
# Applied Statistics: R

Semester 2018-I

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## Table of Contents:

# Introduction to R

# Plan

Week 1:

1. R basics, GitHub and LaTeX
2. graphical methods in R

Week 2:

1. data management (import/export)
2. functions, debugging, condition handling

Week 3:

1. profiling, performance and parallelization
2. numeric methods and simulations

If possible there is time: Rcpp, building packages.

# Classes and Coordination

Classes:

- One exam on mid-term week. 20% of your grade.
- More an R course than an "applied stats" course.
- 3 weeks, 5 hours $\times$ week.
- TA comes the 3rd hour of the three-hour block.

Coordination:

- No Blackboard.
- Course repository here.
- Use the `Homework` file to upload solutions of exercises.

# Reading Material

- Hadley Wickham. Advanced R. The R series. CRC Press, 2015. Available online: `http://adv-r.had.co.nz/`.
- Owen Jones, Robert Maillardet, and Andrew Robinson. Introduction to scientific programming and simulation using R. Chapman & Hall/CRC, 2009.
- Brian Everitt and Torsten Hothorn. A handbook of statistical analyses using R. Chapman & Hall/CRC, 2006.
- R Data Import/Export manual. Available online: `http://cran.r-project.org/doc/manuals/r-release/R-data.pdf`
- Deepayan Sarkar. Lattice: multivariate data visualization with R. Use R! Springer, 2008.
- Roger S Bivand, Edzer J Pebesma, and Virgilio Gómez-Rubio. Applied spatial data analysis with R, volume 10 of Use R! Springer, 2008.

# Who are you?

- Ever used R?
- Text editor for R: Rstudio, emacs, Vim?
- Github, LaTeX?
- Operating system: Linux, Apple, Windows?
- Other programming languages: C, C++, Java, Python, Fortran, Julia, Matlab, Mathematica?

# R-Ladies Announcement

Heard of Laboratoria? kind of like that...

- Worldwide organization.
- Empowers women trough coding.
- Third meet up on April 27th at UP Aula Magna H 15:00.
- Topic: Text-mining in Finance with R.
- Speaker: Leda Basombrío, Strategic Analysis Manager at BCP.

Not mandatory, but recommended. Not only for women.

# R Basics

| | |
|---|---|
| help: | `?topic, help(topic), args(some function)` |
| assignments: | `x <- 5, x = 5, 5 -> x` |
| operators: | `+, -, *, /, ^, &, &&, |, ||; see help("+")` |
| comparisons: | `==, !=, >, >=, <, <=; see help("==")` |
| loops: | `for, while, repeat` |
| comments: | `everything that follows #` |

case sensitive: usage of CAPITAL and small letters matters!

# Basic Data Structures

| | |
|---|---|
| numeric ($\mathbb{R}$): | `1, 301L, .141, 1.23e-3, NaN, Inf, -Inf` |
| complex ($\mathbb{C} \setminus \mathbb{R}$) | `1+0i, 1i, 3+5i` |
| logical: | `TRUE, FALSE, NA` |
| character: | `"hello", "I'm a string"` |
| numeric: | no distinction between integers and doubles |
| missing: | stored as `NA`, and are logical. |

Can check the basic structure with `str()`, `mode()` or `storage.mode()`.

```
str(1)                  ## num 1
mode(1)                 ## [1] "numeric"
storage.mode(1)         ## [1] "double"
storage.mode(1L)        ## [1] "integer"
mode(pi)                ## [1] "numeric"
storage.mode(pi)        ## [1] "double"
str(LETTERS)            ## chr [1:26] "A" "B" "C" "D" "E" ...
```

# Construction & Coercion

- vector can be constructed with `c()`
- coerced to a type `xxx` by `as.xxx()`
- when combining different data types, they will be coerced to the most flexible type
- coercion often happens automatically
- check if `xxx` is a specific type by `is.xxx()`

```
storage.mode(c(1,2L))      ## [1] "double"
storage.mode(c("a",1))     ## [1] "character"
x <- c(FALSE, TRUE, NA)
as.numeric(x)              ## [1] 0 1 NA
# Total number of TRUEs
sum(x, na.rm = TRUE)       ## [1] NA
```

# NA, NaN and NULL

In R, there three ways to represent "nothing", but the reason for the missingness of the information can be distinguished:

| | |
|---|---|
| `NA` | missing sample values |
| `NaN` | wrong math, e.g. `log(-1)`, `1/0`) |
| `NULL` | null pointer |

```
c(3, NA)    ## [1] 3 NA
c(3, 0/0)   ## [1] 3 NaN
c(3, NULL)  ## [1] 3
max(3, NA)  ## [1] NA
```

# Inifinity

Some math operations can be performed with `Inf` and `-Inf`:

```
max(3, Inf)
## [1] Inf

min(3, Inf)
## [1] 3

c(Inf + Inf, (-Inf) * Inf, Inf - Inf)
## [1] Inf -Inf NaN
```

# Convoluted Data Structures

- data structures in R can be organized by their dimensionality and if all their contents are of the same type (or not):

| object | dimension | homogeneous | heterogeneous |
|---|---|---|---|
| 1d | `length()` | atomic vector | list |
| 2d | `dim()` | matrix | data frame |
| nd | `dim()` | array | – |

- a `data.frame` is a matrix with different data type columns.
- a `list` can have different data type elements.

```
x <- matrix(1, nrow = 5, ncol = 2)
is.matrix(x)              ## [1] TRUE
as.vector(x)              ## [1] 1 1 1 1 1 1 1 1 1 1
x <- list(a = "Hallo", b = 1:10, pi = pi)
```

# Attributes

All objects can have arbitrary additional attributes, used to store metadata about the object.

- can be thought of as a named list (with unique names); other frequently encountered attributes: "dimnames", "names", "class" (!)
- can be accessed all at once (as a list) with `attributes()`, or individually with `attr()`.
- arrays are simply vectors with a "dim" attribute.
- factor is a vector with the "levels" attribute
- `as.xxx()` functions delete all attributes including dimensionality

# Attributes

```
x <- matrix(1:10, ncol = 5)
attributes(x)                    ## $dim
                                 ## [1] 2 5
rownames(x) <- c("Eins", "Zwei")
attributes(x)                    ## $dim
                                 ## [1] 2 5
                                 ## $dimnames
                                 ## $dimnames[[1]]
                                 ## [1] "Eins" "Zwei"
                                 ## $dimnames[[2]]
                                 ## NULL
as.character(x)                  ## [1] "1"  "2"  "3"  "4"  "5"...
attributes(as.character(x))      ## NULL
```

# Subsetting

- There are three subsetting operators: `[`, `[[`, and `$`
- the three types of subsetting:
  - Positive integers return elements at the specified positions.
  - Logical vectors select elements where the corresponding logical value is `TRUE`; application of logical expressions.
  - character vectors to return elements with matching names.
- important differences in behaviour of different objects (e.g., vectors, lists, factors, matrices, and data frames).
- More advanced subsetting, in particular in combination with convoluted logical expressions, can be done using the functions `subset()` and `which()`.
- The default `drop=TRUE` simplifies the data type of the result.

# Atomic Vectors

Use "["-operator and number, logical vector or name of the element you want to pull out.

```
x <- c(2.1, 4.2, 3.3, 5.4)
x[c(3, 1)]                          ## [1] 3.3 2.1
x[-c(3, 1)]                         ## [1] 4.2 5.4
x[c(TRUE, TRUE, FALSE, FALSE)]      ## [1] 2.1 4.2

(y <- setNames(x, letters[1:4])) ##   a   b   c   d
                                 ## 2.1 4.2 3.3 5.4
y[c("d", "c", "a")]              ##   d   c   a
                                 ## 5.4 3.3 2.1
```

# Matrices & Arrays

Subsetting matrices and arrays with "["-operator like vectors, while the dimension is separated by comma:

```
x <- matrix(1:10, ncol=2)
colnames(x) <- c("Eins", "Zwei")

x[1:2,]                    # results a matrix
x[,"Zwei"]                 # results a vector
x[,"Zwei", drop = FALSE] # results a matrix
x[-3,]                     # everything, but not third row
```

# Lists

Subsetting lists with "["-operator returns always a list, while [[, and $ pull out elements of the list:

```
x <- list(a = "Hallo", b = 1:10, pi = pi)

x$a        # first element of the list
x[[‘a’]]
x[[1]]
x[1]       # list with one element
x[2:3]     # list with two elements
x[[2:3]]   # wrong result
```

# Data Frames

Data frames possess 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.

```
iris[1:10,]                 # data frame with 10 rows
iris[,1]                    # numerical
iris$Sepal.Length           # the name
iris$Sepa1.Length           # Oops! what happened?
iris[,"Sepal.Length"]       # again first column
iris[,"Sepa1.Length"]       # Error:  undefined columns selected
iris[,1, drop = FALSE]      # data frame with one column
```

# Flow Control

- conditional evaluation: `if`, `else`, `ifelse`
- loops: `for`, `while`, `repeat`, `switch`

basic vocabulary:

```
if, &&, ||
for, while, repeat
next, break
switch
ifelse
```

# `if/else` Conditions

```
 if (<test>) {
  <expression1>
} else {
  <expression2>
}
```

- `else` block is optional
- `<test>` has to result in a value that is `TRUE` or `FALSE`
- only the first element of `<test>` is used, ow a warning is triggered
- to eval more than one statement use `&`, `|` or `all()` and `any()`
- can be nested

# `for` Loop

```
for (<var> in <vector>) {
  <expression>
}
```

```
sum <- 0
for(i in 1 : length(x)) {
  sum <- sum + x[i]
}
```

```
sum <- 0
for(x_value in x) {   ## more efficient
  sum <- sum + x_value
}
```

Use `seq_along(x)` instead of `1:length(x)`

# `while` Loop

```
while(<test>) {
  <expression>
}
```

E.g., the sum until the first `NA`:

```
sum <- 0
i <- 1
while((i <= length(x)) && !is.na(x[i])) {
  sum <- sum + x[i]
  i <- i + 1
}
```

Be aware of infinite loops!

# next & break

- next jumps to the next iteration in for or while loops
- break terminates for or while loops.

```
x <- c(1, 1, 1, NA, 2)
sum <- 0
for(val in x) {
  if(is.na(val)) break
  sum <- sum + val
}
```

```
x <- c(1, 1, 1, NA, 2)
sum <- 0
for(val in x) {
  if(is.na(val)) next
  sum <- sum + val
}
```

# Style Example: Bad

```
fWLM<-function(y,X_mat,w){TO<-t(X_mat)%*%diag(w)%*%X_mat
t<-system.time({t_1<-solve(TO)%*%t(X_mat)%*%(w*y);
t2<-X_mat%*%t_1})
return(list(beta=t_1,hat=t2,stddev=sqrt(sum(w*(t2-y)^2))/
(length(y)-ncol(X_mat)), wts=w,t=t[[3]]))}
```

# Style Example: Good

```
fit_weighted_lm <- function(response, design, weights) {
  n_obs <- length(response)
  n_coef <- ncol(design)
  time_start <- Sys.time()
  wcrossprod_design <- crossprod(design * weights, design)
  weighted_response <- weights * response
  coef <- solve(wcrossprod_design, t(design) %*% weighted_response)
  time <- Sys.time() - time_start
  fitted <- design %*% coef
  residuals <- response - fitted
  weighted_rss <- sum(weights * residuals^2)
  sd_resid <- sqrt(weighted_rss / (n_obs - n_coef))
  list(coef     = coef,
       fitted   = fitted,
       sd_resid = sd_resid,
       weights  = weights,
       time     = time)
}
```

# Notation & Names

- find meaningful file names; if files need to be run in sequence, prefix them with numbers.

  `0-download.R`
  `1-parse.R`
  `2-explore.R`

- avoid uppercase
- use an underscore to separate words within a name
- use nouns for variable names and verbs for function names

# Notation & Names

- strive for names that are concise and meaningful (this is not easy!).

```
# Good          # Bad
day_one         first_day_of_the_month
day_1           dayone
                djm1
```

- avoid using names of existing functions and variables.

```
# Bad
T <- FALSE
c <- 10
t <- temporal_variable
mean <- function(x) sum(x)
```

# Formatting

- strive to limit your code to 80 characters per line.
- when indenting your code, use two spaces. Never use tabs.
- place spaces around all infix operators (=, +, -, <-, etc.), before parentheses, and after comma (just like in regular English)

```
# Good
average <- mean(feet / 12 + inches, na.rm = TRUE)
# Bad
average<-mean(feet/12+inches,na.rm=TRUE)

# Good
if (debug) do(x)
plot(x, y)
# Bad
if(debug)do(x)
plot (x, y)
```

# Formatting

- an opening (or closing) curly brace should always be followed by a new line, unless it's followed by `else`.

```
 if (y == 0) {
  log(x)
} else {
  y^x
}
```

- use commented lines of - and = to break up your file into chunks.

```
# Load data ---------------------------
# Plot data ---------------------------
```

- `formatR::tidy_source(source="input.R",file="output.R")` cleans up and does some automatic formatting

# Advanced Graphics

# Motivation

- creating interest and attention of the reader
- essential meaning can be visualized at a glance
- comprehensive picture of a problem gives more complete and balanced understanding
- the human visual system is very powerful in detecting patterns: outliers, diagnose models, search for perhaps unexpected phenomena

# Graphical Devices

- A graphical device can be thought as a paper on which you can draw with different pens and colours, but nothing can be deleted.
- It can be opened more than one device, but there is only one active.
- There is no difference no matter which device is used.
- Typical steps to produce a graphic is:
  1. start device, e.g. `pdf('testgraphics.pdf')`
  2. generate graphic, e.g. `plot(1:10)`
  3. close device: `dev.off()`
- If no device is open, using a high-level graphics function will cause a device to be opened.

# Graphical Devices

The following graphics devices are currently available:

- `pdf()`: write PDF graphics commands to a file; can be handy for distribution to cooperation partners, integration in PDFLaTeX, or viewing many graphics
- `postscript()`: writes PostScript graphics commands to a file
- `bitmap()`: bitmap pseudo-device via 'Ghostscript' (if available).

Interactive plotting with GUI:

- `x11()`: The graphics device for the X11 windowing system
- `png()`: compressed Bitmap, without loss
- `jpeg()`: compressed Bitmap with information loss, optimized for pictures with many color shades

For more info see `?Devices`.

# High-level Plots

High-level functions generate/initialize a graphic, e.g.:

| `plot()` | depend of context |
|---|---|
| `barplot()` | Barplot |
| `boxplot()` | Boxplot |
| `coplot ()` | Conditioning plots |
| `contour()` | Contour line plot |
| `curve()` | Plotting functions |
| `dotchart()` | Dot Plots |
| `hist()` | Histogram |
| `image()` | Countour Plot (3. Dim. as color) |
| `mosaicplot()` | Mosaicplots (categorial data) |
| `pairs()` | Scatterplot matrix |
| `persp()` | perspective surface |
| `qqplot()` | QQ-Plot |

# High-level Plots

Many functions can be applied to different object types. They react in a "intelligent" way, so that a meaningful graphic can be found.

```
plot(trees)                              ## scatterplot matrix
plot(Volume ~ Girth, data = trees)       ## scatterplot

tree.lm <- lm(Volume ~ Girth, data = trees)
abline(tree.lm)                          ## regression line
plot(tree.lm)                            ## residual/diagnostic plots
boxplot(trees)                           ## boxplots
qqnorm(trees$Volume)                     ## quantile plot
```

# Graphical Parameter

- for nicer graphics, the `par` graphical parameters can be adapted
- some graphical parameters can be adjusted in high-level functions
- for help check `?plot`, `?plot.default`, or more comprehensive `?par`

# Graphical Parameter

Some graphical parameters can can be set in high-level functions like `plot()`. For example:

| | |
|---|---|
| `axes` | should the axes be plotted? |
| `col` | color |
| `log` | logarithmic scale |
| `main, sub` | title and subtitle |
| `pch` | symbol for points |
| `type` | type (l=line, p=point, b=both, n=none) |
| `xlab, ylab` | x-/y-axis label xlim, ylim |
| `xlim, ylim` | x-/y-axis range |

# Graphical Parameter

The most commonly used arguments in `par()`:

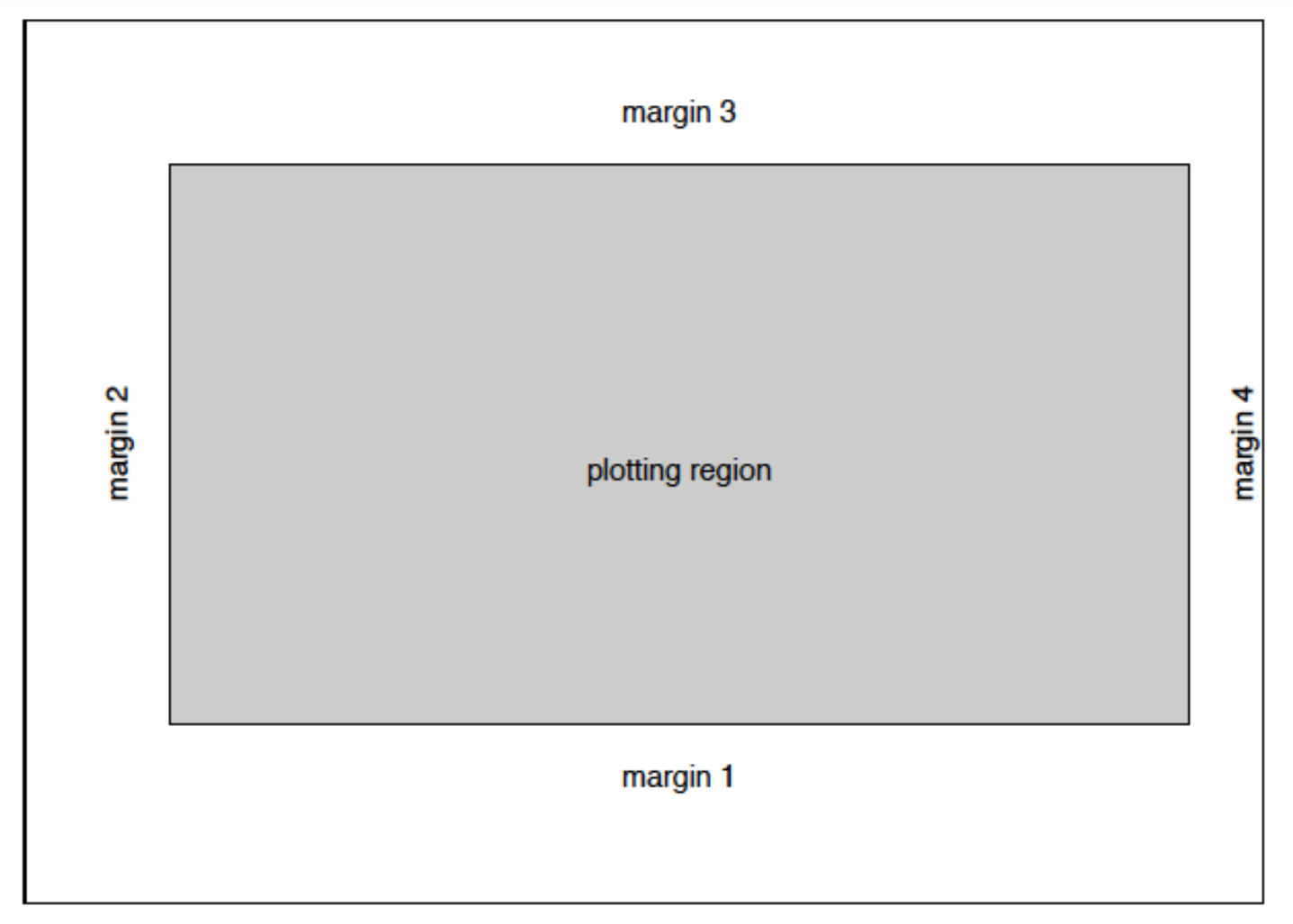
| | |
|---|---|
| `bg` | background color |
| `cex` | size of a point or a letter |
| `las` | should labels be placed parallel wrt the axes |
| `lty, lwd` | line type (dashed, ...) and line width |
| `mar` | size of the margins |
| `mfcol, mfrow` | multiple plots in one device in rows/columns |
| `mfg` | which plot in a device should be chosen? |
| `oma` | size of the outer margins |
| `usr` | current extrema of the user coordinates |
| `xaxt, yaxt` | x-/y-axis scaling |

# Graphical Parameter

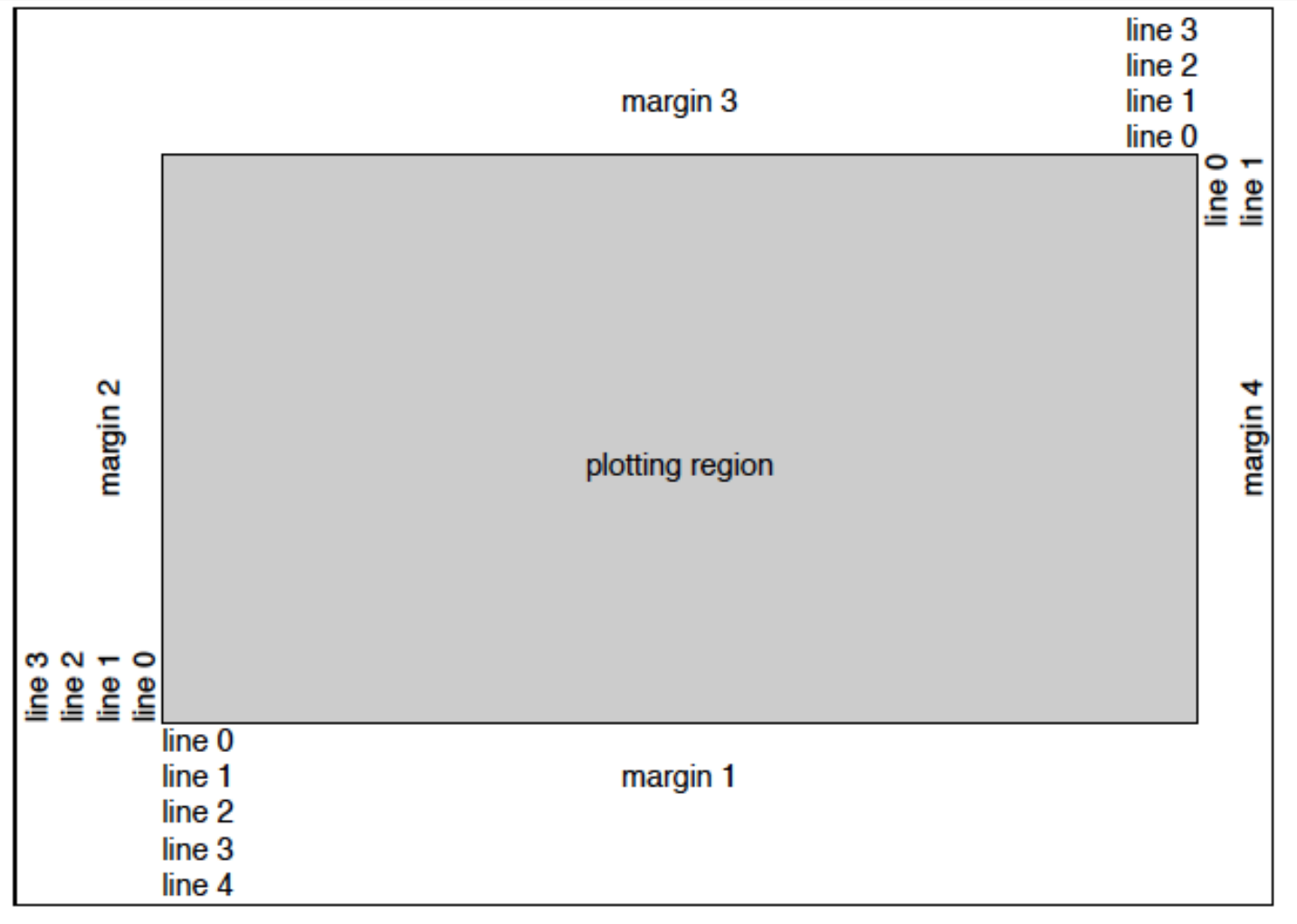
```
opar <- par(mfrow = c(1, 1),bg = "White")
# example 1
par(mfrow = c(2, 2))
boxplot(trees, col = "blue")
hist(trees$Volume, las = 1)
qqnorm(trees$Volume, cex.axis = 2, pch = (trees$Girth > 14) + 8)
plot(trees$Girth,trees$Height,cex = scale(trees$Volume,center=FALSE))
par(opar)

# example 2
set.seed(123)
x <- rnorm(100)
par(bg = "lightgreen")
hist(x, freq = FALSE, col = "red", las = 1,
     xlim = c(-5, 5), ylim = c(0, 0.6),
     main = "100 Draws from N(0,1)-distributed random variables")
curve(dnorm, from = -5, to = 5, add = TRUE, col = "blue", lwd = 3)
par(opar)
```

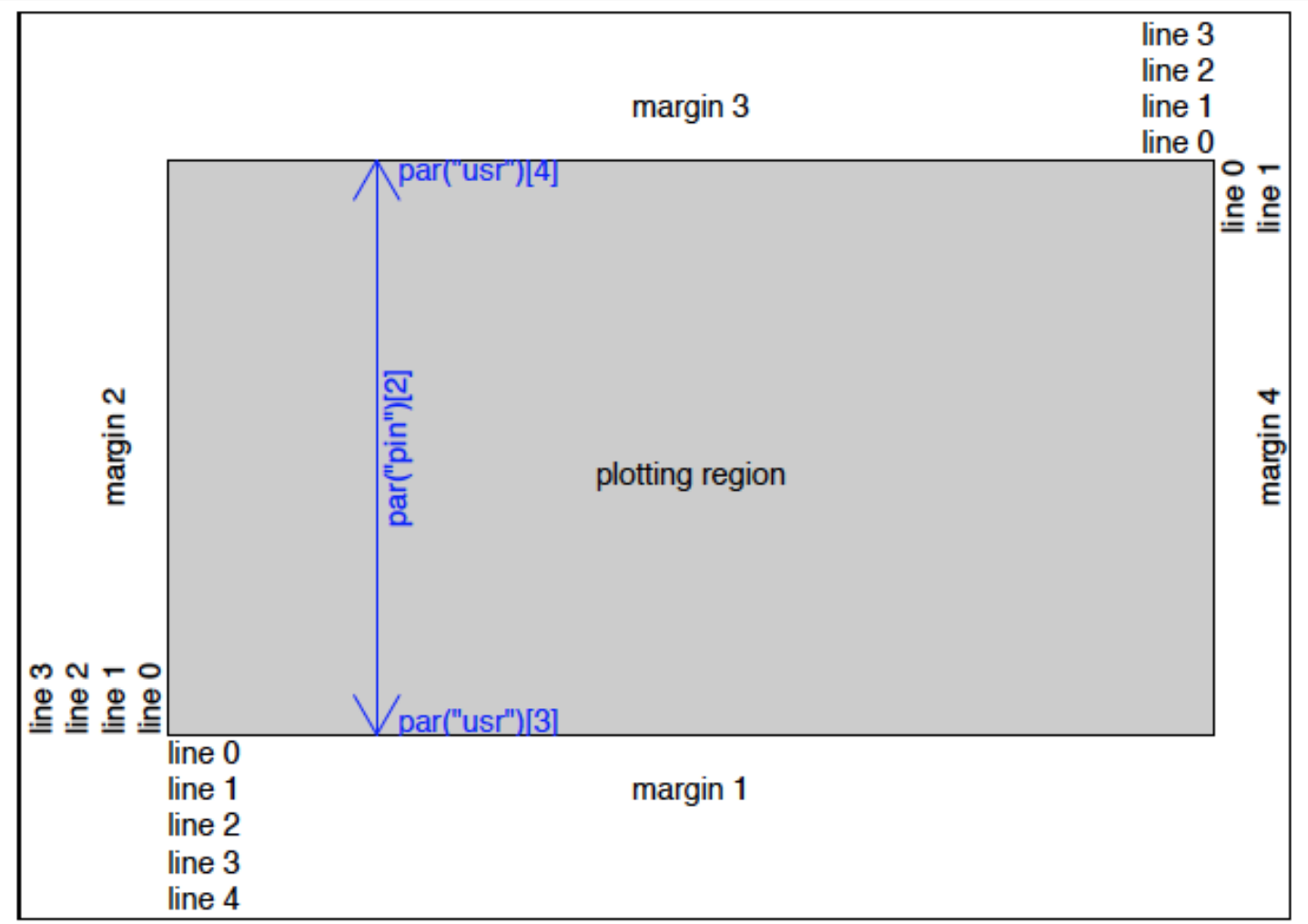
# Device Control



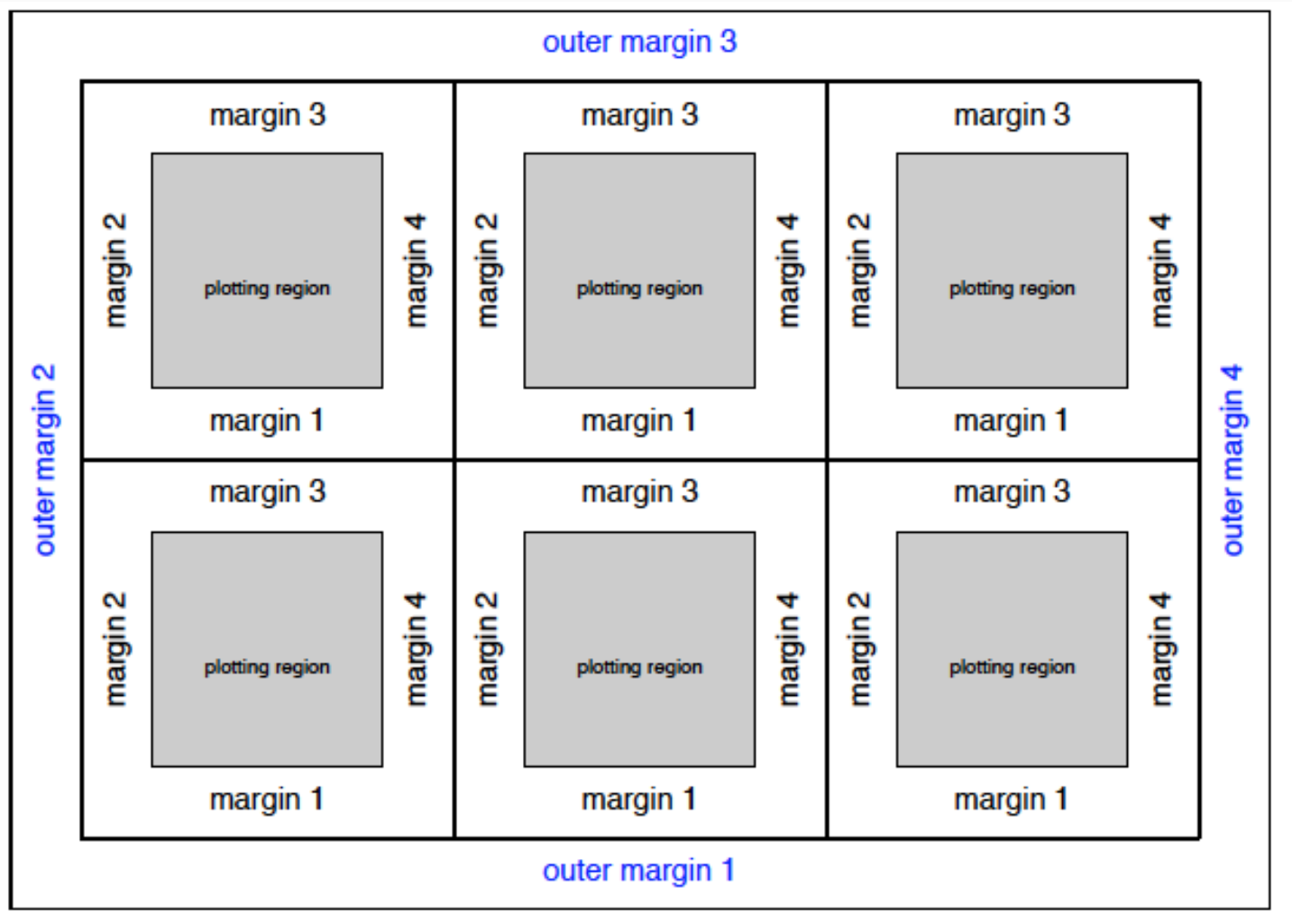
# Device Control



# Device Control



# par(mfrow=c(2,3))



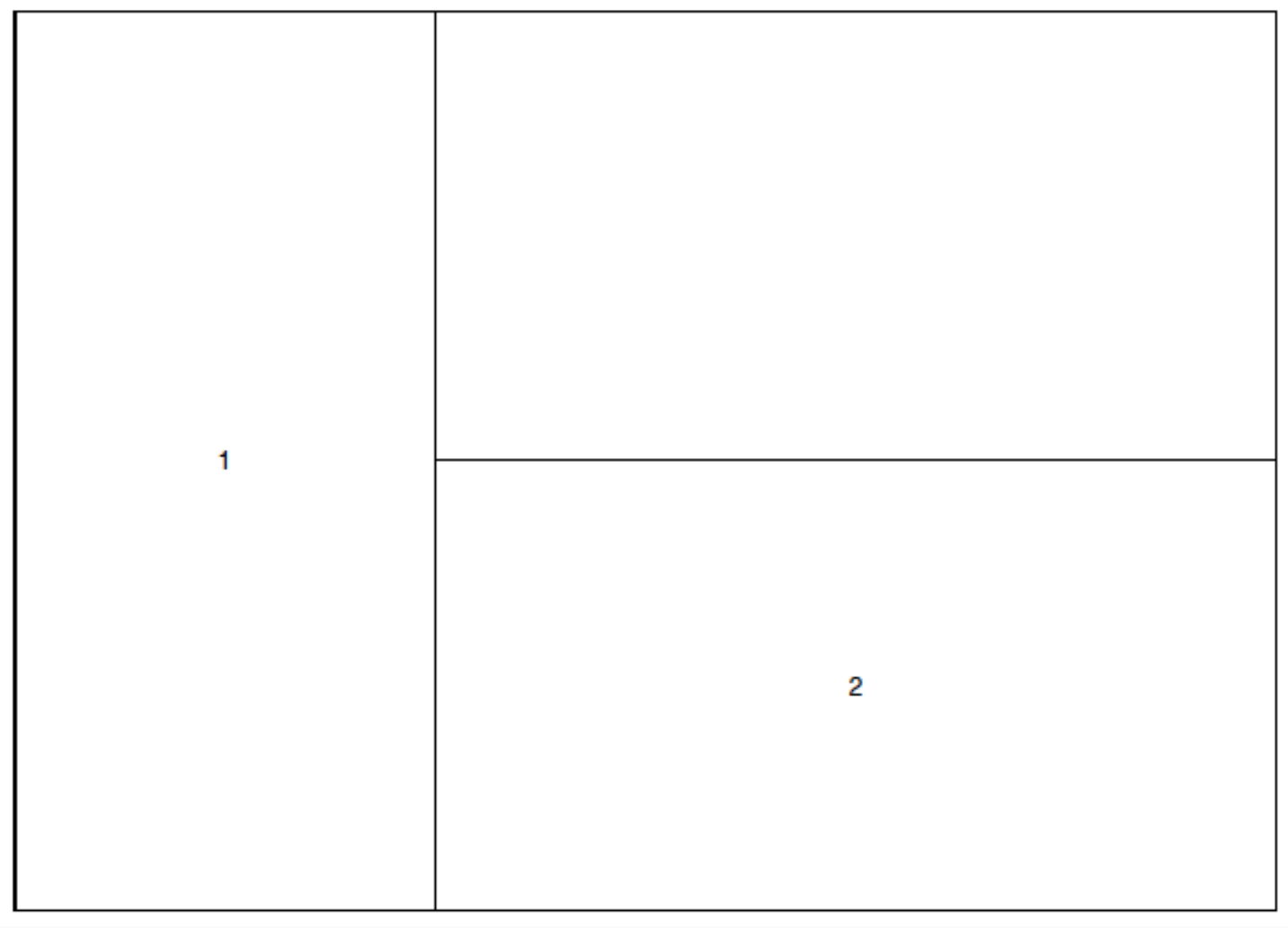
# `layout()` Function

- `layout()` organizes independent plots on one plotting device, also in irregular grids
- boxes can have different widths
- neighboring boxed can be combined
- boxes can be left empty

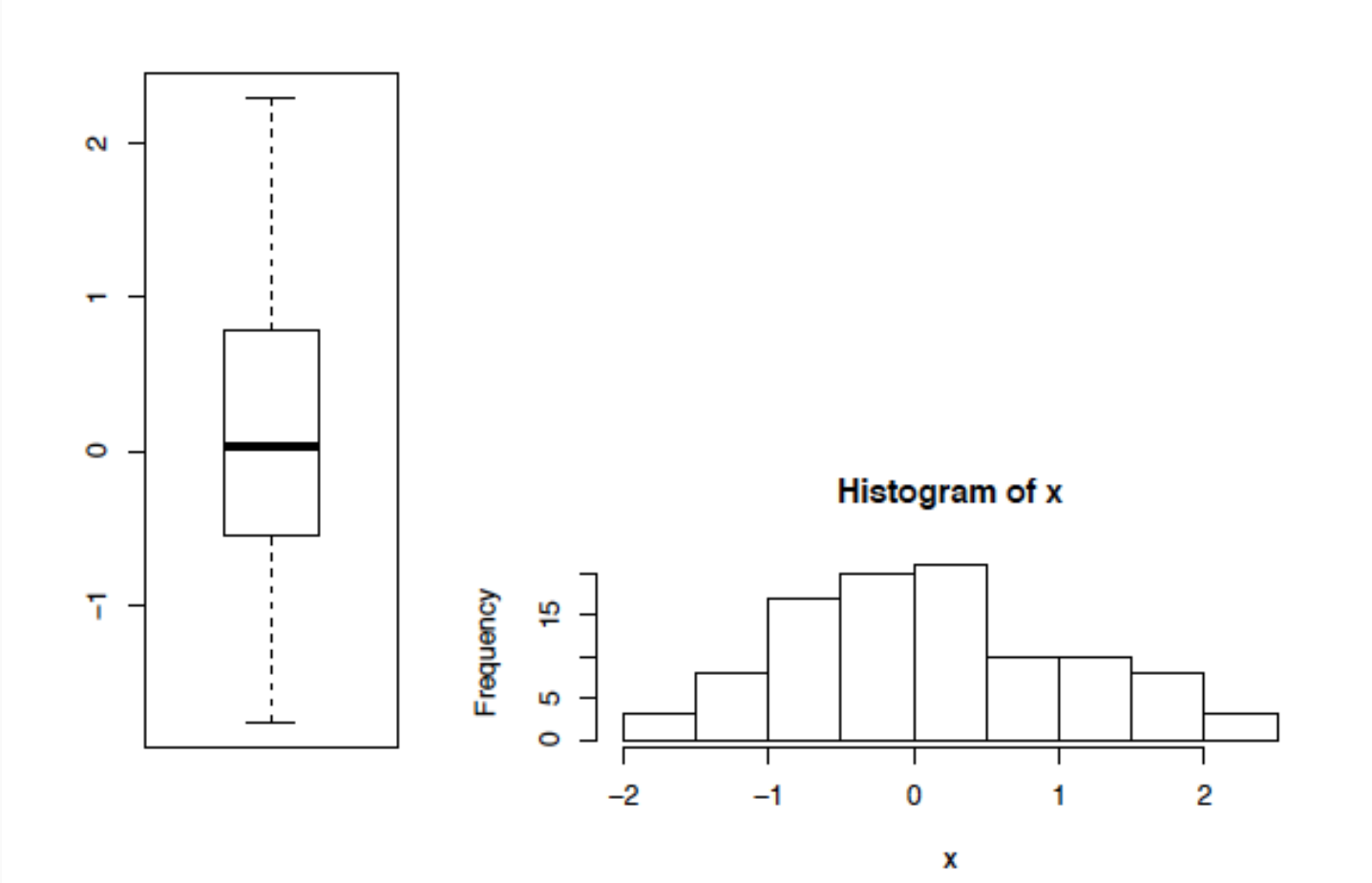
```
m <- matrix(c(1,1,0,2), 2, 2)
m
##      [,1]   [,2]
## [1,]    1      0
## [2,]    1      2

layout(m, widths=c(1,2))
x <- rnorm(100)
boxplot(x)
hist(x)
```

# `layout()` Function



# `layout()` Function



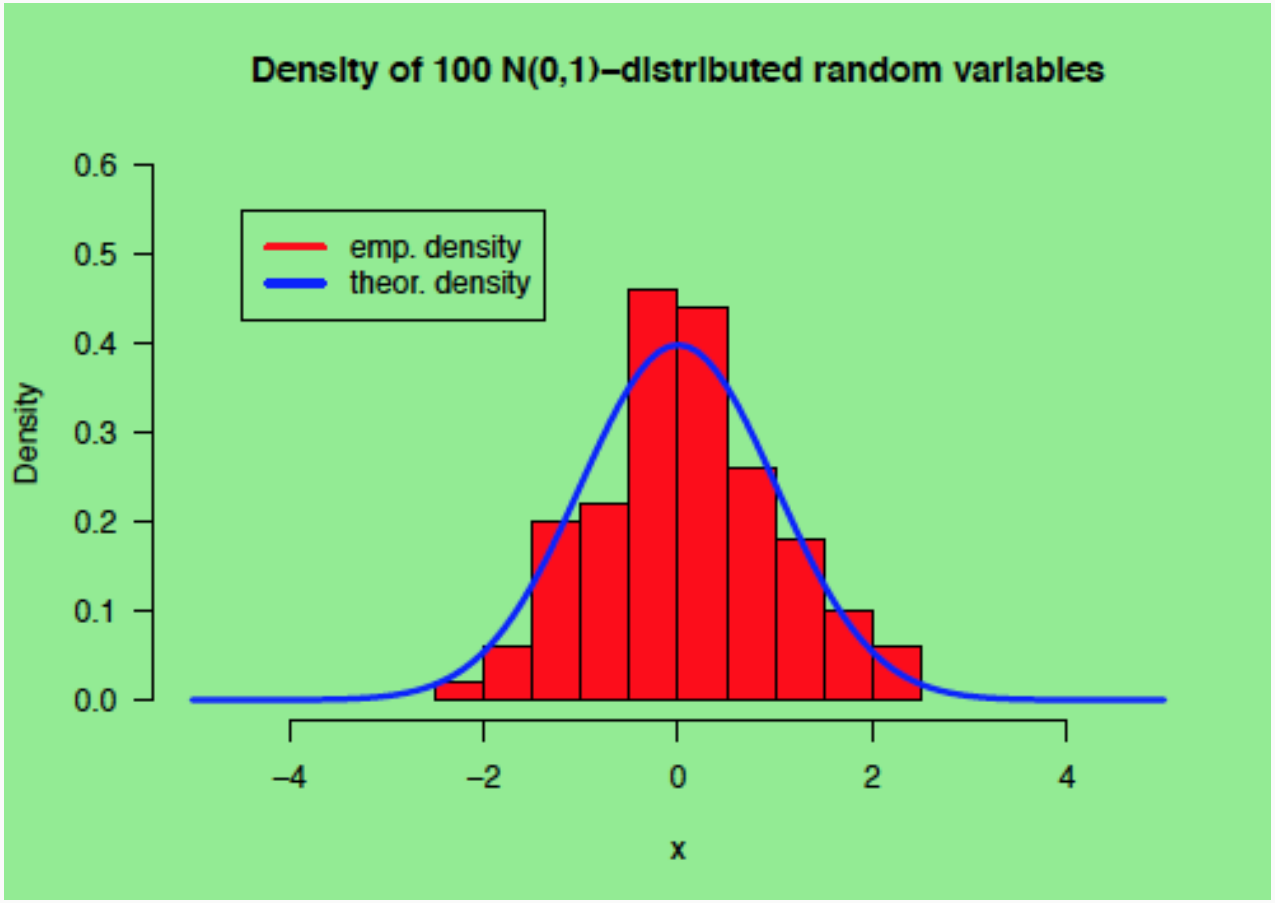
# Low-level Graphics

Low-level functions add elements to a (with high-level function) generated graphic, e.g., additional points, legends, etc.

| | |
|---|---|
| `abline()` | "intelligent" lines |
| `arrows()` | arrows |
| `axis()` | axes |
| `grid()` | gridlines |
| `legend()` | legend |
| `lines()` | (stepwise) lines |
| `mtext()` | text in margins |
| `points()` | points |
| `polygon()` | (filled) polygons |
| `segments()` | vector lines |
| `text()` | text |
| `title()` | title label |

# Low-level Graphics

```
# example 2 (cont.):
legend(-4.5, 0.55, legend = c("emp. density", "theor. density"),
       col = c("red", "blue"), lwd = 3)
```

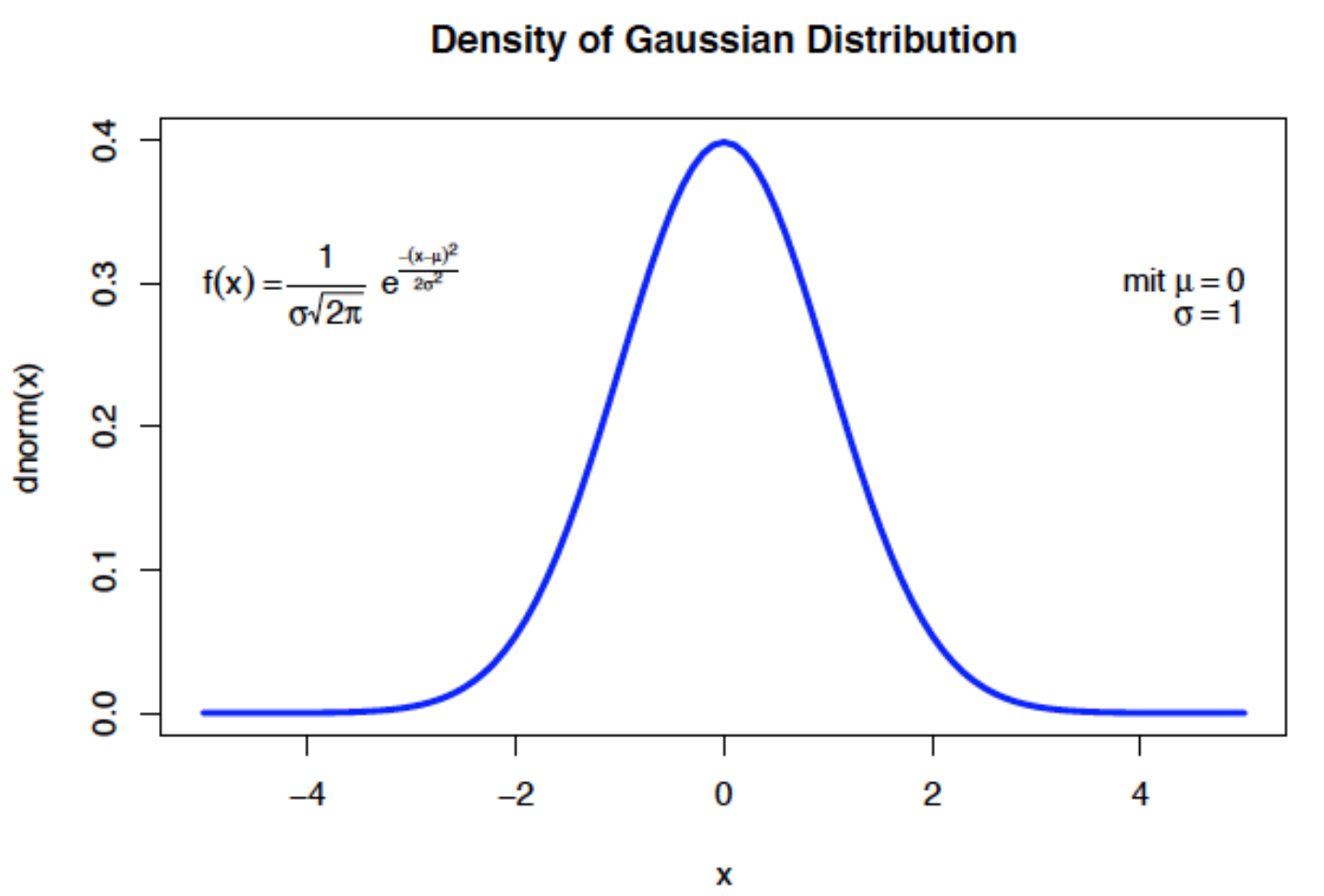


# Mathematical Expressions

- mathematical notation and symbols formatted similar to LaTeXcode can be integrated in functions such as `axis()`, `legend()`, `mtext()`, `text()`, and `title()`
- For help check `?plotmath` or run `demo(plotmath)`

```
curve(dnorm, main = "Density of Gaussian Distribution",
      from = -5, to = 5, col = "blue", lwd = 3)
text(-3, 0.3,
     expression(f(x) == frac(1, sigma * sqrt(2*pi)) ~~
         e^{frac(-(x - mu)^2, 2 * sigma^2)}))
text(4, 0.3, expression(paste("mit ", mu == 0)))
sigma <- 1
text(4.2, 0.28, bquote(sigma == .(sigma)))
```

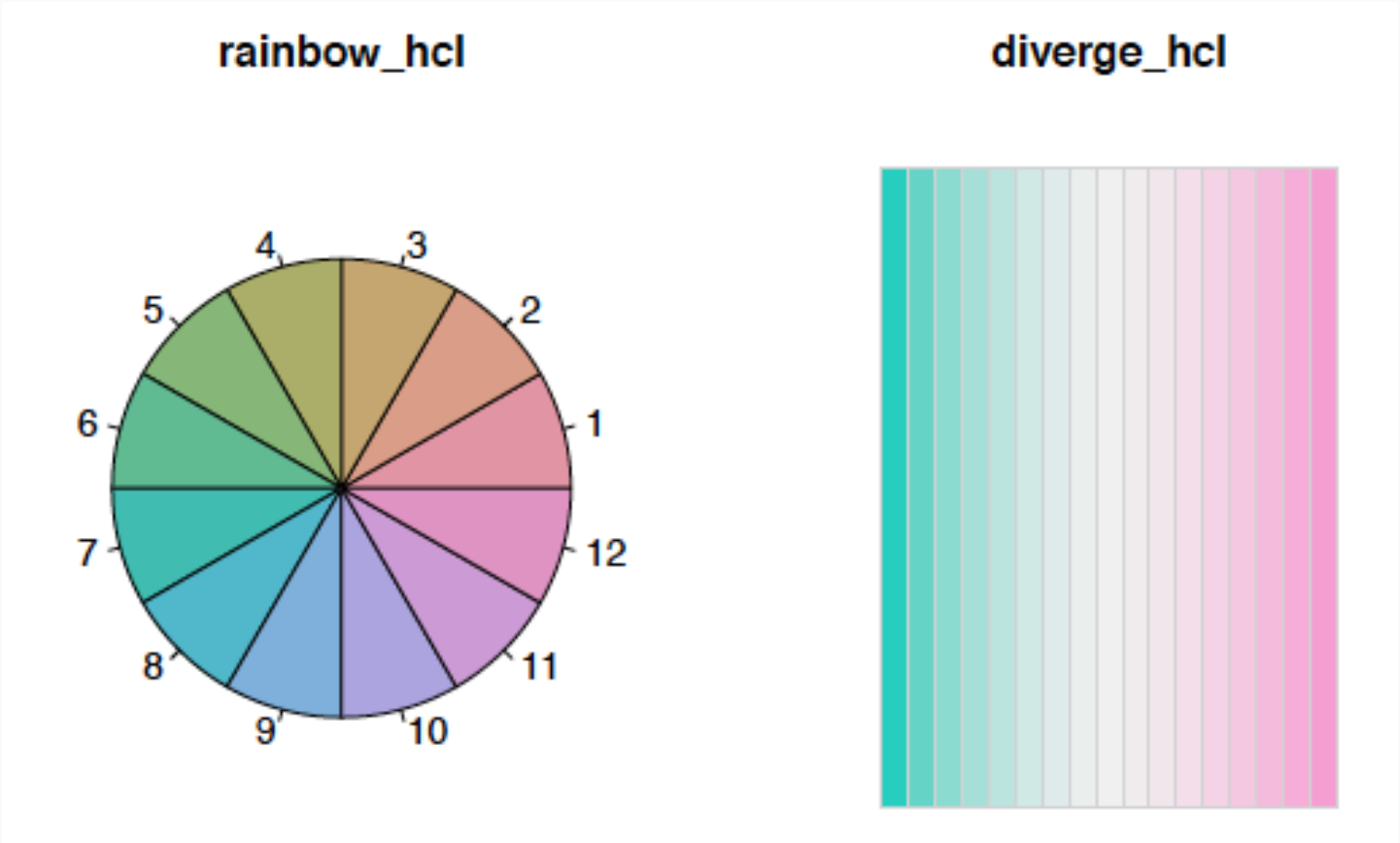
# Mathematical Expressions



# colorspace

The package `colorspace` provides various functions for perceptually-balanced color palettes

```
rainbow_hcl(12)
diverge_hcl(17, h = c(180, 330), c = 59, l = c(75, 95))
```



# Trellis Graphics

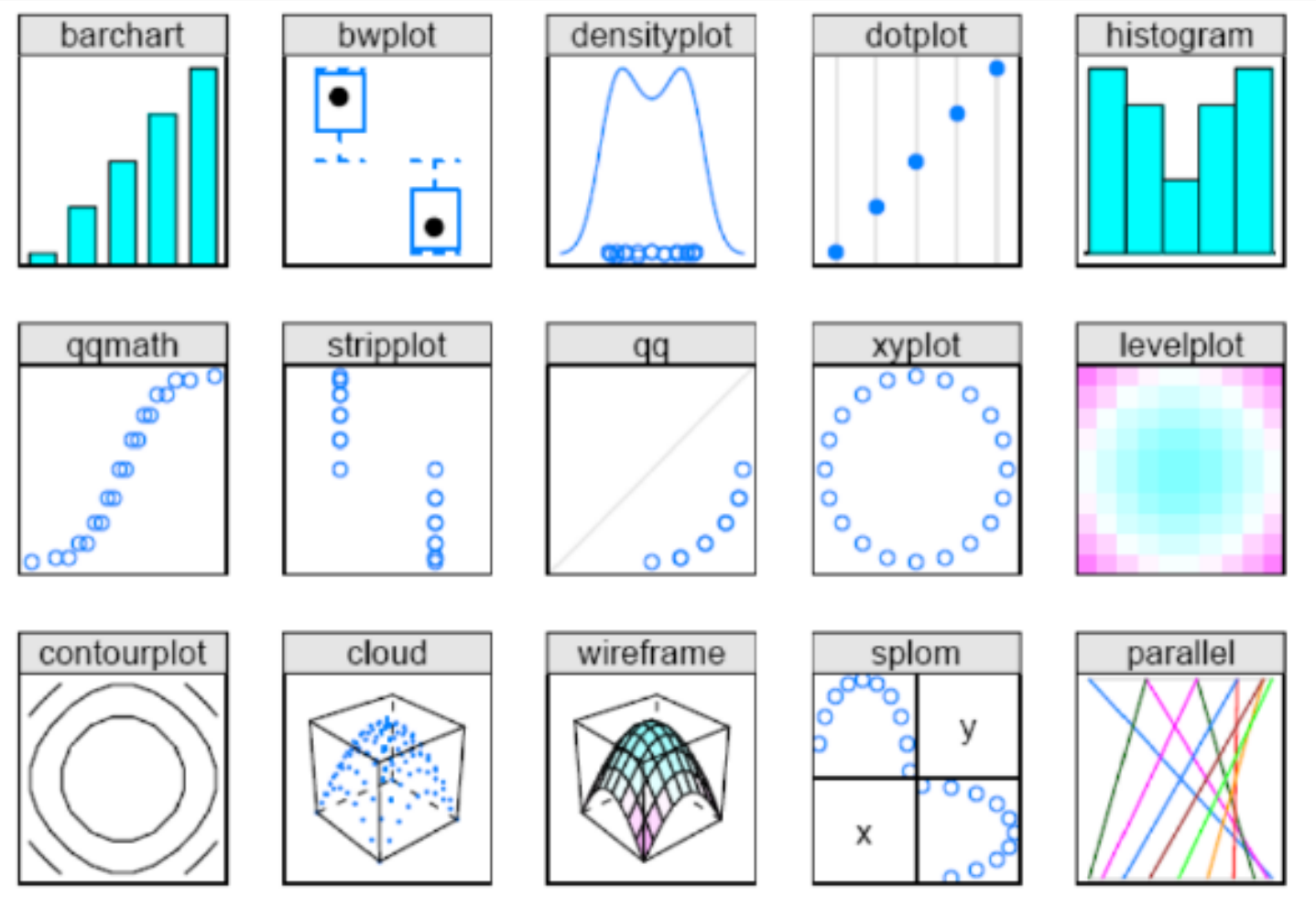
- trellis graphics is a family of techniques for viewing complicated data sets, that are based on basic concepts of human perception
- everything is possible (using a sufficient number of parameters)
- the trellis graphics system is in the `lattice` package
- the typical format is

```
graph_type(formula, data = )
```

# Trellis Graphics

| | |
|---|---|
| `barchart()` | barplot |
| `bwplot()` | boxplot |
| `cloud()` | 3D point clouds |
| `contourplot` | 3D contour plot |
| `densityplot()` | kernel density plot |
| `dotplot()` | point plots |
| `histogram()` | histogram |
| `levelplot()` | levelplots |
| `panel.....()` | functions to add elements |
| `piechart()` | pie diagram |
| `print.trellis()` | plotting trellis object |
| `qq()` | QQ–plots |
| `stripplot` | strip plots |
| `wireframe()` | persp. 3D areas |
| `xyplot()` | scatterplot |

# Trellis Graphics



# Trellis Graphics

```
require(lattice)
attach(mtcars)
# create factors with value labels
gear.f <- factor(gear, levels = c(3,4,5),
   labels = c("3gears", "4gears", "5gears"))
cyl.f <- factor(cyl, levels = c(4,6,8),
   labels = c("4cyl","6cyl","8cyl"))

# kernel density plot
densityplot(~mpg,
   main = "Density Plot",
   xlab = "Miles per Gallon")
# kernel density plots by factor level
densityplot(~mpg|cyl.f,
   main = "Density Plot by Number of Cylinders",
   xlab = "Miles per Gallon")
```

# Interactive Graphics

The basic R system does not allow many possibilities for interactive graphics. Some exceptions are:

- `identify()` identifies a selected data point, e.g.:

```
x <- rnorm(10)
plot(x)
identify(x)
```

- `locator()` returns the coordinates of a selected point, which can be used for instance for the interactive placing of labels:

```
plot(x)
legend(locator(1), legend = "A legend", pch = 1)
```

# Further References

- First analysis: Brian Everitt and Torsten Hothorn. A handbook of statistical analyses using R. Chapman & Hall/CRC, 2006
- Trellis: Deepayan Sarkar. Lattice: multivariate data visualization with R. Use R! Springer, 2008
- Colorspace: Achim Zeileis, Kurt Hornik, and Paul Murrell. Escaping RGBland: Selecting colors for statistical graphics. Computational Statistics & Data Analysis, 53:3259?3270, 2009. doi: 10.1016/j.csda.2008.11.033

# Data Management

# Motivation

Data Import and Export

- can take more time than the statistical analysis itself
- majority of the data is spreadsheet–like data
- Easier to import badly formatted data than explaining what a "good" formatted data is
- R is no good to handle large-scale data
- In practice, you will be often faced with data corrections and updates

# Data Import Vocabulary

```
# Reading data
data                # loads specified data sets
read.table          # Reads a file in table format
read.fwf            # Read a table of fixed width formatted data
load                # Reload 'RData' datasets
library(foreign)    # Read Data Stored by Minitab, SAS, SPSS, ...
```

# Data Import Vocabulary

```
# Files and directories
setwd, getwd      # set and get current working directory
dir               # names of files or directories in a directory
dirname           # returns the directory name
normalizePath     # convert file paths to canonical form
file.choose       # choose a file interactively
download.file     # download a file from the Internet

# low-level interface to the computer's file system:
file.copy, file.create, file.remove, file.rename, dir.create,
file.exists, file.info
```

# Import Spreadsheet-like Data

To read spreadsheet-like data you need the function `read.table()` and variations like `read.csv()`, ...

| | |
|---|---|
| `fileEncoding`: | use `latin1` for Windows data, and utf-8 for Unix data |
| `header`: | names of variables (columns) and observations (rows) |
| `sep`: | field separator vs. record separator |
| `quote`: | protecting separators appearing in strings |
| `na.strings`: | which string (or number) represents missing values? |
| `colClasses`: | which type of variable is contained in which column? |
| `skip`: | number of lines skipped before beginning to read data |

# Importing from other statistical systems

The package `require(foreign)` provides import facilities for files produced by other statistical systems:

| | |
|---|---|
| read.epiinfo: | reads fixed-width text format `.REC` files as R data frames |
| read.mtp: | imports 'Minitab Portable Worksheet' |
| read.xport: | reads a file in SAS Transport (XPORT) format |
| read.ssd: | generates a SAS program to convert the ssd contents to SAS transport format |
| read.spss: | reads files created by SPSS's 'save'/'export' commands |
| read.dta: | imports binary files created by Stata |
| read.S: | reads S's 'data.dump' files |

# Data Export: Basic Vocabulary

```
# Output
print, cat                # print in console
dput                      # Writes an ASCII text representation of
                          # an R object to a file
sink, capture.output      # Evaluates its arguments with the output
                          # being returned as a character string or
                          # sent to a file.

# Writing data
write                     # The data (usually a matrix) are written
                          # to file
write.table, write.csv    # converts the object to a data frame and
                          # prints it to a file
save                      # writes an external representation of
                          # R objects
```

# Data Export

- exporting from R is easier than importing
- normally exporting a text or csv file with `write.table` or `write.csv` is good enough
- `sink` diverts the standard R output to a file, and thereby captures the output of (possibly implicit) print statements
- `foreign::write.foreign` writes a code file that will write this text file into another statistical package
- the precision is governed by the current setting of `options(digits)`: Export for report writing or further analysis?

# Relational Database

Why use a database?

- R is not well suited to large data sets. Large data objects can cause R to run out of memory
- provide fast access to selected parts of large databases.
- powerful ways to summarize and cross–tabulate columns in databases.
- store data in more organized ways than the rectangular grid model of spreadsheets and R data frames.
- concurrent access from multiple clients running on multiple hosts while enforcing security constraints on access to the data.
- ability to act as a server to a wide range of clients.

# R Database Interface Packages

R Database Interface Packages:

| | |
|---|---|
| DBI | interface between R and relational DBMS |
| RJDBC | access to databases through the JDBC interface |
| RMySQL | interface to MySQL database |
| RODBC | ODBC database access |
| ROracle | Oracle database interface driver |
| RpgSQL | interface to PostgreSQL database |
| RSQLite | SQLite interface for R |

Example for SQL queries:

```
SELECT State, Murder FROM USArrests WHERE Rape > 30 ORDER BY Murder
SELECT sex, COUNT(*) FROM student GROUP BY sex
SELECT sch, AVG(sestat) FROM student GROUP BY sch LIMIT 10
```

# Memory Management

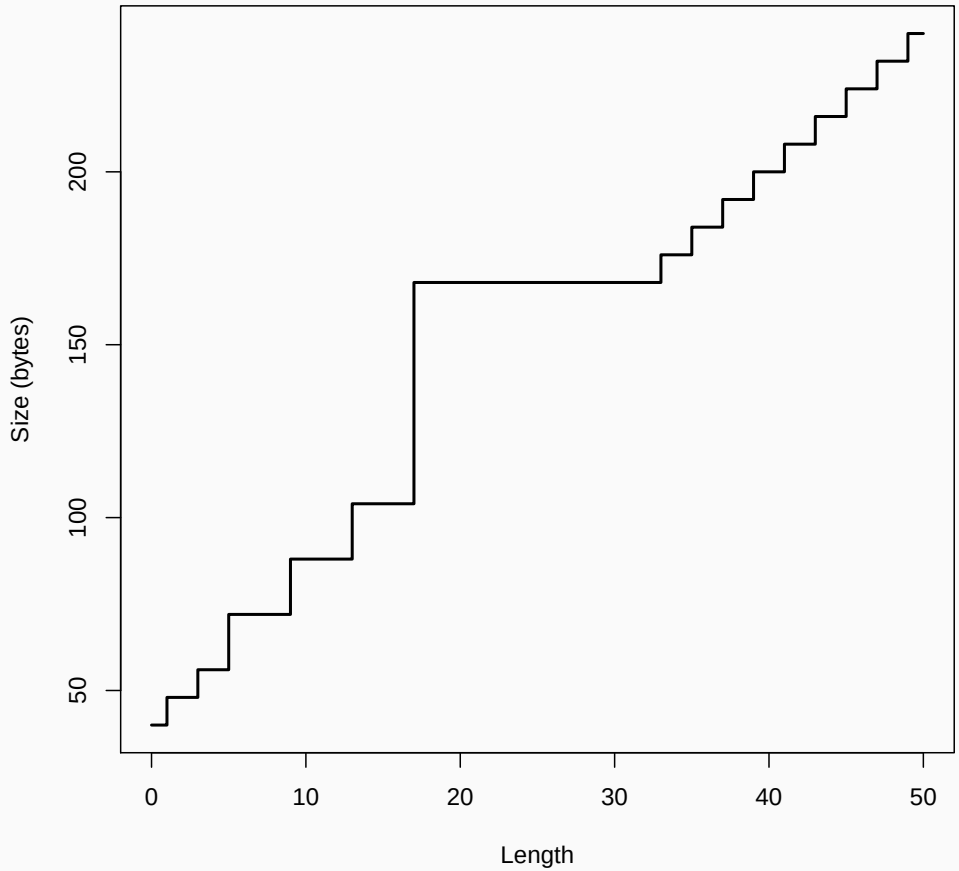
- some understanding of R's memory management will help you predict how much memory you will need
- `pryr::object size()` tells you how much memory an object occupies (including environments)

```
require(pryr)
object_size(1:10)       # 88 B
object_size(mtcars)     # 6.74 kB
object_size(numeric())  # 40 B
```

- for more information see also `?Memory`

# Memory Management

```
sseq = function(n){object_size(seq_len(n))}
sizes = sapply(0:50, sseq)
plot(0:50, sizes, xlab = "Length", ylab = "Size (bytes)",
    type = "s")
```



# Memory Management

- `pryr::mem_used()` tells you the total size of all objects in memory. `pryr::mem_change()` tells you how memory changes during code execution
- R has automatic garbage collection, but it is lazy, so that it won't ask for memory until it is actually needed, otherwise use `gc()`

```
mem_used()                # 44.6 MB
mem_change(x <- 1:1e6)    # 4.01 MB
mem_change(rm(x))         # -4 MB

mem_change(x <- 1:1e6)    # 4 MB
mem_change(y <- x)        # 1.74 kB
mem_change(rm(x))         # 1.62 kB
mem_change(rm(y))         # -4 MB
```

# Project Management

## Object Storage

| | |
|---|---|
| Workspace: | is your current R working environment and includes any user–defined objects (vectors, matrices, data frames, etc). |
| Binary files: | `save()` allows the explicit saving of functions and data in binary file, that can be loaded by `load()` |
| Source code: | `source()` accepts its input from the named file or URL and runs the script in the current session |

# Project Management

Manage your Workspace

| | |
|---|---|
| `ls()` | lists the objects in your workspace. |
| `list.files()` | lists the files located in the folder's workspace |
| `rm()` | removes objects from your workspace; `rm(list = ls())` removes them all. |
| `sessionInfo()` | gives information about your session, i.e., loaded packages, R version, etc. |
| `R.version` | provides information about the R version. |

# Publication Quality Output

Publication Quality Output and Documentation of Analysis:

| | |
|---|---|
| `knitr`: | enables integration of R code into LaTeX, LyX, HTML |
| `xtable`: | converts some R objects into LaTeXcode. |
| `R2HTML`: | converts your output text, tables, graphs in HTML format |
| `odfWeave`: | has functions that allow you to embed R output in ODF |
| `SWordInstaller`: | allows you to add R output to Word |
| `R2PPT`: | provides wrappers for adding R output to PPTs. |

# Sweave: Integration with LaTeX

- `Sweave` allows you to embed R code in LaTeX, producing attractive reports if you know that markup language.
- R's ability to output results for publication quality reports is somewhat rudimentary
- typewrite the results from R can be laborious, time-consuming and is a potential source for errors
- integration of R code and report allows the reproducibility of the analysis and assures good scientific practice
- the reports are easily updated with corrections and extension of the underlying data

# Sweave Example

```
\documentclass[a4paper]{article}
\title{Sweave Example 1}
\author{Friedrich Leisch}
\begin{document}
\maketitle
In this example we embed parts of the examples from the
\texttt{kruskal.test} help page into a \LaTeX{} document:
<<>>=
data(airquality)
kruskal.test(Ozone ~ Month, data = airquality)
@
which shows that the location parameter of the Ozone
distribution varies significantly from month to month.
\begin{center}
<<fig=TRUE,echo=FALSE>>=
boxplot(Ozone ~ Month, data = airquality)
@
\end{center}
\end{document}
```

# Sweave Chunk Options

In recent versions of R the way to run Sweave from the command line:

```
R CMD Sweave example-1.Snw
pdflatex example-1
```

The most important options for Sweave code chunks are:

| | |
|---|---|
| echo: | logical (`TRUE`). Show code in output file? |
| eval: | logical (`TRUE`). Evaluate code? |
| results: | character string: `verbatim`, `tex`, or `hide`. |
| fig: | logical (`FALSE`). Graphics? |
| eps, pdf: | logical (`TRUE`), EPS/PDF-Datei? |
| width, height: | numerical (6), width and height of graphics |

Defaults can be adapted using `SweaveOpts()`

# Further Reading

- R Data Import/Export manual. Available online: `http://cran.r-project.org/doc/manuals/r-release/R-data.pdf`
- Hadley Wickham. Advanced R. The R series. CRC Press, 2015; Chapter 18: Memory.
- Sweave webpage by Friedrich Leisch `http://www.statistik.lmu.de/~leisch/Sweave/`

# Functions, Debugging & Condition Handling

# Motivation: Functions in R

- R is a functional programming language. This means that it provides many tools for the creation and manipulation of functions.
- The structure of a function is given by

```
function(<arglist>){
    <body>
}
```

  - the keyword `function` indicates the beginning of a function
  - arguments `<arglist>` lists the arguments of the function
  - `<body>` is a block of R commands which are executed by the function

# Function Components

All R functions are objects and consist of three parts:

| | |
|---|---|
| `body()` | code inside the function. |
| `formals()` | arguments that controls how you can call the function. |
| `environment()` | location of the function's variables. |

```
f <- function(x){
     x^2
}
f                # > function(x) x^2
formals(f)       # > $x
body(f)          # > x^2
environment(f) # > <environment: R_GlobalEnv>
```

# Function Arguments

- When calling a function you can specify arguments by position, by complete name, or by partial name.
- Arguments are matched first by exact name (perfect matching), then by prefix matching, and finally by position.
- Avoid using positional matching for less commonly used arguments, and only use readable abbreviations with partial matching.

```
f <- function(abcdef, bcde1, bcde2) {
     list(a = abcdef, b1 = bcde1, b2 = bcde2)
}
str(f(1, 2, 3))           # ok
str(f(2, 3, abcdef = 1)) # ok
str(f(2, 3, a = 1))       # ok
str(f(1, 3, b = 1))       # Error
```

# Default and Missing Arguments

- Function arguments in R can have default values.
- They can be also defined in terms of other arguments.
- You can determine if an argument was supplied or not with the `missing()` function.

```
myplot <- function(x, y, mycol = 'red') {
  if(missing(y)) {
    y <- x
    x <- 1:length(y)
  }
  plot(x, y, col = mycol)
}
myplot(1:20)
myplot(1:20, rnorm(20), mycol='darkgreen')
```

# match.arg()

- match.arg matches arguments against a table of candidate values specified by choices

```
match.arg(arg, choices, several.ok = FALSE)
```

- missing argument will be replaced with the first candidate

```
tsex <- function(sex = c("Male", "Female")) {
        match.arg(sex)
}
tsex("F")   # [1] "Female"
tsex()      # [1] "Male"
tsex("W")
# Error in match.arg(sex) (from #2) :
# ‘arg’ should be one of "Male", "Female"
```

# Lazy Evaluation

- R function arguments are evaluated if they're actually used.

```
myfun <- function(x, y){
      if(x < 0){
      return(NaN)
      }else{
      return( y * log(x))
      }
}
myfun(-1)   # NaN
myfun(2,3)  # 2.079442
myfun(2)    # Error in myfun(2) : argument "y" is missing,
            # with no default
```

- If you want to ensure that an argument is evaluated you can use `force()`
- More technically, an unevaluated argument is called a 'promise".

# The Argument ...

- Functions can have any number of arguments using the special argument "..."
- The argument "..." will match any arguments not otherwise matched, and can be easily passed on to other functions.
- Using "..." comes at a price – any misspelled arguments will not raise an error, and any arguments after "..." must be fully named.

```
myplot <- function(x, y, myarg, ...){
       # optional calculation with x, y and myarg
       # call standard plot function with additional
       # unspecified arguments from ...
       plot(x, y, ...)
}
```

# Connecting the "..."

- "..." can be passed to any number of functions, but the arguments are the same
- Different argument lists can be passed to different functions by using `do.call()`:

```
myfun <- function(x, fun2.args = NULL, fun3.args = NULL, ...){
  # calculations
  fun1(x, ...)
  do.call(fun2, fun2.args)        # first arg is either function
  do.call("fun3", fun3.args)      # or character

  # further calculations
}
```

# Return Values

- The last expression evaluated in a function becomes the return value, the result of invoking the function.
- Functions can return only a single object, so that you have to combine a number of objects in a list.
- Functions can return invisible values, which are not printed out by default when you call the function.

```
hist_2by2 <- function(data, args, ...) {
  opar <- par(no.readonly = TRUE)
  on.exit(par(opar))
  par(mfrow = c(2, 2))
  # do histrogram plots for all variables in the data frame
  invisible(apply(data, MARGIN = 2, hist, ...))
}
hist_2by2(trees)
```

# Basic Debugging Vocabulary

- With a good technique, you can debug a problem with just `print()`.
- Wickham [2015] provides an outline for a general procedure for debugging:
  1. realize that you have a bug: implement testing procedures!
  2. make it repeatable: create a minimal example
  3. figure out where it is: identify the line of code that's causing the bug
  4. fix it and test it: ensure you fixed the bug

# Basic Debugging Vocabulary

Make the bug reproducible:

- make sure your workspace is empty
- set seed for drawing random numbers
- create a minimal example

Bug Identification

| | |
|---|---|
| `Binary search`: | you repeatedly remove half of the code until you find the bug. |
| `traceback()`: | determines the sequence of calls that lead up to an error (call stack). |
| `browser()`, `debug()`: | starts an interactive console in the environment where the error occurred. |

```
options(error = c(NULL, browser, recover))
```

# Bug Identification: `traceback()`

The first tool is the call stack, the sequence of calls that lead up to an error.

```
f <- function(a) g(a)
g <- function(b) h(b)
h <- function(c) i(c)
i <- function(d) "a" + d

f(10)
# Error in "a" + d (from #1) : non-numeric argument to binary
# operator

traceback()
# 4: i(c) at #1
# 3: h(b) at #1
# 2: g(a) at #1
# 1: f(10)
```

# Additional Notes on Debugging

- prevent bugs: Instead of trying to write one big function all at once, work interactively on small pieces.
- a function may generate an unexpected message. There is no built-in tool to help solve this problem, but it is possible to create one:

```
message2error <- function(code) {
  withCallingHandlers(code, message = function(e) stop(e))
}
```

- your code might crash R completely, which indicates a bug in the underlying C code.

# Exception Handling

- some error exceptions are no bugs:
  - numerical problems (over-/underflow)
  - unsuitable (user) inputs
  - convergence failure during iterative algorithms
- successful failure of code: When writing a function, you can often anticipate potential problems and communicate these to the user is the job of conditions:

| | |
|---|---|
| `stop()` | Fatal errors force all execution to terminate. |
| `warning()` | Display potential problems |
| `message()` | Give informative output. Also textttsuppressMessages() |

The behavior of error and warning can be adapted with `options()`

# stop()

With `stop()` fatal errors are raised and force all execution to terminate, when there is no way for a function to continue.

```
f <- function(x) {
  if (!is.numeric(x))
    stop("supplied x is not numeric.")
  s <- sum(x)
  message("sum = ", s)
}
f(1:10)   # 55
sum("nonsense")
# Error: invalid ‘type’ (character) of argument
f("nonsense")
# Error: supplied x is not numeric.
```

# try-error()

- `try()` allows execution to continue even after an error has occurred.
- if unsuccessful it will return an (invisible) object of class "try-error"
- suppress the message with `try(..., silent = TRUE)`

```
f <- function(x, silent = TRUE) {
  s <- try(sum(x), silent = silent)
  if (inherits(s, "try-error")) {
    warning("x of wrong type, returning NA.")
    return(NA)
   }
  s
}
f(1:10)
## [1] 55
f("nonsense")
## Warning: x of wrong type, returning NA.
## [1] NA
```

# tryCatch()

tryCatch() is a general tool for handling conditions: take different actions for errors, warnings, messages, and interrupts.

```
f <- function(x, silent = FALSE) {
     s <- tryCatch(sum(x),
          error = function(e) {
                  warning("x of wrong type, sum is NA.")
                  if (!silent) print(e)
                  return(NA)
           },
           finally = cat("buh bye!\n")
           )
      s
}
f("nonsense")
# <simpleError in sum(x): invalid ‘type’ (character) of argument>
# buh bye!
# [1] NA
# Warning: x of wrong type, sum is NA.
```

# Further References

- Hadley Wickham. Advanced R. The R series. CRC Press, 2015. Chapter 6: Functions & Chapter 9: Exceptions and Debugging.
- Robert Gentleman and Luke Tierney. A prototype of a condition system for R. This describes an early version of R's condition system: `http://homepage.stat.uiowa.edu/~luke/R/exceptions/simpcond.html`