

Introduction to Data Science

Session 3: R and the tidyverse

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Hertie School | GRAD-C11/E1339

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¹ Parts of this lecture draws on materials from Grant McDermott's excellent *Data Science for Economists* class.

Tidyverse basics

What is the tidyverse?

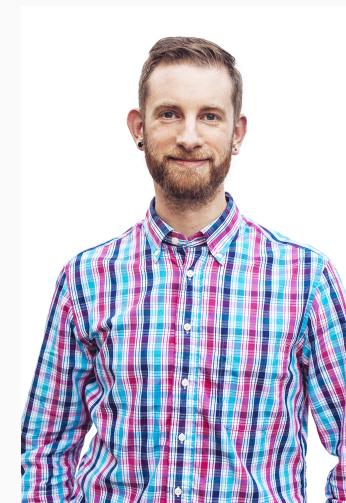
R packages for data science

- Let's take it from the [tidyverse website](#):

"The tidyverse is an opinionated collection of R packages designed for data science. All packages share an underlying design philosophy, grammar, and data structures."

- It's the contribution of many people of the R community.
- [Hadley Wickham](#) had a key role in shaping it by developing many of the core packages, such as `ggplot2`, `dplyr`, `tidyr`, `tibble`, and `stringr`.
- Install the complete tidyverse with:

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



Hadley Wickham

A guide to the tidyverse

Valuable resources

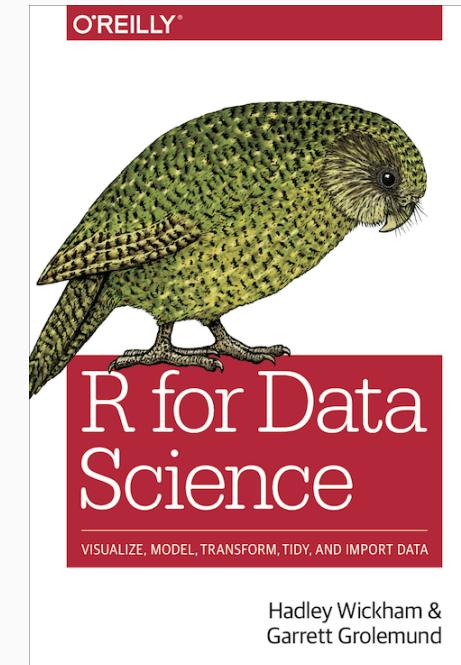
- Welcome to the [Tidyverse](#), a quick overview from many tidyverse contributors)
- [Tidy data](#), a foundational paper on data wrangling and structuring, by Hadley Wickham, 2014, *Journal of Statistical Software*; check [here](#) for a hands-on vignette based on the `tidyverse` package
- [The tidyverse design guide](#), a (soon-to-be book) manifesto to promote design consistency across the tidyverse
- [R for Data Science](#), our main textbook for this course



Tidy Data
Hadley Wickham
RStudio

Abstract
A huge amount of effort is spent cleaning data to get it ready for analysis, but there has been little research on how to make data cleaning as easy and effective as possible. This paper tackles a small, but important, component of data cleaning: data tidying. Tidy datasets are easy to manipulate, model and visualize, and have a specific structure: each variable is a column, each observation is a row, and each type of observational unit is a table. This allows us to use standard tools to process data. In addition, a small set of tools are needed to deal with a wide range of untidy datasets. This structure also makes it easier to develop tidy tools for data analysis, tools that both input and output tidy datasets. The advantages of a consistent data structure and matching tools are demonstrated with a case study free from mundane data manipulation chores.

Keywords: data cleaning, data tidying, relational databases, R.



Tidyverse packages

Loading the tidyverse

```
R> library(tidyverse)

## — Attaching packages ————— tidyverse 1.3.1 —

## ✓ ggplot2 3.3.5      ✓ purrr    0.3.4
## ✓ tibble   3.1.3      ✓ dplyr    1.0.7
## ✓ tidyr    1.1.3      ✓ stringr  1.4.0
## ✓ readr    2.0.0      ✓forcats  0.5.1

## — Conflicts ————— tidyverse_conflicts() —
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()   masks stats::lag()
```

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## — Conflicts ————— tidyverse_conflicts() —
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()   masks stats::lag()
```

- We see that we have actually loaded a number of packages (which could also be loaded individually): `ggplot2`, `tibble`, `dplyr`, etc.
- We can also see information about the package versions and some namespace conflicts.

Tidyverse packages *cont.*

- In addition to the currently 8 core packages, the tidyverse includes many others for more specialized usage.¹
- See [here](#) for an overview, or just in R directly:

```
R> tidyverse_packages()
```

```
## [1] "broom"          "cli"            "crayon"         "dbplyr"  
## [5] "dplyr"          "dtplyr"         "forcats"        "googledrive"  
## [9] "googlesheets4"  "ggplot2"        "haven"          "hms"  
## [13] "httr"           "jsonlite"       "lubridate"      "magrittr"  
## [17] "modelr"         "pillar"         "purrr"          "readr"  
## [21] "readxl"         "reprex"         "rlang"          "rstudioapi"  
## [25] "rvest"          "stringr"        "tibble"         "tidyverse"  
## [29] "xml2"
```

¹ It also includes a *lot* of dependencies upon installation. This is a matter of some [controversy](#).

Tidyverse packages *cont.*

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## [17] "modelr"         "pillar"         "purrr"          "readr"  
## [21] "readxl"         "reprex"         "rlang"          "rstudioapi"  
## [25] "rvest"          "stringr"        "tibble"         "tidyverse"  
## [29] "xml2"
```

- We'll use several of these additional packages during the remainder of this course (e.g., the `lubridate` package for working with dates and the `rvest` package for web scraping).
- However, bear in mind that these packages will have to be loaded separately.

¹ It also includes a *lot* of dependencies upon installation. This is a matter of some [controversy](#).

The tidyverse philosophy

Key philosophy for tidy data

1. Each variable forms a column.
2. Each observation forms a row.
3. Each type of observational unit forms a table.

Basically, tidy data is more likely to be **long (i.e. narrow) format** than wide format.

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More unifying principles

- Today, the tidyverse stands for more than just "tidy data".
- It is guided by the principles of being **human centered, consistent, composable**, and **inclusive**.
- We will learn about these **unifying principles** inductively when working with more and more tidyverse packages.
- Later today, we will learn about [tidyverse style principles])(<https://style.tidyverse.org/>) of low-level code formatting.

The tidyverse philosophy

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Resources

Check out the **tidyverse design guide** for a comprehensive treatment of the tidyverse philosophy.

Tidyverse vs. base R



Tidyverse vs. base R: what's the difference?

- Both are compatible. You can wrangle your data with `dplyr`, plot it with `ggplot2`, and model it with yet another package.
- Ultimately, the tidyverse is just a bunch of (hugely popular!) packages that share design principles.
- Often, tidyverse packages don't reinvent the wheel. Instead, they offer more consistency in naming, arguments, and output (among other things).
- For instance, compare function naming principles (`tidyverse::snake_case` vs `base::period.case` rule; more on these conventions later) in these examples:

tidyverse	base
<code>?readr :: read_csv</code>	<code>?utils :: read.csv</code>
<code>?dplyr :: if_else</code>	<code>?base :: ifelse</code>
<code>?tibble :: tibble</code>	<code>?base :: data.frame</code>

- If you call up the above examples, you'll see that the tidyverse alternative typically offers some enhancements or other useful options (and sometimes restrictions) over its base counterpart.

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<code>?dplyr::if_else</code>	<code>?base::ifelse</code>
<code>?tibble::tibble</code>	<code>?base::data.frame</code>

- If you call up the above examples, you'll see that the tidyverse alternative typically offers some enhancements or other useful options (and sometimes restrictions) over its base counterpart.
- And **remember:** There are (almost) always multiple ways to achieve a single goal in R.

Tidyverse vs. base R: what's the difference? *cont.*

Tidyverse



Credit sawiki.com

Tidyverse vs. base R: what's the difference? *cont.*

Tidyverse



Credit sawiki.com

Base R



Credit multimedialab.be

Tidyverse vs. base R: what to use?

Stories from the past

- When I started to learn R ~13 years ago, there was no tidyverse. The learning curve felt much steeper. I often switched back to Stata for data wrangling.
- As the tidyverse grew, R became more convenient to use for the entire research pipeline.
- There's simply no need for you to live through the same pain.

Why we start with the tidyverse

- Because clever people think it's the right way.
- Documentation + community support are great.
- Having a consistent syntax makes it easier to learn.

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You still will want to check out base R alternatives later

- Base R is extremely flexible and powerful (and stable).
- There are some things that you'll have to venture outside of the tidyverse for.
- A combination of tidyverse and base R is often the best solution to a problem.
- Excellent base R data manipulation tutorials: [here](#) and [here](#).

Now, let's get started with the tidyverse!

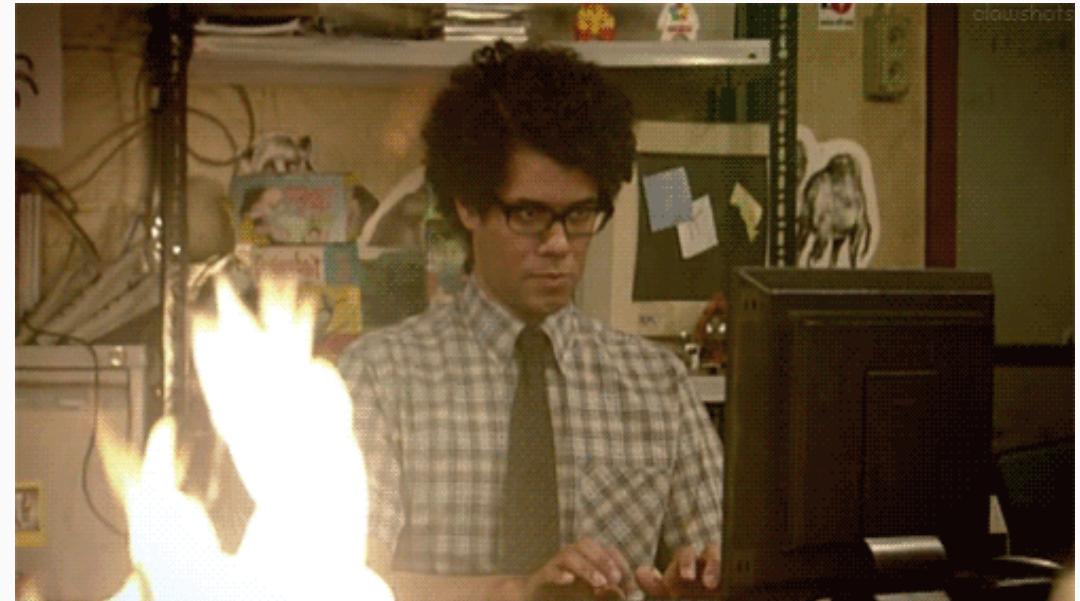
R packages you'll need today

tidyverse

nycflights13

You can install/update them both with the following command.

```
R> install.packages(  
+   c('tidyverse', 'nycflights13'),  
+   repos = 'https://cran.rstudio.com',  
+   dependencies = TRUE  
+ )
```



Pipes



anthropocene man

Ceci n'est pas un gif.

Credit [likestowastetime/imgur](#)

The pipe

%>%

Example

The pipe way

```
R> Alex %>%
+   wake_up(7) %>%
+   shower(temp = 38) %>%
+   breakfast(c("coffee", "croissant")) %>%
+   walk(step_function()) %>%
+   bvg(
+     train = "U2",
+     destination = "Stadtmitte"
+   ) %>%
+   hertie(course = "Intro to DS")
```

The classic way

```
R> hertie(
+   bvg(
+     walk(
+       breakfast(
+         shower(
+           wake_up(
+             Alex, 7
+           ),
+           temp = 38
+         ),
+         c("coffee", "croissant")
+       ),
+       step_function()
+     ),
+     train = "U2",
+     destination = "Stadtmitte"
+   ),
+   course = "Intro to DS"
+ )
```

Example

The pipe way

```
R> Alex %>%
+   wake_up(7) %>%
+   shower(temp = 38) %>%
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+   bvg(
+     train = "U2",
+     destination = "Stadtmitte"
+   ) %>%
+   hertie(course = "Intro to DS")
```

The classic way, nightmare edition

```
R> alex_awake ← wake_up(Alex, 7)
R> alex_showered ← shower(alex_awake,
+                           temp = 38)
R> alex_replete ← breakfast(alex_showered,
+                            c("coffee", "croissant"))
R> alex_underway ← walk(alex_replete,
+                        step_function())
R> alex_on_train ← bvg(alex_underway,
+                       train = "U2",
+                       destination = "Stadtmitte")
R> alex_hertie ← hertie(alex_on_train,
+                        course = "Intro to DS")
```

The beauty of pipes

A simple but powerful tool

- The forward-pipe operator `%>%` pipes the left-hand side values forward into expressions on the right-hand side.
- We replace `f(x)` with `x %>% f()`.

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Why piping is cool

- It structures sequences of data operations as pipes, i.e. left-to-right (as opposed to from the inside and out).
- It serves the natural way of reading ("do this, then this, then this, ...").
- It avoids nested function calls.
- It improves cognitive performance of code writers and readers.
- It minimizes the need for local variables and function definitions.

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Background

- The pipe was originally created in 2014 by [Stefan Milton Bache](#) and published with the `magrittr` package.
- Magrittr? [Get it?](#) 
- The basics come with the tidyverse by default, but `magrittr` can do more (watch out for the "tee" pipe, `%T>%`, the "exposition" pipe, `%%%`, and the "assignment" pipe, `%>=%`). Also, be sure to check out [aliases](#).

Piping etiquette

When to avoid the pipe

- Pipes are not very handy when you need to manipulate more than one object at a time. Reserve pipes for a sequence of steps applied to one primary object.
- Don't use the pipe when there are meaningful intermediate objects that can be given informative names (and that are used later on).

Piping etiquette

When to avoid the pipe

- Pipes are not very handy when you need to manipulate more than one object at a time. Reserve pipes for a sequence of steps applied to one primary object.
- Don't use the pipe when there are meaningful intermediate objects that can be given informative names (and that are used later on).

Instead, here's how to use it

- `%>%` should always have a space before it, and should usually be followed by a new line.
- A one-step pipe can stay on one line, but unless you plan to expand it later on, you should consider rewriting it to a regular function call.
- `magrittr` allows you to omit `()` on functions that don't have arguments (as in `mydata %>% summary`). Avoid this feature.

The base R pipe: |>

The magrittr pipe has proven so successful and popular that the R core team [recently added](#) a "native" pipe operator to base R (version 4.1), denoted `|>.`¹

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- Here's how it works:

```
mtcars |> subset(cyl = 4) |> head()  
mtcars |> subset(cyl = 4) |> (\(x) lm(mpg ~ disp, data = x))()
```

¹ That's actually a `|` followed by a `>.`. The default font on these slides just makes it look extra fancy.

The base R pipe: |>

The magrittr pipe has proven so successful and popular that the R core team [recently added](#) a "native" pipe operator to base R (version 4.1), denoted |>.¹

- Here's how it works:

```
mtcars |> subset(cyl == 4) |> head()  
mtcars |> subset(cyl == 4) |> (\(x) lm(mpg ~ disp, data = x))()
```

- This illustrates how the popularity of the tidyverse has repercussions on the development of base R.
- Note that with the native pipe, the RHS function has to be written out together with the brackets (i.e., ... |> head()) instead of ... |> head).
- Also note the use of the new shorthand inline function syntax, \((x)\), to pass content to the RHS but not to the first argument.
- Now, should we use the "magrittr" pipe or the native pipe? The native pipe might make more sense in the long term, since it avoids dependencies and might be more efficient. Check out [this Stackoverflow post](#) for a discussion of differences.

¹That's actually a | followed by a >. The default font on these slides just makes it look extra fancy.

dplyr

Key dplyr verbs

There are five key `dplyr` verbs that you need to learn.¹

1. `filter()`: Filter (i.e. subset) rows based on their values.
2. `arrange()`: Arrange (i.e. reorder) rows based on their values.
3. `select()`: Select (i.e. subset) columns by their names.
4. `mutate()`: Create new columns.
5. `summarize()`: Collapse multiple rows into a single summary value.²



But let's start with studying the key commands using the `starwars` dataset that comes pre-packaged with `dplyr`.

¹ There is much, much more in `dplyr`, and we will look beyond these core functions later. Have a glimpse at the [overview at tidyverse.org](#) and at this excellent [cheat sheet](#).

² `summarize()` with an "s" works too. I slightly prefer the barbarian version though.

1) dplyr::filter()

We can chain multiple filter commands with the pipe (`%>%`), or just separate them within a single filter command using commas.

```
R> starwars %>%
+   filter(
+     species == "Human",
+     height >= 190
+   )

## # A tibble: 4 × 14
##   name      height  mass hair_color skin_color eye_color birth_year sex   gender
##   <chr>     <int> <dbl> <chr>       <chr>       <dbl> <chr> <chr>
## 1 Darth Va...    202    136 none        white       yellow      41.9 male   mascul...
## 2 Qui-Gon ...    193     89 brown       fair        blue        92    male   mascul...
## 3 Dooku        193     80 white       fair        brown       102    male   mascul...
## 4 Bail Pre...    191     NA black      tan         brown      67    male   mascul...
## # ... with 5 more variables: homeworld <chr>, species <chr>, films <list>,
## #   vehicles <list>, starships <list>
```

1) dplyr::filter() *cont.*

Regular expressions work well, too.

```
R> starwars %>%  
+   filter(stringr::str_detect(name, "Skywalker"))  
  
## # A tibble: 3 × 14  
##   name      height  mass hair_color skin_color eye_color birth_year sex   gender  
##   <chr>     <int> <dbl> <chr>       <chr>       <chr>       <dbl> <chr> <chr>  
## 1 Luke Sk...     172     77 blond      fair        blue         19 male   masculin...  
## 2 Anakin ...    188     84 blond      fair        blue        41.9 male   masculin...  
## 3 Shmi Sk...    163     NA black      fair        brown        72 female feminin...  
## # ... with 5 more variables: homeworld <chr>, species <chr>, films <list>,  
## #   vehicles <list>, starships <list>
```

1) dplyr::filter() *cont.*

A very common `filter()` use case is identifying (or removing) missing data cases.

```
R> starwars %>%  
+   filter(is.na(height))  
  
## # A tibble: 6 × 14  
##   name      height  mass hair_color skin_color eye_color birth_year sex   gender  
##   <chr>     <int> <dbl> <chr>       <chr>       <chr>       <dbl> <chr> <chr>  
## 1 Arvel C...     NA     NA brown      fair       brown        NA male  masculin...  
## 2 Finn          NA     NA black      dark       dark        NA male  masculin...  
## 3 Rey           NA     NA brown      light      hazel        NA female feminin...  
## 4 Poe Dam...    NA     NA brown      light      brown        NA male  masculin...  
## 5 BB8            NA     NA none       none      black        NA none  masculin...  
## 6 Captain...    NA     NA unknown   unknown   unknown        NA <NA> <NA>  
## # ... with 5 more variables: homeworld <chr>, species <chr>, films <list>,  
## #   vehicles <list>, starships <list>
```

1) dplyr::filter() cont.

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## # A tibble: 6 × 14  
##   name      height  mass hair_color skin_color eye_color birth_year sex   gender  
##   <chr>     <int> <dbl> <chr>       <chr>       <dbl> <chr> <chr>  
## 1 Arvel C...     NA     NA brown      fair       brown        NA male  masculin...  
## 2 Finn          NA     NA black      dark       dark        NA male  masculin...  
## 3 Rey           NA     NA brown      light      hazel        NA female feminin...  
## 4 Poe Dam...    NA     NA brown      light      brown        NA male  masculin...  
## 5 BB8            NA     NA none       none      black        NA none  masculin...  
## 6 Captain...    NA     NA unknown   unknown   unknown        NA <NA> <NA>  
## # ... with 5 more variables: homeworld <chr>, species <chr>, films <list>,  
## #   vehicles <list>, starships <list>
```

To remove missing observations, simply use negation: `filter(!is.na(height))`.

1) dplyr::filter() cont.

Importantly, when we list several filter conditions, `filter()` interprets them as a Boolean "AND".

```
R> starwars %>%  
+   filter(str_detect(name, "Skywalker"),  
+          eye_color == "blue")  
  
## # A tibble: 2 × 14  
##   name      height  mass hair_color skin_color eye_color birth_year sex  gender  
##   <chr>     <int> <dbl> <chr>       <chr>       <chr>       <dbl> <chr> <chr>  
## 1 Luke Skywalker 172     77 blond      fair        blue         19 male   masculin...  
## 2 Anakin Skywalker 188     84 blond      fair        blue         41.9 male   masculin...  
## # ... with 5 more variables: homeworld <chr>, species <chr>, films <list>,  
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1) dplyr::filter() cont.

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```
R> starwars %>%  
+   filter(str_detect(name, "Skywalker"),  
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## # A tibble: 2 × 14  
##   name      height  mass hair_color skin_color eye_color birth_year sex  gender  
##   <chr>     <int> <dbl> <chr>     <chr>     <chr>       <dbl> <chr> <chr>  
## 1 Luke Skywalker 172     77 blond     fair      blue        19 male   masculin...  
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## # ... with 5 more variables: homeworld <chr>, species <chr>, films <list>,  
## #   vehicles <list>, starships <list>
```

We can work with operators `|` ("OR") and `&` ("AND") and combine them with parentheses to specify more complex filter commands, as in:

```
R> starwars %>%  
+   filter(species == "Wookiee" | (species == "Human" & height ≥ 200))
```

2) dplyr::arrange()

arrange() sorts observations in increasing order by default.

```
R> starwars %>%  
+   arrange(birth_year)  
  
## # A tibble: 87 × 14  
##   name      height  mass hair_color skin_color eye_color birth_year sex gender  
##   <chr>     <int> <dbl> <chr>       <chr>       <chr>       <dbl> <chr> <chr>  
## 1 Wicket ...     88    20  brown      brown      brown          8 male  masculin...  
## 2 IG-88        200   140  none       metal      red            15 none  masculin...  
## 3 Luke Sk...     172    77  blond      fair       blue           19 male  masculin...  
## 4 Leia Or...     150    49  brown      light      brown           19 female feminin...  
## 5 Wedge A...     170    77  brown      fair       hazel          21 male  masculin...  
## 6 Plo Koon      188    80  none       orange     black           22 male  masculin...  
## 7 Biggs D...     183    84  black      light      brown           24 male  masculin...  
## 8 Han Solo      180    80  brown      fair       brown          29 male  masculin...  
## 9 Lando C...     177    79  black      dark       brown          31 male  masculin...  
## 10 Boba Fe...    183   78.2 black     fair       brown         31.5 male  masculin...  
## # ... with 77 more rows, and 5 more variables: homeworld <chr>, species <chr>,  
## #   films <list>, vehicles <list>, starships <list>
```

2) dplyr::arrange()

arrange() sorts observations in increasing order by default.

```
R> starwars %>%  
+   arrange(birth_year)  
  
## # A tibble: 87 × 14  
##   name      height  mass hair_color skin_color eye_color birth_year sex gender  
##   <chr>     <int> <dbl> <chr>       <chr>       <chr>       <dbl> <chr> <chr>  
## 1 Wicket ...     88    20  brown      brown      brown          8 male  masculin...  
## 2 IG-88        200   140  none       metal      red            15 none  masculin...  
## 3 Luke Sk...     172    77  blond      fair       blue           19 male  masculin...  
## 4 Leia Or...     150    49  brown      light      brown           19 female feminin...  
## 5 Wedge A...     170    77  brown      fair       hazel          21 male  masculin...  
## 6 Plo Koon      188    80  none       orange     black           22 male  masculin...  
## 7 Biggs D...     183    84  black      light      brown           24 male  masculin...  
## 8 Han Solo      180    80  brown      fair       brown          29 male  masculin...  
## 9 Lando C...     177    79  black      dark       brown          31 male  masculin...  
## 10 Boba Fe...    183   78.2 black     fair       brown         31.5 male  masculin...  
## # ... with 77 more rows, and 5 more variables: homeworld <chr>, species <chr>,  
## #   films <list>, vehicles <list>, starships <list>
```

Note: Arranging on a character-based column (i.e. strings) will sort alphabetically.

2) dplyr::arrange() cont.

We can also arrange items in descending order using `arrange(desc())`.

```
R> starwars %>%  
+   arrange(desc(birth_year))  
  
## # A tibble: 87 × 14  
##   name    height  mass hair_color skin_color eye_color birth_year sex gender  
##   <chr>    <int> <dbl> <chr>      <chr>      <chr>      <dbl> <chr> <chr>  
## 1 Yoda        66     17 white       green      brown         896 male   masculin...  
## 2 Jabba ...    175    1358 <NA>      green-tan,... orange        600 herm... masculin...  
## 3 Chewba...    228    112 brown      unknown     blue          200 male   masculin...  
## 4 C-3PO       167     75 <NA>      gold       yellow        112 none   masculin...  
## 5 Dooku       193     80 white      fair       brown         102 male   masculin...  
## 6 Qui-Go...    193     89 brown      fair       blue          92 male   masculin...  
## 7 Ki-Adi...    198     82 white      pale       yellow        92 male   masculin...  
## 8 Finis ...   170      NA blond     fair       blue          91 male   masculin...  
## 9 Palpat...   170      75 grey      pale       yellow        82 male   masculin...  
## 10 Cliegg...   183      NA brown     fair       blue          82 male   masculin...  
## # ... with 77 more rows, and 5 more variables: homeworld <chr>, species <chr>,  
## #   films <list>, vehicles <list>, starships <list>
```

3) dplyr::select()

Use commas to select multiple columns out of a data frame. (You can also use `<first>:<last>` for consecutive columns). Deselect a column with "-".

```
R> starwars %>%  
+   select(name:skin_color, species, -height)  
  
## # A tibble: 87 × 5  
##   name           mass hair_color   skin_color species  
##   <chr>        <dbl> <chr>       <chr>      <chr>  
## 1 Luke Skywalker    77 blond       fair       Human  
## 2 C-3PO              75 <NA>        gold      Droid  
## 3 R2-D2              32 <NA>        white, blue Droid  
## 4 Darth Vader       136 none        white      Human  
## 5 Leia Organa        49 brown       light      Human  
## 6 Owen Lars          120 brown, grey light      Human  
## 7 Beru Whitesun lars 75 brown       light      Human  
## 8 R5-D4              32 <NA>        white, red Droid  
## 9 Biggs Darklighter  84 black       light      Human  
## 10 Obi-Wan Kenobi    77 auburn, white fair      Human  
## # ... with 77 more rows
```

3) dplyr::select() *cont.*

You can also rename some (or all) of your selected variables in place.

```
R> starwars %>%
+   select(alias = name, crib = homeworld, sex = gender)

## # A tibble: 87 × 3
##       alias           crib     sex
##       <chr>          <chr>    <chr>
## 1 Luke Skywalker   Tatooine masculine
## 2 C-3PO            Tatooine masculine
## 3 R2-D2             Naboo    masculine
## 4 Darth Vader      Tatooine masculine
## 5 Leia Organa       Alderaan feminine
## 6 Owen Lars         Tatooine masculine
## 7 Beru Whitesun lars Tatooine feminine
## 8 R5-D4             Tatooine masculine
## 9 Biggs Darklighter Tatooine masculine
## 10 Obi-Wan Kenobi   Stewjon  masculine
## # ... with 77 more rows
```

3) dplyr::select() cont.

You can also rename some (or all) of your selected variables in place.

```
R> starwars %>%  
+   select(alias = name, crib = homeworld, sex = gender)  
  
## # A tibble: 87 × 3  
##   alias           crib     sex  
##   <chr>          <chr>    <chr>  
## 1 Luke Skywalker Tatooine masculine  
## 2 C-3PO           Tatooine masculine  
## 3 R2-D2            Naboo     masculine  
## 4 Darth Vader    Tatooine masculine  
## 5 Leia Organa    Alderaan  feminine  
## 6 Owen Lars      Tatooine masculine  
## 7 Beru Whitesun lars Tatooine feminine  
## 8 R5-D4           Tatooine masculine  
## 9 Biggs Darklighter Tatooine masculine  
## 10 Obi-Wan Kenobi Stewjon  masculine  
## # ... with 77 more rows
```

If you just want to rename columns without subsetting them, you can use `rename()`.

3) dplyr::select() cont.

The `select(contains(<PATTERN>))` option provides a nice shortcut in relevant cases.

```
R> starwars %>%  
+   select(name, contains("color"))  
  
## # A tibble: 87 × 4  
##   name          hair_color    skin_color eye_color  
##   <chr>         <chr>        <chr>      <chr>  
## 1 Luke Skywalker  blond       fair        blue  
## 2 C-3PO           <NA>        gold        yellow  
## 3 R2-D2           <NA>        white, blue red  
## 4 Darth Vader    none        white        yellow  
## 5 Leia Organa    brown       light        brown  
## 6 Owen Lars      brown, grey light        blue  
## 7 Beru Whitesun lars brown       light        blue  
## 8 R5-D4           <NA>        white, red red  
## 9 Biggs Darklighter black       light        brown  
## 10 Obi-Wan Kenobi auburn, white fair        blue-gray  
## # ... with 77 more rows
```

3) dplyr::select() cont.

The `select(contains(<PATTERN>))` option provides a nice shortcut in relevant cases.

```
R> starwars %>%  
+   select(name, contains("color"))  
  
## # A tibble: 87 × 4  
##   name          hair_color    skin_color eye_color  
##   <chr>         <chr>        <chr>      <chr>  
## 1 Luke Skywalker  blond       fair        blue  
## 2 C-3PO           <NA>        gold        yellow  
## 3 R2-D2           <NA>        white, blue red  
## 4 Darth Vader    none        white        yellow  
## 5 Leia Organa    brown       light        brown  
## 6 Owen Lars      brown, grey light        blue  
## 7 Beru Whitesun lars brown       light        blue  
## 8 R5-D4           <NA>        white, red  red  
## 9 Biggs Darklighter black       light        brown  
## 10 Obi-Wan Kenobi auburn, white fair        blue-gray  
## # ... with 77 more rows
```

There are many more useful selection helpers, such as `starts_with()`, `ends_with()`, and `matches()`. See [here](#) for an overview.

3) dplyr::select() cont.

The `select(... , everything())` option is another useful shortcut if you only want to bring some variable(s) to the "front" of a data frame.

```
R> starwars %>%  
+   select(species, homeworld, everything()) %>%  
+   head(5)  
  
## # A tibble: 5 × 14  
##   species homeworld name           height  mass hair_color skin_color eye_color  
##   <chr>     <chr>    <chr>        <int>  <dbl> <chr>       <chr>      <chr>  
## 1 Human     Tatooine  Luke Skywalker     172     77 blond       fair       blue  
## 2 Droid      Tatooine  C-3PO          167     75 <NA>       gold       yellow  
## 3 Droid      Naboo    R2-D2           96      32 <NA>       white, blue red  
## 4 Human     Tatooine  Darth Vader      202    136 none       white       yellow  
## 5 Human     Alderaan  Leia Organa      150     49 brown      light       brown  
## # ... with 6 more variables: birth_year <dbl>, sex <chr>, gender <chr>,  
## #   films <list>, vehicles <list>, starships <list>
```

3) dplyr::select() cont.

The `select(... , everything())` option is another useful shortcut if you only want to bring some variable(s) to the "front" of a data frame.

```
R> starwars %>%  
+   select(species, homeworld, everything()) %>%  
+   head(5)  
  
## # A tibble: 5 × 14  
##   species homeworld name           height  mass hair_color skin_color eye_color  
##   <chr>     <chr>    <chr>        <int>   <dbl> <chr>       <chr>      <chr>  
## 1 Human     Tatooine  Luke Skywalker     172     77 blond       fair       blue  
## 2 Droid      Tatooine  C-3PO          167     75 <NA>       gold       yellow  
## 3 Droid      Naboo    R2-D2           96      32 <NA>       white, blue red  
## 4 Human     Tatooine  Darth Vader      202    136 none       white       yellow  
## 5 Human     Alderaan  Leia Organa      150     49 brown       light      brown  
## # ... with 6 more variables: birth_year <dbl>, sex <chr>, gender <chr>,  
## #   films <list>, vehicles <list>, starships <list>
```

Note: The new `relocate()` function available in dplyr 1.0.0 has brought a lot more functionality to the ordering of columns. See [here](#).

4) dplyr::mutate()

You can create new columns from scratch with `mutate()`, or (more commonly) as transformations of existing columns.

```
R> starwars %>%  
+   select(name, birth_year) %>%  
+   mutate(  
+     dog_years = birth_year * 7, ## Separate with a comma  
+     comment = paste0(name, " is ", dog_years, " in dog years.")  
+   ) %>%  
+   slice(1:6) # Just show first six observations  
  
## # A tibble: 6 × 4  
##   name      birth_year  dog_years comment  
##   <chr>        <dbl>      <dbl> <chr>  
## 1 Luke Skywalker    19        133  Luke Skywalker is 133 in dog years.  
## 2 C-3PO            112       784  C-3PO is 784 in dog years.  
## 3 R2-D2             33        231  R2-D2 is 231 in dog years.  
## 4 Darth Vader     41.9      293. Darth Vader is 293.3 in dog years.  
## 5 Leia Organa      19        133  Leia Organa is 133 in dog years.  
## 6 Owen Lars         52       364  Owen Lars is 364 in dog years.
```

4) dplyr::mutate()

You can create new columns from scratch with `mutate()`, or (more commonly) as transformations of existing columns.

```
R> starwars %>%  
+   select(name, birth_year) %>%  
+   mutate(  
+     dog_years = birth_year * 7, ## Separate with a comma  
+     comment = paste0(name, " is ", dog_years, " in dog years.")  
+   ) %>%  
+   slice(1:6) # Just show first six observations  
  
## # A tibble: 6 × 4  
##   name      birth_year  dog_years comment  
##   <chr>        <dbl>      <dbl> <chr>  
## 1 Luke Skywalker    19        133  Luke Skywalker is 133 in dog years.  
## 2 C-3PO            112       784  C-3PO is 784 in dog years.  
## 3 R2-D2             33        231  R2-D2 is 231 in dog years.  
## 4 Darth Vader      41.9      293. Darth Vader is 293.3 in dog years.  
## 5 Leia Organa       19        133  Leia Organa is 133 in dog years.  
## 6 Owen Lars          52       364  Owen Lars is 364 in dog years.
```

Note: `mutate()` is order aware. So you can chain multiple mutates in a single call.

4) dplyr::mutate() cont.

Boolean, logical and conditional operators all work well with `mutate()` too.

```
R> starwars %>%
+   select(name, height) %>%
+   filter(name %in% c("Luke Skywalker", "Anakin Skywalker")) %>%
+   mutate(tall1 = height > 180) %>%
+   mutate(tall2 = ifelse(height > 180, "Tall", "Short")) ## Same effect, but can choose labels

## # A tibble: 2 × 4
##   name           height tall1 tall2
##   <chr>          <int>  <lgl> <chr>
## 1 Luke Skywalker     172 FALSE Short
## 2 Anakin Skywalker    188 TRUE  Tall
```

4) dplyr::mutate() cont.

Lastly, combining `mutate()` with the `across()` feature allows you to easily work on a subset of variables. For example:

```
R> starwars %>%
+   select(name:eye_color) %>%
+   mutate(across(where(is.character), toupper)) %>%
+   head(5)

## # A tibble: 5 × 6
##   name           height  mass hair_color skin_color eye_color
##   <chr>         <int> <dbl> <chr>       <chr>      <chr>
## 1 LUKE SKYWALKER     172    77 BLOND       FAIR       BLUE
## 2 C-3PO              167    75 <NA>        GOLD       YELLOW
## 3 R2-D2                96    32 <NA>       WHITE, BLUE RED
## 4 DARTH VADER        202   136 NONE        WHITE       YELLOW
## 5 LEIA ORGANA         150    49 BROWN      LIGHT       BROWN
```

4) dplyr::mutate() cont.

Lastly, combining `mutate()` with the `across()` feature allows you to easily work on a subset of variables. For example:

```
R> starwars %>%
+   select(name:eye_color) %>%
+   mutate(across(where(is.character), toupper)) %>%
+   head(5)

## # A tibble: 5 × 6
##   name           height  mass hair_color skin_color eye_color
##   <chr>         <int> <dbl> <chr>       <chr>      <chr>
## 1 LUKE SKYWALKER     172    77 BLOND       FAIR       BLUE
## 2 C-3PO              167    75 <NA>        GOLD       YELLOW
## 3 R2-D2                96    32 <NA>       WHITE, BLUE RED
## 4 DARTH VADER        202   136 NONE        WHITE       YELLOW
## 5 LEIA ORGANA         150    49 BROWN      LIGHT       BROWN
```

Note: More on `across()` and `where()` later!

5) dplyr::summarize()

You can summarize variables with all sorts of operations (e.g., `mean()`, `median()`, `n()`, `n_distinct()`, `sum()`, `first()`, `last()`, ...).

```
R> starwars %>%
+   group_by(species, gender) %>%
+   summarize(mean_height = mean(height, na.rm = TRUE)) %>%
+   head(5)

## `summarise()` has grouped output by 'species'. You can override using the `.groups` argument.

## # A tibble: 5 × 3
## # Groups:   species [5]
##   species   gender   mean_height
##   <chr>     <chr>        <dbl>
## 1 Aleena    masculine      79
## 2 Besalisk  masculine     198
## 3 Cerean    masculine     198
## 4 Chagrian  masculine     196
## 5 Clawdite  feminine     168
```

5) dplyr::summarize()

You can summarize variables with all sorts of operations (e.g., `mean()`, `median()`, `n()`, `n_distinct()`, `sum()`, `first()`, `last()`, ...).

```
R> starwars %>%  
+   group_by(species, gender) %>%  
+   summarize(mean_height = mean(height, na.rm = TRUE)) %>%  
+   head(5)  
  
## `summarise()` has grouped output by 'species'. You can override using the `.groups` argument.  
  
## # A tibble: 5 × 3  
## # Groups:   species [5]  
##   species   gender   mean_height  
##   <chr>     <chr>       <dbl>  
## 1 Aleena    masculine      79  
## 2 Besalisk  masculine     198  
## 3 Cerean    masculine     198  
## 4 Chagrian  masculine     196  
## 5 Clawdite  feminine     168
```

Note: This is particularly useful in combination with the `group_by()` command. Again, more on this later!

5) dplyr::summarize() cont.

Note that including `na.rm = TRUE` is usually a good idea with the functions fed into `summarize()`. Otherwise, any missing value will propagate to the summarized value too.

```
R> ## Probably not what we want
R> starwars %>%
+   summarize(mean_height = mean(height))

## # A tibble: 1 × 1
##   mean_height
##       <dbl>
## 1         NA

R> ## Much better
R> starwars %>%
+   summarize(mean_height = mean(height, na.rm = TRUE))

## # A tibble: 1 × 1
##   mean_height
##       <dbl>
## 1     174.
```

5) dplyr::summarize() cont.

The same `across()`-based workflow that we saw with `mutate()` a few slides back also works with `summarize()`. For example:

```
R> starwars %>%
+   group_by(species) %>%
+   summarize(across(where(is.numeric), mean, na.rm = TRUE)) %>%
+   head(5)

## # A tibble: 5 × 4
##   species  height  mass birth_year
##   <chr>     <dbl> <dbl>     <dbl>
## 1 Aleena      79     15       NaN
## 2 Besalisk    198    102       NaN
## 3 Cerean      198     82       92
## 4 Chagrian    196     NaN       NaN
## 5 Clawdite    168     55       NaN
```

Grouping with dplyr::group_by()

With `group_by()`, you can create a "grouped" copy of a table grouped by unique values of a column. If multiple columns are specified, the function groups by all available combinations of values.

```
R> by_species_gender ← starwars %>% group_by(species, gender)
R> by_species_gender

## # A tibble: 87 × 14
## # Groups:   species, gender [42]
##   name    height  mass hair_color skin_color eye_color birth_year sex   gender
##   <chr>    <int> <dbl> <chr>      <chr>      <chr>          <dbl> <chr> <chr>
## 1 Luke S...     172     77 blond     fair       blue            19 male   mascul...
## 2 C-3PO        167     75 <NA>      gold       yellow         112 none   mascul...
## 3 R2-D2         96      32 <NA>      white, bl... red            33 none   mascul...
## 4 Darth ...     202     136 none      white       yellow         41.9 male   mascul...
## 5 Leia O...     150      49 brown     light      brown            19 fema... femin...
## 6 Owen L...     178     120 brown, grey light      blue            52 male   mascul...
## 7 Beru W...     165      75 brown     light      blue            47 fema... femin...
## 8 R5-D4         97      32 <NA>      white, red red           NA none   mascul...
## 9 Biggs ...     183      84 black     light      brown            24 male   mascul...
## 10 Obi-Wa...     182      77 auburn, wh... fair      blue-gray        57 male   mascul...
## # ... with 77 more rows, and 5 more variables: homeworld <chr>, species <chr>,
## #   films <list>, vehicles <list>, starships <list>
```

Grouping with dplyr::group_by() cont.

More notes on grouping

- Grouping doesn't change how the data looks (apart from listing how it's grouped).
- Grouping changes how it acts with other dplyr verbs such as `summarize()` and `mutate()`, as we've already seen.
- By default, `group_by()` overrides existing grouping. Use `.add = TRUE` to append instead.
- By default, groups formed by factor levels that don't appear in the data are dropped. Set `.drop = FALSE` if you want to keep them.
- `ungroup()` removes existing grouping.
- `dplyr` notifies you about grouping variables every time you do operations on or with them. If you find these messages annoying, **switch them off** with `options(dplyr.summarise.inform = FALSE)`.

```
R> options(dplyr.summarise.inform = FALSE)
R> by_species_gender %>%
+   summarize(mean(height, na.rm = TRUE)) %>%
+   filter(n_distinct(gender) == 2)

## # A tibble: 8 × 3
## # Groups:   species [4]
##   species   gender   `mean(height, na.rm = TRUE)`
##   <chr>     <chr>           <dbl>
## 1 Droid     feminine        96
## 2 Droid     masculine       140
## 3 Human    feminine       160.
## 4 Human    masculine      182.
## 5 Kaminoan feminine      213
## 6 Kaminoan masculine      229
## 7 Twi'lek  feminine      178
## 8 Twi'lek  masculine      180
```

Other dplyr goodies

Other dplyr goodies

`slice()`: Subset rows by position rather than filtering by values. There's also `slice_sample()` to randomly select rows, `slice_head()` and `slice_tail()` to select first or last rows, and more.

```
R> starwars %>% slice(c(1, 5))

## # A tibble: 2 × 14
##   name      height  mass hair_color skin_color eye_color birth_year sex   gender
##   <chr>     <int> <dbl> <chr>       <chr>       <chr>       <dbl> <chr>   <chr>
## 1 Luke Sk...     172    77 blond      fair        blue         19 male    mascul...
## 2 Leia Or...     150    49 brown      light       brown         19 female  femin...
## # ... with 5 more variables: homeworld <chr>, species <chr>, films <list>,
## #   vehicles <list>, starships <list>
```

Other dplyr goodies

`slice()`: Subset rows by position rather than filtering by values. There's also `slice_sample()` to randomly select rows, `slice_head()` and `slice_tail()` to select first or last rows, and more.

```
R> starwars %>% slice(c(1, 5))

## # A tibble: 2 × 14
##   name      height  mass hair_color skin_color eye_color birth_year sex    gender
##   <chr>     <int> <dbl> <chr>       <chr>       <chr>       <dbl> <chr>   <chr>
## 1 Luke Sk...     172     77 blond      fair        blue          19 male    mascul...
## 2 Leia Or...     150     49 brown      light       brown          19 female  feminin...
## # ... with 5 more variables: homeworld <chr>, species <chr>, films <list>,
## #   vehicles <list>, starships <list>
```

`pull()`: Extract a column from as a data frame as a vector or scalar.

```
R> starwars %>% filter(gender=="feminine") %>% pull(height)

## [1] 150 165 150 163 178 184 157 170 166 165 168 213 167 96 178 NA 165
```

Other dplyr goodies *cont.*

`count()` and `distinct()`: Number and isolate unique observations.

```
R> starwars %>% count(species) %>% head(6)
```

```
## # A tibble: 6 × 2
##   species     n
##   <chr>     <int>
## 1 Aleena      1
## 2 Besalisk    1
## 3 Cerean      1
## 4 Chagrian    1
## 5 Clawdite    1
## 6 Droid       6
```

```
R> starwars %>% distinct(species) %>% pull() %>% sort() %>% magrittr::extract(1:5)
```

```
## [1] "Aleena"    "Besalisk"   "Cerean"    "Chagrian"   "Clawdite"
```

Other dplyr goodies *cont.*

`count()` and `distinct()`: Number and isolate unique observations.

```
R> starwars %>% count(species) %>% head(6)
```

```
## # A tibble: 6 × 2
##   species     n
##   <chr>     <int>
## 1 Aleena      1
## 2 Besalisk    1
## 3 Cerean      1
## 4 Chagrian    1
## 5 Clawdite    1
## 6 Droid       6
```

```
R> starwars %>% distinct(species) %>% pull() %>% sort() %>% magrittr::extract(1:5)
```

```
## [1] "Aleena"    "Besalisk"   "Cerean"     "Chagrian"   "Clawdite"
```

You could also use a combination of `mutate()`, `group_by()`, and `n()`, e.g. `starwars %>% group_by(species) %>% mutate(num = n())`.

Other dplyr goodies *cont.*

`where()`: Select the variables for which a function returns true.

```
R> starwars %>% select(where(is.numeric)) %>% names()
```

```
## [1] "height"      "mass"        "birth_year"
```

Other dplyr goodies *cont.*

`where()`: Select the variables for which a function returns true.

```
R> starwars %>% select(where(is.numeric)) %>% names()  
## [1] "height"      "mass"        "birth_year"
```

`across()`: Summarize or mutate multiple variables in the same way. More information [here](#).

```
R> starwars %>%  
+   mutate(across(where(is.numeric), scale)) %>%  
+   head(3)  
  
## # A tibble: 3 × 14  
##   name  height[,1] mass[,1] hair_color skin_color eye_color birth_year[,1] sex  
##   <chr>     <dbl>    <dbl> <chr>       <chr>       <chr>           <dbl> <chr>  
## 1 Luke...    -0.0678   -0.120 blond      fair       blue            -0.443 male  
## 2 C-3PO     -0.212    -0.132 <NA>       gold       yellow          0.158 none  
## 3 R2-D2     -2.25     -0.385 <NA>       white, bl... red            -0.353 none  
## # ... with 6 more variables: gender <chr>, homeworld <chr>, species <chr>,  
## #   films <list>, vehicles <list>, starships <list>
```

Other dplyr goodies *cont.*

`case_when()`: Vectorize multiple `if_else()` (or base R `ifelse()`) statements.

```
R> starwars %>%  
+   mutate(  
+     height_cat = case_when(  
+       height < 160 ~ "tiny",  
+       height ≥ 160 & height < 190 ~ "medium",  
+       height ≥ 190 & height < 220 ~ "tall",  
+       height ≥ 220 ~ "giant"  
+     )  
+   ) %>%  
+   pull(height_cat) %>% table()  
  
## .  
##   giant medium   tall   tiny  
##     5       45      18     13
```

Other dplyr goodies *cont.*

`case_when()`: Vectorize multiple `if_else()` (or base R `ifelse()`) statements.

```
R> starwars %>%  
+   mutate(  
+     height_cat = case_when(  
+       height < 160 ~ "tiny",  
+       height ≥ 160 & height < 190 ~ "medium",  
+       height ≥ 190 & height < 220 ~ "tall",  
+       height ≥ 220 ~ "giant"  
+     )  
+   ) %>%  
+   pull(height_cat) %>% table()  
  
## .  
##   giant medium   tall   tiny  
##     5      45     18     13
```

There are also a whole class of [window functions](#) for getting leads and lags, ranking, creating cumulative aggregates, etc.
See `vignette("window-functions")`.

Other dplyr goodies *cont.*

`case_when()`: Vectorize multiple `if_else()` (or base R `ifelse()`) statements.

```
R> starwars %>%  
+   mutate(  
+     height_cat = case_when(  
+       height < 160 ~ "tiny",  
+       height ≥ 160 & height < 190 ~ "medium",  
+       height ≥ 190 & height < 220 ~ "tall",  
+       height ≥ 220 ~ "giant"  
+     )  
+   ) %>%  
+   pull(height_cat) %>% table()  
  
## .  
##   giant medium   tall   tiny  
##     5      45     18     13
```

There are also a whole class of [window functions](#) for getting leads and lags, ranking, creating cumulative aggregates, etc.
See `vignette("window-functions")`.

`inner_join()`, `left_join()`, `right_join()`: Enough already, we'll talk about this in the next session!

tidyverse

Key `tidyverse` verbs

`tidyverse` is part of the core tidyverse. There are four key `tidyverse` verbs that you need to learn.

1. `pivot_longer()`: Pivot wide data into long format (i.e. "melt").¹
2. `pivot_wider()`: Pivot long data into wide format (i.e. "cast").²
3. `separate()`: Separate (i.e. split) one column into multiple columns.
4. `unite()`: Unite (i.e. combine) multiple columns into one.



¹ Updated version of `tidyverse::gather()`.

² Updated version of `tidyverse::spread()`.

On "longer" and "wider" datasets

Remember the **key philosophy for tidy data?**

1. Each variable forms a column.
2. Each observation forms a row.
3. Each type of observational unit forms a table.

One of the most common tasks for data scientists is to **reshape** data from one form to the other.

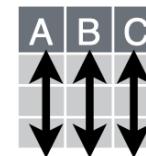
There are **multiple ways to store the same data in a dataset** (or in across multiple tables; but more on that in the next session).

Here, we learn how to shift between

- "**wider**" formats, i.e. data being stored across more columns and
- "**longer**" formats, i.e. data being stored across more rows.

Tidy data in a nutshell

A table is tidy if:



&

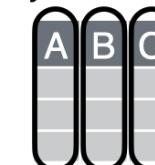


Each **variable** is in its own **column**

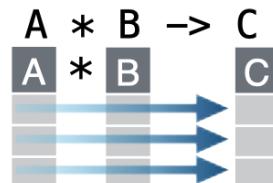
Each **observation**, or **case**, is in its own **row**

Benefits of tidy data

Tidy data:



Makes variables easy to access as vectors



Preserves cases during vectorized operations

From wide to long to wide

From wider to longer

- `pivot_longer()` pivots `cols` columns, moving column names into a `names_to` column, and column values into a `values_to` column.
- Recall a panel study design with multiple observations per unit.
- In the classical long format, each row represents one observation.
- Note how this is approaching the ideal of **tidy data**.

`pivot_longer()`

The diagram illustrates the transformation of a wide data frame into a long data frame using the `pivot_longer()` function. On the left, a wide table has three columns: `country`, `1999`, and `2000`. The `1999` column contains values "0.7K", "37K", and "212K". The `2000` column contains values "2K", "80K", and "213K". An arrow points to the right, where the same data is presented in a long format. The long table has three columns: `country`, `year`, and `cases`. The `country` column lists "A", "B", and "C". The `year` column lists "1999" and "2000" for each country. The `cases` column lists the corresponding values from the original wide table: "0.7K", "37K", "212K" for year 1999, and "2K", "80K", "213K" for year 2000.

country	1999	2000
A	0.7K	2K
B	37K	80K
C	212K	213K

→

country	year	cases
A	1999	0.7K
B	1999	37K
C	1999	212K
A	2000	2K
B	2000	80K
C	2000	213K

From longer to wider

- `pivot_wider()` pivots a `names_from` and a `values_from` column into a rectangular field of cells.
- In a panel study design, this would allow you to have one variable per measurement (e.g., pre- and posttreatment outcome variable).
- While this is nice for the human eye, it is sometimes not what fits the tidyverse workflow. Also, wenn you have multiple repeated measurements (think: variables in a population survey), the number of columns is quickly inflated. Be ready to `pivot_longer()`.

`pivot_wider()`

The diagram illustrates the transformation of a long data frame into a wide data frame using the `pivot_wider()` function. On the left, a long table has four columns: `country`, `year`, `type`, and `count`. The `type` column contains "cases" and "pop" for each country and year combination. The `count` column contains values like "0.7K", "19M", "2K", etc. An arrow points to the right, where the same data is presented in a wide format. The wide table has four columns: `country`, `year`, `cases`, and `pop`. The `country` column lists "A", "B", and "C". The `year` column lists "1999" and "2000" for each country. The `cases` column contains the values from the "cases" row of the long table. The `pop` column contains the values from the "pop" row of the long table.

country	year	type	count
A	1999	cases	0.7K
A	1999	pop	19M
A	2000	cases	2K
A	2000	pop	20M
B	1999	cases	37K
B	1999	pop	172M
B	2000	cases	80K
B	2000	pop	174M
C	1999	cases	212K
C	1999	pop	1T

→

country	year	cases	pop
A	1999	0.7K	19M
A	2000	2K	20M
B	1999	37K	172M
B	2000	80K	174M
C	1999	212K	1T
C	2000	NA	NA

1) tidyverse::pivot_longer()

```
R> stocks = data.frame( ## Could use "tibble" instead of "data.frame" if you prefer
+   time = as.Date('2009-01-01') + 0:1,
+   X = rnorm(2, 0, 1),
+   Y = rnorm(2, 0, 2),
+   Z = rnorm(2, 0, 4)
+ )
R> stocks
```

	time	X	Y	Z
## 1	2009-01-01	0.1890718	-0.5036369	-5.172738
## 2	2009-01-02	-0.1800420	0.2868808	1.193378

1) tidyverse::pivot_longer()

```
R> stocks = data.frame( ## Could use "tibble" instead of "data.frame" if you prefer
+   time = as.Date('2009-01-01') + 0:1,
+   X = rnorm(2, 0, 1),
+   Y = rnorm(2, 0, 2),
+   Z = rnorm(2, 0, 4)
+ )
R> stocks
```

	time	X	Y	Z
## 1	2009-01-01	0.1890718	-0.5036369	-5.172738
## 2	2009-01-02	-0.1800420	0.2868808	1.193378

```
R> tidy_stocks ← stocks %>% pivot_longer(-time, names_to="stock", values_to="price")
R> tidy_stocks
```

	time	stock	price
## 1	2009-01-01	X	0.189
## 2	2009-01-01	Y	-0.504
## 3	2009-01-01	Z	-5.17
## 4	2009-01-02	X	-0.180
## 5	2009-01-02	Y	0.287

2) `tidyverse::pivot_wider()`

```
R> tidy_stocks %>% pivot_wider(names_from = stock, values_from = price)

## # A tibble: 2 × 4
##   time           X     Y     Z
##   <date>     <dbl> <dbl> <dbl>
## 1 2009-01-01  0.189 -0.504 -5.17
## 2 2009-01-02 -0.180  0.287  1.19
```

2) `tidyr::pivot_wider()`

```
R> tidy_stocks %>% pivot_wider(names_from = stock, values_from = price)
```

```
## # A tibble: 2 × 4
##   time           X     Y     Z
##   <date>     <dbl> <dbl> <dbl>
## 1 2009-01-01  0.189 -0.504 -5.17
## 2 2009-01-02 -0.180  0.287  1.19
```

```
R> tidy_stocks %>% pivot_wider(names_from= time, values_from = price)
```

```
## # A tibble: 3 × 3
##   stock `2009-01-01` `2009-01-02`
##   <chr>     <dbl>     <dbl>
## 1 X         0.189    -0.180
## 2 Y        -0.504     0.287
## 3 Z        -5.17     1.19
```

2) `tidyverse::pivot_wider()`

```
R> tidy_stocks %>% pivot_wider(names_from = stock, values_from = price)
```

```
## # A tibble: 2 × 4
##   time           X     Y     Z
##   <date>     <dbl> <dbl> <dbl>
## 1 2009-01-01  0.189 -0.504 -5.17
## 2 2009-01-02 -0.180  0.287  1.19
```

```
R> tidy_stocks %>% pivot_wider(names_from= time, values_from = price)
```

```
## # A tibble: 3 × 3
##   stock `2009-01-01` `2009-01-02`
##   <chr>     <dbl>     <dbl>
## 1 X         0.189    -0.180
## 2 Y        -0.504     0.287
## 3 Z        -5.17      1.19
```

Note: The second example — which has combined different pivoting arguments — has effectively transposed the data.

3) `tidyverse::separate()`

Sometimes, cell values provide information that should be stored in separate columns. `separate()` offers one way of doing this. (*Side note*: Once you learn regular expressions, you will have an even more powerful tool for this task.)

```
R> economists = data.frame(name = c("Adam.Smith", "Paul.Samuelson", "Milton.Friedman"))
R> economists

##           name
## 1      Adam.Smith
## 2  Paul.Samuelson
## 3 Milton.Friedman
```

3) `tidyverse::separate()`

Sometimes, cell values provide information that should be stored in separate columns. `separate()` offers one way of doing this. (*Side note*: Once you learn regular expressions, you will have an even more powerful tool for this task.)

```
R> economists = data.frame(name = c("Adam.Smith", "Paul.Samuelson", "Milton.Friedman"))
R> economists
```

```
##           name
## 1      Adam.Smith
## 2  Paul.Samuelson
## 3 Milton.Friedman
```

`separate()` in action:

```
R> economists %>% separate(name, c("first_name", "last_name"))

##   first_name last_name
## 1      Adam     Smith
## 2      Paul Samuelson
## 3    Milton Friedman
```

3) `tidy::separate()`

Sometimes, cell values provide information that should be stored in separate columns. `separate()` offers one way of doing this. (*Side note*: Once you learn regular expressions, you will have an even more powerful tool for this task.)

```
R> economists = data.frame(name = c("Adam.Smith", "Paul.Samuelson", "Milton.Friedman"))
R> economists

##           name
## 1      Adam.Smith
## 2  Paul.Samuelson
## 3 Milton.Friedman
```

`separate()` in action:

```
R> economists %>% separate(name, c("first_name", "last_name"))

##   first_name last_name
## 1      Adam     Smith
## 2      Paul Samuelson
## 3    Milton Friedman
```

You can also specify the separation character with `separate(... , sep=".")`. The way `sep` works also depends on column type (character vs. numeric). Check out the [function reference](#).

3) `tidyverse::separate()` cont.

A related function is `separate_rows()`, for splitting up cells that contain multiple fields or observations (a frustratingly common occurrence with survey data).

```
R> jobs = data.frame(  
+   name = c("Jack", "Jill"),  
+   occupation = c("Homemaker", "Philosopher, Philanthropist, Troublemaker")  
+ )  
R> jobs
```

```
##   name          occupation  
## 1 Jack          Homemaker  
## 2 Jill Philosopher, Philanthropist, Troublemaker
```

3) `tidyverse::separate()` cont.

A related function is `separate_rows()`, for splitting up cells that contain multiple fields or observations (a frustratingly common occurrence with survey data).

```
R> jobs = data.frame(  
+   name = c("Jack", "Jill"),  
+   occupation = c("Homemaker", "Philosopher, Philanthropist, Troublemaker")  
+ )  
R> jobs
```

```
##   name          occupation  
## 1 Jack          Homemaker  
## 2 Jill Philosopher, Philanthropist, Troublemaker
```

`separate_rows()` in action:

```
R> jobs %>% separate_rows(occupation)  
  
## # A tibble: 4 × 2  
##   name    occupation  
##   <chr>   <chr>  
## 1 Jack    Homemaker  
## 2 Jill    Philosopher
```

4) tidyverse::unite()

`separate()` has a complementary function, `unite()`. Unsurprisingly, it unites values from multiple columns into one.

```
R> gdp = data.frame(  
+   yr = rep(2016, times = 3),  
+   mnth = rep(1, times = 3),  
+   dy = 1:3,  
+   gdp = rnorm(3, mean = 100, sd = 2)  
+ )  
R> gdp  
  
##      yr mnth dy      gdp  
## 1 2016     1  1  98.81436  
## 2 2016     1  2  97.73040  
## 3 2016     1  3 101.38806  
  
R> ## Combine "yr", "mnth", and "dy" into one "date" column  
R> gdp %>% unite(date, c("yr", "mnth", "dy"), sep = "-")  
  
##      date      gdp  
## 1 2016-1-1  98.81436  
## 2 2016-1-2  97.73040  
## 3 2016-1-3 101.38806
```

4) `tidyr::unite()` cont.

Note that `unite()` will automatically create a character variable. You can see this better if we convert it to a tibble.

```
R> gdp_u = gdp %>%  
+   unite(date,  
+         c("yr", "mnth", "dy"),  
+         sep = "-") %>%  
+   as_tibble()  
R> gdp_u
```

```
## # A tibble: 3 × 2  
##   date      gdp  
##   <chr>    <dbl>  
## 1 2016-1-1  98.8  
## 2 2016-1-2  97.7  
## 3 2016-1-3 101.
```

4) `tidyr::unite()` cont.

Note that `unite()` will automatically create a character variable. You can see this better if we convert it to a tibble.

```
R> gdp_u = gdp %>%  
+   unite(date,  
+         c("yr", "mnth", "dy"),  
+         sep = "-") %>%  
+   as_tibble()  
R> gdp_u  
  
## # A tibble: 3 × 2  
##   date      gdp  
##   <chr>    <dbl>  
## 1 2016-1-1  98.8  
## 2 2016-1-2  97.7  
## 3 2016-1-3 101.
```

If you want to convert it to something else (e.g. date or numeric) then you will need to modify it using `mutate()`. See below for an example, using the `lubridate` package's super helpful date conversion functions.

```
R> library(lubridate)  
R> gdp_u %>% mutate(date = ymd(date))  
  
## # A tibble: 3 × 2  
##   date      gdp  
##   <date>    <dbl>  
## 1 2016-01-01  98.8  
## 2 2016-01-02  97.7  
## 3 2016-01-03 101.
```

Other tidyverse goodies

`crossing()`: Get the full combination of a group of variables.¹

```
R> crossing(side=c("left", "right"), height=c("top", "bottom"))

## # A tibble: 4 × 2
##   side  height
##   <chr> <chr>
## 1 left   bottom
## 2 left   top
## 3 right  bottom
## 4 right  top
```

¹ See `?expand()` and `?complete()` for more specialized functions that allow you to fill in (implicit) missing data or variable combinations in existing data frames. Base R alternative: `expand.grid()`.

Other tidyverse goodies

`crossing()`: Get the full combination of a group of variables.¹

```
R> crossing(side=c("left", "right"), height=c("top", "bottom"))

## # A tibble: 4 × 2
##   side  height
##   <chr> <chr>
## 1 left   bottom
## 2 left   top
## 3 right  bottom
## 4 right  top
```

`drop_na(data, ...)`: Drop rows containing NAs in `...` columns.

¹ See `?expand()` and `?complete()` for more specialized functions that allow you to fill in (implicit) missing data or variable combinations in existing data frames. Base R alternative: `expand.grid()`.

Other tidyverse goodies

`crossing()`: Get the full combination of a group of variables.¹

```
R> crossing(side=c("left", "right"), height=c("top", "bottom"))

## # A tibble: 4 × 2
##   side  height
##   <chr> <chr>
## 1 left   bottom
## 2 left   top
## 3 right  bottom
## 4 right  top
```

`drop_na(data, ...)`: Drop rows containing NAs in `...` columns.

`fill(data, ..., direction = c("down", "up"))`: Fill in NAs in `...` columns with most recent non-NA values.

¹ See `?expand()` and `?complete()` for more specialized functions that allow you to fill in (implicit) missing data or variable combinations in existing data frames. Base R alternative: `expand.grid()`.

Tidy programming

Tidy programming basics

"Tidy programming" is not a strictly defined practice in the tidyverse. However, there are some common programming strategies that help you keep your code and workflow tidy. These include:

- Pipes (you already know that )
- User-generated functions
- Functional programming with `purrr`

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"Tidy programming" is not a strictly defined practice in the tidyverse. However, there are some common programming strategies that help you keep your code and workflow tidy. These include:

- Pipes (you already know that 
- User-generated functions
- Functional programming with `purrr`

The latter two are extremely helpful - in particular when you are confronted with iterative tasks.

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"Tidy programming" is not a strictly defined practice in the tidyverse. However, there are some common programming strategies that help you keep your code and workflow tidy. These include:

- Pipes (you already know that 
- User-generated functions
- Functional programming with `purrr`

The latter two are extremely helpful - in particular when you are confronted with iterative tasks.

We will now learn the basics of creating your own functions and functional programming with R. There is much more to learn about these topics, so we will revisit them as the course progresses.

Creating functions

Why creating functions?

That's a legit question. There are 18,000+ **packages** on CRAN (and many, many more on GitHub and other repositories) containing zillions of functions. Why should you create yet another one?

- Every data science project is unique. There are problems only you have to solve.
- For problems that are repetitive, you'll quickly look for options to automate the task.
- Functions are a great way to automate.

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Examples where creating functions makes sense

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Examples where creating functions makes sense

1. You want to scrape thousands of websites. This implies multiple steps, from downloading to parsing and cleaning. All these steps can be achieved with existing functions, but the fine-tuning is specific to the set of websites. You build one (or a set of) scraping functions that take the websites as input and return a cleaned data frame ready to be analyzed.

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Examples where creating functions makes sense

1. You want to scrape thousands of websites. This implies multiple steps, from downloading to parsing and cleaning. All these steps can be achieved with existing functions, but the fine-tuning is specific to the set of websites. You build one (or a set of) scraping functions that take the websites as input and return a cleaned data frame ready to be analyzed.
2. You want to estimate not one but multiple models on your dataset. The models vary both in terms of data input and specification. Again, based on existing modeling functions you tailor your own, allowing you to run all these models automatically and to parse the results into one clean data frame.

Basic syntax

Writing your own function in R is easy with the `function()` function¹. The basic syntax is as follows:

```
R> my_func <- function(ARGUMENTS) {  
+   OPERATIONS  
+   return(VALUE)  
+ }
```

¹ Yes, a function to create functions. 😅

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+   OPERATIONS  
+   return(VALUE)  
+ }
```

- We write functions to apply them later. So, we have to give them a name. Here, we name it "`my_func`".
- Also, our function (almost) always needs input, plus we want to specify how exactly the function should behave. We can use arguments for this, which are specified as arguments of the `function()` function.

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Basic syntax

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```
R> my_func <- function(ARGUMENTS) {  
+     OPERATIONS  
+     return(VALUE)  
+ }
```

- Next, we specify anything we want the function to do.
- This comes in between curly brackets, `{ ... }`.
- Importantly, we can recycle arguments by calling them by their name.

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```
R> my_func <- function(ARGUMENTS) {  
+   OPERATIONS  
+   return(VALUE)  
+ }
```

- Finally, we specify what the function should return.
- This could be a list, data.frame, vector, sentence - or anything else really.

¹ Yes, a function to create functions. 😊

Basic syntax

Writing your own function in R is easy with the `function()` function¹. The basic syntax is as follows:

```
R> my_func <- function(ARGUMENTS) {  
+   OPERATIONS  
+   return(VALUE)  
+ }
```

- Oh, and don't forget to close the curly brackets...

¹ Yes, a function to create functions. 😅

Basic syntax

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```
R> my_func <- function(ARGUMENTS) {  
+   OPERATIONS  
+   return(VALUE)  
+ }
```

Let's try it out with a simple example function - one that converts temperatures from **Fahrenheit to Celsius**:²

```
R> fahrenheit_to_celsius <- function(temp_F) {  
+   temp_C <- (temp_F - 32) * (5/9)  
+   return(temp_C)  
+ }
```

¹ Yes, a function to create functions. 😊

² Courtesy of [Software Carpentry](#).

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```
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+   temp_C <- (temp_F - 32) * (5/9)  
+   return(temp_C)  
+ }
```

- Our function has an intuitive name.
- Also, it takes just one thing as input, which we call `temp_F`.

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Basic syntax

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```

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```
R> fahrenheit_to_celsius <- function(temp_F) {  
+   temp_C <- (temp_F - 32) * (5/9)  
+   return(temp_C)  
+ }
```

- We now take up the argument `temp_F`, do something with it, and store the output in a new object, `temp_C`.
- Importantly, that object only lives within the function. When the function is run, we cannot access it from the environment.

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Basic syntax

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R> my_func <- function(ARGUMENTS) {  
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```

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```
R> fahrenheit_to_celsius <- function(temp_F) {  
+   temp_C <- (temp_F - 32) * (5/9)  
+   return(temp_C)  
+ }
```

- Finally, the output is returned.

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Basic syntax

Writing your own function in R is easy with the `function()` function¹. The basic syntax is as follows:

```
R> my_func <- function(ARGUMENTS) {  
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+ }
```

Let's try it out with a simple example function - one that converts temperatures from **Fahrenheit to Celsius**:

```
R> fahrenheit_to_celsius <- function(temp_F) {  
+   temp_C <- (temp_F - 32) * (5/9)  
+   return(temp_C)  
+ }
```

Now, let's try out the function:

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Basic syntax

Writing your own function in R is easy with the `function()` function¹. The basic syntax is as follows:

```
R> my_func <- function(ARGUMENTS) {  
+   OPERATIONS  
+   return(VALUE)  
+ }
```

Let's try it out with a simple example function - one that converts temperatures from **Fahrenheit to Celsius**:

```
R> fahrenheit_to_celsius <- function(temp_F) {  
+   temp_C <- (temp_F - 32) * (5/9)  
+   return(temp_C)  
+ }
```

Now, let's try out the function:

```
R> fahrenheit_to_celsius(451)  
## [1] 232.7778
```

¹ Yes, a function to create functions. 😊

Basic syntax

Writing your own function in R is easy with the `function()` function¹. The basic syntax is as follows:

```
R> my_func <- function(ARGUMENTS) {  
+   OPERATIONS  
+   return(VALUE)  
+ }
```

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Now, let's try out the function:

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R> fahrenheit_to_celsius(451)  
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```

Pretty hot, isn't it?

¹ Yes, a function to create functions. 😅

Functions: default argument values, if(), else()

Let's make the function a bit more complex, but also more fun.

```
R> temp_convert <-  
+   function(temp, from = "f") {  
+     if (!(from %in% c("f", "c"))){  
+       stop("No valid input  
+               temperature specified.")  
+     }  
+     if (from == "f") {  
+       out <- (temp - 32) * (5/9)  
+     } else {  
+       out <- temp * (9/5) + 32  
+     }  
+     if((from == "c" & temp > 30) |  
+         (from == "f" & out > 30)) {  
+       message("That's damn hot!")  
+     }else{  
+       message("That's not so hot.")  
+     }  
+     return(out) # return temperature  
+ }
```

Functions: default argument values, if(), else()

Let's make the function a bit more complex, but also more fun.

- By giving `from` a default value ("f"), we ensure that the function returns valid output when only the key input, `temp`, is provided.

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- Make R more talkative with `message()`. Future-You will like it!

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```

Functional programming

R is a functional language. It encourages to use and build your own functions to solve problems. Often, this implies decomposing a large problem into small pieces, and solving each of them with independent functions.

There is much more to learn about functions and [functional programming](#). Useful resources include:

- The chapter on functions in [R for Data Science](#).
- The section on functional programming in [Advanced R](#).
- The [R packages](#) book, which we will turn to later in more detail. In a way, bundling functions in a package is sometimes the next logical step.

Iteration

The ubiquity of iteration

- Often we have to run the same task over and over again, with minor variations. Examples:
 - Standardize values of a variable
 - Recode all numeric variables in a dataset
 - Running multiple models with varying covariate sets
- A benefit of scripting languages in data (as opposed to point-and-click solutions) is that we can easily automate the process of iteration

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- A benefit of scripting languages in data (as opposed to point-and-click solutions) is that we can easily automate the process of iteration

Ways to iterate

- A simple approach is to copy-and-paste code with minor modifications (→ "duplicate code", → "copy-and-paste programming"). This is lazy, error-prone, not very efficient, and violates the "Don't repeat yourself" (DRY) principle.
- In R, **vectorization**, that is applying a function to every element of a vector at once, already does a good share of iteration for us.
- `for()` loops are intuitive and straightforward to build, but sometimes not very efficient.
- Finally, we learned about functions. Now, we learn how to unleash their power by applying them to anything we interact with in R at scale.

Iteration with purrr

The tidyverse way to iterate

- For *real* functional programming in base R, we can use the `*apply()` family of functions (`lapply()`, `sapply()`, etc.). See [here](#) for an excellent summary.
- In the tidyverse, this functionality comes with the `purrr` package.
- At its core is the `map*` family of functions.



How `purrr` works

- The idea is always to **apply** a function to **x**, where x can be a list, vector, data.frame, or something more complex.
- The output is then returned as output of a pre-defined type (e.g., a list).
- The set of `map()`-style functions is quite comprehensive; see this [cheat sheet](#) for an overview.

Iteration with purrr: map()

The `map*`() functions all follow a similar syntax:

$map(.x, .f, ...)$

We use it to apply a function `.f`

Overview The map functions <https://r4ds.had.co.nz/iteration.html#the-map-functions> Mapping over multiple arguments
<https://r4ds.had.co.nz/iteration.html#mapping-over-multiple-arguments>

Coding style

Coding style: the basics

Why adhering to a particular style of coding?

- It reduces the number of arbitrary decisions you have to consciously make during coding. We make an arbitrary decision (convention) once, not always ad hoc.
- It provides consistency.
- It makes code easier to write.
- It makes code easier to read, especially in the long term (i.e. two days after you've closed a script).

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What are questions of style?

- Questions of style are a matter of opinion.
- We will mostly follow Hadley Wickham's opinion as expressed in the "[tidyverse style guide](#)".
- We'll consider how to
 - name,
 - comment,
 - structure, and
 - write.

Naming things

Surprisingly many things can go wrong with naming...

"There are only two hard things in Computer Science:
cache invalidation and naming things." - *Phil Karlton*

Credit karlton.org



Credit [Mashable](#)

Naming files

- Code file names should be meaningful and end in `.R`.
- Avoid using special characters in file names. Stick with numbers, letters, dashes (`-`), and underscores (`_`).
- Some examples:

```
# Good
fit_models.R
utility_functions.R
```

```
# Bad
fit models.R
foo.r
stuff.r
```

- If files should be run in a particular order, prefix them with numbers:

```
00_download.R
01_explore.R
...
09_model.R
10_visualize.R
```

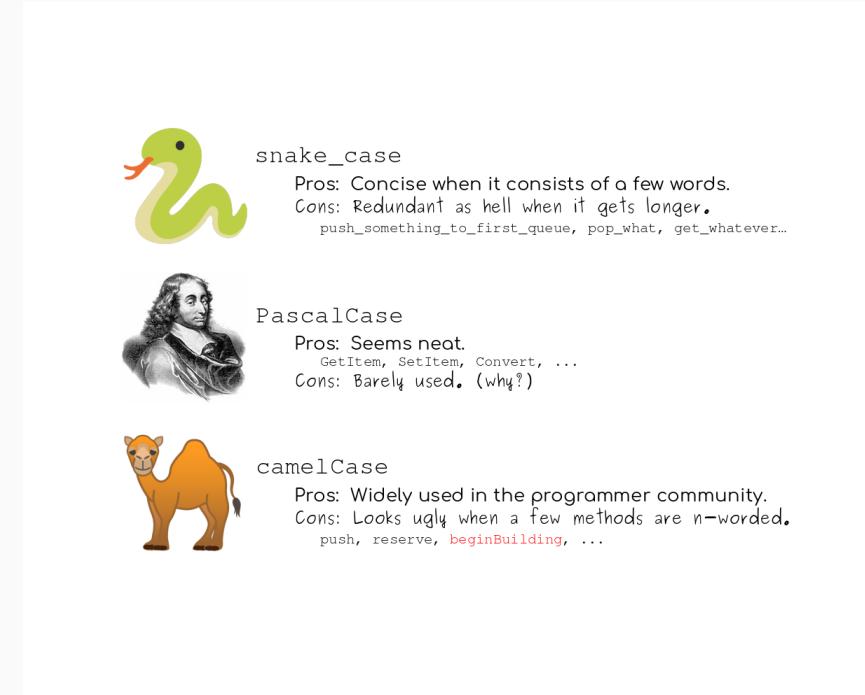
Naming objects and variables

- There are various conventions of how to write phrases without spaces or punctuation. Some of these have been adapted in programming, such as `camelCase`, `PascalCase`, or `snake_case`.
- The `tidyverse` way: Object and variable names should use only lowercase letters, numbers, and underscores.
- Examples:

```
# Good
day_one # snake_case
day_1 # snake_case
```

```
# Less good
dayOne # camelCase
DayOne # PascalCase
day.one # dot.case
```

```
# Dysfunctional
day-one # kebab-case
```



Credit [cassert24/Reddit](#)

Naming functions

- In addition to following the general advice for object names, strive to use verbs for function names:

```
# Good
add_row()
permute()
```

```
# Bad
row_adder()
permutation()
```

- Also, try avoiding function names that already exist, in particular those that come with a loaded package.
- This often implies a trade-off between shortness and uniqueness. In any case, you would try to avoid situations that force you disambiguate functions with the same name (as in `dplyr::select`; see "[R packages](#)").
- Check out this [Wikipedia page](#) or this [Stackoverflow post](#) for more background on naming conventions in programming!

Commenting on things

Why commenting at all?

- It's often tempting to set up a project assuming that you will be the only person working on it, e.g. as homework. But that's almost never true.
- You have project partners, co-authors, principals.
- Even if not, there's someone else who you always have to keep happy: Future-you.
- Comment often to make Future-you happy about Past-you by document what Present-You is doing/thinking/planning to do.

Past-you



Present-you



Future-you



Commenting on things *cont.*

General advice

- Each line of a comment should begin with the comment symbol and a single space: `#`
- Use comments to record important findings and analysis decisions.
- If you need comments to explain what your code is doing, consider rewriting your code to be clearer.
- But: comments can work well as "sub-headlines".
- If you discover that you have more comments than code, consider switching to R Markdown.
- (Longer) comments generally work better if they get their own line.

```
R> # define job status  
R> dat$at_work ← dat$job %in% c(2, 3)  
R> dat$at_work ← dat$job %in% c(2, 3) # define job .
```

Giving structure

- Use commented lines together with dashes to break up your file into easily readable chunks.
- RStudio automatically detects these chunks and turns them into sections in the script outline.

```
R> # Input/output -----  
R>  
R> # input  
R> c("data/survey2021.csv")  
R>  
R> # output  
R> c("survey_2021_cleaned.RData",  
+     "resp_ids.csv")  
R>  
R> # Load data -----  
R>  
R> # Plot data -----
```

Other stuff

- Use **spaces** generously, but not too generously.
Always put a space after a comma, never before, just like in regular English.
- Use `←`, not `=`, for **assignment**.
- For **logical operators**, prefer `TRUE` and `FALSE` over `T` and `F`.
- To facilitate readability, **keep your lines short**. Strive to limit your code to about 80 characters per line.
- If a **function call is too long** to fit on a single line, use one line each for the function name, each argument, and the closing bracket.
- Use **pipes**. When you use them, they should always have a space before it, and should usually be followed by a new line.

Spacing

```
R> # Good  
R> mean(x, na.rm = TRUE)  
R> height ← (feet * 12) + inches  
R>  
R> # Bad  
R> mean(x,na.rm=TRUE)  
R> mean ( x, na.rm = TRUE )  
R> height←feet*12+inches
```

Piping

```
R> babynames %>%  
+   filter(name %>% equals("Kim")) %>%  
+   group_by(year, sex) %>%  
+   summarize(total = sum(n)) %>%  
+   qplot(year, total, color = sex, data = .,  
+         geom = "line") %>%  
+   add(ggtitle('People named "Kim"')) %>%  
+   print
```

Summary

FAQ

Q: How much time should I invest to learn the tidyverse?

A: A week clearly is not enough. You will automatically practice more over the course of the semester. Coding is also self-learning, though. Look out for other tidyverse packages that sound interesting, and practice them!

Q: Should I still learn base R?

A: You are going to, automatically. All I've done is to nudge you to a certain preference. But base R is not evil. It's just a bit less accessible.

Q: Does the tidyverse also work for Big Data

A: Sure! However, when dealing with large datasets, you might want to consider the `data.table` package as an alternative to `dplyr`. Or just use `dtplyr`, a `data.table` backend for `dplyr` that allows you to write `dplyr` code that is automatically translated to the equivalent, but usually much faster, `data.table` code.

Q: What from the tidyverse should I learn next?

```
R> sample(tidyverse_packages(), 1)
```

Coming up

The first **real** assignment

Now we get serious: Assignment 1 is up on GitHub Classroom. Check it out and solve problems with the tidyverse.

Next lecture

Relational databases and SQL