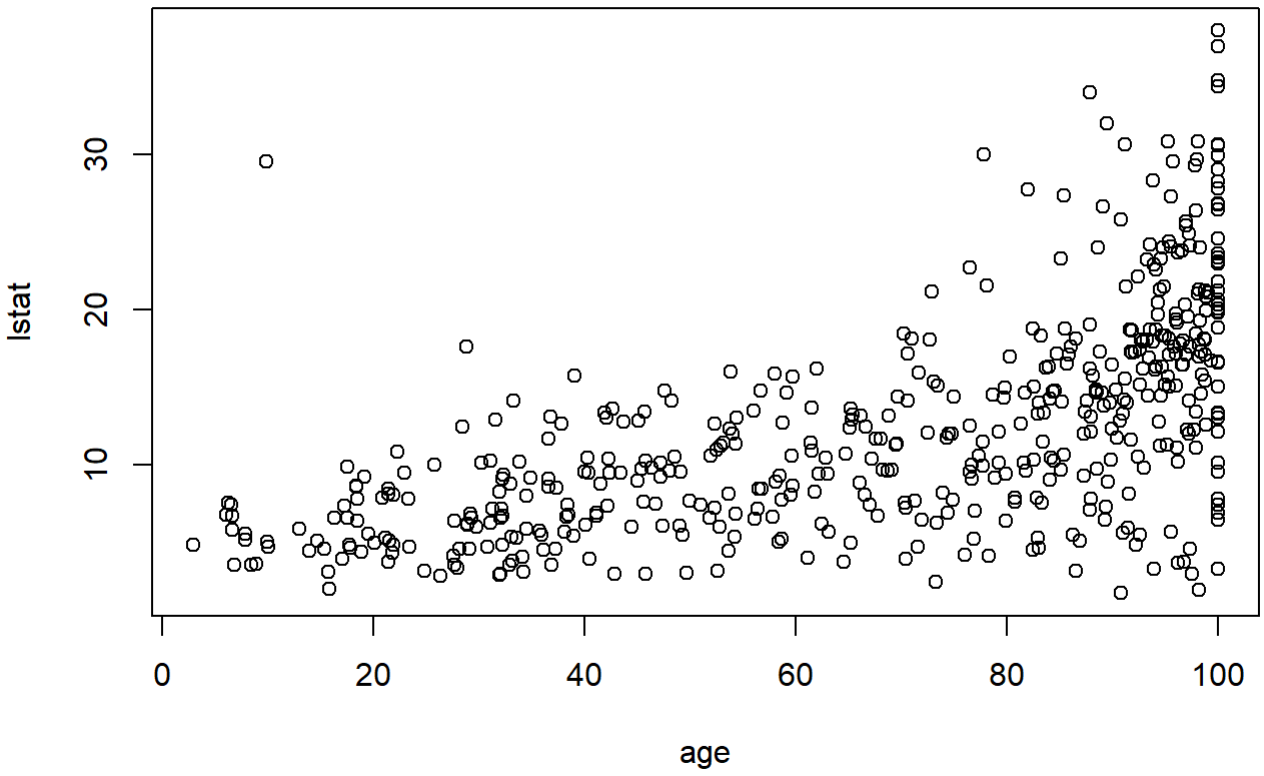
- The Boston dataset present in ISLR2 library has 13 columns and 506 rows.
- Rows represent different suburbs of Boston.
- Columns represent the various variables or features associated with census data.

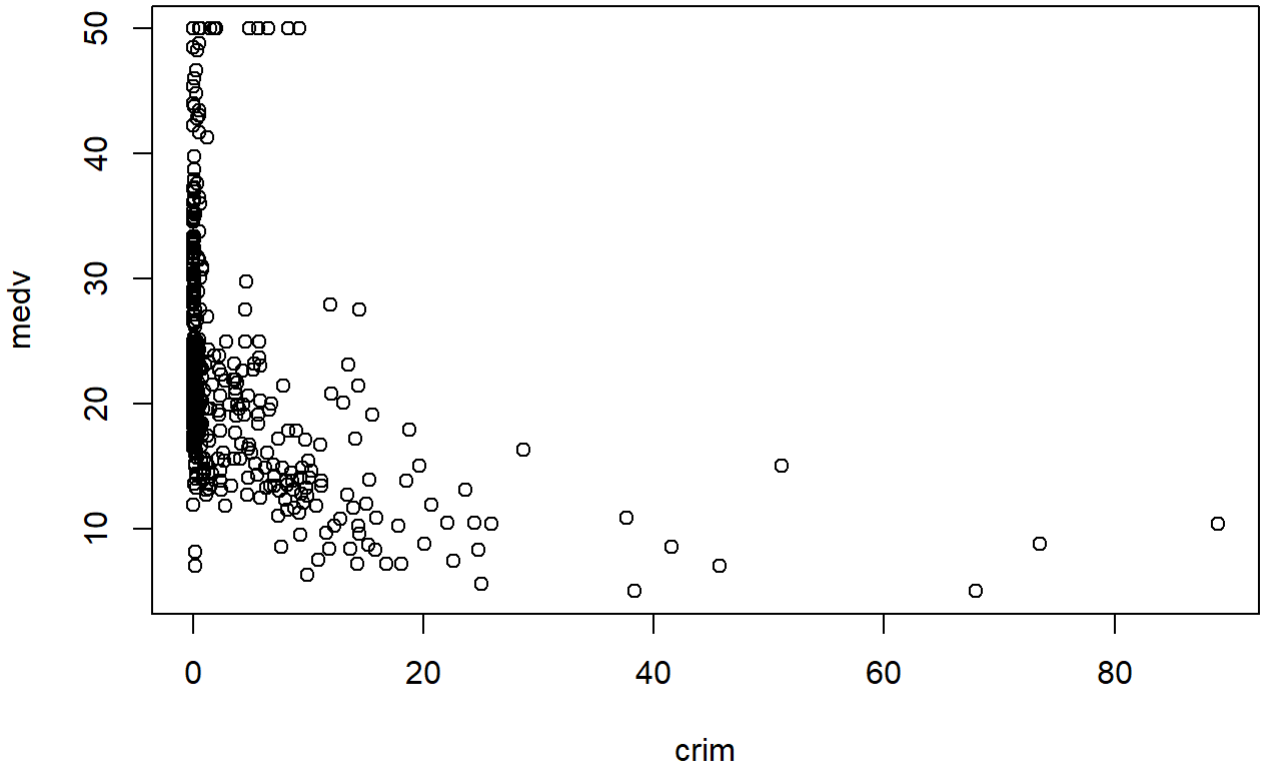
Make some pairwise scatterplots of the predictors (columns) in this data set. Describe your findings.

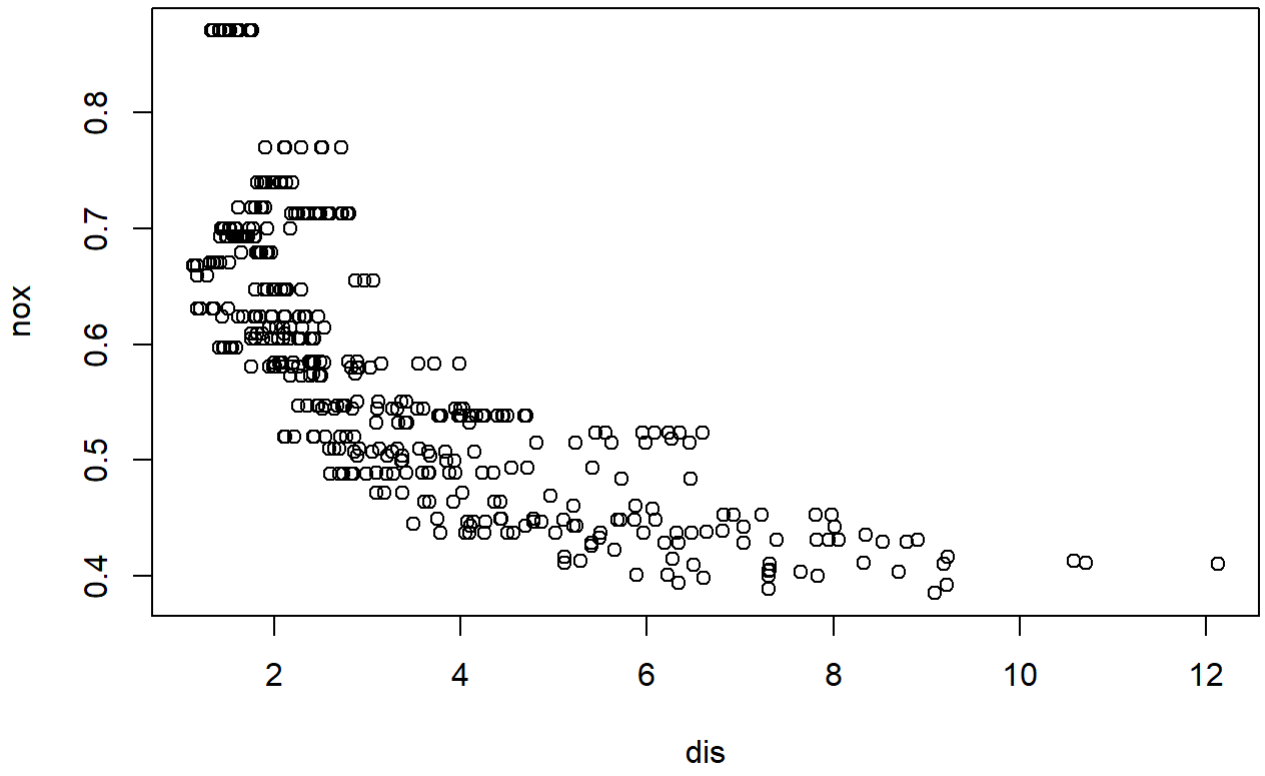

crim
zn
indus
chas
nox
rm
age
dis
rad
tax
ptratio
lstat
medv

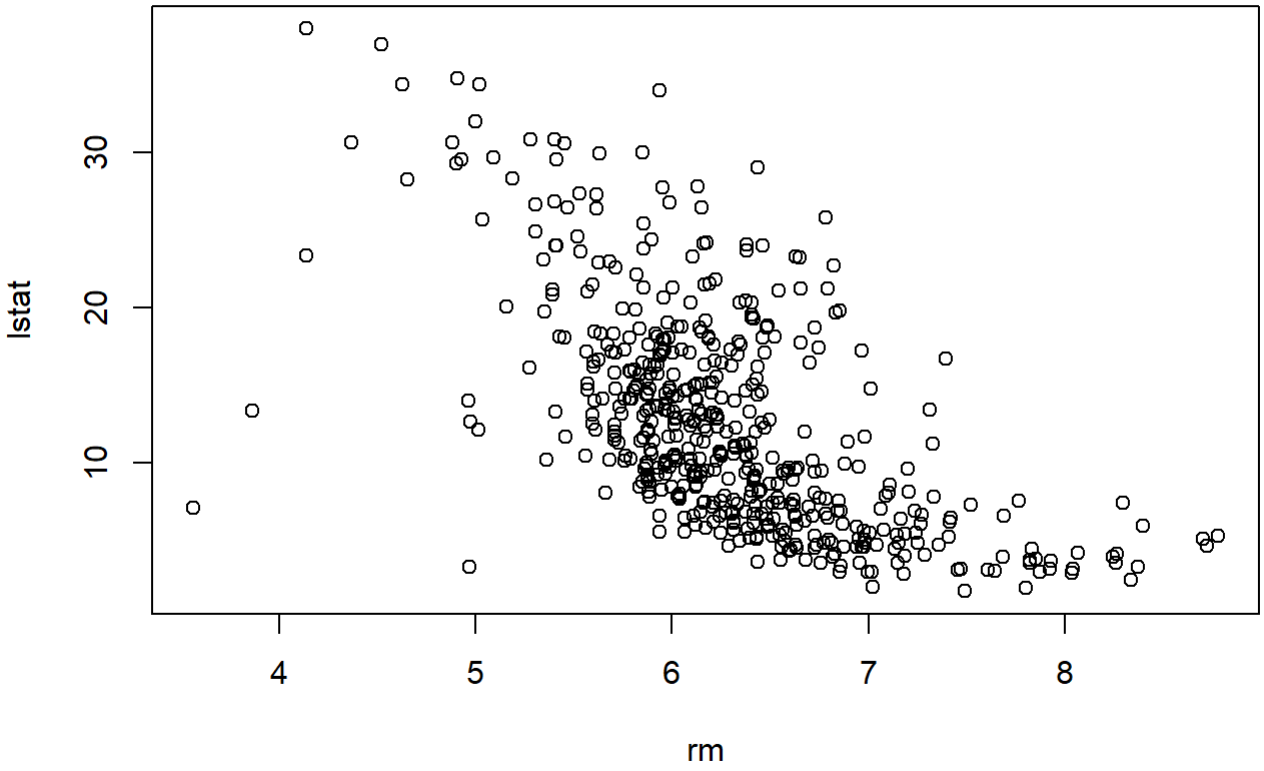

medv
rm
10
20
30
40
50
4
5
6
7
8

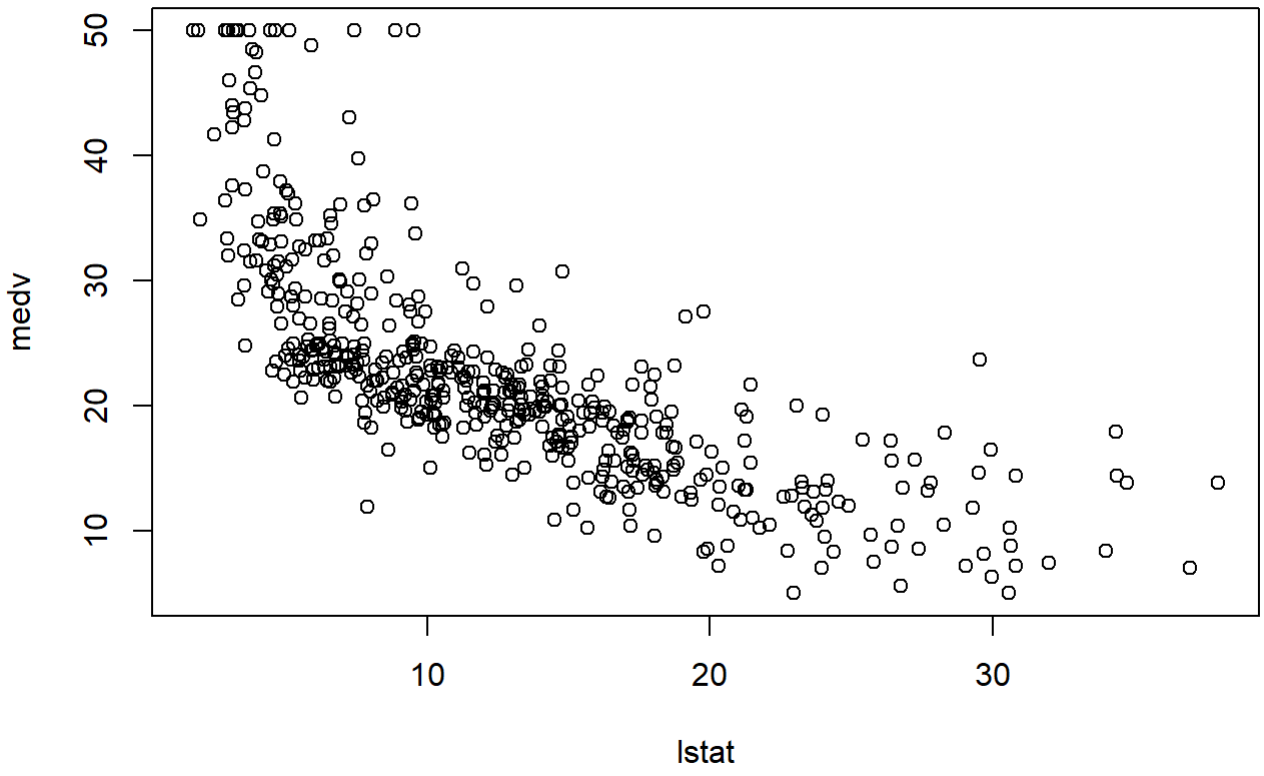

indus
0
5
10
15
20
25
0.4
0.5
0.6
0.7
0.8
nox


lstat
10
20
30
0
20
40
60
80
100
age


medv
10
20
30
40
50
0
20
40
60
80
crim


nox
0.4
0.5
0.6
0.7
0.8
2
4
6
8
10
12
dis


lstat
10
20
30
4
5
6
7
8
rm

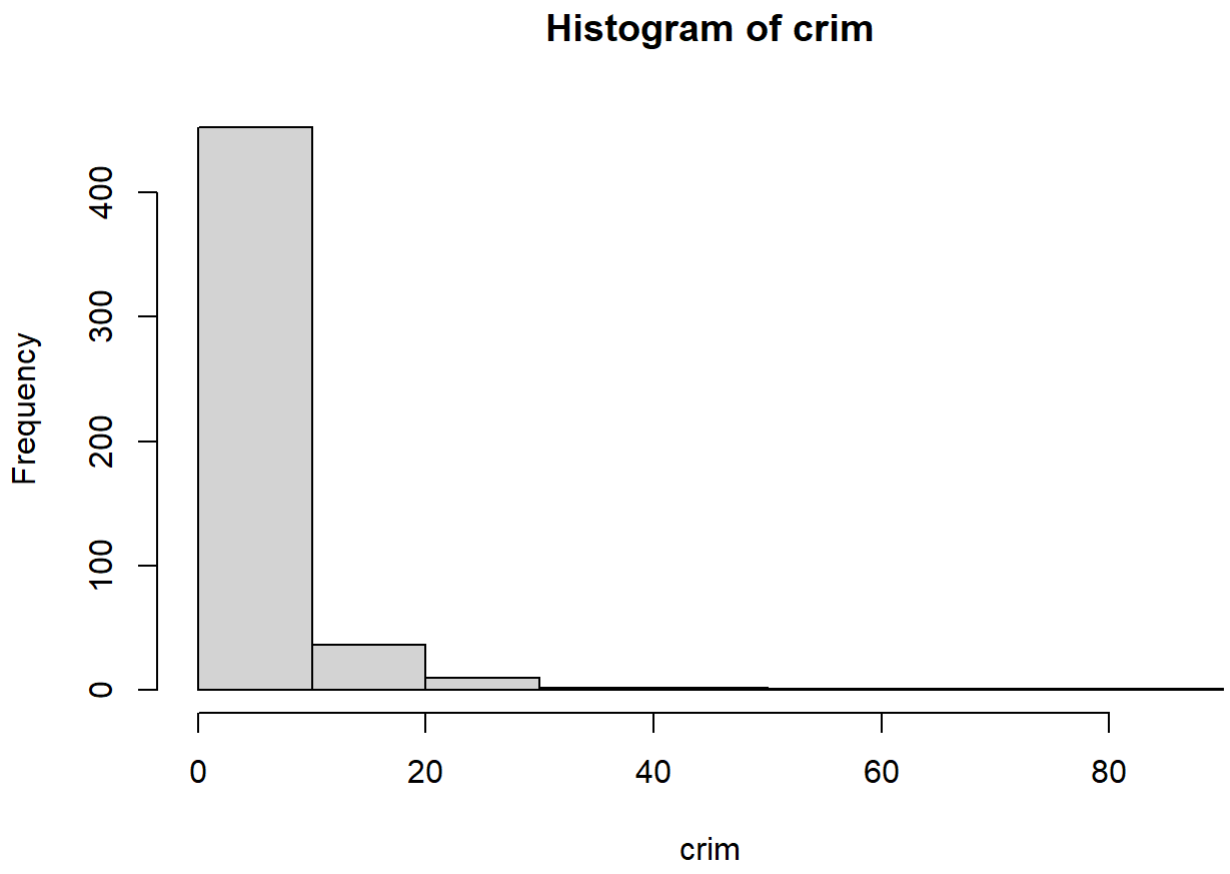

medv
10
20
30
40
50
10
20
30
lstat

Observations

- Positive relationship pairs:
  - rm and medv: properties with higher average rooms per dwelling have higher median value
  - nox and indus : proportion of non-retail business acres per town have higher nitrogen oxide concentration.
  - age and lstat : suburbs with older units have higher percentage of lower status population.
- Negative relationship pairs:
  - medv and crim : Areas with high crime rate have low median home value
  - nox and dis : Distance to Boston employment center is negatively correlated to Nitrogen Oxide concentration
  - rm and lstat : Properties with higher average rooms per dwelling are less likely to have lower status population.
  - Lstat and Medv : Areas with higher pct of lower status population have lower median value of homes.

Are any of the predictors associated with per capita crime rate? If so, explain the relationship.

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
##  0.00632  0.08204  0.25651  3.61352  3.67708 88.97620
```




```
## Correlation of crime rate with other variables
```

```
##                [,1]
## zn      -0.20046922
## indus    0.40658341
## chas    -0.05589158
## nox      0.42097171
## rm      -0.21924670
## age      0.35273425
## dis     -0.37967009
## rad      0.62550515
## tax      0.58276431
## ptratio  0.28994558
## lstat    0.45562148
## medv    -0.38830461
```

Observations

- CRIM Distribution is highly skewed indicating that only certain suburbs have very high crime rates.
- Positve Correlation : index , nox , age , tax , rad , lstat , ptratio.
- Negative Correlation : zn , chas , rm , dis
- Notable Trends:
    - Higher property tax rates are positively correlated to higher crime rates
    - Proximity to employment centers is observed to have relatively higher crime rates
    - High Crime rates in a suburb correlates to lower median value of propertie
    - Crime rates are higher in suburbs with more percentage of lower status population.

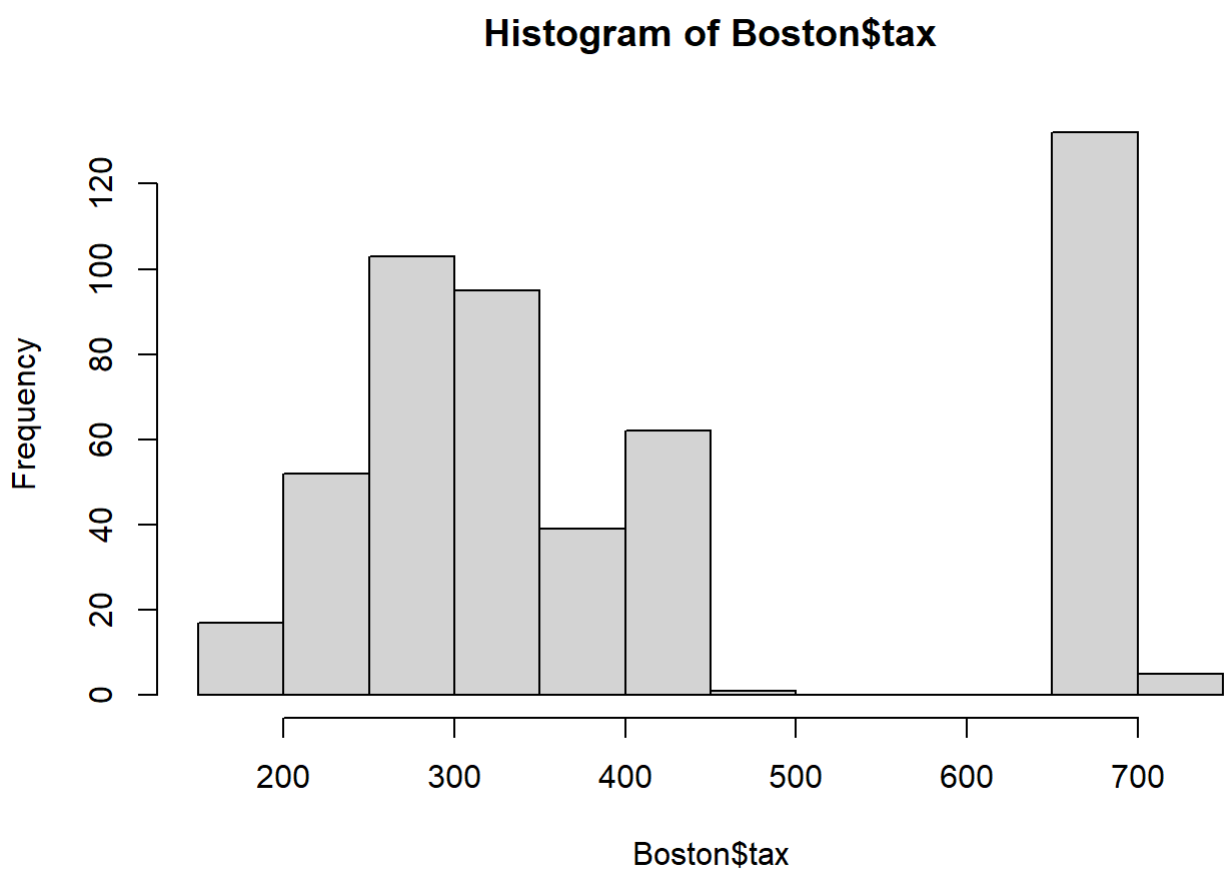
Do any of the census tracts of Boston appear to have particularly high crime rates? Tax rates? Pupil-teacher ratios? Comment on the range of each predicto

Crime Rate

```
## Range of crime rate var: 0.00632  to  88.9762
```

```
## . This shows that the variable has a very high range with a highly skewed distribution as obs
vered in previous question. Considering very high crime rate to be 2 std dev greater then avg :
16  suburbs have very high rates
```

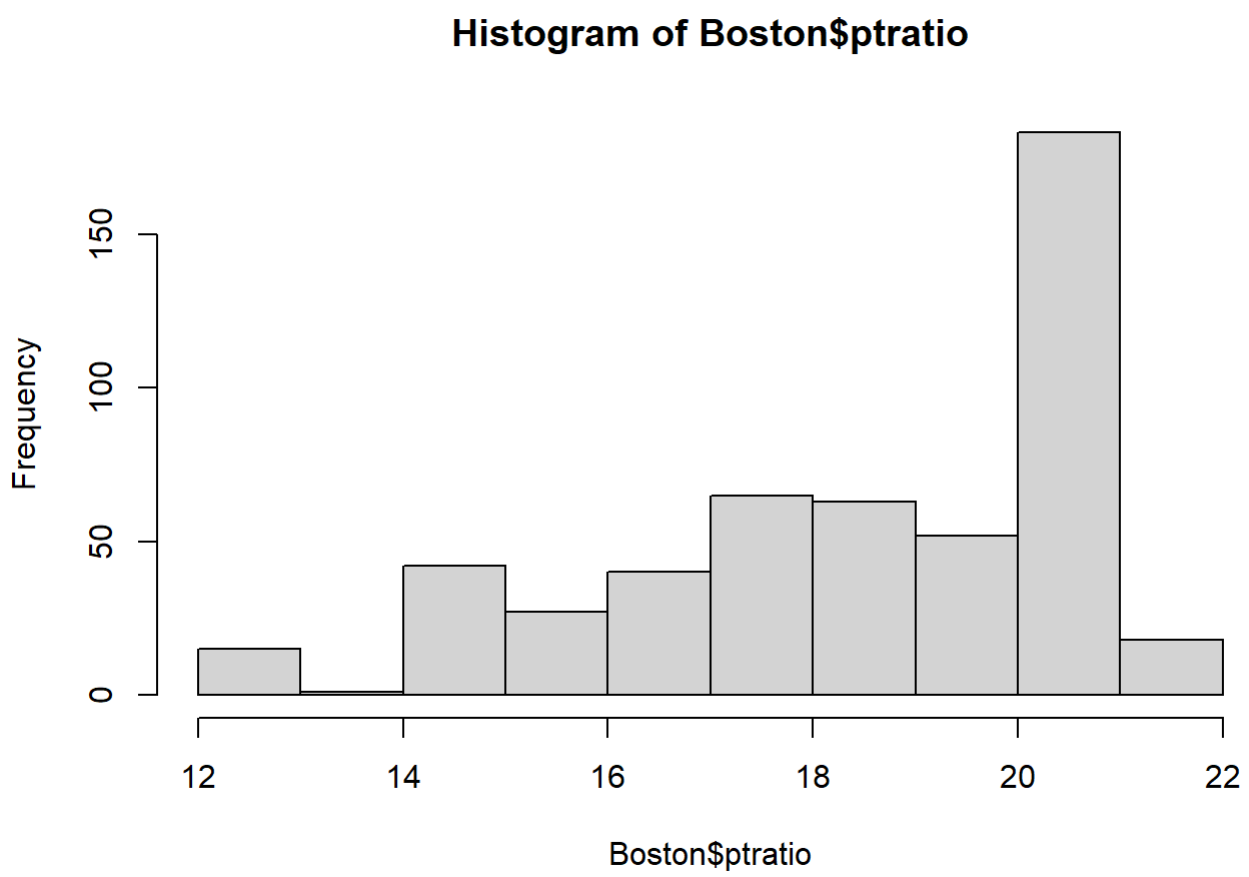
Tax




```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   187.0   279.0   330.0   408.2   666.0   711.0
```

```
## Range of Tax rate: 187  to  711
## Considering very high tax rate to be 2 std dev greater than avg ,  0  suburbs can be consider
ed to have very high tax rate relatively.
##  Considering higher tax rate to be 1 std dev greater than avg ,  137  suburbs can be consider
ed to have higher tax rate relatively.
```

Pupil-Teacher Ratio




```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   12.60   17.40   19.05   18.46   20.20   22.00
```

```
## Range of Pupil-Teacher Ratio: 12.6  to  22
## Considering very high ptratio to be 2 std dev greater than avg ,  0  suburbs can be considere
d to have very ptratio relatively.
##  Considering higher ptratio to be 1 std dev greater than avg ,  506  suburbs can be considere
d to have higher ptratio rate relatively.
```

Observation:

How many of the census tracts in this data set bound the Charles river?

```
## 35 suburbs bound the Charles River.
```

What is the median pupil-teacher ratio among the towns in this data set?

```
## The median pupil-teacher ratio among the towns in the data set  is  19.05
```

Which census tract of Boston has lowest median value of owner- occupied homes? What are the values of the other predictors for that census tract, and how do those values compare to the overall ranges for those predictors? Comment on your findings.

```
## [1] "The suburbs with the lowest median value:"
```

	crim <dbl>	zn <dbl>	indus <dbl>	chas <int>	nox <dbl>	rm <dbl>	age <dbl>	dis <dbl>	rad <int>
399	38.3518	0	18.1	0	0.693	5.453	100	1.4896	24
406	67.9208	0	18.1	0	0.693	5.683	100	1.4254	24

2 rows | 1-10 of 14 columns

```
## [1] "Comparing with original dataset"
```

```
##       crim                zn              indus            chas        
##  Min.   : 0.00632   Min.   :  0.00   Min.   : 0.46   Min.   :0.00000  
##  1st Qu.: 0.08205   1st Qu.:  0.00   1st Qu.: 5.19   1st Qu.:0.00000  
##  Median : 0.25651   Median :  0.00   Median : 9.69   Median :0.00000  
##  Mean   : 3.61352   Mean   : 11.36   Mean   :11.14   Mean   :0.06917  
##  3rd Qu.: 3.67708   3rd Qu.: 12.50   3rd Qu.:18.10   3rd Qu.:0.00000  
##  Max.   :88.97620   Max.   :100.00   Max.   :27.74   Max.   :1.00000  
##       nox               rm              age              dis        
##  Min.   :0.3850   Min.   :3.561   Min.   :  2.90   Min.   : 1.130  
##  1st Qu.:0.4490   1st Qu.:5.886   1st Qu.: 45.02   1st Qu.: 2.100  
##  Median :0.5380   Median :6.208   Median : 77.50   Median : 3.207  
##  Mean   :0.5547   Mean   :6.285   Mean   : 68.57   Mean   : 3.795  
##  3rd Qu.:0.6240   3rd Qu.:6.623   3rd Qu.: 94.08   3rd Qu.: 5.188  
##  Max.   :0.8710   Max.   :8.780   Max.   :100.00   Max.   :12.127  
##       rad              tax           ptratio          lstat       
##  Min.   : 1.000   Min.   :187.0   Min.   :12.60   Min.   : 1.73  
##  1st Qu.: 4.000   1st Qu.:279.0   1st Qu.:17.40   1st Qu.: 6.95  
##  Median : 5.000   Median :330.0   Median :19.05   Median :11.36  
##  Mean   : 9.549   Mean   :408.2   Mean   :18.46   Mean   :12.65  
##  3rd Qu.:24.000   3rd Qu.:666.0   3rd Qu.:20.20   3rd Qu.:16.95  
##  Max.   :24.000   Max.   :711.0   Max.   :22.00   Max.   :37.97  
##       medv      
##  Min.   : 5.00  
##  1st Qu.:17.02  
##  Median :21.20  
##  Mean   :22.53  
##  3rd Qu.:25.00  
##  Max.   :50.00
```

Observation:

- lstat and ptratio values for these 2 suburbs is close to maximum value in original dataset.
- Crime rate for the suburbs is very high relatively although they lie within 2 S.D. from mean value.

In this dataset,how many of the census tracts average more than seven rooms per dwelling? More than eight rooms per dwelling? Comment on the census tracts that average more than eight rooms per dwelling.

```
## 64  suburbs average more than seven rooms per dwelling.
```

```
## 13  suburbs average more than eight rooms per dwelling.
```

```
## [1] "======= Original Dataset ======"
```

```
##       crim                zn              indus            chas        
##  Min.   : 0.00632   Min.   :  0.00   Min.   : 0.46   Min.   :0.00000  
##  1st Qu.: 0.08205   1st Qu.:  0.00   1st Qu.: 5.19   1st Qu.:0.00000  
##  Median : 0.25651   Median :  0.00   Median : 9.69   Median :0.00000  
##  Mean   : 3.61352   Mean   : 11.36   Mean   :11.14   Mean   :0.06917  
##  3rd Qu.: 3.67708   3rd Qu.: 12.50   3rd Qu.:18.10   3rd Qu.:0.00000  
##  Max.   :88.97620   Max.   :100.00   Max.   :27.74   Max.   :1.00000  
##       nox               rm              age              dis        
##  Min.   :0.3850   Min.   :3.561   Min.   :  2.90   Min.   : 1.130  
##  1st Qu.:0.4490   1st Qu.:5.886   1st Qu.: 45.02   1st Qu.: 2.100  
##  Median :0.5380   Median :6.208   Median : 77.50   Median : 3.207  
##  Mean   :0.5547   Mean   :6.285   Mean   : 68.57   Mean   : 3.795  
##  3rd Qu.:0.6240   3rd Qu.:6.623   3rd Qu.: 94.08   3rd Qu.: 5.188  
##  Max.   :0.8710   Max.   :8.780   Max.   :100.00   Max.   :12.127  
##       rad              tax           ptratio          lstat      
##  Min.   : 1.000   Min.   :187.0   Min.   :12.60   Min.   : 1.73  
##  1st Qu.: 4.000   1st Qu.:279.0   1st Qu.:17.40   1st Qu.: 6.95  
##  Median : 5.000   Median :330.0   Median :19.05   Median :11.36  
##  Mean   : 9.549   Mean   :408.2   Mean   :18.46   Mean   :12.65  
##  3rd Qu.:24.000   3rd Qu.:666.0   3rd Qu.:20.20   3rd Qu.:16.95  
##  Max.   :24.000   Max.   :711.0   Max.   :22.00   Max.   :37.97  
##       medv      
##  Min.   : 5.00  
##  1st Qu.:17.02  
##  Median :21.20  
##  Mean   :22.53  
##  3rd Qu.:25.00  
##  Max.   :50.00
```

```
## [1] "======= Filtered Dataset ======"
```

```
##       crim                zn             indus              chas        
##  Min.   :0.02009   Min.   : 0.00   Min.   : 2.680   Min.   :0.0000  
##  1st Qu.:0.33147   1st Qu.: 0.00   1st Qu.: 3.970   1st Qu.:0.0000  
##  Median :0.52014   Median : 0.00   Median : 6.200   Median :0.0000  
##  Mean   :0.71879   Mean   :13.62   Mean   : 7.078   Mean   :0.1538  
##  3rd Qu.:0.57834   3rd Qu.:20.00   3rd Qu.: 6.200   3rd Qu.:0.0000  
##  Max.   :3.47428   Max.   :95.00   Max.   :19.580   Max.   :1.0000  
##       nox               rm              age              dis        
##  Min.   :0.4161   Min.   :8.034   Min.   : 8.40   Min.   :1.801  
##  1st Qu.:0.5040   1st Qu.:8.247   1st Qu.:70.40   1st Qu.:2.288  
##  Median :0.5070   Median :8.297   Median :78.30   Median :2.894  
##  Mean   :0.5392   Mean   :8.349   Mean   :71.54   Mean   :3.430  
##  3rd Qu.:0.6050   3rd Qu.:8.398   3rd Qu.:86.50   3rd Qu.:3.652  
##  Max.   :0.7180   Max.   :8.780   Max.   :93.90   Max.   :8.907  
##       rad              tax           ptratio          lstat           medv      
##  Min.   : 2.000   Min.   :224.0   Min.   :13.00   Min.   :2.47   Min.   :21.9  
##  1st Qu.: 5.000   1st Qu.:264.0   1st Qu.:14.70   1st Qu.:3.32   1st Qu.:41.7  
##  Median : 7.000   Median :307.0   Median :17.40   Median :4.14   Median :48.3  
##  Mean   : 7.462   Mean   :325.1   Mean   :16.36   Mean   :4.31   Mean   :44.2  
##  3rd Qu.: 8.000   3rd Qu.:307.0   3rd Qu.:17.40   3rd Qu.:5.12   3rd Qu.:50.0  
##  Max.   :24.000   Max.   :666.0   Max.   :20.20   Max.   :7.44   Max.   :50.0
```

Observation:

- For the suburbs rm>8:
- lstat and crime rate are much lower for these suburbs
- medv is much higher for these suburbs

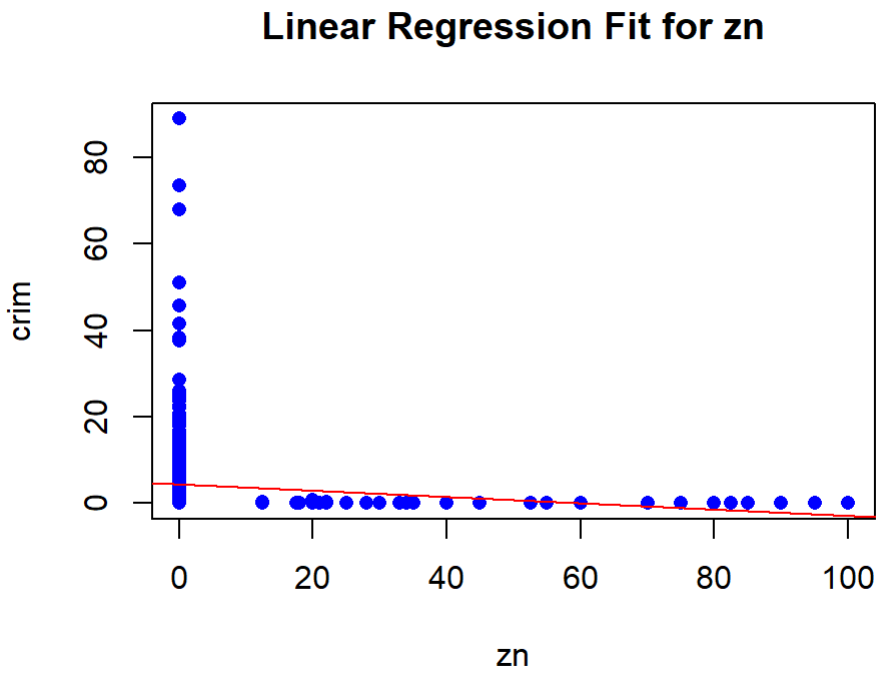
Chapter 3

Question 15

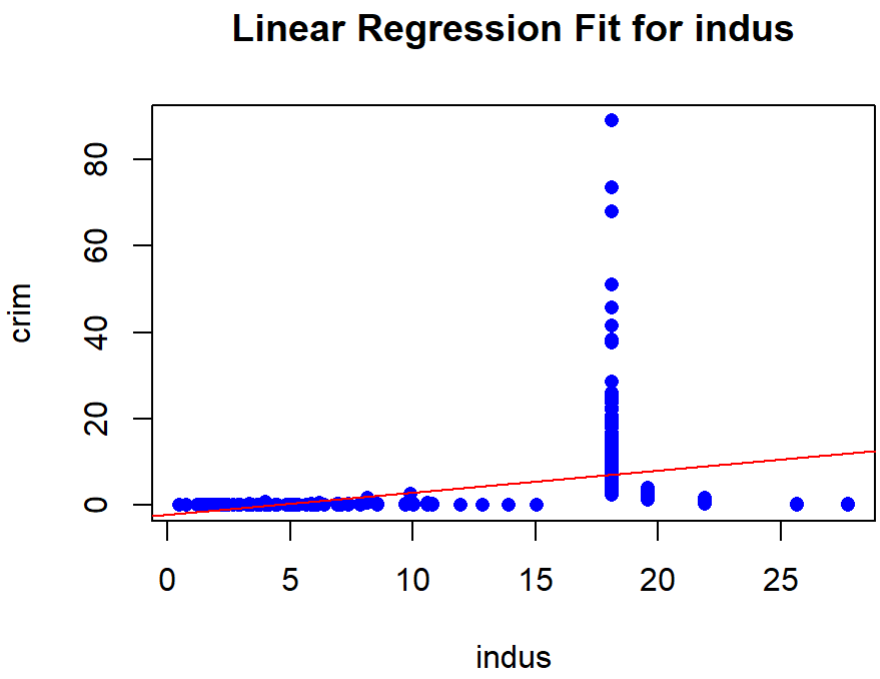
For each predictor, fit a simple linear regression model to predict the per capita crime rate. Describe your results. In which of the models is there a statistically significant association between the predictor and the response? Create some plots to back up your assertions.

Observations

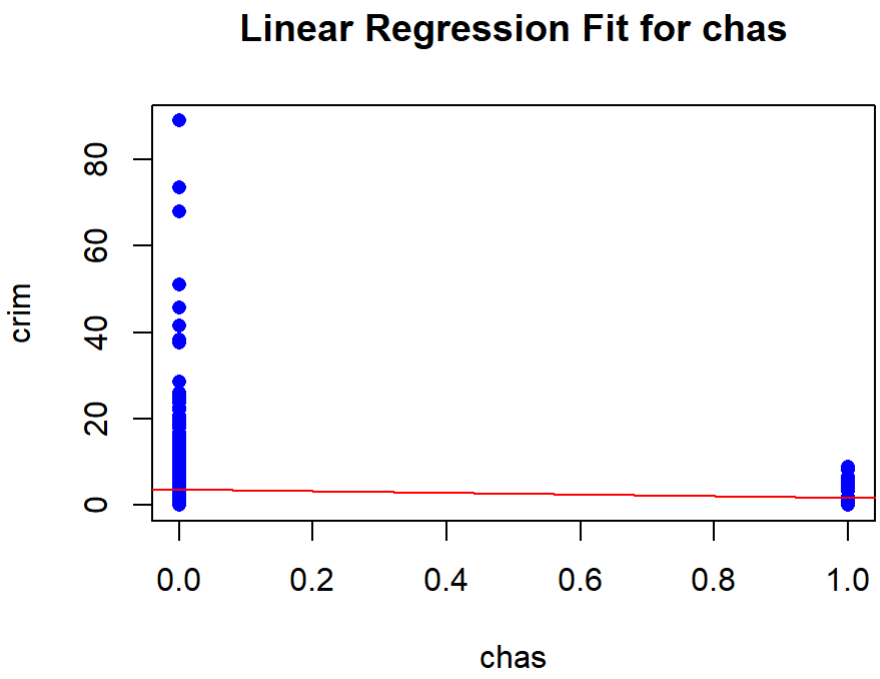
```
## regression for  crim  and  zn
## Call:
## lm(formula = paste(response_var, "~", predictor), data = Boston)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -4.429 -4.222 -2.620  1.250 84.523
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4.45369    0.41722  10.675  < 2e-16 ***
## zn          -0.07393    0.01609  -4.594 5.51e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.435 on 504 degrees of freedom
## Multiple R-squared:  0.04019,    Adjusted R-squared:  0.03828
## F-statistic:  21.1 on 1 and 504 DF,  p-value: 5.506e-06
```



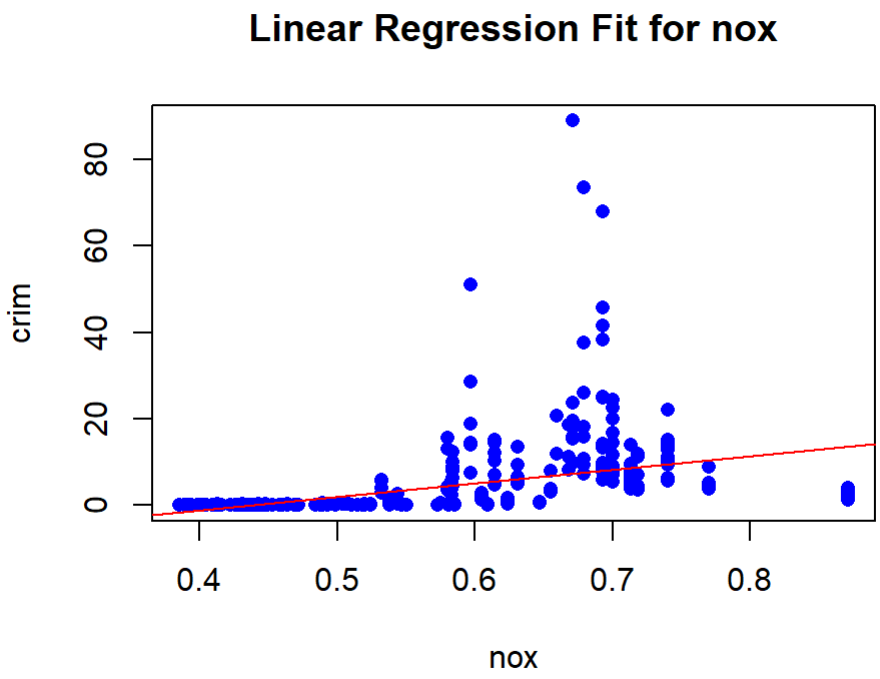
```
## regression for  crim  and  indus
## Call:
## lm(formula = paste(response_var, "~", predictor), data = Boston)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -11.972  -2.698  -0.736   0.712  81.813
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.06374    0.66723  -3.093  0.00209 **
## indus        0.50978    0.05102   9.991  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7.866 on 504 degrees of freedom
## Multiple R-squared:  0.1653, Adjusted R-squared:  0.1637
## F-statistic: 99.82 on 1 and 504 DF,  p-value: < 2.2e-16
```



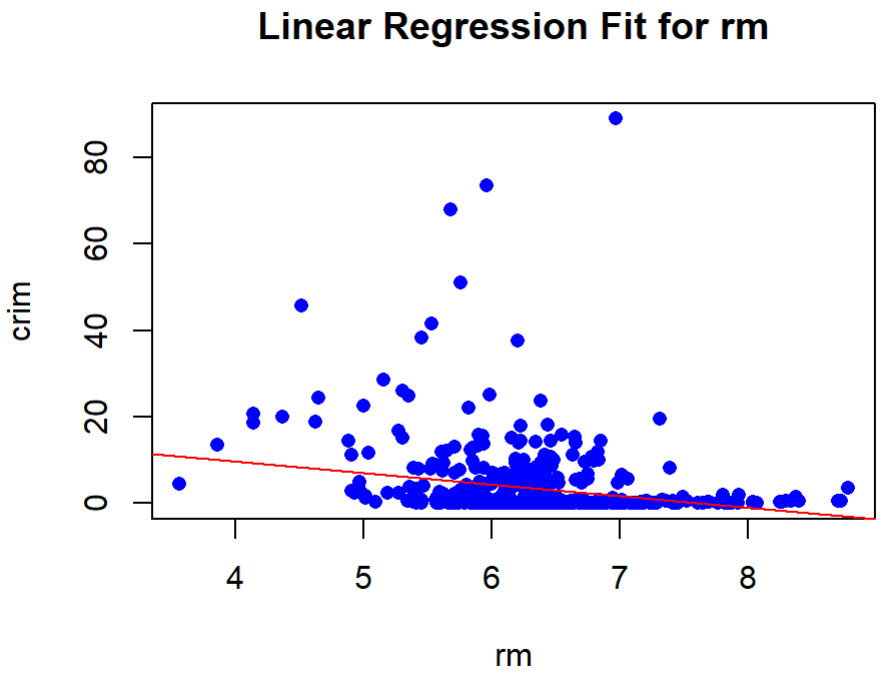
```
## regression for  crim  and  chas
## Call:
## lm(formula = paste(response_var, "~", predictor), data = Boston)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -3.738 -3.661 -3.435  0.018 85.232
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   3.7444     0.3961   9.453   <2e-16 ***
## chas         -1.8928     1.5061  -1.257    0.209
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.597 on 504 degrees of freedom
## Multiple R-squared:  0.003124,   Adjusted R-squared:  0.001146
## F-statistic: 1.579 on 1 and 504 DF,  p-value: 0.2094
```



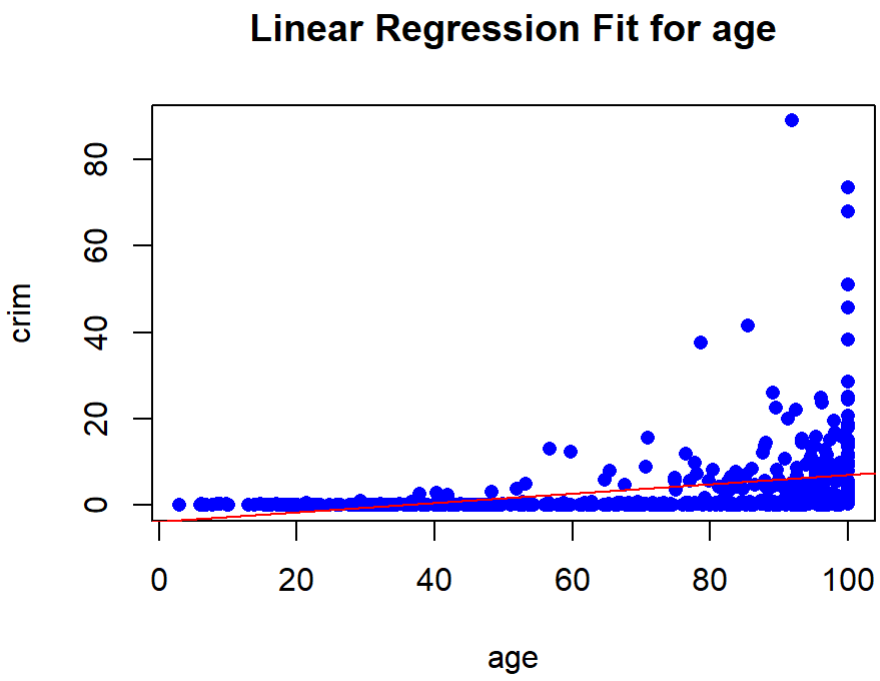
```
## regression for  crim  and  nox
## Call:
## lm(formula = paste(response_var, "~", predictor), data = Boston)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -12.371  -2.738  -0.974   0.559  81.728
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -13.720      1.699  -8.073 5.08e-15 ***
## nox           31.249      2.999  10.419  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7.81 on 504 degrees of freedom
## Multiple R-squared:  0.1772, Adjusted R-squared:  0.1756
## F-statistic: 108.6 on 1 and 504 DF,  p-value: < 2.2e-16
```



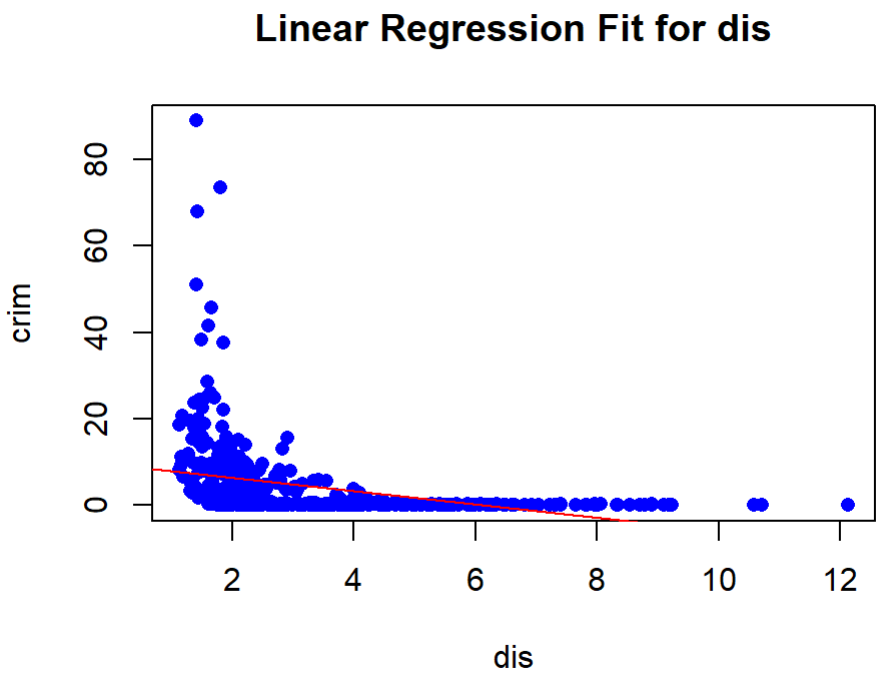
```
## regression for  crim  and  rm
## Call:
## lm(formula = paste(response_var, "~", predictor), data = Boston)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -6.604 -3.952 -2.654  0.989 87.197
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   20.482      3.365   6.088 2.27e-09 ***
## rm            -2.684      0.532  -5.045 6.35e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.401 on 504 degrees of freedom
## Multiple R-squared:  0.04807,    Adjusted R-squared:  0.04618
## F-statistic: 25.45 on 1 and 504 DF,  p-value: 6.347e-07
```



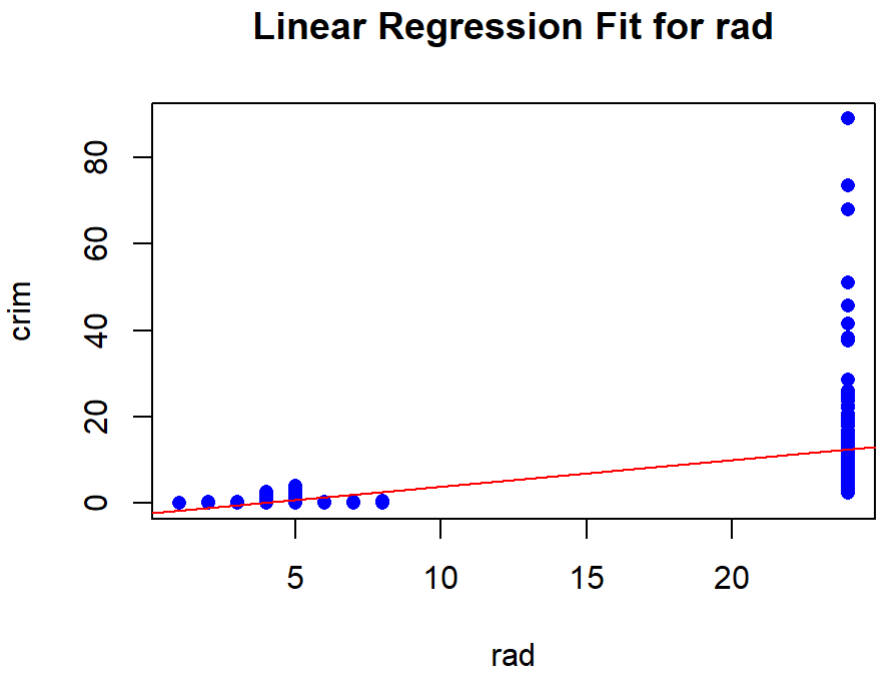
```
## regression for  crim  and  age
## Call:
## lm(formula = paste(response_var, "~", predictor), data = Boston)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -6.789 -4.257 -1.230  1.527 82.849
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -3.77791    0.94398  -4.002 7.22e-05 ***
## age          0.10779    0.01274   8.463 2.85e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.057 on 504 degrees of freedom
## Multiple R-squared:  0.1244, Adjusted R-squared:  0.1227
## F-statistic: 71.62 on 1 and 504 DF,  p-value: 2.855e-16
```



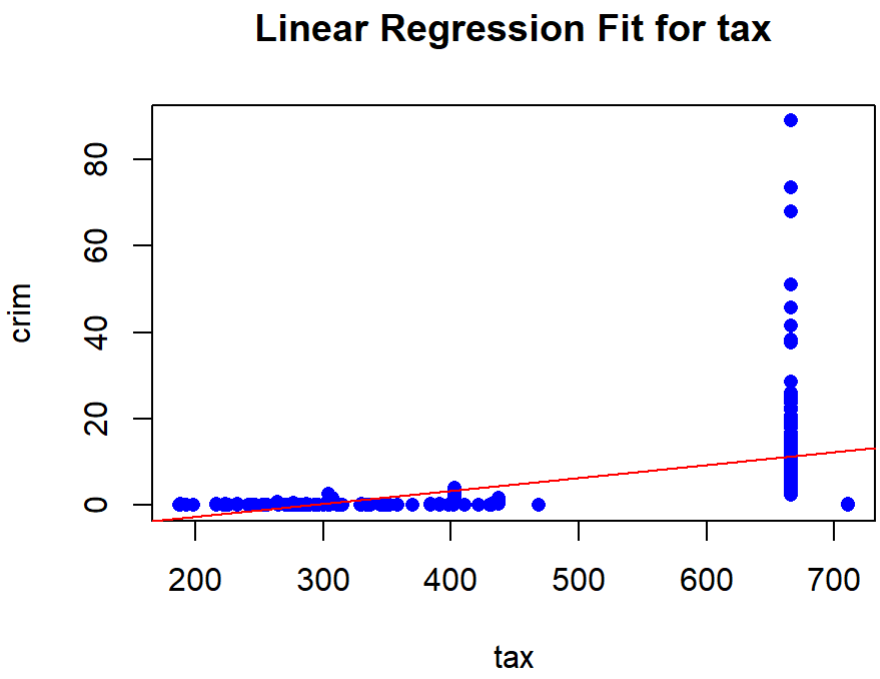
```
## regression for  crim  and  dis
## Call:
## lm(formula = paste(response_var, "~", predictor), data = Boston)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -6.708 -4.134 -1.527  1.516 81.674
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   9.4993     0.7304  13.006   <2e-16 ***
## dis          -1.5509     0.1683  -9.213   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7.965 on 504 degrees of freedom
## Multiple R-squared:  0.1441, Adjusted R-squared:  0.1425
## F-statistic: 84.89 on 1 and 504 DF,  p-value: < 2.2e-16
```



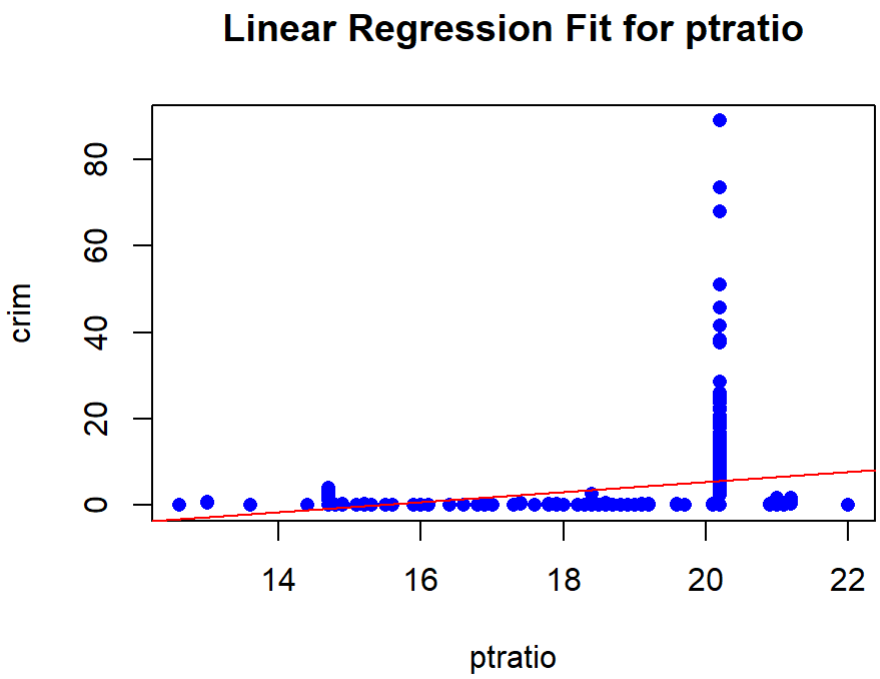
```
## regression for  crim  and  rad
## Call:
## lm(formula = paste(response_var, "~", predictor), data = Boston)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -10.164  -1.381  -0.141   0.660  76.433
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.28716    0.44348  -5.157 3.61e-07 ***
## rad          0.61791    0.03433  17.998  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.718 on 504 degrees of freedom
## Multiple R-squared:  0.3913, Adjusted R-squared:   0.39
## F-statistic: 323.9 on 1 and 504 DF,  p-value: < 2.2e-16
```



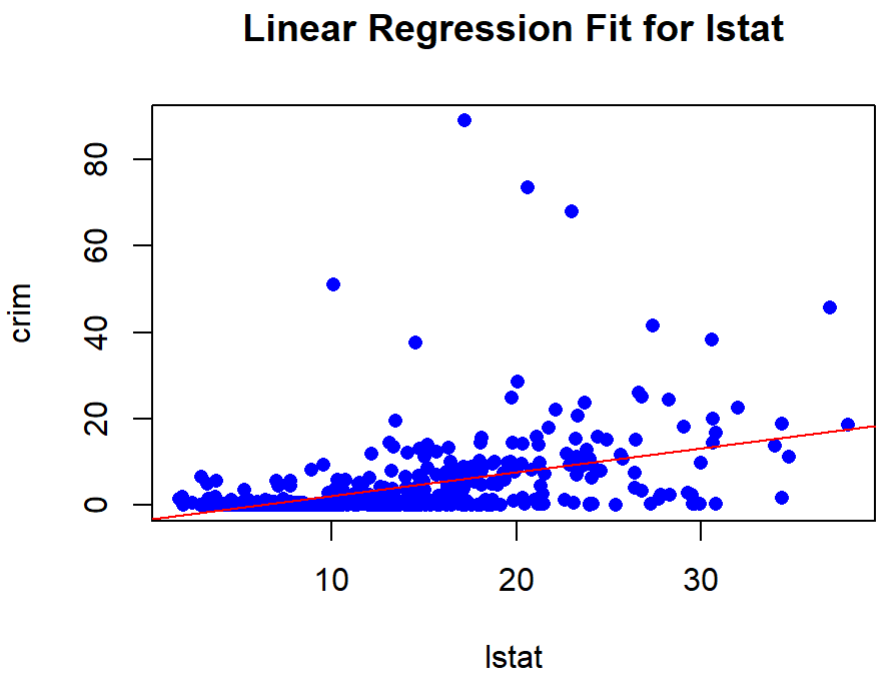
```
## regression for  crim  and  tax
## Call:
## lm(formula = paste(response_var, "~", predictor), data = Boston)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -12.513  -2.738  -0.194   1.065  77.696
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -8.528369   0.815809  -10.45   <2e-16 ***
## tax          0.029742   0.001847   16.10   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.997 on 504 degrees of freedom
## Multiple R-squared:  0.3396, Adjusted R-squared:  0.3383
## F-statistic: 259.2 on 1 and 504 DF,  p-value: < 2.2e-16
```



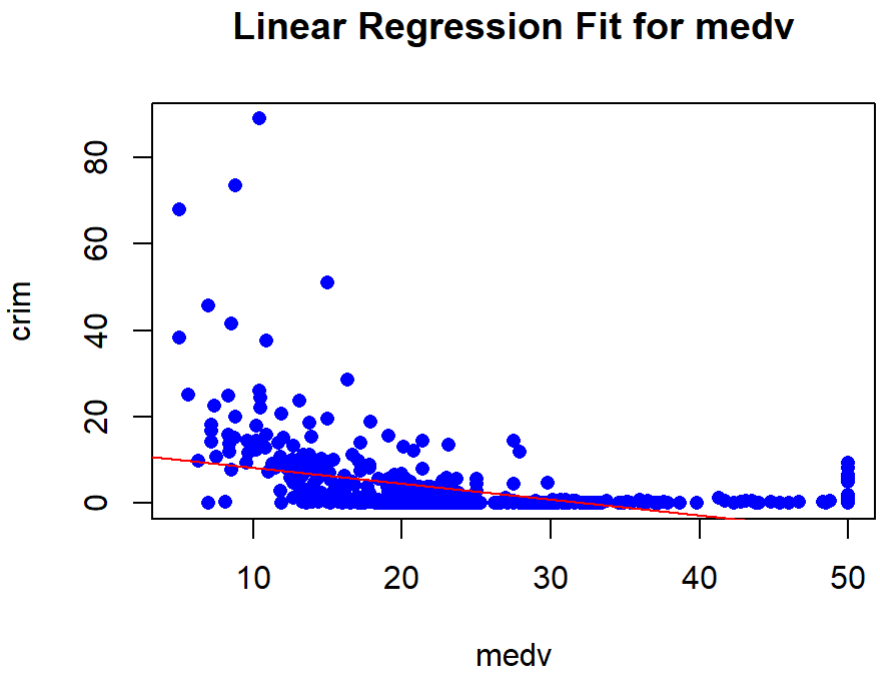
```
## regression for  crim  and  ptratio
## Call:
## lm(formula = paste(response_var, "~", predictor), data = Boston)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -7.654 -3.985 -1.912  1.825 83.353
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -17.6469     3.1473  -5.607 3.40e-08 ***
## ptratio       1.1520     0.1694   6.801 2.94e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.24 on 504 degrees of freedom
## Multiple R-squared:  0.08407,    Adjusted R-squared:  0.08225
## F-statistic: 46.26 on 1 and 504 DF,  p-value: 2.943e-11
```



```
## regression for  crim  and  lstat
## Call:
## lm(formula = paste(response_var, "~", predictor), data = Boston)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -13.925  -2.822  -0.664   1.079  82.862
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -3.33054    0.69376  -4.801 2.09e-06 ***
## lstat        0.54880    0.04776  11.491  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7.664 on 504 degrees of freedom
## Multiple R-squared:  0.2076, Adjusted R-squared:  0.206
## F-statistic:   132 on 1 and 504 DF,  p-value: < 2.2e-16
```



```
## regression for  crim  and  medv
## Call:
## lm(formula = paste(response_var, "~", predictor), data = Boston)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -9.071 -4.022 -2.343  1.298 80.957
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 11.79654    0.93419   12.63   <2e-16 ***
## medv        -0.36316    0.03839   -9.46   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7.934 on 504 degrees of freedom
## Multiple R-squared:  0.1508, Adjusted R-squared:  0.1491
## F-statistic: 89.49 on 1 and 504 DF,  p-value: < 2.2e-16
```



Observations:

- Variables with Positive Relationship with crime rate - indus, nox, age, rad, tax, ptratio,lstat
- Variables with Negative Relationship with crime rate - zn, rm,chas,rm,dis,medv
- The p-value for the variable CHAS is large, indicating that the relationship between CHAS and the crime rate is not statistically significant.
- On the other hand, all the other predictor variables in the model have small p-values, indicating that they have a significant relationship with the crime rate.

Fit a multiple regression model to predict the response using all of the predictors. Describe your results. For which predictors can we reject the null hypothesis H0 : βj = 0?

```
##
## Call:
## lm(formula = crim ~ ., data = Boston)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -8.534 -2.248 -0.348  1.087 73.923
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 13.7783938  7.0818258   1.946 0.052271 .
## zn           0.0457100  0.0187903   2.433 0.015344 *
## indus       -0.0583501  0.0836351  -0.698 0.485709
## chas        -0.8253776  1.1833963  -0.697 0.485841
## nox         -9.9575865  5.2898242  -1.882 0.060370 .
## rm           0.6289107  0.6070924   1.036 0.300738
## age         -0.0008483  0.0179482  -0.047 0.962323
## dis         -1.0122467  0.2824676  -3.584 0.000373 ***
## rad          0.6124653  0.0875358   6.997 8.59e-12 ***
## tax         -0.0037756  0.0051723  -0.730 0.465757
## ptratio     -0.3040728  0.1863598  -1.632 0.103393
## lstat        0.1388006  0.0757213   1.833 0.067398 .
## medv        -0.2200564  0.0598240  -3.678 0.000261 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.46 on 493 degrees of freedom
## Multiple R-squared:  0.4493, Adjusted R-squared:  0.4359
## F-statistic: 33.52 on 12 and 493 DF,  p-value: < 2.2e-16
```

Observations:

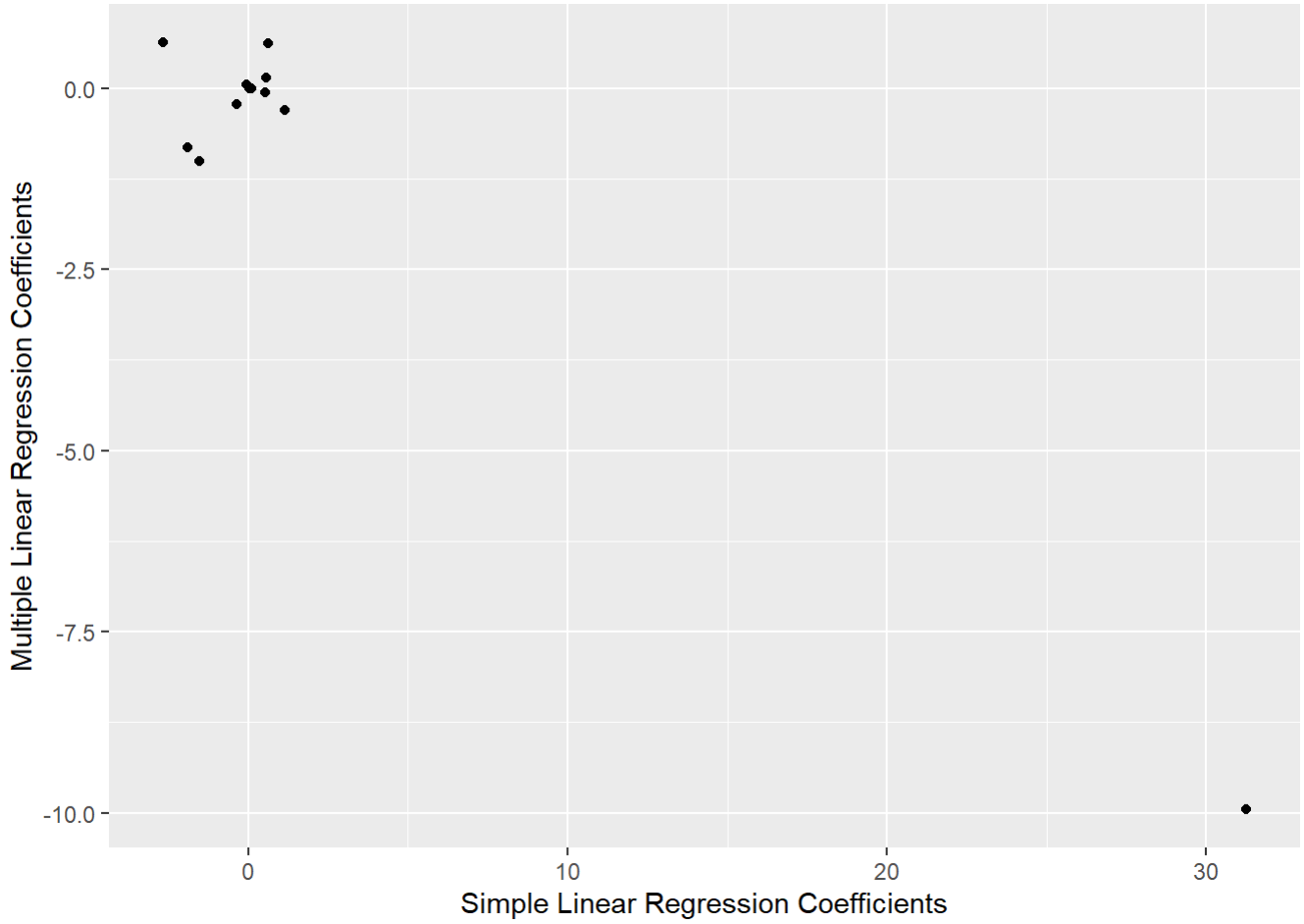
The p-values for the predictors ZN, DIS, RAD, and MEDV are all below 0.05, which suggests that these variables have a significant influence on the response variable. Therefore, we can reject the null hypothesis.

How do your results from (a) compare to your results from (b)? Create a plot displaying the univariate regression coefficients from (a) on the x-axis, and the multiple regression coefficients from (b) on the y-axis. That is, each predictor is displayed as a single point in the plot. Its coefficient in a simple linear regres- sion model is shown on the x-axis, and its coefficient estimate in the multiple linear regression model is shown on the y-axis.

Observations:

- The coefficient estimates of predictors have changed.
- The relationship of a predictor with response has also changed. For example, In simple regression ptratio had a positive relationship but in multiple regression it has a negative relationship with crime.

```
##         multiple_regression_coefs simple_regression_coefs
## zn                     0.0457100386             -0.07393498
## indus                 -0.0583501107              0.50977633
## chas                  -0.8253775522             -1.89277655
## nox                   -9.9575865471             31.24853120
## rm                     0.6289106622             -2.68405122
## age                   -0.0008482791              0.10778623
## dis                   -1.0122467382             -1.55090168
## rad                    0.6124653115              0.61791093
## tax                   -0.0037756465              0.02974225
## ptratio               -0.3040727572              1.15198279
## lstat                  0.1388005968              0.54880478
## medv                  -0.2200563590             -0.36315992
```



Is there evidence of non-linear association between any of the predictors and the response? To answer this question, for each predictor X, fit a model of the form

$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \beta_3 X^3 + \varepsilon$$

```
##    Predictor P_values_degree1 P_values_degree2 P_values_degree3
## 1         zn     4.697806e-06     4.420507e-03     2.295386e-01
## 2      indus     8.854243e-24     1.086057e-03     1.196405e-12
## 3        nox     2.457491e-26     7.736755e-05     6.961110e-16
## 4         rm     5.128048e-07     1.508545e-03     5.085751e-01
## 5        age     4.878803e-17     2.291156e-06     6.679915e-03
## 6        dis     1.253249e-21     7.869767e-14     1.088832e-08
## 7        rad     1.053211e-56     9.120558e-03     4.823138e-01
## 8        tax     6.976314e-49     3.665348e-06     2.438507e-01
## 9    ptratio     1.565484e-11     2.405468e-03     6.300514e-03
## 10     lstat     1.678072e-27     3.780418e-02     1.298906e-01
## 11      medv     4.930818e-27     2.928577e-35     1.046510e-12
##    Coeff_values_degree1 Coeff_values_degree2 Coeff_values_degree3
## 1             -38.74984             23.93983           -10.071868
## 2              78.59082            -24.39480           -54.129763
## 3              81.37202            -28.82859           -60.361894
## 4             -42.37944             26.57677            -5.510342
## 5              68.18201             37.48447            21.353207
## 6             -73.38859             56.37304           -42.621877
## 7             120.90745             17.49230             4.698457
## 8             112.64583             32.08725            -7.996811
## 9              56.04523             24.77482           -22.279737
## 10             88.06967             15.88816           -11.574022
## 11            -75.05761             88.08621           -48.033435
```

Observations:

- Based on p-values, variables with non linear relationship with crim are:
- indus ,nox ,age ,dis ,ptratio ,medv

Chapter 6

Question 9

Split the College data set into a training set and a test set.

```
## Training set dimensions: 543 18
```

```
## Test set dimensions: 234 18
```

Fit a linear model using least squares on the training set, and report the test error obtained.

```
## Linear regression MSE =  1555839
```

Fit a ridge regression model on the training set, with λ chosen by cross-validation. Report the test error obtained.

```
## Ridge regression MSE =  1555797
```

Fit a lasso model on the training set, with λ chosen by cross- validation. Report the test error obtained, along with the number of non-zero coefficient estimates.

```
## [1] 1555851
```

```
## 19 x 1 sparse Matrix of class "dgCMatrix"
##                        s1
## (Intercept) -471.39372052
## (Intercept)    .
## PrivateYes  -491.04485137
## Accept         1.57033288
## Enroll        -0.75961467
## Top10perc     48.14698892
## Top25perc    -12.84690695
## F.Undergrad    0.04149116
## P.Undergrad    0.04438973
## Outstate      -0.08328388
## Room.Board     0.14943472
## Books          0.01532293
## Personal       0.02909954
## PhD           -8.39597537
## Terminal      -3.26800340
## S.F.Ratio     14.59298267
## perc.alumni   -0.04404771
## Expend         0.07712632
## Grad.Rate      8.28950241
```

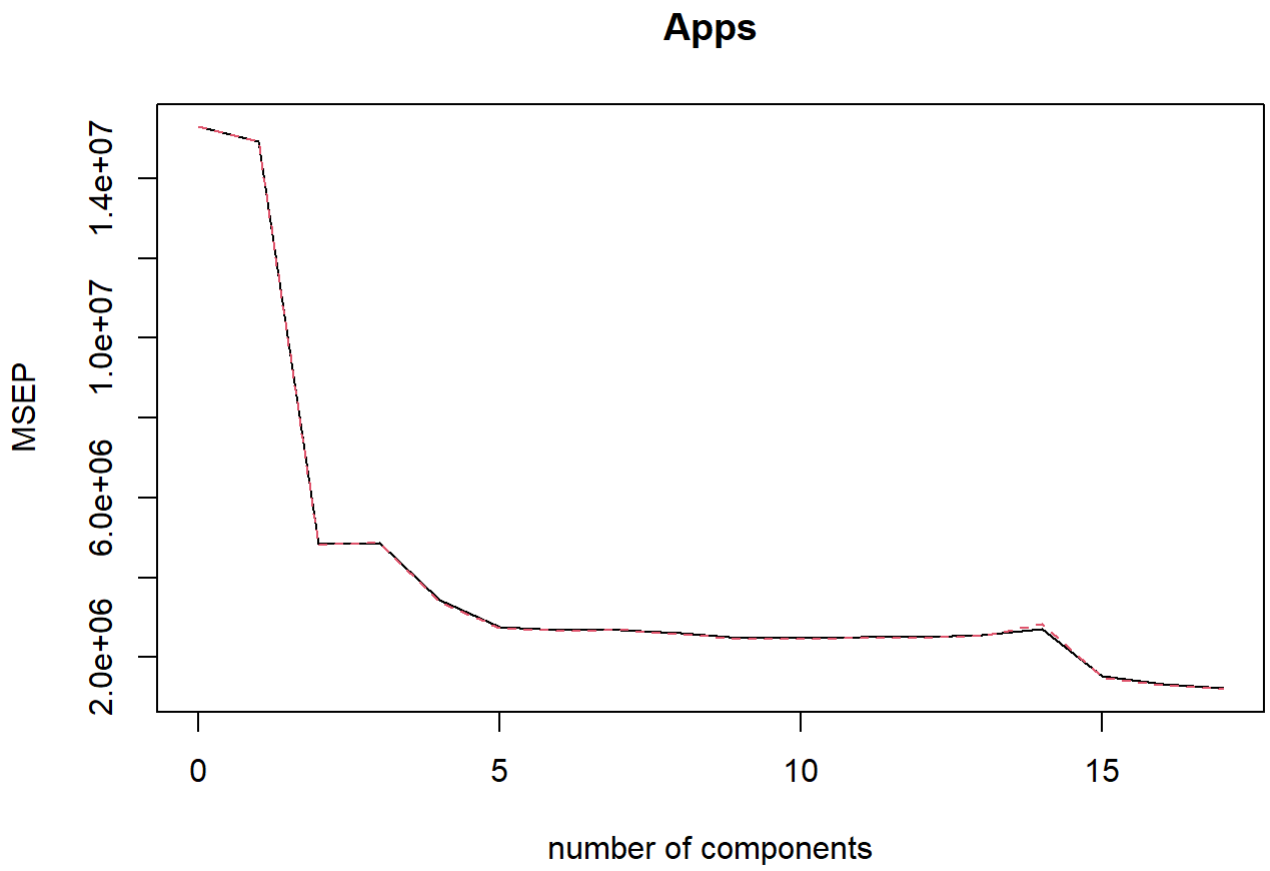
```
## Mean Squared Error for Lasso: 1555851
```

```
## Number of Non-Zero Coefficients: 18
```

Fit a PCR model on the training set, with M chosen by cross validation. Report the test error obtained, along with the value of M selected by cross-validation.

```
## [1] 1780624
```

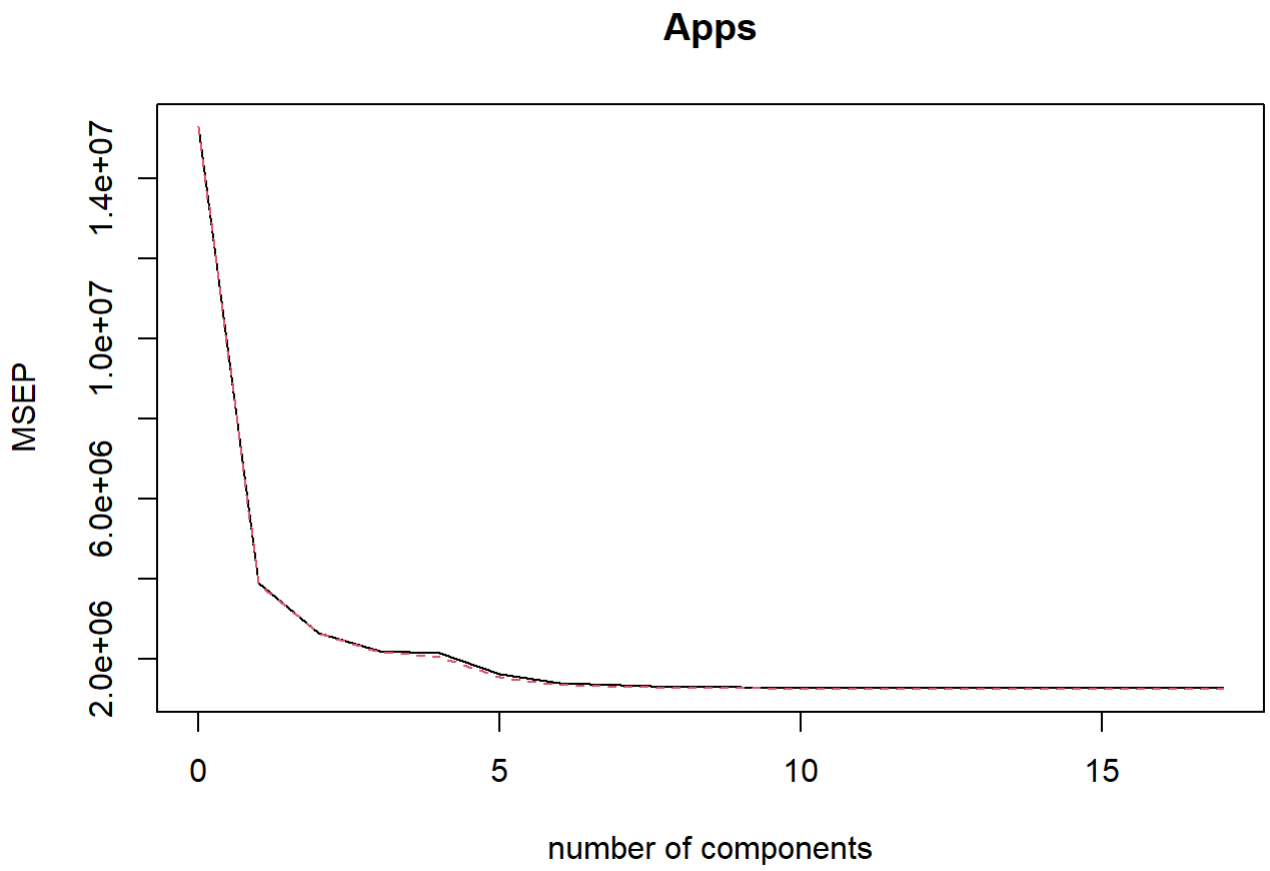
```
## Mean Squared Error for PCR: 1780624
```



Fit a PLS model on the training set, with M chosen by crossvalidation. Report the test error obtained, along with the value of M selected by cross-validation.

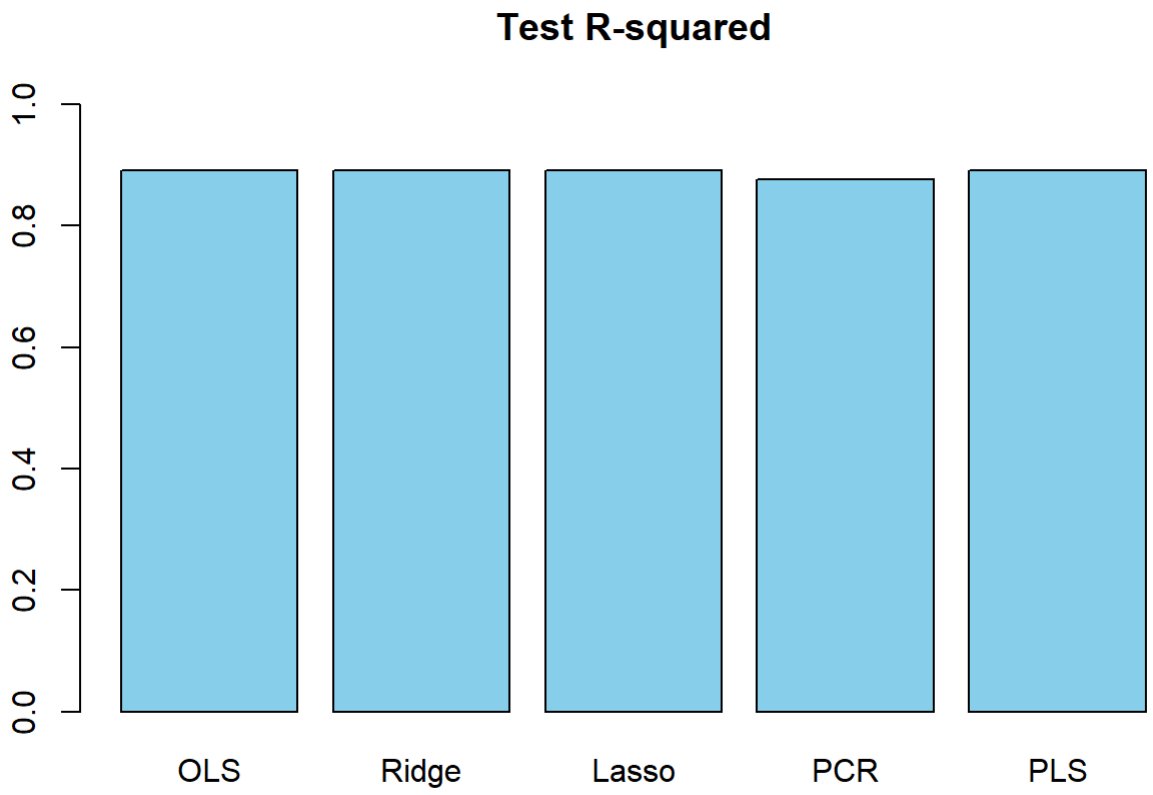
```
## [1] 1558562
```

```
## Mean Squared Error for PLS: 1558562
```



Comment on the results obtained. How accurately can we predict the number of college applications received? Is there much difference among the test errors resulting from these five approaches?

```
## [1] 0.8913273 0.8913302 0.8913264 0.8756264 0.8911371
```



Observations

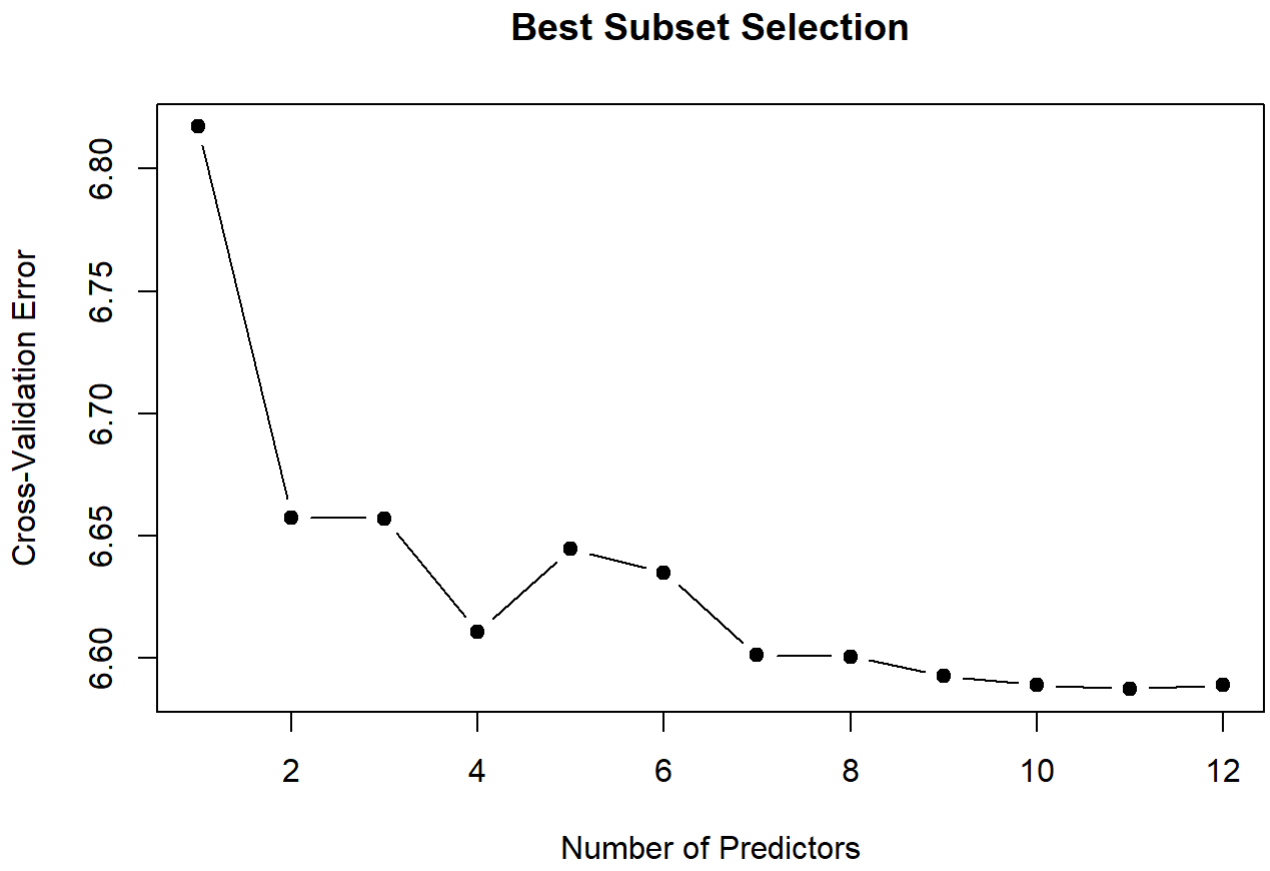
- Lasso reduces F.Undergrad , Books and Personal variables to zero and shrinks coefficients of other variables.
- The plot shows that test R2 for all models are around 0.9, with PCR having slightly lower test R2 than others.

Question 11

Try out some of the regression methods on Boston data, such as best subset selection, the lasso, ridge regression, and PCR. Present and discuss results for the approaches that you consider.

Best Subset Selection

```
## [1] 12
```




```
##  [1] 6.817211 6.657478 6.657168 6.610904 6.644513 6.635045 6.601194 6.600679
##  [9] 6.592704 6.589167 6.587325 6.589047
```

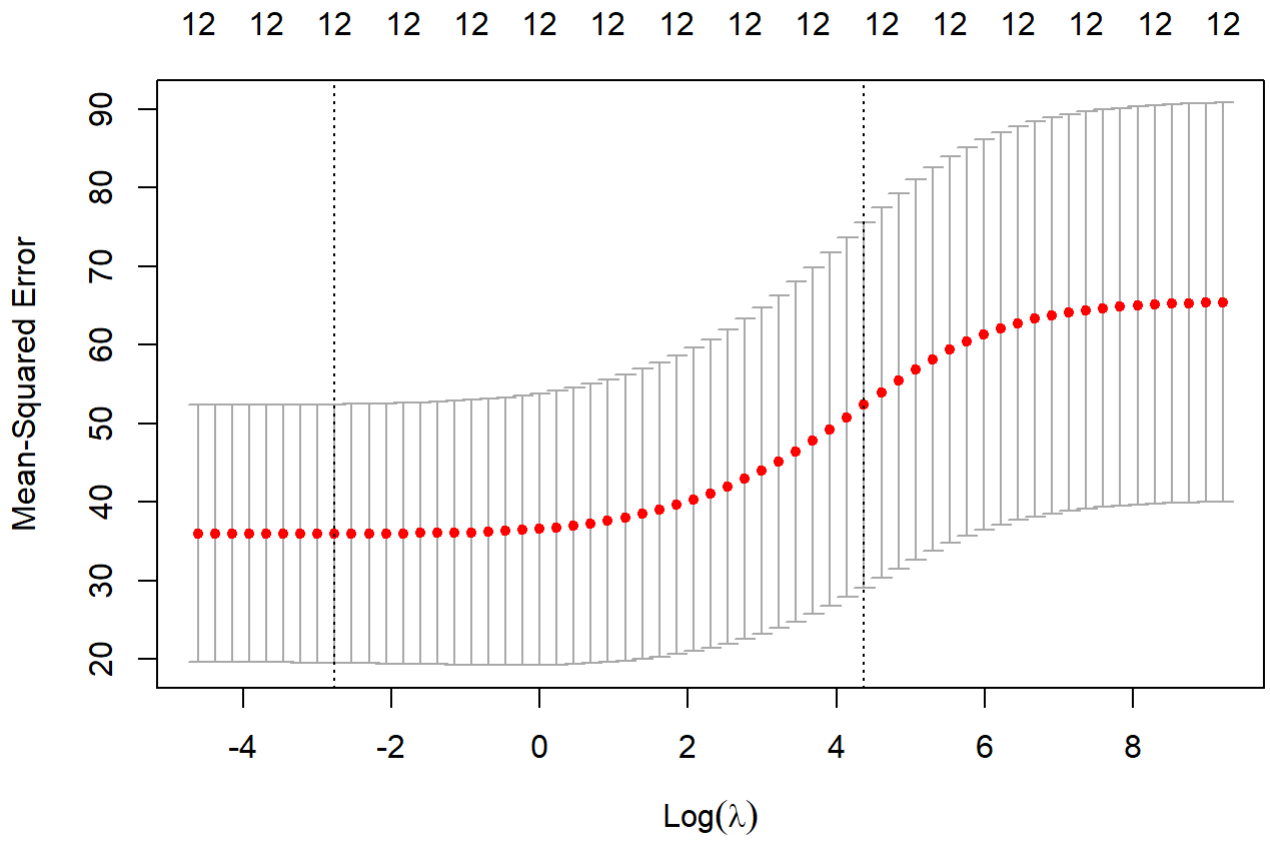
Observation:

- Cross validation error for a model with 11 variables is the lowest.

Ridge Regression

```
## Root Mean Squared Error for Ridge Regression: 7.602275
```

```
## Mean Squared Error for Ridge Regression: 57.79459
```




```
## Optimal Lambda value 0.06309573
```

```
## 13 x 1 sparse Matrix of class "dgCMatrix"
##                       s1
## (Intercept)  0.785984530
## zn          -0.002892501
## indus        0.027226824
## chas        -0.158192556
## nox          1.827244414
## rm          -0.171419430
## age          0.005929627
## dis         -0.086550047
## rad          0.044255312
## tax          0.001991582
## ptratio      0.065220527
## lstat        0.038264057
## medv        -0.021851245
```

Lasso

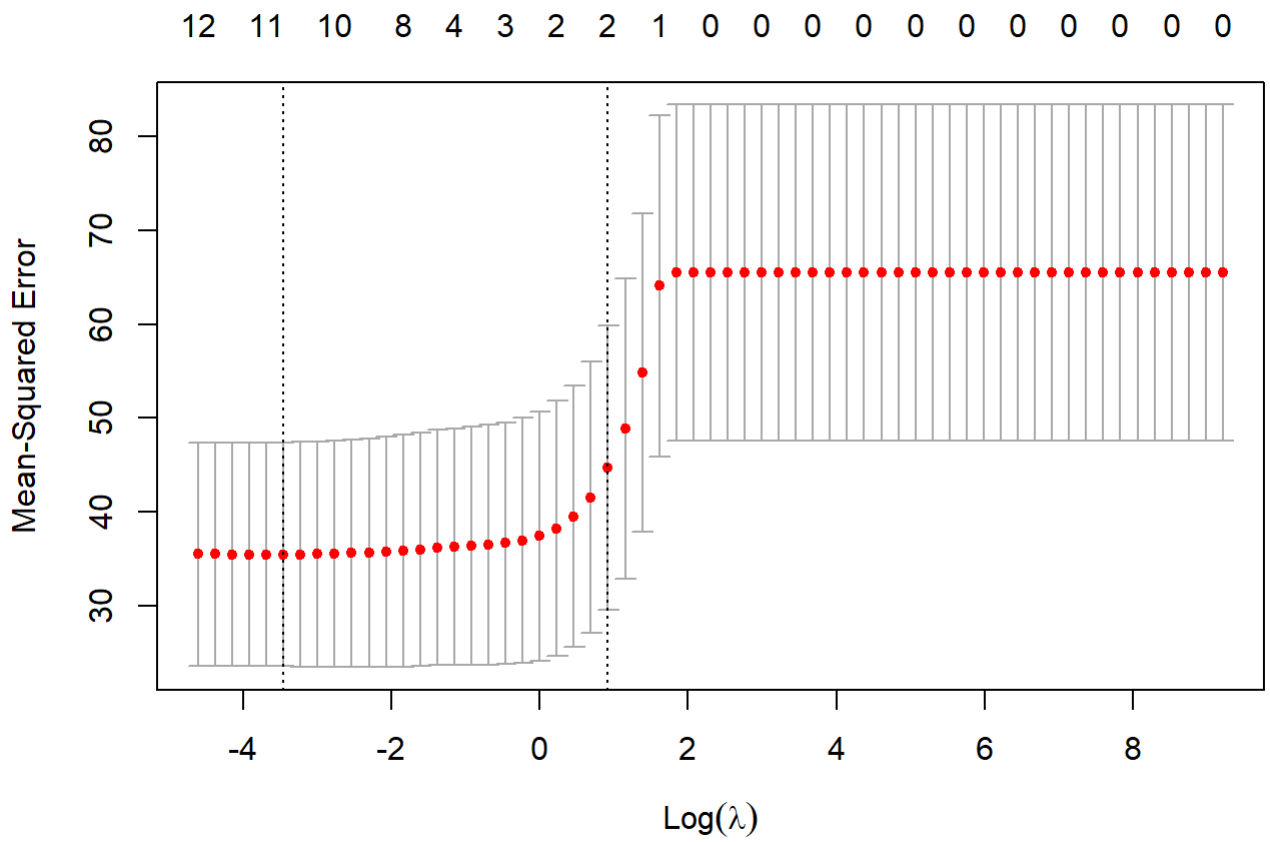
```
##
## Call:  glmnet(x = model.matrix(crim ~ ., train_data)[, -1], y = train_data$crim,      alpha =
1, lambda = lasso_best_lambda)
##
##   Df  %Dev  Lambda
## 1 10 47.94 0.03162
```

```
## Root Mean Squared Error for Lasso Regression: 7.620056
```

```
## Mean Squared Error for Lasso Regression: 58.06525
```

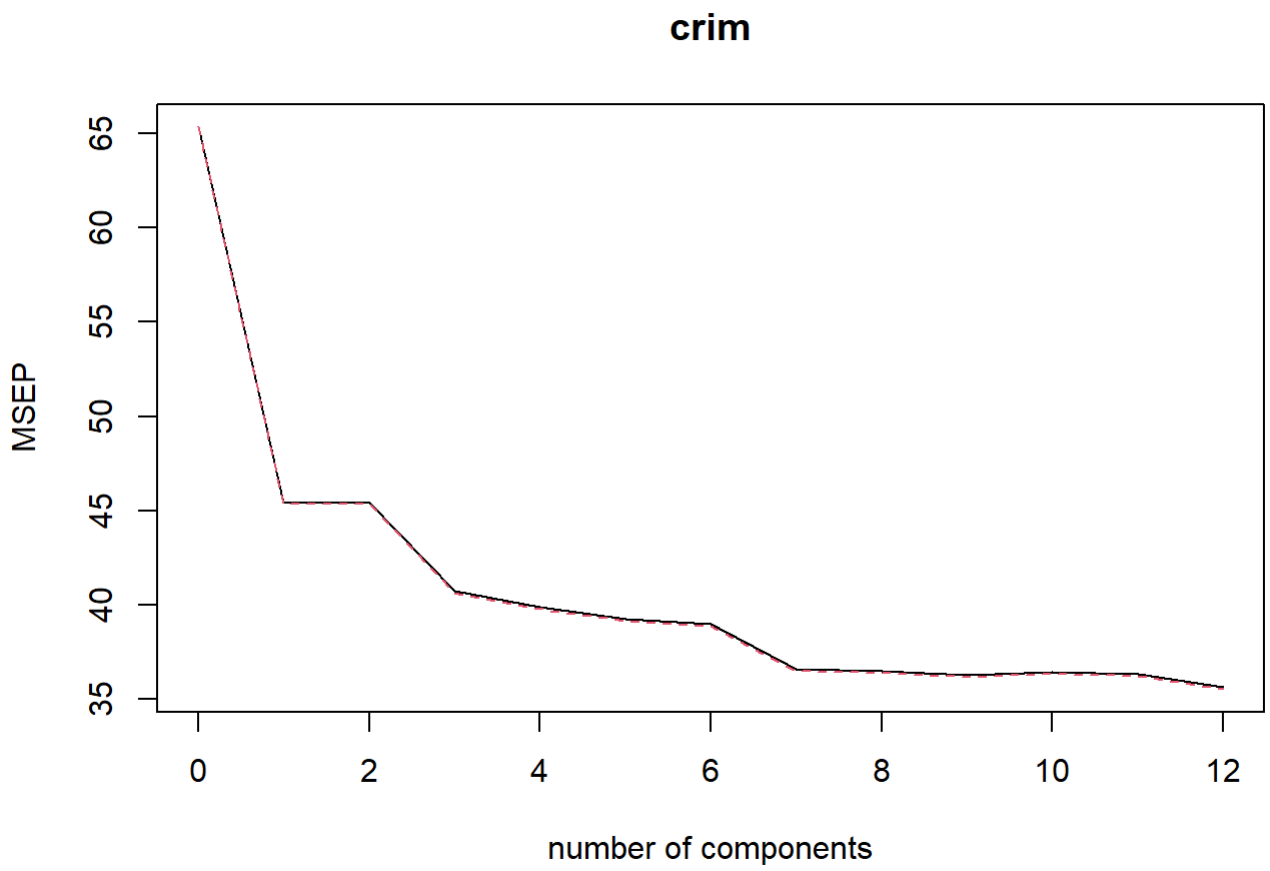
```
## Number of Non-Zero Coefficients in Lasso model: 10
```

```
## Lasso lambda best value =  0.03162278
```



```
## 13 x 1 sparse Matrix of class "dgCMatrix"
##                      s0
## (Intercept)  7.45188921
## zn           0.03198721
## indus       -0.07511476
## chas        -0.64971146
## nox         -4.86238217
## rm           0.31716023
## age          .
## dis         -0.58563461
## rad          0.52110294
## tax          .
## ptratio     -0.28952577
## lstat        0.22519281
## medv        -0.12760552
```

PCR Model



```
## Data:    X dimension: 354 12
##  Y dimension: 354 1
## Fit method: svdpc
## Number of components considered: 12
##
## VALIDATION: RMSEP
## Cross-validated using 10 random segments.
##        (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## CV           8.085    6.738    6.738    6.380    6.316    6.262    6.242
## adjCV        8.085    6.734    6.733    6.374    6.306    6.257    6.236
##        7 comps  8 comps  9 comps  10 comps  11 comps  12 comps
## CV       6.048    6.040    6.021     6.035     6.026     5.967
## adjCV    6.041    6.032    6.013     6.028     6.018     5.959
##
## TRAINING: % variance explained
##       1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps  8 comps
## X       50.57    64.47    73.58    80.72    87.14    90.65    93.18    95.07
## crim    31.52    31.89    39.44    40.88    41.82    42.41    45.89    46.09
##       9 comps  10 comps  11 comps  12 comps
## X       96.86     98.34     99.46    100.00
## crim    46.40     46.46     46.94     48.03
```

```
## Root Mean Squared Error for PCR: 7.816138
```

```
## Mean Squared Error for PCR: 61.09201
```

12 component pcr fit has lowest CV/adjCV RMSEP.

b. Propose a model (or set of models) that seem to perform well on this data set, and justify your answer. Make sure that you are evaluating model performance using validation set error, cross-validation, or some other reasonable alternative, as opposed to using training error.

Observations

- MSE for different techniques are as follows:
- Lasso -> 58.06525
- Ridge Regression -> 58.251
- PCR -> 61.09201

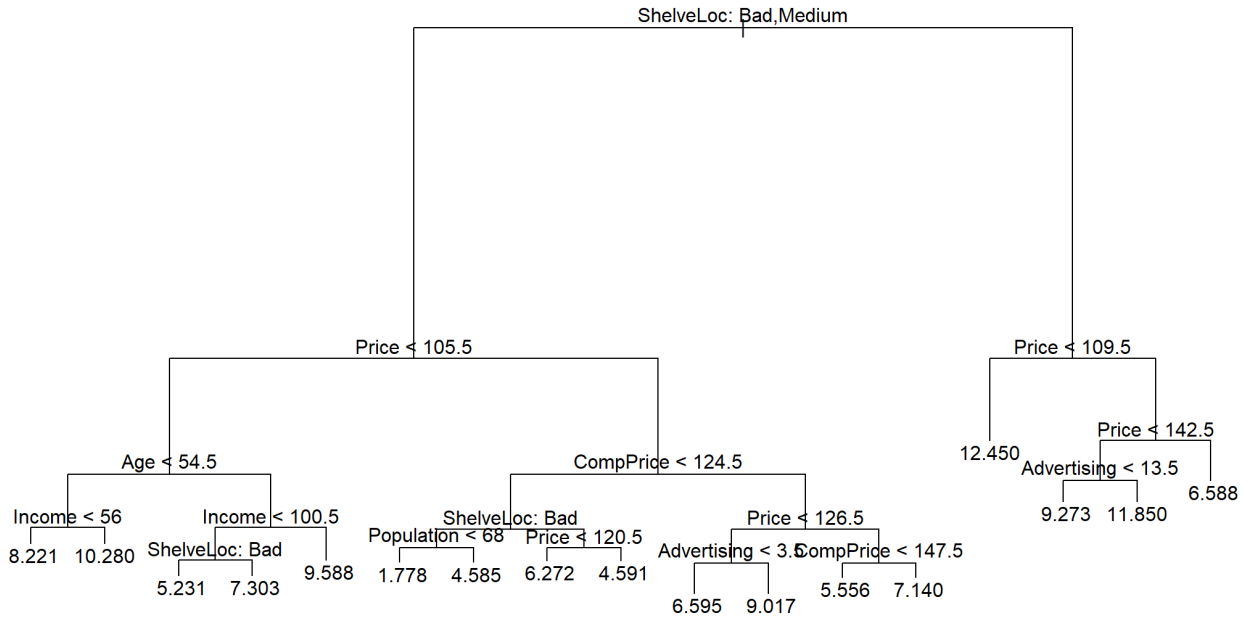
I would chose the Lasso Model because it has the lowest MSE and more interpretable comparatively since it reduces contribution of 2 variables for prediction (age and tax)

c. Does your chosen model involve all of the features in the data set? Why or why not?

Chosen Model has 10 variables as 2 variables contribution has been reduced by lasso technique.

Chapter 8: Question 8

a,b. Split the Carseats data set into a training set and a test set. Fit a regression tree to the training set. Plot the tree, and interpret the results. What test MSE do you obtain?

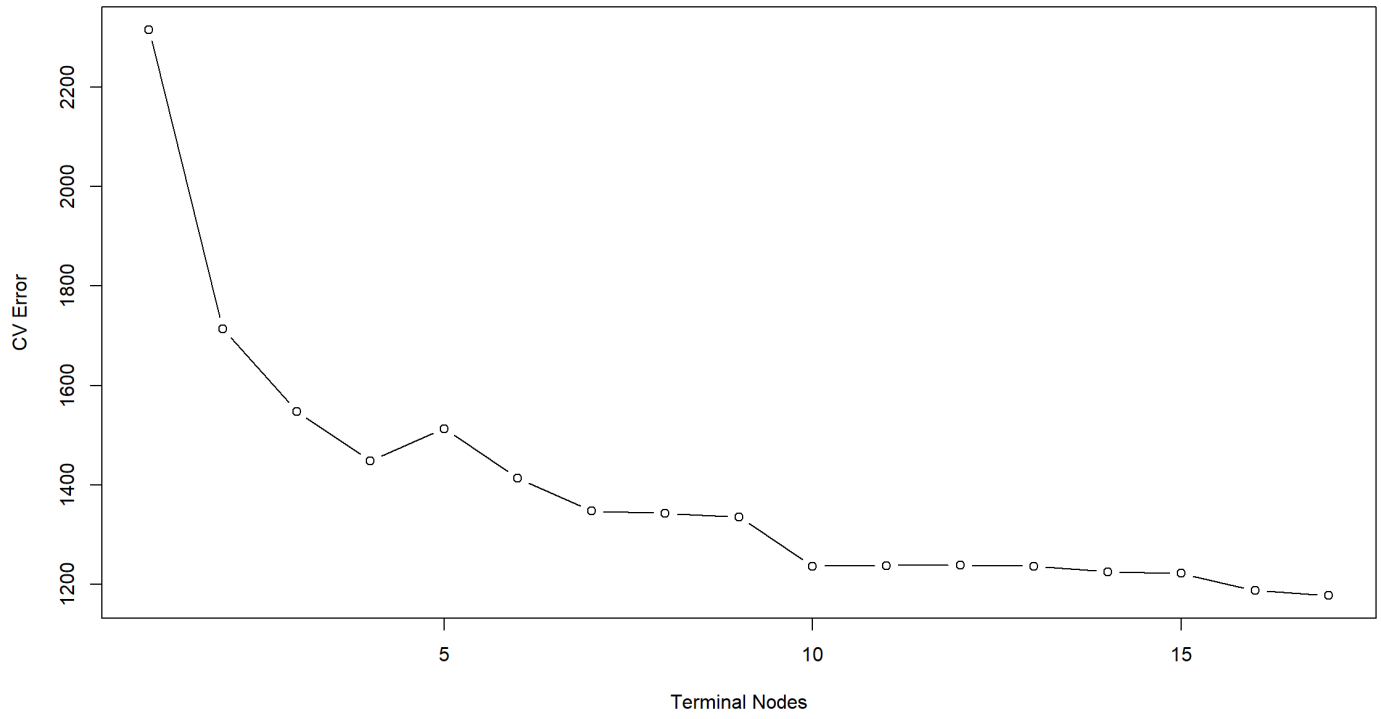



```
## Test MSE for regression tree: 4.359207
```

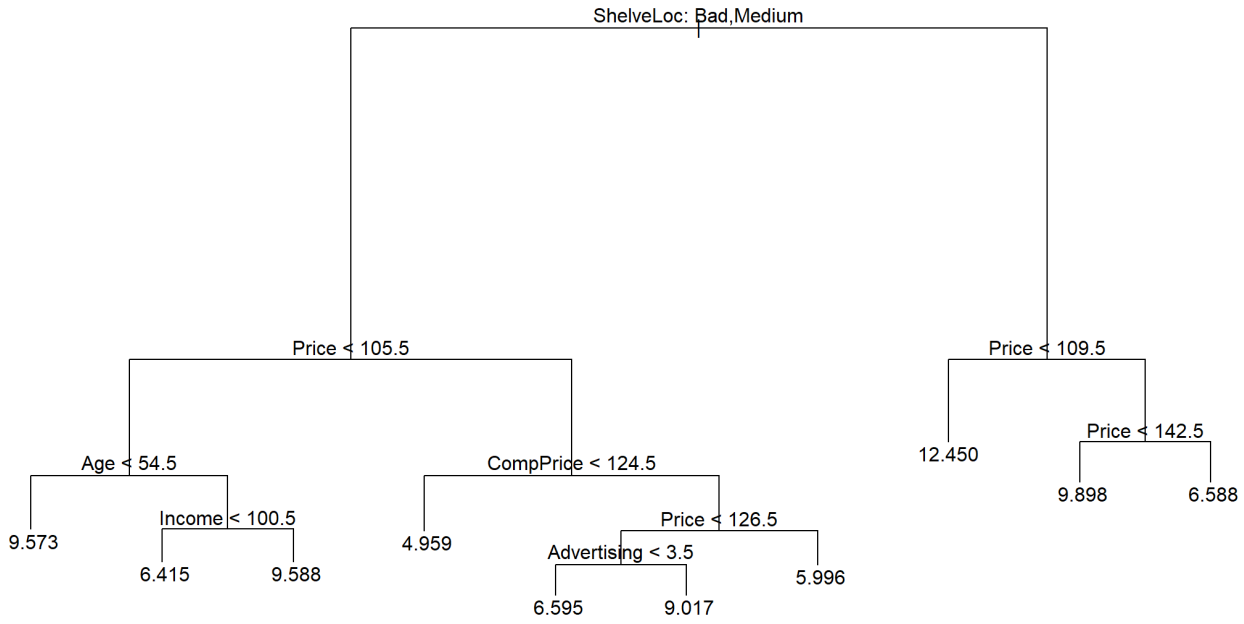
Most important features of the tree model are **ShelveLoc** and **Price**

c. Use cross-validation in order to determine the optimal level of tree complexity. Does pruning the tree improve the test MSE?

```
## $size
##  [1] 17 16 15 14 13 12 11 10  9  8  7  6  5  4  3  2  1
##
## $dev
##  [1] 1177.487 1187.328 1221.951 1224.846 1236.326 1238.141 1237.628 1236.377
##  [9] 1335.368 1342.913 1347.593 1413.206 1513.159 1447.833 1547.726 1714.123
## [17] 2316.023
##
## $k
##  [1]      -Inf  25.11041  27.17616  27.80911  29.44726  30.63478  35.99601
##  [8]  40.25430  58.03645  62.62515  65.54326  77.46582 101.92302 104.51745
## [15] 157.68280 223.52150 634.61364
##
## $method
## [1] "deviance"
##
## attr(,"class")
## [1] "prune"         "tree.sequence"
```



```
## node), split, n, deviance, yval
##       * denotes terminal node
##
##  1) root 280 2296.00  7.603
##    2) ShelveLoc: Bad,Medium 215 1226.00  6.775
##      4) Price < 105.5 68  370.90  8.274
##        8) Age < 54.5 32   86.31  9.573 *
##        9) Age > 54.5 36  182.70  7.120
##         18) Income < 100.5 28  105.20  6.415 *
##         19) Income > 100.5 8   14.83  9.588 *
##      5) Price > 105.5 147  631.10  6.082
##       10) CompPrice < 124.5 53  187.30  4.959 *
##       11) CompPrice > 124.5 94  339.20  6.715
##         22) Price < 126.5 40  110.40  7.685
##           44) Advertising < 3.5 22   37.47  6.595 *
##           45) Advertising > 3.5 18   14.93  9.017 *
##         23) Price > 126.5 54  163.20  5.996 *
##    3) ShelveLoc: Good 65  435.90 10.340
##      6) Price < 109.5 23   62.35 12.450 *
##      7) Price > 109.5 42  215.90  9.188
##       14) Price < 142.5 33  118.00  9.898 *
##       15) Price > 142.5 9   20.40  6.588 *
```




```
## Pruned tree test MSE: 4.835634
```

Pruning the tree in this case increases the test MSE to 5.02

d. Use the bagging approach in order to analyze this data. What test MSE do you obtain? Use the importance() function to de- termine which variables are most important.

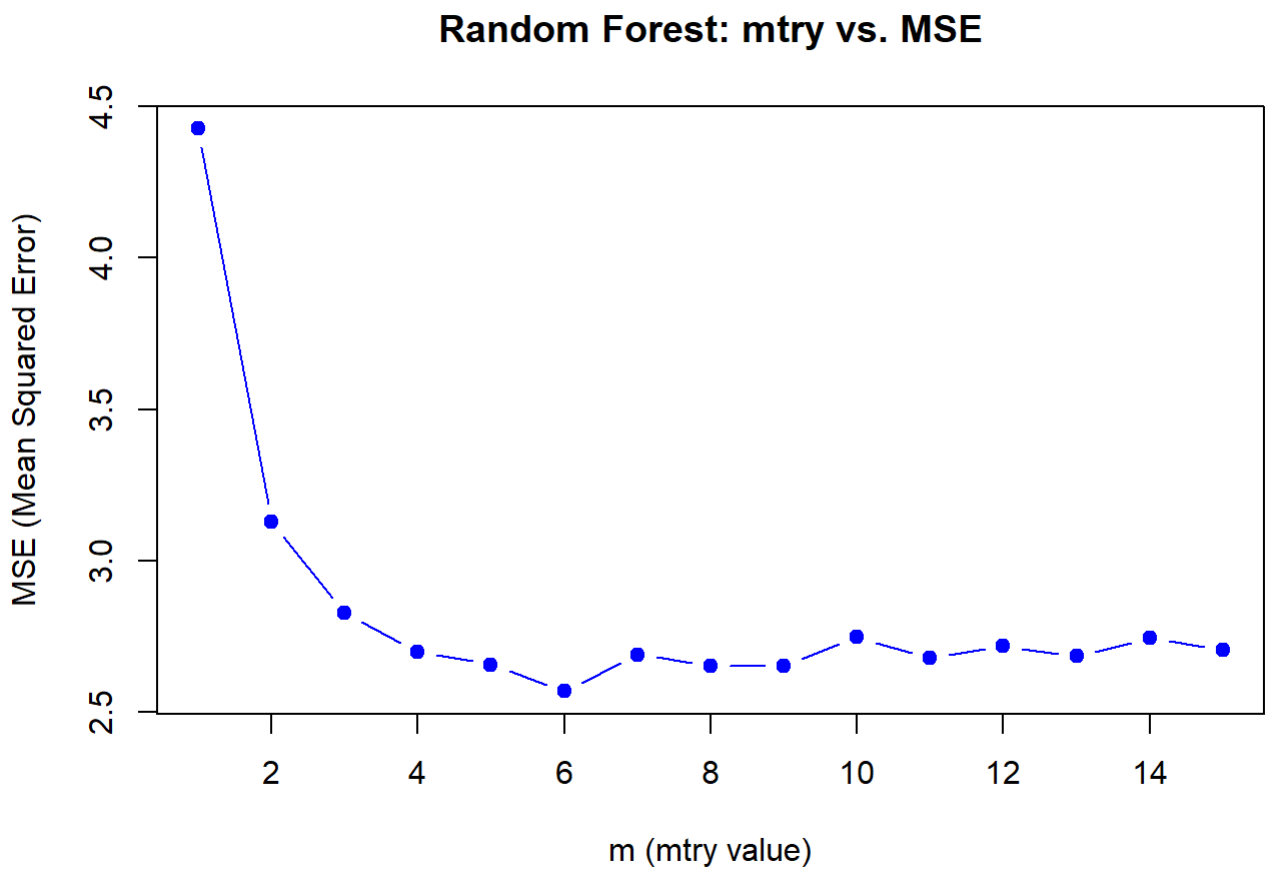
```
##                %IncMSE IncNodePurity
## CompPrice   37.0955879    230.468221
## Income      10.1434917    111.947577
## Advertising 22.6537826    187.171027
## Population   2.2851749     79.466849
## Price       74.6439392    645.545497
## ShelveLoc   75.1237464    713.386182
## Age         22.3025228    188.774611
## Education    6.0214758     56.339201
## Urban        0.7278781      9.285655
## US           3.6121873      7.030894
```

```
## Bagging tree test MSE: 2.659915
```

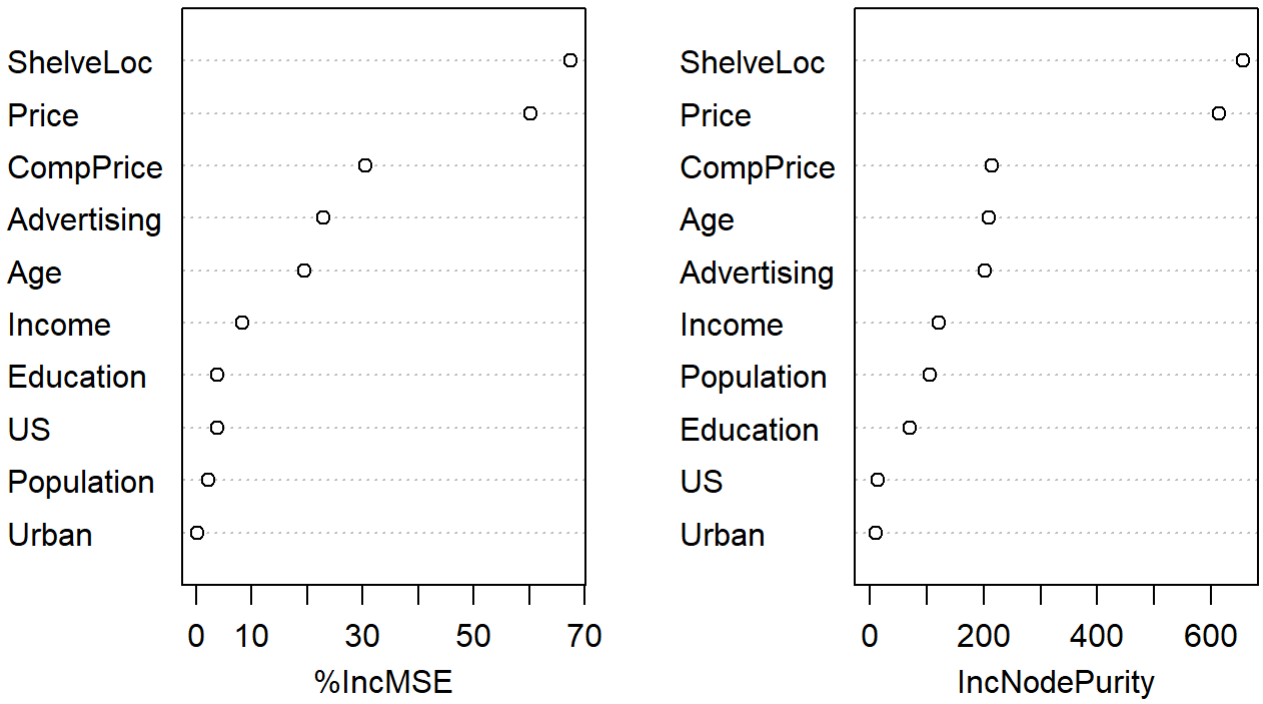
- With the bagging method, we observe the following:
- The most important features continue to remain Shelveloc and Price.
- Test MSE with Bagging model has decreased to the value 2.82.

e. Use random forests to analyze this data. What test MSE do you obtain? Use the importance() function to determine which vari- ables are most important. Describe the effect of m, the number of variables considered at each split, on the error rate obtained.

```
## [1] "M value = 1"
## Root Mean Square Error for mtry =  1   4.426806
## [1] "========================================"
## [1] "M value = 2"
## Root Mean Square Error for mtry =  2   3.12672
## [1] "========================================"
## [1] "M value = 3"
## Root Mean Square Error for mtry =  3   2.82761
## [1] "========================================"
## [1] "M value = 4"
## Root Mean Square Error for mtry =  4   2.698047
## [1] "========================================"
## [1] "M value = 5"
## Root Mean Square Error for mtry =  5   2.656558
## [1] "========================================"
## [1] "M value = 6"
## Root Mean Square Error for mtry =  6   2.568772
## [1] "========================================"
## [1] "M value = 7"
## Root Mean Square Error for mtry =  7   2.690031
## [1] "========================================"
## [1] "M value = 8"
## Root Mean Square Error for mtry =  8   2.653647
## [1] "========================================"
## [1] "M value = 9"
## Root Mean Square Error for mtry =  9   2.653374
## [1] "========================================"
## [1] "M value = 10"
## Root Mean Square Error for mtry =  10   2.746643
## [1] "========================================"
## [1] "M value = 11"
## Root Mean Square Error for mtry =  11   2.677436
## [1] "========================================"
## [1] "M value = 12"
## Root Mean Square Error for mtry =  12   2.718386
## [1] "========================================"
## [1] "M value = 13"
## Root Mean Square Error for mtry =  13   2.683535
## [1] "========================================"
## [1] "M value = 14"
## Root Mean Square Error for mtry =  14   2.744941
## [1] "========================================"
## [1] "M value = 15"
## Root Mean Square Error for mtry =  15   2.705269
## [1] "========================================"
```




```
## Minimum MSE: 2.568772 at m = 6
```



Observations

- For the most optimal random forest model , MSE is lowest. Random forest model with m = 9 has lowest MSE at 2.786.
- Shevloc ,Price and CompPrice are the most important variables in the rf model.

f. Now analyze the data using BART, and report your results.

```
## *****Calling gbart: type=1
## *****Data:
## data:n,p,np: 280, 14, 120
## y1,yn: 2.037107, -0.972893
## x1,x[n*p]: 106.000000, 0.000000
## xp1,xp[np*p]: 113.000000, 1.000000
## *****Number of Trees: 200
## *****Number of Cut Points: 67 ... 1
## *****burn,nd,thin: 100,1000,1
## *****Prior:beta,alpha,tau,nu,lambda,offset: 2,0.95,0.278247,3,0.215265,7.60289
## *****sigma: 1.051239
## *****w (weights): 1.000000 ... 1.000000
## *****Dirichlet:sparse,theta,omega,a,b,rho,augment: 0,0,1,0.5,1,14,0
## *****printevery: 100
##
## MCMC
## done 0 (out of 1100)
## done 100 (out of 1100)
## done 200 (out of 1100)
## done 300 (out of 1100)
## done 400 (out of 1100)
## done 500 (out of 1100)
## done 600 (out of 1100)
## done 700 (out of 1100)
## done 800 (out of 1100)
## done 900 (out of 1100)
## done 1000 (out of 1100)
## time: 8s
## trcnt,tecnt: 1000,1000
```

```
##
## BART RMSE: 1.246607
```

```
##       Price   CompPrice         Age  ShelveLoc3  ShelveLoc2         US2
##      23.968      19.560      18.570      18.231      17.102      16.642
##  ShelveLoc1   Education      Urban1  Population      Urban2      Income
##      16.622      15.981      15.965      15.813      15.568      15.507
## Advertising         US1
##      15.493      15.410
```

- BART technique produces the lowest RMSE among all the tried techniques at 1.24.
- Most important variables are Price , CompPrice , ShelveLoc1

Chapter 8: Question 11

a. Create a training set consisting of the first 1,000 observations on Caravan Dataset, and a test set consisting of the remaining observations.

```
## dimensions of training set :  1000 87
```

```
## dimensions of test set:  4822 87
```

b. Fit a boosting model to the training set with Purchase as the response and the other variables as predictors. Use 1,000 trees, and a shrinkage value of 0.01. Which predictors appear to be the most important?

```
##              var     rel.inf
## PPERSAUT PPERSAUT 14.84712121
## MKOOPKLA MKOOPKLA  9.66048095
## MOPLHOOG MOPLHOOG  8.25537601
## MBERMIDD MBERMIDD  5.47438623
## PBRAND     PBRAND  4.72706545
## ABRAND     ABRAND  4.01193114
## MGODGE     MGODGE  4.00433517
## MOSTYPE   MOSTYPE  3.73848401
## MINK3045 MINK3045  3.63441353
## MSKC         MSKC  2.52724460
## MBERARBG MBERARBG  2.29299662
## PWAPART   PWAPART  2.26545077
## MINKGEM   MINKGEM  2.10526876
## MGODPR     MGODPR  2.04483723
## MAUT2       MAUT2  2.02550612
## PBYSTAND PBYSTAND  1.94412135
## MSKA         MSKA  1.88309582
## MBERHOOG MBERHOOG  1.83575590
## MAUT1       MAUT1  1.80484326
## MSKB1       MSKB1  1.58556667
## MINK7512 MINK7512  1.36118575
## MGODRK     MGODRK  1.33371875
## MHHUUR     MHHUUR  1.18051272
## MAUT0       MAUT0  1.16464125
## MGODOV     MGODOV  1.09171875
## MRELOV     MRELOV  1.00599777
## APERSAUT APERSAUT  0.98773862
## MFWEKIND MFWEKIND  0.93077028
## MFGEKIND MFGEKIND  0.90843790
## MINKM30   MINKM30  0.90434538
## PMOTSCO   PMOTSCO  0.87804244
## MOSHOOFD MOSHOOFD  0.87151606
## MRELGE     MRELGE  0.77114099
## MBERBOER MBERBOER  0.72600774
## MHKOOP     MHKOOP  0.67891044
## MINK4575 MINK4575  0.57309410
## MINK123M MINK123M  0.55367540
## PLEVEN     PLEVEN  0.42876494
## MOPLLAAG MOPLLAAG  0.34831934
## MRELSA     MRELSA  0.32694573
## MGEMLEEF MGEMLEEF  0.31862949
## MGEMOMV   MGEMOMV  0.28151478
## MSKB2       MSKB2  0.26920200
## MOPLMIDD MOPLMIDD  0.26790510
## MZPART     MZPART  0.24092339
## MBERARBO MBERARBO  0.21376690
## MFALLEEN MFALLEEN  0.21136856
## MZFONDS   MZFONDS  0.19384881
## MSKD         MSKD  0.19172431
## MBERZELF MBERZELF  0.07544956
## MAANTHUI MAANTHUI  0.04190195
```

```
## PWABEDR   PWABEDR  0.00000000
## PWALAND   PWALAND  0.00000000
## PBESAUT   PBESAUT  0.00000000
## PVRAAUT   PVRAAUT  0.00000000
## PAANHANG PAANHANG  0.00000000
## PTRACTOR PTRACTOR  0.00000000
## PWERKT     PWERKT  0.00000000
## PBROM       PBROM  0.00000000
## PPERSONG PPERSONG  0.00000000
## PGEZONG   PGEZONG  0.00000000
## PWAOREG   PWAOREG  0.00000000
## PZEILPL   PZEILPL  0.00000000
## PPLEZIER PPLEZIER  0.00000000
## PFIETS     PFIETS  0.00000000
## PINBOED   PINBOED  0.00000000
## AWAPART   AWAPART  0.00000000
## AWABEDR   AWABEDR  0.00000000
## AWALAND   AWALAND  0.00000000
## ABESAUT   ABESAUT  0.00000000
## AMOTSCO   AMOTSCO  0.00000000
## AVRAAUT   AVRAAUT  0.00000000
## AAANHANG AAANHANG  0.00000000
## ATRACTOR ATRACTOR  0.00000000
## AWERKT     AWERKT  0.00000000
## ABROM       ABROM  0.00000000
## ALEVEN     ALEVEN  0.00000000
## APERSONG APERSONG  0.00000000
## AGEZONG   AGEZONG  0.00000000
## AWAOREG   AWAOREG  0.00000000
## AZEILPL   AZEILPL  0.00000000
## APLEZIER APLEZIER  0.00000000
## AFIETS     AFIETS  0.00000000
## AINBOED   AINBOED  0.00000000
## ABYSTAND ABYSTAND  0.00000000
```

- The most important features for the GBM model are **PPERSAUT** , **MKOOPKLA** and **MOPLHOOG** .

c. Use the boosting model to predict the response on the test data. Predict that a person will make a purchase if the estimated prob- ability of purchase is greater than 20 %. Form a confusion ma- trix. What fraction of the people predicted to make a purchase do in fact make one? How does this compare with the results obtained from applying KNN or logistic regression to this data set?

Boosting

```
##
## predicted_purchase    0    1
##                No  4415  253
##                Yes  118   36
```

Logistic Regression

```
##
## log_reg_predicted_purchase    0    1
##                         No  4183  231
##                         Yes  350   58
```

Observations :

- Fraction of the people predicted to make a purchase do in fact make one.
- GBM : 34/(34+127) = 0.211
- Logistic Regression : 0.142

GBM Fares better !

Chapter 10: Question 7

a. Fit a neural network to the Default data. Use a single hidden layer with 10 units, and dropout regularization. Have a look at Labs 10.9.1–10.9.2 for guidance. Compare the classifcation performance of your model with that of linear logistic regression.

```
## Dimensions of original dataset =  10000 4
```

```
## Dimensions of Training dataset =  7000 4
```

```
## Dimensions of Testing dataset =  3000 4
```

```
## # weights:  51
## initial  value 1373.413610
## iter  10 value 199.929221
## iter  20 value 183.149645
## iter  30 value 169.787081
## iter  40 value 166.256003
## iter  50 value 164.583964
## iter  60 value 163.453985
## iter  70 value 162.582715
## iter  80 value 161.724851
## iter  90 value 161.158318
## iter 100 value 160.849820
## final  value 160.849820
## stopped after 100 iterations
```

```
## Accuracy of Neural Network Model =  0.972
```

```
## Accuracy of Logistic Model =  0.974
```

Problem 1: Beauty Pays!

a. Using the data, estimate the effect of “beauty” into course ratings. Make sure to think about the potential many “other determinants”. Describe your analysis and your conclusions

Correlation Matrix

```
##             CourseEvals BeautyScore       female       lower   nonenglish
## CourseEvals  1.00000000  0.40709120 -0.231829451 -0.24864349 -0.079891096
## BeautyScore  0.40709120  1.00000000  0.125719400  0.03257686  0.010293330
## female      -0.23182945  0.12571940  1.000000000 -0.05657933  0.003805072
## lower       -0.24864349  0.03257686 -0.056579333  1.00000000 -0.143448262
## nonenglish  -0.07989110  0.01029333  0.003805072 -0.14344826  1.000000000
## tenuretrack -0.03760944 -0.01913483 -0.074315467 -0.13663972  0.134859291
##             tenuretrack
## CourseEvals -0.03760944
## BeautyScore -0.01913483
## female      -0.07431547
## lower       -0.13663972
## nonenglish   0.13485929
## tenuretrack  1.00000000
```

- According to the correlation matrix, BeautyScore emerges as a crucial factor when estimating course ratings.

- The CourseEvals variable exhibits a positive correlation with the BeautyScore variable, suggesting that higher BeautyScore values are associated with higher CourseEval ratings.
- The impact of the nonenglish and tenuretrack variables on CourseEval appears to be relatively weak.
- Conversely, there is a negative correlation between the Female and lower variables and CourseEvals, indicating that as the values of Female and lower increase, CourseEvals tend to decrease.

Linear Regression model on BeautyScore

```
##
## Call:
## lm(formula = CourseEvals ~ BeautyScore, data = beauty_data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.5936 -0.3346  0.0097  0.3702  1.2321
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.71340    0.02249 165.119   <2e-16 ***
## BeautyScore  0.27148    0.02837   9.569   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4809 on 461 degrees of freedom
## Multiple R-squared:  0.1657, Adjusted R-squared:  0.1639
## F-statistic: 91.57 on 1 and 461 DF,  p-value: < 2.2e-16
```

Linear Regression Model on all variables

```
##
## Call:
## lm(formula = CourseEvals ~ ., data = beauty_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.31385 -0.30202  0.01011  0.29815  1.04929
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4.06542    0.05145  79.020  < 2e-16 ***
## BeautyScore  0.30415    0.02543  11.959  < 2e-16 ***
## female      -0.33199    0.04075  -8.146 3.62e-15 ***
## lower       -0.34255    0.04282  -7.999 1.04e-14 ***
## nonenglish  -0.25808    0.08478  -3.044  0.00247 **
## tenuretrack -0.09945    0.04888  -2.035  0.04245 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4273 on 457 degrees of freedom
## Multiple R-squared:  0.3471, Adjusted R-squared:  0.3399
## F-statistic: 48.58 on 5 and 457 DF,  p-value: < 2.2e-16
```

- As we introduce more predictors in multiple regression, the Adjusted R-squared increases, indicating an improved fit of the data.
- The multiple variable model takes into account all relevant factors, providing a comprehensive analysis Thus, using the more inclusive model for predictions is recommended.
  -BeautyScore has a positive coefficient, indicating professors with higher beauty scores tend to get better course ratings.
- Female professors show a negative coefficient suggesting they tend to receive lower course ratings.
- Lower-division course instructors also have a negative coefficient, implying lower course ratings.
- Non-English speaking professors receive lower course ratings with a negative coefficient , suggesting language barriers impacting effective teaching
- Professors on the tenure track receive lower course ratings

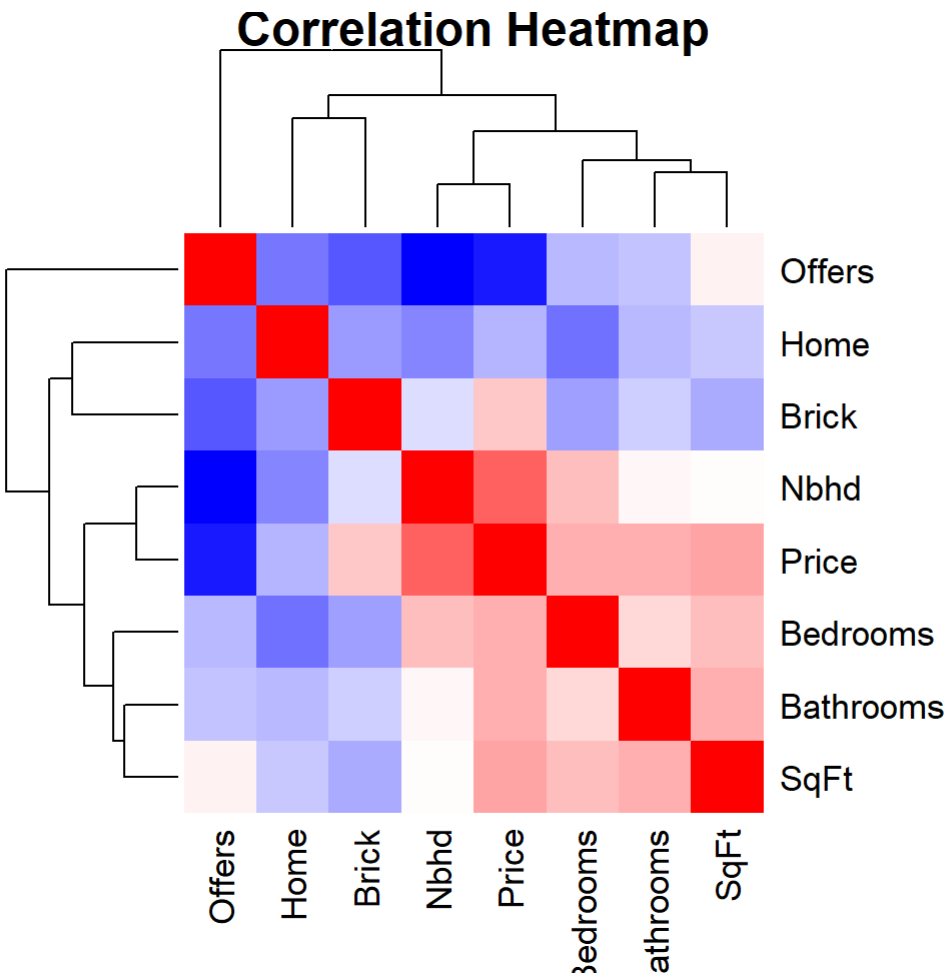
b. In his paper, Dr. Hamermesh has the following sentence: “Disentangling whether this outcome represents productivity or discrimination is, as with the issue generally, probably impossible”. Using the concepts we have talked about so far, what does he mean by that?

- The statement “Disentangling whether this outcome represents productivity or discrimination is, as with the issue generally, probably impossible,” highlights the challenge of understanding certain outcomes in scientific fields.
- Specifically, it questions whether a higher beauty score truly reflects a professor’s teaching ability or if it’s merely a bias on the students’ part, perceiving more conventionally attractive professors as better.
- However, this model lacks enough factors to provide a definitive answer. Since it cannot access students’ thoughts, determining the true reason behind the outcome is difficult.

Problem 2: Housing Price Structure

a. Is there a premium for brick houses everything else being equal?

Simple linear regression model with all variables



```
##
## Call:
## lm(formula = Price ~ ., data = city)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -24940.6  -8383.0    430.7   7430.4  31371.2
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -9814.663   9858.884  -0.996  0.32149
## Home            6.187     28.973   0.214  0.83128
## Nbhd         9832.281   1821.869   5.397 3.47e-07 ***
## Offers      -8351.794   1267.428  -6.590 1.24e-09 ***
## SqFt           49.811      6.769   7.359 2.53e-11 ***
## Brick       15601.818   2261.896   6.898 2.66e-10 ***
## Bedrooms     5671.911   1840.979   3.081  0.00256 **
## Bathrooms    8243.545   2449.897   3.365  0.00103 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 11540 on 120 degrees of freedom
## Multiple R-squared:  0.8256, Adjusted R-squared:  0.8154
## F-statistic: 81.15 on 7 and 120 DF,  p-value: < 2.2e-16
```

- The coefficient of Brick variables shows that it significantly impacts the Price of the house since its highly positive with a value of 15601.818 . This indicates a high premium for brick houses everything else being equal.
- Moreover, the confidence interval for the coefficient of Brick ranges from 13373.88702 to 21220.81203, with all values above zero, confirming that there is a positive premium associated with brick houses.

b. Is there a premium for houses in neighborhood 3?

```
##
## Call:
## lm(formula = Price ~ ., data = city[c("neigh3", "Offers", "SqFt",
##     "Brick", "Bedrooms", "Bathrooms", "Price")])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -26810.5  -5953.6   -266.5   5662.9  26793.0
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3067.471   8746.712   0.351 0.726423
## neigh3      21937.572   2482.393   8.837 9.39e-15 ***
## Offers      -8019.003   1013.011  -7.916 1.32e-12 ***
## SqFt           52.149      5.572   9.359 5.44e-16 ***
## Brick       17058.771   1942.805   8.780 1.28e-14 ***
## Bedrooms     4070.005   1570.921   2.591 0.010751 *
## Bathrooms    7810.698   2109.060   3.703 0.000322 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9995 on 121 degrees of freedom
## Multiple R-squared:  0.8682, Adjusted R-squared:  0.8616
## F-statistic: 132.8 on 6 and 121 DF,  p-value: < 2.2e-16
```

- There is a positive correlation between the price of houses and Neighborhood 3 with coefficient of 21937.572, indicating that houses in Neighborhood 3 have a significant premium.
- The confidence interval for the coefficient of Brick ranges from 17017.713 to 26857.431, all of which are above zero and entirely positive. This strengthens the conclusion that there is a premium for houses made of brick.

c. Is there an extra premium for brick houses in neighborhood 3?

Regression Model with Brick and Nbhd3 variable

```
##
## Call:
## lm(formula = Price ~ . + Brick * neigh3, data = city[c("neigh3",
##     "Offers", "SqFt", "Brick", "Bedrooms", "Bathrooms", "Price")])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -26710.2  -5797.0   -277.9   4337.6  26483.2
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)   3407.487   8559.390   0.398  0.69126
## neigh3       17709.779   2949.399   6.005 2.10e-08 ***
## Offers       -8298.791    997.359  -8.321 1.60e-13 ***
## SqFt            53.728      5.488   9.790  < 2e-16 ***
## Brick        13664.535   2327.643   5.871 3.95e-08 ***
## Bedrooms      4652.044   1554.250   2.993  0.00335 **
## Bathrooms     6407.659   2137.027   2.998  0.00330 **
## neigh3:Brick 10361.809   4100.564   2.527  0.01281 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9780 on 120 degrees of freedom
## Multiple R-squared:  0.8748, Adjusted R-squared:  0.8675
## F-statistic: 119.8 on 7 and 120 DF,  p-value: < 2.2e-16
```

- Brick houses in neighborhood 3 command a substantial premium of approximately 10361.809
- The coefficient estimate for neighborhood 3 is 20681.037, with a confidence interval ranging from 625.392 to 18798.225. The positive interval reinforces the presence of a premium for houses in neighborhood 3

d. For the purposes of prediction could you combine the neighborhoods 1 and 2 into a single “older” neighborhood?

```
##
## Call:
## lm(formula = Price ~ ., data = city[c("neigh12", "Offers", "SqFt",
##     "Brick", "Bedrooms", "Bathrooms", "Price")])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -26810.5  -5953.6   -266.5   5662.9  26793.0
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  25005.043   9658.403   2.589 0.010807 *
## neigh12     -21937.572   2482.393  -8.837 9.39e-15 ***
## Offers       -8019.003   1013.011  -7.916 1.32e-12 ***
## SqFt            52.149      5.572   9.359 5.44e-16 ***
## Brick        17058.771   1942.805   8.780 1.28e-14 ***
## Bedrooms      4070.005   1570.921   2.591 0.010751 *
## Bathrooms     7810.698   2109.060   3.703 0.000322 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9995 on 121 degrees of freedom
## Multiple R-squared:  0.8682, Adjusted R-squared:  0.8616
## F-statistic: 132.8 on 6 and 121 DF,  p-value: < 2.2e-16
```

- In older neighborhood 1 and 2 the price of the house drops significantly as the coefficient is highly negative at -21937.
- Since the premium is negative for neighborhoods 1 and 2 these can be considered “old” neighborhoods.

Problem 3: What causes what??

a. Why can’t I just get data from a few different cities and run the regression of “Crime” on “Police” to understand how more cops in the streets affect crime

- When using data from different cities and conducting a regression of “Crime” on “Police,” the relationship between the presence of more police officers and crime rates may not be straightforward.
- Observing a correlation between the number of police officers and crime rates in various cities does not automatically imply a direct causal relationship.
- A positive correlation might be misinterpreted as more police causing higher crime rates, but it could actually be the other way around, with higher crime rates leading to the hiring of more police officers in response to the situation.
- Data analysis and correlations can provide valuable insights, but they do not directly establish causation.

b. How were the researchers from UPENN able to isolate this effect? Briefly describe their approach and discuss their result in the “Table 2” below.

- The researchers from UPENN utilized a natural experiment, where random assignment is possible, to ensure equal probability of participants being assigned to specific groups in the experiment.
- They focused on crime rate figures in Washington, D.C., specifically on high-alert days with an increased risk of terrorist attacks.
- City officials had no choice but to station more police on high-alert days to protect the public, regardless of the city’s crime rate.
- The results from Table 2 indicate that having more police in a city leads to a lower crime rate, as evidenced by the negative coefficient.
- Thus, it can be reasonably concluded that there is reduced crime on high-alert days when more police are present.

c. Why did they have to control for METRO ridership? What was that trying to capture?

- Data on police and crime presents challenges in determining causation: it cannot distinguish between more police leading to increased crime or vice versa.
- Observing a positive correlation between police presence and crime across cities is possible, as mayors may react to crime by hiring more police.
- Conducting a controlled experiment with random police placement is practically impossible.
  UPENN researchers found a natural experiment in DC, analyzing crime data on high-alert days with increased police presence.
- Controlling for ridership, high-alert days showed lower crime rates, supporting the impact of more police on crime reduction.
- Proving the definitive relationship between more police and less crime remains challenging, but the findings provide strong circumstantial evidence in favor of the connection.

d. In the next page, I am showing you “Table 4” from the research paper. Just focus on the first column of the table. Can you describe the model being estimated here? What is the conclusion?

- Table 4’s model considered the impact of placing more police on high-alert days in different locations across the city.
- Interaction terms, High Alert X District 1 and High Alert X Other Districts, were included to analyze the relationship between high-alert days and district locations.
- The effect of more police was most pronounced in District 1, leading to the greatest decrease in crime rate, which is logical as densely populated districts are more vulnerable to attacks.
- This aligns with the logical assumption that District 1, with more potential terrorist targets in DC, receives increased police deployment during high-alert periods, resulting in a significant crime reduction.
- Other districts also showed a negative effect, with some reduction in crime rate due to more police on high-alert days, but the effect was smaller and not statistically significant.

Problem 5: Final Project

Describe your contribution to the final group project

- Discussed about the potential problem statements to solve and presented multiple datasets to use and finalize a problem statement and ultimately arrived at the conclusion to target a healthcare problem. The original dataset we had selected was not very voluminous. So I searched Kaggle datasets which could be alternatively used for our diabetes prediction model and found a dataset which was usable and checked the data quality to kickstart our work. However we found out that it was required to be balanced as it was highly skewed toward the majority (non diabetic) class . So I applied the ‘oversampling’ method to balance the data while using random sampling to increased the ratio of target population from 16% to 33% in the dataset.
- I checked irregularities in the data through correlation matrix and correlation heatmap. Then , I ran multiple iterations of code process for the model development exercise to include the KNN and Boosting modeling techniques using scikit learn module while integrating feature importance , accuracy and recall value patches. I also included GridSearch CV to add hyperparameter tuning and optimized the code to make it run faster through loops , saving and reloading models through the pickle module.
- Added plots to better demonstrate and visual the code in action using matplotlib and seaborn libraries. Discussed the findings and learnings with my teammates and created my portion of the presentation which included model development and analysis of different modelling techniques. I proactively coordinated with my teammates to make sure they were on the same page with every step of the process and suggested insights to include in their parts of presentation and write-up while incorporating theirs.