Data manipulation in R

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Chapter 2

Getting Started

2.1 Prerequisites

Basic knowledge of working with datasets in R is essential. This course assumes that you're comfortable with reading datasets, working with script files, and navigating in RStudio.

2.2 Software Requirements

2.2.1 R and RStudio

Recent versions of R (version 3.2 or newer) and RStudio (version 1.0 above) are required.

You can download the latest versions from the links below:

- Download R
- Download RStudio

You can find out the version of R installed by typing `version` at the console:

```
version
```

```
##                _
## platform       x86_64-w64-mingw32
## arch           x86_64
## os             mingw32
## system         x86_64, mingw32
## status
## major          3
## minor          6.0
## year           2019
## month          04
## day            26
## svn rev        76424
## language       R
## version.string R version 3.6.0 (2019-04-26)
## nickname       Planting of a Tree
```

2.3 Required Packages

This workshop relies on three packages: `dplyr`, `tidyr`, and `readr`. There are two ways to install these packages:

2.3.1 Option 1: Use `tidyverse`

You can either install these two packages individually or use `tidyverse`. The `tidyverse` package is a collection of packages used for data manipulation and visualization. In addition to `dplyr`, `tidyr`, and `readr`, it also includes the following:

```
##  [1] "broom"         "cli"           "crayon"        "dplyr"         "dbplyr"
##  [6] "forcats"       "ggplot2"       "haven"         "hms"           "httr"
## [11] "jsonlite"      "lubridate"     "magrittr"      "modelr"        "purrr"
## [16] "readr"         "readxl\n(>="   "reprex"        "rlang"         "rstudioapi"
## [21] "rvest"         "stringr"       "tibble"        "tidyr"         "xml2"
## [26] "tidyverse"
```

You can install `tidyverse` using the `install.packages()` function:

```
install.packages("tidyverse")
```

You can find out the version of `tidyverse` installed using the `packageVersion()` function:

```
packageVersion("tidyverse")
```

```
## [1] '1.2.1'
```

To update `tidyverse` packages, you can use the `tidyverse_update()` function:

```
tidyverse::tidyverse_update()
```

2.3.2 Option 2: Install Individual Packages

If you encounter any problems installing `tidyverse`, then the other option is to install `dplyr`, `tidyr`, and `readr` individually.

```
install.packages("dplyr")
install.packages("tidyr")
install.packages("readr")
```

Chapter 3

Basic Operations

Let's start off by creating a new R script and loading `tidyverse`:

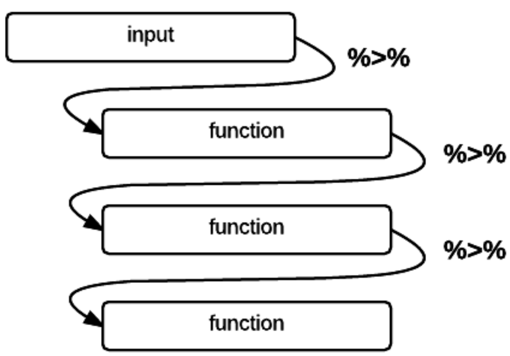
```
library(tidyverse)
```

Clear everything to make sure there's nothing leftover in our environment

```
rm(list = ls())
```

3.1 Data pipelines

Dplyr makes it easy to "chain" functions together using the *pipe* operator `%>%`. The following diagram illustrates the general concept of pipes where data flows from one pipe to another until all the processing is completed.



The syntax of the pipe operator `%>%` might appear unusual at first, but once you get used to it you'll start to appreciate its power and flexibility.

3.2 Dataset

We're using a dataset of flight departures from Houston in 2011.

Filename	Description
flights.csv	Flight departures from Houston in 2011
weather.csv	Hourly weather
planes.csv	Metadata for planes
airports.csv	Metadata for airports

We're going to use the `readr` package which provides improved functions for reading datasets from files. Instead of the usual `read.csv()` function, we'll use the `read_csv()` function from `readr`. https://github.com/SigWeber/data-manipulation-workshop/blob/master/data/flights.csv

```
flights <- read_csv("https://raw.githubusercontent.com/SigWeber/data-manipulation-workshop/master/data/f
weather <- read_csv("https://raw.githubusercontent.com/SigWeber/data-manipulation-workshop/master/data/w
planes <- read_csv("https://raw.githubusercontent.com/SigWeber/data-manipulation-workshop/master/data/pl
airports <- read_csv("https://raw.githubusercontent.com/SigWeber/data-manipulation-workshop/master/data/
```

Now let's examine the dataset

```
flights
```

```
## # A tibble: 227,496 x 14
##    date                 hour minute   dep   arr dep_delay arr_delay carrier
##    <dttm>              <dbl>  <dbl> <dbl> <dbl>     <dbl>     <dbl> <chr>
##  1 2011-01-01 12:00:00    14      0  1400  1500         0       -10 AA
##  2 2011-01-02 12:00:00    14      1  1401  1501         1        -9 AA
##  3 2011-01-03 12:00:00    13     52  1352  1502        -8        -8 AA
##  4 2011-01-04 12:00:00    14      3  1403  1513         3         3 AA
##  5 2011-01-05 12:00:00    14      5  1405  1507         5        -3 AA
##  6 2011-01-06 12:00:00    13     59  1359  1503        -1        -7 AA
##  7 2011-01-07 12:00:00    13     59  1359  1509        -1        -1 AA
##  8 2011-01-08 12:00:00    13     55  1355  1454        -5       -16 AA
##  9 2011-01-09 12:00:00    14     43  1443  1554        43        44 AA
## 10 2011-01-10 12:00:00    14     43  1443  1553        43        43 AA
## # ... with 227,486 more rows, and 6 more variables: flight <dbl>,
## #   dest <chr>, plane <chr>, cancelled <dbl>, time <dbl>, dist <dbl>
```

```
weather
```

```
## # A tibble: 8,723 x 14
##    date        hour  temp dew_point humidity pressure visibility wind_dir
##    <date>     <dbl> <dbl>     <dbl>    <dbl>    <dbl>      <dbl> <chr>
##  1 2011-01-01     0  59        28.9       32     29.9         10 NNE
##  2 2011-01-01     1  57.2      28.4       33     29.9         10 NNE
##  3 2011-01-01     2  55.4      28.4       36     29.9         10 NNW
##  4 2011-01-01     3  53.6      28.4       38     29.9         10 North
##  5 2011-01-01     4  NA        NA         NA     30.0         10 NNW
##  6 2011-01-01     5  NA        NA         NA     30.0         10 North
##  7 2011-01-01     6  53.1      17.1       24     30.0         10 North
##  8 2011-01-01     7  53.1      16         23     30.1         10 North
##  9 2011-01-01     8  54        18         24     30.1         10 North
## 10 2011-01-01     9  55.4      17.6       23     30.1         10 NNE
## # ... with 8,713 more rows, and 6 more variables: wind_dir2 <dbl>,
## #   wind_speed <dbl>, gust_speed <dbl>, precip <dbl>, conditions <chr>,
## #   events <chr>
```

```
planes
```

```
## # A tibble: 2,853 x 9
##    plane   year mfr       model   no.eng no.seats speed engine   type
##    <chr>  <dbl> <chr>     <chr>    <dbl>    <dbl> <dbl> <chr>    <chr>
##  1 N576AA  1991 MCDONNEL~ DC-9-8~      2      172    NA Turbo-f~ Fixed win~
##  2 N557AA  1993 MARZ BAR~ KITFOX~      1        2    NA Recipro~ Fixed win~
##  3 N403AA  1974 RAVEN     S55A        NA        1    60 None     Balloon
##  4 N492AA  1989 MCDONNEL~ DC-9-8~      2      172    NA Turbo-f~ Fixed win~
##  5 N262AA  1985 MCDONNEL~ DC-9-8~      2      172    NA Turbo-f~ Fixed win~
##  6 N493AA  1989 MCDONNEL~ DC-9-8~      2      172    NA Turbo-f~ Fixed win~
##  7 N477AA  1988 MCDONNEL~ DC-9-8~      2      172    NA Turbo-f~ Fixed win~
##  8 N476AA  1988 MCDONNEL~ DC-9-8~      2      172    NA Turbo-f~ Fixed win~
##  9 N504AA    NA AUTHIER ~ TIERRA~      1        2    NA Recipro~ Fixed win~
## 10 N565AA  1987 MCDONNEL~ DC-9-8~      2      172    NA Turbo-f~ Fixed win~
## # ... with 2,843 more rows
```

```
airports
```

```
## # A tibble: 3,376 x 7
##    iata  airport               city              state country   lat   long
##    <chr> <chr>                 <chr>             <chr> <chr>   <dbl>  <dbl>
##  1 00M   Thigpen               Bay Springs       MS    USA      32.0  -89.2
##  2 00R   Livingston Municipal  Livingston        TX    USA      30.7  -95.0
##  3 00V   Meadow Lake           Colorado Springs  CO    USA      38.9 -105.
##  4 01G   Perry-Warsaw          Perry             NY    USA      42.7  -78.1
##  5 01J   Hilliard Airpark      Hilliard          FL    USA      30.7  -81.9
##  6 01M   Tishomingo County     Belmont           MS    USA      34.5  -88.2
##  7 02A   Gragg-Wade            Clanton           AL    USA      32.9  -86.6
##  8 02C   Capitol               Brookfield        WI    USA      43.1  -88.2
##  9 02G   Columbiana County     East Liverpool    OH    USA      40.7  -80.6
## 10 03D   Memphis Memorial      Memphis           MO    USA      40.4  -92.2
## # ... with 3,366 more rows
```

Notice that because we used `read_csv()`, the data frame we received now prints nicely without having to use the `head()` function and does not clutter your screen.

3.3 Select

The `select` function is used to select columns.

- Select the destination, duration and distance columns (`dest`, `time` and `dist`)

```
flights %>%
  select(dest, time, dist)
```

```
## # A tibble: 227,496 x 3
##    dest   time  dist
##    <chr> <dbl> <dbl>
##  1 DFW      40   224
##  2 DFW      45   224
##  3 DFW      48   224
##  4 DFW      39   224
##  5 DFW      44   224
##  6 DFW      45   224
```

```
## 7 DFW      43   224
## 8 DFW      40   224
## 9 DFW      41   224
## 10 DFW     45   224
## # ... with 227,486 more rows
```

Add the arrival delay (`arr_delay`) and departure delay (`dep_delay`) columns as well.

```
flights %>%
  select(dest, time, dist, arr_delay, dep_delay)
```

```
## # A tibble: 227,496 x 5
##    dest   time  dist arr_delay dep_delay
##    <chr> <dbl> <dbl>     <dbl>     <dbl>
##  1 DFW      40   224       -10         0
##  2 DFW      45   224        -9         1
##  3 DFW      48   224        -8        -8
##  4 DFW      39   224         3         3
##  5 DFW      44   224        -3         5
##  6 DFW      45   224        -7        -1
##  7 DFW      43   224        -1        -1
##  8 DFW      40   224       -16        -5
##  9 DFW      41   224        44        43
## 10 DFW      45   224        43        43
## # ... with 227,486 more rows
```

Other ways to do the same

```
flights %>%
  select(dest, time, dist, ends_with("delay"))
```

```
## # A tibble: 227,496 x 5
##    dest   time  dist dep_delay arr_delay
##    <chr> <dbl> <dbl>     <dbl>     <dbl>
##  1 DFW      40   224         0       -10
##  2 DFW      45   224         1        -9
##  3 DFW      48   224        -8        -8
##  4 DFW      39   224         3         3
##  5 DFW      44   224         5        -3
##  6 DFW      45   224        -1        -7
##  7 DFW      43   224        -1        -1
##  8 DFW      40   224        -5       -16
##  9 DFW      41   224        43        44
## 10 DFW      45   224        43        43
## # ... with 227,486 more rows
```

and …

```
flights %>%
  select(dest, time, dist, contains("delay"))
```

```
## # A tibble: 227,496 x 5
##    dest   time  dist dep_delay arr_delay
##    <chr> <dbl> <dbl>     <dbl>     <dbl>
##  1 DFW      40   224         0       -10
##  2 DFW      45   224         1        -9
##  3 DFW      48   224        -8        -8
##  4 DFW      39   224         3         3
```

```
##   5 DFW      44    224         5        -3
##   6 DFW      45    224        -1        -7
##   7 DFW      43    224        -1        -1
##   8 DFW      40    224        -5       -16
##   9 DFW      41    224        43        44
##  10 DFW      45    224        43        43
## # ... with 227,486 more rows
```

Select all columns from `date` to `arr`

```
flights %>%
  select(date:arr)
```

```
## # A tibble: 227,496 x 5
##    date                 hour minute   dep   arr
##    <dttm>              <dbl>  <dbl> <dbl> <dbl>
##  1 2011-01-01 12:00:00    14      0  1400  1500
##  2 2011-01-02 12:00:00    14      1  1401  1501
##  3 2011-01-03 12:00:00    13     52  1352  1502
##  4 2011-01-04 12:00:00    14      3  1403  1513
##  5 2011-01-05 12:00:00    14      5  1405  1507
##  6 2011-01-06 12:00:00    13     59  1359  1503
##  7 2011-01-07 12:00:00    13     59  1359  1509
##  8 2011-01-08 12:00:00    13     55  1355  1454
##  9 2011-01-09 12:00:00    14     43  1443  1554
## 10 2011-01-10 12:00:00    14     43  1443  1553
## # ... with 227,486 more rows
```

Select all *except* `plane` column using the *minus* sign

```
flights %>%
  select(-plane)
```

```
## # A tibble: 227,496 x 13
##    date                 hour minute   dep   arr dep_delay arr_delay carrier
##    <dttm>              <dbl>  <dbl> <dbl> <dbl>     <dbl>     <dbl> <chr>
##  1 2011-01-01 12:00:00    14      0  1400  1500         0       -10 AA
##  2 2011-01-02 12:00:00    14      1  1401  1501         1        -9 AA
##  3 2011-01-03 12:00:00    13     52  1352  1502        -8        -8 AA
##  4 2011-01-04 12:00:00    14      3  1403  1513         3         3 AA
##  5 2011-01-05 12:00:00    14      5  1405  1507         5        -3 AA
##  6 2011-01-06 12:00:00    13     59  1359  1503        -1        -7 AA
##  7 2011-01-07 12:00:00    13     59  1359  1509        -1        -1 AA
##  8 2011-01-08 12:00:00    13     55  1355  1454        -5       -16 AA
##  9 2011-01-09 12:00:00    14     43  1443  1554        43        44 AA
## 10 2011-01-10 12:00:00    14     43  1443  1553        43        43 AA
## # ... with 227,486 more rows, and 5 more variables: flight <dbl>,
## #   dest <chr>, cancelled <dbl>, time <dbl>, dist <dbl>
```

3.4 Filter

The `filter()` function returns rows with matching conditions. We can find all flights to Boston (BOS) like this:

```
flights %>%
  filter(dest == "BOS")
```

```
## # A tibble: 1,752 x 14
##    date                 hour minute   dep   arr dep_delay arr_delay carrier
##    <dttm>              <dbl>  <dbl> <dbl> <dbl>     <dbl>     <dbl> <chr>
##  1 2011-01-31 12:00:00     7     35   735  1220         0         4 CO
##  2 2011-01-31 12:00:00    10     47  1047  1526        -3        -5 CO
##  3 2011-01-31 12:00:00    13      5  1305  1746         0        -3 CO
##  4 2011-01-31 12:00:00    19      1  1901  2332         6        -1 CO
##  5 2011-01-31 12:00:00    15     50  1550  2012         0       -25 CO
##  6 2011-01-30 12:00:00    10     46  1046  1518        -4        -8 CO
##  7 2011-01-30 12:00:00    13     19  1319  1811        14        22 CO
##  8 2011-01-30 12:00:00    19      9  1909    23        14        50 CO
##  9 2011-01-30 12:00:00    15     53  1553  2030         3        -7 CO
## 10 2011-01-29 12:00:00     7     40   740  1227         5        16 CO
## # ... with 1,742 more rows, and 6 more variables: flight <dbl>,
## #   dest <chr>, plane <chr>, cancelled <dbl>, time <dbl>, dist <dbl>
```

Let's build on the previous exercise and find all flights to Boston (BOS) and select only the `dest`, `time`, `dist` columns:

```
flights %>%
  select(dest, time, dist) %>%
  filter(dest == "BOS")
```

```
## # A tibble: 1,752 x 3
##    dest   time  dist
##    <chr> <dbl> <dbl>
##  1 BOS     195  1597
##  2 BOS     188  1597
##  3 BOS     190  1597
##  4 BOS     188  1597
##  5 BOS     180  1597
##  6 BOS     190  1597
##  7 BOS     185  1597
##  8 BOS     198  1597
##  9 BOS     194  1597
## 10 BOS     203  1597
## # ... with 1,742 more rows
```

Now let's do the filter first and then select the columns

```
flights %>%
  filter(dest == "BOS") %>%
  select(dest, time, dist)
```

```
## # A tibble: 1,752 x 3
##    dest   time  dist
##    <chr> <dbl> <dbl>
##  1 BOS     195  1597
##  2 BOS     188  1597
##  3 BOS     190  1597
##  4 BOS     188  1597
##  5 BOS     180  1597
##  6 BOS     190  1597
```

```
##   7 BOS      185   1597
##   8 BOS      198   1597
##   9 BOS      194   1597
##  10 BOS      203   1597
## # ... with 1,742 more rows
```

In this case the order doesn't matter, but when using pipes make sure you understand that each function is executed in sequence and the results are then fed to the next one.

3.4.1 Exercise

Find all flights that match the following conditions:

1. To SFO or OAK
2. In January
3. Delayed by more than an hour
4. Departed between midnight and 5am
5. Arrival delay more than twice the departure delay

Here's a brief summary of operators you can use:

Comparison Operators

Operator	Description	Example (assume x is 5)	Result
>	greater than	x > 5	FALSE
>=	greater than or equal to	x >= 5	TRUE
<	less than	x < 5	FALSE
<=	less than or equal to	x <= 5	TRUE
==	equal to	x == 5	TRUE
!=	not equal to	x != 5	FALSE

Logical Operators

Operator	Description
!	not
|	or
&	and

Other Operators

Operator	Description	Example (assume x is 5)	Result
%in%	check element in a vector	x %in% c(1, 3, 5, 7) x %in% c(2, 4, 6, 8)	TRUE FALSE

3.5 Arrange

The `arrange()` function is used to sort the rows based on one or more columns

```r
flights %>%
  arrange(dest)
```

```
## # A tibble: 227,496 x 14
##    date                 hour minute   dep   arr dep_delay arr_delay carrier
##    <dttm>              <dbl>  <dbl> <dbl> <dbl>     <dbl>     <dbl> <chr>
##  1 2011-01-31 12:00:00    17     33  1733  1901        -2        -4 CO
##  2 2011-01-30 12:00:00    17     50  1750  1913        15         8 CO
##  3 2011-01-29 12:00:00    17     32  1732  1837        -3       -23 CO
##  4 2011-01-28 12:00:00    17     33  1733  1848        -2       -17 CO
```

```
##  5 2011-01-27 12:00:00    17     41  1741  1854         6       -11 CO
##  6 2011-01-26 12:00:00    17     32  1732  1853        -3       -12 CO
##  7 2011-01-25 12:00:00    17     29  1729  1858        -6        -7 CO
##  8 2011-01-24 12:00:00    17     34  1734  1845        -1       -20 CO
##  9 2011-01-23 12:00:00    17     35  1735  1853         0       -12 CO
## 10 2011-01-22 12:00:00    17     33  1733  1843        -2       -17 CO
## # ... with 227,486 more rows, and 6 more variables: flight <dbl>,
## #   dest <chr>, plane <chr>, cancelled <dbl>, time <dbl>, dist <dbl>
```

3.5.1 Exercise

1. Order flights by departure date and time
2. Which flights were most delayed?
3. Which flights caught up the most time during flight?

3.6 Mutate

The `mutate()` function is used to create new variables.

Up until now we've only been examining the dataset but haven't made any changes to it. All our functions so far have simply displayed the results on screen but haven't created or modified existing variables. Let's see how we can create a new variable called `speed` based on the distance and duration in the flights dataframe.

In this exercise we're adding a new variable to an existing dataframe so we'll just overwrite the `flights` variable with the one that has a `speed` column

```r
flights <- flights %>%
  mutate(speed = dist / (time / 60))
```

3.6.1 Exercise

1. Add a variable to show how much time was made up (or lost) during flight

3.7 Summarise

Let's count the number of flights departing each day.

```r
flights %>%
  group_by(date) %>%
  summarise(count = n())
```

```
## # A tibble: 365 x 2
##    date                count
##    <dttm>              <int>
##  1 2011-01-01 12:00:00   552
##  2 2011-01-02 12:00:00   678
##  3 2011-01-03 12:00:00   702
##  4 2011-01-04 12:00:00   583
##  5 2011-01-05 12:00:00   590
##  6 2011-01-06 12:00:00   660
##  7 2011-01-07 12:00:00   661
```

```
##  8 2011-01-08 12:00:00   500
##  9 2011-01-09 12:00:00   602
## 10 2011-01-10 12:00:00   659
## # ... with 355 more rows
```

Here's a nice little trick. You can use `View()` to look at the results of a pipe operation without creating new variables.

```r
flights %>%
  group_by(date) %>%
  summarise(count = n()) %>%
  View()
```

Of course, often times we'd want to save the summary in a variable for further analysis.

Let's find the average departure delay for each destination

```r
delays <- flights %>%
    group_by(dest) %>%
    summarise(mean = mean(dep_delay))

delays
```

```
## # A tibble: 116 x 2
##    dest   mean
##    <chr> <dbl>
##  1 ABQ    NA
##  2 AEX    NA
##  3 AGS    10
##  4 AMA    NA
##  5 ANC    25.0
##  6 ASE    NA
##  7 ATL    NA
##  8 AUS    NA
##  9 AVL    NA
## 10 BFL    NA
## # ... with 106 more rows
```

3.7.1 Exercise

1. What's wrong with the results above, and how would you fix the problem?
2. Can you think of using filter to solve the problem?
3. Use help to find out two other ways to do summarize/n combination in dplyr.
4. How many different destinations can you fly to from Houston?
5. Which destinations have the highest average delays?
6. Which flights (carrier + flight number) happen everyday and where do they fly?
7. How do delays (of non-cancelled flights) vary over the course of a day?

3.8 Unite

The `unite` function is useful for combining multiple columns together. In the example below, we join the `carrier` and `flight` to create a unique `flight_id` column.

```
flights %>%
  unite(flight_id, carrier, flight, sep = "-", remove = FALSE) %>%
  select(date, carrier, flight, flight_id)
```

```
## # A tibble: 227,496 x 4
##    date                carrier flight flight_id
##    <dttm>              <chr>    <dbl> <chr>
##  1 2011-01-01 12:00:00 AA         428 AA-428
##  2 2011-01-02 12:00:00 AA         428 AA-428
##  3 2011-01-03 12:00:00 AA         428 AA-428
##  4 2011-01-04 12:00:00 AA         428 AA-428
##  5 2011-01-05 12:00:00 AA         428 AA-428
##  6 2011-01-06 12:00:00 AA         428 AA-428
##  7 2011-01-07 12:00:00 AA         428 AA-428
##  8 2011-01-08 12:00:00 AA         428 AA-428
##  9 2011-01-09 12:00:00 AA         428 AA-428
## 10 2011-01-10 12:00:00 AA         428 AA-428
## # ... with 227,486 more rows
```

3.9 Separate

The `separate` function works the other way around by splitting a single column into multiple columns. Let's split the `date` column into separate `date` and `time` columns.

```
flights %>%
  separate(date, c("date", "time"), sep = " ")
```

```
## # A tibble: 227,496 x 15
##    date  time   hour minute   dep   arr dep_delay arr_delay carrier flight
##    <chr> <chr> <dbl>  <dbl> <dbl> <dbl>     <dbl>     <dbl> <chr>    <dbl>
##  1 2011~ 12:0~    14      0  1400  1500         0       -10 AA         428
##  2 2011~ 12:0~    14      1  1401  1501         1        -9 AA         428
##  3 2011~ 12:0~    13     52  1352  1502        -8        -8 AA         428
##  4 2011~ 12:0~    14      3  1403  1513         3         3 AA         428
##  5 2011~ 12:0~    14      5  1405  1507         5        -3 AA         428
##  6 2011~ 12:0~    13     59  1359  1503        -1        -7 AA         428
##  7 2011~ 12:0~    13     59  1359  1509        -1        -1 AA         428
##  8 2011~ 12:0~    13     55  1355  1454        -5       -16 AA         428
##  9 2011~ 12:0~    14     43  1443  1554        43        44 AA         428
## 10 2011~ 12:0~    14     43  1443  1553        43        43 AA         428
## # ... with 227,486 more rows, and 5 more variables: dest <chr>,
## #   plane <chr>, cancelled <dbl>, dist <dbl>, speed <dbl>
```

3.9.1 Exercise

1. Split the `date` column into `year`, `month`, and `day` columns
2. Ensure that the `year`, `month`, and `day` columns are of type *integer* (NOT *character*)
    - HINT: Use online help for `separate` for an easy way to do this

Chapter 4

Merging Datasets

Let's start by loading the `tidyverse` package

```
library(tidyverse)
```

Clear everything to make sure there's nothing leftover in our environment

```
rm(list = ls())
```

Next, we load three datasets of universities, cities, and states.

```
universities <- read_csv("https://raw.githubusercontent.com/SigWeber/data-manipulation-workshop/master/d
cities <- read_csv("https://raw.githubusercontent.com/SigWeber/data-manipulation-workshop/master/data/ci
states <- read_csv("https://raw.githubusercontent.com/SigWeber/data-manipulation-workshop/master/data/st
```

Let's see how we can merge the `universities` dataset with the `cities` dataset.

universities

university	city
Cornell	Ithaca
Harvard	Cambridge
MIT	Cambridge
Yale	New Haven

cities

city	state
Cambridge	Massachusetts
Ithaca	New York
Seattle	Washington

4.1 Left Join

```
universities %>%
  left_join(cities, by = "city")
```

university	city	state
Cornell	Ithaca	New York
Harvard	Cambridge	Massachusetts
MIT	Cambridge	Massachusetts
Yale	New Haven	NA

4.2 Right Join

```r
universities %>%
  right_join(cities, by = "city")
```

university	city	state
Harvard	Cambridge	Massachusetts
MIT	Cambridge	Massachusetts
Cornell	Ithaca	New York
NA	Seattle	Washington

4.3 Inner Join

```r
universities %>%
  inner_join(cities, by = "city")
```

university	city	state
Cornell	Ithaca	New York
Harvard	Cambridge	Massachusetts
MIT	Cambridge	Massachusetts

4.4 Full Join

```r
universities %>%
  full_join(cities, by = "city")
```

university	city	state
Cornell	Ithaca	New York
Harvard	Cambridge	Massachusetts
MIT	Cambridge	Massachusetts
Yale	New Haven	NA
NA	Seattle	Washington

4.5 Different Column Names

In the previous example both our datasets included a column named `city`. But what if the names of the columns in the two datasets were not the same? For example, let's take a look at the `states` table:

states

code	statename
CT	Connecticut
MA	Massachusetts
NY	New York
WA	Washington

What if we were to merge the `cities` dataset with `states`?

cities

city	state
Cambridge	Massachusetts
Ithaca	New York
Seattle	Washington

states

code	statename
CT	Connecticut
MA	Massachusetts
NY	New York
WA	Washington

One option would be to rename the columns so their names would match, but you don't really need to do that. You can simply tell the join functions the mapping between the different names.

```
cities %>%
  left_join(states, by = c("state" = "statename"))
```

In the above example, we're telling `left_join()` to merge using the `state` column from the `cities` data frame and `statename` column from the `states` data frame.

city	state	code
Cambridge	Massachusetts	MA
Ithaca	New York	NY
Seattle	Washington	WA

4.6 Exercise

1. Load the following datasets:

```
presidents <- read_csv("https://raw.githubusercontent.com/altaf-ali/tidydata_tutorial/master/data/p
presidents_home <- read_csv("https://raw.githubusercontent.com/altaf-ali/tidydata_tutorial/master/c
```

The datasets include names of U.S. presidents:

presidents

First	Middle	Last	TookOffice	LeftOffice
George	H. W.	Bush	20/01/1989	20/01/1993
George	W.	Bush	20/01/2001	20/01/2009
Dwight	D.	Eisenhower	20/01/1953	20/01/1961
John	F.	Kennedy	20/01/1961	22/11/1963
Franklin	D.	Roosevelt	4/03/1933	12/4/1945

presidents_home

GivenName	Middle	Surname	HomeState
George	H. W.	Bush	Texas
Franklin	D.	Roosevelt	New York
John	Quincy	Adams	Massachusetts
William	Howard	Taft	Ohio
George	W.	Bush	Texas

2. Merge the two datasets so that it ONLY includes observations that exist in BOTH the datasets. There should be no missing values or `NA` in the merged table. The results should match the following:

First	Middle	Last	TookOffice	LeftOffice	HomeState
George	H. W.	Bush	20/01/1989	20/01/1993	Texas
George	W.	Bush	20/01/2001	20/01/2009	Texas
Franklin	D.	Roosevelt	4/03/1933	12/4/1945	New York

3. Merge the two datasets so that it includes ALL the observations from both the datasets. Some `TookOffice`, `LeftOffice` and `HomeState` values will be `NA` and that's ok. The results should match the following:

First	Middle	Last	TookOffice	LeftOffice	HomeState
George	H. W.	Bush	20/01/1989	20/01/1993	Texas
George	W.	Bush	20/01/2001	20/01/2009	Texas
Dwight	D.	Eisenhower	20/01/1953	20/01/1961	NA
John	F.	Kennedy	20/01/1961	22/11/1963	NA
Franklin	D.	Roosevelt	4/03/1933	12/4/1945	New York
John	Quincy	Adams	NA	NA	Massachusetts
William	Howard	Taft	NA	NA	Ohio

4. Merge the two datasets so that ALL observations from the `presidents` datasets are included. Some `HomeState` values will be `NA` and that's ok. The results should match the following:

First	Middle	Last	TookOffice	LeftOffice	HomeState
George	H. W.	Bush	20/01/1989	20/01/1993	Texas
George	W.	Bush	20/01/2001	20/01/2009	Texas
Dwight	D.	Eisenhower	20/01/1953	20/01/1961	NA
John	F.	Kennedy	20/01/1961	22/11/1963	NA
Franklin	D.	Roosevelt	4/03/1933	12/4/1945	New York

5. Merge the two datasets so that ALL observations from the `presidents_home` datasets are included. Some `TookOffice` and `LeftOffice` values will be `NA` and that's ok. The results should match the following:

First	Middle	Last	TookOffice	LeftOffice	HomeState
George	H. W.	Bush	20/01/1989	20/01/1993	Texas
Franklin	D.	Roosevelt	4/03/1933	12/4/1945	New York
John	Quincy	Adams	NA	NA	Massachusetts
William	Howard	Taft	NA	NA	Ohio
George	W.	Bush	20/01/2001	20/01/2009	Texas

Chapter 5

Reshaping

It's fairly common for datasets from public sources to come in formats that need to be reshaped. The World Development Indicators (WDI) is one such dataset that requires reshaping before we can analyse it. Let's go over the steps to see how we can reshape the WDI dataset.

Let's start by loading the `tidyverse` package first.

```
library(tidyverse)
```

Clear everything to make sure there's nothing leftover in our environment

```
rm(list = ls())
```

We're using a small sample of the WDI dataset here to simplify the tasks. Let's load the dataset and see what it looks like.

```
wdi <- read_csv("https://raw.githubusercontent.com/SigWeber/data-manipulation-workshop/master/data/wdi.c

wdi
```

```
## # A tibble: 5 x 7
##   `¬Series.Name` Series.Code Country.Name Country.Code X1995.YR1995
##   <chr>          <chr>       <chr>        <chr>               <dbl>
## 1 Maternal mort~ SH.STA.MMRT France       FRA                 15
## 2 Maternal mort~ SH.STA.MMRT Spain        ESP                  6
## 3 Maternal mort~ SH.STA.MMRT ""           ""                  NA
## 4 Health expend~ SH.XPD.TOT~ France       FRA                 10.4
## 5 Health expend~ SH.XPD.TOT~ Spain        ESP                  7.44
## # ... with 2 more variables: X2000.YR2000 <dbl>, X2005.YR2005 <dbl>
```

But ideally, we'd like our data to look something like this:

```
## # A tibble: 6 x 5
##   CountryCode CountryName  Year MaternalMortality HealthExpenditure
##   <chr>       <chr>       <dbl>             <dbl>             <dbl>
## 1 ESP         Spain        1995                 6              7.44
## 2 ESP         Spain        2000                 5              7.21
## 3 ESP         Spain        2005                 5              8.29
## 4 FRA         France       1995                15             10.4
## 5 FRA         France       2000                12             10.1
## 6 FRA         France       2005                10             10.9
```

We can see that some country names and codes are blank, so let's get rid of them first

```
wdi %>%
  filter(Country.Code != "")
```

```
## # A tibble: 4 x 7
##   `¬Series.Name` Series.Code Country.Name Country.Code X1995.YR1995
##   <chr>          <chr>       <chr>        <chr>               <dbl>
## 1 Maternal mort~ SH.STA.MMRT France       FRA                 15
## 2 Maternal mort~ SH.STA.MMRT Spain        ESP                  6
## 3 Health expend~ SH.XPD.TOT~ France       FRA                 10.4
## 4 Health expend~ SH.XPD.TOT~ Spain        ESP                  7.44
## # ... with 2 more variables: X2000.YR2000 <dbl>, X2005.YR2005 <dbl>
```

So far so good. Note that we're not making any changes yet so we can just add one function at a time to the pipeline and check the results. Once we're satisfied with the results we save them to a variable.

We need to gather all columns that start with "X" that contain per-year values for each series (for example X1960..YR1960)

```
wdi %>%
  filter(Country.Code != "") %>%
  gather(Year, Value, starts_with("X"))
```

```
## # A tibble: 12 x 6
##    `¬Series.Name`    Series.Code  Country.Name Country.Code Year      Value
##    <chr>             <chr>        <chr>        <chr>        <chr>     <dbl>
##  1 Maternal mortali~ SH.STA.MMRT  France       FRA          X1995.YR~ 15
##  2 Maternal mortali~ SH.STA.MMRT  Spain        ESP          X1995.YR~  6
##  3 Health expenditu~ SH.XPD.TOTL~ France       FRA          X1995.YR~ 10.4
##  4 Health expenditu~ SH.XPD.TOTL~ Spain        ESP          X1995.YR~  7.44
##  5 Maternal mortali~ SH.STA.MMRT  France       FRA          X2000.YR~ 12
##  6 Maternal mortali~ SH.STA.MMRT  Spain        ESP          X2000.YR~  5
##  7 Health expenditu~ SH.XPD.TOTL~ France       FRA          X2000.YR~ 10.1
##  8 Health expenditu~ SH.XPD.TOTL~ Spain        ESP          X2000.YR~  7.21
##  9 Maternal mortali~ SH.STA.MMRT  France       FRA          X2005.YR~ 10
## 10 Maternal mortali~ SH.STA.MMRT  Spain        ESP          X2005.YR~  5
## 11 Health expenditu~ SH.XPD.TOTL~ France       FRA          X2005.YR~ 10.9
## 12 Health expenditu~ SH.XPD.TOTL~ Spain        ESP          X2005.YR~  8.29
```

Now all values are in the `Value` column, so we need to spread them out to individual columns based on the `Series.Code`. We have to make sure that we only keep the columns that make the country-year observations unique. We use `select()` to keep `Country.Code`, `Country.Name`, `Year`, plus the two columns (`Series.Code` and `Value`) that will make up the key-value pair for the `spread()` function.

```
wdi %>%
  filter(Country.Code != "") %>%
  gather(Year, Value, starts_with("X")) %>%
  select(Country.Code, Country.Name, Year, Series.Code, Value) %>%
  spread(Series.Code, Value)
```

```
## # A tibble: 6 x 5
##   Country.Code Country.Name Year         SH.STA.MMRT SH.XPD.TOTL.ZS
##   <chr>        <chr>        <chr>              <dbl>          <dbl>
## 1 ESP          Spain        X1995.YR1995           6           7.44
## 2 ESP          Spain        X2000.YR2000           5           7.21
## 3 ESP          Spain        X2005.YR2005           5           8.29
## 4 FRA          France       X1995.YR1995          15          10.4
## 5 FRA          France       X2000.YR2000          12          10.1
```

```
## 6 FRA          France       X2005.YR2005          10           10.9
```

It looks good, so we can rename the variables to something meaningful.

```
wdi %>%
  filter(Country.Code != "") %>%
  gather(Year, Value, starts_with("X")) %>%
  select(Country.Code, Country.Name, Year, Series.Code, Value) %>%
  spread(Series.Code, Value) %>%
  rename(CountryName = Country.Name,
         CountryCode = Country.Code,
         MaternalMortality = SH.STA.MMRT,
         HealthExpenditure = SH.XPD.TOTL.ZS)
```

```
## # A tibble: 6 x 5
##   CountryCode CountryName Year         MaternalMortality HealthExpenditure
##   <chr>       <chr>       <chr>                    <dbl>             <dbl>
## 1 ESP         Spain       X1995.YR1995                 6              7.44
## 2 ESP         Spain       X2000.YR2000                 5              7.21
## 3 ESP         Spain       X2005.YR2005                 5              8.29
## 4 FRA         France      X1995.YR1995                15             10.4
## 5 FRA         France      X2000.YR2000                12             10.1
## 6 FRA         France      X2005.YR2005                10             10.9
```

Now we just need to extract the 4-digit year from the `Year` column. The `Year` column is formatted as `X1995.YR1995` which means that the 4-digits for the year are in position 2,3,4, and 5. We can use the `substring()` function to take all the characters from position 2 to 5 and assign it back to the `Year` column.

Since this is the last step we might as well assign the results to a new variable.

```
wdi_long <- wdi %>%
  filter(Country.Code != "") %>%
  gather(Year, Value, starts_with("X")) %>%
  select(Country.Code, Country.Name, Year, Series.Code, Value) %>%
  spread(Series.Code, Value) %>%
  rename(CountryName = Country.Name,
         CountryCode = Country.Code,
         MaternalMortality = SH.STA.MMRT,
         HealthExpenditure = SH.XPD.TOTL.ZS) %>%
  mutate(Year = as.numeric(substring(Year, 2, 5)))

wdi_long
```

```
## # A tibble: 6 x 5
##   CountryCode CountryName  Year MaternalMortality HealthExpenditure
##   <chr>       <chr>       <dbl>             <dbl>             <dbl>
## 1 ESP         Spain        1995                 6              7.44
## 2 ESP         Spain        2000                 5              7.21
## 3 ESP         Spain        2005                 5              8.29
## 4 FRA         France       1995                15             10.4
## 5 FRA         France       2000                12             10.1
## 6 FRA         France       2005                10             10.9
```

You can assign it back to `wdi` if you want, but we're using a different name in case we make a mistake and have to start again. This way we would've have to reload the file all over again.

Chapter 6

Acknowledgments

Content of this workshop is based on the following:

- Introduction to dplyr
- Data manipulation with dplyr, 2014
- Hands-on dplyr tutorial for faster data manipulation in R