R and Quarto

Modern Plain Text Social Science
Week 03

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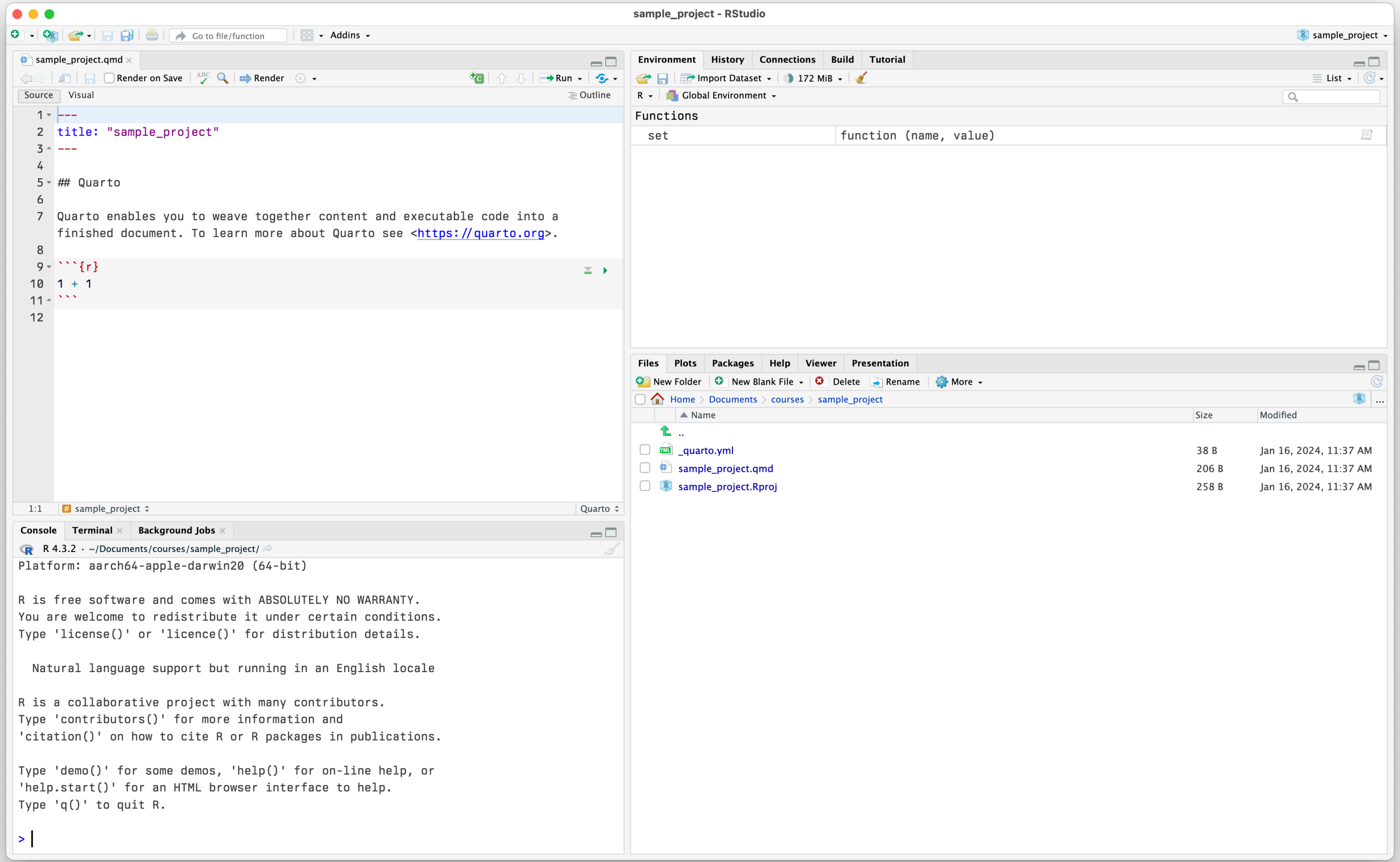
Your Workbench

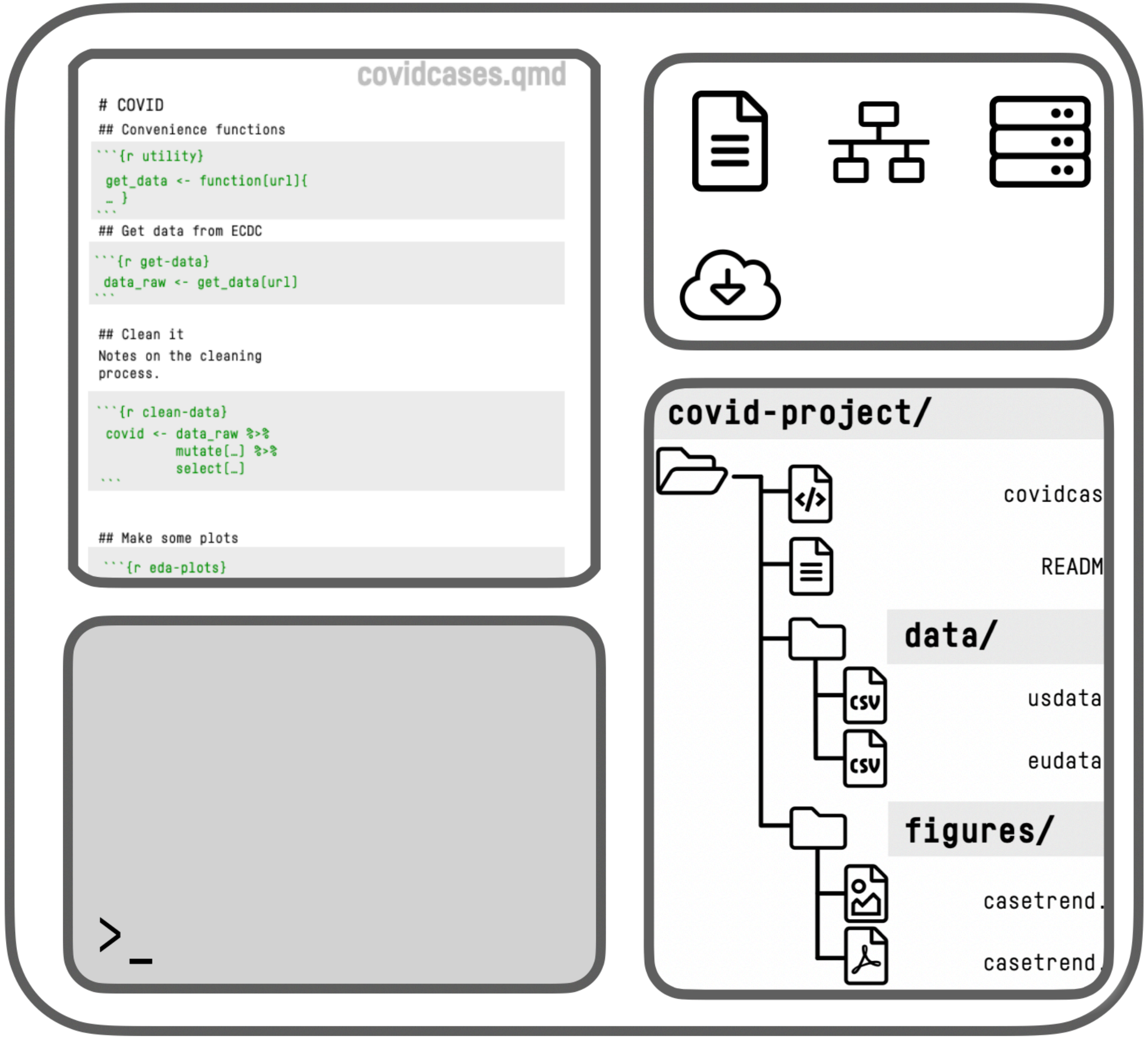
RStudio is an IDE for R

A kitchen is an IDE for Meals

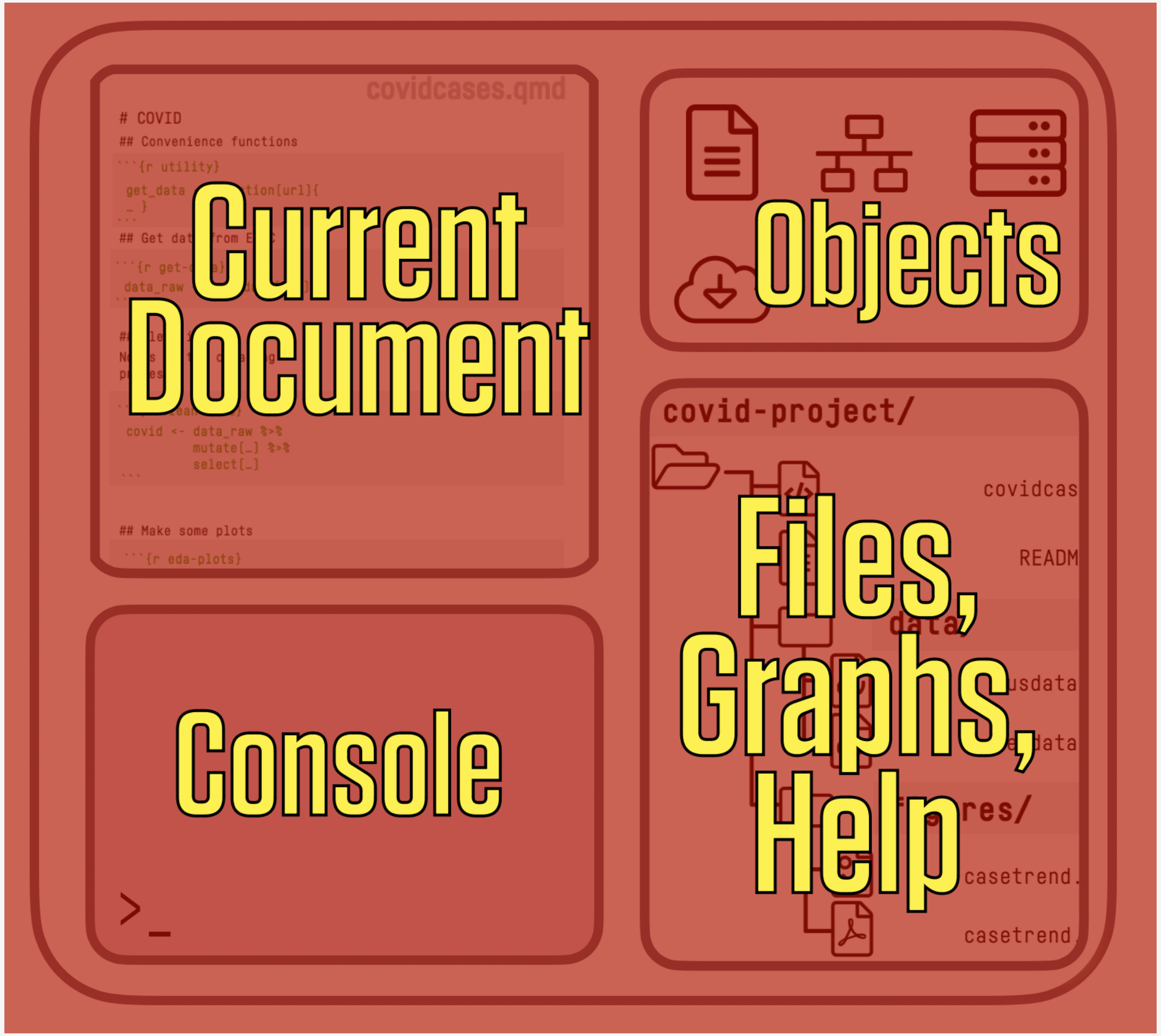
R and RStudio



RStudio at startup



RStudio schematic overview

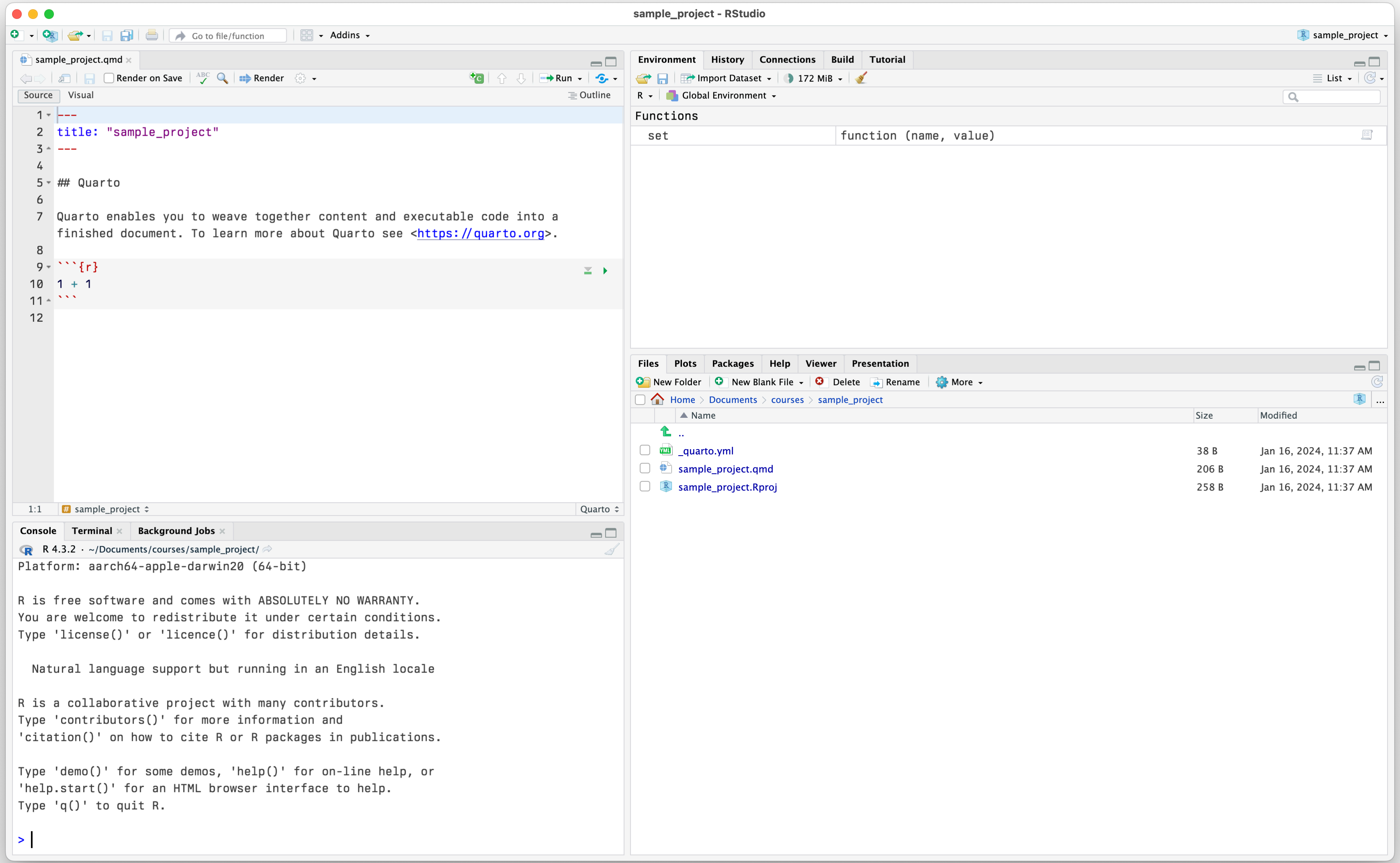


RStudio schematic overview

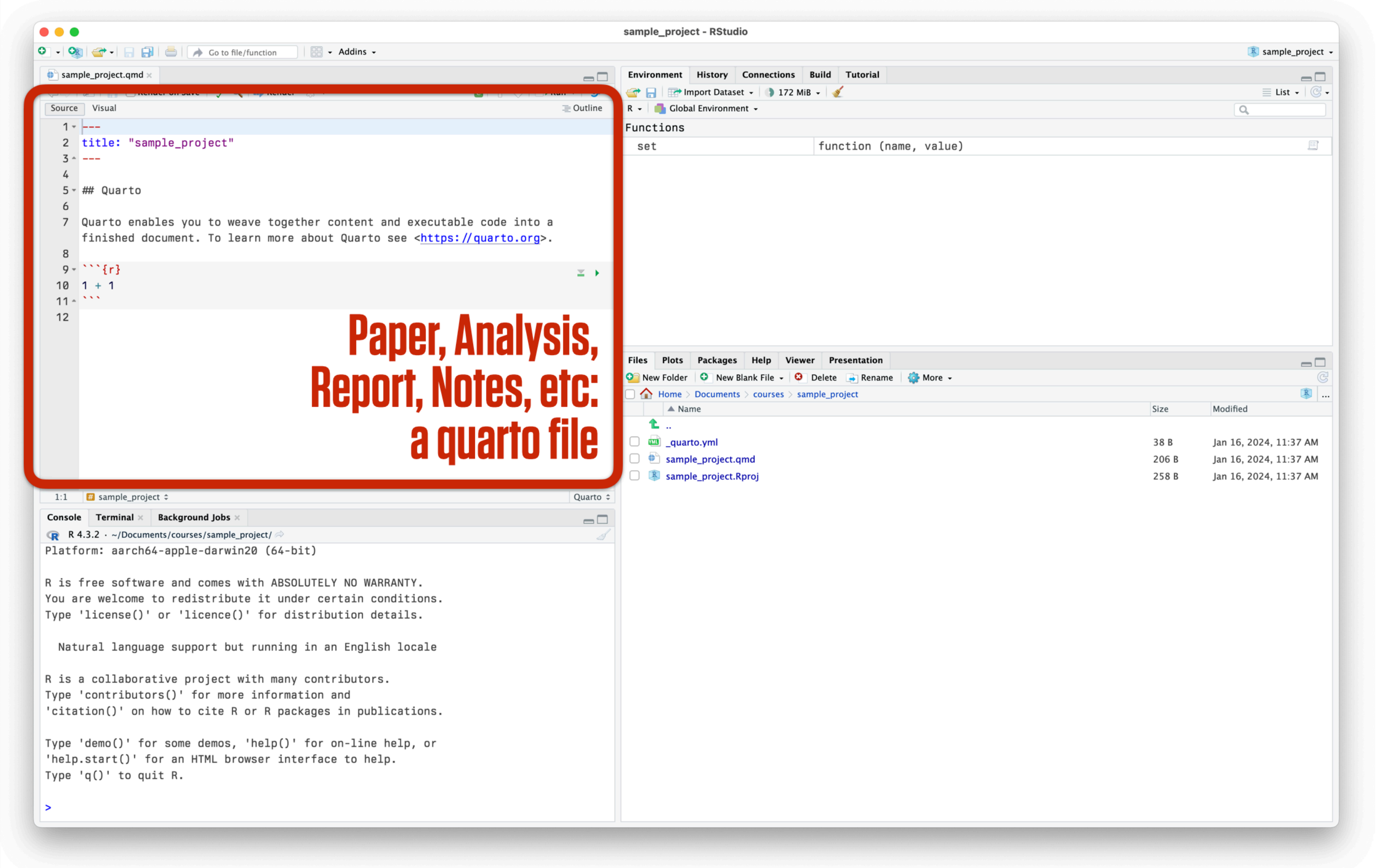
Think in terms of Data + Transformations, written out as code, rather than a series of point-and-click steps

Our starting data + our code is what's "real" in our projects, not the final output or any intermediate objects

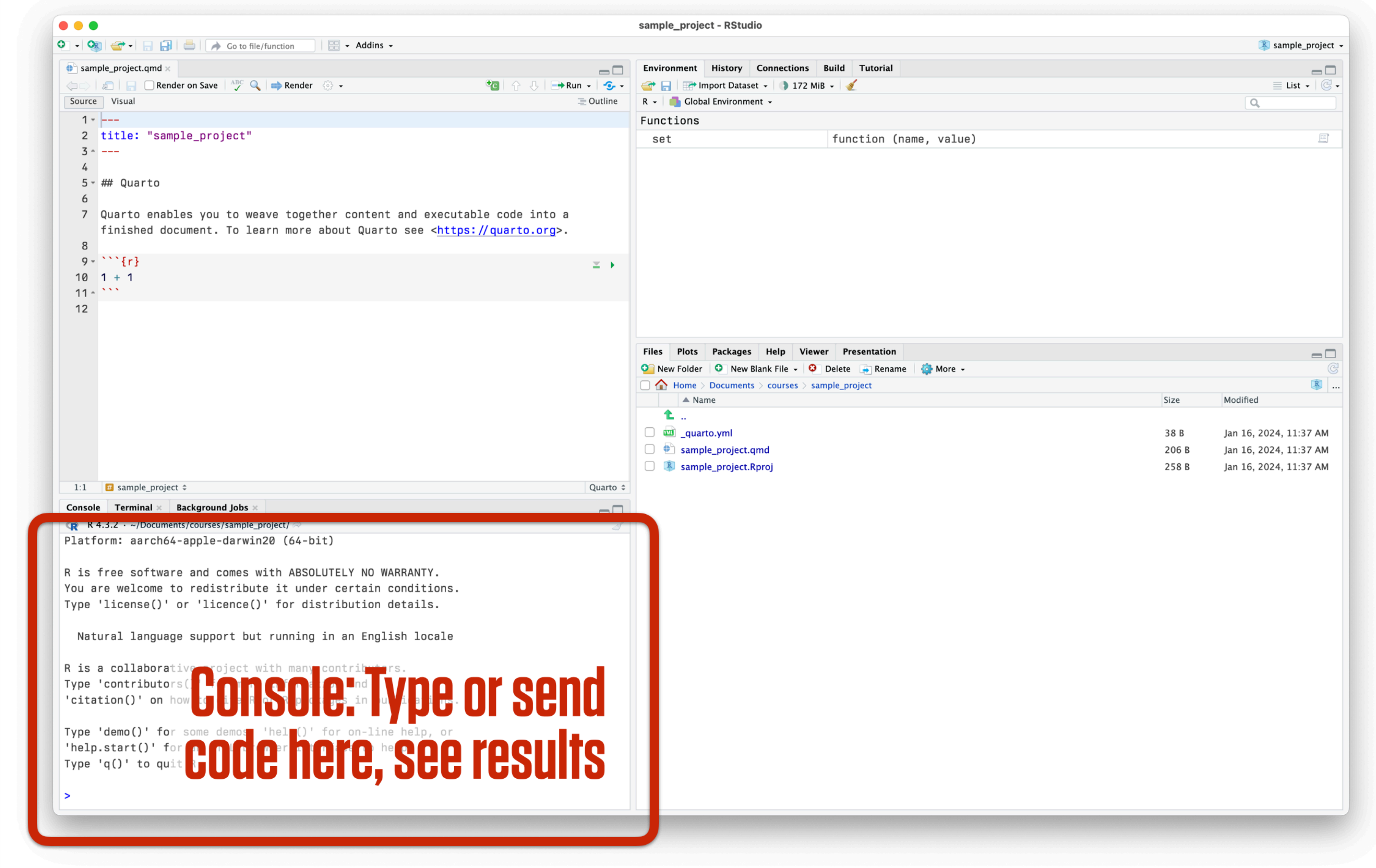
The IDE is the thing that helps us keep track of and control over the code we write and the outputs we produce.



RStudio at startup



RStudio at startup



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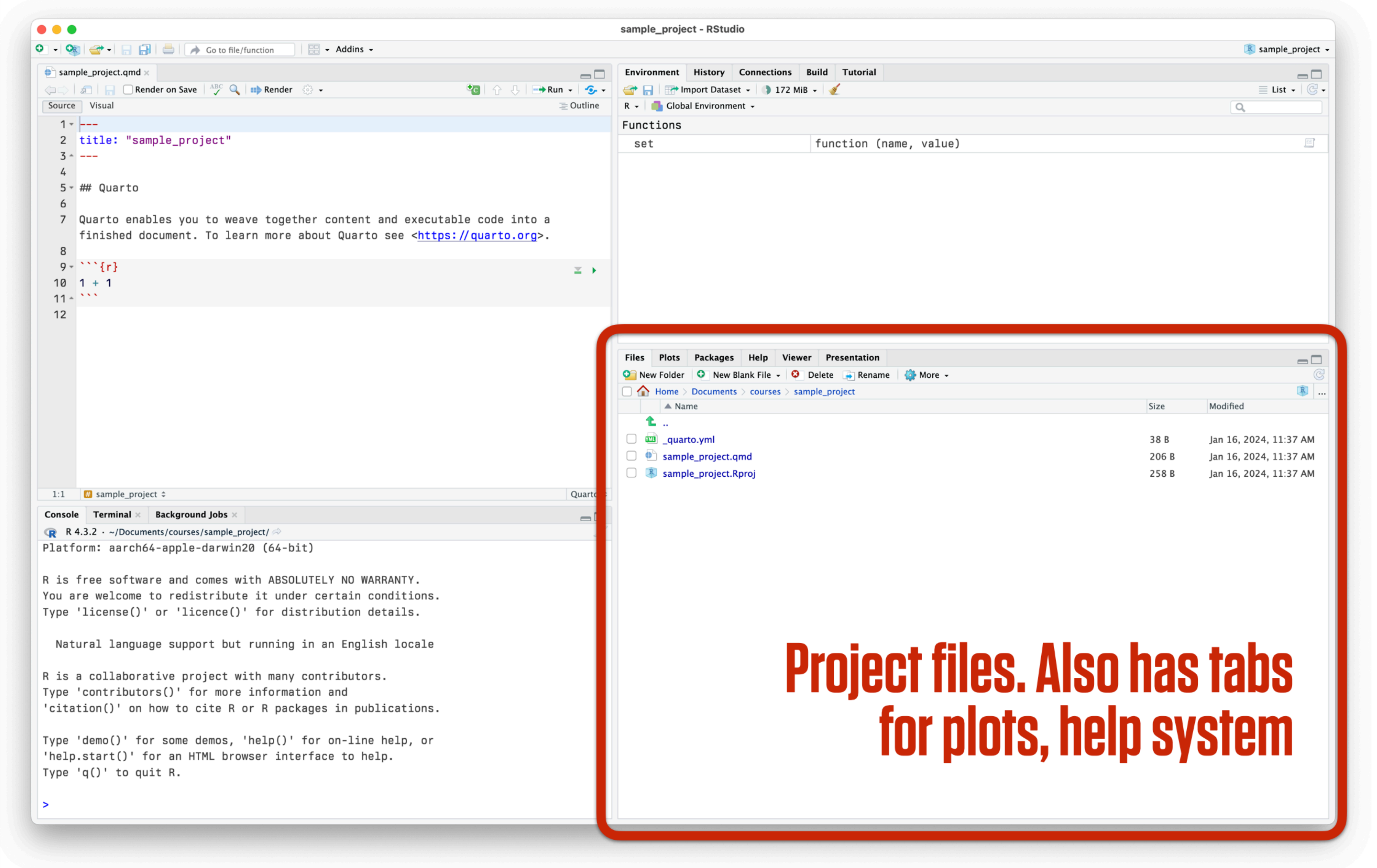
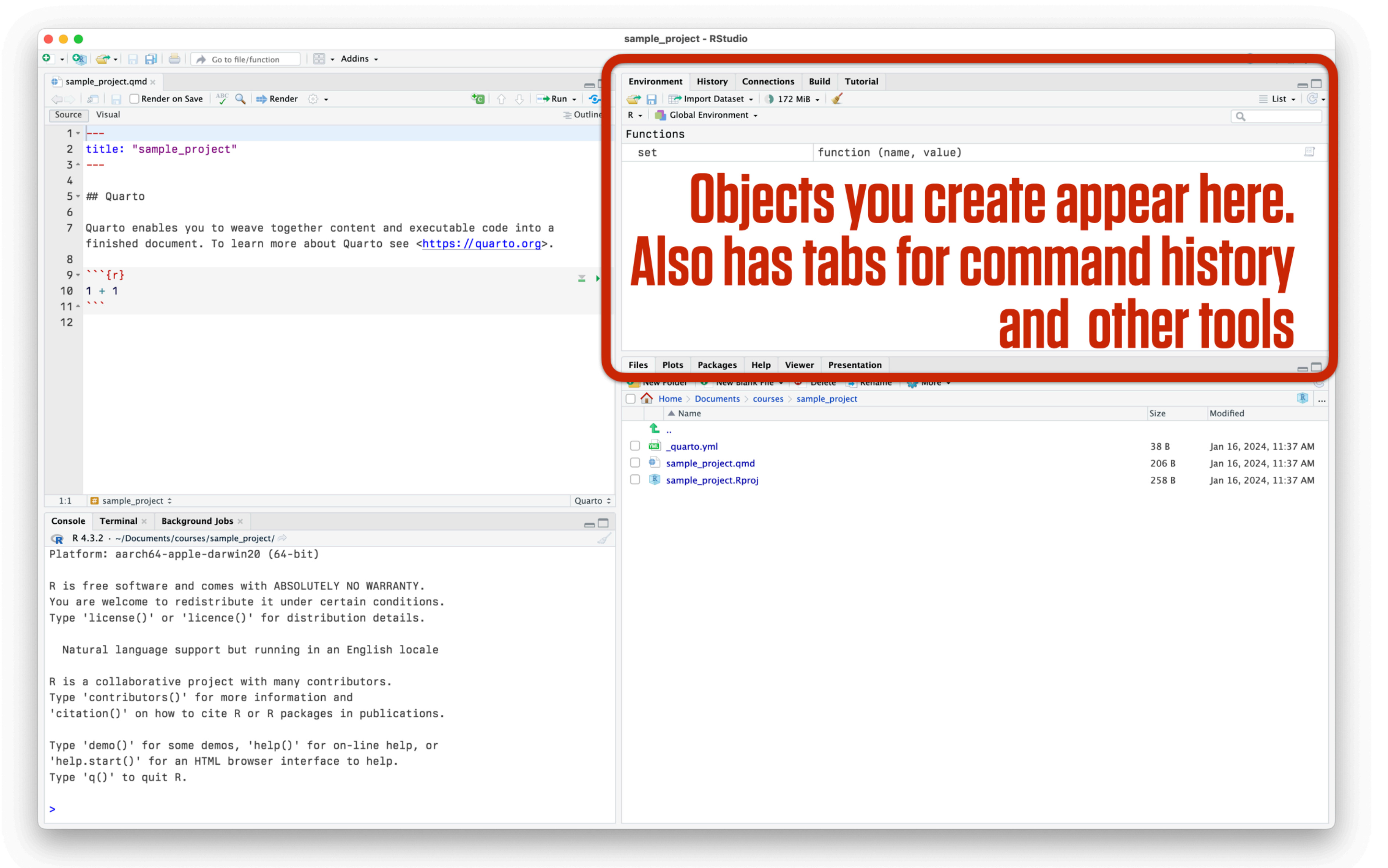
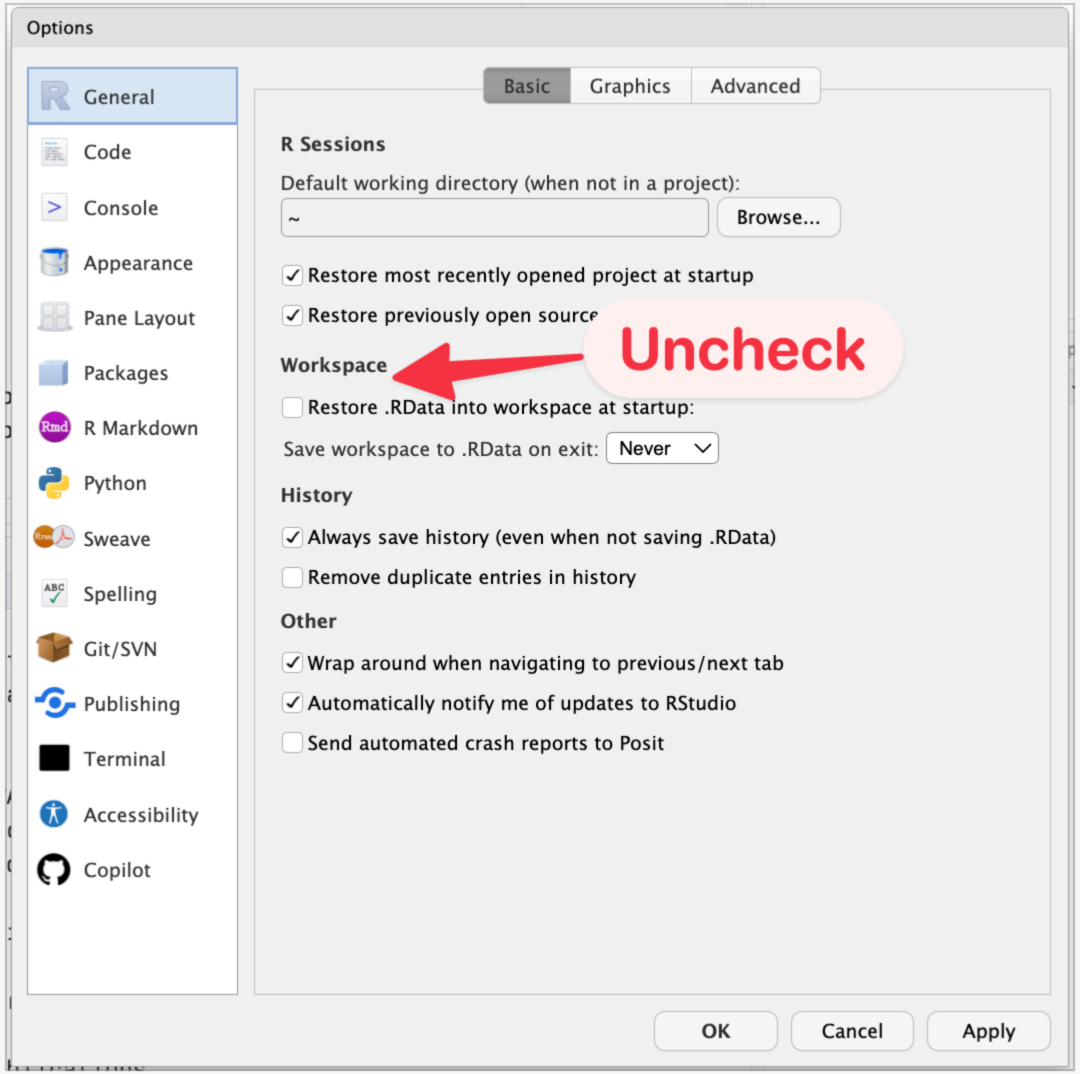


RStudio at startup

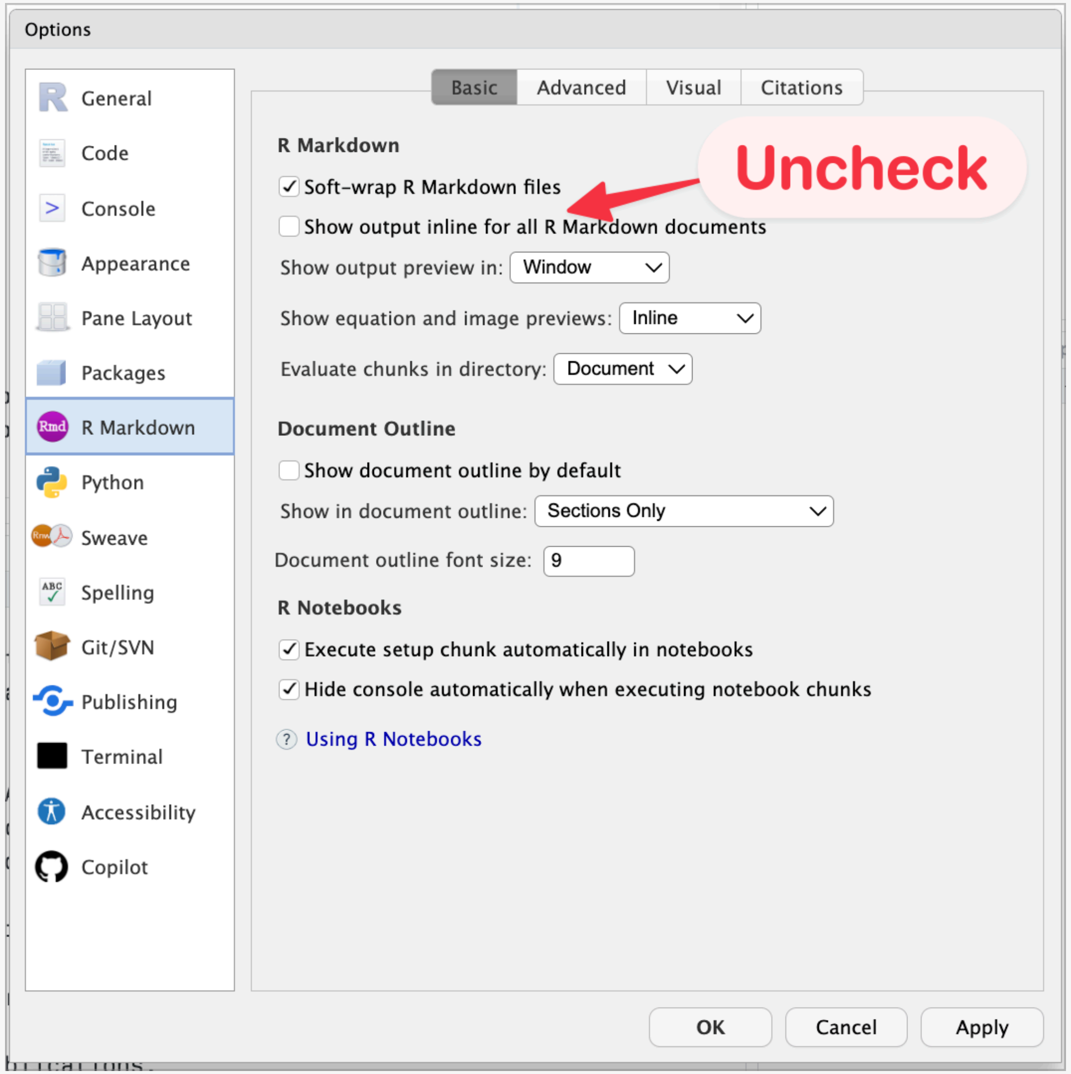


RStudio at startup

Your code is what's real in your project



Consider not showing output inline



Writing documents

Use Quarto to produce and reproduce your work

Where we want to end up

Covid Cases

Kieran Healy

Introduction

We will look at some data from the `covdata` package.

cname	cases
France	2376852
United Kingdom	1849403
United States	16256754

A little graph

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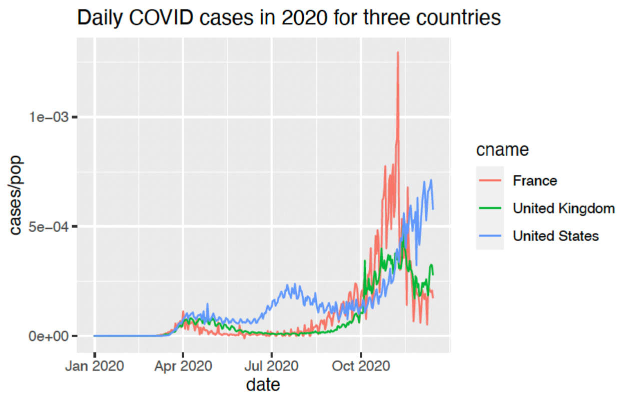

PDF out

Where we want to end up

Covid Cases

AUTHOR
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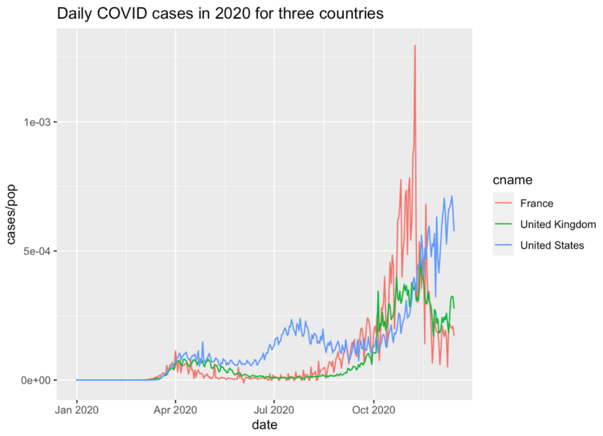
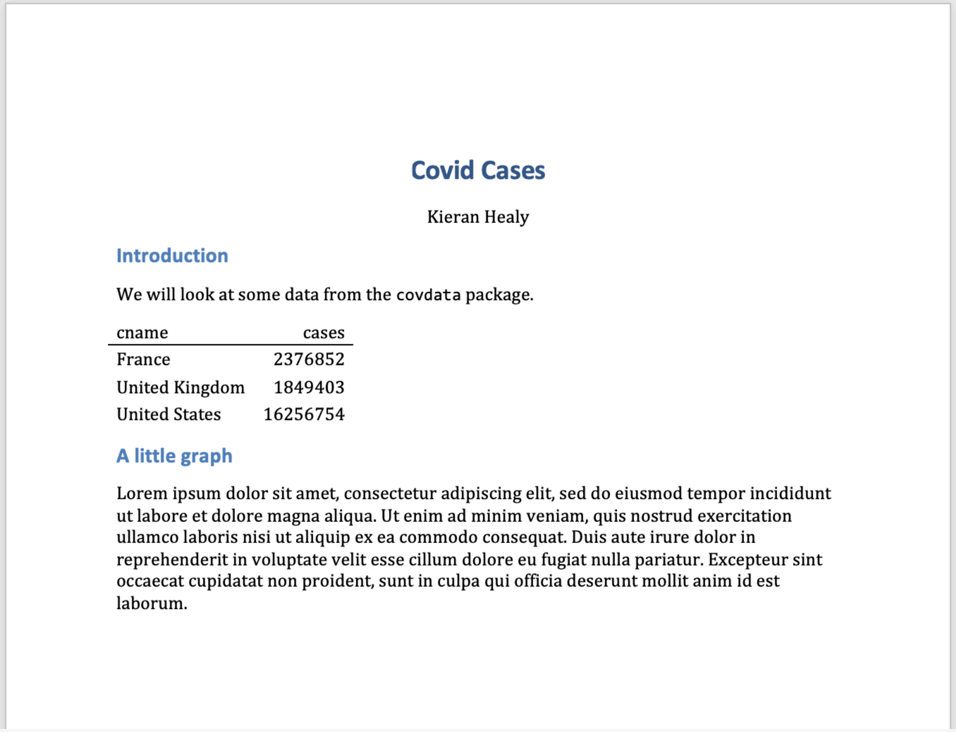


HTML out

Where we want to end up



Covid Cases

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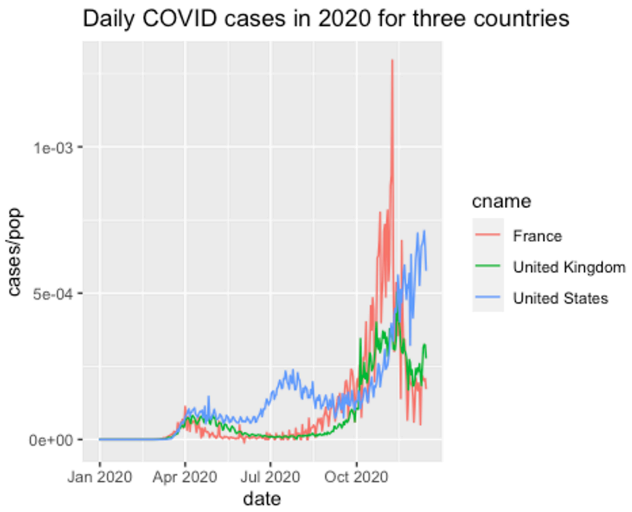

Word out

How to get there?

```
# COVID          covidcases.R
# Get data from ECDC
# FIXME Write a fn to
# do this
data_raw <- read_csv(url)

# Clean it
# Notes on the cleaning
# process.

 covid <- data_raw |>
          mutate(...) |>
          select(...)


# Make a plot
covid |>
     ggpplot(...) +
     geom_line(...) |>
ggsave()
```

We could write an **R script** with some notes inside, using it to create some figures and tables, paste them into our document.

This will work well. The more complex our projects get the more likely it is we will write code like this. It will also look less and less like a single all-in-one-breath script and more like a structured collection R files that combine to do many things.

But to begin we can also do things a little differently, by taking a more *notebook-based* approach. For many simpler and routine uses, this will be better.

We can make this ...

1. Lorem Ipsum

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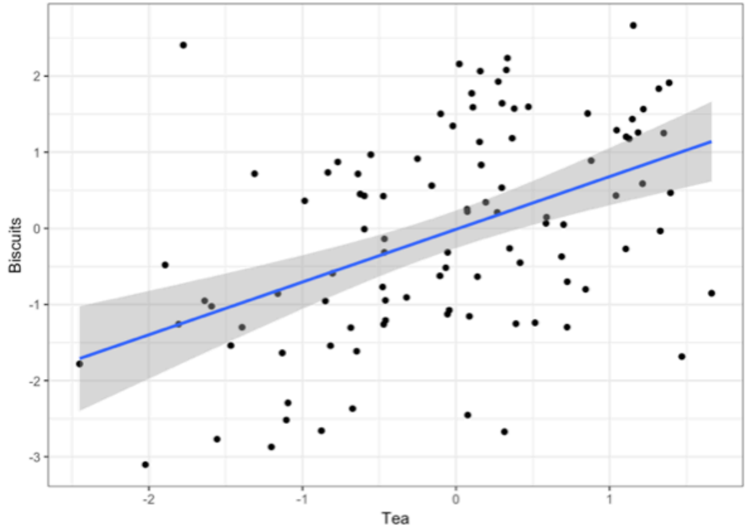

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… by writing this

````markdown
# Lorem Ipsum

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aliqua. Ut enimad minim veniam, quis nostrud exercitation
ullamco laboris nisi ut aliquip ex ea commodo consequat.

```{r}
library(ggplot2)
tea <- rnorm(100)
biscuits <- tea + rnorm(100, 0, 1.3)
data <- data.frame(tea, biscuits)
p <- ggplot(data, aes(x = tea, y = biscuits)) +
    geom_point() +
    geom_smooth(method = "lm") +
    labs(x = "Tea", y = "Biscuits") + theme_bw()
print(p)
```

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occaecat cupidatat non proident, sunt in culpa qui officia
deserunt mollit anim id est laborum.
````

The code gets replaced by its output

This way of doing things is called a *Literate Programming* or *Notebook* approach.

```
# Lorem Ipsum

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sed do *eiusmod tempor* incididunt ut labore et dolore magna
aliqua. Ut enimad minim veniam, quis nostrud exercitation
ullamco laboris nisi ut aliquip ex ea commodo consequat.

library(ggplot2)
tea <- rnorm(100)
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    geom_point() +
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occaecat cupidatat non proident, sunt in culpa qui officia
deserunt mollit anim id est laborum.
```

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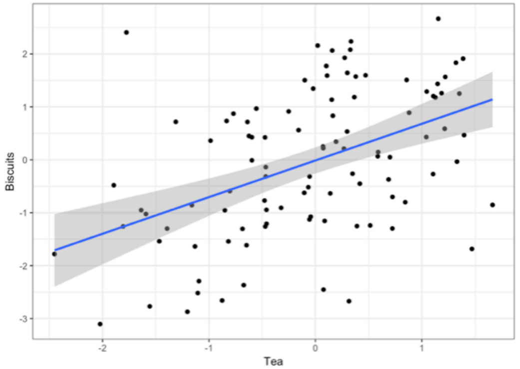

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```
---
title: "Covid Cases"
author: "Kieran Healy"
format: html
---


```{r}
#| label: setup
#| echo: false
#| message: false

# Don't include code chunks in the document
knitr::opts_chunk$set (echo = FALSE)

library(tidyverse)
library(covdata)

```

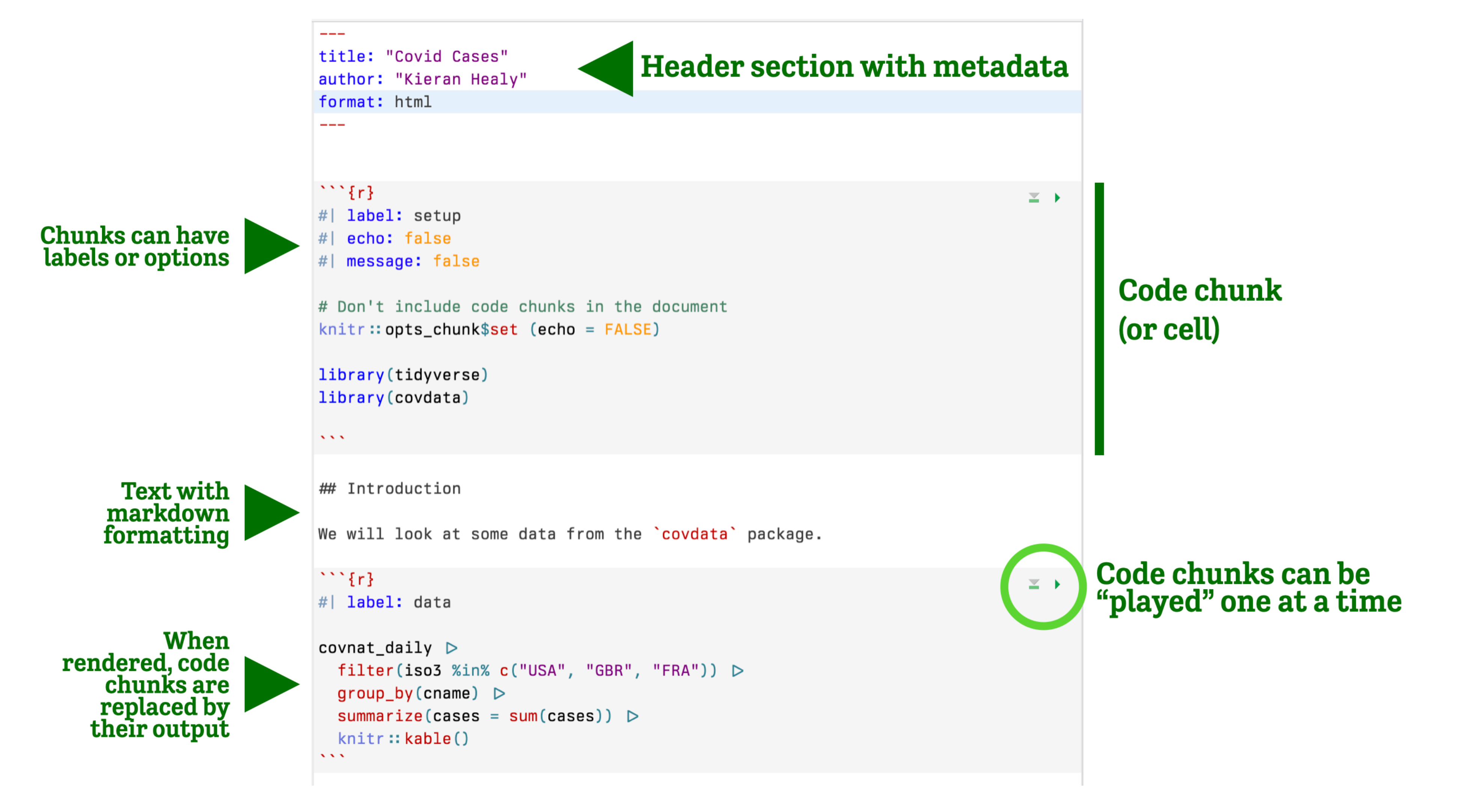
Introduction

We will look at some data from the `covdata` package.

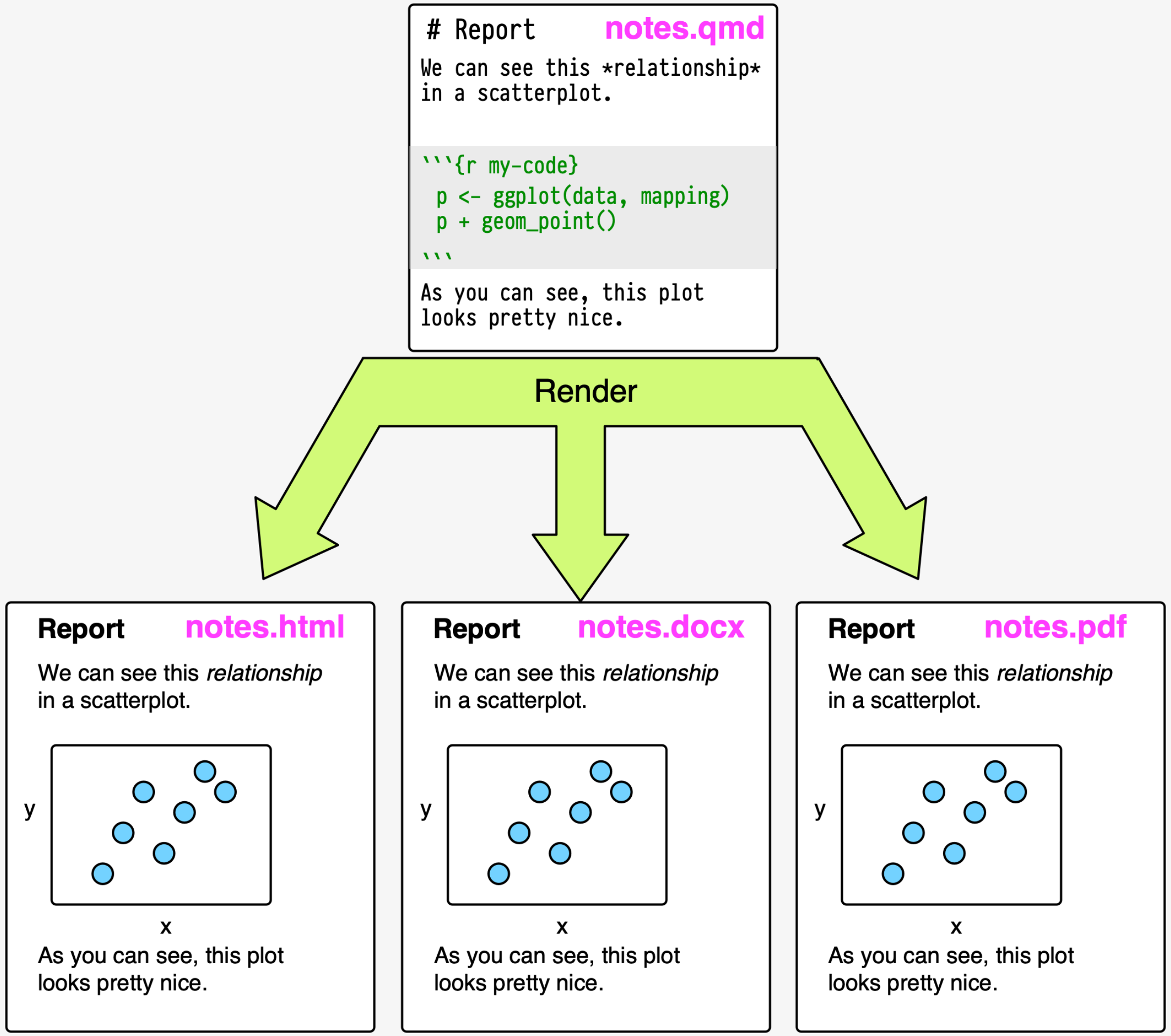
```{r}
#| label: data

covnat_daily |>
  filter(iso3 %in% c("USA", "GBR", "FRA")) |>
  group_by(cname) |>
  summarize(cases = sum(cases)) |>
  knitr::kable()
```
```

A Quarto file with markdown and code chunks



A Quarto file with markdown and code chunks, annotated



This approach has its limitations, which we will return to, but it's *very* useful and has many benefits.

Strengths and weaknesses

Notebooks work smoothly when

- Your document or report is small and self-contained.
- Your analysis is quick or lightweight.
- You are making slides.
- You are making a lot of similar reports from a template.
- You regularly refer to calculated items in the text of your analysis.

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Notebooks can get awkward when

- Your analysis has many pieces.
- Your project has many authors.
- Your analysis needs a lot of scaffolding in code.
- You have a lot of different outputs.

In Practice

Notebook-style documents like Quarto files are great as part of larger projects. The more complex your project, the less likely it will straightforwardly fit into a *single* notebook. More likely you will find yourself, first, splitting parts of a complex project up into different notebooks; and then, second, writing R scripts that programatically clean and pre-process data, run analyses, and produce some outputs—such as key tables and figures—that you then incorporate into a Quarto document indirectly. Not by copying and pasting, but by pointing to those outputs.

Basic markdown summary

Desired style	Use the following Markdown annotation
Heading 1	`# Heading 1`
Heading 2	`## Heading 2`
Heading 3	`### Heading 3` (Actual heading styles will vary.)
Paragraph	Just start typing
Bold	`**Bold**`
Italic	`*Italic*`
Images	`[Alternate text for image](path/image.jpg)`
Hyperlinks	`[Link text](https://www.visualizingsociety.com/)`
Unordered Lists	
- First	`- First`
- Second.	`- Second`
- Third	`- Third`
Ordered Lists	
1. First	`1. First`
2. Second.	`2. Second`
3. Third	`3. Third`
Footnote.[1]	`Footnote[^notelabel]`
[1]The note's content.	`[^notelabel] The note's content.`

The right frame of mind

This is like learning how to drive a car, or how to cook in a kitchen … or learning to speak a language.

After some orientation to what's where, you will learn best by *doing*.

Software is a pain, but you won't crash the car or burn your house down.

Getting Oriented

Before we start

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Keep in mind the kinds of things we want to do.

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We want to do things like group, summarize, count, tally, calculate, model or otherwise work on these columns, singly or all at once.

Before we start

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We want to do things like group, summarize, count, tally, calculate, model or otherwise work on these columns, singly or all at once.

Once we learn how to do things like count up the number of rows within a group, or take the average of the values in a column, we will find that we are just a step or two away from doing much more complex operations in essentially the same fashion.

Split

Apply

Combine

Before we start

```r
gapminder
```

```
# A tibble: 1,704 × 6
   country     continent  year lifeExp      pop gdpPercap
   <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
 1 Afghanistan Asia       1952    28.8  8425333      779.
 2 Afghanistan Asia       1957    30.3  9240934      821.
 3 Afghanistan Asia       1962    32.0 10267083      853.
 4 Afghanistan Asia       1967    34.0 11537966      836.
 5 Afghanistan Asia       1972    36.1 13079460      740.
 6 Afghanistan Asia       1977    38.4 14880372      786.
 7 Afghanistan Asia       1982    39.9 12881816      978.
 8 Afghanistan Asia       1987    40.8 13867957      852.
 9 Afghanistan Asia       1992    41.7 16317921      649.
10 Afghanistan Asia       1997    41.8 22227415      635.
# ℹ 1,694 more rows
```

Before we start

Country	Continent	Year	Lifeexp	Pop	Gdppercap
Afghanistan	Asia	1952	28.8	8425333	779.4
Afghanistan	Asia	1957	30.3	9240934	820.9
Afghanistan	Asia	1962	32.0	10267083	853.1
Afghanistan	Asia	1967	34.0	11537966	836.2
Afghanistan	Asia	1972	36.1	13079460	740.0
Afghanistan	Asia	1977	38.4	14880372	786.1
Afghanistan	Asia	1982	39.9	12881816	978.0
Afghanistan	Asia	1987	40.8	13867957	852.4
Afghanistan	Asia	1992	41.7	16317921	649.3
Afghanistan	Asia	1997	41.8	22227415	635.3
Afghanistan	Asia	2002	42.1	25268405	726.7
Afghanistan	Asia	2007	43.8	31889923	974.6

Before we start

Table 1: Average life expectancy by continent, 1952-2007

Year	Africa	Americas	Asia	Europe	Oceania
1952	39.1	53.3	46.3	64.4	69.3
1957	41.3	56.0	49.3	66.7	70.3
1962	43.3	58.4	51.6	68.5	71.1
1967	45.3	60.4	54.7	69.7	71.3
1972	47.5	62.4	57.3	70.8	71.9
1977	49.6	64.4	59.6	71.9	72.9
1982	51.6	66.2	62.6	72.8	74.3
1987	53.3	68.1	64.9	73.6	75.3
1992	53.6	69.6	66.5	74.4	76.9
1997	53.6	71.2	68.0	75.5	78.2
2002	53.3	72.4	69.2	76.7	79.7
2007	54.8	73.6	70.7	77.6	80.7

Loading the tidyverse libraries

```r
library(tidyverse)
```

```
── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
✔ dplyr     1.1.3     ✔ readr     2.1.4
✔ forcats   1.0.0     ✔ stringr   1.5.0
✔ ggplot2   3.4.4     ✔ tibble    3.2.1
✔ lubridate 1.9.3     ✔ tidyr     1.3.0
✔ purrr     1.0.2
── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
✖ dplyr::filter() masks stats::filter()
✖ dplyr::lag()    masks stats::lag()
ℹ Use the conflicted package to force all conflicts to become errors
```

The tidyverse has several components.

We'll return to this message about Conflicts later.

Tidyverse components

```
library(tidyverse)
Loading tidyverse: ggplot2
Loading tidyverse: tibble
Loading tidyverse: tidyr
Loading tidyverse: readr
Loading tidyverse: purrr
Loading tidyverse: dplyr
```

Call the package and …

- ◁ **Draw graphs**
- ◁ **Nicer data tables**
- ◁ **Tidy your data**
- ◁ **Get data into R**
- ◁ **Fancy Iteration**
- ◁ **Action verbs for tables**

What R looks like

Code you can type and run:

```r
## Inside code chunks, lines beginning with a # character are comments
## Comments are ignored by R

my_numbers <- c(1, 1, 2, 4, 1, 3, 1, 5) # Anything after a # character is ignored as well
```

Output:

```r
my_numbers
```

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

This is equivalent to running the code above, typing `my_numbers` at the console, and hitting enter.

What R looks like

By convention, code output in documents is prefixed by ##

Also by convention, outputting vectors, etc, gets a counter keeping track of the number of elements. For example,

```r
letters
```

```
 [1] "a" "b" "c" "d" "e" "f" "g" "h" "i" "j" "k" "l" "m" "n" "o" "p" "q" "r" "s"
[20] "t" "u" "v" "w" "x" "y" "z"
```

Some things to know about R

0. It's a calculator

Arithmetic

```r
(31 * 12) / 2^4
```

```
[1] 23.25
```

```r
sqrt(25)
```

```
[1] 5
```

```r
log(100)
```

```
[1] 4.60517
```

```r
log10(100)
```

```
[1] 2
```

0. It's a calculator

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(31 * 12) / 2^4
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[1] 23.25
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```

```
[1] 5
```

```r
log(100)
```

```
[1] 4.60517
```

```r
log10(100)
```

```
[1] 2
```

Logic

```r
4 < 10
```

```
[1] TRUE
```

```r
4 > 2 & 1 > 0.5 # The "&" means "and"
```

```
[1] TRUE
```

```r
4 < 2 | 1 > 0.5 # The "|" means "or"
```

```
[1] TRUE
```

```r
4 < 2 | 1 < 0.5
```

```
[1] FALSE
```

Boolean and Logical operators

Logical equality and inequality (yielding a `TRUE` or `FALSE` result) is done with `==` and `!=`. Other logical operators include `<`, `>`, `<=`, `>=`, and `!` for negation.

```r
## A logical test
2 == 2 # Write `=` twice
```

```
[1] TRUE
```

```r
## This will cause an error, because R will think you are trying to assign a value
2 = 2

## Error in 2 = 2 : invalid (do_set) left-hand side to assignment
```

```r
3 != 7 # Write `!` and then `=` to make `!=`
```

```
[1] TRUE
```

1. Everything in R has a name

```r
my_numbers # We created this a few minutes ago
```

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

```r
letters  # This one is built-in
```

```
 [1] "a" "b" "c" "d" "e" "f" "g" "h" "i" "j" "k" "l" "m" "n" "o" "p" "q" "r" "s"
[20] "t" "u" "v" "w" "x" "y" "z"
```

```r
pi  # Also built-in
```

```
[1] 3.141593
```

Some names are forbidden

Or it’s a *really* bad idea to try to use them

```
TRUE
FALSE
Inf
NaN
NA
NULL

for
if
while
break
function
```

2. Everything is an object

There are a few built-in objects:

```
letters
```

```
 [1] "a" "b" "c" "d" "e" "f" "g" "h" "i" "j" "k" "l" "m" "n" "o" "p" "q" "r" "s"
[20] "t" "u" "v" "w" "x" "y" "z"
```

```
pi
```

```
[1] 3.141593
```

```
LETTERS
```

```
 [1] "A" "B" "C" "D" "E" "F" "G" "H" "I" "J" "K" "L" "M" "N" "O" "P" "Q" "R" "S"
[20] "T" "U" "V" "W" "X" "Y" "Z"
```

3. You can create objects

In fact, this is mostly what we will be doing.

Objects are created by assigning a thing to a name:

```r
## name... gets ... this stuff
my_numbers <- c(1, 2, 3, 1, 3, 5, 25, 10)

## name ... gets ... the output of the function `c()`
your_numbers <- c(5, 31, 71, 1, 3, 21, 6, 52)
```

The `c()` function *combines* or *concatenates* things

The assignment operator

The assignment operator performs the action of creating objects

Use a keyboard shortcut to write it:

Press `option` *and* `-` on a Mac

Press `alt` *and* `-` on Windows

4. Do things to objects with functions

```r
## this object... gets ... the output of this function
my_numbers <- c(1, 2, 3, 1, 3, 5, 25, 10)

your_numbers <- c(5, 31, 71, 1, 3, 21, 6, 52)
```

```r
my_numbers
```

```
[1]  1  2  3  1  3  5 25 10
```

4. Do things to objects with functions

Functions can be identified by the parentheses after their names.

```
my_numbers
```

```
[1]  1  2  3  1  3  5 25 10
```

```
## If you run this you'll get an error
mean()
```

What functions usually do

They take **inputs** to **arguments**

They perform **actions**

They produce, or return, **outputs**

```
mean(x = my_numbers)
```

What functions usually do

They take **inputs** to **arguments**

They perform **actions**

They produce, or return, **outputs**

```
mean(x = my_numbers)
[1] 6.25
```

What functions usually do

```r
## Get the mean of what? Of x.
## You need to tell the function what x is
mean(x = my_numbers)
```

```
[1] 6.25
```

```r
mean(x = your_numbers)
```

```
[1] 23.75
```

What functions usually do

If you don't *name* the arguments, R assumes you are providing them in the order the function expects.

```r
mean(your_numbers)
```

```
[1] 23.75
```

What functions usually do

What arguments? Which order? Read the function's help page

```r
help(mean)
```

```r
## quicker
?mean
```

How to read an R help page?

What functions usually do

Arguments often tell the function what to do in specific circumstances

```
missing_numbers <- c(1:10, NA, 20, 32, 50, 104, 32, 147, 99, NA, 45)

mean(missing_numbers)
```

```
[1] NA
```

```
mean(missing_numbers, na.rm = TRUE)
```

```
[1] 32.44444
```

Or select from one of several options

```
## Look at ?mean to see what `trim` does
mean(missing_numbers, na.rm = TRUE, trim = 0.1)
```

```
[1] 27.25
```

What functions usually do

There are all kinds of functions. They return different things.

```r
summary(my_numbers)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
   1.00    1.75    3.00    6.25    6.25   25.00 
```

What functions usually do

You can assign the output of a function to a name, which turns it into an object. (Otherwise it'll send its output to the console.)

```r
my_summary <- summary(my_numbers)

my_summary
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
   1.00    1.75    3.00    6.25    6.25   25.00 
```

What functions usually do

Objects hang around in your work environment until they are overwritten by you, or are deleted.

```
## rm() function removes objects
rm(my_summary)

my_summary

## Error: object 'my_summary' not found
```

Functions can be nested

```r
c(1:20)
```

```
 [1]  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20
```

```r
mean(c(1:20))
```

```
[1] 10.5
```

```r
summary(mean(c(1:20)))
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
   10.5    10.5    10.5    10.5    10.5    10.5 
```

```r
names(summary(mean(c(1:20))))
```

```
[1] "Min."    "1st Qu." "Median"  "Mean"    "3rd Qu." "Max."   
```

```r
length(names(summary(mean(c(1:20)))))
```

```
[1] 6
```

Nested functions are evaluated from the inside out.

Use the pipe operator: |>

Instead of deeply nesting functions in parentheses, we can use the *pipe operator*:

```r
c(1:20) |> mean() |> summary() |> names() |>  length()
```

```
[1] 6
```

Read this operator as “***and then***”

Use the pipe operator: |>

Better, vertical space is free in R:

```r
c(1:20) |>
  mean() |>
  summary() |>
  names() |>
  length()
```

```
[1] 6
```

Pipelines make code more readable

Not great, Bob:

```
serve(stir(pour_in_pan(whisk(crack_eggs(get_from_fridge(eggs), into = "bowl"), len = 40), temp = "med-high")))
```

Notice how the first thing you read is the last operation performed.

Pipelines make code more readable

We can use vertical space and indents, but it's really not much better:

```
serve(
  stir(
    pour_in_pan(
      whisk(
        crack_eggs(
          get_from_fridge(eggs),
        into = "bowl"),
      len = 40),
    temp = "med-high")
  )
)
```

Pipelines make code more readable

Much nicer:

```
eggs ▷
  get_from_fridge() ▷
  crack_eggs(into = "bowl") ▷
  whisk(len = 40) ▷
  pour_in_pan(temp = "med-high") ▷
  stir() ▷
  serve()
```

We'll still use nested parentheses quite a bit, often in the context of a function working inside a pipeline. But it's good not to have too many levels of nesting.

Functions are bundled into packages

Packages are loaded into your working environment using the `library()` function:

```
## A package containing a dataset rather than functions
library(gapminder)

gapminder
```

```
# A tibble: 1,704 × 6
   country     continent  year lifeExp      pop gdpPercap
   <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
 1 Afghanistan Asia       1952    28.8  8425333      779.
 2 Afghanistan Asia       1957    30.3  9240934      821.
 3 Afghanistan Asia       1962    32.0 10267083      853.
 4 Afghanistan Asia       1967    34.0 11537966      836.
 5 Afghanistan Asia       1972    36.1 13079460      740.
 6 Afghanistan Asia       1977    38.4 14880372      786.
 7 Afghanistan Asia       1982    39.9 12881816      978.
 8 Afghanistan Asia       1987    40.8 13867957      852.
 9 Afghanistan Asia       1992    41.7 16317921      649.
10 Afghanistan Asia       1997    41.8 22227415      635.
# ℹ 1,694 more rows
```

Functions are bundled into packages

You need only *install* a package once (and occasionally update it):

```r
## Do at least once for each package. Once done, not needed each time.
install.packages("palmerpenguins", repos = "http://cran.rstudio.com")

## Needed sometimes, especially after an R major version upgrade.
update.packages(repos = "http://cran.rstudio.com")
```

Functions are bundled into packages

But you must *load* the package in each R session before you can access its contents:

```r
## To load a package, usually at the start of your RMarkdown document or script file
library(palmerpenguins)
penguins
```

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

Grabbing a single function with ::

```
# A little glimpse of what we'll do soon
penguins |>
  count(species, sex, year) |>
  pivot_wider(names_from = year, values_from = n) |>
  tinytable::tt()
```

species	sex	2007	2008	2009
Adelie	female	22	25	26
Adelie	male	22	25	26
Adelie	NA	6	NA	NA
Chinstrap	female	13	9	12
Chinstrap	male	13	9	12
Gentoo	female	16	22	20
Gentoo	male	17	23	21
Gentoo	NA	1	1	3

Remember those conflicts?

```
library(tidyverse)
```

```
## ── Attaching packages ─────────────────────────────────────── tidyverse 1.3.0 ──
## ✓ ggplot2 3.3.3     ✓ purrr   0.3.4
## ✓ tibble  3.1.0     ✓ dplyr   1.0.5
## ✓ tidyr   1.1.3     ✓ stringr 1.4.0
## ✓ readr   1.4.0     ✓ forcats 0.5.1
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## x dplyr::filter()  masks stats::filter()
## x purrr::is_null() masks testthat::is_null()
## x dplyr::lag()     masks stats::lag()
## x dplyr::matches() masks tidyr::matches(), testthat::matches()
```

Notice how some functions in different packages have the same names.

Related concepts of *namespaces* and *environments*.

The scope of names

```r
x <- c(1:10)
y <- c(90:100)

x
```

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

```r
y
```

```
 [1]  90  91  92  93  94  95  96  97  98  99 100
```

```r
mean()

## Error in mean.default() : argument "x" is missing, with no default
```

The scope of names

```r
mean(x) # argument names are internal to functions
```

```
[1] 5.5
```

```r
mean(x = x)
```

```
[1] 5.5
```

```r
mean(x = y)
```

```
[1] 95
```

```r
x
```

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

```r
y
```

```
 [1]  90  91  92  93  94  95  96  97  98  99 100
```

5. Vector types; Object classes

I'm going to speak somewhat loosely here for now, and gloss over some distinctions between object classes and data structures, as well as kinds of objects and their attributes.

5. Vector types; Object classes

Objects are made of one or more vectors. A vector can, in effect, have a single type: integer, double, logical, character, factor, date, etc. That is, vectors are “atomic”. Complex objects are mostly lists of vectors of different sorts, or nested lists of other simpler objects that are themselves ultimately made up of vectors of

5. Vector types; Object classes

The object inspector in RStudio is your friend.

You can ask an object what it is at the console, too:

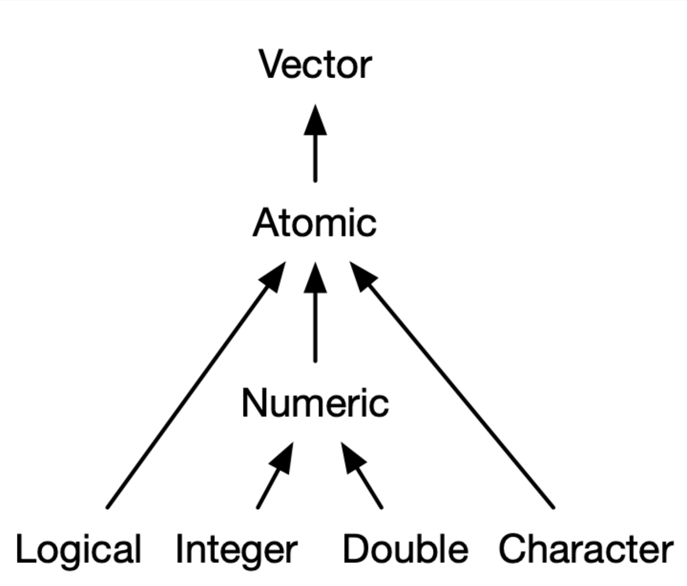
```
class(my_numbers)
```

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

```
typeof(my_numbers)
```

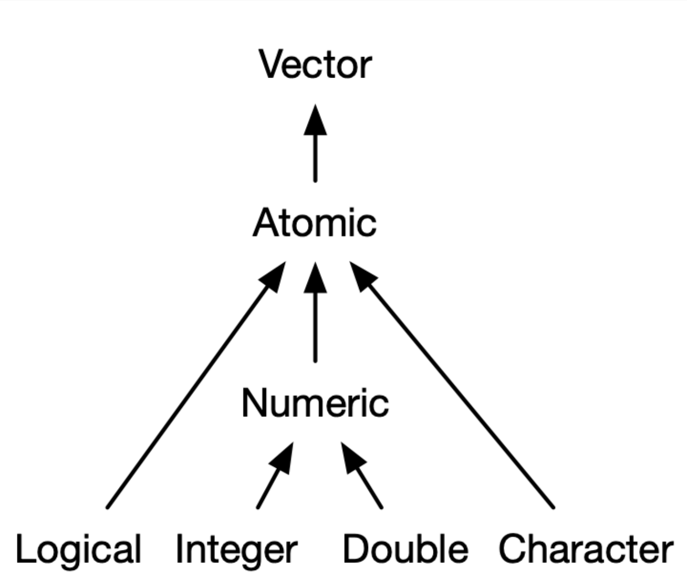
```
[1] "double"
```

Types of vector



Hadley Wickham, *Advanced R*

Types of vector




```r
my_int <- c(1, 3, 5, 6, 10)
is.integer(my_int)
```

```
[1] FALSE
```

```r
is.double(my_int)
```

```
[1] TRUE
```

```r
my_int <- as.integer(my_int)
is.integer(my_int)
```

```
[1] TRUE
```

```r
my_chr <- c("Mary", "had", "a", "little", "lamb")
is.character(my_chr)
```

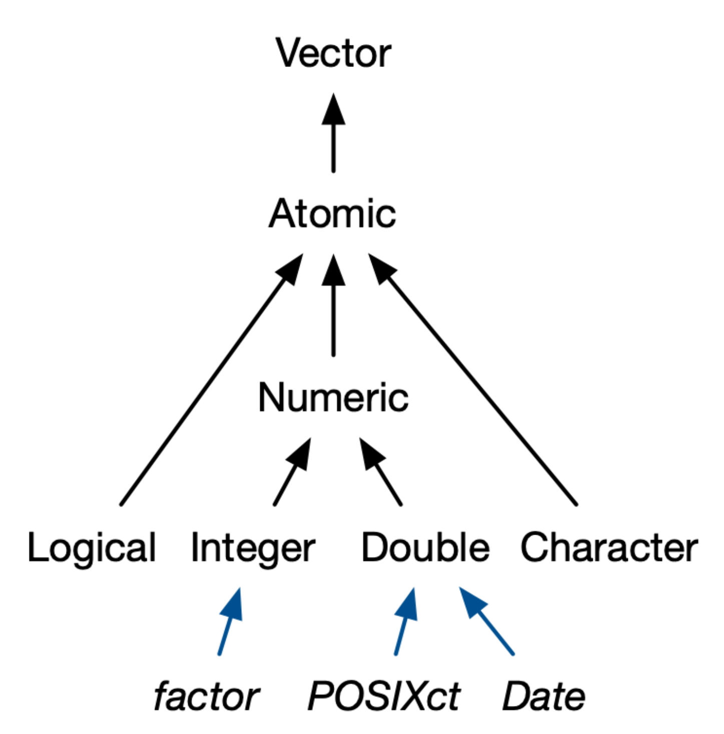
```
[1] TRUE
```

```r
my_lgl <- c(TRUE, FALSE, TRUE)
is.logical(my_lgl)
```

```
[1] TRUE
```

Hadley Wickham, *Advanced R*

Types of vector




```r
## Factors are for storing undordered or ordered categorical variables
x <- factor(c("Yes", "No", "No", "Maybe", "Yes", "Yes", "Yes", "No"))
x
```

```
[1] Yes   No    No    Maybe Yes   Yes   Yes   No
Levels: Maybe No Yes
```

```r
summary(x) # Alphabetical order by default
```

```
Maybe    No   Yes
    1     3     4
```

```r
typeof(x)       # Underneath, a factor is a type of integer ...
```

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

```r
attributes(x)   # ... with labels for its numbers, or "levels"
```

```
$levels
[1] "Maybe" "No"    "Yes"

$class
[1] "factor"
```

```r
levels(x)
```

```
[1] "Maybe" "No"    "Yes"
```

```r
is.ordered(x)
```

```
[1] FALSE
```

Vectors can’t be heterogenous

Objects can be manually or automatically coerced from one class to another. Take care.

```
class(my_numbers)
```

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

```
my_new_vector <- c(my_numbers, "Apple")

my_new_vector # vectors are homogeneous/atomic
```

```
[1] "1"     "2"     "3"     "1"     "3"     "5"     "25"    "10"    "Apple"
```

```
class(my_new_vector)
```

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

Vectors can't be heterogenous

Objects can be manually or automatically coerced from one class to another. Take care.

```r
my_dbl <- c(2.1, 4.77, 30.111, 3.14519)
is.double(my_dbl)
```

```
[1] TRUE
```

```r
my_dbl <- as.integer(my_dbl)

my_dbl
```

```
[1]  2  4 30  3
```

A table of data is a kind of list

```r
gapminder # tibbles and data frames can contain vectors of different types
```

```
# A tibble: 1,704 × 6
   country     continent  year lifeExp      pop gdpPercap
   <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
 1 Afghanistan Asia       1952    28.8  8425333      779.
 2 Afghanistan Asia       1957    30.3  9240934      821.
 3 Afghanistan Asia       1962    32.0 10267083      853.
 4 Afghanistan Asia       1967    34.0 11537966      836.
 5 Afghanistan Asia       1972    36.1 13079460      740.
 6 Afghanistan Asia       1977    38.4 14880372      786.
 7 Afghanistan Asia       1982    39.9 12881816      978.
 8 Afghanistan Asia       1987    40.8 13867957      852.
 9 Afghanistan Asia       1992    41.7 16317921      649.
10 Afghanistan Asia       1997    41.8 22227415      635.
# ℹ 1,694 more rows
```

```r
class(gapminder)
```

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

```r
typeof(gapminder) # hmm
```

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

A table of data is a kind of list

Lists are collections of vectors of possibly different types and lengths, or collections of more complex objects that are themselves ultimately made out of vectors. Underneath, most complex R objects are some kind of list with different components that can be accessed by some function that knows the names of the things inside the list.

A *data frame* is a list of vectors of the same length, where the vectors can be of different types (e.g. numeric, character, logical, etc).

A data frame is a natural representation of what most real tables of data look like. Having it be a basic sort of entity in the programming language IS ONE OF R's BEST IDEAS AND EASILY UNDERRATED!

A *tibble* is an enhanced data frame

Some classes are versions of others

Base R's trusty `data.frame`

```r
library(socviz)
titanic
```

```
      fate    sex    n percent
1 perished   male 1364    62.0
2 perished female  126     5.7
3 survived   male  367    16.7
4 survived female  344    15.6
```

```r
class(titanic)
```

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

```r
## The `$` idiom picks out a named column here;
## more generally, the named element of a list
titanic$percent
```

```
[1] 62.0  5.7 16.7 15.6
```

Some classes are versions of others

Base R's trusty `data.frame`

```r
library(socviz)
titanic
```

```
      fate    sex    n percent
1 perished   male 1364    62.0
2 perished female  126     5.7
3 survived   male  367    16.7
4 survived female  344    15.6
```

```r
class(titanic)
```

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

```r
## The `$` idiom picks out a named column here;
## more generally, the named element of a list
titanic$percent
```

```
[1] 62.0  5.7 16.7 15.6
```

The Tidyverse's enhanced `tibble`

```r
## tibbles are build on data frames
titanic_tb <- as_tibble(titanic)
titanic_tb
```

```
# A tibble: 4 × 4
  fate     sex        n percent
  <fct>    <fct>  <dbl>   <dbl>
1 perished male    1364    62  
2 perished female   126     5.7
3 survived male     367    16.7
4 survived female   344    15.6
```

```r
class(titanic_tb)
```

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

A data frame and a tibble are both fundamentally a list of vectors of the same length, where the vectors can be of different types (e.g. numeric, character, logical, etc)

All of this will be clearer in use

```r
gss_sm
```

```
# A tibble: 2,867 × 32
    year    id ballot       age childs sibs   degree race  sex   region income16
   <dbl> <dbl> <labelled> <dbl>  <dbl> <labe> <fct>  <fct> <fct> <fct>  <fct>
 1  2016     1 1             47      3 2      Bache… White Male  New E… $170000…
 2  2016     2 2             61      0 3      High … White Male  New E… $50000 …
 3  2016     3 3             72      2 3      Bache… White Male  New E… $75000 …
 4  2016     4 1             43      4 3      High … White Fema… New E… $170000…
 5  2016     5 3             55      2 2      Gradu… White Fema… New E… $170000…
 6  2016     6 2             53      2 2      Junio… White Fema… New E… $60000 …
 7  2016     7 1             50      2 2      High … White Male  New E… $170000…
 8  2016     8 3             23      3 6      High … Other Fema… Middl… $30000 …
 9  2016     9 1             45      3 5      High … Black Male  Middl… $60000 …
10  2016    10 3             71      4 1      Junio… White Male  Middl… $60000 …
# ℹ 2,857 more rows
# ℹ 21 more variables: relig <fct>, marital <fct>, padeg <fct>, madeg <fct>,
#   partyid <fct>, polviews <fct>, happy <fct>, partners <fct>, grass <fct>,
#   zodiac <fct>, pres12 <labelled>, wtssall <dbl>, income_rc <fct>,
#   agegrp <fct>, ageq <fct>, siblings <fct>, kids <fct>, religion <fct>,
#   bigregion <fct>, partners_rc <fct>, obama <dbl>
```

Tidyverse tools are generally *type safe*, meaning their functions return the same type of thing every time, or fail if they cannot do this. So it's good to know about the various data types.

6. Arithmetic on vectors

In R, all numbers are vectors of different sorts. Even single numbers ("scalars") are conceptually vectors of length 1.

Arithmetic on vectors (and arrays generally) follows a series of *recycling rules* that favor ease of expression of vectorized, "elementwise" operations.

See if you can predict what the following operations do:

6. Arithmetic on vectors

```r
my_numbers
```

```
[1]  1  2  3  1  3  5 25 10
```

```r
result1 <- my_numbers + 1
```

6. Arithmetic on vectors

```r
my_numbers
```

```
[1]  1  2  3  1  3  5 25 10
```

```r
result1 <- my_numbers + 1
result1
```

```
[1]  2  3  4  2  4  6 26 11
```

6. Arithmetic on vectors

```
result2 <- my_numbers + my_numbers
```

6. Arithmetic on vectors

```r
result2 <- my_numbers + my_numbers
```

```r
result2
```

```
[1]  2  4  6  2  6 10 50 20
```

6. Arithmetic on vectors

```r
two_nums <- c(5, 10)

result3 <- my_numbers + two_nums
```

6. Arithmetic on vectors

```r
two_nums <- c(5, 10)

result3 <- my_numbers + two_nums
```

```r
result3
```

```
[1]  6 12  8 11  8 15 30 20
```

6. Arithmetic on vectors

```r
three_nums <- c(1, 5, 10)

result4 <- my_numbers + three_nums
```

```
Warning in my_numbers + three_nums: longer object length is not a multiple of
shorter object length
```

6. Arithmetic on vectors

```r
three_nums <- c(1, 5, 10)

result4 <- my_numbers + three_nums
```

```
Warning in my_numbers + three_nums: longer object length is not a multiple of
shorter object length
```

```r
result4
```

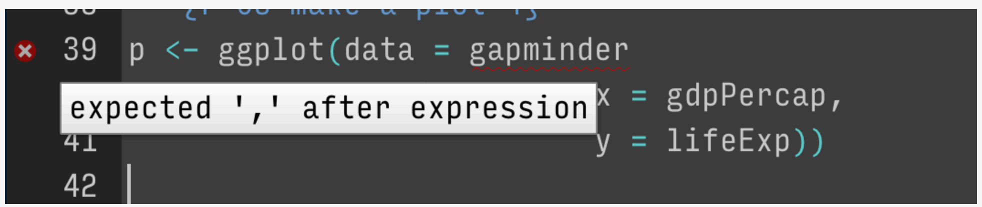
```
[1]  2  7 13  2  8 15 26 15
```

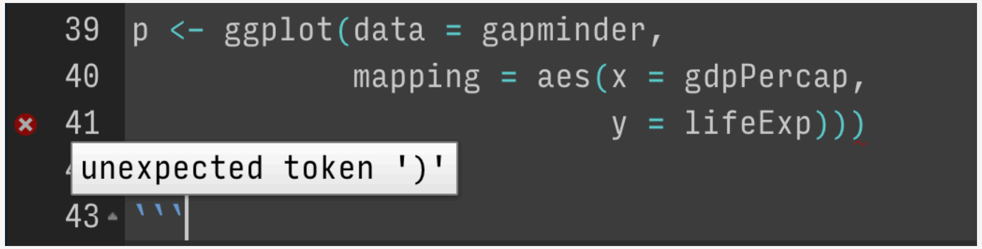
Note that you get a *warning* here. It'll still do it, though! Don't ignore warnings until you understand what they mean.

7. R will be **frustrating**

The IDE tries its best to help you. Learn to attend to what it is trying to say.

```
Warning message:
In my_numbers + two_nums :
  longer object length is not a multiple of shorter object length
```





Let’s Go!

Time to make a plot

Like before:

```
gapminder
```

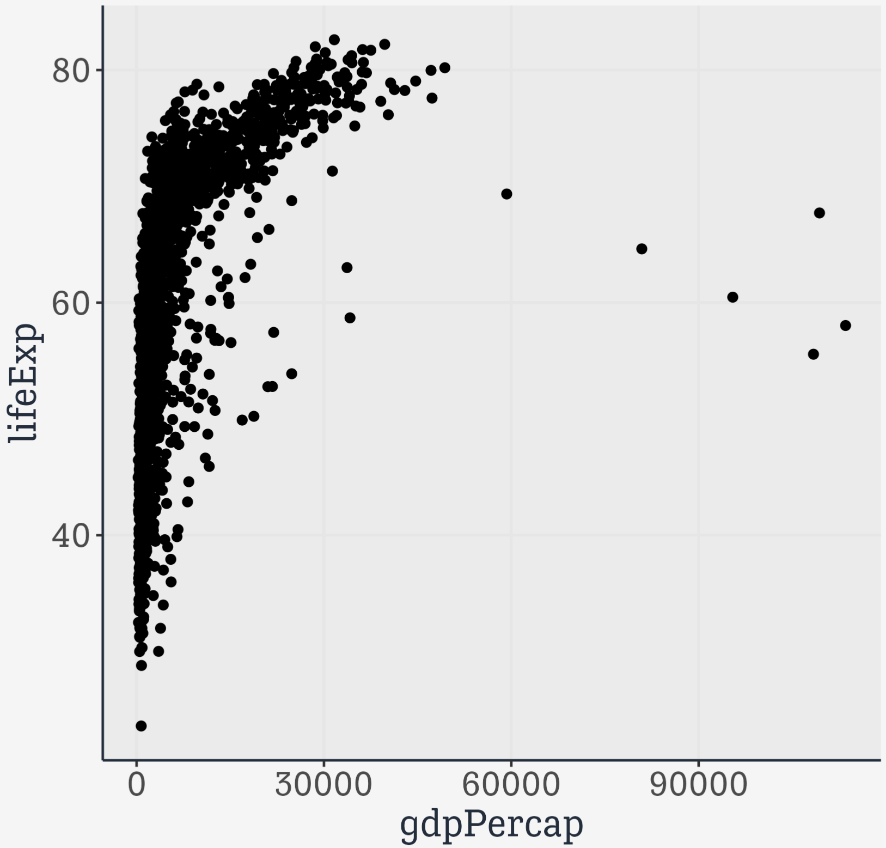
```
# A tibble: 1,704 × 6
   country     continent  year lifeExp      pop gdpPercap
   <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
 1 Afghanistan Asia       1952    28.8  8425333      779.
 2 Afghanistan Asia       1957    30.3  9240934      821.
 3 Afghanistan Asia       1962    32.0 10267083      853.
 4 Afghanistan Asia       1967    34.0 11537966      836.
 5 Afghanistan Asia       1972    36.1 13079460      740.
 6 Afghanistan Asia       1977    38.4 14880372      786.
 7 Afghanistan Asia       1982    39.9 12881816      978.
 8 Afghanistan Asia       1987    40.8 13867957      852.
 9 Afghanistan Asia       1992    41.7 16317921      649.
10 Afghanistan Asia       1997    41.8 22227415      635.
# ℹ 1,694 more rows
```

Like before

```r
library(tidyverse)
library(gapminder)

p <- ggplot(data = gapminder,
            mapping = aes(x = gdpPercap,
                          y = lifeExp))

p + geom_point()
```



What we did

```r
library(gapminder)
```

Load the packages we need: `tidyverse` and `gapminder`

What we did

```
p <- ggplot(data = gapminder,
            mapping = aes(x = gdpPercap,
                          y = lifeExp))
```

New object named `p` `gets` the output of the `ggplot()` *function*, given these *arguments*

Notice how one of the arguments, `mapping`, is itself taking the output of a function named `aes()`

What we did

```
p + geom_point()
```

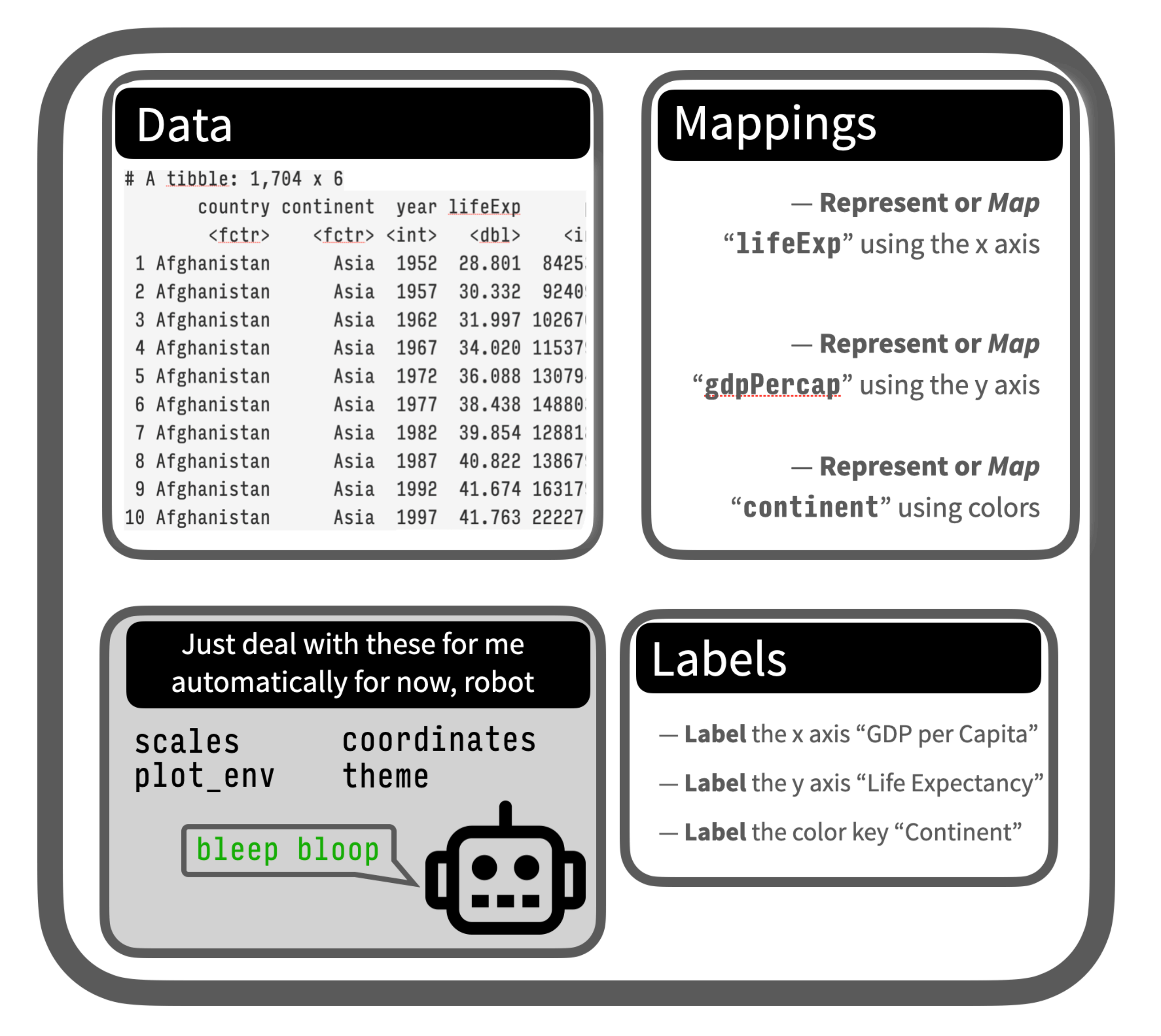
Show me the output of the `p` object and the `geom_point()` function.

The `+` here acts just like the ▷ pipe, but for ggplot functions only. (This is an accident of history.)

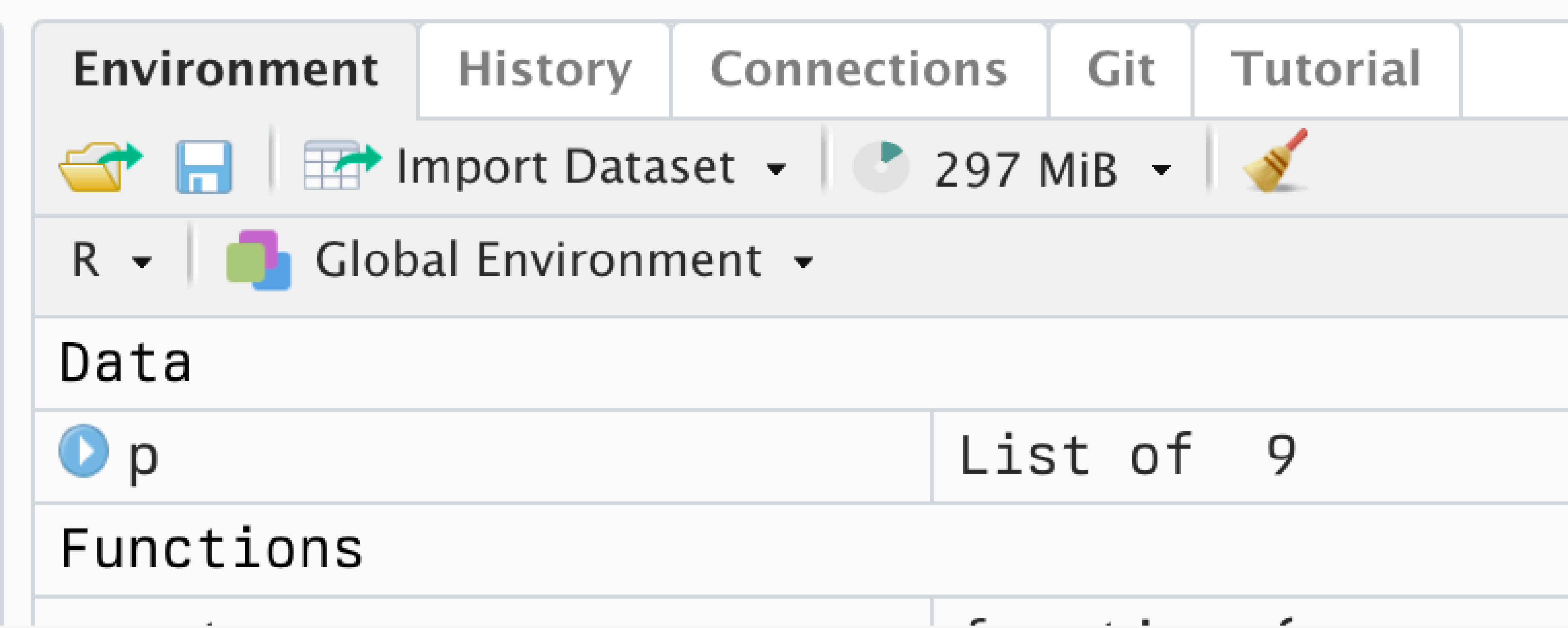
And what is R doing?

R objects are just lists of stuff to use or things to do

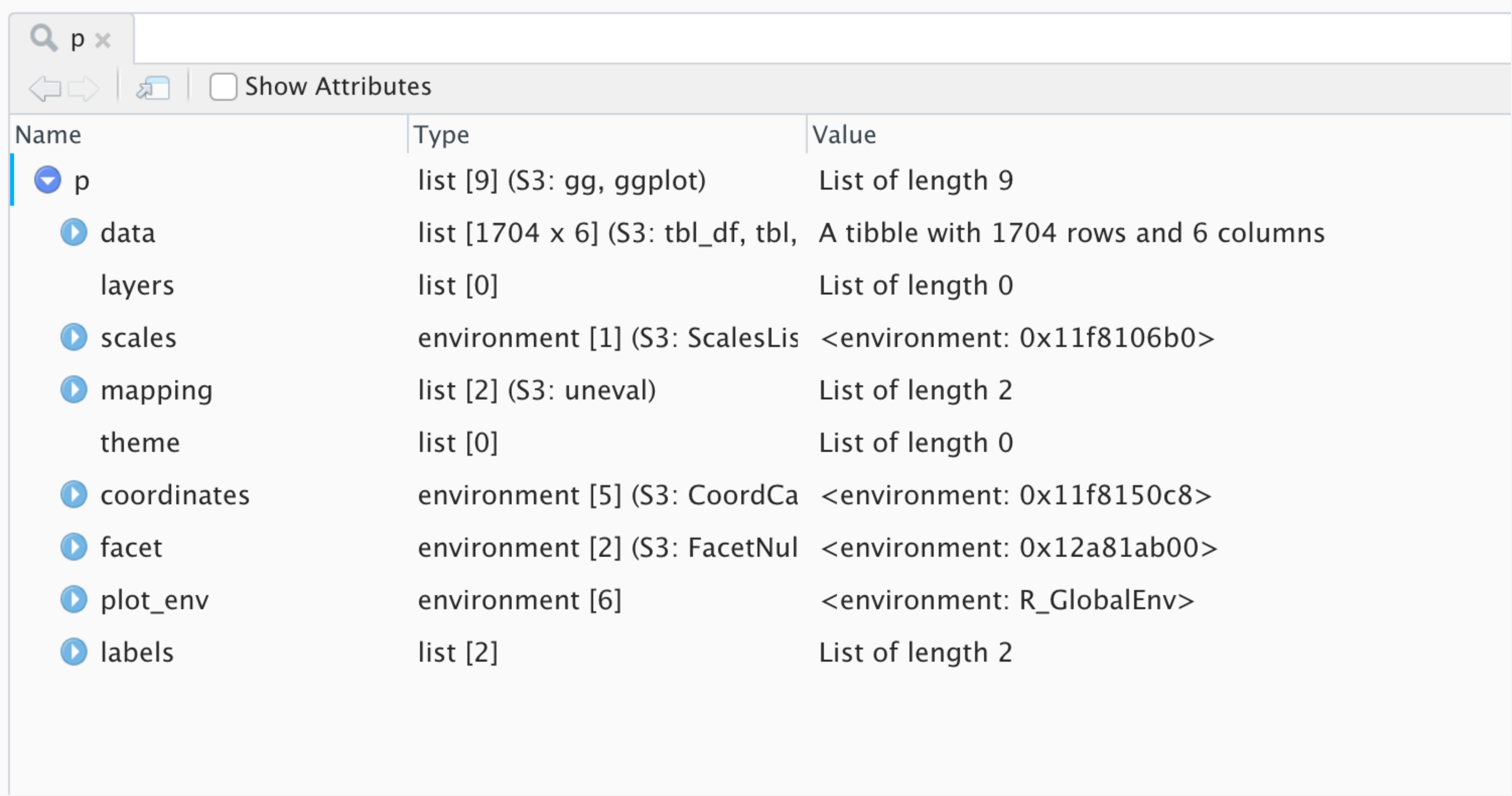
Objects are like Bento Boxes


Data
A tibble: 1,704 x 6
country continent year lifeExp
<fctr> <fctr> <int> <dbl>
1 Afghanistan Asia 1952 28.801
2 Afghanistan Asia 1957 30.332
3 Afghanistan Asia 1962 31.997
4 Afghanistan Asia 1967 34.020
5 Afghanistan Asia 1972 36.088
6 Afghanistan Asia 1977 38.438
7 Afghanistan Asia 1982 39.854
8 Afghanistan Asia 1987 40.822
9 Afghanistan Asia 1992 41.674
10 Afghanistan Asia 1997 41.763
Mappings
— Represent or Map “lifeExp” using the x axis
— Represent or Map “gdpPercap” using the y axis
— Represent or Map “continent” using colors
Just deal with these for me automatically for now, robot
scales
coordinates
plot_env
theme
bleep bloop
Labels
— Label the x axis “GDP per Capita”
— Label the y axis “Life Expectancy”
— Label the color key “Continent”

The p object



Peek in with the object inspector



Peek in with the object inspector

Appendix: A Few More R Details

Logic: Watch out!

Here's a gotcha. You might think you could write `3 < 5 & 7` and have it be interpreted as "Three is less than five and also less than seven [True or False?]":

```
3 < 5 & 7
```

```
[1] TRUE
```

It seems to work!

Logic: Watch out!

But now try `3 < 5 & 1`, where your intention is “Three is less than five and also less than one [True or False?]”

```
3 < 5 & 1
```

```
[1] TRUE
```

What’s happening is that `3 < 5` is evaluated first, and resolves to `TRUE`, leaving us with the expression `TRUE & 1`.

R interprets this as `TRUE & as.logical(1)`.

In Boolean algebra, `1` resolves to `TRUE`. Any other number is `FALSE`. So,

Logic: Watch out!

```r
TRUE & as.logical(1)
```

```
[1] TRUE
```

```r
3 < 5 & 3 < 1
```

```
[1] FALSE
```

You have to make your comparisons explicit.

Logic and floating point arithmetic

Let's evaluate `0.6 + 0.2 == 0.8`

Logic and floating point arithmetic

Let's evaluate `0.6 + 0.2 == 0.8`

```
0.6 + 0.2 == 0.8
```

```
[1] TRUE
```

Logic and floating point arithmetic

Let's evaluate `0.6 + 0.2 == 0.8`

```
0.6 + 0.2 == 0.8
```

```
[1] TRUE
```

Now let's try `0.6 + 0.3 == 0.9`

Logic and floating point arithmetic

Let's evaluate `0.6 + 0.2 == 0.8`

```
0.6 + 0.2 == 0.8
```

```
[1] TRUE
```

Now let's try `0.6 + 0.3 == 0.9`

```
0.6 + 0.3 == 0.9
```

```
[1] FALSE
```

Er. That's not right.

Welcome to floating point math!

In Base 10, you can’t precisely express fractions like $\frac{1}{3}$ and $\frac{1}{9}$. They come out as repeating decimals: 0.3333… or 0.1111… You *can* cleanly represent fractions that use a prime factor of the base, which in the case of Base 10 are 2 and 5.

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In Base 10, you can’t precisely express fractions like $\frac{1}{3}$ and $\frac{1}{9}$. They come out as repeating decimals: 0.3333… or 0.1111… You *can* cleanly represent fractions that use a prime factor of the base, which in the case of Base 10 are 2 and 5.

Computers represent numbers as binary (i.e. Base 2) floating-points. In Base 2, the only prime factor is 2. So $\frac{1}{5}$ or $\frac{1}{10}$ in binary would be repeating.

Logic and floating point arithmetic

When you do binary math on repeating numbers and convert back to decimals you get tiny leftovers, and this can mess up *logical* comparisons of equality. The `all.equal()` function exists for this purpose.

```
print(.1 + .2)
```

```
[1] 0.3
```

```
print(.1 + .2, digits=18)
```

```
[1] 0.300000000000000044
```

```
all.equal(.1 + .2, 0.3)
```

```
[1] TRUE
```

See e.g. https://0.30000000000000004.com

More later on why this might bite you, and how to deal with it

For now, “Be very careful about doing logical comparisons on floating-point numbers” is not a bad rule.

Assignment with =

You can use = as well as ← for assignment.

```
my_numbers = c(1, 2, 3, 1, 3, 5, 25)

my_numbers
```

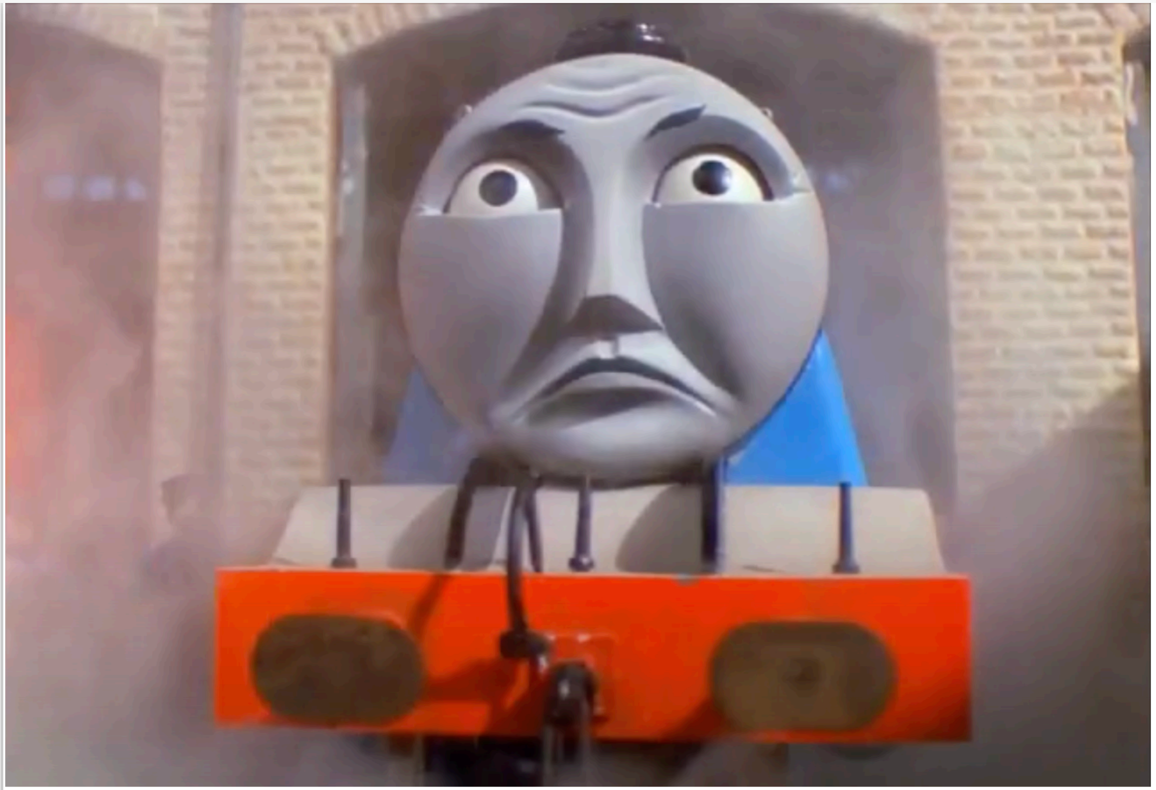
```
[1]  1  2  3  1  3  5 25
```

On the other hand, = has a different meaning when used in functions.

I'm going to use ← for assignment throughout.

Be consistent either way.

Assignment with =



It isn't *wrong*, but we just *don't do it*.

The other pipe: `%>%`

The Base R pipe operator, `|>` is a relatively recent addition to R.

Piping operations were originally introduced in a package called called `magrittr`, where it took the form **`%>%`**

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It's been so successful, a version of it has been incorporated into Base R. It *mostly* but does not *quite* work the same way as `%>%` in every case. We'll use the Base R pipe in this course, but you'll see the Magrittr pipe a lot out in the world.

With the Base R pipe, you can only pass an object to the *first* argument in a function. This is fine for most tidyverse pipelines, where the first argument is usually (implicitly) the data. But it does mean that most Base R functions will continue not to be easily piped, as most of them do not follow the convention of passing the current data as the first argument

Object classes

Objects can have more than one (nested) class:

```
summary(my_numbers)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   1.500   3.000   5.714   4.000  25.000 
```

```
my_smry <- summary(my_numbers) # remember, outputs can be assigned to a name, creating an object

class(summary(my_numbers)) # functions can be nested, and are evaluated from the inside out
```

```
[1] "summaryDefault" "table"
```

```
class(my_smry) # equivalent to the previous line
```

```
[1] "summaryDefault" "table"
```

Object classes

```r
typeof(my_smry)
```

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

```r
attributes(my_smry)
```

```
$names
[1] "Min."    "1st Qu." "Median"  "Mean"    "3rd Qu." "Max."   

$class
[1] "summaryDefault" "table"
```

```r
## In this case, the functions extract the corresponding attribute
class(my_smry)
```

```
[1] "summaryDefault" "table"
```

```r
names(my_smry)
```

```
[1] "Min."    "1st Qu." "Median"  "Mean"    "3rd Qu." "Max."   
```