R and Tidyverse

DS 6410 | Spring 2024

Rintro.pdf

Contents

1 Technical Requirements

- Working and updated version of R and RStudio
  - Update packages as well
- Install R packages: `tidyverse` and `nycflights13`
- Course Webpage: https://mdporter.github.io/DS6410

2 Introduction to R

2.1 Getting Help

- A good source of basic data analysis using R is found in the free book R for Data Science 2e.
- Web search, especially *stackoverflow.com* and *stats.stackexchange.com*
- Troubleshooting/Debugging.
  - Check one line of code at a time.
  - Use scripts
  - Make sure it works in plain R before incorporating into Rmd
- ChatGPT can do a decent job at troubleshooting.
- Post a question on Canvas/Discussion. A classmate or teaching staff will be able to help.

2.2 RStudio

- Install R and RStudio
- Make use of *Projects* in RStudio

2.3 Using R Packages

It takes two steps to use the functions and data in an R package

1. Install the package
   - i.e., download the package to your computer
   - this only needs to be done one time
   - `install.packages()`
2. Load the package
   - i.e., tell R to look for the package functions and/or data
   - this needs to be done every time R is started (and you want to use the package)
   - `library()`

2.3.1 Note on `tidyverse` package

- The `tidyverse` package https://www.tidyverse.org/packages/ is really just a wrapper to load several related R packages
  - `ggplot2` for graphics
  - `dplyr` for data manipulation
  - `tidyr` for getting data into tidy form

  - `readr` for loading in data
  - `tibble` for improved data frames
  - `purrr` for functional programming
  - `stringr` for string manipulation
  - `forcats` for categorical/factor data
- `lubridate` for dealing with dates and times
- This provides a nice shortcut to load all of these packages with `library(tidyverse)` instead of each separately:

```
#- the hard way
library(ggplot2)
library(dplyr)
library(tidyr)
library(readr)
library(tibble)
library(purrr)
library(stringr)
library(forcats)
library(lubridate)
```

```
#- the easy way
library(tidyverse)
```

2.4 Quarto

Quarto is the new RMarkdown.

- Homework will be submitted in .qmd and .html format
- When you *render* a .qmd, it:
  1. starts a new R kernel (clean environment)
  2. in the directory the .qmd is in (important for relative links)
  3. runs all the code blocks
  4. converts the results of the code and other text to plain markdown
  5. uses pandoc to create documents of the desired format (e.g., html, pdf, word, revealjs, beamer)
- Any data or code must first be put into the .qmd file
  - The .qmd won't know about anything in another script or in another R environment
  - Any `source()` or data paths are relative to the current directory of the qmd.
- A homework .qmd template will be provided for each homework. You will modify this template to create your homework solution.
- The course uses a special formatting to ensure all submissions look consistent and are thus easier to grade. The formatting is applied with a special quarto extension. Follow the instructions to install the extension.

2.5 Graphics with the `ggplot2` package

The `ggplot2` package is an approach for creating graphics for data analysis.

- See https://ggplot2.tidyverse.org/

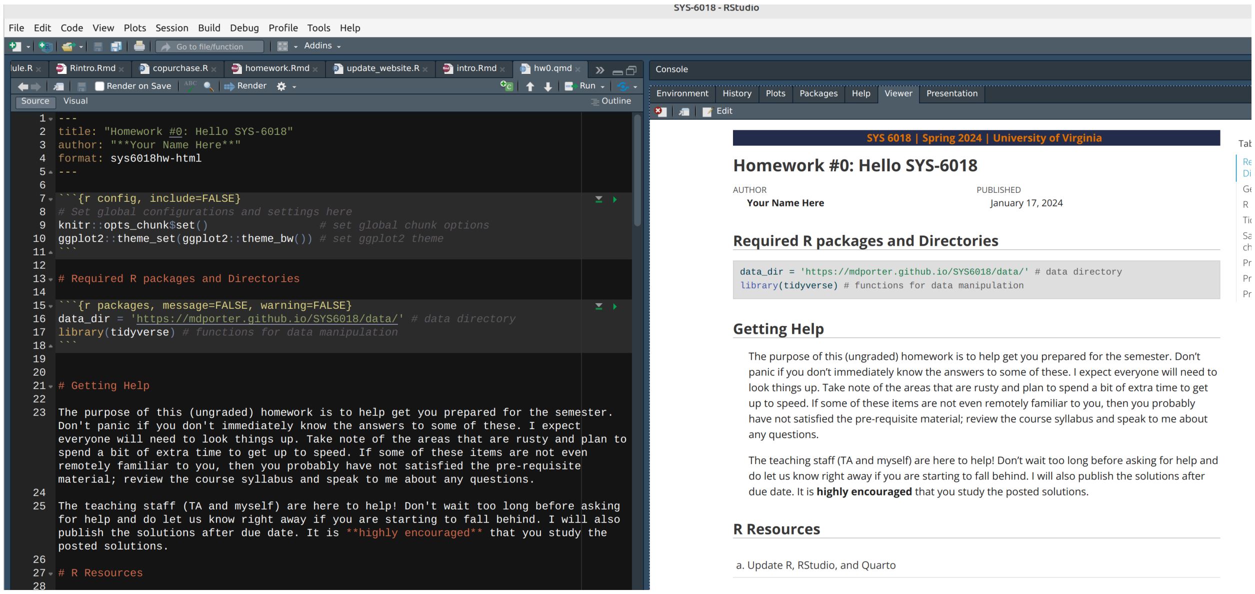


Figure 1: Quarto Screen Shot

- Keep the ggplot2 cheatsheet handy

2.6 Data Transformation with the `dplyr` package

- See https://dplyr.tidyverse.org/
- Keep the dplyr cheatsheet handy

2.6.1 single table verbs

1. `filter()`: find/keep certain rows
   - alternative to `base::subset()`
   - `slice()` to keep by row number
   - helper functions: `between()`: numeric values in a range
2. `arrange()`: reorder rows
   - alternative to `base::order()`
   - helper functions: `desc()` to use descending order
3. `select()`: find/keep certain columns
   - helper functions: `starts_with()`, `ends_with()`, `matches()`, `contains()`, `?select`
4. `mutate()`: add/create new variables
   - alternative to `base::transform()`
   - `transmute()`: only return new variables
5. `summarize()`: produce summary statistics
   - don't confuse with `summary()`
   - most useful when data is *grouped*

2.6.2 Chaining/Pipes

- Multiple operations can be chained together with the *pipe* operator, `%>%`, (pronounced as *then*). Technically, it performs `x %>% f(y) -> f(x, y)`. This lets you focus on the verbs, or actions you are performing.

```
x = c(1:5, NA)
x %>% mean(na.rm=TRUE)
#> [1] 3
mean(x, na.rm=TRUE)
#> [1] 3
```

- **Update:** newer versions of R have introduced a native pipe `|>`. This can be used instead of `%>%`.

```
x = c(1:5, NA)
x |> mean(na.rm=TRUE)
#> [1] 3
mean(x, na.rm=TRUE)
#> [1] 3
```

Your Turn #1

1. Load the `nycflights13` package, which contains airline on-time data for all flights departing NYC in 2013. Also includes useful 'metadata' on airlines, airports, weather, and planes.
2. Load the `tidyverse` package
3. Using the `flights` data,
   - find all flights that were less than 1000 miles (`distance`)
   - Keep only the columns: `dep_delay`, `arr_delay`, `origin`, `dest`, `air_time`, and `distance`
   - Add the Z-score for departure delays
   - Convert the departure and arrival delays into hours
   - Calculate the average flight speed (in mph)
   - order by average flight speed (fastest to slowest)
   - return the first 12 rows

2.6.3 Other useful `dplyr` functions

- `distinct()`: retain unique/distinct rows
- `slice_sample()`: select random rows
- `slice_min/slice_max()`: select rows with smallest/highest values
- `mutate()/add_column()` add new column in particular position
- `coalesce(x, y)` replaces the `NA` in `x` with `y`

```
x = c(1, 2, NA, 5, 5, NA)
coalesce(x, 0)          # replace NA with 0
#> [1] 1 2 0 5 5 0
```

2.7 Groupwise operations

2.7.1 Split - Apply - Combine

The dplyr operations are more powerful when they can be used with grouping variables. Split - Apply - Combine.

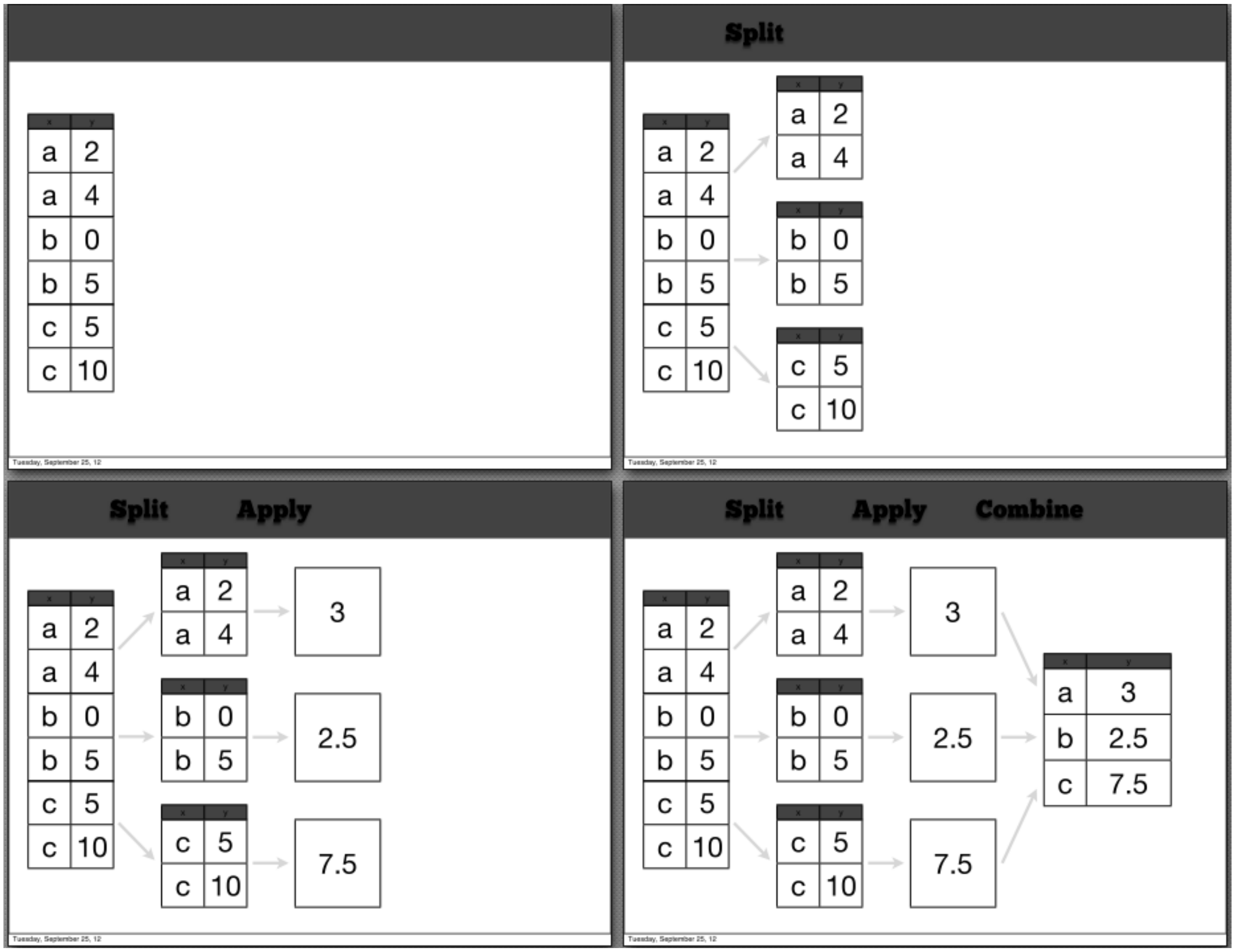


Image from Hadley Wickham UseR tutorial June 2014 http://www.dropbox.com/sh/i8qnluwmuieicxc/AAAgt9tIKoIm7WZKIyK25lh6a

These steps can be performed, at scale, with the MapReduce framework.

2.7.2 group_by()

First use the `group_by()` function to group the data (determines how to split), then apply function(s) to each group using the `summarise()` function. Note: grouping should to be applied on discrete variables (categorical, factor, or maybe integer valued columns).

```
flights |>
  group_by(origin, dest) |>    # group by both origin and dest
  summarize(
    n_flights = n(), # n() gives the group count
    max_delay = max(arr_delay, na.rm=TRUE),
    avg_delay = mean(arr_delay, na.rm=TRUE),
    min_delay = min(arr_delay, na.rm=TRUE)
  )
#> Warning: There were 2 warnings in `summarize()`.
#> The first warning was:
#> i In argument: `max_delay = max(arr_delay, na.rm = TRUE)`.
#> i In group 41: `origin = "EWR"`, `dest = "LGA"`.
#> Caused by warning in `max()`:
#> ! no non-missing arguments to max; returning -Inf
```

```
#> i Run `dplyr::last_dplyr_warnings()` to see the 1 remaining warning.
#> # A tibble: 224 x 6
#>   origin dest  n_flights max_delay avg_delay min_delay
#>   <chr>  <chr>     <int>     <dbl>     <dbl>     <dbl>
#> 1 EWR    ALB         439       328    14.4         -34
#> 2 EWR    ANC           8        39    -2.5         -47
#> 3 EWR    ATL        5022       796    13.2         -39
#> 4 EWR    AUS         968       349    -0.474       -59
#> 5 EWR    AVL         265       228     8.80        -26
#> 6 EWR    BDL         443       266     7.05        -43
#> # i 218 more rows
```

- `count(...)` is a shortcut for `group_by(...) |> summarize(n=n())`
- `ungroup()` removes the grouping

2.7.3 Grouped Mutate and Filter

- When data is *grouped*, `mutate()` and `filter()` operate on each group independently

```
#- proportion of carrier at each dest
flights |>
  count(dest, carrier) |>
  group_by(dest) |>                   # group by dest
    mutate(
      total = sum(n),             # grouped mutate sum(n) is by group
      p = n/sum(n)
    ) |>
  arrange(desc(total), -p)              # arrange by most freq dest and prop
#> # A tibble: 314 x 5
#>   dest  carrier     n total        p
#>   <chr> <chr>   <int> <int>    <dbl>
#> 1 ORD   UA       6984 17283 0.404
#> 2 ORD   AA       6059 17283 0.351
#> 3 ORD   MQ       2276 17283 0.132
#> 4 ORD   9E       1056 17283 0.0611
#> 5 ORD   B6        905 17283 0.0524
#> 6 ORD   EV          2 17283 0.000116
#> # i 308 more rows
```

2.7.4 Update: grouping with `.by`

In newer versions of `dplyr`, many functions that were used with grouped data frames have been given an additional argument that allows grouping specification without the need to use `group_by()`.

```
#- proportion of carrier at each dest
flights |>
  count(dest, carrier) |>
    mutate(.by = dest,            # <-- specify grouping
      total = sum(n),             # grouped mutate sum(n) is by group
      p = n/sum(n)
    ) |>
  arrange(desc(total), -p)              # arrange by most freq dest and prop
#> # A tibble: 314 x 5
#>   dest  carrier     n total        p
#>   <chr> <chr>   <int> <int>    <dbl>
#> 1 ORD   UA       6984 17283 0.404
#> 2 ORD   AA       6059 17283 0.351
```

```
#> 3 ORD   MQ       2276 17283 0.132
#> 4 ORD   9E       1056 17283 0.0611
#> 5 ORD   B6        905 17283 0.0524
#> 6 ORD   EV          2 17283 0.000116
#> # i 308 more rows
```

```
flights |>
  summarize(.by = c(origin, dest),  # <-- specify grouping
    n_flights = n(), # n() gives the group count
    max_delay = max(arr_delay, na.rm=TRUE),
    avg_delay = mean(arr_delay, na.rm=TRUE),
    min_delay = min(arr_delay, na.rm=TRUE)
  )
#> # A tibble: 224 x 6
#>   origin dest  n_flights max_delay avg_delay min_delay
#>   <chr>  <chr>     <int>     <dbl>     <dbl>     <dbl>
#> 1 EWR    IAH        3973       374      5.41       -63
#> 2 LGA    IAH        2951       435      1.45       -59
#> 3 JFK    MIA        3314       614     -1.99       -64
#> 4 JFK    BQN         599       183      6.94       -32
#> 5 LGA    ATL       10263       895     11.3        -49
#> 6 EWR    ORD        6100      1109      9.00       -59
#> # i 218 more rows
```

2.8 Data Importing

2.8.1 readr package

- See https://readr.tidyverse.org/
- Keep the data import cheatsheet handy

```
## Load data from course website
library(tidyverse)

#: specify path to url
data_dir = 'https://mdporter.github.io/SYS6018/data/' # path to course data
url = file.path(data_dir, 'crashes16.csv') # the crashes 16 data set

#: load directly from web
crashes = read_csv(url)
crashes
#> # A tibble: 456 x 2
#>    mile   time
#>   <dbl>  <dbl>
#> 1   87   6.62
#> 2  118   6.70
#> 3  120   0.0549
#> 4   90   0.206
#> 5  124.  0.726
#> 6  118   3.88
#> # i 450 more rows
```

```
## Download data first, then load into R

#: specify path to url
data_dir = 'https://mdporter.github.io/SYS6018/data/'
url = file.path(data_dir, 'crashes16.csv') # the crashes 16 data set
```

```r
#: download file
save.path = "data/crashes16.csv"  # can be relative path!
download.file(url, save.path)

#: load data from hard drive
library(tidyverse)
crashes = read_csv(save.path)
```

2.8.2 `readxl` package

- See https://readxl.tidyverse.org/ for importing excel files

2.9 Tidy Data with the `tidyr` package

- https://tidyr.tidyverse.org/
- Keep the tidy data cheatsheet handy.

2.9.1 Why Tidy Data?

- Tidy data (in form of a data frame) is usually the best form for analysis
  - some exceptions are for modeling (e.g., matrix manipulations and algorithms)
- For presentation of data (e.g., in tables), non-tidy form can often do better
- the functions in `tidyr` usually allow us to covert from non-tidy to tidy for analysis and also from tidy to non-tidy for presentation

2.9.2 Main `tidyr` functions

function	description
`pivot_wider()/spread()`	Spreads a pair of key:value columns into a set of tidy columns
`pivot_longer()/gather()`	Gather takes multiple columns and collapses into key-value pairs, duplicating all other columns as needed. You use `pivot_longer()/gather()` when you notice that you have columns that are not variables
`separate()`	turns a single character column into multiple columns
`unite()`	paste together multiple columns into one (reverse of `separate()`)

See R4DS Pivoting for more details.

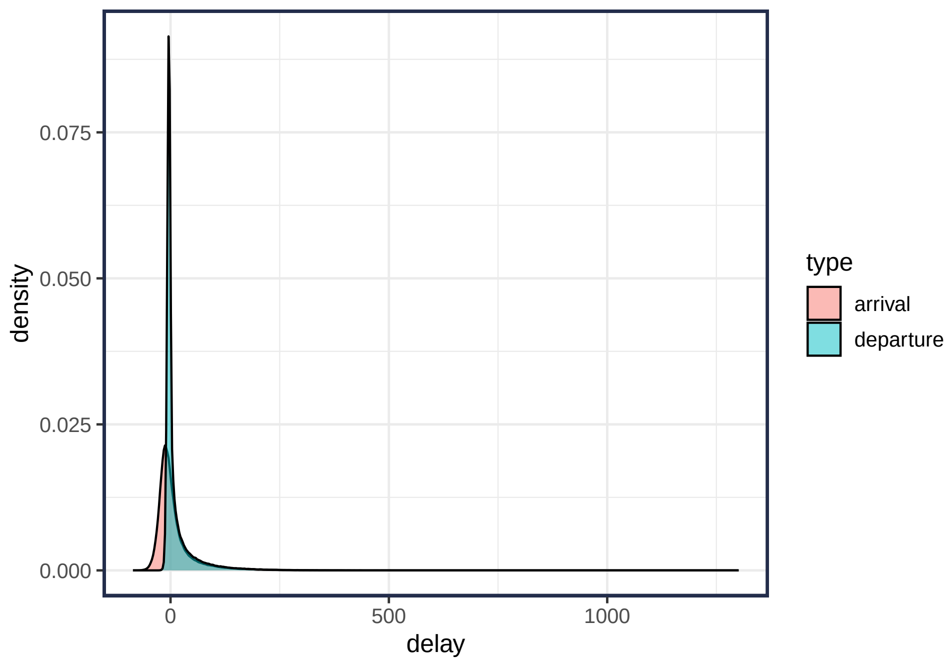
```r
## Converting to longer format for grouped summaries and plotting
delays_long = flights |>
  select(year, month, day, dep_delay, arr_delay) |>
  pivot_longer(cols = c(dep_delay, arr_delay), names_to="type", values_to="delay") |>
  mutate(type = ifelse(type == "dep_delay", "departure", "arrival"))
```

```r
delays_long
#> # A tibble: 673,552 x 5
#>    year month   day type      delay
#>   <int> <int> <int> <chr>     <dbl>
#> 1  2013     1     1 departure     2
#> 2  2013     1     1 arrival      11
#> 3  2013     1     1 departure     4
```

```
#> 4  2013     1     1 arrival      20
#> 5  2013     1     1 departure     2
#> 6  2013     1     1 arrival      33
#> # i 673,546 more rows
```

```
#: average delays of each type
delays_long |>
  group_by(type) |>
  summarize(avg_delay = mean(delay, na.rm=TRUE))
#> # A tibble: 2 x 2
#>   type      avg_delay
#>   <chr>         <dbl>
#> 1 arrival        6.90
#> 2 departure     12.6
```

```
#: plot density (kernel density estimation)
delays_long |>
  ggplot(aes(delay, fill=type)) +
  geom_density(alpha = .5)
```



2.10 Iteration

We will make good use of iteration in this course. Be sure to review R4DS Iteration for more details.

Suppose we want to compare the performance of two models over multiple subsets of a data set.

```
#: simulate fake data
set.seed(2023)
data = tibble(x = runif(100), y = rnorm(100))

#: fake model output
model_1 <- function(x) rnorm(length(x), mean = -.5, sd = 1)
model_2 <- function(x) rnorm(length(x), mean = .5, sd = 2)
```

We can consider using a for loop to simulate and assess performance in each subset.

```r
n_subsets = 5

set.seed(876)
output = vector("list", n_subsets)  # initiate empty list
for(i in 1:n_subsets){

  #: sub-sample data (25 samples)
  data_sub = dplyr::slice_sample(data, n = 25)

  #: get output from the models
  yhat_1 = model_1(data_sub$x)
  yhat_2 = model_2(data_sub$x)

  #: score models (using MSE)
  perf_1 = mean( (yhat_1 - data_sub$y)^2 )
  perf_2 = mean( (yhat_2 - data_sub$y)^2 )

  #: save results
  output[[i]] = tibble(perf_1, perf_2, iter = i)
}

#: convert to tibble and summarize
bind_rows(output) |>
  summarize(
    avg_perf_1 = mean(perf_1),          # avg MSE of model 1
    avg_perf_2 = mean(perf_2),          # avg MSE of model 2
    avg_diff = mean(perf_1 - perf_2),   # average MSE difference
    n = n()                             # number of iterations
  )
#> # A tibble: 1 x 4
#>   avg_perf_1 avg_perf_2 avg_diff     n
#>        <dbl>      <dbl>    <dbl> <int>
#> 1       2.12       3.50    -1.37     5
```

Notice that every *for* loop requires three elements:

1. Initializing the **output** structure to store results.
   - In the above example, set the output to be a list with `n_subsets` empty elements. The list is unnamed.
2. The sequence to iterate over.
   - In this example, indexes over 1 to `n_subsets`. It is common to use `seq_len(n_subsets)` or `seq_along(output)` instead of the explicit sequence.
3. The body of the loop.
   - In the body of the loop, do the stuff of interest.

2.10.1 Vectorization

R works best (i.e., fastest) when you use *vectorized* calculations. This means you should avoid loops whenever a vectorized function is available.

```r
x = 1:100

#: Find squared value
x_sq = x^2 # using vectorized power operator

x_sq_slow = numeric(length(x))
```

```
for(i in seq_along(x)) {
  x_sq_slow[i] = x[i]^2
}

#: replace all even values with -1
x_even = ifelse(x %% 2 == 0, -1, x)
```

Note: check out the `dplyr::case_when()` for more complex handling of multiple if-else statements.

2.10.2 Iterate over elements of a list or vector with `purrr::map()`

Sometimes there are no vectorized solutions and we have to loop. The `purrr` library provides a nice set of functions to help you make better loops. See R4DS The map functions

We saw above that every *for* loop requires three elements: 1. Initializing the output structure to store results. 2. The sequence to iterate over. 3. The body of the loop.

The Base R approach explicitly requires each step. Alternatively, the `purrr::map()` solution hides the output and sequence steps and let's you focus on the body. This has other advantages - cleaner and easier to understand code, and ability to more easily parallelize the operations (see https://furrr.futureverse.org/).

The first step is to make a function that does everything in the body; in this example it calculates the mean squared error (mse) of each predictive model:

```
calculate_mse <- function(data, model_1, model_2){

  #: sub-sample data (25 samples)
  data_sub = dplyr::slice_sample(data, n = 25)

  #: get output from the models
  yhat_1 = model_1(data_sub$x)
  yhat_2 = model_2(data_sub$x)

  #: score models (using MSE)
  perf_1 = mean( (yhat_1 - data_sub$y)^2 )
  perf_2 = mean( (yhat_2 - data_sub$y)^2 )

  #: output
  tibble(perf_1, perf_2)
}
```

Then we use the `map()` function to run the loop:

```
library(purrr)
set.seed(876)
map_df(1:n_subsets, ~calculate_mse(data, model_1, model_2)) |>
  summarize(
    avg_perf_1 = mean(perf_1),          # avg MSE of model 1
    avg_perf_2 = mean(perf_2),          # avg MSE of model 2
    avg_diff = mean(perf_1 - perf_2),   # average MSE difference
    n = n()                             # number of iterations
  )
#> # A tibble: 1 x 4
#>   avg_perf_1 avg_perf_2 avg_diff     n
#>        <dbl>      <dbl>    <dbl> <int>
#> 1       2.12       3.50    -1.37     5
```