

# ETC4500/ETC5450

## Advanced R programming

Week 1: Foundations of R programming



# Outline

1 Scalars and vectors

2 Lists and data frames

3 Subsetting

4 Functions

5 Environments

6 Conditions

# Introduction

## Expectations

- You know R and RStudio
- You have a basic understanding of programming (for loops, if statements, functions)
- You can use Git and GitHub (<https://happygitwithr.com>)

## Unit resources

- Everything on **<https://arp.numbat.space>**
- Assignments submitted on Github Classroom
- Discussion on Ed

- Use your monash.edu address.
- Apply to GitHub Education as a student (<https://github.com/education/students>).
- Gives you free access to private repos and GitHub Copilot.
- Add GitHub Copilot to RStudio settings, or sign into GitHub in Positron.

# R history

- S (1976, Chambers, Becker and Wilks; Bell Labs, USA)
- S-PLUS (1988, Doug Martin; Uni of Washington, USA)
- R (1993, Ihaka and Gentleman; Uni of Auckland, NZ)

# R history

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## R influenced by

- Lisp (functional programming, environments, dynamic typing)
- Scheme (functional programming, lexical scoping)
- S and S-PLUS (syntax)

# Why R?

- Free, open source, and on every major platform.
- A diverse and welcoming community
- A massive set of packages, often cutting-edge.
- Powerful communication tools (Shiny, Rmarkdown, quarto)
- RStudio and Positron IDEs
- Deep-seated language support for data analysis.
- A strong foundation of functional programming.
- Posit
- Easy connection to high-performance programming languages like C, Fortran, and C++.

# R challenges

- R users are not usually programmers. Most R code by ordinary users is not very elegant, fast, or easy to understand.
- R users more focused on results than good software practices.
- R packages are inconsistent in design.
- R can be slow.

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# Scalars

- **Logicals:** TRUE or FALSE, or abbreviated (T or F).
- **Doubles:** decimal (0.1234), scientific (1.23e4), or hexadecimal (0xcafe). Special values: Inf, -Inf, and NaN (not a number).
- **Integers:** 1234L, 1e4L, or 0xcafeL. Can not contain fractional values.
- **Strings:** "hi" or 'bye'. Special characters are escaped with \.

# Making longer vectors with c()

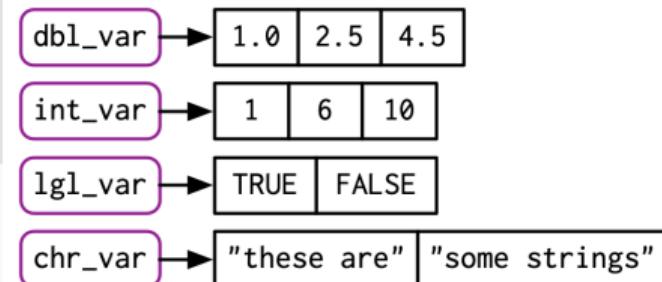
Use c() to create vectors.

```
lgl_var <- c(TRUE, FALSE)  
int_var <- c(1L, 6L, 10L)  
dbl_var <- c(1, 2.5, 4.5)  
chr_var <- c("these are", "some strings")
```

When the inputs are atomic vectors,  
c() always flattens.

```
c(c(1, 2), c(3, 4))
```

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



# Atomic vectors

- Four primary types of atomic vectors: logical, double, integer, and character (which contains strings).
- Two rare types: complex, raw.
- Collectively integer and double vectors are known as numeric vectors
- NULL is like a zero length vector
- Scalars are just vectors of length 1
- Every vector can also have **attributes**: a named list of arbitrary metadata.
- The **dimension** attribute turns vectors into matrices and arrays.

# Types and length

You can determine the type of a vector with `typeof()` and its length with `length()`.

```
typeof(lgl_var)
```

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

```
typeof(int_var)
```

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

```
typeof(dbl_var)
```

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

```
typeof(chr_var)
```

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

# Missing values

Most computations involving a missing value will return another missing value.

```
NA > 5
```

```
[1] NA
```

```
10 * NA
```

```
[1] NA
```

```
! NA
```

```
[1] NA
```

# Missing values

## Exceptions:

```
NA ^ 0
```

```
[1] 1
```

```
NA | TRUE
```

```
[1] TRUE
```

```
NA & FALSE
```

```
[1] FALSE
```

# Missing values

Use `is.na()` to check for missingness

```
x <- c(NA, 5, NA, 10)  
x == NA
```

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

```
is.na(x)
```

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

There are actually four missing values: `NA` (logical), `NA_integer_` (integer), `NA_real_` (double), and `NA_character_` (character).

# Coercion

- For atomic vectors, all elements must be the same type.
- When you combine different types they are **coerced** in a fixed order: logical → integer → double → character.

```
str(c("a", 1))
```

```
chr [1:2] "a" "1"
```

```
x <- c(FALSE, FALSE, TRUE)  
as.numeric(x)
```

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

```
sum(x)
```

```
[1] 1
```

```
as.integer(c("1", "1.5", "a"))
```

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

# Exercises

1 Predict the output of the following:

```
c(1, FALSE)  
c("a", 1)  
c(TRUE, 1L)
```

2 Why is `1 == "1"` true? Why is `-1 < FALSE` true? Why is `"one" < 2` false?

3 Why is the default missing value, `NA`, a logical vector? What's special about logical vectors? (Hint: think about `c(FALSE, NA_character_)`)

# Getting and setting attributes

- You can think of attributes as name-value pairs that attach metadata to an object.
- Individual attributes can be retrieved and modified with `attr()`, or retrieved en masse with `attributes()`, and set en masse with `structure()`.

```
a <- 1:3  
attr(a, "x") <- "abcdef"  
a
```

```
[1] 1 2 3  
attr("x")  
[1] "abcdef"
```

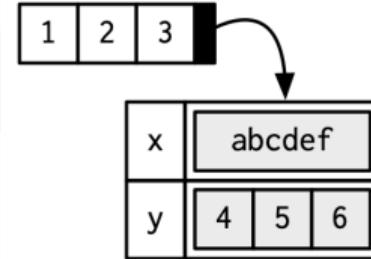
# Getting and setting attributes

```
attr(a, "y") <- 4:6  
str(attributes(a))
```

```
List of 2  
$ x: chr "abcdef"  
$ y: int [1:3] 4 5 6
```

```
# Or equivalently  
a <- structure(  
  1:3,  
  x = "abcdef",  
  y = 4:6  
)  
str(attributes(a))
```

```
List of 2  
$ x: chr "abcdef"  
$ y: int [1:3] 4 5 6
```



# Names

- Names are a type of attribute.
- You can name a vector in three ways:

```
# When creating it:  
x <- c(a = 1, b = 2, c = 3)  
  
# By assigning a character vector to names()  
x <- 1:3  
names(x) <- c("a", "b", "c")  
  
# Inline, with setNames():  
x <- setNames(1:3, c("a", "b", "c"))
```

```
x
```

```
a b c  
1 2 3
```

# Names

- Avoid using `attr(x, "names")` as it requires more typing and is less readable than `names(x)`.
- You can remove names from a vector by using  
`x <- unname(x)` or `names(x) <- NULL`.

# Dimensions

- Adding a `dim` attribute to a vector allows it to behave like a 2-dimensional **matrix** or a multi-dimensional **array**.
- You can create matrices and arrays with `matrix()` and `array()`, or by using the assignment form of `dim()`:

```
# Two scalar arguments specify row and column sizes
x <- matrix(1:6, nrow = 2, ncol = 3)
x
```

```
[,1] [,2] [,3]
[1,]    1    3    5
[2,]    2    4    6
```

# Dimensions

```
# One vector argument to describe all dimensions  
y <- array(1:12, c(2, 3, 2))  
y
```

, , 1

	[,1]	[,2]	[,3]
[1,]	1	3	5
[2,]	2	4	6

, , 2

	[,1]	[,2]	[,3]
[1,]	7	9	11
[2,]	8	10	12

# Dimensions

```
# You can also modify an object in place by setting dim()  
z <- 1:6  
dim(z) <- c(3, 2)  
z
```

```
[,1] [,2]  
[1,]    1    4  
[2,]    2    5  
[3,]    3    6
```

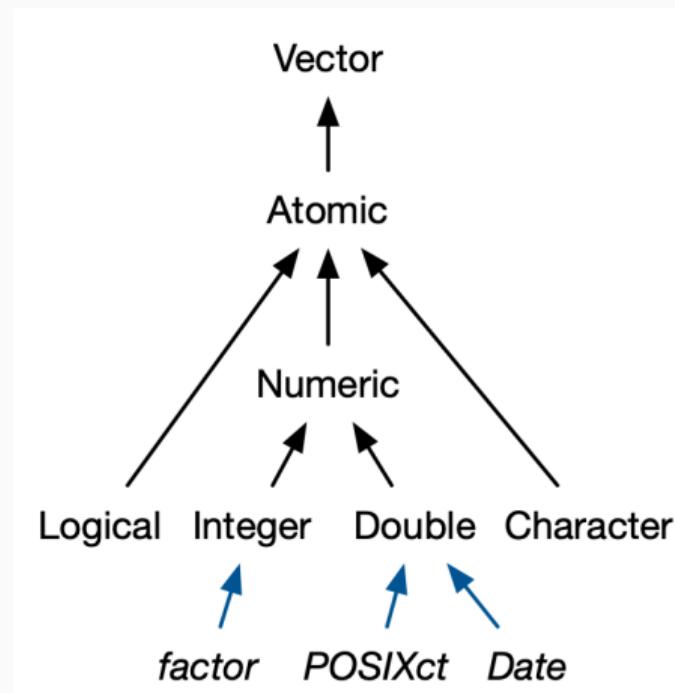
# Exercises

- 4 What does `dim()` return when applied to a 1-dimensional vector?
- 5 When might you use `NROW()` or `NCOL()`?
- 6 How would you describe the following three objects?  
What makes them different from `1:5`?

```
x1 <- array(1:5, c(1, 1, 5))
x2 <- array(1:5, c(1, 5, 1))
x3 <- array(1:5, c(5, 1, 1))
```

# S3 atomic vectors

- class is a vector attribute.
- It turns object into **S3 object**.
- Four important S3 vectors:
  - ▶ **factor** vectors.
  - ▶ **Date** vectors with day resolution.
  - ▶ **POSIXct** vectors for date-times.
  - ▶ **difftime** vectors for durations.



# Factors

- A vector that can contain only predefined values.
- Used to store categorical data.
- Built on top of an integer vector with two attributes: a class, “factor”, and levels, which defines the set of allowed values.

```
x <- factor(c("a", "b", "b", "a"))
x
```

```
[1] a b b a
Levels: a b
```

# Factors

```
typeof(x)
```

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

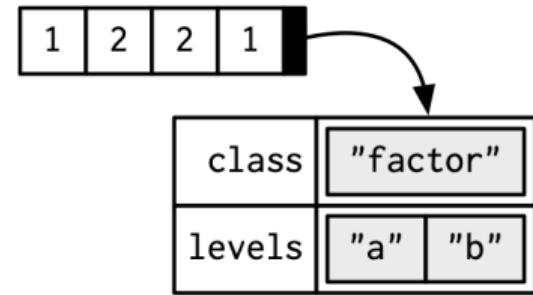
```
attributes(x)
```

```
$levels
```

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

```
$class
```

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



# Factors

```
sex_char <- c("m", "m", "m")
sex_factor <- factor(sex_char, levels = c("m", "f"))
```

```
table(sex_char)
```

```
sex_char
```

```
m
```

```
3
```

```
table(sex_factor)
```

```
sex_factor
```

```
m f
```

```
3 0
```

# Factors

- Be careful: some functions convert factors to integers!
- ggplot preserves ordering of levels in graphs – useful to reorder panels or legends.
- Ordered factors are useful when the order of levels is meaningful.

```
grade <- ordered(c("b", "b", "a", "c"), levels = c("c", "b", "a"))
grade
```

```
[1] b b a c
Levels: c < b < a
```

# Dates

- Date vectors are built on top of double vectors.
- Class “Date” with no other attributes:

```
today <- Sys.Date()
```

```
typeof(today)
```

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

```
attributes(today)
```

```
$class
```

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

# Dates

The value of the double (which can be seen by stripping the class), represents the number of days since 1970-01-01 (the “Unix Epoch”).

```
date <- as.Date("1970-02-01")
unclass(date)
```

```
[1] 31
```

# Date-times

- Base R provides two ways of storing date-time information, POSIXct, and POSIXlt.
- “POSIX” is short for Portable Operating System Interface
- “ct” stands for calendar time; “lt” for local time
- POSIXct vectors are built on top of double vectors, where the value represents the number of seconds since 1970-01-01.

```
now_ct <- as.POSIXct("2018-08-01 22:00", tz = "UTC")  
now_ct
```

```
[1] "2018-08-01 22:00:00 UTC"
```

```
typeof(now_ct)
```

# Date-times

The `tzone` attribute controls only how the date-time is formatted; it does not control the instant of time represented by the vector. Note that the time is not printed if it is midnight.

```
structure(now_ct, tzone = "Asia/Tokyo")
```

```
[1] "2018-08-02 07:00:00 JST"
```

```
structure(now_ct, tzone = "America/New_York")
```

```
[1] "2018-08-01 18:00:00 EDT"
```

```
structure(now_ct, tzone = "Australia/Lord_Howe")
```

```
[1] "2018-08-02 08:30:00 +1030"
```

# Exercises

- 7 What sort of object does `table()` return? What is its type?  
What attributes does it have? How does the dimensionality change as you tabulate more variables?
- 8 What happens to a factor when you modify its levels?

```
f1 <- factor(letters)
levels(f1) <- rev(levels(f1))
```

- 9 What does this code do? How do `f2` and `f3` differ from `f1`?

```
f2 <- rev(factor(letters))
f3 <- factor(letters, levels = rev(letters))
```

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# Lists

- More complex than atomic vectors
- Elements are *references* to objects of any type

```
l1 <- list(  
  1:3, "a", c(TRUE, FALSE, TRUE), c(2.3, 5.9)  
)  
typeof(l1)
```



```
[1] "list"  
str(l1)
```

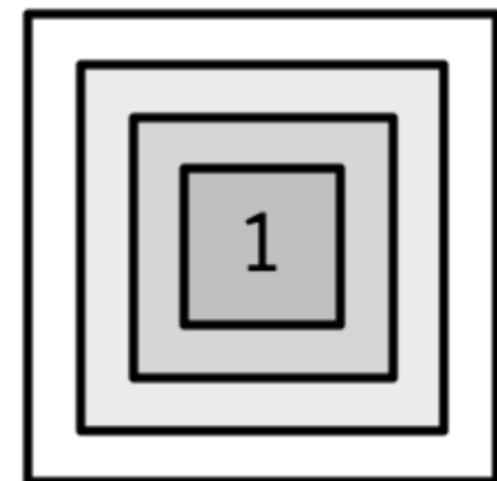
```
List of 4  
$ : int [1:3] 1 2 3  
$ : chr "a"  
$ : logi [1:3] TRUE FALSE TRUE  
$ : num [1:2] 2.3 5.9
```

# Lists

- Lists can be recursive: a list can contain other lists.

```
l3 <- list(list(list(1)))  
str(l3)
```

```
List of 1  
$ :List of 1  
..$ :List of 1  
...$ : num 1
```



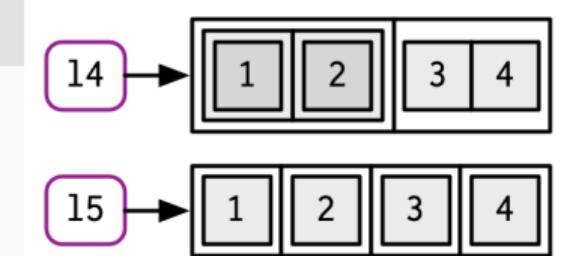
# Lists

- c() will combine several lists into one.

```
l4 <- list(list(1, 2), c(3, 4))  
l5 <- c(list(1, 2), c(3, 4))  
str(l4)
```

```
List of 2  
$ :List of 2  
..$ : num 1  
..$ : num 2  
$ : num [1:2] 3 4
```

```
str(l5)
```



```
List of 4  
$ : num 1  
$ : num 2  
$ : num 3  
$ : num 4
```

# Testing and coercion

```
list(1:3)
```

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

```
as.list(1:3)
```

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

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

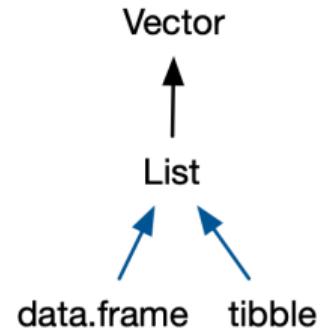
```
[[3]]  
[1] 3
```

- You can turn a list into an atomic vector with `unlist()`.

# Data frames and tibbles

- Most important S3 vectors built on lists:  
data frames and tibbles.

```
df1 <- data.frame(x = 1:3, y = letters[1:3])  
typeof(df1)
```



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

```
attributes(df1)
```

```
$names
```

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

```
$class
```

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

```
$row.names
```

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

	x	y
1	1	"a"
2	2	"b"
3	3	"c"

# Data frames and tibbles

- A data frame has a constraint: the length of each of its vectors must be the same.
- A data frame has `rownames()` and `colnames()`. The `names()` of a data frame are the column names.
- A data frame has `nrow()` rows and `ncol()` columns. The `length()` of a data frame gives the number of columns.

# Tibbles

- Modern reimagining of the data frame.
- tibbles are “lazy and surly”: they do less and complain more.

```
library(tibble)
df2 <- tibble(x = 1:3, y = letters[1:3])
typeof(df2)
```

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

```
attributes(df2)
```

```
$class
```

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

```
$row.names
```

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

```
$names
```

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

# Creating data frames and tibbles

```
names(data.frame(`1` = 1))
```

```
[1] "X1"
```

```
names(tibble(`1` = 1))
```

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

# Creating data frames and tibbles

```
data.frame(x = 1:4, y = 1:2)
```

```
  x y  
1 1 1  
2 2 2  
3 3 1  
4 4 2
```

```
tibble(x = 1:4, y = 1:2)
```

```
Error in `tibble()`:  
! Tibble columns must have compatible sizes.  
* Size 4: Existing data.  
* Size 2: Column `y`.  
i Only values of size one are recycled.
```

# Creating data frames and tibbles

```
tibble(  
  x = 1:3,  
  y = x * 2,  
  z = 5  
)
```

```
# A tibble: 3 x 3  
      x     y     z  
  <int> <dbl> <dbl>  
1     1     2     5  
2     2     4     5  
3     3     6     5
```

## Row names

Data frames allow you to label each row with a name, a character vector containing only unique values:

```
df3 <- data.frame(  
  age = c(35, 27, 18),  
  hair = c("blond", "brown", "black"),  
  row.names = c("Bob", "Susan", "Sam"))  
df3
```

	age	hair
Bob	35	blond
Susan	27	brown
Sam	18	black

# Row names

- tibbles do not support row names
- convert row names into a regular column with either `rownames_to_column()`, or the `rownames` argument:

```
as_tibble(df3, rownames = "name")
```

```
# A tibble: 3 x 3
  name    age hair
  <chr> <dbl> <chr>
1 Bob      35  blond
2 Susan    27  brown
3 Sam      18  black
```

# Printing

```
dplyr::starwars
```

```
# A tibble: 87 x 14
  name      height  mass hair_color skin_color eye_color birth_year sex
  <chr>     <int> <dbl> <chr>       <chr>       <chr>       <dbl> <chr>
1 Luke Skywalker 172     77 blond      fair        blue         19   male
2 C-3PO            167     75 <NA>       gold        yellow      112  none
3 R2-D2             96     32 <NA>       white, bl~ red          33  none
4 Darth Vader     202    136 none       white        yellow      41.9 male
5 Leia Organa     150     49 brown      light       brown         19 female
6 Owen Lars       178    120 brown, gr~ light       blue         52   male
7 Beru Whitesun  165     75 brown      light       blue         47 female
8 R5-D4            97     32 <NA>       white, red red          NA  none
9 Biggs Darko     183     84 black      light       brown        24   male
10 Obi-Wan Kenobi 182     77 auburn, w~ fair        blue-gray     57   male
# i 77 more rows
# i 6 more variables: gender <chr>, homeworld <chr>, species <chr>,
#   films <list>, vehicles <list>, starships <list>
```

# Printing

- Tibbles only show first 10 rows and all columns that fit on screen. Additional columns shown at bottom.
- Each column labelled with its type, abbreviated to 3–4 letters.
- Wide columns truncated.

# List columns

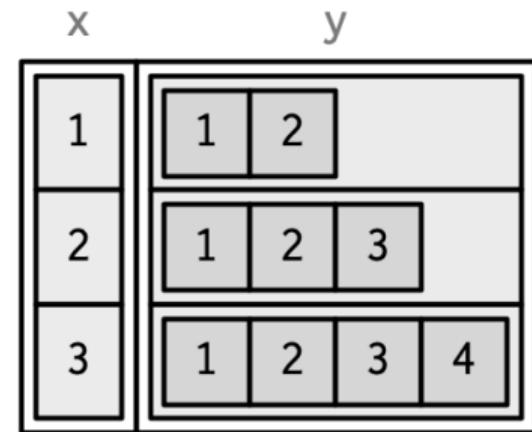
```
df <- data.frame(x = 1:3)
df$y <- list(1:2, 1:3, 1:4)
df
```

```
x           y
1 1          1, 2
2 2          1, 2, 3
3 3          1, 2, 3, 4
```

```
tibble(
  x = 1:3,
  y = list(1:2, 1:3, 1:4)
)
```

```
# A tibble: 3 x 2
```

```
  x     y
  <int> <list>
1     1 <int [2]>
2     2 <int [3]>
3     3 <int [4]>
```



# Matrix and data frame columns

```
dfm <- tibble(  
  x = 1:3 * 10,  
  y = matrix(1:9, nrow = 3),  
  z = data.frame(a = 3:1, b = letters[1:3])  
)  
str(dfm)
```

```
tibble [3 x 3] (S3: tbl_df/tbl/data.frame)  
$ x: num [1:3] 10 20 30  
$ y: int [1:3, 1:3] 1 2 3 4 5 6 7 8 9  
$ z:'data.frame': 3 obs. of 2 variables:  
..$ a: int [1:3] 3 2 1  
..$ b: chr [1:3] "a" "b" "c"
```

x	y	z
10	1 4 7	a
20	2 5 8	b
30	3 6 9	c

# Exercises

- 10** What happens if you attempt to set rownames that are not unique?
- 11** If `df` is a data frame, what can you say about `t(df)`, and `t(t(df))`? Perform some experiments, making sure to try different column types.
- 12** What does `as.matrix()` do when applied to a data frame with columns of different types? How does it differ from `data.matrix()`?

# NULL

```
length(NULL)
```

```
[1] 0
```

You can test for NULLs with `is.null()`:

```
x <- NULL  
x == NULL
```

```
logical(0)
```

```
is.null(x)
```

```
[1] TRUE
```

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# Exercises

- 13 What is the result of subsetting a vector with positive integers, negative integers, a logical vector, or a character vector?
- 14 What's the difference between `[`, `[[`, and `$` when applied to a list?
- 15 When should you use `drop = FALSE`?

# Exercises

- 16 Fix each of the following common data frame subsetting errors:

```
mtcars[mtcars$cyl = 4, ]  
mtcars[-1:4, ]  
mtcars[mtcars$cyl <= 5]  
mtcars[mtcars$cyl == 4 | 6, ]
```

- 17 Extract the residual degrees of freedom from mod

```
mod <- lm(mpg ~ wt, data = mtcars)
```

- 18 Extract the R squared from the model summary (summary(mod))

# Exercises

- 19 How would you randomly permute the columns of a data frame?
- 20 How would you select a random sample of  $m$  rows from a data frame? What if the sample had to be contiguous (i.e., with an initial row, a final row, and every row in between)?
- 21 How could you put the columns in a data frame in alphabetical order?

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# Function fundamentals

- Almost all functions can be broken down into three components: arguments, body, and environment.
  - ▶ The `formals()`, the list of arguments that control how you call the function.
  - ▶ The `body()`, the code inside the function.
  - ▶ The `environment()`, the data structure that determines how the function finds the values associated with the names.
- Functions are objects and have attributes.

# Function components

```
f02 <- function(x, y) {  
  # A comment  
  x + y  
}  
formals(f02)
```

\$x

\$y

```
body(f02)
```

```
{  
  x + y  
}
```

```
environment(f02)
```

```
<environment: R_GlobalEnv>
```

# Invoking a function

```
mean(1:10, na.rm = TRUE)
```

```
[1] 5.5
```

```
mean(, TRUE, x = 1:10)
```

```
[1] 5.5
```

```
args <- list(1:10, na.rm = TRUE)  
do.call(mean, args)
```

```
[1] 5.5
```

# Function composition

```
square <- function(x) { x^2 }
deviation <- function(x) { x - mean(x) }
x <- runif(100)
```

Nesting:

```
sqrt(mean(square(deviation(x))))
```

```
[1] 0.307
```

Intermediate variables:

```
out <- deviation(x)
out <- square(out)
out <- mean(out)
out <- sqrt(out)
out
```

```
[1] 0.307
```

Pipe:

```
x |>
  deviation() |>
  square() |>
  mean() |>
  sqrt()
```

```
[1] 0.307
```

# Lexical scoping

Names defined inside a function mask names defined outside a function.

```
x <- 10
y <- 20
g02 <- function() {
  x <- 1
  y <- 2
  c(x, y)
}
g02()
```

```
[1] 1 2
```

# Lexical scoping

Names defined inside a function mask names defined outside a function.

```
x <- 2
g03 <- function() {
  y <- 1
  c(x, y)
}
g03()
```

```
[1] 2 1
```

```
# And this doesn't change the previous value of y
y
```

```
[1] 20
```

# Lexical scoping

Names defined inside a function mask names defined outside a function.

```
x <- 1
g04 <- function() {
  y <- 2
  i <- function() {
    z <- 3
    c(x, y, z)
  }
  i()
}
g04()
```

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

# Functions versus variables

```
g07 <- function(x) { x + 1 }
g08 <- function() {
  g07 <- function(x) { x + 100 }
  g07(10)
}
g08()
```

```
[1] 110
```

```
g09 <- function(x) { x + 100 }
g10 <- function() {
  g09 <- 10
  g09(g09)
}
g10()
```

```
[1] 110
```

# A fresh start

What happens to values between invocations of a function?

```
g11 <- function() {  
  if (!exists("a")) {  
    a <- 1  
  } else {  
    a <- a + 1  
  }  
  a  
}  
  
g11()
```

```
[1] 1
```

```
g11()
```

```
[1] 1
```

# Dynamic lookup

```
g12 <- function() { x + 1 }
x <- 15
g12()
```

```
[1] 16
```

```
x <- 20
g12()
```

```
[1] 21
```

```
codetools::findGlobals(g12)
```

```
[1] "{" "+" "x"
```

# Dynamic lookup

```
g12 <- function() { x + 1 }
x <- 15
g12()
```

```
[1] 16
```

```
x <- 20
g12()
```

```
[1] 21
```

```
codetools::findGlobals(g12)
```

```
[1] "{" "+" "x"
```

**It is good practice to pass all the inputs to a function as arguments.**

# Lazy evaluation

This code doesn't generate an error because x is never used:

```
h01 <- function(x) {  
  10  
}  
h01(stop("This is an error!"))
```

```
[1] 10
```

# Promises

Lazy evaluation is powered by a data structure called a **promise**.

A promise has three components:

- An expression, like  $x + y$ , which gives rise to the delayed computation.
- An environment where the expression should be evaluated
- A value, which is computed and cached the first time a promise is accessed when the expression is evaluated in the specified environment.

# Promises

```
y <- 10
h02 <- function(x) {
  y <- 100
  x + 1
}
h02(y)
```

```
[1] 11
```

# Promises

```
double <- function(x) {  
  message("Calculating...")  
  x * 2  
}  
h03 <- function(x) {  
  c(x, x)  
}  
h03(double(20))
```

Calculating...

[1] 40 40

# Promises

```
double <- function(x) {  
  message("Calculating...")  
  x * 2  
}  
h03 <- function(x) {  
  c(x, x)  
}  
h03(double(20))
```

Calculating...

[1] 40 40

Promises are like a quantum state: any attempt to inspect them with R code will force an immediate evaluation, making the promise disappear.

# Default arguments

Thanks to lazy evaluation, default values can be defined in terms of other arguments, or even in terms of variables defined later in the function:

```
h04 <- function(x = 1, y = x * 2, z = a + b) {  
  a <- 10  
  b <- 100  
  c(x, y, z)  
}  
h04()
```

```
[1] 1 2 110
```

# Default arguments

Thanks to lazy evaluation, default values can be defined in terms of other arguments, or even in terms of variables defined later in the function:

```
h04 <- function(x = 1, y = x * 2, z = a + b) {  
  a <- 10  
  b <- 100  
  c(x, y, z)  
}  
h04()
```

```
[1] 1 2 110
```

**Not recommended!**

# ... (dot-dot-dot)

Allows for any number of additional arguments.

You can use ... to pass additional arguments to another function.

```
i01 <- function(y, z) {  
  list(y = y, z = z)  
}  
i02 <- function(x, ...) {  
  i01(...)  
}  
str(i02(x = 1, y = 2, z = 3))
```

List of 2

```
$ y: num 2  
$ z: num 3
```

# ... (dot-dot-dot)

list(...) evaluates the arguments and stores them in a list:

```
i04 <- function(...) {  
  list(...)  
}  
str(i04(a = 1, b = 2))
```

```
List of 2  
$ a: num 1  
$ b: num 2
```

## ... (dot-dot-dot)

- Allows you to pass arguments to a function called within your function, without having to list them all explicitly.

# ... (dot-dot-dot)

- Allows you to pass arguments to a function called within your function, without having to list them all explicitly.

## Two downsides:

- When you use it to pass arguments to another function, you have to carefully explain to the user where those arguments go.
- A misspelled argument will not raise an error. This makes it easy for typos to go unnoticed:

```
sum(1, 2, NA, na_rm = TRUE)
```

```
[1] NA
```

# Exercises

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Explain the following results:

```
sum(1, 2, 3)
```

```
[1] 6
```

```
mean(1, 2, 3)
```

```
[1] 1
```

```
sum(1, 2, 3, na.omit = TRUE)
```

```
[1] 7
```

```
mean(1, 2, 3, na.omit = TRUE)
```

```
[1] 1
```

# Exiting a function

Most functions exit in one of two ways:

- return a value, indicating success
- throw an error, indicating failure.

# Implicit versus explicit returns

Implicit return, where the last evaluated expression is the return value:

```
j01 <- function(x) {  
  if (x < 10) {  
    0  
  } else {  
    10  
  }  
}  
j01(5)
```

```
[1] 0
```

```
j01(15)
```

```
[1] 10
```

# Implicit versus explicit returns

Explicit return, by calling `return()`:

```
j02 <- function(x) {  
  if (x < 10) {  
    return(0)  
  } else {  
    return(10)  
  }  
}  
j02(5)
```

```
[1] 0
```

```
j02(15)
```

```
[1] 10
```

# Invisible values

Most functions return visibly: calling the function in an interactive context prints the result.

```
j03 <- function() { 1 }  
j03()
```

```
[1] 1
```

However, you can prevent automatic printing by applying `invisible()` to the last value:

```
j04 <- function() { invisible(1) }  
j04()
```

# Invisible values

The most common function that returns invisibly is <-:

```
a <- 2  
(a <- 2)
```

```
[1] 2
```

This is what makes it possible to chain assignments:

```
a <- b <- c <- d <- 2
```

In general, any function called primarily for a side effect (like <-, print(), or plot()) should return an invisible value (typically the value of the first argument).

# Errors

If a function cannot complete its assigned task, it should throw an error with `stop()`, which immediately terminates the execution of the function.

```
j05 <- function() {  
  stop("I'm an error")  
  return(10)  
}  
j05()
```

```
Error in `j05()`:  
! I'm an error
```

# Function forms

*To understand computations in R, two slogans are helpful:*

- *Everything that exists is an object.*
  - *Everything that happens is a function call.*
- John Chambers

# Function forms

- **prefix**: the function name comes before its arguments, like `foofy(a, b, c)`.
- **infix**: the function name comes in between its arguments, like `x + y`.
- **replacement**: functions that replace values by assignment, like `names(df) <- c("a", "b", "c")`.
- **special**: functions like `[], if, and for`.

# Rewriting to prefix form

Everything can be written in prefix form.

```
x + y  
`+`(x, y)
```

```
names(df) <- c("x", "y", "z")  
`names<-` (df, c("x", "y", "z"))
```

```
for(i in 1:10) print(i)  
`for`(i, 1:10, print(i))
```

# Don't be evil!

```
`(` <- function(e1) {  
  if (is.numeric(e1) && runif(1) < 0.1) {  
    e1 + 1  
  } else {  
    e1  
  }  
}  
replicate(50, (1 + 2))
```

# Prefix form

You can specify arguments in three ways:

- By position, like `help(mean)`.
- By name, like `help(topic = mean)`.
- Using partial matching, like `help(top = mean)`.

# Exercises

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Clarify the following list of odd function calls:

```
x <- sample(replace = TRUE, 20, x = c(1:10, NA))
y <- runif(min = 0, max = 1, 20)
cor(m = "k", y = y, u = "p", x = x)
```

# Infix functions

Functions with 2 arguments, and the function name comes between the arguments:

`::, :::, ::::, $, @, ^, *, /, +, -, >, >=, <, <=, ==, !=, !, &, &&, |, ||, ~, <-`, and `<<-`.

```
1 + 2
```

```
[1] 3
```

```
`+`(1, 2)
```

```
[1] 3
```

# Infix functions

You can also create your own infix functions that start and end with %.

```
`%+%` <- function(a, b) paste0(a, b)  
"new " %+% "string"
```

```
[1] "new string"
```

# Replacement functions

- Replacement functions act like they modify their arguments in place, and have the special name `xxx<-`.
- They must have arguments named `x` and `value`, and must return the modified object.

```
`second<-` <- function(x, value) {  
  x[2] <- value  
  x  
}  
x <- 1:10  
second(x) <- 5L  
x
```

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

# Replacement functions

```
`modify<-` <- function(x, position, value) {  
  x[position] <- value  
  x  
}  
modify(x, 1) <- 10  
x
```

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

When you write `modify(x, 1) <- 10`, behind the scenes R turns it into:

```
x <- `modify<-`(x, 1, 10)
```

# Outline

1 Scalars and vectors

2 Lists and data frames

3 Subsetting

4 Functions

5 Environments

6 Conditions

# Environment basics

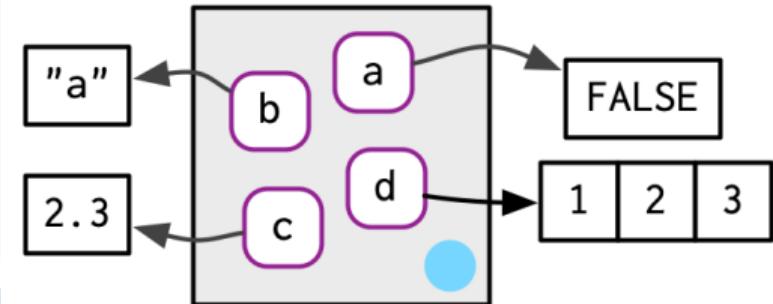
Environments are data structures that power scoping.

An environment is similar to a named list, with four important exceptions:

- Every name must be unique.
- The names in an environment are not ordered.
- An environment has a parent.
- Environments are not copied when modified.

# Environment basics

```
library(rlang)
e1 <- env(
  a = FALSE,
  b = "a",
  c = 2.3,
  d = 1:3,
)
```



## Special environments

- The **current environment** is the environment in which code is currently executing.
- The **global environment** is where all interactive computation takes place. Your “workspace”.

# Parent environments

- Every environment has a parent.
- If a name is not found in an environment, R looks in the parent environment.
- The ancestors of the global environment include every attached package.

```
env_parents(e1, last = empty_env())
```

```
[[1]] $ <env: global>
[[2]] $ <env: package:rlang>
[[3]] $ <env: package:tibble>
[[4]] $ <env: package:dplyr>
[[5]] $ <env: package:stats>
[[6]] $ <env: package:graphics>
[[7]] $ <env: package:grDevices>
[[8]] $ <env: package:datasets>
[[9]] $ <env: renv:shims>
[[10]] $ <env: package:utils>
[[11]] $ <env: package:methods>
[[12]] $ <env: Autoloads>
[[13]] $ <env: package:base>
[[14]] $ <env: empty>
```

# Super assignment

- Regular assignment (`<-`) creates a variable in the current environment.
- Super assignment (`<<-`) modifies a variable in a parent environment.
- If it can't find an existing variable, it creates one in the global environment.

# Package environments

- Every package attached becomes one of the parents of the global environment (in order of attachment).

```
search()
```

```
[1] ".GlobalEnv"           "package:rlang"      "package:tibble"  
[4] "package:dplyr"        "package:stats"     "package:graphics"  
[7] "package:grDevices"    "package:datasets"  "renv:shims"  
[10] "package:utils"        "package:methods"   "Autoloads"  
[13] "package:base"
```

- Attaching a package changes the parent of the global environment.
- Autoloads uses delayed bindings to save memory by only loading package objects when needed.

# Function environments

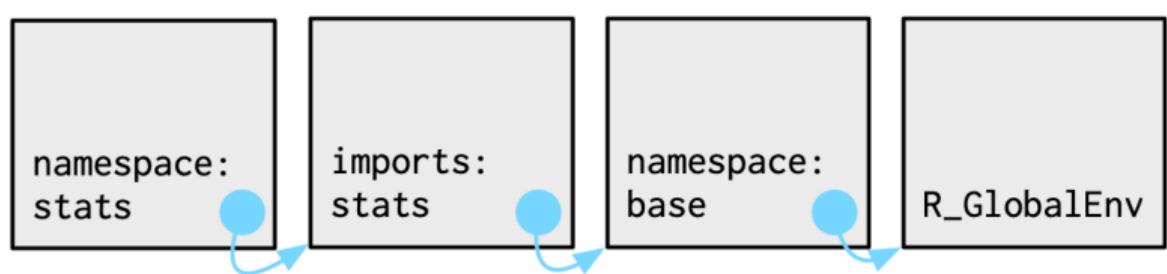
A function binds the current environment when it is created.

```
y <- 1
f <- function(x) {
  env_print(current_env())
  x + y
}
f(2)
```

```
<environment: 0x5bedcba0e3c0>
Parent: <environment: global>
Bindings:
* x: <lazy>
[1] 3
```

# Namespaces

- Package environment: how an R user finds a function in an attached package (only includes exports)
- Namespace environment: how a package finds its own objects (includes non-exports as well)
- Each namespace environment has an imports environment (controlled via NAMESPACE file).



# Caller environments

```
f <- function(x) {  
  g(x = 2)  
}  
g <- function(x) {  
  h(x = 3)  
}  
h <- function(x) {  
  stop()  
}
```

```
f(x = 1)  
#> Error: in h(x = 3)  
traceback()  
#> 4: stop() at #3  
#> 3: h(x = 3) at #3  
#> 2: g(x = 2) at #3  
#> 1: f(x = 1)
```

# Lazy evaluation

```
a <- function(x) b(x)
b <- function(x) c(x)
c <- function(x) x
a(f())
#> Error: in h(x = 3)
traceback()
#> 7: stop() at #3
#> 6: h(x = 3) at #3
#> 5: g(x = 2) at #3
#> 4: f() at #1
#> 3: c(x) at #1
#> 2: b(x) at #1
#> 1: a(f())
unused argument (clas
```

# Outline

1 Scalars and vectors

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6 Conditions

# Conditions

```
message("This is what a message looks like")
#> This is what a message looks like

warning("This is what a warning looks like")
#> Warning: This is what a warning looks like

stop("This is what an error looks like")
#> Error in eval(expr, envir, enclos): This is what an error looks like
```

# Conditions

```
message("This is what a message looks like")
#> This is what a message looks like

warning("This is what a warning looks like")
#> Warning: This is what a warning looks like

stop("This is what an error looks like")
#> Error in eval(expr, envir, enclos): This is what an error looks like
```

- Ignore messages with `suppressMessages()`.
- Ignore warnings with `suppressWarnings()`.
- Ignore errors with `try()`.

# try()

- Allows execution to continue even if an error occurs.
- Returns a special object that captures the error.

```
f1 <- function(x) {  
  log(x)  
  10  
}  
f1("x")
```

Error in `log()`:

! non-numeric argument to mathematical function

```
f2 <- function(x) {  
  try(log(x))  
  10  
}  
f2("a")
```

Error in log(x) : non-numeric argument to m

# Handling conditions

Allow you to specify what should happen when a condition occurs.

```
tryCatch(  
  error = function(cond) {  
    # code to run when error is thrown  
  },  
  code_to_run_while_handlers_are_active  
)  
withCallingHandlers(  
  warning = function(cond) {  
    # code to run when warning is signalled  
  },  
  message = function(cond) {  
    # code to run when message is signalled  
  },  
  code_to_run_while_handlers_are_active  
)
```

# tryCatch()

```
f3 <- function(x) {  
  tryCatch(  
    error = function(cond) NA,  
    log(x)  
  )  
}  
  
f3("x")
```

```
[1] NA
```

# withCallingHandlers()

```
f4 <- function(x) {  
  withCallingHandlers(  
    warning = function(cond) cat("How did this happen?\n"),  
    log(x)  
  )  
}  
  
f4(-1)
```

How did this happen?

[1] NaN

# Exercise

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Explain the results of running the following code

```
show_condition <- function(code) {  
  tryCatch(  
    error = function(cnd) "error",  
    warning = function(cnd) "warning",  
    message = function(cnd) "message",  
    {  
      code  
      5  
    }  
  )  
}  
show_condition(stop("!"))  
show_condition(10)  
show_condition(warning("?!"))
```

# Activity

Write a function to take a single integer input and return:

- fizz if the number is divisible by 5
- buzz if the number is divisible by 7
- fizzbuzz if the number is divisible by both 5 and 7
- the number otherwise

Your function should contain a `stop()` if the input is not an integer.