Module 4

Tidy and Manipulate: Tidy Data Principles and Manipulating Data

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Overview

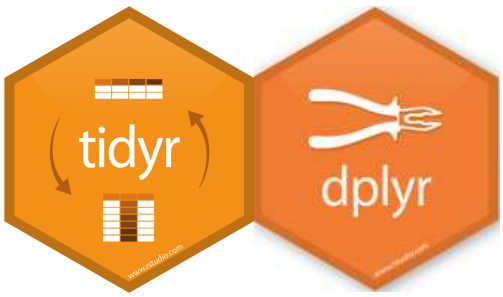
Summary

In this module, I will present Hadley Wickham's "**Tidy Data**" principles (Hadley Wickham and others (2014)) and discuss the main benefits of following these principles. We will identify most common problems with messy data sets and explore the powerful `tidyr` package to tidy messy data sets. Lastly, we will cover the "**Grammar of Data Manipulation**" - the powerful `dplyr` package using examples.

In preparation of this section, I heavily used our recommended textbooks (Boehmke (2016) and Hadley Wickham and Grolemund (2016)), R Studio's Data wrangling with R and RStudio webinar (https://www.rstudio.com/resources/webinars/data-wrangling-with-r-and-rstudio/), tidyr ((https://cran.r-project.org/web/packages/tidyr/tidyr.pdf)) and dplyr (https://cran.r-project.org/web/packages/dplyr/dplyr.pdf) reference manuals (H Wickham (2014), H Wickham et al. (2017)).

Learning Objectives

The learning objectives of this module are as follows:



- Identify and understand the underlying tidy data principles.
- Identify common problems with messy data sets.
- Learn how to get your data into a tidy form using `tidyr` package tools.
- Learn data manipulation tasks (i.e., select, filter, arrange, join, merge) using the powerful `dplyr` package functions.

Tidy Data Principles

"*Happy families are all alike; every unhappy family is unhappy in its own way.*" —Leo Tolstoy

"*Tidy datasets are all alike, but every messy dataset is messy in its own way.*" —Hadley Wickham

Hadley Wickham wrote a stellar article called "Tidy Data (https://www.jstatsoft.org/article/view/v059i10/v59i10.pdf)" in Journal of Statistical Software to provide a standard way to organise data values within a dataset. In his paper, Wickham developed the framework of "**Tidy Data Principles**" to provide a standard and consistent way of storing data that makes transformation, visualization, and modeling easier. Along with the tidy data principles, he also developed the `tidyr` package, which provides a bunch of tools to help tidy up the messy data sets.

In this section, I will give you a practical introduction to tidy data and the accompanying tools in the `tidyr` package. If you'd like to learn more about the underlying theory, you might enjoy the Tidy Data paper (https://www.jstatsoft.org/article/view/v059i10/v59i10.pdf) published in the Journal of Statistical Software.

Once you've imported and understand the structure of your data, it is a good idea to tidy it. Tidying your data means storing it in a consistent form that matches the semantics of the data set with the way it is stored.

In brief, there are three interrelated rules which make a dataset tidy (Hadley Wickham and Grolemund (2016)). In tidy data:

1. Each variable must have its own column.
2. Each observation must have its own row.
3. Each value must have its own cell.

The following illustration taken from Hadley Wickham and Grolemund (2016) shows these three rules visually:

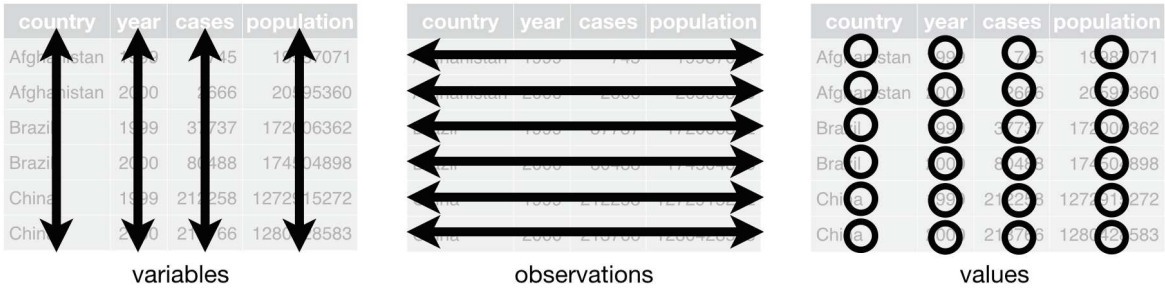
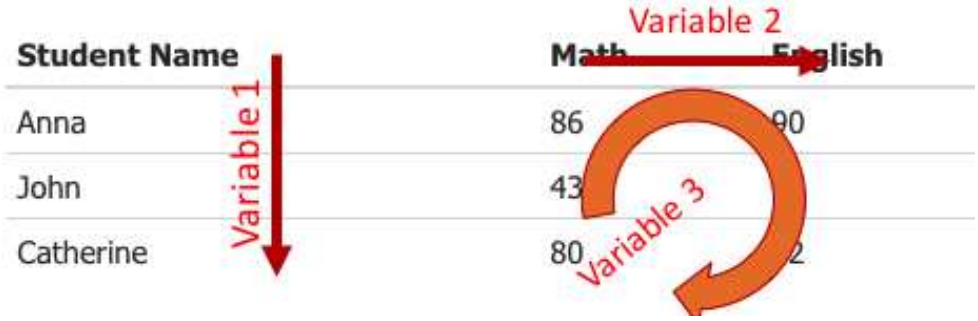


Fig1. Tidy data rules: variables are in columns, observations are in rows, and values are in cells (taken from Hadley Wickham and Grolemund (2016))

To demonstrate these rules, we will use a simple data set:

Student Name	Math	English
Anna	86	90
John	43	75
Catherine	80	82

In this simple data, actually there are three variables illustrated in the following table:



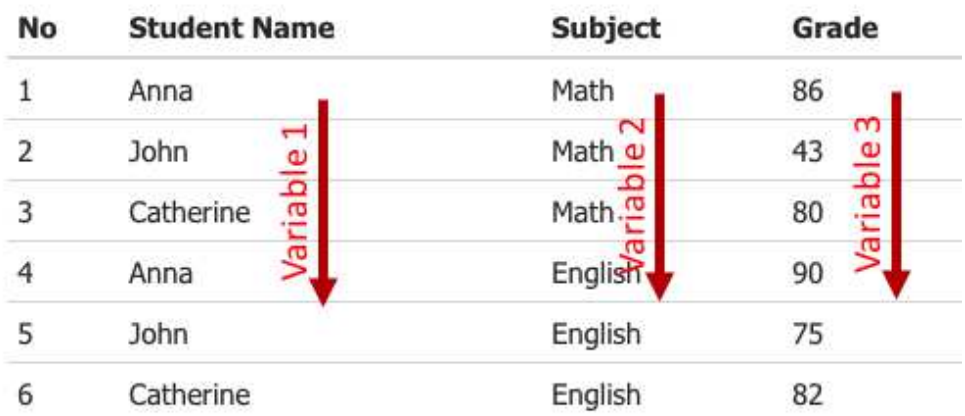
First variable is "Student Name", the second is "Subject" that represents whether the subject is Maths or English, and the third one is the "Grade" information inside the data matrix.

When we arrange each variable in columns and each student in a row then we will get the tidy version of the same data as follows:

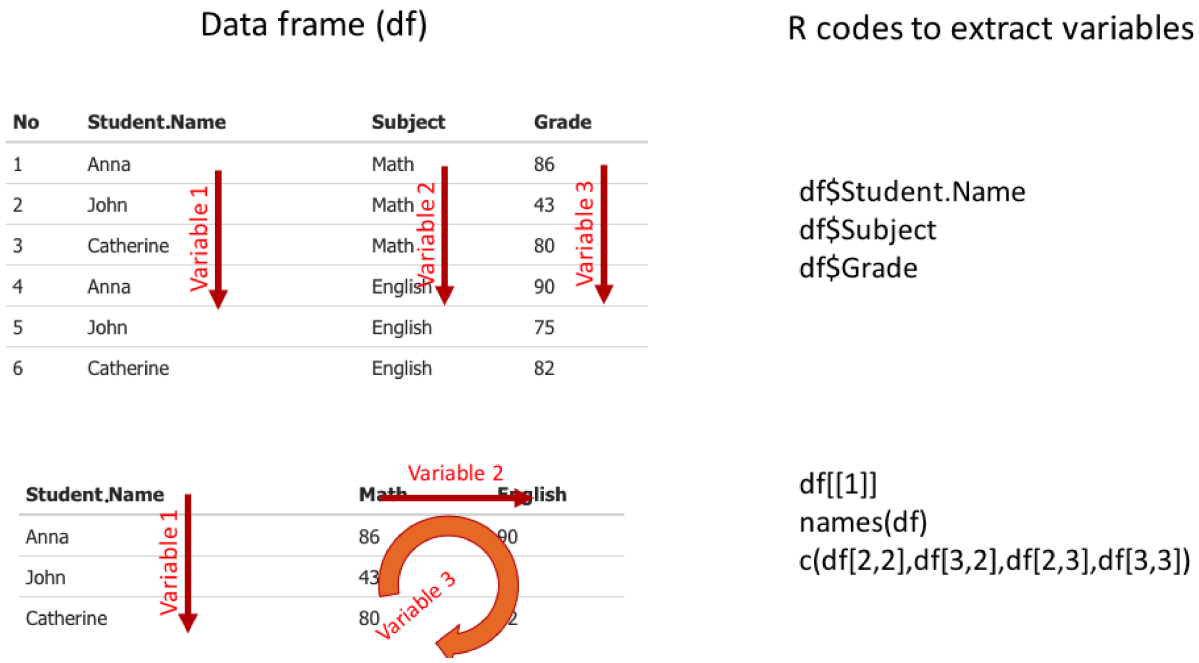
No	Student Name	Subject	Grade
1	Anna	Math	86
2	John	Math	43
3	Catherine	Math	80

No	Student Name	Subject	Grade
4	Anna	English	90
5	John	English	75
6	Catherine	English	82

You can see that in this format, each variable forms a column and each student forms a row:



The main advantage of using tidy principles is it allows R's vectorised nature to shine. One can extract variables in a simple, standard way. Have a look at the following illustration. Which would you rather work with?

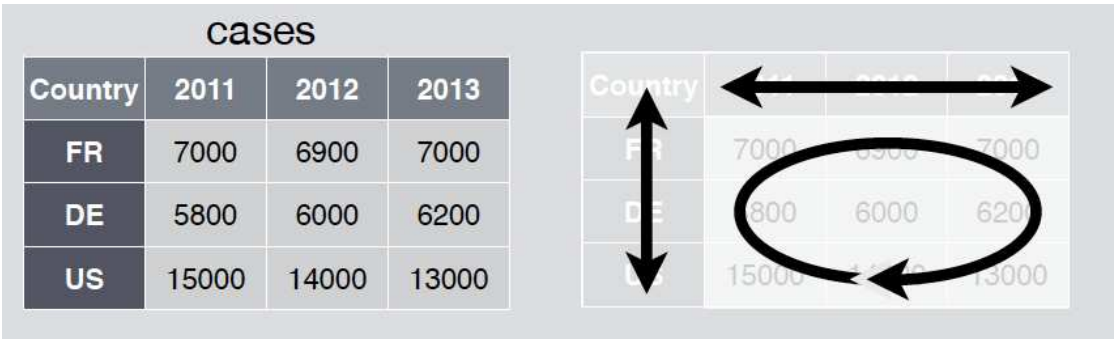


Tidy data is important because the consistent structure lets you focus on questions about the data, not fighting to get the data into the right form for different functions.

Common problems with messy data sets

Real data sets can, and often do, violate the three principles of tidy data. This section describes most common problems with messy datasets:

- **Column headers are values, not variable names:** A common problem is a dataset where some (or all) of the column names are not names of variables, but values of a variable. Here is an illustration of this problem:

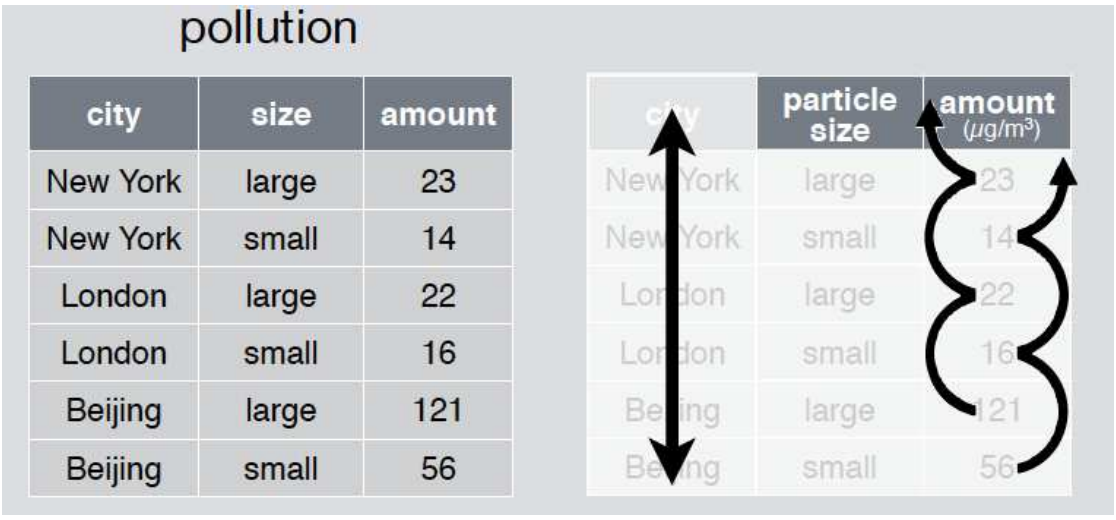


cases

Country	2011	2012	2013
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000

In the example above, the column names 2011, 2012, and 2013 represent values of the year variable, and each row represents three observations, not one.

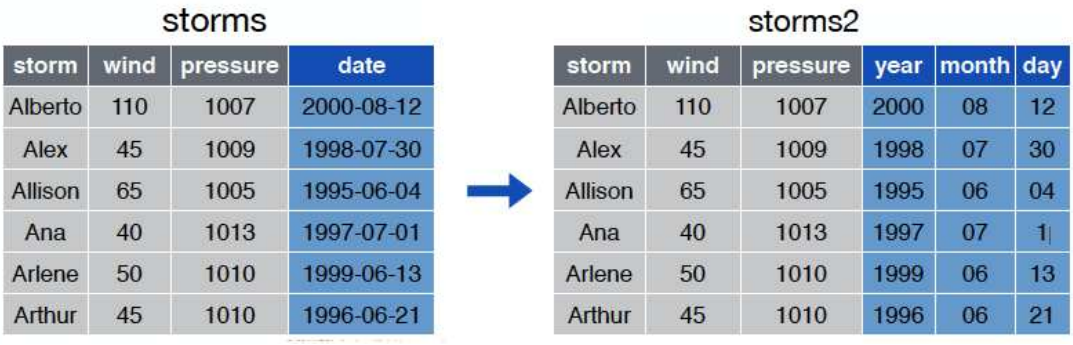
- **Multiple variables are stored in rows:** The opposite of the first problem can also occur when the variables are stored in rows. In such cases, cells include the actual variables, not the observations. Here is an example:



pollution

city	size	amount
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

- **Multiple variables are stored in one column:** Sometimes, one column stores the information of two or more variables. Therefore, multiple variables can be extracted from one column. Here is an illustration of this problem:



storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21

storms2

storm	wind	pressure	year	month	day
Alberto	110	1007	2000	08	12
Alex	45	1009	1998	07	30
Allison	65	1005	1995	06	04
Ana	40	1013	1997	07	1
Arlene	50	1010	1999	06	13
Arthur	45	1010	1996	06	21

In the example above, date variable actually stores three new variable information, namely; year, month, and day.

- **Multiple columns forms a variable:** You may need to combine multiple columns into a single column to form a new variable. Here is an illustration of this problem:

storms2

storm	wind	pressure	year	month	day
Alberto	110	1007	2000	08	12
Alex	45	1009	1998	07	30
Allison	65	1005	1995	06	04
Ana	40	1013	1997	07	1
Arlene	50	1010	1999	06	13
Arthur	45	1010	1996	06	21

storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21

In this example, the year, month, and day variables are given separately in the original data, but assume that we need to combine these three columns into a single variable called date for the time series analysis.

The `tidyr` package

Most messy datasets can be tidied with a small set of tools. The `tidyr` package is a very useful package that reshapes the layout of data sets. In the next section you will be introduced the `tidyr` package and its functions with examples.

We will use the subset of the data contained in the World Health Organization Global Tuberculosis Report (also given in `tidyr` package documentation) to illustrate the functions in the `tidyr` package. Before loading this dataset, we need to install and load the package using:

```
# install the tidyr package

install.packages("tidyr")

# load the tidyr package

library(tidyr)
```

The following example shows the same data organized in four different ways (`table1` , `table2` , `table3` , `table4a` , `table4b`). Each dataset shows the same values of four variables, `country` , `year` , `population` , and cases, but each dataset organizes the values in a different way as follows:

```
# load the example data organized in four different ways

table1
```

```
## # A tibble: 6 x 4
##   country      year  cases population
##   <chr>       <int>  <int>      <int>
## 1 Afghanistan  1999    745   19987071
## 2 Afghanistan  2000   2666   20595360
## 3 Brazil       1999  37737  172006362
## 4 Brazil       2000  80488  174504898
## 5 China        1999 212258 1272915272
## 6 China        2000 213766 1280428583
```

```
table2
```

```
## # A tibble: 12 x 4
##    country      year type            count
##    <chr>       <int> <chr>           <int>
##  1 Afghanistan  1999 cases             745
##  2 Afghanistan  1999 population   19987071
##  3 Afghanistan  2000 cases            2666
##  4 Afghanistan  2000 population   20595360
##  5 Brazil       1999 cases           37737
##  6 Brazil       1999 population  172006362
##  7 Brazil       2000 cases           80488
##  8 Brazil       2000 population  174504898
##  9 China        1999 cases          212258
## 10 China        1999 population 1272915272
## 11 China        2000 cases          213766
## 12 China        2000 population 1280428583
```

```
table3
```

```
## # A tibble: 6 x 3
##   country      year rate
## * <chr>       <int> <chr>
## 1 Afghanistan  1999 745/19987071
## 2 Afghanistan  2000 2666/20595360
## 3 Brazil       1999 37737/172006362
## 4 Brazil       2000 80488/174504898
## 5 China        1999 212258/1272915272
## 6 China        2000 213766/1280428583
```

```
table4a
```

```
## # A tibble: 3 x 3
##   country     `1999` `2000`
## * <chr>        <int>  <int>
## 1 Afghanistan    745   2666
## 2 Brazil       37737  80488
## 3 China       212258 213766
```

```
table4b
```

```
## # A tibble: 3 x 3
##   country         `1999`     `2000`
## * <chr>            <int>      <int>
## 1 Afghanistan   19987071   20595360
## 2 Brazil       172006362  174504898
## 3 China       1272915272 1280428583
```

`gather()` function

When column names are values instead of variables, we need to gather or in other words, we need to transform data from wide to long format.

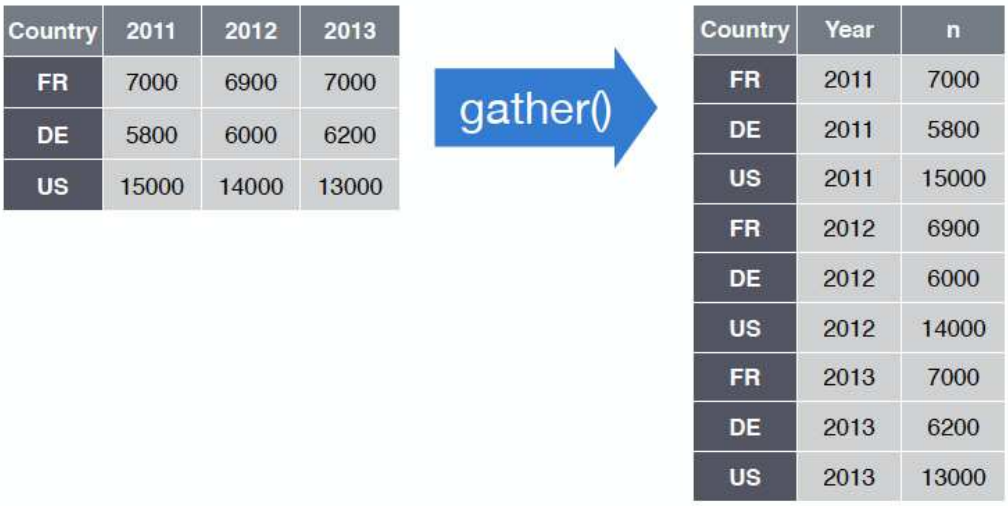


Fig2. gather() – tidyr by RStudio (https://www.rstudio.com/resources/webinars/data-wrangling-with-r-and-rstudio/)

To illustrate `gather()` function, let's have a look at the data given in `table4a` :

```
table4a
```

```
## # A tibble: 3 x 3
##   country     `1999` `2000`
## * <chr>        <int>  <int>
## 1 Afghanistan    745   2666
## 2 Brazil       37737  80488
## 3 China       212258 213766
```

To tidy a dataset like this, we need to gather those columns into a new pair of variables using `gather()` function. To describe that operation we need three parameters:

- The set of columns that represent values, not variables. In this example, those are the columns 1999 and 2000.
- The name of the variable whose values form the column names. The argument name `key` stands for that variable. For this example, the `key` argument is `year` .
- The name of the variable whose values are spread over the cells. The argument name `value` stands for that, in this example `value` argument is the number of cases.

```
table4a %>%
gather(`1999`, `2000`, key = "year", value = "cases")
```

```
## # A tibble: 6 x 3
##   country     year   cases
##   <chr>       <chr>  <int>
## 1 Afghanistan 1999     745
## 2 Brazil      1999   37737
## 3 China       1999  212258
## 4 Afghanistan 2000    2666
## 5 Brazil      2000   80488
## 6 China       2000  213766
```

Note that in the R code below, I used the pipe (`%>%`) operator to take the data first, then use the gather function. The `tidyr` package functions can also be used along with the pipe operator `%>%` which is developed by Stefan Milton Bache in the R package `magrittr`. Remember that the functions in `tidyr` can be used without the pipe operator. For more information on the pipe operator, its pros and cons please refer to Dr. James Baglin's R Bootcamp Course 1 (https://astral-theory-157510.appspot.com/secured/RBootcamp_Course_01.html#pipes).

`spread()` function

When multiple variables are stored in rows, the `spread()` function generates columns from rows. In other words, it transforms data from long to wide format. The `spread()` function is the opposite of `gather()` function.

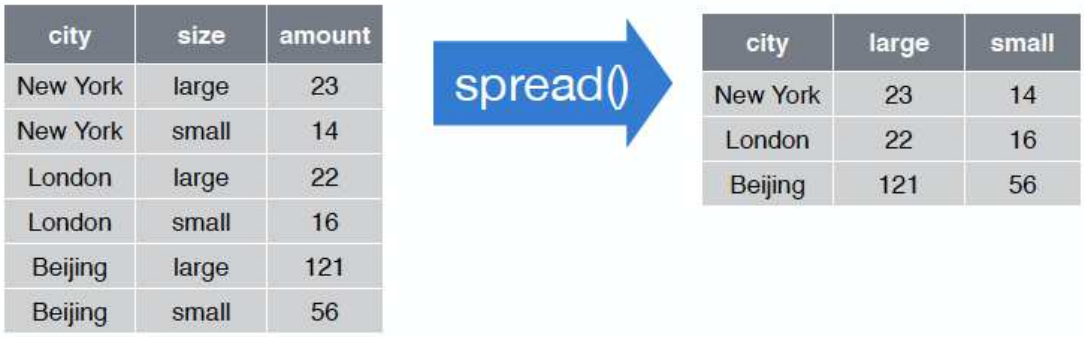


Fig3. spread() – tidyr by RStudio (https://www.rstudio.com/resources/webinars/data-wrangling-with-r-and-rstudio/)

Let's look at `table2` and assume that we are required to turn long formatted data into wide formatted data by generating columns from cases.

```
table2
```

```
## # A tibble: 12 x 4
##    country      year type            count
##    <chr>       <int> <chr>           <int>
##  1 Afghanistan  1999 cases             745
##  2 Afghanistan  1999 population   19987071
##  3 Afghanistan  2000 cases            2666
##  4 Afghanistan  2000 population   20595360
##  5 Brazil       1999 cases           37737
##  6 Brazil       1999 population  172006362
##  7 Brazil       2000 cases           80488
##  8 Brazil       2000 population  174504898
##  9 China        1999 cases          212258
## 10 China        1999 population 1272915272
## 11 China        2000 cases          213766
## 12 China        2000 population 1280428583
```

To tidy this up, we first analyse the representation in a similar way to `gather()`. This time, however, we only need two parameters:

- The column that contains variable names, the key column. Here, it's type.
- The column that contains values forms multiple variables, the value column. Here, it's count.

Once we've figured that out, we can use `spread()`:

```
spread(table2, key = type, value = count)
```

```
## # A tibble: 6 x 4
##   country      year  cases population
##   <chr>       <int>  <int>      <int>
## 1 Afghanistan  1999    745   19987071
## 2 Afghanistan  2000   2666   20595360
## 3 Brazil       1999  37737  172006362
## 4 Brazil       2000  80488  174504898
## 5 China        1999 212258 1272915272
## 6 China        2000 213766 1280428583
```

Now, `cases` and `population` are separate variables given in columns, therefore, generating a new variable from these two variables is super easy! Let's calculate the Tuberculosis rate (rate = cases/population) using:

```
rate = spread(table2, key = type, value = count)$cases / spread(table2, key =
type, value = count)$population

rate
```

```
## [1] 0.0000372741 0.0001294466 0.0002193930 0.0004612363 0.0001667495
## [6] 0.0001669488
```

`separate()` function

The `separate()` function is used when multiple variables are stored in one column and you want to split them according to the separator character. Take `table3` for example:

```
table3
```

```
## # A tibble: 6 x 3
##   country      year rate
## * <chr>       <int> <chr>
## 1 Afghanistan  1999 745/19987071
## 2 Afghanistan  2000 2666/20595360
## 3 Brazil       1999 37737/172006362
## 4 Brazil       2000 80488/174504898
## 5 China        1999 212258/1272915272
## 6 China        2000 213766/1280428583
```

The rate column contains both cases and population variables, and we need to split it into two variables.

```
table3 %>%
separate(rate, into = c("cases", "population"), sep = "/")
```

```
## # A tibble: 6 x 4
##   country      year cases  population
## * <chr>       <int> <chr>  <chr>
## 1 Afghanistan  1999 745    19987071
## 2 Afghanistan  2000 2666   20595360
## 3 Brazil       1999 37737  172006362
## 4 Brazil       2000 80488  174504898
## 5 China        1999 212258 1272915272
## 6 China        2000 213766 1280428583
```

`unite()` function

`unite()` is the inverse of `separate()` function. One can use it to combine multiple columns into a single column.
Now let's look at this data:

```
table5
```

```
## # A tibble: 6 x 4
##   country     century year  rate
## * <chr>       <chr>   <chr> <chr>
## 1 Afghanistan 19      99    745/19987071
## 2 Afghanistan 20      00    2666/20595360
## 3 Brazil      19      99    37737/172006362
## 4 Brazil      20      00    80488/174504898
## 5 China       19      99    212258/1272915272
## 6 China       20      00    213766/1280428583
```

In this data, assume that we want to combine the `century` and `year` variables into one variable called `new_year`. We can use `unite()` for this purpose:

```
table5 %>%
unite(new_year, century, year)
```

```
## # A tibble: 6 x 3
##   country     new_year rate
##   <chr>       <chr>    <chr>
## 1 Afghanistan 19_99    745/19987071
## 2 Afghanistan 20_00    2666/20595360
## 3 Brazil      19_99    37737/172006362
## 4 Brazil      20_00    80488/174504898
## 5 China       19_99    212258/1272915272
## 6 China       20_00    213766/1280428583
```

In this case we also need to use the `sep` argument. The default will place an underscore `(_)` between the values from different columns. Here we don't want any separator so we use `sep=""` as follows:

```
table5 %>%
unite(new_year, century, year, sep="")
```

```
## # A tibble: 6 x 3
##   country     new_year rate
##   <chr>       <chr>    <chr>
## 1 Afghanistan 1999     745/19987071
## 2 Afghanistan 2000     2666/20595360
## 3 Brazil      1999     37737/172006362
## 4 Brazil      2000     80488/174504898
## 5 China       1999     212258/1272915272
## 6 China       2000     213766/1280428583
```

The `dplyr` package

Although there are many data manipulation packages/functions in R, most of them lack consistent coding and the ability to easily flow together. This leads to difficult-to-read nested functions and/or choppy code. Hadley Wickham developed the very popular `dplyr` package to make these data processing tasks more efficient along with a syntax that is consistent and easier to remember and read.

The `dplyr` package is regarded as the "**Grammar of Data Manipulation**" in R and it originates from the popular `plyr` package, also developed by Hadley Wickham. The `plyr` package covers data manipulation for a range of data structures (i.e., data frames, lists, arrays) whereas `dplyr` is focused on data frames. In this section, I will focus on `dplyr`. We will cover primary functions inside `dplyr` for data manipulation. The full list of capabilities can be found in the dplyr reference manual (https://cran.r-project.org/web/packages/dplyr/dplyr.pdf). I highly recommend going through it as there are many great functions provided by `dplyr` that I will not cover here.

I will use the `nycflights13` package and the data sets to explore the basic data manipulation verbs of `dplyr`. First, we need to install and load the `dplyr` and `nycflights13` packages using:

```
# install the dplyr package

install.packages("dplyr")

# load the dplyr package

library(dplyr)
```

```
# install the nycflights13 package for the data set

install.packages("nycflights13")

# load the nycflights13 package

library(nycflights13)
```

The `nycflights13` package includes five data frames containing information on airlines, airports, flights, weather, and planes that departed from New York City in 2013. The data comes from the US Bureau of Transportation Statistics (https://www.transtats.bts.gov/DatabaseInfo.asp?DB_ID=120&Link=0). Let's look at the `nycflights13::flights` data set:

```
# View the flights data set under the nycflights13 package

nycflights13::flights
```

```
## # A tibble: 336,776 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013     1     1      517            515        2.      830
##  2  2013     1     1      533            529        4.      850
##  3  2013     1     1      542            540        2.      923
##  4  2013     1     1      544            545       -1.     1004
##  5  2013     1     1      554            600       -6.      812
##  6  2013     1     1      554            558       -4.      740
##  7  2013     1     1      555            600       -5.      913
##  8  2013     1     1      557            600       -3.      709
##  9  2013     1     1      557            600       -3.      838
## 10  2013     1     1      558            600       -2.      753
## # ... with 336,766 more rows, and 12 more variables: sched_arr_time <int>,
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
## #   minute <dbl>, time_hour <dttm>
```

You might notice that this data frame prints differently from other data frames you might have used in the past: it only shows the first few rows and all the columns that fit on one screen. It prints differently because it's a tibble. Tibbles are a modern take on data frames. They are slightly tweaked to work better with `tidyr` and `dplyr` (and many others). For now, you don't need to worry about the differences (you may refer to here (https://cran.r-project.org/web/packages/tibble/vignettes/tibble.html) to learn more on tibbles.

`select()` function

When working with a large data frame, often we want to only assess specific variables. The `select()` function allows us to select and/or rename variables.

In addition to the existing functions like `:` and `c()`, there are a number of special functions that can work inside select. Some of them are given in the following table.

Functions	Usage
-	Select everything but
:	Select range
`contains()`	Select columns whose name contains a character string
`ends_with()`	Select columns whose name ends with a string
`everything()`	Select every column
`matches()`	Select columns whose name matches a regular expression
`num_range()`	Select columns named x1, x2, x3, x4, x5
`one_of()`	Select columns whose names are in a group of names
`starts_with()`	Select columns whose name starts with a character string

To illustrate we will use the `flights` data. Let's select year, month and day columns using:

```
# Select columns: year, month and day

select(flights, year, month, day)
```

```
## # A tibble: 336,776 x 3
##     year month   day
##    <int> <int> <int>
##  1  2013     1     1
##  2  2013     1     1
##  3  2013     1     1
##  4  2013     1     1
##  5  2013     1     1
##  6  2013     1     1
##  7  2013     1     1
##  8  2013     1     1
##  9  2013     1     1
## 10  2013     1     1
## # ... with 336,766 more rows
```

Like `tidyr`, `dplyr` can also work with the `%>%` operator. Therefore, we can use the following code to do the same selection:

```
# Select columns by name using the pipe operator

flights %>%  select(year, month, day)
```

Here are other examples of using `select()`:

```
# Select all columns between year and day (inclusive)

flights %>% select(year:day)
```

```
## # A tibble: 336,776 x 3
##     year month   day
##    <int> <int> <int>
##  1  2013     1     1
##  2  2013     1     1
##  3  2013     1     1
##  4  2013     1     1
##  5  2013     1     1
##  6  2013     1     1
##  7  2013     1     1
##  8  2013     1     1
##  9  2013     1     1
## 10  2013     1     1
## # ... with 336,766 more rows
```

```
# Select all columns except those from year to day (inclusive)

flights %>% select( -(year:day) )
```

```
## # A tibble: 336,776 x 16
##    dep_time sched_dep_time dep_delay arr_time sched_arr_time arr_delay
##       <int>          <int>     <dbl>    <int>          <int>     <dbl>
##  1      517            515        2.      830            819       11.
##  2      533            529        4.      850            830       20.
##  3      542            540        2.      923            850       33.
##  4      544            545       -1.     1004           1022      -18.
##  5      554            600       -6.      812            837      -25.
##  6      554            558       -4.      740            728       12.
##  7      555            600       -5.      913            854       19.
##  8      557            600       -3.      709            723      -14.
##  9      557            600       -3.      838            846       -8.
## 10      558            600       -2.      753            745        8.
## # ... with 336,766 more rows, and 10 more variables: carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>,
## #   distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dttm>
```

For more information on available functions in `select`, type `?select`.

`filter()` function

The `filter()` function allows us to identify or select observations in which a particular variable matches a specific value/condition. The condition in the `filter()` function can be any kind of logical comparison and Boolean operators, such as:

Symbol	Usage
`<`	Less than
`>`	Greater than
`==`	Equal to
`<=`	Less than or equal to
`>=`	Greater than or equal to
`!=`	Not equal to
`%in%`	Group membership
`is.na`	Is NA
`!is.na`	Is not NA
`&`	Boolean and
`|`	Boolean or
`xor`	exactly or
`!`	not
`any`	any true
`all`	all true

For example, we can select all flights on January 1st using the following:

```
# Filter the flights on January 1st

flights %>%  filter( month == 1, day == 1)
```

```
## # A tibble: 842 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013     1     1      517            515        2.      830
##  2  2013     1     1      533            529        4.      850
##  3  2013     1     1      542            540        2.      923
##  4  2013     1     1      544            545       -1.     1004
##  5  2013     1     1      554            600       -6.      812
##  6  2013     1     1      554            558       -4.      740
##  7  2013     1     1      555            600       -5.      913
##  8  2013     1     1      557            600       -3.      709
##  9  2013     1     1      557            600       -3.      838
## 10  2013     1     1      558            600       -2.      753
## # ... with 832 more rows, and 12 more variables: sched_arr_time <int>,
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
## #   minute <dbl>, time_hour <dttm>
```

When you run that line of code, `dplyr` executes the filtering operation and returns a new data frame. `dplyr` functions never modify their inputs, so if you want to save the result, you'll need to use the assignment operator, `<-` :

```
# Filter the flights on January 1st and save this result

jan1 <- flights %>%  filter( month == 1, day == 1)
```

The following code finds all flights that departed in November **or** December:

```
# Filter the flights departing in November or December

flights %>%  filter( month == 11 | month == 12)
```

```
## # A tibble: 55,403 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013    11     1        5           2359         6.      352
##  2  2013    11     1       35           2250       105.      123
##  3  2013    11     1      455            500        -5.      641
##  4  2013    11     1      539            545        -6.      856
##  5  2013    11     1      542            545        -3.      831
##  6  2013    11     1      549            600       -11.      912
##  7  2013    11     1      550            600       -10.      705
##  8  2013    11     1      554            600        -6.      659
##  9  2013    11     1      554            600        -6.      826
## 10  2013    11     1      554            600        -6.      749
## # ... with 55,393 more rows, and 12 more variables: sched_arr_time <int>,
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
## #   minute <dbl>, time_hour <dttm>
```

If we want to find flights that aren't delayed (on arrival or departure) by more than two hours, we can use either of the following two filters:

```
# Filter the flights that aren't delayed (on arrival or departure) by more th
an two hours

flights %>% filter( arr_delay <= 120, dep_delay <= 120 )
```

```
## # A tibble: 316,050 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013     1     1      517            515        2.      830
##  2  2013     1     1      533            529        4.      850
##  3  2013     1     1      542            540        2.      923
##  4  2013     1     1      544            545       -1.     1004
##  5  2013     1     1      554            600       -6.      812
##  6  2013     1     1      554            558       -4.      740
##  7  2013     1     1      555            600       -5.      913
##  8  2013     1     1      557            600       -3.      709
##  9  2013     1     1      557            600       -3.      838
## 10  2013     1     1      558            600       -2.      753
## # ... with 316,040 more rows, and 12 more variables: sched_arr_time <int>,
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
## #   minute <dbl>, time_hour <dttm>
```

```
# gives the same result as above

flights %>% filter( ! (arr_delay > 120 | dep_delay > 120) )
```

For more information on available functions in `filter`, type `?filter`.

`arrange()` function

The `arrange()` function allows us to order data by variables in ascending or descending order.
Let's order the `flights` data in an ascending order using year, month and day.

```
# Order the data set according to three variables

flights %>% arrange( year, month, day )
```

```
## # A tibble: 336,776 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013     1     1      517            515        2.      830
##  2  2013     1     1      533            529        4.      850
##  3  2013     1     1      542            540        2.      923
##  4  2013     1     1      544            545       -1.     1004
##  5  2013     1     1      554            600       -6.      812
##  6  2013     1     1      554            558       -4.      740
##  7  2013     1     1      555            600       -5.      913
##  8  2013     1     1      557            600       -3.      709
##  9  2013     1     1      557            600       -3.      838
## 10  2013     1     1      558            600       -2.      753
## # ... with 336,766 more rows, and 12 more variables: sched_arr_time <int>,
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
## #   minute <dbl>, time_hour <dttm>
```

We can also apply a descending argument to rank-order from highest to lowest. The following shows the same data but in descending order by applying `desc()` within the `arrange()` function.

```
# Order the data set according to departure time in a descending order

flights %>% arrange( desc(dep_time) )
```

```
## # A tibble: 336,776 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013    10    30     2400           2359        1.      327
##  2  2013    11    27     2400           2359        1.      515
##  3  2013    12     5     2400           2359        1.      427
##  4  2013    12     9     2400           2359        1.      432
##  5  2013    12     9     2400           2250       70.       59
##  6  2013    12    13     2400           2359        1.      432
##  7  2013    12    19     2400           2359        1.      434
##  8  2013    12    29     2400           1700      420.      302
##  9  2013     2     7     2400           2359        1.      432
## 10  2013     2     7     2400           2359        1.      443
## # ... with 336,766 more rows, and 12 more variables: sched_arr_time <int>,
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
## #   minute <dbl>, time_hour <dttm>
```

Note that the missing values will always be sorted at the end.

`mutate()` function

The `mutate()` function allows us to add new variables while preserving the existing variables. Here is the list of some useful functions used inside the `mutate()` .

Functions	Usage
`pmin()`, `pmax()`	Element wise min and max
`cummin()`, `cummax()`	Cumulative min and max
`cumsum()`, `cumprod()`	Cumulative sum and product
`between()`	Are values between a and b?
`cume_dist()`	Cumulative distribution of values
`cumall()`, `cumany()`	Cumulative all and any
`cummean()`	Cumulative mean
`lead()`, `lag()`	Copy with values one position
`ntile()`	Bin vector into n buckets
`dense_rank()`, `min_rank()`, `percent_rank()`, `row_number()`	Various ranking methods

```
# Select specific variables from the data and store them in a new data frame

flights_sub<- flights %>% select(arr_delay, dep_delay, air_time)


# Create new variables "gain", "hours", and "gain_per_hour"

mutate(flights_sub,
        gain = arr_delay - dep_delay,
        hours = air_time / 60,
        gain_per_hour = gain / hours
)
```

```
## # A tibble: 336,776 x 6
##    arr_delay dep_delay air_time  gain hours gain_per_hour
##        <dbl>     <dbl>    <dbl> <dbl> <dbl>         <dbl>
##  1       11.        2.     227.    9. 3.78           2.38
##  2       20.        4.     227.   16. 3.78           4.23
##  3       33.        2.     160.   31. 2.67          11.6
##  4      -18.       -1.     183.  -17. 3.05          -5.57
##  5      -25.       -6.     116.  -19. 1.93          -9.83
##  6       12.       -4.     150.   16. 2.50           6.40
##  7       19.       -5.     158.   24. 2.63           9.11
##  8      -14.       -3.      53.  -11. 0.883        -12.5
##  9       -8.       -3.     140.   -5. 2.33          -2.14
## 10        8.       -2.     138.   10. 2.30           4.35
## # ... with 336,766 more rows
```

Note that the new variables will appear at the end of the `flights` data frame.
An alternative to `mutate()` is `transmute()` which creates a new variable and then drops the other variables. Essentially, it allows you to create a new data frame with only the new variables created.

```
transmute(flights,
          gain = arr_delay - dep_delay,
          hours = air_time / 60,
          gain_per_hour = gain / hours
)
```

```
## # A tibble: 336,776 x 3
##     gain hours gain_per_hour
##    <dbl> <dbl>         <dbl>
##  1    9. 3.78           2.38
##  2   16. 3.78           4.23
##  3   31. 2.67          11.6
##  4  -17. 3.05          -5.57
##  5  -19. 1.93          -9.83
##  6   16. 2.50           6.40
##  7   24. 2.63           9.11
##  8  -11. 0.883        -12.5
##  9   -5. 2.33          -2.14
## 10   10. 2.30           4.35
## # ... with 336,766 more rows
```

`summarise()` (or `summarize()`) function

The `summarise()` (a.k.a. `summarize()`) function allows us to perform the majority of summary statistics when performing exploratory data analysis. Here is the list of some useful functions that can be used inside `summary()`.

Functions	Usage
`min()`, `max()`	Minimum and maximum values
`mean()`	Mean value
`median()`	Median value
`sum()`	Sum of values
`var()`, `sd()`	Variance and standard deviation of a vector
`first()`	First value in a vector
`last()`	Last value in a vector
`nth()`	Nth value in a vector
`n()`	The number of values in a vector
`n_distinct()`	The number of distinct values in a vector

All functions in this list takes a vector of values and returns a single summary value. We can get the average delay using:

```
# Take the average of departure delay

summarise(flights, delay = mean(dep_delay, na.rm = TRUE))
```

```
## # A tibble: 1 x 1
##   delay
##   <dbl>
## 1  12.6
```

The `na.rm = TRUE` argument in `mean()` function will allow us to ignore the missing values while computing the average. We will revisit `na.rm = TRUE` argument in the next section (in Module 5).

`group_by()` + `summarise()` function

If we want to take the summary statistics grouped by a variable, then we need to use another function called `group_by()`. `group_by()` along with `summarise()` functions will allow us to take and compare summary statistics grouped by a factor variable.

For example, if we applied exactly the same code to a data frame grouped by destination, we can get the average delay for each destination.

```
# Group by destination and use summarise to calculate the mean delay

flights %>% group_by(dest) %>% summarise(mean_delay = mean(dep_delay, na.rm =
 TRUE))
```

```
## # A tibble: 105 x 2
##    dest  mean_delay
##    <chr>      <dbl>
##  1 ABQ        13.7
##  2 ACK         6.46
##  3 ALB        23.6
##  4 ANC        12.9
##  5 ATL        12.5
##  6 AUS        13.0
##  7 AVL         8.19
##  8 BDL        17.7
##  9 BGR        19.5
## 10 BHM        29.7
## # ... with 95 more rows
```

Joining data sets

Often we have separate data frames that can have common and differing variables for similar observations. These types of data sets are referred as relational data sets.

We will revisit the `nycflights13` package. The `nycflights13` package contains the following data sets:

- `airlines` includes the names of airline companies and their abbreviated code:

```
airlines
```

```
## # A tibble: 16 x 2
##    carrier name
##    <chr>   <chr>
##  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.
##  7 F9      Frontier Airlines Inc.
##  8 FL      AirTran Airways Corporation
##  9 HA      Hawaiian Airlines Inc.
## 10 MQ      Envoy Air
## 11 OO      SkyWest Airlines Inc.
## 12 UA      United Air Lines Inc.
## 13 US      US Airways Inc.
## 14 VX      Virgin America
## 15 WN      Southwest Airlines Co.
## 16 YV      Mesa Airlines Inc.
```

- `airports` gives information about each airport, identified by the airport code (`faa`):

```
airports
```

```
## # A tibble: 1,458 x 8
##    faa   name                   lat    lon   alt    tz dst   tzone
##    <chr> <chr>                <dbl>  <dbl> <int> <dbl> <chr> <chr>
##  1 04G   Lansdowne Airport     41.1  -80.6  1044   -5. A     America/New_…
##  2 06A   Moton Field Municip…  32.5  -85.7   264   -6. A     America/Chic…
##  3 06C   Schaumburg Regional   42.0  -88.1   801   -6. A     America/Chic…
##  4 06N   Randall Airport       41.4  -74.4   523   -5. A     America/New_…
##  5 09J   Jekyll Island Airpo…  31.1  -81.4    11   -5. A     America/New_…
##  6 0A9   Elizabethton Munici…  36.4  -82.2  1593   -5. A     America/New_…
##  7 0G6   Williams County Air…  41.5  -84.5   730   -5. A     America/New_…
##  8 0G7   Finger Lakes Region…  42.9  -76.8   492   -5. A     America/New_…
##  9 0P2   Shoestring Aviation…  39.8  -76.6  1000   -5. U     America/New_…
## 10 0S9   Jefferson County In…  48.1 -123.    108   -8. A     America/Los_…
## # ... with 1,448 more rows
```

- `planes` gives information about each plane, identified by its tail number (`tailnum`):

```
planes
```

```
## # A tibble: 3,322 x 9
##    tailnum  year type      manufacturer  model  engines seats speed engine
##    <chr>   <int> <chr>     <chr>         <chr>    <int> <int> <int> <chr>
##  1 N10156   2004 Fixed wi… EMBRAER       EMB-1…       2    55    NA Turbo…
##  2 N102UW   1998 Fixed wi… AIRBUS INDUS… A320-…       2   182    NA Turbo…
##  3 N103US   1999 Fixed wi… AIRBUS INDUS… A320-…       2   182    NA Turbo…
##  4 N104UW   1999 Fixed wi… AIRBUS INDUS… A320-…       2   182    NA Turbo…
##  5 N10575   2002 Fixed wi… EMBRAER       EMB-1…       2    55    NA Turbo…
##  6 N105UW   1999 Fixed wi… AIRBUS INDUS… A320-…       2   182    NA Turbo…
##  7 N107US   1999 Fixed wi… AIRBUS INDUS… A320-…       2   182    NA Turbo…
##  8 N108UW   1999 Fixed wi… AIRBUS INDUS… A320-…       2   182    NA Turbo…
##  9 N109UW   1999 Fixed wi… AIRBUS INDUS… A320-…       2   182    NA Turbo…
## 10 N110UW   1999 Fixed wi… AIRBUS INDUS… A320-…       2   182    NA Turbo…
## # ... with 3,312 more rows
```

- `weather` gives the weather conditions at each NYC airport for each hour:

```
weather
```

```
## # A tibble: 26,130 x 15
##    origin  year month   day  hour  temp  dewp humid wind_dir wind_speed
##    <chr>  <dbl> <dbl> <int> <int> <dbl> <dbl> <dbl>    <dbl>      <dbl>
##  1 EWR    2013.    1.     1     0  37.0  21.9  54.0     230.      10.4
##  2 EWR    2013.    1.     1     1  37.0  21.9  54.0     230.      13.8
##  3 EWR    2013.    1.     1     2  37.9  21.9  52.1     230.      12.7
##  4 EWR    2013.    1.     1     3  37.9  23.0  54.5     230.      13.8
##  5 EWR    2013.    1.     1     4  37.9  24.1  57.0     240.      15.0
##  6 EWR    2013.    1.     1     6  39.0  26.1  59.4     270.      10.4
##  7 EWR    2013.    1.     1     7  39.0  27.0  61.6     250.       8.06
##  8 EWR    2013.    1.     1     8  39.0  28.0  64.4     240.      11.5
##  9 EWR    2013.    1.     1     9  39.9  28.0  62.2     250.      12.7
## 10 EWR    2013.    1.     1    10  39.0  28.0  64.4     260.      12.7
## # ... with 26,120 more rows, and 5 more variables: wind_gust <dbl>,
## #   precip <dbl>, pressure <dbl>, visib <dbl>, time_hour <dttm>
```

Therefore, for `nycflights13`:

- `flights` connects to `planes` via a single variable, `tailnum`.
- `flights` connects to `airlines` through the `carrier` variable.
- `flights` connects to `airports` in two ways: via the `origin` and `dest` variables.
- `flights` connects to `weather` via `origin` (the location), and `year`, `month`, `day`, and `hour` (the time).

The following illustration (adapted from Hadley Wickham and Grolemund (2016)) shows the relationship between `flights`, `airlines`, `airports` and `weather` data sets, and the key variables connecting them.

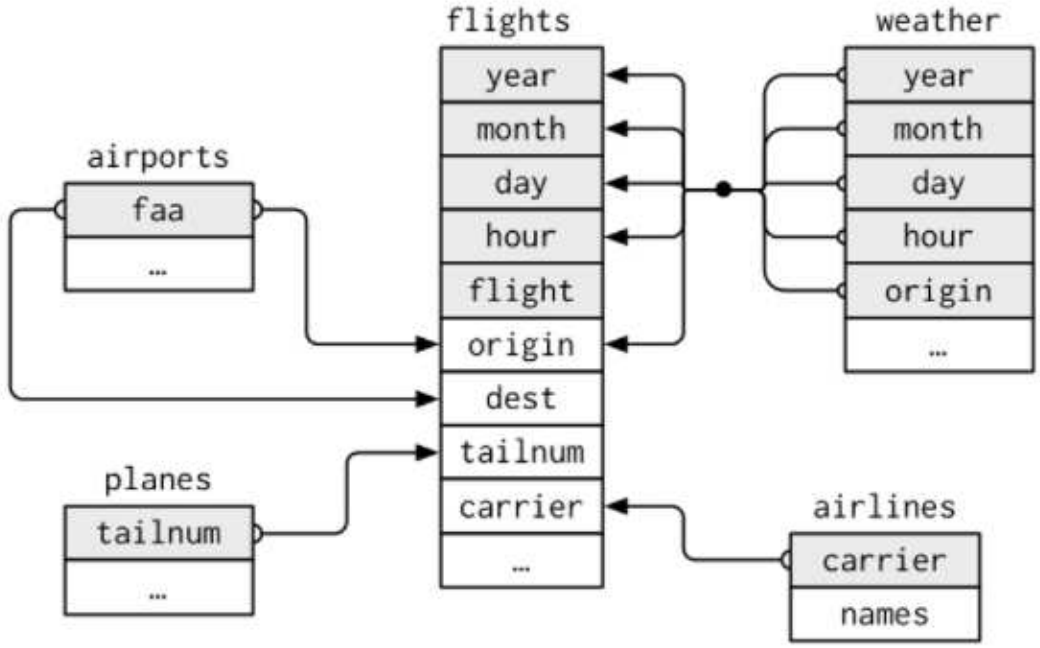


Fig4. Chain of relations between the data sets in `nycflights13` (taken from Hadley Wickham and Grolemund (2016))

The `dplyr` package offers three sets of joining functions to provide alternative ways to join data frames. These are:

- **Mutating joins:** This group of functions add new variables to one data frame from matching observations in another.
- **Filtering joins:** This group of functions filter observations from one data frame based on whether or not they match an observation in the other table.
- **Set operations:** This group of functions treat observations as if they were set elements.

Mutating joins

The first set of functions to combine data sets is called "**mutating joins**". `left_join()`, `right_join()`, `inner_join()`, and `full_join()` functions are in this group. The mutating join functions allow you to combine variables from two tables and add variables to the right (like `mutate`).

Note that, mutating join functions add variables to the right. Therefore if you have a lot of variables already in the data, the new variables won't get printed out. As `flights` data set has many variables, I will first create a narrower data set named `flights2` to easily show you what's going on in the examples.

```
# Create a new data set named flights2 including year - day, hour, origin, de
stination, tailnum and carrier variables

flights2 <- flights %>% select(year:day, hour, origin, dest, tailnum, carrie
r)

flights2
```

```
## # A tibble: 336,776 x 8
##     year month   day  hour origin dest  tailnum carrier
##    <int> <int> <int> <dbl> <chr>  <chr> <chr>   <chr>
##  1  2013     1     1    5. EWR    IAH   N14228  UA
##  2  2013     1     1    5. LGA    IAH   N24211  UA
##  3  2013     1     1    5. JFK    MIA   N619AA  AA
##  4  2013     1     1    5. JFK    BQN   N804JB  B6
##  5  2013     1     1    6. LGA    ATL   N668DN  DL
##  6  2013     1     1    5. EWR    ORD   N39463  UA
##  7  2013     1     1    6. EWR    FLL   N516JB  B6
##  8  2013     1     1    6. LGA    IAD   N829AS  EV
##  9  2013     1     1    6. JFK    MCO   N593JB  B6
## 10  2013     1     1    6. LGA    ORD   N3ALAA  AA
## # ... with 336,766 more rows
```

Imagine you want to add the full airline name (from airlines) to the `flights2` data. You can combine the `airlines` and `flights2` data frames using `left_join()`. Remember that we will need a key variable and the key variable will be the `carrier` variable to join these two data sets.

```
# joining flights2 and airlines using the carrier name.

flights2 %>% left_join(airlines, by = "carrier")
```

```
## # A tibble: 336,776 x 9
##     year month   day  hour origin dest  tailnum carrier name
##    <int> <int> <int> <dbl> <chr>  <chr> <chr>   <chr>   <chr>
##  1  2013     1     1    5. EWR    IAH   N14228  UA      United Air Lines …
##  2  2013     1     1    5. LGA    IAH   N24211  UA      United Air Lines …
##  3  2013     1     1    5. JFK    MIA   N619AA  AA      American Airlines…
##  4  2013     1     1    5. JFK    BQN   N804JB  B6      JetBlue Airways
##  5  2013     1     1    6. LGA    ATL   N668DN  DL      Delta Air Lines I…
##  6  2013     1     1    5. EWR    ORD   N39463  UA      United Air Lines …
##  7  2013     1     1    6. EWR    FLL   N516JB  B6      JetBlue Airways
##  8  2013     1     1    6. LGA    IAD   N829AS  EV      ExpressJet Airlin…
##  9  2013     1     1    6. JFK    MCO   N593JB  B6      JetBlue Airways
## 10  2013     1     1    6. LGA    ORD   N3ALAA  AA      American Airlines…
## # ... with 336,766 more rows
```

Controlling how the data sets are matched

Each mutating join takes an argument `by` that controls which variables are used to match observations in the two data sets. There are a few ways to specify it:

- `NULL`: The default value. `dplyr` will will use all variables that appear in both tables, a natural join. For example, the `flights` and `weather` data sets match on their common variables: `year`, `month`, `day`, `hour` and `origin`.

```
# joining flights2 and weather using the default key = NULL.

flights2 %>% left_join(weather)
```

```
## Joining, by = c("year", "month", "day", "hour", "origin")
```

```
## # A tibble: 336,776 x 18
##     year month   day  hour origin dest  tailnum carrier  temp  dewp humid
##    <dbl> <dbl> <int> <dbl> <chr>  <chr> <chr>   <chr>   <dbl> <dbl> <dbl>
##  1 2013.    1.     1    5. EWR    IAH   N14228  UA       NA    NA    NA
##  2 2013.    1.     1    5. LGA    IAH   N24211  UA       NA    NA    NA
##  3 2013.    1.     1    5. JFK    MIA   N619AA  AA       NA    NA    NA
##  4 2013.    1.     1    5. JFK    BQN   N804JB  B6       NA    NA    NA
##  5 2013.    1.     1    6. LGA    ATL   N668DN  DL       39.9  26.1  57.3
##  6 2013.    1.     1    5. EWR    ORD   N39463  UA       NA    NA    NA
##  7 2013.    1.     1    6. EWR    FLL   N516JB  B6       39.0  26.1  59.4
##  8 2013.    1.     1    6. LGA    IAD   N829AS  EV       39.9  26.1  57.3
##  9 2013.    1.     1    6. JFK    MCO   N593JB  B6       39.0  26.1  59.4
## 10 2013.    1.     1    6. LGA    ORD   N3ALAA  AA       39.9  26.1  57.3
## # ... with 336,766 more rows, and 7 more variables: wind_dir <dbl>,
## #   wind_speed <dbl>, wind_gust <dbl>, precip <dbl>, pressure <dbl>,
## #   visib <dbl>, time_hour <dttm>
```

- A character vector, `by = "x"`. For example, `flights` and `planes` have `tailnum` in common.

```
# joining flights2 and planes using the tailnum.
flights2 %>% left_join(planes, by = "tailnum")
```

```
## # A tibble: 336,776 x 16
##    year.x month   day  hour origin dest  tailnum carrier year.y type
##     <int> <int> <int> <dbl> <chr>  <chr> <chr>   <chr>    <int> <chr>
##  1   2013     1     1    5. EWR    IAH   N14228  UA        1999 Fixed win…
##  2   2013     1     1    5. LGA    IAH   N24211  UA        1998 Fixed win…
##  3   2013     1     1    5. JFK    MIA   N619AA  AA        1990 Fixed win…
##  4   2013     1     1    5. JFK    BQN   N804JB  B6        2012 Fixed win…
##  5   2013     1     1    6. LGA    ATL   N668DN  DL        1991 Fixed win…
##  6   2013     1     1    5. EWR    ORD   N39463  UA        2012 Fixed win…
##  7   2013     1     1    6. EWR    FLL   N516JB  B6        2000 Fixed win…
##  8   2013     1     1    6. LGA    IAD   N829AS  EV        1998 Fixed win…
##  9   2013     1     1    6. JFK    MCO   N593JB  B6        2004 Fixed win…
## 10   2013     1     1    6. LGA    ORD   N3ALAA  AA          NA <NA>
## # ... with 336,766 more rows, and 6 more variables: manufacturer <chr>,
## #   model <chr>, engines <int>, seats <int>, speed <int>, engine <chr>
```

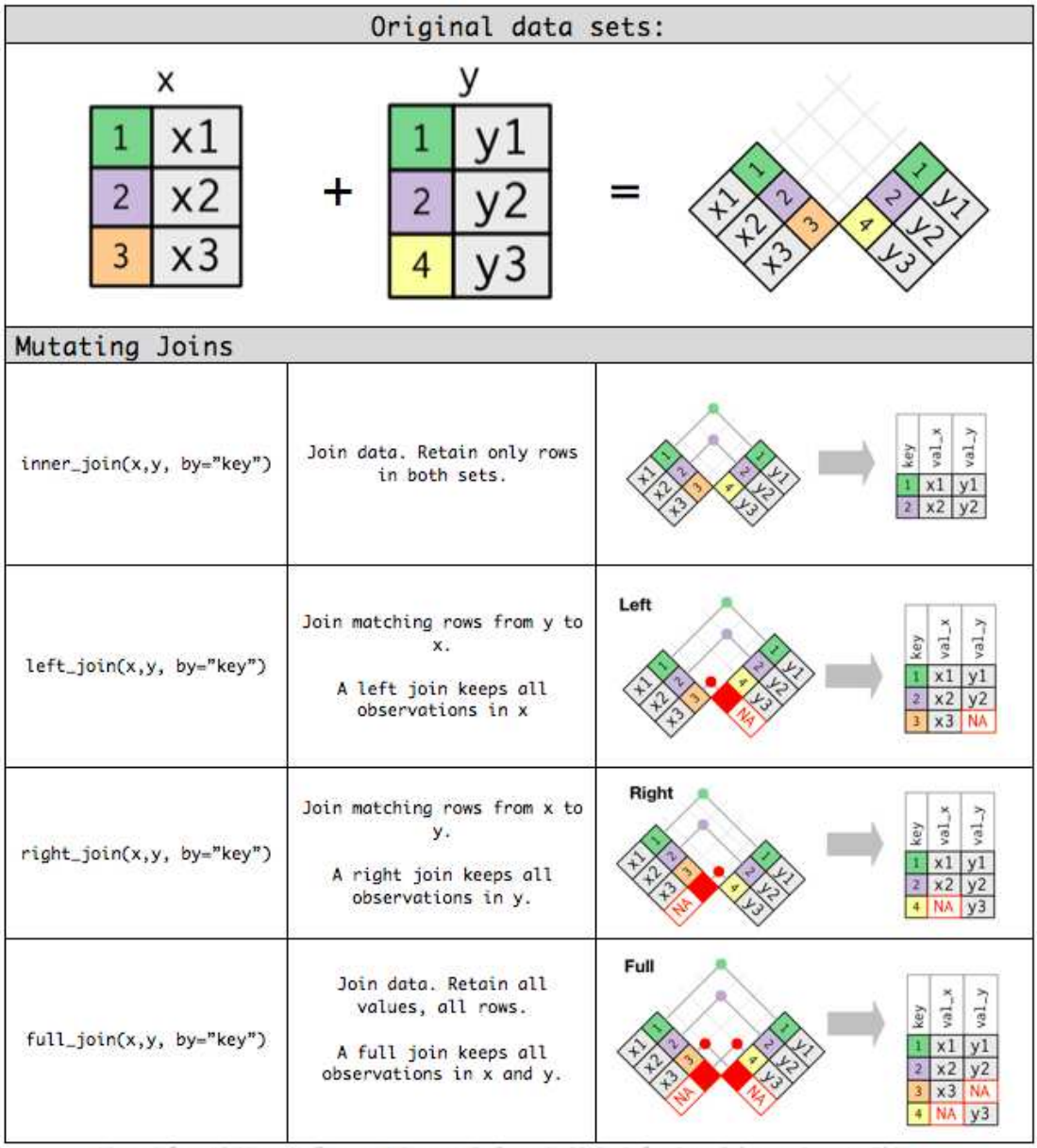
- A named character vector: `by = c("a" = "b")`. This will match variable `a` in table `x` to variable `b` in table `y`. This is useful when the key variables in both data sets are not given the same name. For example, flights data set has the destination airport code (`dest`) and the airports data set has the `faa` code. Essentially these two are

equivalent. Therefore we can use the following to join these two data sets:

```
flights2 %>% left_join(airports, c("dest" = "faa"))
```

```
## # A tibble: 336,776 x 15
##     year month   day  hour origin dest  tailnum carrier name     lat   lon
##    <int> <int> <int> <dbl> <chr>  <chr> <chr>   <chr>   <chr>  <dbl> <dbl>
##  1  2013     1     1    5. EWR    IAH   N14228  UA      Georg…  30.0 -95.3
##  2  2013     1     1    5. LGA    IAH   N24211  UA      Georg…  30.0 -95.3
##  3  2013     1     1    5. JFK    MIA   N619AA  AA      Miami…  25.8 -80.3
##  4  2013     1     1    5. JFK    BQN   N804JB  B6      <NA>    NA    NA
##  5  2013     1     1    6. LGA    ATL   N668DN  DL      Harts…  33.6 -84.4
##  6  2013     1     1    5. EWR    ORD   N39463  UA      Chica…  42.0 -87.9
##  7  2013     1     1    6. EWR    FLL   N516JB  B6      Fort …  26.1 -80.2
##  8  2013     1     1    6. LGA    IAD   N829AS  EV      Washi…  38.9 -77.5
##  9  2013     1     1    6. JFK    MCO   N593JB  B6      Orlan…  28.4 -81.3
## 10  2013     1     1    6. LGA    ORD   N3ALAA  AA      Chica…  42.0 -87.9
## # ... with 336,766 more rows, and 4 more variables: alt <int>, tz <dbl>,
## #   dst <chr>, tzone <chr>
```

To help you learn how different types of `xxx_join()` functions work, I'm going to use Hadley Wickham's visual representation (Hadley Wickham and Grolemund (2016)):



Adapted from Wickham, Hadley, and Garrett Grolemund. 2016. R for Data Science: Import, Tidy, Transform, Visualize, and Model Data. O'Reilly Media, Inc.

Filtering Joins

Filtering joins match observations in the same way as mutating joins, but affect the observations, not the variables. There are two types of filtering joins: `semi_join()` and anti_join().

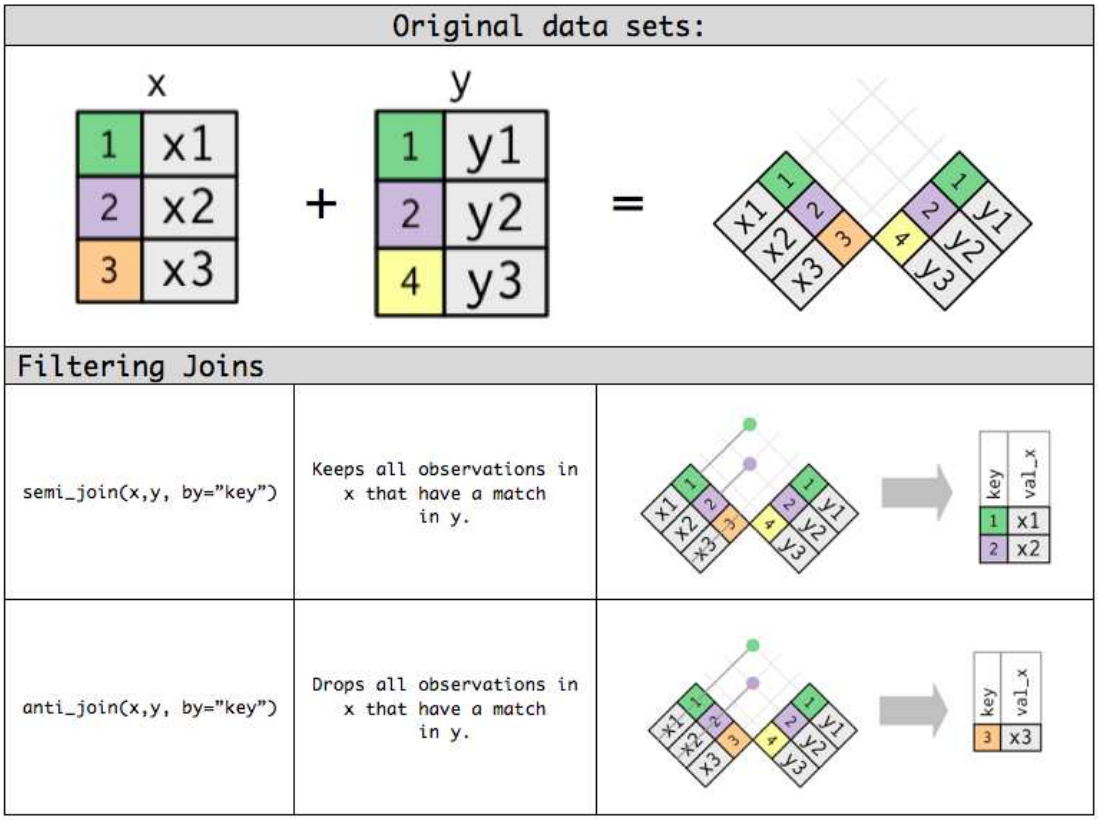
- `semi_join(x, y)` : keeps all observations in x that have a match in y.
- `anti_join(x, y)` : drops all observations in x that have a match in y.

Anti-joins are useful for diagnosing join mismatches. For example, when connecting `flights` and `planes` , you might be interested to know that there are many flights that don't have a match in planes:

```
flights %>% anti_join(planes, by = "tailnum") %>% count(tailnum, sort = TRUE)
```

```
## # A tibble: 722 x 2
##    tailnum     n
##    <chr>   <int>
##  1 <NA>     2512
##  2 N725MQ    575
##  3 N722MQ    513
##  4 N723MQ    507
##  5 N713MQ    483
##  6 N735MQ    396
##  7 N0EGMQ    371
##  8 N534MQ    364
##  9 N542MQ    363
## 10 N531MQ    349
## # ... with 712 more rows
```

Here is a visual representation of these two filtering joins.

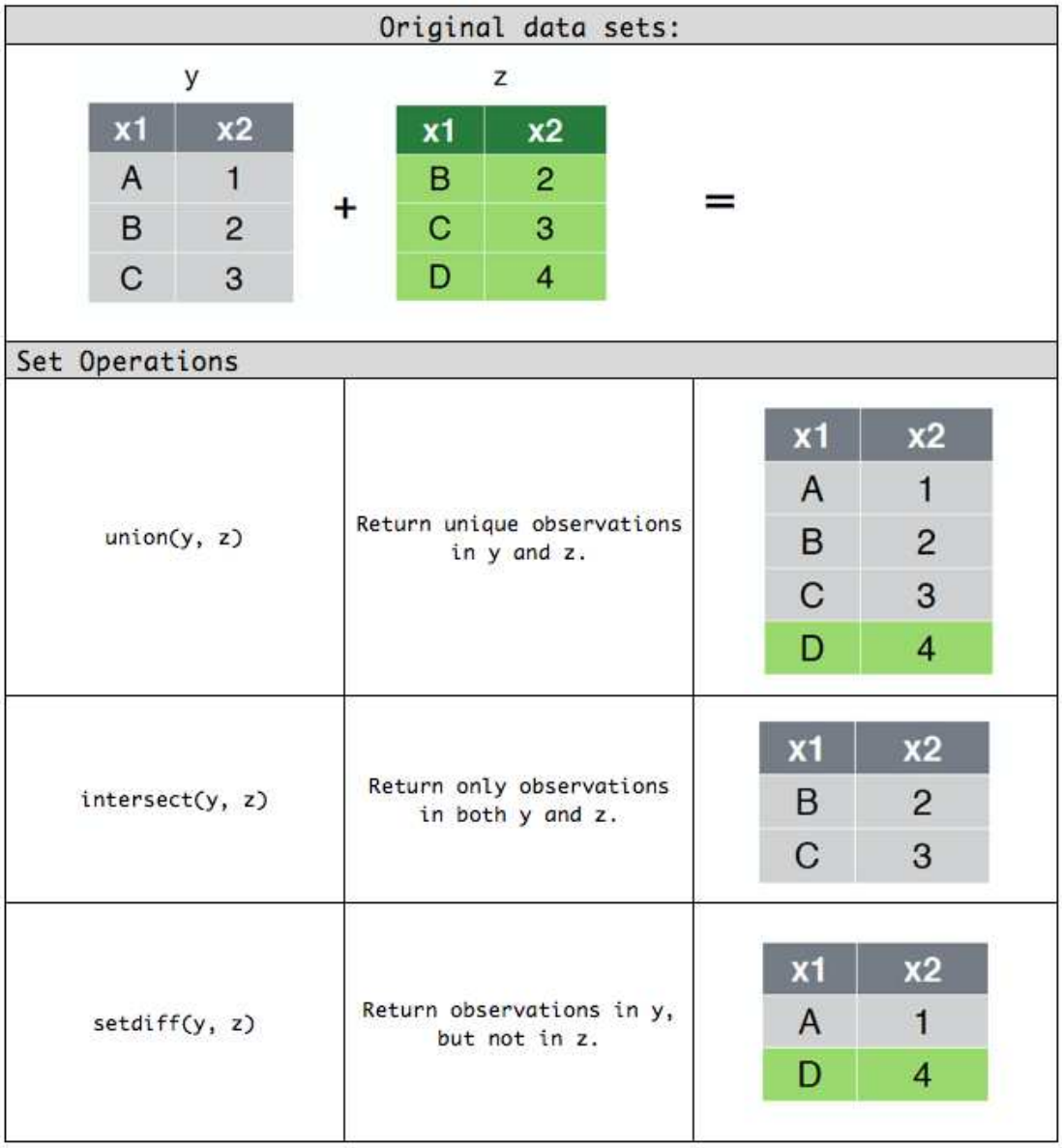


Adapted from Wickham, Hadley, and Garrett Grolemund. 2016. R for Data Science: Import, Tidy, Transform, Visualize, and Model Data. O'Reilly Media, Inc.

Set operations

Set operations expect the x and y inputs to have the same variables and treat the observations like sets. There are three types of set operations:

- `intersect(x, y)` : return only observations in both x and y.
- `union(x, y)` : return unique observations in x and y.
- `setdiff(x, y)` : return observations in x, but not in y.

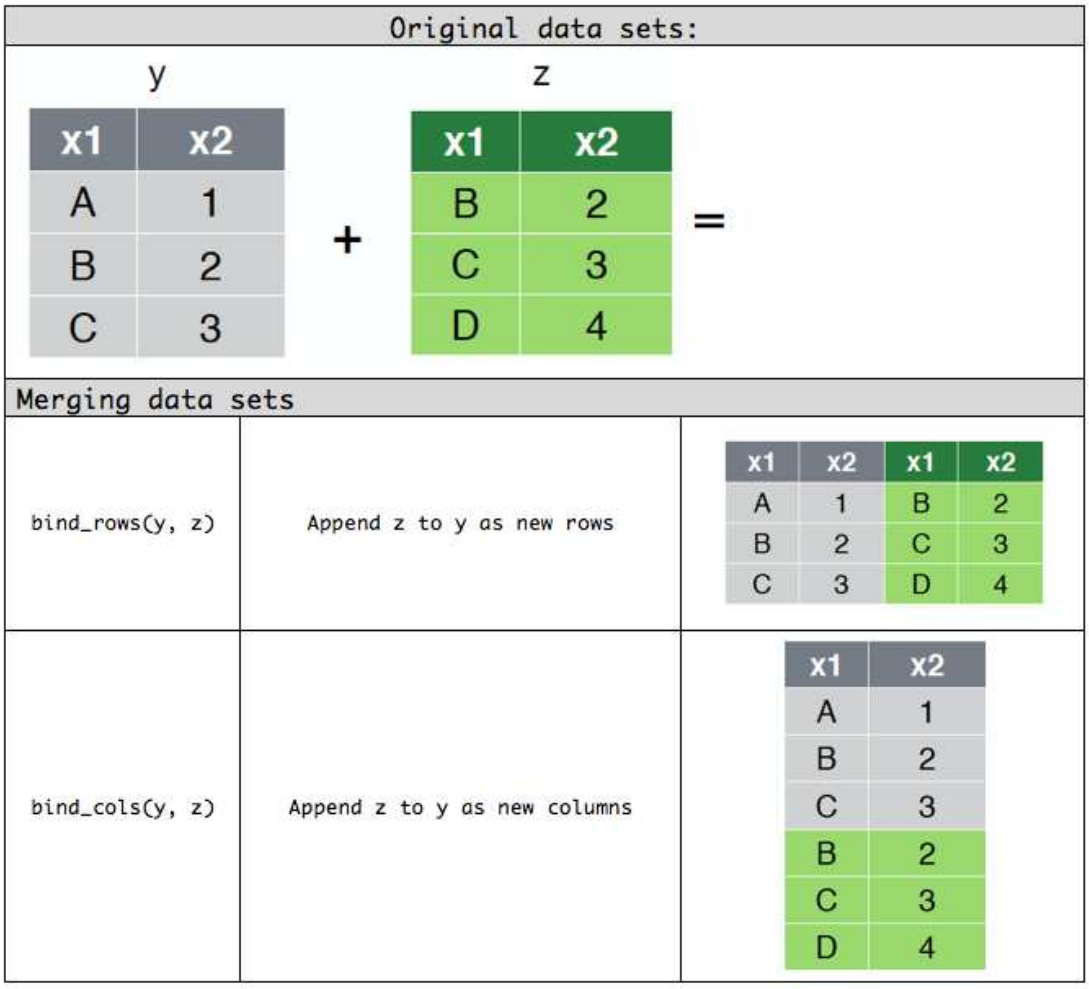


Adapted from Wickham, Hadley, and Garrett Grolemund. 2016. R for Data Science: Import, Tidy, Transform, Visualize, and Model Data. O'Reilly Media, Inc.

Merging data sets

Often you may just need to merge data frames by row and column. The `bind_rows()` and `bind_cols()` bind the multiple data frames by row and column, respectively.

- `bind_rows(x, y)` : Append y to x as new rows.
- `bind_cols(x, y)` : Append y to x as new columns.



Adapted from Wickham, Hadley, and Garrett Grolemund. 2016. R for Data Science: Import, Tidy, Transform, Visualize, and Model Data. O'Reilly Media, Inc.

Additional Resources and Further Reading

You can refer to the `tidyr` package manual (https://cran.r-project.org/web/packages/tidyr/tidyr.pdf) (H Wickham (2014)) and the Tidy Data paper (https://www.jstatsoft.org/article/view/v059i10/v59i10.pdf) for a detailed information on tidy data principles and `tidyr` package.

Our recommended textbooks (Boehmke (2016) and Hadley Wickham and Grolemund (2016)), R Studio's Data wrangling with R and RStudio webinar (https://www.rstudio.com/resources/webinars/data-wrangling-with-r-and-rstudio/), and dplyr (https://cran.r-project.org/web/packages/dplyr/dplyr.pdf) reference manual (H Wickham (2014), H Wickham et al. (2017)) are great resources to excel your knowledge in Data Manipulation with `dplyr` .

References

Boehmke, Bradley C. 2016. *Data Wrangling with R*. Springer.

Wickham, H. 2014. "Tidyr: Easily Tidy Data with Spread () and Gather () Functions. R Package." *Version 0.2. 0. Available at Http://CRAN. R-Project. Org/Package= Tidyr [Verified 7 June 2016]*.

Wickham, H, R Francois, L Henry, and K Müller. 2017. "Dplyr: A Grammar of Data Manipulation. R Package Version 0.7. 0." URL https://CRAN. R-project. org/package= dplyr.

Wickham, Hadley, and Garrett Grolemund. 2016. *R for Data Science: Import, Tidy, Transform, Visualize, and Model Data*. " O'Reilly Media, Inc."

Wickham, Hadley, and others. 2014. "Tidy Data." *Journal of Statistical Software* 59 (10). Foundation for Open Access Statistics: 1–23.