Introduction to Programming with R

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Zurich R Courses

Introduction

Introduction

Who are we?

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Who are you?

1. Institution and Status
2. Previous knowledge and experience
   - with R
   - with other statistic software
   - with other programming languages
3. Specific interest/motivation for this workshop?

Motivation

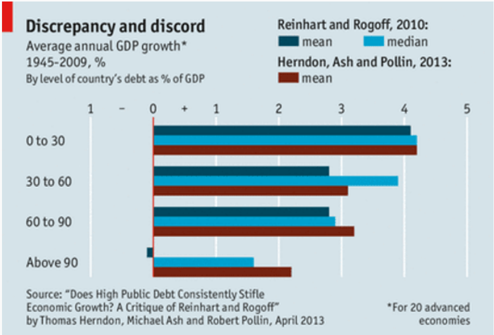
- Being more efficient in your research
  - Save time and nerves
  - Avoid errors and bugs
  - High transfer effect to all projects (with data analyses)
- Successful collaborations (with your future self?)
- Code as part of paper submissions

Motivation

Two of your worst enemies

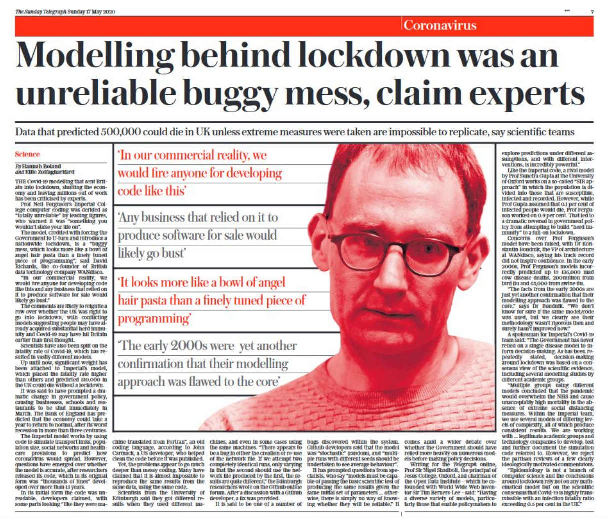
- Past Self
  - Is the biggest mess in existence
  - Did not document anything
  - Uses a completely different style of writing code than yourself
  - Is the worst collaborator (does not reply to e-mails)
- Future Self
  - Has the memory of a goldfish
  - Will have zero understanding for your current brilliance

Motivation



Discrepancy and discord
Average annual GDP growth*
1945-2009, %
By level of country's debt as % of GDP
Reinhart and Rogoff, 2010:
mean
median
Herndon, Ash and Pollin, 2013:
mean
1
-
0
+
1
2
3
4
5
0 to 30
30 to 60
60 to 90
Above 90
Source: "Does High Public Debt Consistently Stifle Economic Growth? A Critique of Reinhart and Rogoff" by Thomas Herndon, Michael Ash and Robert Pollin, April 2013
*For 20 advanced economies

Motivation



The Sunday Telegraph Sunday 17 May 2020 7

Coronavirus

Modelling behind lockdown was an unreliable buggy mess, claim experts

Data that predicted 500,000 could die in UK unless extreme measures were taken are impossible to replicate, say scientific teams

Science

By Hannah Boland *and* Ellie Zolfagharifard

THE Covid-19 modelling that sent Britain into lockdown, shutting the economy and leaving millions out of work has been criticised by experts.

Prof Neil Ferguson's Imperial College computer coding was derided as "totally unreliable" by leading figures, who warned it was "something you wouldn't stake your life on".

The model, credited with forcing the Government to U-turn and introduce a nationwide lockdown, is a "buggy mess, which looks more like a bowl of angel hair pasta than a finely tuned piece of programming", said David Richards, the co-founder of British data technology company WANdisco.

"In our commercial reality, we would fire anyone for developing code like this and any business that relied on it to produce software for sale would likely go bust."

The comments are likely to reignite a row over whether the UK was right to go into lockdown, with conflicting models suggesting people may have already acquired substantial herd immunity and Covid-19 may have hit Britain earlier than first thought.

Scientists have also been split on the fatality rate of Covid-19, which has resulted in vastly different models.

Up until now, significant weight has been attached to Imperial's model, which placed the fatality rate higher than others and predicted 510,000 in the UK could die without a lockdown.

It was said to have prompted a dramatic change in government policy, causing businesses, schools and restaurants to be shut immediately in March. The Bank of England has predicted that the economy could take a year to return to normal, after its worst recession in more than three centuries.

The Imperial model works by using code to simulate transport links, population size, social networks and healthcare provisions to predict how coronavirus would spread. However, questions have emerged over whether the model is accurate, after researchers released its code, which in its original form was "thousands of lines" developed over more than 13 years.

In its initial form the code was unreadable, developers claimed, with some parts looking "like they were machine translated from Fortran", an old coding language, according to John Carmack, a US developer, who helped clean the code before it was published.

Yet, the problems appear to go much deeper than messy coding. Many have claimed that it is almost impossible to reproduce the same results from the same data, using the same code.

Scientists from the University of Edinburgh said they got different results when they used different machines, and even in some cases using the same machines. "There appears to be a bug in either the creation or re-use of the network file. If we attempt two completely identical runs, only varying in that the second should use the network file produced by the first, the results are quite different," the Edinburgh researchers wrote on the Github online forum. After a discussion with a Github developer, a fix was provided.

It is said to be one of a number of bugs discovered within the system. Github developers said that the model was "stochastic" (random), and "multiple runs with different seeds should be undertaken to see average behaviour".

It has prompted questions from specialists, who say "models must be capable of passing the basic scientific test of producing the same results given the same initial set of parameters ... otherwise, there is simply no way of knowing whether they will be reliable." It comes amid a wider debate over whether the Government should have relied more heavily on numerous models before making policy decisions.

Writing for the *Telegraph* online, Prof Sir Nigel Shadbolt, the principal of Jesus College, Oxford, and chairman of the Open Data Institute – which he co-founded with World Wide Web inventor Sir Tim Berners-Lee – said: "Having a diverse variety of models, particularly those that enable policymakers to explore predictions under different assumptions, and with different interventions, is incredibly powerful."

Like the Imperial code, a rival model by Prof Sunetra Gupta at the University of Oxford works on a so-called "SIR approach" in which the population is divided into those that are susceptible, infected and recorded. However, while Prof Gupta assumed that 0.1 per cent of infected people would die, Prof Ferguson worked on 0.9 per cent. That led to a dramatic reversal in government policy from attempting to build "herd immunity" to a full-on lockdown.

Concerns over Prof Ferguson's model have been raised, with Dr Konstantin Boudnik, the VP of architecture at WANdisco, saying his track record did not inspire confidence. In the early 2000s, Prof Ferguson's models incorrectly predicted up to 136,000 mad cow disease deaths, 200 million from bird flu and 65,000 from swine flu.

"The facts from the early 2000s are just yet another confirmation that their modelling approach was flawed to the core," says Dr Boudnik. "We don't know for sure if the same model/code was used, but we clearly see their methodology wasn't rigorous then and surely hasn't improved now."

A spokesman for Imperial's Covid-19 team said: "The Government has never relied on a single disease model to inform decision-making. As has been repeatedly stated, decision-making around lockdown was based on a consensus view of the scientific evidence, including several modelling studies by different academic groups.

"Multiple groups using different models concluded that the pandemic would overwhelm the NHS and cause unacceptably high mortality in the absence of extreme social distancing measures. Within the Imperial team, we use several models of differing levels of complexity, all of which produce consistent results. We are working with ... legitimate academic groups and technology companies to develop, test and further document the simulation code referred to. However, we reject the partisan reviews of a few clearly ideologically motivated commentators.

"Epidemiology is not a branch of computer science and the conclusions around lockdown rely not on any mathematical model but on the scientific consensus that Covid-19 is highly transmissible with an infection fatality ratio exceeding 0.5 per cent in the UK."

'In our commercial reality, we would fire anyone for developing code like this'

'Any business that relied on it to produce software for sale would likely go bust'

'It looks more like a bowl of angel hair pasta than a finely tuned piece of programming'

'The early 2000s were yet another confirmation that their modelling approach was flawed to the core'

Motivation

Concept of Technical Debt

- We write (messy) code for data cleaning/analyses
- We decide on data sets/models/graphs/tables/...
- We try to publish it, get a major revision
- We need to rerun some analyses
- Modifying/extending our code is more difficult than it should be

Trade-off

- Being fast vs. writing (or refactoring) perfect code

But also

- Write better R code

Goal of this workshop

An introduction to R as a Programming language

- Better practical R skills
- Better theoretical understanding of R (and programming)
- Different framing: R as a programming language

Agenda

Day 1

- RStudio setup
- Basic elements & data types of the R language
- Flow & conditional programming
- Loops & iteration
- Writing & using functions (part I)

Day 2

- Writing & using functions (part II)
- Programming tools in R: run time analysis, debugging, exception handling
- Good programming practices

RStudio setup

RStudio setup

1. Copy the course content from the usb-stick to a directory on your machine
2. Open RStudio
3. Choose `File < New Project ...`
4. Choose `Existing Directory`
5. Browse to the directory on your machine where you copied the course content and select the “Intro-R-programming” folder as the `Project working directory`
6. Click `Open in new session`
7. Click `Create Project`

RStudio setup - optional

1. Choose `Tools < Global options`
2. Under `General`
    - DON'T `Restore .RData into workspace at startup`
    - NEVER `Save workspace to .Rdata on exit:`
3. Further personalize RStudio

Basic elements & data types

"To understand computations in R, two slogans are helpful: Everything that exists is an object. Everything that happens is a function call."

— John Chambers

Basic elements & data types

- What are objects?
- Atomic vectors
- Vector structures
- Subsetting
- Replacement

What are objects?

- Data-structures that can be used in computations
- Collections of data of all kinds that are dynamically created and manipulated
- Can be very small, or very big. $\rightarrow$ *Everything in R is an object*
- Elementary data structures can be combined in more complex data structures
- Creating new types of *complex* objects is part of programming in R (S3, S4)

Atomic Vectors - Basic Building Blocks

Basic object types	
logical	`TRUE`, `FALSE`, `NA`
integer	`1L`, `142`, `-5`, ..., `NA`
double	`1.0`, `1.25784`, `pi`, ..., `NA`
	`NaN`, `-Inf`, `Inf`
character	`"1"`, `"Some other string"`, ..., `NA`

mulitple values in one object $\rightarrow$ `length()` starting from `0`

Atomic Vectors - Basic Building Blocks

Elements of the same type can be combined into an atomic vector using c.

```
c(3.3, 2.44, 9, 634)
```

[1] 3.30 2.44 9.00 634.00

All elements are of the same type!

Atomic Vectors - Basic Building Blocks

An important object type with special behavior is `NULL`.
It is an empty object that can be interpreted as *nothing*. It's length is 0.

```
length(NULL)

# [1] 0
```

`NULL` is mostly used as a default argument in functions, in order to create some default behavior.

Useful Functions

`?seq` Creates a vector with a sequence of numerical values.

```
seq(0, 10, by = 2)

[1] 0 2 4 6 8 10

seq(0, 1, length.out = 11)

[1] 0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
```

seq$_{a}long(letters)$

[1] 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 [26] 26

seq$_{l}en(10)$

\begin{frame}{Useful Functions}

\texttt{?rep} Creates a new vector by repeating the elements of a vector.

\begin{knitrout}\small

\definecolor{shadecolor}{rgb}{0.933 0.933 0.933}\color{fgcolor}\begin{kframe}

\begin{alltt}

\hlkwd{rep}\hlstd{(}\hlnum{1}\hlopt{:}\hlnum{3}\hlstd{} \hlkwc{each} \hlstd{=} \hlnum{2}\hlstd{)}

\end{alltt}

\begin{verbatim}

[1] 1 1 2 2 3 3

```
\begin{alltt}

\hlkwd{rep}\hlstd{(}\hlnum{1}\hlopt{:}\hlnum{3}\hlstd{}
\hlkwc{times} \hlstd{=} \hlnum{2}\hlstd{)}

\end{alltt}

\begin{verbatim}

# [1] 1 2 3 1 2 3

\begin{alltt}

\hlkwd{rep}\hlstd{(}\hlkwd{c}\hlstd{(}\hlstr{"a"}\hlstd{}
\hlstr{"b"}\hlstd{} \hlstr{"c"}\hlstd{)} \hlkwc{times}
\hlstd{=} \hlnum{2}\hlstd{)}

\end{alltt}

\begin{verbatim}
```

```
# [1] "a" "b" "c" "a" "b" "c"

\begin{alltt}

\hlkwd{rep}\hlstd{(}\hlkwd{c}\hlstd{(}\hlstr{"this"}\hlstd{}
\hlstr{"may"}\hlstd{} \hlstr{"be"}\hlstd{}
\hlstr{"useful"}\hlstd{} \hlstr{"!"}\hlstd{)}
\hlnum{1}\hlopt{:}\hlnum{5}\hlstd{)}

\end{alltt}

\begin{verbatim}

#  [1] "this"   "may"    "may"    "be"     "be"     "be"
"useful" "useful"

#  [9] "useful" "useful" "!"      "!"      "!"      "!"      "!"
```

Useful Functions

`?paste` Creates a character vector by pasting multiple vectors together.

```
paste("one", "big", "string", sep = " ")
```

```
[1] "one big string"
```

```
paste0("word",seq(1,10))
```

[1]
"word$_1$"" $word_2$"" $word_3$"" $word_4$"" $word_5$"" $word_6$"" $word_7$" [8]" $word_8$"" $word_9$"" wo

```
paste(c("ONE", "TWO"), seq(1, 3), sep = " || ", collapse =
"_")
```

[1] "ONE || 1$_{_T}WO||2_{_O}NE||3$"

\begin{frame}{Useful Functions}

\texttt{?unique} Creates a vector with the unique values of a vector.

\begin{knitrout}\small

\definecolor{shadecolor}{rgb}{0.933 0.933 0.933}\color{fgcolor}\begin{kframe}

\begin{alltt}

\hlkwd{unique}\hlstd{(}\hlkwd{c}\hlstd{(}\hlstr{"b"}\hlstd{} \hlstr{"a"}\hlstd{} \hlstr{"a"}\hlstd{} \hlstr{"b"}\hlstd{))}

\end{alltt}

\begin{verbatim}

[1] "b" "a"

\end{kframe}

\end{knitrout}

\texttt{?sort} Creates a sorted version a Vector.

\begin{knitrout}\small

\definecolor{shadecolor}{rgb}{0.933 0.933 0.933}\color{fgcolor}\begin{kframe}

\begin{alltt}

\hlkwd{sort}\hlstd{(}\hlkwd{c}\hlstd{(}\hlstr{"b"}\hlstd{} \hlstr{"a"}\hlstd{} \hlnum{NA}\hlstd{} \hlstr{"a"}\hlstd{} \hlstr{"b"}\hlstd{))}

\end{alltt}

\begin{verbatim}

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

\begin{alltt}

\hlkwd{sort}\hlstd{(}\hlkwd{c}\hlstd{(}\hlstr{"b"}\hlstd{}
\hlstr{"a"}\hlstd{} \hlnum{NA}\hlstd{} \hlstr{"a"}\hlstd{}
\hlstr{"b"}\hlstd{)} \hlkwc{na.last} \hlstd{=}
\hlnum{TRUE}\hlstd{)}

\end{alltt}

\begin{verbatim}

[1] "a" "a" "b" "b" NA

```
sort(c(4, 2, 6, 1, 3, 5), decreasing = TRUE)
```

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

Coercion/Conversion

Automatic conversion:
NULL → logical → integer → double → character

```
1 + TRUE

# [1] 2
```

Explicit conversion:
`as."type"()` `as.vector(, mode = "type")`

```
as.logical(0:5)

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

atomic vectors - check type

Check type using: `is."type"()`

```
is.null(NULL)

# [1] TRUE
```

Check type using: `typeof()`

```
typeof(TRUE + FALSE)

# [1] "integer"
```

Assignment

In order to compute with objects efficiently, names can be assigned to the objects using the assignment operator `<-` (or `=`)

```
my_object <- TRUE
my_object

# [1] TRUE
```

- The objects (with references) that are available to a user can be seen in the global environment using `ls()`.
- R overrides previous assignments without a message. Removed objects (`rm(objectName)`) cannot be restored.

→ ***May the source code be with you!***

Attributes

Attributes can be attached to objects. An attribute:

- has a name
- is itself also an object
- attributes are easily lost in computations. (One of the reasons to use OOP with classes and methods.)

```
my_object <- structure(5,
                       my_attribute = "string",
                       other_attribute = FALSE)
attributes(my_object)

# $my_attribute
# [1] "string"
#
# $other_attribute
# [1] FALSE
```

Attributes

There are several attributes with a specific use: `"names"`, `"dim"`, `"class"`, `"levels"`

- `"names"` is a character vector that contains the names of elements of the vector/object. Names can be printed and set using `names(object) <- .`
- `"dim"` is an integer vector that specifies how we should interpret the vector (i.e., as a matrix, as an array). The dimensions of a vector can be printed and set using `dim(object) <- .`
  $\rightarrow$ a `matrix` or `array` is a vector with a `"dim"` attribute.

Attributes

- `"class"` is a character vector that contains class names. Classes can be printed and set using `class(object) <-` . See Oriented Programming (S3).
- `"levels"` is a character vector that contains the names levels of a factor. Levels can be printed and set using `levels(factor) <-` .

Attributes

A factor in R is actually an integer vector with

- a `"class"` attribute set to `"factor"`
- a `"levels"` attribute set to the level-labels that correspond to the integer values from 1 to the highest integer value in the integer vector.

More Basic Object Types

More basic object types	
complex	`1 + 2.31i`, ... `NA`
raw	`as.raw(2)`, `charToRaw("a")`
expression	`expression(1+1, sum(a, b))`
language	a function call, `quote(1 + y)`
closure	`function(x) x - 1`, `mean`
builtin	`sum`, `c`
special	`for`, `return`
environment	an environment
symbol	`quote(x)`
...	...

Vector Structures

More basic object types	
list	`list()`, `as.list()`, ...
matrix	a **vector** with `"dim"` argument: two dimensions `matrix()`, `as.matrix()` matrix algebra
array	a **vector** with with `"dim"` argument
data.frame	a **list** with vectors of equal length `data.frame()`, `as.data.frame()`

List

A list is a "vector" that can contain any type of elements

- the types of elements can differ $\leftrightarrow$ atomic vectors
- possible elements including lists $\rightarrow$ recursive
- can have attributes

```
my_list <- list("this",
                a = list(a = c(1:2)))
my_list


# [[1]]
# [1] "this"
#
# $a
# $a$a
# [1] 1 2
```

Matrix & Array

A matrix or an array is a vector with a `"dim"`-attribute

- mostly usefull for numeric vectors (integer and double)
- matrix algebra! `t(matrix)`, `%*%`, `aperm(array)`, ...
- matrix has two dimensions, array has n dimensions
- `cbind(vector1, vector2)`
- `rbind(vector1, vector2)`
- `matrix(vector, ncol = 4, nrow = 2)`
- `array(vector), dim = c())`

Data.frame

A data.frame is a list of (named) vectors of equal length.

- has dimensions (but not a `"dim"`-attribute)
- the columns are the vectors
- the vectors can be lists (using `I()`).
- a data.frame has row names (but ignore these)

Subsetting - Atomic vectors

A subset of elements from a vector can be accessed using `object[selection]`, where `selection` is:

- a **logical** vector with the same length of the original vector (`TRUE`: select; `FALSE`: don't select)
- an **integer** vector indicating the indexes of the elements to select (or exclude)
- a **character** vector with the names of the elements to select

Subsetting - Atomic vectors

Using a **logical** vector:

- the logical vector should have the same length as the object. If shorter, the logical is repeated; if longer, `NA`s are added if `TRUE`. $\rightarrow$ always use the same length!
- handy when you want to select based on a condition related to the object values

Subsetting - Atomic vectors

Using a **logical** vector:

```
my_object <- c(a = 1, b = 5, c = 3, d = 8)
my_object[my_object > 4]

# b d
# 5 8
```

Subsetting - Atomic vectors

Using an **integer** vector:

- the integer vector can have any length (repeated indices are repeatedly selected)
- positive values mean *select*, negative values mean *drop*
- positive and negative values cannot be combined
- for integers higher than the number of elements in the vector, `NA`s are added
- using `which()` a logical vector is transformed in an integer vector with the indices of the elements that were `TRUE`
- double elements are truncated towards zero (using `as.integer()`)

Subsetting - Atomic vectors

Using an **integer** vector:

```
my_object <- c(a = 1, b = 5, c = 3, d = 8)
my_object[c(1, 2, 1, 2, 1, 2, 1 , 2, 1, 2, 1, 2)]

# a b a b a b a b a b a b
# 1 5 1 5 1 5 1 5 1 5 1 5
```

Subsetting - Atomic vectors

Using a **character** vector:

- the strings that match with the names of the elements in the vector are returned
- the character vector can have any length (repeated names are repeatedly selected)
- only selection is possible (dropping is not)
- strings that are not matched with names return `NA`

Subsetting - Atomic vectors

Using a **character** vector:

```
my_object <- c(a = 1, b = 5, c = 3, d = 8)
my_object[c("a", "b")]

# a b
# 1 5
```

Subsetting - Atomic vectors

A **sinlge** element from a vector can be accessed using `object[[selection]]`, where `selection` is:

- an **integer** value indicating the index of the element to select
- a **character** vector with the name of the element to select

```
my_object <- c(a = 1, b = 5, c = 3, c2 = 8)
my_object[[2]]

# [1] 5
```

Subsetting - Matrix & Arrays

Because arrays and matrices are atomic vectors (with a `"dim"` argument), the rules for atomic vectors apply.

Subsetting - Matrix & Arrays

In addition, selection is possible per dimension:

- separated by a comma `[, ]`
- selection via character (match row or column names), integer (row and column number) or logical vectors
- the first vector selects the rows, the second the columns (and so on)
- dimensions are dropped, unless `drop = FALSE`

```
my_matrix <- matrix(c(11, 12, 21, 22), ncol = 2,
                    dimnames = list(paste0("row", 1:2),
                                    paste0("col", 1:2)))
my_matrix[,2]


# row1 row2
#   21   22
```

Subsetting - Matrix & Arrays

Finally, the selection element can also be a matrix (with one column per dimension). Each row in the matrix selects one value.

```
my_matrix <- matrix(c(11, 12, 21, 22), ncol = 2,
                    dimnames = list(paste0("row", 1:2),
                                    paste0("col", 1:2)))
selection_matrix <- rbind(c(1, 1), c(1, 2), c(2, 1))
my_matrix[selection_matrix]

# [1] 11 21 12
```

Subsetting - Lists

For lists, the rules are similar as for atomic vectors.

- `list[selection]` gives a list (i.e., a subset of the original list)
- `list[[selection]]` gives the element (which can be a list)
- `list[["element_name"]]` is the same as `list$element_name`

```
my_list<- list(a = 1, b = 5, c = 3, d = 8)
is.list(my_list["a"])

# [1] TRUE

is.list(my_list[["a"]])

# [1] FALSE
```

Subsetting - data.frames

Because data.frames are lists, the rules for lists apply.

```
my_dat <- data.frame(col1 = c(11, 21),
                     col2 = c(12, 22))
my_dat[1]

#   col1
# 1   11
# 2   21
```

Subsetting - data.frames

In addition, the selection rules for matrices can be used:

- selection per row and column (note the `drop` argument)
- selection via a matrix with two columns

```
my_dat <- data.frame(col1 = c(11, 21),
                     col2 = c(12, 22))
my_dat[,"col1", drop = FALSE]

#   col1
# 1   11
# 2   21
```

Element Replacement

A subset of elements from a vector or vector structure can be replaced using `object[selection] <- new_values`:

- the modifications are done in place
- the structure and class of the object stay unchanged
- the length of the new values should correspond with the length of the selection (the number of elements to replace should be a multiple of the number of new values)
- only for lists, the replacement can be `NULL` (which removes the element from the list)

Element Replacement

```r
my_dat <- data.frame(col1 = c(11, 21),
                     col2 = c(12, 22))
my_dat[1, 2] <- 33
```

"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 Calls

- Computing in R happens through function calls. A function is applied to one or more objects, and returns an object after the computation.
- The typical use is:
  `function_name(object1, argument_name = object2)`
- Computations that seem not to be done using functions are actually also functions. Check `` `<-`(a, 5) `` or `` `>`(5, 2) ``
- most functions that seem not to return an object, return it invisibly. Check `(a <- 5)`.

Flow & conditional programming

Flow & conditional programming

R has specific tools (functions) that help organize the flow of computations.
You can make computations conditional on other objects ("conditional computation") The most commonly used tools are:

- `if` (+ `else`)
- `ifelse`
- `switch`

Conditional Computation - if

`if` statements have the basic form

```
if(test){
  some_computations
}
```

- `test` should be either `TRUE` or `FALSE` (or code that results in one of both).
- If `test == TRUE`, than `some_computations` is executed, if `test == FALSE`, than not.
- **Important**: `test` should have length 1. If not, only the first element is considered.

Conditional Computation - if

else can be added, but it is optional

```
if(test){
  some_computations
} else if (test_2){
  other_computations
} else {
  more_computations
}
```

Typical test functions

Vectorized

- `==`, `!=`, `>`, `>=`, ...
- `is.na()`
- `&`, `|`

Not vectorized

- `identical()`
- `all.equal()`
- `&&`, `||`
- `any()`, `all()`
- `is.character()`, `is.data.frame()`, ...

Conditional Computation - if

The *test* should have length 1!

```
# only the first element is evaluated
age <- c(8, 17, 39, 55)
if (age >= 18) {
  "can vote"
} else {
    "too young"
}

# [1] "too young"
```

Conditional Computation - if

Typical uses

```
if(any(is.na(x))){
  stop("computation impossible due to NA values")
}

if(!is.integer(vector)){
  warning("'vector' is automatically converted to interger.
          This may affect the results")
  vector <- as.integer(vector)
}

if(is.null(default_argument)){
  <default computations>
} else if (default_argument == specific value) {
  ...
}
```

Programming advice

- *if* is almost always used inside of functions or loops
- If possible, avoid using *else*
- Use meaningful initialisation, early return(), stop(), etc. instead

Solution using *if* and *else*

```
# only the first element is evaluated
age <- 17
if (age >= 18) {
  vote <- "can vote"
} else {
  vote <- "too young"
}
vote

# [1] "too young"
```

Conditional Computation - if

Solution using meaningful initialisation

```r
# only the first element is evaluated
age <- 17
vote <- "too young"
if (age >= 18) {
  vote <- "can vote"
}
vote

# [1] "too young"
```

Conditional Computation - ifelse

A vectorized version is `ifelse()`.

```
# all elements are evaluated
age <- c(8, 17, 39, 55)
ifelse(age >= 18, yes = "can vote",
       no = "too young")

# [1] "too young" "too young" "can vote"  "can vote"
```

Conditional Computation - ifelse

Go-to tool for conditional recoding

```
age_estimated <- c(10, 20, 35, 60)
age_self_rep <- c(NA, 17, 39, NA)

# Use available information, prioritize self report
ifelse(!is.na(age_self_rep), yes = age_self_rep,
       no = age_estimated)

# [1] 10 17 39 60
```

Conditional Computation - Vectorization

Pure vectorization can bring you a long way. But it is certainly less readable

```
age <- c(8, 17, 39, 55)
c("too young", "can vote")[1 + (age >= 18)]

# [1] "too young" "too young" "can vote"  "can vote"
```

Conditional Computation - switch

`switch()` is often a more elegant solution than using `else if ()` multiple times.

```
method <- "method 5"
switch(method,
       "method 1" = <computations>,
       "method 2" = <computations>,
       "method 3" = <computations>,
       "method 4" = <computations>,
       "method 5" = <computations>,
       "method 6" = <computations>,
       "method 7" = <computations>,
       "method 8" = <computations>,
       stop("Not an existing method"))
```

Exercises

Loops & Iteration

Loops & iteration

R has specific tools (functions) that help organize the flow of computations.
You can repeat a similar computation multiple times typically with changing options ("iteration"). The most commonly used tools are:

- loops (`repeat`, `while`, `for`)
- functionals (`apply` - family)

Loops & Iteration - for

`for` statements have the basic form

```
for (element in vector) {
  computation
}
```

For each element in the vector, the computation is executed. Often, the computation depends on the element in that iteration.

Loops & Iteration - for

```r
for (index in 1:3){
  cat(" computation -")
}

#  computation - computation - computation -

for (name in c("Alice", "Bob", "Casey")){
  if(name == "Bob") cat(" This was Bob -")
  else cat(" Not Bob -")
}

#  Not Bob - This was Bob - Not Bob -
```

Loops & Iteration - for

```r
matrix <- matrix(NA, nrow = 2, ncol = 3)
for (rowNr in 1:2){
  for (colNr in 1:3){
    matrix[rowNr, colNr] <- rowNr * 10 + colNr
  }
}
matrix

#      [,1] [,2] [,3]
# [1,]   11   12   13
# [2,]   21   22   23
```

Loops & Iteration - while

`while` statements have the basic form

```
while (condition){
  computation
}
```

As long as the condition is TRUE, the computation is executed. Often, the computation depends on something that is related to the condition.

Loops & Iteration - while

```
max_abs <- 0
while (max_abs <= 3){
  cat("|")
  values <- rnorm(20)
  max_abs <- max(abs(values))
}
max_abs
```

Loops & Iteration - repeat

`repeat` statements have the basic form

```
repeat {
  computation
}
```

Without a `break` the computation is repeated infinite times

Loops & Iteration - next break

- `next` starts next iteration
- `break` ends iteration (of the innermost loop)

```
index <- 0
repeat {
  index <- index + 1
  if (index %in% c(3, 5)) next
  if (index > 6) break
  print(index)
}

# [1] 1
# [1] 2
# [1] 4
# [1] 6
```

Iteration - Good practice

Programming advice

Use `seq()`, `seq_len()`, or `seq_along()`.

```
x <- numeric()
for (index in 1:length(x)){
  print(index)
}

# [1] 1
# [1] 0

for (index in seq_along(x)){
  print(index)
}
```

Loops & Iteration - Good practice

Programming advice

Don't grow, replace.

```
x <- letters
result1 <- numeric()            # grow
result2 <- numeric(length(x)) # replace
for (index in seq_along(x)){
  result1 <- c(result1, paste(index, x[index]))  # grow
  result2[index] <- paste(index, x[index])        # replace
}
```

Loops & Iteration - Functionals

A functional is a function that takes another function as an argument.
Focus on the `apply`-family. These functions *apply* a function repeatedly.
Can be seen as an abstraction of a for loop, with the following advantages

- requires less code to write
- does not store intermediate results
- no need to replace / grow

Functionals

The most commonly used functionals are:

- `lapply` vector / list $\rightarrow$ list
- `sapply` vector / list $\rightarrow$ vector (matrix)
- `apply` matrix / array / data.frame $\rightarrow$ vector (matrix)
- `tapply`, `by`, `aggregate`
- `mapply`, `Map`
- `rapply`, `eapply`, `vapply`

All of which have an argument that should be a function.

lapply

Data.frames are lists

```
lapply(iris, FUN = class)


# $Sepal.Length
# [1] "numeric"
#
# $Sepal.Width
# [1] "numeric"
#
# $Petal.Length
# [1] "numeric"
#
# $Petal.Width
# [1] "numeric"
#
# $Species
# [1] "factor"
```

lapply

- any type of element can be used
- other arguments can be passed through
- an annonymous function can be used

```
lapply(airquality, FUN = mean, rm.na = TRUE)


# $Ozone
# [1] NA
#
# $Solar.R
# [1] NA
#
# $Wind
# [1] 9.957516
#
# $Temp
# [1] 77.88235
#
```

sapply

- wrapper around lapply
- if possible, the ouput is combined into a atomic vector or matrix

```
sapply(airquality, FUN = sd)

#     Ozone   Solar.R      Wind      Temp     Month       Day
#        NA        NA  3.523001  9.465270  1.416522  8.864520

sapply(airquality, FUN = quantile, prob = c(.1, .9),
       na.rm = TRUE)

#      Ozone Solar.R  Wind Temp Month Day
# 10%     11    47.5  5.82 64.2     5   4
# 90%     87   288.5 14.90 90.0     9  28
```

apply

- for objects with dimension (matrix, array, data.frame)
- apply over (a) chosen dimension(s)

```
my_matrix <- matrix(1:6, nrow = 2)
apply(my_matrix, 1, max)    # apply per row

# [1] 5 6

apply(my_matrix, 2, max)    # apply per column

# [1] 2 4 6
```

apply

```
my_array <- array(1, dim = c(2, 3, 4))
apply(my_array, c(1, 2), sum)    # apply per row and column

#      [,1] [,2] [,3]
# [1,]    4    4    4
# [2,]    4    4    4

apply(my_array, 3, sum)

# [1] 6 6 6 6
```

Exercises

Functions I

Building Blocks

Functions are the building blocks of R code. As frequent users of functions we know that they should:

- have a clear purpose
- be well documented
- be portable

Stepping Stone

Central stepping stone for R users:
Move from solely using functions written by others to writing your own functions.

Reasons

Why write functions?

- Readability
    - Shortens the code
    - Removes distractions, like references in a paper
    - Avoids repetition (DRY)
    - Easier understanding
- Transferability
    - Other use cases
    - Other projects
    - Other persons

Readability

Writing a function:

```
mean(mtcars$mpg)
```

[1] 20.09062

Not writing a function:

```
sum(mtcars$mpg)/dim(mtcars)[1]
```

[1] 20.09062

Writing a function:

```
summary(mtcars$mpg)

#    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
#   10.40   15.43   19.20   20.09   22.80   33.90
```

Readability

Not writing a function:

```
round(c("Min." = min(mtcars$mpg),
  "1st Qu." = as.numeric(quantile(mtcars$mpg)[2]),
  "Median" = median(mtcars$mpg),
  "Mean" = mean(mtcars$mpg),
  "3rd Qu." = as.numeric(quantile(mtcars$mpg)[4]),
  "Max." = max(mtcars$mpg)), 2)

#     Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
#    10.40   15.43   19.20   20.09   22.80   33.90
```

Elements of a function

- Name
- Arguments/Formals (input)
- Body (what happens inside)
- Output

Function definition

```
countNA <- function(x) {     # Name, Arguments/Formals
  out <- sum(is.na(x))       # Body
  out                        # Output
}
```

Function Names

Every function needs a (meaningful) name!

- Usually a verb (what does the function do?)
- Avoid existing names
- Better longer than unclear
- CamelCase vs Snake_Case

Arguments

Most functions take one or multiple inputs. These are usually:

- One or two data arguments
- Additional Options

Programming advice

The less arguments, the better!

Output

Functions usually return a single object, namely the last evaluated object.

```
add_things_standard <- function(x = 1) {
  x2 <- x*2
  out <- x + x2
  out
}
add_things_standard(2)
```

[1] 6

Exercises

That's it for today!

That's it for today!

Questions? Remarks?