

# Lab 1: Tidy Data

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## Swirl: Getting and Cleaning Data Solutions

### Lesson 1: Manipulating Data with dplyr

Q1. I've created a variable called `path2csv`, which contains the full file path to the dataset. Call `read.csv()` with two arguments, `path2csv` and `stringsAsFactors | = FALSE`, and save the result in a new variable called `mydf`.

A1. `mydf <- read.csv(path2csv, stringsAsFactors = FALSE)`

Q2. Use `dim()` to look at the dimensions of `mydf`.

A2. `dim(mydf)`

Q3. Now use `head()` to preview the data.

A3. `head(mydf)`

Q4. The `dplyr` package was automatically installed (if necessary) and loaded at the beginning of this lesson. Normally, this is something you would have to do on your own. Just to build the habit, type `library(dplyr)` now to load the package again.

A4. `library(dplyr)`

Q5. It's important that you have `dplyr` version 0.4.0 or later. To confirm this, type `packageVersion("dplyr")`.

A5. `packageVersion("dplyr")`

Q6. The first step of working with data in `dplyr` is to load the data into what the package authors call a 'data frame tbl' or 'tbl\_df'.

A6. `cran <- tbl_df(mydf)`

Q7. As may often be the case, particularly with larger datasets, we are only interested in some of the variables. Use `select(cran, ip_id, package, country)` to select only the `ip_id`, `package`, and `country` variables from the `cran` dataset.

A7. `select(cran, ip_id, package, country)`

Q8. Recall that in R, the `:` operator provides a compact notation for creating a sequence of numbers. For example, try `5:20`.

A8. `5:20`

Q9. Normally, this notation is reserved for numbers, but `select()` allows you to specify a sequence of columns this way, which can save a bunch of typing. Use `select(cran, r_arch:country)` to select all columns starting from `r_arch` and ending with `country`.

A9. `select (cran, r_arch:country)`

Q10. We can also select the same columns in reverse order. Give it a try.

A10. `select (cran, country:r_arch)`

Q11. Print the entire dataset again, just to remind yourself of what it looks like. You can do this at anytime during the lesson.

A11. `cran`

Q12. Instead of specifying the columns we want to keep, we can also specify the columns we want to throw away. To see how this works, do `select(cran, -time)` to omit the time column.

A12. `select(cran, -time)`

Q13. The negative sign in front of `time` tells `select()` that we DON'T want the time column. Now, let's combine strategies to omit all columns from `X` through `size` (`X:size`). To see how this might work, let's look at a numerical example with `-5:20`.

A13. `-5:20`

Q14. we want to negate the entire sequence of numbers from 5 through 20, so that we get -5, -6, -7, ... , -18, -19, -20. Try the same thing, except surround `5:20` with parentheses so that R knows we want it to first come up with the sequence of numbers, then apply the negative sign to the whole thing.

A14. `-(5:20)`

Q15. Use this knowledge to omit all columns `X:size` using `select()`.

A15. `select(cran, -(X:size))`

Q16. use `filter(cran, package == "swirl")` to select all rows for which the package variable is equal to "swirl". Be sure to use two equals signs side-by-side!

A16. `filter(cran, package == "swirl")`

Q17. You can specify as many conditions as you want, separated by commas. For example `filter(cran, r_version == "3.1.1", country == "US")` will return all rows of `cran` corresponding to downloads from users in the US running R version 3.1.1. Try it out.

A17. `filter(cran, r_version == "3.1.1", country == "US")`

Q18. Edit your previous call to `filter()` to instead return rows corresponding to users in "IN" (India) running an R version that is less than or equal to "3.0.2". The up arrow on your keyboard may come in handy here. Don't forget your double quotes!

A18. `filter(cran, r_version <= "3.0.2", country == "IN")`

Q19. Our last two calls to `filter()` requested all rows for which some condition AND another condition were TRUE. We can also request rows for which EITHER one condition OR another condition are TRUE. For example, `filter(cran, country == "US" | country == "IN")` will give us all rows for which the country variable equals either "US" or "IN". Give it a go.

A19. `filter(cran, country == "US" | country == "IN")`

Q20. Now, use `filter()` to fetch all rows for which `size` is strictly greater than (`>`) 100500 (no quotes, since `size` is numeric) AND `r_os` equals "linux-gnu". Hint: You are passing three arguments to `filter()`: the name of the dataset, the first condition, and the second condition.

A20. `filter(cran, size > 100500, r_os == "linux-gnu")`

Q21. Okay, ready to put all of this together? Use `filter()` to return all rows of `cran` for which `r_version` is NOT NA. Hint: You will need to use `!is.na()` as part of your second argument to `filter()`.

A21. `filter(cran, !is.na(r_version))`

Q22. To see how `arrange()` works, let's first take a subset of `cran`. `select()` all columns from `size` through `ip_id` and store the result in `cran2`.

A22. `cran2 <- select(cran, size:ip_id)`

Q23. Now, to order the ROWS of `cran2` so that `ip_id` is in ascending order (from small to large), type `arrange(cran2, ip_id)`. You may want to make your console wide enough so that you can see `ip_id`, which is the last column.

A23. `arrange(cran2, ip_id)`

Q24. To do the same, but in descending order, change the second argument to `desc(ip_id)`, where `desc()` stands for ‘descending’. Go ahead.

A24. `arrange(cran2, desc(ip_id))`

Q25. Arrange `cran2` by the following three variables, in this order: `country` (ascending), `r_version` (descending), and `ip_id` (ascending).

A25. `arrange(cran2, country, desc(r_version), ip_id)`

Q26. To illustrate the next major function in `dplyr`, let’s take another subset of our original data. Use `select()` to grab 3 columns from `cran` – `ip_id`, `package`, and `size` (in that order) – and store the result in a new variable called `cran3`.

A26. `cran3 <- select(cran, ip_id, package, size)`

Q27. One very nice feature of `mutate()` is that you can use the value computed for your second column (`size_mb`) to create a third column, all in the same line of code. To see this in action, repeat the exact same command as above, except add a third argument creating a column that is named `size_gb` and equal to `size_mb / 2^10`

A27. `mutate(cran3, size_mb = size / 2^20, size_gb = size_mb / 2^10)`

Q28. Let’s try one more for practice. Pretend we discovered a glitch in the system that provided the original values for the `size` variable. All of the values in `cran3` are 1000 bytes less than they should be. Using `cran3`, create just one new column called `correct_size` that contains the correct size.

A28. `mutate(cran3, correct_size = size + 1000)`

Q29. The last of the five core `dplyr` verbs, `summarize()`, collapses the dataset to a single row. Let’s say we’re interested in knowing the average download size. `summarize(cran, avg_bytes = mean(size))` will yield the mean value of the `size` variable. Here we’ve chosen to label the result ‘`avg_bytes`’, but we could have named it anything. Give it a try.

A29. `summarize(cran, avg_bytes = mean(size))`

## Lesson 2: Grouping and Chaining with `dplyr`

Q1. I’ve made the dataset available to you in a data frame called `mydf`. Put it in a ‘data frame `tbl`’ using the `tbl_df()` function and store the result in a object called `cran`. If you’re not sure what I’m talking about, you should start with the previous lesson. Otherwise, practice makes perfect!

A1. `cran <- tbl_df(mydf)`

Q2. Group `cran` by the `package` variable and store the result in a new object called `by_package`.

A2. `by_package <- group_by(cran, package)`

Q3. That’s exactly what you’ll get if you use `summarize()` to apply `mean(size)` to the grouped data in `by_package`. Give it a shot.

A3. `summarize(by_package, mean(size))`

Q4. Compute four values, in the following order, from the grouped data.

A4. `pack_sum <- summarize(by_package, count = n(), unique = n_distinct(ip_id), countries = n_distinct(country), avg_bytes = mean(size))`

Q5. Now we can isolate only those packages which had more than 679 total downloads. Use `filter()` to select all rows from `pack_sum` for which ‘count’ is strictly greater ( $>$ ) than 679. Store the result in a new object called `top_counts`.

A5. `top_counts <- filter(pack_sum, count > 679)`

Q6. `arrange()` the rows of `top_counts` based on the ‘count’ column and assign the result to a new object called `top_counts_sorted`. We want the packages with the highest number of downloads at the top, which means we want ‘count’ to be in descending order. If you need help, check out `?arrange` and/or `?desc`.

A6. `top_counts_sorted <- arrange(top_counts, desc(count))`

Q7. Apply `filter()` to `pack_sum` to select all rows corresponding to values of ‘unique’ that are strictly greater than 465. Assign the result to a object called `top_unique`.

A7. `top_unique <- filter(pack_sum, unique > 465)`

Q8. Now `arrange()` `top_unique` by the ‘unique’ column, in descending order, to see which packages were downloaded from the greatest number of unique IP addresses. Assign the result to `top_unique_sorted`.

A8. `top_unique_sorted <- arrange(top_unique, desc(unique))`

A9. `cran %>% select(ip_id, country, package, size) %>% print`

Q10. Use `mutate()` to add a column called `size_mb` that contains the size of each download in megabytes (i.e.  $\text{size} / 2^{20}$ ).

A10. `cran %>% select(ip_id, country, package, size) %>% mutate(size_mb = size / 2^20)`

Q11. Use `filter()` to select all rows for which `size_mb` is less than or equal to ( $\leq$ ) 0.5.

A11. `cran %>% select(ip_id, country, package, size) %>% mutate(size_mb = size / 2^20) %>% filter(size_mb <= 0.5)`

Q12. `arrange()` the result by `size_mb`, in descending order.

A12. `cran %>% select(ip_id, country, package, size) %>% mutate(size_mb = size / 2^20) %>% filter(size_mb <= 0.5) %>% arrange(desc(size_mb))`

### Lesson 3: Tidying Data with tidy

Q1. Using the help file as a guide, call `gather()` with the following arguments (in order): `students`, `sex`, `count`, `-grade`. Note the minus sign before `grade`, which says we want to gather all columns EXCEPT `grade`.

A1. `gather(students, sex, count, -grade)`

Q2. Let’s start by using `gather()` to stack the columns of `students2`, like we just did with `students`. This time, name the ‘key’ column `sex_class` and the ‘value’ column `count`. Save the result to a new variable called `res.c`. Consult `?gather` again if you need help.

A2. `res <- gather(students2, sex_class, count, -grade)`

Q3. Call `separate()` on `res` to split the `sex_class` column into `sex` and `class`. You only need to specify the first three arguments: `data = res`, `col = sex_class`, `into = c(“sex”, “class”)`. You don’t have to provide the argument names as long as they are in the correct order.

A3. `separate(res, sex_class, c(“sex”, “class”))`

Q4. Repeat your calls to `gather()` and `separate()`, but this time use the `%>%` operator to chain the commands together without storing an intermediate result.

A4. `students2 %>% gather(sex_class, count, -grade) %>% separate(sex_class, c(“sex”, “class”)) %>% print`

Q5. Call `gather()` to gather the columns `class1` through `class5` into a new variable called `class`. The ‘key’ should be `class`, and the ‘value’ should be `grade`.

A5. `students3 %>% gather(class, grade, class1:class5, na.rm = TRUE) %>% print`

Q6. This script builds on the previous one by appending a call to `spread()`, which will allow us to turn the values of the `test` column, `midterm` and `final`, into column headers (i.e. variables).

A6. `students3 %>% gather(class, grade, class1:class5, na.rm = TRUE) %>% spread(test, grade) %>% print`

Q7. We want the values in the `class` columns to be 1, 2, ..., 5 and not `class1`, `class2`, ..., `class5`. Use the `mutate()` function from `dplyr` along with `parse_number()`

A7. `students3 %>% gather(class, grade, class1:class5, na.rm = TRUE) %>% spread(test, grade) %>% mutate(class = parse_number(class)) %>% print`

Q8. Complete the chained command below so that we are selecting the `id`, `name`, and `sex` column from `students4` and storing the result in `student_info`.

A8. `student_info <- students4 %>% select(id, name, sex) %>% print`

Q9. Add a call to `unique()` below, which will remove duplicate rows from `student_info`.

A9. `student_info <- students4 %>% select(id, name, sex) %>% unique %>% print`

Q10. Now, using the script I just opened for you, create a second table called `gradebook` using the `id`, `class`, `midterm`, and `final` columns (in that order).

A10. `gradebook <- students4 %>% select(id, class, midterm, final) %>% print`

Q11. Use `dplyr`’s `mutate()` to add a new column to the passed table. The column should be called `status` and the value, “passed” (a character string), should be the same for all students. ‘Overwrite’ the current version of `passed` with the new one.

A11. `passed <- passed %>% mutate(status = “passed”)`

Q12. Now, do the same for the failed table, except the `status` column should have the value “failed” for all students.

A12. `failed <- failed %>% mutate(status = “failed”)`

Q13. Now, pass as arguments the `passed` and `failed` tables (in order) to the `dplyr` function `bind_rows()`, which will join them together into a single unit. Check `?bind_rows` if you need help.

A13. `bind_rows(passed, failed)`

Q14. Accomplish the following three goals: 1.`select()` 2.`gather()` 3.`separate()`

A14. `sat %>% select(-contains(“total”)) %>% gather(part_sex, count, -score_range) %>% separate(part_sex, c(“part”, “sex”)) %>% print`

Q15. Append two more function calls to accomplish the following: 1.`group_by()` 2.`mutate`

A15. `sat %>% select(-contains(“total”)) %>% gather(part_sex, count, -score_range) %>% separate(part_sex, c(“part”, “sex”)) %>% group_by(part, sex) %>% mutate(total = sum(count), prop = count / total) %>% print`

## Lesson 4: Dates and Times with lubridate

Q1. There are three components to this date. In order, they are year, month, and day. We can extract any of these components using the `year()`, `month()`, or `day()` function, respectively. Try any of those on `this_day` now.

A1. `month(this_day)`

Q2. We can also get the day of the week from `this_day` using the `wday()` function. It will be represented as a number, such that 1 = Sunday, 2 = Monday, 3 = Tuesday, etc. Give it a shot.

A2. `wday(this_day)`

Q3. Now try the same thing again, except this time add a second argument, `label = TRUE`, to display the *name* of the weekday (represented as an ordered factor).

A3. `wday(this_day, label = TRUE)`

Q4. In addition to handling dates, `lubridate` is great for working with date and time combinations, referred to as date-times. The `now()` function returns the | date-time representing this exact moment in time. Give it a try and store the result in a variable called `this_moment`.

A4. `this_moment <- now()`

Q5. Just like with dates, we can extract the year, month, day, or day of week. However, we can also use `hour()`, `minute()`, and `second()` to extract specific time information. Try any of these three new functions now to extract one piece of time information from `this_moment`.

A5. 49.77503

Q6. We can even throw something funky at it and `lubridate` will often know the right thing to do. Parse 25081985, which is supposed to represent the 25th day of August 1985. Note that we are actually parsing a numeric value here – not a character string – so leave off the quotes.

A6. `dmy(25081985)`

Q7. What if we have a time, but no date? Use the appropriate `lubridate` function to parse “03:22:14” (hh:mm:ss).

A7. `hms(“03:22:14”)`

Q8. Unless you’re a superhero, some time has passed since you first created `this_moment`. Use `update()` to make it match the current time, specifying at least | hours and minutes. Assign the result to `this_moment`, so that `this_moment` will contain the new time.

A8. `this_moment <- update(this_moment, hours = 10, minutes = 16, seconds = 0)`

Q9. To find the current date in New York, we’ll use the `now()` function again. This time, however, we’ll specify the time zone that we want: “America/New\_York”. Store the result in a variable called `nyc`. Check out ?now if you need help.

A9. `nyc <- now(“America/New_York”)`

Q10. So now `depart` contains the date of the day after tomorrow. Use `update()` to add the correct hours (17) and minutes (34) to `depart`. Reassign the result to `depart`.

A10. `depart <- update(depart, hours = 17, minutes = 34)`

Q11. The first step is to add 15 hours and 50 minutes to your departure time. Recall that `nyc + days(2)` added two days to the current time in New York. Use the same approach to add 15 hours and 50 minutes to the date-time stored in `depart`. Store the result in a new variable called `arrive`.

A11. `arrive <- depart + hours(15) + minutes(50)`

Q12. Use `with_tz()` to convert `arrive` to the “Asia/Hong\_Kong” time zone. Reassign the result to `arrive`, so that it will get the new value.

A12. `arrive <- with_tz(arrive, “Asia/Hong_Kong”)`

Q13. Use the appropriate `lubridate` function to parse “June 17, 2008”, just like you did near the beginning of this lesson. This time, however, you should specify an extra argument, `tz = “Singapore”`. Store the result in a variable called `last_time`.

A13. `last_time <- mdy("June 17, 2008", tz = "Singapore")`

Q14. Create an `interval()` that spans from `last_time` to `arrive`. Store it in a new variable called `how_long`.

A14. `how_long <- interval(last_time, arrive)`