471

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HW 1

Q1

a. The given experiment has extremely large sample size of `n`, and the number of predictors `p` is very small, so the fixible statistical learning be used, since the large number of parameters that are present in the model could be estimated, due to large number of the sample size.

b. The given experiment has small sample size, that is small `n`, and large number of parameters `p`, hence the flexible statistical method cann't be used, as the already there are a large number of parameters, and now more parameters will include a large error in the model, since the sample size is small, and all cann't be obtained.

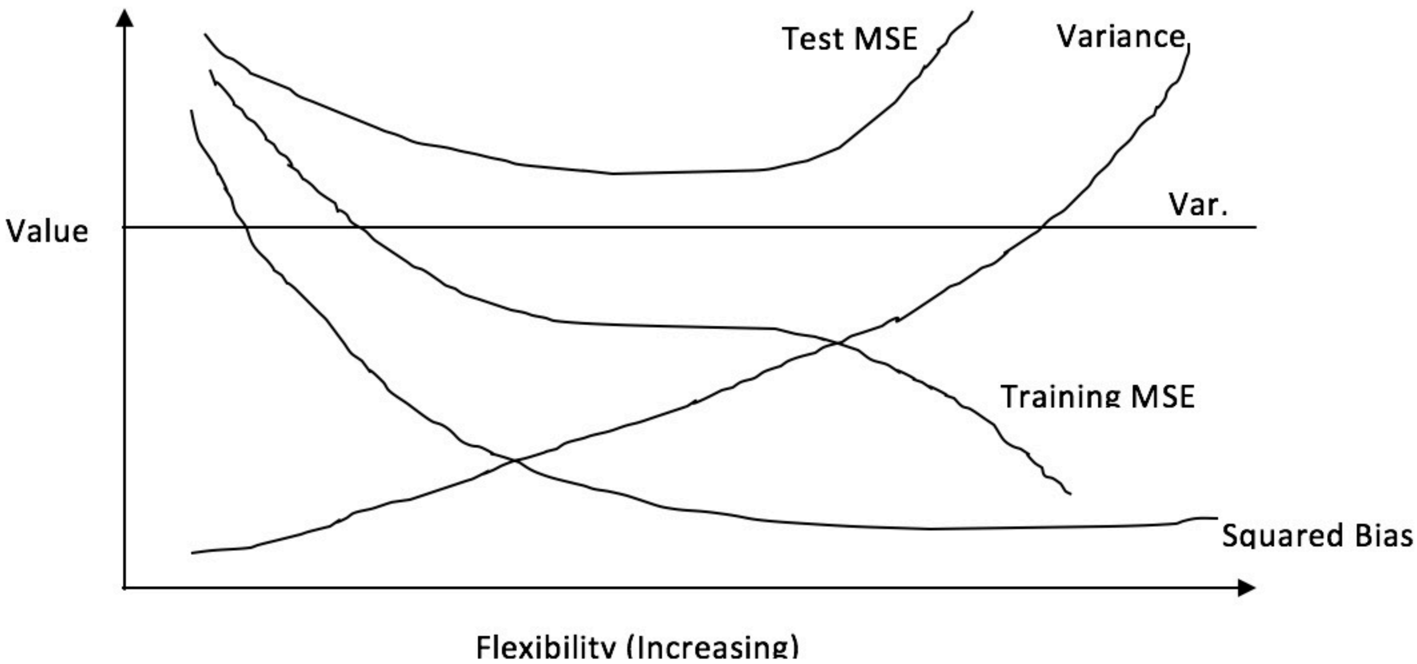
c. When the relationship between the predictors and the response is highly non-linear, then it is better to use the flexible statitical learning, as it will fit a curve for the give model, which maybe better able to picture the model, since the relationship is not linear.

d. If the variance of the error terms is extremely high, then if the flexible method is used, due to the risk of over-estimation, the error may increase all the more, due to addition of noise. Hence it is better to avoid the use of flexible statistical learning in all those cases.

Q2

a.

```
knitr::include_graphics("/Users/huangjiajian/Desktop/471/WechatIMG1.jpeg")
```



b. The squared bias for the given experiment, keeps on decreasing monotonically along withe the increase in the flexibility of the experiment, since more the flexible is the experiment, less will be the bias, since the model is better able to describe the relationship.

The variance keeps on increasing along with increasing in the flexibility, since withe inclusion of more variables, the variance of the errors will increase, since the risk of over-estimation increase all the more.

The model gets a much better fit than the previous situation, but only up to an optimal level, where the model obtained is the best one to depict the nature of the response, and the variable, after which over-estimation leads to larger error variance, and deviation from the original model. Thus, the test MSE decrease, reaches the minimum and then increases, after attaining the optimum position.

Q3

a.

```
write.table(College, file = "College.csv", row.names=F, sep = ",")
```

```
college <- read.csv("college.csv")
```

b.

```
head(college[,1:4])
```

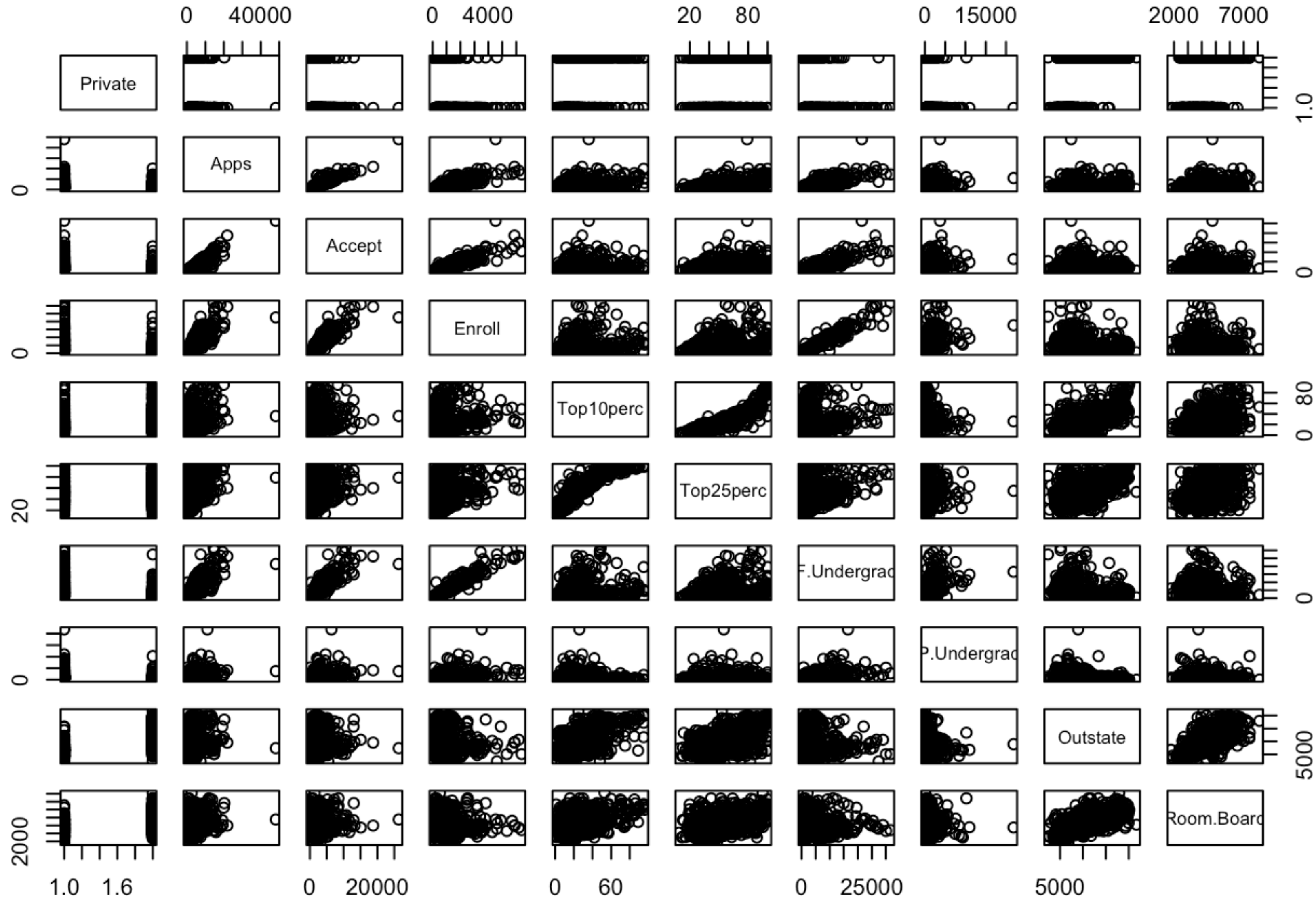
```
##   Private Apps Accept Enroll
## 1     Yes 1660   1232    721
## 2     Yes 2186   1924    512
## 3     Yes 1428   1097    336
## 4     Yes  417    349    137
## 5     Yes  193    146     55
## 6     Yes  587    479    158
```

c.

```
summary(college)
```

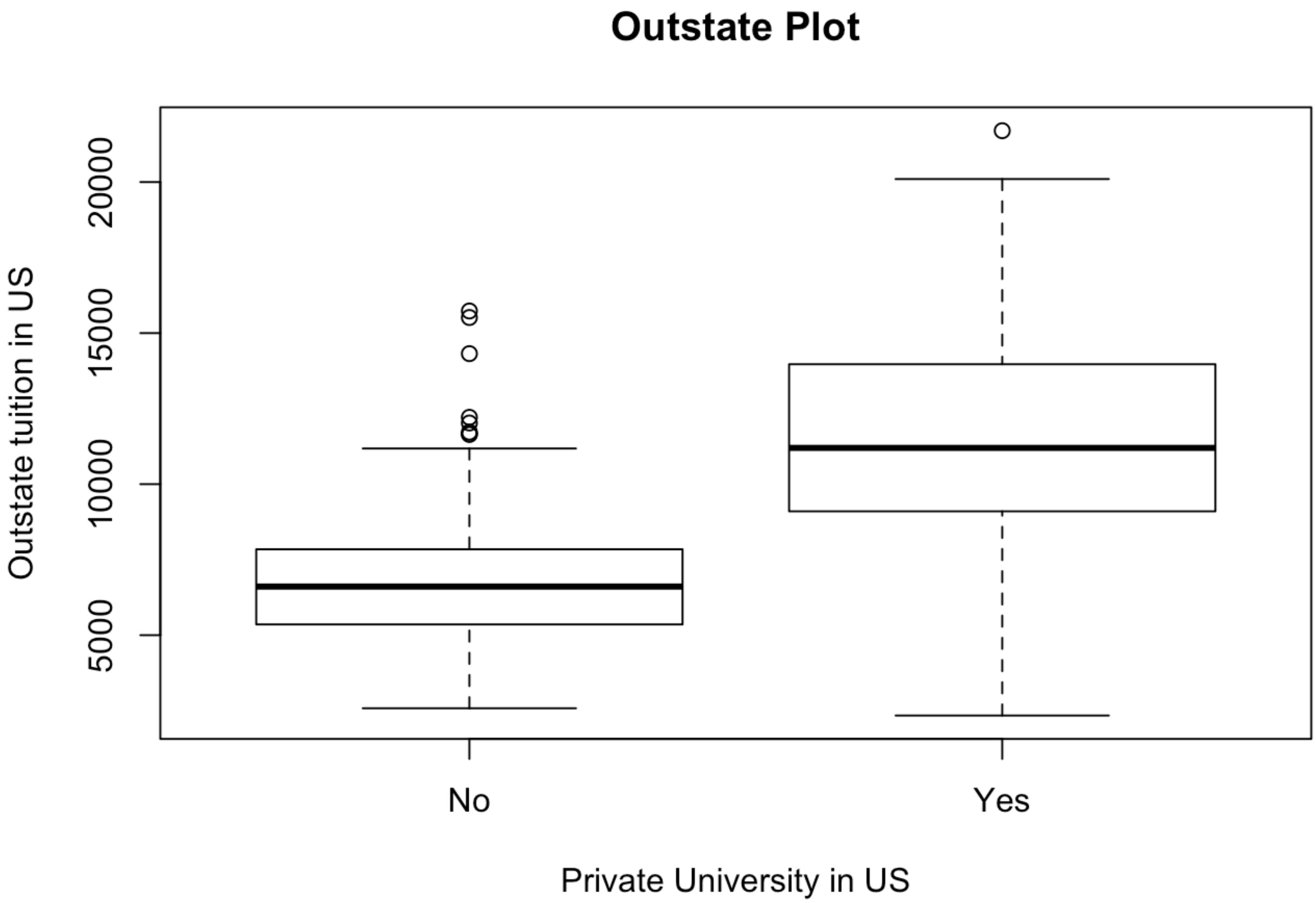
```
##  Private        Apps           Accept          Enroll       Top10perc
##  No :212   Min.   :   81   Min.   :   72   Min.   :  35   Min.   : 1.00
##  Yes:565   1st Qu.:  776   1st Qu.:  604   1st Qu.: 242   1st Qu.:15.00
##            Median : 1558   Median : 1110   Median : 434   Median :23.00
##            Mean   : 3002   Mean   : 2019   Mean   : 780   Mean   :27.56
##            3rd Qu.: 3624   3rd Qu.: 2424   3rd Qu.: 902   3rd Qu.:35.00
##            Max.   :48094   Max.   :26330   Max.   :6392   Max.   :96.00
##    Top25perc      F.Undergrad     P.Undergrad         Outstate
##  Min.   :  9.0   Min.   :  139   Min.   :    1.0   Min.   : 2340
##  1st Qu.: 41.0   1st Qu.:  992   1st Qu.:   95.0   1st Qu.: 7320
##  Median : 54.0   Median : 1707   Median :  353.0   Median : 9990
##  Mean   : 55.8   Mean   : 3700   Mean   :  855.3   Mean   :10441
##  3rd Qu.: 69.0   3rd Qu.: 4005   3rd Qu.:  967.0   3rd Qu.:12925
##  Max.   :100.0   Max.   :31643   Max.   :21836.0   Max.   :21700
##    Room.Board       Books           Personal         PhD
##  Min.   :1780   Min.   :  96.0   Min.   : 250   Min.   :  8.00
##  1st Qu.:3597   1st Qu.: 470.0   1st Qu.: 850   1st Qu.: 62.00
##  Median :4200   Median : 500.0   Median :1200   Median : 75.00
##  Mean   :4358   Mean   : 549.4   Mean   :1341   Mean   : 72.66
##  3rd Qu.:5050   3rd Qu.: 600.0   3rd Qu.:1700   3rd Qu.: 85.00
##  Max.   :8124   Max.   :2340.0   Max.   :6800   Max.   :103.00
##     Terminal       S.F.Ratio      perc.alumni        Expend
##  Min.   : 24.0   Min.   : 2.50   Min.   : 0.00   Min.   : 3186
##  1st Qu.: 71.0   1st Qu.:11.50   1st Qu.:13.00   1st Qu.: 6751
##  Median : 82.0   Median :13.60   Median :21.00   Median : 8377
##  Mean   : 79.7   Mean   :14.09   Mean   :22.74   Mean   : 9660
##  3rd Qu.: 92.0   3rd Qu.:16.50   3rd Qu.:31.00   3rd Qu.:10830
##  Max.   :100.0   Max.   :39.80   Max.   :64.00   Max.   :56233
##    Grad.Rate
##  Min.   : 10.00
##  1st Qu.: 53.00
##  Median : 65.00
##  Mean   : 65.46
##  3rd Qu.: 78.00
##  Max.   :118.00
```

```
pairs(college[,1:10])
```

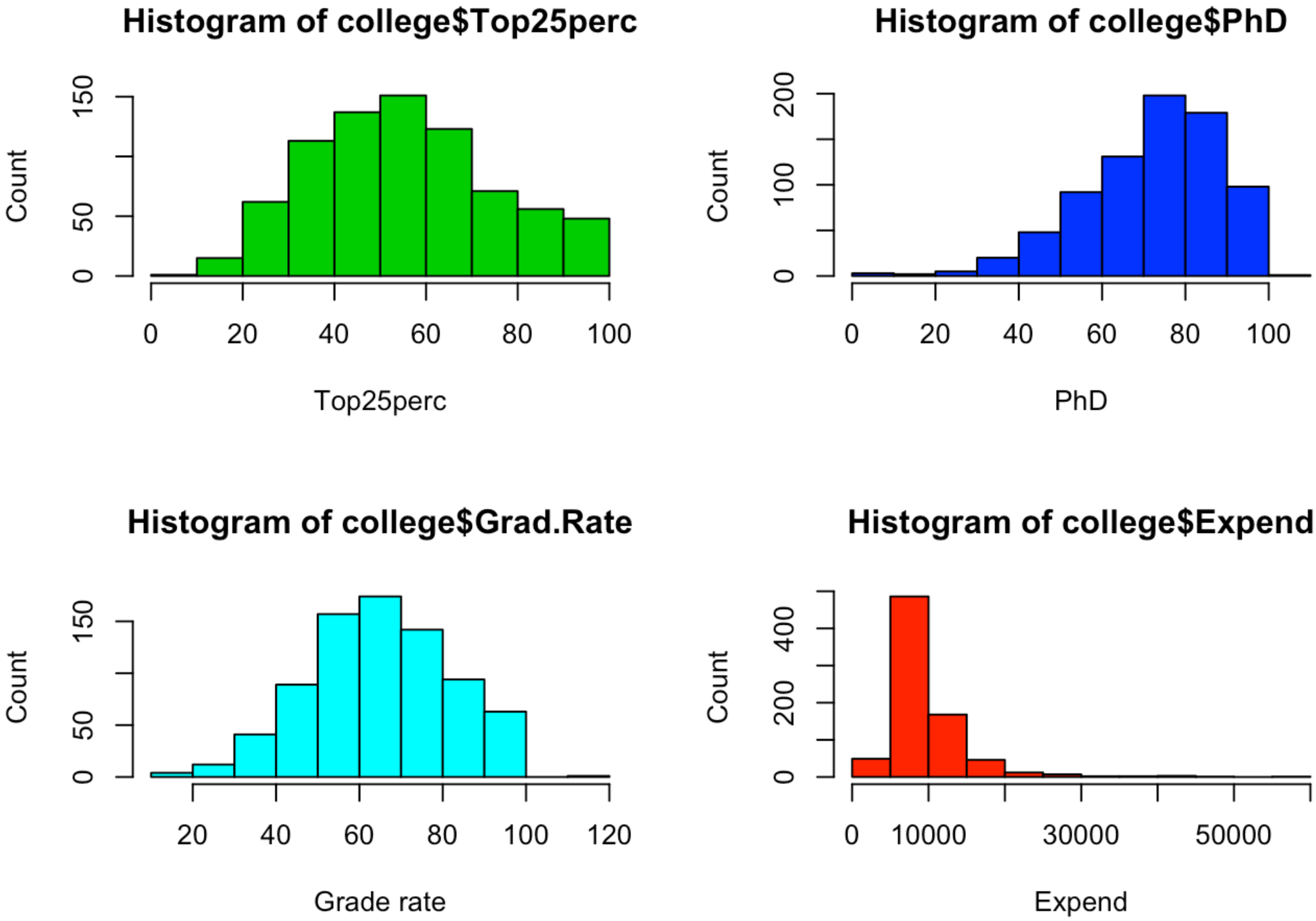


Now the scatter plot for each of the variables, in the same widow is obtained by using the below given code, and the result thus obtained is also given above.

```
plot(college$Private,college$Outstate, xlab = "Private University in US", ylab = "Out
state tuition in US", main = "Outstate Plot")
```




```
par(mfrow = c(2,2))
hist(college$Top25perc, col = 3, xlab = "Top25perc", ylab = "Count")
hist(college$PhD, col = 4, xlab = "PhD", ylab = "Count")
hist(college$Grad.Rate, col = 5, xlab = "Grade rate", ylab = "Count")
hist(college$Expend, col = 2, xlab = "Expend", ylab = "Count")
```




```
summary(college$Top25perc)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     9.0    41.0    54.0    55.8    69.0   100.0
```

```
summary(college$Grad.Rate)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   10.00   53.00   65.00   65.46   78.00  118.00
```

```
summary(college$PhD)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    8.00   62.00   75.00   72.66   85.00  103.00
```

```
summary(college$Expend)
```

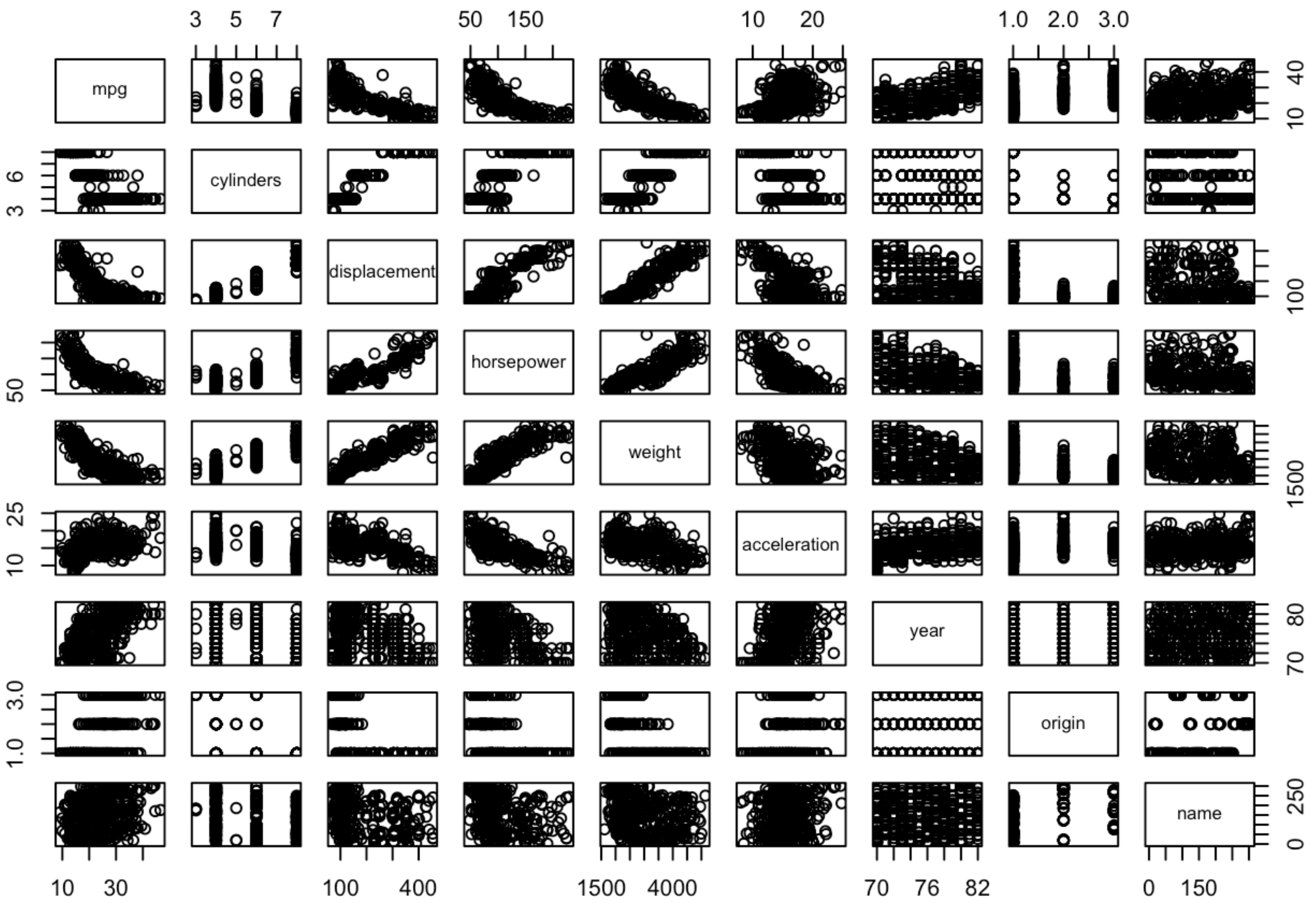
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    3186    6751    8377    9660   10830   56233
```

HW 2

Q1

a.

```
pairs(Auto)
```



b.

```
cor(Auto[1:8])
```

```
##                     mpg  cylinders displacement horsepower     weight
## mpg           1.0000000 -0.7776175   -0.8051269 -0.7784268 -0.8322442
## cylinders    -0.7776175  1.0000000    0.9508233  0.8429834  0.8975273
## displacement -0.8051269  0.9508233    1.0000000  0.8972570  0.9329944
## horsepower   -0.7784268  0.8429834    0.8972570  1.0000000  0.8645377
## weight       -0.8322442  0.8975273    0.9329944  0.8645377  1.0000000
## acceleration  0.4233285 -0.5046834   -0.5438005 -0.6891955 -0.4168392
## year          0.5805410 -0.3456474   -0.3698552 -0.4163615 -0.3091199
## origin        0.5652088 -0.5689316   -0.6145351 -0.4551715 -0.5850054
##              acceleration       year     origin
## mpg             0.4233285  0.5805410  0.5652088
## cylinders      -0.5046834 -0.3456474 -0.5689316
## displacement   -0.5438005 -0.3698552 -0.6145351
## horsepower     -0.6891955 -0.4163615 -0.4551715
## weight         -0.4168392 -0.3091199 -0.5850054
## acceleration    1.0000000  0.2903161  0.2127458
## year            0.2903161  1.0000000  0.1815277
## origin          0.2127458  0.1815277  1.0000000
```

c.

```
fit <- lm(mpg ~ .-name, data = Auto)
summary(fit)
```

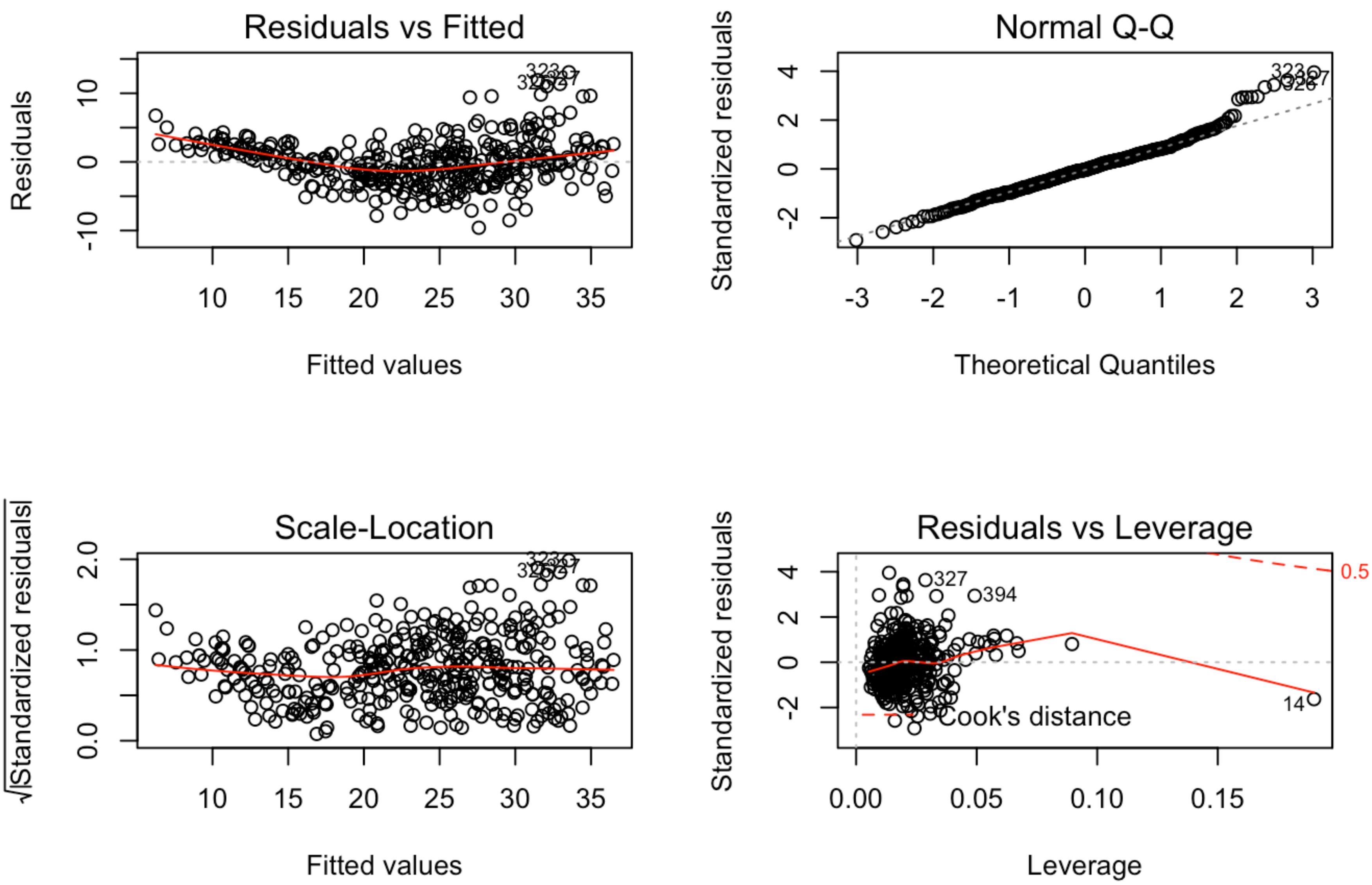
```
##
## Call:
## lm(formula = mpg ~ . - name, data = Auto)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.5903 -2.1565 -0.1169  1.8690 13.0604
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -17.218435   4.644294  -3.707  0.00024 ***
## cylinders     -0.493376   0.323282  -1.526  0.12780
## displacement   0.019896   0.007515   2.647  0.00844 **
## horsepower    -0.016951   0.013787  -1.230  0.21963
## weight        -0.006474   0.000652  -9.929  < 2e-16 ***
## acceleration   0.080576   0.098845   0.815  0.41548
## year           0.750773   0.050973  14.729  < 2e-16 ***
## origin         1.426141   0.278136   5.127 4.67e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.328 on 384 degrees of freedom
## Multiple R-squared:  0.8215, Adjusted R-squared:  0.8182
## F-statistic: 252.4 on 7 and 384 DF,  p-value: < 2.2e-16
```

From the p-value obtained above, it can be said that all the variables, except only the variables `horsepower` , `cylinder` and `acceleration` are statistically significant.

The coefficient of `year` conveys that for unit change in the variable `year` , the variable under study changes by an amount of 0.7507, porvided all the other values are kept constant.

d.

```
par(mfrow = c(2,2))
plot(fit)
```



e.

```
fit1 <- lm(mpg ~ cylinders*displacement + displacement*weight, data = Auto)
summary(fit1)
```

```
##
## Call:
## lm(formula = mpg ~ cylinders * displacement + displacement *
##     weight, data = Auto)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -13.2934  -2.5184  -0.3476   1.8399  17.7723
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)             5.262e+01  2.237e+00  23.519  < 2e-16 ***
## cylinders               7.606e-01  7.669e-01   0.992    0.322
## displacement           -7.351e-02  1.669e-02  -4.403 1.38e-05 ***
## weight                 -9.888e-03  1.329e-03  -7.438 6.69e-13 ***
## cylinders:displacement -2.986e-03  3.426e-03  -0.872    0.384
## displacement:weight     2.128e-05  5.002e-06   4.254 2.64e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.103 on 386 degrees of freedom
## Multiple R-squared:  0.7272, Adjusted R-squared:  0.7237
## F-statistic: 205.8 on 5 and 386 DF,  p-value: < 2.2e-16
```

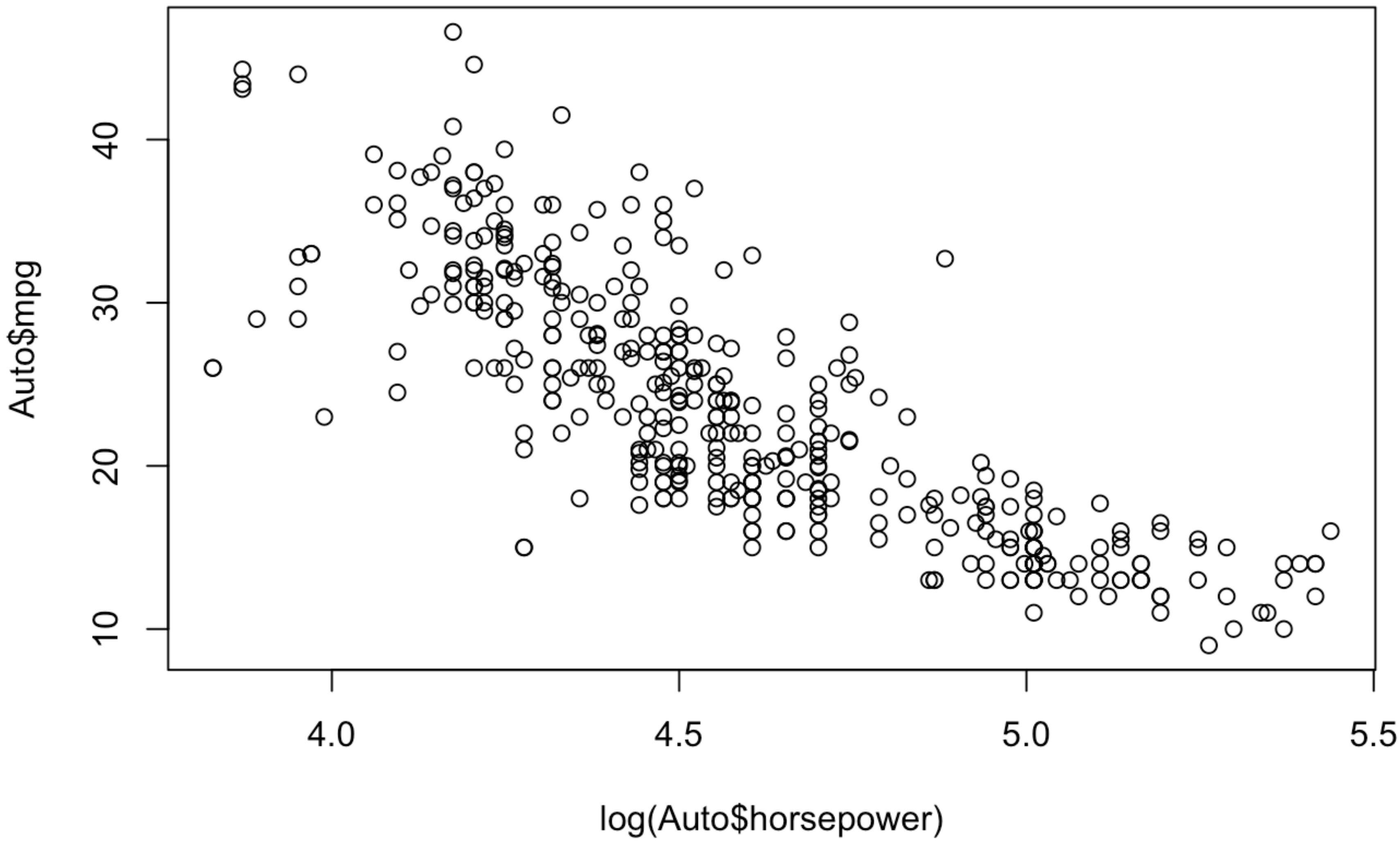
From the p-value, we could say that the relationship between `cylinder` and `displacement` is not statistically significant.

f.

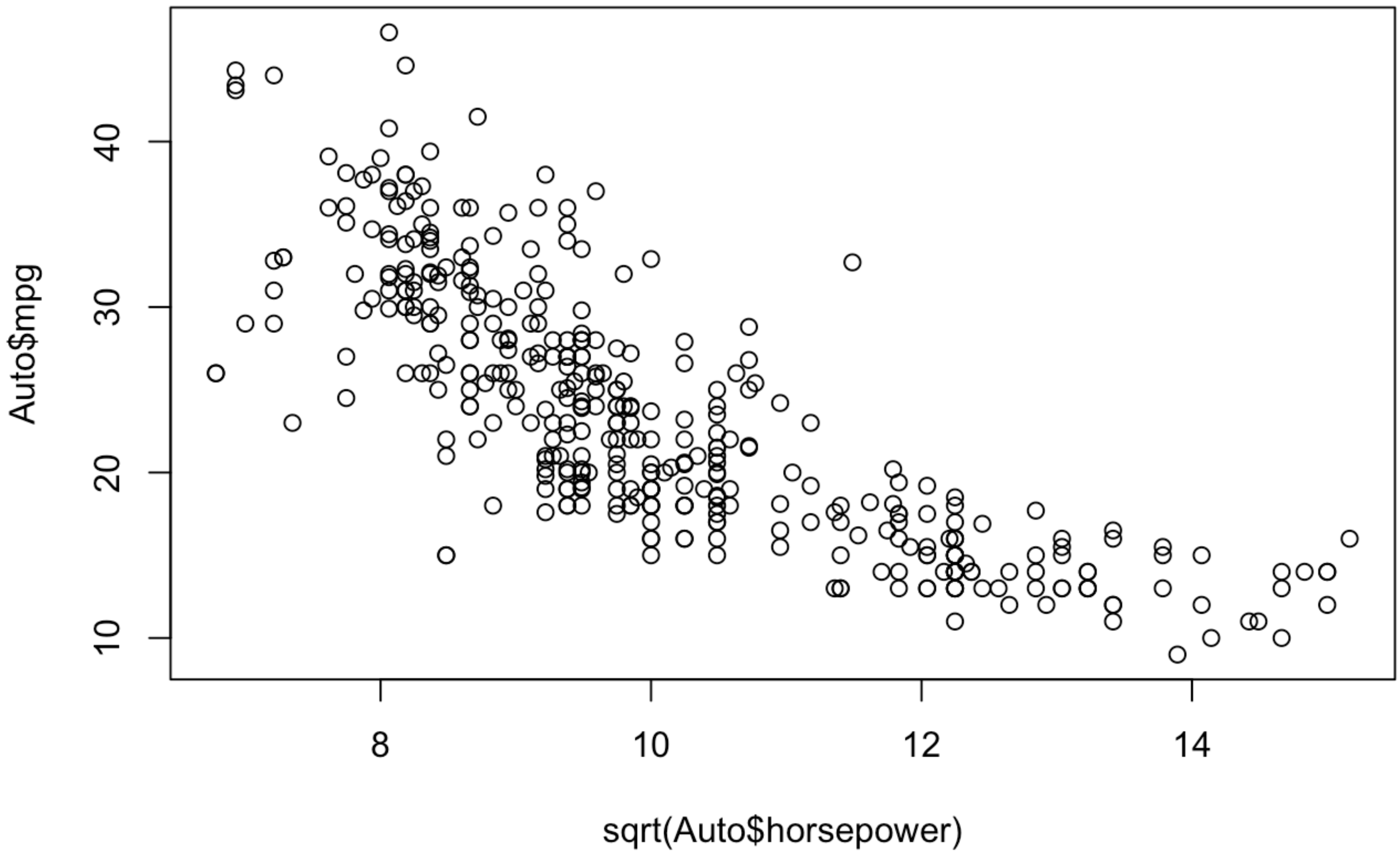
```
par(mforw = c(2,2))
```

```
## Warning in par(mforw = c(2, 2)): "mforw" is not a graphical parameter
```

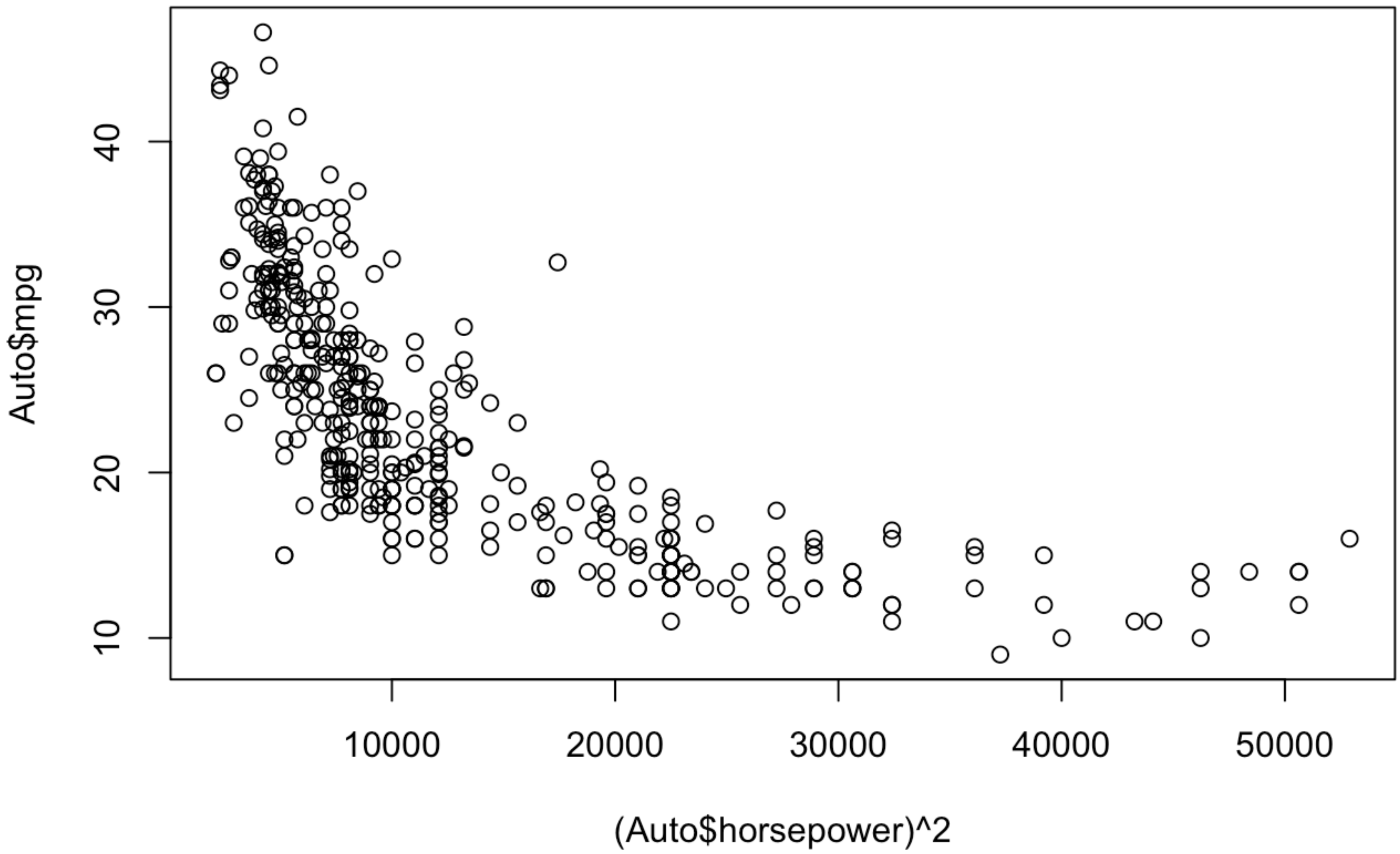
```
plot(log(Auto$horsepower), Auto$mpg)
```




```
plot(sqrt(Auto$horsepower), Auto$mpg)
```




```
plot((Auto$horsepower)^2, Auto$mpg)
```



Q15

a.

```
data(Boston)
coefs <- data.frame("predictor"=character(0), "Estimate"=numeric(0), "Std.Error"=nume
ric(0), "t.value"=numeric(0), "Pr.t"=numeric(0), "r.squared"=numeric(0), stringsAsFac
tors = FALSE)
j <- 1
for(i in names(Boston)){
  if(i != "crim"){
    summ.lm.fit <- summary(lm(crim ~ eval(parse(text=i)), data=Boston))
    coefs[j,] = c(i, summ.lm.fit$coefficients[2,], summ.lm.fit$r.squared)
    j <- j+1
  }
}

coefs[,-1] <- lapply(coefs[,-1], FUN=function(x) as.numeric(x))
coefs <- coefs[order(coefs$r.squared, decreasing = T),]
print(coefs)
```

```
##    predictor    Estimate   Std.Error   t.value         Pr.t   r.squared
## 8        rad  0.61791093 0.034331820 17.998199 2.693844e-56 0.391256687
## 9        tax  0.02974225 0.001847415 16.099388 2.357127e-47 0.339614243
## 12     lstat  0.54880478 0.047760971 11.490654 2.654277e-27 0.207590933
## 4        nox 31.24853120 2.999190381 10.418989 3.751739e-23 0.177217182
## 2      indus  0.50977633 0.051024332  9.990848 1.450349e-21 0.165310070
## 13      medv -0.36315992 0.038390175 -9.459710 1.173987e-19 0.150780469
## 11     black -0.03627964 0.003873154 -9.366951 2.487274e-19 0.148274239
## 7        dis -1.55090168 0.168330031 -9.213458 8.519949e-19 0.144149375
## 6        age  0.10778623 0.012736436  8.462825 2.854869e-16 0.124421452
## 10   ptratio  1.15198279 0.169373609  6.801430 2.942922e-11 0.084068439
## 5         rm -2.68405122 0.532041083 -5.044819 6.346703e-07 0.048069117
## 1         zn -0.07393498 0.016094596 -4.593776 5.506472e-06 0.040187908
## 3       chas -1.89277655 1.506115484 -1.256727 2.094345e-01 0.003123869
```

By p-value parameters, all predictors have a relevant association with response, rejecting the null hypothesis. By the R2 parameter, the response variance explained by the predictor, the most meaningful and also the best t-value is the rad variable. Either the tax variable is very well associated with the response, and it is the second of higher `R2` value.

b.

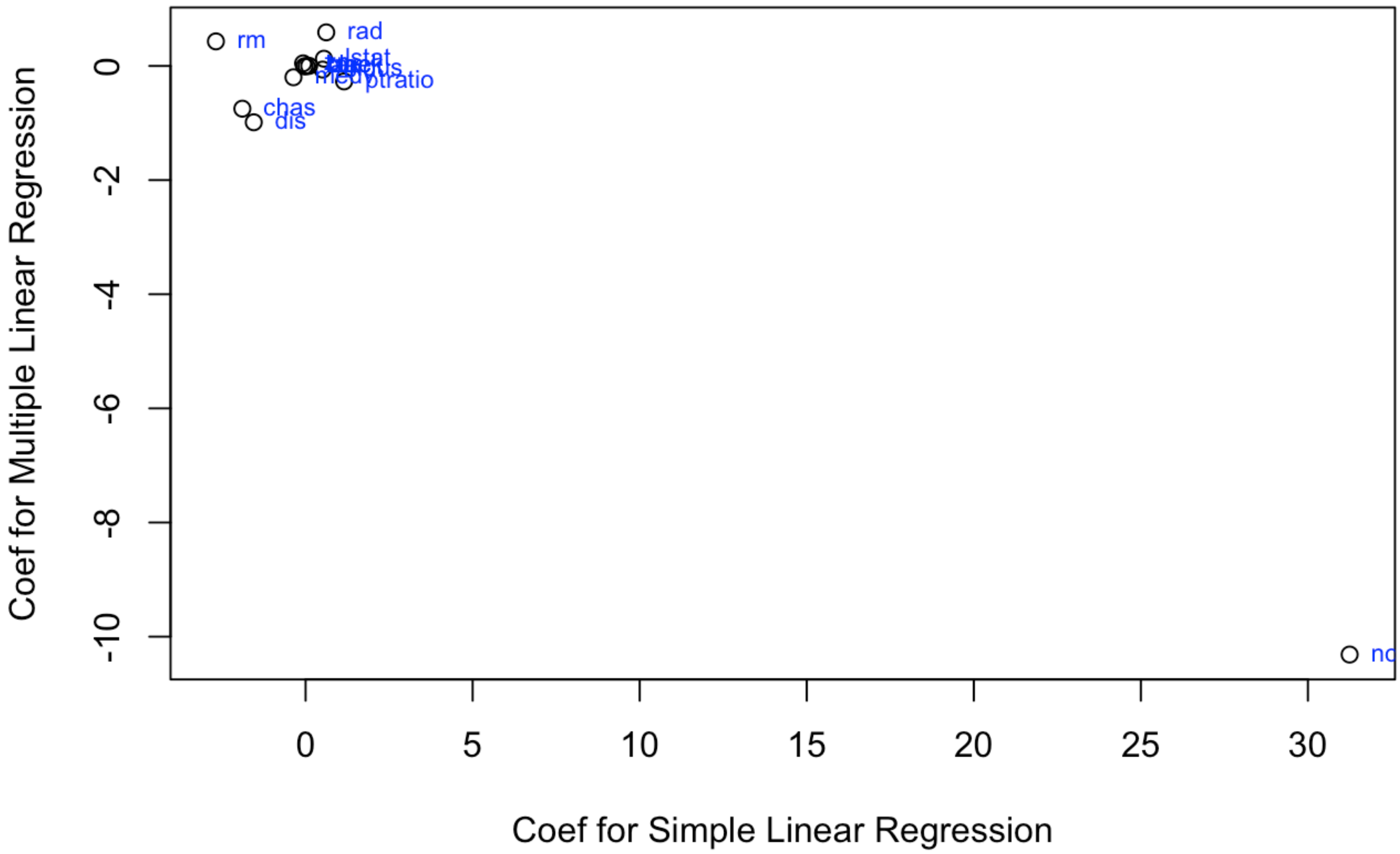
```
lm.fit.b <- lm(crim ~ ., data=Boston)
summary(lm.fit.b)
```

```
##
## Call:
## lm(formula = crim ~ ., data = Boston)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -9.924 -2.120 -0.353  1.019 75.051
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  17.033228   7.234903   2.354 0.018949 *
## zn            0.044855   0.018734   2.394 0.017025 *
## indus        -0.063855   0.083407  -0.766 0.444294
## chas         -0.749134   1.180147  -0.635 0.525867
## nox         -10.313535   5.275536  -1.955 0.051152 .
## rm            0.430131   0.612830   0.702 0.483089
## age           0.001452   0.017925   0.081 0.935488
## dis          -0.987176   0.281817  -3.503 0.000502 ***
## rad           0.588209   0.088049   6.680 6.46e-11 ***
## tax          -0.003780   0.005156  -0.733 0.463793
## ptratio      -0.271081   0.186450  -1.454 0.146611
## black        -0.007538   0.003673  -2.052 0.040702 *
## lstat         0.126211   0.075725   1.667 0.096208 .
## medv         -0.198887   0.060516  -3.287 0.001087 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.439 on 492 degrees of freedom
## Multiple R-squared:  0.454,  Adjusted R-squared:  0.4396
## F-statistic: 31.47 on 13 and 492 DF,  p-value: < 2.2e-16
```

We can reject the null hypothesis for: zn, nox, dis, rad, black, lstat and medv. They're 7 from 14 of the predictors.

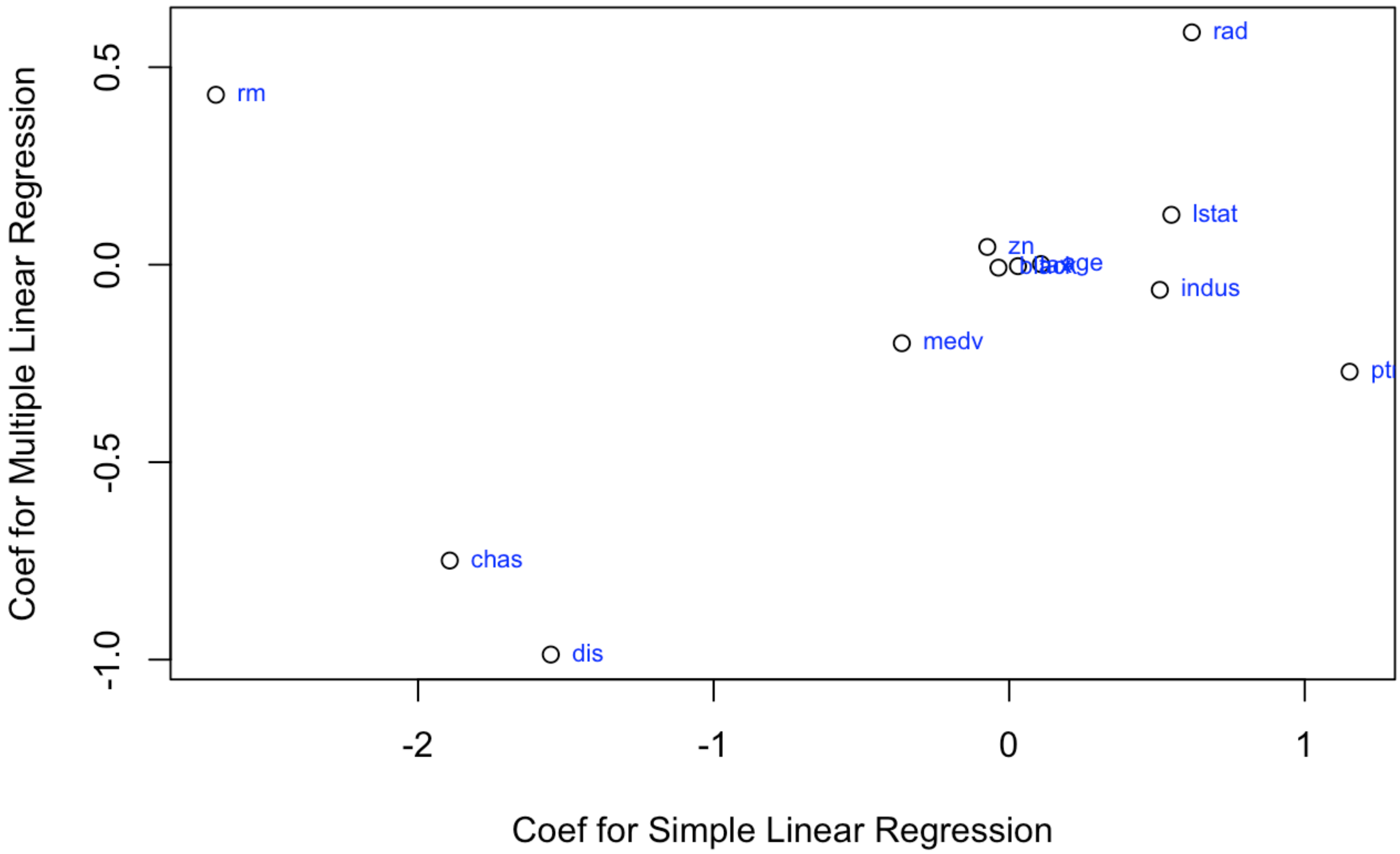
c.

```
df = data.frame("mult"=summary(lm.fit.b)$coefficients[-1,1])
df$simple <- NA
for(i in row.names(df)){
  df[row.names(df)==i, "simple"] = coefs[coefs[,1]==i, "Estimate"]
}
plot(df$simple, df$mult, xlab="Coef for Simple Linear Regression", ylab="Coef for Mul
tiple Linear Regression")
text(x=df$simple, y=df$mult, labels=row.names(df), cex=.7, col="blue", pos=4)
```



The `nox` variable appears with a large displacement, messing the neatness of the graph, so i'll cut-off the `nox` to enhance the visualization.

```
df.clean = df[!(row.names(df)%in%"nox"),]
plot(df.clean$simple, df.clean$mult, xlab="Coef for Simple Linear Regression", ylab="Coef for Multiple Linear Regression")
text(x=df.clean$simple, y=df.clean$mult, labels=row.names(df.clean), cex=.7, col="blue", pos=4)
```



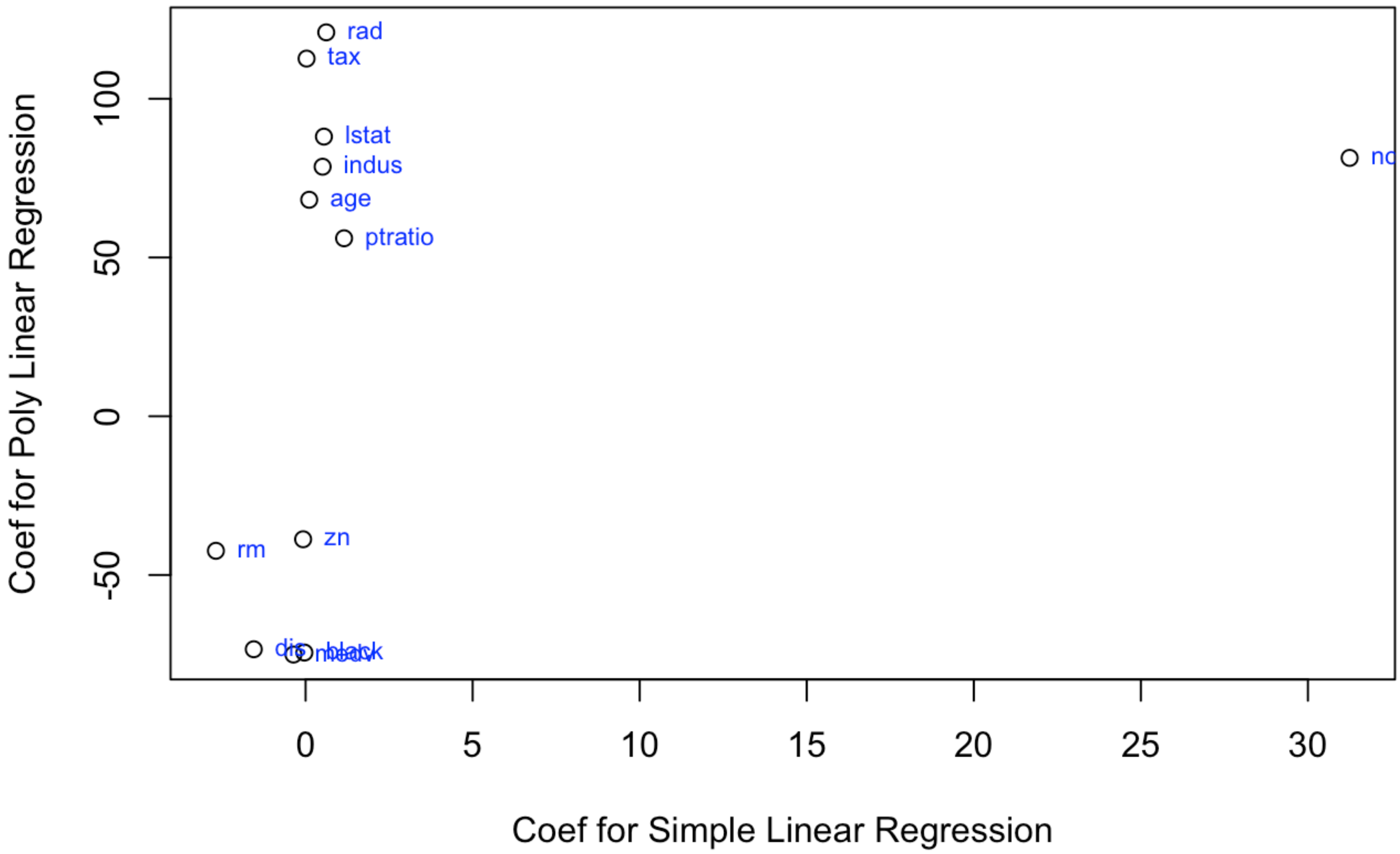
d.

```
coefs.poly <- data.frame("predictor"=character(0), "Estimate"=numeric(0), "Std.Error"
=numeric(0), "t.value"=numeric(0), "Pr.t"=numeric(0), "r.squared"=numeric(0), strings
AsFactors = FALSE)
j <- 1
for(i in names(Boston)){
  if(!(i %in% c("crim", "chas"))){
    summ.lm.fit <- summary(lm(crim ~ poly(eval(parse(text=i)),3), data=Boston))
    coefs.poly[j,] = c(i, summ.lm.fit$coefficients[2,], summ.lm.fit$r.squared)
    j <- j+1}}
coefs.poly[,-1] <- lapply(coefs.poly[,-1], FUN=function(x) as.numeric(x))
coefs.poly <- coefs.poly[order(coefs.poly$r.squared, decreasing = T),]
print(coefs.poly)
```

```
##    predictor  Estimate Std.Error    t.value         Pr.t  r.squared
## 12      medv -75.05761  6.569152 -11.425768 4.930818e-27 0.42020026
## 7        rad 120.90745  6.682402  18.093412 1.053211e-56 0.40003687
## 8        tax 112.64583  6.853707  16.435751 6.976314e-49 0.36888208
## 3        nox  81.37202  7.233605  11.249165 2.457491e-26 0.29697790
## 6        dis -73.38859  7.331479 -10.010066 1.253249e-21 0.27782477
## 2      indus  78.59082  7.423121  10.587301 8.854243e-24 0.25965786
## 11     lstat  88.06967  7.629436  11.543404 1.678072e-27 0.21793243
## 5        age  68.18201  7.839703   8.697015 4.878803e-17 0.17423099
## 10     black -74.43120  7.954643  -9.356951 2.730082e-19 0.14983983
## 9    ptratio  56.04523  8.121583   6.900777 1.565484e-11 0.11378158
## 4         rm -42.37944  8.329676  -5.087766 5.128048e-07 0.06778606
## 1         zn -38.74984  8.372207  -4.628389 4.697806e-06 0.05824197
```

For better analysis, i plot a graph between the coefficients in the simple linear graph and simple linear model with polynomial order.

```
df = data.frame("simple"=coefs[,2])
row.names(df) <- coefs[, 1]
df$poly <- NA
for(i in coefs.poly[,1]){
  df[row.names(df)==i, "poly"] <- coefs.poly[coefs.poly[,1]==i, "Estimate"]}
plot(df$simple, df$poly, xlab="Coef for Simple Linear Regression", ylab="Coef for Pol
y Linear Regression")
text(x=df$simple, y=df$poly, labels=row.names(df), cex=.7, col="blue", pos=4)
```



Titanic

```
library(titanic)
```

HW 3

Q13

```
summary(Boston)
```

```
##       crim                zn             indus           chas
##  Min.   : 0.00632   Min.   :  0.00   Min.   : 0.46   Min.   :0.00000
##  1st Qu.: 0.08204   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          black
##  Min.   : 1.000   Min.   :187.0   Min.   :12.60   Min.   :  0.32
##  1st Qu.: 4.000   1st Qu.:279.0   1st Qu.:17.40   1st Qu.:375.38
##  Median : 5.000   Median :330.0   Median :19.05   Median :391.44
##  Mean   : 9.549   Mean   :408.2   Mean   :18.46   Mean   :356.67
##  3rd Qu.:24.000   3rd Qu.:666.0   3rd Qu.:20.20   3rd Qu.:396.23
##  Max.   :24.000   Max.   :711.0   Max.   :22.00   Max.   :396.90
##      lstat            medv
##  Min.   : 1.73   Min.   : 5.00
##  1st Qu.: 6.95   1st Qu.:17.02
##  Median :11.36   Median :21.20
##  Mean   :12.65   Mean   :22.53
##  3rd Qu.:16.95   3rd Qu.:25.00
##  Max.   :37.97   Max.   :50.00
```

```
data("Boston")
crim01 <- rep(0, length(Boston$crim))
crim01[Boston$crim > median(Boston$crim)] <- 1
Boston <- data.frame(Boston, crim01)
summary(Boston)
```

```
##       crim                zn             indus            chas        
##  Min.   : 0.00632   Min.   :  0.00   Min.   : 0.46   Min.   :0.00000  
##  1st Qu.: 0.08204   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          black       
##  Min.   : 1.000   Min.   :187.0   Min.   :12.60   Min.   :  0.32  
##  1st Qu.: 4.000   1st Qu.:279.0   1st Qu.:17.40   1st Qu.:375.38  
##  Median : 5.000   Median :330.0   Median :19.05   Median :391.44  
##  Mean   : 9.549   Mean   :408.2   Mean   :18.46   Mean   :356.67  
##  3rd Qu.:24.000   3rd Qu.:666.0   3rd Qu.:20.20   3rd Qu.:396.23  
##  Max.   :24.000   Max.   :711.0   Max.   :22.00   Max.   :396.90  
##      lstat            medv           crim01   
##  Min.   : 1.73   Min.   : 5.00   Min.   :0.0  
##  1st Qu.: 6.95   1st Qu.:17.02   1st Qu.:0.0  
##  Median :11.36   Median :21.20   Median :0.5  
##  Mean   :12.65   Mean   :22.53   Mean   :0.5  
##  3rd Qu.:16.95   3rd Qu.:25.00   3rd Qu.:1.0  
##  Max.   :37.97   Max.   :50.00   Max.   :1.0
```

```
set.seed(2019)
train <- sample(1:dim(Boston)[1], dim(Boston)[1]*.7, rep=FALSE)
test <- train
Boston.train <- Boston[train, ]
Boston.test <- Boston[test, ]
crim01.test <- crim01[test]
```

```
fit.glm13 <- glm(crim01 ~ . - crim01 - crim, data = Boston, family = binomial)
fit.glm13
```

```
##
## Call:  glm(formula = crim01 ~ . - crim01 - crim, family = binomial,
##     data = Boston)
##
## Coefficients:
## (Intercept)           zn        indus         chas          nox
##  -34.103704    -0.079918    -0.059389     0.785327    48.523782
##          rm          age          dis          rad          tax
##   -0.425596     0.022172     0.691400     0.656465    -0.006412
##     ptratio        black        lstat         medv
##    0.368716    -0.013524     0.043862     0.167130
##
## Degrees of Freedom: 505 Total (i.e. Null);  492 Residual
## Null Deviance:       701.5
## Residual Deviance: 211.9     AIC: 239.9
```

```
fit.glm <- glm(crim01 ~ nox + indus + age + rad, data = Boston, family = binomial)
```

```
probs <- predict(fit.glm, Boston.test, type = "response")
pred.glm <- rep(0, length(probs))
pred.glm[probs > 0.5] <- 1
table(pred.glm, crim01.test)
```

```
##         crim01.test
## pred.glm   0   1
##        0 158  34
##        1  18 144
```

```
mean(pred.glm != crim01.test)
```

```
## [1] 0.1468927
```

For the logistic regression, we have a test error rate of 12.5%.

LDA

```
fit.lda <- lda(crim01 ~ nox + indus + age + rad , data = Boston)
pred.lda <- predict(fit.lda, Boston.test)
table(pred.lda$class, crim01.test)
```

```
##    crim01.test
##       0   1
##   0 166  46
##   1  10 132
```

```
mean(pred.lda$class != crim01.test)
```

```
## [1] 0.1581921
```

For the LDA regression model, we have a test error rate of 15.1%.

KNN

```
data = scale(Boston[,-c(1,15)])
set.seed(2019)
train <- sample(1:dim(Boston)[1], dim(Boston)[1]*.7, rep=FALSE)
test <- -train
training_data = data[train, c("nox" , "indus" , "age" , "rad")]
testing_data = data[test, c("nox" , "indus" , "age" , "rad")]
train.crime01 = Boston$crim01[train]
test.crime01= Boston$crim01[test]
```

```
set.seed(2019)
knn_pred_y = knn(training_data, testing_data, train.crime01, k = 1)
table(knn_pred_y, test.crime01)
```

```
##            test.crime01
## knn_pred_y  0  1
##           0 71  3
##           1  6 72
```

```
mean(knn_pred_y != test.crime01)
```

```
## [1] 0.05921053
```

For this KNN (k=1), we have a test error rate of 9.21%

```
knn_pred_y = NULL
error_rate = NULL
for(i in 1:dim(testing_data)[1]){
set.seed(2019)
knn_pred_y = knn(training_data,testing_data,train.crime01,k=i)
error_rate[i] = mean(test.crime01 != knn_pred_y)
}
min_error_rate = min(error_rate)
print(min_error_rate)
```

```
## [1] 0.03947368
```

Minimum error rate is 6.57%.