Basics of Programming: if…else, iterations, custom functions

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Conditional Programming

Conditional statements like `if`, `if...else`, and `ifelse` in R are essential tools for automating tasks and assisting decision making in data science. What follows are a few simple "toy examples", but focus on the underlying logic. This will be greatly useful in more advanced applications

---

`if` statement

the `if` statement performs an action *only if* a condition is met

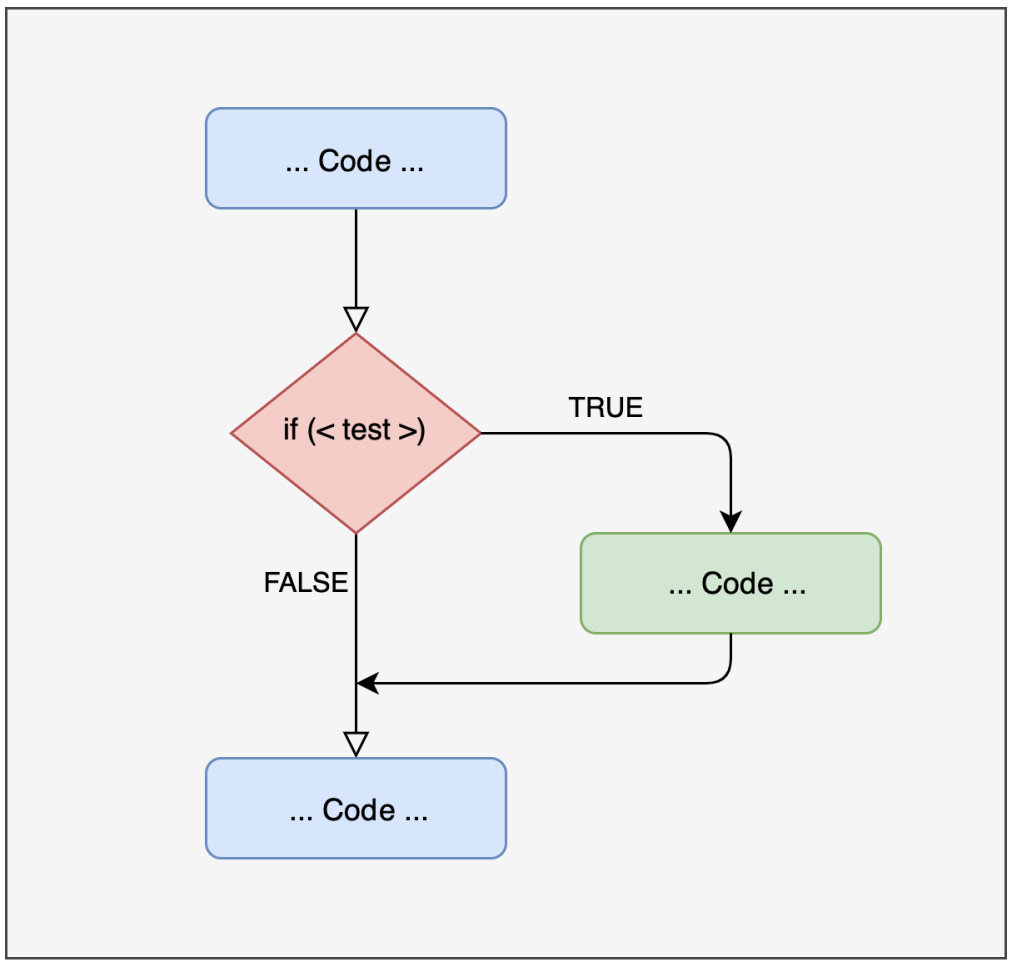
```
age = 20
```

```
if(age >= 18){
  print("Adult")
}
```

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

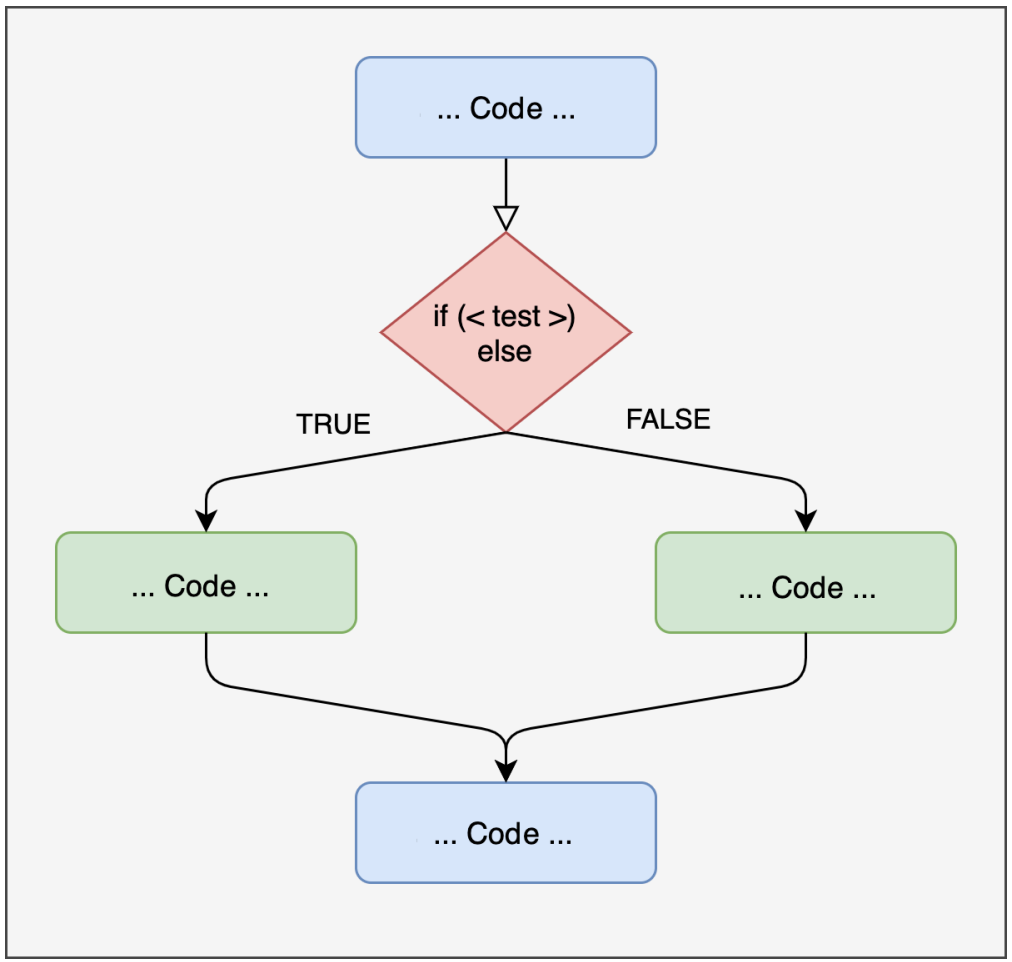
`if` statement

Basic flowchart showing the logic of the `if` statement:



`if...else` statement

Sometimes, however, you may need to perform *alternative* actions



`if...else` statement

Sometimes, however, you may need to perform *alternative* actions

Here is a practical example of the `if...else` statement

```
age = 15
```

```
if(age >= 18){
  print("Adult")
} else {
  print("Minor")
}
```

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

In the above example:

- *if* `age` is 18 or older, R will print `"Adult"`;
- otherwise (*else*) it will print `"Minor"`

`if...else if...else` statement

When you need to evaluate more than just two alternative conditions, you can use **nested conditional statements**, that is you combine multiple `if...else` statements

```
age = 10
```

```
if (age >= 18) {
  print("Adult")
} else if (age >= 13) {
  print("Adolescent")
} else if (age >= 2){
  print("Child")
} else {
  print("Infant")
}
```

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

`if...else` statement

Possible, pratical use of `if...else` in a preplanned analysis for a hypothetical preregistered study: automate the decision to conduct additional analyses based on the result of a preliminary test. This helps create a reproducible analysis pipeline with a clear set of decisions

```
## PREPLANNED ANALYSIS

# preliminary test
tt1 = t.test(x1, x2, data=df, paired=TRUE)

# based on the p-value of the preliminary t-test, choose the next step
if (tt1$p.value < 0.05) {
  # If significant, perform an additional analysis with a linear model
  print("Significant result: proceeding with follow-up analysis")
  fit = lm(outcome ~ pred1 + pred2 * moder1, data = df)
  summary(fit)
} else {
  # else, report only the preliminary test
  print("No significant result: reporting preliminary results only")
  print(tt1)
}
```

`if...else` statement

All previous examples required to evaluate a single particular condition that might be `TRUE` or `FALSE`. However, you often want to apply this type of operation to an entire vector

Using `if` and `if..else` directly on a vector will **NOT** work as intended:

```
age = c(2, 28, 15, 1, 4, 67, 42, 14, 7)

if(age >= 18){
  print("Adult")
} else {
  print("Minor")
}
```

```
Error in if (age >= 18) {: the condition has length > 1
```

ifelse()

All previous examples required to evaluate a single particular condition that might be TRUE or FALSE. However, you often want to apply this type of operation to an entire vector

To handle such cases you can use the base **ifelse()** function, that evaluates each element of a vector individually:

```
        age = c(2, 28, 15, 1, 4, 67, 42, 14, 7)

        ifelse(age >= 18, "Adult", "Minor")
```

```
[1] "Minor" "Adult" "Minor" "Minor" "Minor" "Adult" "Adult"
"Minor" "Minor"
```

— *Best practices: store results and set type as appropriate!*

```
        ageCategory = ifelse(age >= 18, "Adult", "Minor")
        ageCategory = factor(ageCategory, levels=c("Minor", "Adult"))
        ageCategory
```

```
[1] Minor Adult Minor Minor Minor Adult Adult Minor Minor
Levels: Minor Adult
```

ifelse()

The **ifelse()** function can also be nested to manage multiple conditions, such as in the following example:

```
        age = c(2, 28, 15, 1, 4, 67, 42, 14, 7)

        ifelse(age >= 18, "Adult" ,
                       ifelse(age >= 13, "Adolescent" ,
                                      ifelse(age >= 2, "Child",
                                                    "Infant")))
```

```
[1] "Child"      "Adult"      "Adolescent" "Infant"     "Child"
[6] "Adult"      "Adult"      "Adolescent" "Child"
```

dplyr::case_when()

While this works, the nested structure can become cumbersome as the number of conditions increases.

The above case may become cumbersome and less readable when you need to combine a large number of conditions. In such cases, the **case_when()** function from the dplyr package (part of the *tidyverse* collection)

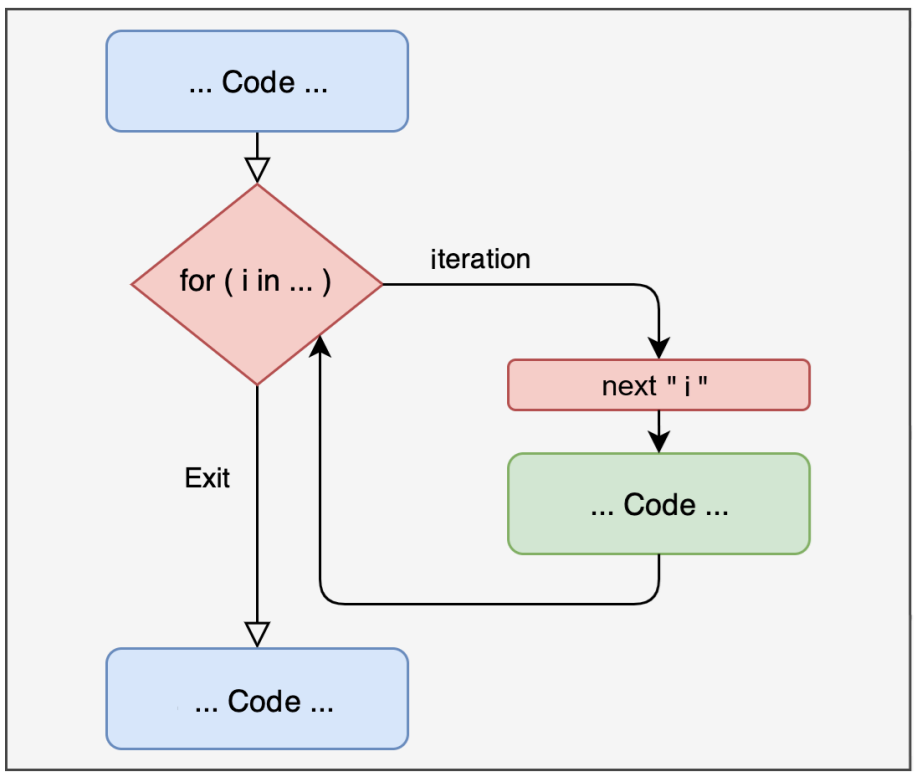
```
        age = c(2, 28, 15, 1, 4, 67, 42, 14, 7)

        library(dplyr)

        case_when(
          age >= 18 ~ "Adult",
          age >= 13 ~ "Adolescent",
          age >= 2  ~ "Child",
          TRUE      ~ "Infant"
        )
```

```
[1] "Child"      "Adult"      "Adolescent" "Infant"     "Child"
[6] "Adult"      "Adult"      "Adolescent" "Child"
```

Iterative Programming

Iterative programming allows you to repeat one or a series of actions automatically, for a predetermined number of times or until a condition is met

Let's start with understanding the basics of iterative programming with the `for` loop:



for loop

Here are a few simple examples of using the **for** loop

```
for(i in 1:5){
  print(i)
}
```

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

```
for(i in 1:5){
  print(i^2)
}
```

```
[1] 1
[1] 4
[1] 9
[1] 16
[1] 25
```

```
for(i in 1:5){
  print(Sys.time())
  Sys.sleep(1)
}
```

```
[1] "2024-11-23 14:46:26 CET"
[1] "2024-11-23 14:46:27 CET"
[1] "2024-11-23 14:46:28 CET"
[1] "2024-11-23 14:46:29 CET"
[1] "2024-11-23 14:46:30 CET"
```

```
for(i in 1:5){
  print(Sys.time())
  Sys.sleep(2)
}
```

```
[1] "2024-11-23 14:46:31 CET"
[1] "2024-11-23 14:46:33 CET"
[1] "2024-11-23 14:46:35 CET"
[1] "2024-11-23 14:46:37 CET"
[1] "2024-11-23 14:46:39 CET"
```

`for` loop

Here's a more interesting example of iterative `for` loop with practical usefulness: we want to repeat a data simulation for a predetermined number of times (5 iterations), each time drawing $n = 30$ values from a *standard normal distribution*, computing and displaying the average …

```
set.seed(0) # set a seed for reproducibility: best practic

for(i in 1:5){
  x = rnorm(n = 30, mean = 0, sd = 1)
  print(mean(x))
}
```

```
[1] 0.02195079
[1] -0.02577153
[1] -0.009581231
[1] 0.03212316
[1] -0.2946441
```

This is actually the starting point of a Monte Carlo simulation! 😀

`for` loop

in the previous example, the `for` loop displayed the results but didn't store it. For more effective use, you can combine the `for` loop with indexing with `[]` to save each result:

```
        set.seed(0) # set a seed for reproducibility: best practic
        niter = 5 # set the desired number of iterations: best pra
        # initialize a results vector with NAs: best practice!
        results = rep(NA, niter)
        # now run the for loop! :-)
        for(i in 1:niter){
          x = rnorm(n = 30, mean = 0, sd = 1)
          results[i] = mean(x)
        }
        results # display results
```

```
[1]  0.021950789 -0.025771530 -0.009581231  0.032123159
-0.294644080
```

```
        sd(results) # estimate standard error of the mean
```

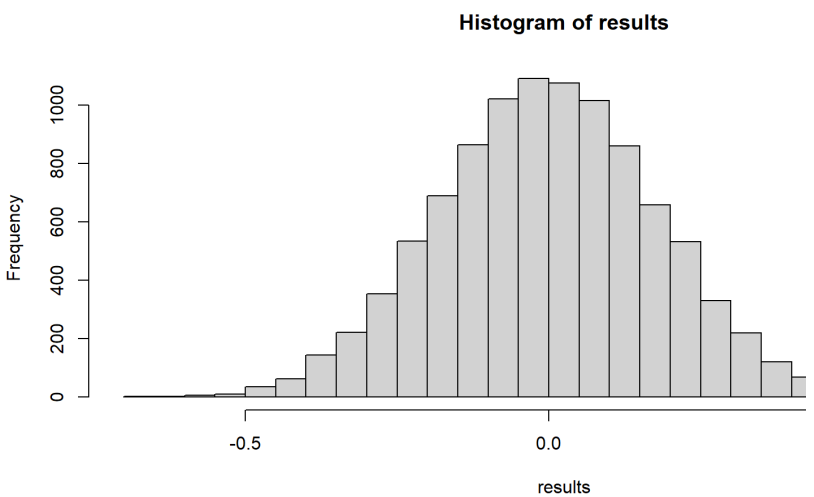
```
[1] 0.1358843
```

for loop

Let's extend the previous example with … a few more iterations!

```r
# STEP 1: RUN SIMULATION

# set number of iterations
niter = 10000
# initialize results vector
results = rep(NA, niter)
# actually run simulation
for(i in 1:niter){
  x = rnorm(n = 30, mean = 0, sd = 1)
  results[i] = mean(x)
}
```

```r
# STEP 2: PLOT RESULTS

# histogram, with a large
hist(results, breaks=50)
```




```r
# STEP 3: COMPUTE SD OF RESULTS
sd(results)
```

```
[1] 0.1806616
```

→ Enjoy it! This is a proper estimati
Standard Error of the Mean via Mon
simulation! 😊

`for` loop

You don't necessarily have to iterate over a sequence of integers (e.g., "`i in 1:10000`"; "`j in 1:ncol(df)`"), although this is the most common practice. You could iterate over whatever, for example, directly over the elements of a vector or other data structures

```
myVect = c("this", "is", "a", "vector", "of", "strings")

for(x in myVect){
  print(toupper(x))
}
```

```
[1] "THIS"
[1] "IS"
[1] "A"
[1] "VECTOR"
[1] "OF"
[1] "STRINGS"
```

`while` loop

The `while` loop is another type of iterative structure in R. It may be useful when the precise number of iterations is *not* predetermined, but depends on a target being reached

```
amount = 1000
month = 0
interest_rate = 0.001 # 0.1% monthly interest rate

while(amount < 1500){
  month = month + 1
  amount = amount + amount * interest_rate
}

month
```

```
[1] 406
```

Interpretation: it takes 406 months to reach an amount of $€1,500$ *when starting with an amount of* $€1,000$ *with a* 0.1% *monthly interest rate*

`repeat` loop

The `repeat` loop has a logic similar to the `while` loop but 1) it always runs at least one iteration, 2) It explicitly emphasizes repetition until a condition (not necessarily a target) is met, using a `break` statement to terminate

```
repeat{
  roll_die = sample(1:6, 1)
  print(roll_die)
  if(roll_die == 6) break
}
```

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

```
attemptedExper = 0

repeat{
  attemptedExper = attemptedExper +
  tt = t.test(rnorm(10),rnorm(10))
  if(tt$p.value < 0.05) break
}

# number of experiments I attempted
# get a false positive :-)
attemptedExper
```

```
[1] 12
```

```
round( tt$p.value , 3 )
```

```
[1] 0.041
```

`apply` family

`apply` is a family of base functions that provide **efficient tools** for running iterations on structures like dataframes, vectors, matrices, lists

Traditional loops provide a straghtforward, intuitive way to compute sequences of operations, but the `apply` **family allows you to run faster computations**… this may become particularly important when you need to *parallelize* for computationally intensive tasks

The following is *not* a computationally heavy task — but for example, let's say we want to compute the mean value *per column* in this dataframe:

	BD	SI	DS	PCn	CD	VC	LN	MR	CO	SS
1	13	10	7	10	15	7	10	16	8	13
2	7	11	6	8	13	10	9	5	9	14
3	12	6	5	7	9	7	7	6	9	8
4	8	7	9	11	1	5	7	6	8	4
5	12	13	8	10	10	10	9	11	13	12
6	13	17	13	7	10	19	13	10	15	13
7	12	10	9	5	10	8	7	9	11	11
8	9	12	15	14	7	11	14	13	8	14
9	11	14	8	11	8	12	14	12	10	9
10	13	12	14	11	5	15	17	14	14	8
11	7	7	7	6	6	6	4	7	12	9
12	10	11	8	8	10	7	7	8	8	15
13	5	6	4	6	7	4	7	4	4	6
14	13	14	11	12	13	17	13	12	15	13

`apply` family

Here is how you could use the base **`apply` function** for computing the *mean* value by column:

```
apply(df, MARGIN=2, FUN=mean, na.rm=T)
```

```
       BD         SI         DS        PCn         CD         VC         LN
MR
 9.824121   9.856423   9.706767   9.889169   9.781955   9.867168   9.987437
9.904762
       CO         SS
 9.889447  10.005051
```

In fact, for such a simple task, even `colMeans()` could be sufficient:

```
colMeans(df, na.rm=T)
```

```
       BD         SI         DS        PCn         CD         VC         LN
MR
 9.824121   9.856423   9.706767   9.889169   9.781955   9.867168   9.987437
9.904762
       CO         SS
 9.889447  10.005051
```

but let consider slightly more complex cases

`apply` family

Let's say you need to compute the *standard deviation* per column …

```
        apply(df, MARGIN=2, FUN=sd, na.rm=T)
```

```
      BD       SI       DS      PCn       CD       VC       LN       MR
2.941790 3.137753 3.072283 2.855583 3.022541 3.167819 2.951726 2.989253
      CO       SS
2.999217 2.896523
```

… or to count the number of `NA` occurrences per column

```
        apply(df, MARGIN=2, FUN=function(x) sum(is.na(x)) )
```

```
 BD  SI  DS PCn  CD  VC  LN  MR  CO  SS
  2   3   1   3   1   1   2   1   2   4
```

in the latter case, we had to define a custom function, but that's relatively simple to do!

`apply` family

Although any of such tasks could be done using a `for` loop, the code would be more cumbersome and less efficient. For example, here's how the exact same result as the latter `apply` example could be obtained using a `for` loop:

```
results = rep(NA, ncol(df))
names(results) = colnames(df)

for(i in 1:length(results)){
  results[i] = sum(is.na(df[,i]))
}

results
```

```
BD  SI  DS PCn  CD  VC  LN  MR  CO  SS
 2   3   1   3   1   1   2   1   2   4
```

`apply` family

FYI, other functions within the **`apply` family**:

- **`tapply()`**: applies a function to subsets of a vector grouped by a factor, example `tapply(df$values, df$group, FUN=mean)` (know that the function `aggregate()` might be more convenient in some cases)
- **`lapply()`**: applies a function to each element of a *list*, returning results in a *list* format, example `lapply(my_list, length)`
- **`sapply()`**: the same as the previous one but returns results as a *vector* if possible, example `sapply(my_list, length)`
- **`mapply()`** multivariate version of `sapply()` that runs across more lists or vectors

```
mapply(rnorm, n=c(2, 6, 4), mean=c(0, 100, 200), sd=c(1, 15, 30))
```

```
[[1]]
[1] -0.08178004  2.88841825

[[2]]
[1] 117.59238 108.24465 111.68657  91.52303 101.54431 104.22282

[[3]]
[1] 185.7671 186.2599 215.0463 187.8461
```

sapply

Here's how **sapply()** can be used to help compute the *standard error of the mean* via *Monte Carlo simulation*

```
myList = list()
for(i in 1:10000) myList[[i]] = rnorm(30)

ms = sapply(myList, mean)

sd(ms)
```

```
[1] 0.1851159
```

1. an empty list is initialized;

2. a `for` loop is used to fill each slot in the list with a vector of 30 randomly generated numbers;

3. `sapply` is used to compute the `mean` of each vector in the list;

4. standard error of the mean is computed as the `sd` on the vector of the means

Saving all generated data allows for more flexibility in analysis, although it uses more memory

`lapply` and `sapply`

Here's another, even more compact way of doing the same, without using any `for` loop, but this requires defining a small custom function:

```
        results = lapply(1:10000, function(i) rnorm(30) )

        ms = sapply(results, mean)

        sd(ms)
```

```
[1] 0.1836006
```

Note: `"i"` represents the current element of `1:10000` over which `lapply` iterates. Even though it is practically useless here, because only random numbers are generated at each iteration, it must be included because `sapply` must pass an alement as the argument to the function by default

Define Custom Functions with `function()`

Previously, we saw a few cases of custom functions, for example for counting NAs in vectors, or computing the mean of a randomly generated vector

Here is the schema for defining custom functions with input (argument[s]), body, and output (return):

```
# define new function with some argument(s) as input
myFunctName = function(arg1 = NA, arg2 = NA, arg3 = TRUE){

  # body, series of operations
    computes several operations
    variously uses arg1, arg2, arg3
    get an object named "res" as final result

  # gives an output
  return(res)
}
```

Define Custom Functions with `function()`

Here's a full example:

```
z_score = function(vect = NA){

  vectM = mean(vect, na.rm=T)
  vectSD = sd(vect, na.rm=T)
  z = (vect - vectM) / vectSD

  return(z)
}
```

After creating it, a custom function can be used like any other function:

```
x = c(101, 90, NA, NA, 114, 87, 106, 98, 93)
z_score(x)
```

```
[1]  0.27162785 -0.89033574          NA          NA  1.64485756 -1.20723491
[7]  0.79979313 -0.04527131 -0.57343658
```

Define Custom Functions with `function()`

Here's a slightly more sophisticated example:

```
z_score = function(vect = NA, naRemove = FALSE){

  vectM = mean(vect, na.rm=naRemove)
  vectSD = sd(vect, na.rm=naRemove)
  z = (vect - vectM) / vectSD

  return(z)
}
```

Let's use it:

```
x = c(101, 90, NA, NA, 114, 87, 106, 98, 93)
z_score(x)
```

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

```
z_score(x, naRemove=TRUE)
```

```
[1]  0.27162785 -0.89033574          NA          NA  1.64485756 -1.20723491
[7]  0.79979313 -0.04527131 -0.57343658
```

Define Custom Functions with `function()`

In some previous examples, custom functions were used directly in combination with `apply()`, without curly brackets `{}` or `return()`, yet they worked!

Why?

Generally, curly brackets `{}` and `return()` enhance clarity and are best practice, but in some cases they can be omitted for more compact code:

- Curly brackets `{}` can be skipped if all code fits on a single line
- `return()` can be omitted if the last (or only) code line represents the output

Define Custom Functions with `function()`

To clarify the previous slide, these are **four alternative and increasingly compact ways** of writing the same function:

```
naCount = function(vect){
  whereNAs = is.na(vect)
  totalNAs = sum(whereNAs)
  return(totalNAs)
}

naCount = function(vect){
  whereNAs = is.na(vect)
  totalNAs = sum(whereNAs)
  totalNAs
}

naCount = function(vect){
  sum(is.na(vect))
}

naCount = function(vect) sum(is.na(vect))
```