The tidyverse

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Pipe (%>%), Tibbles, dplyr-verbs, long/wide format and more from the tidyverse.

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When using R, you will sooner or later hear about the {tidyverse}. The tidyverse is a collection of R packages that "share an underlying design philosophy, grammar, and data structures"

of tidy data. The individual tidyverse packages comprise some of the most downloaded R packages.

Install the complete tidyverse with:

```
install.packages("tidyverse")
# or
pacman::p_load("tidyverse")
```

Table 1: Some of my favorite tidyverse packages

ggplot2	dplyr	tibble	forcats	stringr

I did not use the tidyverse packages in my first years using R, but I wish I did. While you can often reach your goal with or without using the tidyverse packages, I personally prefer using them. Thus, they are used extensively throughout the chapters of this website.

During the next sections I will try to explain how to use some of these packages and sometimes compare them to the Base R (= non-tidyverse) alternative.

Additional Resources

- "R for Data Science" (Wickham and Grolemund 2017), which is a book that can be read online for free and was written by the package authors themselves.

1 Tables

Finally, we can now talk about data tables with rows and columns. In R, I like to think of a table as multiple vectors side by side, so that each column is a vector.

1.1 data.frame

Base R has a standard format for data tables called `data.frame`. Here is an example table that is an R built-in, just like `pi` is - it is called `PlantGrowth`:

```
PlantGrowth
```

```
   weight group
1    4.17  ctrl
2    5.58  ctrl
3    5.18  ctrl
4    6.11  ctrl
5    4.50  ctrl
6    4.61  ctrl
7    5.17  ctrl
8    4.53  ctrl
9    5.33  ctrl
10   5.14  ctrl
11   4.81  trt1
12   4.17  trt1
13   4.41  trt1
14   3.59  trt1
15   5.87  trt1
16   3.83  trt1
17   6.03  trt1
18   4.89  trt1
19   4.32  trt1
20   4.69  trt1
21   6.31  trt2
22   5.12  trt2
23   5.54  trt2
24   5.50  trt2
25   5.37  trt2
26   5.29  trt2
27   4.92  trt2
28   6.15  trt2
29   5.80  trt2
30   5.26  trt2
```

Let us create a copy of this table called `df` (**d**ata**f**rame) and then use some helpful functions to get a first impression of this data:

```
df <- PlantGrowth
str(df)
```

```
'data.frame':   30 obs. of  2 variables:
 $ weight: num  4.17 5.58 5.18 6.11 4.5 4.61 5.17 4.53 5.33 5.14 ...
 $ group : Factor w/ 3 levels "ctrl","trt1",..: 1 1 1 1 1 1 1 1 1 1 ...
```

```
summary(df)
```

```
     weight       group
 Min.   :3.590   ctrl:10
 1st Qu.:4.550   trt1:10
 Median :5.155   trt2:10
 Mean   :5.073
 3rd Qu.:5.530
 Max.   :6.310
```

We can see that this dataset has 30 observations (=rows) and 2 variables (=columns) and is of the type "data.frame". Furthermore, the first variable is called `weight` and contains numeric values for which we get some measures of central tendency like the minimum, maximum, mean and median. The second variable is called `group` and is of the type factor containing a total of three different levels, which each appear 10 times.

If you want to extract/use values of only one column of such a data.frame, you write the name of the data.frame, then a `$` and finally the name of the respective column. It returns the values of that column as a vector:

```
df$weight
```

```
 [1] 4.17 5.58 5.18 6.11 4.50 4.61 5.17 4.53 5.33 5.14 4.81 4.17 4.41 3.59 5.87
[16] 3.83 6.03 4.89 4.32 4.69 6.31 5.12 5.54 5.50 5.37 5.29 4.92 6.15 5.80 5.26
```

```
df$group
```

```
 [1] ctrl ctrl ctrl ctrl ctrl ctrl ctrl ctrl ctrl ctrl trt1 trt1 trt1 trt1 trt1
[16] trt1 trt1 trt1 trt1 trt1 trt2 trt2 trt2 trt2 trt2 trt2 trt2 trt2 trt2 trt2
Levels: ctrl trt1 trt2
```

1.2 tibble

One major aspect of the tidyverse is formatting tables as **tibble instead of data.frame**. A tibble *"is a modern reimagining of the data.frame, keeping what time has proven to be effective, and throwing out what is not."* It is super simple to convert a data.frame into a tibble, but you must have the tidyverse R package {tibble} installed and loaded - which it is if you are loading the entire {tidyverse}. Let us convert our `df` into a tibble and call it `tbl`:

```
pacman::p_load(tidyverse)
tbl <- as_tibble(df)
tbl
```

```
# A tibble: 30 x 2
   weight group
    <dbl> <fct>
 1   4.17 ctrl
 2   5.58 ctrl
 3   5.18 ctrl
 4   6.11 ctrl
 5   4.5  ctrl
 6   4.61 ctrl
 7   5.17 ctrl
 8   4.53 ctrl
 9   5.33 ctrl
10   5.14 ctrl
# i 20 more rows
```

Of course, the data itself does not change - only its format and the way it is displayed to us in R. If you compare the output we get from printing `tbl` here to that of printing `df` above, I would like to point out some things I find extremely convenient for tibbles:

1. There is an extra first line telling us about the number of rows and columns.
2. There is an extra line below the column names telling us about the data type of each column.
3. Only the first ten rows of data are printed and a *"… with 20 more rows"* is added below.
4. It can't be seen here, but this would analogously happen if there were too many columns.
5. It can't be seen here, but missing values `NA` and negative numbers are printed in red.

Finally, note that in its heart, a tibble is still a data.frame and in most cases you can do everything with a tibble that you can do with a data.frame:

```
class(tbl)
```

```
[1] "tbl_df"     "tbl"        "data.frame"
```

```
str(tbl)
```

```
tibble [30 x 2] (S3: tbl_df/tbl/data.frame)
 $ weight: num [1:30] 4.17 5.58 5.18 6.11 4.5 4.61 5.17 4.53 5.33 5.14 ...
 $ group : Factor w/ 3 levels "ctrl","trt1",..: 1 1 1 1 1 1 1 1 1 1 ...
```

```
summary(tbl)
```

```
     weight       group
 Min.   :3.590   ctrl:10
 1st Qu.:4.550   trt1:10
 Median :5.155   trt2:10
 Mean   :5.073
 3rd Qu.:5.530
 Max.   :6.310
```

```
tbl$weight
```

```
 [1] 4.17 5.58 5.18 6.11 4.50 4.61 5.17 4.53 5.33 5.14 4.81 4.17 4.41 3.59 5.87
[16] 3.83 6.03 4.89 4.32 4.69 6.31 5.12 5.54 5.50 5.37 5.29 4.92 6.15 5.80 5.26
```

```
tbl$group
```

```
 [1] ctrl ctrl ctrl ctrl ctrl ctrl ctrl ctrl ctrl ctrl trt1 trt1 trt1 trt1 trt1
[16] trt1 trt1 trt1 trt1 trt1 trt2 trt2 trt2 trt2 trt2 trt2 trt2 trt2 trt2 trt2
Levels: ctrl trt1 trt2
```

```
class(df)
```

```
[1] "data.frame"
```

```
str(df)
```

```
'data.frame':   30 obs. of  2 variables:
 $ weight: num  4.17 5.58 5.18 6.11 4.5 4.61 5.17 4.53 5.33 5.14 ...
 $ group : Factor w/ 3 levels "ctrl","trt1",..: 1 1 1 1 1 1 1 1 1 1 ...
```

```
summary(df)
```

```
     weight       group
 Min.   :3.590   ctrl:10
 1st Qu.:4.550   trt1:10
 Median :5.155   trt2:10
 Mean   :5.073
 3rd Qu.:5.530
 Max.   :6.310
```

```
df$weight
```

```
 [1] 4.17 5.58 5.18 6.11 4.50 4.61 5.17 4.53 5.33 5.14 4.81 4.17 4.41 3.59 5.87
[16] 3.83 6.03 4.89 4.32 4.69 6.31 5.12 5.54 5.50 5.37 5.29 4.92 6.15 5.80 5.26
```

```
df$group
```

```
 [1] ctrl ctrl ctrl ctrl ctrl ctrl ctrl ctrl ctrl ctrl trt1 trt1 trt1 trt1 trt1
[16] trt1 trt1 trt1 trt1 trt1 trt2 trt2 trt2 trt2 trt2 trt2 trt2 trt2 trt2 trt2
Levels: ctrl trt1 trt2
```

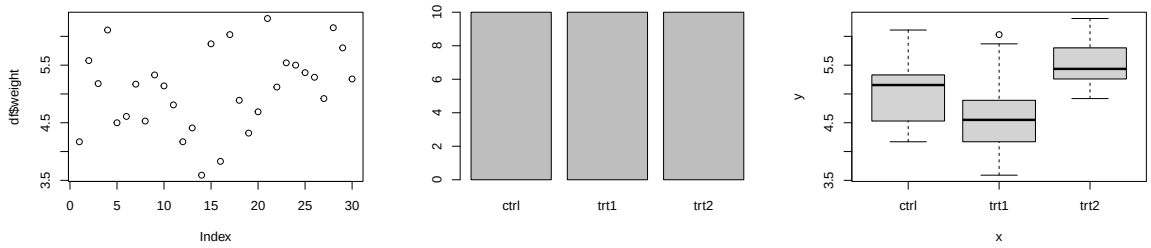
Therefore, I almost always format my datasets as tibbles.

2 Plots

Base R has a `plot()` function which is good at getting some first data visualizations with very little code. It guesses what type of plot you would like to see via the data type of the respective data to be plotted:

```
plot(df$weight) # scatter plot of values in the order they appear
plot(df$group) # bar plot of frequency of each level
plot(x = df$group, y = df$weight) # boxplot for values of each level
```

However, I really just use `plot()` to get a quick first glance at data. In order to get professional visualizations I always use the tidyverse package `{ggplot2}` and its function `ggplot()`. It seems like it can create any plot you can imagine and there are multiple examples with increasing complexity spread out through this website's chapters.



Additional Resources

- Cédric Scherer's (2022) A ggplot2 tutorial for beautiful plotting in R
- ggplot2 extensions gallery

3 The pipe operator

The pipe operator *"completely changed the way how we code in R, making it more simple and readable"* (Álvarez 2021). I started using the pipe as `%>%` from the {dplyr} package[1]. However, since May 18, 2021 (= R 4.1.0) the pipe is officially part of Base R - although written as `|>`[2].

To understand what makes it so great we need to start using more than one function at a time. So far, we have only used functions individually. Yet, in real life you will often find yourself having to combine multiple functions. As a fictional example, let's say that from the `PlantGrowth` data, we want to extract a sorted vector of the square root of all weight-values that belong to the `ctrl` group. I will show three approaches how to accomplish this

3.1 No pipe - intermediate steps

Using one function at a time and saving the output in the variables `a` - `d`, we can do this:

```
a <- filter(PlantGrowth, group == "ctrl")
b <- pull(a, weight) # same as: b <- a$weight
c <- sqrt(b)
d <- round(c, digits = 1)
sort(d)
```

[1]But it was not the first package to use it. This blog post has a nice summary of the history of the pipe operator in R.

[2]Note that there are some differences between `%>%` and `|>` - find more about it *e.g.* here, here or here.

```
 [1] 2.0 2.1 2.1 2.1 2.3 2.3 2.3 2.3 2.4 2.5
```

3.2 No pipe - nesting functions

Just like in MS Excel, it is possible to write functions inside of functions so that we can do this:

```
sort(round(sqrt(pull(filter(PlantGrowth, group == "ctrl"), weight)), digits = 1))
```

```
 [1] 2.0 2.1 2.1 2.1 2.3 2.3 2.3 2.3 2.4 2.5
```

3.3 Pipe!

This approach (i) allows you to write functions from left to right / top to bottom and thus in the order they are executed and the way you think about them and (ii) does not create extra variables for intermediate steps:

```
PlantGrowth %>%
  filter(group == "ctrl") %>%
  pull(weight) %>%
  sqrt() %>%
  round(digits = 1) %>%
  sort()
```

```
 [1] 2.0 2.1 2.1 2.1 2.3 2.3 2.3 2.3 2.4 2.5
```

You can think about it like this: Something (in this case the `PlantGrowth` data.frame) goes into the pipe and is directed to the next function `filter()`. By default, this function takes what came out of the previous pipe and puts it as its first argument. This happens with every pipe. You'll notice that all the functions who required two arguments above, now only need one argument, *i.e.* the additional argument, because the main argument stating which data is to be used is by default simply what came out of the previous pipe. Accordingly, the functions `sqrt()` and `sort()` appear empty here, because they only need one piece of information and that is which data they should work with. Finally note that you can easily highlight only some of the lines up until one of the pipes to see the intermediate results.

> **Note**
>
> The keyboard shortcut for writing `%>%` in RStudio is **CTRL+SHIFT+M**. Keyboard shortcuts can be customized in RStudio as described here.

4 dplyr verbs

Taken directly from the documentation:

> {dplyr} is a grammar of data manipulation, providing a consistent set of verbs that help you solve the most common data manipulation challenges:
>
> - `mutate()` adds new variables that are functions of existing variables.
> - `select()` picks variables based on their names.
> - `filter()` picks cases based on their values.
> - `summarise()` reduces multiple values down to a single summary.
> - `arrange()` changes the ordering of the rows.
>
> These all combine naturally with `group_by()` which allows you to perform any operation "by group". If you are new to dplyr, the best place to start is the data transformation chapter in *R for data science* (Wickham and Grolemund 2017).

In my experience you really can do most of the data manipulation before and after the actual statistics with these functions. In other words, it is exactly these functions who can and should replace the manual work you may currently even be doing in MS Excel. In the following sections I will give very brief examples of how to use these functions while always pointing to more thorough resources.

4.1 mutate()

This function is useful whenever you want to change existing columns or add new columns to your table. To keep the following examples short and simple, let's create `tbl2` as only the first six rows of `tbl` via the `head()` function:

```
tbl2 <- head(tbl)
tbl2
```

```
# A tibble: 6 x 2
  weight group
   <dbl> <fct>
1   4.17 ctrl
2   5.58 ctrl
3   5.18 ctrl
4   6.11 ctrl
5   4.5  ctrl
6   4.61 ctrl
```

Let's start by adding 2 to the `weight` in our data. Below, we do this two different ways: by adding a column named `new` to the dataset (left) and by replacing/overwriting the original `weight` column (right):

```
tbl2 %>%
  mutate(new = weight + 2)
```

```
# A tibble: 6 x 3
  weight group   new
   <dbl> <fct> <dbl>
1   4.17 ctrl   6.17
2   5.58 ctrl   7.58
3   5.18 ctrl   7.18
4   6.11 ctrl   8.11
5   4.5  ctrl   6.5
6   4.61 ctrl   6.61
```

```
tbl2 %>%
  mutate(weight = weight + 2)
```

```
# A tibble: 6 x 2
  weight group
   <dbl> <fct>
1   6.17 ctrl
2   7.58 ctrl
3   7.18 ctrl
4   8.11 ctrl
5   6.5  ctrl
6   6.61 ctrl
```

We can also create multiple columns at once (left) and make the values of the new column

dynamically depend on the other columns via `case_when()` (right):

```
tbl2 %>%
  mutate(
    `Name with Space` = "Hello!",
    number10 = 10
  )
```

```
# A tibble: 6 x 4
  weight group `Name with Space` number10
   <dbl> <fct> <chr>                 <dbl>
1   4.17 ctrl  Hello!                   10
2   5.58 ctrl  Hello!                   10
3   5.18 ctrl  Hello!                   10
4   6.11 ctrl  Hello!                   10
5   4.5  ctrl  Hello!                   10
6   4.61 ctrl  Hello!                   10
```

```
tbl2 %>%
  mutate(size = case_when(
    weight > 5.5 ~ "large",
    weight < 4.5 ~ "small",
    TRUE ~ "normal" # everything else
  ))
```

```
# A tibble: 6 x 3
  weight group size
   <dbl> <fct> <chr>
1   4.17 ctrl  small
2   5.58 ctrl  large
3   5.18 ctrl  normal
4   6.11 ctrl  large
5   4.5  ctrl  normal
6   4.61 ctrl  normal
```

Finally, we can efficiently apply the same function to multiple columns at once via `across()`. We can select the columns e.g. manually via their names in a vector (left) or via a function such as `is.numeric` (right):

```
tbl2 %>%
  mutate(v1 = 1, v2 = 2, v3 = 3) %>%
```

```
  mutate(
    across(c(v1, v2), ~ .x + 20)
    )
```

```
# A tibble: 6 x 5
  weight group    v1    v2    v3
   <dbl> <fct> <dbl> <dbl> <dbl>
1   4.17 ctrl     21    22     3
2   5.58 ctrl     21    22     3
3   5.18 ctrl     21    22     3
4   6.11 ctrl     21    22     3
5   4.5  ctrl     21    22     3
6   4.61 ctrl     21    22     3
```

```
tbl2 %>%
  mutate(v1 = 1, v2 = 2, v3 = 3) %>%
  mutate(
    across(where(is.numeric), ~ .x + 20)
    )
```

```
# A tibble: 6 x 5
  weight group    v1    v2    v3
   <dbl> <fct> <dbl> <dbl> <dbl>
1   24.2 ctrl     21    22    23
2   25.6 ctrl     21    22    23
3   25.2 ctrl     21    22    23
4   26.1 ctrl     21    22    23
5   24.5 ctrl     21    22    23
6   24.6 ctrl     21    22    23
```

Additional Resources

- 5.5 Add new variables with mutate() in *R for data science* (Wickham and Grolemund 2017)
- Create, modify, and delete columns with mutate()
- A general vectorised if with case_when()
- Apply a function (or functions) across multiple columns with across()

4.2 select()

This function is useful whenever you want to select a subset of columns or change the order of columns. To provide better examples, let's first create a table `tbl3` with a few more columns:

```
tbl3 <- tbl2 %>%
  mutate(var1 = 1, var2 = 2, var3 = "text", var4 = "word")

tbl3
```

```
# A tibble: 6 x 6
  weight group  var1  var2 var3  var4
   <dbl> <fct> <dbl> <dbl> <chr> <chr>
1   4.17 ctrl      1     2 text  word
2   5.58 ctrl      1     2 text  word
3   5.18 ctrl      1     2 text  word
4   6.11 ctrl      1     2 text  word
5   4.5  ctrl      1     2 text  word
6   4.61 ctrl      1     2 text  word
```

We can now select individual columns manually by giving all names (left) and even select all columns `from:to` by writing a colon between them (right):

```
tbl3 %>%
  select(group, var1, var4)
```

```
# A tibble: 6 x 3
  group  var1 var4
  <fct> <dbl> <chr>
1 ctrl      1 word
2 ctrl      1 word
3 ctrl      1 word
4 ctrl      1 word
5 ctrl      1 word
6 ctrl      1 word
```

```
tbl3 %>%
  select(group, var1:var4)
```

```
# A tibble: 6 x 5
  group  var1  var2 var3  var4
  <fct> <dbl> <dbl> <chr> <chr>
1 ctrl      1     2 text  word
2 ctrl      1     2 text  word
3 ctrl      1     2 text  word
4 ctrl      1     2 text  word
5 ctrl      1     2 text  word
6 ctrl      1     2 text  word
```

We can also delete specific columns by putting a `-` in fornt of their name or use functions like `starts_with()`, `ends_with()`, `contains()`, `matches()` and `num_range()` to select all columns based on (parts of) their name:

```
tbl3 %>%
  select(-group)
```

```
# A tibble: 6 x 5
  weight  var1  var2 var3  var4
   <dbl> <dbl> <dbl> <chr> <chr>
1   4.17     1     2 text  word
2   5.58     1     2 text  word
3   5.18     1     2 text  word
4   6.11     1     2 text  word
5   4.5      1     2 text  word
6   4.61     1     2 text  word
```

```
tbl3 %>%
  select(contains("r"))
```

```
# A tibble: 6 x 5
  group  var1  var2 var3  var4
  <fct> <dbl> <dbl> <chr> <chr>
1 ctrl      1     2 text  word
2 ctrl      1     2 text  word
3 ctrl      1     2 text  word
4 ctrl      1     2 text  word
5 ctrl      1     2 text  word
6 ctrl      1     2 text  word
```

Finally, we can select based on a function like `is.numeric` via `where()` (left) or simply rear-

range while keeping all columns by using `everything()` (right)

```
tbl3 %>%
  select(where(is.numeric))
```

```
# A tibble: 6 x 3
  weight  var1  var2
   <dbl> <dbl> <dbl>
1   4.17     1     2
2   5.58     1     2
3   5.18     1     2
4   6.11     1     2
5   4.5      1     2
6   4.61     1     2
```

```
tbl3 %>%
  select(var1, everything())
```

```
# A tibble: 6 x 6
   var1 weight group  var2 var3  var4
  <dbl>  <dbl> <fct> <dbl> <chr> <chr>
1     1   4.17 ctrl      2 text  word
2     1   5.58 ctrl      2 text  word
3     1   5.18 ctrl      2 text  word
4     1   6.11 ctrl      2 text  word
5     1   4.5  ctrl      2 text  word
6     1   4.61 ctrl      2 text  word
```

Additional Resources

- 5.4 Select columns with select() in *R for data science* (Wickham and Grolemund 2017)
- Subset columns using their names and types with select()
- Select variables that match a pattern with starts_with() etc.
- Select variables with a function with where()

4.3 filter()

This function is useful whenever you want to subset rows based on their values. Note that for the examples here, we use the original `tbl` with 30 observations.

Let's immediately filter for two conditions: Observations that belong to group `trt2` **and** (`&`) are larger than 6 (left); Observations that are larger than 6 **or** (`|`) smaller than 4 (right):

```
tbl %>%
  filter(weight > 6 & group == "trt2")
```

```
# A tibble: 2 x 2
  weight group
   <dbl> <fct>
1   6.31 trt2
2   6.15 trt2
```

```
tbl %>%
  filter(weight > 6 | weight < 4)
```

```
# A tibble: 6 x 2
  weight group
   <dbl> <fct>
1   6.11 ctrl
2   3.59 trt1
3   3.83 trt1
4   6.03 trt1
5   6.31 trt2
6   6.15 trt2
```

Instead of writing a lot of conditions separated by `|`, it is often more efficient to use `%in%`:

```
tbl %>%
  filter(group == "trt1" | group == "trt2")
```

```
# A tibble: 20 x 2
   weight group
    <dbl> <fct>
 1   4.81 trt1
 2   4.17 trt1
 3   4.41 trt1
 4   3.59 trt1
 5   5.87 trt1
 6   3.83 trt1
 7   6.03 trt1
```

```
 8   4.89 trt1
 9   4.32 trt1
10   4.69 trt1
11   6.31 trt2
12   5.12 trt2
13   5.54 trt2
14   5.5  trt2
15   5.37 trt2
16   5.29 trt2
17   4.92 trt2
18   6.15 trt2
19   5.8  trt2
20   5.26 trt2
```

```
tbl %>%
  filter(group %in% c("trt1", "trt2"))
```

```
# A tibble: 20 x 2
   weight group
    <dbl> <fct>
 1   4.81 trt1
 2   4.17 trt1
 3   4.41 trt1
 4   3.59 trt1
 5   5.87 trt1
 6   3.83 trt1
 7   6.03 trt1
 8   4.89 trt1
 9   4.32 trt1
10   4.69 trt1
11   6.31 trt2
12   5.12 trt2
13   5.54 trt2
14   5.5  trt2
15   5.37 trt2
16   5.29 trt2
17   4.92 trt2
18   6.15 trt2
19   5.8  trt2
20   5.26 trt2
```

We can also filter for values that **are not** of the `ctrl` group (left) or that are larger than the

mean weight (right):

```
tbl %>%
  filter(group != "ctrl")
```

```
# A tibble: 20 x 2
   weight group
    <dbl> <fct>
 1   4.81 trt1
 2   4.17 trt1
 3   4.41 trt1
 4   3.59 trt1
 5   5.87 trt1
 6   3.83 trt1
 7   6.03 trt1
 8   4.89 trt1
 9   4.32 trt1
10   4.69 trt1
11   6.31 trt2
12   5.12 trt2
13   5.54 trt2
14   5.5  trt2
15   5.37 trt2
16   5.29 trt2
17   4.92 trt2
18   6.15 trt2
19   5.8  trt2
20   5.26 trt2
```

```
tbl %>%
  filter(weight > mean(weight))
```

```
# A tibble: 17 x 2
   weight group
    <dbl> <fct>
 1   5.58 ctrl
 2   5.18 ctrl
 3   6.11 ctrl
 4   5.17 ctrl
 5   5.33 ctrl
 6   5.14 ctrl
```

```
 7   5.87 trt1
 8   6.03 trt1
 9   6.31 trt2
10   5.12 trt2
11   5.54 trt2
12   5.5  trt2
13   5.37 trt2
14   5.29 trt2
15   6.15 trt2
16   5.8  trt2
17   5.26 trt2
```

Additional Resources

- 5.2 Filter rows with filter() in *R for data science* (Wickham and Grolemund 2017)
- Subset rows using column values with filter()

4.4 arrange()

This function is useful whenever you want to sort rows based on their values. We'll once more create a new version of our original dataset to best show what this function can do:

```
tbl4 <- tbl %>%
  slice(1:3, 11:13, 21:23)
# this keeps only rows 1,2,3,11,12,13,21,22,23
```

We can arrange rows via writing the column name (or column index/number). Note that by default values are sorted in ascending order and strings are sorted alphabetically, but this can be reversed by using `desc()`:

```
tbl4 %>%
  arrange(weight)
```

```
# A tibble: 9 x 2
  weight group
   <dbl> <fct>
1   4.17 ctrl
2   4.17 trt1
3   4.41 trt1
4   4.81 trt1
```

```
5   5.12 trt2
6   5.18 ctrl
7   5.54 trt2
8   5.58 ctrl
9   6.31 trt2
```

```
tbl4 %>%
  arrange(desc(weight))
```

```
# A tibble: 9 x 2
  weight group
   <dbl> <fct>
1   6.31 trt2
2   5.58 ctrl
3   5.54 trt2
4   5.18 ctrl
5   5.12 trt2
6   4.81 trt1
7   4.41 trt1
8   4.17 ctrl
9   4.17 trt1
```

You can also sort via multiple columns and you can provide a custom sorting order in a vector:

```
tbl4 %>%
  arrange(group, weight)
```

```
# A tibble: 9 x 2
  weight group
   <dbl> <fct>
1   4.17 ctrl
2   5.18 ctrl
3   5.58 ctrl
4   4.17 trt1
5   4.41 trt1
6   4.81 trt1
7   5.12 trt2
8   5.54 trt2
9   6.31 trt2
```

```r
myorder <- c("trt1", "ctrl", "trt2")

tbl4 %>%
  arrange(
    match(group, myorder),
    weight
  )
```

```
# A tibble: 9 x 2
  weight group
   <dbl> <fct>
1   4.17 trt1
2   4.41 trt1
3   4.81 trt1
4   4.17 ctrl
5   5.18 ctrl
6   5.58 ctrl
7   5.12 trt2
8   5.54 trt2
9   6.31 trt2
```

Note that `NA` (= missing values) are always sorted to the end[3], even when using `desc()`.

> Additional Resources
>
> - 5.3 Arrange rows with arrange() in *R for data science* (Wickham and Grolemund 2017)
> - Arrange rows by column values with arrange()
> - How to have NA's displayed first using arrange()

4.5 summarise()

This function can be useful whenever you want to summarise data. Yet, it is not very useful (left) unless it is paired with `group_by()` (right).

```r
tbl %>%
  # no group_by
  summarise(my_mean = mean(weight))
```

[3]See the additional resources below if you want it differently.

```
# A tibble: 1 x 1
  my_mean
    <dbl>
1    5.07
```

```
tbl %>%
  group_by(group) %>%
  summarise(my_mean = mean(weight))
```

```
# A tibble: 3 x 2
  group my_mean
  <fct>   <dbl>
1 ctrl     5.03
2 trt1     4.66
3 trt2     5.53
```

You can create multiple summary output columns (left) and have multiple grouping columns (right):

```
tbl %>%
  group_by(group) %>%
  summarise(
    Mean = mean(weight),
    StdDev = sd(weight),
    Min = min(weight),
    Median = median(weight),
    Max = max(weight),
    n_Obs = n(),
  )
```

```
# A tibble: 3 x 7
  group  Mean StdDev   Min Median   Max n_Obs
  <fct> <dbl>  <dbl> <dbl>  <dbl> <dbl> <int>
1 ctrl   5.03  0.583  4.17   5.15  6.11    10
2 trt1   4.66  0.794  3.59   4.55  6.03    10
3 trt2   5.53  0.443  4.92   5.44  6.31    10
```

```
tbl %>%
  mutate(larger5 = case_when(
    weight > 5 ~ "yes",
```

```
    weight < 5 ~ "no"
  )) %>%
  group_by(group, larger5) %>%
  summarise(
    n_Obs = n(),
    Mean = mean(weight)
  )
```

```
# A tibble: 6 x 4
# Groups:   group [3]
  group larger5 n_Obs  Mean
  <fct> <chr>   <int> <dbl>
1 ctrl  no          4  4.45
2 ctrl  yes         6  5.42
3 trt1  no          8  4.34
4 trt1  yes         2  5.95
5 trt2  no          1  4.92
6 trt2  yes         9  5.59
```

Just like with `mutate()`, we can make use of `across()` to deal with multiple columns:

```
tbl %>%
  mutate(v1 = 1, v2 = 2, v3 = 3) %>%
  group_by(group) %>%
  summarise(across(
    where(is.numeric),
    ~ mean(.x)
    ))
```

```
# A tibble: 3 x 5
  group weight    v1    v2    v3
  <fct>  <dbl> <dbl> <dbl> <dbl>
1 ctrl    5.03     1     2     3
2 trt1    4.66     1     2     3
3 trt2    5.53     1     2     3
```

```
tbl %>%
  mutate(v1 = 1, v2 = 2, v3 = 3) %>%
  group_by(group) %>%
  summarise(across(
```

```
    c(weight, v3),
    list(
    Min = ~ min(.x),
    Max = ~ max(.x)
    )
  ))
```

```
# A tibble: 3 x 5
  group weight_Min weight_Max v3_Min v3_Max
  <fct>      <dbl>      <dbl>  <dbl>  <dbl>
1 ctrl        4.17       6.11      3      3
2 trt1        3.59       6.03      3      3
3 trt2        4.92       6.31      3      3
```

! Important

Once you used `group_by()` on a table, it stays grouped unless you use `ungroup()` on it afterwards. This was not relevant in the examples above, but you must be aware of this if you are using the grouped (summary) results for further steps, since this can lead to unexpected results. You can find an example and further resources on such unintended outcomes here.

Additional Resources

- 5.6 Grouped summaries with summarise() in *R for data science* (Wickham and Grolemund 2017)
- Summarise each group to fewer rows with summarise()
- Group by one or more variables with group_by()

5 long/wide format

Sometimes, data is referred to as being in *long format* or *wide format*. As the name suggests, long formatted tables have more rows, but fewer columns than wide formatted tables, while containing the same information. I find the easiest way to understand the two is by looking at examples like in the following image, which was taken from statology.org:

Converting one format into the other is called *pivoting* in the tidyverse and the relevant functions `pivot_longer()` and `pivot_wider()` are provided in {tidyr}.

Wide Format

Team	Points	Assists	Rebounds
A	88	12	22
B	91	17	28
C	99	24	30
D	94	28	31

Long Format

Team	Variable	Value
A	Points	88
A	Assists	12
A	Rebounds	22
B	Points	91
B	Assists	17
B	Rebounds	28
C	Points	99
C	Assists	24
C	Rebounds	30
D	Points	94
D	Assists	28
D	Rebounds	31

> **Note**
>
> You may have used other functions in this context. Here are some alternatives that are superseded:
>
> - `melt()` & `dcast()` of {data.table}
> - `fold()` & `unfold()` of {databases}
> - `melt()` & `cast()` of {reshape}
> - `melt()` & `dcast()` of {reshape2}
> - `unpivot()` & `pivot()` of {spreadsheets}
> - `gather()` & `spread()` of {tidyr} < v1.0.0

The `PlantGrowth` data from above is actually already in long format, yet I create a version of it that is shorter (only 3 instead of 10 observations per group) and has an additional column called `nr` with is a running number per observation in each group:

```
long_dat <- PlantGrowth %>%
  group_by(group) %>% # for each level in the "group" column
  slice(1:3) %>% # keep only the rows 1-3
  mutate(nr = 1:n(), # add a "nr" column with numbers 1 - ...
         .before = "weight") %>% # add this column left of "weight" column
  ungroup() # remove the grouping from above
```

We can now use `pivot_wider()` and create a wide formatted version of the `long_dat` table and save it as `wide_dat`. Note that the function has multiple arguments you can use, but for me it is usually enough to use `names from =` and `values_from =`. In the former you provide the name of the column whose entries should be the names of the new columns in the wide formatted data. In the latter you provide the name of the column whose values should be written in the new columns in the wide formatted data:

```
long_dat
```

```
# A tibble: 9 x 3
     nr weight group
  <int>  <dbl> <fct>
1     1   4.17 ctrl
2     2   5.58 ctrl
3     3   5.18 ctrl
4     1   4.81 trt1
5     2   4.17 trt1
6     3   4.41 trt1
7     1   6.31 trt2
8     2   5.12 trt2
9     3   5.54 trt2
```

```
wide_dat <- long_dat %>%
  pivot_wider(names_from = "group",
              values_from = "weight")

wide_dat
```

```
# A tibble: 3 x 4
     nr  ctrl  trt1  trt2
  <int> <dbl> <dbl> <dbl>
1     1  4.17  4.81  6.31
2     2  5.58  4.17  5.12
3     3  5.18  4.41  5.54
```

We can use `pivot_longer` to reverse the step above, i.e. create a long formatted version of the `wide_dat` table. Again, the function has multiple arguments you can use, but for me it is usually enough to use `cols =`, `names_to =` and `values_to =`. In the first one, you provide the names of the columns who should be reduced to fewer columns with more rows. In the other two you simply give the names that the created columns should have instead of the default `name` and `value`. Note that it is sometimes easier to provide the names of columns that should not go into `cols =` (right) instead of the ones that should (left).

```r
wide_dat %>%
  pivot_longer(
    cols = c(ctrl, trt1, trt2),
    names_to = "group",
    values_to = "weight"
  )
```

```
# A tibble: 9 x 3
     nr group weight
  <int> <chr>  <dbl>
1     1 ctrl    4.17
2     1 trt1    4.81
3     1 trt2    6.31
4     2 ctrl    5.58
5     2 trt1    4.17
6     2 trt2    5.12
7     3 ctrl    5.18
8     3 trt1    4.41
9     3 trt2    5.54
```

```r
wide_dat %>%
  pivot_longer(
    cols = -nr,
    names_to = "group",
    values_to = "weight"
  )
```

```
# A tibble: 9 x 3
     nr group weight
  <int> <chr>  <dbl>
1     1 ctrl    4.17
2     1 trt1    4.81
3     1 trt2    6.31
4     2 ctrl    5.58
5     2 trt1    4.17
6     2 trt2    5.12
7     3 ctrl    5.18
8     3 trt1    4.41
9     3 trt2    5.54
```

Additional Resources

- 12.3 Pivoting in *R for data science* (Wickham and Grolemund 2017)
- Pivoting with tidyr
- tidyr cheat sheet

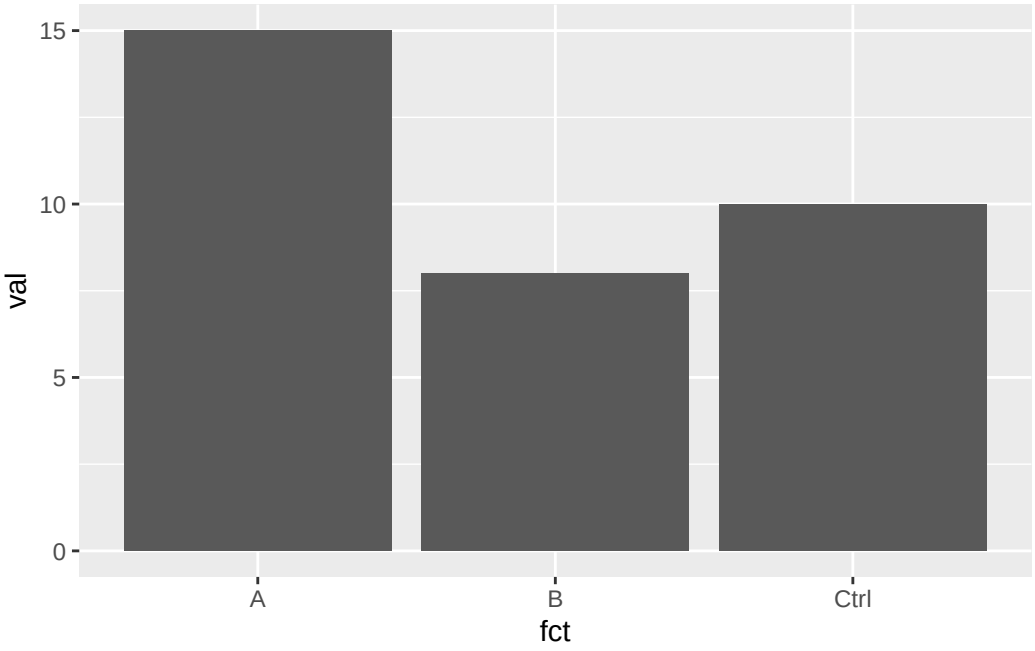
6 forcats

In my experience, R beginners really only care about the difference between `factor` and `character` variables once the factor level order is not as they want it to be - typically on the x-axis of a plot. Luckily, {forcats} can deal with this.

In the following example, we create a column `fct` that is a copy of the column `chr`, except that they are formatted as `factor` and `character`, respectively.

```
dat <- tribble(
     ~val,   ~chr,
       10, "Ctrl",
       15,    "A",
        8,    "B"
) %>%
  mutate(fct = as.factor(chr))

ggplot(dat) +
  aes(y = val, x = fct) +
  geom_col()
```



Even though the data is sorted so that Ctrl is first, then A, then B, the x-Axis is sorted differently[4]. This is because factor levels are always sorted alphabetically by default. We can reorder them via different functions in {forcats}:

```
dat <- dat %>%
  mutate(
    fct2 = fct_relevel(fct, c("Ctrl", "A", "B")),
    fct3 = fct_reorder(fct, val, mean)
    )

str(dat)
```

```
tibble [3 x 5] (S3: tbl_df/tbl/data.frame)
 $ val : num [1:3] 10 15 8
 $ chr : chr [1:3] "Ctrl" "A" "B"
 $ fct : Factor w/ 3 levels "A","B","Ctrl": 3 1 2
 $ fct2: Factor w/ 3 levels "Ctrl","A","B": 1 2 3
 $ fct3: Factor w/ 3 levels "B","Ctrl","A": 2 3 1
```

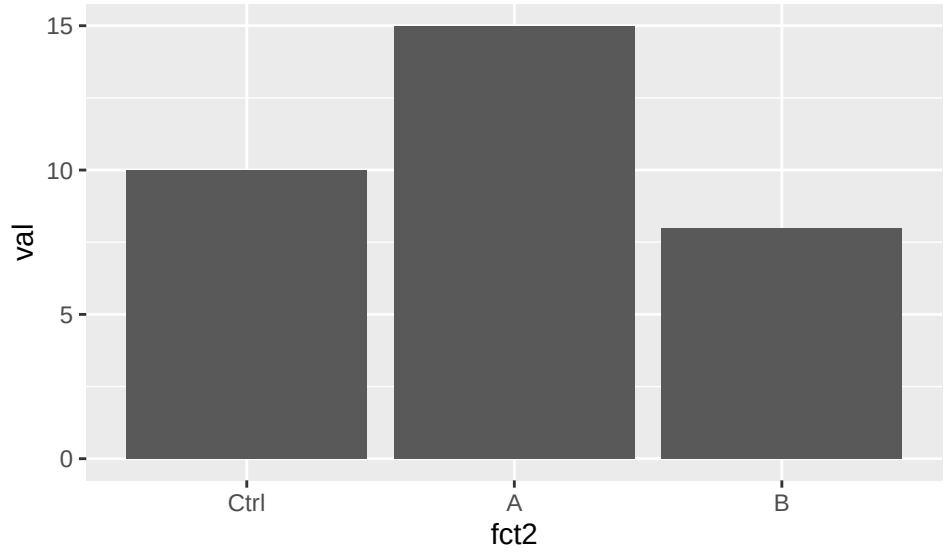
Above are just two popular examples for sorting factor levels: `fct_relevel` sorts the levels manually by providing a vector with the level names in the order they should appear, while

[4]It does not make a difference here, whether we put `x = chr` or `x = fct` in the ggplot statement.

`fct_reorder` here sorts the levels according to their respective group mean[5] of the values in the `val` column.

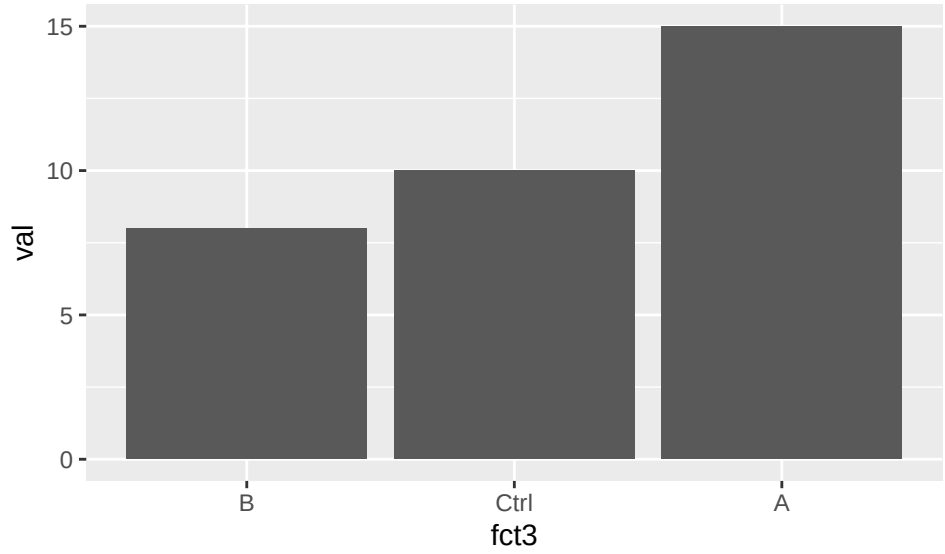
You can see that it worked in the output of `str(dat)` above and in the plots below.

```
ggplot(dat) +
  aes(y = val, x = fct2) +
  geom_col()
```




```
ggplot(dat) +
  aes(y = val, x = fct3) +
  geom_col()
```

[5]Yes, the mean in this example is not really a mean, since there is only one number per group.



7 stringr

In computer programming, a string is traditionally a sequence of characters (or *text* if you will). Taken directly from the documentation:

> Strings are not glamorous, high-profile components of R, but they do play a big role in many data cleaning and preparation tasks. The stringr package provide a cohesive set of functions designed to make working with strings as easy as possible. If you're not familiar with strings, the best place to start is the chapter on strings in R for Data Science.

Below are some brief examples of {stringr} functions I use regularly. To show what they can do, let's first create some strings[6]:

```
a_string <- "  a  string with irregular  spaces. "
strings <-c("String 1", "String Two", "third string")
```

To remove part of a string, use `str_remove()`. To replace it, use `str_replace()`.

```
strings %>%
  str_remove(pattern = "ing")
```

[6]Note that while I create two vectors in this example, this will work just as well with columns of a table via 'table %>% mutate(new = stringrfunction(old))'

```
[1] "Str 1"     "Str Two"   "third str"
```

```
strings %>%
  str_replace(pattern = "ing",
              replacement = ".")
```

```
[1] "Str. 1"     "Str. Two"   "third str."
```

The functions `str_trim()` and `str_squish()` help remove unnecessary spaces from strings. The former removes them only from from start and end, while the latter also reduces repeated whitespace inside a string.

```
a_string %>%
  str_trim()
```

```
[1] "a  string with irregular  spaces."
```

```
a_string %>%
  str_squish()
```

```
[1] "a string with irregular spaces."
```

Finally, you can check if a pattern appears in a string, or extract part of a string:

```
strings %>%
  str_detect(pattern = "Two")
```

```
[1] FALSE  TRUE FALSE
```

```
strings %>%
  str_sub(start = 1, end = 4)
```

```
[1] "Stri" "Stri" "thir"
```

Additional Resources

- 14 Strings in *R for data science* (Wickham and Grolemund 2017)
- stringr cheat sheet
- Regular expressions

Álvarez, Adolfo. 2021. "Plumbers, Chains, and Famous Painters: The (Updated) History of the Pipe Operator in r." *Adolfo Álvarez Blog*. http://adolfoalvarez.cl/blog/2021-09-16-plumbers-chains-and-famous-painters-the-history-of-the-pipe-operator-in-r/.

Scherer, Cédric. 2022. "A Ggplot2 Tutorial for Beautiful Plotting in r." *Cédric Scherer Blog*. https://www.cedricscherer.com/2019/08/05/a-ggplot2-tutorial-for-beautiful-plotting-in-r/.

Wickham, Hadley, and Garrett Grolemund. 2017. *R for Data Science: Import, Tidy, Transform, Visualize, and Model Data*. 1st ed. O'Reilly Media, Inc. https://r4ds.had.co.nz/.