# Practical 204

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2020-11-30

# Data wrangling Pt. 1

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## R Projects

RStudio provides an extremely useful functionality to organise all your code and data, that is **R Projects**. Those are specialised files that RStudio can use to store all the information it has on a specific project that you are working on – *Environment*, *History*, working directory, and much more, as we will see in the coming weeks.

In RStudio Server, in the *Files* tab of the bottom-left panel, click on *Home* to make sure you are in your home folder – if you are working on your own computer, create a folder for these practicals wherever most convenient. Click on *New Folder* and enter *Practicals* in the prompt dialogue, to create a folder named *Practicals*.

Select File > New Project ... from the main menu, then from the prompt menu, New Directory, and then New Project. Insert Practical\_204 as the directory name, and select the Practicals folder for the field Create project as subdirectory of. Finally, click Create Project.

RStudio has now created the project, and it should have activated it. If that is the case, the *Files* tab in the bottom-right panel should be in the *Practical\_204* folder, which contains only the *Practical\_204.Rproj* file. The *Practical\_204.Rproj* stores all the *Environment* information for the current project and all the project files (e.g., R scripts, data, output files) should be stored within the *Practical\_204* folder. Moreover, the *Practical\_204* is now your working directory, which means that you can refer to a file in the folder by using only its name and if you save a file that is the default directory where to save it.

On the top-right corner of RStudio, you should see a blue icon representing an R in a cube, next to the name of the project ( $Practical\_204$ ). That also indicates that you are within the  $Practical\_204$  project. Click on  $Practical\_204$  and select  $Close\ Project$  to close the project. Next to the R in a cube icon, you should now see Project: (None). Click on Project: (None) and select  $Practical\_204$  from the list to reactivate the  $Practical\_204$  project.

With the  $Practical\_204$  project activated, select from the top menu File > New File > R Script. That opens the embedded RStudio editor and a new empty R script folder. Copy the two lines below into the file. The first loads the tidyverse library, whereas the second loads another library that the code below uses to produce well-formatted tables.

library(tidyverse)
library(knitr)

From the top menu, select File > Save, type in  $My\_script\_Practical\_204.R$  (make sure to include the underscore and the .R extension) as  $File\ name$ , and click Save.

### Install libraries

RStudio and RStudio Server come with a number of libraries already pre-installed. However, you might find yourself in the position of wanting to install additional libraries to work with.

The remainder of this practical requires the library nycflights13. To install it, select Tools > Install Packages... from the top menu. Insert nycflights13 in the Packages (separate multiple with space or comma) field and click install. RStudio will automatically execute the command install.packages("nycflights13") (so, no need to execute that yourself) and install the required library.

As usual, use the function library to load the newly installed library.

```
library(nycflights13)
```

The library nycflights13 contains a dataset storing data about all the flights departed from New York City in 2013. The code below, loads the data frame flights from the library nycflights13 into the variable flights\_from\_nyc, using the :: operator to indicate that the data frame flights is situated within the library nycflights13.

```
flights_from_nyc <- nycflights13::flights
```

Add both lines above to your R script, as well as the code snippets provided as an example below.

#### Loading R scripts

It is furthermore possible to load the function(s) defined in one script from another script – in a fashion similar to when a library is loaded. Create a new R script named Practical\_204\_RS\_functions.R, copy the code below in that R script and save the file

```
cube_root <- function (input_value) {
  result <- input_value ^ (1 / 3)
  result
}</pre>
```

Create a second R script named Practical\_204\_RS\_main.R, copy the code below in that second R script and save the file.

```
source("Practical_204_RS_functions.R")
cube_root(27)
```

Executing the Practical\_204\_RS\_main.R instructs the interpreter first to run the Practical\_204\_RS\_functions.R script, thus creating the cube\_root function, and then invoke the function using 27 as an argument, thus returning again 3. That is a simple example, but this can be an extremely powerful tool to create your own library of functions to be used by different scripts.

### Data manipulation

The analysis below uses the dplyr library (also part of the Tidyverse), which it offers a grammar for data manipulation.

For instance, the function count can be used to count the number rows of a data frame. The code below provides flights\_from\_nyc as input to the function count through the pipe operator, thus creating a new tibble with only one row and one column.

As discussed in the previous lecture, a tibble is data type similar to data frames, used by all the Tidyverse libraries.

All Tidyverse functions output tibble rather than data.frame objects when representing a table. However, data.frame object can be provided as input, as they are automatically converted by Tidyverse functions before proceeding with the processing steps.

In the tibble outputted by the count function below, the column n provides the count. The function kable of the library knitr is used to produce a well-formatted table.

The example above already shows how the **pipe operator** can be used effectively in a multi-step operation.

The function **count** can also be used to count the number rows of a table that have the same value for a given column, usually representing a category.

In the example below, the column name origin is provided as an argument to the function count, so rows representing flights from the same origin are counted together – EWR is the Newark Liberty International Airport, JFK is the John F. Kennedy International Airport, and LGA is LaGuardia Airport.

```
flights_from_nyc %>%
  dplyr::count(origin) %>%
  knitr::kable()
```

| origin      | n      |
|-------------|--------|
| EWR         | 120835 |
| $_{ m JFK}$ | 111279 |
| LGA         | 104662 |

As you can see, the code above is formatted in a way similar to a code block, although it is not a code block. The code goes to a new line after every %>%, and space is added at the beginning of new lines. That is very common in R programming (especially when functions have many parameters) as it makes the code more readable.

#### Summarise

To carry out more complex aggregations, the function summarise can be used in combination with the function group\_by to summarise the values of the rows of a data frame. Rows having the same value for a selected column (in the example below, the same origin) are grouped together, then values are aggregated based on the defined function (using one or more columns in the calculation).

In the example below, the function sum is applied to the column distance to calculate distance\_traveled\_from (the total distance travelled by flights starting from each airport).

```
flights_from_nyc %>%
  dplyr::group_by(origin) %>%
  dplyr::summarise(
    distance_traveled_from = sum(distance)
) %>%
  knitr::kable()
```

| origin      | $distance\_traveled\_from$ |
|-------------|----------------------------|
| EWR         | 127691515                  |
| $_{ m JFK}$ | 140906931                  |
| LGA         | 81619161                   |

#### Select and filter

The function select can be used to select some **columns** to output. For instance in the code below, the function select is used to select the columns origin, dest, and dep\_delay, in combination with the function slice\_head, which can be used to include only the first n rows (5 in the example below) to output.

```
flights_from_nyc %>%
  dplyr::select(origin, dest, dep_delay) %>%
  dplyr::slice_head(n = 5) %>%
  knitr::kable()
```

| origin      | dest | dep_delay |
|-------------|------|-----------|
| EWR         | IAH  | 2         |
| LGA         | IAH  | 4         |
| $_{ m JFK}$ | MIA  | 2         |
| $_{ m JFK}$ | BQN  | -1        |
| LGA         | ATL  | -6        |

The function filter can instead be used to filter **rows** based on a specified condition. In the example below, the output of the filter step only includes the rows where the value of month is 11 (i.e., the eleventh month, November).

```
flights_from_nyc %>%
  dplyr::select(origin, dest, year, month, day, dep_delay) %>%
  dplyr::filter(month == 11) %>%
  dplyr::slice_head(n = 5) %>%
  knitr::kable()
```

| origin      | dest | year | month | day | dep_delay |
|-------------|------|------|-------|-----|-----------|
| JFK         | PSE  | 2013 | 11    | 1   | 6         |
| $_{ m JFK}$ | SYR  | 2013 | 11    | 1   | 105       |
| EWR         | CLT  | 2013 | 11    | 1   | -5        |
| LGA         | IAH  | 2013 | 11    | 1   | -6        |
| JFK         | MIA  | 2013 | 11    | 1   | -3        |

Notice how filter is used in combination with select. All functions in the dplyr library can be combined, in any other order that makes logical sense. However, if the select step didn't include month, that same column couldn't have been used in the filter step.

#### Mutate

The function mutate can be used to add a new column to an output table. The mutate step in the code below adds a new column air\_time\_hours to the table obtained through the pipe, that is the flight air time in hours, dividing the flight air time in minutes by 60.

```
flights_from_nyc %>%
  dplyr::select(flight, origin, dest, air_time) %>%
  dplyr::mutate(
    air_time_hours = air_time / 60
) %>%
  dplyr::slice_head(n = 5) %>%
  knitr::kable()
```

| flight | origin      | dest | $air\_time$ | air_time_hours |
|--------|-------------|------|-------------|----------------|
| 1545   | EWR         | IAH  | 227         | 3.783333       |
| 1714   | LGA         | IAH  | 227         | 3.783333       |
| 1141   | $_{ m JFK}$ | MIA  | 160         | 2.666667       |
| 725    | $_{ m JFK}$ | BQN  | 183         | 3.050000       |
| 461    | LGA         | ATL  | 116         | 1.933333       |
|        |             |      |             |                |

#### Arrange

The function arrange can be used to sort a tibble by ascending order of the values in the specified column. If the operator – is specified before the column name, the descending order is used. The code below would produce a table showing all the rows when ordered by descending order of air time.

```
flights_from_nyc %>%
  dplyr::select(flight, origin, dest, air_time) %>%
  dplyr::arrange(-air_time) %>%
  knitr::kable()
```

In the examples above, we have used slice\_head to present only the first n (in the examples 5) rows in a table, based on the existing order. The dplyr library also provides the functions slice\_max and slice\_min which incorporate the sorting functionality (see slice reference page).

As such, the following code uses slice\_max to produce a table including only the 5 rows with the *highest* air time.

```
flights_from_nyc %>%
  dplyr::select(flight, origin, dest, air_time) %>%
  dplyr::slice_max(air_time, n = 5) %>%
  knitr::kable()
```

| flight | origin | dest | air_time |
|--------|--------|------|----------|
| 15     | EWR    | HNL  | 695      |
| 51     | JFK    | HNL  | 691      |
| 51     | JFK    | HNL  | 686      |
| 51     | JFK    | HNL  | 686      |
| 51     | JFK    | HNL  | 683      |
|        |        |      |          |

The following code, instead, uses slice\_min, thus producing a table including only the 5 rows with the lowest air time.

```
flights_from_nyc %>%
  dplyr::select(flight, origin, dest, air_time) %>%
  dplyr::slice_min(air_time, n = 5) %>%
  knitr::kable()
```

| flight | origin | dest | air_time |
|--------|--------|------|----------|
| 4368   | EWR    | BDL  | 20       |
| 4631   | EWR    | BDL  | 20       |
| 4276   | EWR    | BDL  | 21       |
| 4619   | EWR    | PHL  | 21       |
| 4368   | EWR    | BDL  | 21       |
| 4619   | EWR    | PHL  | 21       |
| 2132   | LGA    | BOS  | 21       |

| flight | origin | dest | air_time |
|--------|--------|------|----------|
| 3650   | JFK    | PHL  | 21       |
| 4118   | EWR    | BDL  | 21       |
| 4276   | EWR    | BDL  | 21       |
| 4276   | EWR    | BDL  | 21       |
| 4276   | EWR    | BDL  | 21       |
| 4276   | EWR    | BDL  | 21       |
| 4577   | EWR    | BDL  | 21       |
| 6062   | EWR    | BDL  | 21       |
| 3847   | EWR    | BDL  | 21       |

In both cases, if the table contains ties, all rows containing a value that is present among the maximum or minimum selected values are presented, as it is the case with the rows containing the value 21 in the example above.

## Data manipulation example

Finally, the code below illustrates a more complex, multi-step operation using all the functions discussed above.

- 1. Start from the flights\_from\_nyc data.
- 2. Select origin, destination, departure delay, year, month, and day.
- 3. Filter only rows referring to flights in November.
- 4. Filter only rows where departure delay is not (notice that the negation operator! is used) NA.
- That is necessary because the function mean would return NA as output if any of the values in the column is NA.
- 5. Group by destination.
- 6. Calculated the average delay per destination.
- 7. Add a column with the delay calculated in hours (minutes over 60).
- 8. Sort the table by descending delay (note that is used before the column name).
- 9. Only show the first 5 rows.
- 10. Create a well-formatted table.

```
flights_from_nyc %>%
  dplyr::select(origin, dest, year, month, day, dep_delay) %>%
  dplyr::filter(month == 11) %>%
  dplyr::filter(!is.na(dep_delay)) %>%
  dplyr::group_by(dest) %>%
  dplyr::summarize(
    avg_dep_delay = mean(dep_delay)
) %>%
  dplyr::mutate(
    avg_dep_delay_hours = avg_dep_delay / 60
) %>%
  dplyr::arrange(-avg_dep_delay_hours) %>%
  dplyr::slice_head(n = 5) %>%
  knitr::kable()
```

| dest | avg_dep_delay | avg_dep_delay_hours |
|------|---------------|---------------------|
| SBN  | 67.50000      | 1.1250000           |
| BDL  | 26.66667      | 0.4444444           |
| CAK  | 19.70909      | 0.3284848           |

| dest | avg_dep_delay | avg_dep_delay_hours |
|------|---------------|---------------------|
| BHM  | 19.61905      | 0.3269841           |
| DSM  | 16.14815      | 0.2691358           |

#### Exercise 204.1

Extend the code in the script My\_script\_Practical\_204.R to include the code necessary to solve the questions below.

Question 204.1.1: Write a piece of code using the pipe operator and the dplyr library to generate a table showing the average air time in hours, calculated grouping flights by carrier, but only for flights starting from the JFK airport.

Question 204.1.2: Write a piece of code using the pipe operator and the dplyr library to generate a table showing the average arrival delay compared to the overall air time (tip: use manipulate to create a new column that takes the result of arr\_delay / air\_time) calculated grouping flights by carrier, but only for flights starting from the JFK airport.

Question 204.1.3: Write a piece of code using the pipe operator and the dplyr library to generate a table showing the average arrival delay compared to the overall air time calculated grouping flights by origin and destination, sorted by destination.