Chapter 3

Basic Data Wrangling in R

Whether we call it data wrangling, data management, data munging, or even data manipulation, the ability to transform data into a format suitable for analysis is an incredibly valuable skill. But as data has increased in size, the skills associated with this process have changed. In the 1990s, pioneers in what we now call data science were making meaningful contributions to a wide range of fields using spreadsheets. Today, data scientists write code to do most of their data wrangling. What has brought about this transition?

Consider the evolution of baseball analytics (often called *sabermetrics*), which in many ways mirrors the evoluation of analytics in other domains. The *use* of statistics in baseball has a long and storied history – in part because the game itself is naturally discrete, and in part because Henry Chadwick began publishing boxscores in the early 1900s [107]. For these reasons, a rich catalog of baseball data began to accumulate. However, while more and more baseball data was piling up, *analysis* of that data was not so prevalent. That is, the extant data provided a means to keep records, and as a result some numerical elements of the game's history took on a life of their own (e.g. Babe Ruth's 714 home runs). But it's not as clear how much people were learning about the game of baseball from the data. Knowing that Babe Ruth hit more home runs than Mel Ott tells us something about two players, but doesn't provide any insight into the nature of the game itself.

In 1947 – Jackie Robinson's rookie season – Brooklyn Dodgers' GM Branch Rickey made another significant innovation: he hired Allan Roth to be baseball's first statistical analyst. Roth's *analysis* of baseball data led to insights that the Dodgers used to win more games. In particular, Roth convinced Rickey that a measurement of how often a batter reaches first base via any means (e.g. hit, walk, or being hit by the pitch) was a better indicator of that batter's value than how often he reaches first base via a hit (which was – and probably still is – the most commonly-cited batting statistic). The logic supporting this insight was based on both Roth's understanding of the game of baseball (what we call *domain knowledge*) and his statistical analysis of baseball data.

During the next 50 years, many important contributions to baseball analytics were made by a variety of people (most notably "The Godfather of Sabermetrics" Bill James [57]), most of whom had little formal training in statistics, and for most of whom, the weapon of choice was a spreadsheet. They were able to use their creativity, domain knowledge, and a keen sense of what the interesting questions were, in order to make interesting discoveries.

But the 2002 publication of *Moneyball* [73] – which showcased how Billy Beane and Paul DePodesta used statistical analysis to run the Oakland A's – triggered a revolution in how front offices in baseball were managed [11]. Over the next decade, the size of the data expanded so rapidly that a spreadsheet was no longer a viable mechanism for storing – let alone analyzing – all of the available data. Today, more than a handful of teams have research and development groups headed by people with Ph.D.'s in statistics or computer science along with graduate training in machine learning [10].

Thus, the contributions made by the next generation of baseball analysts will *require* coding ability. While the creativity and domain knowledge that fueled the work of Allan Roth and Bill James will remain necessary traits, they are no longer sufficient. And yet there is nothing special about baseball in this respect. For data scientists of all application domains, creativity, domain knowledge, and technical ability are absolutely essential.

A similar profusion of data is now available in many other areas, including astronomy, health services research, genomics, and climate change, among others.

Previously, we described the five main steps of data science: loading (or ingesting it), manipulation, visualization, modeling, and reporting. In this chapter, we introduce the basics of how to manage (or wrangle) data in R. These skills will provide a intellectual and practical foundation for working with modern data.

3.1 The Five Idioms of Single Table Analysis

In his ongoing work to improve's R flexibility and power for data wrangling [129, 131], Hadley Wickham has identified five idioms for working with data in a single data frame:

1. *select*: take a subset of the columns (i.e. features, variables)
2. *filter*: take a subset of the rows (i.e. observations)
3. *mutate*: add or change columns
4. *arrange*: sort the rows
5. *summarise*: aggregate the data across rows (e.g. group it according to some criteria)

These five idioms, used in conjunction with each other, provide a powerful means to slice-and-dice a single table of data. Mastery of these five idioms can make the computation of most any descriptive statistic a breeze and facilitate further analysis. Wickham's approach is inspired by his desire to blur the boundaries between R and the ubiquitous relational database querying syntax SQL. When we revisit SQL in Ch. 8.1, we will see the close relationship between these two computing paradigms.

3.1.1 `filter` and `select`

The two most commonly used of the five idioms are `filter` and `select`, which allow you to return only a subset of the rows or columns of a data frame, respectively.

Generally, if we have a data frame that consists of n rows and p columns, Figures 3.1 and 3.2 illustrate the effect of filtering this data frame based on a condition on one of the columns, and selecting a subset of the columns, respectively.

Specifically, we will demonstrate the use of these functions on the `presidential` data frame, which contains $p = 4$ variables about the terms of $n = 10$ recent U.S. Presidents.

```
> presidential

        name      start        end      party
1 Eisenhower 1953-01-20 1961-01-20 Republican
2    Kennedy 1961-01-20 1963-11-22 Democratic
3     Johson 1963-11-22 1969-01-20 Democratic
```

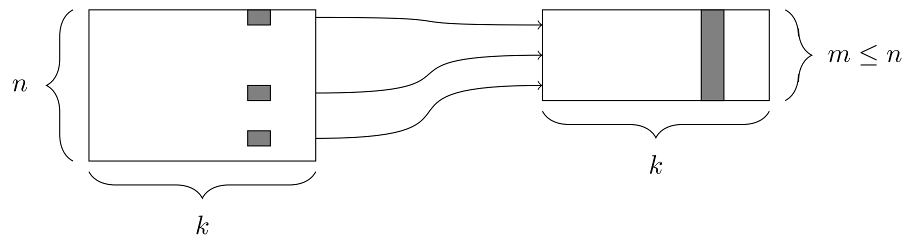


Figure 3.1: `filter`. At left, a data frame that contains matching entries in a certain column for only a subset of the rows. At right, the resulting data frame after filtering.

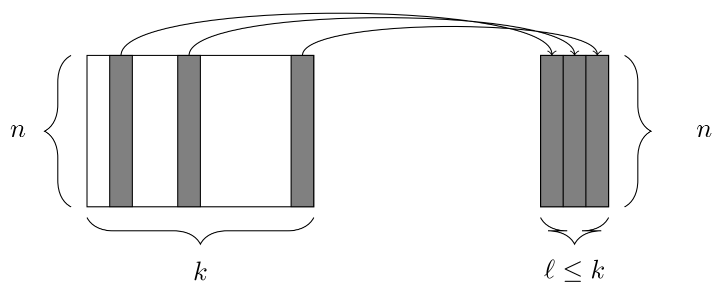


Figure 3.2: `select`. At left, a data frame, from which we retrieve only a few of the columns. At right, the resulting data frame after selecting those columns.

```
4       Nixon 1969-01-20 1974-08-09 Republican
5        Ford 1974-08-09 1977-01-20 Republican
6      Carter 1977-01-20 1981-01-20 Democratic
7      Reagan 1981-01-20 1989-01-20 Republican
8        Bush 1989-01-20 1993-01-20 Republican
9     Clinton 1993-01-20 2001-01-20 Democratic
10       Bush 2001-01-20 2009-01-20 Republican
```

To retrieve only the names and party affiliations of these presidents, we would use `select`. The first *argument* to the `select` function is the data frame, followed by an arbitrarily long list of column names, separated by commas. Note that it is not necessary to wrap the column names in quotation marks.

```
> select(presidential, name, party)

         name      party
1  Eisenhower Republican
2     Kennedy Democratic
3      Johson Democratic
4       Nixon Republican
5        Ford Republican
6      Carter Democratic
7      Reagan Republican
8        Bush Republican
9     Clinton Democratic
10       Bush Republican
```

Similarly, the first argument to `filter` is a data frame, and subsequent arguments are logical conditions that are evaluated on any involved columns. Thus, if we want to retrieve only those rows that pertain to Republican presidents, we need to specify that the value of the `party` variable is equal to `Republican`.

```
> filter(presidential, party == "Republican")

        name      start        end      party
1 Eisenhower 1953-01-20 1961-01-20 Republican
2      Nixon 1969-01-20 1974-08-09 Republican
3       Ford 1974-08-09 1977-01-20 Republican
4     Reagan 1981-01-20 1989-01-20 Republican
5       Bush 1989-01-20 1993-01-20 Republican
6       Bush 2001-01-20 2009-01-20 Republican
```

Note that the `==` is a *test for equality*. If we were to use only a single equal sign here, we would be asserting that `party = "Republican"`. This would cause all of the rows of `presidential` to be returned, since we would have overwritten the actual values of the `party` variable. Note also the the quotation marks around `"Republican"` are necessary here, since `"Republican"` is a literal value, and not a variable name.

Naturally, combining `filter` and `select` commands enable one to drill down to very specific pieces of information. For example, we can find which Democratic presidents served since Watergate.

```
> select(filter(presidential, start > 1973 & party == "Democratic"), name)

     name
1  Carter
2 Clinton
```

The same output could be generated using the `%>%`) (pipe) operator. Pipe-forwarding is an alternative to nesting that yields code that can be read from top to bottom.

```
> presidential %>%
    filter(start > 1973 & party == "Democratic") %>%
    select(name)

     name
1  Carter
2 Clinton
```

In later chapters we will see how this operator can make our code more efficient, particularly for complex operations on large datasets.

3.1.2 `mutate` and `rename`

Frequently, in the process of conducting our analysis, we will create, re-define, and rename some of our variables. The functions `mutate` and `rename` provide these capabilities. An illustration of `mutate` is shown in Figure 3.3.

While we have the raw data on when each of these presidents took and relinquished office, we don't actually have a numeric variable giving the length of each president's term. Of course, we can derive this information from the dates given, and add the result as a

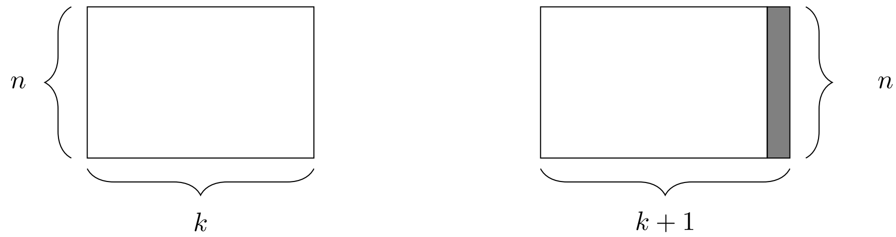


Figure 3.3: `mutate`. At left, a data frame. At right, the data frame resulting after adding a new column.

new column to our data frame. The date arithmetic is made easier through the use of the `lubridate` package, which in this case, we use to compute the number of exact years (`eyears(1)`) that elapsed since during the `interval` from the `start` until the `end` of the president's term.

In this situation, it's generally considered good style to create a new object (and avoid clobbering the old one). To preserve the existing `presidential` data frame, we save the result of mutate as a new object called `mypresidents`.

```
> require(lubridate)
> mypresidents <- mutate(presidential,
    term.length = interval(start, end)/eyears(1))
> mypresidents

         name      start        end      party term.length
1  Eisenhower 1953-01-20 1961-01-20 Republican    8.005479
2     Kennedy 1961-01-20 1963-11-22 Democratic    2.838356
3      Johson 1963-11-22 1969-01-20 Democratic    5.167123
4       Nixon 1969-01-20 1974-08-09 Republican    5.553425
5        Ford 1974-08-09 1977-01-20 Republican    2.452055
6      Carter 1977-01-20 1981-01-20 Democratic    4.002740
7      Reagan 1981-01-20 1989-01-20 Republican    8.005479
8        Bush 1989-01-20 1993-01-20 Republican    4.002740
9     Clinton 1993-01-20 2001-01-20 Democratic    8.005479
10       Bush 2001-01-20 2009-01-20 Republican    8.005479
```

`mutate` can also be used to modify the data in an existing column. Suppose that we wanted to add to our data frame a variable containing the year in which each president was elected. Our first näive attempt is to assume that every president was elected in the year before he took office. Note that `mutate` returns a data frame, so if we want to modify our existing data frame, we need to overwrite it with the result of the `mutate` command.

```
> mypresidents <- mutate(mypresidents, elected = year(start) - 1)
> mypresidents

         name      start        end      party term.length elected
1  Eisenhower 1953-01-20 1961-01-20 Republican    8.005479    1952
2     Kennedy 1961-01-20 1963-11-22 Democratic    2.838356    1960
3      Johson 1963-11-22 1969-01-20 Democratic    5.167123    1962
4       Nixon 1969-01-20 1974-08-09 Republican    5.553425    1968
```

```
5         Ford 1974-08-09 1977-01-20 Republican    2.452055    1973
6       Carter 1977-01-20 1981-01-20 Democratic    4.002740    1976
7       Reagan 1981-01-20 1989-01-20 Republican    8.005479    1980
8         Bush 1989-01-20 1993-01-20 Republican    4.002740    1988
9      Clinton 1993-01-20 2001-01-20 Democratic    8.005479    1992
10        Bush 2001-01-20 2009-01-20 Republican    8.005479    2000
```

Some aspects of this dataset are wrong, because presidential elections are only held every four years. Lyndon Johnson assumed the office after President Kennedy was assassinated in 1963, and Gerald Ford took over after President Nixon resigned in 1974. Thus, there were no presidential elections in 1962 or 1973, as suggested in our data frame. We should overwrite these values with `NA`'s. We can use the `ifelse` function to do this.

```
> mypresidents <- mutate(mypresidents,
    elected = ifelse((elected %in% c(1962, 1973)), NA, elected))
> mypresidents

         name      start        end      party term.length elected
1  Eisenhower 1953-01-20 1961-01-20 Republican    8.005479    1952
2     Kennedy 1961-01-20 1963-11-22 Democratic    2.838356    1960
3      Johson 1963-11-22 1969-01-20 Democratic    5.167123      NA
4       Nixon 1969-01-20 1974-08-09 Republican    5.553425    1968
5        Ford 1974-08-09 1977-01-20 Republican    2.452055      NA
6      Carter 1977-01-20 1981-01-20 Democratic    4.002740    1976
7      Reagan 1981-01-20 1989-01-20 Republican    8.005479    1980
8        Bush 1989-01-20 1993-01-20 Republican    4.002740    1988
9     Clinton 1993-01-20 2001-01-20 Democratic    8.005479    1992
10       Bush 2001-01-20 2009-01-20 Republican    8.005479    2000
```

Here, if the value of `elected` is either 1962 or 1973, we overwrite that value with `NA` [1]. Otherwise, we overwrite it with the same value that it currently has.

Finally, it is considered bad practice to use periods in the name of functions, data frames, and variables in R. Ill-advised periods could conflict with R's use of *generic* functions (i.e. R's mechanism for method overloading). Thus, we should change the name of the `term.length` column that we created earlier. In this book, we will use camelCase for function and variable names.

Pro Tip 1 *Don't use periods in the names of functions, data frames, and variables.*

```
> mypresidents <- rename(mypresidents, termLength = term.length)
> mypresidents

         name      start        end      party termLength elected
1  Eisenhower 1953-01-20 1961-01-20 Republican   8.005479    1952
2     Kennedy 1961-01-20 1963-11-22 Democratic   2.838356    1960
3      Johson 1963-11-22 1969-01-20 Democratic   5.167123      NA
4       Nixon 1969-01-20 1974-08-09 Republican   5.553425    1968
5        Ford 1974-08-09 1977-01-20 Republican   2.452055      NA
6      Carter 1977-01-20 1981-01-20 Democratic   4.002740    1976
```

[1] Incidentally, Johnson was elected in 1964 as an incumbent.

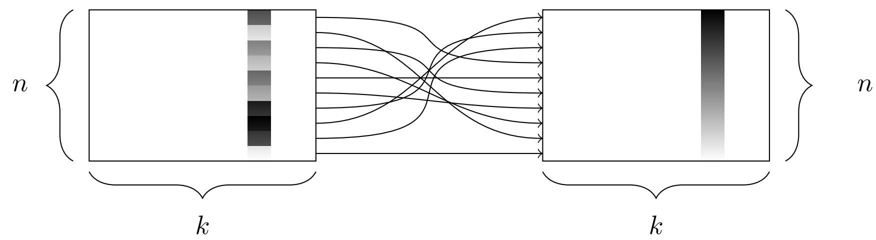


Figure 3.4: **arrange**. At left, a data frame with an ordinal variable. At right, the resulting data frame after sorting the rows in descending order of that variable.

```
7      Reagan 1981-01-20 1989-01-20 Republican   8.005479    1980
8        Bush 1989-01-20 1993-01-20 Republican   4.002740    1988
9     Clinton 1993-01-20 2001-01-20 Democratic   8.005479    1992
10       Bush 2001-01-20 2009-01-20 Republican   8.005479    2000
```

3.1.3 arrange

It's tempting to think that the function `sort` will sort a data frame in R—but that doesn't work. There is a function called `sort`, and it does exactly what you think it does, but it works on vectors, not data frames. The function that will sort a data frame is called `arrange`. It's functionality is illustrated in Figure 3.4.

In order to arrange a data frame, you have to specify the data frame, and the column by which you want it to be sorted. You also have to specify the direction in which you want it to be sorted. Specifying multiple sort conditions will results in ties being broken.

Thus, to sort our `presidential` data frame by the length of each president's term, we specify that we want the column `termLength` in descending order.

```
> arrange(mypresidents, desc(termLength))

         name      start        end      party termLength elected
1  Eisenhower 1953-01-20 1961-01-20 Republican   8.005479    1952
2      Reagan 1981-01-20 1989-01-20 Republican   8.005479    1980
3     Clinton 1993-01-20 2001-01-20 Democratic   8.005479    1992
4        Bush 2001-01-20 2009-01-20 Republican   8.005479    2000
5       Nixon 1969-01-20 1974-08-09 Republican   5.553425    1968
6      Johson 1963-11-22 1969-01-20 Democratic   5.167123      NA
7      Carter 1977-01-20 1981-01-20 Democratic   4.002740    1976
8        Bush 1989-01-20 1993-01-20 Republican   4.002740    1988
9     Kennedy 1961-01-20 1963-11-22 Democratic   2.838356    1960
10       Ford 1974-08-09 1977-01-20 Republican   2.452055      NA
```

A number of presidents completed both one and two full terms, and thus have the exact same term length. We can futher sort by `party` and `elected`.

```
> arrange(mypresidents, desc(termLength), party, elected)

         name      start        end      party termLength elected
1     Clinton 1993-01-20 2001-01-20 Democratic   8.005479    1992
```

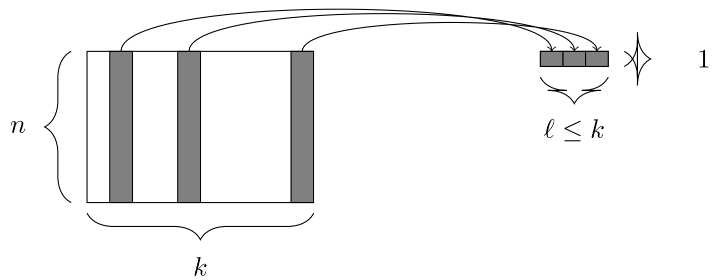


Figure 3.5: `summarise`. At left, a data frame. At right, the resulting data frame after aggregating three of the columns.

```
2  Eisenhower 1953-01-20 1961-01-20 Republican   8.005479    1952
3      Reagan 1981-01-20 1989-01-20 Republican   8.005479    1980
4        Bush 2001-01-20 2009-01-20 Republican   8.005479    2000
5       Nixon 1969-01-20 1974-08-09 Republican   5.553425    1968
6      Johson 1963-11-22 1969-01-20 Democratic   5.167123      NA
7      Carter 1977-01-20 1981-01-20 Democratic   4.002740    1976
8        Bush 1989-01-20 1993-01-20 Republican   4.002740    1988
9     Kennedy 1961-01-20 1963-11-22 Democratic   2.838356    1960
10       Ford 1974-08-09 1977-01-20 Republican   2.452055      NA
```

Note that the default sort order is ascending order, so we do not need to specify that if that is what we want.

3.1.4 `summarise` with `group_by`

Our last of the five idioms for single-table analysis is `summarise`, which is nearly always used in conjunction with `group_by`. The previous four idioms provided us with means to manipulate a data frame in powerful and flexible ways. But the extent of the analysis we can perform with these four idioms alone is limited. On the other hand, `summarise` with `group_by` enables us to make comparisons.

When used alone, `summarise` collapses a data frame into a single row. This is illustrated in Figure 3.5. Critically, we have to specify *how* we want to reduce an entire column of data into a single value. The method of aggregation that we specify controls what will appear in the output.

```
> summarise(mypresidents, numPresidents = n()
            , firstYear = min(year(start)), lastYear = max(year(end))
            , numDemocrats = sum(party == "Democratic")
            , tTermLength = sum(termLength), mTermLength = mean(termLength))

  numPresidents firstYear lastYear numDemocrats tTermLength mTermLength
1            10      1953     2009            4    56.03836    5.603836
```

Once again, the first argument to `summarise` is a data frame, followed by a list of columns that will appear in the output. Note that every column in the output is defined by operations performed on *vectors* – not on individual values. This is essential, since if the specification of an output column is not an operation on a vector, there is no way for R to know how to collapse each column.

In this example, the function `n` simply counts the number of rows. This is almost always useful information.

Pro Tip 2 *Use `n` every time you use `summarise`.*

The next two columns determine the first year that one of these presidents assumed office. This is the smallest year in the `start` column. Similarly, the most recent year is the largest year in the `end` column. The column `numDemocrats` simply counts the number of rows in which the value of the `party` variable was `"Democratic"`. Finally, the last two columns compute the sum and average of the `termLength` variable. Thus, we can quickly see that 4 of the 10 presidents who served from 1953 to 2009 were Democrats, and the average term length over these 56 years was about 5.6 years.

This begs the question of whether Democratic or Republican presidents served a longer average term during this time period. To figure this out, we can just execute `summarise` again, but this time, instead of the first argument being the data frame `mypresidents`, we will specify that the rows of the `mypresidents` data frame should by grouped by the values of the `party` variable. In this manner, the same computations as above will be carried out for each party separately.

```
> summarise(group_by(mypresidents, party), numPresidents = n()
            , firstYear = min(year(start)), lastYear = max(year(end))
            , numDemocrats = sum(party == "Democratic")
            , tTermLength = sum(termLength), mTermLength = mean(termLength))

Source: local data frame [2 x 7]

       party numPresidents firstYear lastYear numDemocrats tTermLength
1 Democratic             4      1961     2001            4    20.01370
2 Republican             6      1953     2009            0    36.02466
Variables not shown: mTermLength (dbl)
```

This provides us with the valuable information that the six Republican presidents served an average of 6 years in office, while the four Democratic presidents served an average of only 5. The results are presented as a data table, which has a number of attractive properties.

3.2 Extended Example: Ben's Time with the Mets

In this extended example, we will explore Sean Lahman's historical baseball database, which contains complete seasonal records for all players on all teams going back to 1871. These data are made available in R via the `Lahman` package [33].

```
> require(Lahman)
> dim(Teams)

[1] 2745   48
```

The `Teams` table contains the seasonal results of every major league team in every season since 1871. There are 2745 rows and 48 columns in this table, which is far too much to show here, and would make for a quite unwieldy spreadsheet.

Of course, we can take a peek at what this table looks like by printing the first few rows of the table to the screen, but we won't print that on the page of this book.

```
> head(Teams)
```

Ben worked for the New York Mets from 2004 to 2012. How did the team do during those years? We can use `filter` and `select` to quickly identify only those pieces of information that we care about.

```
> mets <- filter(Teams, teamID == "NYN")
> myMets <- filter(mets, yearID %in% 2004:2012)
> select(myMets, yearID, teamID, W, L)

  yearID teamID  W  L
1   2004    NYN 71 91
2   2005    NYN 83 79
3   2006    NYN 97 65
4   2007    NYN 88 74
5   2008    NYN 89 73
6   2009    NYN 70 92
7   2010    NYN 79 83
8   2011    NYN 77 85
9   2012    NYN 74 88
```

Notice that we have broken this down into three steps. First, we filter the rows of the `Teams` data frame into only those years which corresponds to the New York Mets. There are 52 of those, since the Mets joined the National League in 1962.

```
> nrow(mets)

[1] 52
```

Next, we filtered these data so as to include only those seasons in which Ben worked for the team – those with `yearID` between 2004 and 2012. Finally, we wanted to print to the screen only those columns that were relevant to our question: the year, the team's ID, and the numbers of wins and losses that the team had.

While this process is logical, the code can get unruly, and notice that two ancillary data frames (`mets` and `myMets`) were created during the process. It may be the case that we'd like to go back to those data frames later in the analysis. But if not, they are just cluttering our workspace, and eating up memory. A more streamlined way to achieve the same result would be to *nest* these commands together.

```
> select(filter(mets, teamID == "NYN" & yearID %in% 2004:2012)
         , yearID, teamID, W, L)

  yearID teamID  W  L
1   2004    NYN 71 91
2   2005    NYN 83 79
3   2006    NYN 97 65
4   2007    NYN 88 74
5   2008    NYN 89 73
6   2009    NYN 70 92
7   2010    NYN 79 83
8   2011    NYN 77 85
9   2012    NYN 74 88
```

This way, no additional data frames were created. However, it's easy to see that as we nest more and more of these operations together, this line of code could become very difficult to read. To maintain readability, we instead *chain* these operations, rather than nest them.

```
> Teams %>%
    select(yearID, teamID, W, L) %>%
    filter(teamID == "NYN" & yearID %in% 2004:2012)

  yearID teamID  W  L
1   2004    NYN 71 91
2   2005    NYN 83 79
3   2006    NYN 97 65
4   2007    NYN 88 74
5   2008    NYN 89 73
6   2009    NYN 70 92
7   2010    NYN 79 83
8   2011    NYN 77 85
9   2012    NYN 74 88
```

This *piping* syntax provided by `dplyr` was introduced in section 3.1.1. It retains the step-by-step logic of our original code, while being easily readable, and efficient with respect to memory and the creation of temporary data frames. In fact, there are also performance enhancements under the hood that make this the most efficient way to do these kinds of computations. For these reasons we will use this syntax whenever possible throughout the book. Note that we only have to type `"Teams"` once—it is implied by the pipe operator (`%>%`) that the subsequent command takes the previous data frame as its first argument. Thus, `df %>% f(y)` is equivalent to `f(df, y)`.

We've answered the simple question of how the Mets performed during the time that Ben was there, but since we are data scientists, we're interested in deeper questions. For example, some of these seasons were subpar. Did the team just get unlucky in those seasons? Or did they actually play as badly as their record indicates?

In order to answer this question, we need a model for *expected winning percentage*. It turns out that one of the most widely-used contributions to the field of baseball analytics (by Bill James) is exactly that. The model translates the number of runs that a team scores and allows *over the course of an entire season* into an expectation for how many games they should have won. The simplest version of this model is this:

$$\widehat{WPct} = \frac{1}{1 + \left(\frac{RA}{RS}\right)^2},$$

where RA is the number of runs the team allows, RS is the number of runs that the team scores, and $\widehat{WPct}$ is the team's expected winning percentage. Luckily for us, the runs scored and allowed are present in the `Teams` table, so let's grab them and save them in a new data frame.

```
> metsBen <- Teams %>%
    select(yearID, teamID, W, L, R, RA) %>%
    filter(teamID == "NYN" & yearID %in% 2004:2012)
> metsBen

  yearID teamID  W  L   R  RA
```

```
1   2004    NYN 71 91 684 731
2   2005    NYN 83 79 722 648
3   2006    NYN 97 65 834 731
4   2007    NYN 88 74 804 750
5   2008    NYN 89 73 799 715
6   2009    NYN 70 92 671 757
7   2010    NYN 79 83 656 652
8   2011    NYN 77 85 718 742
9   2012    NYN 74 88 650 709
```

First, note that the runs scored is called `R` in the `Teams` table, but we want to call it `RS`. Thus, we need to `rename` this variable in our data frame.

```
> metsBen <- rename(metsBen, RS = R)
> metsBen

  yearID teamID  W  L  RS  RA
1   2004    NYN 71 91 684 731
2   2005    NYN 83 79 722 648
3   2006    NYN 97 65 834 731
4   2007    NYN 88 74 804 750
5   2008    NYN 89 73 799 715
6   2009    NYN 70 92 671 757
7   2010    NYN 79 83 656 652
8   2011    NYN 77 85 718 742
9   2012    NYN 74 88 650 709
```

Next, we need to compute the team's actual winning percentage in each of these seasons. Thus, we need to add a new column to our data frame, and we do this with the `mutate` command.

```
> metsBen <- mutate(metsBen, WPct = W / (W + L))
> metsBen

  yearID teamID  W  L  RS  RA      WPct
1   2004    NYN 71 91 684 731 0.4382716
2   2005    NYN 83 79 722 648 0.5123457
3   2006    NYN 97 65 834 731 0.5987654
4   2007    NYN 88 74 804 750 0.5432099
5   2008    NYN 89 73 799 715 0.5493827
6   2009    NYN 70 92 671 757 0.4320988
7   2010    NYN 79 83 656 652 0.4876543
8   2011    NYN 77 85 718 742 0.4753086
9   2012    NYN 74 88 650 709 0.4567901
```

We also need to compute the model estimates for winning percentage, which we can do similarly.

```
> metsBen <- mutate(metsBen, WPctHat = 1 / (1 + (RA/RS)^2))
> metsBen

  yearID teamID  W  L  RS  RA      WPct   WPctHat
```

```
1   2004    NYN 71 91 684 731 0.4382716 0.4668211
2   2005    NYN 83 79 722 648 0.5123457 0.5538575
3   2006    NYN 97 65 834 731 0.5987654 0.5655308
4   2007    NYN 88 74 804 750 0.5432099 0.5347071
5   2008    NYN 89 73 799 715 0.5493827 0.5553119
6   2009    NYN 70 92 671 757 0.4320988 0.4399936
7   2010    NYN 79 83 656 652 0.4876543 0.5030581
8   2011    NYN 77 85 718 742 0.4753086 0.4835661
9   2012    NYN 74 88 650 709 0.4567901 0.4566674
```

The expected number of wins is then equal to the product of the expected winning percentage times the number of games.

```
> metsBen <- mutate(metsBen, WHat = WPctHat * (W + L))
> metsBen

  yearID teamID  W  L  RS  RA      WPct   WPctHat     WHat
1   2004    NYN 71 91 684 731 0.4382716 0.4668211 75.62501
2   2005    NYN 83 79 722 648 0.5123457 0.5538575 89.72491
3   2006    NYN 97 65 834 731 0.5987654 0.5655308 91.61600
4   2007    NYN 88 74 804 750 0.5432099 0.5347071 86.62255
5   2008    NYN 89 73 799 715 0.5493827 0.5553119 89.96053
6   2009    NYN 70 92 671 757 0.4320988 0.4399936 71.27896
7   2010    NYN 79 83 656 652 0.4876543 0.5030581 81.49541
8   2011    NYN 77 85 718 742 0.4753086 0.4835661 78.33771
9   2012    NYN 74 88 650 709 0.4567901 0.4566674 73.98012
```

In this case, the Mets' fortunes were better than expected in three of these seasons, and worse than expected in the other six (but you won't hear any Mets fans claiming the team exceeded expectations in 2007!).

```
> filter(metsBen, W > WHat)

  yearID teamID  W  L  RS  RA      WPct   WPctHat     WHat
1   2006    NYN 97 65 834 731 0.5987654 0.5655308 91.61600
2   2007    NYN 88 74 804 750 0.5432099 0.5347071 86.62255
3   2012    NYN 74 88 650 709 0.4567901 0.4566674 73.98012

> filter(metsBen, W < WHat)

  yearID teamID  W  L  RS  RA      WPct   WPctHat     WHat
1   2004    NYN 71 91 684 731 0.4382716 0.4668211 75.62501
2   2005    NYN 83 79 722 648 0.5123457 0.5538575 89.72491
3   2008    NYN 89 73 799 715 0.5493827 0.5553119 89.96053
4   2009    NYN 70 92 671 757 0.4320988 0.4399936 71.27896
5   2010    NYN 79 83 656 652 0.4876543 0.5030581 81.49541
6   2011    NYN 77 85 718 742 0.4753086 0.4835661 78.33771
```

Naturally, the Mets experienced ups and downs during Ben's time with the team. Which seasons were best? To figure this out, we can simply sort the rows of the data frame.

```
> arrange(metsBen, desc(WPct))

  yearID teamID  W  L  RS  RA      WPct   WPctHat     WHat
1   2006    NYN 97 65 834 731 0.5987654 0.5655308 91.61600
2   2008    NYN 89 73 799 715 0.5493827 0.5553119 89.96053
3   2007    NYN 88 74 804 750 0.5432099 0.5347071 86.62255
4   2005    NYN 83 79 722 648 0.5123457 0.5538575 89.72491
5   2010    NYN 79 83 656 652 0.4876543 0.5030581 81.49541
6   2011    NYN 77 85 718 742 0.4753086 0.4835661 78.33771
7   2012    NYN 74 88 650 709 0.4567901 0.4566674 73.98012
8   2004    NYN 71 91 684 731 0.4382716 0.4668211 75.62501
9   2009    NYN 70 92 671 757 0.4320988 0.4399936 71.27896
```

In 2006, the Mets had the best record in baseball during the regular season and nearly made the World Series. But how do these seasons rank in terms of the team's performance relative to our model?

```
> metsBen %>%
    mutate(Diff = W - WHat) %>%
    arrange(desc(Diff))

  yearID teamID  W  L  RS  RA      WPct   WPctHat     WHat        Diff
1   2006    NYN 97 65 834 731 0.5987654 0.5655308 91.61600  5.38400315
2   2007    NYN 88 74 804 750 0.5432099 0.5347071 86.62255  1.37744558
3   2012    NYN 74 88 650 709 0.4567901 0.4566674 73.98012  0.01988152
4   2008    NYN 89 73 799 715 0.5493827 0.5553119 89.96053 -0.96052803
5   2009    NYN 70 92 671 757 0.4320988 0.4399936 71.27896 -1.27895513
6   2011    NYN 77 85 718 742 0.4753086 0.4835661 78.33771 -1.33770571
7   2010    NYN 79 83 656 652 0.4876543 0.5030581 81.49541 -2.49540821
8   2004    NYN 71 91 684 731 0.4382716 0.4668211 75.62501 -4.62501135
9   2005    NYN 83 79 722 648 0.5123457 0.5538575 89.72491 -6.72490937
```

So 2006 was the Mets' most fortunate year, but 2005 was the least fortunate, relative to the expectations of our model.

This type of analysis helps us understand how the Mets performed in individual seasons, but we know that any randomness that occurs in individual years is likely to average out over time. So while it is clear that the Mets performed well in some seasons and poorly in others, what can we say about their overall performance?

We can easily summarize a single variable with `favstats`.

```
> favstats(~W, data=metsBen)

 min Q1 median Q3 max     mean       sd n missing
  70 74     79 88  97 80.88889 9.102808 9       0
```

This tells us that the Mets won nearly 81 games on average during Ben's tenure, which corresponds almost exactly to a .500 winning percentage, since there are 162 games in a regular season. But we may be interested in aggregating more than one variable at a time. To do this, we use `summarise`.

```
> summarise(metsBen, numYears = n(), totalW = sum(W), totalL = sum(L)
            , totalWPct = sum(W) / sum(W + L), sumResid = sum(W - WHat))

  numYears totalW totalL totalWPct  sumResid
1        9    728    730 0.4993141 -10.64119
```

In these nine years, the Mets went a combined 728-730, for an overall winning percentage of .499. Just one extra win would have made them exactly .500! (If I could pick which game, I would definitely pick the final game of the 2007 season!!) However, we've also learned that the team underperformed relative to our model by a total of 10.6 games over those nine seasons.

Usually, when we are summarizing a data frame like we did above, it is interesting to consider different groups. In this case, we can discretize the years into three chunks: one for each of the three general managers under whom Ben worked. Jim Duquette was the Mets' GM in 2004, Omar Minaya from 2005 to 2010, and Sandy Alderson from 2011 to the present. We can define these eras using the `rep` function, which simply repeats something.

```
> metsBen = mutate(metsBen,
    gm = c("Duquette", rep("Minaya", 6), rep("Alderson", 2)))
> metsBen

  yearID teamID  W  L  RS  RA      WPct   WPctHat     WHat       gm
1   2004    NYN 71 91 684 731 0.4382716 0.4668211 75.62501 Duquette
2   2005    NYN 83 79 722 648 0.5123457 0.5538575 89.72491   Minaya
3   2006    NYN 97 65 834 731 0.5987654 0.5655308 91.61600   Minaya
4   2007    NYN 88 74 804 750 0.5432099 0.5347071 86.62255   Minaya
5   2008    NYN 89 73 799 715 0.5493827 0.5553119 89.96053   Minaya
6   2009    NYN 70 92 671 757 0.4320988 0.4399936 71.27896   Minaya
7   2010    NYN 79 83 656 652 0.4876543 0.5030581 81.49541   Minaya
8   2011    NYN 77 85 718 742 0.4753086 0.4835661 78.33771 Alderson
9   2012    NYN 74 88 650 709 0.4567901 0.4566674 73.98012 Alderson
```

Now, we define these groups using the `group_by` operator. The combination of summarizing data by groups can be very powerful.

```
> metsBen %>%
    group_by(gm) %>%
    summarise(numYears = n(), totalW = sum(W), totalL = sum(L)
              , totalWPct = sum(W) / sum(W + L), sumResid = sum(W - WHat)) %>%
    arrange(desc(sumResid))

Source: local data frame [3 x 6]

        gm numYears totalW totalL totalWPct  sumResid
1 Alderson        2    151    173 0.4660494 -1.317824
2 Duquette        1     71     91 0.4382716 -4.625011
3   Minaya        6    506    466 0.5205761 -4.698352
```

Note that while the Mets were far more successful during Minaya's regime, they underperformed expectations in all three periods.

The full power of the chaining operator is revealed below, where we do all the analysis at once, but retain the step-by-step logic.

```
> Teams %>%
    select(yearID, teamID, W, L, R, RA) %>%
    filter(teamID == "NYN" & yearID %in% 2004:2012) %>%
    rename(RS = R) %>%
    mutate(WPct = W / (W + L), WPctHat = 1 / (1 + (RA/RS)^2),
           WHat = WPctHat * (W + L),
           gm = c("Duquette", rep("Minaya", 6), rep("Alderson", 2))) %>%
    group_by(gm) %>%
    summarise(numYears = n(), totalW = sum(W), totalL = sum(L),
              totalWPct = sum(W) / sum(W + L), sumResid = sum(W - WHat)) %>%
    arrange(desc(sumResid))

Source: local data frame [3 x 6]

        gm numYears totalW totalL totalWPct  sumResid
1 Alderson        2    151    173 0.4660494 -1.317824
2 Duquette        1     71     91 0.4382716 -4.625011
3   Minaya        6    506    466 0.5205761 -4.698352
```

Or, we might be more interested in how the Mets performed relative to our model, in the context of all teams during that nine year period. All we need to do is remove the `teamID` filter and group by `franchID` instead.

```
> Teams %>%
    select(yearID, teamID, franchID, W, L, R, RA) %>%
    filter(yearID %in% 2004:2012) %>%
    rename(RS = R) %>%
    mutate(WPct = W / (W + L), WPctHat = 1 / (1 + (RA/RS)^2),
           WHat = WPctHat * (W + L)) %>%
    group_by(franchID) %>%
    summarise(numYears = n(), totalW = sum(W), totalL = sum(L)
              , totalWPct = sum(W) / sum(W + L), sumResid = sum(W - WHat)) %>%
    arrange(desc(sumResid)) %>%
    print.data.frame()

   franchID numYears totalW totalL totalWPct    sumResid
1       ANA        9    822    636 0.5637860  27.1167986
2       CIN        9    720    738 0.4938272  17.6438473
3       HOU        9    683    774 0.4687714  17.2187506
4       SFG        9    745    712 0.5113246  14.9703332
5       CHW        9    764    695 0.5236463  13.1029118
6       FLA        9    707    750 0.4852437  11.3709575
7       ARI        9    686    772 0.4705075  11.3095084
8       NYY        9    866    592 0.5939643  10.1965274
9       MIL        9    732    725 0.5024022  10.0192633
10      BAL        9    651    806 0.4468085   8.8994321
11      SEA        9    647    811 0.4437586   7.9684757
12      WSN        9    657    799 0.4512363   5.6058122
13      MIN        9    748    712 0.5123288   4.0616769
14      SDP        9    721    738 0.4941741   2.8528704
15      PIT        9    611    845 0.4196429  -0.8455256
```

```
16      STL        9    807    650 0.5538778  -0.9311621
17      TBD        9    722    735 0.4955388  -3.2570533
18      PHI        9    813    645 0.5576132  -5.8647021
19      DET        9    750    709 0.5140507  -7.2477066
20      BOS        9    813    645 0.5576132  -7.4006098
21      LAD        9    761    696 0.5223061  -8.2413318
22      OAK        9    747    710 0.5126973  -9.6249699
23      TEX        9    768    690 0.5267490  -9.6992750
24      KCR        9    595    863 0.4080933 -10.0399779
25      NYM        9    728    730 0.4993141 -10.6411876
26      CLE        9    710    748 0.4869684 -13.9168440
27      CHC        9    706    750 0.4848901 -14.5435094
28      COL        9    687    772 0.4708705 -22.7103018
29      ATL        9    781    677 0.5356653 -24.0046567
30      TOR        9    717    740 0.4921071 -29.1605418
```

We can see now that only five other teams fared worse than the Mets, relative to our model, during this time period. Perhaps we were cursed!

3.3 Combining Multiple Tables

In the previous section, we illustrated how the five idioms can be chained to perform operations on a single table. This single table is reminiscent of a single spreadsheet. But in the same way that a workbook can contain multiple spreadsheets, we will often work with multiple tables. In Ch. 8.1, we will see how the notion of multiple tables related by unique identifiers called *keys* can be systemized into a *relational database management system*.

It is more efficient for the computer to store and search tables in which "like is stored with like". Thus, a database maintained by the Bureau of Transportation Statistics on the arrival times of U.S. commercial flights will consist of multiple tables, each of which contains data about different things. For example, the `nycflights13` package contains one table about `flights` – each row in this table is a single flight. As there are many flights, you can imagine that this table will get very long – hundreds of thousands of rows per year. But there are other related kinds of information that we will want to know about these flights. We would certainly be interested in the particular airline to which each flight belonged. It would be inefficient to store the complete name of the airline (e.g. `American Airlines Inc.`) in every row of the flights table. A simple code (e.g. `AA`) would literally take up less space on disk. For small tables, the savings of storing two characters instead of 25 is insignficant, but for large tables, it can add up to big savings both in terms of the size of data on disk, and the speed with which we can search it. However, we still want to have the full names of the airlines available if we need them! The solution is to store the data *about airlines* in a separate table called `airlines`, and to provide a *key* that links the data in the two tables together.

```
> require(nycflights13)
```

3.3.1 inner_join

If we examine the first few rows of the `flights` table, we observe that the `carrier` column contains a two-character string corresponding to the airline.

```
> head(flights)

Source: local data frame [6 x 16]

  year month day dep_time dep_delay arr_time arr_delay carrier tailnum
1 2013     1   1      517         2      830        11      UA  N14228
2 2013     1   1      533         4      850        20      UA  N24211
3 2013     1   1      542         2      923        33      AA  N619AA
4 2013     1   1      544        -1     1004       -18      B6  N804JB
5 2013     1   1      554        -6      812       -25      DL  N668DN
6 2013     1   1      554        -4      740        12      UA  N39463
Variables not shown: flight (int), origin (chr), dest (chr), air_time
  (dbl), distance (dbl), hour (dbl), minute (dbl)
```

In the **airlines** table, we have those same two-character strings, but also the full names of the airline.

```
> head(airlines)

Source: local data frame [6 x 2]

  carrier                     name
1      9E        Endeavor Air Inc.
2      AA   American Airlines Inc.
3      AS     Alaska Airlines Inc.
4      B6          JetBlue Airways
5      DL     Delta Air Lines Inc.
6      EV ExpressJet Airlines Inc.
```

In order to retrieve a list of flights and the full names of the airlines that managed each flight, we need to match up the rows in the **flights** table with those rows in the **airlines** table that have the corresponding values for the **carrier** column in *both* tables. This is achieved with the function **inner_join**.

```
> flightsJoined <- inner_join(flights, airlines,
    by = c("carrier" = "carrier"))

Warning:  joining character vector and factor, coercing into character vector

> names(flightsJoined)

 [1] "year"      "month"     "day"       "dep_time"  "dep_delay"
 [6] "arr_time"  "arr_delay" "carrier"   "tailnum"   "flight"
[11] "origin"    "dest"      "air_time"  "distance"  "hour"
[16] "minute"    "name"
```

Notice that the **flightsJoined** data frame now has an additional variable called **name**. This is the columns from **airlines** that is now attached to our combined data frame. Now we can view the full names of the airlines instead of the cryptic two-character codes.

```
> head(select(flightsJoined, carrier, name, flight, origin, dest))

Source: local data frame [6 x 5]

  carrier                   name flight origin dest
1      UA  United Air Lines Inc.   1545    EWR  IAH
2      UA  United Air Lines Inc.   1714    LGA  IAH
3      AA American Airlines Inc.   1141    JFK  MIA
4      B6        JetBlue Airways    725    JFK  BQN
5      DL   Delta Air Lines Inc.    461    LGA  ATL
6      UA  United Air Lines Inc.   1696    EWR  ORD
```

In an `inner_join`, the result set contains only those rows that have matches in both tables. In this case, all of the rows in `flights` have a corresponding entry in `airlines`, so the numner of rows in `flightsJoined` is the same as the number of rows in `flights`. This will not always be the case.

```
> nrow(flights)

[1] 336776

> nrow(flightsJoined)

[1] 336776
```

3.3.2 `left_join`

Another commonly-used type of join is a `left_join`. Here the rows of the first table are *always* returned, regardless of whether there is a match in the second table.

Suppose that we are only interested in flights from the NYC airports to the West Coast. Specifically, we're only interested in airports in the Pacific Time Zone. Thus, we filter the `airports` data frame to only include those 152 airports.

```
> airportsPT <- filter(airports, tz == -8)
> nrow(airportsPT)

[1] 152
```

Now, if we perform an `inner_join` on `flights` and `airportsPT`, matching the destinations in `flights` to the FAA codes in `airports`, we retrieve only those flights that flew to our airports in the Pacific Time Zone.

```
> nycDestsPT <- inner_join(flights, airportsPT, by = c("dest" = "faa"))
> nrow(nycDestsPT)

[1] 46324
```

However, if we use a `left_join` with the same conditions, we retrieve all of the rows of `flights`. `NA`'s are inserted into the columns where no matched data was found.

```
> nycDests <- left_join(flights, airportsPT, by = c("dest" = "faa"))
> nrow(nycDests)

[1] 336776

> sum(is.na(nycDests$name))

[1] 290452
```

Left joins can be extraordinarily useful in databases in which *referential integrity* is broken (not all of the *keys* are present).

3.4 Extended Example: Manny Ramirez

In the context of baseball and the `Lahmann` package, multiple tables are used to store information. The batting statistics of players are stored in one table (`Batting`), while information about people (most of whom are players) are in a different table (`Master`).

Every row in the `Batting` table contains the statistics accumulated by a single player during a single stint for a single team in a single year. Thus, a player like Manny Ramirez has many rows in the `Batting` table (21, in fact).

```
> manny <- filter(Batting, playerID == "ramirma02")
> nrow(manny)

[1] 21
```

Using what we've learned, we can quickly tabulate Ramirez's most common career statistics.

```
> manny %>%
    summarise(span = paste(min(yearID), max(yearID), sep="-")
              , numYears = length(unique(yearID))
              , numTeams = length(unique(teamID))
              , BA = sum(H)/sum(AB), tH = sum(H), tHR = sum(HR),
              tRBI = sum(RBI))

       span numYears numTeams        BA   tH tHR tRBI
1 1993-2011       19        5 0.3122271 2574 555 1831
```

Breaking this down by team, or by league, is as easy as adding a `group_by` clause.

```
> manny %>%
    group_by(teamID) %>%
    summarise(span = paste(min(yearID), max(yearID), sep="-")
              , numYears = length(unique(yearID))
              , numTeams = length(unique(teamID))
              , BA = sum(H)/sum(AB), tH = sum(H), tHR = sum(HR), tRBI = sum(RBI)) %>%
    arrange(span)

Source: local data frame [5 x 8]
```

```
  teamID      span numYears numTeams         BA   tH tHR tRBI
1    CLE 1993-2000        8        1 0.31296830 1086 236  804
2    BOS 2001-2008        8        1 0.31166203 1232 274  868
3    LAN 2008-2010        3        1 0.32244898  237  44  156
4    CHA 2010-2010        1        1 0.26086957   18   1    2
5    TBA 2011-2011        1        1 0.05882353    1   0    1
```

```
> manny %>%
    group_by(lgID) %>%
    summarise(span = paste(min(yearID), max(yearID), sep="-")
              , numYears = length(unique(yearID))
              , numTeams = length(unique(teamID))
              , BA = sum(H)/sum(AB), tH = sum(H), tHR = sum(HR), tRBI = sum(RBI)) %>%
    arrange(span)

Source: local data frame [2 x 8]

  lgID      span numYears numTeams        BA   tH tHR tRBI
1   AL 1993-2011       18        4 0.3112265 2337 511 1675
2   NL 2008-2010        3        1 0.3224490  237  44  156
```

If Ramirez played in only 19 different seasons, why were there 21 rows attributed to him? Notice that in 2008, he was traded from Boston to the Dodgers, and thus played for both teams. Similarly, in 2010 he played for both the Dodgers and the Chicago White Sox. When summarizing data, it is critically important to understand exactly how the rows of your data frame are organized. To see what can go wrong here, suppose we were interested in tabulating the number of seasons in which Ramirez hit at least 30 home runs. The simplest solution is:

```
> nrow(filter(manny, HR >= 30))

[1] 11
```

But this answer is wrong, because in 2008, Ramirez hit 20 home runs for Boston and 17 more for the Dodgers. Neither of those rows were counted, since they were *both* filtered out. The correct solution is:

```
> manny %>%
    group_by(yearID) %>%
    summarise(tHR = sum(HR)) %>%
    filter(tHR >= 30) %>%
    nrow()

[1] 12
```

Note that the `filter` operation is applied to `tHR`, the total number of home runs in a season, and not `HR`, the number of home runs in a single stint for a single team in a single season.

We began this exercise by filtering the `Batting` table for the player with `playerID` equal to `ramirma02`. How did we know to use this identifier? This player ID is known as a *key*, and in fact, `playerID` is the *primary key* defined in the `Master` table. That is, every row in the `Master` table is uniquely identified by the value of `playerID`. Thus there is exactly one row in that table for which `playerID` is equal to `ramirma02`.

But how did we know that this ID corresponds to Manny Ramirez? We can search the table:

```
> filter(Master, nameLast == "Ramirez" & nameFirst == "Manny")

   playerID birthYear birthMonth birthDay birthCountry        birthState
1 ramirma02      1972          5       30         D.R. Distrito Nacional
     birthCity deathYear deathMonth deathDay deathCountry deathState
1 Santo Domingo        NA         NA       NA         <NA>       <NA>
  deathCity nameFirst nameLast        nameGiven weight height bats throws
1      <NA>     Manny  Ramirez Manuel Aristides    225     72    R      R
       debut  finalGame  retroID   bbrefID deathDate  birthDate
1 1993-09-02 2011-04-06 ramim002 ramirma02      <NA> 1972-05-30
```

Note the data in this table are things about Manny Ramirez that do not change across multiple seasons (with the possible exception of his weight).

The `playerID` column forms a primary key in the `Master` table, but it does not in the `Batting` table, since as we saw previously, there were 21 rows with that `playerID`. In the `Batting` table, the `playerID` column is known as a *foreign key*, in that it references a key in another table. For our purposes, the presence of this column in both tables allows us to link them together. This way, we can combine data from the `Batting` table with data in the `Master` table. We do this with `inner_join` by specifying the two tables that we want to join, and the corresponding columns in each table that provide the link.

Thus, if we want to display Ramirez's name in our previous result, as well as his age, we must join the `Batting` and `Master` tables together.

Pro Tip 3 *Always specify the* `by` *argument that defines the join condition. Don't rely on the defaults!*

```
> Batting %>%
    filter(playerID == "ramirma02") %>%
    inner_join(Master, by = c("playerID" = "playerID"))  %>%
    group_by(yearID) %>%
    summarise(name = paste(nameFirst, nameLast, sep=" ")
              , Age = max(yearID - birthYear)
              , numTeams = length(unique(teamID))
              , BA = sum(H)/sum(AB), tH = sum(H)
              , tHR = sum(HR), tRBI = sum(RBI)) %>%
    arrange(yearID)

Source: local data frame [19 x 8]

   yearID          name Age numTeams         BA  tH tHR tRBI
1    1993 Manny Ramirez  21        1 0.16981132   9   2    5
2    1994 Manny Ramirez  22        1 0.26896552  78  17   60
3    1995 Manny Ramirez  23        1 0.30785124 149  31  107
4    1996 Manny Ramirez  24        1 0.30909091 170  33  112
5    1997 Manny Ramirez  25        1 0.32798574 184  26   88
6    1998 Manny Ramirez  26        1 0.29422067 168  45  145
```

```
7    1999 Manny Ramirez  27        1 0.33333333 174  44  165
8    2000 Manny Ramirez  28        1 0.35079727 154  38  122
9    2001 Manny Ramirez  29        1 0.30623819 162  41  125
10   2002 Manny Ramirez  30        1 0.34862385 152  33  107
11   2003 Manny Ramirez  31        1 0.32513181 185  37  104
12   2004 Manny Ramirez  32        1 0.30809859 175  43  130
13   2005 Manny Ramirez  33        1 0.29241877 162  45  144
14   2006 Manny Ramirez  34        1 0.32071269 144  35  102
15   2007 Manny Ramirez  35        1 0.29606625 143  20   88
16   2008 Manny Ramirez  36        2 0.33152174 183  37  121
17   2009 Manny Ramirez  37        1 0.28977273 102  19   63
18   2010 Manny Ramirez  38        2 0.29811321  79   9   42
19   2011 Manny Ramirez  39        1 0.05882353   1   0    1
```

Notice that even though Ramirez's age is a constant for each season, we have to use a vector operation (i.e. `max`) in order to reduce any potential vector to a single number.

Which season was Ramirez's best as a hitter? One relatively simple measurement of batting prowess is OPS, or On-Base Plus Slugging Percentage. Let's add this to our results and use it to rank them.

```
> mannyBySeason <- Batting %>%
    filter(playerID == "ramirma02") %>%
    inner_join(Master, by = c("playerID" = "playerID"))  %>%
    group_by(yearID) %>%
    summarise(name = paste(nameFirst, nameLast, sep=" "), Age = max(yearID - birthYear)
              , numTeams = length(unique(teamID))
              , BA = sum(H)/sum(AB), tH = sum(H), tHR = sum(HR), tRBI = sum(RBI)
              , OPS = sum(H + BB + HBP)/sum(AB + BB + SF + HBP) +
                      sum(H + X2B + 2*X3B + 3*HR)/sum(AB)) %>%
    arrange(desc(OPS))
> mannyBySeason

Source: local data frame [19 x 9]

   yearID          name Age numTeams         BA  tH tHR tRBI       OPS
1    2000 Manny Ramirez  28        1 0.35079727 154  38  122 1.1538056
2    1999 Manny Ramirez  27        1 0.33333333 174  44  165 1.1050227
3    2002 Manny Ramirez  30        1 0.34862385 152  33  107 1.0965959
4    2006 Manny Ramirez  34        1 0.32071269 144  35  102 1.0582218
5    2008 Manny Ramirez  36        2 0.33152174 183  37  121 1.0311129
6    2003 Manny Ramirez  31        1 0.32513181 185  37  104 1.0140934
7    2001 Manny Ramirez  29        1 0.30623819 162  41  125 1.0135344
8    2004 Manny Ramirez  32        1 0.30809859 175  43  130 1.0093578
9    2005 Manny Ramirez  33        1 0.29241877 162  45  144 0.9815551
10   1996 Manny Ramirez  24        1 0.30909091 170  33  112 0.9805817
11   1998 Manny Ramirez  26        1 0.29422067 168  45  145 0.9760231
12   1995 Manny Ramirez  23        1 0.30785124 149  31  107 0.9603117
13   1997 Manny Ramirez  25        1 0.32798574 184  26   88 0.9530710
14   2009 Manny Ramirez  37        1 0.28977273 102  19   63 0.9488834
15   2007 Manny Ramirez  35        1 0.29606625 143  20   88 0.8811543
16   1994 Manny Ramirez  22        1 0.26896552  78  17   60 0.8778325
```

```
17   2010 Manny Ramirez  38        2 0.29811321  79   9   42 0.8697524
18   1993 Manny Ramirez  21        1 0.16981132   9   2    5 0.5018868
19   2011 Manny Ramirez  39        1 0.05882353   1   0    1 0.1176471
```

We see that Ramirez's OPS was highest in 2000. But 2000 was the height of the steroid era, when many sluggers were putting up tremendous offensive numbers. As data scientists, we know that it would be more instructive to put Ramirez's OPS in context by comparing it to the league average in each season. To do this, we will need to compute those averages. Note that because there is missing data in some of these columns in some of these years, we need to invoke the `na.rm` argument to ignore that data.

```
> mlb <- Batting %>%
    filter(yearID %in% 1993:2011) %>%
    group_by(yearID) %>%
    summarise(lgOPS =
      sum(H + BB + HBP, na.rm=TRUE)/sum(AB + BB + SF + HBP, na.rm=TRUE) +
      sum(H + X2B + 2*X3B + 3*HR, na.rm=TRUE)/sum(AB, na.rm=TRUE))
```

Next, we need to match these league average OPS values to the corresponding entries for Ramirez. We can do this by joining these tables together, and computing the ratio of Ramirez's OPS to that of the league average.

```
> mannyBySeason %>%
    inner_join(mlb, by = c("yearID" = "yearID")) %>%
    mutate(OPSplus = OPS/lgOPS) %>%
    select(yearID, Age, OPS, lgOPS, OPSplus) %>%
    arrange(desc(OPSplus))

Source: local data frame [19 x 5]

   yearID Age       OPS     lgOPS   OPSplus
1    2000  28 1.1538056 0.7820671 1.4753281
2    2002  30 1.0965959 0.7478627 1.4663065
3    1999  27 1.1050227 0.7783929 1.4196209
4    2006  34 1.0582218 0.7684427 1.3770991
5    2008  36 1.0311129 0.7492645 1.3761667
6    2003  31 1.0140934 0.7546290 1.3438304
7    2001  29 1.0135344 0.7588417 1.3356334
8    2004  32 1.0093578 0.7628892 1.3230727
9    2005  33 0.9815551 0.7492401 1.3100675
10   1998  26 0.9760231 0.7553377 1.2921679
11   1996  24 0.9805817 0.7671281 1.2782503
12   1995  23 0.9603117 0.7551293 1.2717182
13   2009  37 0.9488834 0.7506920 1.2640117
14   1997  25 0.9530710 0.7560340 1.2606192
15   2010  38 0.8697524 0.7283150 1.1941980
16   2007  35 0.8811543 0.7584827 1.1617330
17   1994  22 0.8778325 0.7630205 1.1504703
18   1993  21 0.5018868 0.7355733 0.6823070
19   2011  39 0.1176471 0.7195697 0.1634964
```

In this case, 2000 still ranks as Ramirez's best season relative to his peers, but notice that his 1999 season has fallen from 2nd to 3rd. His own steroid use notwithstanding, Ramirez posted 17 consecutive seasons with an OPS that was at least 15% better than the average across the major leagues – a truly impressive feat.

Finally, not all joins are the same. An `inner_join` requires corresponding entries in *both* tables. Conversely, a `left_join` returns result for as many rows as there are in the first table, regardless of whether there are matches in the second table. Thus, an `inner_join` is bidirectional, whereas in a `left_join`, the order in which you specify the tables matters.

Consider the career of Cal Ripken, who played in 21 seasons from 1981 to 2001. His career overlapped with Ramirez's in the nine seasons from 1993 to 2001, so for those, the league averages we computed before are useful.

```
> ripken <- filter(Batting, playerID == "ripkeca01")
> nrow(inner_join(ripken, mlb, by = c("yearID" = "yearID")))

[1] 9

> nrow(inner_join(mlb, ripken, by = c("yearID" = "yearID"))) #same

[1] 9
```

On the other hand, Ripken played in 21 seasons regardless of whether Ramirez played in those same seasons, so for those missing seasons, `NA`'s will be returned.

```
> ripken %>%
    left_join(mlb, by = c("yearID" = "yearID")) %>%
    select(yearID, playerID, lgOPS)

   yearID  playerID     lgOPS
1    1981 ripkeca01        NA
2    1982 ripkeca01        NA
3    1983 ripkeca01        NA
4    1984 ripkeca01        NA
5    1985 ripkeca01        NA
6    1986 ripkeca01        NA
7    1987 ripkeca01        NA
8    1988 ripkeca01        NA
9    1989 ripkeca01        NA
10   1990 ripkeca01        NA
11   1991 ripkeca01        NA
12   1992 ripkeca01        NA
13   1993 ripkeca01 0.7355733
14   1994 ripkeca01 0.7630205
15   1995 ripkeca01 0.7551293
16   1996 ripkeca01 0.7671281
17   1997 ripkeca01 0.7560340
18   1998 ripkeca01 0.7553377
19   1999 ripkeca01 0.7783929
20   2000 ripkeca01 0.7820671
21   2001 ripkeca01 0.7588417
```

Conversely, by reversing the order of the tables in the join, we return the 19 seasons for which we have already computed the league averages, regardless of whether there is a match for Ripken.

```
> mlb %>%
    left_join(ripken, by = c("yearID" = "yearID")) %>%
    select(yearID, playerID, lgOPS)

Source: local data frame [19 x 3]

   yearID  playerID     lgOPS
1    1993 ripkeca01 0.7355733
2    1994 ripkeca01 0.7630205
3    1995 ripkeca01 0.7551293
4    1996 ripkeca01 0.7671281
5    1997 ripkeca01 0.7560340
6    1998 ripkeca01 0.7553377
7    1999 ripkeca01 0.7783929
8    2000 ripkeca01 0.7820671
9    2001 ripkeca01 0.7588417
10   2002        NA 0.7478627
11   2003        NA 0.7546290
12   2004        NA 0.7628892
13   2005        NA 0.7492401
14   2006        NA 0.7684427
15   2007        NA 0.7584827
16   2008        NA 0.7492645
17   2009        NA 0.7506920
18   2010        NA 0.7283150
19   2011        NA 0.7195697
```

3.5 Further Reading

Hadley Wickham of Rice University and RStudio is an enormously influential innovator in the field of data wrangling in R. His work on a number of widely-used packages, notably **dplyr** [131] and **tidyr** [129] is highly recommended reading. In particular, his paper on tidy data [132] builds upon notions of normal forms – common to database designers from computer science – to describe a process of thinking about how data should be stored and formatted. Finzer [28] writes of a "data habit of mind" among data scientists.

Sean Lahman, a self-described "database journalist", has long curated his baseball data set, which feeds the popular website baseball-reference.com. Michael Friendly maintains the **Lahman** R package [33]. For the baseball enthusiast, Cleveland Indians analyst Max Marchi and Jim Albert have written an excellent book on analyzing baseball data in R [81].

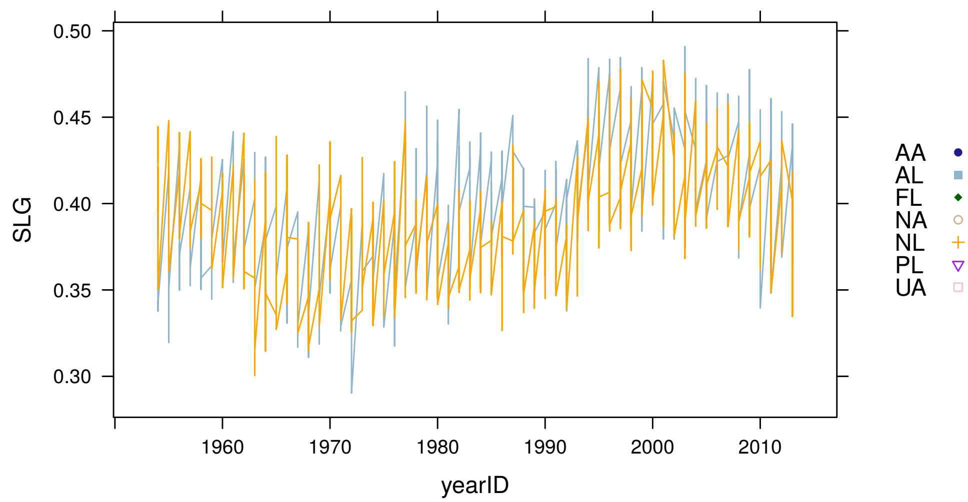
3.6 Exercises

1. Define two new variables in the `Teams` data frame: batting average (BA) and slugging percentage (SLG). Batting average is the ratio of hits (`H`) to at-bats (`AB`), and slugging percentage is total bases divided by at-bats. To compute total bases, you get 1 for a single, 2 for a double, 3 for a triple, and 4 for a home run.

```
> Teams <- mutate(Teams, BA = H/AB, SLG = (H + X2B + 2*X3B + 3*HR)/AB)
```

2. Plot a time series of `SLG` since 1954 conditioned by `lgID`. Is slugging percentage typically higher in the American League (AL) or the National League (NL)? Can you think of why this might be the case?

```
> xyplot(SLG ~ yearID, groups=lgID, data=filter(Teams, yearID >= 1954)
      , type=c("l"), auto.key=list(space = "right"))
```



3. Display the top 25 teams ranked in terms of slugging percentage in MLB history. Also do this for only teams since 1969.

```
> Teams %>%
    filter(yearID >= 1969) %>%
    select(yearID, teamID, lgID, SLG) %>%
    arrange(desc(SLG)) %>%
    head(25)

   yearID teamID lgID       SLG
1    2003    BOS   AL 0.4908996
2    1997    SEA   AL 0.4845030
3    1994    CLE   AL 0.4838389
4    1996    SEA   AL 0.4835921
5    2001    COL   NL 0.4829525
6    1995    CLE   AL 0.4787192
7    1999    TEX   AL 0.4786763
8    1997    COL   NL 0.4777798
9    2009    NYA   AL 0.4775618
10   2000    HOU   NL 0.4766607
11   2003    ATL   NL 0.4754850
12   1996    CLE   AL 0.4752684
```

```
13   2000    ANA   AL 0.4724591
14   1996    COL   NL 0.4724508
15   2004    BOS   AL 0.4723776
16   2000    SFN   NL 0.4720058
17   1996    BAL   AL 0.4719634
18   1999    COL   NL 0.4716585
19   1995    COL   NL 0.4707649
20   2001    TEX   AL 0.4707124
21   2000    CLE   AL 0.4701742
22   2000    CHA   AL 0.4700673
23   2000    TOR   AL 0.4692619
24   1996    TEX   AL 0.4686075
25   2005    TEX   AL 0.4683345
```

4. The Angels have at times been called the California Angels (CAL), the Anaheim Angels (ANA), and the Los Angeles Angels of Anaheim (LAA). Find the 10 most successful seasons in Angels history. Have they ever won the World Series?

```
> Teams %>%
    filter(teamID %in% c("CAL", "ANA", "LAA")) %>%
    select(yearID, teamID, lgID, W, L, WSWin) %>%
    mutate(WPct = W / (W + L)) %>%
    arrange(desc(WPct)) %>%
    head(10)

   yearID teamID lgID   W  L WSWin      WPct
1    2008    LAA   AL 100 62     N 0.6172840
2    2002    ANA   AL  99 63     Y 0.6111111
3    2009    LAA   AL  97 65     N 0.5987654
4    2005    LAA   AL  95 67     N 0.5864198
5    2007    LAA   AL  94 68     N 0.5802469
6    1982    CAL   AL  93 69     N 0.5740741
7    1986    CAL   AL  92 70     N 0.5679012
8    2004    ANA   AL  92 70     N 0.5679012
9    1989    CAL   AL  91 71     N 0.5617284
10   1985    CAL   AL  90 72     N 0.5555556
```

5. Create a factor called `election` that divides the `yearID` into four-year blocks that correspond to U.S. presidential terms. During which term have the most home runs been hit?

```
> Teams <- mutate(Teams, election = factor(cut(yearID
                       , breaks = seq(from = 1789, to = 2017, by=4))))
> sort(sum(HR ~ election, data=Teams))

(1869,1873] (1873,1877] (1877,1881] (1905,1909] (1897,1901] (1901,1905]
        133         148         219        1035        1358        1360
(1881,1885] (1909,1913] (1893,1897] (1913,1917] (1885,1889] (1889,1893]
       1429        1787        1882        2064        2207        2224
```

```
(1917,1921] (1941,1945] (1921,1925] (1925,1929] (1929,1933] (1933,1937]
       2249        4017        4100        4227        5059        5463
(1937,1941] (1945,1949] (1949,1953] (1953,1957] (1957,1961] (1965,1969]
       5822        6039        7713        8657        9348       10156
(1961,1965] (1973,1977] (1977,1981] (1969,1973] (1981,1985] (1989,1993]
      11155       11226       11257       11928       13540       13768
(1985,1989] (1993,1997] (2009,2013] (2005,2009] (2001,2005] (1997,2001]
      14534       16989       18760       20263       20734       21743
```

6. Name every player in baseball history who has accumulated at least 300 home runs and at least 300 stolen bases.

```
> Batting %>%
    group_by(playerID) %>%
    summarise(tHR = sum(HR), tSB = sum(SB)) %>%
    filter(tHR >= 300 & tSB >= 300) %>%
    left_join(Master, by = c("playerID" = "playerID")) %>%
    select(nameFirst, nameLast, tHR, tSB)

Source: local data frame [8 x 4]

  nameFirst  nameLast tHR tSB
1    Carlos   Beltran 358 308
2     Barry     Bonds 762 514
3     Bobby     Bonds 332 461
4     Andre    Dawson 438 314
5     Steve    Finley 304 320
6    Willie      Mays 660 338
7      Alex Rodriguez 654 322
8    Reggie   Sanders 305 304
```

7. Name every pitcher in baseball history who has accumulated at least 300 wins and at least 3000 strikeouts.

```
> Pitching %>%
    group_by(playerID) %>%
    summarise(tW = sum(W), tSO = sum(SO)) %>%
    filter(tW >= 300 & tSO >= 3000) %>%
    left_join(Master, by = c("playerID" = "playerID")) %>%
    select(nameFirst, nameLast, tW, tSO)

Source: local data frame [10 x 4]

   nameFirst nameLast  tW  tSO
1      Steve  Carlton 329 4136
2      Roger  Clemens 354 4672
3      Randy  Johnson 303 4875
4     Walter  Johnson 417 3509
5       Greg   Maddux 355 3371
```

```
6       Phil   Niekro 318 3342
7    Gaylord    Perry 314 3534
8      Nolan     Ryan 324 5714
9        Tom   Seaver 311 3640
10       Don   Sutton 324 3574
```

8. Identify the name and year of every player who has hit at least 50 home runs in a single season. Which player had the lowest batting average in that season?

```
> Batting %>%
    group_by(playerID, yearID) %>%
    summarise(tHR = sum(HR), BA = sum(H)/sum(AB)) %>%
    filter(tHR >= 50) %>%
    left_join(Master, by = c("playerID" = "playerID")) %>%
    select(nameFirst, nameLast, tHR, BA) %>%
    ungroup() %>%
    arrange(BA)

Source: local data frame [43 x 5]

    playerID nameFirst nameLast tHR        BA
1  bautijo02      Jose Bautista  54 0.2601054
2  jonesan01    Andruw    Jones  51 0.2627986
3  marisro01     Roger    Maris  61 0.2694915
4  vaughgr01      Greg   Vaughn  50 0.2722513
5  mcgwima01      Mark  McGwire  58 0.2740741
6  fieldce01     Cecil  Fielder  51 0.2774869
7  mcgwima01      Mark  McGwire  65 0.2783109
8  griffke02       Ken  Griffey  56 0.2843602
9  davisch02     Chris    Davis  53 0.2859589
10 ortizda01     David    Ortiz  54 0.2867384
..       ...       ...      ... ...       ...
```

9. Make one of these Baseball Records plots from the New York Times.