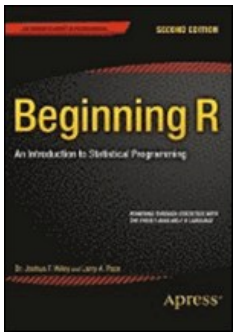


Beginning R: An Introduction to Statistical Programming, Second Edition

by Joshua F. Wiley and Larry A. Pace

Chapter 2: Dealing with Dates, Strings, and Data Frames

Overview

The world of data and data analytics is changing rapidly. Data analysts are facing major issues related to the use of larger datasets, including cloud computing and the creation of so-called data lakes, which are enterprise-wide data management platforms consisting of vast amounts of data in their original format stored in an single unmanaged and unstructured location available to the entire organization. This flies in the face of the carefully structured and highly managed data most of us have come to know and love.

Data lakes solve the problem of independently managed information silos (an old problem in information technology), and the newer problem of dealing with Big Data projects, which typically require large amounts of highly varied data. If you are particularly interested in using R for cloud computing, I recommend Ajay Ohri's book `R for Cloud Computing: An Approach for Data Scientists`. We will touch lightly on the issues of dealing with R in the cloud and with big (or at least bigger) data in subsequent chapters.

You learned about various data types in Chapter 1. To lay the foundation for discussing some ways of dealing with real-world data effectively, we first discuss working with dates and times and then discuss working with data frames in more depth. In later chapters, you will learn about data tables, a package that provides a more efficient way to work with large datasets in R.

2.1 Working with Dates and Times

Dates and times are handled differently by R than other data. Dates are represented as the number of days since January 1, 1970, with negative numbers representing earlier dates. You can return the current date and time by using the `date()` function and the current day by using the `Sys.Date()` function:

```
> date ()
[1] "Fri Dec 26 07:00:28 2014 "
> Sys . Date ()
[1] " 2014 -12 -26 "
```

By adding symbols and using the `format()` command, you can change how dates are shown. These symbols are as follows:

- %d The day as a number
- %a Abbreviated week day
- %A Unabbreviated week day
- %b Abbreviated month
- %B Unabbreviated month
- %y Two-digit year
- %Y Four-digit year

See the following example run by the author on 1 January 2015. Notice the use of `cat()` to concatenate and output the desired objects:

```
> today <- Sys . Date ()
> cat ( format (today, format = "%A, %B %d, %Y")," Happy New Year !", "\n")
Thursday,January 01, 2015 Happy New Year !
```

2.2 Working with Strings

You have already seen character data, but let's spend some time getting familiar with how to manipulate strings in R. This is a good precursor to our more detailed discussion of text mining later on. We will look at how to get string data into R, how to manipulate such data, and how to format string data to maximum advantage. Let's start with a quote from a famous statistician, R. A. Fisher:

> *The null hypothesis is never proved or established, but is possibly disproved, in the course of experimentation. Every experiment may be said to exist only to give the facts a chance of disproving the null hypothesis." R. A. Fisher*

Although it would be possible to type this quote into R directly using the console or the R Editor, that would be a bit clumsy and error-prone. Instead, we can save the quote in a plain text file. There are many good text editors, and I am using Notepad++. Let's call the file "fishersays.txt" and save it in the current working directory:

```
> dir ()
[1] " fishersays . txt " " mouse _ weights _ clean . txt"
[3] " mouseSample . csv " " mouseWts . rda "
[5] " zScores . R"
```

You can read the entire text file into R using either `readLines()` or `scan()`. Although `scan()` is more flexible, in this case a text file consisting of a single line of text with a "carriage return" at the end is very easy to read into R using the `readLines()` function:

```
> fisherSays <- readLines ("fishersays.txt")
> fisherSays
[1] "The null hypothesis is never proved or established, but is possibly disproved,
    in the course of experimentation . Every experiment may be said to exist only to
    give the facts a chance of disproving the null hypothesis . R. A. Fisher "
>
```

Note that I haven't had to type the quote at all. I found the quote on a statistics quotes web page, copied it, saved it into a text file, and then read it into R.

As a statistical aside, Fisher's formulation did not (ever) require an alternative hypothesis. Fisher was a staunch advocate of declaring a null hypothesis that stated a certain population state of affairs, and then determining the probability of obtaining the sample results (what he called facts), assuming that the null hypothesis was true. Thus, in Fisher's formulation, the absence of an alternative hypothesis meant that Type II errors were simply ignored, whereas Type I errors were controlled by establishing a reasonable significance level for rejecting the null hypothesis. We will have much more to discuss about the current state and likely future state of null hypothesis significance testing (NHST), but for now, let's get back to strings.

A regular expression is a specific pattern in a string or a set of strings. R uses three types of such expressions:

- Regular expressions
- Extended regular expressions
- Perl-like regular expressions

The functions that use regular expressions in R are as follows (see Table 2-1). You can also use the `glob2rx()` function to create specific patterns for use in regular expressions. In addition to these functions, there are many extended regular expressions, too many to list here. We can search for specific characters, digits, letters, and words. We can also use functions on character strings as we do with numbers, including counting the number of characters, and indexing them as we do with numbers. We will continue to work with our quotation, perhaps making Fisher turn over in his grave by our alterations.

Table 2-1: R Functions that use regular expressions

Purpose	Function	Explanation
Substitution	`sub()`	Both `sub()` and `gsub()` are used to make substitutions in a string
Extraction	`grep()`	Extract some value from a string
Detection	`grepl()`	Detect the presence of a pattern

The simplest form of a regular expression are ones that match a single character. Most characters, including letters and digits, are also regular expressions. These expressions match themselves. R also includes special reserved characters called metacharacters in the extended regular expressions. These have a special status, and to use them, you must use a double backslash \\to escape these when you need to use them as literal characters. The reserved characters are `.`, `\`, `|`, `(`, `)`, `[`, `{`, `$`, `*`, `+`, and `?`.

Let us pretend that Jerzy Neyman actually made the quotation we attributed to Fisher. This is certainly not true, because Neyman and Egon Pearson formulated both a null and an alternative hypothesis and computed two probabilities rather than one, determining which hypothesis had the higher probability of having generated the sample data. Nonetheless, let's make the substitution. Before we do, however, look at how you can count the characters in a string vector. As always, a vector with one element has an index of `[1]`, but we can count the actual characters using the `nchar()` function:

```
> length ( fisherSays )
[1] 1
> nchar ( fisherSays )
[1] 230
sub ("R. A. Fisher", "Jerzy Neyman", fisherSays )
[1] "The null hypothesis is never proved or established, but is possibly disproved, in the
course of experimentation. Every experiment may be said to exist only to give the facts a
chance of disproving the null hypothesis." Jerzy Neyman"
```

2.3 Working with Data Frames in the Real World

Data frames are the workhorse data structure for statistical analyses. If you have used other statistical packages, a data frame will remind you of the data view in SPSS or of a spreadsheet. Customarily, we use columns for variables and rows for units of analysis (people, animals, or objects). Sometimes we need to change the structure of the data frame to accommodate certain situations, and you will learn how to stack and unstack data frames as well as how to recode data when you need to.

There are many ways to create data frames, but for now, let's work through a couple of data frames built into R. The data frame comes from the 1974 *Motor Trend* US Magazine, and contains miles per gallon, number of cylinders, displacement, gross horsepower, rear axle ratio, weight, quarter mile time in seconds, 'V' or Straight engine, transmission, number of forward gears, and number of carburetors.

The complete dataset has 32 cars and 10 variables for each car. We will also learn how to find specific rows of data:

```
> str(mtcars)
'data.frame': 32 obs. of 11 variables:
 $ mpg : num  21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
 $ cyl : num  6 6 4 6 8 6 8 4 4 6 . . .
 $ disp: num  160 160 108 258 360 . . .
 $ hp  : num  110 110 93 110 175 105 245 62 95 123 . . .
 $ drat: num  3.9 3.9 3.85 3.08 3.15 2.76 3.21 3.69 3.92 3.92 . . .
 $ wt  : num  2.62 2.88 2.32 3.21 3.44 . . .
 $ qsec: num  16.5 17 18.6 19.4 17 . . .
 $ vs  : num  0 0 1 1 0 1 0 1 1 1 . . .
 $ am  : num  1 1 1 0 0 0 0 0 0 0 . . .
 $ gear: num  4 4 4 3 3 3 3 4 4 4 . . .
 $ carb: num  4 4 1 1 2 1 4 2 2 4 . . .

> summary(mtcars $ mpg)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  10.40   15.42  19.20    20.09   22.80   33.90

> summary mtcars $ wt)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  1.513   2.581   3.325   3.217   3.610   5.424
```

To refer to a given column in a data fame, you can use either indexing or the $ operator with the data frame name followed by the variable name. Because data frames have both rows and columns, you must use indexes for both the row and the column. To refer to an entire row or an entire column, you can use a comma, as you can with a matrix. To illustrate, the rear axle ratio variable is the fifth column in the data frame. We can refer to this column in two ways. We can use the `dataset$variable` notation `mtcars $ drat`, or we can equivalently use matrix-type indexing, as in `[, 5]` using the column number. The `head( )` function returns the first part or parts of a vector, matrix, data frame, or function, and is useful for a quick "sneak preview":

```
> head( mtcars $ drat)
[1] 3.90 3.90 3.85 3.08 3.15 2.76

> head( mtcars [,5] )
[1] 3.90 3.90 3.85 3.08 3.15 2.76
```

2.3.1 Finding and Subsetting Data

Sometimes, it is helpful to locate in which row a particular set of data may be. We can find the row containing a particular value very easily using the `which( )` function:

```
> which ( mtcars $ hp >= 300)
[1] 31
> mtcars [31 ,]
             mpg cyl disp  hp  drat    wt qsec vs am gear carb
Maserati Bora  15   8  301 335  3.54  3.57 14.6  0  1    5    8
```

Suppose the Maserati's horsepower need to be recoded to NA because it turns out there was an error in recording the data (note: this occurs on occasion in real world data), just do the following:

```
mtcars $ hp [ mtcars $ hp >= 300] <- NA
> mtcars [31 ,]
             mpg cyl disp hp drat   wt qsec vs am gear carb
Maserati Bora  15   8  301 NA 3.54 3.57 14.6  0  1    5    8
```

With the one observation recoded to missing, a histogram of the horsepower data is shown (see Figure 2-1):

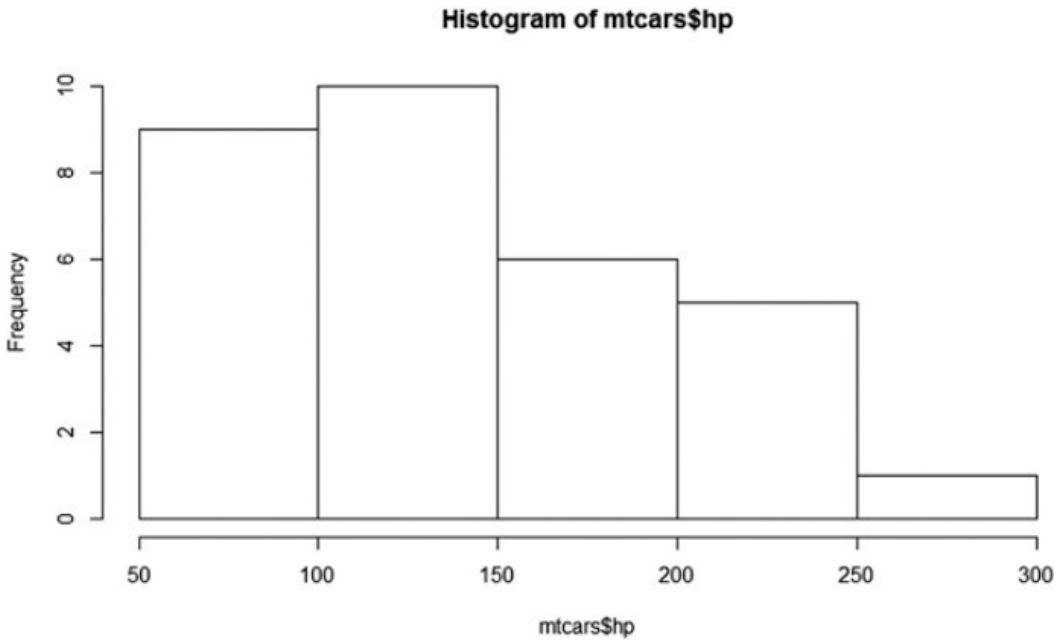


Figure 2-1: Car horsepower (with Maserati removed) vs frequency

The data frame indexing using square brackets is similar to that of a matrix. As with vectors, we can use the colon separator to refer to ranges of columns or rows. For example, say that we are interested in reviewing the car data for vehicles with manual transmission. Here is how to subset the data in R. Attaching the data frame makes it possible to refer to the variable names directly, and thus makes the subsetting operation a little easier. As you can see, the resulting new data frame contains only the manual transmission vehicles:

```
> attach ( mtcars )
> mpgMan <- subset ( mtcars , am == 1, select = mpg : disp )
> summary ( mpgMan $ mpg)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  15.00   21.00   22.80   24.39   30.40   33.90
```

You can remove a column in a data frame by assigning it the special value `NULL`. For this illustration, let us use a small sample of the data. We will remove the displacement variable. First, recall the data frame:

```
> mpgMan
                  mpg cyl  disp
Mazda RX4        21.0   6 160.0
Mazda RX4 Wag    21.0   6 160.0
Datsun 710       22.8   4 108.0
Fiat 128         32.4   4  78.7
Honda Civic      30.4   4  75.7
Toyota Corolla   33.9   4  71.1
Fiat X1-9        27.3   4  79.0
Porsche 914-2    26.0   4 120.3
Lotus Europa     30.4   4  95.1
Ford Pantera L   15.8   8 351.0
Ferrari Dino     19.7   6 145.0
Maserati Bora    15.0   8 301.0
Volvo 142E       21.4   4 121.0
```

Now, simply type the following to remove the variable, and note that the `disp` variable is no longer part of the data frame. Also, don't try this at home unless you make a backup copy of your important data first.

```
> mpgMan $ disp <- NULL
> mpgMan
                 mpg cyl
Mazda RX4       21.0   6
Mazda RX4 Wag   21.0   6
Datsun 710      22.8   4
Fiat 128        32.4   4
Honda Civic     30.4   4
Toyota Corolla  33.9   4
Fiat X1-9       27.3   4
Porsche 914-2   26.0   4
Lotus Europa    30.4   4
Ford Pantera L  15.8   8
```

```
Ferrari Dino    19.7   6
Maserati Bora   15.0   8
Volvo 142E      21.4   4
```

We can add a new variable to a data frame simply by creating it, or by using the `cbind()` function. Here's a little trick to make up some data quickly. I used the `rep()` function (for replicate) to generate 15 "observations" of the color of the vehicle. First, I created a character vector with three color names, then I replicated the vector five times to fabricate my new variable. By defining it as `mpgMan$colors`, I was able to create it and add it to the data frame at the same time. Notice I only used the first 13 entries of colors as `mpgMan` only has 13 manual vehicles:

```
colors <- c(" black ", " white ", " gray ")
> colors <- rep (colors, 5)
> mpgMan $ colors <- colors[1:13]
> mpgMan
                 mpg  cyl  colors
Mazda RX4       21.0    6  black
Mazda RX4 Wag   21.0    6  white
Datsun 710      22.8    4   gray
Fiat 128        32.4    4  black
Honda Civic     30.4    4  white
Toyota Corolla 33.9    4   gray
Fiat X1-9       27.3    4  black
Porsche 914-2   26.0    4  white
Lotus Europa    30.4    4   gray
Ford Pantera L 15.8    8  black
Ferrari Dino    19.7    6  white
Maserati Bora   15.0    8   gray
Volvo 142E      21.4    4  black
```

2.4 Manipulating Data Structures

Depending on the required data analysis, we sometimes need to restructure data by changing narrow format data to wide-format data, and vice versa. Let's take a look at some ways data can be manipulated in R. Wide and narrow data are often referred to as unstacked and stacked, respectively. Both can be used to display tabular data, with wide data presenting each data value for an observation in a separate column. Narrow data, by contrast, present a single column containing all the values, and another column listing the "context" of each value. Recall our roster data from Chapter 1.

It is easier to show this than it is to explain it. Examine the following code listing to see how this works. We will start with a narrow or stacked representation of our data, and then we will unstack the data into the more familiar wide format:

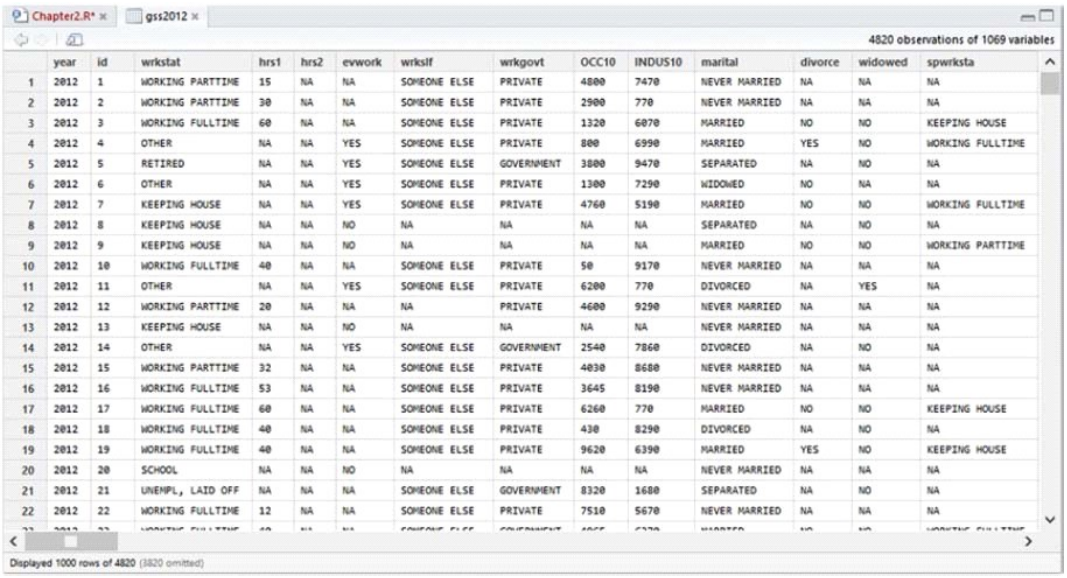
```
> roster <- read.csv("roster.csv")
> sportsExample <- c("Jersey", "Class")
> stackedData <- roster [ sportsExample ]
> stackedData
   Jersey     Class
1       0  freshman
2       1 sophomore
3       3    junior
4       5 sophomore
5      10  freshman
6      12    senior
7      15  freshman
8      20    junior
9      21    senior
10     33    junior
11     35    junior
12     44    junior
13     50 sophomore
> unstack(stackedData)
$freshman
[1]  0 10 15

$junior
[1]  3 20 33 35 44

$senior
[1] 12 21

$sophomore
[1]  1  5 50
```

2.5 The Hard Work of Working with Larger Datasets

As I have found throughout my career, real-world data present many challenges. Datasets often have missing values and outliers. Real data distributions are rarely normally distributed. The majority of the time I have spent with data analysis has been in preparation of the data for subsequent analyses, rather than the analysis itself. Data cleaning and data munging are rarely included as a subject in statistics classes, and included datasets are generally either fabricated or scrubbed squeaky clean.

The General Social Survey (GSS) has been administered almost annually since 1972. One commentator calls the GSS "America's mood ring." The data for 2012 contain the responses to a 10-word vocabulary test. Each correct and incorrect responses are labeled as such, with missing data coded as NA. The GSS data are available in SPSS and STATA format, but not in R format. I downloaded the data in SPSS format and then use the R library `foreign` to read that into R as follows. As you learned earlier, the `View` function allows you to see the data in a spreadsheet-like layout (see Figure 2-2):

```
> library(foreign)
> gss2012 <- read.spss("GSS2012merged_R5.sav", to.data.frame = TRUE)
> View(gss2012)
```



	year	id	wrkstat	hrs1	hrs2	evwork	wrkslf	wrkgovt	OCC10	INDUS10	marital	divorce	widowed	spwrksta
1	2012	1	WORKING PARTTIME	15	NA	NA	SOMEONE ELSE	PRIVATE	4800	7470	NEVER MARRIED	NA	NA	NA
2	2012	2	WORKING PARTTIME	30	NA	NA	SOMEONE ELSE	PRIVATE	2900	770	NEVER MARRIED	NA	NA	NA
3	2012	3	WORKING FULLTIME	60	NA	NA	SOMEONE ELSE	PRIVATE	1320	6070	MARRIED	NO	NO	KEEPING HOUSE
4	2012	4	OTHER	NA	NA	YES	SOMEONE ELSE	PRIVATE	800	6990	MARRIED	YES	NO	WORKING FULLTIME
5	2012	5	RETIRED	NA	NA	YES	SOMEONE ELSE	GOVERNMENT	3800	9470	SEPARATED	NA	NO	NA
6	2012	6	OTHER	NA	NA	YES	SOMEONE ELSE	PRIVATE	1300	7290	WIDOWED	NO	NA	NA
7	2012	7	KEEPING HOUSE	NA	NA	YES	SOMEONE ELSE	PRIVATE	4760	5190	MARRIED	NO	NO	WORKING FULLTIME
8	2012	8	KEEPING HOUSE	NA	NA	NO	NA	NA	NA	NA	SEPARATED	NA	NO	NA
9	2012	9	KEEPING HOUSE	NA	NA	NO	NA	NA	NA	NA	MARRIED	NO	NO	WORKING PARTTIME
10	2012	10	WORKING FULLTIME	40	NA	NA	SOMEONE ELSE	PRIVATE	50	9170	NEVER MARRIED	NA	NA	NA
11	2012	11	OTHER	NA	NA	YES	SOMEONE ELSE	PRIVATE	6200	770	DIVORCED	NA	YES	NA
12	2012	12	WORKING PARTTIME	20	NA	NA	NA	PRIVATE	4600	9290	NEVER MARRIED	NA	NA	NA
13	2012	13	KEEPING HOUSE	NA	NA	NO	NA	NA	NA	NA	NEVER MARRIED	NA	NA	NA
14	2012	14	OTHER	NA	NA	YES	SOMEONE ELSE	GOVERNMENT	2540	7860	DIVORCED	NA	NO	NA
15	2012	15	WORKING PARTTIME	32	NA	NA	SOMEONE ELSE	PRIVATE	4030	8680	NEVER MARRIED	NA	NA	NA
16	2012	16	WORKING FULLTIME	53	NA	NA	SOMEONE ELSE	PRIVATE	3645	8190	NEVER MARRIED	NA	NA	NA
17	2012	17	WORKING FULLTIME	60	NA	NA	SOMEONE ELSE	PRIVATE	6260	770	MARRIED	NO	NO	KEEPING HOUSE
18	2012	18	WORKING FULLTIME	40	NA	NA	SOMEONE ELSE	PRIVATE	430	8290	DIVORCED	NA	NO	NA
19	2012	19	WORKING FULLTIME	40	NA	NA	SOMEONE ELSE	PRIVATE	9620	6390	MARRIED	YES	NO	KEEPING HOUSE
20	2012	20	SCHOOL	NA	NA	NO	NA	NA	NA	NA	NEVER MARRIED	NA	NA	NA
21	2012	21	UNEMPL, LAID OFF	NA	NA	NA	SOMEONE ELSE	GOVERNMENT	8320	1680	SEPARATED	NA	NO	NA
22	2012	22	WORKING FULLTIME	12	NA	NA	SOMEONE ELSE	PRIVATE	7510	5670	NEVER MARRIED	NA	NA	NA

Figure 2-2: Viewing the GSS dataset

Here's a neat trick: The words are in columns labeled "worda", "wordb',' . . ., "word]" I want to subset the data, as we discussed earlier, to keep from having to work with the entire set of 1069 variables and 4820 observations. I can use R to make my list of variable names without having to type as much as you might suspect. Here's how I used the `paste0` function and the built-in `letters` function to make it easy. There is an acronym among computer scientists called DRY that was created by Andrew Hunt and David Thomas: "Don't repeat yourself." According to Hunt and Thomas, pragmatic programmers are early adopters, fast adapters, inquisitive, critical thinkers, realistic, and jacks of all trades:

```
> myWords <- paste0 ("word", letters [1:10])
> myWords
 [1] "worda" "wordb" "wordc" "wordd" "worde" "wordf" "wordg" "wordh" "wordi" "wordj"
> vocabTest <- gss2012 [ myWords ]
> head ( vocabTest )
    worda   wordb     wordc   wordd   worde   wordf     wordg     wordh   wordi     wordj
1 CORRECT CORRECT INCORRECT CORRECT CORRECT CORRECT INCORRECT INCORRECT CORRECT   CORRECT
2    <NA>    <NA>      <NA>    <NA>    <NA>    <NA>      <NA>      <NA>    <NA>      <NA>
3    <NA>    <NA>      <NA>    <NA>    <NA>    <NA>      <NA>      <NA>    <NA>      <NA>
4 CORRECT CORRECT   CORRECT CORRECT CORRECT CORRECT   CORRECT   CORRECT CORRECT INCORRECT
5 CORRECT CORRECT INCORRECT CORRECT CORRECT CORRECT INCORRECT      <NA> CORRECT INCORRECT
6 CORRECT CORRECT   CORRECT CORRECT CORRECT CORRECT   CORRECT      <NA> CORRECT INCORRECT
```

We will also apply the DRY principle to our analysis of our subset data. For each of the words, it would be interesting to see how many respondents were correct versus incorrect. This is additionally interesting because we have text rather than numerical data (a frequent enough phenomena in survey data). There are many ways perhaps to create the proportions we seek, but let us explore one such path. Of note here is that we definitely recommend using the top left Rscript area of Rstudio to type in these functions, then selecting that code and hitting `<Ctrl>` + R to run it all in the console.

First, some exploration of a few new functions. The `table()` function creates a contingency table with a count of each combination of factors. Secondly, note the output of `myWords[1]`. Keeping in mind the DRY principle, notice the difference between our first use of `table` versus the second use. It seems a little changed, no? And yet, if we wanted to get counts for each of our words a through j, the second is much more powerful if we could simply find a way to increase that counter by 1 each time we ran the code.

```
> myWords[1]
```

```
[1] "worda"

> table(vocabTest[, "worda"], useNA = "ifany")

INCORRECT  CORRECT  <NA>
      515     2619  1686
> table(vocabTest[, myWords[1]], useNA = "ifany")

INCORRECT  CORRECT  <NA>
      515     2619  1686
```

Thinking of increasing a counter by 1 and repeating several times is called *looping*, and we will explore looping more later. For now, we'll secretly loop via `lapply` to apply `table` to the entire dataset. Our goal is to count all corrects/incorrects at once, rather than doing it piecemeal by typing in the same commands repeatedly and just changing variable names. Also, while headcounts are nice enough, we generally see such data summarized via proportions. Let's work our way backward. At the end, we use `do.call` to use the `rbind` function on the `percents` of each word correct vs incorrect; `do.call` simply runs `rbind` on *each* `percents` value in sequence - more looping! The `rbind` function is used to simply make it all look pretty (consider typing in `percents` into your Rstudio console *after* running the below code to see why `rbind` is so helpful). Before we could do that, we needed to build up `percents`, which we did by running a proportion table to create those percents. Since we want a proportion table for *each* word, we use `lapply` on our dataset. Of course, the above tables we had created for just `worda` were not enough, so we had to create each `table`, take a `prop.table` of their data, store all proportion data into `percents`, and finally make it all look good as we've done on the next page:

```
> proportion.table <- function(x) {
+   prop.table( table( x ) )
+ }
>
> percents <- lapply(vocabTest, proportion.table)
>
> do.call(rbind, percents)
       INCORRECT   CORRECT
worda 0.16432674 0.8356733
wordb 0.06868752 0.9313125
wordc 0.76188761 0.2381124
wordd 0.04441624 0.9555838
worde 0.17356173 0.8264383
wordf 0.18032787 0.8196721
wordg 0.65165877 0.3483412
wordh 0.63088235 0.3691176
wordi 0.23732057 0.7626794
wordj 0.71540984 0.2845902
```

The GSS dataset also has a variable for the total score on the vocabulary test, which is simply the sum of the number of words defined correctly. We have added that to the data frame using the `cbind` function. I won't show all the steps here, but will show you after all the recoding of missing data that the distribution of scores on the vocabulary test is negatively skewed but pretty "normal-looking" by the eyeball test (see Figure 2-3).

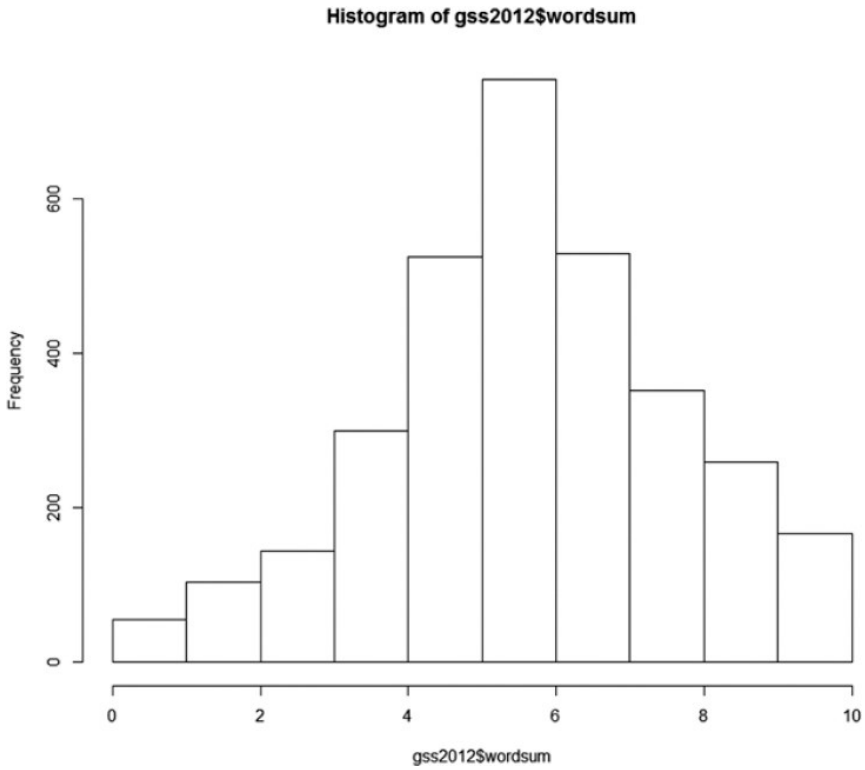


Figure 2-3: Histogram of scores on the 10-word vocabulary test