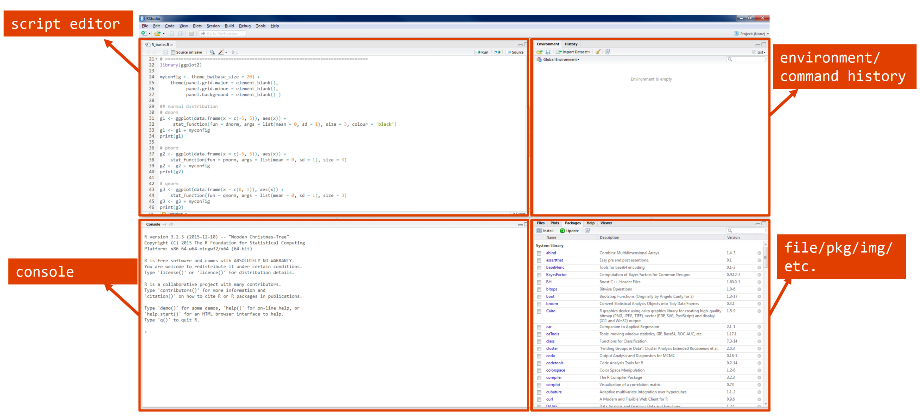
An introduction to R/RStudio

An overview of data structures, functions, packages and data visualization

`R` is a powerful open-source programming language and software environment primarily designed for statistical computing, data analysis, and graphical visualization. `R` has its own interface; when you install `R` onto your own computer(Windows/Mac) you can open `R` on it's own. However, working in this way with `R` ('base `R`') isn't very user friendly!

Instead, we use an IDE (Integrated Development Environment) to work with the `R` programming language. A popular example - and the one that we will be using - is RStudio.



The RStudio interface consists of 4 windows:

1. Script editor: Where you write and edit your `R` code **2. Console:** Where you run `R` commands and see their output **3. Environment/History:** Shows your workspace variables and command history **4. Files/Plots/Packages/Help:** A multi-purpose pane for viewing files, plots, managing packages, and accessing help documentation

You can check your versions of both `R` and RStudio using the following commands:

```r
R.version
```

```
               _
platform       x86_64-apple-darwin20
arch           x86_64
os             darwin20
system         x86_64, darwin20
status
major          4
minor          4.1
year           2024
month          06
day            14
svn rev        86737
language       R
version.string R version 4.4.1 (2024-06-14)
nickname       Race for Your Life
```

```r
RStudio.version()
```

```
$version
[1] '2024.12.0.467'

$long_version
[1] "2024.12.0+467"

$release_name
[1] "Kousa Dogwood"
```

> **! Asking for help**
>
> Some problems in `R` may be specific to the version, so make sure to include the version that you are using if asking for help online!

Basic R operations

We will now cover some basic operations and values within `R`.

Calculator Functions

We can perform basic mathematical operations:

```r
# Addition and Subtraction
3 + 2
```

```
[1] 5
```

```r
3 - 2
```

```
[1] 1
```

```r
# Multiplication and Division
3 * 2
```

```
[1] 6
```

```r
3 / 2
```

```
[1] 1.5
```

```r
# Exponents
3^2
```

```
[1] 9
```

```r
2^3
```

```
[1] 8
```

```r
# Constants
pi
```

```
[1] 3.141593
```

```r
exp(1)  # base of natural logarithm
```

```
[1] 2.718282
```

Special values

In addition to numbers, variables can also take on other values:

```r
# Infinite Values
Inf
1 + Inf

# Missing Values
NA
1 + NA

# NULL Values
NULL
1 + NULL
```

> **Missing values in behavioural experiments**
>
> An example where you might get a missing value would be in a behavioral experiment providing a fixed window for the participant to respond (e.g., 3 seconds). If they don't respond in time, you can code their response as a missing value (NA), instead of leaving it blank. This is useful for any subsequent analyses where you might want to exclude or perform an operation on the missing values.

Data types, classes and variables

There are many types of data in `R`, here are some commonly used:

Numeric - Decimal numbers (the most common numeric type)

```r
1.1
2.0
5.7892
```

Integer - Whole numbers only

```r
1L  # Note: L suffix denotes integer
2L
3L
```

Character/String - Text data in quotes

```r
"hello world!"
'R programming'
"42"   # Numbers in quotes are strings
```

Logical - Boolean values for conditional logic

```r
TRUE
FALSE
T     # Shorthand for TRUE
F     # Shorthand for FALSE
```

Factor - a data type for categorical variables with fixed levels (categories).

In the example below, we create a vector of letters, some of which are repeated. However, the levels within are limited to each individual letter.

```r
# Define a factor using letters
f <- factor(letters[c(1, 1, 2, 2, 3:10)])  # Create factor from letters with some repetit
f
```

```
 [1] a a b b c d e f g h i j
Levels: a b c d e f g h i j
```

```r
class(f)  # Check class
```

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

Checking your data type

You can check data types using the following commands: `class`, `typeof` and `str`

```r
class(1.1)      # Shows type
```

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

```r
typeof("text")   # Shows underlying type
```

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

```r
str(data)       # Shows structure
```

```
function (..., list = character(), package = NULL, lib.loc = NULL, verbose = getOption("ve
    envir = .GlobalEnv, overwrite = TRUE)
```

Storing and manipulating variables

We commonly assign numbers and data to variables, which we can then compute directly:

```r
# Define objects x and y with values of 3 and 2 respectively:
x <- 3
y <- 2

# Some calculations with the defined objects x and y:
x + y
```

```
[1] 5
```

```r
x * y
```

```
[1] 6
```

> **Case sensitivity**
>
> R is case sensitive, so `X` and `x` are not the same object!

Basic `R` functions

We can perform basic statistics and operations on variables, such as getting the variance, standard deviation and summary statistics:

```r
# Combine variables together to form a vector (a sequence of elements of the same type)
c(1, 3, -2)                          # Creates numeric vector
```

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

```r
c("a", "a", "b", "b", "a")          # Creates character vector
```

```
[1] "a" "a" "b" "b" "a"
```

```r
# Create a vector to work with
x <- c(1, 3, -2)

# Variance and Standard Deviation
var(x)   # Calculates variance
```

```
[1] 6.333333
```

```r
sd(x)    # Calculates standard deviation
```

```
[1] 2.516611
```

```r
# Basic Statistics
sum(x)   # Sums all elements
```

```
[1] 2
```

```r
mean(x)  # Calculates mean
```

```
[1] 0.6666667
```

```r
# Range Functions
min(x)   # Finds minimum
```

```
[1] -2
```

```r
max(x)   # Finds maximum
```

```
[1] 3
```

We can also manipulate and combine vectors together - either as columns or rows - and perform statistics on the combined output:

```r
# Define two vectors
x <- c(1, 3, 4, 6, 8)    # First vector
y <- c(2, 3, 5, 7, 9)    # Second vector

# Combine vectors as columns
cbind(x, y)              # Creates a matrix with columns x and y
```

```
     x y
[1,] 1 2
[2,] 3 3
[3,] 4 5
[4,] 6 7
[5,] 8 9
```

```r
# Combine vectors as rows
rbind(x, y)              # Creates a matrix with rows x and y
```

```
  [,1] [,2] [,3] [,4] [,5]
x    1    3    4    6    8
y    2    3    5    7    9
```

```r
# Calculate correlation between x and y
cor(x, y)                # Pearson correlation coefficient
```

```
[1] 0.988765
```

```r
# Calculate covariance between x and y
cov(x, y)                # Covariance
```

```
[1] 7.65
```

> **Using `cbind`**
>
> `cbind` can be used to combine data across different files. For example, we can use `cbind` to combine data for a single participant that was recorded across multiple platforms or studies.

Miscellaneous commands

Here are some other commands that will be useful when working with `R` more generally:

Directory and Workspace Management

```r
# Get current working directory
getwd()

# Set working directory (example with different OS paths)
setwd("C:/Users/Documents/R")           # Windows style
setwd("/home/user/Documents/R")         # Unix/Mac style
setwd("~/Documents/R")                  # Universal home directory

# List files in current directory
dir()                                   # Same as list.files()
```

Environment Management

```r
# List objects in workspace
ls()

# Remove all objects from workspace
rm(list = ls())
```

Basic Output Functions

```r
# Simple print statement
print("Hello World")                    # Basic output
```

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

```r
#> [1] "Hello World"

# Concatenate with spaces
cat("Hello", "World")                   # Prints: Hello World
```

```
Hello World
```

```r
cat("Hello", "World", sep = "_")        # Prints: Hello_World
```

```
Hello_World
```

```r
# Join strings
paste0("C:/", "Group1")                 # Prints: C:/Group1
```

```
[1] "C:/Group1"
```

```r
paste("C:/", "Group1", sep = "")        # Same result
```

```
[1] "C:/Group1"
```

Getting Help

```r
# Get help on functions
?mean                                   # Help for mean function
```

```
help("mean")                          # Same as above

# Find functions containing keyword
help.search("correlation")            # Search help for "correlation"
??correlation                         # Same as above
```

Essential RStudio Shortcuts

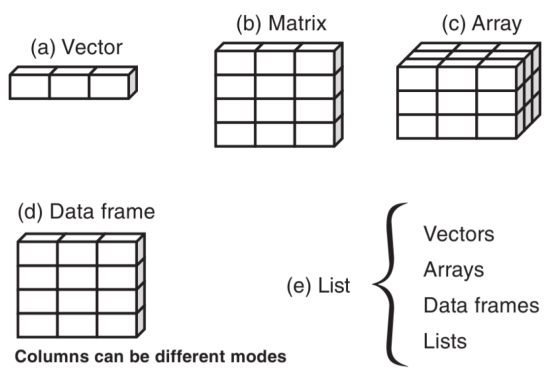
Here are some shortcuts that you can use in RStudio:

Shortcut	Action
`Ctrl + L`	Clean console
`Ctrl + Shift + N`	Create a new script
`↑`	Access command history
`Ctrl(hold) + ↑`	Search command history with current input
`Ctrl + Enter`	Execute selected code in script

These shortcuts work on Windows/Linux. For Mac, replace Ctrl with Cmd ( ).

Data structures

`R` offers several data structures that serve different purposes. Each structure is designed to handle specific types of data organization, from simple one-dimensional vectors to complex nested lists[1].



Vector (1-dimensional)

[1]Kabacoff, R. I. (2022). R in action: data analysis and graphics with R and Tidyverse. Simon and Schuster.

- One-dimensional sequence of elements
- All elements must be of the same type (numeric, character, etc.)
- Example: `c(1, 2, 3) or c("a", "b", "c")`

Matrix (2-dimensional)

- Two-dimensional arrangement of elements
- All elements must be of the same type
- Organized in rows and columns
- Example: `matrix(1:9, nrow = 3, ncol = 3)`

Array (n-dimensional)

- Extension of matrices to multiple dimensions
- All elements must be of the same type
- Can have 3 or more dimensions
- Example: `array(1:27, dim = c(3, 3, 3))`

Data Frame

- Two-dimensional structure similar to a spreadsheet
- Different columns can contain different types of data
- Most common structure for statistical analysis

Here are some examples of each datatype:

Vector

```
v1 <- 1:12  # Create numeric vector using sequence
v2 <- c(2,4,1,5,1,6, 13:18)  # Create numeric vector by combining values and sequence
v3 <- c(rep('aa',4), rep('bb',4), rep('cc',4))  # Create character vector with repeated v
class(v1)  # Check class of v1
```

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

```
class(v2)  # Check class of v2
```

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

```
class(v3)  # Check class of v3
```

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

Matrix and array

```r
m1 <- matrix(v1, nrow=3, ncol=4)  # Create matrix filled by column
m2 <- matrix(v1, nrow=3, ncol=4, byrow = T)  # Create matrix filled by row
arr <- array(v1, dim=c(2,2,3))  # Create 3D array
```

```r
class(m1)  # Check class of matrix
```

```
[1] "matrix" "array"
```

```r
class(arr)  # Check class of array
```

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

Data frame

```r
df <- data.frame(v1=v1, v2=v2, v3=v3, f=f)  # Create dataframe from vectors
class(df)  # Check class of dataframe
```

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

```r
str(df)    # Display structure of dataframe
```

```
'data.frame':   12 obs. of  4 variables:
 $ v1: int  1 2 3 4 5 6 7 8 9 10 ...
 $ v2: num  2 4 1 5 1 6 13 14 15 16 ...
 $ v3: chr  "aa" "aa" "aa" "aa" ...
 $ f : Factor w/ 10 levels "a","b","c","d",..: 1 1 2 2 3 4 5 6 7 8 ...
```

```r
class(df$v1)  # Check class of first column
```

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

```r
class(df$v2)  # Check class of second column
```

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

```r
class(df$v3)  # Check class of third column
```

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

```r
class(df$f)   # Check class of fourth column (factor)
```

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

Using the `$` Operator in `R`

The `$` operator is used to access specific columns or elements within a list or data frame by name.
Suppose we have a data frame of students' grades and want to access the 'Math' column:

```r
# Create a data frame
students <- data.frame(
  Name = c("Alice", "Bob", "Charlie"),
  Math = c(95, 88, 92),
  Science = c(89, 94, 90)
)

# Access the Math column
math_scores <- students$Math
print(math_scores)
```

```
[1] 95 88 92
```

Or if we wanted to get the `class` type for a column:

```r
# Get the class of the "Math" column
math_class <- class(students$Math)
print(math_class)
```

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

```r
# Get the class of the "Name" column
name_class <- class(students$Name)
print(name_class)
```

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

Exercise 1: Basic `R` commands

1. Open the `R_basics.R` script (within `_scripts`) and practice basic `R` commands and data types.
Only work up until the "Control Flow" section of code.
TIP: use the `class()` and `str` commands.

Logical operators, control flow and functions

We commonly use logical operators in `R` to help make decisions in code and are essential in tasks like subsetting data, controlling loops, writing conditional statements, and filtering data.

Operator	Summary
`<`	Less than
`>`	Greater than
`<=`	Less than or equal to
`>=`	Greater than or equal to
`==`	Equal to
`!=`	Not equal to
`!x`	NOT x
`x | y`	x OR y
`x & y`	x AND y

Control flow

Control flow structures are fundamental building blocks in programming that determine how code executes. Two essential control flow mechanisms are **if-else statements and for-loops:**

- **If-else statements** allow programs to make decisions based on conditions, enabling different code execution paths depending on whether conditions are true or false.
- **For-loops** provide a way to automate repetitive tasks by executing code multiple times over a sequence of elements.

Here's a simple example involving reaction time (RT) data, which we often want to clean by removing outliers and incorrect responses. We typically exclude RTs that are too fast (suggesting anticipatory responses) or too slow (suggesting inattention), as well as trials where participants made errors.

Here's how we can do that using an if-else statement and a for-loop:

```r
# Sample reaction time data (in milliseconds) with accuracy (1 = correct, 0 = error)
rt_data <- c(245, 892, 123, 456, 2891, 567, 432, 345, 178, 654)
accuracy <- c(1, 1, 0, 1, 1, 1, 0, 1, 1, 1)

# Initialize vector for cleaned data
clean_rt <- numeric(length(rt_data))

# Process each trial
for (i in 1:length(rt_data)) {
    if (accuracy[i] == 1 && rt_data[i] > 200 && rt_data[i] < 2000) {
        # Include trial if:
        # - Response was correct (accuracy = 1)
        # - RT is above 200ms (not anticipatory)
        # - RT is below 2000ms (not too slow)
        clean_rt[i] <- rt_data[i]
    } else {
        clean_rt[i] <- NA  # Mark excluded trials as NA
    }
}

# Calculate mean RT for clean trials only
mean_rt <- mean(clean_rt, na.rm = TRUE)
mean_rt
```

```
[1] 526.5
```

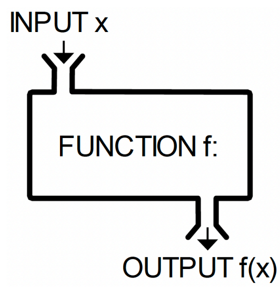
In this example, the for-loop processes each trial, while the if-else statement excludes responses that are too fast (<200ms), too slow (>2000ms), or incorrect.

Functions

Functions are operation(s) that are performed to obtain some quantity based on another quantity. They are often analagous to a 'black box' which processes some input x, to generate an output $f(x)$.

There are three broad sources of functions within `R`:

- **Built-in functions:** functions available automatically within `R` (e.g., `mean`, `sum`)
- **External functions:** functions written by others (e.g., as part of a package)
- **User-defined functions:** functions written by the user



A practical example of a user-defined functions is calculating the Standard Error of the Mean (SEM). The SEM measures the precision of a sample mean and is calculated as the standard deviation divided by the square root of the sample size minus one:

$$SEM = \sqrt{\frac{s^2}{n-1}}$$

Here's how to implement this as a function in R:

```
# function to calculate Standard Error of Mean (SEM)
sem <- function(x) {
    # Calculate: sqrt(variance / (n-1))
    # na.rm=TRUE removes NA values
    # na.omit(x) gives us the actual sample size excluding NAs
    sqrt(var(x, na.rm=TRUE) / (length(na.omit(x))-1))
}

# Example usage:
data <- c(23, 45, 12, 67, 34, 89, 21)
sem(data)
```

```
[1] 11.31336
```

Exercise 2: Control flow and user-defined functions

1. Write an if-else statement to do the following:

- Generate a random number between 0 and 1.
- Compare it against 1/3 and 2/3
- Print the random number and its position relative to 1/3 and 2/3

Click to see the solution

```r
t <- runif(1) # random number between 0 and 1
if (t <= 1/3) {
    cat("t =", t, ", t <= 1/3. \n")
} else if (t > 2/3) {
    cat("t =", t, ", t > 2/3. \n")
} else {
    cat("t =", t, ", 1/3 < t <= 2/3. \n")
}
```

```
t = 0.7960411 , t > 2/3.
```

2. Write a for-loop to do the following:

- Get the name of each month of this calendar year
- Print it one by one

Click to see the solution

```r
month_name <- format(ISOdate(2025,1:12,1),"%B")
for (j in 1:length(month_name) ) {
    cat()
}

print(month_name)
```

```
 [1] "January"   "February"  "March"     "April"     "May"       "June"     
 [7] "July"      "August"    "September" "October"   "November"  "December" 
```

Packages

Packages are collections of functions, data sets, and documentation bundled together to extend the functionality of `R`. They are not part of the base `R` installation but can be easily added and used in your environment.

`R` packages can:

- **Add functions:** They contain pre-written functions that simplify common tasks or complex analyses. For example, packages like `ggplot2` and `dplyr` offer powerful tools for data visualization and manipulation.
- **Provide data:** Some packages include data sets that can be used for testing or teaching purposes. For example, the `datasets` package provides a collection of sample data sets.

- **Enable special features:** Packages can implement specialized features like statistical models, machine learning algorithms, or tools for web scraping, reporting, and more.

How to use packages in R

Installing: You can install a package from CRAN (the Comprehensive R Archive Network) using the `install.packages()` function.

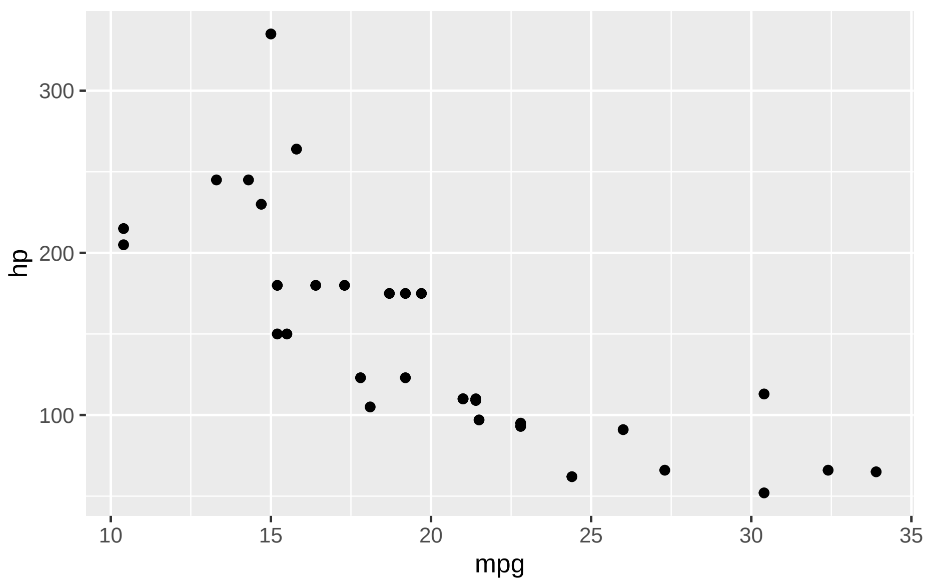
```
install.packages("ggplot2")
```

Loading: Once installed, you can load the package into your R session with the `library()` function.

```
library('ggplot2')
```

Usage: After loading the package, you can use its functions. For example, with `ggplot2`, you can create a plot like this:

```
ggplot(data = mtcars, aes(x = mpg, y = hp)) +
  geom_point()
```



Popular R packages include:

- `ggplot2`: A powerful package for data visualization based on the grammar of graphics.
- `dplyr`: A package for data manipulation (filtering, selecting, grouping, etc.).
- `tidyr`: Used for tidying data, such as reshaping and pivoting.
- `shiny`: For building interactive web applications in `R`.

You can find and install R packages from a number of sources:

- CRAN: The main repository for `R` packages.
- Bioconductor: A repository specializing in bioinformatics packages.
- GitHub: Many `R` developers host their packages on GitHub, which you can install using `devtools` or `remotes` packages.

Data visualization using `ggplot2()`

One of the main benefits of `R` is to create publication quality figures and graphs. There are a number of different functions within `R` that we can use:

- built-in plotting functions e.g., `plot()`
- `lattice` - similar to built-in plotting functions
- `ggplot2()` - making nicer plots using a layering approach

We will now briefly cover `ggplot2()` as it is the most versatile and used approach to create complex figures.

`ggplot2` is a powerful `R` package for creating complex and customizable data visualizations. It provides a systematic approach to building plots by combining two main components: geometries (`geom`) and aesthetics (`aes`).

`plot = geometric (points, lines, bars) + aesthetic (color, shape, size)`

Geometries (`geom`): These define the type of plot or visual elements you want to display. Common `geoms` include:

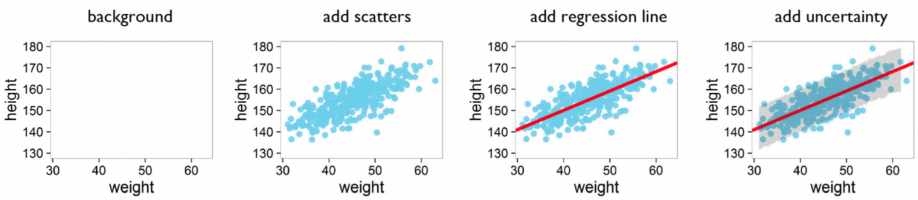
- `geom_point()`: Displays data points (scatter plot).
- `geom_line()`: Plots lines connecting data points.
- `geom_bar()`: Creates bar charts.

Aesthetics (`aes`): These define how data is mapped to visual properties. The aesthetics determine the appearance of the plot, such as:

- `color`: Specifies the color of the points, lines, or bars.

- `shape`: Defines the shape of data points (e.g., circles, squares).
- `size`: Controls the size of the points or lines.

Importantly, `ggplot2()` is built upon the layering of different components. For example, you can simply add more `aes` components to add a line of best fit, and standard error:



The R Graph Gallery

You can create many, many, many different types of graphs and plots using `ggplot2()`. You can check out it's versatility by seeing examples at the R Graph Gallery.