

# An Introduction to Statistical Learning with Applications in R

—  
Second Edition  
—

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## 2 Statistical Learning

### 2.1

- (a) Given a very large sample size  $n$  and a small number of predictors  $p$ , an inflexible method would be better than a flexible one, since the risk of overfitting is less.
- (b) For the same reasons as (a), a flexible method would yield better results for small  $n$  and large  $p$ .
- (c) A flexible method would yield better results, since non-linear functions cannot be accurately modelled by linear functions.
- (d) If there is high variance in the error terms, an inflexible method would be better, since a flexible method would introduce even more variance in the values of  $\hat{f}$ .

### 2.2

- (a) This is a classification problem, since we are trying to identify a qualitative trend in the data. It is an inference problem, since we are not trying to estimate future values of  $f$ . In this case, we have  $n = 500$  and  $p = 4$ .

- (b) This is a classification problem, since we are trying to classify the product as either a success or a failure. It is also a prediction problem, since we are looking to estimate a future output. We have  $n = 20$  and  $p = 14$ .
- (c) This is a regression problem since we have quantitative data and assume that it fits some function  $f$ , which we are attempting to estimate. Since this is a future estimate, it is a prediction problem. We have  $n = 52$  and  $p = 4$ .

## 2.3

- (a) We have an R plot of various error curves in Figure 1: Arbitrary polyno-

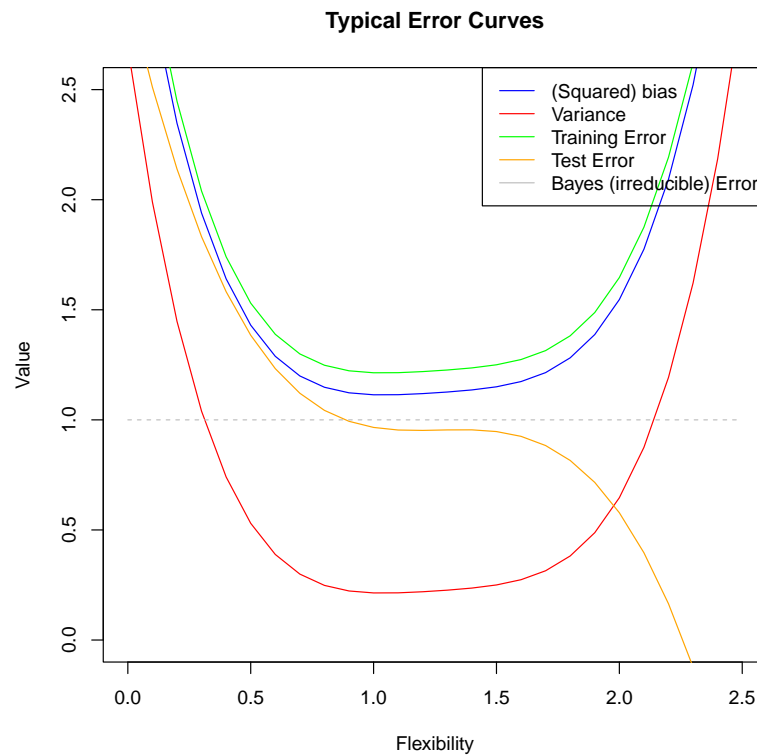


Figure 1: Typical (squared) bias, variance, training error, test error, and Bayes (irreducible) error

mials of the appropriate degree were used to generate these plots, since they are approximations, using the following script:

```
# Exercise 2.3(a) - Plots of error curves
squared_bias <- function(x) {
```

```

    return((x - 1.25)^4 + 0.01 * x^3 + 0.05 * x^2 - 0.1 * x + 1.15)
}

variance <- function(x) {
  return((x - 1.25)^4 + 0.01 * x^3 + 0.05 * x^2 - 0.1 * x + 0.25)
}

training_err <- function(x) {
  return((x - 1.25)^4 + 0.01 * x^3 + 0.05 * x^2 - 0.1 * x + 1.25)
}

test_err <- function(x) {
  return(-(x - 1.25)^3 + 0.05 * x^2 - 0.1 * x + 1.0)
}

bayes_err <- function(x) {
  return(rep(1.0, length(x)))
}

x <- seq(0, 2.5, by = 0.1)

y1 <- squared_bias(x)
y2 <- variance(x)
y3 <- training_err(x)
y4 <- test_err(x)
y5 <- bayes_err(x)

pdf("ex2_3_a.pdf")

plot(x, y1,
     type = "l", col = "blue", lwd = 1, ylim = c(0, 2.5), xlab = "Flexibility",
     ylab = "Value", main = "Typical Error Curves"
)

lines(x, y2, col = "red", lwd = 1)
lines(x, y3, col = "green", lwd = 1)
lines(x, y4, col = "orange", lwd = 1)
lines(x, y5, col = "gray", lwd = 1, lty = 2)

legend("topright",
     legend = c(
       "(Squared) bias", "Variance", "Training Error", "Test Error",
       "Bayes (irreducible) Error"
     ),
     col = c("blue", "red", "green", "orange", "gray"), lwd = 1
)

dev.off()

```

- (b) We are given that the training error will always be greater than the (squared) bias, and that both will be u-shaped. The variance will always be less than the (squared) bias, while the test error will decrease as the model becomes more flexible. The Bayes error is irreducible, so it remains constant.

## 2.4

- (a) Three real-life applications in which classification might be useful include:
- (i) Determining a voter's party preference based upon the results of a census. The response would be a classification of a voter as being

likely to vote for one of the possible political parties and the predictors would be features such as age, demographic, or location, which could be quantitative or qualitative. The goal in this case would be prediction, since we would most likely want to determine their vote in the next election.

- (ii) Classification could also be used to determine the medical condition causing certain symptoms via medical imaging analysis. The response would be any of a number of medical conditions and the predictors would be features of the image, like abnormal textures or shapes within images provided by medical scanning. The goal would be inference, given that the condition already exists and we would like to determine its nature.
  - (iii) Another application would be determining a credit score for an individual. The response would be a natural number within a predetermined range and the predictors would be factors such as time taken to repay debts, number of credit lines awarded to the individual, and total accumulated debt. The goal would be prediction, since the credit score is used to determine the likelihood that the individual will repay their debts on time.
- (b) Three real-life applications in which regression might be useful include:
- (i) Attempting to predict the performance of a stock, given its past history would be a suitable application for regression. The response would be a numerical value indicating the expected price at a certain time and the predictors would be past values on a set of times. The goal would be prediction, given that we are estimating future performance.
  - (ii) Regression could also be used to determine the probability that a person will purchase a certain item from a retailer, given their past purchase history. The response would be a probability ( $\Pr(X) \in [0, 1]$ ) and the predictors would be factors such as number of past purchases from that same retailer, spending history, credit rating, etc. The goal would also be prediction.
  - (iii) Another application would be determining the levels of a contaminant in a water supply, based upon readings from sources which are not directly drawn from the water supply itself, e.g., taps and waste water. The response would be a numeric value (say in mg/L) and the predictors would be the equivalent values in the other sources. The goal would be inference, since we are attempting to determine a current value.
- (c) Three real-life applications in which cluster analysis might be useful include:

- (i) A useful application of cluster analysis would be attempting to determine the species of certain related organisms given the degree to which they exhibit certain features.
- (ii) Cluster analysis could also be used to determine whether certain geological samples fit within distinct groups based upon their chemical composition.
- (iii) Another application of cluster analysis could be using segmenting consumers into certain target markets based upon their response to marketing surveys.

## 2.5

The advantages of a very flexible approach for regression or classification include accuracy if over-fitting has not been exhibited, while the disadvantages include interpretability, large variance in errors, and tendency for over-fitting to occur. A more flexible approach might be preferred when a set of data contains a large variation in the response and a less flexible approach would be preferable if the data tends to contain few outliers.

## 2.6

When utilising a parametric statistical learning approach, we attempt to estimate a countable number of parameters  $\beta_i$  for  $i \in \{1, \dots, p\}$  s.t. the observation  $(X, Y)$  has  $Y$  s.t.

$$Y \approx f(X) = \beta_0 + \beta_1 X_1 + \dots + \beta_p X_p.$$

This means we need to select the number of parameters used in order to minimize the error. In doing so, we risk overfitting the model to the data, so that the approximation does not closely match the form of  $f$ .

In contrast, a non-parametric method makes no assumption about the parameters used, with the advantage that we do not need to concern ourselves with the number of parameters used, but with the disadvantage that we must select a level of smoothness which makes the approximation to  $f$  easy to calculate without introducing unnecessary variation in the shape of the approximation relative to  $f$ .

## 2.7

- (a) If we denote the number of observations by  $n$  and the number of variables by  $p$ , then we let  $x_{ij}$  denote the  $i$ th observation of the  $j$ th variable. We calculate the Euclidian distances using the formula

$$\begin{aligned} & d((X_1 = 0, X_2 = 0, X_3 = 0), (x_{i1}, x_{i2}, x_{i3})) \\ &= \sqrt{(0 - x_{i1})^2 + (0 - x_{i2})^2 + (0 - x_{i3})^2} \\ &= \sqrt{(-x_{i1})^2 + (-x_{i2})^2 + (-x_{i3})^2}, \end{aligned}$$

for  $i \in \{1, \dots, 6\}$ .

Thus we have

$$\begin{aligned} & d((X_1 = 0, X_2 = 0, X_3 = 0), (x_{11}, x_{12}, x_{13})) \\ &= \sqrt{9^2} \\ &= 9, \end{aligned}$$

$$\begin{aligned} & d((X_1 = 0, X_2 = 0, X_3 = 0), (x_{21}, x_{22}, x_{23})) \\ &= \sqrt{2^2} \\ &= 2, \end{aligned}$$

$$\begin{aligned} & d((X_1 = 0, X_2 = 0, X_3 = 0), (x_{31}, x_{32}, x_{33})) \\ &= \sqrt{1^2 + 3^2} \\ &= \sqrt{10} \\ &\approx 3.162278, \end{aligned}$$

$$\begin{aligned} & d((X_1 = 0, X_2 = 0, X_3 = 0), (x_{41}, x_{42}, x_{43})) \\ &= \sqrt{1^2 + 2^2} \\ &= \sqrt{5} \\ &\approx 2.236068, \end{aligned}$$

$$\begin{aligned} & d((X_1 = 0, X_2 = 0, X_3 = 0), (x_{51}, x_{52}, x_{53})) \\ &= \sqrt{(-1)^2 + 1^2} \\ &= \sqrt{2} \\ &\approx 1.414214, \end{aligned}$$

and

$$\begin{aligned} & d((X_1 = 0, X_2 = 0, X_3 = 0), (x_{61}, x_{62}, x_{63})) \\ &= \sqrt{1^2 + 1^2 + 1^2} \\ &= \sqrt{3} \\ &\approx 1.732051. \end{aligned}$$

- (b) Our prediction with  $K = 1$  is that  $Y = \text{Green}$  since the nearest neighbour to the point  $(X_1 = 0, X_2 = 0, X_3 = 0)$  is the point given by  $(x_{51}, x_{52}, x_{53})$  corresponding to observation 5, which yields the value  $y = \text{Green}$ .
- (c) With  $K = 3$ , we have  $Y = \text{Red}$ , since of the 3 nearest neighbours calculated in (a), we have two with value  $y = \text{Red}$  and only one with value  $y = \text{Green}$ .
- (d) We would expect the best value to be small, since this would yield a decision boundary which is highly flexible and more easily approximates the non-linear nature of the Bayes decision boundary.

## 2.8

- (c) i. We have the following output from the `summary` function:

```
> 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
```

- ii. In Figure 2, we have the scatterplot matrix of the first ten columns of `College` data.
- iii. In Figure 3, we have the plots of the `Outstate` versus `Private` `College` data.
- iv. We have the following output from the `summary(Elite)` function call:

```
> summary(Elite)
No Yes
699  78
```

In Figure 4, we have the plots of the `Outstate` versus `Elite` `College` data.

- v. In Figure 5, we have the histogram plots for four of the variables.
- vi. We can say broadly that the elite colleges have higher out-of-state tuition costs and that the number of applications received is strongly correlated with the number of applicants accepted (obviously this is to be expected), but not as strongly correlated with the number of new students enrolled.

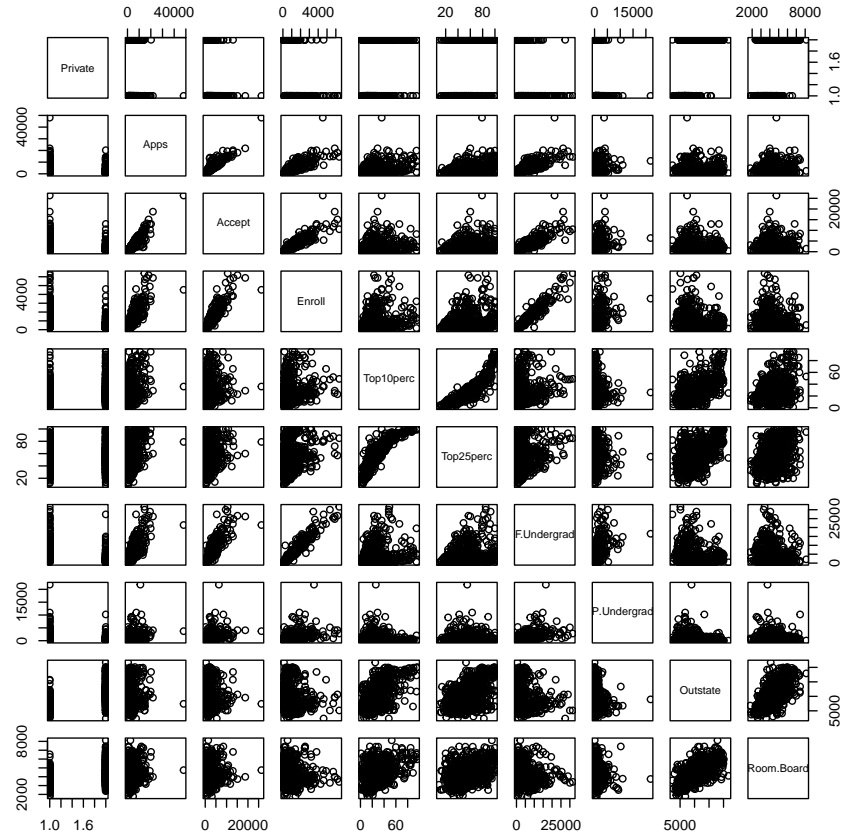


Figure 2: Scatterplot matrix of the first ten columns of College data

## 2.9

- (a) The quantitative predictors are `mpg`, `cylinders`, `displacement`, `horsepower`, `weight`, `acceleration`, `year`, and `origin`. The only qualitative predictor is `name`.
- (b) The range of each quantitative predictor is as follows:



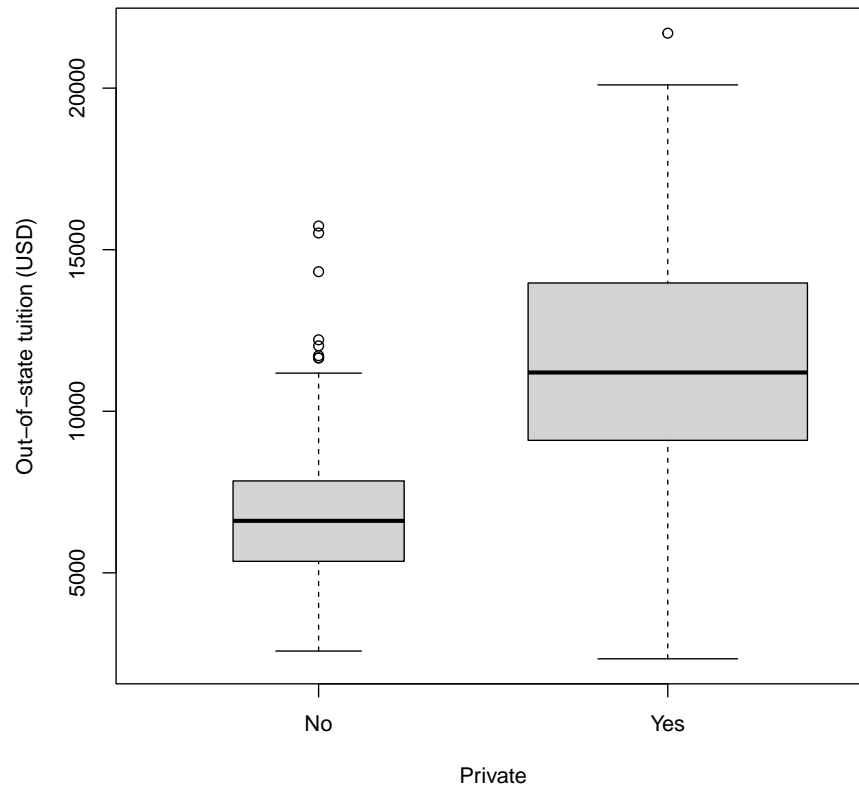


Figure 3: Outstate versus Private College data

Predictor	Minimum	Maximum
mpg	9.0	46.6
cylinders	3	8
displacement	68	455
horsepower	46	230
weight	1649	4997
acceleration	8.0	24.8
year	70	82
origin	1	3

(c) We have the following values for the mean and standard deviation:

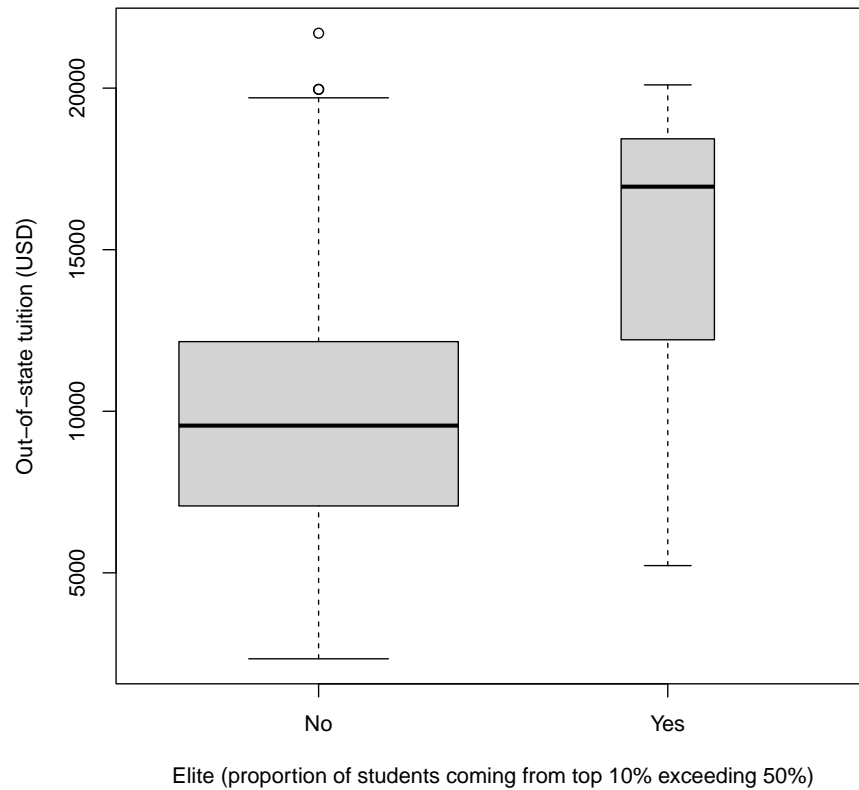


Figure 4: Outstate versus Elite College data

Predictor	Mean	Standard Deviation
mpg	23.44592	7.805007
cylinders	5.471939	1.705783
displacement	194.412	104.644
horsepower	104.4694	38.49116
weight	2977.584	849.4026
acceleration	15.54133	2.758864
year	75.97959	3.683737
origin	1.576531	0.8055182

- (d) We have the following adjusted values for the range, mean, and standard deviation:

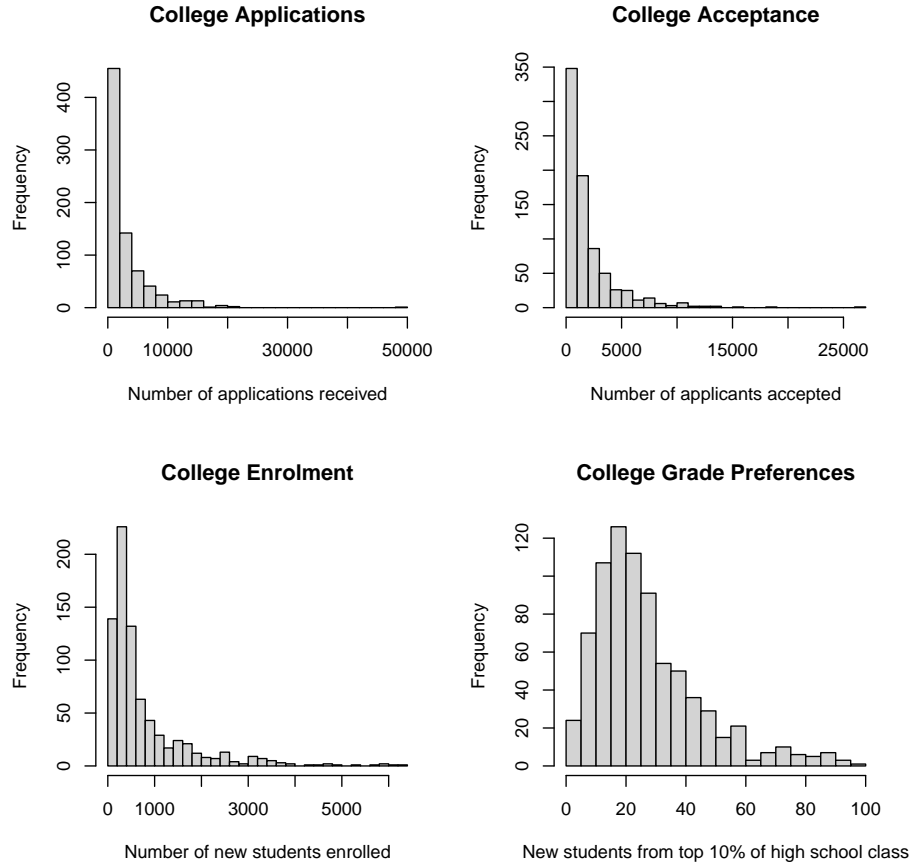


Figure 5: Plots of College data

Predictor	Min.	Max.	Mean	S.D.
mpg	11.0	46.6	24.40443	7.867283
cylinders	3	8	5.373418	1.654179
displacement	68	455	187.2405	99.67837
horsepower	46	230	100.7215	35.70885
weight	1649	4997	2935.972	811.3002
acceleration	8.5	24.8	15.7269	2.693721
year	70	82	77.14557	3.106217
origin	1	3	1.601266	0.81991

- (e) In Figure 6, we have plots of the Auto data highlighting the relationships between some of the variables. As can be seen by these plots, there is a strong correlation between the number of cylinders and the gas mileage (mpg) of the vehicle in question. This relationship is somewhat the inverse

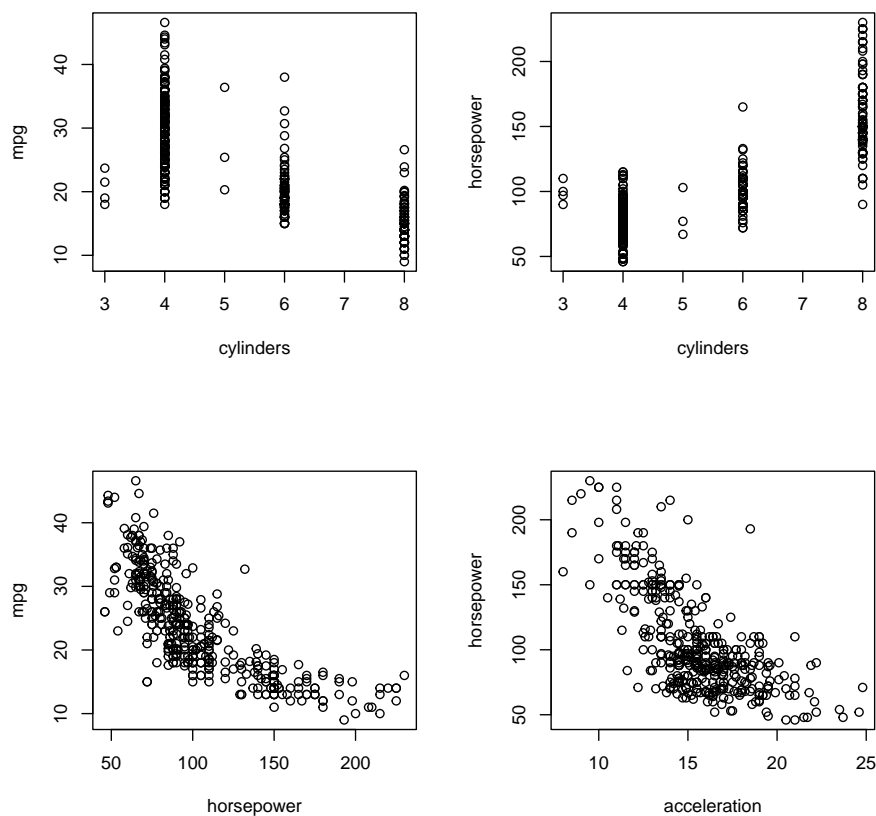


Figure 6: Scatterplots of Auto data

of that between cylinders and horsepower. We can also see that mpg and horsepower as well and, to a lesser extent, acceleration and horsepower are correlated.

- (f) Yes, we can use both the number of cylinders and the horsepower to estimate the gas mileage of the vehicle, since these two variables have a strongly correlated relationship to gas mileage.

## 2.10

- (a) We have the following output from calling `?Boston`:

```
Boston                package:ISLR2                R Documentation
Boston Data
```

Description:

A data set containing housing values in 506 suburbs of Boston.

Usage:

Boston

Format:

A data frame with 506 rows and 13 variables.

'crim' per capita crime rate by town.

'zn' proportion of residential land zoned for lots over 25,000 sq.ft.

'indus' proportion of non-retail business acres per town.

'chas' Charles River dummy variable (= 1 if tract bounds river; 0 otherwise).

'nox' nitrogen oxides concentration (parts per 10 million).

'rm' average number of rooms per dwelling.

'age' proportion of owner-occupied units built prior to 1940.

'dis' weighted mean of distances to five Boston employment centres.

'rad' index of accessibility to radial highways.

'tax' full-value property-tax rate per \$10,000.

'ptratio' pupil-teacher ratio by town.

'lstat' lower status of the population (percent).

'medv' median value of owner-occupied homes in \$1000s.

- (b) In Figure 7, we have some of the data from the `Boston` data set displayed in scatterplots.

From the scatterplots in this figure, we may see that as the distance to employment centres increases, the nitrogen oxide concentration decreases, perhaps indicating higher levels of nitrogen oxide in the inner city due to vehicles and industrial pollution, which coincides with where employment centres are located. Likewise, we see that owner-occupied units built prior to the year 1940 are concentrated in the city centre.

We also see that a higher number of rooms and value of owner-occupied homes tend to be concentrated amongst the lower status of the population.

- (c) We can see that per capita crime rates are correlated with the lower status of the population by looking at Figure 8. It appears that high per capita crime rates are associated with a larger population in the lower status category.

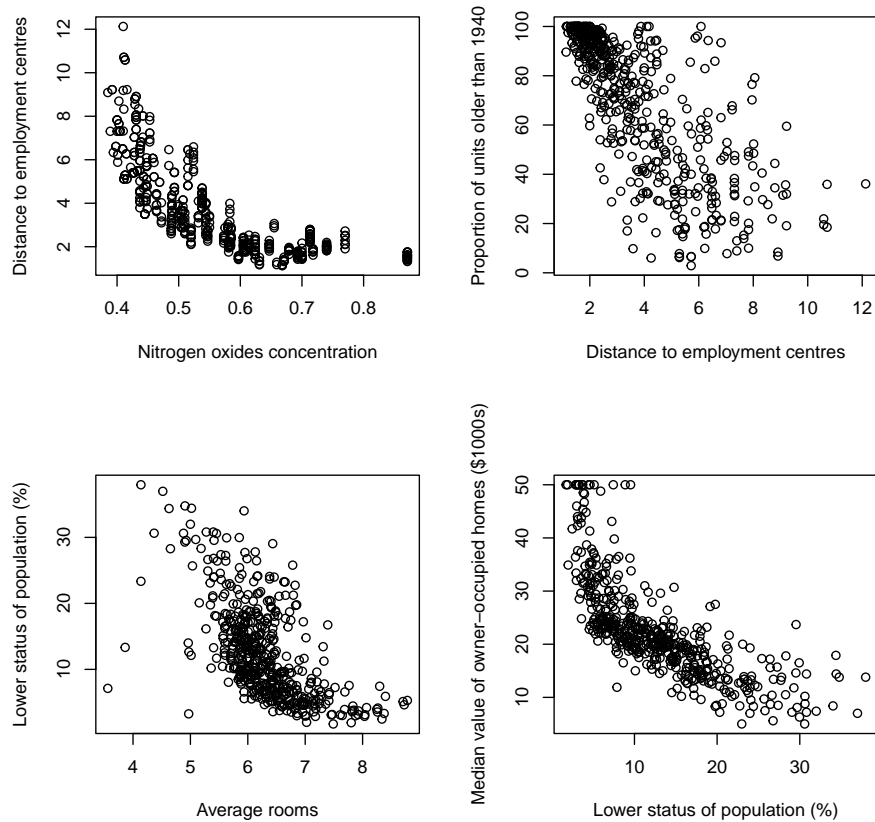


Figure 7: Scatterplots of Boston data

(d) Yes, we have the following summary:

```
> summary(Boston$crim)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
0.00632 0.08204 0.25651 3.61352 3.67708 88.97620
```

While the median and mean for the `crim` data are 0.25651 and 3.61352, respectively, the range is  $[0.00632, 88.97620]$ , so that some census tracts must have particularly high crime rates. Tax rates appear to be more evenly distributed, as can be seen from the following:

```
> summary(Boston$tax)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 187.0  279.0  330.0  408.2  666.0  711.0
```

The same applies to pupil-teacher ratios:

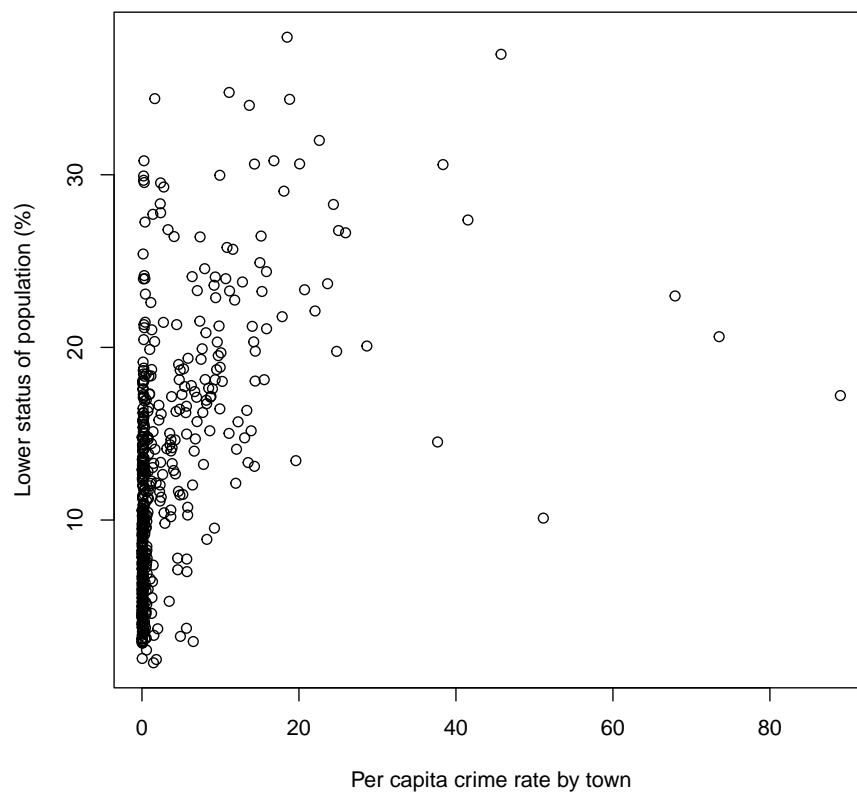


Figure 8: Scatterplot of crim vs lstat data

```
> summary(Boston$ptratio)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  12.60  17.40   19.05  18.46  20.20   22.00
```

(e) We have the following:

```
> sum(Boston$chas)
[1] 35
```

(f) We have the following:

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

(g) The tract corresponding to observation  $i = 399$ , for which we have

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

For that census tract, we have the following data:

```
> Boston[399,]
      crim zn  indus chas   nox   rm age   dis rad tax ptratio lstat medv
399 38.3518  0  18.1    0 0.693 5.453 100 1.4896 24 666    20.2 30.59    5
```

We can see that the `crim` variable is far higher than the median value of 3.61352, and is also in the higher range for the variables `tax` and `ptratio` for which the range was determined in (d). This would likely indicate a correlation between these variables.

- (h) We have the following code to find the number of census tracts which average more than 7 and 8 rooms per dwelling:

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

We have the following summary of all census tracts averaging more than 8 rooms:

```
> summary(Boston[Boston$rm > 8, ])
      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
```

From the above summary, it becomes clear that census tracts with a large average number of rooms per dwelling have correspondingly low crime rates, relatively high tax rates, and relatively high pupil-teacher ratios.