11

Manipulating Data with `dplyr`

The **`dplyr`**[1] ("dee-ply-er") package is the preeminent tool for data wrangling in R (and perhaps in data science more generally). It provides programmers with an intuitive vocabulary for executing data management and analysis tasks. Learning and using this package will make your data preparation and management process faster and easier to understand. This chapter introduces the philosophy behind the package and provides an overview of how to use the package to work with data frames using its expressive and efficient syntax.

11.1 A Grammar of Data Manipulation

Hadley Wickham, the original creator of the `dplyr` package, fittingly refers to it as a *Grammar of Data Manipulation*. This is because the package provides a set of **verbs** (functions) to describe and perform common data preparation tasks. One of the core challenges in programming is mapping from questions about a data set to specific programming operations. The presence of a data manipulation *grammar* makes this process smoother, as it enables you to use the same vocabulary to both *ask* questions and *write* your program. Specifically, the `dplyr` grammar lets you easily talk about and perform tasks such as the following:

- **Select** specific features (columns) of interest from a data set
- **Filter** out irrelevant data and keep only observations (rows) of interest
- **Mutate** a data set by adding more features (columns)
- **Arrange** observations (rows) in a particular order
- **Summarize** data in terms of aggregates such as the mean, median, or maximum
- **Join** multiple data sets together into a single data frame

You can use these words when describing the *algorithm* or process for interrogating data, and then use `dplyr` to write code that will closely follow your "plain language" description because it uses

[1] **`dplyr`**: http://dplyr.tidyverse.org

functions and procedures that share the same language. Indeed, many real-world questions about a data set come down to isolating specific rows/columns of the data set as the "elements of interest" and then performing a basic comparison or computation (e.g., mean, count, max). While it is possible to perform such computation with base R functions (described in the previous chapters), the dplyr package makes it much easier to write and read such code.

11.2 Core dplyr Functions

The dplyr package provides functions that mirror the verbs mentioned previously. Using this package's functions will allow you to quickly and effectively write code to ask questions of your data sets.

Since dplyr is an external package, you will need to install it (once per machine) and load it in each script in which you want to use the functions:

```
install.packages("dplyr") # once per machine
library("dplyr")          # in each relevant script
```

> **Fun Fact:** dplyr is a key part of the **tidyverse**[a] collection of R packages, which also includes tidyr (Chapter 12) and ggplot2 (Chapter 16). While these packages are discussed individually, you can install and use them all at once by installing and loading the collected "tidyverse" package.
>
> [a] https://www.tidyverse.org

After loading the package, you can call any of the functions just as if they were the built-in functions you've come to know and love.

To demonstrate the usefulness of the dplyr package as a tool for asking questions of real data sets, this chapter applies the functions to historical data about U.S. presidential elections. The presidentialElections data set is included as part of the pscl package, so you will need to install and load that package to access the data:

```
# Install the `pscl` package to use the `presidentialElections` data frame
install.packages("pscl") # once per machine
library("pscl")          # in each relevant script

# You should now be able to interact with the data set
View(presidentialElections)
```

This data set contains the percentage of votes that were cast in each state for the Democratic Party candidate in each presidential election from 1932 to 2016. Each row contains the state, year, percentage of Democrat votes (demVote), and whether each state was a member of the former Confederacy during the Civil War (south). For more information, see the pscl package reference manual,[2] or use ?presidentialElections to view the documentation in RStudio.

[2] **pscl reference manual**: https://cran.r-project.org/web/packages/pscl/pscl.pdf

11.2.1 Select

The **select()** function allows you to choose and extract columns of interest from your data frame, as illustrated in Figure 11.1.

```
# Select `year` and `demVotes` (percentage of vote won by the Democrat)
# from the `presidentialElections` data frame
votes <- select(presidentialElections, year, demVote)
```

The `select()` function takes as arguments the data frame to select from, followed by the names of the columns you wish to select (*without quotation marks*)!

This use of `select()` is equivalent to simply extracting the columns using base R syntax:

```
# Extract columns by name (i.e., "base R" syntax)
votes <- presidentialElections[, c ("year", "demVote")]
```

While this base R syntax achieves the same end, the `dplyr` approach provides a more **expressive** syntax that is easier to read and write.

> **Remember**: Inside the function argument list (inside the parentheses) of `dplyr` functions, you specify data frame columns without quotation marks—that is, you just give the column names as *variable names*, rather than as *character strings*. This is referred to as **non-standard evaluation** (NSE).[a] While this capability makes `dplyr` code easier to write and read, it can occasionally create challenges when trying to work with a column name that is stored in a variable.
>
> If you encounter errors in such situations, you can and should fall back to working with base R syntax (e.g., dollar sign and bracket notation).
>
> [a] http://dplyr.tidyverse.org/articles/programming.html

	state	demVote	year	south
1	Alabama	84.76	1932	TRUE
2	Arizona	67.03	1932	FALSE
3	Arkansas	86.27	1932	TRUE
4	California	58.41	1932	FALSE
5	Colorado	54.81	1932	FALSE
6	Connecticut	47.40	1932	FALSE
7	Delaware	48.11	1932	FALSE
8	Florida	74.49	1932	TRUE
9	Georgia	91.60	1932	TRUE
10	Idaho	58.70	1932	FALSE

```
select(
  presidentialElections,
  year,
  demVote
)
```

	year	demVote
1	1932	84.76
2	1932	67.03
3	1932	86.27
4	1932	58.41
5	1932	54.81
6	1932	47.40
7	1932	48.11
8	1932	74.49
9	1932	91.60
10	1932	58.70

Figure 11.1 Using the `select()` function to select the columns `year` and `demVote` from the `presidentialElections` data frame.

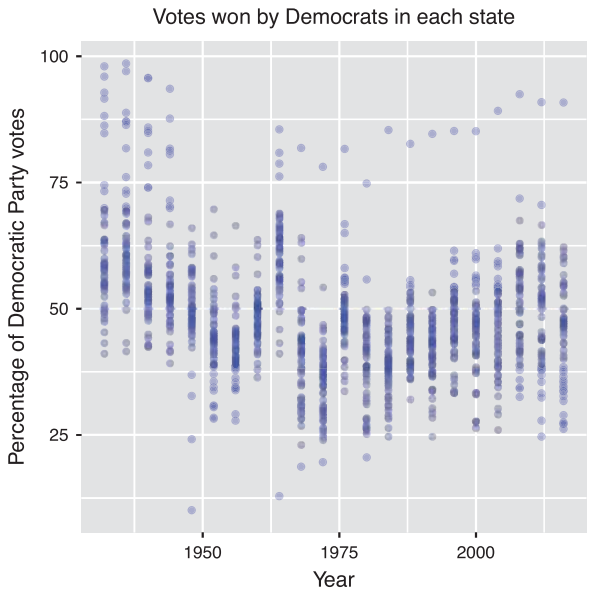


Figure 11.2 Percentage of votes cast for Democratic Party candidates in U.S. presidential elections, built with the `ggplot2` package.

This selection of data could be used to explore trends in voting patterns across states, as shown in Figure 11.2. For an interactive exploration of how state voting patterns have shifted over time, see this piece by the *New York Times*.[3]

Note that the arguments to the `select()` function can also be vectors of column names—you can write exactly what you would specify inside bracket notation, just without calling `c()`. Thus you can both select a range of columns using the `:` operator, and exclude columns using the `-` operator:

```
# Select columns `state` through `year` (i.e., `state`, `demVote`, and `year`)
select(presidentialElections, state:year)

# Select all columns except for `south`
select(presidentialElections, -south)
```

[3] **Over the Decades, How States Have Shifted:** https://archive.nytimes.com/www.nytimes.com/interactive/2012/10/15/us/politics/swing-history.html

Caution: Unlike with the use of bracket notation, using `select()` to select a single column will return a data frame, not a vector. If you want to extract a specific column or value from a data frame, you can use the `pull()` function from the `dplyr` package, or use base R syntax. In general, use `dplyr` for manipulating a data frame, and then use base R for referring to specific values in that data.

11.2.2 Filter

The **`filter()`** function allows you to choose and extract *rows* of interest from your data frame (contrasted with `select()`, which extracts *columns*), as illustrated in Figure 11.3.

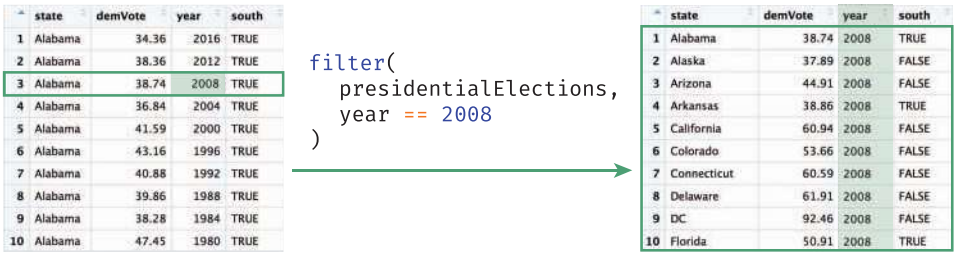
```
# Select all rows from the 2008 election
votes_2008 <- filter(presidentialElections, year == 2008)
```

The `filter()` function takes in the data frame to filter, followed by a comma-separated list of conditions that each returned *row* must satisfy. Again, column names must be specified without quotation marks. The preceding `filter()` statement is equivalent to extracting the rows using the following base R syntax:

```
# Select all rows from the 2008 election
votes_2008 <- presidentialElections[presidentialElections$year == 2008, ]
```

The `filter()` function will extract rows that match **all** given conditions. Thus you can specify that you want to filter a data frame for rows that meet the first condition *and* the second condition (and so on). For example, you may be curious about how the state of Colorado voted in 2008:

```
# Extract the row(s) for the state of Colorado in 2008
# Arguments are on separate lines for readability
votes_colorado_2008 <- filter(
  presidentialElections,
  year == 2008,
  state == "Colorado"
)
```



	state	demVote	year	south
1	Alabama	34.36	2016	TRUE
2	Alabama	38.36	2012	TRUE
3	Alabama	38.74	2008	TRUE
4	Alabama	36.84	2004	TRUE
5	Alabama	41.59	2000	TRUE
6	Alabama	43.16	1996	TRUE
7	Alabama	40.88	1992	TRUE
8	Alabama	39.86	1988	TRUE
9	Alabama	38.28	1984	TRUE
10	Alabama	47.45	1980	TRUE

	state	demVote	year	south
1	Alabama	38.74	2008	TRUE
2	Alaska	37.89	2008	FALSE
3	Arizona	44.91	2008	FALSE
4	Arkansas	38.86	2008	TRUE
5	California	60.94	2008	FALSE
6	Colorado	53.66	2008	FALSE
7	Connecticut	60.59	2008	FALSE
8	Delaware	61.91	2008	FALSE
9	DC	92.46	2008	FALSE
10	Florida	50.91	2008	TRUE

Figure 11.3 Using the `filter()` function to select observations from the `presidentialElections` data frame in which the `year` column is `2008`.

In cases where you are using multiple conditions—and therefore might be writing really long code—you should break the single statement into multiple lines for readability (as in the preceding example). Because you haven't closed the parentheses on the function arguments, R will treat each new line as part of the current statement. See the tidyverse style guide[4] for more details.

> **Caution**: If you are working with a data frame that has row names (`presidentialElections` does not), the `dplyr` functions will remove row names. If you need to retain these names, consider instead making them a column (*feature*) of the data, thereby allowing you to include those names in your wrangling and analysis. You can add row names as a column using the `mutate` function (described in Section 11.2.3):
>
> ```
> # Add row names of a dataframe `df` as a new column called `row_names`
> df <- mutate(df, row_names = rownames(df))
> ```

11.2.3 Mutate

The **`mutate()`** function allows you to create additional columns for your data frame, as illustrated in Figure 11.4. For example, it may be useful to add a column to the `presidentialElections` data frame that stores the percentage of votes that went to other candidates:

```
# Add an `other_parties_vote` column that is the percentage of votes
# for other parties
# Also add an `abs_vote_difference` column of the absolute difference
# between percentages
# Note you can use columns as you create them!
presidentialElections <- mutate(
  presidentialElections,
  other_parties_vote = 100 - demVote, # other parties is 100% - Democrat %
  abs_vote_difference = abs(demVote - other_parties_vote)
)
```

The `mutate()` function takes in the data frame to mutate, followed by a comma-separated list of columns to create using the same `name = vector` syntax you use when creating lists or data frames from scratch. As always, the names of the columns in the data frame are specified without quotation marks. Again, it is common to put each new column declaration on a separate line for spacing and readability.

> **Caution**: Despite the name, the `mutate()` function doesn't actually change the data frame; instead, it returns a *new* data frame that has the extra columns added. You will often want to replace your old data frame variable with this new value (as in the preceding code).

[4] **tidyverse style guide:** http://style.tidyverse.org

	state	demVote	year	south
1	Alabama	84.76	1932	TRUE
2	Arizona	67.03	1932	FALSE
3	Arkansas	86.27	1932	TRUE
4	California	58.41	1932	FALSE
5	Colorado	54.81	1932	FALSE
6	Connecticut	47.40	1932	FALSE
7	Delaware	48.11	1932	FALSE
8	Florida	74.49	1932	TRUE
9	Georgia	91.60	1932	TRUE
10	Idaho	58.70	1932	FALSE

	state	demVote	year	south	other_parties_vote	abs_vote_difference
1	Alabama	84.76	1932	TRUE	15.24	69.52
2	Arizona	67.03	1932	FALSE	32.97	34.06
3	Arkansas	86.27	1932	TRUE	13.73	72.54
4	California	58.41	1932	FALSE	41.59	16.82
5	Colorado	54.81	1932	FALSE	45.19	9.62
6	Connecticut	47.40	1932	FALSE	52.60	5.20
7	Delaware	48.11	1932	FALSE	51.89	3.78
8	Florida	74.49	1932	TRUE	25.51	48.98
9	Georgia	91.60	1932	TRUE	8.40	83.20
10	Idaho	58.70	1932	FALSE	41.30	17.40

```
mutate(
  presidentialElections,
  other_parties_vote = 100 - demVote,
  abs_vote_difference = abs(demVote - other_parties_vote)
)
```

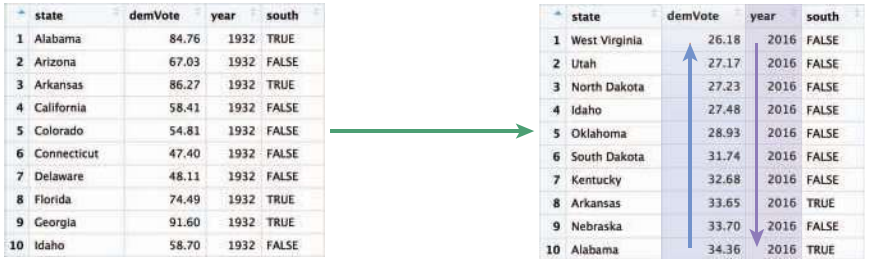
Figure 11.4 Using the `mutate()` function to create new columns on the `presidentialElections` data frame. Note that the `mutate()` function does not actually change a data frame (you need to assign the result to a variable).

> **Tip**: If you want to rename a particular column rather than adding a new one, you can use the `dplyr` function `rename()`, which is actually a variation of passing a *named argument* to the `select()` function to select columns aliased to different names.

11.2.4 Arrange

The **`arrange()`** function allows you to sort the rows of your data frame by some feature (column value), as illustrated in Figure 11.5. For example, you may want to sort the `presidentialElections` data frame by year, and then within each year, sort the rows based on the percentage of votes that went to the Democratic Party candidate:

```
# Arrange rows in decreasing order by `year`, then by `demVote`
# within each `year`
presidentialElections <- arrange(presidentialElections, -year, demVote)
```



	state	demVote	year	south
1	Alabama	84.76	1932	TRUE
2	Arizona	67.03	1932	FALSE
3	Arkansas	86.27	1932	TRUE
4	California	58.41	1932	FALSE
5	Colorado	54.81	1932	FALSE
6	Connecticut	47.40	1932	FALSE
7	Delaware	48.11	1932	FALSE
8	Florida	74.49	1932	TRUE
9	Georgia	91.60	1932	TRUE
10	Idaho	58.70	1932	FALSE

	state	demVote	year	south
1	West Virginia	26.18	2016	FALSE
2	Utah	27.17	2016	FALSE
3	North Dakota	27.23	2016	FALSE
4	Idaho	27.48	2016	FALSE
5	Oklahoma	28.93	2016	FALSE
6	South Dakota	31.74	2016	FALSE
7	Kentucky	32.68	2016	FALSE
8	Arkansas	33.65	2016	TRUE
9	Nebraska	33.70	2016	FALSE
10	Alabama	34.36	2016	TRUE

```
arrange(presidentialElections, -year, demVote)
```

Figure 11.5 Using the `arrange()` function to sort the `presidentialElections` data frame. Data is sorted in *decreasing* order by year (`-year`), then sorted by the `demVote` column *within* each year.

As demonstrated in the preceding code, you can pass multiple arguments into the `arrange()` function (in addition to the data frame to arrange). The data frame will be sorted by the column provided as the second argument, then by the column provided as the third argument (in case of a "tie"), and so on. Like `mutate()`, the `arrange()` function doesn't actually modify the argument data frame; instead, it returns a new data frame that you can store in a variable to use later.

By default, the `arrange()` function will sort rows in *increasing* order. To sort in *reverse* (decreasing) order, place a minus sign (`-`) in front of the column name (e.g., `-year`). You can also use the `desc()` helper function; for example, you can pass `desc(year)` as the argument.

11.2.5 Summarize

The **`summarize()`** function (equivalently `summarise()` for those using the British spelling) will generate a new data frame that contains a "summary" of a column, computing a single value from the multiple elements in that column. This is an **aggregation** operation (i.e., it will reduce an entire column to a single value—think about taking a sum or average), as illustrated in Figure 11.6. For example, you can calculate the average percentage of votes cast for Democratic Party candidates:

```
# Compute summary statistics for the `presidentialElections` data frame
average_votes <- summarize(
  presidentialElections,
  mean_dem_vote = mean(demVote),
  mean_other_parties = mean(other_parties_vote)
)
```

The `summarize()` function takes in the data frame to aggregate, followed by values that will be computed for the resulting summary table. These values are specified using `name = value` syntax,

Figure 11.6 Using the `summarize()` function to calculate summary statistics for the `presidentialElections` data frame.

similar to using `mutate()` or defining a list. You can use multiple arguments to include multiple aggregations in the same statement. This will return a data frame with a single row and a different column for each value that is computed by the function, as shown in Figure 11.6.

The `summarize()` function produces a data frame (a table) of summary values. If you want to reference any of those individual aggregates, you will need to extract them from this table using base `R` syntax or the `dplyr` function `pull()`.

You can use the `summarize()` function to aggregate columns with any function that takes a vector as a parameter and returns a single value. This includes many built-in `R` functions such as `mean()`, `max()`, and `median()`. Alternatively, you can write your own summary functions. For example, using the `presidentialElections` data frame, you may want to find the *least close election* (i.e., the one in which the `demVote` was furthest from 50% in absolute value). The following code constructs a function to find the *value furthest from 50* in a vector, and then applies the function to the `presidentialElections` data frame using `summarize()`:

```
# A function that returns the value in a vector furthest from 50
furthest_from_50 <- function(vec) {
  # Subtract 50 from each value
  adjusted_values <- vec - 50

  # Return the element with the largest absolute difference from 50
  vec[abs(adjusted_values) == max(abs(adjusted_values))]
}

# Summarize the data frame, generating a column `biggest_landslide`
# that stores the value furthest from 50%
summarize(
  presidentialElections,
  biggest_landslide = furthest_from_50(demVote)
)
```

The true power of the `summarize()` function becomes evident when you are working with data that has been *grouped*. In that case, each different group will be summarized as a different row in the summary table (see Section 11.4).

11.3 Performing Sequential Operations

If you want to do more complex analysis, you will likely want to combine these functions, taking the results from one function call and passing them into another function—this is a very common workflow. One approach to performing this sequence of operations is to create *intermediary variables* for use in your analysis. For example, when working with the `presidentialElections` data set, you may want to ask a question such as the following:

> *"Which state had the highest percentage of votes for the Democratic Party candidate (Barack Obama) in 2008?"*

Answering this seemingly simple question requires a few steps:

1. *Filter* down the data set to only observations from 2008.
2. Of the percentages in 2008, *filter* down to the one with the highest percentage of votes for a Democrat.
3. *Select* the name of the state that meets the above criteria.

You could then implement each step as follows:

```
# Use a sequence of steps to find the state with the highest 2008
# `demVote` percentage

# 1. Filter down to only 2008 votes
votes_2008 <- filter(presidentialElections, year == 2008)

# 2. Filter down to the state with the highest `demVote`
most_dem_votes <- filter(votes_2008, demVote == max(demVote))

# 3. Select name of the state
most_dem_state <- select(most_dem_votes, state)
```

While this approach works, it clutters the work environment with variables you won't need to use again. It *does* help with readability (the result of each step is explicit), but those extra variables make it harder to modify and change the algorithm later (you have to change them in two places).

An alternative to saving each step as a distinct, named variable would be to use **anonymous variables** and **nest** the desired statements within other functions. While this is possible, it quickly becomes difficult to read and write. For example, you could write the preceding algorithm as follows:

```
# Use nested functions to find the state with the highest 2008
# `demVote` percentage
most_dem_state <- select(    # 3. Select name of the state
  filter(                    # 2. Filter down to the highest `demVote`
    filter(                  # 1. Filter down to only 2008 votes
      presidentialElections, # arguments for the Step 1 `filter`
      year == 2008
    ),
    demVote == max(demVote)  # second argument for the Step 2 `filter`
  ),
  state                      # second argument for the Step 3 `select`
)
```

This version uses anonymous variables—result values that are not assigned to variables (and so are anonymous)—but instead are immediately used as the arguments to other functions. You've used these anonymous variables frequently with the `print()` function and with filters (those vectors of `TRUE` and `FALSE` values)—even the `max(demVote)` in the Step 2 filter is an anonymous variable!

This nested approach achieves the same result as the previous example does without creating extra variables. But, even with only three steps, it can get quite complicated to read—in a large part because you have to think about it "inside out," with the code in the middle being evaluated first. This will obviously become undecipherable for more involved operations.

11.3.1 The Pipe Operator

Luckily, `dplyr` provides a cleaner and more effective way of performing the same task (that is, using the result of one function as an argument to the next). The **pipe operator** (written as **`%>%`**) takes the result from one function and passes it in as *the first argument* to the next function! You can answer the question asked earlier much more directly using the pipe operator as follows:

```
# Ask the same question of our data using the pipe operator
most_dem_state <- presidentialElections %>% # data frame to start with
  filter(year == 2008) %>% # 1. Filter down to only 2008 votes
  filter(demVote == max(demVote)) %>% # 2. Filter down to the highest `demVote`
  select(state) # 3. Select name of the state
```

Here the `presidentialElections` data frame is "piped" in as the first argument to the first `filter()` call; because the argument has been piped in, the `filter()` call takes in only the remaining arguments (e.g., `year == 2008`). The result of that function is then piped in as the first argument to the *second* `filter()` call (which needs to specify only the remaining arguments), and so on. The additional arguments (such as the filter criteria) continue to be passed in as normal, as if no data frame argument is needed.

Because all `dplyr` functions discussed in this chapter take as a first argument the data frame to manipulate, and then return a manipulated data frame, it is possible to "chain" together any of these functions using a pipe!

Yes, the `%>%` operator can be awkward to type and takes some getting use to (especially compared to the command line's use of `|` to pipe). However, you can ease the typing by using the RStudio keyboard shortcut `cmd+shift+m`.

> **Tip**: You can see all RStudio keyboard shortcuts by navigating to the `Tools > Keyboard Shortcuts Help` menu, or you can use the keyboard shortcut `alt+shift+k` (yes, this is the keyboard shortcut to show the keyboard shortcuts menu!).

The pipe operator is loaded when you load the `dplyr` package (it is available only if you load that package), but it will work with *any* function, not just `dplyr` ones. This syntax, while slightly odd, can greatly simplify the way you write code to ask questions about your data.

> **Fun Fact**: Many packages load other packages (which are referred to as *dependencies*). For example, the pipe operator is actually part of the `magrittr`[a] package, which is loaded as a dependency of `dplyr`.
>
> [a]https://cran.r-project.org/web/packages/magrittr/vignettes/ magrittr.html

Note that as in the preceding example, it is best practice to put each "step" of a pipe sequence on its own line (indented by two spaces). This allows you to easily rearrange the steps (simply by moving lines), as well as to "comment out" particular steps to test and debug your analysis as you go.

11.4 Analyzing Data Frames by Group

`dplyr` functions are powerful, but they are truly awesome when you can apply them to *groups of rows* within a data set. For example, the previously described use of `summarize()` isn't particularly useful since it just gives a single summary for a given column (which you could have done easily using base `R` functions). However, a **grouped operation** would allow you to compute the same summary measure (e.g., `mean`, `median`, `sum`) automatically for multiple groups of rows, enabling you to ask more nuanced questions about your data set.

The **`group_by()`** function allows you to create associations among *groups of rows* in a data frame so that you can easily perform such aggregations. It takes as arguments a data frame to do the grouping on, followed by which column(s) you wish to use to group the data—each row in the table will be grouped with other rows that have the same value in that column. For example, you can group all of the data in the `presidentialElections` data set into groups whose rows share the same `state` value:

```
# Group observations by state
grouped <- group_by(presidentialElections, state)
```

The `group_by()` function returns a **tibble**,[5] which is a version of a data frame used by the "tidyverse"[6] family of packages (which includes `dplyr`). You can think of this as a "special" kind of data frame—one that is able to keep track of "subsets" (groups) within the same variable. While this grouping is not visually apparent (i.e., it does not sort the rows), the tibble keeps track of each row's group for computation, as shown in Figure 11.7.

The `group_by()` function is useful because it lets you apply operations to groups of data without having to explicitly break your data into different variables (sometimes called *bins* or *chunks*). Once you've used `group_by()` to group the rows of a data frame, you can apply other verbs (e.g., `summarize()`, `filter()`) to that tibble, and they will be automatically applied to *each* group (as if they were separate data frames). Rather than needing to explicitly extract different sets of data into separate data frames and run the same operations on each, you can use the `group_by()` function to accomplish all of this with a single command:

[5] **`tibble` package website**: http://tibble.tidyverse.org
[6] **`tidyverse` website**: https://www.tidyverse.org

```
> group_by(presidentialElections, state)
# A tibble: 1,097 x 4
# Groups:   state [51]
   state       demVote  year south
   <chr>         <dbl> <int> <lgl>
 1 Alabama        84.8  1932 TRUE
 2 Arizona        67.0  1932 FALSE
 3 Arkansas       86.3  1932 TRUE
 4 California     58.4  1932 FALSE
 5 Colorado       54.8  1932 FALSE
 6 Connecticut    47.4  1932 FALSE
 7 Delaware       48.1  1932 FALSE
 8 Florida        74.5  1932 TRUE
 9 Georgia        91.6  1932 TRUE
10 Idaho          58.7  1932 FALSE
# ... with 1,087 more rows
```

Result is grouped by state

Figure 11.7 A tibble—created by the `group_by()` function—that stores associations by the grouping variable (`state`). Red notes are added.

```
# Compute summary statistics by state: average percentages across the years
state_voting_summary <- presidentialElections %>%
  group_by(state) %>%
  summarize(
    mean_dem_vote = mean(demVote),
    mean_other_parties = mean(other_parties_vote)
  )
```

The preceding code will first group the rows together by `state`, then compute summary information (`mean()` values) for each one of these groups (i.e., for each state), as illustrated in Figure 11.8. A summary of groups will still return a tibble, where each row is the summary of a

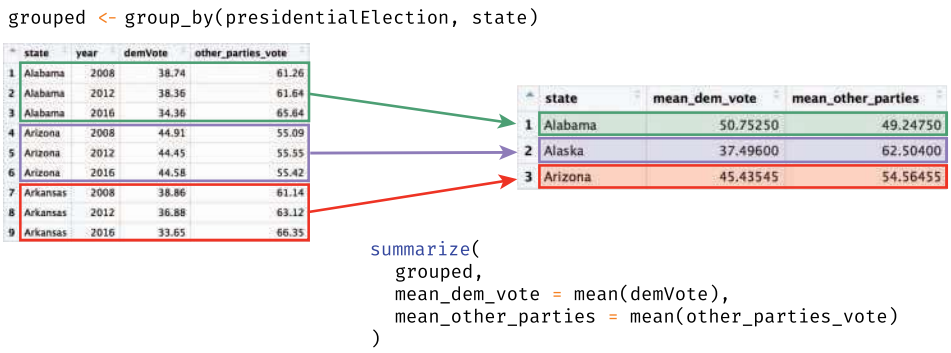


Figure 11.8 Using the `group_by()` and `summarize()` functions to calculate summary statistics in the `presidentialElections` data frame by state.

different group. You can extract values from a tibble using dollar sign or bracket notation, or convert it back into a normal data frame with the `as.data.frame()` function.

This form of grouping can allow you to quickly compare different subsets of your data. In doing so, you're redefining your **unit of analysis**. Grouping lets you frame your analysis question in terms of comparing *groups of observations*, rather than individual observations. This form of abstraction makes it easier to ask and answer complex questions about your data.

11.5 Joining Data Frames Together

When working with real-world data, you will often find that the data is stored across *multiple* files or data frames. This can be done for a number of reasons, such as reducing memory usage. For example, if you had a data frame containing information on a fundraising campaign that tracked donations (e.g., dollar amount, date), you would likely store information about each donor (e.g., email, phone number) in a separate data file (and thus data frame). See Figure 11.9 for an example of what this structure would look like.

This structure has a number of benefits:

1. **Data storage**: Rather than duplicating information about each donor every time that person makes a donation, you can store that information a single time. This will reduce the amount of space your data takes up.
2. **Data updates**: If you need to update information about a donor (e.g., the donor's phone number changes), you can make that change in a *single location*.

This separation and organization of data is a core concern in the design of *relational databases*, which are discussed in Chapter 13.

At some point, you will want to access information from both data sets (e.g., you need to email donors about their contributions), and thus need a way to reference values from both data frames at once—in effect, to *combine* the data frames. This process is called a **join** (because you are "joining" the data frames together). When you perform a join, you identify columns which are present in both tables, and use those columns to "match" corresponding rows to one another. Those column values are used as **identifiers** to determine which rows in each table correspond to one another, and thus will be combined into a single row in the resulting (joined) table.

Donations

	donor_name	amout	date
1	Maria Franca Fissolo	100	2018-02-15
2	Yang Huiyan	50	2018-02-15
3	Maria Franca Fissolo	75	2018-02-15
4	Alice Walton	25	2018-02-16
5	Susanne Klatten	100	2018-02-17
6	Yang Huiyan	150	2018-02-18

Donors

	donor_name	email
1	Alice Walton	alice.walton@gmail.com
2	Jacqueline Mars	jacqueline.mars@gmail.com
3	Maria Franca Fissolo	maria.franca.fissolo@gmail.com
4	Susanne Klatten	susanne.klatten@gmail.com
5	Laurene Powell Jobs	laurene.powell.jobs@gmail.com
6	Francoise Bettencourt Meyers	francoise.bettencourt.meyers@gmail.com

Figure 11.9 An example data frame of donations (left) and donor information (right). Notice that not all donors are present in both data frames.

The **`left_join()`** function is one example of a join. This function looks for matching columns between two data frames, and then returns a new data frame that is the first ("left") argument with extra columns from the second ("right") argument added on—in effect, "merging" the tables. You specify which columns you want to "match" on by specifying a **`by`** argument, which takes a vector of columns names (as strings).

For example, because both of the data frames in Figure 11.9 have a `donor_name` column, you can "match" the rows from the `donor` table to the `donations` table by this column and merge them together, producing the joined table illustrated in Figure 11.10.

```
# Combine (join) donations and donors data frames by their shared column
# ("donor_name")
combined_data <- left_join(donations, donors, by = "donor_name")
```

When you perform a **left join** as in the preceding code, the function performs the following steps:

1. It goes through each row in the table on the "left" (the first argument; e.g., `donations`), considering the values from the shared columns (e.g., `donor_name`).
2. For each of these values from the left-hand table, the function looks for a row in the right-hand table (e.g., `donors`) that has the *same* value in the specified column.
3. If it finds such a matching row, it adds any other data values from columns that are in `donors` but *not* in `donations` *to that left-hand row* in the resulting table.
4. It repeats steps 1–3 for each row in the left-hand table, until all rows have been given values from their matches on the right (if any).

You can see in Figure 11.10 that there were elements in the left-hand table (`donations`) that did not match to a row in the right-hand table (`donors`). This may occur because there are some donations whose donors do not have contact information (there is no matching `donor_name` entry): those rows will be given `NA` (*not available*) values, as shown in Figure 11.10.

> **Remember**: A left join returns all of the rows from the *first* table, with all of the columns from *both* tables.

For rows to match, they need to have the same data in *all* specified shared columns. However, if the names of your columns don't match or if you want to match only on specific columns, you can use a *named vector* (one with tags similar to a list) to indicate the different names from each data frame. If you don't specify a `by` argument, the join will match on *all* shared column names.

```
# An example join in the (hypothetical) case where the tables have
# different identifiers; e.g., if `donations` had a column `donor_name`,
# while `donors` had a column `name`
combined_data <- left_join(donations, donors, by = c("donor_name" = "name"))
```

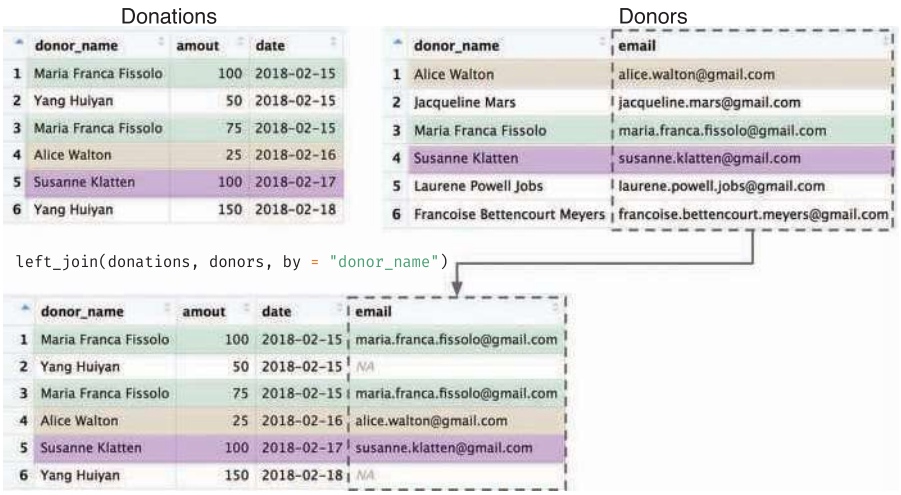


Figure 11.10 In a left join, columns from the right hand table (`Donors`) are added to the end of the left-hand table (`Donations`). Rows are on matched on the shared column (`donor_name`). Note the observations present in the left-hand table that don't have a corresponding row in the right-hand table (`Yang Huiyan`).

> **Caution**: Because of how joins are defined, the argument order matters! For example, in a `left_join()`, the resulting table has rows for only the elements in the *left* (first) table; any unmatched elements in the second table are lost.

If you switch the order of the arguments, you will instead keep all of the information from the `donors` data frame, adding in available information from `donations` (see Figure 11.11).

```
# Combine (join) donations and donors data frames (see Figure 11.11)
combined_data <- left_join(donors, donations, by = "donor_name")
```

Since some `donor_name` values show up multiple times in the right-hand (`donations`) table, the rows from `donors` end up being repeated so that the information can be "merged" with each set of values from `donations`. Again, notice that rows that lack a match in the right-hand table don't get any additional information (representing "donors" who gave their contact information to the organization, but have not yet made a donation).

Because the order of the arguments matters, `dplyr` (and relational database systems in general) provide several different kinds of joins, each influencing *which* rows are included in the final table. Note that in all joins, columns from *both* tables will be present in the resulting table—the join type dictates which rows are included. See Figure 11.12 for a diagram of these joins.

- **`left_join`**: All rows from the first (left) data frame are returned. That is, you get all the data from the left-hand table, with extra column values added from the right-hand table. Left-hand rows without a match will have `NA` in the right-hand columns.

Figure 11.11 Switching the order of the tables in a left-hand join (compared to Figure 11.10) returns a different set of rows. All rows from the left-hand table (`donors`) are returned with additional columns from the right-hand table (`donations`).

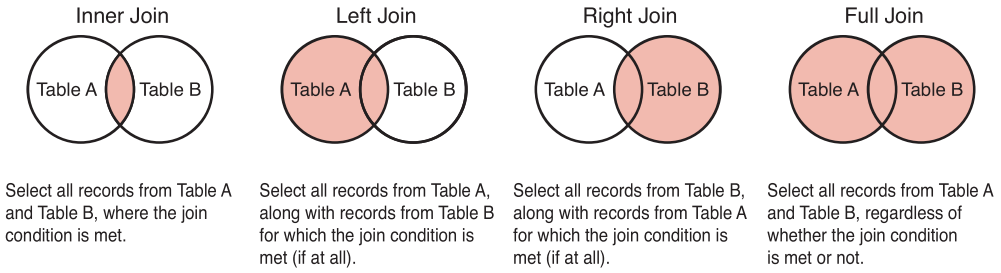


Figure 11.12 A diagram of different join types, downloaded from http://www.sql-join.com/sql-join-types/.

- **`right_join`**: All rows from the second (right) data frame are returned. That is, you get all the data from the right-hand table, with extra column values added from the left-hand table. Right-hand rows without a match will have `NA` in the left-hand columns. This is the "opposite" of a `left_join`, and the equivalent of switching the order of the arguments.
- **`inner_join`**: Only rows in *both* data frames are returned. That is, you get any rows that had matching observations in both tables, with the column values from both tables. There will be no additional `NA` values created by the join. Observations from the left that had no match

in the right, or observations from the right that had no match in the left, will not be returned at all—the order of arguments *does not matter*.

- **`full_join`**: All rows from *both* data frames are returned. That is, you get a row for any observation, whether or not it matched. If it happened to match, values from both tables will appear in that row. Observations without a match will have `NA` in the columns from the other table—the order of arguments *does not matter*.

The key to deciding between these joins is to think about which set of data you want as your set of observations (rows), and which columns you'd be okay with being `NA` if a record is missing.

Tip: Jenny Bryan has created an excellent "cheatsheet"[a] for `dplyr` join functions that you can reference.

[a] http://stat545.com/bit001_dplyr-cheatsheet.html

Going Further: All the joins discussed here are *mutating joins*, which add columns from one table to another. `dplyr` also provides *filtering joins*, which exclude rows based on whether they have a matching observation in another table, and *set operations*, which combine observations as if they were set elements. See the package documentation[a] for more detail on these options—but to get started you can focus primarily on the mutating joins.

[a] https://cran.r-project.org/web/packages/dplyr/vignettes/two- table.html

11.6 `dplyr` in Action: Analyzing Flight Data

In this section, you will learn how `dplyr` functions can be used to ask interesting questions of a more complex data set (the complete code for this analysis is also available online in the book's code repository[7]). You'll use a data set of flights that departed from New York City airports (including Newark, John F. Kennedy, and Laguardia airports) in 2013. This data set is also featured online in the *Introduction to dplyr* vignette,[8] and is drawn from the Bureau of Transportation Statistics database.[9] To load the data set, you will need to install and load the `nycflights13` package. This will load the `flights` data set into your environment.

```
# Load the `nycflights13` package to access the `flights` data frame
install.packages("nycflights13") # once per machine
library("nycflights13")          # in each relevant script
```

Before you can start asking targeted questions of the data set, you will need to understand the structure of the data set a bit better:

[7] **`dplyr` in Action**: https://github.com/programming-for-data-science/in-action/tree/master/dplyr
[8] **Introduction to `dplyr`:** http://dplyr.tidyverse.org/articles/dplyr.html
[9] **Bureau of Labor Statistics:** air flights data: https://www.transtats.bts.gov/DatabaseInfo.asp?DB_ID=120

```
# Getting to know the `flights` data set
?flights          # read the available documentation
dim(flights)      # check the number of rows/columns
colnames(flights) # inspect the column names
View(flights)     # look at the data frame in the RStudio Viewer
```

A subset of the `flights` data frame in RStudio's Viewer is shown in Figure 11.13.

Given this information, you may be interested in asking questions such as the following:

1. Which *airline* has the *highest number of delayed* departures?
2. On *average*, to which *airport* do flights arrive *most early*?
3. In which *month* do flights tend to have the *longest delays*?

Your task here is to map from these questions to specific procedures so that you can write the appropriate `dplyr` code.

You can begin by asking the first question:

> *"Which **airline** has the **highest number of delayed** departures?"*

This question involves comparing observations (flights) that share a particular feature (airline), so you perform the analysis as follows:

1. Since you want to consider all the flights from a particular airline (based on the `carrier` feature), you will first want to *group* the data by that feature.
2. You need to figure out the largest number of delayed departures (based on the `dep_delay` feature)—which means you need to find the flights that were delayed (*filtering* for them).
3. You can take the found flights and aggregate them into a count (*summarize* the different groups).

flights ×

Filter

	year	month	day	dep_time	sched_dep_time	dep_delay	arr_time	sched_arr_time
1	2013	1	1	517	515	2	830	819
2	2013	1	1	533	529	4	850	830
3	2013	1	1	542	540	2	923	850
4	2013	1	1	544	545	-1	1004	1022
5	2013	1	1	554	600	-6	812	837
6	2013	1	1	554	558	-4	740	728
7	2013	1	1	555	600	-5	913	854

Figure 11.13 A subset of the `flights` data set, which is included as part of the `nycflights13` package.

4. You will then need to find which group has the highest count (*filtering*).
5. Finally, you can choose (*select*) the airline of that group.

> **Tip**: When you're trying to find the right operation to answer your question of interest, the phrase *"Find the entry that..."* usually corresponds to a `filter()` operation!

Once you have established this algorithm, you can directly map it to `dplyr` functions:

```
# Identify the airline (`carrier`) that has the highest number of
# delayed flights
has_most_delays <- flights %>%            # start with the flights
  group_by(carrier) %>%                   # group by airline (carrier)
  filter(dep_delay > 0) %>%               # find only the delays
  summarize(num_delay = n()) %>%          # count the observations
  filter(num_delay == max(num_delay)) %>% # find most delayed
  select(carrier)                         # select the airline
```

> **Remember:** Often many approaches can be used to solve the same problem. The preceding code shows one possible approach; as an alternative, you could filter for delayed departures before grouping. The point is to think through how you might solve the problem (by hand) in terms of the *Grammar of Data Manipulation*, and then convert that into `dplyr`!

Unfortunately, the final answer to this question appears to be an abbreviation: `UA`. To reduce the size of the `flights` data frame, information about each airline is stored in a *separate* data frame called `airlines`. Since you are interested in combining these two data frames (your answer and the airline information), you can use a join:

```
# Get name of the most delayed carrier
most_delayed_name <- has_most_delays %>%  # start with the previous answer
  left_join(airlines, by = "carrier") %>% # join on airline ID
  select(name)                            # select the airline name

print(most_delayed_name$name) # access the value from the tibble
# [1] "United Air Lines Inc."
```

After this step, you will have learned that the carrier that had the largest *absolute number* of delays was *United Air Lines Inc.* Before criticizing the airline too strongly, however, keep in mind that you might be interested in the *proportion of flights that are delayed*, which would require a separate analysis.

Next, you can assess the second question:

> *"On average, to which* ***airport*** *do flights arrive* ***most early****?"*

To answer this question, you can follow a similar approach. Because this question pertains to how early flights arrive, the *outcome* (feature) of interest is `arr_delay` (noting that a *negative* amount of delay indicates that the flight arrived *early*). You will want to *group* this information by *destination*

airport (dest) where the flight arrived. And then, since you're interested in the *average* arrival delay, you will want to *summarize* those groups to aggregate them:

```
# Calculate the average arrival delay (`arr_delay`) for each destination
# (`dest`)
most_early <- flights %>%
  group_by(dest) %>% # group by destination
  summarize(delay = mean(arr_delay)) # compute mean delay
```

It's always a good idea to check your work as you perform each step of an analysis—don't write a long sequence of manipulations and hope that you got the right answer! By printing out the most_early data frame at this point, you notice that it has *a lot* of NA values, as seen in Figure 11.14.

This kind of unexpected result occurs frequently when doing data programming—and the best way to solve the problem is to work backward. By carefully inspecting the arr_delay column, you may notice that some entries have NA values—the arrival delay is not available for that record. Because you can't take the mean() of NA values, you decide to exclude those values from the analysis. You can do this by passing an na.rm = TRUE argument ("NA remove") to the mean() function:

```
# Compute the average delay by destination airport, omitting NA results
most_early <- flights %>%
  group_by(dest) %>% # group by destination
  summarize(delay = mean(arr_delay, na.rm = TRUE)) # compute mean delay
```

	dest	delay
1	ABQ	4.381890
2	ACK	NA
3	ALB	NA
4	ANC	-2.500000
5	ATL	NA
6	AUS	NA
7	AVL	NA
8	BDL	NA
9	BGR	NA

Figure 11.14 Average delay by destination in the flights data set. Because NA values are present in the data set, the mean delay for many destinations is calculated as NA. To remove NA values from the mean() function, set na.rm = FALSE.

Removing NA values returns numeric results, and you can continue working through your algorithm:

```
# Identify the destination where flights, on average, arrive most early
most_early <- flights %>%
  group_by(dest) %>% # group by destination
  summarize(delay = mean(arr_delay, na.rm = TRUE)) %>% # compute mean delay
  filter(delay == min(delay, na.rm = TRUE)) %>% # filter for least delayed
  select(dest, delay) %>% # select the destination (and delay to store it)
  left_join(airports, by = c("dest" = "faa")) %>% # join on `airports` data
  select(dest, name, delay) # select output variables of interest

print(most_early)
# A tibble: 1 x 3
#  dest  name       delay
#  <chr> <chr>      <dbl>
#1 LEX   Blue Grass   -22
```

Answering this question follows a very similar structure to the first question. The preceding code reduces the steps to a single statement by including the `left_join()` statement in the sequence of piped operations. Note that the column containing the airport code has a different name in the `flights` and `airports` data frames (`dest` and `faa`, respectively), so you use a named vector value for the `by` argument to specify the match.

As a result, you learn that *LEX—Blue Grass Airport* in Lexington, Kentucky—is the airport with the earliest average arrival time (*22* minutes early!).

A final question is:

> *"In which **month** do flights tend to have the **longest delays**?"*

These kinds of summary questions all follow a similar pattern: *group* the data by a column (feature) of interest, compute a *summary* value for (another) feature of interest for each group, *filter* down to a row of interest, and *select* the columns that answer your question:

```
# Identify the month in which flights tend to have the longest delays
flights %>%
  group_by(month) %>% # group by selected feature
  summarize(delay = mean(arr_delay, na.rm = TRUE)) %>% # summarize delays
  filter(delay == max(delay)) %>% # filter for the record of interest
  select(month) %>% # select the column that answers the question
  print() # print the tibble out directly
# A tibble: 1 x 1
#  month
#  <int>
#1   7
```

If you are okay with the result being in the form of a tibble rather than a vector, you can even pipe the results directly to the `print()` function to view the results in the R console (the answer being

July). Alternatively, you can use a package such as ggplot2 (see Chapter 16) to visually communicate the delays by month, as in Figure 11.15.

```
# Compute delay by month, adding month names for visual display
# Note, `month.name` is a variable built into R
delay_by_month <- flights %>%
  group_by(month) %>%
  summarize(delay = mean(arr_delay, na.rm = TRUE)) %>%
  select(delay) %>%
  mutate(month = month.name)

# Create a plot using the ggplot2 package (described in Chapter 17)
ggplot(data = delay_by_month) +
  geom_point(
    mapping = aes(x = delay, y = month),
    color = "blue",
    alpha = .4,
    size = 3
  ) +
  geom_vline(xintercept = 0, size = .25) +
  xlim(c(-20, 20)) +
  scale_y_discrete(limits = rev(month.name)) +
  labs(title = "Average Delay by Month", y = "", x = "Delay (minutes)")
```

Overall, understanding how to formulate questions, translate them into data manipulation steps (following the *Grammar of Data Manipulation*), and then map those to dplyr functions will enable you to quickly and effectively learn pertinent information about your data set. For practice wrangling data with the dplyr package, see the set of accompanying book exercises.[10]

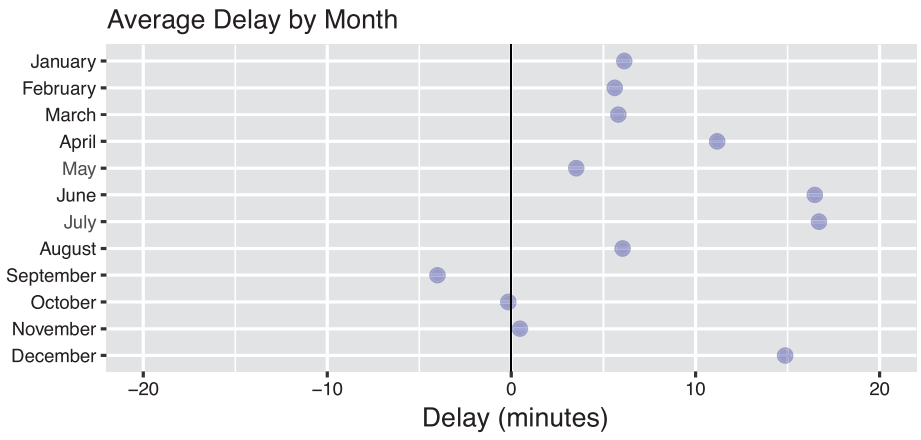


Figure 11.15 Average flight arrival delay in each month, calculated using the flights data set. The plot is built using ggplot2 (discussed in Chapter 16).

[10] **dplyr exercises:** https://github.com/programming-for-data-science/chapter-11-exercises

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12

Reshaping Data with `tidyr`

One of the most common data wrangling challenges is adjusting how exactly row and columns are used to represent your data. Structuring (or restructuring) data frames to have the desired shape can be the most difficult part of creating a visualization, running a statistical model, or implementing a machine learning algorithm.

This chapter describes how you can use the **`tidyr`** ("tidy-er") package to effectively transform your data into an appropriate shape for analysis and visualization.

12.1 What Is "Tidy" Data?

When wrangling data into a data frame for your analysis, you need to decide on the *desired structure* of that data frame. You need to determine what each row and column will represent, so that you can consistently and clearly manipulate that data (e.g., you know what you will be *selecting* and what you will be *filtering*). The `tidyr` package is used to structure and work with data fames that follow three *principles of tidy data* (as described by the package's documentation[1]):

1. Each variable is in a column.
2. Each observation is a row.
3. Each value is a cell.

Indeed, these principles lead to the data structuring described in Chapter 9: rows represent observations, and columns represent features of that data.

However, asking different questions of a data set may involve different interpretations of what constitutes an "observation." For example, Section 11.6 described working with the `flights` data set from the `nycflights13` package, in which each observation is a *flight*. However, the analysis made comparisons between *airlines*, *airports*, and *months*. Each question worked with a different unit of analysis, implying a different data structure (e.g., what should be represented by each row). While the example somewhat changed the nature of these rows by grouping and joining different data sets, having a more specific data structure where each row represented a *specific* unit of analysis

[1] **`tidyr`**: https://tidyr.tidyverse.org

(e.g., an *airline* or a *month*) may have made much of the wrangling and analysis more straightforward.

To use multiple different definitions of an "observation" when investigating your data, you will need to create multiple representations (i.e., data frames) of the same data set—each with its own configuration of rows and columns.

To demonstrate how you may need to adjust what each observation represents, consider the (fabricated) data set of music concert prices shown in Table 12.1. In this table, each observation (row) represents a *city*, with each city having features (columns) of the ticket price for a specific *band*.

But consider if you wanted to analyze the ticket price across all concerts. You could not do this easily with the data in its current form, since the data is organized by city (not by concert)! You would prefer instead that all of the prices were listed in a single column, as a feature of a row representing a single concert (a city-and-band combination), as in Table 12.2.

Table 12.1 **A "wide" data set of concert ticket price in different cities. Each observation (i.e., unit of analysis) is a city, and each feature is the concert ticket price for a given band.**

city	greensky_bluegrass	trampled_by_turtles	billy_strings	fruition
Seattle	40	30	15	30
Portland	40	20	25	50
Denver	20	40	25	40
Minneapolis	30	100	15	20

Table 12.2 **A "long" data set of concert ticket price by city and band. Each observation (i.e., unit of analysis) is a city–band combination, and each has a single feature that is the ticket price.**

city	band	price
Seattle	greensky_bluegrass	40
Portland	greensky_bluegrass	40
Denver	greensky_bluegrass	20
Minneapolis	greensky_bluegrass	30
Seattle	trampled_by_turtles	30
Portland	trampled_by_turtles	20
Denver	trampled_by_turtles	40
Minneapolis	trampled_by_turtles	100
Seattle	billy_strings	15
Portland	billy_strings	25
Denver	billy_strings	25
Minneapolis	billy_strings	15
Seattle	fruition	30
Portland	fruition	50
Denver	fruition	40
Minneapolis	fruition	20

Both Table 12.1 and Table 12.2 represent the same set of data—they both have prices for 16 different concerts. But by representing that data in terms of different *observations*, they may better support different analyses. These data tables are said to be in a different **orientation**: the price data in Table 12.1 is often referred to being in **wide format** (because it is spread wide across multiple columns), while the price data in Table 12.2 is in **long format** (because it is in one long column). Note that the long format table includes some duplicated data (the names of the cities and bands are repeated), which is part of why the data might instead be stored in wide format in the first place!

12.2 From Columns to Rows: `gather()`

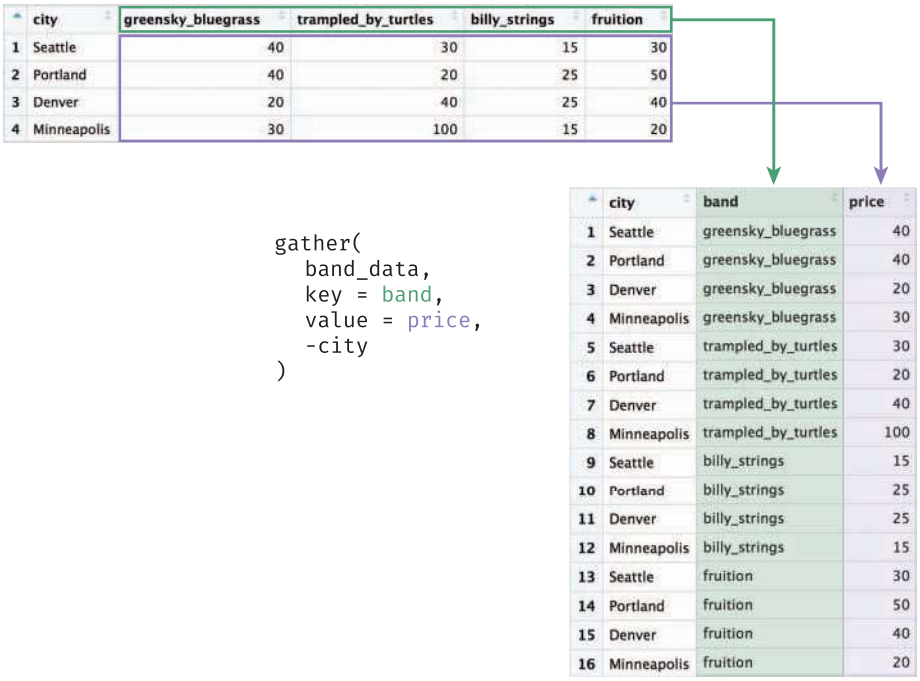
Sometimes you may want to change the structure of your data—how your data is organized in terms of observations and features. To help you do so, the `tidyr` package provides elegant functions for transforming between orientations.

For example, to move from wide format (Table 12.1) to long format (Table 12.2), you need to *gather* all of the prices into a single column. You can do this using the **`gather()`** function, which collects data values stored across multiple columns into a single new feature (e.g., "price" in Table 12.2), along with an additional new column representing which feature that value was gathered from (e.g., "band" in Table 12.2). In effect, it creates two columns representing *key–value pairs* of the feature and its value from the original data frame.

```
# Reshape by gathering prices into a single feature
band_data_long <- gather(
  band_data_wide, # data frame to gather from
  key = band,     # name for new column listing the gathered features
  value = price,  # name for new column listing the gathered values
  -city           # columns to gather data from, as in dplyr's `select()`
)
```

The `gather()` function takes in a number of arguments, starting with the data frame to gather from. It then takes in a `key` argument giving a name for a column that will contain as values the column names the data was gathered from—for example, a new `band` column that will contains the values `"greensky_bluegrass"`, `"trampled_by_turtles"`, and so on. The third argument is a `value`, which is the name for the column that will contain the gathered values—for example, `price` to contain the price numbers. Finally, the function takes in arguments representing which columns to gather data from, using syntax similar to using `dplyr` to `select()` those columns (in the preceding example, `-city` indicates that it should gather from all columns except `city`). Again, any columns provided as this final set of arguments will have their names listed in the `key` column, and their values listed in the `value` column. This process is illustrated in Figure 12.1. The `gather()` function's syntax can be hard to intuit and remember; try tracing where each value "moves" in the table and diagram.

Note that once data is in long format, you can continue to analyze an individual feature (e.g., a specific band) by filtering for that value. For example, `filter(band_data_long, band == "greensky_bluegrass")` would produce just the prices for a single band.



	city	greensky_bluegrass	trampled_by_turtles	billy_strings	fruition
1	Seattle	40	30	15	30
2	Portland	40	20	25	50
3	Denver	20	40	25	40
4	Minneapolis	30	100	15	20

```
gather(
  band_data,
  key = band,
  value = price,
  -city
)
```

	city	band	price
1	Seattle	greensky_bluegrass	40
2	Portland	greensky_bluegrass	40
3	Denver	greensky_bluegrass	20
4	Minneapolis	greensky_bluegrass	30
5	Seattle	trampled_by_turtles	30
6	Portland	trampled_by_turtles	20
7	Denver	trampled_by_turtles	40
8	Minneapolis	trampled_by_turtles	100
9	Seattle	billy_strings	15
10	Portland	billy_strings	25
11	Denver	billy_strings	25
12	Minneapolis	billy_strings	15
13	Seattle	fruition	30
14	Portland	fruition	50
15	Denver	fruition	40
16	Minneapolis	fruition	20

Figure 12.1 The `gather()` function takes values from multiple columns (`greensky_bluegrass`, `trampled_by_turtles`, etc.) and *gathers* them into a (new) single column (`price`). In doing so, it also creates a new column (`band`) that stores the names of the columns that were gathered (i.e., the column name in which each value was stored prior to gathering).

12.3 From Rows to Columns: `spread()`

It is also possible to transform a data table from long format into wide format—that is, to *spread* out the prices into multiple columns. Thus, while the `gather()` function collects multiple features into two columns, the **`spread()`** function creates multiple features from two existing columns. For example, you can take the long format data shown in Table 12.2 and spread it out so that each observation is a band, as in Table 12.3:

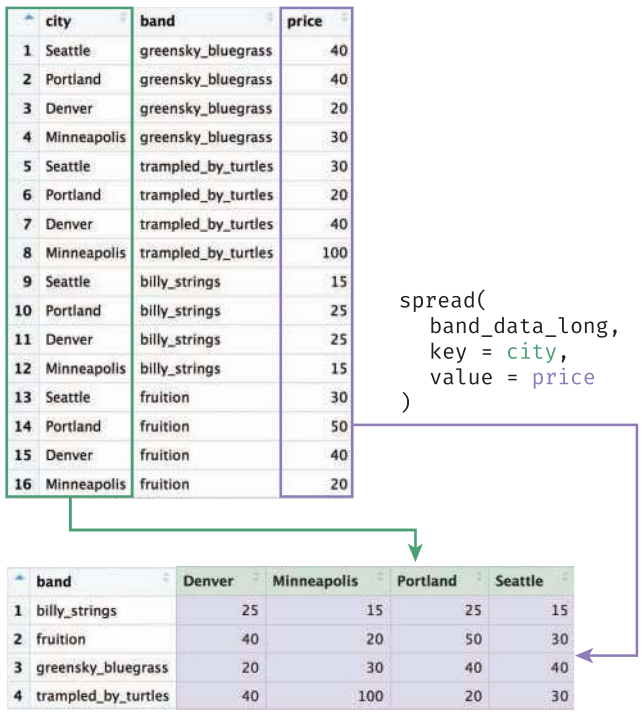
Table 12.3 **A "wide" data set of concert ticket prices for a set of bands. Each observation (i.e., unit of analysis) is a band, and each feature is the ticket price in a given city.**

band	Denver	Minneapolis	Portland	Seattle
billy_strings	25	15	25	15
fruition	40	20	50	30
greensky_bluegrass	20	30	40	40
trampled_by_turtles	40	100	20	30

```
# Reshape long data (Table 12.2), spreading prices out among multiple features
price_by_band <- spread(
  band_data_long, # data frame to spread from
  key = city,     # column indicating where to get new feature names
  value = price   # column indicating where to get new feature values
)
```

The `spread()` function takes arguments similar to those passed to the `gather()` function, but applies them in the opposite direction. In this case, the `key` and `value` arguments are where to get the column names and values, respectively. The `spread()` function will create a new column for each unique value in the provided `key` column, with values taken from the `value` feature. In the preceding example, the new column names (e.g., `"Denver"`, `"Minneapolis"`) were taken from the `city` feature in the long format table, and the values for those columns were taken from the `price` feature. This process is illustrated in Figure 12.2.

By combining `gather()` and `spread()`, you can effectively change the "shape" of your data and what concept is represented by an observation.



	city	band	price
1	Seattle	greensky_bluegrass	40
2	Portland	greensky_bluegrass	40
3	Denver	greensky_bluegrass	20
4	Minneapolis	greensky_bluegrass	30
5	Seattle	trampled_by_turtles	30
6	Portland	trampled_by_turtles	20
7	Denver	trampled_by_turtles	40
8	Minneapolis	trampled_by_turtles	100
9	Seattle	billy_strings	15
10	Portland	billy_strings	25
11	Denver	billy_strings	25
12	Minneapolis	billy_strings	15
13	Seattle	fruition	30
14	Portland	fruition	50
15	Denver	fruition	40
16	Minneapolis	fruition	20

	band	Denver	Minneapolis	Portland	Seattle
1	billy_strings	25	15	25	15
2	fruition	40	20	50	30
3	greensky_bluegrass	20	30	40	40
4	trampled_by_turtles	40	100	20	30

Figure 12.2 The `spread()` function *spreads out* a single column into multiple columns. It creates a new column for each unique value in the provided `key` column (`city`). The values in each new column will be populated with the provided `value` column (`price`).

Tip: Before spreading or gathering your data, you will often need to *unite* multiple columns into a single column, or to *separate* a single column into multiple columns. The `tidyr` functions `unite()`[a] and `separate()`[b] provide a specific syntax for these common data preparation tasks.

[a]https://tidyr.tidyverse.org/reference/unite.html
[b]https://tidyr.tidyverse.org/reference/separate.html

12.4 `tidyr` in Action: Exploring Educational Statistics

This section uses a real data set to demonstrate how reshaping your data with `tidyr` is an integral part of the data exploration process. The data in this example was downloaded from the *World Bank Data Explorer*,[2] which is a data collection of hundreds of indicators (measures) of different economic and social development factors. In particular, this example considers *educational indicators*[3] that capture a relevant signal of a country's level of (or investment in) education—for example, government expenditure on education, literacy rates, school enrollment rates, and dozens of other measures of educational attainment. The imperfections of this data set (unnecessary rows at the top of the .csv file, a substantial amount of missing data, long column names with special characters) are representative of the challenges involved in working with real data sets. All graphics in this section were built using the `ggplot2` package, which is described in Chapter 16. The complete code for this analysis is also available online in the book's code repository.[4]

After having downloaded the data, you will need to load it into your R environment:

```
# Load data, skipping the unnecessary first 4 rows
wb_data <- read.csv(
  "data/world_bank_data.csv",
  stringsAsFactors = F,
  skip = 4
)
```

When you first load the data, each observation (row) represents an indicator for a country, with features (columns) that are the values of that indicator in a given year (see Figure 12.3). Notice that many values, particularly for earlier years, are missing (`NA`). Also, because R does not allow column names to be numbers, the `read.csv()` function has *prepended* an `X` to each column name (which is just a number in the raw `.csv` file).

While in terms of the indicator this data is in long format, in terms of the indicator and year the data is in wide format—a single column contains all the values for a single year. This structure allows you to make comparisons between years for the indicators by filtering for the indicator of interest. For example, you could compare each country's educational expenditure in 1990 to its expenditure in 2014 as follows:

[2]**World Bank Data Explorer:** https://data.worldbank.org
[3]**World Bank education:** http://datatopics.worldbank.org/education
[4]**`tidyr` in Action**: https://github.com/programming-for-data-science/in-action/tree/master/tidyr

	Country.Name	Country.Code	Indicator.Name	Indicator.Code	X1960	X1961	X1962
1	Aruba	ABW	Population ages 15-64 (% of total)	SP.POP.1564.TO.ZS	53.66992	54.05678	54.38328
2	Aruba	ABW	Population ages 0-14 (% of total)	SP.POP.0014.TO.ZS	43.84719	43.35835	42.92574
3	Aruba	ABW	Unemployment, total (% of total labor force) (modeled...	SL.UEM.TOTL.ZS	NA	NA	NA
4	Aruba	ABW	Unemployment, male (% of male labor force) (modele...	SL.UEM.TOTL.MA.ZS	NA	NA	NA
5	Aruba	ABW	Unemployment, female (% of female labor force) (mod...	SL.UEM.TOTL.FE.ZS	NA	NA	NA
6	Aruba	ABW	Labor force, total	SL.TLF.TOTL.IN	NA	NA	NA
7	Aruba	ABW	Labor force, female (% of total labor force)	SL.TLF.TOTL.FE.ZS	NA	NA	NA

Figure 12.3 Untransformed World Bank educational data used in Section 12.4.

```
# Visually compare expenditures for 1990 and 2014

# Begin by filtering the rows for the indicator of interest
indicator <- "Government expenditure on education, total (% of GDP)"
expenditure_plot_data <- wb_data %>%
  filter(Indicator.Name == indicator)

# Plot the expenditure in 1990 against 2014 using the `ggplot2` package
# See Chapter 16 for details
expenditure_chart <- ggplot(data = expenditure_plot_data) +
  geom_text_repel(
    mapping = aes(x = X1990 / 100, y = X2014 / 100, label = Country.Code)
  ) +
  scale_x_continuous(labels = percent) +
  scale_y_continuous(labels = percent) +
  labs(title = indicator, x = "Expenditure 1990", y = "Expenditure 2014")
```

Figure 12.4 shows that the expenditure (relative to gross domestic product) is fairly correlated between the two time points: countries that spent more in 1990 also spent more in 2014 (specifically, the correlation—calculated in R using the `cor()` function—is .64).

However, if you want to extend your analysis to visually compare how the expenditure across all years varies for a given country, you would need to reshape the data. Instead of having each observation be an indicator for a country, you want each observation to be an indicator for a country for a year—thereby having all of the values for all of the years in a single column and making the data *long(er) format*.

To do this, you can `gather()` the year columns together:

```
# Reshape the data to create a new column for the `year`
long_year_data <- wb_data %>%
  gather(
    key = year, # `year` will be the new key column
    value = value, # `value` will be the new value column
    X1960:X # all columns between `X1960` and `X` will be gathered
  )
```

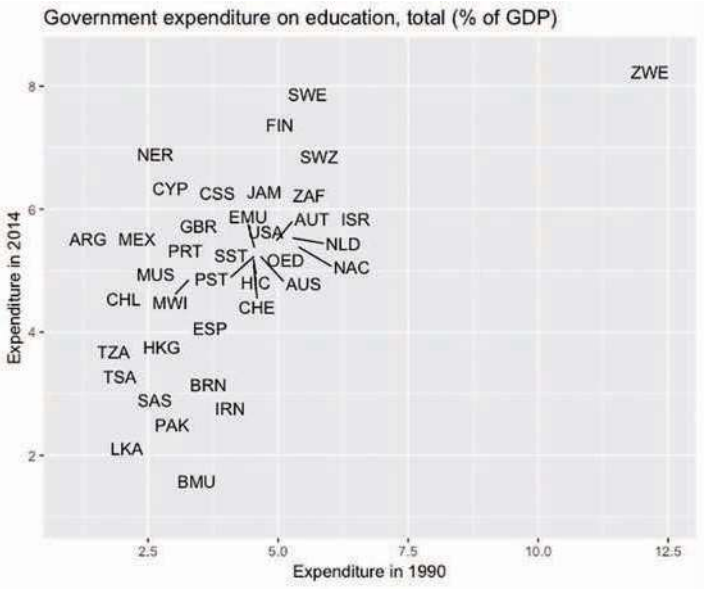


Figure 12.4 A comparison of each country's education expenditures in 1990 and 2014.

	Country.Name	Country.Code	Indicator.Name	year	value
1	Aruba	ABW	Population ages 15-64 (% of total)	X1960	53.66992
2	Aruba	ABW	Population ages 0-14 (% of total)	X1960	43.84719
3	Aruba	ABW	Unemployment, total (% of total labor force) (modeled...	X1960	NA
4	Aruba	ABW	Unemployment, male (% of male labor force) (modele...	X1960	NA
5	Aruba	ABW	Unemployment, female (% of female labor force) (mod...	X1960	NA
6	Aruba	ABW	Labor force, total	X1960	NA
7	Aruba	ABW	Labor force, female (% of total labor force)	X1960	NA
8	Aruba	ABW	Government expenditure on education, total (% of GDP)	X1960	NA
9	Aruba	ABW	Government expenditure on education, total (% of gov...	X1960	NA
10	Aruba	ABW	Expenditure on tertiary education (% of government e...	X1960	NA
11	Aruba	ABW	Government expenditure per student, tertiary (% of G...	X1960	NA

Figure 12.5 Reshaped educational data (long format by `year`). This structure allows you to more easily create visualizations across multiple years.

As shown in Figure 12.5, this `gather()` statement creates a `year` column, so each observation (row) represents the value of an indicator in a particular country in a given year. The expenditure for each year is stored in the `value` column created (coincidentally, this column is given the name `"value"`).

This structure will now allow you to compare fluctuations in an indicator's value over time (across all years):

```
# Filter the rows for the indicator and country of interest
indicator <- "Government expenditure on education, total (% of GDP)"
spain_plot_data <- long_year_data %>%
  filter(
    Indicator.Name == indicator,
    Country.Code == "ESP" # Spain
  ) %>%
  mutate(year = as.numeric(substr(year, 2, 5))) # remove "X" before each year

# Show the educational expenditure over time
chart_title <- paste(indicator, " in Spain")
spain_chart <- ggplot(data = spain_plot_data) +
  geom_line(mapping = aes(x = year, y = value / 100)) +
  scale_y_continuous(labels = percent) +
  labs(title = chart_title, x = "Year", y = "Percent of GDP Expenditure")
```

The resulting chart, shown in Figure 12.6, uses the available data to show a timeline of the fluctuations in government expenditures on education in Spain. This produces a more complete picture of the history of educational investment, and draws attention to major changes as well as the absence of data in particular years.

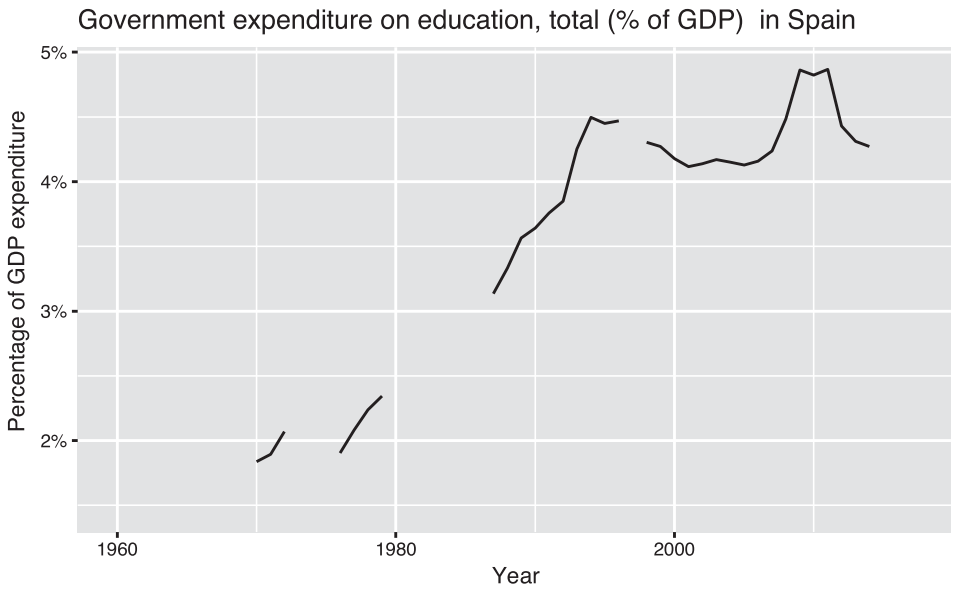


Figure 12.6 Education expenditures over time in Spain.

You may also want to compare two indicators to each other. For example, you may want to assess the relationship between each country's literacy rate (a first indicator) and its unemployment rate (a second indicator). To do this, you would need to reshape the data again so that each observation is a particular country and each column is an indicator. Since indicators are currently in one column, you need to spread them out using the `spread()` function:

```
# Reshape the data to create columns for each indicator
wide_data <- long_year_data %>%
  select(-Indicator.Code) %>% # do not include the `Indicator.Code` column
  spread(
    key = Indicator.Name, # new column names are `Indicator.Name` values
    value = value # populate new columns with values from `value`
  )
```

This wide format data shape allows for comparisons between two different indicators. For example, you can explore the relationship between female unemployment and female literacy rates, as shown in Figure 12.7.

```
# Prepare data and filter for year of interest
x_var <- "Literacy rate, adult female (% of females ages 15 and above)"
y_var <- "Unemployment, female (% of female labor force) (modeled
  ILO estimate)"

lit_plot_data <- wide_data %>%
  mutate(
    lit_percent_2014 = wide_data[, x_var] / 100,
    employ_percent_2014 = wide_data[, y_var] / 100
  ) %>%
  filter(year == "X2014")

# Show the literacy vs. employment rates
lit_chart <- ggplot(data = lit_plot_data) +
  geom_point(mapping = aes(x = lit_percent_2014, y = employ_percent_2014)) +
  scale_x_continuous(labels = percent) +
  scale_y_continuous(labels = percent) +
  labs(
    x = x_var,
    y = "Unemployment, female (% of female labor force)",
    title = "Female Literacy Rate versus Female Unemployment Rate"
  )
```

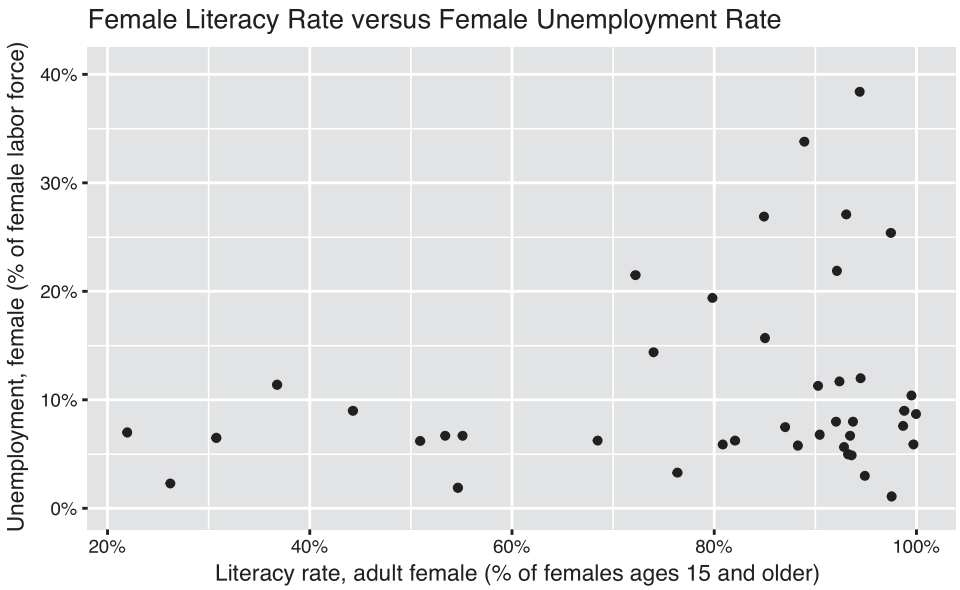


Figure 12.7 Female literacy rate versus unemployment rate in 2014.

Each comparison in this analysis—between two time points, over a full time-series, and between indicators—required a different representation of the data set. Mastering use of the `tidyr` functions will allow you to quickly transform the shape of your data set, allowing for rapid and effective data analysis. For practice reshaping data with the `tidyr` package, see the set of accompanying book exercises.[5]

[5] **`tidyr` exercises:** https://github.com/programming-for-data-science/chapter-12-exercises

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