Advanced R
Cheat Sheet

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Environment Basics

Environment – **Data structure** (with two components below) that powers lexical scoping

Create environment: env1<-new.env()

1. **Named list** ("Bag of names") – each name points to an object stored elsewhere in memory.

   If an object has no names pointing to it, it gets automatically deleted by the garbage collector.

   - Access with: **ls('env1')**
2. **Parent environment** – used to implement lexical scoping. If a name is not found in an environment, then R will look in its parent (and so on).
   - Access with: **parent.env('env1')**

Four special environments

1. **Empty environment** – ultimate ancestor of all environments
   - Parent: none
   - Access with: **emptyenv()**
2. **Base environment** - environment of the base package
   - Parent: empty environment
   - Access with: **baseenv()**
3. **Global environment** – the interactive workspace that you normally work in
   - Parent: environment of last attached package
   - Access with: **globalenv()**
4. **Current environment** – environment that R is currently working in (may be any of the above and others)
   - Parent: empty environment
   - Access with: **environment()**

Environments

Search Path

Search path – mechanism to look up objects, particularly functions.

- Access with : **search() –** lists all parents of the global environment (see Figure 1)
- Access any environment on the search path: **as.environment('package:base')**

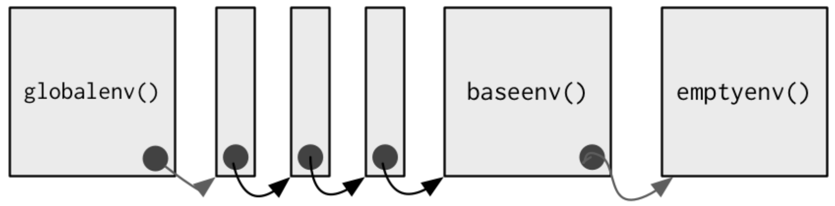


Figure 1 – The Search Path

- Mechanism : always start the search from global environment, then inside the latest attached package environment.
  - New package loading with **library()/require()** : new package is attached right after global environment. (See Figure 2)
  - Name conflict in two different package : functions with the same name, latest package function will get called.

search() :

'.GlobalEnv' ... 'Autoloads' 'package:base'

library(reshape2); search()

'.GlobalEnv' 'package:reshape2' ... 'Autoloads' 'package:base'

NOTE: Autoloads : special environment used for saving memory by only loading package objects (like big datasets) when needed

Figure 2 – Package Attachment

Binding Names to Values

Assignment – act of binding (or rebinding) a name to a value in an environment.

1. **<-** (Regular assignment arrow) – always creates a variable in the current environment
2. **<<-** (Deep assignment arrow) - modifies an existing variable found by walking up the parent environments

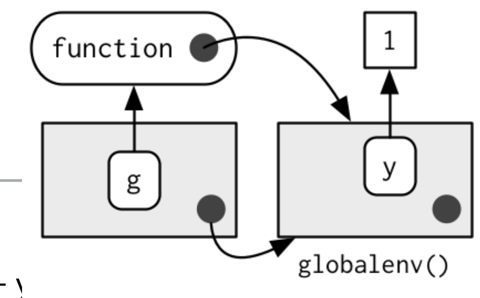
Warning: If <<- doesn't find an existing variable, it will create one in the global environment.

Function Environments

1. **Enclosing environment -** an environment where the function is created. It determines how function finds value.
   - Enclosing environment never changes, even if the function is moved to a different environment.
   - Access with: **environment('func1')**
2. **Binding environment -** all environments that the function has a binding to. It determines how we find the function.
   - Access with: **pryr::where('func1')**

   Example (for enclosing and binding environment):

```
y <- 1
e <- new.env()
e$g <- function(x) x + y
```



- function g enclosing environment is the global environment,
- the binding environment is "e".

3. **Execution environment -** new created environments to host a function call execution.
   - Two parents :

     I. Enclosing environment of the function

     II. Calling environment of the function
   - Execution environment is thrown away once the function has completed.
4. **Calling environment** - environments where the function was called.
   - Access with: **parent.frame('func1')**
   - Dynamic scoping :
     - About : look up variables in the calling environment rather than in the enclosing environment
     - Usage : most useful for developing functions that aid interactive data analysis

Data Structures

	Homogeneous	Heterogeneous
1d	Atomic vector	List
2d	Matrix	Data frame
nd	Array	

Note: R has no 0-dimensional or scalar types. Individual numbers or strings, are actually vectors of length one, NOT scalars.

Human readable description of any R data structure :

```
str(variable)
```

Every **Object** has a mode and a class

1. **Mode**: represents how an object is stored in memory
   - 'type' of the object from R's point of view
   - Access with: **typeof()**
2. **Class**: represents the object's abstract type
   - 'type' of the object from R's object-oriented programming point of view
   - Access with: **class()**

	typeof()	class()
strings or vector of strings	character	character
numbers or vector of numbers	numeric	numeric
list	list	list
data.frame	list	data.frame

Factors

1. Factors are built on top of integer vectors using two attributes :

```
class(x) -> 'factor'
levels(x)  # defines the set of allowed values
```

2. Useful when you know the possible values a variable may take, even if you don't see all values in a given dataset.

Warning on Factor Usage:

1. Factors look and often behave like character vectors, they are actually integers. Be careful when treating them like strings.
2. Most data loading functions automatically convert character vectors to factors. (Use argument stringAsFactors = FALSE to suppress this behavior)

Object Oriented (OO) Field Guide

Object Oriented Systems

R has three object oriented systems :

1. **S3** is a very casual system. It has no formal definition of classes. It implements generic function OO.
   - **Generic-function OO** - a special type of function called a generic function decides which method to call.

Example:	drawRect(canvas, 'blue')
Language:	R

   - **Message-passing OO** - messages (methods) are sent to objects and the object determines which function to call.

Example:	canvas.drawRect('blue')
Language:	Java, C++, and C#

2. **S4** works similarly to S3, but is more formal. Two major differences to S3 :
   - **Formal class definitions** - describe the representation and inheritance for each class, and has special helper functions for defining generics and methods.
   - **Multiple dispatch** - generic functions can pick methods based on the class of any number of arguments, not just one.
3. **Reference classes** are very different from S3 and S4:
   - **Implements message-passing OO** - methods belong to classes, not functions.
   - **Notation** - $ is used to separate objects and methods, so method calls look like **canvas$drawRect('blue')**.

S3

1. **About S3 :**
   - R's first and simplest OO system
   - Only OO system used in the base and stats package
   - Methods belong to functions, not to objects or classes.
2. **Notation :**
   - **generic.class()**

mean.Date()	Date method for the generic - mean()

3. **Useful 'Generic' Operations**
   - Get all methods that belong to the 'mean' generic:
     - **Methods('mean')**
   - List all generics that have a method for the 'Date' class :
     - **methods(class = 'Date')**
4. **S3 objects** are usually built on top of lists, or atomic vectors with attributes.
   - Factor and data frame are S3 class
   - Useful operations:

Check if object is an S3 object	is.object(x) & !isS4(x) or pryr::otype()
Check if object inherits from a specific class	inherits(x, 'classname')
Determine class of any object	**class(x)**

Base Type (C Structure)

R base types - the internal C-level types that underlie the above OO systems.

- **Includes :** atomic vectors, list, functions, environments, etc.
- **Useful operation :** Determine if an object is a base type (Not S3, S4 or RC) **is.object(x)** returns FALSE
- **Internal representation :** C structure (or struct) that includes :
  - Contents of the object
  - Memory Management Information
  - Type
    - Access with: **typeof()**

Functions

Function Basics

Functions – objects in their own right

All R functions have three parts:

body()	code inside the function
formals()	list of arguments which controls how you can call the function
environment()	"map" of the location of the function's variables (see "Enclosing Environment")

Every operation is a function call

- +, for, if, [, $, { …
- x + y is the same as \`+\`(x, y)

Note: the backtick (\`), lets you refer to functions or variables that have otherwise reserved or illegal names.

Lexical Scoping

What is Lexical Scoping?

- Looks up value of a symbol. (see "Enclosing Environment")
- **findGlobals() -** lists all the external dependencies of a function

```
f <- function() x + 1
codetools::findGlobals(f)
> '+' 'x'
```

```
environment(f) <- emptyenv()
f()
# error in f(): could not find function "+"
```

- R relies on lexical scoping to find everything, even the + operator.

Function Arguments

Arguments – passed by reference and copied on modify

1. Arguments are matched first by exact name (perfect matching), then by prefix matching, and finally by position.
2. Check if an argument was supplied : **missing()**

```
i <- function(a, b) {
  missing(a) -> # return true or false
}
```

3. Lazy evaluation – since x is not used **stop("This is an error!")** never get evaluated.

```
f <- function(x) {
  10
}
f(stop('This is an error!')) -> 10
```

4. Force evaluation

```
f <- function(x) {
  force(x)
  10
}
```

5. Default arguments evaluation

```
f <- function(x = ls()) {
  a <- 1
  x
}
```

f() -> 'a' 'x'	ls() evaluated inside f
f(ls())	ls() evaluated in global environment

Return Values

- **Last expression evaluated or explicit return().** Only use explicit return() when returning early.
- **Return ONLY single object.** Workaround is to return a list containing any number of objects.
- **Invisible return object value** - not printed out by default when you call the function.

```
f1 <- function() invisible(1)
```

Primitive Functions

What are Primitive Functions?

1. Call C code directly with **.Primitive()** and contain no R code

```
print(sum) :
> function (..., na.rm = FALSE)  .Primitive('sum')
```

2. **formals()**, **body()**, and **environment()** are all NULL
3. Only found in base package
4. More efficient since they operate at a low level

Influx Functions

What are Influx Functions?

1. Function name comes in between its arguments, like + or –
2. All user-created infix functions must start and end with %.

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

3. Useful way of providing a default value in case the output of another function is NULL:

```
`%||%` <- function(a, b) if (!is.null(a)) a else b
function_that_might_return_null() %||% default value
```

Replacement Functions

What are Replacement Functions?

1. Act like they modify their arguments in place, and have the special name xxx <-
2. Actually create a modified copy. Can use **pryr::address()** to find the memory address of the underlying object

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

Subsetting

Subsetting returns a copy of the original data, NOT copy-on modified

Simplifying vs. Preserving Subsetting

1. **Simplifying subsetting**
   - Returns the **simplest** possible data structure that can represent the output
2. **Preserving subsetting**
   - Keeps the structure of the output the **same** as the input.
   - When you use drop = FALSE, it's preserving

	Simplifying*	Preserving
Vector	x[[1]]	x[1]
List	x[[1]]	x[1]
Factor	x[1:4, drop = T]	x[1:4]
Array	x[1,] or x[, 1]	x[1, , drop = F] or x[, 1, drop = F]
Data frame	x[, 1] or x[[1]]	x[, 1, drop = F] or x[1]

Simplifying behavior varies slightly between different data types:

1. **Atomic Vector**
   - x[[1]] is the same as x[1]
2. **List**
   - [ ] always returns a list
   - Use [[ ]] to get list contents, this returns a single value piece out of a list
3. **Factor**
   - Drops any unused levels but it remains a factor class
4. **Matrix or Array**
   - If any of the dimensions has length 1, that dimension is dropped
5. **Data Frame**
   - If output is a single column, it returns a vector instead of a data frame

Data Frame Subsetting

Data Frame – possesses the **characteristics of both lists and matrices**. If you subset with a single vector, they behave like lists; if you subset with two vectors, they behave like matrices

1. **Subset with a single vector** : Behave like lists

```
df1[c('col1', 'col2')]
```

2. **Subset with two vectors** : Behave like matrices

```
df1[, c('col1', 'col2')]
```

The results are the same in the above examples, however, results are different if subsetting with only one column. (see below)

1. **Behave like matrices**

```
str(df1[, 'col1']) -> int [1:3]
```

   - Result: the result is a vector

2. **Behave like lists**

```
str(df1['col1']) -> 'data.frame'
```

   - Result: the result remains a data frame of 1 column

$ Subsetting Operator

1. **About Subsetting Operator**
   - Useful shorthand for [[combined with character subsetting

```
x$y is equivalent to x[['y', exact = FALSE]]
```

2. **Difference vs. [[**
   - $ does partial matching, [[does not

```
x <- list(abc = 1)
x$a -> 1        # since "exact = FALSE"
x[['a']] ->     # would be an error
```

3. **Common mistake with $**
   - Using it when you have the name of a column stored in a variable

```
var <- 'cyl'
x$var

# doesn't work, translated to x[['var']]
# Instead use x[[var]]
```

Examples

1. **Lookup tables** (character subsetting)

```
x <- c('m', 'f', 'u', 'f', 'f', 'm', 'm')
lookup <- c(m = 'Male', f = 'Female', u = NA)
lookup[x]
> m  f  u  f  f  m  m
> 'Male'  'Female'  NA  'Female'  'Female'  'Male'  'Male'
unname(lookup[x])
> 'Male'  'Female'  NA  'Female'  'Female'  'Male'  'Male'
```

2. **Matching and merging by hand** (integer subsetting)

   Lookup table which has multiple columns of information:

```
grades <- c(1, 2, 2, 3, 1)
info <- data.frame(
   grade = 3:1,
   desc = c('Excellent', 'Good', 'Poor'),
   fail = c(F, F, T)
)
```

   First Method

```
id <- match(grades, info$grade)
info[id, ]
```

   Second Method

```
rownames(info) <- info$grade
info[as.character(grades), ]
```

3. **Expanding aggregated counts** (integer subsetting)
   - **Problem**: a data frame where identical rows have been collapsed into one and a count column has been added
   - **Solution**: rep() and integer subsetting make it easy to uncollapse the data by subsetting with a repeated row index: rep(x, y) rep replicates the values in x, y times.

```
df1$countCol is c(3, 5, 1)
rep(1:nrow(df1), df1$countCol)
> 1 1 1 2 2 2 2 2 3
```

4. **Removing columns from data frames** (character subsetting)

   There are two ways to remove columns from a data frame:

Set individual columns to NULL	df1$col3 <- NULL
Subset to return only columns you want	df1[c('col1', 'col2')]

5. **Selecting rows based on a condition** (logical subsetting)
   - This is the most commonly used technique for extracting rows out of a data frame.

```
df1[df1$col1 == 5 & df1$col2 == 4, ]
```

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Subsetting continued

Boolean Algebra vs. Sets
(Logical and Integer Subsetting)

1. **Using integer subsetting** is more effective when:
   - You want to find the first (or last) TRUE.
   - You have very few TRUEs and very many FALSEs; a set representation may be faster and require less storage.
2. **which()** - conversion from boolean representation to integer representation

```
which(c(T, F, T F)) -> 1 3
```

   - Integer representation length : is always <= boolean representation length
   - Common mistakes :
     I. Use **x[which(y)]** instead of **x[y]**
     II. **x[-which(y)]** is not equivalent to **x[!y]**

Recommendation:
Avoid switching from logical to integer subsetting unless you want, for example, the first or last TRUE value

Subsetting with Assignment

1. All subsetting operators can be combined with assignment to modify selected values of the input vector.

```
df1$col1[df1$col1 < 8] <- 0
```

2. Subsetting with nothing in conjunction with assignment :
   - Why : Preserve original object class and structure

```
df1[] <- lapply(df1, as.integer)
```

Debugging, Condition Handling and Defensive Programming

Debugging Methods

1. **traceback()** or **RStudio's error inspector**
   - Lists the sequence of calls that lead to the error
2. **browser()** or **RStudio's breakpoints tool**
   - Opens an interactive debug session at an arbitrary location in the code
3. **options(error = browser)** or **RStudio's "Rerun with Debug" tool**
   - Opens an interactive debug session where the error occurred
   - Error Options:

   options(error = recover)
   - Difference vs. 'browser': can enter environment of any of the calls in the stack

   options(error = dump_and_quit)
   - Equivalent to 'recover' for non-interactive mode
   - Creates **last.dump.rda** in the current working directory

   In batch R process :

```
dump_and_quit <- function() {
    # Save debugging info to file
    last.dump.rda
    dump.frames(to.file = TRUE)
    # Quit R with error status
    q(status = 1)
}
options(error = dump_and_quit)
```

   In a later interactive session :

```
load("last.dump.rda")
debugger()
```

Condition Handling of Expected Errors

1. **Communicating potential problems to users:**
   I. **stop()**
   - Action : raise fatal error and force all execution to terminate
   - Example usage : when there is no way for a function to continue

   II. **warning()**
   - Action : generate warnings to display potential problems
   - Example usage : when some of elements of a vectorized input are invalid

   III. **message()**
   - Action : generate messages to give informative output
   - Example usage : when you would like to print the steps of a program execution
2. **Handling conditions programmatically**:
   I. **try()**
   - Action : gives you the ability to continue execution even when an error occurs

   II. **tryCatch()**
   - Action : lets you specify handler functions that control what happens when a condition is signaled

```
result = tryCatch(code,
    error = function(c) "error",
    warning = function(c) "warning",
    message = function(c) "message"
)
```

Use conditionMessage(c) or c$message to extract the message associated with the original error.

Defensive Programming

Basic principle : "fail fast", to raise an error as soon as something goes wrong

1. **stopifnot()** or use 'assertthat' package - check inputs are correct
2. **Avoid subset(), transform() and with()** - these are non-standard evaluation, when they fail, often fail with uninformative error messages.
3. **Avoid [and sapply()** - functions that can return different types of output.
   - Recommendation : Whenever subsetting a data frame in a function, you should always use **drop = FALSE**