Chapter 2: Statistics with R - 2nd Edition

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Student Exercises

The csv data sets used in these exercises can be found on the website:

1. `check.csv`
2. `parabolic.csv`
3. `negative.csv`
4. `positive.csv`

Although throughout the book we use the `ggplot2` package to create publication-quality images (see the Chapter 1 Appendix for the introduction to `ggplot2`), in the exercises we will use the graphical procedures that are part of the base R installation. While the images they produce are not always of the same high quality that we can achieve using the `ggplot2` package, they are normally easier and more convenient to make. Because students of statistics and R should be able to use both graphical systems, we will use the R basic installation graphical methods in the exercises but `ggplot2` in the book. In exercise 3 below, we use the another one of these procedures, the `barplot()` function, to produce a bar graph.

1. A marketing research survey of 1095 households investigating attitudes toward the following brands—A, B, C, D, E and F—in a certain product category reveals the following brand preference structure: 272 prefer brand A, 212 prefer brand B, 297 prefer C, 38 prefer D, 181 E, and 95 F. Create an object, named `E2_1`, which contains this information, and then provide the frequency disribution of preferences across the six brands.

```
# (1) Use the rep() function to produce the data values and
# read data into object named E2_1.

E2_1 <- c(rep('A', 272), rep('B', 212), rep('C', 297), rep('D', 38),
          rep('E', 181), rep('F', 95))

# (2) Use the table() function to produce a frequency
# distribution and read the result into object named fd.

fd <- table(E2_1)
```

```
# (3) Examine contents of fd.
fd

## E2_1
##   A   B   C   D   E   F
## 272 212 297  38 181  95
```

Thus the `table()` function provides the frequency distribution across the six brands.

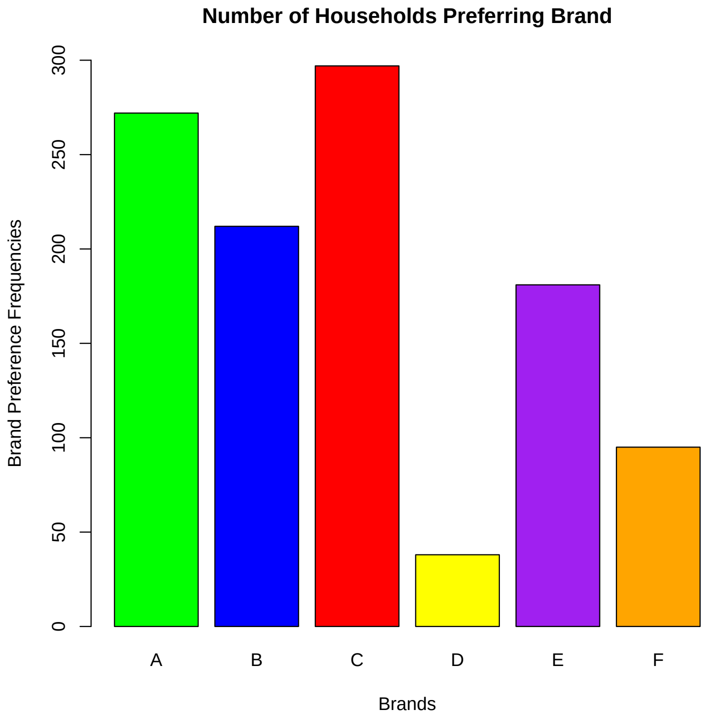
2. Create the relative frequency distribution of brand preference. Use the `E2_1` data.

```
# (1) Use the table() function to produce a frequency
# distribution and assign the result to object named fd.

fd <- table(E2_1)

# (2) Create relative frequencies and assign to object rf.

rf <- fd / sum(fd)

# (3) Examine contents of rf.

rf

## E2_1
##          A          B          C          D          E          F
## 0.24840183 0.19360731 0.27123288 0.03470320 0.16529680 0.08675799
```

The relative frequency distribution of brand preference: A is 0.25, B is 0.19, C is 0.27, D is 0.03, E is 0.17, and F is 0.09.

3. Show the bar graph of brand preference frequencies. Set the range of the vertical axis from 0 to 300. Define the colors of the bars, from left to right, as green, blue, red, yellow, purple, and orange. Provide a label for both horizontal and vertical axes as well as a main title for the picture. Use the `E2_1` data.

```
# (1) Use the table() function to produce a frequency
# distribution and read the result into object named fd.

fd <- table(E2_1)

# (2) Use the barplot() function to make a bar graph.

barplot(fd,
        col = c('green', 'blue', 'red', 'yellow', 'purple', 'orange'),
        ylim = c(0, 300),
        main = 'Number of Households Preferring Brand',
        xlab = 'Brands',
        ylab = 'Brand Preference Frequencies')
```

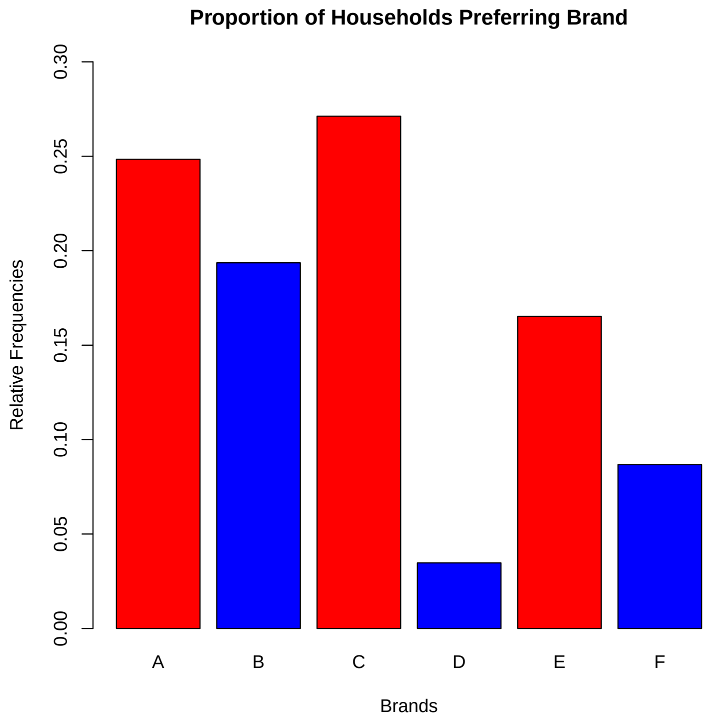


We have listed the arguments of the `barplot()` function, one per line, for the sake of minimizing clutter and improving visual clarity. In practice, however, there is no need to do so, and we can just as easily write the entire function (with its six arguments) on one line.

4. Show the bar graph of brand preference relative frequencies. Set the range of the vertical axis from 0 to 0.30. Define the colors of the bars, from left to right, as red, blue, red, blue, red, and blue. Provide a label for both horizontal and vertical axes as well as a main title for the picture. Use the `E2_1` data.

```
# (1) Use the table() function to produce a frequency
# distribution and read the result into object named fd.

fd <- table(E2_1)

# (2) Create relative frequencies and assign to object rf.

rf <- fd / sum(fd)

# (3) Use the barplot() function to produce bar graph.
```

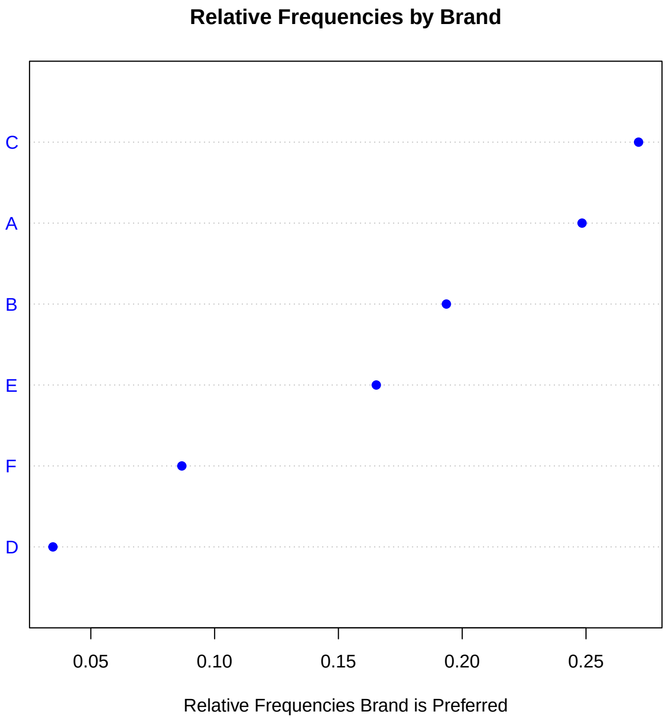
```
barplot(rf,
        col = c('red', 'blue', 'red', 'blue', 'red', 'blue'),
        ylim = c(0, 0.30),
        xlab = 'Brands',
        ylab = 'Relative Frequencies',
        main = 'Proportion of Households Preferring Brand')
```



5. Show the dot plot of the relative frequency of brand preferences. Use the E2_1 data.

```
# (1) Use the table() function to produce a frequency
# distribution and read the result into object named fd.

fd <- table(E2_1)

# (2) Create relative frequencies and assign to object rf.

rf <- fd / sum(fd)

# (3) Use the dotchart() function to create a dot plot.

dotchart(sort(rf),
         xlab = 'Relative Frequencies Brand is Preferred',
         main = 'Relative Frequencies by Brand',
         pch = 19,
         col = 'blue')
```

```
## Warning in dotchart(sort(rf), xlab = "Relative Frequencies Brand is
Preferred", :  'x' is neither a vector nor a matrix:  using as.numeric(x)
```



Note: it is necessary to sort the relative frequency data if we want the points in the dot plot to run in sequential order from the lower-left to the upper-right. This is done by nesting the `sort()` function as an argument in the `dotchart()` function. If we omit the `sort()` function, and include only the object name (in this case `rf`), the points in the plot are ordered alphabetically by default.

Note: This routine provides a warning message that we are free to ignore because the `dotchart()` function executes successfully and produces the dot plot image.

6. Make a frequency distribution of these values: 24, 29, 34, 29, 37, 26, 30, 34, 30, 11, 12, 14, 18, 38, 17, 13, 16, 12, 33, 35, 35, 29, 28, 26, 25, 34, 11, 16, 19, 11, 13, 36, 12, 12, 12, 26, 36, 16, 26, 22, 15, 29, 38, 34, and 30. Set the classwidth at 5. Note: a convenient way of doing this is simply to copy and paste these values directly into the R Console (see Comment 1 below).

```
# (1) Use the c() function to create a vector; name it E2_2.

E2_2 <- c(24, 29, 34, 29, 37, 26, 30, 34, 30, 11, 12, 14, 18, 38, 17,
          13, 16, 12, 33, 35, 35, 29, 28, 26, 25, 34, 11, 16, 19, 11,
          13, 36, 12, 12, 12, 26, 36, 16, 26, 22, 15, 29, 38, 34, 30)

# (2) Read data into the object brks.
```

```r
brks <- c(10, 14.99, 19.99, 24.99, 29.99, 34.99, 39.99)

# (3) Use cut() function to assign values in E2_2 to categories
# defined by brks: (10,15], (15,20], (20,25], (25,30], (30,35],
# (35,40]; read this result into object named categ.

categ <- cut(E2_2, brks)

# (4) Use table() function to produce frequency distribution of
# data items in categ; assign the result to fd.

fd <- table(categ)

# (5) Examine contents of fd.

fd


## categ
## (10,15] (15,20] (20,25] (25,30] (30,35] (35,40]
##      11       7       2      10       8       7
```

Thus, 11 values fall in the first category (between 10 and 15), 7 in the second (from 15 to 20), 2 in the third, 10 in the fourth, 8 in the fifth, and 7 in the sixth.

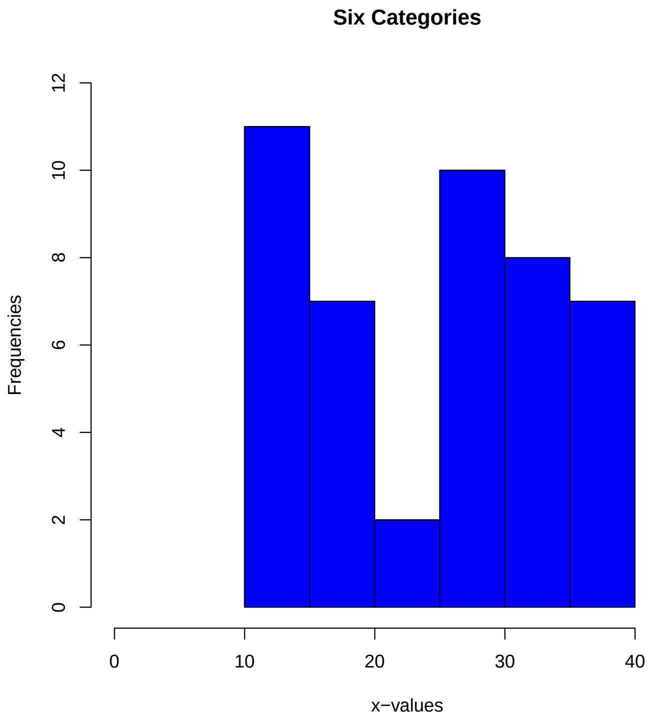
7. Create a relative frequency distribution of the E2_2 data.

```r
# (1) Create relative frequencies by dividing each element in
# fd by total number of data values; assign result to object rf.

rf <- fd / sum(fd)

# (2) Examine contents of rf.

rf


## categ
##    (10,15]    (15,20]    (20,25]    (25,30]    (30,35]    (35,40]
## 0.24444444 0.15555556 0.04444444 0.22222222 0.17777778 0.15555556
```

Thus, 0.24 of observations fall in the first class, 0.16 fall in the second, 0.04 in the third, 0.22 in the fourth, 0.18 in the fifth, and 0.16 fall in the sixth class.

8. Show the histogram of the frequencies for the E2_2 data. Set the range of the horizontal axis between 0 and 45, the range of the vertical axis between 0 and 12. Add a main title and labels for the vertical and horizontal axes. Specify that the classwidth is 5; set blue as the color.

```r
# Use the hist() function to create a histogram

hist(E2_2,
    breaks = c(9.99, 14.99, 19.99, 24.99, 29.99, 34.99, 39.99),
    xlim = c(0, 45),
    ylim = c(0, 12),
    xlab = 'x-values',
    ylab = 'Frequencies',
    main = 'Six Categories',
    col = 'blue')
```



9. A large fast food restaurant located in central Birmingham collects a sample of $n = 199$ customer checks compiled during a recent weekday with the purpose of gaining insight into the distribution of the amount their customers spend (£). Use the `check.csv` data set (found on companion website) for Exercises 9-13. As a first step to determining a good width for the categories of a frequency distribution, use the `summary()` function. What do these statistics tell us?

```r
E2_3 <- read.csv('check.csv') # Import check.csv data; name it E2_3.
```

```r
# Find the mean, median, minimum, and maximum values of E2_3.

summary(E2_3)


##       amount
##  Min.   : 6.72
##  1st Qu.:28.34
##  Median :51.18
##  Mean   :50.01
##  3rd Qu.:70.35
##  Max.   :97.74
```

Since the minimum and maximum values are 6.72 and 97.74, respectively, we need to partition the histogram into five categories roughly $(97.74 - 6.72/5) = 91.02/5 \approx 20$ units wide. Since the median and mean are almost equal, the data appear to be symmetrically distributed.

10. Create a frequency distribution for E2_3. Hint: first use the `names()` function to determine what the variable name might be.

```
# (1) Use the names() function to identify the variable name.

names(E2_3) # variable name is amount

## [1] "amount"

# (2) Read data into the object brks.

brks <- c(0, 20, 40, 60, 80, 100)

# (3) Use the cut() function to assign values in E2_3 to
# categories defined by brks: (0,20], (20,40], (40,60], (60,80],
# (80,100]; assign this result to the object named categ.

categ <- cut(E2_3$amount, brks)

# (4) Use table() function to produce frequency distribution of
# data items in categ and assign the result to object named fd.

fd <- table(categ)

# (5) Examine contents of fd.

fd

## categ
##   (0,20]  (20,40]  (40,60]  (60,80] (80,100]
##       18       68       30       67       16
```

Thus, there are 18 values falling in the first category, 68 in the second, 30 in the third, 67 in the fourth, and 16 in the fifth. It appears that a frequency distribution with five classes spreads out and classifies the 199 data items reasonably well. Interestingly, although the summary statistics seem to suggest that the distribution might be somewhat normally distributed—since the mean and median are nearly equal—the frequency distribution makes clear that the data are not distributed normally, but bimodally.

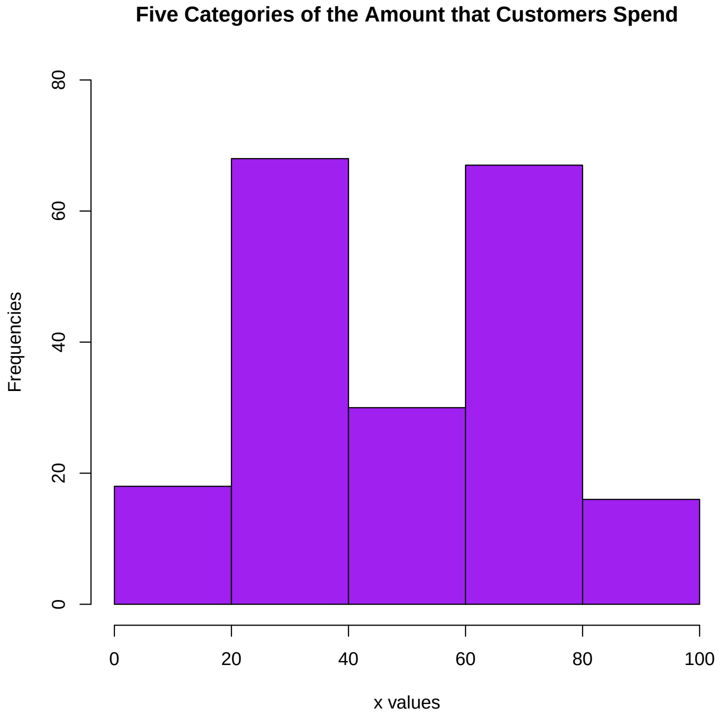
11. Show the relative frequency distribution of the E2_3 data.

```
# (1) Create relative frequencies by dividing fd by total
# number of data values. Assign result to object named rf.

rf <- fd / sum(fd)

# (2) Show the relative frequency distribution.

rf


## categ
##   (0,20]  (20,40]  (40,60]  (60,80] (80,100]
##  0.09045  0.34171  0.15075  0.33668  0.08040
```

Thus, 0.09 (of counts) fall in the first category, 0.34 fall in the second, 0.15 in the third, 0.34 in the fourth, and 0.08 in the fifth.

12. Make a histogram of the E2_3 data using the five categories. Include a main title and labels for the horizontal and vertical axes. Define the range of the vertical axis from 0 to 80, and set purple as the color.

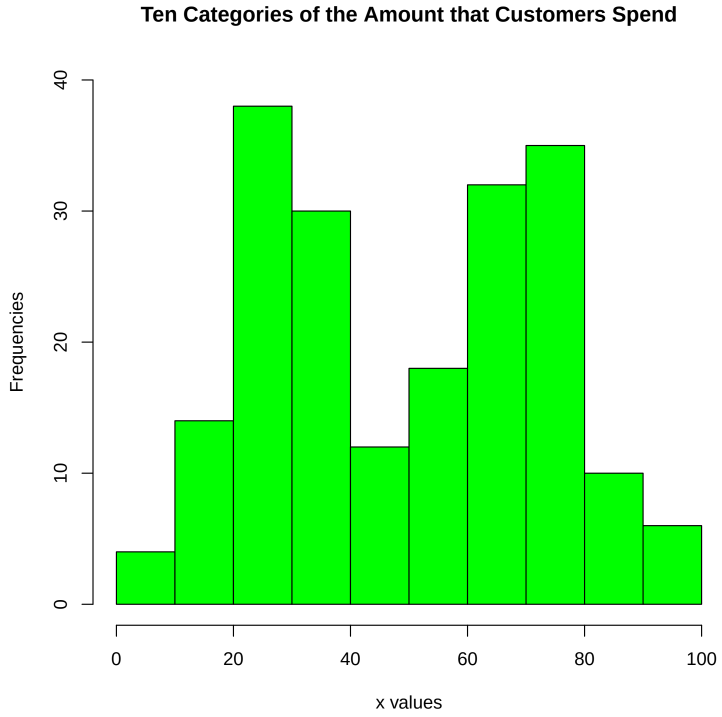
```
# Use the hist() function to create a histogram.

hist(E2_3$amount,
     breaks = c(0, 20, 40, 60, 80, 100),
     col = 'purple',
     ylim = c(0, 80),
     xlab = 'x values',
     ylab = 'Frequencies',
     main = 'Five Categories of the Amount that Customers Spend')
```



The histogram makes clear that even though the central tendency of the distribution is about 50 (according to the mean and the median), the data are indeed bimodal, not normal.

13. Show the histogram with ten classes. Does the added precision of ten classes provide any additional insight when attempting to interpret the distribution of the data? Once again, add a main title and labels for the vertical and horizontal axes. Specify the range of the vertical axis running from 0 to 40, and set green as the color.

```r
# Use the hist() function to create a histogram.

hist(E2_3$amount,
     breaks = 10,
     col = 'green',
     ylim = c(0, 40),
     xlab = 'x values',
     ylab = 'Frequencies',
     main = 'Ten Categories of the Amount that Customers Spend')
```



Note that instead of defining the classes using `breaks=c()` as we did in the previous exercise, we can also use `breaks=10`. See the second argument of the `hist()` function above.

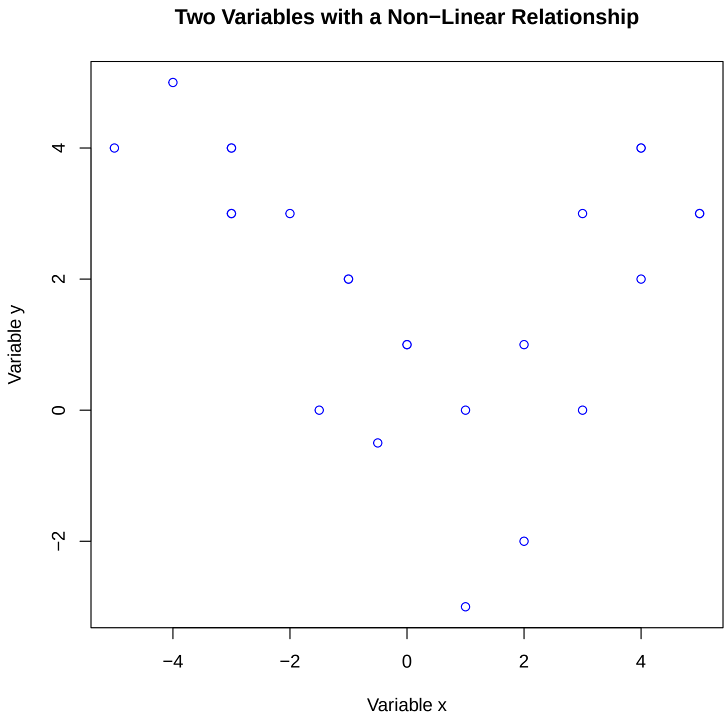
On closer inspection, it appears that using ten categories rather than five offers no further insight into the nature of the distribution of the data values. Even so, it is sometimes advantageous to break up the data into more (but narrower) categories because patterns that were not discernable with a smaller number of categories may be revealed when the data are spread out into more categories.

The Exercises 14-16 provide a bit of practice writing code for the purpose of creating images and interpreting their meaning. The three data sets are `parabolic.csv`, `negative.csv`, and `positive.csv`, and can be found on the website.

14. Using the `parabolic.csv` data, display the relationship between the two variables, `x` and `y`. Which descriptive method do you think works best in this case?

```
parabolic <- read.csv('parabolic.csv') # Import data into Workspace.
```

```
# Use the plot() function.

plot(parabolic$x, parabolic$y,
     pch = 21,
     col = "blue",
     xlab = "Variable x",
     ylab = "Variable y",
     main = "Two Variables with a Non-Linear Relationship")
```

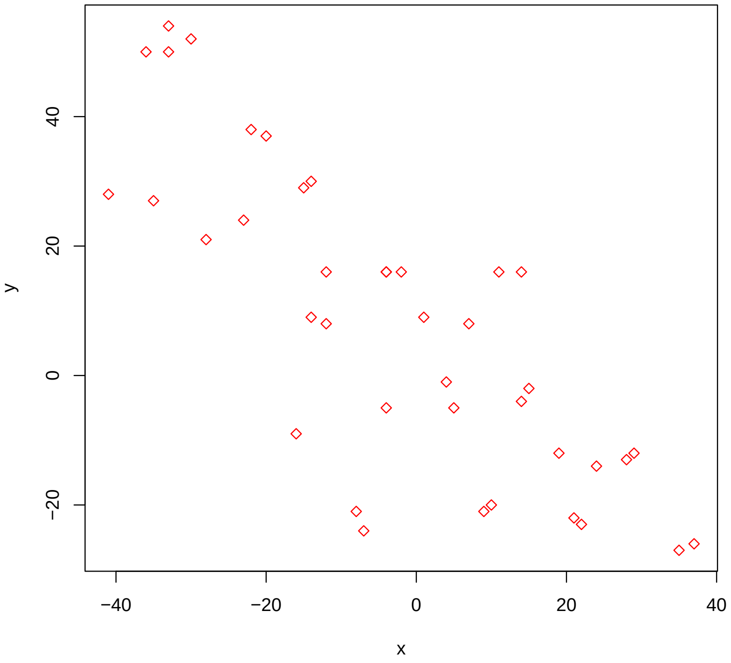


The scatter plot probably works best of all because it provides a clear picture of the association between two variables. In this case, the relationship between the two variables `x` and `y` is not linear but more parabolic.

15. Using the `negative.csv` data, display the relationship between the two variables, `x` and `y`. How should we describe this relationship?

```
negative <- read.csv('negative.csv') # Import data into R Workspace.
```

```
# Use the plot() function.

plot(negative$x, negative$y,
     pch = 23,
     col = "red",
     xlab = "x",
     ylab = "y")
```

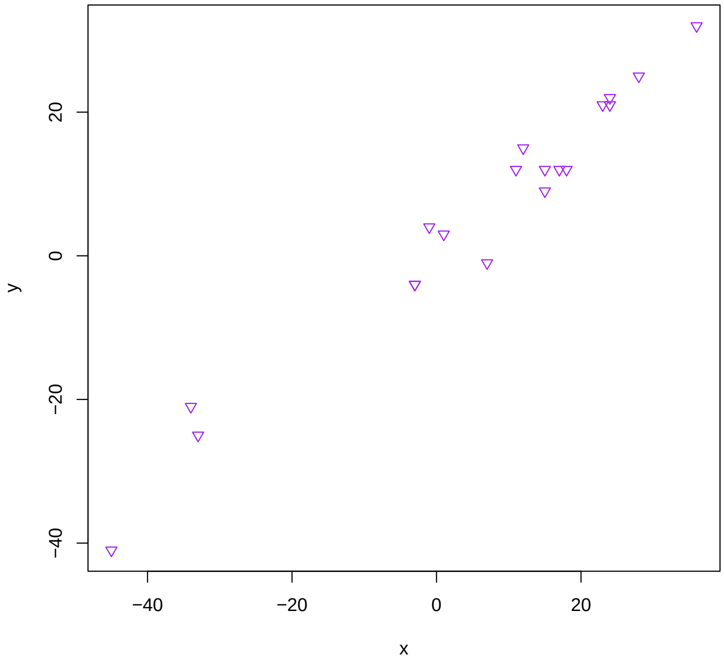


The two variables `x` and `y` appear to be negatively (and linearly) related.

16. Using the `positive.csv` data, show the relationship between the two variables, `x` and `y`. What can we say about this relationship?

```
positive <- read.csv('positive.csv') # Import data into R Workspace.
```

```
# Use the plot() function.

plot(positive$x, positive$y,
     pch = 25,
     col = "purple",
     xlab = "x",
     ylab = "y")
```



The variables x and y seem to be positively (and linearly) related.

Exercises 17-33 make use of the Cars93 data set that includes information on 93 makes and models of passenger vehicles for the 1993 model year. Because the Cars93 data set is part of the MASS package, you will need to install and load that package from the R system (to do this, you should consult the Chapter 1 Appendix if necessary).

```
# Load the MASS package (contains the Cars93 data set).

library(MASS)
```

17. Report the first seven observations and first seven columns (variables) of the Cars93 data set. As a first step, import the data into E2_4. Make a frequency distribution of the variable Type.

```
# (1) Read the Cars93 data into E2_4.

E2_4 <- Cars93




# (2) Use head() to display the 7 rows and 7 columns of Cars93.

head(E2_4[1 : 7], 7)
```

```
##   Manufacturer   Model    Type Min.Price Price Max.Price MPG.city
## 1        Acura Integra   Small      12.9  15.9      18.8       25
## 2        Acura  Legend Midsize      29.2  33.9      38.7       18
## 3         Audi      90 Compact      25.9  29.1      32.3       20
## 4         Audi     100 Midsize      30.8  37.7      44.6       19
## 5          BMW    535i Midsize      23.7  30.0      36.2       22
## 6        Buick Century Midsize      14.2  15.7      17.3       22
## 7        Buick LeSabre   Large      19.9  20.8      21.7       19

# (3) Use the table() function to produce a frequency
# distribution of Type; assign result to fd.

fd <- table(E2_4$Type)




# (4) Examine the contents of fd.

fd

##
## Compact   Large Midsize   Small  Sporty     Van
##      16      11      22      21      14       9
```

The frequency distribution of Type shows that the 93 vehicles are distributed across six vehicle types: 22 vehicles are midsize, 21 are small, 16 are compact, 14 are sporty, 11 are large, and 9 are vans.

18. Make the relative frequency distribution of vehicle Type for the Cars93 data and assign the result to rfd. What percentage are large cars? Verify that all the proportions (percentages) add to 1.

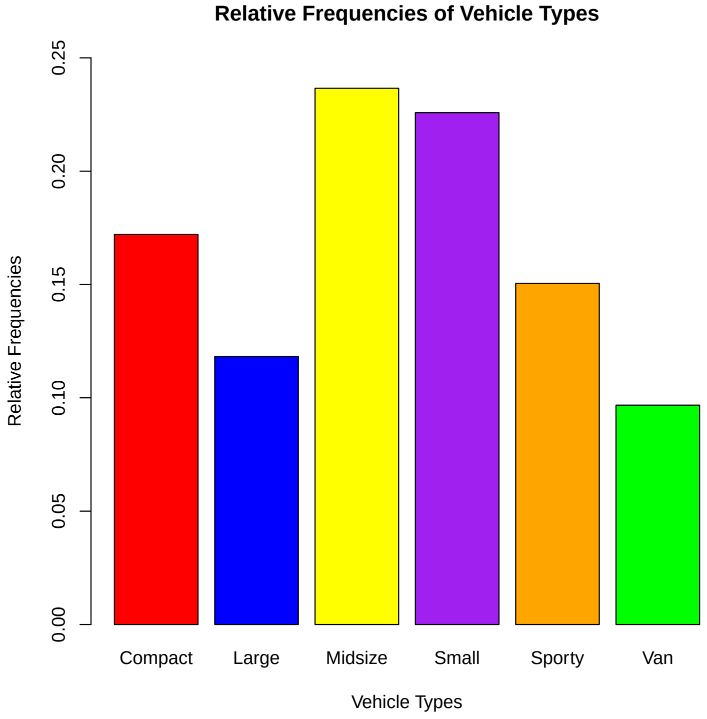
```
# (1) Divide frequency distribution by number of observations.
# Assign the result to the object named rfd.

rfd <- fd / nrow(E2_4)




# (2) To examine the contents of rfd.

rfd

##
```

```
## Compact   Large Midsize   Small  Sporty     Van
## 0.17204 0.11828 0.23656 0.22581 0.15054 0.09677

# (3) Check to make sure the proportions sum to 1.

sum(rfd)

## [1] 1
```

The proportion of large passenger vehicles in the `Cars93` data set is almost 0.12 (0.11828), or roughly 12%. When added up, the proportions sum to one.

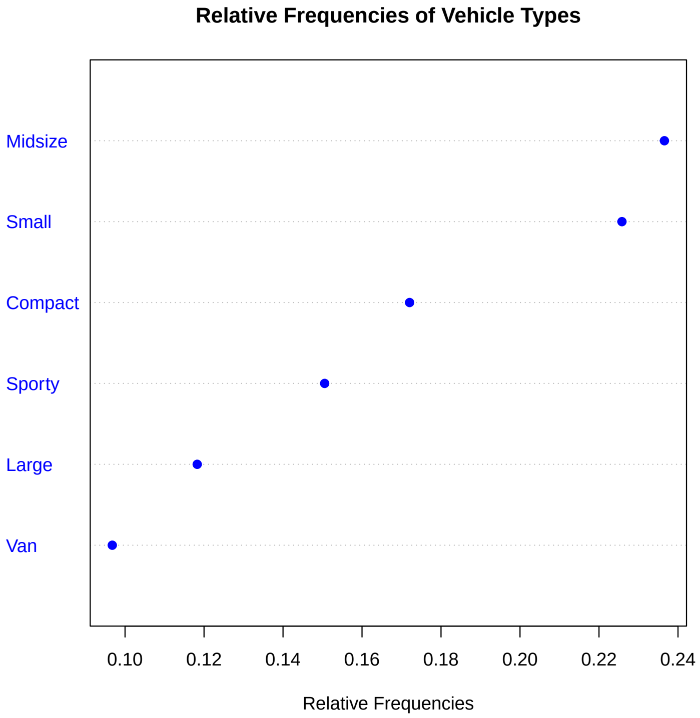
19. Make a bar graph of the relative frequencies of the `Type` variable in the `Cars93` data set. Define the colors of the bars, from left to right, as red, blue, yellow, purple, orange, and green. Set the range of the vertical axis to run between 0 and 0.25. Add "Vehicle Types" as a label for the horizontal axis, "Relative Frequencies" for the vertical axis. Finally, add "Relative Frequencies of Vehicle Types" as a title.

```
# Use the barplot() function to make a bar graph.

barplot(rfd,
        col = c('red', 'blue', 'yellow', 'purple', 'orange', 'green'),
        xlab = 'Vehicle Types',
        ylab = 'Relative Frequencies',
        main = 'Relative Frequencies of Vehicle Types',
        ylim = c(0, 0.25))
```



20. Make a dot plot of the relative frequencies of the `Type` variable in the `Cars93` data. Use the `sort()` function to rank order the vehicle types from most representative to least. Set the dot plot points as blue, and include "Relative Frequencies" as a label for the horizontal axis. Add "Relative Frequencies of Vehicle Types" as a title.

```
# Use the dotchart() function to make a dot plot.

dotchart(sort(rfd),
         main = 'Relative Frequencies of Vehicle Types',
         xlab = 'Relative Frequencies',
         pch = 19,
         col = 'blue')

## Warning in dotchart(sort(rfd), main = "Relative Frequencies of Vehicle
Types", : 'x' is neither a vector nor a matrix: using as.numeric(x)
```



21. Using the `Cars93` data, make a frequency distribution of the `Max.Price` variable (the maximum price for each of the 93 makes and models). Set the classwidth at 10, defining the lowest price range at or below $\$10,000$, the second-from-lowest price range from $\$10,000$ to $\$20,000$, up to the highest price range of $\$70,000$ to $\$80,000$. Comment on the distribution of prices across the 93 vehicles in `Cars93`.

```
# (1) Read data into the object brks.

brks <- c(0, 10, 20, 30, 40, 50, 60, 70, 80)
```

```
# (2) Use the cut() function to assign values in E2_4 to
# categories defined by brks: (0,10], (10,20], (20,30], (30,40],
# (40,50], (50,60], (60,70],and (70,80]; read this result into
# object named categ.

categ <- cut(E2_4$Max.Price, brks)




# (3) Use the table() function to make frequency distribution
# of data items in categ.  Read the result into object named fd.

fd <- table(categ)




# (4) Examine the contents of fd.
fd

## categ
##  (0,10] (10,20] (20,30] (30,40] (40,50] (50,60] (60,70] (70,80]
##       8      39      30      11       3       1       0       1
```

The frequency distribution indicates that only 5 vehicles have prices above $\$40,000$; 8 have prices at $\$10,000$ or below. Most vehicles, 69 of them, are priced in the $\$10,000$ to $\$30,000$ range.

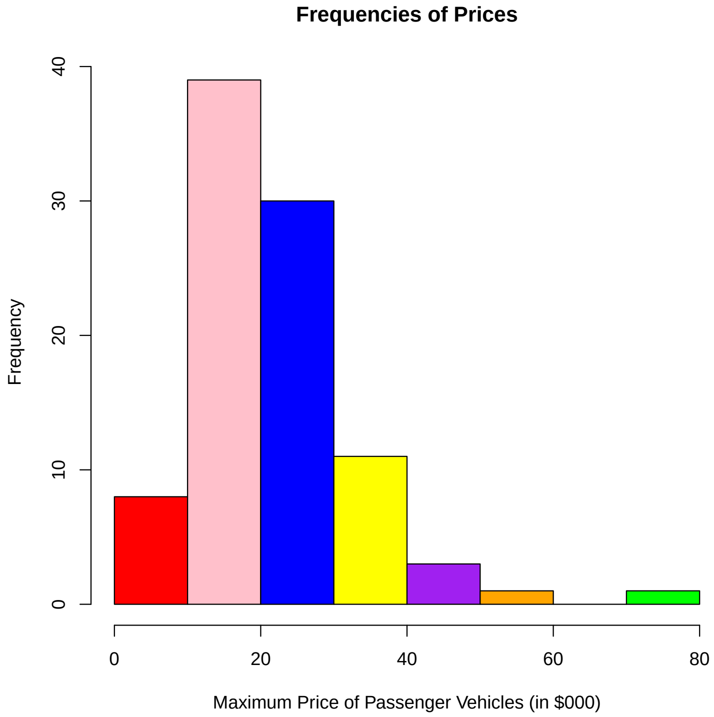
22. Find the relative frequencies of the `Max.Price` variable of the `Cars93` data. Comment on the price ranges, and make sure that the relative frequencies sum to one.

```
# (1) Create relative frequencies by dividing fd by total
# number of data values. Read the result into object named rfd.

rfd <- fd / sum(fd)




# (2) Examine contents of rfd.

rfd

## categ
##  (0,10] (10,20] (20,30] (30,40] (40,50] (50,60] (60,70] (70,80]
## 0.08602 0.41935 0.32258 0.11828 0.03226 0.01075 0.00000 0.01075

# (3) Check to make sure the relative frequencies sum to 1.

sum(rfd)

## [1] 1
```

From the relative frequencies, it is clear that nearly 75% of the maximum prices for all passenger vehicles in the `Cars93` data fall in the $10,000 to $30,000 range; just over 17% are priced over $30,000 while less than 9% come in at under $10,000. All frequencies sum to one.

23. Make a histogram of the frequencies of the `Max.Price` variable from the `Cars93` data. Set the colors for the histogram bars (running from left to right) as: red, pink, blue, yellow, purple, orange, grey, and green. Add "Maximum Price of Passenger Vehicles (in $000)" as a label for the horizontal axis; include the title "Frequencies of Prices." Include `breaks=8` as an argument of the `hist()` function.

```
# Use the hist() function with breaks=8.

hist(E2_4$Max.Price,
        breaks = 8,
        xlab = 'Maximum Price of Passenger Vehicles (in $000)',
        main = 'Frequencies of Prices',
        col = c('red', 'pink', 'blue', 'yellow', 'purple', 'orange',
                'grey','green'))
```



The frequency distribution as depicted by the histogram appears to be somewhat skewed (from the normal distribution) to the right. Two outliers appear, one at $80,000 (the Mercedes Benz 300E) and one at $50,400 (the Infiniti Q45).

24. Organize the `Cars93` data into a basic cross-tabulation table that reports vehicle `Type` against the country of `Origin`. In this particular sample, is it true that most of the large vehicles are of US-origin?

```
# (1) Use the table() function to create a cross-tabulation
# table of Type and Origin. Name the resulting object crosstab.

crosstab <- table(E2_4$Type, E2_4$Origin)




# (2) Exam the contents of crosstab.

crosstab

##
##            USA non-USA
##   Compact    7       9
##   Large     11       0
##   Midsize   10      12
##   Small      7      14
##   Sporty     8       6
##   Van        5       4
```

As the cross-tabulation table makes clear, all of the large vehicles are of US-origin.

25. Organize the Cars93 data into cross-tabulation with the variables Man.trans.avail (is a manual transmission available?) and Origin organized along the two margins.

```
# (1) Use the table() function to create a cross-tabulation
# table of Man.trans.avail and Origin. Assign result to crosstab.

crosstab <- table(E2_4$Man.trans.avail, E2_4$Origin)




# (2) Examine the contents of crosstab.

crosstab

##
##       USA non-USA
##   No   26       6
##   Yes  22      39
```

26. Add column and row totals to the cross-tabulation of Man.trans.avail and Origin of the Cars93 data. Are US vehicles more likely (than non-US vehicles) to offer buyers the option of a manual transmission?

```
# (1) Use the rowSums() function to get totals across rows of
# crosstab; name the result Totals.

Totals <- rowSums(crosstab)




# (2) Use the cbind() function to bind column Totals to
# crosstab; recycle the result into the object crosstab.

crosstab <- cbind(crosstab, Totals)




# (3) Use the colSums() function to get totals down columns of
# crosstab; name the result Totals.

Totals <- colSums(crosstab)
```

```r
# (4) Use the rbind() function to bind row Totals to crosstab;
# recycle the result into the object crosstab.

crosstab <- rbind(crosstab, Totals)



# (5) Examine the contents of crosstab.

crosstab
```

```
##         USA non-USA Totals
## No       26       6     32
## Yes      22      39     61
## Totals  48      45     93
```

The cross-tabulation table makes clear that a much larger proportion of vehicles offering buyers the option of a manual transmission are of non-US origin, 87% (or 39 of 45) to only 46% (or 22 of 48) for vehicles of US origin.

27. Organize the `Cars93` data into a cross-tabulation with variables `Max.Price` and `EngineSize`. Collapse the number of price categories to four—(0,20], (20,40], (40,60], and (60,80]—and the number of engine size categories (in liters of displacement) to three—(0,2], (2,4], and (4,6].

```r
# (1) Read data into the object brks.

brks <- c(0, 2, 4, 6)



# (2) Use the cut() function to assign values in E2_4
# (EngineSize) to categories defined by brks: (0,2], (2,4],
# and (4,6]; read this result into object named displacement.

displacement <- cut(E2_4$EngineSize, brks)



# (3) Read data into the object brks.
```

```
brks <- c(0, 20, 40, 60, 80)


# (4) Use the cut() function to assign values in E2_4
# (Max.Price) to categories defined by brks: (0,20], (20,40],
# (40,60], and (60,80]; read this result into object named price.

price <- cut(E2_4$Max.Price, brks)


# (5)  Use the table() function to create a cross-tabulation
# table of EngineSize and Max.Price. Name the table crosstab.

crosstab <- table(displacement, price)


# (6) Exam the contents of crosstab.

crosstab

##              price
## displacement (0,20] (20,40] (40,60] (60,80]
##        (0,2]     27       2       0       0
##        (2,4]     18      35       1       1
##        (4,6]      2       4       3       0
```

28. For the crosstabulation table of the `Cars93` data set (variables are `Max.Price` and `EngineSize`), rename the rows: `1 to 2 liters`, `2 to 4 liters`, and `4 to 6 liters`. Rename the columns: `Economy`, `Mid-Price`, `Higher-Price`, and `Luxury`.

```
# (1) Apply rownames() function to crosstab, incorporating
# the new row names: 1 to 2 liters, 2 to 4 liters, 4 to 6 liters.

rownames(crosstab) <- c( '1 to 2 liters', '2 to 4 liters',
        '4 to 6 liters')


# (2) Apply colnames() function to crosstab, incorporating
# the new column names: Economy, Mid-Price, Higher-Price, Luxury.
```

```
colnames(crosstab) <- c('Economy', 'Mid-Price', 'Higher-Price',
        'Luxury')




# (3) Examine contents of crosstab.

crosstab

##                 price
## displacement     Economy Mid-Price Higher-Price Luxury
##    1 to 2 liters      27         2            0      0
##    2 to 4 liters      18        35            1      1
##    4 to 6 liters       2         4            3      0
```

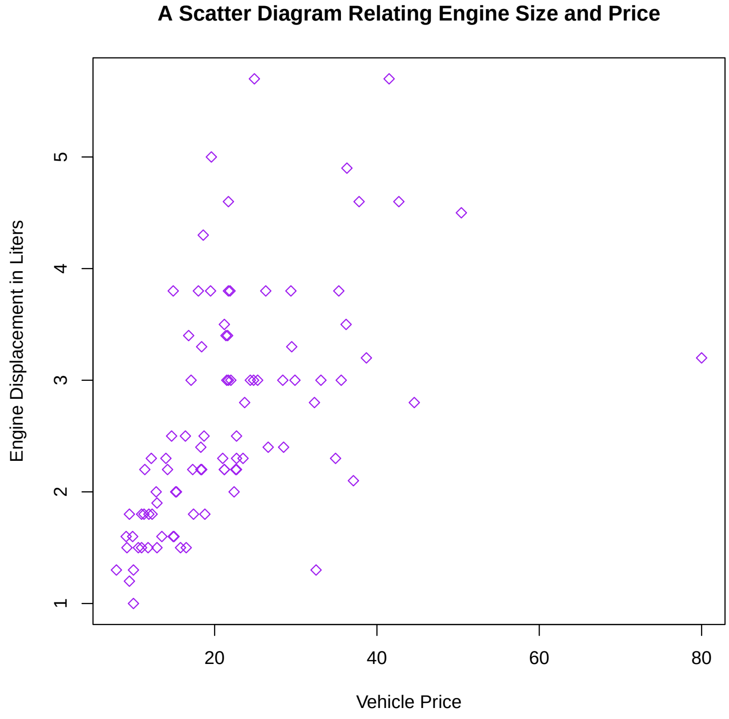
29. Add row and column totals to the cross-tabulation table of the `Cars93` data set where the variables are `Max.Price` and `EngineSize`.

```
# (1) Use the rowSums() function to get totals across rows of
# crosstab; name the result Totals.

Totals <- rowSums(crosstab)




# (2) Use the cbind() function to bind column Totals to crosstab;
# recycle the result into the object crosstab.

crosstab <- cbind(crosstab, Totals)




# (3) Use the colSums() function to get totals down columns of
# crosstab; name the result Totals.

Totals <- colSums(crosstab)




# (4) Use the rbind() function to bind row Totals to crosstab;
# recycle the result into the object crosstab.

crosstab <- rbind(crosstab, Totals)
```

```
# (5) Examine the contents of crosstab.

crosstab

##                Economy Mid-Price Higher-Price Luxury Totals
## 1 to 2 liters       27         2            0      0     29
## 2 to 4 liters       18        35            1      1     55
## 4 to 6 liters        2         4            3      0      9
## Totals              47        41            4      1     93
```

30. Using the `Cars93` data, make a scatter plot to show the relationship between `EngineSize` and `Max.Price`. Add `A Scatter Diagram Relating Engine Size and Price` as a title; define the axes as `Vehicle Price` and `Engine Displacement in Liters`. Comment on the relationship between the two variables.

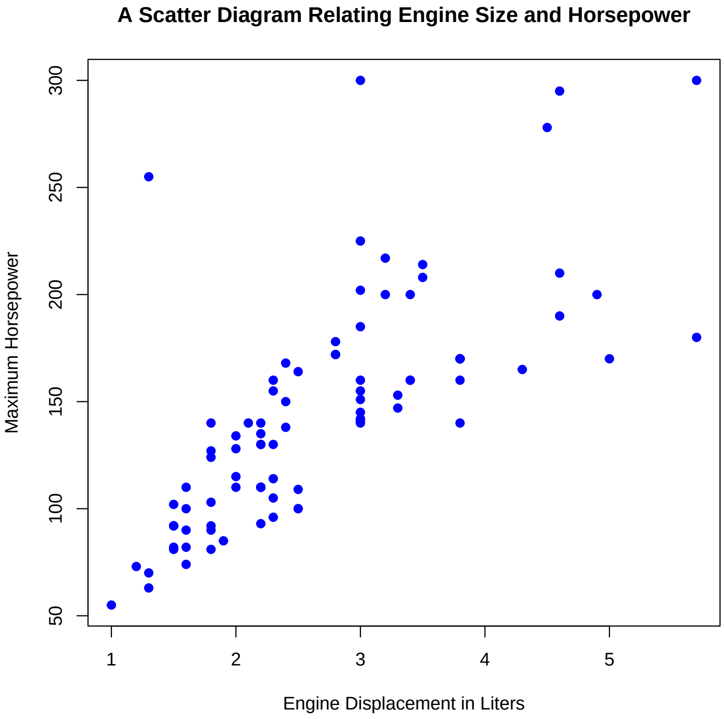
```
# Use the plot() function with Max.Price on the horizontal
# axis and EngineSize on the vertical.

plot(E2_4$Max.Price, E2_4$EngineSize,
      main = 'A Scatter Diagram Relating Engine Size and Price',
      pch = 23,
      col = 'purple',
      ylab = 'Engine Displacement in Liters',
      xlab = 'Vehicle Price')
```



In general, there appears to be a positive relationship between engine size and price: engine size is (roughly) positively related to vehicle price.

31. Construct a scatter plot (using the Cars93 data) of two variables: EngineSize (in liters of displacement) against Horsepower (maximum horsepower). Add label names Maximum Horsepower and Engine Displacement in Liters to the vertical and horizontal axes, respectively. Also include A Scatter Diagram Relating Engine Size and Horsepower as a title; set blue as the plotting character color. Comment on the relationship.

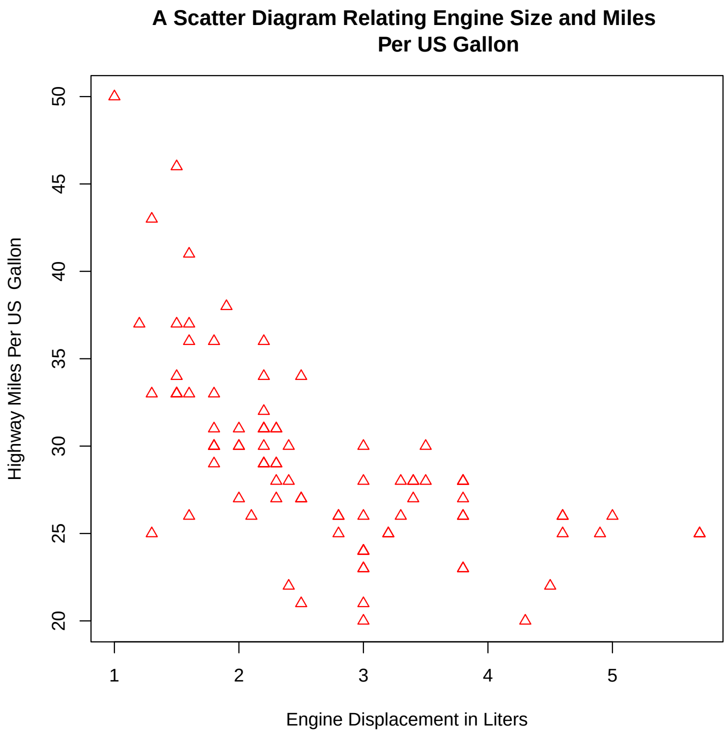
```
# Use the plot() function with EngineSize on the horizontal
# axis and Horsepower on the vertical.

plot(E2_4$EngineSize, E2_4$Horsepower,
      main = 'A Scatter Diagram Relating Engine Size and Horsepower',
      xlab = 'Engine Displacement in Liters',
      ylab = 'Maximum Horsepower',
      pch = 19,
      col = 'blue')
```



As expected, these two variables are positively and linearly related: in general, the larger the engine, the greater the horsepower.

32. Using the Cars93 data, make a scatter plot of EngineSize (in liters displacement) against MPG.highway (highway miles per US gallon). Add label names to the horizontal and vertical axes as well as a main title. Comment on the relationship.

```
# Use plot() function with EngineSize on the horizontal
# axis and MPG.highway on the vertical.

plot(E2_4$EngineSize, E2_4$MPG.highway,
      main = 'A Scatter Diagram Relating Engine Size and Miles
              Per US Gallon',
      xlab = 'Engine Displacement in Liters',
      ylab = 'Highway Miles Per US  Gallon',
      pch = 24,
      col = 'red')
```

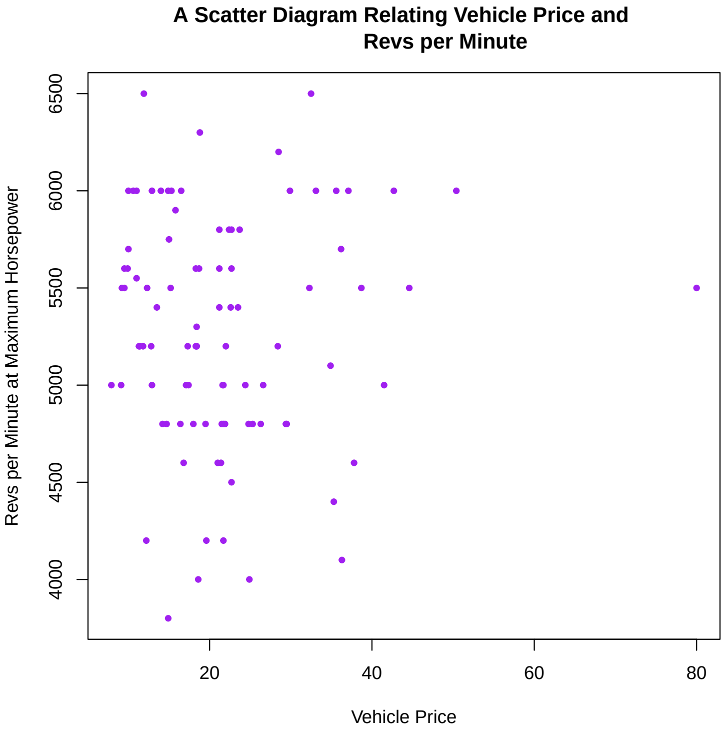


Unsurprisingly, the two variables are negatively (and somewhat linearly) related: in general, the larger the engine size, the lower the gasoline mileage.

33. Making further use of the `Cars93` data, create a scatter plot showing the relationship of `Max.Price` and `RPM` (revolutions per minute). Are these two variables related in a positive or negative manner? Or do they appear to be unrelated? Add the labels `Revs per Minute at Maximum Horsepower` and `Vehicle Price` to the vertical and horizontal axes, respectively. Include `A Scatter Diagram Relating Vehicle Price and Revs per Minute` as a title. Set purple as the plotting character color.

```
# Use the plot() function with Max.Price on the horizontal
# axis and RPM on the vertical.

plot(E2_4$Max.Price, E2_4$RPM,
      main = 'A Scatter Diagram Relating Vehicle Price and
```

```
             Revs per Minute',
     ylab = 'Revs per Minute at Maximum Horsepower',
     xlab = 'Vehicle Price',
     pch = 20,
     col = 'purple')
```



Since there is no reason to suspect that these two particular variables are related, either positively or negatively, we are not surprised to see this cloud of data points.