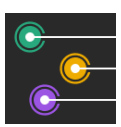
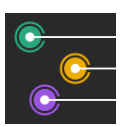
Reproducible Data Analysis with R

— Introduction to R —

Cédric Scherer // R Course TU Dresden // Feb 27–Mar 3, 2023



Introduction to R (and RStudio)



What is R?

R is a programming language and free software environment for statistical computing and graphics.

R was conceived in 1992 by **Ross Ihaka** and **Robert Gentleman** as an open source implementation of the S programming language and released in 1995.

Since then, R has outgrown its original purpose and is used to:

- run statistical analyses and data-science workflows
- design high-level, publication–ready visualizations
- generate automated reports
- develop stand-alone web applications
- create presentation slides, books, and web pages

Why (not) R?

Pros:

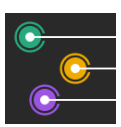
- free, open source, and platform-independent
- wide range of dedicated packages provide extra functionality
- highly compatible with many other programming languages
- strong capabilities for data analysis and visualization
- huge (and open) online community
- often experienced as *easy to code* (from a non-programmer perspective)

Cons:

- performance: scalability, memory and speed
- steep learning curve (as likely any programming language)
- potential security issues (relevant for web applications)
- often experienced as *strange to code* (from a programmer perspective)

Illustration by Allison Horst

R versus RStudio



R Engine

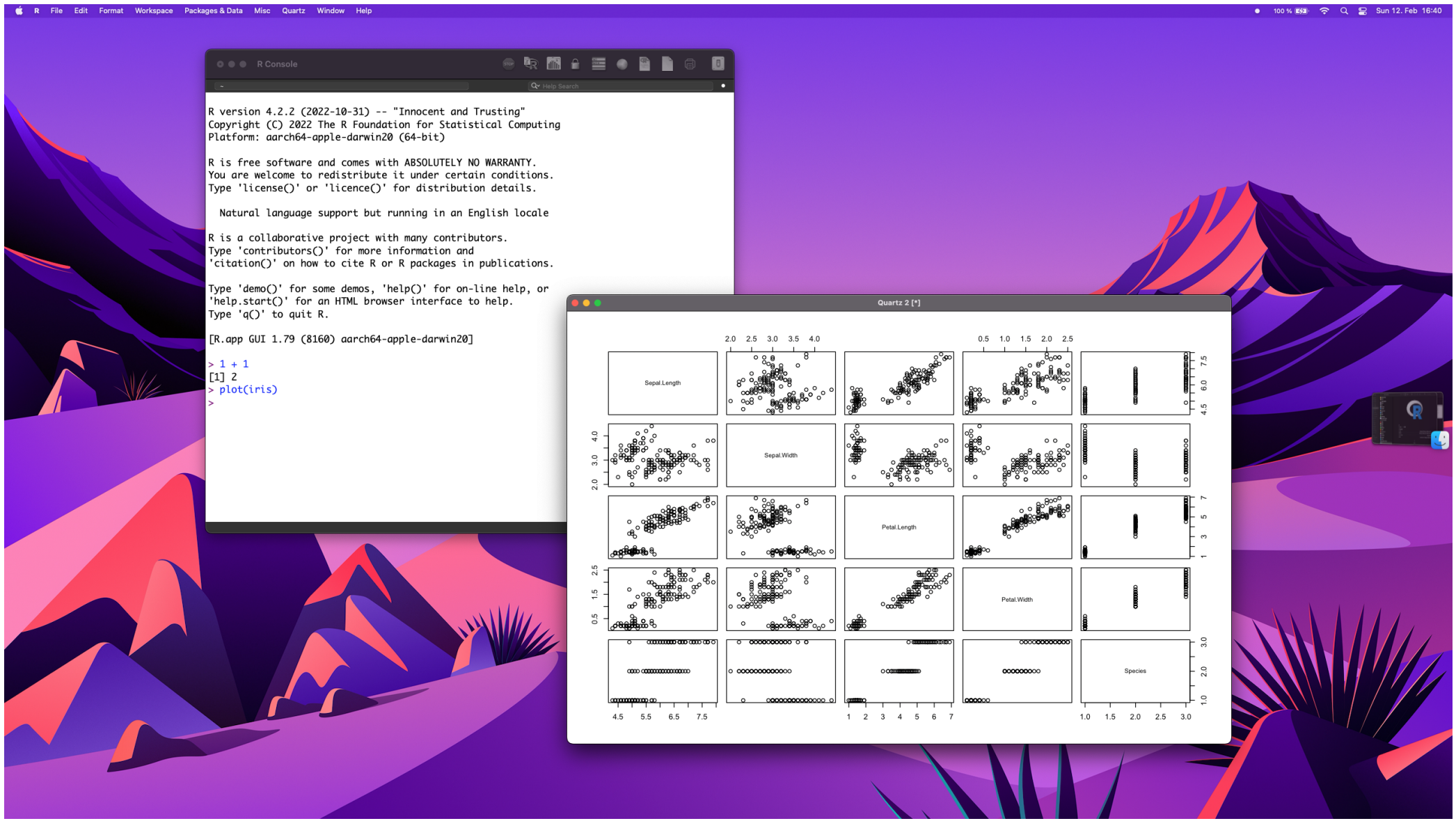
RStudio Dashboard

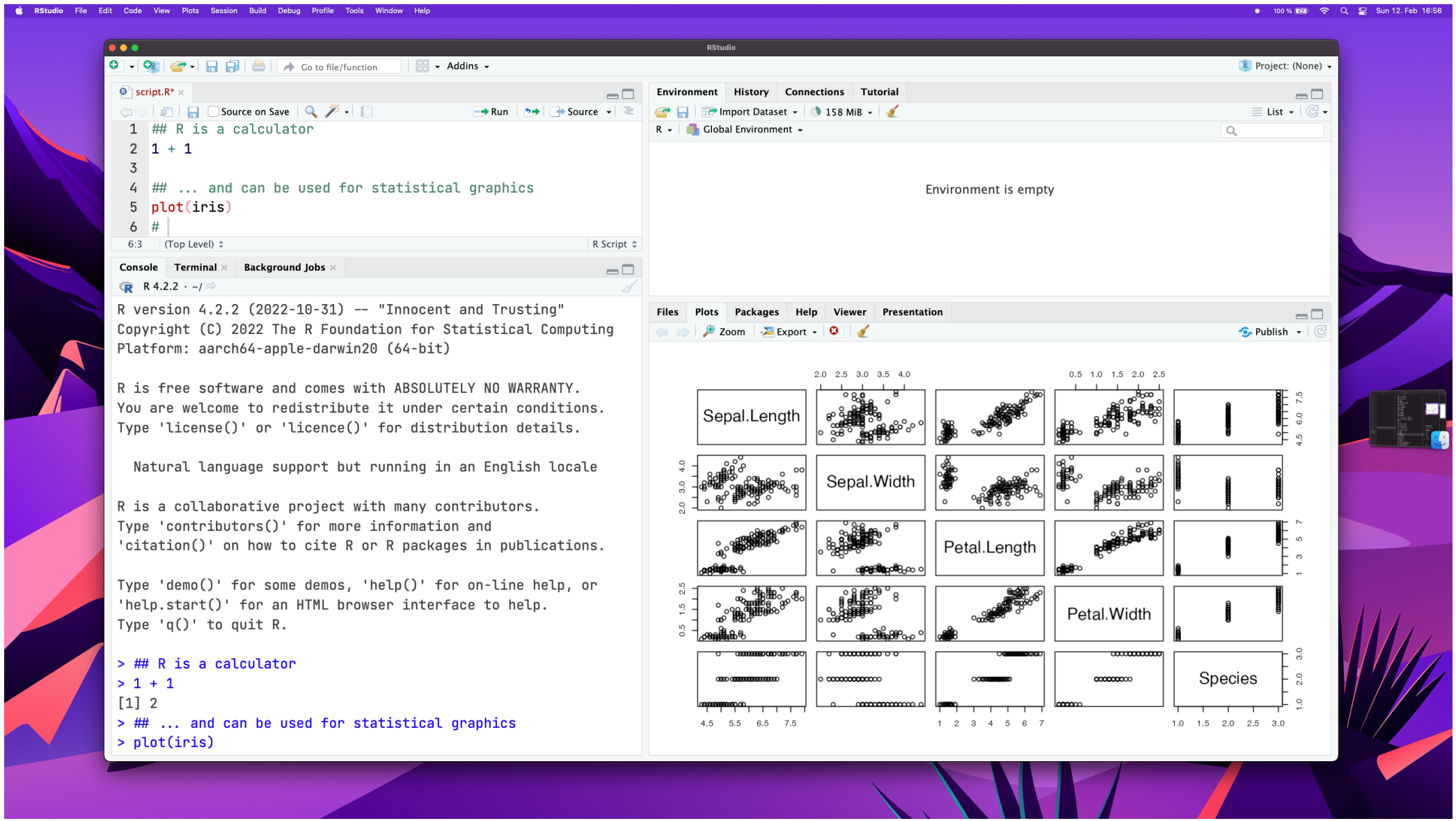
Modified from ModernDive

- **RStudio** is an open-source IDE (integrated development environment) for R
- most popular R IDE since several years (what is tinnR?!)
- many features + extensions to facilitate workflows (version control, toc, add-ins, ...)
- availability of R projects and Rmarkdown/Quarto (later more)

Your Turn: Install R & RStudio

- Download and install **R** via
  cloud.r-project.org
- Download and install **RStudio Desktop** via
  posit.co/download/rstudio-desktop


R File Edit Format Workspace Packages & Data Misc Quartz Window Help
Sun 12. Feb 16:40
R Console
R version 4.2.2 (2022-10-31) -- "Innocent and Trusting"
Copyright (C) 2022 The R Foundation for Statistical Computing
Platform: aarch64-apple-darwin20 (64-bit)
R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.
Natural language support but running in an English locale
R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.
Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.
[R.app GUI 1.79 (8160) aarch64-apple-darwin20]
> 1 + 1
[1] 2
> plot(iris)
>
Quartz 2 [*]
Sepal.Length
Sepal.Width
Petal.Length
Petal.Width
Species


RStudio
script.R*
R is a calculator
1 + 1
... and can be used for statistical graphics
plot(iris)
Environment is empty
R version 4.2.2 (2022-10-31) -- "Innocent and Trusting"
Copyright (C) 2022 The R Foundation for Statistical Computing
Platform: aarch64-apple-darwin20 (64-bit)
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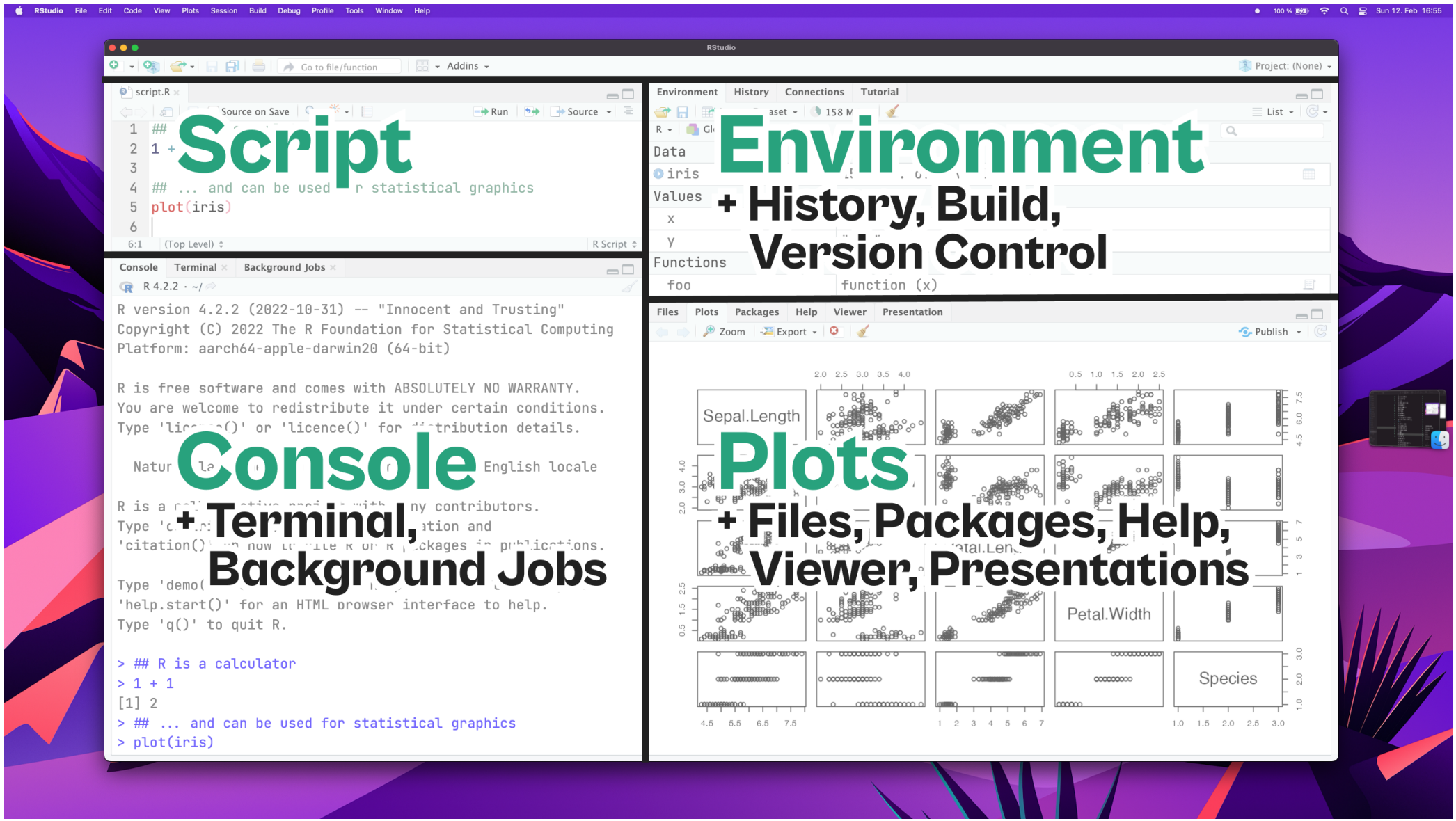
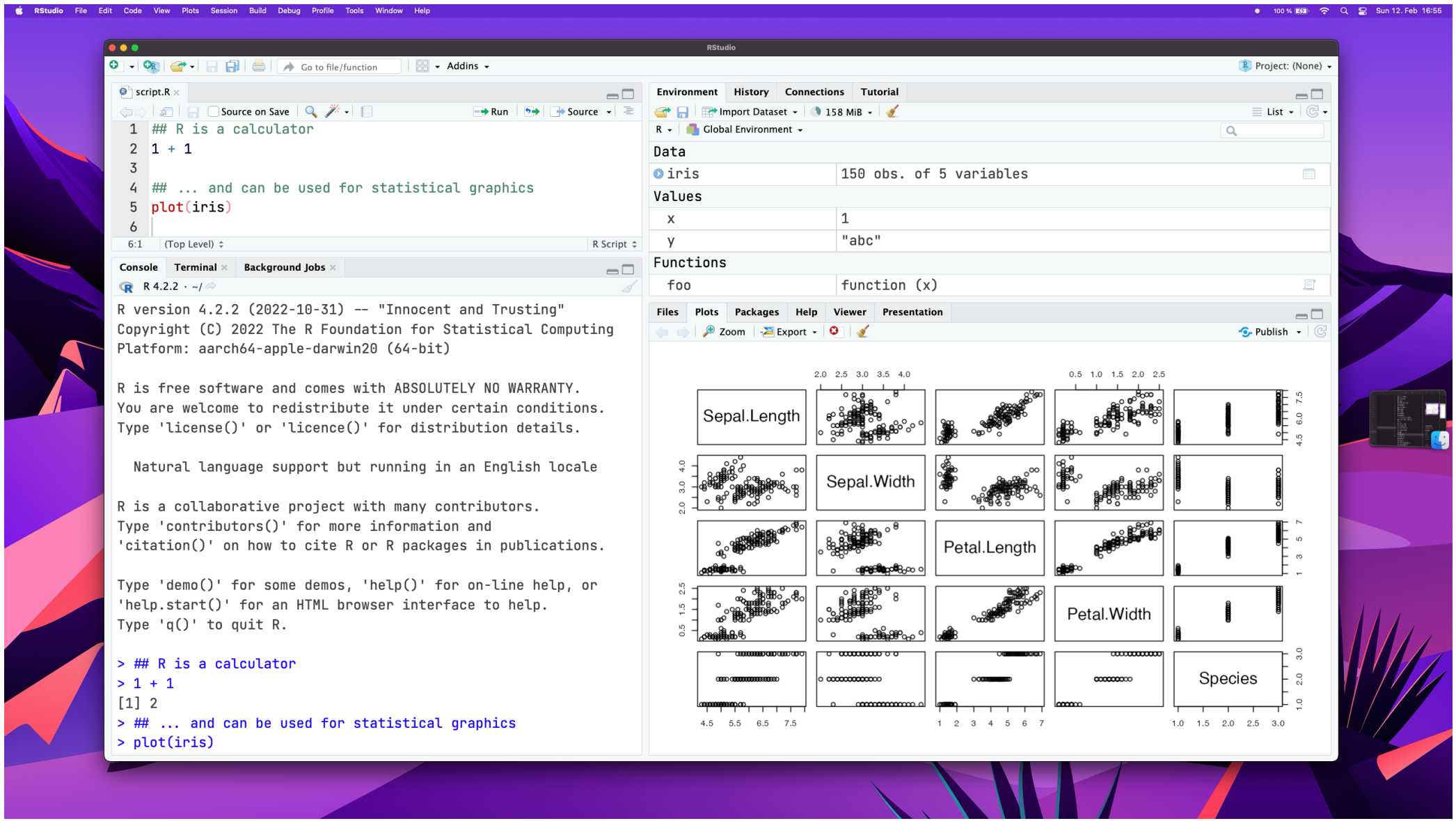
Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.
> ## R is a calculator
> 1 + 1
[1] 2
> ## ... and can be used for statistical graphics
> plot(iris)
Sepal.Length
Sepal.Width
Petal.Length
Petal.Width
Species


Script
Environment
+ History, Build,
Version Control
Console
+ Terminal,
Background Jobs
Plots
+ Files, Packages, Help,
Viewer, Presentations


RStudio
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1 + 1
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Background Jobs
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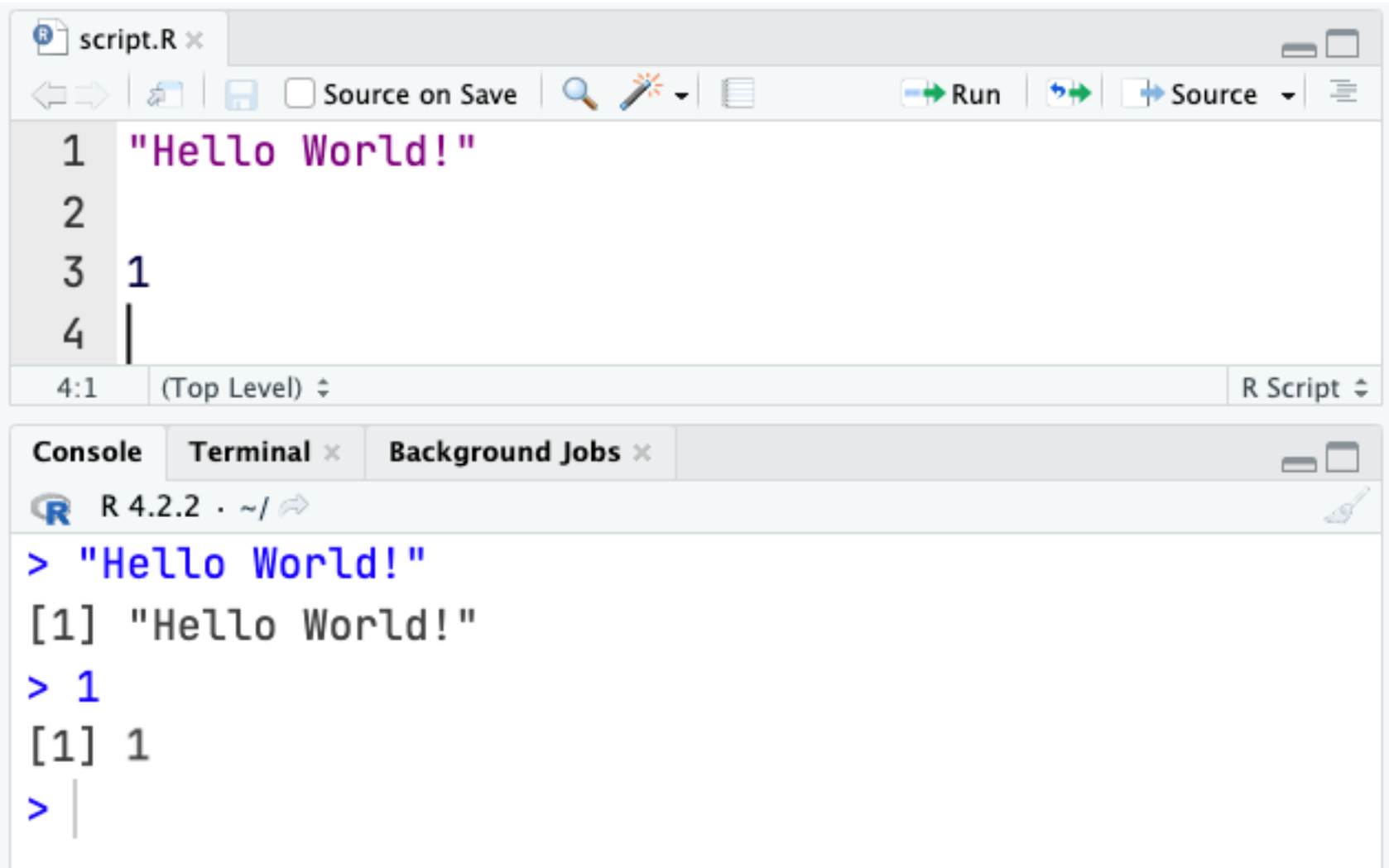
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.
> ## R is a calculator
> 1 + 1
[1] 2
> ## ... and can be used for statistical graphics
> plot(iris)
Environment
History
Connections
Tutorial
Data
iris
150 obs. of 5 variables
Values
x
1
y
"abc"
Functions
foo
function (x)
Files
Plots
Packages
Help
Viewer
Presentation
Sepal.Length
Sepal.Width
Petal.Length
Petal.Width
Species

Your Turn: “Hello World!”

- Open **R** and run the following:
  - `"Hello World!"`
  - `1`
- Open **RStudio** and get familiar with its environment.
  - Go to `Help > Cheatsheets > RStudio IDE Cheat Sheet` and study the document.
  - Go to `View > Panes > Pane Layout` and arrange the panes as you prefer.
  - Open a script via `File > New File... > R Script`, add the three commands from above and save the script.
  - Run the commands by placing your cursor in the first line of your script and clicking the `Run` button or via the shortcut `Cmd + Enter`.
  - Save the script.

The Console

Code you are running appears here—the line starts with `>`.
It also prints the output—the line starts with `[1]`.



Comments

Comments are useful to

1. inactivate code that you don't want to run
2. add comments explaining your thoughts and reasoning

In R, comments are encoded by a hash #.
Everything on the same line will not be treated as actual code.

My personal convention is to use # to comment code and ## to add comments:

```
1 # "Hello World!" ## I don't need this anymore but prefer to keep it
```


R Projects

R projects (or RStudio projects) give you a solid workflow that will serve you well in the future:

- it builds on the idea that all files associated with your project should be stored in the same folder
  - helps to find files
  - increases reproducibility
  - facilitates collaboration
- it sets the working directory to the folder the `.Rproj` files is placed in
  - ensures a correct working directory
  - independent of the operating setup and general folder structure
  - reduces hurdles when collaborating

> Please re-open RStudio by double-clicking the `.Rproj file`.

Introduction to R

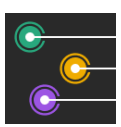
— Values —

Values

```
1
```

```
"Hello World!"
```

```
"2023-02-27 09:00:00"
```

Values

```
1 1
```

```
[1] 1
```

```
1 "Hello World!"
```

```
[1] "Hello World!"
```

```
1 "2023-02-27 09:00:00"
```

```
[1] "2023-02-27 09:00:00"
```

```
1 x
```

```
Error in eval(expr, envir, enclos): object 'x' not found
```

```
1 "x"
```

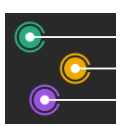
```
[1] "x"
```

```
1 pi
```

```
[1] 3.141593
```


Introduction to R

— Functions —



Your Turn: Arithmetic Operations

- Type `2 + 3` and run it.
- Play around with other calculus operators such as `-`, `*`, `/`, or `^`.
- Calculate the square root of a number with `sqrt()`.

- What is the difference between the first 5 and the `sqrt` calculation?

R is a Calculator!

```
2 + 3
```

```
[1] 5
```

```
(59 + 73 + 2) * 5
```

```
[1] 670
```

```
1 / 200 * 30
```

```
[1] 0.15
```

```
sin(pi / 2)
```

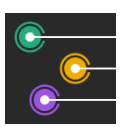
```
[1] 1
```

```
10^12 * sqrt(4312)
```

```
[1] 6.566582e+13
```

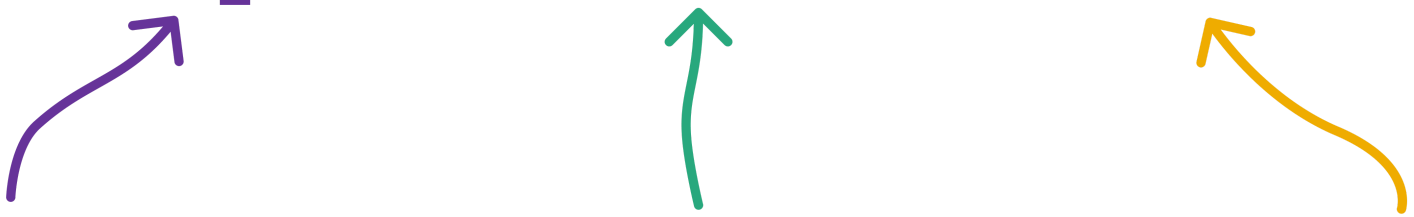
```
log(exp(5))
```

```
[1] 5
```

Functions

```
sqrt(x = 25)
```



function name **argument name** **argument value**

Functions

```
sqrt(x = 25)
[1] 5
```

return value

Functions

R has a large collection of built-in functions that are called like this:

```
function_name(arg1 = val1, arg2 = val2, ...)
```

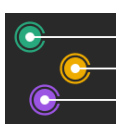
We already have seen some functions in the exercise before:
`+`, `-`, `*`, `^`, `sqrt()`, `log()` all are functions.

Functions

```
1 sqrt()
2 log()
3 sin()
4 exp()
5 mean()
```

```
1 sqrt(x = 25)
```

```
[1] 5
```

Infix Functions

```
1 +
2 -
3 ^
4 %%
5 %in%
```

Unary Operator:

```
1 -1
```

```
[1] -1
```

Binary Operator:

```
1 12 %% 5
```

```
[1] 2
```


Function Body

```
1 log
```

```
function (x, base = exp(1))  .Primitive("log")
```

```
1 mean
```

```
function (x, ...)
UseMethod("mean")
<bytecode: 0x133b79950>
<environment: namespace:base>
```

```
1 methods(mean)
```

```
[1] mean.Date        mean.default     mean.difftime    mean.POSIXct     mean.POSIXlt     mean.quosure*
[7] mean.vctrs_vctr*
see '?methods' for accessing help and source code
```

```
1 `+`
```

```
function (e1, e2)  .Primitive("+")
```

```
1 read.csv
```

```
function (file, header = TRUE, sep = ",", quote = "\"", dec = ".",
    fill = TRUE, comment.char = "", ...)
read.table(file = file, header = header, sep = sep, quote = quote,
    dec = dec, fill = fill, comment.char = comment.char, ...)
<bytecode: 0x124488690>
<environment: namespace:utils>
```


Function Body

```
  1  read.table
```

```
function (file, header = FALSE, sep = "", quote = "\"'", dec = ".",
    numerals = c("allow.loss", "warn.loss", "no.loss"), row.names,
    col.names, as.is = !stringsAsFactors, na.strings = "NA",
    colClasses = NA, nrows = -1, skip = 0, check.names = TRUE,
    fill = !blank.lines.skip, strip.white = FALSE, blank.lines.skip = TRUE,
    comment.char = "#", allowEscapes = FALSE, flush = FALSE,
    stringsAsFactors = FALSE, fileEncoding = "", encoding = "unknown",
    text, skipNul = FALSE)
{
    if (missing(file) && !missing(text)) {
        file <- textConnection(text, encoding = "UTF-8")
        encoding <- "UTF-8"
        on.exit(close(file))
    }
    if (is.character(file)) {
        file <- if (nzchar(fileEncoding))
            file(file, "rt", encoding = fileEncoding)
        else file(file, "rt")
        on.exit(close(file))
```


Function Arguments

```
log(x = 25)  ## `base = exp(1)` as default
```

```
[1] 3.218876
```

```
log(x = 25, base = 10)
```

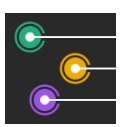
```
[1] 1.39794
```

```
log10(x = 25)  ## wrapper for `log(x, base = 10)`
```

```
[1] 1.39794
```

```
log2(x = 25)  ## wrapper for `log(x, base = 2)`
```

```
[1] 4.643856
```

Learn How to Use a Function

```
1 help(log)
2 ?log
3 # cursor + F1
```

Description

`log` computes logarithms, by default natural logarithms, `log10` computes common (i.e., base 10) logarithms, and `log2` computes binary (i.e., base 2) logarithms. The general form `log(x, base)` computes logarithms with base base.

Learn How to Use a Function

```
help(log)
?log
# cursor + F1
```

Usage

```
log(x, base = exp(1))
logb(x, base = exp(1))
log10(x)
log2(x)

log1p(x)

exp(x)
expm1(x)
```


Learn How to Use a Function

```
1 help(log)
2 ?log
3 # cursor + F1
```

Arguments

x	a numeric or complex vector.
base	the base with respect to which logarithms are computed.

Function Arguments: Implicit Matching

```
log(x = 25, base = 5)
```

```
[1] 2
```

```
log(25, 5)  ## the 1st argument is `x`, the 2nd `base`
```

```
[1] 2
```

```
log(5, 25)  ## the 1st argument is `x`, the 2nd `base`
```

```
[1] 0.5
```

```
log(25, base = 5)  ## the 1st argument is `x`
```

```
[1] 2
```

```
log(base = 5, 25)  ## it works but don't do this
```

```
[1] 2
```

```
log(base = 5, x = 25)  ## be explicit if you want to switch argument positions
```

```
[1] 2
```


Implicit Matching: Be Careful!

Explicit argument names:

```
1 quantile(x = c(5, 1, 3), probs = c(0.25, 0.5, 0.75))
```

```
25% 50% 75%
  2   3   4
```

Implicit matching by position:

```
1 quantile(c(5, 1, 3), c(0.25, 0.5, 0.75))
```

```
25% 50% 75%
  2   3   4
```

Erroneously switching positions can lead to all kinds of trouble:

```
1 quantile(c(0.25, 0.5, 0.75), c(5, 1, 3))
```

```
Error in quantile.default(c(0.25, 0.5, 0.75), c(5, 1, 3)): 'probs' outside [0,1]
```

```
1 quantile(c(0.25, 0.5, 0.75), c(0.95, 0.345, 1))
```

```
   95%  34.5%   100%
0.7250 0.4225 0.7500
```


Your Turn: Function Arguments

Which of these will work?

```
log(x = 1)
log(x = "1")
log(x)
log(value = 1)
log(`1`)
log(1)
```


Introduction to R

— Assignments & Objects —

Your Turn: Assignments & Objects

- Run `x <- 1` and afterwards `x`.
- Next, run `x + 2`.
- Now run `x <- 5` and again `x + 2`.

- Why is there no output when you run the first command?
- What is the arrow symbol `<-` doing?
- What is the value of `x` in the end?
- What happens if you type `y <- x` and what if `y <- x <- 2`?
- And what if you type `y <- 2 <- x` ?
- Can you assign a value and show the object output at the same time?

Assignments & Objects

Assignments & Objects

```
1 x <- 1
2 x
```

```
[1] 1
```

```
1 x + 2
```

```
[1] 3
```

```
1 x <- 5
2 x + 2
```

```
[1] 7
```

```
1 x
```

```
[1] 5
```


Assignments & Objects

```
1 y <- x
2 y
```

```
[1] 5
```

```
1 y <- x
2 y
```

```
[1] 5
```

```
1 y <- x <- 2
2 x
```

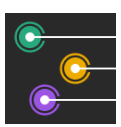
```
[1] 2
```

```
1 y
```

```
[1] 2
```

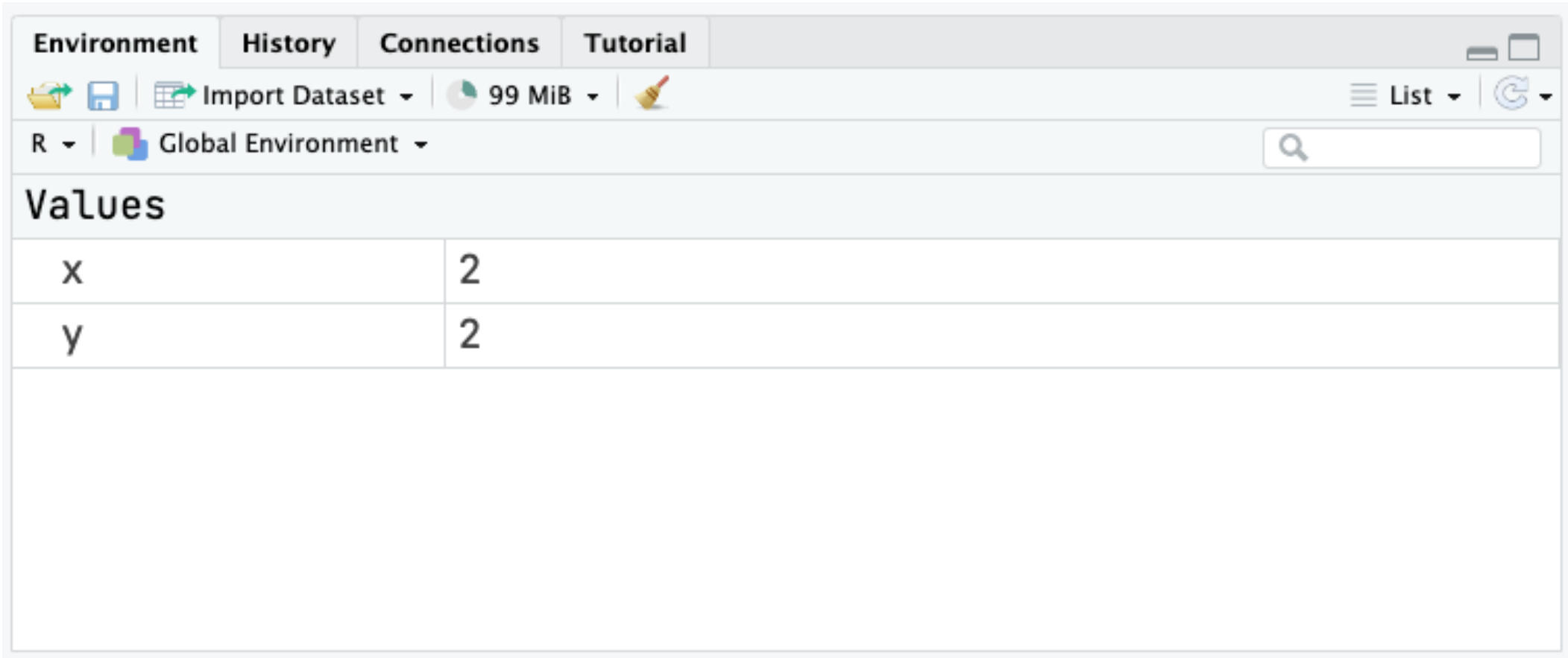
```
1 y <- 2 <- x
```

```
Error in 2 <- x : invalid (do_set) left-hand side to assignment
```

The Environment

By default, assigned objects exist in the **global environment** called `R_GlobalEnv`.
You can find an overview of everything you have defined in the **environment pane**.



Assign & Print Objects

```
print(a <- 123)
```

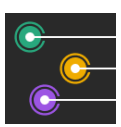
```
[1] 123
```

```
show(a <- 123)
```

```
[1] 123
```

```
(a <- 123)
```

```
[1] 123
```

Syntactic Object Names

- **should be descriptive**
  - trade-off between effort to type and being precise
- **must begin with a letter**
  - `val1` works – `1val` and `.val1` will not work
- **can contain other symbols** inside the name
  - such as numbers, periods, and/or underscores, e.g. `val_1`
  - hyphens do **not** work (do not use "kebab-style", see next slide)
- **are case-sensitive**
  - `myvalues`, `myValues`, and `MyValues` are not the same objects!
- **ideally follow a coherent convention**
  - do not mix different styles, e.g. avoid `val1`, `val_2`, and `val.3`
- **cannot use names that are reserved** and have a certain function in R
  - e.g. `if`, `in`, `function`, `TRUE`, `FALSE`, `NA`, `NaN`

in that case...

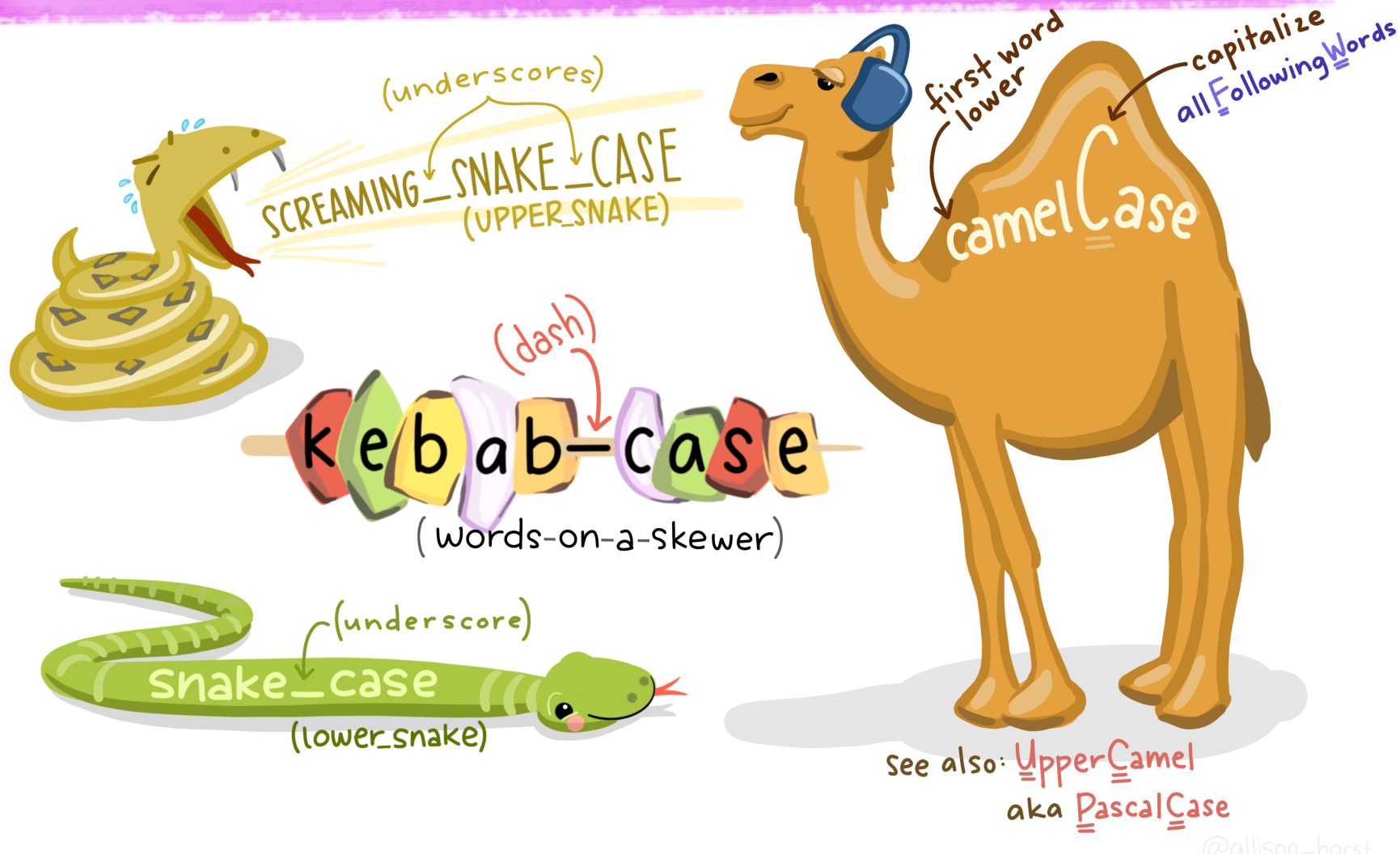


Illustration by Allison Horst

Syntactic Object Names

It's all about readability—decide yourself:

```
1 i_prefer_snake_case
```

```
1 otherPeopleLikeToUseCamelCase
```

```
1 some.people.use.periods
```

```
1 And_aFew.PeopleRENOUNCEconvention
```

```
1 df_population_us
```

```
1 dfPopulationUs
```

```
1 df.population.us
```

```
1 df_Population.US
```


Syntactic Object Names

Potential object names:

- `myvalue1`
- **`myValue1`**
- `MyValue1`
- **`my_value_1`**
- `my.value.1`
- … and all combinations of cases and symbols from above

Most importantly:

Use your preferred style but be consistent!

Assignment Syntax

```
1 name <- "Cedric"
2 name
```

```
[1] "Cedric"
```

```
1 "Dresden" -> city  ## right-hand asignment
2 city
```

```
[1] "Dresden"
```

```
1 country = "Germany"  ## a single `=` can also be used for assignment
2 country
```

```
[1] "Germany"
```

Using = is controversially discussed as it can cause confusion but is much more common in other languages.

```
1 country == "Germany" ## a double `=` compares two values!
```

```
[1] TRUE
```

```
1 language == "English" ## a double `=` compares two values!
```

```
Error in eval(expr, envir, enclos): object 'language' not found
```

```
1 log(25, base = 5) ## inside functions a single `=` defines argument inputs!
```

```
[1] 2
```


Using Objects in Functions

```
one <- 1
log(one)
```


Using Objects in Functions

```
1 one <- 1
2 one
```

```
[1] 1
```

```
1 log(one)
```

```
[1] 0
```

```
1 one <- "1"
2 one
```

```
[1] "1"
```

```
1 log(one)
```

```
Error in log(one): non-numeric argument to mathematical function
```


Introduction to R

— Data Types —

Data Types

There are several basic data types in R
including character, double, integer, complex, and logical.

```
1 typeof("Hello World!")
```

```
[1] "character"
```

```
1 typeof(1)
```

```
[1] "double"
```

```
1 typeof(1L)
```

```
[1] "integer"
```

```
1 typeof(1i)
```

```
[1] "complex"
```

```
1 typeof(TRUE)
```

```
[1] "logical"
```

Each of these data types has its own characteristics and use cases.

Data Types & Atomic Classes

```
1 typeof(1)
```

```
[1] "double"
```

```
1 class(1)
```

```
[1] "numeric"
```

```
1 typeof(1L)
```

```
[1] "integer"
```

```
1 class(1L)
```

```
[1] "integer"
```

```
1 typeof(1i)
```

```
[1] "complex"
```

```
1 class(1i)
```

```
[1] "complex"
```

However, even though “integer” and “complex” are specific classes in R, they are still considered subtypes of the more general “numeric” data type.

Coercion into Other Data Types

The `as.*()` functions allow you to change the data type of a value:

```
1 as.character(1)
```

```
[1] "1"
```

```
1 as.integer(1)
```

```
[1] 1
```

```
1 as.complex(1)
```

```
[1] 1+0i
```

```
1 as.logical(1)
```

```
[1] TRUE
```

```
1 as.logical(0)
```

```
[1] FALSE
```


Dates & Timestamps

```
1 typeof("2023-02-27 09:00:00")
```

```
[1] "character"
```

Date Objects

```
1 as.Date("2023-02-27 09:00:00")
```

```
[1] "2023-02-27"
```

```
1 typeof(as.Date("2023-02-27 09:00:00"))
```

```
[1] "double"
```

Datetime Objects

```
1 as.POSIXct("2023-02-27 09:00:00")
```

```
[1] "2023-02-27 09:00:00 CET"
```

```
1 typeof(as.POSIXct("2023-02-27 09:00:00"))
```

```
[1] "double"
```

```
1 as.POSIXlt("2023-02-27 09:00:00")
```

```
[1] "2023-02-27 09:00:00 CET"
```


Dates & Timestamps

```
1 date <- "27.02.2023 09:00"
```

```
1 as.POSIXct(date)
```

```
Error in as.POSIXlt.character(x, tz, ...): character string is not in a standard unambiguous format
```

```
1 as.POSIXct(date, format = "%d.%m.%Y %H:%M")
```

```
[1] "2023-02-27 09:00:00 CET"
```

```
1 as.POSIXct(date, format = "%d.%m.%Y %H:%M", tz = "EST")
```

```
[1] "2023-02-27 09:00:00 EST"
```

```
1 as.POSIXct(date, format = "%d.%m.%Y %H:%M", tz = "America/New_York")
```

```
[1] "2023-02-27 09:00:00 EST"
```

```
1 as.POSIXct(date, format = "%d.%m.%Y %H:%M", tz = "US/Eastern")
```

```
[1] "2023-02-27 09:00:00 EST"
```


Introduction to R

— Unknown Values —

“Not Available”

NA is a special value that is used to represent missing or undefined data.

```
typeof(NA)
```

```
[1] "logical"
```

```
typeof(NA_character_)
```

```
[1] "character"
```

```
typeof(NA_integer_)
```

```
[1] "integer"
```

```
typeof(NA_real_)
```

```
[1] "double"
```

```
typeof(NA_complex_)
```

```
[1] "complex"
```


“Not a Number”

The NaN value is another special value that is used to represent undefined values in mathematical operations:

```
1 NaN
```

```
[1] NaN
```

… such as the result of dividing zero by zero:

```
1 0 / 0
```

```
[1] NaN
```

```
1 is.nan(0 / 0)
```

```
[1] TRUE
```

```
1 is.na(0 / 0)
```

```
[1] TRUE
```


Unknown Values

As they are unknown, the special values NA and NaN are not equal to any other value, including themselves:

```
1 NA == "Cedric"
```

```
[1] NA
```

```
1 NaN == 1
```

```
[1] NA
```

```
1 NA == NA
```

```
[1] NA
```

```
1 NaN == (0 / 0)
```

```
[1] NA
```

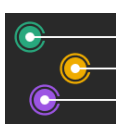
Also, you can't assign any value to the NA and NaN special values:

```
1 NA <- 1
```

```
Error in NA <- 1 : invalid (do_set) left-hand side to assignment
```


Introduction to R

— Vectors —



Your Turn: Calculate Averages

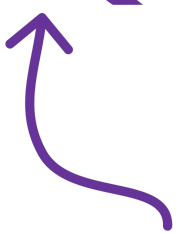
- Calculate the average of these numeric values: `140`, `97`, and `222`

```
1 mean(140, 97, 222)
```

```
[1] 140
```

Vectors

```
c(135, 97, 222)
```



vector function

vector elements

Your Turn: Calculate Averages

- Calculate the average of these numeric values: `140`, `97`, and `222`

```
1 mean(c(140, 97, 222))
```

```
[1] 153
```

Your Turn: Calculate Averages

- Calculate the average of these numeric values: `140`, `97`, and `222`

```
1 values <- c(140, 97, 222)
2 mean(values)
```

```
[1] 153
```

```
1 values <- c(140L, 97L, 222L)
2 mean(values)
```

```
[1] 153
```


But... How Am I Supposed to Know?

```
1 help(mean)
2 ?mean
3 # cursor + F1
```

Usage

```
1 mean(x, ...)
2
3 ## Default S3 method:
4 mean(x, trim = 0, na.rm = FALSE, ...)
```

Examples

```
1 x <- c(0:10, 50)
2 x
```

```
 [1]  0  1  2  3  4  5  6  7  8  9 10 50
```

```
1 xm <- mean(x)
2 xm
```

```
[1] 8.75
```


Vectors

Just like values, vectors can be of different types:

```
1 ids <- c(1:5)
2 ids
```

```
[1] 1 2 3 4 5
```

```
1 typeof(ids)
```

```
[1] "integer"
```

```
1 names <- c("Manisha", "Julien", "Cornelia", "Tatyana", "Eman")
2 names
```

```
[1] "Manisha"  "Julien"   "Cornelia" "Tatyana"  "Eman"
```

```
1 typeof(names)
```

```
[1] "character"
```


Named Vectors

```
1 (colors <- c(green = "#28A87D", purple = "#9C55E3", yellow = "#EFAC00"))
```

```
    green    purple    yellow
"#28A87D" "#9C55E3" "#EFAC00"
```

Alternatively, you can create an unnamed vector and add names via `names(x)`:

```
1 colors <- c("#28A87D", "#9C55E3", "#EFAC00")
2 names(colors) <- c("green", "purple", "yellow")
3 colors
```

```
    green    purple    yellow
"#28A87D" "#9C55E3" "#EFAC00"
```

If you want to get rid of the names, use `unname()`

```
1 unname(colors)
```

```
[1] "#28A87D" "#9C55E3" "#EFAC00"
```


Accessing Elements of Vectors

```
1 names
```

```
[1] "Manisha"  "Julien"   "Cornelia" "Tatyana"  "Eman"
```

```
1 names[1]
```

```
[1] "Manisha"
```

```
1 names[3:5]
```

```
[1] "Cornelia" "Tatyana"  "Eman"
```

```
1 names[c(1:3, 5)]
```

```
[1] "Manisha"  "Julien"   "Cornelia" "Eman"
```

```
1 names[-2]
```

```
[1] "Manisha"  "Cornelia" "Tatyana"  "Eman"
```


Accessing Elements of Named Vectors

```
colors
```

```
    green    purple    yellow
"#28A87D" "#9C55E3" "#EFAC00"
```

```
colors[c(1, 3)]
```

```
    green    yellow
"#28A87D" "#EFAC00"
```

Named vectors can also be assessed by element names:

```
colors["purple"]
```

```
   purple
"#9C55E3"
```

```
colors[c("green", "yellow")]
```

```
    green    yellow
"#28A87D" "#EFAC00"
```


NA and NaN in Vectors

When used inside a vector, the type of `NA` is determined by the data type of the other values—no need to specify e.g. `NA_character_`:

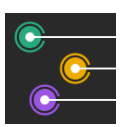
```
1 x <- c(1, 2, 3, NA, 5)
2 y <- c("A", "B", NA, "D", "E")
```

```
1 typeof(x)
```

```
[1] "double"
```

```
1 typeof(y)
```

```
[1] "character"
```

NA and NaN in Vectors

As they are unknown, any mathematical operation will return `NA` or `NaN`:

```
1 x <- c(5, 12, NA, 2, 18)
2 mean(x)
```

```
[1] NA
```

```
1 y <- c(5, 12, NaN, 2, 18)
2 mean(y)
```

```
[1] NaN
```

To ignore unknown values, you can set the argument `na.rm` to `TRUE`:

```
1 mean(x, na.rm = TRUE)  ## `na.rm = FALSE` by default
```

```
[1] 9.25
```

```
1 mean(y, na.rm = TRUE)
```

```
[1] 9.25
```


Vector Extension & Combination

```
colors_ext <- c(colors, c("#000000", "#ffffff"))
```

```
colors_ext
```

```
    green    purple    yellow     black     white
"#28A87D" "#9C55E3" "#EFAC00" "#000000" "#ffffff"
```

```
colors_ext <- c(colors, c(black = "#000000", white = "#ffffff"))
```

```
colors_ext
```

```
    green    purple    yellow     black     white
"#28A87D" "#9C55E3" "#EFAC00" "#000000" "#ffffff"
```

```
comb_vec <- c(ids, names)
```

```
comb_vec
```

```
 [1] "1"        "2"        "3"        "4"        "5"        "Manisha"  "Julien"   "Cornelia" "Tatyana"
[10] "Eman"
```

Note that in the last example **all values are coerced to the same data type** as atomic vectors can only contain a single type.

Coercion

Atomic vectors only contain one data type and

all values will be coerced implicitly to the same data type:

```
1 v1 <- c("ggplot2", 2023, TRUE)
2 v1
```

```
[1] "ggplot2" "2023"    "TRUE"
```

```
1 typeof(v1)
```

```
[1] "character"
```

```
1 v2 <- c(0.2, 1L, 3 + 0i)
2 v2
```

```
[1] 0.2+0i 1.0+0i 3.0+0i
```

```
1 typeof(v2)
```

```
[1] "complex"
```


Coercion

The coercion rule goes:

`logical` → `integer` → `double` → `complex` → `character`

```
1 typeof(c(TRUE))
```

```
[1] "logical"
```

```
1 typeof(c(TRUE, 1L))
```

```
[1] "integer"
```

```
1 typeof(c(TRUE, 1L, 0.2))
```

```
[1] "double"
```

```
1 typeof(c(TRUE, 1L, 0.2, 1 + 0i))
```

```
[1] "complex"
```

```
1 typeof(c(TRUE, 1L, 0.2, 1 + 0i, "a"))
```

```
[1] "character"
```


Explicit Coercion

One can **explicitly coerce** values of an atomic vectors to a particular data type:

```
1 v1
```

```
[1] "ggplot2" "2023"    "TRUE"
```

```
1 as.numeric(v1)
```

```
[1]   NA 2023   NA
```

```
1 as.logical(v1)
```

```
[1]   NA   NA TRUE
```


Explicit Coercion

One can **explicitly coerce** values of an atomic vectors to a particular data type:

```
1 v1
```

```
[1] "ggplot2" "2023"    "TRUE"
```

```
1 as.numeric(v1)
```

```
[1]   NA 2023   NA
```

```
1 as.logical(v1)
```

```
[1]   NA   NA TRUE
```

Note that all numbers except `0` are coerced to `TRUE`:

```
1 as.logical(2023)
```

```
[1] TRUE
```

... and all strings except `"TRUE"`, `"FALSE"`, `"T"`, and `"F"` get coerced to `NA`:

```
1 as.logical("2023")
```

```
[1] NA
```


Explicit Coercion

One can **explicitly coerce** values of an atomic vectors to a particular data type:

```
1 v2
```

```
[1] 0.2+0i 1.0+0i 3.0+0i
```

```
1 as.integer(v2)
```

```
[1] 0 1 3
```

```
1 as.character(v2)
```

```
[1] "0.2+0i" "1+0i"   "3+0i"
```

```
1 as.logical(v2)
```

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

```
1 as.logical(as.character(v2))
```

```
[1] NA NA NA
```

```
1 as.logical(as.integer(v2))
```

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


Your Turn: Vector Coercion

::: exercise ::: {.incremental} * Discuss what the following vectors look like without running them first: - `a <- c(1.7, "1.7")` and `as.numeric(a)` - `b <- c(TRUE, 2022, 1.375)` and `as.logical(as.complex(b))` - `c <- c(TRUE, "TRUE", "T", FALSE, "False", "f")` and `as.logical(c)` - `as.integer(c(45L, 0.237, 4.9))` :::

- What does `as.factor(c("red", "blue"))` do?

Your Turn: Vector Coercion

```
1 (a <- c(1.7, "1.7"))
```

```
[1] "1.7" "1.7"
```

```
1 as.numeric(a)
```

```
[1] 1.7 1.7
```

```
1 (b <- c(FALSE, 2022, 1.375))
```

```
[1]    0.000 2022.000    1.375
```

```
1 as.logical(as.complex(b))
```

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

```
1 (c <- c(TRUE, "t", "TRUE", "T"))
```

```
[1] "TRUE" "t"    "TRUE" "T"
```

```
1 as.logical(c)
```

```
[1] TRUE   NA TRUE TRUE
```

```
1 as.integer(c(45L, 0.237, 4.9))
```

```
[1] 45  0  4
```


Your Turn: Vector Coercion

```
1 c("red", "blue")
```

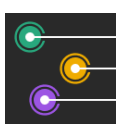
```
[1] "red"  "blue"
```

```
1 as.factor(c("red", "blue"))
```

```
[1] red  blue
Levels: blue red
```


Introduction to R

— Factors —



Factors

Factors represent categorical data in a **specific order**:

```
1 (v <- c("good", "neutral", "bad"))
```

```
[1] "good"    "neutral" "bad"
```

```
1 as.factor(v)
```

```
[1] good    neutral bad
Levels: bad good neutral
```

```
1 factor(v)
```

```
[1] good    neutral bad
Levels: bad good neutral
```

```
1 factor(v, levels = c("good", "neutral", "bad"))
```

```
[1] good    neutral bad
Levels: good neutral bad
```

```
1 factor(v, levels = rev(v))
```

```
[1] good    neutral bad
Levels: bad neutral good
```


Factors

... even if the variable is encoded by numbers:

```
(n <- 0:3)
```

```
[1] 0 1 2 3
```

```
(f <- factor(n))
```

```
[1] 0 1 2 3
Levels: 0 1 2 3
```

```
(f <- factor(n, levels = c(1:3, 0)))
```

```
[1] 0 1 2 3
Levels: 1 2 3 0
```

```
mean(n)
```

```
[1] 1.5
```

```
mean(f)
```

```
[1] NA
```


Factor Levels & Labels

`levels()` just returns unique levels in the specified order:

```
1 levels(f)
```

```
[1] "1" "2" "3" "0"
```

You can also set labels which basically overwrite the original encodings:

```
1 (ff <- factor(n, levels = c(1:3, 0), labels = c("bad", "neutral", "good", "n/a")))
```

```
[1] n/a     bad     neutral good
Levels: bad neutral good n/a
```

```
1 levels(ff)
```

```
[1] "bad"     "neutral" "good"    "n/a"
```


Coercion of Factors

```
1 ff
```

```
[1] n/a     bad     neutral good
Levels: bad neutral good n/a
```

If you want to turn a factor into numbers, use `as.numeric()`:

```
1 as.numeric(ff)
```

```
[1] 4 1 2 3
```

Note that this returns the factor elements as numbers based on the level position!

To turn it back into a strings, use `as.character()`:

```
1 as.character(ff)
```

```
[1] "n/a"     "bad"     "neutral" "good"
```


Coercion of Factors: Be Careful!

```
1 f
```

```
[1] 0 1 2 3
Levels: 1 2 3 0
```

Returns numbers based on levels:

```
1 as.numeric(f)
```

```
[1] 4 1 2 3
```

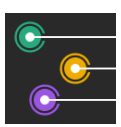
Returns numbers based on elements:

```
1 as.numeric(as.character(f))
```

```
[1] 0 1 2 3
```


Introduction to R

— Packages —



What are Packages?

A package is a **collection of functions, data, and other objects** that are designed to **perform specific tasks or solve certain problems**.

These packages are created and maintained by the R community, and are often shared on the Comprehensive R Archive Network (CRAN) or other repositories such as BioConductor.

Installing Additional Packages

To use the functionality from a dedicated package, you need to install the package on your machine:

```
1 install.packages("forcats")
2 ## provides functions to work with factors
```

```
1 install.packages("palmerpenguins")
2 ## contains data sets for educational use
```


Using Packages: Load Libraries

To use the functionality from installed packages, you usually load the package:

```
1 library(forcats)
```

```
1 f <- factor(0:10)
2 levels(f)
```

```
 [1] "0"  "1"  "2"  "3"  "4"  "5"  "6"  "7"  "8"  "9"  "10"
```

```
1 fct_rev(f)
```

```
 [1] 0  1  2  3  4  5  6  7  8  9  10
Levels: 10 9 8 7 6 5 4 3 2 1 0
```

```
1 fct_relevel(f, "0", after = Inf)
```

```
 [1] 0  1  2  3  4  5  6  7  8  9  10
Levels: 1 2 3 4 5 6 7 8 9 10 0
```


Using Packages: Load Libraries

To use the functionality from installed packages, you usually load the package:

```
1 library(palmerpenguins)
```

```
1 penguins
```

```
# A tibble: 344 × 8
   species island    bill_length_mm bill_depth_mm flipper_length_mm body_mass_g sex     year
   <fct>   <fct>              <dbl>         <dbl>             <int>       <int> <fct>  <int>
 1 Adelie  Torgersen           39.1          18.7               181        3750 male    2007
 2 Adelie  Torgersen           39.5          17.4               186        3800 female  2007
 3 Adelie  Torgersen           40.3          18                 195        3250 female  2007
 4 Adelie  Torgersen           NA            NA                  NA          NA <NA>    2007
 5 Adelie  Torgersen           36.7          19.3               193        3450 female  2007
 6 Adelie  Torgersen           39.3          20.6               190        3650 male    2007
 7 Adelie  Torgersen           38.9          17.8               181        3625 female  2007
 8 Adelie  Torgersen           39.2          19.6               195        4675 male    2007
 9 Adelie  Torgersen           34.1          18.1               193        3475 <NA>    2007
10 Adelie  Torgersen           42            20.2               190        4250 <NA>    2007
# … with 334 more rows
```


Using Packages: Name Conflicts

Note that in some cases, multiple packages may contain functions (or data sets) with the same name.

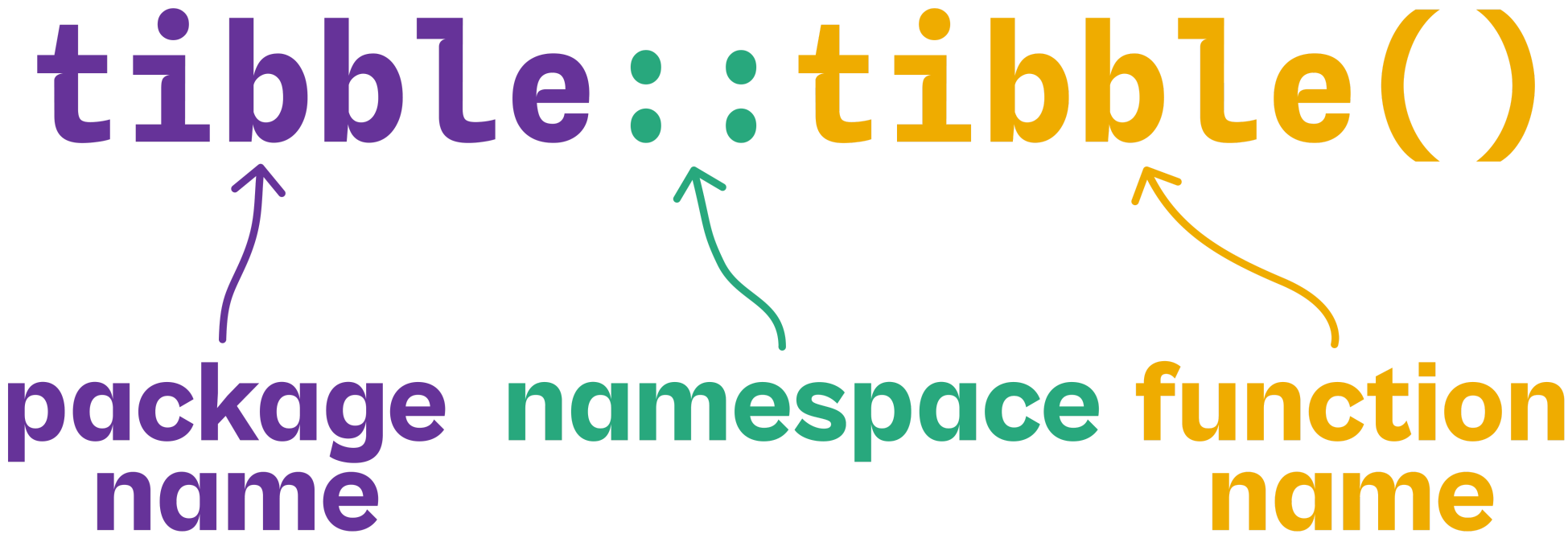
```
1 install.packages("dplyr")
2 ## provides functions to wrangle tabular data
```

```
1 library(dplyr)
```

```
Attaching package: 'dplyr'

The following objects are masked from 'package:stats':

    filter, lag

The following objects are masked from 'package:base':

    intersect, setdiff, setequal, union
```

In case you load two functions with the same name,
the function of the package that is loaded most recently is used!

Using Packages: Namespace



Using Packages: Namespace

To avoid conflicts, one can explicitly refer to specific functions with namespaces:

```
1 install.packages("stringr")
2 ## provides functions to work with character strings
```

```
1 stringr::str_to_sentence(c("coffee", "latte machiatto", "espresso"))
```

```
[1] "Coffee"          "Latte machiatto" "Espresso"
```

Namespaces are helpful in several situations:

- solving name conflicts
- using functions without loading the full package functionality
- being explicit about non-base functions

Introduction to R

— Tabular Data —

Data Frames

You can store several vectors, also of different data types, as tabular data in so-called **data frames**:

```
1 (df_participants <- data.frame(ids, names))
```

```
  ids    names
1   1  Manisha
2   2   Julien
3   3 Cornelia
4   4  Tatyana
5   5     Eman
```

Explicitly declaring column names:

```
1 (df_participants <- data.frame(id = ids, participant_name = names))
```

```
  id participant_name
1  1          Manisha
2  2           Julien
3  3         Cornelia
4  4          Tatyana
5  5             Eman
```


Accessing Data Frame Elements

Rows:

```
df_participants[2,]
```

```
  id participant_name
2  2           Julien
```

Columns:

```
df_participants[,2]
```

```
[1] "Manisha"  "Julien"   "Cornelia" "Tatyana"  "Eman"
```

```
df_participants$participant_name
```

```
[1] "Manisha"  "Julien"   "Cornelia" "Tatyana"  "Eman"
```

```
df_participants[[2]]
```

```
[1] "Manisha"  "Julien"   "Cornelia" "Tatyana"  "Eman"
```


Accessing Data Frame Elements

Cells:

```
1 df_participants$participant_name[2]
```

```
[1] "Julien"
```

```
1 df_participants[[2]][2]
```

```
[1] "Julien"
```

```
1 df_participants[,2][2]
```

```
[1] "Julien"
```


Accesing Data Frame Elements

Data frames support partial matching...

```
1 df_participants
```

```
  id participant_name
1  1          Manisha
2  2           Julien
3  3         Cornelia
4  4          Tatyana
5  5             Eman
```

`participant` is **not** a column of `df_participants` but matches by name with `participant_name`:

```
1 df_participants$participant
```

```
[1] "Manisha"  "Julien"   "Cornelia" "Tatyana"  "Eman"
```


The Modern Data Frame: Meet the Tibble

> *Tibbles are a modern reimagining of the data.frame, keeping what time has proven to be effective, and throwing out what is not.*

```
1 install.packages("tibble")
```

The name comes from the way you originally created these objects: `tbl_df()`, which was most easily pronounced as *"tibble diff"* or *"tibble d. f."*.

```
1 (tbl_participants <- tibble::tibble(id = ids, participant_name = names))
```

```
# A tibble: 5 × 2
     id participant_name
  <int> <chr>
1     1 Manisha
2     2 Julien
3     3 Cornelia
4     4 Tatyana
5     5 Eman
```

Similarly as the functions we have used before, `tibble()` is a function. While `mean()` and `+` are **base functions**, `tibble()` belongs to an **add-on package** which is named **{tibble}** as well.

Data Frame vs Tibble

> *Tibbles are a modern reimagining of the data.frame, keeping what time has proven to be effective, and throwing out what is not.*

Main differences in the usage of a data frame vs a tibble:

- **tibbles have a refined print method**
  - show only the first 10 rows, and all the columns that fit on screen
  - in addition to its name, each column reports its type
  - also, the type of the data and its dimensions are shown

Data Frame vs Tibble

Tibbles have a refined print method.

```
1  df_long  <- data.frame(id = 1:1000 %% 10, value = runif(n = 1000, min = 0, max = 1000))
2  tbl_long <- tibble::tibble(id = 1:1000 %% 10, value = runif(n = 1000, min = 0, max = 1000))
```

```
1  df_long
```

```
    id       value
1    1 466.6139435
2    2 335.1909537
3    3 162.8175615
4    4 396.1200174
5    5  30.3917308
6    6 120.8848702
7    7 426.1656571
8    8 617.8578807
9    9 263.2082594
10   0 476.3238712
11   1 862.3189987
12   2 148.8786321
13   3 180.4300796
14   4 999.2733120
15   5 841.7411824
16   6 142.6490599
17   7 344.8483865
18   8 889.6254539
```

```
1  tbl_long
```

```
# A tibble: 1,000 × 2
      id value
   <dbl> <dbl>
 1     1 881.
 2     2 691.
 3     3 787.
 4     4  79.0
 5     5 206.
 6     6 923.
 7     7 987.
 8     8 134.
 9     9 940.
10     0 165.
# … with 990 more rows
```


Data Frame vs Tibble

Tibbles have a refined print method.

```
1  as.data.frame(penguins)
```

```
      species    island bill_length_mm bill_depth_mm
1      Adelie Torgersen           39.1          18.7
2      Adelie Torgersen           39.5          17.4
3      Adelie Torgersen           40.3          18.0
4      Adelie Torgersen             NA            NA
5      Adelie Torgersen           36.7          19.3
6      Adelie Torgersen           39.3          20.6
7      Adelie Torgersen           38.9          17.8
8      Adelie Torgersen           39.2          19.6
9      Adelie Torgersen           34.1          18.1
10     Adelie Torgersen           42.0          20.2
11     Adelie Torgersen           37.8          17.1
12     Adelie Torgersen           37.8          17.3
13     Adelie Torgersen           41.1          17.6
14     Adelie Torgersen           38.6          21.2
15     Adelie Torgersen           34.6          21.1
16     Adelie Torgersen           36.6          17.8
17     Adelie Torgersen           38.7          19.0
18     Adelie Torgersen           42.5          20.7
```

```
1  tibble::as_tibble(penguins)
```

```
# A tibble: 344 × 8
   species island bill_…¹ bill_…² flipp…³ body_…⁴ sex
   <fct>   <fct>    <dbl>   <dbl>   <int>   <int> <fct>
 1 Adelie  Torge…    39.1    18.7     181    3750 male
 2 Adelie  Torge…    39.5    17.4     186    3800 fema…
 3 Adelie  Torge…    40.3    18       195    3250 fema…
 4 Adelie  Torge…    NA      NA        NA      NA <NA>
 5 Adelie  Torge…    36.7    19.3     193    3450 fema…
 6 Adelie  Torge…    39.3    20.6     190    3650 male
 7 Adelie  Torge…    38.9    17.8     181    3625 fema…
 8 Adelie  Torge…    39.2    19.6     195    4675 male
 9 Adelie  Torge…    34.1    18.1     193    3475 <NA>
10 Adelie  Torge…    42      20.2     190    4250 <NA>
# … with 334 more rows, 1 more variable: year <int>,
#   and abbreviated variable names ¹bill_length_mm,
#   ²bill_depth_mm, ³flipper_length_mm, ⁴body_mass_g
```


Data Frame vs Tibble

> *Tibbles are a modern reimagining of the data.frame, keeping what time has proven to be effective, and throwing out what is not.*

Main differences in the usage of a data frame vs a tibble:

- **tibbles have a refined print method**
  - show only the first 10 rows, and all the columns that fit on screen
  - in addition to its name, each column reports its type
  - also, the type of the data and its dimensions are shown
- **tibbles are strict about subsetting**

Data Frame vs Tibble

Tibbles are strict about subsetting.

```
1  df_long$val
```

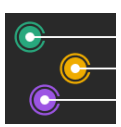
```
  [1] 466.6139435 335.1909537 162.8175615 396.1200174
  [5]  30.3917308 120.8848702 426.1656571 617.8578807
  [9] 263.2082594 476.3238712 862.3189987 148.8786321
 [13] 180.4300796 999.2733120 841.7411824 142.6490599
 [17] 344.8483865 889.6254539 319.8482955 709.0158337
 [21] 628.1517190 438.1725660 339.8960282 933.0925872
 [25] 712.9544122 630.8518730 746.4494368 111.4502875
 [29] 273.2885152  98.5180892 757.5294827 663.5921039
 [33] 724.3610939 458.9465314 674.3985806 700.5136148
 [37] 815.0722187 691.1814879 716.4123438 890.5798914
 [41] 340.2968822 668.5628453 384.2539703 235.1133667
 [45] 888.4970285 801.4516588 596.4277368 977.0177414
 [49] 328.1049675 805.1800283  32.3153806 448.2898777
 [53] 264.7317180 409.2675177 194.5968003 543.4875141
 [57] 935.1037010 774.0376103 996.8832501 822.6258415
 [61] 391.7053440 385.2494801 899.1378001 318.8530235
 [65] 208.6884824 564.1771706 482.0844352  65.1146327
 [69] 261.2773522 330.3356417 330.5641250  92.3532958
 [73] 693.9935274 116.4896260 870.5973122 128.6706002
```

```
1  tbl_long$val
```

```
NULL
```


Inspect a Data Set

```
1 View(tbl_long)
```

Inspect a Data Set

```
1 dim(tbl_long)
```

```
[1] 1000    2
```

```
1 str(tbl_long)
```

```
tibble [1,000 × 2] (S3: tbl_df/tbl/data.frame)
 $ id    : num [1:1000] 1 2 3 4 5 6 7 8 9 0 ...
 $ value: num [1:1000] 881 691 787 79 206 ...
```

```
1 tibble::glimpse(tbl_long)
```

```
Rows: 1,000
Columns: 2
$ id    <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 0, 1, 2…
$ value <dbl> 880.849571, 690.568330, 786.657729, 78.981368, 206.086510, 923.498811, 987.393297, 133.562790,…
```

```
1 summary(tbl_long)
```

```
       id          value       
 Min.   :0.0   Min.   :  1.341  
 1st Qu.:2.0   1st Qu.:230.005  
 Median :4.5   Median :475.317  
 Mean   :4.5   Mean   :482.438  
 3rd Qu.:7.0   3rd Qu.:739.410  
 Max.   :9.0   Max.   :999.169  
```


Inspect a Data Set

```
1 mean(tbl_long$value)
```

```
[1] 482.4375
```

```
1 range(tbl_long$value)
```

```
[1]   1.34083 999.16861
```

```
1 unique(tbl_long$id)
```

```
 [1] 1 2 3 4 5 6 7 8 9 0
```

```
1 sort(unique(tbl_long$id))
```

```
 [1] 0 1 2 3 4 5 6 7 8 9
```

```
1 length(tbl_long$id)
```

```
[1] 1000
```

```
1 length(unique(tbl_long$id))
```

```
[1] 10
```


Your Turn: Working with Tabular Data

- If not done yet: install and load the **palmerpenguins** package
- Explore the `penguins` data set:
  - Inspect the number of unique observations.
  - Count the number of observations per sex.
  - Check the years the penguins were monitored.
  - Calculate the average bill length.
  - Report the quartiles of measured flipper lengths.
  - Store the body mass column in a vector called `penguin_weights`.

Your Turn: Working with Tabular Data

```
dim(penguins) ## or: `nrow(penguins)`, `length(penguins$species)`, ...
```

```
[1] 344   8
```

```
summary(penguins$sex)
```

```
female   male   NA's
   165    168     11
```

```
unique(penguins$year)
```

```
[1] 2007 2008 2009
```

```
mean(penguins$bill_length_mm)
```

```
[1] NA
```

```
mean(penguins$bill_length_mm, na.rm = TRUE)
```

```
[1] 43.92193
```

```
quantile(penguins$flipper_length_mm, na.rm = TRUE)
```

```
  0%  25%  50%  75% 100%
 172  190  197  213  231
```

```
penguin_weights <- penguins$body_mass_g
```


Lists

Lists are by far the most flexible data structure in R. They can be seen as a collection of elements without any restriction on the class, length or structure of each element.

```
1  my_list <- list(ids = 1:5, names = c("Manisha", "Julien", "Cornelia", "Tatyana", "Eman"))
```

```
1  my_list
```

```
$ids
[1] 1 2 3 4 5

$names
[1] "Manisha"  "Julien"   "Cornelia" "Tatyana"  "Eman"
```

Note that data frames can be seen as simple tabular lists as well.

Accessing List Elements

```
1 my_list$names
```

```
[1] "Manisha"  "Julien"   "Cornelia" "Tatyana"  "Eman"
```

```
1 my_list$names[1]
```

```
[1] "Manisha"
```

```
1 my_list[[2]]
```

```
[1] "Manisha"  "Julien"   "Cornelia" "Tatyana"  "Eman"
```

```
1 my_list[[2]][1]
```

```
[1] "Manisha"
```

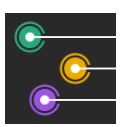

Nested Lists

Usually, when we talk about lists we often mean nested data structure:

```
1 my_nested_list <- list(
2   ids = list(1:5, 1),
3   names = list(c("Manisha", "Julien", "Cornelia", "Tatyana", "Eman"), "Cedric"),
4   type = list(rep("participant", 5), "instructor")
5 )
```

```
1 my_nested_list
```

```
$ids
$ids[[1]]
[1] 1 2 3 4 5

$ids[[2]]
[1] 1


$names
$names[[1]]
[1] "Manisha"   "Julien"    "Cornelia" "Tatyana"   "Eman"

$names[[2]]
[1] "Cedric"


$type
$type[[1]]
[1] "participant" "participant" "participant" "participant" "participant"
```

Nested Lists

```
1 my_nested_list$names
```

```
[[1]]
[1] "Manisha"  "Julien"   "Cornelia" "Tatyana"  "Eman"

[[2]]
[1] "Cedric"
```

```
1 my_nested_list$names[[1]]
```

```
[1] "Manisha"  "Julien"   "Cornelia" "Tatyana"  "Eman"
```

```
1 my_nested_list$names[[1]][1]
```

```
[1] "Manisha"
```

```
1 my_nested_list[[2]][[1]][1]
```

```
[1] "Manisha"
```


Nested Lists as Tibbles

```
1 my_tbl_list <- tibble::as_tibble(my_nested_list)
```

```
1 my_tbl_list
```

```
# A tibble: 2 × 3
  ids       names     type
  <list>    <list>    <list>
1 <int [5]> <chr [5]> <chr [5]>
2 <dbl [1]> <chr [1]> <chr [1]>
```


Unnesting Nested Lists

```
1 install.packages("tidyr")
```

```
1 my_tbl <- tidyr::unnest(my_tbl_list)
```

```
Warning: `cols` is now required when using `unnest()`.
ℹ Please use `cols = c(ids, names, type)`.
```

```
1 my_tbl <- tidyr::unnest(my_tbl_list, cols = c(ids, names, type))
```

```
1 my_tbl
```

```
# A tibble: 6 × 3
    ids names    type
  <dbl> <chr>    <chr>
1     1 Manisha  participant
2     2 Julien   participant
3     3 Cornelia participant
4     4 Tatyana  participant
5     5 Eman     participant
6     1 Cedric   instructor
```


Nesting Lists

```
my_nested_tbl <- tidyr::nest(my_tbl, data = !type)
```

```
my_nested_tbl
```

```
# A tibble: 2 × 2
  type        data
  <chr>       <list>
1 participant <tibble [5 × 2]>
2 instructor  <tibble [1 × 2]>
```

```
my_nested_tbl$data
```

```
[[1]]
# A tibble: 5 × 2
    ids names
  <dbl> <chr>
1     1 Manisha
2     2 Julien
3     3 Cornelia
4     4 Tatyana
5     5 Eman

[[2]]
# A tibble: 1 × 2
    ids names
  <dbl> <chr>
1     1 Cedric
```


Introduction to R

— Generating Data Sets —

Generate ~~Data Sets~~Vectors in R

You can combine vectors to a data frame or tibble. Helpful functions to create vectors are `:`, `seq()`, and `rep()`:

```
1 1:10
```

```
 [1]  1  2  3  4  5  6  7  8  9 10
```

```
1 seq(from = 0, to = 150, by = 25)
```

```
[1]   0  25  50  75 100 125 150
```

```
1 0:6*25
```

```
[1]   0  25  50  75 100 125 150
```

```
1 seq(from = 0, to = 150, length.out = 5)
```

```
[1]   0.0  37.5  75.0 112.5 150.0
```

```
1 rep(1:3, times = 3)
```

```
[1] 1 2 3 1 2 3 1 2 3
```

```
1 rep(1:3, each = 3)
```

```
[1] 1 1 1 2 2 2 3 3 3
```


Generate Data Sets in R

You can combine vectors to a data frame or tibble. Helpful functions to create vectors are `:`, `seq()`, and `rep()`:

```
1  name <- c("Brian", "Jason", "Tyler", "Sam")
2  age <- seq(23, 29, by = 2)  ## or: c(23, 24, 25, 26)
3  sex <- rep("male", length(name))
4  id <- 1:length(name)
```

```
1  tibble::tibble(id, name, age, sex) ## or `data.frame()`
```

```
# A tibble: 4 × 4
     id name    age sex
  <int> <chr> <dbl> <chr>
1     1 Brian    23 male
2     2 Jason    25 male
3     3 Tyler    27 male
4     4 Sam      29 male
```


Generate Data Sets in R

From scratch, you would create these columns within the `data.frame()` or `tibble()` call:

```
1 tibble::tibble(
2   name = c("Brian", "Jason", "Tyler", "Sam"),
3   age = seq(23, 29, by = 2),
4   sex = rep("male", 4),
5   id = 1:4
6 )
```

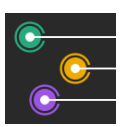
```
# A tibble: 4 × 4
  name    age sex      id
  <chr> <dbl> <chr> <int>
1 Brian    23 male      1
2 Jason    25 male      2
3 Tyler    27 male      3
4 Sam      29 male      4
```


Generate Data Sets in R

You can also create tibbles using an easier to read row-by-row layout–a `tribble`:

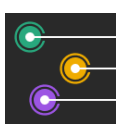
```
tibble::tribble(
  ~id, ~name,    ~age,  ~sex,
  1,   "Brian",  23,    "male",
  2,   "Jason",  25,    "male",
  3,   "Tyler",  27,    "male",
  4,   "Sam",    29,    "male"
)
```

```
# A tibble: 4 × 4
     id name    age sex
  <dbl> <chr> <dbl> <chr>
1     1 Brian    23 male
2     2 Jason    25 male
3     3 Tyler    27 male
4     4 Sam      29 male
```

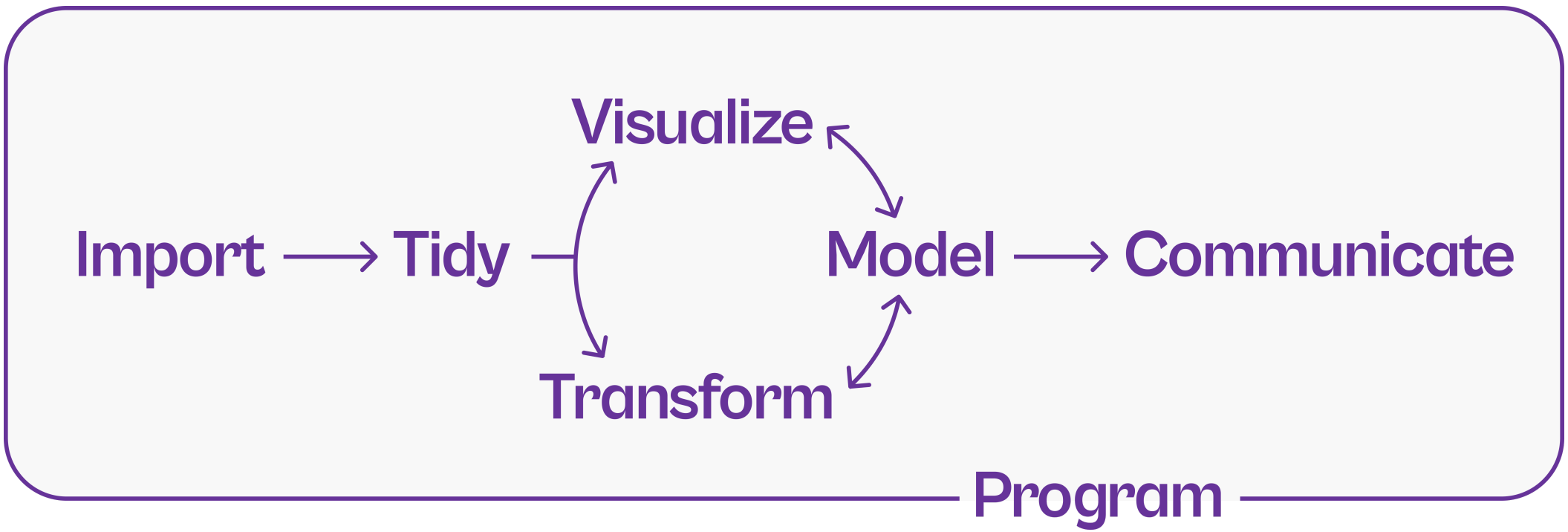



Introduction to R

— Data Import —

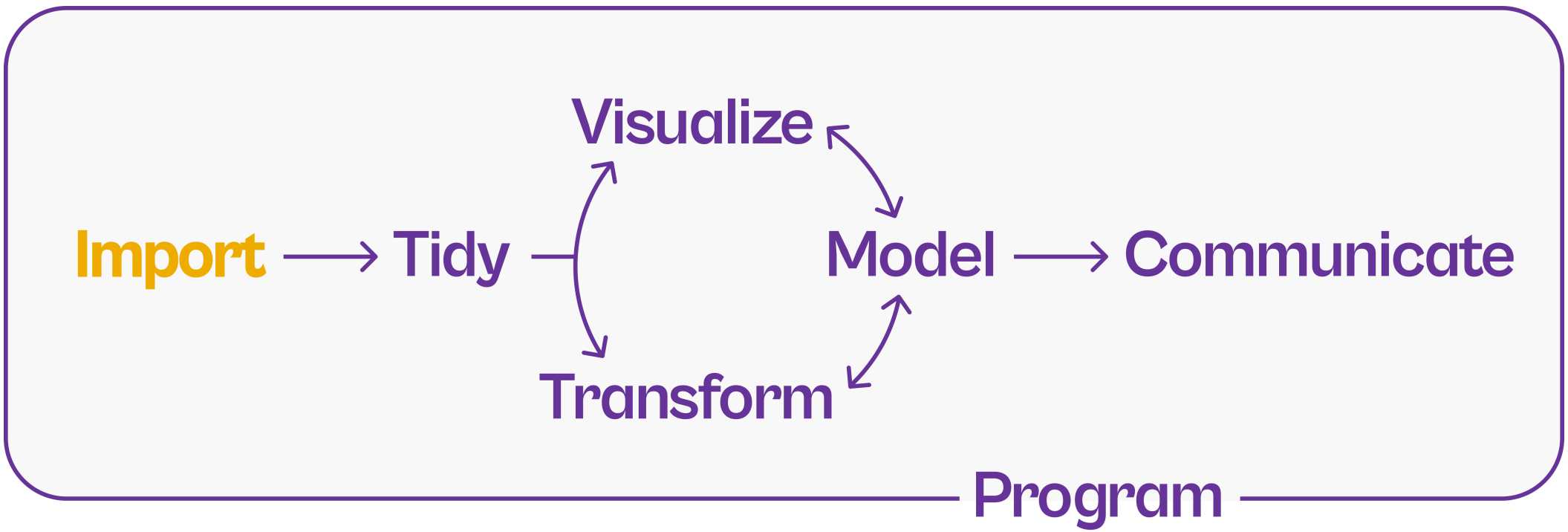


The Data Science Workflow



The data science workflow, modified from "R for Data Science"

The Data Science Workflow



The data science workflow, modified from "R for Data Science"

Data Import

Usually, you create data frames by loading data files such as `.txt`, `.csv`, ...

```
1 my_data <- read.delim("./data/cool_data.txt", sep = "\t")
```

```
1 my_data <- read.csv("./data/cool_data.csv")
```

The `./` refers to a relative path, starting at your **working directory**.
You can check your "wd" by running `getwd()`.

You can also import data from a web resource by passing a valid URL:

```
1 my_data <- read.csv("https://some-webpage.com/online-data.csv")
```


Data Import: Tibbles

The **{readr}** package provides a fast and friendly way to read rectangular data which are stored as tibbles:

```
my_data <- readr::read_delim("./data/cool_data.txt", delim = "\t")
```

```
my_data <- readr::read_csv("./data/cool_data.csv")
```

```
my_data <- readr::read_csv2("./data/actually_not_a_csv_but_okay.csv") ## ';' as sep
```


Data Import: Excel Files (sigh)

The **{readxl}** package provides functionality to import Excel sheets:

```
1 my_data <- readxl::read_xls("./data/oh_no_excel_data.xls", sheet = 1)
```

```
1 my_data <- readxl::read_xlsx("./data/oh_no_excel_data.xlsx", sheet = 1)
```


Data Import: R-Specific Formats

There are also R-specific formats such as `.Rds` and `.Rdata`/`.Rda`

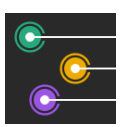
```
## base R:
my_data <- readRDS("./data/one_of_Rs_data_formats.Rds")
```

```
## readr package:
my_data <- readr::read_rds("./data/one_of_Rs_data_formats.Rds")
```


Data Import: Too Slow?

The **{data.table}** package provides functionality for data I/O, wrangling and more.
The function to import and export data are known to be very fast:

```
1  my_data <- data.table::fread("./data/cool_data.csv", sep = ",")
```

Data Import: The I/O Swiss-Army Knife

The **{rio}** package aims to unify data importing and exporting into two functions. Based on the file format, **{rio}** will pick a suitable import/export function.

```
my_data <- rio::import("./data/cool_data.txt")
```

```
my_data <- rio::import("./data/one_of_Rs_data_formats.Rds")
```

```
my_data <- rio::import("./data/one_of_Rs_data_formats.Rds")
```

```
my_data <- rio::import("./data/spatial_data_formats_can_be_annoyiong.shp")
```

```
my_data <- rio::import("./data/spatial_data_formats_can_be_annoyiong.geojson")
```

```
my_data <- rio::import("./data/spatial_data_formats_can_be_annoyiong.gpkg")
```

```
my_data <- rio::import("./data/spatial_data_formats_can_be_annoyiong.tif")
```


Data Export

In general, the same logic applies when exporting data sets:

```
write(my_data, file = "./data/cool_data.txt", sep = "\t")
```

```
write.csv(my_data, file = "./data/cool_data.csv")
```

```
readr::write_csv(my_data, file = "./data/cool_data.csv")
```

```
data.table::fwrite(my_data, file = "./data/cool_data.csv", sep = ",")
```

```
saveRDS(my_data, file = "./data/one_of_Rs_data_formats.Rds")
```

```
readr::write_rds(my_data, file = "./data/one_of_Rs_data_formats.Rds")
```

```
rio::export(my_data, "./data/spatial_data_formats_can_be_annoyiong.tif")
```


Your Turn: Data Import & Export

- Import the TfL bikes data set (`london-bikes-custom.csv`), stored in the `data` folder or load it directly from the following URL:
  `https://cedricscherer.com/data/london-bikes-custom.csv`
- Check the data set—do the values and data types look fine?
- Save the file as a Rds file.
- Bonus: import your own data set or other data sets and formats.

Your Turn: Data Import

```
1 df_bikes <- read.delim("./data/london-bikes-custom.csv", sep = ",")
2 tibble::glimpse(df_bikes)
```

```
Rows: 1,454
Columns: 14
$ date         <chr> "2015-01-04", "2015-01-04", "2015-01-05", "2015-01-05", "2015-01-06", "2015-01-06", "20…
$ day_night    <chr> "day", "night", "day", "night", "day", "night", "day", "night", "day", "night", "day", …
$ year         <int> 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 201…
$ month        <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, …
$ season       <chr> "winter", "winter", "winter", "winter", "winter", "winter", "winter", "winter", "winter…
$ count        <int> 6830, 2404, 14763, 5609, 14501, 6112, 16358, 4706, 9971, 5630, 16568, 5536, 10413, 4296…
$ is_workday   <int> 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, …
$ is_weekend   <int> 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, …
$ is_holiday   <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, …
$ temp         <dbl> 2.166667, 2.791667, 8.958333, 7.125000, 9.000000, 6.708333, 8.166667, 6.681818, 9.45833…
$ temp_feel    <dbl> -0.75000000, 2.04166667, 7.70833333, 5.70833333, 6.45833333, 4.20833333, 5.08333333, 3.…
$ humidity     <dbl> 95.16667, 93.37500, 81.08333, 79.54167, 80.20833, 77.58333, 75.20833, 81.27273, 79.4166…
$ wind_speed   <dbl> 10.416667, 4.583333, 8.666667, 9.041667, 19.208333, 12.791667, 21.250000, 18.136364, 18…
$ weather_type <chr> "broken clouds", "clear", "broken clouds", "cloudy", "broken clouds", "clear", "scatter…
```


Your Turn: Data Import

```
1 df_bikes <- read.csv("./data/london-bikes-custom.csv")
2 tibble::glimpse(df_bikes)
```

```
Rows: 1,454
Columns: 14
$ date         <chr> "2015-01-04", "2015-01-04", "2015-01-05", "2015-01-05", "2015-01-06", "2015-01-06", "20…
$ day_night    <chr> "day", "night", "day", "night", "day", "night", "day", "night", "day", "night", "day", …
$ year         <int> 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 201…
$ month        <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, …
$ season       <chr> "winter", "winter", "winter", "winter", "winter", "winter", "winter", "winter", "winter…
$ count        <int> 6830, 2404, 14763, 5609, 14501, 6112, 16358, 4706, 9971, 5630, 16568, 5536, 10413, 4296…
$ is_workday   <int> 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, …
$ is_weekend   <int> 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, …
$ is_holiday   <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, …
$ temp         <dbl> 2.166667, 2.791667, 8.958333, 7.125000, 9.000000, 6.708333, 8.166667, 6.681818, 9.45833…
$ temp_feel    <dbl> -0.75000000, 2.04166667, 7.70833333, 5.70833333, 6.45833333, 4.20833333, 5.08333333, 3.…
$ humidity     <dbl> 95.16667, 93.37500, 81.08333, 79.54167, 80.20833, 77.58333, 75.20833, 81.27273, 79.4166…
$ wind_speed   <dbl> 10.416667, 4.583333, 8.666667, 9.041667, 19.208333, 12.791667, 21.250000, 18.136364, 18…
$ weather_type <chr> "broken clouds", "clear", "broken clouds", "cloudy", "broken clouds", "clear", "scatter…
```


Your Turn: Data Import

```
1 df_bikes <- rio::import("./data/london-bikes-custom.csv")
2 tibble::glimpse(df_bikes)
```

```
Rows: 1,454
Columns: 14
$ date         <IDate> 2015-01-04, 2015-01-04, 2015-01-05, 2015-01-05, 2015-01-06, 2015-01-06, 2015-01-07, 2…
$ day_night    <chr> "day", "night", "day", "night", "day", "night", "day", "night", "day", "night", "day", …
$ year         <int> 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 201…
$ month        <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, …
$ season       <chr> "winter", "winter", "winter", "winter", "winter", "winter", "winter", "winter", "winter…
$ count        <int> 6830, 2404, 14763, 5609, 14501, 6112, 16358, 4706, 9971, 5630, 16568, 5536, 10413, 4296…
$ is_workday   <int> 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, …
$ is_weekend   <int> 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, …
$ is_holiday   <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, …
$ temp         <dbl> 2.166667, 2.791667, 8.958333, 7.125000, 9.000000, 6.708333, 8.166667, 6.681818, 9.45833…
$ temp_feel    <dbl> -0.75000000, 2.04166667, 7.70833333, 5.70833333, 6.45833333, 4.20833333, 5.08333333, 3.…
$ humidity     <dbl> 95.16667, 93.37500, 81.08333, 79.54167, 80.20833, 77.58333, 75.20833, 81.27273, 79.4166…
$ wind_speed   <dbl> 10.416667, 4.583333, 8.666667, 9.041667, 19.208333, 12.791667, 21.250000, 18.136364, 18…
$ weather_type <chr> "broken clouds", "clear", "broken clouds", "cloudy", "broken clouds", "clear", "scatter…
```


Your Turn: Data Import

```
1 df_bikes <- rio::import("./data/london-bikes-custom.csv", setclass = "tbl_df")
2 tibble::glimpse(df_bikes)
```

```
Rows: 1,454
Columns: 14
$ date         <IDate> 2015-01-04, 2015-01-04, 2015-01-05, 2015-01-05, 2015-01-06, 2015-01-06, 2015-01-07, 2…
$ day_night    <chr> "day", "night", "day", "night", "day", "night", "day", "night", "day", "night", "day", …
$ year         <int> 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 201…
$ month        <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, …
$ season       <chr> "winter", "winter", "winter", "winter", "winter", "winter", "winter", "winter", "winter…
$ count        <int> 6830, 2404, 14763, 5609, 14501, 6112, 16358, 4706, 9971, 5630, 16568, 5536, 10413, 4296…
$ is_workday   <int> 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, …
$ is_weekend   <int> 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, …
$ is_holiday   <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, …
$ temp         <dbl> 2.166667, 2.791667, 8.958333, 7.125000, 9.000000, 6.708333, 8.166667, 6.681818, 9.45833…
$ temp_feel    <dbl> -0.75000000, 2.04166667, 7.70833333, 5.70833333, 6.45833333, 4.20833333, 5.08333333, 3.…
$ humidity     <dbl> 95.16667, 93.37500, 81.08333, 79.54167, 80.20833, 77.58333, 75.20833, 81.27273, 79.4166…
$ wind_speed   <dbl> 10.416667, 4.583333, 8.666667, 9.041667, 19.208333, 12.791667, 21.250000, 18.136364, 18…
$ weather_type <chr> "broken clouds", "clear", "broken clouds", "cloudy", "broken clouds", "clear", "scatter…
```


Your Turn: Data Import

```
1 df_bikes <- readr::read_csv("./data/london-bikes-custom.csv")
2 tibble::glimpse(df_bikes)
```

```
Rows: 1,454
Columns: 14
$ date         <date> 2015-01-04, 2015-01-04, 2015-01-05, 2015-01-05, 2015-01-06, 2015-01-06, 2015-01-07, 20…
$ day_night    <chr> "day", "night", "day", "night", "day", "night", "day", "night", "day", "night", "day", …
$ year         <dbl> 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 201…
$ month        <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, …
$ season       <chr> "winter", "winter", "winter", "winter", "winter", "winter", "winter", "winter", "winter…
$ count        <dbl> 6830, 2404, 14763, 5609, 14501, 6112, 16358, 4706, 9971, 5630, 16568, 5536, 10413, 4296…
$ is_workday   <dbl> 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, …
$ is_weekend   <dbl> 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, …
$ is_holiday   <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, …
$ temp         <dbl> 2.166667, 2.791667, 8.958333, 7.125000, 9.000000, 6.708333, 8.166667, 6.681818, 9.45833…
$ temp_feel    <dbl> -0.75000000, 2.04166667, 7.70833333, 5.70833333, 6.45833333, 4.20833333, 5.08333333, 3.…
$ humidity     <dbl> 95.16667, 93.37500, 81.08333, 79.54167, 80.20833, 77.58333, 75.20833, 81.27273, 79.4166…
$ wind_speed   <dbl> 10.416667, 4.583333, 8.666667, 9.041667, 19.208333, 12.791667, 21.250000, 18.136364, 18…
$ weather_type <chr> "broken clouds", "clear", "broken clouds", "cloudy", "broken clouds", "clear", "scatter…
```


Your Turn: Data Import

```
1 df_bikes <- readr::read_csv("./data/london-bikes-custom.csv",
2                             col_types = "Dcficilllddddf")
3 tibble::glimpse(df_bikes)
```

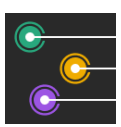
```
Rows: 1,454
Columns: 14
$ date         <date> 2015-01-04, 2015-01-04, 2015-01-05, 2015-01-05, 2015-01-06, 2015-01-06, 2015-01-07, 20…
$ day_night    <chr> "day", "night", "day", "night", "day", "night", "day", "night", "day", "night", "day", …
$ year         <fct> 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 201…
$ month        <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, …
$ season       <chr> "winter", "winter", "winter", "winter", "winter", "winter", "winter", "winter", "winter…
$ count        <int> 6830, 2404, 14763, 5609, 14501, 6112, 16358, 4706, 9971, 5630, 16568, 5536, 10413, 4296…
$ is_workday   <lgl> FALSE, FALSE, TRUE, TRUE, TRUE, TRUE, TRUE, TRUE, TRUE, TRUE, TRUE, TRUE, FALSE, FALSE,…
$ is_weekend   <lgl> TRUE, TRUE, FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, TRUE,…
$ is_holiday   <lgl> FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FAL…
$ temp         <dbl> 2.166667, 2.791667, 8.958333, 7.125000, 9.000000, 6.708333, 8.166667, 6.681818, 9.45833…
$ temp_feel    <dbl> -0.75000000, 2.04166667, 7.70833333, 5.70833333, 6.45833333, 4.20833333, 5.08333333, 3.…
$ humidity     <dbl> 95.16667, 93.37500, 81.08333, 79.54167, 80.20833, 77.58333, 75.20833, 81.27273, 79.4166…
$ wind_speed   <dbl> 10.416667, 4.583333, 8.666667, 9.041667, 19.208333, 12.791667, 21.250000, 18.136364, 18…
$ weather_type <fct> broken clouds, clear, broken clouds, cloudy, broken clouds, clear, scattered clouds, cl…
```


Your Turn: Data Export

```
1 saveRDS(df_bikes, file = "./data/london-bikes-custom.Rds")
```

```
1 readr::write_rds(df_bikes, file = "./data/london-bikes-custom.Rds")
```

```
1 rio::export(df_bikes, file = "./data/london-bikes-custom.Rds")
```

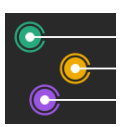
Introduction to R

— Getting Help —

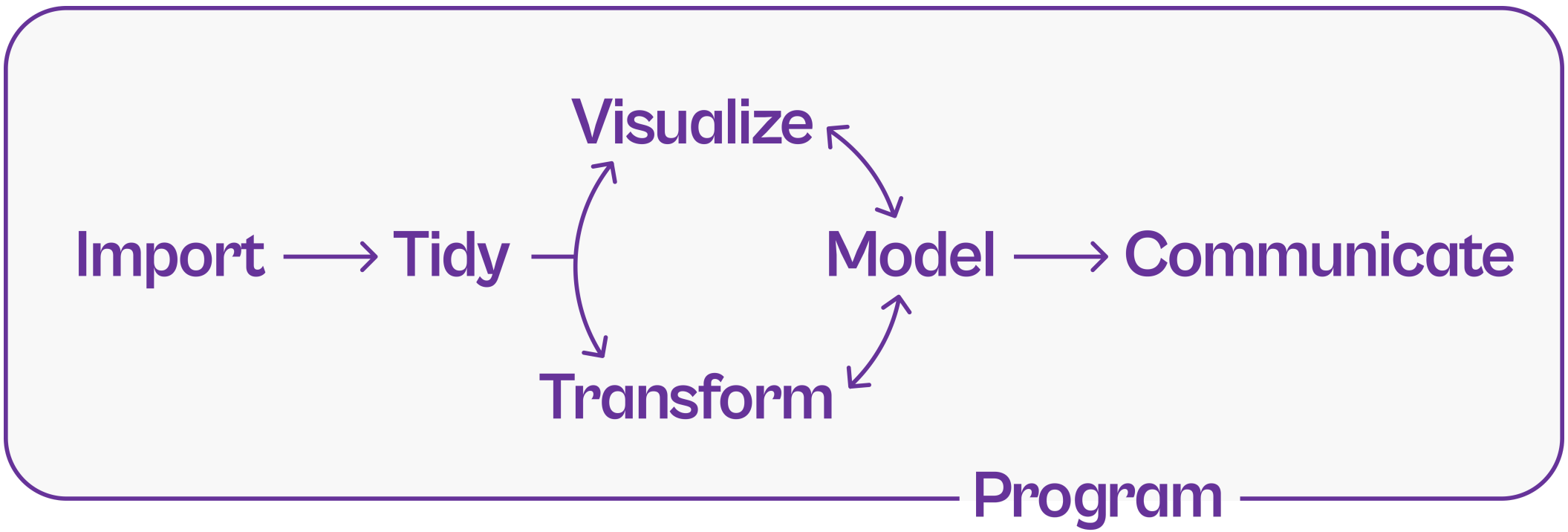
Getting Help with R

- R Foundation Help Page: r-project.org/help.html
- Posit / RStudio Community: community.rstudio.com
- R For Data Science Online Learning Community: rfordatasci.com
- Stack Overflow: stackoverflow.com
- R User Groups (local): benubah.github.io/r-community-explorer/rugs.html
- R Ladies (global & local): rladies.org
- Twitter: #rstats, #tidyverse, #ggplot2
- Books:
  - Modern Dive
  - R for Data Science
  - The Big Book of R

What's Next?

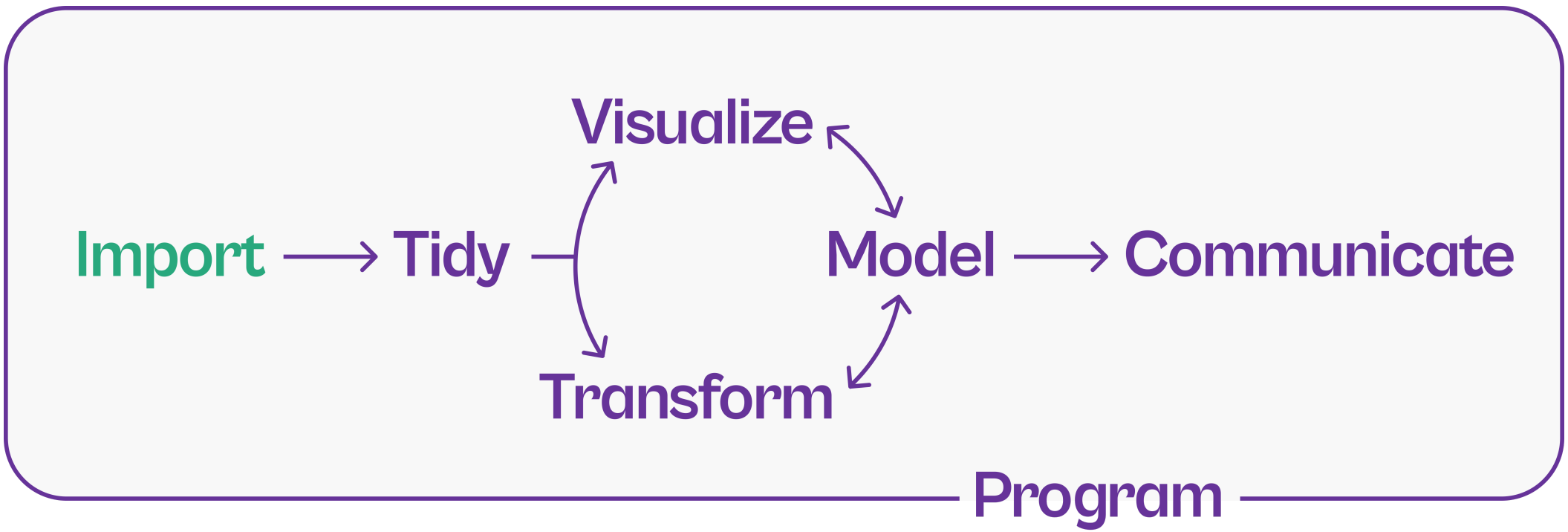


The Data Science Workflow



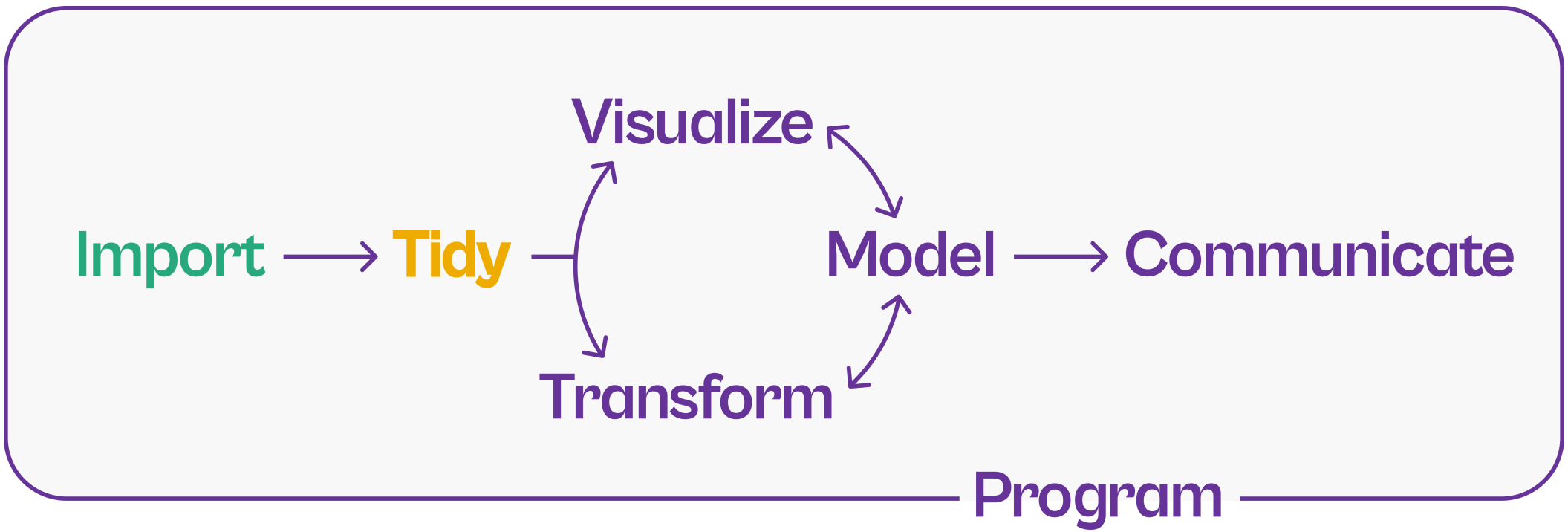
The data science workflow, modified from "R for Data Science"

The Data Science Workflow



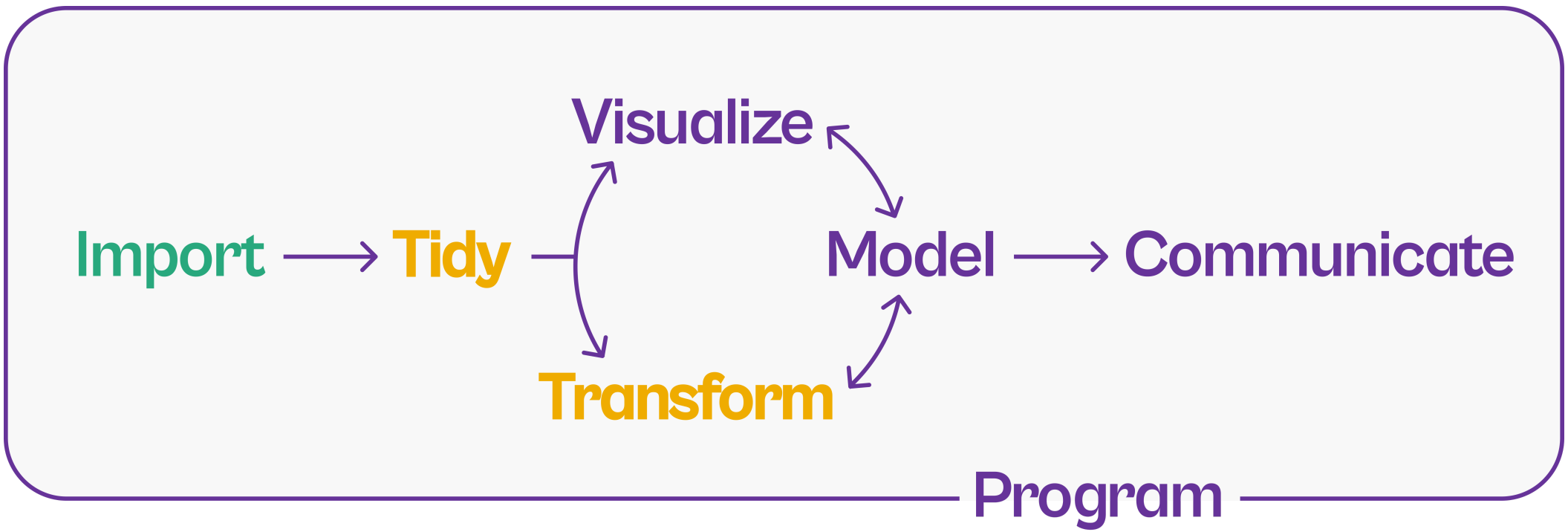
The data science workflow, modified from "R for Data Science"

The Data Science Workflow



The data science workflow, modified from "R for Data Science"

The Data Science Workflow



The data science workflow, modified from "R for Data Science"

That's it Folks...

— Thank you! —