Introduction to R

Basics, *Tidyverse* and spatial data

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Outline

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- Base-R plotting
- *Tidyverse*
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  - Intro to *ggplot2*
- Spatial data
  - Rasters
  - Vectors
  - Plotting

Course details

- You can opt for a certificate of participation
- Requisites:
    - Assist to all lessons (sign attendance sheet daily)
        - Absence justified only with *sick certificate* or major issue
    - Do all exercises and final presentation
        - You can work in couples

Background DQ

- Studied Civil Engineering at the University of Costa Rica
  - Worked for 3 years as hydrologist and hydraulic engineer for hydropower projects
- *Hydroscience and Engineering* masters at the *TU Dresden*
  - Master thesis dealt with *statistical downscaling* of CMIP5 projections for Costa Rica using machine learning (paper)
- Doctoral candidate since 2020, *ESF* scholarship

PhD project DQ

Working title:

Potential species trajectories under climate change in low mountain ranges (Ore Mountains)

1. Statistical downscaling of local variables with Deep Learning (DL, paper)
   - ERA5 dataset as predictors
   - Observations: REKIS gridded daily data, 1 km resolution (1961 — 2015)
   - Focus on precipitation → *extreme events*
2. Use CMIP5 — EURO-CORDEX model output to obtain an ensemble of downscaled climate projections (2005 — 2100)
3. Implement the generated high-resolution climate data in *Species Distribution Models* (SDMs) for the Ore Mountains
   - Focus on endangered plant species of the region

Background AH

- Studied Civil Engineering at the University of Khartoum, Sudan
  - Have three years experience in working as *Irrigation Engineer* at the Sudanese Federal Ministry of Water resources, *Resident Engineer* in the Construction Sector (Sudan), and *Teaching Assistant* in many sudanese universities
- *Hydroscience and Engineering* masters at the *TU Dresden*
  - Master thesis theme: Objective Identification and Characterization of Double ITCZ in CMIP5 Models and its Effects on Regional Climate Models. (preprint)
- Research Assistant & PhD Student since October 2021

PhD project AH

Working title:

Convective Precipitation Systems on the Arabian Peninsula: Current Situation and Future Trends

1. Identification and Description of Precipitation systems using Object Based Methods (OBM) and Tracking algorithm
    - GPM dataset as input
2. Linkage of Meso- to Synoptic-Scale Predictors to precipitation Regimes
    - ERA5 dataset to obtain predictors (i.e. atmospheric conditions) concurrent to precipitation systems
3. Dynamically downscale CMIP6 models output to obtain convective resolved precipitation projections (i.e. 1 km)
    - The WRF will be used for downscaling, and OBM will applied to its output to communicate uncertainties

Your turn!

- Background
- Programming experience?
- Expectations of this course

Prerequisites

1. Install R, version *4.x*:
   - Download from https://cloud.r-project.org/
   - I encountered package compatibility issues with *v4.2* some months ago, if persistent, install *v4.1.3* from here (Windows)
2. Install RStudio
   - Download from here
3. *Swirl* exercises

Reserved words

- There are some words that have a special meaning in R:

if	else	repeat	while	function
for	in	next	break	TRUE
FALSE	NULL	Inf	NaN	NA
NA_integer_	NA_real_	NA_complex_	NA_character_	…

Variables and constants

- Variables are used to store data, which can be changed afterwards
- The name given to a variable is known as *identifier*
- Rules for *identifiers*:
    - Can be a combination of letters, digits, period (`.`) and underscore (`_`)
    - Needs to start with a letter or period
        - If starts with period, can not be followed by a digit, e.g. `.4var`
    - *Reserved words* can not be used as *identifiers*
- *Constants* can not be modified, like *numbers* and *strings*

Basic data types

Everything in is an ***object***

This basic data types are also known as *atomic classes*

is *case sensitive*

- **Logical**
  - TRUE, FALSE
- **Numeric**
  - 3, 1.5, pi
  - Real or decimal, *floating numbers*
  - Also known as *double*
- **Integer**
  - 2L, 11L
  - Note the ***L***
- **Complex**
  - 1+2i, 4+7i
- **Characters**
  - "A", 'climate', "38.89", 'FALSE'
  - Note that either *single* or *double* quotes surround the desired *string*
- **Raw**
  - Hexadecimal representation of data

Checking the data types

```r
y <- TRUE
class(y) # Function to ask: What is it?
[1] "logical"

x <- pi/2
typeof(x) # Similar
[1] "double"

z <- 3L
storage.mode(z) # Also!
[1] "integer"

str(z) # Structure!
 int 3
```

```r
u <- 1 + 2i
class(u)
[1] "complex"

v <- "Corcovado"
typeof(v)
[1] "character"

w <- charToRaw("Learning R")
print(w)
[1] 4c 65 61 72 6e 69 6e 67 20 52

storage.mode(w)
[1] "raw"
```

Data structures

- **Vectors**
  - Most basic data object
  - Collection of *atomic elements*
  - Two types:
    - Atomic vector
    - List
- **Lists**
  - *Universal* container
  - Unlike vectors, not restricted to be of a single *type*
- **Matrices**
  - Two-dimensional layout of elements of the **same** type
- **Arrays**
  - Can contain data of more than two dimensions
  - Just one *atomic* type
  - Contigous memory allocation
- **Data frames**
  - Two-dimensional structure
  - Columns contain the value of one variable
  - Rows contain the values of each column
- **Factors**
  - Used to categorize data and store it as levels
  - Can be *strings* and *integers*

Operators

Arithmetic

Operator	Description
+	Addition
–	Subtraction
*	Multiplication
/	Division
^ or **	Exponent
%%	Modulus (Remainder From division)
%/%	Integer Division

Relational

Operator	Description
<	Less than
>	Greater than
<=	Less than or equal to
>=	Greater than or equal to
==	Equal to
!=	Not equal to

Assignment

Operator	Description
<-, <<-, =	Leftwards assignment
->, ->>	Rightwards assignment

Logical

Operator	Description
!	Logical NOT
&	Element-wise logical AND
&&	Logical AND
|	Element-wise logical OR
||	Logical OR

Testing the operators

```
x <- 2
y <- 7
x+y
[1] 9
x-y
[1] -5
x*y
[1] 14
x/y
[1] 0.2857143
x%/%y
[1] 0
x%%y
[1] 2
x^y
[1] 128
```

```
x <- 2
y <- 7
x<y
[1] TRUE
x>y
[1] FALSE
x>=35
[1] FALSE
x<=35
[1] TRUE
y==10
[1] FALSE
x!=y
[1] TRUE
y!=10
[1] TRUE
```

```
a <- c(TRUE,TRUE,FALSE,0,6,7)
b <- c(FALSE,TRUE,FALSE,TRUE,TRUE,TRUE)
a&b
[1] FALSE  TRUE FALSE FALSE  TRUE  TRUE
a&&b
[1] FALSE
a|b
[1]  TRUE  TRUE FALSE  TRUE  TRUE  TRUE
a||b
[1] TRUE
!a
[1] FALSE FALSE  TRUE  TRUE FALSE FALSE
!b
[1]  TRUE FALSE  TRUE FALSE FALSE FALSE
```

Functions

- There are thousands of functions implemented on base-R, e.g.:
  - `sin(pi/2)`, `log(x)`, `max(y)`, `min(z)`
- Functions have the following structure:
  - `function ( argument list ) {body}`
  - Note the parentheses types above
- When the functions have several arguments, they should be given in the predefined order
- Or, provide them with the corresponding names:
  - `plot(1:6, c(5,1,3, 4, 3, 6), type = "l", col = "blue")`
- Users can define functions:

```
sum_squares <- function(x) {
    return(sum(x**2))
}
z <- 1:5
sum_squares(z)
[1] 55
```

Other useful base functions

- `abs` → Compute the absolute value of a numeric data object
- `attributes` → Return or set all attributes of a data object
- `c` → Combine values into a vector or list
- `cat` → Return character string in readable format
- `cbind` → Combine vectors, matrices and/or data frames by column
- `ceiling` → Round numeric up to the next higher integer
- `do.call` → Execute function by its name and a list of corresponding arguments
- `floor` → Round numeric down to the next lower integer
- `gc` → Collect garbage to clean up memory
- `hist` → Create histogram
- `lapply` → Apply function to all list elements
- `ls` → List all variables in the environment
- `ncol` → Return the number of columns of a matrix or data frame
- `print` → Return data object to the console
- `rbind` → Combine vectors, matrices and/or data frames by row
- `rm` → Clear specific data object from R workspace
- `rep` → Replicate elements of vectors and lists
- `sd` → Compute standard deviation
- `setwd` → Change the current working directory
- `t` → Transpose data frame
- `var` → Compute sample variance

Function’s help

- There is a comprehensive pre-built help system
- To access it, try the following from the command prompt:

```
help.start()    # general help
help(foo)       # help about function foo
?foo            # same thing
apropos("foo") # list all functions containing string foo
example(foo)    # show an example of function foo
```

Using libraries

- `install.packages("tidyverse")` → install new libraries
    - *tidyverse* is very useful, will come back to it later
- `library(tidyverse)` → loads the package into the active session
    - Installing the libraries is not enough to use the functions they contain
- `dplyr::select` → use the `select` function from `dplyr` without loading the whole library

> The form `library::function` is considered good practice, particularly when several libraries have the same function name (avoids conflicts)

Vectors

- Several ways of creating vectors:

```
c("a","B","c")
[1] "a" "B" "c"

1:8 # Creates consecutive integers
[1] 1 2 3 4 5 6 7 8

seq(1, 3, by=0.5) # Increment given
[1] 1.0 1.5 2.0 2.5 3.0

rep(1:2, times=3)
[1] 1 2 1 2 1 2

rep(1:2, each=3) # Notice the difference from the previous
[1] 1 1 1 2 2 2

vector(mode = "raw", length = 5)
[1] 00 00 00 00 00
```

- They all can of course be saved into a variable…

Selecting vector elements

```r
x <- c(-5, -2, 1, 3:6, 8, 10)
x
[1] -5 -2  1  3  4  5  6  8 10

x[5] # Access the fifth element
[1] 4

x[-3] # All but the third
[1] -5 -2  3  4  5  6  8 10

x[2:4] # Elements two to four
[1] -2  1  3

x[-(2:4)] # All elements but two to four
[1] -5  4  5  6  8 10
```

```r
x[c(2,5)] # Elements two and five
[1] -2  4

x[x == 10] # Elements equal to 10
[1] 10

x[x < 0] # Elements less than zero
[1] -5 -2

x[x >= 3] # Elements greater or equal than three
[1]  3  4  5  6  8 10

x[x %in% c(1,2,5)] # Elements in the set 1,2,5
[1] 1 5
```

Matrices

```
y <- matrix(1:16, nrow = 4, byrow = FALSE)
# byrow = FALSE is the default
y
     [,1] [,2] [,3] [,4]
[1,]    1    5    9   13
[2,]    2    6   10   14
[3,]    3    7   11   15
[4,]    4    8   12   16

y <- matrix(1:16, nrow = 4, byrow = TRUE)
# Note how it changes the order
y
     [,1] [,2] [,3] [,4]
[1,]    1    2    3    4
[2,]    5    6    7    8
[3,]    9   10   11   12
[4,]   13   14   15   16

class(y)
[1] "matrix" "array"
typeof(y)
[1] "integer"
dim(y) # Show the dimensions of the object
[1] 4 4
```

```
# Binding vectors also creates matrices
z <- cbind(c("A", "B", "C"), c("a", "b", "c"))
class(z)
[1] "matrix" "array"

typeof(z)
[1] "character"

dim(z)
[1] 3 2

# Recycling of elements
x <- matrix(c(TRUE, FALSE), nrow = 3, ncol = 2)
x
      [,1]  [,2]
[1,]  TRUE FALSE
[2,] FALSE  TRUE
[3,]  TRUE FALSE

typeof(x)
[1] "logical"
```

Matrices elements

```
y <- matrix(1:24, nrow = 4, byrow = TRUE)
y[2,] # Access the second row
[1]  7  8  9 10 11 12

y[,4] # Access the fourth column
[1]  4 10 16 22

y[3,5] # Element on the third row and fifth column
[1] 17

y[2:3, 4:5] # Elements between the second and third row
# and the fourth and fifth column
     [,1] [,2]
[1,]   10   11
[2,]   16   17

y[4:1,] # Change the order of the rows
     [,1] [,2] [,3] [,4] [,5] [,6]
[1,]   19   20   21   22   23   24
[2,]   13   14   15   16   17   18
[3,]    7    8    9   10   11   12
[4,]    1    2    3    4    5    6
```

```
z <- matrix(1:24, nrow = 5, byrow = FALSE)
Warning message:
In matrix(1:24, nrow = 5, byrow = FALSE) :
  data length [24] is not a sub-multiple or
  multiple of the number of rows [5]

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

z[5,5] <- 25 # Modify element

z[21:25] # Access also as if it was a vector
[1] 21 22 23 24 25
```

Arrays

```
v <- array(1:24, dim = c(4,3,2))
v # Ordered column-wise
, , 1

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

, , 2

     [,1] [,2] [,3]
[1,]   13   17   21
[2,]   14   18   22
[3,]   15   19   23
[4,]   16   20   24

class(v)
[1] "array"

typeof(v)
[1] "integer"
```

```
dim(v)
[1] 4 3 2

str(v)
 int [1:4, 1:3, 1:2] 1 2 3 4 5 6 7 8 9 10 ...

v[2,3,2] # Access single element
[1] 22

v[, 2, 1] # Access second column of first layer
[1] 5 6 7 8

v[4, ,2] # Access fourth row of second layer
[1] 16 20 24

v[3,,] # Access third row of all the layers
     [,1] [,2]
[1,]    3   15
[2,]    7   19
[3,]   11   23
```

Dataframes

- A dataframe is a two-dimensional structure
- The columns should be named
- Row names, if existent, should be unique
- Data can be *numeric*, *factors* or *strings*
- Several ways to create a *dataframe*

data.frame function

```
df <- data.frame(id = c(1:5),
                 Names = c("Nick", "Dan", "Lis", "Kate", "Jose"),
                 Salary = c(1900, 1750, 2100, 2500, 2100),
                 start_date = as.Date(c("2012-01-01","2013-09-23","2014-11-15",
                 "2014-05-11","2015-03-27")))
str(df) # Notice the different types
'data.frame':	5 obs. of  4 variables:
 $ id        : int  1 2 3 4 5
 $ Names     : chr  "Nick" "Dan" "Lis" "Kate" ...
 $ Salary    : num  1900 1750 2100 2500 2100
 $ start_date: Date, format: "2012-01-01" "2013-09-23" "2014-11-15" "2014-05-11" ...

print(summary(df)) # summary function calculates some statistics
       id       Names                Salary        start_date        
 Min.   :1   Length:5           Min.   :1750   Min.   :2012-01-01  
 1st Qu.:2   Class :character   1st Qu.:1900   1st Qu.:2013-09-23  
 Median :3   Mode  :character   Median :2100   Median :2014-05-11  
 Mean   :3                      Mean   :2070   Mean   :2014-01-14  
 3rd Qu.:4                      3rd Qu.:2100   3rd Qu.:2014-11-15  
 Max.   :5                      Max.   :2500   Max.   :2015-03-27  
```

From vectors

```
df1 <- cbind(id, Names, Salary, start_date)
str(df1)
# Note that its coerced as all strings

 chr [1:5, 1:4] "1" "2" "3" "4" "5" "Nick" "Dan" "Lis" "Kate" "Jose" "1900" "1750" "2100" "2500" "2100" ...
 - attr(*, "dimnames")=List of 2
  ..$ : NULL
  ..$ : chr [1:4] "id" "Names" "Salary" "start_date"

df2 <- cbind.data.frame(id, Names, Salary, start_date)
str(df2)
# Now is ok!
'data.frame':|5 obs. of  4 variables:
 $ id        : int  1 2 3 4 5
 $ Names     : chr  "Nick" "Dan" "Lis" "Kate" ...
 $ Salary    : num  1900 1750 2100 2500 2100
 $ start_date: Date, format: "2012-01-01" "2013-09-23" "2014-11-15" "2014-05-11" ...
```

Adding data

```
df$dept <- c("IT","Operations","IT","HR","Finance") # Add additional columns
df
  id Names Salary start_date       dept
1  1  Nick   1900 2012-01-01         IT
2  2   Dan   1750 2013-09-23 Operations
3  3   Lis   2100 2014-11-15         IT
4  4  Kate   2500 2014-05-11         HR
5  5  Jose   2100 2015-03-27    Finance

new.employee <- data.frame(id= 6, Names= "Ana", Salary=2300,
                           start_date = as.Date("2016-05-01"),
                           dept = "IT")
# Note that the column names should match
df <- rbind(df, new.employee)
print(df)
  id Names Salary start_date       dept
1  1  Nick   1900 2012-01-01         IT
2  2   Dan   1750 2013-09-23 Operations
3  3   Lis   2100 2014-11-15         IT
4  4  Kate   2500 2014-05-11         HR
5  5  Jose   2100 2015-03-27    Finance
6  6   Ana   2300 2016-05-01         IT
7  6   Ana   2300 2016-05-01         IT
```

Column names need to match!

```
#Note ID instead of id

new.employee <- data.frame(ID= 6, Names= "Ana", Salary=2300,
                           start_date = as.Date("2016-05-01"),
                           dept = "IT")
df <- rbind(df, new.employee)

Error in match.names(clabs, names(xi)) :
  names do not match previous names

# Also, subsetting according to a value:
subset(df, dept=="IT")
  id Names Salary start_date dept
1  1  Nick   1900 2012-01-01   IT
3  3   Lis   2100 2014-11-15   IT
```

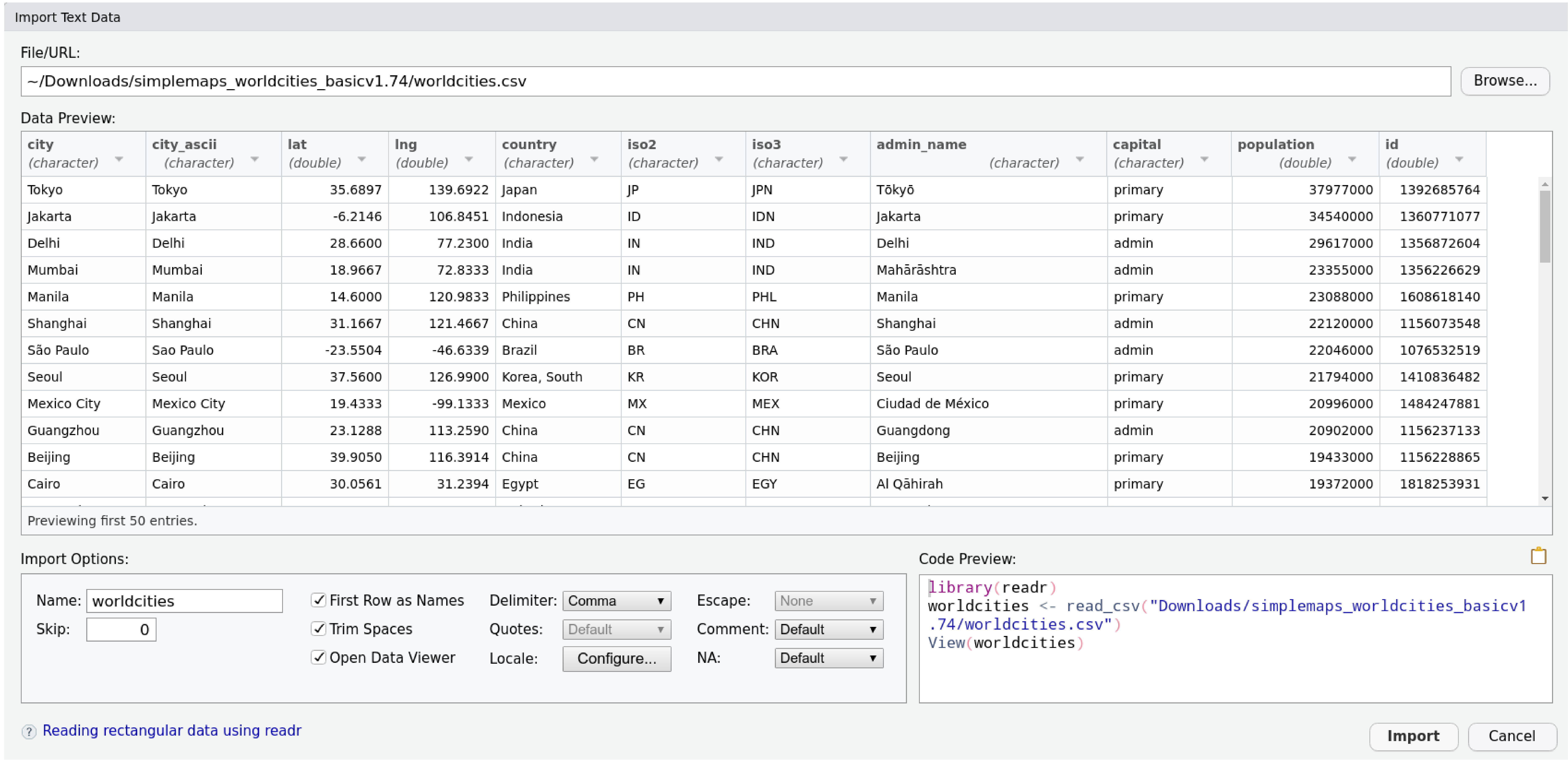
Load csv file

- Download and unzip this file to a desired *path*

```
cities <- read.csv(file = "/home/dqc/Downloads/simplemaps_worldcities_basicv1.74/worldcities.csv",
                   header = TRUE, sep = ",", dec = ".") # Change path accordingly!
# Note that the delimiters and decimal separator can be changed
nrow(cities)
[1] 41001

head(cities) # head() prints only the first 6 rows
      city city_ascii     lat      lng     country iso2 iso3  admin_name capital population         id
1    Tokyo      Tokyo 35.6897 139.6922       Japan   JP  JPN       Tōkyō primary   37977000 1392685764
2  Jakarta    Jakarta -6.2146 106.8451   Indonesia   ID  IDN     Jakarta primary   34540000 1360771077
3    Delhi      Delhi 28.6600  77.2300       India   IN  IND       Delhi   admin   29617000 1356872604
4   Mumbai     Mumbai 18.9667  72.8333       India   IN  IND Mahārāshtra   admin   23355000 1356226629
5   Manila     Manila 14.6000 120.9833 Philippines   PH  PHL      Manila primary   23088000 1608618140
6 Shanghai   Shanghai 31.1667 121.4667       China   CN  CHN    Shanghai   admin   22120000 1156073548

tail(cities, 2) # tail() the last 6, but can be changed
             city  city_ascii     lat      lng   country iso2 iso3         admin_name capital population
41000 Timmiarmiut Timmiarmiut 62.5333 -42.2167 Greenland   GL  GRL           Kujalleq                10
41001     Nordvik     Nordvik 74.0165 111.5100    Russia   RU  RUS Krasnoyarskiy Kray                 0
              id
41000 1304206491
41001 1643587468
```

Other ways of importing

- *File* → *Import dataset* → *From text*
  - *(base)* → same as before but with visual help
  - *(readr)* → using the *readr* library



Factors

- *Factors* categorize the data and store it as levels
- Use strings and integers
- Will prove very useful with *tidyverse* and plotting with *ggplot2*

```
data <- c("East","West","East","North","North","East","West","West","West","East","North")
print(data)
 [1] "East"  "West"  "East"  "North" "North" "East"  "West"  "West"  "West"  "East"  "North"

print(is.factor(data))
[1] FALSE

factor_data <- factor(data) # Change the data to factors
print(factor_data)
 [1] East  West  East  North North East  West  West  West  East  North
Levels: East North West

print(is.factor(factor_data))
[1] TRUE
```

Factors in data frames

```
height <- c(132,151,162,139,166,147,122)
weight <- c(48,49,66,53,67,52,40)
gender <- c("male","male","female","female","male","female","male")

input_data <- data.frame(height,weight,gender, stringsAsFactors = TRUE) # Create DF
# Note stringsAsFactors, changed to default FALSE from R 4.0

print(is.factor(input_data$gender))
[1] TRUE

print(input_data$gender)
[1] male   male   female female male   female male
Levels: female male

str(input_data)
'data.frame':	7 obs. of  3 variables:
 $ height: num  132 151 162 139 166 147 122
 $ weight: num  48 49 66 53 67 52 40
 $ gender: Factor w/ 2 levels "female","male": 2 2 1 1 2 1 2
```

Change order of factors

```
data <- c("East","West","East","North","North","East","West",
          "West","West","East","North")
factor_data <- factor(data)
print(factor_data)
 [1] East  West  East  North North East  West  West  West  East  North
Levels: East North West

new_order_data <- factor(factor_data,levels = c("East","West","North"))
print(new_order_data)
 [1] East  West  East  North North East  West  West  West  East  North
Levels: East West North
```

Lists

- Universal container → Can contain every other structure type

```
list_data <- list("Red", "Green", c(21,32,11),
                  TRUE, 51.23, 119.1)
print(list_data)
[[1]]
[1] "Red"
[[2]]
[1] "Green"
[[3]]
[1] 21 32 11
[[4]]
[1] TRUE
[[5]]
[1] 51.23
[[6]]
[1] 119.1
str(list_data)
List of 6
 $ : chr "Red"
 $ : chr "Green"
 $ : num [1:3] 21 32 11
 $ : logi TRUE
 $ : num 51.2
 $ : num 119
```

```
list_data <- list(c("Jan","Feb","Mar"),
             matrix(c(3,9,5,1,-2,8), nrow = 2),
             list("green",12.3))
str(list_data)
List of 3
 $ : chr [1:3] "Jan" "Feb" "Mar"
 $ : num [1:2, 1:3] 3 9 5 1 -2 8
 $ :List of 2
  ..$ : chr "green"
  ..$ : num 12.3

names(list_data) <- c("1st Quarter", "Matrix", "Random")
str(list_data)
List of 3
 $ 1st Quarter: chr [1:3] "Jan" "Feb" "Mar"
 $ Matrix     : num [1:2, 1:3] 3 9 5 1 -2 8
 $ Other list :List of 2
  ..$ : chr "green"
  ..$ : num 12.3
```

Lists II

```
list1 <- list(w=matrix(12:1, nrow = 4), x=c(1,5,7,11), y=c(TRUE,FALSE), z="Blah")
str(list1)
List of 4
 $ w: int [1:4, 1:3] 12 11 10 9 8 7 6 5 4 3 ...
 $ x: num [1:4] 1 5 7 11
 $ y: logi [1:2] TRUE FALSE
 $ z: chr "Blah"

list2 <- list(u=2:6, v=list1) # Merging lists
str(list2)
# Note the tree-like structure
List of 2
 $ u: int [1:5] 2 3 4 5 6
 $ v:List of 4
  ..$ w: int [1:4, 1:3] 12 11 10 9 8 7 6 5 4 3 ...
  ..$ x: num [1:4] 1 5 7 11
  ..$ y: logi [1:2] TRUE FALSE
  ..$ z: chr "Blah"
```

Accessing elements of lists

```
list2[1] # Content of first element as a list
$u
[1] 2 3 4 5 6

list2[[1]] # Contents of first element
[1] 2 3 4 5 6
list2$v # Accessing by names
$w
     [,1] [,2] [,3]
[1,]   12    8    4
[2,]   11    7    3
[3,]   10    6    2
[4,]    9    5    1

$x
[1]  1  5  7 11

$y
[1]  TRUE FALSE

$z
[1] "Blah"

list2$v$z # Nested list by name
[1] "Blah"
```

Convert list to vector

```
unlist(list2)
     u1      u2      u3      u4      u5    v.w1    v.w2    v.w3    v.w4    v.w5    v.w6    v.w7    v.w8    v.w9
    "2"     "3"     "4"     "5"     "6"    "12"    "11"    "10"     "9"     "8"     "7"     "6"     "5"     "4"
  v.w10   v.w11   v.w12    v.x1    v.x2    v.x3    v.x4    v.y1    v.y2     v.z
    "3"     "2"     "1"     "1"     "5"     "7"    "11"  "TRUE" "FALSE"  "Blah"
```

```
unlist(list2, recursive = FALSE) # Remove only the first level
$u1
[1] 2

$u2
[1] 3

$u3
[1] 4

$u4
[1] 5

$u5
[1] 6
```

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

$v.x
[1]  1  5  7 11

$v.y
[1]  TRUE FALSE

$v.z
[1] "Blah"
```

apply functions

```r
df <- data.frame(matrix(1:20, nrow = 4))
print(df)
  X1 X2 X3 X4 X5
1  1  5  9 13 17
2  2  6 10 14 18
3  3  7 11 15 19
4  4  8 12 16 20

apply(df, MARGIN = 1, sum) # apply function row-wise
[1] 45 50 55 60

apply(df, MARGIN = 1, mean)
[1]  9 10 11 12

apply(df, MARGIN = 2, sum) # column-wise
X1 X2 X3 X4 X5
10 26 42 58 74
```

```r
# Note that their are applied column-wise (MARGIN=2)

lapply(df, mean) # "list" apply, returns list
$X1
[1] 2.5
$X2
[1] 6.5
$X3
[1] 10.5
$X4
[1] 14.5
$X5
[1] 18.5

sapply(df, mean) # "simple" apply, returns vector
  X1   X2   X3   X4   X5
 2.5  6.5 10.5 14.5 18.5
```

User defined functions can be used

Control structures

- *if — if-else*
- *ifelse*
- *for*
- *while*
- *repeat*
- *switch*

Several *reserved words* are used here

if-else

- The general syntax of an *if* is:

```
if (<condition>)
  <statement>
else if (<condition>) # This must not be present
  <statement>
else                  # This either
  <statement>
```

```
# Example
x <- 5
if (x == 0) {
  print("x is Zero")
} else if (x < 0) {
  print("x is negative")
} else {
  print("x is positive")
}
[1] "x is positive"
```

Note the curly brackets

The indentation helps readability

Vectorized if

- Sometimes we need to apply conditions to vectors
  - Could be done with loops, but sometimes unnecessary
- Example: we now that *9999* is a flag for a missing value, so we change it to *Not Available*

```
x <- c(1:3, 9999, 8:6, 9999, 15)
print(x)
[1]    1    2    3 9999    8    7    6 9999   15

ifelse(x == 9999, NA, x)
[1]  1  2  3 NA  8  7  6 NA 15
```

for loop

- Used when the length of the variable to iterate is known

```
for (i in 1:5) {
    j <- 2**i
    print(j)
}
[1] 2
[1] 4
[1] 8
[1] 16
[1] 32
```

while loop

- The condition is evaluated before executing the code

```
k <- 1
x <- 0

while (k > 1e-5) {
    k <- 0.1 * k
    x <- x + k
    print(paste(k, x))
}
[1] "0.1 0.1"
[1] "0.01 0.11"
[1] "0.001 0.111"
[1] "1e-04 0.1111"
[1] "1e-05 0.11111"
[1] "1e-06 0.111111"
```

repeat loop

- Similar to *while* but condition is within the body

```
z <- 1

repeat {
    z <- 0.1*z
    print(z)
    if (z < 1e-5) break
}
[1] 0.1
[1] 0.01
[1] 0.001
[1] 1e-04
[1] 1e-05
[1] 1e-06
```

switch

- Tests an expression against elements of a list
- If the value from the expression matches an element from the list, the corresponding value is returned
- Basic syntax is `switch (expression, list)`

```
print(switch(0,"red","green","blue")) # if no match, NULL is returned
NULL
print(switch(1,"red","green","blue"))
[1] "red"
print(switch(2,"red","green","blue"))
[1] "green"
print(switch(4,"red","green","blue"))
NULL

# The list can also be named and therefore use strings for matching
switch("color", "color" = "red", "shape" = "square", "length" = 5)
[1] "red"

switch("length", "color" = "red", "shape" = "square", "length" = 5)
[1] 5
```

Mixed example

```r
# Transpose a matrix
# Self made version of the built-in t() function

mytranspose <- function(x) {
    if (!is.matrix(x)) {
        warning("argument is not a matrix: returning NA")
        return(NA_real_)
    }
    y <- matrix(1, nrow=ncol(x), ncol=nrow(x))
    for (i in 1:nrow(x)) {
        for (j in 1:ncol(x)) {
            y[j,i] <- x[i,j]
        }
    }
    return(y)
}

mytranspose(1:4)
[1] NA
Warning message:
In mytranspose(1:4) : argument is not a matrix: returning NA
```

```r
mytranspose(array(1:24, dim = c(4,3,2)))
[1] NA
Warning message:
In mytranspose(array(1:24, dim = c(4, 3, 2))) :
  argument is not a matrix: returning NA

z <- matrix(1:15, nrow=5, ncol=3)
print(z)
     [,1] [,2] [,3]
[1,]    1    6   11
[2,]    2    7   12
[3,]    3    8   13
[4,]    4    9   14
[5,]    5   10   15

tz <- mytranspose(z)
print(tz)
     [,1] [,2] [,3] [,4] [,5]
[1,]    1    2    3    4    5
[2,]    6    7    8    9   10
[3,]   11   12   13   14   15
```

Deeper into functions

- Syntax: `function ( argument list ) {body}`
- A function can have several arguments
- They can *return* an object and/or have a side effect
  - `min()` and `sum()` *return values*
  - `print` and `plot` have *side effects*
  - `hist()` has both
- The variables inside a function are local
  - No conflicts with the upper environment
  - Also, not accessible from it

Check arguments

- We can use the `args` function to check the arguments of other functions

```
args(rnorm) # rnorm generated random numbers from the normal distribution
function (n, mean = 0, sd = 1)
NULL

set.seed(42) # Do random numbers less random
rnorm(5, -3, 4) # Unnamed arguments must be ordered
[1]  2.4838338 -5.2587927 -1.5474864 -0.4685496 -1.3829267

set.seed(42)
rnorm(sd = 4, mean = -3, n = 5) # Named not
[1]  2.4838338 -5.2587927 -1.5474864 -0.4685496 -1.3829267

args(plot)
function (x, y, ...)
NULL
```

- The ... means that other arguments can be passed on to other functions
  - Pro: makes R very flexible
  - Con: quickly becomes complicated to track what is going on behind the scenes

More about arguments

- Arguments can be hardcoded
  - So, if no arguments given still work

```
sum_pow <- function(x,y) {
    return(sum(x**y))
}
sum_pow(1:5, 3)
[1] 225

sum_pow <- function(x=1:5, y=3) {
    return(sum(x**y))
}
sum_pow()
[1] 225
```

- Lazy evaluation of function
  - Arguments are only evaluated when needed

```
random_function <- function(a, b) {
    print(a^2)
    print(a)
    print(b)
}
random_function(6)

[1] 36
[1] 6
Error in print(b) : argument "b" is missing, with no default
```

- Error only encountered when `b` was evaluated

Some statistics

- Linear model fit → `lm(x ~ y, data=df)`
- Generalised linear model → `glm(x ~ y, data=df)`
- Detailed information of models and dataframes → `summary()`
- T-test for difference between means → `t.test(x,y)`
- T-test for paired data → `pairwise.t.test()`
- Test for difference between proportions → `prop.test()`
- Analysis of variance → `aov()`
- More… → check package `stats`

Give them a try!

Built-in distributions

Distribution	Random variates	Density function	Cumulative distribution	Quantile
Normal	rnorm	dnorm	pnorm	qnorm
Lognormal	rlnorm	dlnorm	plnorm	qlnorm
Poison	rpois	dpois	ppois	qpois
Binomial	rbinom	dbinom	pbinom	qbinom
Uniform	runif	dunif	punif	qunif

For more distributions check here

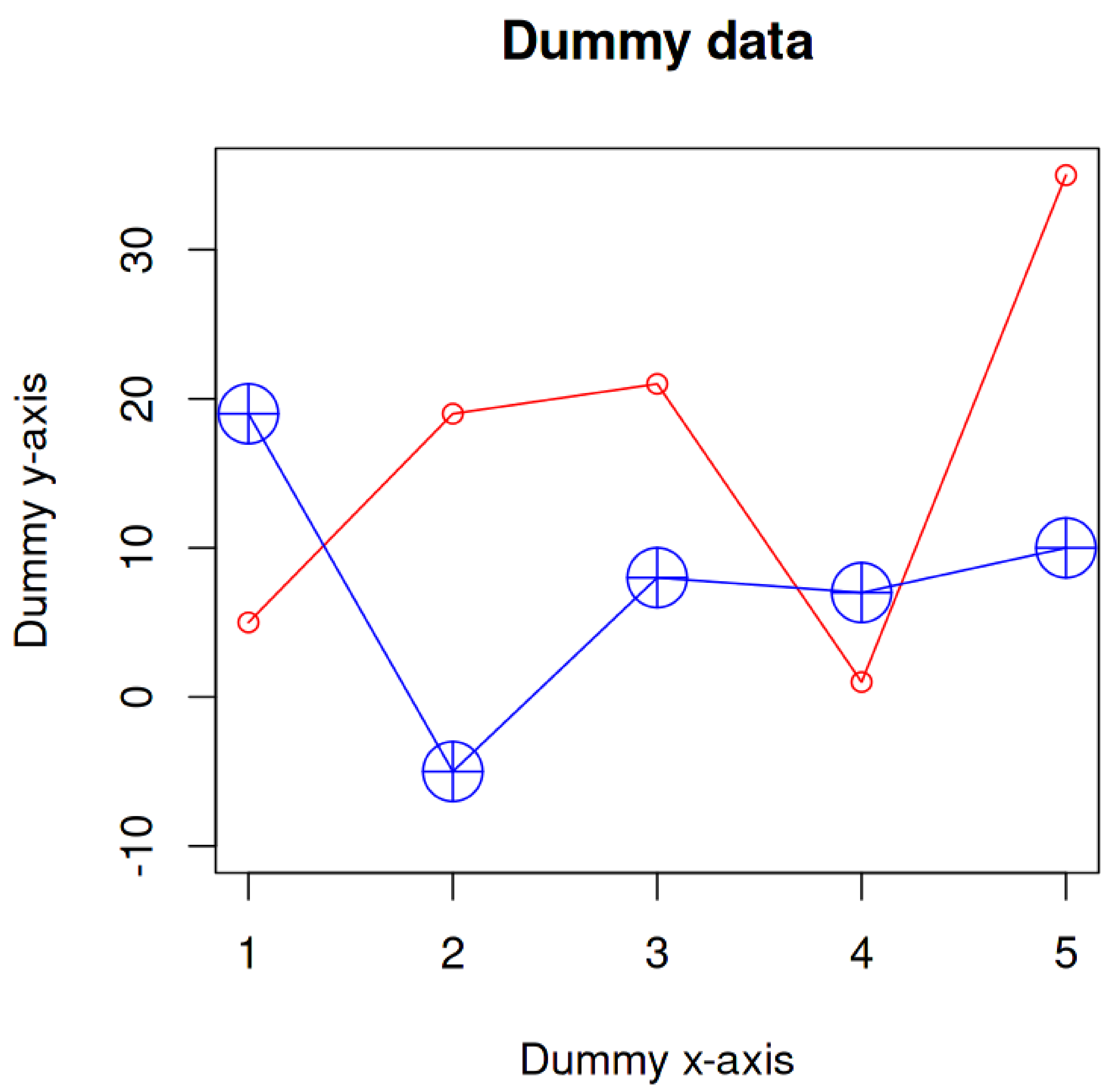
Base-R plotting

- Base-R includes plotting routines for:
  - Line graphs → `plot()`
  - Scatter plots → `plot()`
  - Histograms → `hist()`
  - Density plots → `density()`
  - Quantile — Quantile plots → `qqplot()`
  - Pie charts → `pie()`
  - Bar charts → `barplot()`
  - Boxplots → `boxplot()`
  - More…
- Multiple plots in one with `par()`

- Generic plots → `plot()`, depends on the type of data
  - x and y: the coordinates of points to plot
  - type: the type of graph to create
    - `type="p"`: for points (by default)
    - `type="l"`: for lines
    - `type="b"`: for both, points are connected by a line
    - `type="o"`: for both *overplotted*
    - `type="h"`: for *histogram* like vertical lines
    - `type="s"`: for stair steps
    - `type="n"`: for no plotting

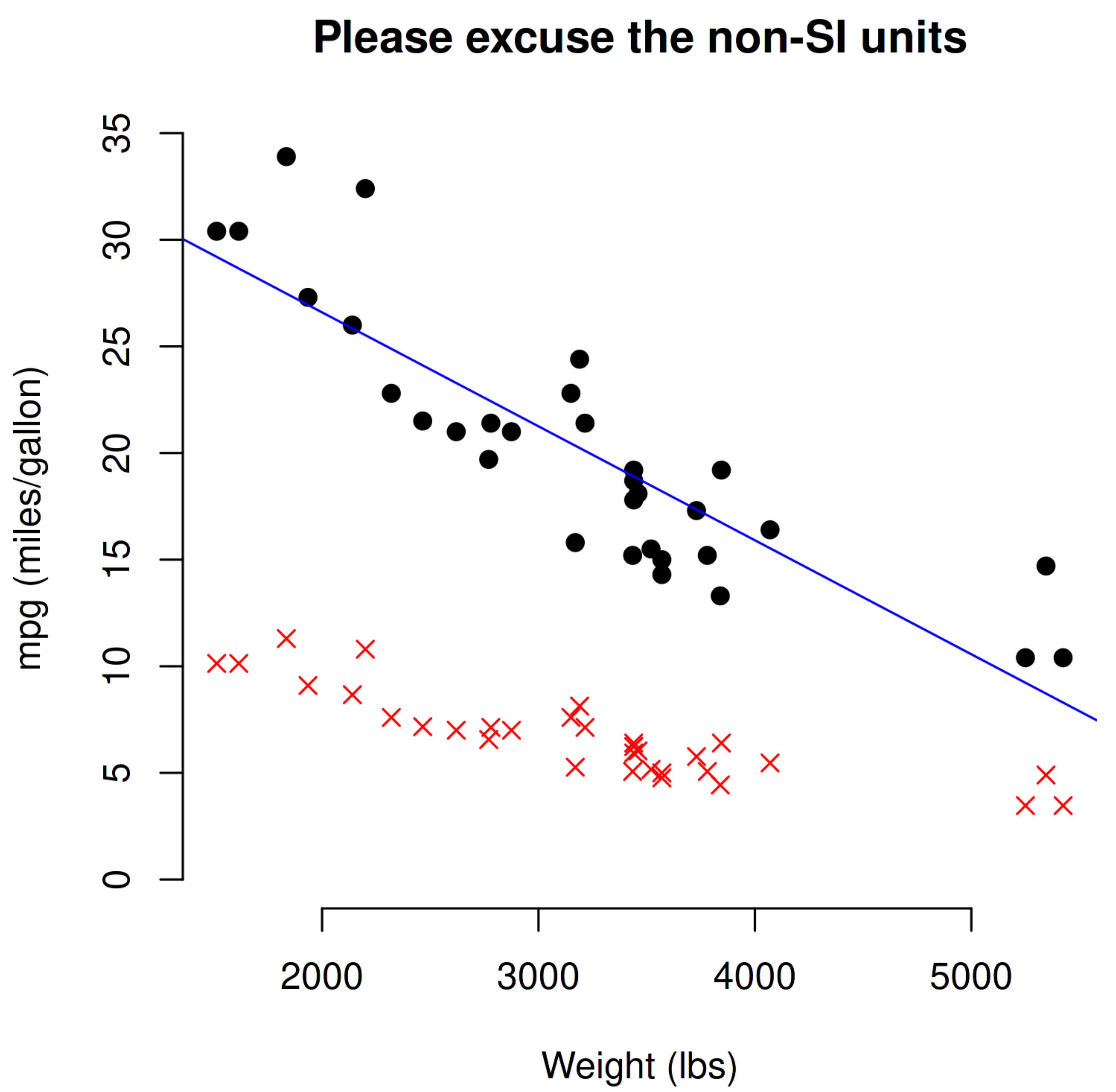
Line graphs and save

```
# Change path accordingly
setwd("Documents/PhD/Students/R_course/FRM/images/")

x <- c(5,19,21,1,35)
y <- c(19,2,8,7,10)

# Save as png, note the dpi and sizes
png(file = "dummy_line.png", res=150, width=800,
    height=800, units = "px", pointsize = "14")

plot(x, type = "o",col = "red", xlab = "Dummy x-axis",
     ylab = "Dummy y-axis", main = "Dummy data")

# add second vector
lines(y, type = "o", col = "blue", pch=10, cex=3)

dev.off() # to save the file
RStudioGD
        2
```



Scatter plots

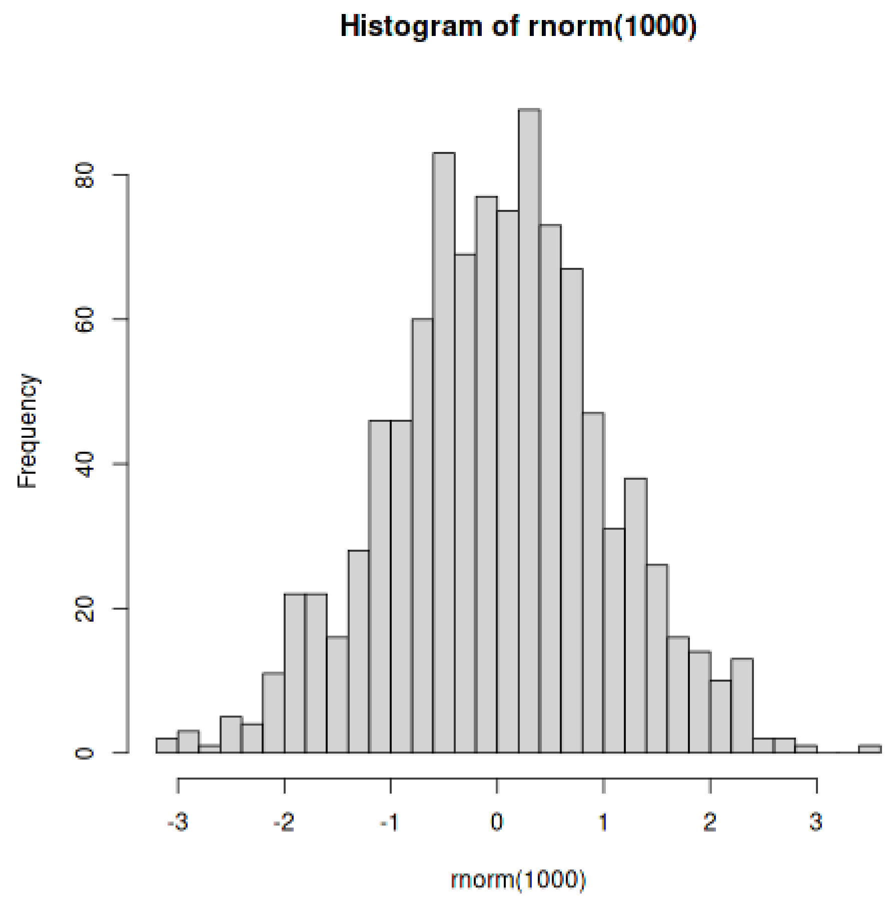
```
# let's use the mtcars dataset
?mtcars

x <- mtcars$wt * 1000
y <- mtcars$mpg

png(file = "dummy_scatter.png", res=300, width=1600,
    height=1600, units = "px", pointsize = "12")

plot(x, y, xlab = "Weight (lbs)",
     ylab = "mpg (miles/gallon)",
     main = paste0("Please excuse the non-SI units"),
     pch = 19, frame = FALSE, ylim = c(0, max(y)))

# Add more points to the plot
points(x, y/3, col="red", pch=4)

# Add linear fit, play more with the lm function
abline(lm(y ~ x), col = "blue")

dev.off()
```

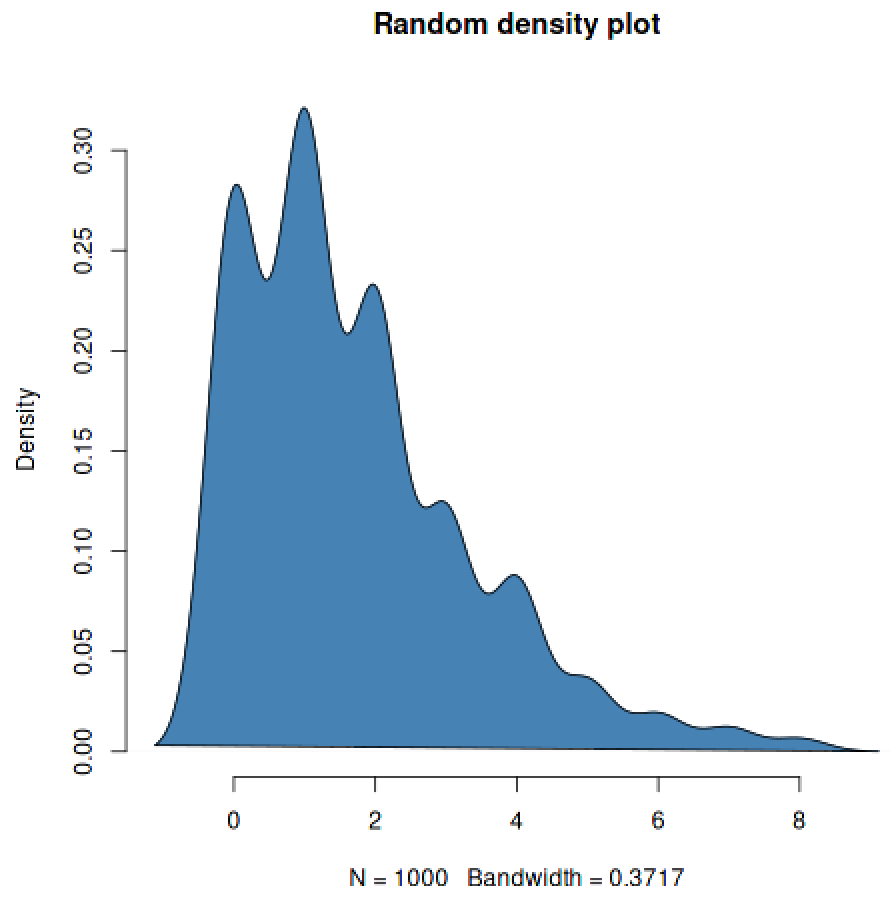


Histogram and density plots

```
# Plot should be different to mine if
# seed number is changed
set.seed(42)

png(filename = "dummy_hist.png")

# Change breaks and note the differences
hist(rnorm(1000), breaks = 25)

dev.off()
```

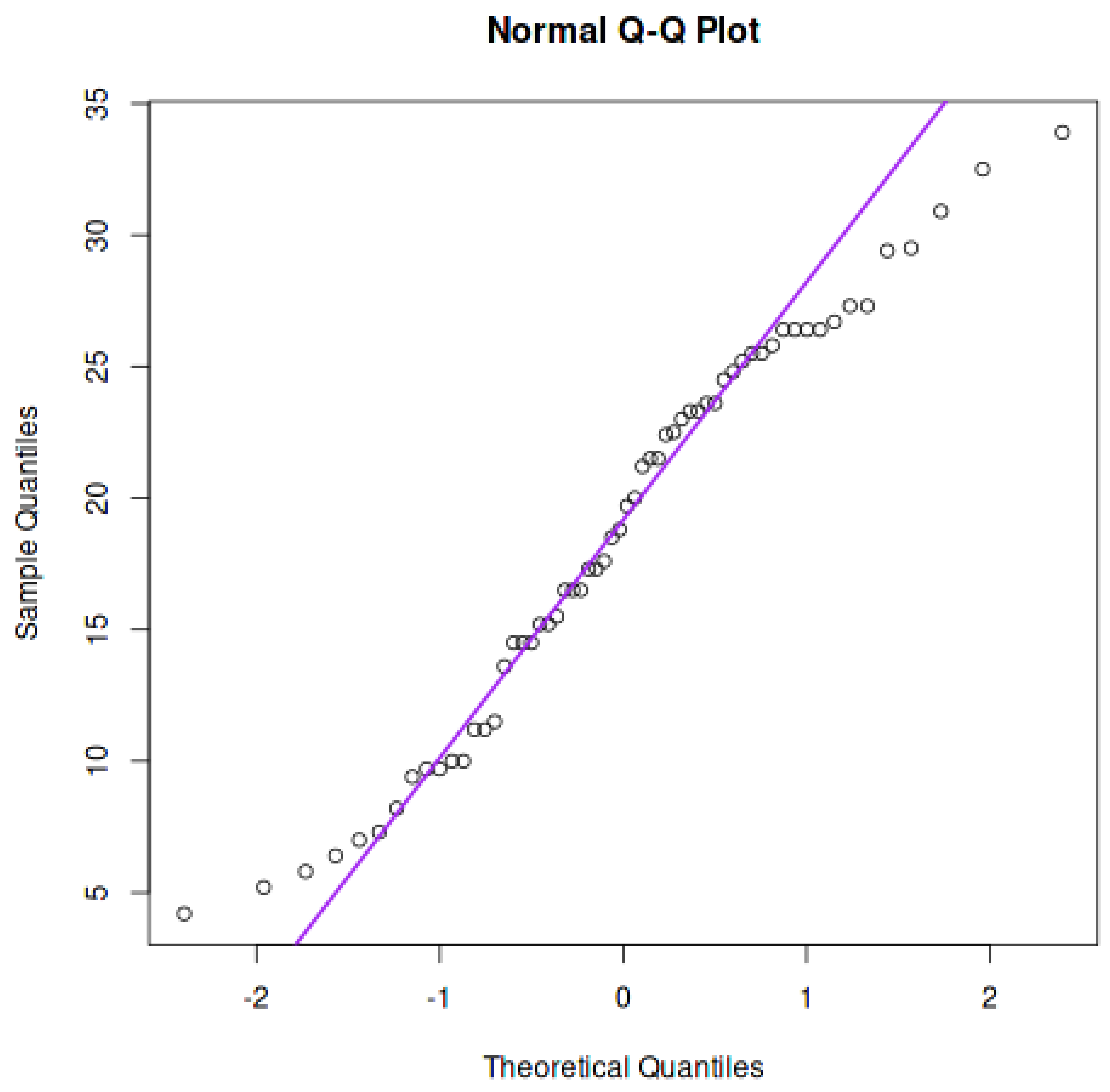
```
set.seed(42)
# Random numbers from the negative binomial distribution
dens <- density(rnbinom(1000, size = 3,
                        prob = 0.64))

png(filename = "dummy_hist.png")

plot(dens, frame = FALSE, col = "steelblue",
     main = "Random density plot")
polygon(dens, col = "steelblue") # to fill the plot
dev.off()
```





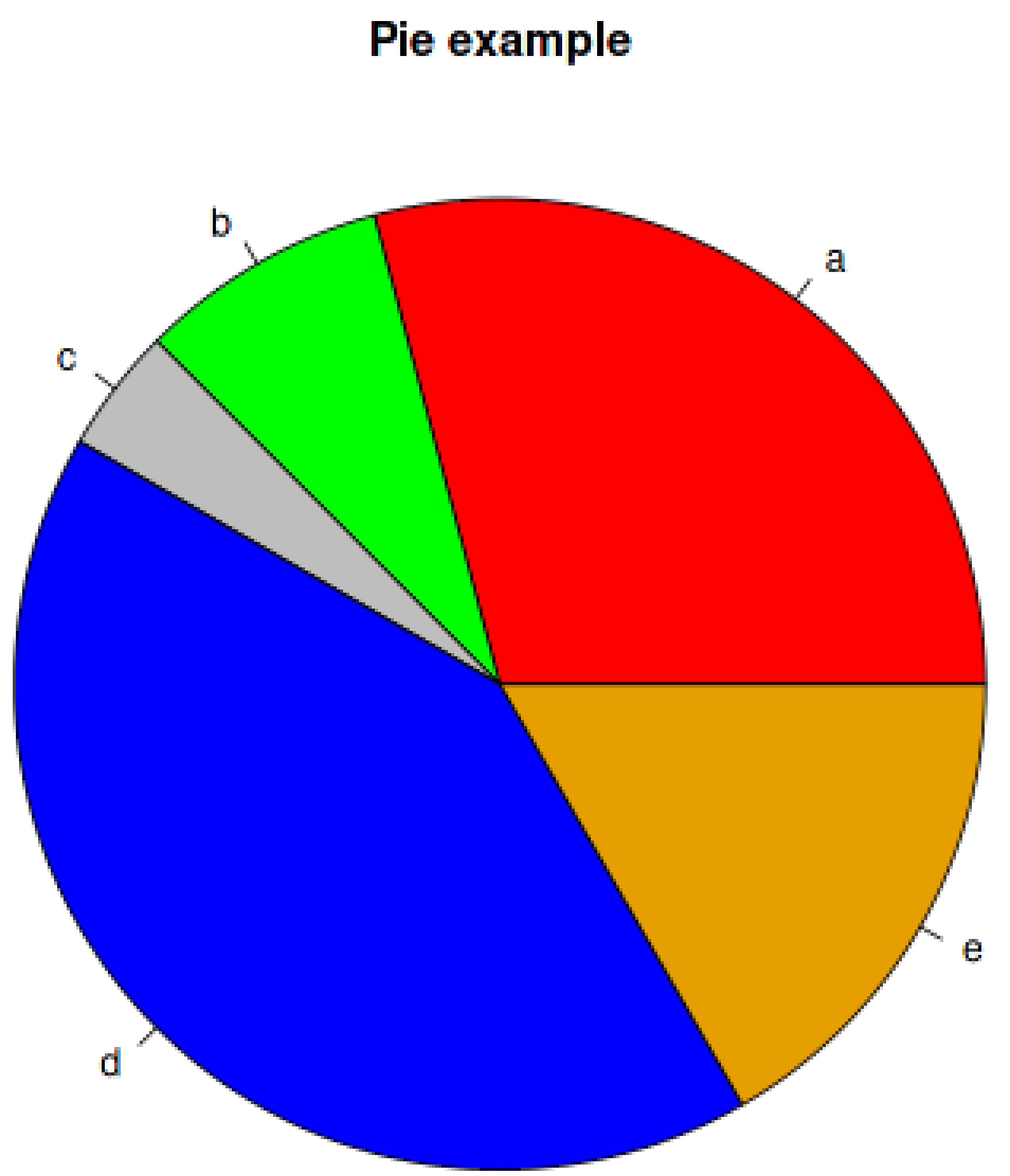
Quantile — Quantile

```
# ToothGrowth dataset
?ToothGrowth

png("dummy_qq.png")
qqnorm(ToothGrowth$len, pch = 1)
qqline(ToothGrowth$len, col = "purple", lwd = 2)

dev.off()
```



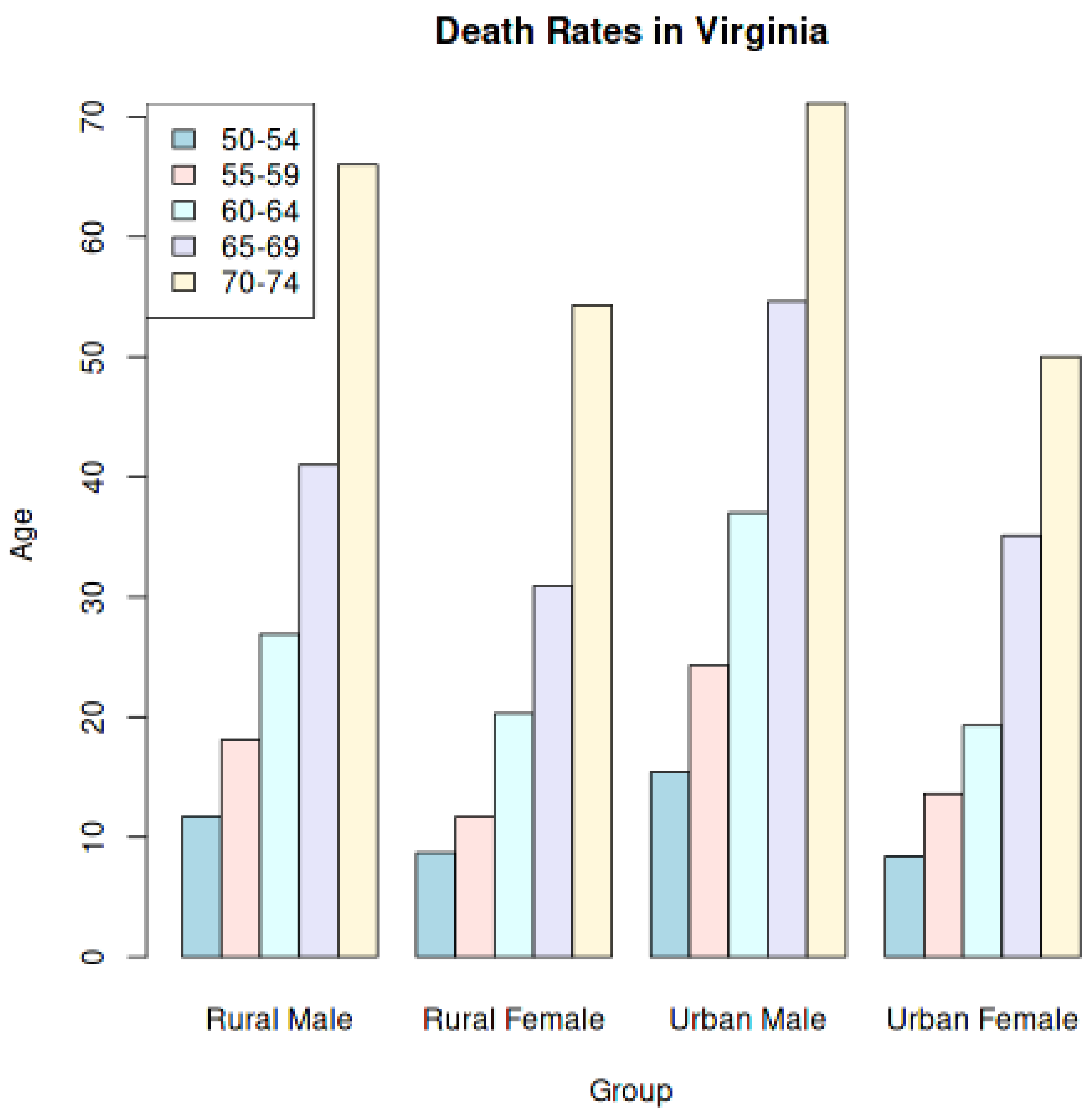
Pie charts

```
to_pie <- c(7,2,1,10,4)

png(filename = "dummy_pie.png")
pie(to_pie, labels = c("a", "b", "c", "d", "e"),
    col = c("red", "green", "gray", "blue", "#E69F00"),
    radius = .95, main = "Pie example")

dev.off()
```



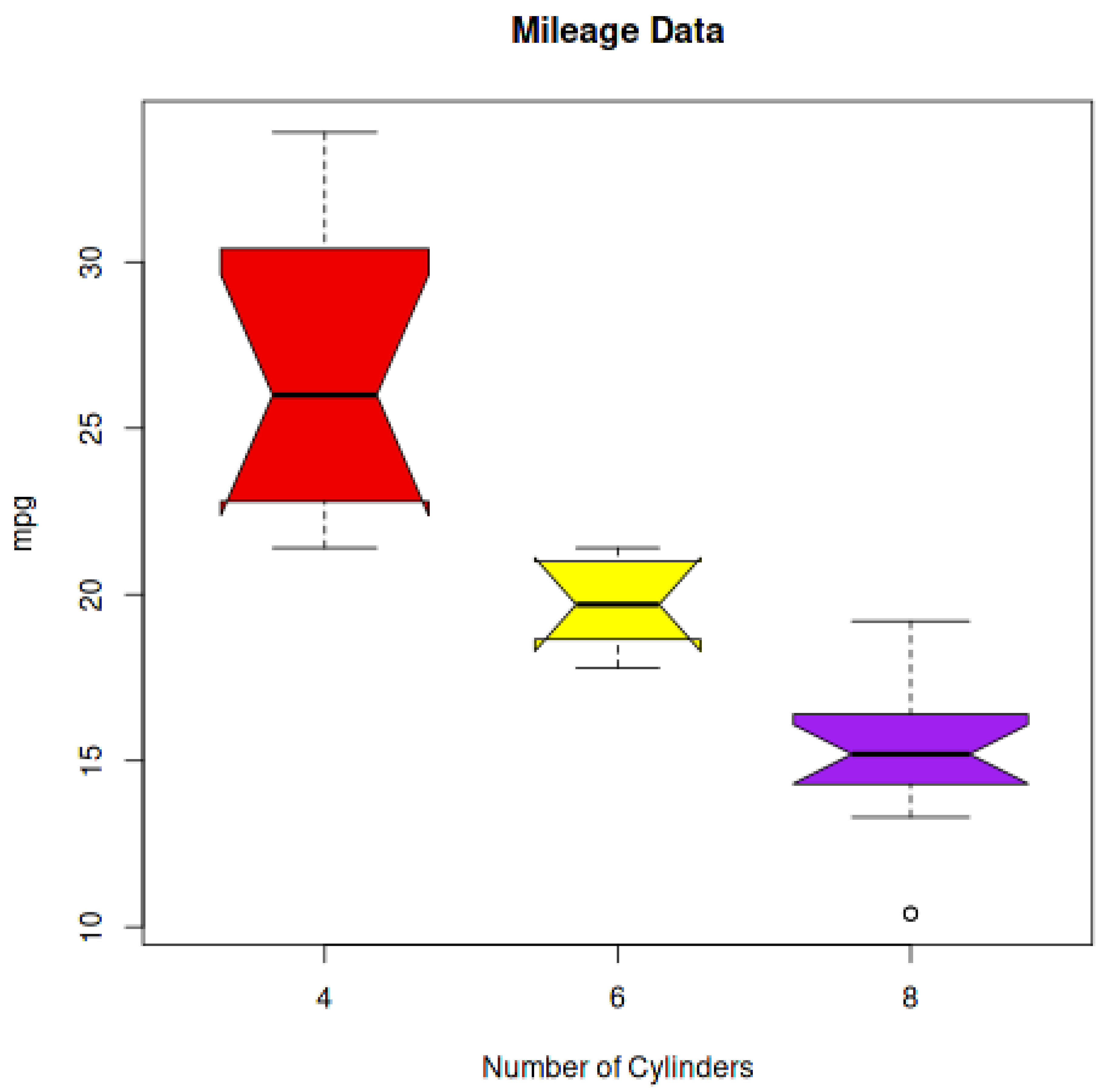
Barplots

```r
# Other dataset
?VADeaths

my_colors <- c("lightblue", "mistyrose", "lightcyan",
               "lavender", "cornsilk")
png("dummy_bar.png")
barplot(VADeaths, col = my_colors, beside = TRUE,
        main = "Death Rates in Virginia",
        xlab = "Group", ylab = "Age")

# Add legend
legend("topleft", legend = rownames(VADeaths),
       fill = my_colors)

dev.off()
```



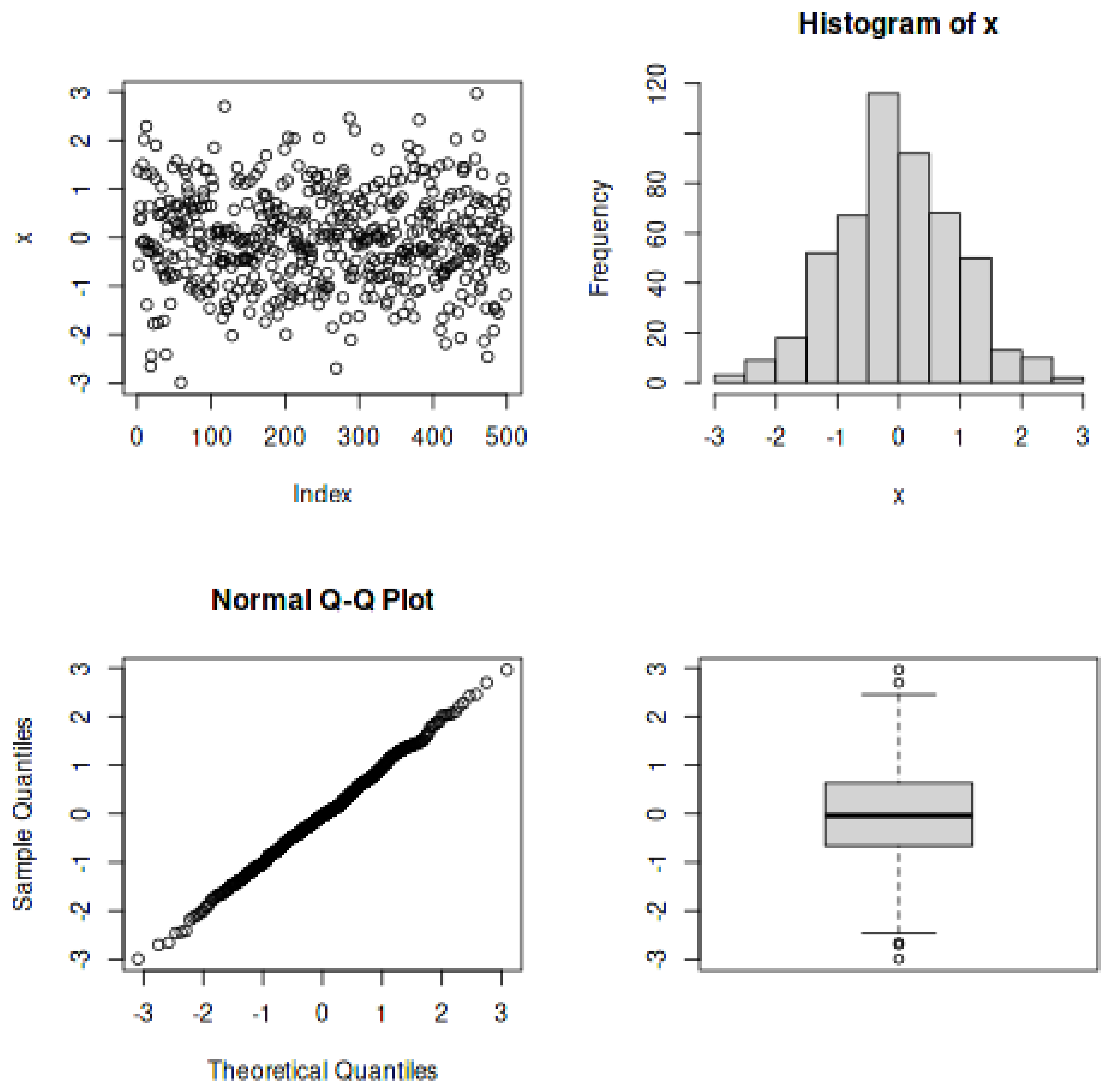
Boxplots

```
# mtcars dataset again
png(file = "dummy_boxplot.png")

# We can also do plots with the ~ sign
boxplot(mpg ~ cyl, data = mtcars,
        xlab = "Number of Cylinders",
        ylab = "mpg",
        main = "Mileage Data",
        notch = TRUE,
        varwidth = TRUE,
        col = c("red2","yellow","purple"))

dev.off()
```



Multiple plots

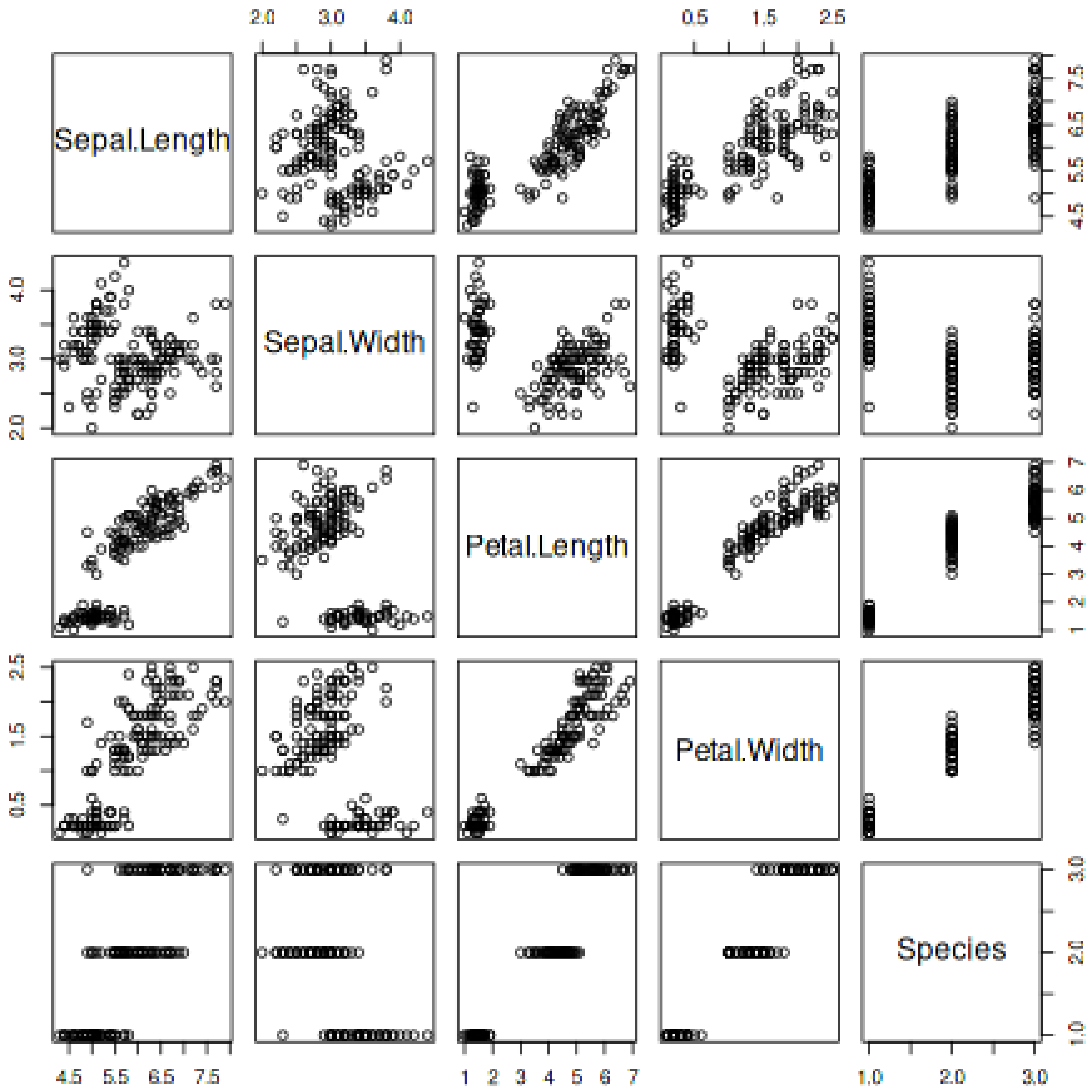
```
set.seed(42)
x <- rnorm(500)

png("dummy_multi.png")

par(mfrow=c(2,2))
plot(x)
hist(x)
qqnorm(x)
boxplot(x)

dev.off()
```



More about generic plots

- Sometimes, depending on the dataset, a complex comparative plot is generated automatically

```
# iris dataset
?iris

png("iris.png")
plot(iris)
dev.off()
```



Last remarks about base plotting

- The built-in help system is your friend
- There are a lot more details and parameters to play with:
  - Margins
  - Types of `pch`
  - `cex` → scaling of plotting characters
  - `lty` → line type
  - `lwd` → line width
  - `xlim` and `ylim`
- Plots can be saved as:
  - `png()` → used here so far
  - `jpeg()` → used mostly for photographs, not that useful here
  - `tiff()` → similar to *png*, some journals ask for it
  - `svg()` → vector, allows editing
  - `pdf()` → vector, very useful
- Will go in more detail with `ggplot2` → allows more modifications

Exercise I

1. List all CSV files using `list.files`. Check the options `full.names` & `recursive`
2. Loop over the listed files and read them as dataframes or time series
3. Pick CSV files of your choice and:
    1. Plot different types of plots
    2. Run some statistical tests.
    3. Explore the climate conditions of your area
4. You may do some aggregation, e.g., monthly, seasonally, and annually
5. You can perform trend analysis or any time series analysis you would like.
6. You may convert the variables to common units such as Celsius or mm/day

> Climate Variables:
>
> 1. sfcWind → Surface wind [m/s]
> 2. pr → Precipitation [kg m-2 s-1]
> 3. tas → Surface temperature [k]

Tidyverse

> *The tidyverse is an opinionated collection of R packages designed for* ***data science****. All packages share an underlying design philosophy, grammar, and data structures.*

— tidiverse.org

- `ggplot2` → system for declaratively creating graphics
- `purrr` → tools to work with functions and vectors
- `tibble` → re-design of data frames
- `dplyr` → data manipulation
- `tidyr` → functions to *tidy* the data up
- `stringr` → to work with strings easily
- `readr` → easy way to read data like *csv*, *tsv*, *fwf*
- `forcats` → tools to solve issues with *factors*

Tidy philosophy

- *Tidy* data is where:
  1. Every column is a variable
  2. Every row is an observation
  3. Every cell is a single value
- Check `vignette("tidy-data")`
  - It is often said that 80% of data analysis is spent on the cleaning and preparing data…
- Check this book
- `lubridate` is not part of `tidyverse` but very useful to work with dates
  - `hms` to work with time of day values

Pipes

- The pipe operator `%>%` eases readability and coding
  - `x %>% f` is equivalent to `f(x)`
  - `x %>% f(y)` is equivalent to `f(x, y)`
  - `x %>% f %>% g %>% h` is equivalent to `h(g(f(x)))`
  - `x %>% f(y, .)` is equivalent to `f(y, x)`
  - `x %>% f(y, z = .)` is equivalent to `f(y, z = x)`

Analysing the *Gapminder* dataset

```
install.packages("gapminder")
library(gapminder)
library(tidyverse)
?gapminder

head(gapminder)
# A tibble: 6 x 6
  country     continent  year lifeExp      pop gdpPercap
  <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
1 Afghanistan Asia       1952    28.8  8425333      779.
2 Afghanistan Asia       1957    30.3  9240934      821.
3 Afghanistan Asia       1962    32.0 10267083      853.
4 Afghanistan Asia       1967    34.0 11537966      836.
5 Afghanistan Asia       1972    36.1 13079460      740.
6 Afghanistan Asia       1977    38.4 14880372      786.

str(as.data.frame(gapminder))
'data.frame':	1704 obs. of  6 variables:
 $ country  : Factor w/ 142 levels "Afghanistan",..: 1 1 1 1 1 1 1 1 1 1 ...
 $ continent: Factor w/ 5 levels "Africa","Americas",..: 3 3 3 3 3 3 3 3 3 3 ...
 $ year     : int  1952 1957 1962 1967 1972 1977 1982 1987 1992 1997 ...
 $ lifeExp  : num  28.8 30.3 32 34 36.1 ...
 $ pop      : int  8425333 9240934 10267083 11537966 13079460 14880372 12881816 13867957 16317921 22227415 ...
 $ gdpPercap: num  779 821 853 836 740 ...
```

Filtering according to values

```
gapminder %>%
    filter(
        str_detect(country, "Costa"),
        year %in% c(1987, 1997, 2007)
    )

# A tibble: 3 x 6
  country    continent  year lifeExp     pop gdpPercap
  <fct>      <fct>     <int>   <dbl>   <int>     <dbl>
1 Costa Rica Americas   1987    74.8 2799811     5630.
2 Costa Rica Americas   1997    77.3 3518107     6677.
3 Costa Rica Americas   2007    78.8 4133884     9645.

gapminder %>%
    filter(
        str_detect(country, "Costa"),
        year %in% c(1987, 1997, 2007)
    ) %>%
    summarize(AvgLife=mean(lifeExp))

# A tibble: 1 x 1
  AvgLife
    <dbl>
1    76.9
```

Grouping

```
gapminder %>%
    filter(year %in% c(1997,2007)) %>%
    group_by(continent, year) %>%
    summarize(AvgLife = mean(lifeExp),
              GDP = mean(gdpPercap))

# A tibble: 10 x 4
# Groups:   continent [5]
   continent  year AvgLife    GDP
   <fct>     <int>   <dbl>  <dbl>
 1 Africa     1997    53.6  2379.
 2 Africa     2007    54.8  3089.
 3 Americas   1997    71.2  8889.
 4 Americas   2007    73.6 11003.
 5 Asia       1997    68.0  9834.
 6 Asia       2007    70.7 12473.
 7 Europe     1997    75.5 19077.
 8 Europe     2007    77.6 25054.
 9 Oceania    1997    78.2 24024.
10 Oceania    2007    80.7 29810.
```

Arranging data

```
gapminder %>%
    filter(year == 2007) %>%
    group_by(continent) %>%
    summarise(totalPop = sum(pop)) %>%
    arrange(desc(totalPop))

# Note the desc() descending

# A tibble: 5 x 2
  continent   totalPop
  <fct>          <dbl>
1 Asia      3811953827
2 Africa     929539692
3 Americas   898871184
4 Europe     586098529
5 Oceania     24549947
```

Creating new columns

```
gapminder %>%
    filter(year == 2007) %>%
    mutate(totalGdp = pop * gdpPercap/1000000) # To have it in millions

# A tibble: 142 x 7
   country     continent  year lifeExp       pop gdpPercap totalGdp
   <fct>       <fct>     <int>   <dbl>     <int>     <dbl>    <dbl>
 1 Afghanistan Asia       2007    43.8  31889923      975.   31079.
 2 Albania     Europe     2007    76.4   3600523     5937.   21376.
 3 Algeria     Africa     2007    72.3  33333216     6223.  207445.
 4 Angola      Africa     2007    42.7  12420476     4797.   59584.
 5 Argentina   Americas   2007    75.3  40301927    12779.  515034.
 6 Australia   Oceania    2007    81.2  20434176    34435.  703658.
 7 Austria     Europe     2007    79.8   8199783    36126.  296229.
 8 Bahrain     Asia       2007    75.6    708573    29796.   21113.
 9 Bangladesh  Asia       2007    64.1 150448339     1391.  209312.
10 Belgium     Europe     2007    79.4  10392226    33693.  350141.
# … with 132 more rows
```

Top 10 life expectancy

```
gapminder %>%
    filter(year == 2007) %>%
    mutate(percentile = ntile(lifeExp, 100)) %>%
    filter(percentile > 90) %>%
    arrange(desc(percentile)) %>%
    top_n(10, wt = percentile) %>%
    select(continent, country, lifeExp, percentile)

# A tibble: 10 x 4
   continent country          lifeExp percentile
   <fct>     <fct>              <dbl>      <int>
 1 Asia      Japan               82.6        100
 2 Asia      Hong Kong, China    82.2         99
 3 Europe    Iceland             81.8         98
 4 Europe    Switzerland         81.7         97
 5 Oceania   Australia           81.2         96
 6 Europe    Spain               80.9         95
 7 Europe    Sweden              80.9         94
 8 Asia      Israel              80.7         93
 9 Europe    France              80.7         92
10 Americas  Canada              80.7         91
```

Last 10 life expectancy

```
gapminder %>%
    filter(year == 2007) %>%
    mutate(percentile = ntile(lifeExp, 100)) %>%
    filter(percentile < 10) %>%
    arrange(percentile) %>%
    top_n(-10, wt = percentile) %>%
    select(continent, country, lifeExp, percentile)

# A tibble: 10 x 4
   continent country                  lifeExp percentile
   <fct>     <fct>                      <dbl>      <int>
 1 Africa    Mozambique                  42.1          1
 2 Africa    Swaziland                   39.6          1
 3 Africa    Sierra Leone                42.6          2
 4 Africa    Zambia                      42.4          2
 5 Africa    Angola                      42.7          3
 6 Africa    Lesotho                     42.6          3
 7 Asia      Afghanistan                 43.8          4
 8 Africa    Zimbabwe                    43.5          4
 9 Africa    Central African Republic    44.7          5
10 Africa    Liberia                     45.7          5
```

Example of *un-tidy* data

```
relig_income
# Column headers are values, not variable names
# A tibble: 18 x 11
   religion                `<$10k` `$10-20k` `$20-30k` `$30-40k` `$40-50k` `$50-75k` `$75-100k`
   <chr>                     <dbl>     <dbl>     <dbl>     <dbl>     <dbl>     <dbl>      <dbl>
 1 Agnostic                     27        34        60        81        76       137        122
 2 Atheist                      12        27        37        52        35        70         73
 3 Buddhist                     27        21        30        34        33        58         62
 4 Catholic                    418       617       732       670       638      1116        949
 5 Don’t know/refused           15        14        15        11        10        35         21
 6 Evangelical Prot            575       869      1064       982       881      1486        949
 7 Hindu                         1         9         7         9        11        34         47
 8 Historically Blac…          228       244       236       238       197       223        131
 9 Jehovahs Witness           20        27        24        24        21        30         15
10 Jewish                       19        19        25        25        30        95         69
11 Mainline Prot               289       495       619       655       651      1107        939
12 Mormon                       29        40        48        51        56       112         85
13 Muslim                       6         7         9        10         9        23         16
14 Orthodox                     13        17        23        32        32        47         38
15 Other Christian               9         7        11        13        13        14         18
16 Other Faiths                 20        33        40        46        49        63         46
17 Other World Relig…            5         2         3         4         2         7          3
18 Unaffiliated                217       299       374       365       341       528        407
# … with 3 more variables: $100-150k <dbl>, >150k <dbl>, Don't know/refused <dbl>
```

Tidying it up

- `pivot_longer()` helps us to change it to a *long* format which later will be needed for `ggplot`

```
relig_income %>%
    pivot_longer(!religion, names_to = "income", values_to = "count") %>%
    group_by(religion) %>%
    mutate(total=sum(count), percent= count/total*100)

# A tibble: 180 x 5
# Groups:   religion [18]
   religion income                count total percent
   <chr>    <chr>                 <dbl> <dbl>   <dbl>
 1 Agnostic <$10k                    27   826    3.27
 2 Agnostic $10-20k                  34   826    4.12
 3 Agnostic $20-30k                  60   826    7.26
 4 Agnostic $30-40k                  81   826    9.81
 5 Agnostic $40-50k                  76   826    9.20
 6 Agnostic $50-75k                 137   826   16.6
 7 Agnostic $75-100k                122   826   14.8
 8 Agnostic $100-150k               109   826   13.2
 9 Agnostic >150k                    84   826   10.2
10 Agnostic Dont know/refused        96   826   11.6
# … with 170 more rows
```

More about data *wrangling*

> Data wrangling is the process of cleaning and unifying messy and complex data sets for easy access and analysis.

- Useful functions within `tidyverse` for data *wrangling*:

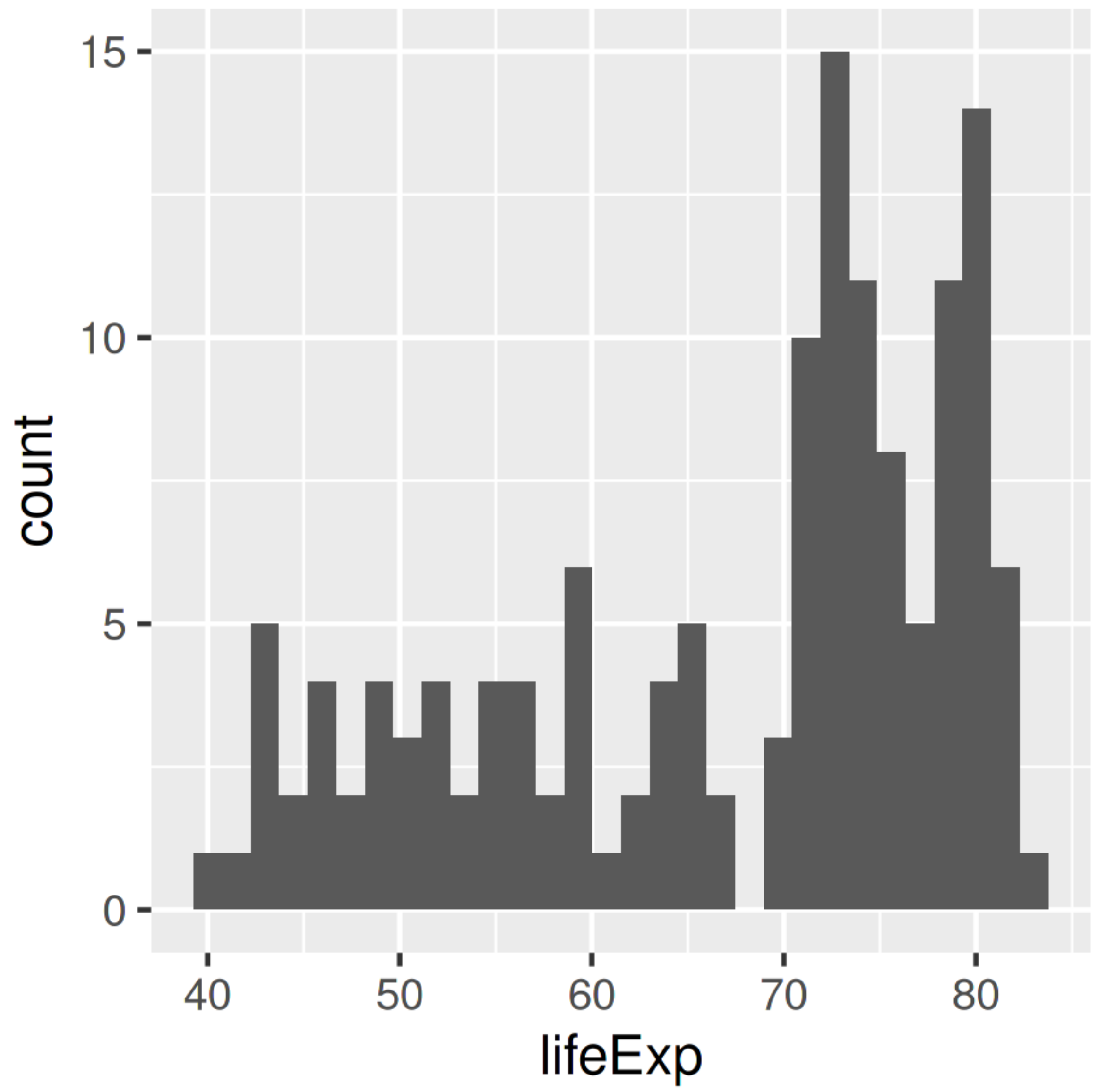
- `arrange` → order rows by values (low to high, `desc` for high to low)
- `distinct` → remove duplicate rows
- `filter` → extract rows
- `slice` → select rows by position
- `pull` → extract column values as vector
- `relocate` → change order of columns
- `mutate` → add new column
- `transmute` → compute new column, drop others
- `*_join` → join columns to table (several options)
- `rename` → rename columns, use `rename_with` with function
- `cum*` → cumulative aggregate (several options)
- `lag` → offset elements by 1
- `lead` → offset elements by -1
- `n` → number of rows
- `n_distinct` → number of uniques
- `dense_rank` → rank with no gaps
- `percent_rank` → rank scaled to [0,1]
- More…

Intro to *ggplot2*

- Based on *The Grammar of Graphics*
- Major components of *ggplot*:
  - `data` → data to plot
  - Geometries `geom_` → The geometric shapes that will represent the data
  - Aesthetics `aes()` → Aesthetics of the geometric and statistical objects
    - Position, color, size, shape, and transparency
  - Scales `scale_` → Maps between the data and the aesthetic dimensions
  - Statistical transformations `stat_` → Statistical summaries of the data
    - Quantiles, fitted curves, and sums
  - Coordinate system `coord_` → Coordinate transformation
  - Facets `facet_` → plot the data into a grid
  - Visual themes `theme()` → visual defaults of a plot
    - Background, grids, axes, default typeface, sizes and colors

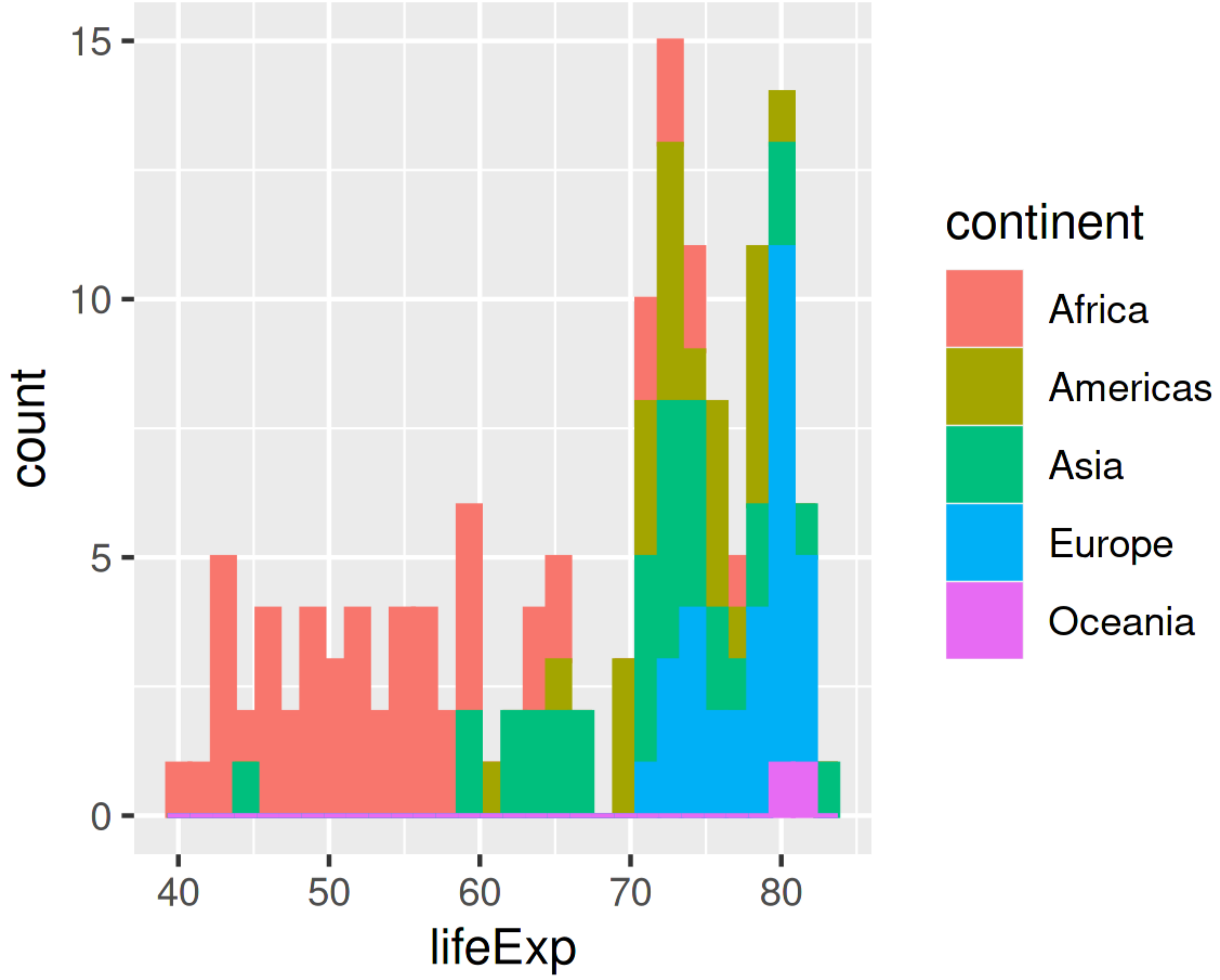
Basic plots

```
library(tidyverse)
setwd("Documents/PhD/Students/R_course/FRM/images/")

gapminder_07 <- gapminder %>%
    filter(year == 2007)

ex_plot <- ggplot(gapminder_07, aes(x = lifeExp)) +
    geom_histogram(bins = 30)

ggsave(plot = ex_plot, filename = "gg_hist_1.png",
       width = 80, height = 80,
       units = "mm", dpi = 300)
```



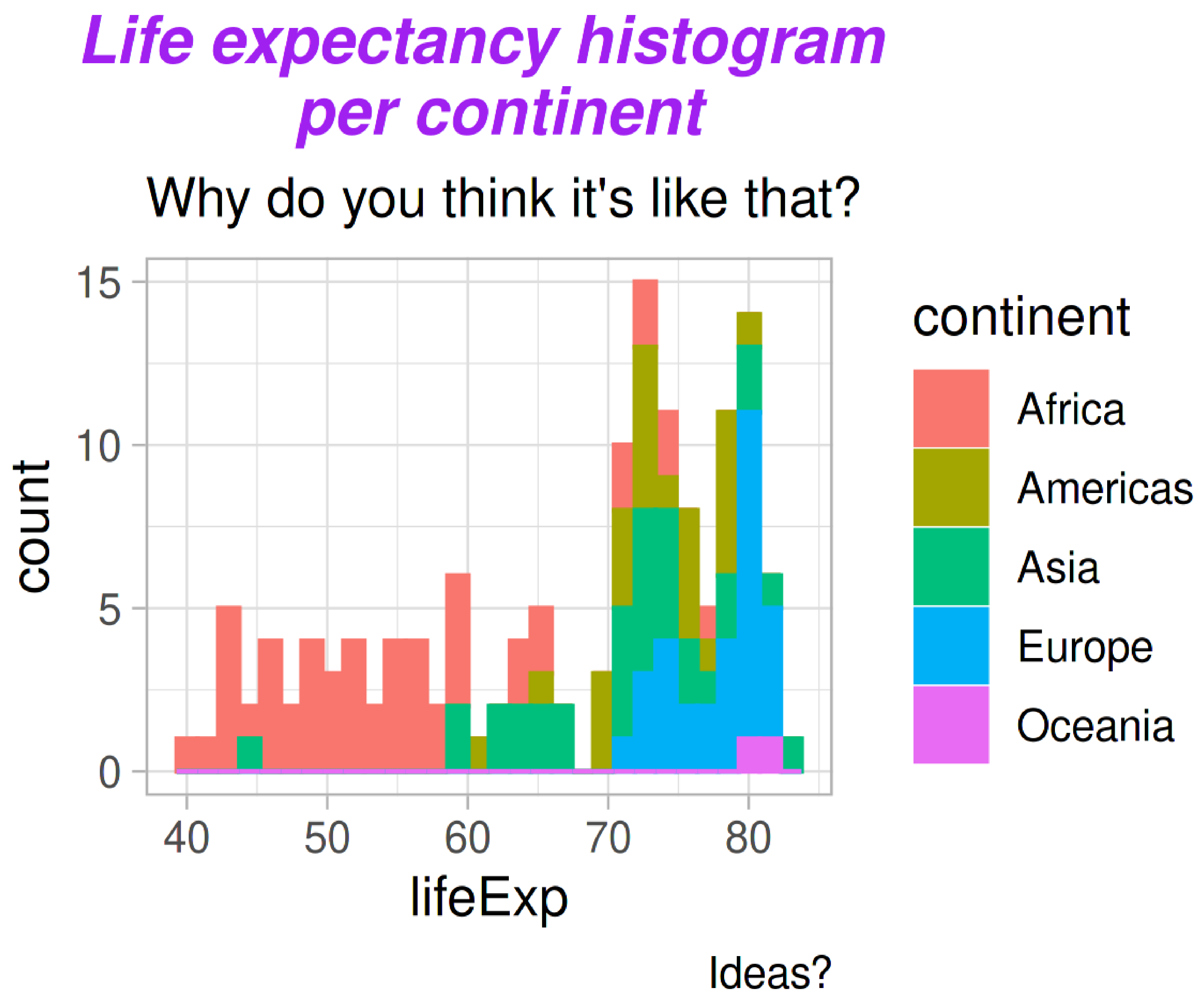
- Let's add some colors

```
ex_plot <- ggplot(gapminder_07, aes(x = lifeExp,
                                     fill=continent)) +
    geom_histogram(bins = 30)

ggsave(plot = ex_plot, filename = "gg_hist_2.png",
       width = 100, height = 80,
       units = "mm", dpi = 300)
```



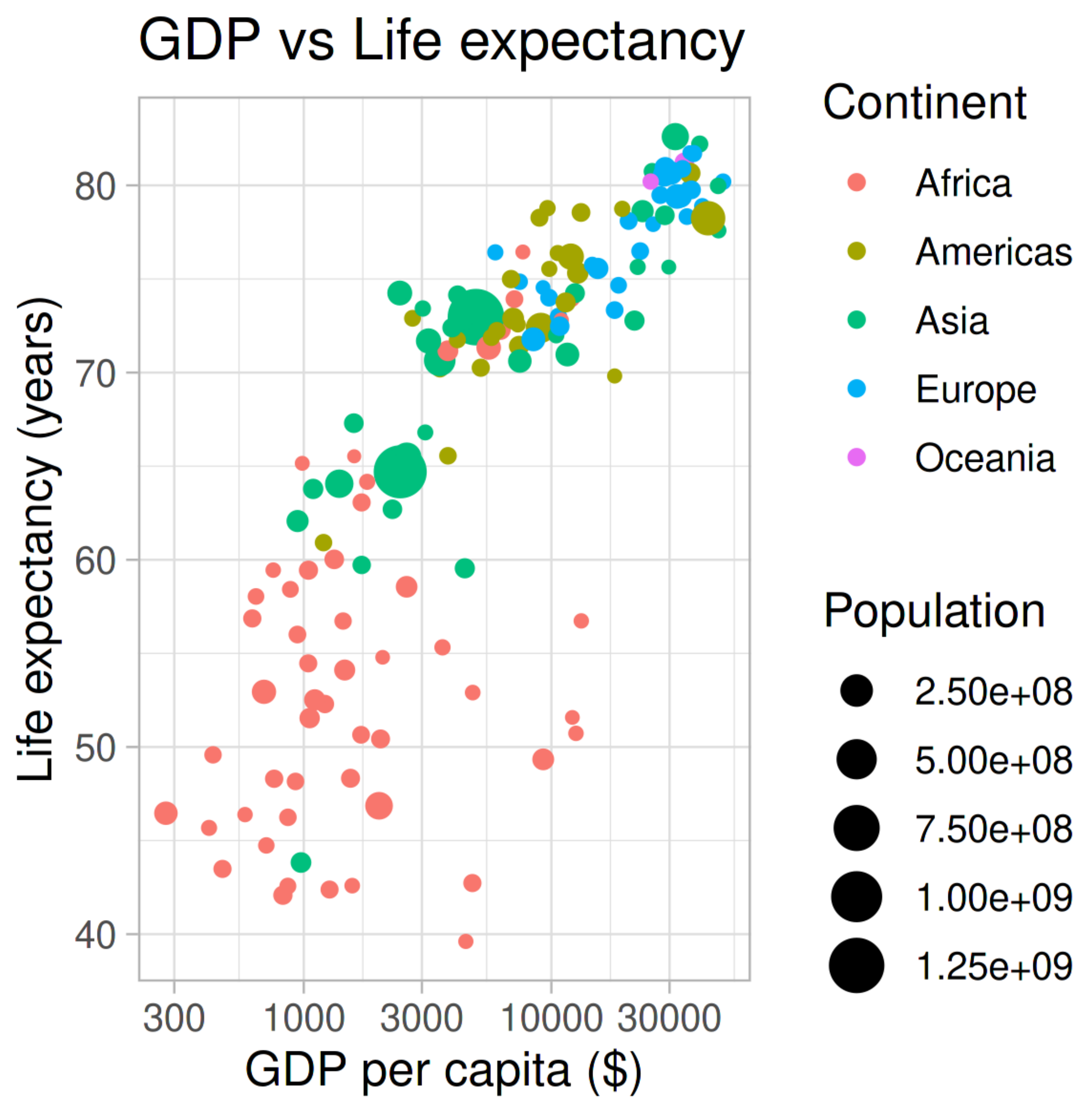
Title and other tweaks

```
ex_plot <- ggplot(gapminder_07, aes(x = lifeExp,
                                  fill=continent)) +
    geom_histogram(bins = 30) +
    ggtitle("Life expectancy histogram \n per continent") +
    labs(subtitle = "Why do you think it's like that?",
         caption = "Ideas?") +
    theme_light(base_size = 12) +
    theme(plot.title = element_text(hjust = 0.5,
                                    face = "bold.italic",
                                    colour = "purple"))

ggsave(plot = ex_plot, filename = "gg_hist_3.png",
       width = 100, height = 80,
       units = "mm", dpi = 300)
```



Other *geom* types

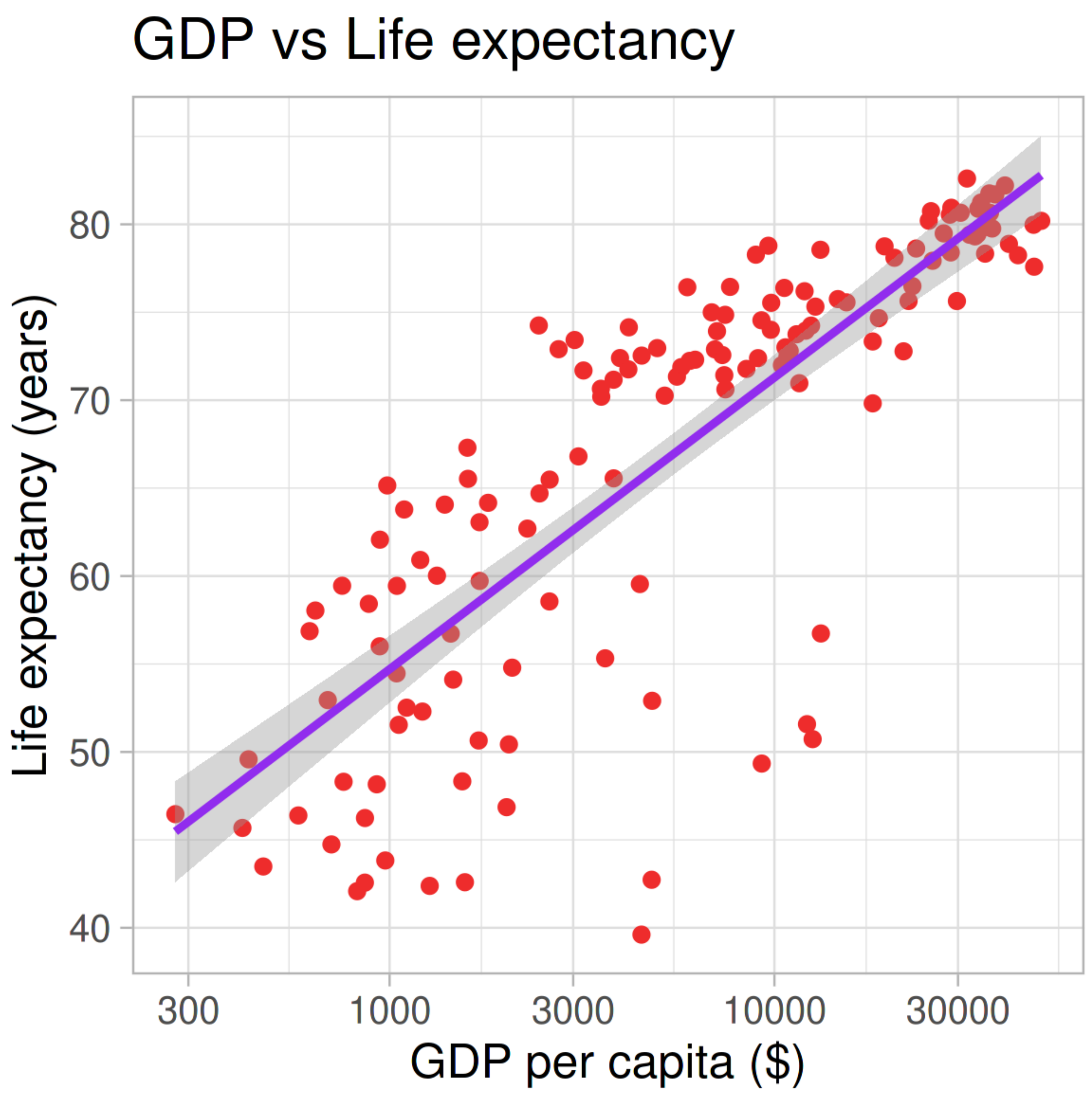
```
ex_plot <- ggplot(gapminder_07, aes(y = lifeExp,
                                    x = gdpPercap,
                                    color= continent,
                                    size= pop)) +
    geom_point() +
    labs(x = "GDP per capita ($)",
         y = "Life expectancy (years)",
         color= "Continent",
         size = "Population",
         title = "GDP vs Life expectancy") +
    guides(color = guide_legend(order = 1)) +
    scale_x_log10() +
    theme_light(base_size = 12)
```



Adding fits

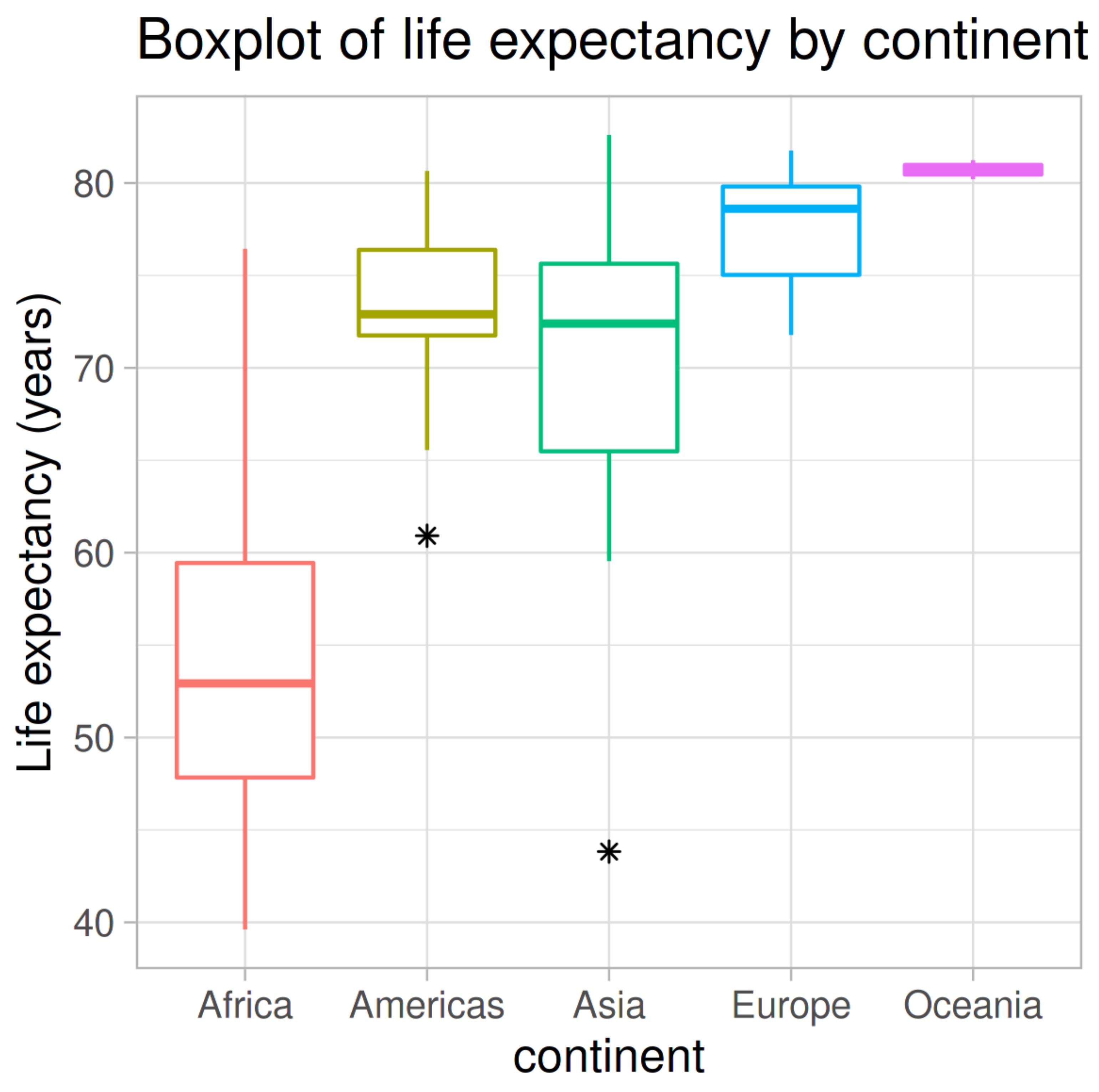
- Options: `lm`, `glm`, `loess`, etc.
- Check `?geom_smooth`

```
ex_plot <- ggplot(gapminder_07, aes(y = lifeExp,
                                     x = gdpPercap)) +
    geom_point(color="firebrick2") +
    labs(x = "GDP per capita ($)",
         y = "Life expectancy (years)",
         color= "Continent",
         size = "Population",
         title = "GDP vs Life expectancy") +
    geom_smooth(method = "lm", color= "purple2") +
    scale_x_log10() +
    theme_light(base_size = 12)

ggsave(plot = ex_plot, filename = "gg_point_2.png",
       width = 100, height = 100, units = "mm", dpi = 300)
```



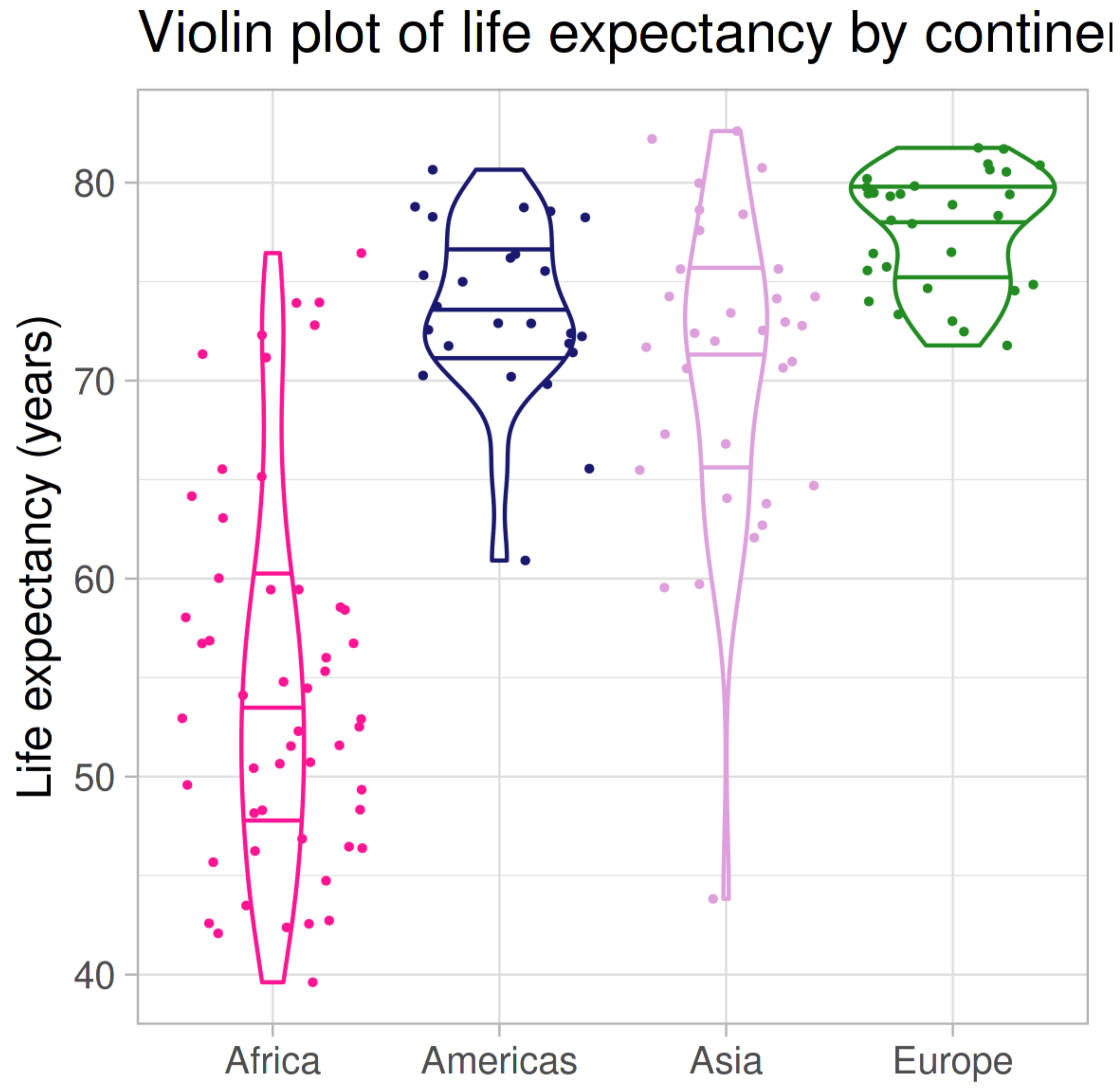
Boxplots

```
ex_plot <- ggplot(gapminder_07, aes(y = lifeExp,
                                    group = continent,
                                    x = continent,
                                    color = continent)) +
    geom_boxplot(outlier.colour = "black", outlier.shape = 8) +
    labs(y = "Life expectancy (years)",
         title = "Boxplot of life expectancy by continent") +
    guides(color = FALSE) +
    theme_light(base_size = 12)

ggsave(plot = ex_plot, filename = "gg_box_1.png",
       width = 100, height = 100, units = "mm", dpi = 300)
```



Violin plots

```
ex_plot <- ggplot(gapminder_07 %>% filter(!continent=="Oceania"),
                aes(y = lifeExp,
                    group = continent,
                    x = continent,
                    color = continent)) +
    geom_violin(draw_quantiles = c(0.25, 0.5, 0.75)) +
    geom_jitter(size = 0.5) +
    scale_color_manual(values = c("deeppink", "midnightblue",
                                  "plum", "forestgreen")) +
    labs(y = "Life expectancy (years)",
         title = "Violin plot of life expectancy by continent",
         x = NULL) +
    guides(color = FALSE) +
    theme_light(base_size = 12)

ggsave(plot = ex_plot, filename = "gg_vio_1.png",
       width = 100, height = 100, units = "mm", dpi = 300)
```



Facets and more tweaks

```
ex_plot <- ggplot(gapminder %>% filter(!continent=="Oceania",
                                       year %in% c(1997,2007)),
                  aes(y = lifeExp,
                      group = continent,
                      x = gdpPercap,
                      color = continent)) +
    geom_point(size = 0.5) +
    labs(y = "Life expectancy (years)",
         title = "Faceted plot of life exp. vs GDP",
         x = "GDPpC ($)") +
    guides(color = FALSE) +
    scale_x_log10(labels = scales::scientific) +
    geom_smooth(method = "lm") +
    facet_grid(year ~ continent) +
    theme_light(base_size = 12) +
    theme(strip.background = element_rect(fill = "white"),
          strip.text = element_text(color= "black"),
          axis.text.x = element_text(angle = 90, vjust = 0.5),
          axis.title.x =
              element_text(margin = margin(5,0,0,0, unit = "mm")))

ggsave(plot = ex_plot, filename = "gg_facet_1.png",
       width = 100, height = 100, units = "mm", dpi = 300)
```