Introduction to R
Part I/II

aktuell für R version 4.3.3

Version 8

März 2025

Alexander Hirner & Aleksandra Tyjan

R - Part I

Version 8.0 (March 2025)

Alexander Hirner

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1 Getting Started

1.1 Installation

1. Download R from **https://www.r-project.org**.
2. Install the `tidyverse` package by typing in `install.packages("tidyverse")`.
3. Install an editor. Recommendations:
    - **Visual Studio Code** from **https://code.visualstudio.com/** or
    - **RStudio** from **https://www.rstudio.com/**.

> Order of Installation
>
> If you are using RStudio, the order of installation (first R, then the editor) matters (otherwise you will get an error during installation).

1.2 Recommended Packages

- `tidyverse` - **A collection of packages for data science**.
- `ggplot2` - Elegant data visualisations using *The Grammar of Graphics*.
- `XLConnect` - Excel connector for R.
- `foreign` - Read data stored by Minitab, SPSS, SAS, etc.
- `dplyr` - A grammar of data manipulation.
- `tidyr` - Tidy messy data.
- `data.table` - Extension of `data.frame` (fast!)
- `doBy` - Groupwise Statistics, LSmeans, Linear Estimates, Utilities.
- `cowplot` - Various features to create publication-quality figures (e.g. combining plots).
- `questionr` - Functions to Make Surveys Processing Easier.
- `summarytools` - Tools to Quickly and Neatly Summarize Data.

> Installing Packages
>
> The command to install additional packages is `install.packages("...")`. However, it is possible that the editor which you are using, supports you, i.e. in RStudio you can click on `Tools` and `Install packages` (and then simply follow the instructions).

Functions from previously installed packages can be invoked by

1. using the syntax `packagename::functionname(...)` or
2. "loading" the package using `library(packagename)` or `require(packagename)` (preferably at the beginning of a script) which makes the prefix `packagename::` unnecessary then (to "remove" the package again use `detach`).

Note that each way has its advantages and disadvantages.

1.3 Basic R Commands

Let us start with the "basics" first, e.g. creating simple objects, inspecting and deleting them, managing file paths and getting help:

Command	Description
`getwd()`	Gets working directory.
`setwd("path")`	Sets working directory (R uses forward slashes in file paths!).
`variable <- value`	Assigning a value to a variable.
`variable <- c(val1, val2, ...)`	Assigning values to a variable (c is for *combine*).
`ls()`	Lists all objects in the workspace.
`rm(object)`	Removes an object.
`help()`	Getting help.
`?object`	An alias for `help()`.
`help.search("searchstring")`	Searches the help system for a given string.
`??searchstring`	An alias for `help.search()`.
`#`	The hash sign introduces a comment.
`data()`	Lists built-in sample data.

Functions can also be nested (i.e. "a function in a function"), e.g. the command `rm(list=ls())` deletes everything from memory.

⚠ Using `rm(list=ls())`

The command `rm(list=ls())` is helpful to clean up the memory before starting a new script or project. However, use it with caution since there is no "undo" for this command.

2 The Most Important R Objects (Overview)

2.1 Vectors

Usage and Important Operations

Vectors can be used as “containers” to store univariate data.

Command	Description
`x <- c(val1, val2, ...)`	Creates a vector. Use quotes for string literals.
`x[i]`	Value on position **i** of vector **x**. The first element is on position **1** in R.
`x[-i]`	All values except for the one on position **i**.
`x[j:k]`	Observations from position **j** to position **k**.
`x[c(j,m)]`	Observations on position **j** and **m**.
`length(x)`	Number of Observations in **x**.
`rev(x)`	Reverses elements of **x**.
`x <- seq(from, to , by)`	Generates an arithmetic progression. Use `1:n` as an alias for `seq(1,n,1)`.
`x <- rep(pattern, n)`	Repeats a pattern **n** times

> ⚠ About R Objects
>
> Commands like `x[-1]` or `rev(x)` never change the object *in situ* - these commands (when used in interactive mode) simply print out the values to the console. If you want to change the vector permanently, the assignment operator (`<-`) must be used.

Example

```r
# a vector:
height <- c(180, 167, 198.5, 156, 170, 172, 169, 155)
height <- height[-3] # drop the third entry
summary(height) # summary statistics
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  155.0   161.5   169.0   167.0   171.0   180.0 
```

2.2 Objects of the `data.frame`-Class

Usage and Important Operations

A `data.frame` is the appropriate structure to store multivariate data, i.e. data consisting of **n** rows (observations) and **k** columns (variables or data fields).

Command	Description
`X <- data.frame(v1, v2, ...)`	Creates a `data.frame`. Here, **v1** and **v2** are **vectors of the same length**.
`X[i, ]`	Row (observation) **i**.
`X[ ,k]`	Column (variable) **k**.
`X[i:j, ]`	Observations from row **i** to **j** (and all variables).
`X[c(i,k), ]`	Observations in row **i** and **k** (and all variables).
`X[-c(i,k), ]`	All observations except those in row **i** and **k** (and all variables).
`X[, c(i,k)]`	All rows, only column **i** and **k**.
`X[, -c(i,k)]`	All rows, drop values in column **i** and **k**.
`X$varname`	Addresses a column by its name.
`names(X)`	Gets (or assigns) variable names.

Example

In the following example we will create a small `data.frame` with n=5 observations (cats) and k=3 variables from scratch:

```
id <- c(1,2,3,4,5) # or 1:5
sex <- c("male", "female", "female", "female", "male")
weight <- c(3, 4, 3.7, 2.5, 0.9)
cats <- data.frame(id, sex, weight)
rm(id, sex, weight) # drop original vectors now!
```

This is our data:

```
print(cats)
```

```
  id    sex weight
1  1   male    3.0
2  2 female    4.0
3  3 female    3.7
4  4 female    2.5
5  5   male    0.9
```

Now let us address one of the columns, i.e. "weight" (weight of the cat in kilos) to calculate their average:

```
mean(cats$weight)
```

```
[1] 2.82
```

Now let us drop the column "id" because we do not need it and display the `data.frame`:

```
cats <- cats[ , -1]
cats
```

```
     sex weight
1   male    3.0
2 female    4.0
3 female    3.7
4 female    2.5
5   male    0.9
```

2.3 Lists

Usage and Important Operations

- Lists in R are capable of storing different data types (strings, numbers, vectors, data.frames or even lists).
- If you want to create a list "from scratch", use the function `list` and simply pass the objects that you want to store in the list. With `names()` it is possible to assign names to the elements stored in the list.
- Whenever you run a statistical procedure (e.g. ANOVA, linear regression, cluster analysis, ...) the output **should always be stored in a variable**. This variable is often a list (or at least "behaves" like a list). List elements can be addressed by using the $-symbol or double square brackets and an index.
- Note that a `data.frame` is a special kind of a `list` - it is a `list` where all elements are vectors of the same length.

Example

```
v1 <- c(1, 2, 3)
v2 <- c("a","b","c")
v3 <- data.frame(v1, v2)
v4 <- 7
v5 <- "hello world"
mylist <- list(v1,v2,v3,v4,v5)
names(mylist) <- c("v1","v2", "DF", "a_number", "a_string")
```

We can now address single elements from the list:

```
print(mylist$v1)
```

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

```
print(mylist$a_string)
```

```
[1] "hello world"
```

2.4 Matrices

Usage

You might need the `matrix` data type if you do linear algebra with R.

Example

```
x <- seq(1,12,1) # or simply  x <- 1:12
y <- matrix(x, nrow=3, byrow=TRUE)
print(y)
```

```
     [,1] [,2] [,3] [,4]
[1,]    1    2    3    4
[2,]    5    6    7    8
[3,]    9   10   11   12
```

In the example above, a matrix with 12 elements (numbers from 1 to 12) and three rows (`nrow`) was created. Alternatively, you can specify `ncol` (the number of columns). The flag `byrow` indicates whether the matrix should be filled up "row-wise" (if `TRUE`) or "column-wise" (if `FALSE`).

With `t(X)` you can transpose a matrix X. This command also works for objects of the `data.frame`-class.

2.5 Type Conversions

Sometimes the following type conversion functions can be helpful:

- `as.numeric`
- `as.character`
- `as.vector`
- `as.matrix`
- `as.data.frame`

2.6 More Data Types

There are more data types (i.e. there are objects of the `tibble`-class and some more). These data types require additional packages but their behaviour and purpose (storing multivariate data) is similar to a `data.frame`.

3 Data Managment (`data.frame` Objects in Detail)

3.1 Logical Operators

For some operations (e.g. filtering data or creating new variables) we need comparison operators:

Command	Description
`<`	less than
`<=`	less than or equal to
`>`	greater than
`>=`	greater than or equal to
`==`	equality
`!=`	inequality
`%in%`	match with one element of a vector?

These operators can be combined using `&` (logical AND) or `|` (logical OR).

3.2 Working with Files

Command	Description
`read.table`	Reads a file and creates a `data.frame` from it.
`read.csv`	Reads a file and creates a `data.frame` from it.
`read.csv2`	Reads a file and creates a `data.frame` from it.
`write.table`	Prints a `data.frame` to a file.
`write.csv`	Prints a `data.frame` to a file.
`write.csv2`	Prints a `data.frame` to a file.

If you want to import data from an Excel-file directly (i.e. without saving it as a csv-file), you can use the function `readWorksheetFromFile` from the library `XLConnect`.

⚠ Possible pitfalls when dealing with files

- Make sure you are in the right directory. You might need the `setwd`-command.
- The functions listed above differ with respect to their default settings (i.e. for the field separator string and the decimal symbol). Use the `help` function to find out details.
- Commands such as `write.table` (or related functions) overwrite existing files **without warning (!)**.

3.3 Data Managment Operations in Detail

Command	Description
`dim(X)`	Displays number of rows and columns.
`head(X, n)`	Returns the first **n** rows of **X**.
`tail(X, n)`	Returns the last **n** rows of **X**.
`str(X)`	Compactly displays structure of **X**.
`Z <- rbind(X, Y)`	Adding observations from **X** and **Y**.
`Z <- cbind(X, Y)`	Adding a column to X.
`X$new <- formula`	Creates a **new** column in **X** with a **formula**.
`X <- transform(X, new1=f1, new2=f2,...)`	Calculates new columns **new1** and **new2** with the formula **f1** or **f2**, respectively.
`names(X)`	Displays (or changes) variable names.
`ifelse(cond, ifpart, elsepart)`	Conditional execution (i.e. for recoding).
`Y <- subset(X, conditions)`	Creates a subset **Y** based on logical conditions.
`X <- X[order(X$var), ]`	Sorts your `data.frame` by one or more variables. Use `decreasing=TRUE` for descending order.
`Y <- split(X, X$splitvar)`	Creates a list of `data.frame`-objects (for each value of **splitvar**).
`Y <- merge(x, y, by.x, by.y)`	Merges (i.e. joins) `data.frame`-objects by a common column.

3.4 Example

At first let us create some data, e.g. 10 observations and three variables:

```
id <- 1:10
sex <- rep(c("m", "f"), 5)
set.seed(123)
height <- round(rnorm(10, mean=172, sd=10), 1)
X <- data.frame(id, sex, height)
head(X)
```

```
  id sex height
1  1   m  166.4
2  2   f  169.7
3  3   m  187.6
4  4   f  172.7
5  5   m  173.3
6  6   f  189.2
```

Now let us sort the `data.frame` in descending order by the variable height:

```
Y <- X
Y <- Y[order(Y$height, decreasing=TRUE), ]
head(Y, 3)
```

```
  id sex height
6  6   f  189.2
3  3   m  187.6
7  7   m  176.6
```

Now we can create another column, the height in meters:

```
Y <- X
Y <- transform(Y, heightm = height/100)
head(Y, 2)
```

```
  id sex height heightm
1  1   m  166.4   1.664
2  2   f  169.7   1.697
```

We can also classify the subjects as follows (lte… *less than or equal*, gt… *greater than*):

```
Y <- X
Y$class <- ifelse(Y$height > median(Y$height),
"height gt median", "height lte median")
Y[6:8,]
```

```
  id sex height             class
6  6   f  189.2  height gt median
7  7   m  176.6  height gt median
8  8   f  159.3 height lte median
```

We want to create a new `data.frame` using a query and the `subset`-command to copy only females taller than 172 cm:

```
Y <- X
Y1 <- subset(Y, (height > 172) & (sex=="f"))
Y1
```

```
  id sex height
4  4   f  172.7
6  6   f  189.2
```

The following example illustrates the usage of the `split`-function. It returns a list of `data.frame`-objects:

```
Y <- X
by_sex <- split(Y, Y$sex)
by_sex
```

```
$f
   id sex height
2   2   f  169.7
4   4   f  172.7
6   6   f  189.2
8   8   f  159.3
10 10   f  167.5

$m
  id sex height
1  1   m  166.4
3  3   m  187.6
5  5   m  173.3
7  7   m  176.6
9  9   m  165.1
```

Recoding a variable into more than two categories:

```
Y <- X
Y$category[Y$height <= 170] <- "category 1"
Y$category[Y$height >= 170 & Y$height <= 176] <- "category 2"
Y$category[Y$height > 176] <- "category 3"
head(Y, 4)
```

```
  id sex height   category
1  1   m  166.4 category 1
2  2   f  169.7 category 1
3  3   m  187.6 category 3
4  4   f  172.7 category 2
```

4 Selected Functions

4.1 Preliminary Remarks

Applying Functions to Columns

Applying functions to columns

Functions can also be applied to whole vectors of data (columns in your `data.frame`) - in contrast to other programming languages, there is no need to use loops here.

Possible Pitfalls

Possible pitfalls

- The function `log()` is the "natural" logarithm.
- Trigonometric functions (and inverse trigonometric functions) return/expect the angle in radians (not in degrees!)

4.2 Common Functions in R

Function	Description
`+`, `-`, `*`, `/`	Basic math.
`a^b` or `a**b`	Returns a^b.
`sqrt(x)`	$\sqrt{x}$
`pi`, `exp(1)`	Mathematical constants.
`sin(x)`, `cos(x)`, `tan(x)`	Trigonometric Functions.
`asin(x)`,`acos(x)`, `atan(x)`	Inverse trigonmetric functions.
`floor(x)`, `ceiling(x)`	Rounding to the next integer.
`round(x, digits)`	Rounding to a given precision.
`log(x)`	(natural) logarithm.
`log10(x)`	logarithm (base 10).
`exp(x)`	Returns e^x.
`sum(x)`	Returns the sum of all elements in vector **x**.
`cumsum(x)`	Returns the cumulated sum of all elements in vector **x**.
`prod(x)`	Returns the product of all elements in vector **x**.
`cumprod(x)`	Returns the cumulated product of all elements in vector **x**.
`paste(x, y)`	Concatenates strings.
`class(x)`	Object classes.
`cat(x, y)`	Concatenates and prints.
`unique(x)`	Removes duplicates.
`set.seed(seed)`	Sets seed for random number generation.

4.3 Using any, all and which

Functions

Function	Description
`any(...)`	Are some values TRUE?
`all(...)`	Are all values TRUE?
`which(...)`	Which indices are TRUE?

Examples

```
x1 <- c(1, 3, 5, 9, 7)
any(is.na(x1))
```

```
[1] FALSE
```

```
all(x1 > 2)
```

```
[1] FALSE
```

```
which(x1 > 6)
```

```
[1] 4 5
```

4.4 Set Functions

Function	Description
`union(A, B)`	$A \cup B$
`intersect(A, B)`	$A \cap B$
`setdiff(A, B)`	$A \backslash B$
`setequal(A, B)`	Is A = B?
`is.element(x, A)`	$x \in A$?

4.5 Combinatorics

Function	Description
`factorial(x)`	Returns $x!$ (number of permutations).
`choose(n, k)`	Binomial coefficient, i.e. $\binom{n}{k}$.
`combn(x, m)`	Generates all combinations with **m** objects of the elements in **x**.
`sample(x, size, replace)`	Randomly selects elements.

4.6 Basic Descriptive Statistics

Functions

Function	Description
`mean(x)`	Arithmetic mean.
`median(x)`	Median.
`sd(x)`	Standard deviation.
`var(x)`	Variance.
`fivenum(x)`	Tukey's five number statistics.
`min(x)`	Minimum.
`max(x)`	Maximum.
`quantile(x, probs)`	Quantiles. Use `type=2` to get the same results as from `fivenum` for quartiles.
`cor(x)`	Correlation.
`cov(x)`	Covariance.

Examples

```
set.seed(789); x <- rnorm(15)
x[1:4]
```

```
[1]  0.52409671 -2.26076788 -0.01967972  0.18313989
```

```
fivenum(x)
```

```
[1] -2.26076788 -0.57710626 -0.36135148  0.08173009  0.92790739
```

```
quantile(x, probs=seq(0, 1, 0.2))
```

```
        0%        20%        40%        60%        80%       100% 
-2.2607679 -0.7336064 -0.4351714 -0.1764192  0.2513313  0.9279074 
```

4.7 Probability Distributions

All functions dealing with probability distributions always consist of a prefix (`d`, `p`, `q` or `r`) plus the (abbreviated) name of the distribution (e.g. `norm`, `unif`, `chisq`, etc.).

Example 1

We want to draw five numbers from a χ^2 distribution with 3 degrees of freedom:

```
set.seed(123); rchisq(n=5, df=3)
```

```
[1] 1.03611518 5.08870916 0.04818784 2.26693313 6.90085393
```

Example 2

If the height of male students follows a normal distribution with $\mu = 174$ cm and $\sigma = 7$ cm, what percentage is taller than 180 cm? (Solution: ≈ 19.57 %)

```
pnorm(180, mean=174, sd=7, lower.tail=FALSE)
```

```
[1] 0.195683
```

4.8 Notes on Missing Values

Missing Values

- The function `is.na(x)` returns `TRUE` for missing and `FALSE` for non-missing values in a vector **x**. Therefore you can easily count the missing values by using `is.na` and the function `sum`.
- Other comparison operators (`==`, `!=`) can **not** be used to detect missing values (Comparisons involving missing values always return `NA`).
- The function `length` counts **all** values in a vector (regardless of their "missing status").
- Functions such as `mean` or `sd` fail (return `NA`) whenever there is at least one value missing - unless you specify `na.rm=TRUE` in the function call.
- The `table` command (which creates a frequency table) by default will **ignore** missing values unless you specify `useNA="always"` or `useNA="ifany"` in the function call.
- Sometimes missing values are coded as **999** (or similar) in your data. You can replace them using the `which` command.

Example

```
# weight... weight of students in kilos, 999 means "missing" here.
weight <- c(79, 88, 59, 999, 91, 60)
mean(weight)
```

```
[1] 229.3333
```

Replace **999** by `NA`

```
weight[which(weight==999)] <- NA
weight
```

```
[1] 79 88 59 NA 91 60
```

```
mean(weight)
```

```
[1] NA
```

```
mean(weight, na.rm=TRUE)
```

```
[1] 75.4
```

5 Groupwise Descriptive Statistics

5.1 Properties of the Function `doBy::summaryBy`

1. Install the package `doBy`
2. We will use the function `summaryBy` to create summary tables that contain exactly the information which we want to see.

Syntax of `doBy::summaryBy`
`doBy::summaryBy(var(s) ~ groupvar(s), data=..., FUN=...)`

Notes:

- If there are more variables in the “formula”, use + to separate them.
- It is possible to use built-in functions as well as your own functions.
- The function `length` applied to **any** column of your data counts the observations.
- If there are more functions to apply groupwise to your `data.frame`, pack the function names in a list, i.e. `FUN=list(fun1, fun2, ...)`.
- The function `doBy::summaryBy` returns a handy `data.frame`!

5.2 Examples

Creating Sample Data

```
set.seed(123)
group <- rep(c("A","B"), 30)
treatment <- rep(c("group1", "group2", "group3"), 10)
values <- rchisq(30, df=5)
mydata <- data.frame(group, treatment, values)
print(head(mydata,5))
```

```
  group treatment     values
1     A    group1  2.5718020
2     B    group2  8.0747086
3     A    group3  0.6485141
4     B    group1  4.3740386
5     A    group2 10.3216603
```

Example 1

Average of *values* by *treatment*:

```
summary1 <- doBy::summaryBy(values ~ treatment,
data=mydata, FUN=mean)
print(summary1)
```

```
  treatment values.mean
1     group1    3.207749
2     group2    5.004441
3     group3    4.296330
```

Example 2

Minimum, maximum and a frequency count of *values* by *treatment* and *group*:

```
summary2 <- doBy::summaryBy(values ~ treatment + group,
 data=mydata, FUN=list(min, max, length))
# change name of last column in summary table:
names(summary2)[5] <- "N"
print(summary2)
```

```
  treatment group values.min values.max  N
1     group1     A  1.2220565   3.208945 10
2     group1     B  1.3825887   6.184881 10
3     group2     A  1.4285405  10.321660 10
4     group2     B  0.6062728   8.500349 10
5     group3     A  0.6485141   8.211414 10
6     group3     B  3.1459618   5.409890 10
```

6 Graphs

6.1 Create Sample Data

```
x1 <- rep(c("A","B"), 50)
set.seed(111)
x2 <- sample(c("U","V","W"), 100, replace=TRUE)
set.seed(345)
x3 <- rnorm(100, 100, 15)
set.seed(567)
x4 <- rchisq(100, 3)
X <- data.frame(x1, x2, x3, x4)
head(X,3)
```

```
  x1 x2       x3        x4
1  A  V 88.22638 3.5291558
2  B  W 95.80728 2.7358626
3  A  W 97.57813 0.9237687
```

6.2 Colours

Here are some ways to specify colors in your plot:

1. Colour name (use `colours()` to display all available colors)
2. As an RGB or HEX value.
3. Using colour palettes from external libraries.

6.3 Saving Graphs to a File

```
pdf("filename.pdf") # or png(...), jpeg(...), ...
# graphics commands here
dev.off()
```

If you want to save output from a statistical procedure, you can use

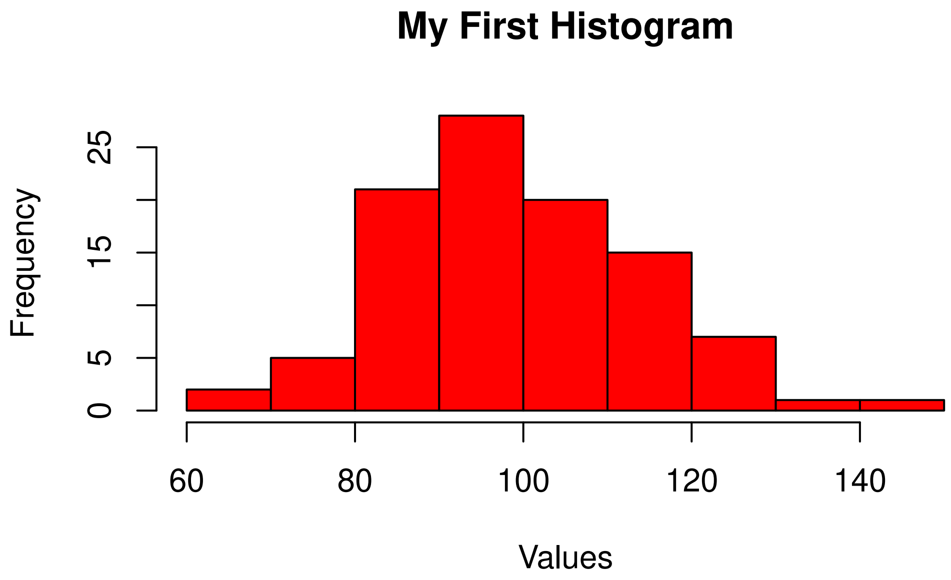
```
sink("filename.txt")
# ...statistics...
sink()
```

6.4 Example: Histogram

```
head(X, 3)
```

```
  x1 x2       x3        x4
1  A  V 88.22638 3.5291558
2  B  W 95.80728 2.7358626
3  A  W 97.57813 0.9237687
```

```
hist(X$x3, col=rgb(1,0,0), main="My First Histogram", xlab="Values")
```

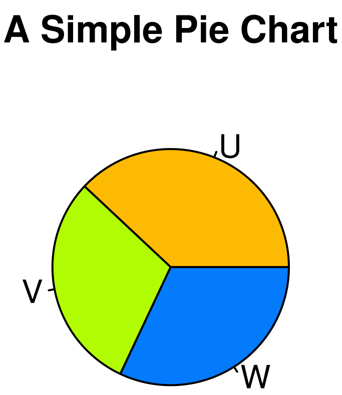


6.5 Example: Pie Chart

```
head(X, 3)
```

```
  x1 x2       x3        x4
1  A  V 88.22638 3.5291558
2  B  W 95.80728 2.7358626
3  A  W 97.57813 0.9237687
```

```
mytab <- table(X$x2) # Create frequency table first!
pie(mytab, col=c("#fcba03", "#b1fc03", "#037bfc"),
main="A Simple Pie Chart")
```

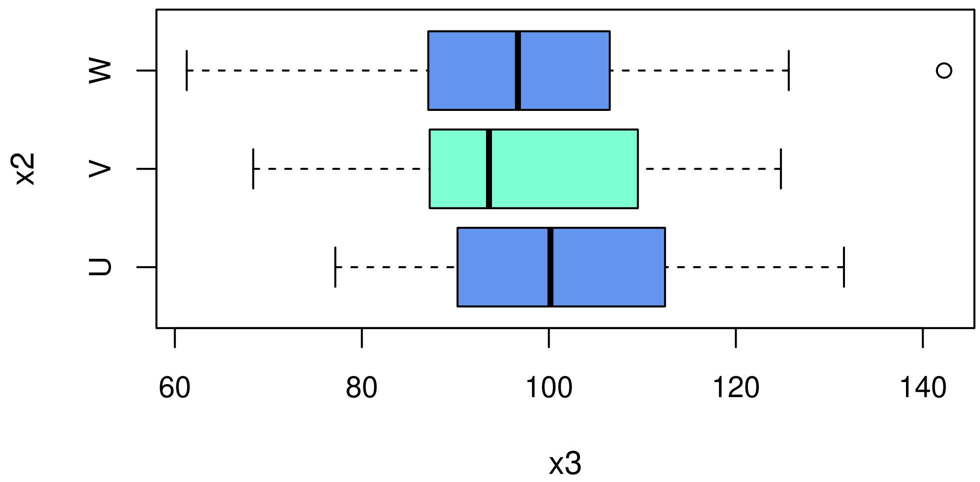


6.6 Example: Grouped Boxplot

```
head(X, 3)
```

```
  x1 x2       x3        x4
1  A  V 88.22638 3.5291558
2  B  W 95.80728 2.7358626
3  A  W 97.57813 0.9237687
```

```
boxplot(x3 ~ x2, data=X, horizontal=TRUE,
col = c("cornflowerblue", "aquamarine"), cex.axis=0.9)
```



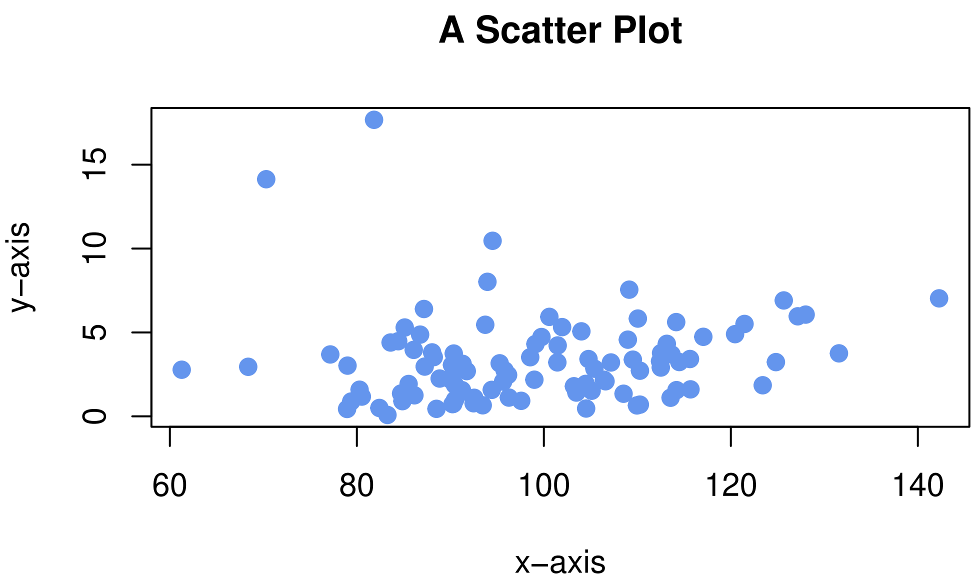
Note that we have three categories but we only passed a vector with two different colours. In this case, the vector is “recycled” here.

6.7 Example: Scatter Plot

```
head(X, 3)
```

```
  x1 x2       x3        x4
1  A  V 88.22638 3.5291558
2  B  W 95.80728 2.7358626
3  A  W 97.57813 0.9237687
```

```
plot(X$x3, X$x4, col="cornflowerblue", lwd=2, pch=19, xlab="x-axis",
 ylab="y-axis", main="A Scatter Plot")
```

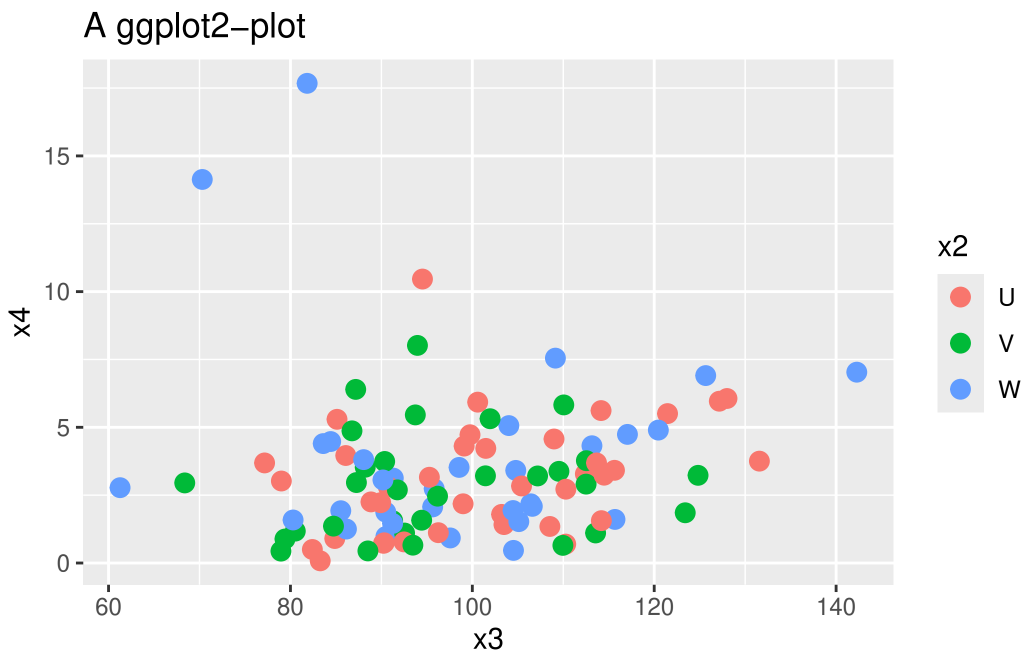


6.8 Example: Scatter Plot - `ggplot2`

```
head(X, 3)
```

```
  x1 x2       x3        x4
1  A  V 88.22638 3.5291558
2  B  W 95.80728 2.7358626
3  A  W 97.57813 0.9237687
```

```
library(ggplot2)
plt <-  ggplot(X, aes(x=x3, y=x4, color=x2))
plt <- plt + geom_point(size=3)
plt <- plt + ggtitle("A ggplot2-plot")
plt
```



7 Summarizing Data Using `summarytools`

7.1 Create Sample Data

```r
x1 <- rep(c("A","B"), 50)
set.seed(111)
x2 <- sample(c("U","V","W"), 100, replace=TRUE)
set.seed(345)
x3 <- rnorm(100, 100, 15)
set.seed(567)
x4 <- rchisq(100, 3)
X <- data.frame(x1, x2, x3, x4)
head(X,3)
```

```
  x1 x2       x3        x4
1  A  V 88.22638 3.5291558
2  B  W 95.80728 2.7358626
3  A  W 97.57813 0.9237687
```

7.2 Example: summarytools::descr()

```
summarytools::descr(X)
```

```
Non-numerical variable(s) ignored: x1, x2

Descriptive Statistics
X
N: 100

                         x3       x4
----------------- -------- --------
             Mean    98.86     3.33
          Std.Dev    14.73     2.67
              Min    61.27     0.08
               Q1    88.37     1.54
           Median    96.22     2.96
               Q3   109.74     4.36
              Max   142.27    17.67
              MAD    15.08     2.10
              IQR    21.19     2.79
               CV     0.15     0.80
         Skewness     0.29     2.41
      SE.Skewness     0.24     0.24
         Kurtosis    -0.07     9.03
          N.Valid   100.00   100.00
        Pct.Valid   100.00   100.00
```

7.3 Example: summarytools::dfSummary()

```
summarytools::dfSummary(X, varnumbers=FALSE, valid.col=FALSE)
```

```
Data Frame Summary
X
Dimensions: 100 x 4
Duplicates: 0

-------------------------------------------------------------------------------------
Variable       Stats / Values             Freqs (% of Valid)    Graph          Missing
-------------- -------------------------- --------------------- -------------- ---------
x1             1. A                        50 (50.0%)            IIIIIIIIII      0
[character]    2. B                        50 (50.0%)            IIIIIIIIII      (0.0%)

x2             1. U                        38 (38.0%)            IIIIIII         0
[character]    2. V                        30 (30.0%)            IIIIII          (0.0%)
               3. W                        32 (32.0%)            IIIIII

x3             Mean (sd) : 98.9 (14.7)     100 distinct values         :         0
[numeric]      min < med < max:                                      : : .       (0.0%)
               61.3 < 96.2 < 142.3                                    : : : .
               IQR (CV) : 21.2 (0.1)                                  : : : :
                                                                  . : : : : : :

x4             Mean (sd) : 3.3 (2.7)       100 distinct values   . :             0
[numeric]      min < med < max:                                 : :              (0.0%)
               0.1 < 3 < 17.7                                    : : .
               IQR (CV) : 2.8 (0.8)                              : : :
                                                                 : : : .
-------------------------------------------------------------------------------------
```

7.4 Example: summarytools::ctable()

```
summarytools::ctable(x = X$x1, y = X$x2)
```

```
Cross-Tabulation, Row Proportions
x1 * x2
Data Frame: X

------- ---- ------------ ------------ ------------ --------------
          x2            U            V            W          Total
     x1
      A          22 (44.0%)   15 (30.0%)   13 (26.0%)    50 (100.0%)
      B          16 (32.0%)   15 (30.0%)   19 (38.0%)    50 (100.0%)
  Total          38 (38.0%)   30 (30.0%)   32 (32.0%)   100 (100.0%)
------- ---- ------------ ------------ ------------ --------------
```

7.5 Example: summarytools::freq()

```
summarytools::freq(X$x1)
```

```
Frequencies
X$x1
Type: Character

              Freq   % Valid   % Valid Cum.   % Total   % Total Cum.
----------- ------ --------- -------------- --------- --------------
          A     50     50.00          50.00     50.00          50.00
          B     50     50.00         100.00     50.00         100.00
       <NA>      0                               0.00         100.00
      Total    100    100.00         100.00    100.00         100.00
```

8 Functions and Control Flow by Example

8.1 Loops with for

```
for (i in 1:3)
        {
                print("Hello")
        }
```

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

8.2 Loops with repeat

```
n <- 1
repeat
{
  print(n)
  if (n >= 5)
    {
    break
    }
n <- n + 1
}
```

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

8.3 Loops with `repeat` and `break`

```
n <- 1
repeat {

  if (n == 3) {
    n <- n + 1
    next
  }
  print(n)


  if (n >= 5) {
    break
  }

 n <- n + 1
}
```

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

8.4 Loops with `while`

```
i <- 1
while (i <= 3)
        {
                print("Hello")
                i <- i + 1
        }
```

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

8.5 Conditional Execution - Two Branches

```
x <- 2
if (x == 1) {
  print("x is one")
} else {
  print("x is something else")
}
```

```
[1] "x is something else"
```

8.6 Conditional Execution - More Branches

```r
x <- 2
if (x == 1) {
  print("x is one")
} else if (x == 2) {
  print("x is two")
} else if (x == 3) {
  print("x is three")
} else {
  print("hm...")
}
```

```
[1] "x is two"
```

8.7 Conditional Execution - Using switch

```r
x <- 2

message <- switch(x,
                  "Value equals 1",
                  "Value equals 2",
                  "Value equals 3",
                  "Value is something else"
                  )

cat(message)
```

```
Value equals 2
```

8.8 Functions

```r
squareandroundme <- function(x)
{
        result <- x * x
        result <- round(result, 1)
        return(result)
}

test <- squareandroundme(7.123)
test
```

```
[1] 50.7
```

9 Recommended Reading

- Kabacoff, R. (2011). *R in Action. Data Analysis and Graphics with R.* Shelter Island: Manning Publications.
- Ligges, U. (2008). *Programmieren mit R.* (3. Auflage). Berlin/Heidelberg: Springer.
- Sauer, S. (2019). *Moderne Datenanalyse mit R: Daten einlesen, aufbereiten, visualisieren, modellieren und kommunizieren.* Wiesbaden: Springer.
- Wickham, H., Grolemund, G. (2016). R for Data Science. Import, tidy, transform, visualize and model data. Sebastopol: O'Reilly Media.