

How to Use R for Data Science

Lecture Notes

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Preface

About R

The programming language R enables you to handle, visualize, and analyze data. It is compatible with various operating systems (Windows, Mac, Linux) and can do a lot of things better compared to other programs like Python, Stata, Eviews, SPSS, SAS, and Excel. R is open source, extensively utilized, and there are abundant resources available for learning it. These notes are just my five cents.

About the cover of the notes

Data science is a buzzword that combines different fields of knowledge such as computer science, software engineering, informatics, database management, statistics, econometrics, business intelligence, and mathematics. However, there is no universally accepted definition of it and I think it is not important to define it precisely. [Kelleher and Tierney \(2018, p. 97\)](#) wrote “Data science is best understood as a partnership between a data scientist and a computer.” So data science is about embracing the power of computers for scientific, commercial or social purposes. Of course, empirical models and statistics play a role in gaining meaningful insights. The graphic on the cover page may illustrate that R combines four important fields, that are, data, science, computer, and statistics.

About the notes

- These notes aims to support my lecture at the HS Fresenius but are incomplete and no substitute for taking actively part in class.
- A pdf version of these notes is available [here](#)
- I host the notes in a [GitHub repo](#).
- I appreciate you reading it, and I appreciate any comments.
- This is work in progress so please check for updates regularly.
- These notes offer a curated collection of explanations, exercises, and tips to facilitate learning R without causing unnecessary frustration. However,

these notes don't aim to rival comprehensive textbooks such as [Wickham and Grolemund \(2023\)](#).

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About the author



Figure 1: Prof. Dr. Stephan Huber

I am a Professor of International Economics and Data Science at HS Fresenius, holding a Diploma in Economics from the University of Regensburg and a Doctoral Degree (summa cum laude) from the University of Trier. I completed postgraduate studies at the Interdisciplinary Graduate Center of Excellence at the Institute for Labor Law and Industrial Relations in the European Union (IAAEU) in Trier. Prior to my current position, I worked as a research assistant to Prof. Dr. Dr. h.c. Joachim Möller at the University of Regensburg, a post-doc at the Leibniz Institute for East and Southeast European Studies (IOS) in Regensburg, and a freelancer at Charles University in Prague.

Throughout my career, I have also worked as a lecturer at various institutions, including the TU Munich, the University of Regensburg, Saarland University, and the Universities of Applied Sciences in Frankfurt and Augsburg. Additionally, I have had the opportunity to teach abroad for the University of Cordoba in Spain, the University of Perugia in Italy, and the Petra Christian University in Surabaya, Indonesia. My published work can be found in international journals such as the Canadian Journal of Economics and the Stata Journal. For more information on my work, please visit my private homepage at hubchev.github.io.

I began my journey into data science in 2003 with the introductory course Statistics by [Daniel Rösch](#). I learned a lot. In particular, that probabilities often play a role

when analyzing data. After that, I joined [Harry Haupt's *Introductory Econometrics*](#) course, where I studied the infamous Jeffrey M. Wooldridge (2002) textbook. It got me hooked and I took all the courses [Rolf Tschernig](#) offered at his chair of Econometrics, where I became a tutor at the University of Regensburg and a research assistant of [Joachim Möller](#). Despite everything we did had to do with how to make sense out of data, we never actually used the term *data science* which is also absent in the more 850 pages long textbook by Wooldridge (2002). The book also remains silent about *machine learning* or *artificial intelligence*. These terms became popular only after I graduated. The *Harvard Business Review* article by [Davenport and Patil \(2012\)](#) who claimed that data scientist is “The Sexiest Job of the 21st Century” may have boosted the popularity.

This makes me wonder if its okay that I and so many of my former comilitons, colleagues, and students call themselves now data scientists even though the term basically played no role in our education.

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Chapter 1

Getting started with R

Before we can start exploring data in R, there are some key concepts to understand first:

1. Why R?
2. How to learn R?
3. What are R and RStudio?
4. How to use R and RStudio without installation
5. How to install R and RStudio
6. How to write and run code in R
7. What are R packages?
8. What is a function in R?
9. What are objects in R?
10. Are there some guidelines for working with R?

1.1 Why R?

R is a free and open-source programming language that provides a wide range of advanced statistics capabilities, state-of-the-art graphics, and powerful data manipulation capabilities. It supports larger data sets, reads any type of data, and runs on multiple platforms. R makes it easier to automate tasks, organize projects, ensure reproducibility, and find and fix errors, and anyone can contribute packages to improve its functionality. Moreover, the following points are worth to emphasize:

- **R is an artist!** Check out:
 - <https://www.r-graph-gallery.com/>
 - <http://r-statistics.co/Top50-Ggplot2-Visualizations-MasterList-R-Code.html>

– <https://www.r-bloggers.com/2020/05/7-useful-interactive-charts-in-r/>

- **R is an employment insurance.** If you are good in R programming or if you are good in writing programming code in general, you have plenty of opportunities to earn a decent salary.
- **R uses the computer and computers are great!** Doing statistics on a computer is faster, easier and more powerful than doing it by hand. Computers excel at mindless repetitive tasks. For most people, the only reason to ever do statistical calculations with pencil and paper is for learning purposes.
- **Excel is bad!** Doing statistics in a spreadsheet (e.g., Microsoft Excel) is often a bad idea. Although many people are likely feel more familiar with them, spreadsheets are very limited in terms of what analyses they allow you to do. You can easily lose the overview and it is hard to keep track of what you have done and in comparison with command line driven programs. In particular, the ability to make your analysis *replicable* is limited.
- **R is good, proprietary software is bad!** Avoiding proprietary software is a very good idea because it costly, support is exclusively provided by the owner of the software (if they stop supporting your version you are lost), security issues cannot be checked as the source code is not available, and possibilities for customization are limited.
- **R is big!** Something that you might not appreciate now, but will love later on if you do anything involving data analysis, is the fact that R is highly extensible. When you download and install R, you get all the basic packages, and those are very powerful on their own. However, because R is so open and so widely used, it's become something of a standard tool in statistics, and so lots of people write their own packages that extend the system. And these are freely available too. One of the consequences of this, I've noticed, is that if you open up an advanced textbook (a recent one, that is) rather than introductory textbooks, is that a *lot* of them use R. In other words, if you learn how to do your basic statistics in R, then you're a lot closer to being able to use the state of the art methods than you would be if you'd started out with a "simpler" system: so if you want to become a genuine expert in data analysis, learning R is a very good use of your time.
- **R is the future!** Programming is a core skill in research, economics, and business. R is one of the most widely used programming languages in the world today. It is used in almost every industry such as finance, banking, medicine or manufacturing. R is used for portfolio management, risk analytics in finance and banking industries.

However, R has weaknesses: It's not easy to learn for people without programming

experience. It has some annoying quirks that we all have to deal with, it's slower than other object oriented languages (Phyton, MATLAB, C/C++, Java), and R's algorithms and sources are spread across many packages (since there's no big company behind it that wants you to buy it). While the lack of centralized support for R comes with a supportive online community and many package developers who provide their code generously, it sometimes makes it very difficult for beginners to find what they are looking for.

1.2 How to learn R

There are many different approaches to learning R. It pretty much depends on your preferences, needs, goals, prerequisites and limitations. It is up to you to search and find a suitable way to achieve your learning goals. While I hope you find my notes helpful, I additionally provide in section 1.3 a list of other resources that are worth considering.

My notes walk you through the most important things when working with R and RStudio by introducing some building blocks of the programming language and offering some exercises with solutions. If you want to dig deeper you should come back to the sources mentioned in section 1.3. To start with, I recommend my swirl courses, see section 2. They provide an interactive learning environment.

Tips on learning to code:

Learning a programming language can, like learning a foreign language, be daunting and frustrating. However, if you put in the effort and are not afraid to make mistakes, anybody can learn it. You don't have to be a nerd. The key is taking action and getting involved. I mean, do write code. Try to copy the code that you read here and see how it works on your machine. Make your hands dirty! Don't be afraid to make errors. Your PC will not explode. In this paper, most of the code is written in a manner that allows you to effortlessly copy and reproduce the output on your PC. Take advantage of this opportunity and go for it! Hands-on practice is far more enjoyable than merely reading through the material.

Here I summarize some useful tips:

- **Remember that computers are not actually that smart:** You may think your computer or smartphone is "smart," but it is not. In reality, you have to tell a computer everything it needs to do. The instructions you give your computer can't have any mistakes in them, nor can they be ambiguous in any way. The computer simply will not understand. For example, if you forget a comma or closing a bracket, the code will break.

- **Take the “copy, paste, and tweak” approach:** While learning code from scratch is sometimes essential, you can speed up your work by modifying code that already exists. I call this the “*copy, paste, and tweak*” approach. It is a good way to learn code and get a job done quick.
- **Have a purpose when coding:** Rather than learning to code for its own sake, it is more fun and you’ll probably learn faster when you have a goal in mind. Try to analyze data that you are interested in. Another good exercise is replicating a research paper.
- **Practice is key:** The best method to improving your coding skills is through lots of practice. Consequently, these notes give you plenty of exercises.

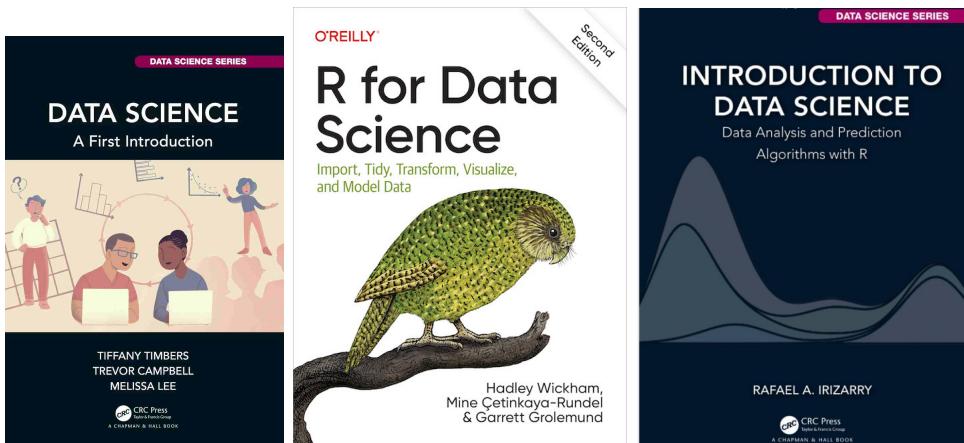
1.3 Learning resources



Thousands of freely available books and resources exist. On bookdown.org and in the [Big Book of R](#) is a big collection of links to R books that verifies my claim. Another nice collection of learning resources can be found here: [AWESOME R Learning-Resources](#)

In RStudio you find in the left panel at the bottom a panel that is called *Help*. There you find a lot of links, manuals, and references that offer you tons of resources to learn R for free including: education.rstudio.com and [Links for Getting Help with R](#)

Since you may feel overwhelmed by the number of resources, I would like to highlight five books:



1. Timbers, Campbell, and Lee (2022): **Data Science: A First Introduction** is a free and up to date book that comes with exercises with worksheets that are available on [UBC-DSCI GitHub repository](#)
2. Wickham and Grolemund (2023): **R for Data Science: Import, Tidy, Transform, Visualize, and Model Data** is the most popular source to learn R. It focuses on introducing the tidyverse package and is freely available online.
3. Irizarry (2022): **Introduction to Data Science: Data Analysis and Prediction Algorithms With R** is a complete, up to date, and applied introduction.
4. Venables, Smith, and R Core Team (2022) **An Introduction to R: Notes on R: A Programming Environment for Data Analysis and Graphics** is a manual from the R Core Development Team that shows how to use R without having to install and load additional packages.
5. Neth (2023): **Data Science for Psychologists** is a comprehensive introduction to R and data science for non experts of both programming and data science. It uses a variety of data types and includes many examples and exercises.

Some other sources that are worth mentioning are these:

- The search engine www.rseek.org is R specific and often better than www.google.com as it only searches for content that has to do with the programming language R.
- On rdocumentation.org you can find the complete documentation of all R packages.
- Many find these [cheatsheets](#) helpful.

1.4 What are R and RStudio?

Throughout this book, I will assume that you are using R via RStudio. First time users often confuse the two. At its simplest, R is like a car's engine while RStudio is like a car's dashboard as illustrated in Figure 1.1.

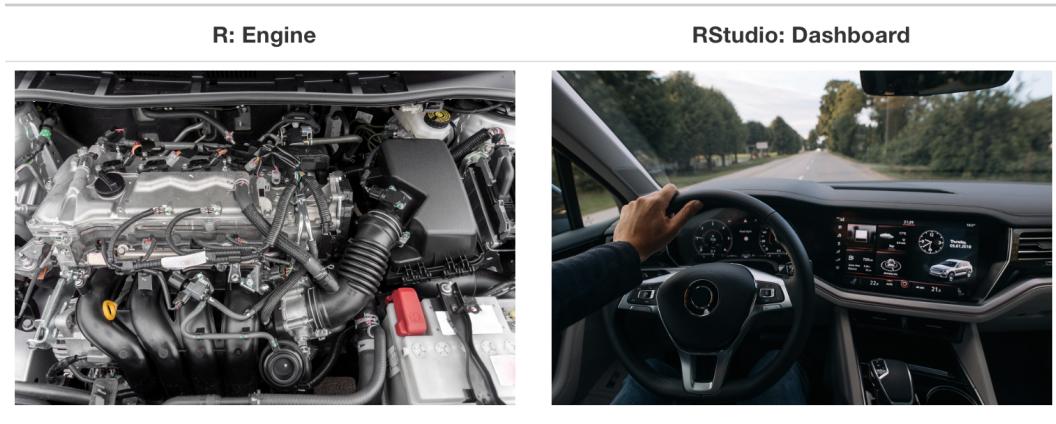


Figure 1.1: Analogy of difference between R and RStudio.

More precisely, R is a programming language that runs computations, while RStudio is an *integrated development environment (IDE)* that provides an interface by adding many convenient features and tools. So just as the way of having access to a speedometer, rearview mirrors, and a navigation system makes driving much easier, using RStudio's interface makes using R much easier as well.

Much as we don't drive a car by interacting directly with the engine but rather by interacting with elements on the car's dashboard, we won't be using R directly but rather we will use RStudio's interface. After you install R and RStudio on your computer, you'll have two new *programs* (also called *applications*) you can open. We'll always work in RStudio and not in the R application. Figure 1.2 shows what icon you should be clicking on your computer.

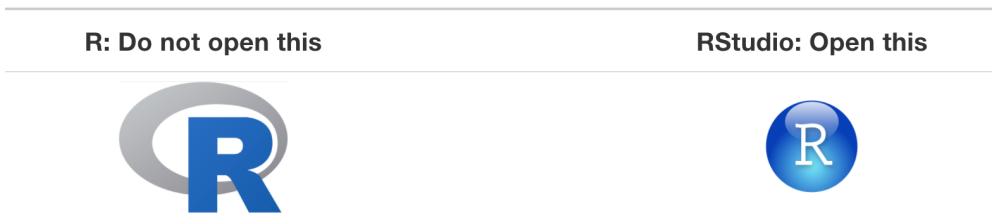


Figure 1.2: Icons of R versus RStudio on your computer.

After you open RStudio, you should see something similar to Figure 1.3 where three or four panels dividing the screen.

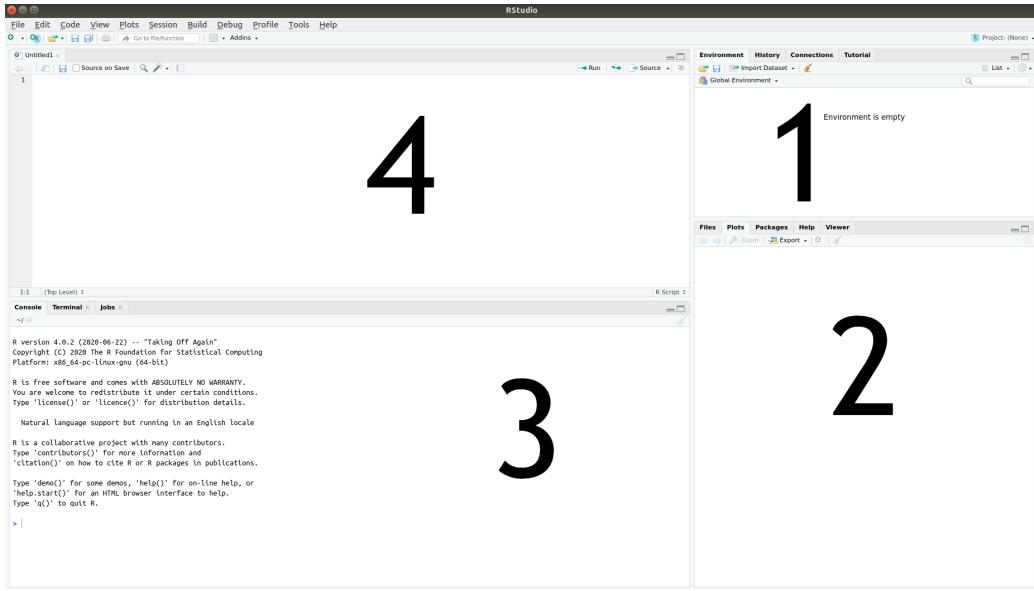


Figure 1.3: RStudio interface to R.

1. The *Environment* panel, where a list of the data you have imported and created can be found.
2. The *Files*, *Plots* and *Help* panel, where you can see a list of available files, will be able to view graphs that you produce, and can find help documents for different parts of R.
3. The *Console* panel, used for running code. This is where we'll start with the first few examples.
4. The *Script* panel, used for writing code. This is where you'll spend most of your time working.

The *Console* panel will contain R's startup message, which shows information about which version of R you're running. My startup message at the time of writing was as follows:

```
R version 4.1.2 (2021-11-01) – “Bird Hippie” Copyright (C) 2021 The R
Foundation for Statistical Computing Platform: x86_64-pc-linux-gnu
(64-bit)
```

R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions. Type
'license()' or 'licence()' for distribution details.

Natural language support but running in an English locale

R is a collaborative project with many contributors. Type ‘contributors()’ for more information and ‘citation()’ on how to cite R or R packages in publications.

Type ‘demo()’ for some demos, ‘help()’ for on-line help, or ‘help.start()’ for an HTML browser interface to help. Type ‘q()’ to quit R.

If you don’t have panel number 4, open it by opening an existing R-script or creating a new one. You can create a new one by clicking *Ctrl+Shift+N* (alternatively, you can use the menu: File→New File→R Script).

You can resize the panels as you like, either by clicking and dragging their borders or using the minimise/maximise buttons in the upper right corner of each panel. Clicking *Ctrl++* and *Ctrl+-* allows to make the fonts larger or smaller.

When you exit RStudio, you will be asked if you wish to *save your workspace*, meaning that the data that you’ve worked with will be stored so that it is available the next time you run R. That might sound like a good idea, but in general, I recommend that you don’t save your workspace, as that often turns out to cause problems down the line. It is almost invariably a much better idea to simply rerun the code you worked with in your next R session.

1.5 How to use R and RStudio without installation

If you don’t want to install R on your PC or you don’t have admin rights to do so, you can use RStudio online doing *cloud computing* on <https://posit.cloud/>. Posit Cloud (formerly RStudio Cloud) is a cloud-based solution that allows anyone to do, share, teach and learn data science online. It is free for individuals with some restrictions and limited capacities.

1.6 Installing R and RStudio

You will first need to download and install both R and RStudio (Desktop version) on your computer. It is important that you install R first and then install RStudio.

1. **Do this firstly:** Download and install R by going to <https://cloud.r-project.org/>.
 - If you are a Windows user: Click on “Download R for Windows”, then click on “base”, then click on the Download link.

- If you are macOS user: Click on “Download R for (Mac) OS X”, then under “Latest release:” click on R-X.X.X.pkg, where R-X.X.X is the version number. For example, the latest version of R as of November 25, 2019 was R-3.6.1.
 - If you are a Linux user: Click on “Download R for Linux” and choose your distribution for more information on installing R for your setup.
2. **Do this secondly:** Download and install RStudio at <https://www.rstudio.com/products/rstudio/download/>.
 - Scroll down to “Installers for Supported Platforms” near the bottom of the page.
 - Click on the download link corresponding to your computer’s operating system.

1.7 What is a function in R?

One of the keys to understand R is a *functional programming language*. Or, to put in the words of Chambers (2017, p. 4): “Everything that happens is a function call.” When you like to exit R, for example, you do it with the function `q()`:

```
> q()  
Save workspace image? [y/n/c] :
```

If you don’t want to be asked what you want to do with your workspace (that is the place where you store all your objects, see section 1.8) you can do it with an argument that is part of the function:

```
> q(save = "no")
```

1.8 What are objects in R?

Everything you do is made with a function and “everything that exists in R is an object” (Chambers, 2017, p. 4). Objects are the fundamental units that are used to store information. Objects can be created using a variety of data types, including vectors, matrices, data frames, lists, functions. All objects are shown in the *workspace* which is shown in the *Environment* panel.

In R, you can show the content of the workspace with `ls()`. The function `rm()` allows to remove objects and with `rm(list=ls())` you clear all objects from the workspace.

1.9 What are R packages?

A package is a collection of functions, data sets and other R objects that are all grouped together under a common name. More than 10,000 packages are available at the official repository (CRAN) and many more are publicly available through the internet.

In this section, I'll describe how to work with packages using the Rstudio tools. Along the way, you'll see that whenever you get Rstudio to do something (e.g., install a package), you'll actually see the R commands that get created.

However, before we get started, there's a critical distinction that you need to understand, which is the difference between having a package **installed** on your computer, and having a package **loaded** in R. When you install R on your computer only a small number of packages come bundled with the basic R installation. The installed packages are on your computer. The critical thing to remember is that just because something is on your computer doesn't mean R can use it. In order for R to be able to *use* one of your installed packages, that package must also be *loaded*. Generally, when you open up R, only a few of these packages (about 7 or 8) are actually loaded. Basically what it boils down to is this:

1. A package must be installed before it can be loaded.
2. A package must be loaded before it can be used.

We only need to install a package once on our computer. However, to use the package, we need to load it every time we start a new R environment or R Studio, respectively.

1.9.1 Package installation

To install an R package you can use the GUI of R Studio or the command line. In R Studio you can click on the *Packages* tab, then on the *Install* button, then you must search for a package and click *Install*. An alternative way to install a package is by typing

```
install.packages("package_name")
```

in the console pane of RStudio and pressing Return/Enter on your keyboard. Note you must include the quotation marks around the name of the package.

If you want to update a previously installed package to a newer version, you need to re-install it by repeating the earlier steps or you use `update.packages()`. To uninstall packages you can use `remove.packages()`.

The installation of packages can take some time. However, if your CPU has many cores, you can speed up the process a lot using the argument `Ncpus` like this `update.packages(ask = F, Ncpus = 4L)`. This option allows you to adjust the number of parallel processes R can use on your PC. So, if you have a CPU with many cores you can increase that number. A tutorial on how to set the number of cores used by R permanently can be found here: <https://www.jumpingrivers.com/blog/speeding-up-package-installation/>

1.9.2 Package loading

Recall that after you've installed a package, you need to *load it*. We do this by using the `library()` command.

For example, to load the `ggplot2` package, run the following code in the console pane. What do we mean by “run the following code”? Either type or copy-and-paste the following code into the console pane and then hit the Enter key.

```
library("ggplot2")
```

If after running the earlier code, a blinking cursor returns next to the > “prompt” sign, it means you were successful and the `ggplot2` package is now loaded and ready to use. If, however, you get a red “error message” that reads

```
Error in library(ggplot2) : there is no package called 'ggplot2'
```

It means that you didn't successfully install it. If you get this error message, go back to section 1.9.1 on R package installation and make sure to install the `ggplot2` package before proceeding.

One very common mistake new R users make when wanting to use particular packages is they forget to *load* them first by using the `library()` command we just saw. Remember: *you have to load each package you want to use every time you start RStudio*. If you don't first *load* a package, but attempt to use one of its features, you'll see an error message similar to:

```
Error: could not find function
```

R is informing you that you are attempting to use a function from a package that has not yet been loaded. Forgetting to load packages is a common mistake made by new users, and it can be a bit frustrating to get used to at first. However, with practice, it will become second nature for you. Unloading packages can be done with `detach(, unload=TRUE)`.

1.9.3 Simplified package management with `p_load`

There is a convenient way to handle both package installation and loading without the need for manual checks. The `p_load()` function does this seamlessly by verifying if a package is installed; if not, it installs the package.

For instance, instead of the traditional approach:

```
install.packages(
  c("arrow", "babynames", "curl", "duckdb", "gapminder",
    "ggrepel", "ggridges", "ggthemes", "hexbin", "janitor", "Lahman",
    "leaflet", "maps", "nycflights13", "openxlsx", "palmerpenguins",
    "repurrrsive", "tidymodels", "writexl")
)
library(
  c("arrow", "babynames", "curl", "duckdb", "gapminder",
    "ggrepel", "ggridges", "ggthemes", "hexbin", "janitor", "Lahman",
    "leaflet", "maps", "nycflights13", "openxlsx", "palmerpenguins",
    "repurrrsive", "tidymodels", "writexl")
)
```

You can streamline the process as follows:

```
# Install and load the required packages using p_load
if (!require(pacman)) install.packages("pacman")

pacman::p_load(
  arrow, babynames, curl, duckdb, gapminder,
  ggrepel, ggridges, ggthemes, hexbin, janitor, Lahman,
  leaflet, maps, nycflights13, openxlsx, palmerpenguins,
  repurrrsive, tidymodels, writexl
)
```

The line

```
if (!require(pacman)) install.packages("pacman")
```

ensures the installation of the `pacman` package, which is necessary for using the `p_load` function.

Before you load packages in a script, I recommend to *unload* all other packages with

```
pacman::p_unload(all)
```

to avoid conflicts of functions.

1.10 Are there some guidelines for working with R?

To avoid running into issues with R, it's important to be aware of the some conventions, rules, and best practices that apply to the language. While it can be tedious to go through all of the do's and don'ts in detail, following them can make your life with R much easier. Trust me, the benefits of adhering to these guidelines will become clear over time. Here is a non-exhaustive list:

1. Do remember that R programming language is case sensitive.
2. Do start names of objects such as vectors, numbers, variables, and data frames with a letter, not a number.
3. Do avoid using dots in names of objects.
4. Do avoid using certain keywords in naming objects, such as if, else, repeat, while, function, for, in, next, break, TRUE, FALSE, NULL, Inf, NaN, and NA.
5. Do use front slash / instead of backslash \ for navigating the file system.
6. Do not use whitespace and indentation for naming files, directories, or objects.
7. Do not ignore warnings or errors unless you know what they mean.
8. Do define objects to represent hard-coded values instead of using them directly in code.
9. Do remember to (install and) load packages that contain functions you want to use.
10. Do remember to set your working directory. (Tip: Use R Studio projects, see [8.2.4](#))
11. Do remember to comment your code.
12. Do use <- instead of = for assignment.

An exhaustive style guide on how to write code can be found here: <https://style.tidyverse.org>

Chapter 2

Learn interactively with *swirl*

The R package *swirl* makes it fun and easy to learn R programming and data science. *swirl* teaches you R programming and data science interactively, at your own pace, and right in the R console! You get immediate feedback on your progress. If you are new to R, have no fear. *swirl* will walk you through each of the steps required to employ Rstudio and R for your purpose. To start it, please follow my instructions precisely!

Open Rstudio and type in the console the following:

```
install.packages("swirl")
library("swirl")
install_course_github("hubchev", "swirl-it")
swirl()
```

The above lines of code do the following:

- Install the *swirl* package.
- Load the *swirl* package.
- Install my *swirl* course that is hosted on GitHub.
- With *swirl* you start *swirl* and your learning experience.

If the course has failed to install, you can try to download the file `swirl-it.swc` from <https://github.com/hubchev/swirl-it> and install the course with loading the *swirl* package and typing `install_course()` into the console.

Please choose the course *swirl-it* and the learning module *huber-intro-1*. You can exit *swirl* at any time by typing `bye()` or by clicking the *Esc* on your keyboard.

After you have successfully finished learning module *huber-intro-1* please go ahead with the learning module *huber-intro-2* that is also part of my swirl course *swirl-it*.

***swirl* modules on data analytical basics**

In my swirl modules *huber-data-1*, *huber-data-2*, and *huber-data-3* I introduce some very basic statistical principles on how to analyse data.

***swirl* module on the `tidyverse` package**

I compiled a short *swirl* module to introduce the *tidyverse* universe. This is a powerful collection of packages which I discuss later on. The learning module is also part of my *swirl-it* course.

Other *swirl* modules

You can also install some other courses. You find a list of courses here <http://swirlstats.com/scn/index.html> or here https://github.com/swirldev/swirl_courses.

I recommend this one as it gives a general overview on very basic principles of R:

```
library(swirl)
install_course_github("swirldev", "R_Programming_E")
swirl()
```

Chapter 3

Work with R scripts

3.1 R Scripts: Why they are useful

Typing functions into the console to run code may seem simple, but this interactive style has limitations:

- Typing commands one at a time can be cumbersome and time-consuming.
- It's hard to save your work effectively.
- Going back to the beginning when you make a mistake is annoying.
- You can't leave notes for yourself.
- Reusing and adapting analyses can be difficult.
- It's hard to do anything except the basics.
- Sharing your work with others can be challenging.

That's where having a transcript of all the code, which can be re-run and edited at any time, becomes useful. An R script is precisely that - a plain text file that contains code and comments and this comes with advantages:

- Scripts provide a record of everything you did during your data analysis.
- You can easily edit and re-run code in a script.
- Scripts allow you to leave notes for yourself.
- Scripts make it easy to reuse and adapt analyses.
- Scripts allow you to do more complex analyses.
- Scripts make it easy to share your work with others.

3.2 Generate, write, and run R scripts

To generate a script you can

1. Go to the *File* menu, select *New File* and then choose *R Script* or
2. Use the keyboard shortcut *Ctrl+Shift+N* (Windows) or *Cmd+Shift+N* (Mac)
or
3. Type the following command in the Console:

```
file.create("hello.R")
```

In the first two ways, a new R script window will open which can be edited and should be saved either by clicking on the *File* menu and selecting *Save*, clicking the disk icon, or by using the shortcut *Ctrl+S* (Windows) or *Cmd+S* (Mac). If you go for the third way, you need to open it manually.

Regardless of your preferred way of generating a script, we can now start **writing** our first script:

```
setwd("/home/sthu/Dropbox/hsf/23-ss/ds/")
x <- "hello world"
print(x)
```

Then save the script using the menus (*File > Save*) as `hello.R`.

The above lines of code do the following:

- `setwd()` allows to set the working directory. If you are not familiar with file systems, please read section [8.2](#) in the appendix.
- With the assignment operator `<-` we create an object that stores the words “hello world” in an object entitled `x`. In the next section [3.3](#) the assignment operator is further explained.
- With the third input we print the content of the object `x`.

So how do we **run the script**? Assuming that the `hello.R` file has been saved to your working directory, then you can run the script using the following command:

```
source( "hello.R" )
```

Suppose you saved the script in a sub-folder called `scripts` of your working directory, then you need to run the script using the following command:

```
source("./scripts/hello.R")
```

Just note that the dot, `..`, means the current folder. Instead of using the `source` function, you can click on the `source` button in Rstudio.

With the character `#` you can write a comment in a script and R will simply ignore everything that follows in that line onwards.

3.3 The assignment operator: <-

Suppose I'm trying to calculate how much money I'm going to make from this book. I agree, it is an unrealistic example but it will help you to understand R. Let's assume I'm only going to sell 350 copies. To create a variable called `sales` and assigns a value to it, we need to use the *assignment operator* of R, which is `<-` as follows:

```
sales <- 350
```

When you hit enter, R doesn't print out any output. If you are using Rstudio, and the *environment panel* you can see that something happened there, can you? It just gives you another command prompt. However, behind the scenes R has created a variable called `sales` and given it a value of 350. You can check that this has happened by asking R to print the variable on screen. And the simplest way to do that is to type the name of the variable and hit enter.

```
sales
```

```
## [1] 350
```

Worth a mentioning is the curious features of R that there are several different ways of making assignments. In addition to the `<-` operator, we can also use `->` and `=`. If you want to use `->`, you might expect from just looking at the symbol you should write it like this:

```
350 -> sales
```

However, it is common practice to use `<-` and I recommend only to use this one because it is easier to read in scripts.

3.4 Doing calculation in scripts

R can do any kind of arithmetic calculation with the arithmetic operators given in the table below. Using the assignment operator, R functions, and the features of a R script is easy and gives an idea how R works and how you should embrace the power of the programming language.

operation	operator	example input	example output
addition	+	10+2	12
subtraction	-	9-3	6
multiplication	*	5*5	25
division	/	10/3	3

operation	operator	example input	example output
power	\wedge	5^2	25

So please copy and past the following lines of code into a R script of yours, try to run it on your PC, and try to understand it. Of course, you have to tweak the script a bit to make it run on your PC. For example, I doubt you have the same working directory that I decided to use.

```
# Set working directory
setwd("~/Dropbox/hsf/23-ss/ds")
# Create a vector that contains the sales data
sales_by_month <- c(0, 100, 200, 50, 3, 4, 8, 0, 0, 0, 0, 0)
sales_by_month
sales_by_month[2]
sales_by_month[4]
february_sales <- sales_by_month[2]
february_sales
sales_by_month[5] <- 25 # added May sales data
sales_by_month
# Do I have 12 month?
length( x = sales_by_month )
# Assume each unit costs 7 Euro, then the revenue is
price <- 7
revenue <- sales_by_month*price
revenue
# To get statistics for daily revenue we define the number of days:
days_per_month <- c(31, 28, 31, 30, 31, 30, 31, 31, 30, 31, 30, 31)
# Calculate the daily revenue
revenue_per_day <- revenue/days_per_month
revenue_per_day
# round number
round(revenue_per_day)
```

Use the “?” to search for the documentation of all functions used. In particular, do you understand how the function `round()` works? What arguments does the function contain? How can you manipulate the pre-defined arguments. For example, can you calculate the rounded revenue per day with two or four digits? Try it out!

```
?round()
```

3.5 User-defined functions

One of the great strengths of R is the user's ability to add functions. Sometimes there is a small task (or series of tasks) you need done and you find yourself having to repeat it multiple times. In these types of situations it can be helpful to create your own custom function. The structure of a function is given below:

```
name_of_function <- function(argument1, argument2) {
  statements or code that does something
  return(something)
}
```

First you give your function a name. Then you assign value to it, where the value is the function. When defining the function you will want to provide the list of arguments required (inputs and/or options to modify behavior of the function), and wrapped between curly brackets place the tasks that are being executed on/using those arguments. The argument(s) can be any type of object (like a scalar, a matrix, a dataframe, a vector, a logical, etc), and it's not necessary to define what it is in any way. Finally, you can return the value of the object from the function, meaning pass the value of it into the global environment. The important idea behind functions is that objects that are created within the function are local to the environment of the function – they don't exist outside of the function. Note, a function doesn't require any arguments.

Let's try creating a simple example function. This function will take in a numeric value as input, and return the squared value.

```
square_it <- function(x) {
  square <- x * x
  return(square)
}
```

Now, we can use the function as we would any other function. We type out the name of the function, and inside the parentheses we provide a numeric value `x`:

```
square_it(5)
```

```
## [1] 25
```

Let us get back to script with sales and try to calculate the monthly growth rates of revenue using a self-written function.

The formula of a growth rate is clear:

$$g = \left(\frac{y_t - y_{t-1}}{y_{t-1}} \right) \cdot 100 = \left(\frac{y_t}{y_{t-1}} - 1 \right) \cdot 100$$

So the challenge is to divide the value of `revenue` with the value of the previous period, a.k.a. the lagged value. Let us assume that the function `lag()` can give you exactly that value of a vector. Lets try it out:

```
lag(revenue)

## [1] 0 700 1400 350 175 28 56 0 0 0 0 0

## attr(",tsp")
## [1] 0 11 1

(revenue/lag(revenue)-1)*100

## [1] NaN 0 0 0 0 0 NaN NaN NaN NaN NaN

## attr(",tsp")
## [1] 0 11 1
```

Unfortunately, this does not work out. The `lag()` function does not work as we think it should. Well, the reason is simply that we are using the wrong function. The current `lag()` function is part of the `stats` package which is part of the package `stats` which is part of R base and is loaded automatically. The `lag()` function we aim to use stems from the `dplyr` package which we must install and load to be able to use it. So let's do it:

```
# check if the package is installed
find.package("dplyr")

## [1] "/home/sthu/R/x86_64-pc-linux-gnu-library/4.2/dplyr"

# I already installed the package so I can just load it
# install.packages("dplyr")
library("dplyr")

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
## 
##     filter, lag

## The following objects are masked from 'package:base':
## 
##     intersect, setdiff, setequal, union
```

This message informs us that among other functions the `lag()` function is *masked*. That means that now the function of the newly loaded package is active. So, let's try again:

```
lag(revenue)

## [1] NA    0   700 1400  350  175   28   56    0    0    0    0
```

```
(revenue/lag(revenue)-1)*100
```

```
## [1] NA Inf 100 -75 -50 -84 100 -100 NaN  NaN  NaN  NaN
```

That looks good now. And here is a way to calculate growth rates with a self-written function:

```
growth_rate <- function(x)(x/lag(x)-1)*100
growth_rate(revenue)
```

```
## [1] NA Inf 100 -75 -50 -84 100 -100 NaN  NaN  NaN  NaN
```

```
sales_gr_rate <- growth_rate(revenue)
```

```
sales_gr_rate
```

```
## [1] NA Inf 100 -75 -50 -84 100 -100 NaN  NaN  NaN  NaN
```

In R, all functions are written by users, and it is not uncommon for two people to name their functions identically. In such cases, we must resolve the conflict by choosing which function to use. To use the `lag` function from the `stats` package, you can use the double colon operator `::` like this `stats::lag(arguments)`.

Chapter 4

Visualizing data

Data visualization is an art. The purposes of visualizing data are manifold. You can emphasize facts, get known to data, detect anomalies, and communicate a large amount of information simply and intuitive. Whatever your goal is, thousand of appropriate ways exist to visualize data. Many decisions to take are simply a matter of taste. However, there are some conventions and guidelines that help you to make on average better decisions when designing a visualization:

- Good graphs are easy to understand and eye catching.
- Graphs can be misleading and manipulative and that is opposing to the ideas of science. Thus, be responsible and honest.
- Minimize colors and other attention-grabbing elements that are not directly related to the data of interest. Worldwide, there are approximately 300 million color blind people. In particular, red, green or blue light are problematic to color blind people. Thus, better rely on color schemes that are designed for colorblind people.
- Don't truncate an axis or change the scaling within an axis just to make your story more appealing. Show the full scale of the graph, then zoom to show the data of interest, if necessary.
- Label and describe your chart sufficiently so that everybody can fully understand the content of the shown data set and statistics without having to study the notes of the graph for too long.
- Don't do pie charts. They may look simple, but they're tricky to get right and there are usually better alternatives. Humans are not very good at comparing the size of angles and as there's no scale in pie plots, reading accurate values is difficult. Figure 4.1 may proof this.
- For more tips, see:
 - [Data Visualization: Chart Dos and Don'ts \(by Duke University\)](#)

- [Graphs and Visualising Data](#) by Oliver Kirchkamp. In particular, I highly recommend his handout ([Kirchkamp, 2018](#)). It discusses many pitfalls of visualizing data, instructs how to do good graphs, and he shows the corresponding R code of all graphs.
- The [R Graph Gallery](#) offers shows graphs and the corresponding R code to replicate the graphs
- The work of [Edward Tufte](#) and his book *The Visual Display of Quantitative Information* ([Tufte, 2022](#)) are classical readings.

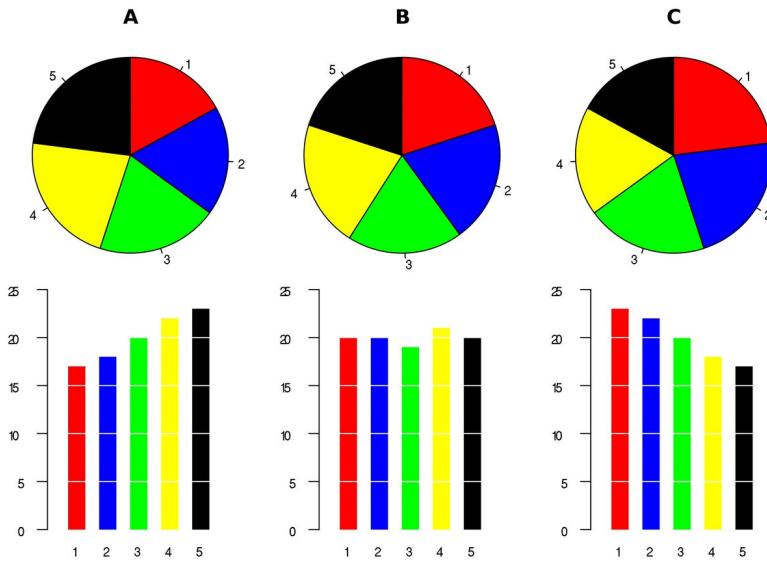


Figure 4.1: Pie charts are problematic¹

When it comes to data visualization, there's no better resource than the book by [Wickham and Grolemund \(2023\)](#). It introduces the ggplot function which is part of the ggplot2 package which, in turn, is part of the tidyverse package. Thus, if you've installed and loaded tidyverse, you automatically have access to ggplot. Creating beautiful and informative graphs is easy with ggplot. To proof that claim, study section 2 ([Data visualization](#)) of [Wickham and Grolemund \(2023\)](#). To reap the best benefits from studying, I recommend to copy all the code that is shown in the book into a R script and try to run it on your PC. That is the best way to learn, understand, and create your own notes that may guide you later on. Whenever you see interesting code somewhere, try to run it on your PC. Moreover, I recommend the exercises of the book, they are challenging sometimes but to really understand code you need to run code yourself.

¹Picture is taken from https://en.wikipedia.org/wiki/Pie_chart

Chapter 5

Manage data

5.1 The tidyverse universe



Figure 5.1: The tidyverse universe

The R package *tidyverse* is a collection of R packages. All packages share an underlying design philosophy, grammar, and data structures. The most popular packages are *ggplot2*, *dplyr*, *tidyr*, *readr*, *purrr*, *tibble*, *stringr*, and *forcats*. They provide functionality to model, transform, and visualize data. Tidyverse is extremely popular and many individual packages of tidyverse are regularly in the top 10 most downloaded R packages on CRAN¹. How to do data science with tidyverse is the subject of multiple books and tutorials. In particular, the popular book *R for Data Science* by Wickham and Grolemund (2023) is all about the tidyverse universe. Thus, I highly recommend reading sections 3 (Workflow: basics), 4

¹CRAN is a network of ftp and web servers around the world that store identical, up-to-date, versions of code and documentation for R, see: <https://cran.r-project.org>.

([Data transformation](#)), and 6 ([Data tidying](#)) of Wickham and Grolemund (2023). Additionally, visit www.tidyverse.org and, if you still haven't done so, do the tidyverse module of my swirl package, called *swirl-it*, see section 2.

To install and load tidyverse run the following lines of code:

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

5.2 The pipe operator

The pipe operator, `%>%`, comes from the *magrittr* package, which is also part of the tidyverse package. The pipe operator, `|>`, has been part of base R since version 4.1.0. For most cases, these two operators are identical. The pipe operator is designed to help you write code in a way that is easier to read and understand. As R is a functional language, code often contains a lot of parentheses, (and). Nesting these parentheses together can be complex and make your R code hard to read and understand, which is where `|>` comes to the rescue! It allows you to use the output of a function as the input of the next function. Consider the following example of code to explain the usage of the pipe operator:

```
# create some data `x`
x <- c(1, 1.002, 1.004, .99, .99)
# take the logarithm of `x`,
log_x <- log(x)
# compute the lagged and iterated differences (see `diff()`)
growth_rate_x <- diff(log_x)
growth_rate_x

## [1] 0.001998003 0.001994019 -0.014042357 0.000000000

# round the result (4 digit)
growth_rate_x_round <- round(growth_rate_x, 4)
growth_rate_x_round

## [1] 0.002 0.002 -0.014 0.000
```

That is rather long and we actually don't need objects `log_x`, `growth_rate_x`, and `growth_rate_x_round`. Well, then let us write that in a nested function:

```
round(diff(log(x)), 4)

## [1] 0.002 0.002 -0.014 0.000
```

This is short but hard to read and understand. The solution is the *pipe*:

```
# load one of these packages: `magrittr` or `tidyverse`
library(tidyverse)

# Perform the same computations on `x` as above
x |>
  log() |>
  diff() |>
  round(4)

## [1] 0.002 0.002 -0.014 0.000
```

You can read the `|>` with “*and then*” because it takes the results of some function “*and then*” does something with that in the next. For example, reading out loud the following code would sound something like this:

- I take the mtcars data, *and then*
- I consider only cars with more than 4 cylinders, *and then*
- I group the cars by the number of cylinders the cars have, *and then*
- I summarize the data and show the means of miles per gallon (mpg) and horse powers (hp) by groups of cars that distinguish by their number of cylinders.

```
mtcars |>
  filter(cyl>4) |>
  group_by(cyl) |>
  summarise_at(c("mpg", "hp"), mean)

## # A tibble: 2 x 3
##       cyl   mpg     hp
##   <dbl> <dbl> <dbl>
## 1     6 19.7 122.
## 2     8 15.1 209.
```

5.3 Import data

5.3.1 Vectors and matrices

We already got known to the `c()` function which allows to combine multiple values into a vector or list. Here are some examples how you can use this function to create vectors and matrices:

```
# defining multiple vectors using the colon operator `:`  
v_a <- c(1:3)  
v_a  
  
## [1] 1 2 3  
  
v_b <- c(10:12)  
v_b  
  
## [1] 10 11 12  
  
# creating matrix  
m_ab <- matrix(c(v_a, v_b), ncol = 2)  
m_cbind <- cbind(v_a, v_b)  
m_rbind <- rbind(v_a, v_b)  
  
# print matrix  
print(m_ab)  
  
##      [,1] [,2]  
## [1,]     1   10  
## [2,]     2   11  
## [3,]     3   12  
  
print(m_cbind)  
  
##      v_a v_b  
## [1,]  1 10  
## [2,]  2 11  
## [3,]  3 12  
  
print(m_rbind)  
  
##      [,1] [,2] [,3]  
## v_a    1    2    3  
## v_b   10   11   12  
  
# defining row names and column names  
rown <- c("row_1", "row_2", "row_3")  
coln <- c("col_1", "col_2")  
  
# creating matrix  
m_ab_label <- matrix(m_ab, ncol = 2, byrow = FALSE,  
                      dimnames = list(rown, coln))
```

```
# print matrix
print(m_ab_label)

##      col_1 col_2
## row_1     1    10
## row_2     2    11
## row_3     3    12
```

The two most common formats to store and work with data in R are `dataframe` and `tibble`. Both formats store table-like structures of data in rows and columns. We will learn more on that in section 5.4

```
# convert the matrix into dataframe
df_ab=as.data.frame(m_ab_label)
tbl_ab=as_tibble(m_ab_label)
```

5.3.2 Open RData files

You can save some of your objects with `save()` or all with `save.image()`. Load data that are stored in the `.RData` format can be loaded with `load()`. Please note, when you delete an object in R, you cannot recover it by clicking some *Undo button*. With `rm()` you remove objects from your workspace and with `rm(list = ls())` you clear all objects from the workspace.

5.3.3 Open datasets of packages

The `datasets` package contains numerous datasets that are commonly used in textbooks. To get an overview of all the datasets provided by the package, you can use the command `help(package = datasets)`. One such dataset that we will be using further is the `mtcars` dataset:

```
library("datasets")
head(mtcars, 3)

##          mpg cyl disp  hp drat    wt  qsec vs am gear carb
## Mazda RX4   21.0   6 160 110 3.90 2.620 16.46  0  1    4    4
## Mazda RX4 Wag 21.0   6 160 110 3.90 2.875 17.02  0  1    4    4
## Datsun 710  22.8   4 108  93 3.85 2.320 18.61  1  1    4    1
?mtcars # data dictionary
```

5.3.4 Import data using public APIs

An API which stands for *application programming interface* specifies how computers can exchange information. There are many R packages available that provide a convenient way to access data from various online sources directly within R using the API of webpages. In most cases, it's better to download and import data within R using these tools than to navigate through the website's interface. This ensures that changes can be made easily at any time and that the data is always up-to-date. For instance, `wbstats` provides access to World Bank data, `eurostat` allows users to access Eurostat databases, `fredr` makes it easy to obtain data from the Federal Reserve Economic Data (FRED) platform, which offers economic data for the United States, `ecb` provides an interface to the European Central Bank's Statistical Data Warehouse, and the `OECD` package facilitates the extraction of data from the Organization for Economic Cooperation and Development (OECD). Here is an example using the `wbstats` package:

```
# install.packages("wbstats")
library("wbstats")
# GDP at market prices (current US$) for all available countries and regions
df_gdp <- wb(indicator = "NY.GDP.MKTP.CD")
head(df_gdp, 3)

##   iso3c date      value indicatorID      indicator iso2c
## 1 AFE 2022 1.185138e+12 NY.GDP.MKTP.CD GDP (current US$) ZH
## 2 AFE 2021 1.086531e+12 NY.GDP.MKTP.CD GDP (current US$) ZH
## 3 AFE 2020 9.288802e+11 NY.GDP.MKTP.CD GDP (current US$) ZH
##                                     country
## 1 Africa Eastern and Southern
## 2 Africa Eastern and Southern
## 3 Africa Eastern and Southern

glimpse(df_gdp)

## #> #> Rows: 13,198
## #> #> Columns: 7
## #> #> $ iso3c      <chr> "AFE", "AFE", "AFE", "AFE", "AFE", "AFE", "AFE"~
## #> #> $ date       <chr> "2022", "2021", "2020", "2019", "2018", "2017", ~
## #> #> $ value      <dbl> 1.185138e+12, 1.086531e+12, 9.288802e+11, 1.006~
## #> #> $ indicatorID <chr> "NY.GDP.MKTP.CD", "NY.GDP.MKTP.CD", "NY.GDP.MKT~
## #> #> $ indicator    <chr> "GDP (current US$)", "GDP (current US$)", "GDP ~
## #> #> $ iso2c      <chr> "ZH", "ZH", "ZH", "ZH", "ZH", "ZH", "ZH", "ZH", ~
## #> #> $ country     <chr> "Africa Eastern and Southern", "Africa Eastern ~
```

```
summary(df_gdp)

##      iso3c          date        value
##  Length:13198    Length:13198    Min.   :8.825e+06
##  Class :character Class :character 1st Qu.:2.435e+09
##  Mode   :character Mode  :character Median  :1.786e+10
##                                         Mean   :1.224e+12
##                                         3rd Qu.:2.264e+11
##                                         Max.   :1.009e+14
##      indicatorID     indicator      iso2c
##  Length:13198    Length:13198    Length:13198
##  Class :character Class :character Class  :character
##  Mode   :character Mode  :character Mode  :character
##                                         ...
##                                         ...
##                                         ...
##      country
##  Length:13198
##  Class :character
##  Mode   :character
##                                         ...
##                                         ...
##                                         ...
```

5.3.5 Import various file formats

RStudio provides convenient data import tools that can be accessed by clicking *File > Import Dataset*. In addition, tidyverse offers packages for importing data in various formats. This [cheatsheet](#), for example, is about the packages `readr`, `readxl` and `googlesheets4`. The first allows you to read data in various file formats, including fixed-width files like `.csv` and `.tsv`. The package `readxl` can read in Excel files, i.e., `.xls` and `.xlsx` file formats and `googlesheets4` allows to read and write data from Google Sheets directly from R.

For more information, I recommend once again the second version book *R for Data Science* by [Wickham and Grolemund \(2023\)](#). In particular, check out the “[Data tidying](#)” section for importing CSV and TSV files, the “[Spreadsheets](#)” section for Excel files, the “[Databases](#)” section for retrieving data with SQL, the “[Arrow](#)” section for working with large datasets, and the “[Web scraping](#)” section for extracting data from web pages.



Figure 5.2: The logo of the packages `readr`, `haven`, and `readxl`

For an overview on packages for reading data that are provided by the tidyverse universe, see [here](#).

5.4 Data

5.4.1 Data frames and tibbles



Figure 5.3: The logos of the `tidyr` and `tibble` packages

Both *data frames* and *tibbles* are two of the most commonly used data structures in R for handling tabular data. A tibble actually is a data frame and you can use all functions that work with a data frame also with a tibble. However, a tibble has some additional features in printing and subsetting. Please note, data frames are

provided by base R while tibbles are provided by the `tidyverse` package. This means that if you want to use tibbles you must load `tidyverse`. It turned out that it is helpful that a tibble has the following features to simplify working with data:

- Each vector is labeled by the variable name.
- Variable names don't have spaces and are not put in quotes.
- All variables have the same length.
- Each variable is of a single type (numeric, character, logical, or a categorical).

5.4.2 Tidy data

A popular quote from Hadley Wickham is that “*tidy datasets are all alike, but every messy dataset is messy in its own way*” (Hadley, 2014, p. 2). It paraphrases the fact that it is a good idea to set rules how a dataset should structure its information to make it easier to work with the data. The tidyverse requires the data to be structured like is illustrated in Figure 5.4. The rules are:

1. Each variable is a column and vice versa.
2. Each observation is a row and vice versa.
3. Each value is a cell.

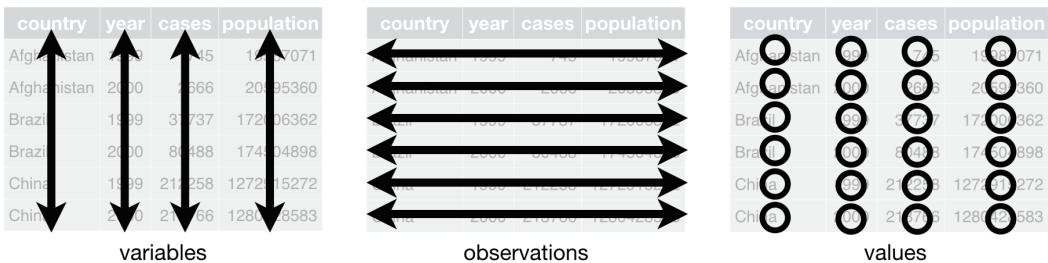


Figure 5.4: Features of a tidy dataset: variables are columns, observations are rows, and values are cells²

Whenever data follow that consistent structure, we speak of *tidy data*. The underlying uniformity of tidy data facilitates learning and using data manipulation tools.

One difference between data frames and tibbles is that dataframes store the row names. For example, take the `mtcars` dataset which consists of 32 different cars and the names of the cars are not stored as rownames:

²The figure stems from Wickham and Grolemund (2023)

```

class(mtcars) # mtcars is a data frame

## [1] "data.frame"

rownames(mtcars)

##  [1] "Mazda RX4"           "Mazda RX4 Wag"
##  [3] "Datsun 710"          "Hornet 4 Drive"
##  [5] "Hornet Sportabout"   "Valiant"
##  [7] "Duster 360"          "Merc 240D"
##  [9] "Merc 230"             "Merc 280"
## [11] "Merc 280C"            "Merc 450SE"
## [13] "Merc 450SL"           "Merc 450SLC"
## [15] "Cadillac Fleetwood"  "Lincoln Continental"
## [17] "Chrysler Imperial"   "Fiat 128"
## [19] "Honda Civic"          "Toyota Corolla"
## [21] "Toyota Corona"       "Dodge Challenger"
## [23] "AMC Javelin"          "Camaro Z28"
## [25] "Pontiac Firebird"    "Fiat X1-9"
## [27] "Porsche 914-2"        "Lotus Europa"
## [29] "Ford Pantera L"       "Ferrari Dino"
## [31] "Maserati Bora"        "Volvo 142E"

```

To store `mtcars` as a tibble, we can use the `as_tibble` function:

```

tbl_mtcars <- as_tibble(mtcars)
class(tbl_mtcars) # check if it is a tibble now

## [1] "tbl_df"     "tbl"        "data.frame"

is_tibble(tbl_mtcars) # alternative check

## [1] TRUE

head(tbl_mtcars, 3)

## # A tibble: 3 x 11
##   mpg   cyl  disp    hp  drat    wt  qsec    vs    am  gear  carb
##   <dbl> <dbl>
## 1 21      6    160   110   3.9    2.62   16.5     0     1     4     4
## 2 21      6    160   110   3.9    2.88   17.0     0     1     4     4
## 3 22.8    4    108    93   3.85   2.32   18.6     1     1     4     1

```

When we look at the data, we've lost the names of the cars. To store the these,

you need to first add a column to the dataframe containing the rownames and then you can generate the tibble:

```
tbl_mtcars <- mtcars |>
 rownames_to_column(var = "car") |>
  as_tibble()
class(tbl_mtcars)

## [1] "tbl_df"     "tbl"        "data.frame"

head(tbl_mtcars, 3)

## # A tibble: 3 x 12
##   car      mpg   cyl  disp    hp  drat    wt  qsec    vs    am  gear
##   <chr>    <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 Mazda ~  21      6   160   110   3.9   2.62  16.5     0     1     4
## 2 Mazda ~  21      6   160   110   3.9   2.88  17.0     0     1     4
## 3 Datsun~ 22.8     4   108   93    3.85  2.32  18.6     1     1     4
## # i 1 more variable: carb <dbl>
```

5.4.3 Data types

In R, different data classes, or types of data exist:

- *numeric*: can be any real number
- *character*: strings and characters
- *integer*: any whole numbers
- *factor*: any categorical or qualitative variable with finite number of distinct outcomes
- *logical*: contain either TRUE or FALSE
- *Date*: special format that describes time

The following example should exemplify these types of data:

```
integer_var <- c(1, 2, 3, 4, 5)
numeric_var <- c(1.1, 2.2, NA, 4.4, 5.5)
character_var <- c("apple", "banana", "orange", "cherry", "grape")
factor_var <- factor(c("red", "yellow", "red", "blue", "green"))
logical_var <- c(TRUE, TRUE, TRUE, FALSE, TRUE)
date_var <- as.Date(c("2022-01-01", "2022-02-01", "2022-03-01", "2022-04-01", "2022-05-01"))

date_var[2] - date_var[5] # number of days in between these two dates

## Time difference of -89 days
```

There are some special data values used in R that needs further explanation:

- `NA` stands for *not available* or *missing* and is used to represent missing or undefined values.
- `Inf` stands for *infinity* and is used to represent mathematical infinity, such as the result of dividing a non-zero number by zero. Can be positive or negative.
- `NULL` represents an empty or non-existent object. It is often used as a placeholder when a value or object is not yet available or when an object is intentionally removed.
- `NaN` stands for *not a number* and is used to represent an undefined or unrepresentable value, such as the result of taking the square root of a negative number. It can also occur as a result of certain arithmetic operations that are undefined. In contrast to `NA` it can only exist in numerical data.

5.5 Tools to manipulate data

5.5.1 The `%in%` operator

`%in%` is used to subset a vector by comparison. Here's an example:

```
x <- c(1, 3, 5, 7)
y <- c(2, 4, 6, 8)
z <- c(1, 2, 3)

x %in% y

## [1] FALSE FALSE FALSE FALSE

x %in% z

## [1] TRUE TRUE FALSE FALSE

z %in% x

## [1] TRUE FALSE TRUE
```

The `%in%` operator can be used in combination with other functions like `subset()` and `filter()`.

5.5.2 Extract operators

The *extract operators* are used to retrieve data from objects in R. The operator may take four forms, including `[]`, `[[]]`, and `$`.

`[]` allows to extract content from vector, lists, or data frames. For example,

```
a <- mtcars[3, ]
b <- mtcars["Datsun 710", ]
identical(a, b)

## [1] TRUE
a

##          mpg cyl disp hp drat    wt  qsec vs am gear carb
## Datsun 710 22.8   4 108 93 3.85 2.32 18.61  1  1     4     1
```

extracts the third observation of the `mtcars` dataset, and

```
c <- mtcars[, "cyl"]
d <- mtcars[, 2]
identical(x, y)

## [1] FALSE
c

## [1] 6 6 4 6 8 6 8 4 4 6 6 8 8 8 8 8 4 4 4 4 8 8 8 8 4 4 4 8 6 8 4
```

extracts the variable/vector `cyl`.

The operators, `[[]]` and `$` extract a single item from an object. It is used to refer to an element in a list or a column in a data frame. For example,

```
e <- mtcars$cyl
f <- mtcars[["cyl"]]
identical(e, f)

## [1] TRUE
e

## [1] 6 6 4 6 8 6 8 4 4 6 6 8 8 8 8 8 4 4 4 4 8 8 8 8 4 4 4 8 6 8 4
```

will return the values of the variable `cyl` from the data frame `mtcars`. Thus, `x$y` is actually just a short form for `x[["y"]]`.

5.5.3 Logical operators

The extract operators can be combined with the *logical operators* (more precisely, I should call these *binary relational operators*) that are shown in table Table 1.

Table 1: Logical operators

operation	operator	example input	answer
less than	<	2 < 3	TRUE
less than or equal to	<=	2 <= 2	TRUE
greater than	>	2 > 3	FALSE
greater than or equal to	>=	2 >= 2	TRUE
equal to	==	2 == 3	FALSE
not equal to	!=	2 != 3	TRUE
not	!	!(1==1)	FALSE
or		(1==1) (2==3)	TRUE
and	&	(1==1) & (2==3)	FALSE

Here are some examples: Select rows where the number of cylinders is greater than or equal to 6:

```
mtcars[mtcars$cyl >= 6, ]
```

```
##          mpg cyl  disp  hp drat    wt  qsec vs am gear
## Mazda RX4     21.0   6 160.0 110 3.90 2.620 16.46  0  1    4
## Mazda RX4 Wag 21.0   6 160.0 110 3.90 2.875 17.02  0  1    4
## Hornet 4 Drive 21.4   6 258.0 110 3.08 3.215 19.44  1  0    3
## Hornet Sportabout 18.7   8 360.0 175 3.15 3.440 17.02  0  0    3
## Valiant        18.1   6 225.0 105 2.76 3.460 20.22  1  0    3
## Duster 360      14.3   8 360.0 245 3.21 3.570 15.84  0  0    3
## Merc 280         19.2   6 167.6 123 3.92 3.440 18.30  1  0    4
## Merc 280C        17.8   6 167.6 123 3.92 3.440 18.90  1  0    4
## Merc 450SE       16.4   8 275.8 180 3.07 4.070 17.40  0  0    3
## Merc 450SL       17.3   8 275.8 180 3.07 3.730 17.60  0  0    3
## Merc 450SLC      15.2   8 275.8 180 3.07 3.780 18.00  0  0    3
## Cadillac Fleetwood 10.4   8 472.0 205 2.93 5.250 17.98  0  0    3
## Lincoln Continental 10.4   8 460.0 215 3.00 5.424 17.82  0  0    3
## Chrysler Imperial 14.7   8 440.0 230 3.23 5.345 17.42  0  0    3
## Dodge Challenger 15.5   8 318.0 150 2.76 3.520 16.87  0  0    3
## AMC Javelin      15.2   8 304.0 150 3.15 3.435 17.30  0  0    3
```

```

## Camaro Z28      13.3   8 350.0 245 3.73 3.840 15.41 0 0 3
## Pontiac Firebird 19.2   8 400.0 175 3.08 3.845 17.05 0 0 3
## Ford Pantera L 15.8   8 351.0 264 4.22 3.170 14.50 0 1 5
## Ferrari Dino    19.7   6 145.0 175 3.62 2.770 15.50 0 1 5
## Maserati Bora    15.0   8 301.0 335 3.54 3.570 14.60 0 1 5
##
## carb
## Mazda RX4        4
## Mazda RX4 Wag     4
## Hornet 4 Drive    1
## Hornet Sportabout  2
## Valiant           1
## Duster 360         4
## Merc 280           4
## Merc 280C          4
## Merc 450SE          3
## Merc 450SL          3
## Merc 450SLC         3
## Cadillac Fleetwood 4
## Lincoln Continental 4
## Chrysler Imperial   4
## Dodge Challenger    2
## AMC Javelin          2
## Camaro Z28           4
## Pontiac Firebird     2
## Ford Pantera L       4
## Ferrari Dino          6
## Maserati Bora          8

```

Select rows where the number of cylinders is either 4 or 6:

```
mtcars[mtcars$cyl == 4 | mtcars$cyl == 6 , ]
```

```

##          mpg cyl disp hp drat    wt  qsec vs am gear carb
## Mazda RX4    21.0   6 160.0 110 3.90 2.620 16.46 0  1    4    4
## Mazda RX4 Wag 21.0   6 160.0 110 3.90 2.875 17.02 0  1    4    4
## Datsun 710   22.8   4 108.0  93 3.85 2.320 18.61 1  1    4    1
## Hornet 4 Drive 21.4   6 258.0 110 3.08 3.215 19.44 1  0    3    1
## Valiant     18.1   6 225.0 105 2.76 3.460 20.22 1  0    3    1
## Merc 240D    24.4   4 146.7  62 3.69 3.190 20.00 1  0    4    2
## Merc 230     22.8   4 140.8  95 3.92 3.150 22.90 1  0    4    2
## Merc 280     19.2   6 167.6 123 3.92 3.440 18.30 1  0    4    4
## Merc 280C    17.8   6 167.6 123 3.92 3.440 18.90 1  0    4    4

```

```

## Fiat 128      32.4   4 78.7  66 4.08 2.200 19.47  1 1 4 1
## Honda Civic   30.4   4 75.7  52 4.93 1.615 18.52  1 1 4 2
## Toyota Corolla 33.9   4 71.1  65 4.22 1.835 19.90  1 1 4 1
## Toyota Corona 21.5   4 120.1 97 3.70 2.465 20.01  1 0 3 1
## Fiat X1-9     27.3   4 79.0  66 4.08 1.935 18.90  1 1 4 1
## Porsche 914-2  26.0   4 120.3 91 4.43 2.140 16.70  0 1 5 2
## Lotus Europa   30.4   4 95.1 113 3.77 1.513 16.90  1 1 5 2
## Ferrari Dino  19.7   6 145.0 175 3.62 2.770 15.50  0 1 5 6
## Volvo 142E     21.4   4 121.0 109 4.11 2.780 18.60  1 1 4 2

```

Select rows where the number of cylinders is 4 and the mpg is greater than 22:

```
mtcars[mtcars$cyl == 4 & mtcars$mpg > 22, ]
```

```

##          mpg cyl disp hp drat    wt  qsec vs am gear carb
## Datsun 710 22.8   4 108.0 93 3.85 2.320 18.61  1 1 4 1
## Merc 240D  24.4   4 146.7 62 3.69 3.190 20.00  1 0 4 2
## Merc 230   22.8   4 140.8 95 3.92 3.150 22.90  1 0 4 2
## Fiat 128    32.4   4 78.7  66 4.08 2.200 19.47  1 1 4 1
## Honda Civic 30.4   4 75.7  52 4.93 1.615 18.52  1 1 4 2
## Toyota Corolla 33.9   4 71.1  65 4.22 1.835 19.90  1 1 4 1
## Fiat X1-9    27.3   4 79.0  66 4.08 1.935 18.90  1 1 4 1
## Porsche 914-2 26.0   4 120.3 91 4.43 2.140 16.70  0 1 5 2
## Lotus Europa 30.4   4 95.1 113 3.77 1.513 16.90  1 1 5 2

```

Select rows where the weight is less than 3.5 or the number of gears is greater than 4:

```
mtcars[mtcars$wt < 3.5 | mtcars$gear > 4, ]
```

```

##          mpg cyl disp hp drat    wt  qsec vs am gear
## Mazda RX4   21.0   6 160.0 110 3.90 2.620 16.46  0 1 4
## Mazda RX4 Wag 21.0   6 160.0 110 3.90 2.875 17.02  0 1 4
## Datsun 710   22.8   4 108.0 93 3.85 2.320 18.61  1 1 4
## Hornet 4 Drive 21.4   6 258.0 110 3.08 3.215 19.44  1 0 3
## Hornet Sportabout 18.7   8 360.0 175 3.15 3.440 17.02  0 0 3
## Valiant     18.1   6 225.0 105 2.76 3.460 20.22  1 0 3
## Merc 240D    24.4   4 146.7 62 3.69 3.190 20.00  1 0 4
## Merc 230     22.8   4 140.8 95 3.92 3.150 22.90  1 0 4
## Merc 280     19.2   6 167.6 123 3.92 3.440 18.30  1 0 4
## Merc 280C    17.8   6 167.6 123 3.92 3.440 18.90  1 0 4
## Fiat 128     32.4   4 78.7  66 4.08 2.200 19.47  1 1 4
## Honda Civic   30.4   4 75.7  52 4.93 1.615 18.52  1 1 4

```

```

## Toyota Corolla    33.9   4 71.1  65 4.22 1.835 19.90  1  1   4
## Toyota Corona    21.5   4 120.1 97 3.70 2.465 20.01  1  0   3
## AMC Javelin     15.2   8 304.0 150 3.15 3.435 17.30  0  0   3
## Fiat X1-9        27.3   4 79.0  66 4.08 1.935 18.90  1  1   4
## Porsche 914-2    26.0   4 120.3 91 4.43 2.140 16.70  0  1   5
## Lotus Europa      30.4   4 95.1 113 3.77 1.513 16.90  1  1   5
## Ford Pantera L   15.8   8 351.0 264 4.22 3.170 14.50  0  1   5
## Ferrari Dino     19.7   6 145.0 175 3.62 2.770 15.50  0  1   5
## Maserati Bora     15.0   8 301.0 335 3.54 3.570 14.60  0  1   5
## Volvo 142E        21.4   4 121.0 109 4.11 2.780 18.60  1  1   4
##                           carb
## Mazda RX4          4
## Mazda RX4 Wag      4
## Datsun 710          1
## Hornet 4 Drive     1
## Hornet Sportabout   2
## Valiant             1
## Merc 240D           2
## Merc 230             2
## Merc 280             4
## Merc 280C            4
## Fiat 128             1
## Honda Civic          2
## Toyota Corolla       1
## Toyota Corona         1
## AMC Javelin          2
## Fiat X1-9             1
## Porsche 914-2          2
## Lotus Europa           2
## Ford Pantera L          4
## Ferrari Dino            6
## Maserati Bora            8
## Volvo 142E              2

```

Select rows where either mpg is greater than 25 or carb is less than 2, and the number of cylinders is either 4 or 8.

```

mtcars[(mtcars$mpg > 25 | mtcars$carb < 2) & mtcars$cyl %in% c(4,8), ]

```

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
## Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
## Fiat 128	32.4	4	78.7	66	4.08	2.200	19.47	1	1	4	1

```
## Honda Civic    30.4   4 75.7  52 4.93 1.615 18.52  1  1   4   2
## Toyota Corolla 33.9   4 71.1  65 4.22 1.835 19.90  1  1   4   1
## Toyota Corona 21.5   4 120.1 97 3.70 2.465 20.01  1  0   3   1
## Fiat X1-9     27.3   4 79.0  66 4.08 1.935 18.90  1  1   4   1
## Porsche 914-2  26.0   4 120.3 91 4.43 2.140 16.70  0  1   5   2
## Lotus Europa   30.4   4 95.1 113 3.77 1.513 16.90  1  1   5   2
```

5.5.4 If statements

In many cases, it's necessary to execute certain code only when a particular condition is met. To achieve this, there are several conditional statements that can be used in code. These include:

- The `if` statement: This is used to execute a block of code if a specified condition is true.
- The `else` statement: This is used to execute a block of code if the same condition is false.
- The `else if` statement: This is used to specify a new condition to test if the first condition is false.
- The `ifelse()` function: This is used to check a condition for every element of a vector.

The following examples should exemplify how these statements work:

```
# Example of if statement
if (mean(mtcars$mpg) > 20) {
  print("The average miles per gallon is greater than 20.")
}

## [1] "The average miles per gallon is greater than 20."

# Example of if-else statement
if (mean(mtcars$mpg) > 20) {
  print("The average miles per gallon is greater than 20.")
} else {
  print("The average miles per gallon is less than or equal to 20.")
}

## [1] "The average miles per gallon is greater than 20."

# Example of if-else if statement
if (mean(mtcars$mpg) > 25) {
  print("The average miles per gallon is greater than 25.")
} else if (mean(mtcars$mpg) > 20) {
```

```

    print("The average miles per gallon is between 20 and 25.")
} else {
  print("The average miles per gallon is less than or equal to 20.")
}

## [1] "The average miles per gallon is between 20 and 25."
# Example of if_else function
mtcars_2 <- mtcars
mtcars_2$mpg_category <- ifelse(mtcars_2$mpg > 20, "High", "Low")

```

When you have a fixed number of cases and don't want to use a long chain of if-else statements, you can use `case_when()`:

```

mtcars_cyl <- mtcars %>%
  mutate(cyl_category = case_when(
    cyl == 4 ~ "four",
    cyl == 6 ~ "six",
    cyl == 8 ~ "eight"
  ))

```

The `mutate()` function is used to add the new variable, and `case_when()` is used to assign the values “four”, “six”, or “eight” to the new variable based on the number of cylinders in each car. Both functions are part of the `dplyr` package (see chapter 5.6).

It evaluates one of several expressions based on the value of a given control expression. It takes two arguments: the control expression and a list of named expressions, each of which is evaluated if its name matches the value of the control expression. If no match is found, an optional default expression is evaluated. The `switch()` function is particularly useful

5.6 Data manipulation with `dplyr`

The `dplyr` package is part of tidyverse and makes data manipulation easy:

- Reorder the rows (`arrange()`).
- Pick observations by their values (`filter()`).
- Pick variables by their names (`select()`).
- Create new variables with functions of existing variables (`mutate()`).
- Collapse many values down to a single summary (`summarise()`).
- Rename variables (`rename()`).



Figure 5.5: The logo of the `dplyr` package

These functions can all be used in conjunction with `group_by()`, which changes the scope of each function from operating on the entire dataset to operating on it group-by-group.

All functions work similarly:

1. The first argument is a data frame.
2. The subsequent arguments describe what to do with the data frame.
3. The result is a new data frame.

Here are some examples that may help to understand these functions:

```
library(tidyverse)

# load mtcars dataset
data(mtcars)

# arrange rows by mpg in descending order
mtcars |>
  arrange(desc(mpg))

##          mpg cyl  disp  hp drat    wt  qsec vs am gear
## Toyota Corolla 33.9   4  71.1  65 4.22 1.835 19.90  1  1    4
## Fiat 128      32.4   4  78.7  66 4.08 2.200 19.47  1  1    4
## Honda Civic   30.4   4  75.7  52 4.93 1.615 18.52  1  1    4
## Lotus Europa  30.4   4  95.1 113 3.77 1.513 16.90  1  1    5
## Fiat X1-9     27.3   4  79.0  66 4.08 1.935 18.90  1  1    4
## Porsche 914-2 26.0   4 120.3  91 4.43 2.140 16.70  0  1    5
## Merc 240D     24.4   4 146.7  62 3.69 3.190 20.00  1  0    4
## Datsun 710    22.8   4 108.0  93 3.85 2.320 18.61  1  1    4
## Merc 230      22.8   4 140.8  95 3.92 3.150 22.90  1  0    4
## Toyota Corona 21.5   4 120.1  97 3.70 2.465 20.01  1  0    3
## Hornet 4 Drive 21.4   6 258.0 110 3.08 3.215 19.44  1  0    3
```

```

## Volvo 142E      21.4   4 121.0 109 4.11 2.780 18.60  1  1   4
## Mazda RX4       21.0   6 160.0 110 3.90 2.620 16.46  0  1   4
## Mazda RX4 Wag   21.0   6 160.0 110 3.90 2.875 17.02  0  1   4
## Ferrari Dino    19.7   6 145.0 175 3.62 2.770 15.50  0  1   5
## Merc 280        19.2   6 167.6 123 3.92 3.440 18.30  1  0   4
## Pontiac Firebird 19.2   8 400.0 175 3.08 3.845 17.05  0  0   3
## Hornet Sportabout 18.7   8 360.0 175 3.15 3.440 17.02  0  0   3
## Valiant          18.1   6 225.0 105 2.76 3.460 20.22  1  0   3
## Merc 280C        17.8   6 167.6 123 3.92 3.440 18.90  1  0   4
## Merc 450SL       17.3   8 275.8 180 3.07 3.730 17.60  0  0   3
## Merc 450SE       16.4   8 275.8 180 3.07 4.070 17.40  0  0   3
## Ford Pantera L   15.8   8 351.0 264 4.22 3.170 14.50  0  1   5
## Dodge Challenger 15.5   8 318.0 150 2.76 3.520 16.87  0  0   3
## Merc 450SLC      15.2   8 275.8 180 3.07 3.780 18.00  0  0   3
## AMC Javelin       15.2   8 304.0 150 3.15 3.435 17.30  0  0   3
## Maserati Bora     15.0   8 301.0 335 3.54 3.570 14.60  0  1   5
## Chrysler Imperial 14.7   8 440.0 230 3.23 5.345 17.42  0  0   3
## Duster 360         14.3   8 360.0 245 3.21 3.570 15.84  0  0   3
## Camaro Z28        13.3   8 350.0 245 3.73 3.840 15.41  0  0   3
## Cadillac Fleetwood 10.4   8 472.0 205 2.93 5.250 17.98  0  0   3
## Lincoln Continental 10.4   8 460.0 215 3.00 5.424 17.82  0  0   3
##                           carb
## Toyota Corolla     1
## Fiat 128           1
## Honda Civic         2
## Lotus Europa        2
## Fiat X1-9           1
## Porsche 914-2       2
## Merc 240D           2
## Datsun 710          1
## Merc 230           2
## Toyota Corona        1
## Hornet 4 Drive       1
## Volvo 142E          2
## Mazda RX4           4
## Mazda RX4 Wag        4
## Ferrari Dino         6
## Merc 280            4
## Pontiac Firebird     2
## Hornet Sportabout     2

```

```

## Valiant          1
## Merc 280C       4
## Merc 450SL      3
## Merc 450SE      3
## Ford Pantera L  4
## Dodge Challenger 2
## Merc 450SLC     3
## AMC Javelin     2
## Maserati Bora    8
## Chrysler Imperial 4
## Duster 360       4
## Camaro Z28       4
## Cadillac Fleetwood 4
## Lincoln Continental 4

# filter rows where cyl = 4
mtcars |>
  filter(cyl == 4)

##             mpg cyl  disp  hp drat   wt  qsec vs am gear carb
## Datsun 710 22.8   4 108.0 93 3.85 2.320 18.61  1  1    4    1
## Merc 240D  24.4   4 146.7 62 3.69 3.190 20.00  1  0    4    2
## Merc 230  22.8   4 140.8 95 3.92 3.150 22.90  1  0    4    2
## Fiat 128   32.4   4  78.7 66 4.08 2.200 19.47  1  1    4    1
## Honda Civic 30.4   4  75.7 52 4.93 1.615 18.52  1  1    4    2
## Toyota Corolla 33.9   4  71.1 65 4.22 1.835 19.90  1  1    4    1
## Toyota Corona 21.5   4 120.1 97 3.70 2.465 20.01  1  0    3    1
## Fiat X1-9   27.3   4  79.0 66 4.08 1.935 18.90  1  1    4    1
## Porsche 914-2 26.0   4 120.3 91 4.43 2.140 16.70  0  1    5    2
## Lotus Europa 30.4   4  95.1 113 3.77 1.513 16.90  1  1    5    2
## Volvo 142E   21.4   4 121.0 109 4.11 2.780 18.60  1  1    4    2

# select columns mpg, cyl, and hp
mtcars |>
  select(mpg, cyl, hp) |>
  head()

##             mpg cyl  hp
## Mazda RX4    21.0   6 110
## Mazda RX4 Wag 21.0   6 110
## Datsun 710   22.8   4  93
## Hornet 4 Drive 21.4   6 110

```

```
## Hornet Sportabout 18.7   8 175
## Valiant          18.1   6 105

# select columns all variables except wt and hp
mtcars |>
  select(-wt, -hp) |>
  head()

##                         mpg cyl disp drat qsec vs am gear carb
## Mazda RX4           21.0   6 160 3.90 16.46  0  1    4    4
## Mazda RX4 Wag       21.0   6 160 3.90 17.02  0  1    4    4
## Datsun 710          22.8   4 108 3.85 18.61  1  1    4    1
## Hornet 4 Drive      21.4   6 258 3.08 19.44  1  0    3    1
## Hornet Sportabout   18.7   8 360 3.15 17.02  0  0    3    2
## Valiant            18.1   6 225 2.76 20.22  1  0    3    1

# select only variables starting with `c`
mtcars |>
  select(starts_with("c"))

##                         cyl carb
## Mazda RX4             6    4
## Mazda RX4 Wag         6    4
## Datsun 710            4    1
## Hornet 4 Drive        6    1
## Hornet Sportabout     8    2
## Valiant               6    1
## Duster 360            8    4
## Merc 240D              4   2
## Merc 230               4   2
## Merc 280               6   4
## Merc 280C              6   4
## Merc 450SE              8   3
## Merc 450SL              8   3
## Merc 450SLC             8   3
## Cadillac Fleetwood     8   4
## Lincoln Continental     8   4
## Chrysler Imperial       8   4
## Fiat 128                 4   1
## Honda Civic                4   2
## Toyota Corolla             4   1
## Toyota Corona              4   1
```

```

## Dodge Challenger      8   2
## AMC Javelin         8   2
## Camaro Z28          8   4
## Pontiac Firebird    8   2
## Fiat X1-9            4   1
## Porsche 914-2        4   2
## Lotus Europa          4   2
## Ford Pantera L       8   4
## Ferrari Dino         6   6
## Maserati Bora         8   8
## Volvo 142E             4   2

# summarize avg mpg by number of cylinders
mtcars |>
  group_by(cyl) |>
  summarize(avg_mpg = mean(mpg))

## # A tibble: 3 x 2
##       cyl   avg_mpg
##   <dbl>     <dbl>
## 1     4     26.7
## 2     6     19.7
## 3     8     15.1

# create new column wt_kg, which is wt in kg
mtcars |>
  select(wt) |>
  mutate(wt_kg = wt / 2.205) |>
  head()

##                  wt     wt_kg
## Mazda RX4      2.620 1.188209
## Mazda RX4 Wag  2.875 1.303855
## Datsun 710     2.320 1.052154
## Hornet 4 Drive 3.215 1.458050
## Hornet Sportabout 3.440 1.560091
## Valiant        3.460 1.569161

# Create a new variable by calculating hp divided by wt
mtcars_new <- mtcars |>
  select(wt, hp) |>
  mutate(hp_per_t = hp/wt) |>
  head()

```

5.7 How to explore a dataset

```
# Creating dataframe
df <- tibble(
  integer_var, numeric_var, character_var, factor_var, logical_var, date_var,
)
# Overview of the data
head(df)
```

```

## # A tibble: 5 x 6
##   integer_var numeric_var character_var factor_var logical_var
##       <dbl>      <dbl> <chr>        <fct>     <lgl>
## 1         1      1.1 apple       red      TRUE
## 2         2      2.2 banana    yellow    TRUE
## 3         3       NA orange     red      TRUE
## 4         4      4.4 cherry    blue     FALSE
## 5         5      5.5 grape     green    TRUE
## # i 1 more variable: date_var <date>

summary(df)

##   integer_var  numeric_var  character_var  factor_var
##   Min. :1     Min. :1.100  Length:5       blue  :1
##   1st Qu.:2   1st Qu.:1.925  Class :character green :1
##   Median :3   Median :3.300  Mode  :character red   :2
##   Mean   :3   Mean   :3.300                    yellow:1
##   3rd Qu.:4   3rd Qu.:4.675
##   Max.   :5   Max.   :5.500
##             NA's   :1

##   logical_var    date_var
##   Mode :logical  Min.   :2022-01-01
##   FALSE:1        1st Qu.:2022-02-01
##   TRUE :4        Median :2022-03-01
##                  Mean   :2022-03-02
##                  3rd Qu.:2022-04-01
##                  Max.   :2022-05-01
##              

## Rows: 5
## Columns: 6
## $ integer_var  <dbl> 1, 2, 3, 4, 5
## $ numeric_var   <dbl> 1.1, 2.2, NA, 4.4, 5.5
## $ character_var <chr> "apple", "banana", "orange", "cherry", "grape"
## $ factor_var    <fct> red, yellow, red, blue, green
## $ logical_var   <lgl> TRUE, TRUE, TRUE, FALSE, TRUE
## $ date_var      <date> 2022-01-01, 2022-02-01, 2022-03-01, 2022-04-0~

# look closer at variables

```

```
# unique values
unique(df$integer_var)

## [1] 1 2 3 4 5

unique(df$factor_var)

## [1] red     yellow blue   green
## Levels: blue green red yellow
table(df$factor_var)

##
##   blue   green   red yellow
##       1       1       2       1

length(unique(df$factor_var))

## [1] 4

# distributions
df |> count(factor_var)

## # A tibble: 4 x 2
##   factor_var     n
##   <fct>     <int>
## 1 blue         1
## 2 green        1
## 3 red          2
## 4 yellow       1

prop.table(table(df$factor_var))

##
##   blue   green   red yellow
##   0.2    0.2    0.4    0.2

df |>
  count(factor_var) |>
  mutate(prop = n / sum(n))

## # A tibble: 4 x 3
##   factor_var     n   prop
##   <fct>     <int> <dbl>
## 1 blue         1    0.2
```

```

## 2 green      1   0.2
## 3 red       2   0.4
## 4 yellow    1   0.2

aggregate(df$numeric_var,
          by = list(fruit = df$factor_var),
          mean)

##   fruit   x
## 1 blue 4.4
## 2 green 5.5
## 3 red  NA
## 4 yellow 2.2

# --> the mean of red cannot be calculated as there is a NA in it
# Solution: exclude NAs from calculation:
aggregate(df$numeric_var,
          by = list(fruit = df$factor_var),
          mean,
          na.rm = TRUE)

##   fruit   x
## 1 blue 4.4
## 2 green 5.5
## 3 red 1.1
## 4 yellow 2.2

#install.packages("janitor")
require("janitor")
mtcars |>
  tabyl(cyl)

## cyl n percent
##   4 11 0.34375
##   6  7 0.21875
##   8 14 0.43750

mtcars |>
  tabyl(cyl, hp)

## cyl 52 62 65 66 91 93 95 97 105 109 110 113 123 150 175 180 205 215
##   4  1  1  1  2  1  1  1  1  0  1  0  1  0  0  0  0  0  0
##   6  0  0  0  0  0  0  0  0  1  0  3  0  2  0  1  0  0  0
##   8  0  0  0  0  0  0  0  0  0  0  0  0  0  2  2  3  1  1

```

```
## 230 245 264 335
## 0 0 0 0
## 0 0 0 0
## 1 2 1 1
```

Chapter 6

Collection of exercises

Links...

...to the R scripts with the solutions

- [exe_duplicates.R](#)
- [exe_import_covid.R](#)
- [exe_genanddrop.R](#)
- [exe_base_pipe.R](#)
- [exe_subset.R](#)
- [exe_data_transformation.R](#)
- [exe_poser.R](#)
- [exe.datasauRus.R](#)
- [exe_convergence.R](#)
- [exe_un_gdp_ger_fra.R](#)
- [exe_hortacsu_figure_3.R](#)
- [exe_regress_lecture.R](#)
- [exe_calories.R](#)
- [exe_bundesliga.R](#)
- [exe_okun_solution.R](#)
- [exe_zipf_solution.R](#)

...to the output of the scripts

Here you find the output

EXERCISE: Generate and drop variables

Use the *mtcars* dataset. It is part of the package *datasets* and can be called with `mtcars`

- Create a new tibble called `mtcars_new` using the pipe operator `|>`. Generate a new dummy variable called `d_cyl_6to8` that takes the value 1 if the number of cylinders (`cyl`) is greater than 6, and 0 otherwise. Do all of this in a single pipe.
- Generate a new dummy variable called `posercar` that takes a value of 1 if a car has more than 6 cylinders (`cyl`) and can drive less than 18 miles per gallon (`mpg`), and 0 otherwise. Add this variable to the tibble `mtcars_new`.
- Remove the variable `d_cyl_6to8` from the data frame.

Please find solutions [here](#).

EXERCISE: Import data

Table 2 shows COVID for three states in Germany:

Table 2: Covid cases and deaths till August 2022

state	Bavaria	North Rhine-Westphalia	Baden-Württemberg
deaths (in mio)	4,92M	5,32M	3,69M
cases	24.111	25.466	16.145

Write down the code you would need to put into the R-console...

- ... to store each of variables `state` and `deaths` in a vector.
- ... to store both vectors in a data frame with the name `df_covid`.
- ... to store both vectors in a tibble with the name `tbl_covid`.

Please find solution to the exercise [here](#)

EXERCISE: Base R or pipe

- Using the *mtcars* dataset, write code to create a new dataframe that includes only the rows where the number of cylinders is either 4 or 6, and the weight (`wt`) is less than 3.5.

Do this in two different ways using:

1. The `%in%` operator and the pipe `|>`.
2. Base R without the pipe `|>`.

Compare the resulting dataframes using the `identical()` function.

- b) Using the `mtcars` dataset, generate a logical variable that indicates with `TRUE` all cars with either 4 or 6 cylinders that `wt` is less than 3.5 and add this variable to a new dataset.

Please find solutions [here](#).

EXERCISE: Subsetting

1. Check to see if you have the `mtcars` dataset by entering the command `mtcars`.
2. Save the `mtcars` dataset in an object named `cars`.
3. What class is `cars`?
4. How many observations (rows) and variables (columns) are in the `mtcars` dataset?
5. Rename `mpg` in `cars` to `MPG`. Use `rename()`.
6. Convert the column names of `cars` to all upper case. Use `rename_all`, and the `toupper` command.
7. Convert the rownames of `cars` to a column called `car` using `rownames_to_column`.
8. Subset the columns from `cars` that end in “p” and call it `pvars` using `ends_with()`.
9. Create a subset `cars` that only contains the columns: `wt`, `qsec`, and `hp` and assign this object to `carsSub`. (Use `select()`.)
10. What are the dimensions of `carsSub`? (Use `dim()`.)
11. Convert the column names of `carsSub` to all upper case. Use `rename_all()`, and `toupper()` (or `colnames()`).
12. Subset the rows of `cars` that get more than 20 miles per gallon (`mpg`) of fuel efficiency. How many are there? (Use `filter()`.)
13. Subset the rows that get less than 16 miles per gallon (`mpg`) of fuel efficiency and have more than 100 horsepower (`hp`). How many are there? (Use `filter()` and the pipe operator.)
14. Create a subset of the `cars` data that only contains the columns: `wt`, `qsec`, and `hp` for cars with 8 cylinders (`cyl`) and reassign this object to `carsSub`. What are the dimensions of this dataset? Do not use the pipe operator.
15. Create a subset of the `cars` data that only contains the columns: `wt`, `qsec`, and `hp` for cars with 8 cylinders (`cyl`) and reassign this object to `carsSub2`.

Use the pipe operator.

16. Re-order the rows of carsSub by weight (wt) in increasing order. (Use `arrange()`.)
17. Create a new variable in carsSub called wt2, which is equal to wt^2 , using `mutate()` and piping `%>%`.

Please find solutions [here](#).

EXERCISE: Data transformation

Please download and open the R-script you find [here](#) and try to answer the questions therein.

Solutions to the questions are linked in the script.

EXERCISE: Load the Stata dataset “auto” using R

1. Create a scatter plot illustrating the relationship between the price and weight of a car. Provide a meaningful title for the graph and try to make it clear which car each observation corresponds to.
2. Save this graph in the formats of .png and .pdf.
3. Create a variable “lp100km” that indicates the fuel consumption of an average car in liters per 100 kilometers. (Note: One gallon is approximately equal to 3.8 liters, and one mile is about 1.6 kilometers.)
4. Create a dummy variable “larger6000” that is equal to 1 if the price of a car is above \$6000.
5. Now, search for the “most unreasonable poser car” that costs no more than \$6000. A “poser” car is defined as one that is expensive, has a large turning radius, consumes a lot of fuel, and is often defective (`rep78` is low). For this purpose, create a metric indicator for each corresponding variable that indicates a value of 1 for the car that is the most unreasonable in that variable and 0 for the most reasonable car. All other cars should fall between 0 and 1.

Please find the solutions [here](#).

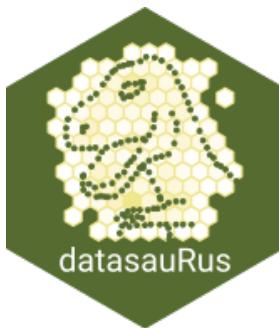


Figure 6.1: The logo of the DatasauRus package¹

EXERCISE: DatasauRus

- a) Load the packages `datasauRus` and `tidyverse`. If necessary, install these packages.
- b) The packaged `datasauRus` comes with a dataset in two different formats: `datasaurus_dozen` and `datasaurus_dozen_wide`. Store them as `ds` and `ds_wide`.
- c) Open and read the R vignette of the `datasauRus` package. Also open the R documentation of the dataset `datasaurus_dozen`.
- d) Explore the dataset: What are the dimensions of this dataset? Look at the descriptive statistics.
- e) How many unique values does the variable `dataset` of the tibble `ds` have?
Hint: The function `unique()` return the unique values of a variable and the function `length()` returns the length of a vector, such as the unique elements.
- f) Compute the mean values of the `x` and `y` variables for each entry in `dataset`.
Hint: Use the `group_by()` function to group the data by the appropriate column and then the `summarise()` function to calculate the mean.
- g) Compute the standard deviation, the correlation, and the median in the same way. Round the numbers.
- h) What can you conclude?
- i) Plot all datasets of `ds`. Hide the legend. Hint: Use the `facet_wrap()` and the `theme()` function.

¹Figure is taken from <https://github.com/jumpingrivers/datasauRus>

- j) Create a loop that generates separate scatter plots for each unique dataset of the tibble `ds`. Export each graph as a png file.
- k) Watch the video [Animating the Datasaurus Dozen Dataset in R](#) from The Data Digest on YouTube.

Please find the solutions [here](#).

EXERCISE: Convergence

The dataset `convergence.dta`, see <https://github.com/hubchev/courses/blob/main/dta/convergence.dta>, contains the per capita GDP of 1960 (`gdppc60`) and the average growth rate of GDP per capita between 1960 and 1995 (`growth`) for different countries (`country`), as well as 3 dummy variables indicating the belonging of a country to the region Asia (`asia`), Western Europe (`weurope`) or Africa (`africa`).

- Some countries are not assigned to a certain country group. Name the countries which are assigned to be part of Western Europe, Africa or Asia. If you find countries that are members of the EU, assign them a ‘1’ in the variable `weurope`.
- Create a table that shows the average GDP per capita for all available points in time. Group by Western European, Asian, African, and the remaining countries.
- Create the growth rate of GDP per capita from 1960 to 1995 and call it `gdpgrowth`. (Note: The log value X minus the log value X of the previous period is approximately equal to the growth rate).
- Calculate the unconditional convergence of all countries by constructing a graph in which a scatterplot shows the GDP per capita growth rate between 1960 and 1995 (`gdpgrowth`) on the y-axis and the 1960 GDP per capita (`gdppc60`) on the x-axis. Add to the same graph the estimated linear relationship. You do not need to label the graph further, just two things: title the graph `world` and label the individual observations with the country names.
- Create three graphs describing the same relationship for the sample of Western European, African and Asian countries. Title the graph accordingly with `weurope`, `africa` and `asia`.
- Combine the four graphs into one image. Discuss how an upward or downward sloping regression line can be interpreted.
- Estimate the relationships illustrated in the 4 graphs using the least squares method. Present the 4 estimation results in a table, indicating the significance level with stars. In addition, the Akaike information criterion, and the number of observations should be displayed in the table. Interpret the four estimation

results regarding their significance.

- Put the data set into the so-called long format and calculate the GDP per capita growth rates for the available time points in the countries.

Please find solutions [here](#).

EXERCISE: Unemployment and GDP in Germany and France

The following exercise was a former exam.

Please answer all (!) questions in an R script. Normal text should be written as comments, using the ‘#’ to comment out text. Make sure the script runs without errors before submitting it. Each task (starting with 1) is worth five points. You have a total of 120 minutes of editing time. Please do not forget to number your answers.

When you are done with your work, save the R script, export the script to pdf format and upload the pdf file.

Suppose you aim to empirically examine unemployment and GDP for Germany and France. The data set that we use in the following is ‘forest.Rdata’.

- (0) Write down your name, matriculation number, and date.
- (1) Set your working directory.
- (2) Clear your global environment.
- (3) Install and load the following packages: ‘tidyverse’, ‘sjPlot’, and ‘ggpubr’
- (4) Download and load the data, respectively, with the following code:

```
load(url("https://github.com/hubchev/courses/raw/main/dta/forest.Rdata"))
```

If that is not working, you can also download the data from ILIAS, save it in your working directory and load it from there with:

```
# load("forest.Rdata")
```

- (5) Show the **first eight** observations of the dataset ‘df’.
- (6) Show the **last observation** of the dataset ‘df’.
- (7) Which type of data do we have here (Panel, cross-section, time series, . . .)?
Name the variable(s) that are necessary to identify the observations in the

dataset.

- (8) Explain what the **assignment operator** in R is and what it is good for.
- (9) Write down the R code to store the number of observations and the number of variables that are in the dataset ‘df’. Name the object in which you store these numbers ‘observations_df’.
- (10) In the dataset ‘df’, rename the variable ‘country.x’ to ‘nation’ and the variable ‘date’ to ‘year’.
- (11) Explain what the **pipe operator** in R is and what it is good for.
- (12) For the upcoming analysis you are only interested the following **variables** that are part of the dataframe ‘df’: nation, year, gdp, pop, gdppc, and unemployment. Drop all other variables from the dataframe ‘df’.
- (13) Create a variable that indicates the GDP per capita (‘gdp’ divided by ‘pop’). Name the variable ‘gdp_pc’. (Hint: If you fail here, use the variable ‘gdppc’ which is already in the dataset as a replacement for ‘gdp_pc’ in the following tasks.)
- (14) For the upcoming analysis you are only interested the following **countries** that are part of the dataframe ‘df’: Germany and France. Drop all other countries from the dataframe ‘df’.
- (15) Create a table showing the **average** unemployment rate and GDP per capita for Germany and France in the given years. Use the pipe operator. (Hint: See below for how your results should look like.)

```
## # A tibble: 2 x 3
##   nation `mean(unemployment)` `mean(gdppc)`
##   <chr>          <dbl>        <dbl>
## 1 France          9.75       34356.
## 2 Germany         7.22       36739.
```

- (16) Create a table showing the unemployment rate and GDP per capita for Germany and France in the **year 2020**. Use the pipe operator. (Hint: See below for how your results should look like.)

```
## # A tibble: 2 x 3
##   nation `mean(unemployment)` `mean(gdppc)`
##   <chr>          <dbl>        <dbl>
## 1 France          8.01       35786.
## 2 Germany         3.81       41315.
```

- (17) Create a table showing the **highest** unemployment rate and the **highest** GDP per capita for Germany and France during the given period. Use the pipe operator. (Hint: See below for how your results should look like.)

```
## # A tibble: 2 x 3
##   nation `max(unemployment)` `max(gdppc)`
##   <chr>      <dbl>        <dbl>
## 1 France      12.6       38912.
## 2 Germany     11.2       43329.
```

- (18) Calculate the standard deviation of the unemployment rate and GDP per capita for Germany and France in the given years. (Hint: See below for how your result should look like.)

```
## # A tibble: 2 x 3
##   nation `sd(gdppc)` `sd(unemployment)`
##   <chr>      <dbl>        <dbl>
## 1 France     2940.       1.58
## 2 Germany    4015.       2.37
```

- (19) In statistics, the coefficient of variation (COV) is a standardized measure of dispersion. It is defined as the ratio of the standard deviation (σ) to the mean (μ): $COV = \frac{\sigma}{\mu}$. Write down the R code to calculate the coefficient of variation (COV) for the **unemployment rate** in Germany and France. (Hint: See below for what your result should look like.)

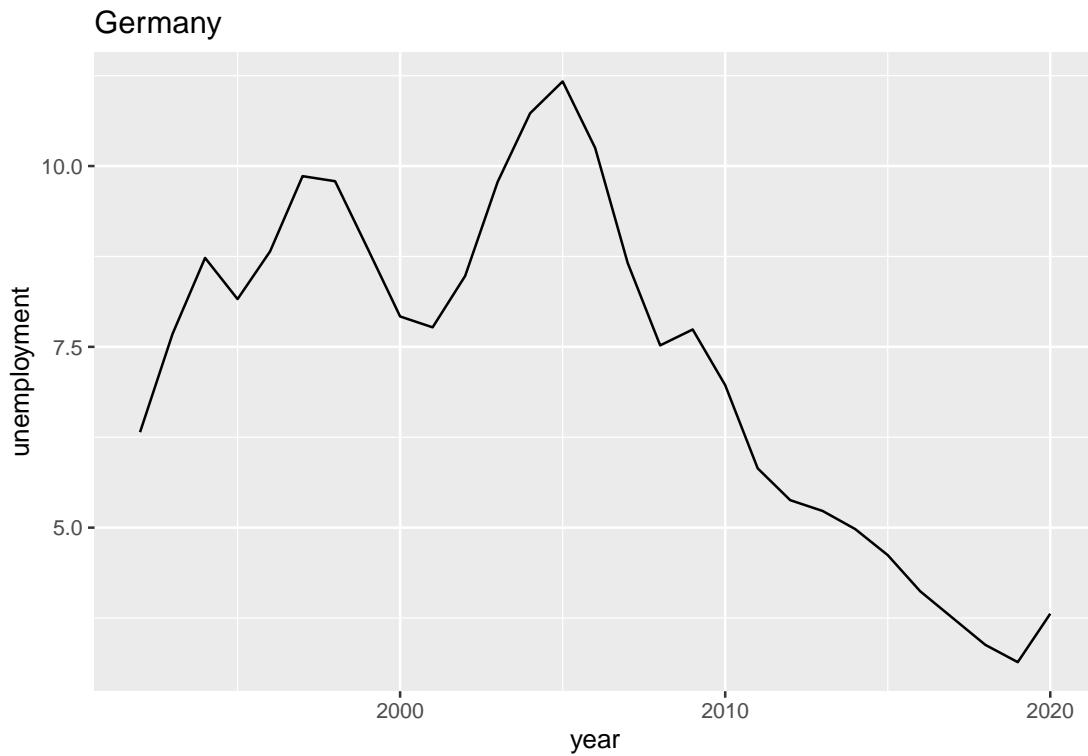
```
## # A tibble: 2 x 4
##   nation `sd(unemployment)` `mean(unemployment)` cov
##   <chr>      <dbl>        <dbl> <dbl> <dbl>
## 1 France      1.58         9.75  0.162
## 2 Germany     2.37         7.22  0.328
```

- (20) Write down the R code to calculate the coefficient of variation (COV) for the **GDP per capita** in Germany and France. (Hint: See below for what your result should look like.)

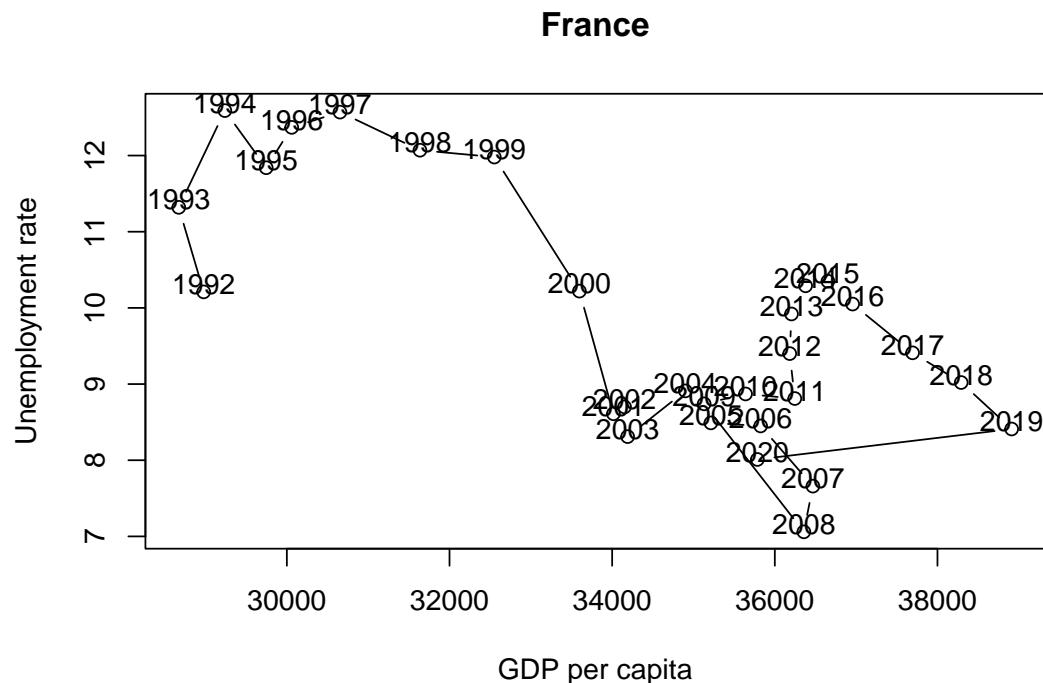
```
## # A tibble: 2 x 4
##   nation `sd(gdppc)` `mean(gdppc)` cov
##   <chr>      <dbl>        <dbl> <dbl>
## 1 France     2940.       34356. 0.0856
## 2 Germany    4015.       36739. 0.109
```

- (21) Create a chart (bar chart, line chart, or scatter plot) that shows the unemployment rate of **Germany** over the available years. Label the chart

‘Germany’ with ‘ggtitle(“Germany”)’. Please note that you may choose any type of graphical representation. (Hint: Below you can see one of many |> of what your result may look like).



- (22) and 23. (*This task is worth 10 points*) The following chart shows the simultaneous development of the unemployment rate and GDP per capita over time for **France**.

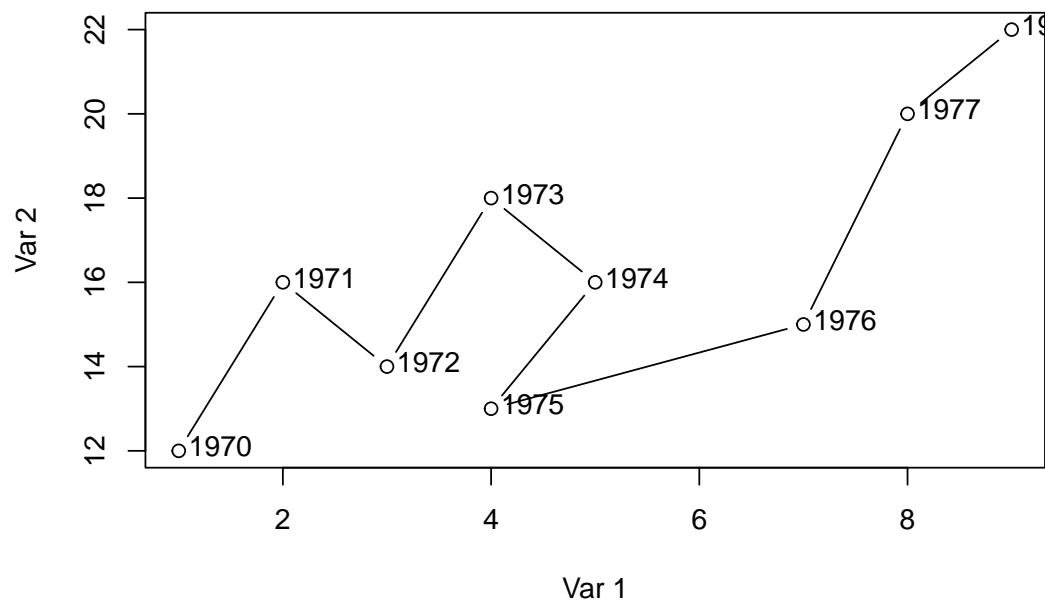


Suppose you want to visualize the simultaneous evolution of the unemployment rate and GDP per capita over time for Germany as well.

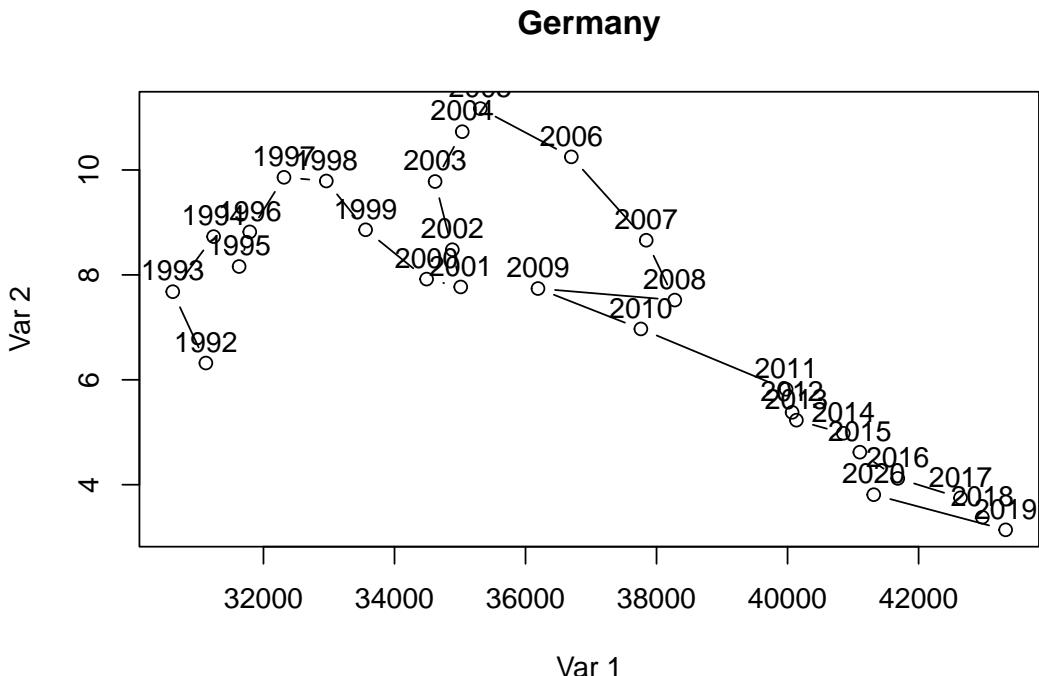
Suppose further that you have found the following lines of code that create the kind of chart you are looking for.

```
# Data
x <- c(1, 2, 3, 4, 5, 4, 7, 8, 9)
y <- c(12, 16, 14, 18, 16, 13, 15, 20, 22)
labels <- 1970:1978

# Connected scatter plot with text
plot(x, y, type = "b", xlab = "Var 1", ylab = "Var 2"); text(x + 0.4, y + 0.1, lab
```



Use these lines of code and customize them to create the co-movement visualization for **Germany** using the available ‘df’ data. The result should look something like this:



- (24) Interpret the two graphs above, which show the simultaneous evolution of the unemployment rate and GDP per capita over time for Germany and France. What are your expectations regarding the correlation between the unemployment rate and GDP per capita variables? Can you see this expectation in the figures? Discuss.

Please find solutions [here](#).

EXERCISE: Import data and write a report

Reproduce Figure 3 of [Hortaçsu and Syverson \(2015, p. 99\)](#) using R. Write a clear report about your work, i.e., document everything with a R script or a R Markdown file.

Here are the required steps:

1. Go to <https://www.aeaweb.org/articles?id=10.1257/jep.29.4.89> and download the *replication package* from the *OPENICPSR* page. Please note, that you can download the replication package after you have registered for the platform.
2. Unzip the replication package.

3. In the file *diffusion_curves_figure.xlsx* you find the required data. Import them to R.
4. Reproduce the plot using `ggplot()`.

Please find solutions [here](#).

EXERCISE: Explain the weight

In the statistic course of WS 2020, I asked 23 students about their weight, height, sex, and number of siblings. I wonder how good the height can explain the weight of students. Examine with corelations and a regression analysis the association. Load the data as follows:

```
library("haven")
classdata <- read.csv("https://raw.githubusercontent.com/hubchev/courses/main/dta/
```

A sketch of a solution is provided [here](#).

EXERCISE: Calories and weight

- a) Write down your name, your matriculation number, and the date.
- b) Set your working directory.
- c) Clear your global environment.
- d) Load the following package: `tidyverse`

The following table stems from a survey carried out at the Campus of the German Sport University of Cologne at Opening Day (first day of the new semester) between 8:00am and 8:20am. The survey consists of 6 individuals with the following information:

id	sex	age	weight	calories	sport
1	f	21	48	1700	60
2	f	19	55	1800	120
3	f	23	50	2300	180
4	m	18	71	2000	60
5	m	20	77	2800	240
6	m	61	85	2500	30

Data Description:

- **id:** Variable with an anonymized identifier for each participant.

- **sex:** Gender, i.e., the participants replied to be either male (m) or female (f).
- **age:** The age in years of the participants at the time of the survey.
- **weight:** Number of kg the participants pretended to weight.
- **calories:** Estimate of the participants on their average daily consumption of calories.
- **sport:** Estimate of the participants on their average daily time that they spend on doing sports (measured in minutes).

- Which type of data do we have here? (Panel data, repeated cross-sectional data, cross-sectional data, time Series data)
- Store each of the five variables in a vector and put all five variables into a data frame with the title `df`. If you fail here, read in the data using this line of code:

```
df <- read_csv("https://raw.githubusercontent.com/hubchev/courses/main/dta/df-calories.csv")
```

```
## Rows: 6 Columns: 5
## -- Column specification -----
## Delimiter: ","
## chr (1): sex
## dbl (4): age, weight, calories, sport
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message
```

- Show for all numerical variables the summary statistics including the mean, median, minimum, and the maximum.
- Show for all numerical variables the summary statistics including the mean and the standard deviation, **separated by male and female**. Use therefore the pipe operator.
- Suppose you want to analyze the general impact of average calories consumption per day on the weight. Discuss if the sample design is appropriate to draw conclusions on the population. What may cause some bias in the data? Discuss possibilities to improve the sampling and the survey, respectively.
- The following plot visualizes the two variables weight and calories. Discuss what can be improved in the graphical visualization.
- Make a scatterplot matrix containing all numerical variables.
- Calculate the Pearson Correlation Coefficient of the two variables
 - `calories` and `sport`

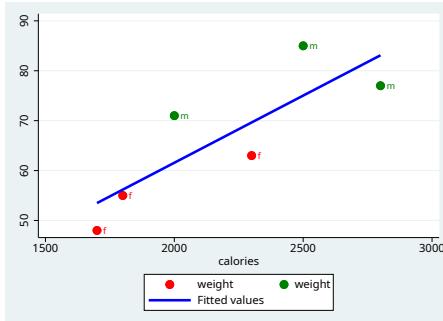


Figure 6.2: Weight vs. Calories

2. weight and calories

- m) Make a scatterplot with `weight` in the y-axis and `calories` on the x-axis. Additionally, the plot should contain a linear fit and the points should be labeled with the `sex` just like in the figure shown above.
- n) Estimate the following regression specification using the OLS method:

$$\text{weight}_i = \beta_0 + \beta_1 \text{calories}_i + \epsilon_i$$

Show a summary of the estimates that look like the following:

```
## 
## Call:
## lm(formula = weight ~ calories, data = df)
## 
## Residuals:
##      1      2      3      4      5      6 
## -5.490 -1.182 -6.640  9.435 -6.099  9.976 
## 
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept) 7.730275  20.197867   0.383   0.7214    
## calories     0.026917   0.009107   2.956   0.0417 *  
## ---        
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 
## 
## Residual standard error: 8.68 on 4 degrees of freedom
## Multiple R-squared:  0.6859, Adjusted R-squared:  0.6074  
## F-statistic: 8.735 on 1 and 4 DF,  p-value: 0.04174
```

- o) Interpret the results. In particular, interpret how many kg the estimated weight increases—on average and ceteris paribus—if calories increase by 100 calories. Additionally, discuss the statistical properties of the estimated coefficient $\hat{\beta}_1$ and the meaning of the **Adjusted R-squared**.
- p) OLS estimates can suffer from omitted variable bias. State the two conditions that need to be fulfilled for omitted bias to occur.
- q) Discuss potential confounding variables that may cause omitted variable bias. Given the dataset above how can some of the confounding variables be *controlled for*?

Solutions are provided [here](#).

EXERCISE: Bundesliga

Open the script that you find [here](#) and work on the following tasks:

1. Set your working directory.
2. Clear th environment.
3. Install and load the `bundesligR` and `tidyverse`.
4. Read in the data `bundesligR` as a tibble.
5. Replace “Bor. Moenchengladbach” with “Borussia Moenchengladbach.”
6. Check for the data class.
7. View the data.
8. Glimpse on the data.
9. Show the first and last observations.
10. Show summary statistics to all variables.
11. How many teams have played in the league over the years?
12. Which teams have played Bundesliga so far?
13. How many teams have played Bundesliga?
14. How often has each team played in the Bundesliga?
15. Show summary statistics of variable `Season` only.
16. Show summary statistics of all numeric variables (`Team` is a character).

17. What is the highest number of points ever received by a team? Show only the name of the club with the highest number of points ever received.
18. Create a new tibble using `liga` removing the variable `Pts_pre_95` from the data.
19. Create a new tibble using `liga` renaming W, D, and L to Win, Draw, and Loss. Additionally rename GF, GA, GD to Goals_shot, Goals_received, Goal_difference.
20. Create a new tibble using `liga` without the variable `Pts_pre_95` and only observations before the year 1996.
21. Remove the three tibbles just created from the environment.
22. Rename all variables of `liga` to lowercase and store it as `dfb`.
23. Show the winner and the runner up after the year 2010. Additionally show the points received.
24. Create a variable that counts how often a team was ranked first.
25. How often has each team played in the Bundesliga?
26. Make a ranking that shows which team has played the Bundesliga most often.
27. Add a variable to `dfb` that contains the number of appearances of a team in the league.
28. Create a number that indicates how often a team has played Bundesliga in a given year.
29. Make a ranking with the number of titles of all teams that ever won the league.
30. Create a numeric identifying variable for each team.
31. When a team is in the league, what is the probability that it wins the league?
32. Make a scatterplot with points on the y-axis and position on the x-axis.
33. Make a scatterplot with points on the y-axis and position on the x-axis. Additionally, only consider seasons with 18 teams and add lines that make clear how many points you needed to be placed in between rank 2 and 15.
34. Remove all objects from the environment except `dfb` and `liga`.
35. In Figure 6.3, the ranking history of *1. FC Kaiserslautern* is shown. Replicate that plot.

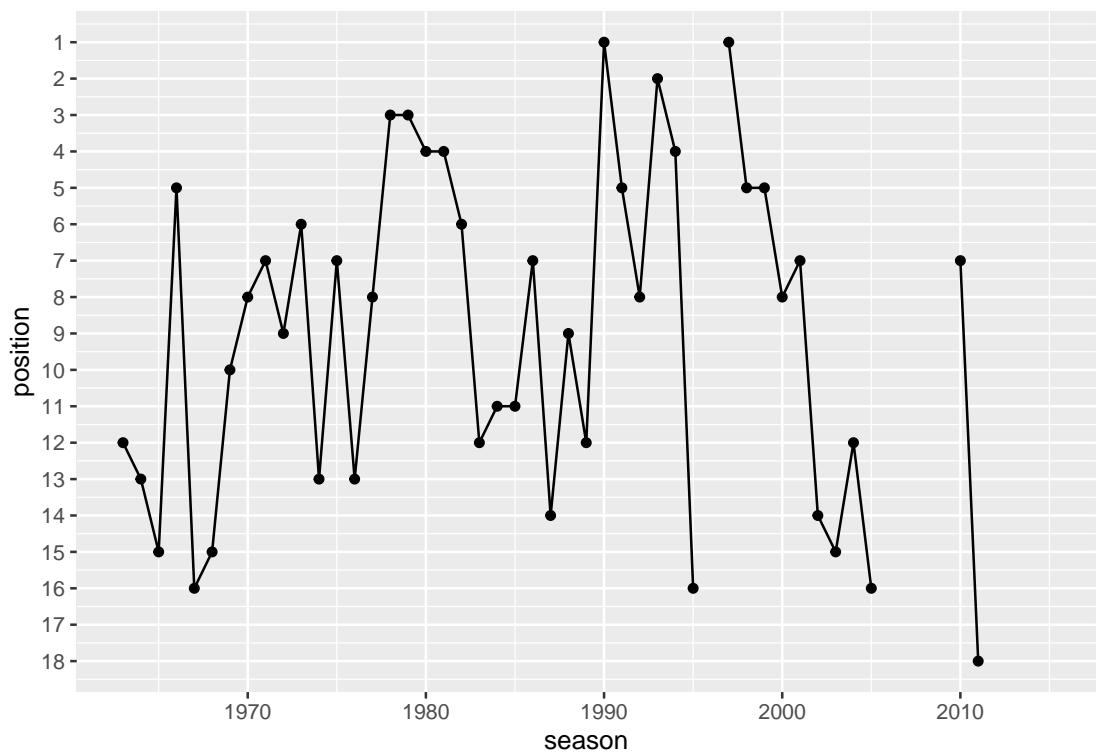


Figure 6.3: Ranking history: 1. FC Kaiserslautern

34. In Figure 6.4, I made the graph a bit nicer. Can you spot all differences and can you guess what the dashed line and the triangles mean? How could the visualization be improved further? Replicate the plot.

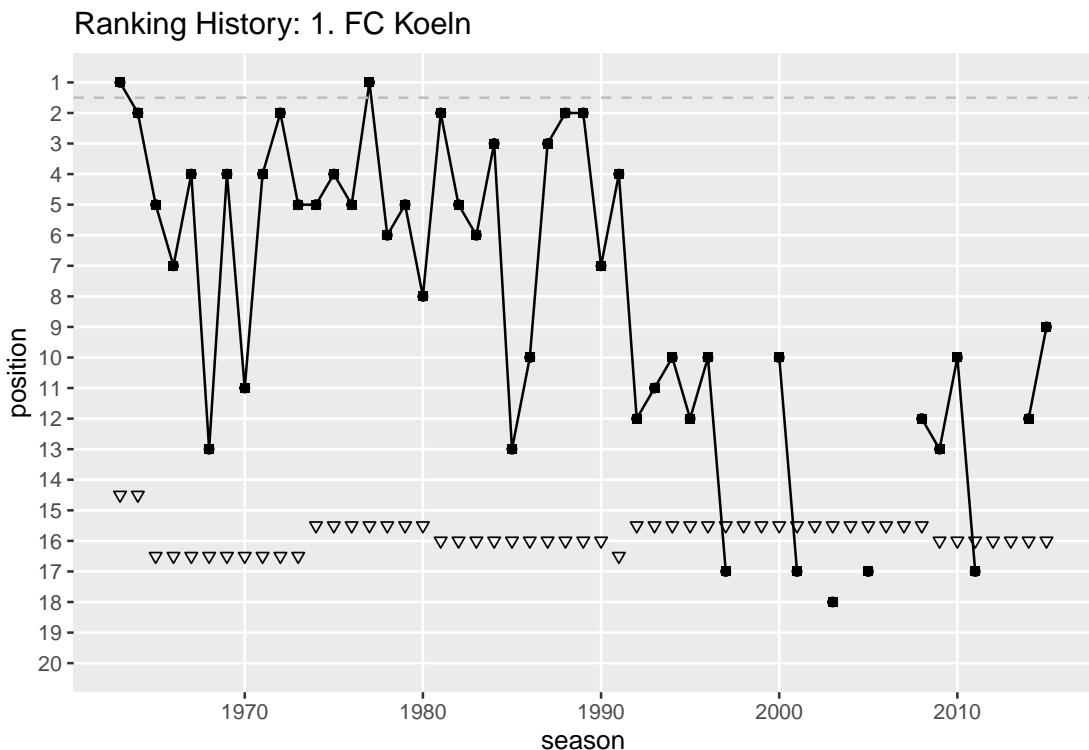


Figure 6.4: Ranking history: 1. FC Köln

35. Try to make the ranking history for each club ever played the league and export the graph as a `png` file.

Solutions are provided [here](#).

EXERCISE: Okun's Law

Suppose you aim to empirically examine unemployment and GDP for Germany and France. The data set that we use in the following is ‘forest.Rdata’ and should already been known to you from the lecture.

- (0) Write down your name, matriculation number, and date.
- (1) Set your working directory.
- (2) Clear your global environment.

(3) Install and load the following packages: ‘tidyverse’, ‘sjPlot’, and ‘ggpubr’

(4) Download and load the data, respectively, with the following code:

```
load(url("https://github.com/hubchev/courses/raw/main/dta/forest.Rdata"))
```

If that is not working, you can also download the data from ILIAS, save it in your working directory and load it from there with:

```
load("forest.Rdata")
```

(5) Show the **first eight** observations of the dataset ‘df’.

(6) Show the **last observation** of the dataset ‘df’.

(7) Which type of data do we have here (Panel, cross-section, time series, . . .)?
Name the variable(s) that are necessary to identify the observations in the dataset.

(8) Explain what the **assignment operator** in R is and what it is good for.

(9) Write down the R code to store the number of observations and the number of variables that are in the dataset ‘df’. Name the object in which you store these numbers ‘observations_df’.

(10) In the dataset ‘df’, rename the variable ‘country.x’ to ‘nation’ and the variable ‘date’ to ‘year’.

(11) Explain what the **pipe operator** in R is and what it is good for.

(12) For the upcoming analysis you are only interested the following **variables** that are part of the dataframe ‘df’: nation, year, gdp, pop, gdppc, and unemployment. Drop all other variables from the dataframe ‘df’.

(13) Create a variable that indicates the GDP per capita (‘gdp’ divided by ‘pop’).
Name the variable ‘gdp_pc’. (Hint: If you fail here, use the variable ‘gdppc’ which is already in the dataset as a replacement for ‘gdp_pc’ in the following tasks.)

(14) For the upcoming analysis you are only interested the following **countries** that are part of the dataframe ‘df’: Germany and France. Drop all other countries from the dataframe ‘df’.

(15) Create a table showing the **average** unemployment rate and GDP per capita for Germany and France in the given years. Use the pipe operator. (Hint: See below for how your results should look like.)

```
## # A tibble: 2 x 3
```

```
##   nation `mean(unemployment)` `mean(gdppc)`
##   <chr>          <dbl>        <dbl>
## 1 France         9.75        34356.
## 2 Germany        7.22        36739.
```

- (16) Create a table showing the unemployment rate and GDP per capita for Germany and France in the **year 2020**. Use the pipe operator. (Hint: See below for how your results should look like.)

```
## # A tibble: 2 x 3
##   nation `mean(unemployment)` `mean(gdppc)`
##   <chr>          <dbl>        <dbl>
## 1 France         8.01        35786.
## 2 Germany        3.81        41315.
```

- (17) Create a table showing the **highest** unemployment rate and the **highest** GDP per capita for Germany and France during the given period. Use the pipe operator. (Hint: See below for how your results should look like.)

```
## # A tibble: 2 x 3
##   nation `max(unemployment)` `max(gdppc)`
##   <chr>          <dbl>        <dbl>
## 1 France         12.6        38912.
## 2 Germany        11.2        43329.
```

- (18) Calculate the standard deviation of the unemployment rate and GDP per capita for Germany and France in the given years. (Hint: See below for how your result should look like.)

```
## # A tibble: 2 x 3
##   nation `sd(gdppc)` `sd(unemployment)`
##   <chr>      <dbl>        <dbl>
## 1 France     2940.       1.58
## 2 Germany    4015.       2.37
```

- (19) In statistics, the coefficient of variation (COV) is a standardized measure of dispersion. It is defined as the ratio of the standard deviation (σ) to the mean (μ): $COV = \frac{\sigma}{\mu}$. Write down the R code to calculate the coefficient of variation (COV) for the **unemployment rate** in Germany and France. (Hint: See below for what your result should look like.)

```
## # A tibble: 2 x 4
##   nation `sd(unemployment)` `mean(unemployment)` cov
##   <chr>      <dbl>        <dbl>      <dbl> <dbl>
```

```
## 1 France           1.58      9.75 0.162
## 2 Germany          2.37      7.22 0.328
```

- (20) Write down the R code to calculate the coefficient of variation (COV) for the **GDP per capita** in Germany and France. (Hint: See below for what your result should look like.)

look like.)

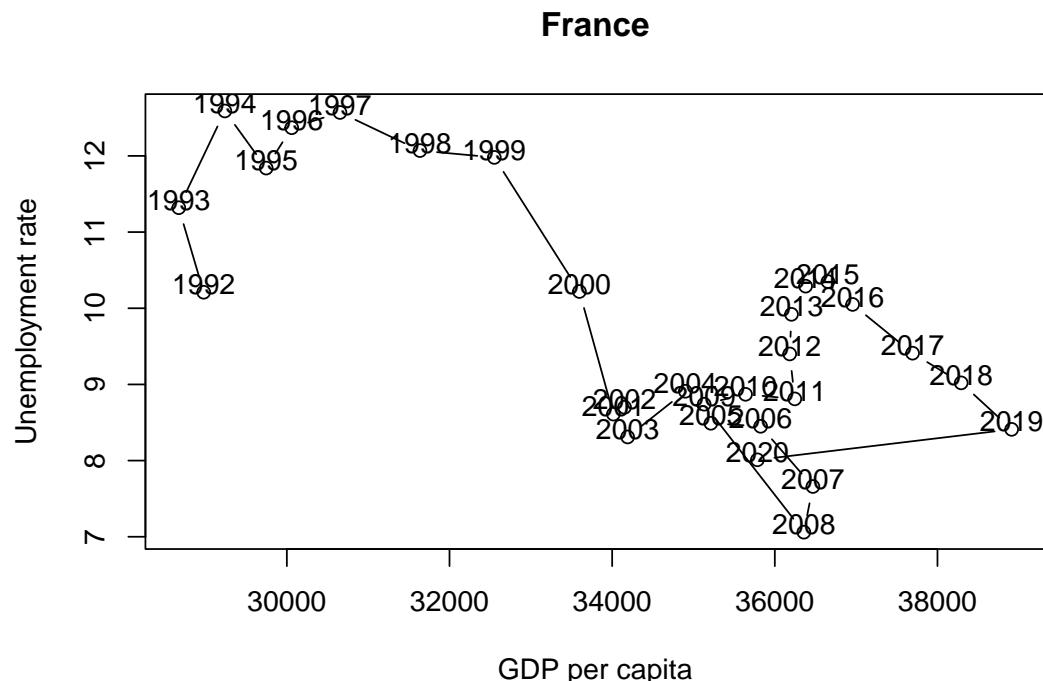
```
## # A tibble: 2 x 4
##   nation `sd(gdppc)` `mean(gdppc)` cov
##   <chr>     <dbl>        <dbl>    <dbl>
## 1 France     2940.       34356.  0.0856
## 2 Germany    4015.       36739.  0.109
```

- (21) Create a chart (bar chart, line chart, or scatter plot) that shows the unemployment rate of **Germany** over the available years. Label the chart ‘Germany’ with ‘`ggtitle("Germany")`’. Please note that you may choose any type of graphical representation. (Hint: Below you can see one of many possible examples of what your result may look like).



- (22) and 23. (*This task is worth 10 points*) The following chart shows the simulta-

neous development of the unemployment rate and GDP per capita over time for **France**.

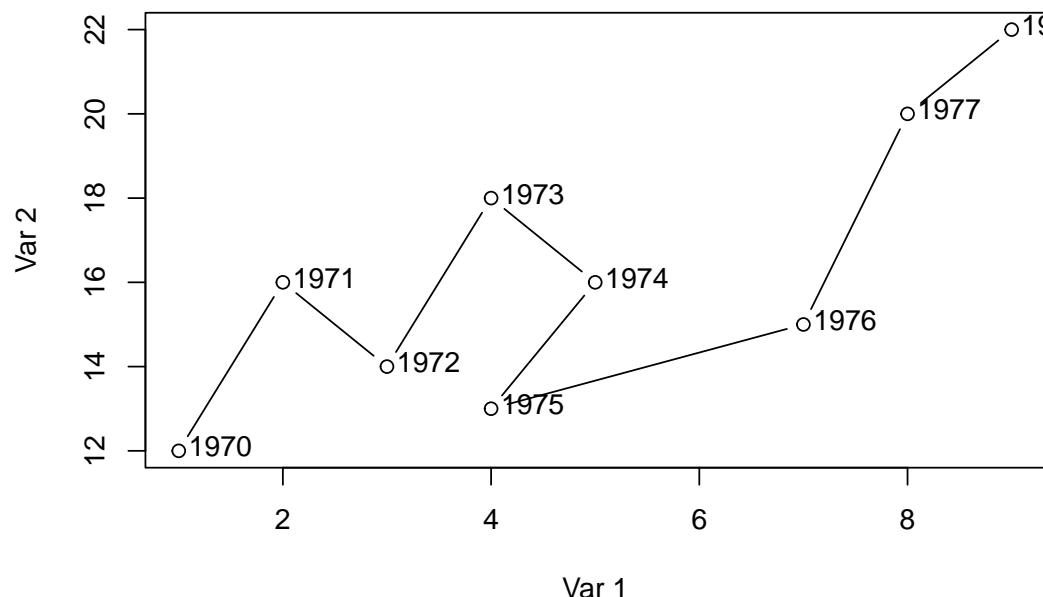


Suppose you want to visualize the simultaneous evolution of the unemployment rate and GDP per capita over time for Germany as well.

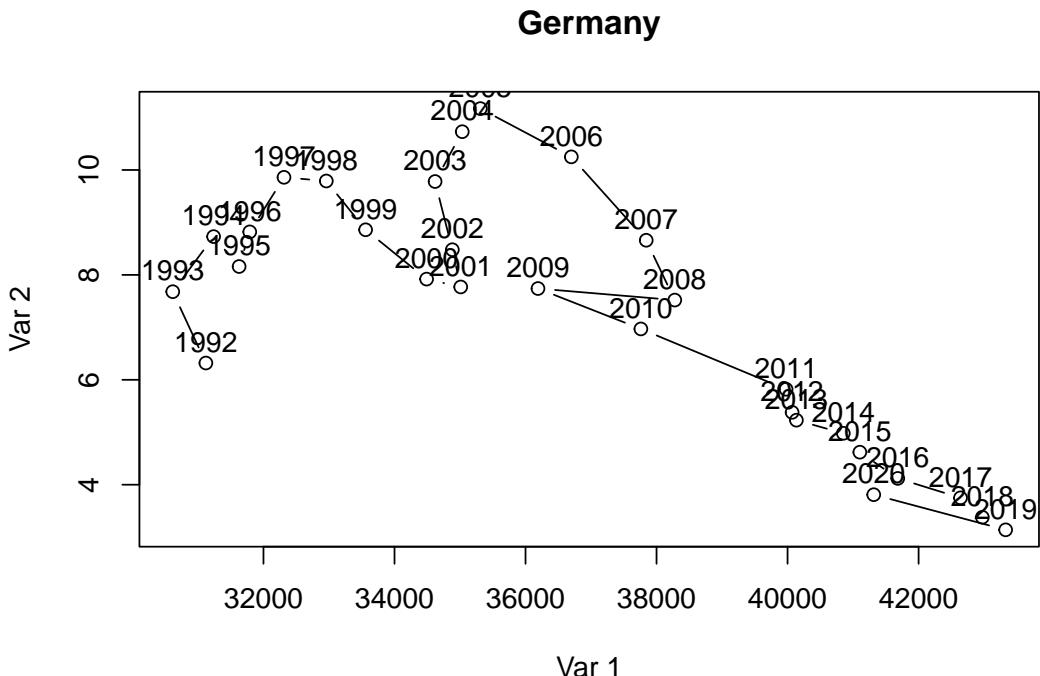
Suppose further that you have found the following lines of code that create the kind of chart you are looking for.

```
# Data
x <- c(1, 2, 3, 4, 5, 4, 7, 8, 9)
y <- c(12, 16, 14, 18, 16, 13, 15, 20, 22)
labels <- 1970:1978

# Connected scatter plot with text
plot(x, y, type = "b", xlab = "Var 1", ylab = "Var 2"); text(x + 0.4, y + 0.1, lab
```



Use these lines of code and customize them to create the co-movement visualization for **Germany** using the available ‘df’ data. The result should look something like this:



- (24) Interpret the two graphs above, which show the simultaneous evolution of the unemployment rate and GDP per capita over time for Germany and France. What are your expectations regarding the correlation between the unemployment rate and GDP per capita variables? Can you see this expectation in the figures? Discuss.

Solutions are provided [here](#).

EXERCISE: Names and duplicates

1. Load the required packages (`pacman`, `tidyverse`, `janitor`, `babynames`, `stringr`).
2. Load the dataset from the URL: https://github.com/hubchev/courses/raw/main/dta/df_names.RData. Make yourself familiar with the data.
3. After loading the dataset, remove all objects except `df_2022` and `df_2022_error`.
4. Reorder the data using the `relocate` function so that `surname`, `name`, and `age` appear first. Save the changed data in a tibble called `df`.
5. Sort the data according to `surname`, `name`, and `age`.
6. Make a variable named `born` that contains the year of birth. How is the `born`

- variable calculated?
7. Create a new variable named `id` that identifies each person by `surname`, `name`, and their birth year (`born`). Why is this identifier useful?
 8. Investigate how the data is identified. Are there any duplicates? If so, can you think of strategies to identify and how to deal with these duplicates.
 9. Unload the packages used in the script. Why is unloading packages considered good practice?

Solutions are provided [here](#).

EXERCISE: Zipf's law

The data under investigation includes population information for various German cities, identified by the variable `stadt`, spanning the years 1970, 1987, and 2010. The variable `status` provides details about the legislative status of the cities, and the variable `state` (Bundesland) indicates the state in which each respective city is situated.

Preamble

- (1) Set your working directory.
- (2) Clear your global environment.
- (3) Install and load the following packages: ‘tidyverse’, ‘haven’, and ‘janitor’.

Read in, inspect, and clean the data

- (4) Download and load the data, respectively, with the following code:

```
df <- read_dta(
  "https://github.com/hubchev/courses/raw/main/dta/city.dta",
  encoding="latin1") |>
  as_tibble()
```

If that is not working, you can also download the data from ILIAS, save it in your working directory and load it from there with:

```
load("city.RData")
```

- (5) Show the first six and the last six observations of the dataset ‘df’.
- (6) How many observations (rows) and variables (columns) are in the dataset?

- (7) Show for all numerical variables the summary statistics including the mean, median, minimum, and the maximum.
- (8) Rename the variable `stadt` to `city`.
- (9) Remove the variables `pop1970` and `pop1987`.
- (10) Replicate the following table which contains some summary statistics.

```
## # A tibble: 17 x 3
##   state           `mean(pop2011)` `sum(pop2011)`
##   <chr>          <dbl>        <dbl>
## 1 Baden-Wrttemberg    7580        7580
## 2 Baden-Württemberg  23680.      7837917
## 3 Bayern            23996.      7558677
## 4 Berlin             3292365    3292365
## 5 Brandenburg       18472.      1865632
## 6 Bremen             325432.     650863
## 7 Hamburg            1706696    1706696
## 8 Hessen              22996.      5036121
## 9 Mecklenburg-Vorpommern  27034.     811005
## 10 Niedersachsen     24107.      6219515
## 11 Nordrhein-Westfalen  47465.      18036727
## 12 Rheinland-Pfalz    25644.      1871995
## 13 Saarland           NA          NA
## 14 Sachsen            27788.      2973351
## 15 Sachsen-Anhalt     21212.      1993915
## 16 Schleswig-Holstein  24157.      1739269
## 17 Th_ringen          29192.      1167692
```

- (11) The states “Baden-Wrttemberg” and “Th_ringen” are falsely pronounced. Correct the names and regenerate the summary statistics table presented above. Your result should look like this:

```
## # A tibble: 16 x 3
##   state           `mean(pop2011)` `sum(pop2011)`
##   <chr>          <dbl>        <dbl>
## 1 Baden-Württemberg  23631.      7845497
## 2 Bayern            23996.      7558677
## 3 Berlin             3292365    3292365
## 4 Brandenburg       18472.      1865632
## 5 Bremen             325432.     650863
## 6 Hamburg            1706696    1706696
```

## 7 Hessen	22996.	5036121
## 8 Mecklenburg-Vorpommern	27034.	811005
## 9 Niedersachsen	24107.	6219515
## 10 Nordrhein-Westfalen	47465.	18036727
## 11 Rheinland-Pfalz	25644.	1871995
## 12 Saarland	NA	NA
## 13 Sachsen	27788.	2973351
## 14 Sachsen-Anhalt	21212.	1993915
## 15 Schleswig-Holstein	24157.	1739269
## 16 Thüringen	29192.	1167692

- (12) To investigate the reason for observing only NAs for Saarland, examine all cities within Saarland. Therefore, please display all observations for cities in Saarland in the Console, as illustrated below.

```
## # A tibble: 47 x 5
##   city           status state  pop2011 rankX
##   <chr>          <chr>  <chr>    <dbl>  <dbl>
## 1 Perl            Commune Saarland    7775  2003
## 2 Freisen         Commune Saarland    8270  1894
## 3 Großrosseln    Commune Saarland    8403  1868
## 4 Nonnweiler     Commune Saarland    8844  1775
## 5 Nalbach         Commune Saarland    9302  1678
## 6 Wallerfangen   Commune Saarland    9542  1642
## 7 Kirkel          Commune Saarland   10058  1541
## 8 Merchweiler    Commune Saarland   10219  1515
## 9 Nohfelden      Commune Saarland   10247  1511
## 10 Friedrichsthal City    Saarland   10409  1489
## 11 Marpingen     Commune Saarland   10590  1461
## 12 Mandelbachtal Commune Saarland   11107  1390
## 13 Kleinblittersdorf Commune Saarland   11396  1354
## 14 Überherrn      Commune Saarland   11655  1317
## 15 Mettlach        Commune Saarland   12180  1241
## 16 Tholey          Commune Saarland   12385  1217
## 17 Saarwellingen  Commune Saarland   13348  1104
## 18 Quierschied    Commune Saarland   13506  1088
## 19 Spiesen-Elversberg Commune Saarland   13509  1086
## 20 Rehlingen-Siersburg Commune Saarland   14526  996
## 21 Riegelsberg    Commune Saarland   14763  982
## 22 Ottweiler       City    Saarland   14934  969
## 23 Beckingen      Commune Saarland   15355  931
```

## 24 Losheim am See	Commune	Saarland	15906	887
## 25 Schiffweiler	Commune	Saarland	15993	882
## 26 Wadern	City	Saarland	16181	874
## 27 Schmelz	Commune	Saarland	16435	857
## 28 Sulzbach/Saar	City	Saarland	16591	849
## 29 Illingen	Commune	Saarland	16978	827
## 30 Schwalbach	Commune	Saarland	17320	812
## 31 Eppelborn	Commune	Saarland	17726	793
## 32 Wadgassen	Commune	Saarland	17885	785
## 33 Bexbach	City	Saarland	18038	777
## 34 Heusweiler	Commune	Saarland	18201	762
## 35 Püttlingen	City	Saarland	19134	718
## 36 Lebach	City	Saarland	19484	701
## 37 Dillingen/Saar	City	Saarland	20253	654
## 38 Blieskastel	City	Saarland	21255	601
## 39 St. Wendel	City	Saarland	26220	460
## 40 Merzig	City	Saarland	29727	392
## 41 Saarlouis	City	Saarland	34479	323
## 42 St. Ingbert	City	Saarland	36645	299
## 43 Völklingen	City	Saarland	38809	279
## 44 Homburg	City	Saarland	41502	247
## 45 Neunkirchen	City	Saarland	46172	206
## 46 Saarbrücken	City	Saarland	175853	43
## 47 Perl	Commune	Saarland	NA	NA

- (13) With reference to the table above, we have identified an entry for the city of Perl that solely consists of NAs. This city is duplicated in the dataset, appearing at positions 1 and 47. The latter duplicate contains only NAs and can be safely removed without the loss of valuable information. Please eliminate this duplication and regenerate the list of all cities in the Saarland.
- (14) Calculate the total population and average size of cities in Saarland.
- (15) Check if any other city is recorded more than once in the dataset. To do so, reproduce the table below.

```
## # A tibble: 23 x 5
## # Groups:   city [11]
##   city           status             state    pop2011 unique_count
##   <chr>          <chr>            <chr>    <dbl>      <int>
## 1 Bonn          City with County Rights Nordrhei~  305765        3
## 2 Bonn          City with County Rights Nordrhei~  305765        3
```

## 3 Bonn	City with County Rights	Nordrhei~	305765	3
## 4 Brühl	Commune	Baden-Wü~	13805	2
## 5 Brühl	City	Nordrhei~	43568	2
## 6 Erbach	City	Baden-Wü~	13024	2
## 7 Erbach	City	Hessen	13245	2
## 8 Fürth	City with County Rights	Bayern	115613	2
## 9 Fürth	Commune	Hessen	10481	2
## 10 Lichtenau	City	Nordrhei~	10473	2
## 11 Lichtenau	Commune	Sachsen	7544	2
## 12 Münster	Commune	Hessen	14071	2
## 13 Münster	City with County Rights	Nordrhei~	289576	2
## 14 Neunkirchen	Commune	Nordrhei~	13930	2
## 15 Neunkirchen	City	Saarland	46172	2
## 16 Neuried	Commune	Baden-Wü~	9383	2
## 17 Neuried	Commune	Bayern	8277	2
## 18 Petersberg	Commune	Hessen	14766	2
## 19 Petersberg	Commune	Sachsen~~	10097	2
## 20 Senden	City	Bayern	21560	2
## 21 Senden	Commune	Nordrhei~	19976	2
## 22 Staufenberg	City	Hessen	8114	2
## 23 Staufenberg	Commune	Niedersa~	7983	2

- (16) The table indicates that the city of Bonn appears three times in the dataset, and all three observations contain identical information. Thus, remove two of these observations to ensure that Bonn is uniquely represented in the dataset. All other cities that occur more than once in the data are situated in different states. That means, these are distinct cities that coincidentally share the same name.

Data analysis (Zipf's Law)

Note: If you have failed to solve the data cleaning tasks above, you can download the cleaned data from ILIAS, save it in your working directory and load it from there with: `load("city_clean.RData")`

In the following, you aim to examine the validity of Zipf's Law for Germany. Zipf's Law postulates how the size of cities is distributed. The "law" states that there is a special relationship between the size of a city and the rank it occupies in a series sorted by city size. In the estimation equation

$$\log(M_j) = c - q \log(R_j),$$

the law postulates a coefficient of $q = 1$ (c is a constant; M_j is the size of city j ; R_j is the rank that city j occupies in a series sorted by city size).

(17)

Create a variable named `rank` that includes a ranking of cities based on the population size in the year 2011. Therefore, Berlin should have a rank of 1, Hamburg a rank of 2, Munich a rank of 3, and so on.

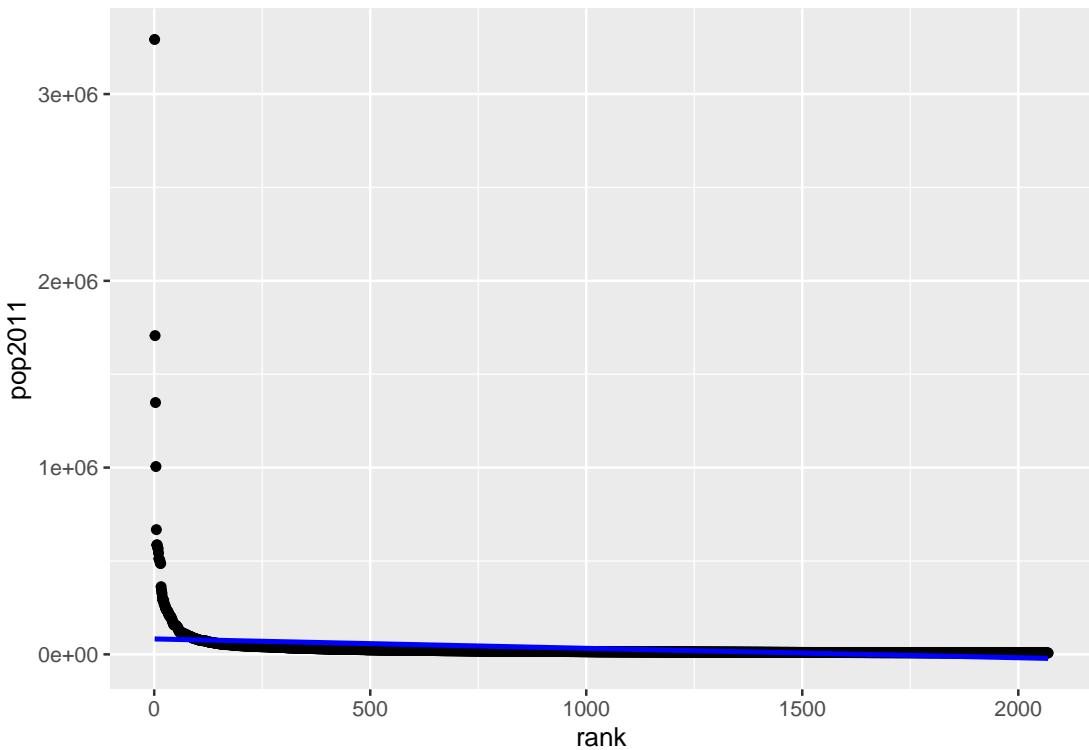
Note: If you cannot solve this task, use the variable `rankX` as a substitute for the variable `rank` that was not generated.

```
## # A tibble: 6 x 3
##   city           pop2011   rank
##   <chr>          <dbl> <int>
## 1 Berlin        3292365     1
## 2 Hamburg       1706696     2
## 3 München [Munich] 1348335     3
## 4 Köln [Cologne] 1005775     4
## 5 Frankfurt am Main 667925     5
## 6 Düsseldorf [Dusseldorf] 586291     6
```

(18) Calculate the Pearson Correlation Coefficient of the two variables ‘pop2011’ and ‘rank’. The result should be:

```
## [1] -0.2948903
```

(19) Create a scatter plot. On the x-axis, plot the variable `rank`, and on the y-axis, plot `pop2011`. Add a regression line representing the observed relationship to the same scatter plot.



- (20) Logarithmize the variables `rank` and `pop2011`. Title the new variables as `lnrank` and `lnpop2011`, respectively. Here is a snapshot of the resulting variables:

```
## # A tibble: 6 x 5
##   city              rank  lnrank pop2011 lnpop2011
##   <chr>          <int>   <dbl>   <dbl>      <dbl>
## 1 Berlin            1     0    3292365    15.0
## 2 Hamburg           2     0.693 1706696    14.4
## 3 München [Munich]  3     1.10   1348335    14.1
## 4 Köln [Cologne]    4     1.39   1005775    13.8
## 5 Frankfurt am Main 5     1.61    667925    13.4
## 6 Düsseldorf [Dusseldorf] 6     1.79    586291    13.3
```

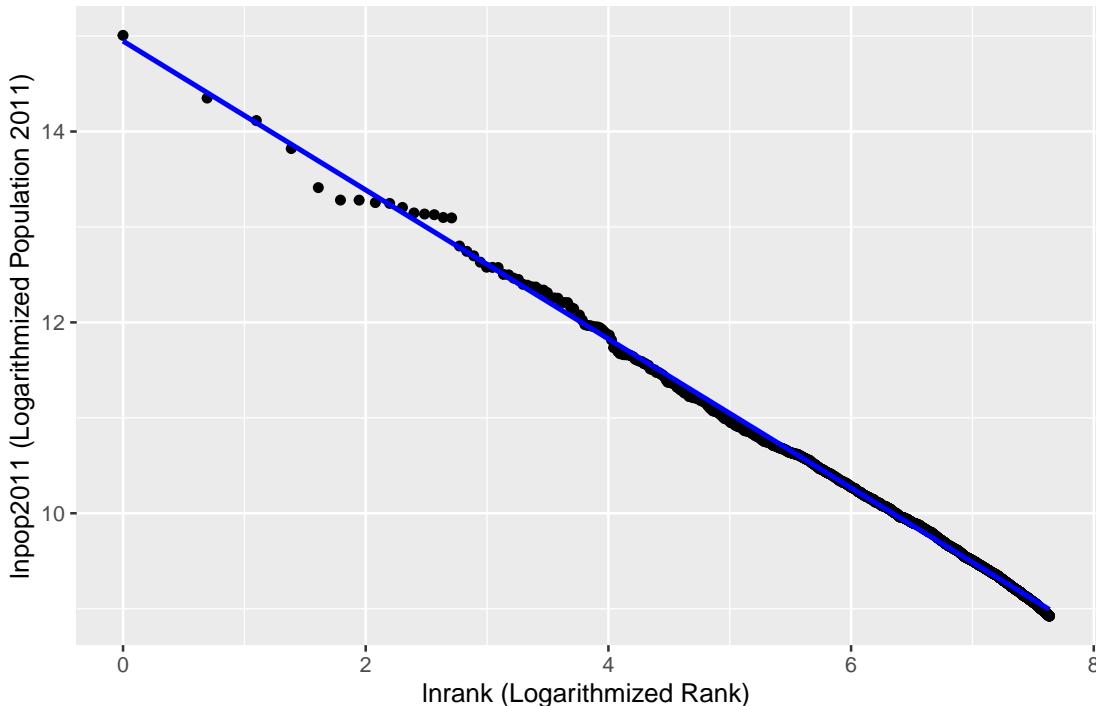
- (21) Calculate the Pearson Correlation Coefficient of the two variables ‘`lnpop2011`’ and ‘`lnrank`’. The result should be:

```
## [1] -0.9990053
```

- (22) Create a scatter plot. On the x-axis, plot the variable `lnrank`, and on the y-axis, plot `lnpop2011`. Add a regression line representing the observed relationship to the same scatter plot. Additionally, add a title and label the

axes like is shown here:

Scatterplot with Regression Line



- (23) Now, test the relationship postulated in Zipf's Law. Regress the logarithmized city size in the year 2011 on the logarithmized rank of a city in a series sorted by city size. Briefly interpret the results, addressing the coefficient of determination. Show the regression results. Here is one way to present the results of the regression (*Note: The way how you present your regression results do not matter*):

```
##
## Call:
## lm(formula = lnpop2011 ~ lnrank, data = df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.28015 -0.01879  0.01083  0.02005  0.25973
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 14.947859   0.005141   2908 <2e-16 ***
## lnrank      -0.780259   0.000766   -1019 <2e-16 ***
##
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.03454 on 2067 degrees of freedom
## Multiple R-squared:  0.998, Adjusted R-squared:  0.998
## F-statistic: 1.038e+06 on 1 and 2067 DF,  p-value: < 2.2e-16
```

(24) Explain the following lines of code.

```
df <- df |>
  mutate(prediction = predict(zipf, newdata = df)) |>
  mutate(pred_pop = exp(prediction))
df |>
  select(city, pop2011, pred_pop) |>
  filter(city == "Regensburg")

## # A tibble: 1 x 3
##   city      pop2011 pred_pop
##   <chr>     <dbl>    <dbl>
## 1 Regensburg 135403  134194.
```

Solutions are provided [here](#).

Chapter 7

Write with R Markdown

7.1 Introduction

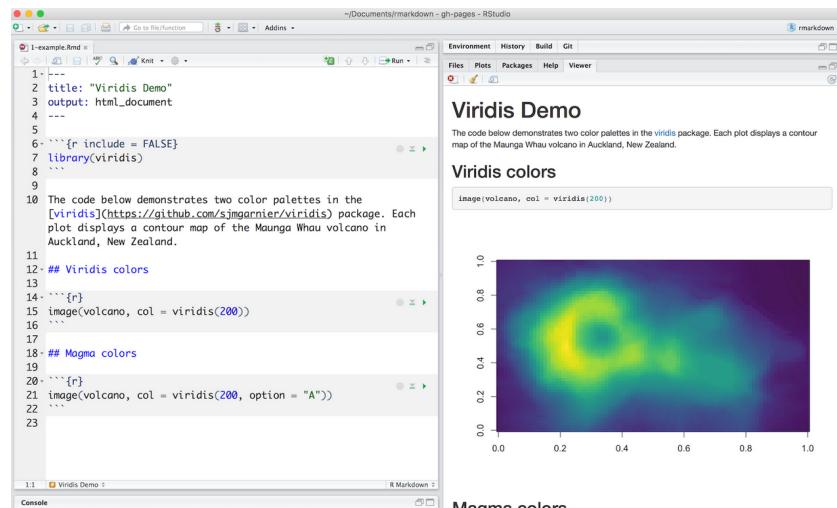


Figure 7.1: Example of an R Markdown file

R Markdown provides an authoring framework for data science. You can use a single R Markdown file to transcript your work, run code, and generate high quality reports, books, websites, articles, theses, blogs, and many more.

In contrast to Quarto (see: <https://quarto.org> and <https://quarto.org/docs/get-started/hello/rstudio.html>), which is the more recent format, R Markdown is around for some time and hence there are uncountable resources to learn it. For example:

- The [R Markdown Cheatsheet](#) from posit offers an overview on the most important features of R Markdown.

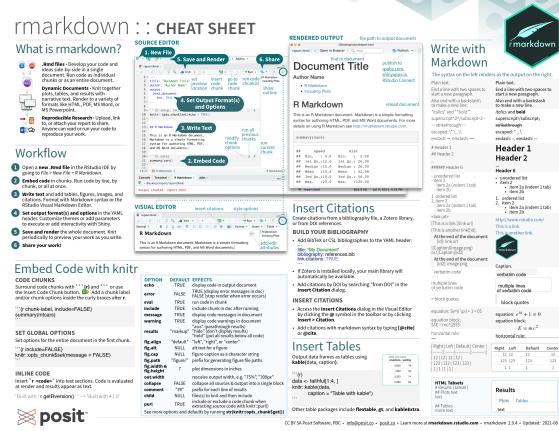


Figure 7.2: R Markdown Cheatsheet from posit

- The book *R Markdown Cookbook* by Xie, Dervieux, and Riederer (2020) offers an introduction. The [online version of the book](#) is regularly updated and free of costs.

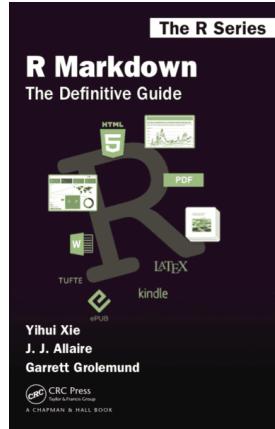


Figure 7.3: Xie et al. (2020): R Markdown Cookbook

- The book *R Markdown: The Definitive Guide* by Xie, Allaire, and Grolemund (2018) offers a comprehensive introduction. The online version of the book is regularly updated and free of costs.

Please watch the video [What is R Markdown?](#) and then study the [R Markdown tutorial from RStudio](#).

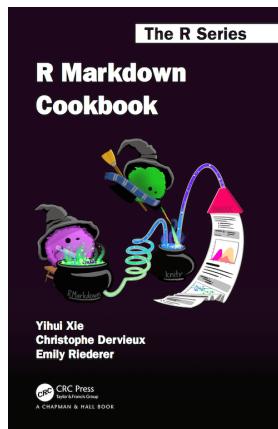


Figure 7.4: [Xie et al. \(2018\)](#): R Markdown: The Definitive Guide

7.2 Working directory in R Markdown

The working directory is by default set to the directory that contains the Rmd document. In case you want to use another directory you can do so by changing the working directory with `setwd()`. However, that is not persistent in R Markdown and only works for the current code chunk. After the code chunk has been evaluated, the working directory will be restored to the directory where the Rmd file is placed.

EXERCISE: Start Markdown and R Markdown

- a) You can learn Markdown (not R Markdown!) in 10 minutes. Just go to <https://www.markdowntutorial.com> and work through the interactive lessons.
- b) Now create your first R Markdown file in 3 minutes by doing the following:
 - click in RStudio on *File > New File > R Markdown*
 - click *OK*
 - look for a button entitled *Knit* and click it
 - save your file (it will be saved with .Rmd file extension)
- c) Play around with the file. For example, change the output format can you create a word file or a presentation. Play around with the code chunks. Add a picture that you find somewhere online.
- d) Set your working directory to the folder where you have saved your first Rmd-file. Can you come up with a way to generate different output format with just one function.

EXERCISE: R Markdown cite literature

- a) Create a new R Markdown file (*File > New File > R Markdown*), save the file in an empty folder, and knit it.
- b)
 - Make a new script with *File > New File > R Script*.
 - Go to <https://scholar.google.de/> and search for *osrmtim*e.
 - Click on “*cite*” and “*BibTeX*”. Copy and paste everything that you see into your script and save the script as *lit.bib*. R Studio will ask you if you confirm the file type change. Click yes. Your *lit.bib* file should look like this:

```
@article{huber2016calculate,
  title={Calculate travel time and distance with OpenStreetMap data using the Open
author={Huber, Stephan and Rust, Christoph},
journal={The Stata Journal},
volume={16},
number={2},
pages={416--423},
year={2016},
publisher={SAGE Publications Sage CA: Los Angeles, CA}
}
```

- Add the text “*bibliography: references.bib*” to your YAML header of your R Markdown file so that it looks somehow like that:

```
---
title: "Untitled"
author: "Stephan Huber"
date: "`r Sys.Date()`"
output: html_document
bibliography: lit.bib
---
```

- Now you can cite the OSRMTIME paper with `@huber2016calculate` somewhere in the text of your R Markdown file.
- Knit the R Markdown file and you should see the paper cited and a reference list at the end of the html report.
- You can manipulate the citation style you can specify a CSL (Citation Style Language) file in the YAML header. For example the APA style can be chosen with:

```
csl: "https://raw.githubusercontent.com/citation-style-language/styles/master/apa.csl"
```

Many more citation styles can be found [here](#).

EXERCISE: Preparing APA journal articles (papaja)

There is an easy way to write a manuscript that follows all the APA rules using the package `papaja` written by two psychologists from Cologne. Please read their [manual](#) and consider their [repository on GitHub](#).

Now, install and load the package:

```
install.packages("papaja")
library("papaja")
```

Then, click “File > New File > R Markdown” and choose the “APA-style manuscript” from the section “from template”. Knit the R markdown template and you will have a template for a APA manuscript.

Apart from the obvious adjustments, I recommend to make at least two general adjustments: Change `classoption` to “doc” and `linenumbers` to “no”.

EXERCISE: R Markdown template

Please follow the instructions below to access the file “23-09_ds-project-desc.Rmd” from my GitHub account:

1. Download the file from my GitHub account by clicking on the link provided [here](#).
2. Save the file in your working directory.
3. Use the knit function to run the file, but be aware that it may not work properly at first. If you encounter any issues, troubleshooting may be required. Don’t worry, error messages will usually provide guidance to help you resolve the issue. Please note that the YAML header is sensitive to spacing, so be careful when setting it up to avoid breaking the code.
4. In the project template, I have used BibTeX to cite literature. This method is excellent for automating tedious tasks such as citing papers and generating reference lists based on citation styles, saving time and reducing the likelihood of citation errors. The literature cited is in a separate file, which can be found on one of my GitHub repositories.

Chapter 8

Appendix

8.1 Helpful shortcuts

Table 1: Different OS, different keys

Key in Windows/Linux	Key in Mac
CTRL	Command Key
Alt	Option Key

Table 2: Helpful shortcuts

Action	Shortcut Keys	Description
Run code	Ctrl + Enter	Runs the current line and jumps to the next one, or runs the selected part without jumping further.
	Alt + Enter	Allows running code without moving the cursor to the next line if you want to run one line of code multiple times without selecting it.
	Ctrl + Alt + R	Runs the entire script.
	Ctrl + Alt + B/E	Run the script from the Beginning to the current line and from the current line to the End.
Write code	Alt + (-)	Inserts the assignment operator (<-) with spaces surrounding it.
	Ctrl + Shift + M	Inserts the magrittr/pipe operator (%>%) with spaces surrounding it.

Action	Shortcut Keys	Description
Navigating in RStudio	Ctrl + Shift + C	Comments out code by putting a # in front of each line of marked code of a script.
	Ctrl + Shift + R	Creates a foldable comment section in your code.
	Ctrl + 1	Move focus to editor.
	Ctrl + 2	Move focus to console.
	Ctrl+Tab and Ctrl+Shift+Tab	to switch between tabs.
	Ctrl + Shift + N	Open a new R script.
	Ctrl + w	Close a tab.

8.2 Navigating the file system

It is essential to know how R interacts with the file system on your computer. Modern operating systems are incredibly user-friendly and try to hide boring and annoying stuff from the customer. In the following, I will try to give a brief introduction on how to navigate around a computer using a DOS or UNIX shell. If you familiar with that, you can skip this part of the notes.

8.2.1 The file system

In this section, I describe the basic idea behind file locations and file paths. Regardless of whether you are using Windows, macOS, or Linux, every file on the computer is assigned a human-readable address, and every address has the same basic structure: it describes a path that starts from a root location, through a series of folders (or directories), and finally ends up at the file.

On a Windows computer, the root is the storage device on which the file is stored, and for many home computers, the name of the storage device that stores all your files is C:. After that comes the folders, and on Windows, the folder names are separated by a backslash symbol \. So, the complete path to this book on my Windows computer might be something like this:

C:\Users\huber\Rbook\rcourse-book.pdf

On Linux, Unix, and macOS systems, the addresses look a little different, but they are more or less identical in spirit. Instead of using the backslash, folders

are separated using a forward slash, and unlike Windows, they do not treat the storage device as being the root of the file system. So, the path on a Mac might be something like this:

```
/Users/huber/Rbook/rcourse-book.pdf
```

That is what we mean by the *path* to a file. The next concept to grasp is the idea of a working directory and how to change it. For those of you who have used command-line interfaces previously, this should be obvious already. But if not, here is what I mean. The working directory is just whatever folder I am currently looking at. Suppose that I am currently looking for files in Explorer (if you are using Windows) or using Finder (on a Mac). The folder I currently have open is my user directory (i.e., C:\Users\huber or /Users/huber). That is my current working directory.

8.2.2 Working directory

The next concept to grasp is the idea of a *working directory* and how to change it. For those of you who have used command line interfaces previously, this should be obvious already. But if not, here's what I mean. The working directory is just “whatever folder I'm currently looking at”. Suppose that I'm currently looking for files in Explorer (if you're using Windows) or using Finder (on a Mac). The folder I currently have open is my user directory (i.e., C:\Users\huber or /Users/huber). That's my current working directory.

The fact that we can imagine that the program is “in” a particular directory means that we can talk about moving *from* our current location *to* a new one. What that means is that we might want to specify a new location in relation to our current location. To do so, we need to introduce two new conventions. Regardless of what operating system you're using, we use . to refer to the current working directory, and .. to refer to the directory above it. This allows us to specify a path to a new location in relation to our current location, as the following examples illustrate. Let's assume that I'm using my Windows computer, and my working directory is C:\Users\huber\Rbook. The table below shows several addresses in relation to my current one:

Absolute path	Relative path
C:\Users\huber	..
C:\Users	..\..
C:\Users\huber\Rbook\source	.\source
C:\Users\huber\nerdstuff	..\nerdstuff

It is quite common on computers that have multiple users to define `~` to be the user's *home directory*. The home directory on a Mac for the 'huber' user is `/Users/huber/`. And so, not surprisingly, it is possible to define other directories in terms of their relationship to the home directory. For example, an alternative way to describe the location of `thercourse-book.pdf` file on a Mac would be

```
~\Rbook\rcourse-book.pdf
```

You can find out your home directory with the `path.expand()` function:

```
path.expand("~/")
```

```
## [1] "/home/sthu"
```

Thus, on my machine `~` is an abbreviation for the path `/home/sthu`.

```
getwd()
```

```
## [1] "/home/sthu/Dropbox/hsf/courses/ds"
```

8.2.3 Navigating the file system using the R console

When you want to load or save a file in R it's important to know what the working directory is. You can find out by using the `getwd()` command. For the moment, let's assume that I'm using Mac OS or Linux, since things are different on Windows, see section 8.2.5. Let's check the current active working directory:

```
getwd()
```

```
## [1] "/home/sthu/Dropbox/hsf/courses/ds"
```

The function `setwd()` allows to change the working directory:

```
setwd("/Users/huber/Rbook/data")
setwd("./Rbook/data")
```

The function `list.files()` lists all the files in that directory:

```
list.files()
```

8.2.4 R Studio projects

Setting the working directory repeatedly can be a cumbersome task. Fortunately, R Studio projects can automate this process for you. When you open an R Studio project, the working directory is automatically set to the project directory.

Creating a new project in R Studio is simple. Just click on *File > New Project*. . . . This will create a directory on your computer with a `_*Rproj_` file that can be used to open the saved project at a later date. The newly created directory contains your R code, data files, and other project-related files. By working within projects, all of your files and data are organized in one place, making it easier to share your work with others, reproduce your analyses, and keep track of changes over time.

8.2.5 Why do the Windows paths use the back-slash?

Let's suppose I'm using a computer with Windows. As before, I can find out what my current working directory is like this:

```
getwd()  
[1] "C:/Users/huber/"
```

R is displaying a Windows path using the wrong type of slash, the back-slash. The answer has to do with the fact that R treats the \ character as *special*. If you're deeply wedded to the idea of specifying a path using the Windows style slashes, then what you need to use two back-slashes \\ whenever you mean \. In other words, if you want to specify the working directory on a Windows computer, you need to use one of the following commands:

```
setwd( "C:/Users/huber" )  
setwd( "C:\\\\Users\\\\huber" )
```

8.3 Troubleshooting

Troubleshooting is perhaps the most important skill for a data scientist. To tackle problems effectively, you need to understand them, replicate them, and then work to solve them. To help you with this process, here are some guidelines:

When seeking help, be sure to provide information about your machine, including the operating system, the version of R, and the packages you have loaded. You can use the `sessionInfo()` function to gather this information. Here's an example from my machine:

```
sessionInfo()  
  
## R version 4.2.2 Patched (2022-11-10 r83330)  
## Platform: x86_64-pc-linux-gnu (64-bit)  
## Running under: Debian GNU/Linux 12 (bookworm)  
##  
## Matrix products: default
```

```

## BLAS:    /usr/lib/x86_64-linux-gnu/openblas-pthread/libblas.so.3
## LAPACK:  /usr/lib/x86_64-linux-gnu/openblas-pthread/liblapack.so.3
##
## locale:
## [1] LC_CTYPE=en_US.UTF-8          LC_NUMERIC=C
## [3] LC_TIME=en_US.UTF-8          LC_COLLATE=en_US.UTF-8
## [5] LC_MONETARY=en_US.UTF-8       LC_MESSAGES=en_US.UTF-8
## [7] LC_PAPER=en_US.UTF-8         LC_NAME=C
## [9] LC_ADDRESS=C                  LC_TELEPHONE=C
## [11] LC_MEASUREMENT=en_US.UTF-8   LC_IDENTIFICATION=C
##
## attached base packages:
## [1] stats      graphics   grDevices utils     datasets  methods
## [7] base
##
## other attached packages:
## [1] dplyr_1.1.4      jtools_2.2.2      sjPlot_2.8.15
## [4] ggpubr_0.6.0     datasauRus_0.1.8   haven_2.5.4
## [7] janitor_2.2.0    wbstats_1.0.4     scales_1.3.0
## [10] lubridate_1.9.3  forcats_1.0.0     purrr_1.0.2
## [13] readr_2.1.4      tidyverse_2.0.0   tibble_3.2.1
## [16] ggplot2_3.5.0    tidyverse_2.0.0   stringr_1.5.1
## [19] bundesligR_0.1.0 captioner_2.2.3  knitr_1.45
## [22] pacman_0.5.1
##
## loaded via a namespace (and not attached):
## [1] minqa_1.2.6        TH.data_1.1-2      colorspace_2.1-0
## [4] ggsignif_0.6.4     class_7.3-22      rsconnect_1.2.0
## [7] sjlabelled_1.2.0    estimability_1.4.1  snakecase_0.11.1
## [10] rstudioapi_0.15.0  listenv_0.9.0     farver_2.1.1
## [13] bit64_4.0.5       prodlim_2023.08.28 fansi_1.0.6
## [16] mvtnorm_1.2-4      codetools_0.2-19   splines_4.2.2
## [19] cachem_1.0.8      sjmisc_2.8.9     jsonlite_1.8.8
## [22] nloptr_2.0.3      ggeffects_1.3.4   broom_1.0.5
## [25] compiler_4.2.2     httr_1.4.7       sjstats_0.18.2
## [28] emmeans_1.9.0      backports_1.4.1   Matrix_1.6-4
## [31] fastmap_1.1.1      cli_3.6.2       htmltools_0.5.7
## [34] tools_4.2.2        coda_0.19-4     gtable_0.3.4
## [37] glue_1.6.2         tinytex_0.49    Rcpp_1.0.11
## [40] carData_3.0-5     jquerylib_0.1.4  vctrs_0.6.5

```

```

## [43] nlme_3.1-164      insight_0.19.7    timeDate_4032.109
## [46] gower_1.0.1        xfun_0.41       globals_0.16.2
## [49] lme4_1.1-35.1     timechange_0.2.0  lifecycle_1.0.4
## [52] rstatix_0.7.2      future_1.33.1   zoo_1.8-12
## [55] MASS_7.3-60        ipred_0.9-14   vroom_1.6.5
## [58] ragg_1.2.7         hms_1.1.3      sandwich_3.1-0
## [61] parallel_4.2.2     yaml_2.3.8     curl_5.2.0
## [64] pandoc_0.6.5       sass_0.4.8     rpart_4.1.23
## [67] stringi_1.8.3     highr_0.10    bayestestR_0.13.1
## [70] boot_1.3-28.1     hardhat_1.3.0  lava_1.7.3
## [73] rlang_1.1.2        pkgconfig_2.0.3 systemfonts_1.0.5
## [76] evaluate_0.23      lattice_0.22-5 recipes_1.0.9
## [79] labeling_0.4.3     bit_4.0.5      tidyselect_1.2.0
## [82] parallelly_1.36.0  magrittr_2.0.3 bookdown_0.37
## [85] R6_2.5.1           generics_0.1.3  multcomp_1.4-25
## [88] mgcv_1.9-1         pillar_1.9.0   withr_2.5.2
## [91] survival_3.5-7    abind_1.4-5   nnet_7.3-19
## [94] future.apply_1.11.1 performance_0.10.8 modelr_0.1.11
## [97] crayon_1.5.2       car_3.1-2     utf8_1.2.4
## [100] tzdb_0.4.0         rmarkdown_2.25  grid_4.2.2
## [103] data.table_1.14.10 digest_0.6.33  xtable_1.8-4
## [106] textshaping_0.3.7  munsell_0.5.0  bslib_0.6.1

```

8.4 Operators

8.4.1 Assignment:

- `<-` (assignment operator)

8.4.2 Arithmetic:

- `+` (addition)
- `-` (subtraction)
- `*` (multiplication)
- `/` (division)
- `^` or `**` (exponentiation)
- `%%` (modulo, remainder)
- `%%/%` (integer division)

8.4.3 Relational:

- < (less than)
- > (greater than)
- <= (less than or equal to)
- >= (greater than or equal to)
- == (equal to)
- != or <> (not equal to)

8.4.4 Logical:

- & (element-wise AND)
- | (element-wise OR)
- ! (logical NOT)
- && (scalar AND)
- || (scalar OR)

8.4.5 Others:

- %*% (matrix multiplication)
- %in% (checks if an element is in a vector)
- %>% or |> (pipe operator from the magrittr package)
- []: Extract content from vectors, lists, or data frames.
- [[]] and \$: Extract a single item from an object.

8.5 Popular functions

8.5.1 Help

- ?: Search R documentation for a specific term.
- ?? Search R help files for a word or phrase.
- RSiteSearch: Search search.r-project.org
- findFn: Search search.r-project.org for functions (Hint: requires the “sos” library loaded!)
- help.start: Access to html manuals and documentations implemented in R
- apropos: Returns a character vector giving the names of objects in the search list matching (as a regular expression) what.
- find: Returns where objects of a given name can be found.
- vignette: View a specified package vignette, i.e., supporting material such as introductions.

8.5.2 Package management

- `install.packages`: Installs packages from CRAN.
- `pacman::p_load`: Installs and loads specified R packages.
- `library`: (Install and) loads specified R packages.

8.5.3 General

- `setwd`: Sets the working directory to the specified path.
- `rm`: Removes objects (variables) from the workspace.
- `sessionInfo`: Information about the R environment.
- `source`: Executes R code from a file.

8.5.4 Tools

- `else`: Execute a block of code if the preceding condition is false.
- `else if`: Specify a new condition to test if the first condition is false.
- `if`: Execute a block of code if a specified condition is true.
- `ifelse`: Check a condition for every element of a vector.

8.5.5 Data import

- `c`: Combine values into a vector or list.
- `read.csv`: Reads a CSV file into a data frame.
- `read_dta`: Read Stata dataset.
- `load`: Loads an RData file.

8.5.6 Inspect data

- `dim`: Returns the dimensions (number of rows and columns) of a data frame.
- `glimpse`: Provide a concise summary.
- `head`: Returns the first elements.
- `length`: Returns the number of elements in an object.
- `print`: Prints the specified object.
- `names`: Returns the variable names in a data frame.
- `n()` or `nrow()`: Counts the number of observations in a data frame or group of observations.
- `ncol`: Returns the number of columns in a data frame.
- `summary`: Summary statistics.
- `table`: Create a table of counts or cross-tabulation.
- `tail`: Returns the first n elements.

- **unique**: Extracts unique elements from a vector.
- **view**: Opens a viewer for data frames.

8.5.7 Graphics

- **abline**: Adds lines to a plot.
- **aes**: Aesthetic mapping in ggplot.
- **facet_wrap**: Creates a grid of faceted plots.
- **geom_hline**: Adds horizontal lines to a ggplot.
- **geom_line**: Adds lines to a ggplot.
- **geom_point**: Adds points to a ggplot.
- **geom_smooth**: Adds a smoothed line to a ggplot.
- **geom_text**: Adds text to a ggplot.
- **geom_vline**: Adds vertical lines to a ggplot.
- **ggsave**: Saves a ggplot to a file.
- **labs**: Adds or modifies plot labels.
- **plot**: Creates a scatter plot.
- **scale_y_reverse**: Reverses the y-axis in a ggplot.
- **stat_smooth**: Adds a smoothed line to a ggplot.
- **theme_classic**: Applies a classic theme to a ggplot.
- **theme_minimal**: Applies a minimal theme to a ggplot.

8.5.8 Data management

- **arrange**: Reorder the rows of a data frame.
- **clean_names**: Cleans names of an object (usually a data.frame).
- **complete**: Completes a data frame with all combinations of specified columns.
- **data.frame**: Creates a data frame.
- **distinct**: Removes duplicate rows from a data frame.
- **identical**: Check if two objects are identical.
- **is(na)**: Identify and flag a missing or undefined value (NA).
- **is_tibble**: Check if an object is a tibble.
- **rm**: Removes objects (variables) from the workspace.
- **relocate**: Reorders columns in a data frame.
- **round**: Rounds a numeric vector to the nearest integer.
- **rownames**: Get or set the row names of a matrix-like object.
- **tibble**: Creates a tibble, a modern and tidy data frame.

8.5.9 dplyr functions

- **arrange**: Reorder the rows of a data frame.

- `complete`: Completes a data frame with all combinations of specified columns.
- `ends_with`: matches to a specified suffix
- `filter`: Pick observations by their values.
- `first`: Returns the first element.
- `group_by`: Group data by one or more variables.
- `last`: Returns the last element.
- `mutate`: Add new variables or modify existing variables in a data frame.
- `nth`: Returns the nth element.
- `n_distinct`: Returns the number of distinct elements.
- `rename`: Rename variables in a data frame.
- `rename_all`: Renames all variables in a data frame.
- `row_number`: Adds a column with row numbers.
- `rowwise`: Perform operations row by row.
- `select`: Pick variables by their names.
- `select_all`: Selects all columns in a data frame.
- `slice_head`: Selects the top N rows from each group.
- `starts_with`: Select variables whose names start with a certain string.
- `summarise`: Reduce data to a single summary value.

8.5.10 Data analysis

- `aggregate`: Apply a function to the data by levels of one or more factors.
- `anti_join`: Return rows from the first data frame that do not have a match in the second data frame.
- `cor`: Computes correlation coefficients.
- `cov`: Computes covariance.
- `diff`: Calculates differences between consecutive elements.
- `get_dupes`: Identify duplicate rows in a data frame (from the janitor package).
- `paste0`: Concatenate vectors after converting to character.
- `predict`: Predict method for model fits.
- `prop.table`: Create a table of proportions.

8.5.11 Statistical functions

- `cor()`: Computes correlation coefficients.
- `cov()`: Computes the covariance.
- `exp()`: Exponential function.
- `IQR()`: Computes the interquartile range.
- `kurtosis()`: Computes the kurtosis.
- `log()`: Natural logarithm.
- `mad()`: Computes the mean absolute deviation.

- `max()`: Returns the maximum value.
- `mean()`: Calculates the mean.
- `median()`: Computes the median.
- `min()`: Returns the minimum value.
- `quantile()`: Computes sample quantiles.
- `sd()`: Calculates the standard deviation.
- `skewness()`: Calculates the skewness.
- `var()`: Calculates the variance.

8.6 Links to solutions

1. [exe_duplicates.R](#)
2. [exe_import_covid.R](#)
3. [exe_genanddrop.R](#)
4. [exe_base_pipe.R](#)
5. [exe_subset.R](#)
6. [data_transformation.R](#)
7. [exe_poser.R](#)
8. [datasaurus_solution.html](#)
9. [convergence.R](#)
10. [un_gdp_ger_fra.R](#)
11. [hortacsu_figure_3.R](#)
12. [regress_lecture.R](#)
13. [exe_calories.R](#)
14. [bundesliga.R](#)
15. [exe_okun_solution.R](https://raw.githubusercontent.com/hubchev/courses/main/scr/exe_ok# Script: exe_duplicates.R (not in the lecture notes)

References

- John M. Chambers. *Extending R*. CRC Press, 2017.
- Thomas H Davenport and DJ Patil. Data scientist: The sexiest job of the 21st century. *Harvard Business Review*, 90(5):70–76, 2012.
- Wickham Hadley. Tidy data. *Journal of Statistical Software*, 59(10):1–23, 2014.
- Ali Hortaçsu and Chad Syverson. The ongoing evolution of US retail: A format tug-of-war. *Journal of Economic Perspectives*, 29(4):89–112, 2015.
- Rafael A. Irizarry. *Introduction to Data Science: Data Analysis and Prediction Algorithms With R*. CRC Press, 2022. URL <https://rafalab.github.io/dsbook/>.
- Chester Ismay and Albert Y. Kim. *Statistical inference via data science: A ModernDive into R and the tidyverse*. CRC Press, 2022. URL <https://moderndive.com/>.
- John D Kelleher and Brendan Tierney. *Data Science*. MIT Press, 2018.
- Oliver Kirchkamp. Using graphs and visualising data. Technical report, 2018. <https://www.kirchkamp.de/oekonometrie/pdf/gra-p.pdf> (retrieved on 2022/05/20).
- John Muschelli and Andrew Jaffe. Introduction to R for public health researchers. Technical report, GitHub, 2022. https://github.com/muschellij2/intro_to_r.
- Danielle Navarro. *Learning Statistics With R*. Version 0.6 edition, 2020. URL <https://learningstatisticswithr.com>.
- Hansjörg Neth. *ds4psy: Data Science for Psychologists*. Social Psychology and Decision Sciences, University of Konstanz, Konstanz, Germany, 2023. URL <https://CRAN.R-project.org/package=ds4psy>. R package (version 0.9.0, October 20, 2022); Textbook at <<https://bookdown.org/hneth/ds4psy/>>.
- Måns Thulin. *Modern Statistics With R: From Wrangling and Exploring Data to Inference and Predictive Modelling*. Eos Chasma Press, 2021. URL <https://www.modernstatisticswithr.com/>.
- Tiffany Timbers, Trevor Campbell, and Melissa Lee. *Data Science: A First Introduction*. CRC Press, 2022. URL <https://datasciencebook.ca/>.
- Edward R. Tufte. *The Visual Display of Quantitative Information*. Graphics Press,

- 2 edition, 2022.
- William N. Venables, David M. Smith, and R Core Team. *An Introduction to R: Notes on R: A Programming Environment for Data Analysis and Graphics*. Version 4.3.2 (2023-10-31) edition, 2022. URL <http://cran.r-project.org/doc/manuals/R-intro.pdf>. <http://cran.r-project.org/doc/manuals/R-intro.pdf> (retrieved on 2022/04/06).
- Hadley Wickham and Garrett Grolemund. R for data science (2e). Accessed November 30, 2023, 2023. URL <https://r4ds.hadley.nz/>.
- Jeffrey M. Wooldridge. *Introductory Econometrics: A Modern Approach*. South-Western, 2nd edition, 2002.
- Yihui Xie, Joseph J. Allaire, and Garrett Grolemund. *R Markdown: The Definitive Guide*. Chapman and Hall/CRC, 2018.
- Yihui Xie, Christophe Dervieux, and Emily Riederer. *R Markdown Cookbook*. Chapman and Hall/CRC, 2020. available at <https://bookdown.org/yihui/rmarkdown-cookbook>.