

How to Use R for Data Science

Lecture Notes (currently under revision)

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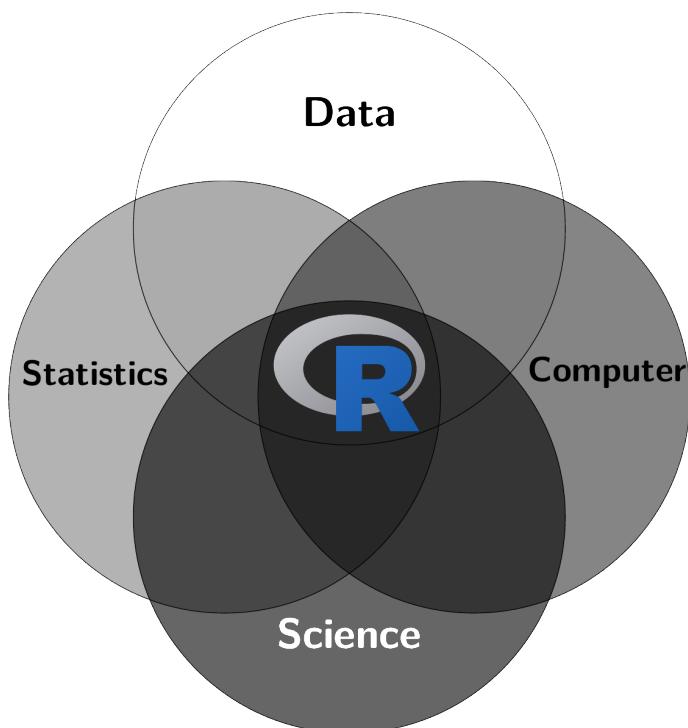
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Preface



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

 A PDF version of these notes is available [here](#).. Please note that while the PDF contains the same content, it has not been optimized for PDF format. Therefore, some parts may not appear as intended.

- These notes aims to support my lecture at the HS Fresenius but are incomplete and no substitute for taking actively part in class.
- I hope you find this book helpful. Any feedback is both welcome and appreciated.
- 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 \[2023\]](#).
- These notes are published under the [Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License](#). This means it can be reused, remixed, retained, revised and redistributed as long as appropriate credit is given to the authors. If you remix, or modify the original version of this open textbook, you must redistribute all versions of this open textbook under the same license. This script draws from the work of [Navarro \[2020\]](#), [Muschelli and Jaffe \[2022\]](#), [Thulin \[2021\]](#), and [Ismay and Kim \[2022\]](#)



which is also published under the same license.

- I host the notes in a [GitHub repo](#).

Structure of these notes

Chapter	Explanations
Getting started with R	Learn the basics everyone should know about R and RStudio, including how to install them.
Kickstart	A quick start guide for beginners on how to dive into R, showcasing some of its capabilities.
Pitfalls	Discover common mistakes beginners often make and how to avoid them to save time on troubleshooting.
An interactive introduction using Swirl	A hands-on tutorial on how to use the swirl package. This section is optional.
Working with R scripts	Learn how to use R scripts and their benefits.
Managing data	Learn how to manipulate data in R.
Visualizing data	A quick guide on where to find resources to learn about creating graphical visualizations in R.
Collection of exercises	A set of exercises to practice R programming skills.
Appendix	A set of useful stuff that will help you to navigate through your file system, find the reight operator and function, or to learn some usefull shortcuts.

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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 was always fascinated by data and statistics. For example, in 1992 I could name all soccer players in Germany's first division including how many goals they scored. Later, in 2003 I joined the introductory statistics course of [Daniel Rösch](#). I learned among others that probabilities often play a role when analyzing data. I continued my data science journey with [Harry Haupt's Introductory Econometrics](#) course, where I studied the infamous Jeffrey M. [Wooldridge \[2002\]](#) textbook. It got me hooked and so 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.

Preface

The term “data scientist” has become remarkably popular, and many people are eager to adopt this title. Although I am a professor of *data science*, my professional identity is more like that of an applied, empirically-oriented international economist. My hesitation to adopt the title “data scientist” also stems from the deep respect I have developed through my interactions with econometricians and statisticians. Considering their in-depth expertise, I feel like a passionate amateur.

Ultimately, I poke around in data to find something interesting. Much like my ten-year-old younger self who analyzed soccer statistics to gain a deeper understanding of the sport. The only thing that has changed since then is that I know more promising methods and can efficiently use tools for data processing and data analysis.

1. Getting started with R

Learning Objectives

- Understand the reasons for choosing R as a programming language.
- Learn effective strategies and resources for mastering R programming.
- Learn the basic principles of R.
- Distinguish between R and RStudio.
- Demonstrate how to write and execute code in R and RStudio.
- Learn how to install R, RStudio, and R packages.
- Explore options to use R and RStudio without installing them on your machine, such as through cloud-based platforms.

Content

1. Why R?
2. How to learn R?
3. Learning resources
4. What is a function in R?
5. What are objects in R?
6. What are R and RStudio?
7. How to install R and RStudio
8. How to write and run code in R and RStudio
9. What are R packages?
10. Base R and the tidyverse universe

1.1. Why R?

R is an open-source programming language that allows to analyse and manipulate data, create state-of-the-art graphics, and many more. It supports larger data sets, reads any type of data, and runs on multiple platforms (Windows, Mac, Linux) and CPU architectures (x86_64, arm64). 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:
 - [The R Graph Gallery](#)
 - [R CHARTS by R CODER](#)
- **R is an employment insurance!** Programming is a core skill in research, economics, and business. If you can write code, you have plenty of opportunities to earn a decent salary. 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. Even if you need to learn a new programming language later, knowing R makes it much easier to pick up another one.

- **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 are an extension to your brain and can do repetitive tasks better and faster without making logical errors. The only reason to do statistical calculations with pencil and paper is for learning purposes.
- **Low-code and no-code applications such as Excel are limited!** Using spreadsheets software like Microsoft Excel for research can be problematic. It's easy to lose track of operations, making the process difficult to oversee and document. Command-line programs are maybe not as easy to learn but offer a more straightforward approach that allows the results to be replicated easily.
- **R is open source!** Proprietary software is expensive, support can only be provided by the copyright owner which means the software expires and you can't do anything against it. Moreover, security issues cannot be checked as the source code is not available, and possibilities for customization are limited. R is yours and everybody can contribute to its success.
- **R is big!** When you download and install R, you get some basic packages, that contain functions that allow you to do already a lot of things. Beyond that, you can write your own packages or install user-written packages that extend your possibilities. With over 20,684 packages on the CRAN repository and many more available on GitHub and other platforms, R's extensive library supports a wide variety of data science tasks. Its widespread use and open-source availability have cemented R as a standard tool in data science and ensured that there are multiple approaches to most data handling processes. These can be easily adopted.



R has weaknesses

For newcomers to programming, the learning curve is rather flat at the beginning. One reason is that R tools are spread across many packages, which can overwhelm beginners. There is no centralized support and the helpful and active online community have different backgrounds. It can be difficult for beginners to find the right solution as there are often many different ways to tackle the same problem. Moreover, R can be slower than languages like Python, MATLAB, C/C++ or Java.

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 [Section 1.3](#) a list of other resources that are worth considering. To start with, I recommend my swirl courses that provide an interactive learning environment, see [Chapter 4](#).



Make your hands dirty!

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. To have a guide next to you can help and speed up your progress significantly. The key is taking action and getting involved. I mean, do

1. Getting started with R

write code. Try to copy the code that you read here and elsewhere. Explore what the code does on your machine. 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.

Figure 1.1.: Play around with code
How to actually learn any new programming concept



O RLY?

@ThePracticalDev

Source: [DEV Community on GitHub](#)

Here are some comments that may help you to learn efficiently:

- **Computers need clear and precise instructions to work:** They can't handle mistakes or unclear directions. They are actually sort of stupid as they do not have an intuition. They just take you literally. Even small errors like a missing comma or an unclosed bracket can cause your code to not work. Computers do exactly what you tell them, no more and no less.

i Computers take you literally

Let me illustrate what I mean: Suppose you send your grandfather the following message:

“Let's eat grandpa.”

He will probably understand that you're inviting him to dinner. However, if you sent the same message to a computer, it would interpret the sentence literally due to the missing comma:

“Let's eat, grandpa.”

The comma makes all the difference in clarifying that you're speaking to your grandpa, not about eating him! Similarly, in programming, an incorrectly placed comma can break your code or change the meaning of your code.

- **Copy, paste, and tweak:** 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. While this is not the only way to learn code, it gets a job done quick, and it is fun, see Figure 1.1.
- **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.
- **Use ChatGPT:** The usage of supporting tools is not forbidden. ChatGPT can help you to understand code and brainstorm solutions. However, it’s important to know that ChatGPT might suggest complex methods when there are shorter and more elegant solutions available. Absolute beginners might find ChatGPT’s solutions overwhelming and have difficulties to tweak the proposed sketch of a solution. So, use it thoughtfully.

1.3. Learning resources

Thousands of freely available books and resources exist. [bookdown.org](#) and the [Big Book of R](#) are two vast collections of links to R books that might verify my claim.

In RStudio you find in the right side 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](#). At the top right of RStudio you find a panel called *tutorial*. Here you can install the `learnr` package that offers some nice interactive tutorials.

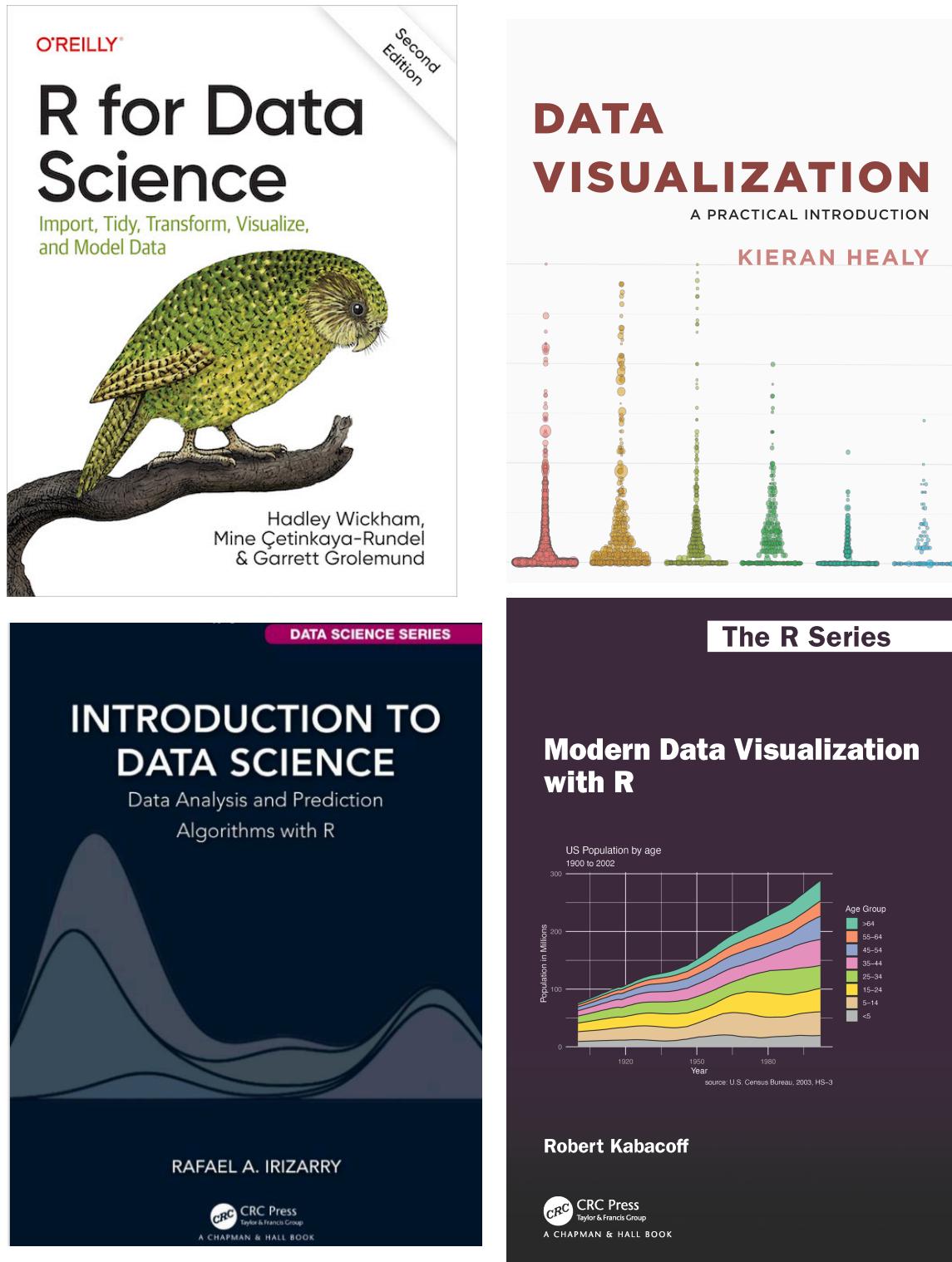
Since you may feel overwhelmed by the number of resources, I would like to highlight some books:

1. [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.
2. [Healy \[2018\]: Data Visualization: A Practical Introduction](#) is a hands-on introduction to the principles and practice of looking at and presenting data using R and `ggplot`.
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 et al. \[2022\] 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.
6. [Kabacoff \[2024\]: Modern Data Visualization with R](#) teaches how to create graphs from scratch providing a lot of examples that you can copy, paste and tweak.

Some other sources that are worth mentioning are these:

1. Getting started with R

Figure 1.2.: A collection of textbooks



1. Getting started with R

- 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 is a function in R?

R is a *functional programming language*. If you want R to do something, you need to use a function. Or, in the words of Chambers [2017, p. 4]:

“Everything that happens is a function call.”

For example, when you like to exit R, you do it with the function `q()`:

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

If you want to specify what exactly you want R to do for you, you need to refer to the arguments of a function. For example, if you don't want to be asked interactively what you want to do with your workspace (this is the place where you store all your objects, see section [Section 1.5](#)), you can do this with an argument that is part of the `q()` function:

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

To learn more about a function, you can access its documentation by typing a question mark followed by the function name into the Console:

```
?q()
```

Unfortunately, the documentation can sometimes be a bit confusing for beginners in applied contexts. However, the documentation for all functions is structured similarly, typically featuring several key sections:

- **Description:** A brief overview of what the function does.
- **Usage:** How to use the function, including the function name and its arguments.
- **Arguments:** Detailed descriptions of each argument the function accepts, including what types of values are expected.
- **Details:** Additional details about the function's behavior and any important notes.
- **Examples:** Practical examples demonstrating how to use the function in various contexts.

Understanding these sections can significantly enhance your ability to navigate and utilize R.

An excerpt of the *R Documentation* for the function `q()` is shown in Figure 1.3. Here, we observe that the function has three arguments that you can manipulate. If you do not specify any of these arguments explicitly, we see that *by default*, R sets the three arguments as shown.

1. Getting started with R

Figure 1.3.: The R Documentation of `q()`

The screenshot shows the R documentation interface. At the top, there is a menu bar with tabs: Files, Plots, Packages, Help, Viewer, and Presentation. Below the menu bar, there is a toolbar with icons for back, forward, search, and help. A dropdown menu says "R: Terminate an R Session" and a "Find in Topic" input field. The main content area has a title "quit {base}" and a subtitle "R Documentation". The page content includes sections for "Description", "Usage", "Arguments", "Details", and "Value". The "Usage" section contains the code: `quit(save = "default", status = 0, runLast = TRUE)` and `q(save = "default", status = 0, runLast = TRUE)`. The "Arguments" section describes `save` (a character string indicating whether the environment (workspace) should be saved, one of "no", "yes", "ask" or "default"), `status` (the (numerical) error status to be returned to the operating system, where relevant. Conventionally 0 indicates successful completion), and `runLast` (should `.Last()` be executed?). The "Details" section states that `save` must be one of "no", "yes", "ask" or "default". In the first case the workspace is not saved, in the second it is saved and in the third the user is prompted and can also decide *not* to quit. The default is to ask in interactive use but may be overridden by command-line arguments (which must be supplied in non-interactive use).

1.5. What are objects in R?

R is an object oriented programming language. That means,

“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 a variety of data types, including vectors, matrices, data frames, lists, functions. Moreover, you can store empirical results, tables, figures and many more in form of so-called objects. 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.

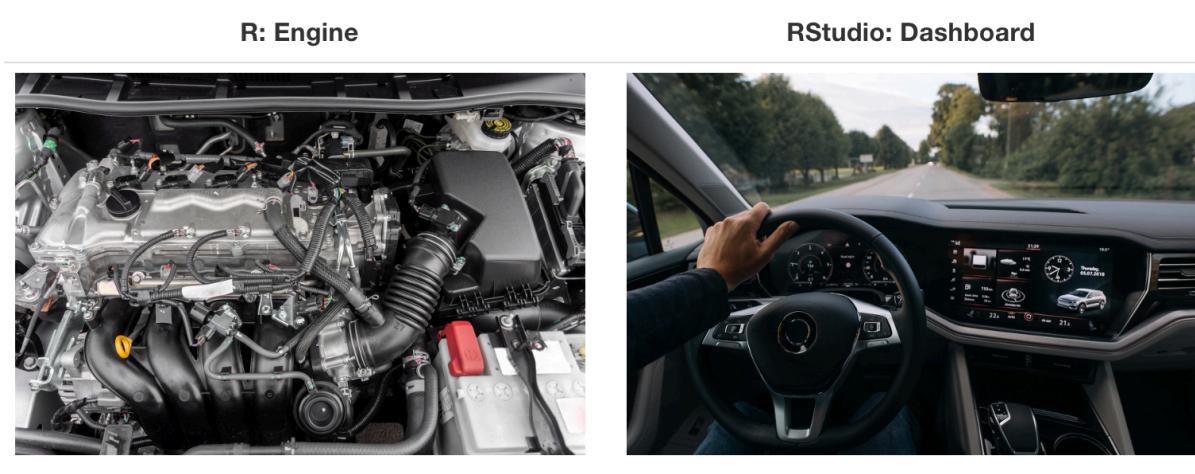
1.6. What are R and RStudio?

While R has a command line interface, there are multiple third-party graphical user interfaces available that improve the user experience a lot. The most successful graphical user interface or integrated development environment (IDE) is 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 Figure 1.4.

More precisely, R is a functional 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

1. Getting started with R

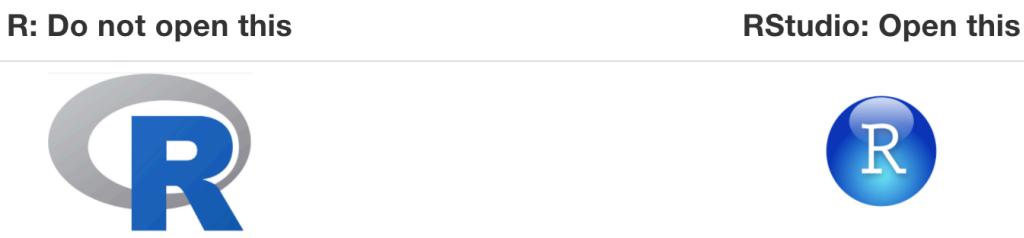
Figure 1.4.: Analogy of difference between R and RStudio



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 Figure 1.5 shows what icon you should be clicking on your computer.

Figure 1.5.: Icons of R versus RStudio on your computer



After you open RStudio, you should see something similar to Figure Figure 1.6 where three or four panels dividing the screen.

1. The *Environment* panel, where a list of all objects is shown.
2. The *Files*, *Plots* and *Help* panel, allow you to manage files, preview plots, and find help for different functions of R.
3. The *Console* panel, used for running code.
4. The *Script* panel, used for writing code.

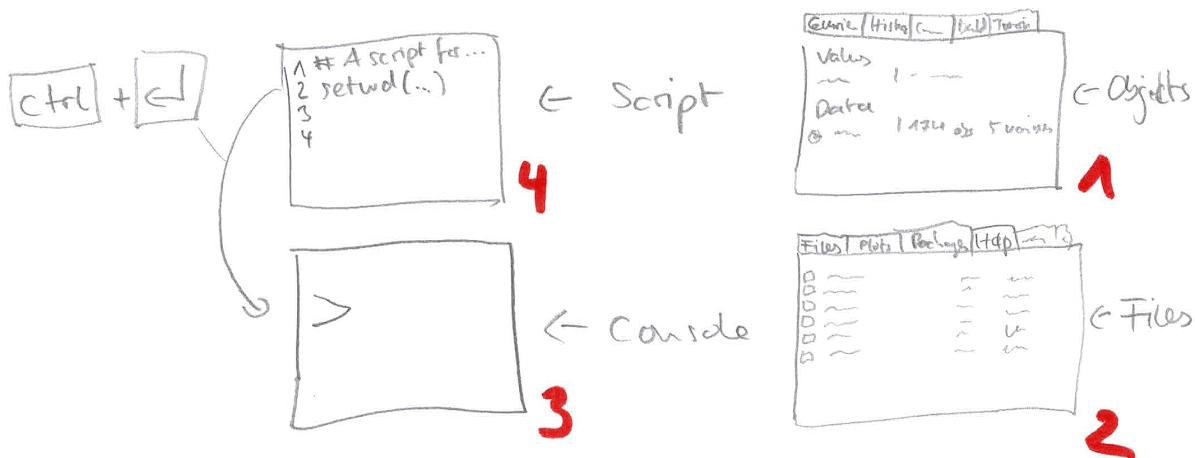
If you don’t have panel number 4,

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).

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:

1. Getting started with R

Figure 1.6.: A sketch of RStudio interface to R



```
R version 4.3.3 (2024-02-29) -- "Angel Food Cake"  
Copyright (C) 2024 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.
```

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.

1.7. How to write and run code in R and RStudio

In the Console you can type in code and push Enter to run the line of code. For example, you can calculate:

1+4

[1] 5

While working in the Console is possible, we usually work in RStudio using so-called *scripts*. These scripts are plain text files with the file extension “.R”. Scripts are discussed in detail in Chapter 5. To create a script, go to the *File* menu, select *New File* and then choose *R Script*.

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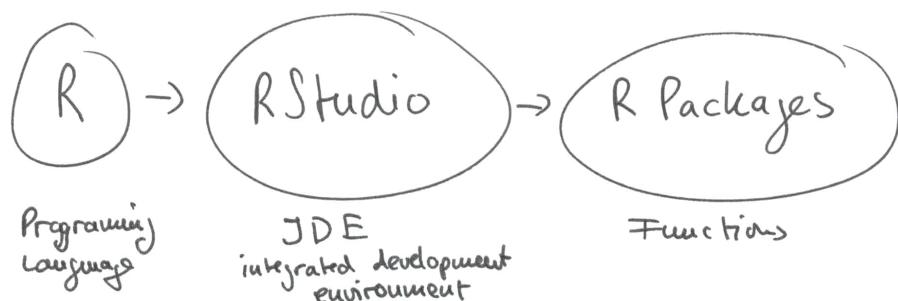
With the key shortcut **Ctrl+Enter** for Windows and Linux user or by **Cmd+Enter** for MacOs users (or by clicking **Run**) you can run a line of a script, that means you send one line of code to the Console. See Figure 1.7 how this looks like in RStudio.

Figure 1.7.: One plus four in a R script

The screenshot shows the RStudio interface. At the top is a menu bar with File, Edit, Code, View, Plots, Session, Build, Debug, Profile, Tools, Help. Below the menu is a toolbar with various icons. A script editor window titled "Untitled1*" is open, containing the code "1 1+4" on line 1 and "2" on line 2. Below the script editor is a status bar showing "2:1 (Top Level) R Script". At the bottom is a tab bar with "Console", "Terminal", "Markers", and "Background Jobs". The "Console" tab is active, showing the command "> 1+4" and its output "[1] 5".

1.8. How to install R, RStudio, and R packages

Figure 1.8.: Set up R in three steps



As shown in Figure 1.8, setting up R on your personal computer (Windows, Mac, Linux) is a three step process: You will first need to download and install R. After that has been successful you can download and install RStudio. Please note that it is important that you install R first and then install RStudio. As a third but optional step you can install R packages.

1. Do this firstly: Download and install R [here](#).

- 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 March 29, 2024 was R-4.3.3.
- 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 [here](#).

1. Getting started with R

- 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.
3. **Do this thirdly:** Install R packages. This step is optionally as you can install R packages at any time. However, it may be a good idea to install frequently used packages in one take because the installation of some packages can be time consuming. Therefore, I recommend to read Section 1.9 and follow the instructions therein.

💡 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 or if you want to run R on your tablet (IPad or Chromebook) or even your smartphone, 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 use RStudio online and navigate it through your web browser. It is free for individuals with some restrictions and limited capacities.

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 20,000 packages are available at the official repository (CRAN)¹ and many more are publicly available through the internet.

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.

ℹ️ Package management

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")
```

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>.

1. Getting started with R

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()`.

💡 How to speed up the installation of 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](#).

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 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(package:ggplot2, unload=TRUE)`.

1. Getting started with R

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. I highly recommend this function and in all my scripts I will use it.

For example, instead of the traditional approach:

```
install.packages(  
  c("arrow", "babynames", "curl", "duckdb", "gapminder", "ggrepel", "ggridges",  
    "ggthemes", "hexbin", "janitor", "Lahman", "leaflet", "learnr", "maps",  
    "nycflights13", "openxlsx", "palmerpenguins", "repurrrsive", "tidyverse",  
    "usethis", "WDI", "wbstats", "writexl")  
)  
library(  
  c("arrow", "babynames", "curl", "duckdb", "gapminder", "ggrepel", "ggridges",  
    "ggthemes", "hexbin", "janitor", "Lahman", "leaflet", "learnr", "maps",  
    "nycflights13", "openxlsx", "palmerpenguins", "repurrrsive", "tidyverse",  
    "usethis", "WDI", "wbstats", "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, tidyverse,  
  usethis, WDI, wbstats, 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 (see Section 6.5).

1.10. Base R and the tidyverse universe

Upon successfully installing R, you gain access to functions that are part of *Base R*. This includes standard packages automatically installed and loaded with each R session, such as `stats`, `utils`, and `graphics`, providing a broad spectrum of functionalities for statistical analysis and graphical capabilities [see [Venables et al., 2022](#)]. However, the syntax in *Base R* can become complex and less intuitive for users. Consequently, many individuals, including Hadley Wickham, the Chief Data Scientist at *Posit* (formerly RStudio), and his team, have developed an alternative suite of packages known as the `tidyverse`. These packages share a common philosophy and syntax, emphasizing readability and ease of use. We will heavily utilize the `tidyverse` in the following sections.

Figure 1.9.: The tidyverse universe



The R package `tidyverse` (see Figure 1.9) is a comprehensive collection of R packages including popular packages such as `ggplot2`, `dplyr`, `tidyr`, `readr`, `purrr`, `tibble`, `stringr`, and `forcats`, which together offer extensive capabilities for data modeling, transformation, and visualization.

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 [Workflow: basics](#)), [Data transformation](#), and [Data tidying](#). Additionally, explore www.tidyverse.org for more resources, and consider completing the *tidyverse* module in my `swirl` package, *swirl-it*, as detailed in section Chapter 4.

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

```
if (!require(pacman)) install.packages("pacman")
pacman::p_load(tidyverse)
```

Exercise 1.1. Set up R, RStudio, and R packages
Open [this interactive tutorial](#) and work through it.

2. Kickstart

Ever got a kick that actually moved you forward? Well, let's kickstart your R adventure by walking you through a typical data analysis workflow in R, covering everything from setting up your environment to performing data analysis and visualization. Along the way, we'll also tackle some common troubleshooting to smooth out any bumps in the road. Please don't worry if you don't understand some lines of code. You will learn that later on, however, you hopefully will get a sense of what it is like to work with a command line based program.

2.1. Analysing the association of weight and the price of cars

Before we start, we need to ensure that all necessary libraries are installed and loaded. We use the pacman package for convenient package management.

```
# Install and load required libraries
# Installs 'pacman' if not already available, which is used for package management
if (!require(pacman)) install.packages("pacman")

# Unload all previously loaded packages to start fresh
suppressMessages(pacman::p_unload(all))

# Load necessary packages for data manipulation, cleaning, and visualization
pacman::p_load(
  tidyverse, # A suite of packages designed for data science that includes tools for data ma
  haven,    # Used for importing and exporting data with SPSS, Stata, and SAS formats.
  janitor,  # Provides functions for examining and cleaning data, such as `clean_names()` `a
  WDI,      # Facilitates downloading data from the World Bank's World Development Indicate
  wbstats   # Provides an interface to the World Bank's APIs for a comprehensive range of d
)

# Set the working directory to a project-specific folder
setwd("~/Dropbox/hsf/courses/dsr")

# Clear the current environment of any objects
rm(list = ls())
```

Now, let us load the dataset from a Stata file (`auto.dta`) and explore its basic properties.

```
# Load data from a Stata file available online
auto <- read_dta("http://www.stata-press.com/data/r8/auto.dta")
# 'auto': Dataset contains information about different car models

# Display basic information about the dataset
ncol(auto) # Number of columns
```

2. Kickstart

```
[1] 12
```

```
nrow(auto) # Number of rows
```

```
[1] 74
```

```
dim(auto) # Dimensions of the dataset
```

```
[1] 74 12
```

```
names(auto) # Names of variables
```

```
[1] "make"          "price"         "mpg"           "rep78"          "headroom"  
[6] "trunk"         "weight"        "length"        "turn"           "displacement"  
[11] "gear_ratio"    "foreign"
```

```
head(auto) # First few rows
```

```
# A tibble: 6 x 12  
  make      price   mpg rep78 headroom trunk weight length turn displacement  
  <chr>     <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>  
1 AMC Concord  4099    22     3    2.5    11  2930    186    40     121  
2 AMC Pacer    4749    17     3     3    11  3350    173    40     258  
3 AMC Spirit   3799    22    NA     3    12  2640    168    35     121  
4 Buick Centur~ 4816    20     3    4.5    16  3250    196    40     196  
5 Buick Electr~ 7827    15     4     4    20  4080    222    43     350  
6 Buick LeSab~  5788    18     3     4    21  3670    218    43     231  
# i 2 more variables: gear_ratio <dbl>, foreign <dbl+lbl>
```

```
tail(auto) # Last few rows
```

```
# A tibble: 6 x 12  
  make      price   mpg rep78 headroom trunk weight length turn displacement  
  <chr>     <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>  
1 Toyota Coro~  5719    18     5     2    11  2670    175    36     134  
2 VW Dasher    7140    23     4    2.5    12  2160    172    36      97  
3 VW Diesel    5397    41     5     3    15  2040    155    35      90  
4 VW Rabbit    4697    25     4     3    15  1930    155    35      89  
5 VW Scirocco  6850    25     4     2    16  1990    156    36      97  
6 Volvo 260    11995   17     5    2.5    14  3170    193    37     163  
# i 2 more variables: gear_ratio <dbl>, foreign <dbl+lbl>
```

```
summary(auto) # Summary statistics for each column
```

2. Kickstart

```

      make          price         mpg        rep78
Length:74      Min.   : 3291   Min.   :12.00   Min.   :1.000
Class :character  1st Qu.: 4220   1st Qu.:18.00   1st Qu.:3.000
Mode  :character  Median : 5006   Median :20.00   Median :3.000
                  Mean    : 6165   Mean    :21.30   Mean    :3.406
                  3rd Qu.: 6332   3rd Qu.:24.75   3rd Qu.:4.000
                  Max.    :15906   Max.    :41.00   Max.    :5.000
                               NA's    :5

      headroom       trunk        weight       length      turn
Min.   :1.500   Min.   : 5.00   Min.   :1760   Min.   :142.0   Min.   :31.00
1st Qu.:2.500  1st Qu.:10.25  1st Qu.:2250  1st Qu.:170.0  1st Qu.:36.00
Median :3.000  Median :14.00  Median :3190  Median :192.5  Median :40.00
Mean   :2.993  Mean   :13.76  Mean   :3019  Mean   :187.9  Mean   :39.65
3rd Qu.:3.500  3rd Qu.:16.75  3rd Qu.:3600  3rd Qu.:203.8  3rd Qu.:43.00
Max.   :5.000  Max.   :23.00  Max.   :4840  Max.   :233.0  Max.   :51.00

      displacement   gear_ratio     foreign
Min.   : 79.0   Min.   :2.190   Min.   :0.0000
1st Qu.:119.0  1st Qu.:2.730  1st Qu.:0.0000
Median :196.0   Median :2.955  Median :0.0000
Mean   :197.3   Mean   :3.015  Mean   :0.2973
3rd Qu.:245.2  3rd Qu.:3.353  3rd Qu.:1.0000
Max.   :425.0   Max.   :3.890  Max.   :1.0000

```

```
glimpse(auto) # Compact display of the structure of the dataset
```

```

Rows: 74
Columns: 12
$ make           <chr> "AMC Concord", "AMC Pacer", "AMC Spirit", "Buick Century"~
$ price          <dbl> 4099, 4749, 3799, 4816, 7827, 5788, 4453, 5189, 10372, 40~
$ mpg            <dbl> 22, 17, 22, 20, 15, 18, 26, 20, 16, 19, 14, 14, 21, 29, 1~
$ rep78          <dbl> 3, 3, NA, 3, 4, 3, NA, 3, 3, 3, 3, 2, 3, 3, 4, 3, 2, 2, 3~
$ headroom        <dbl> 2.5, 3.0, 3.0, 4.5, 4.0, 4.0, 3.0, 2.0, 3.5, 3.5, 4.0, 3.~
$ trunk           <dbl> 11, 11, 12, 16, 20, 21, 10, 16, 17, 13, 20, 16, 13, 9, 20~
$ weight          <dbl> 2930, 3350, 2640, 3250, 4080, 3670, 2230, 3280, 3880, 340~
$ length          <dbl> 186, 173, 168, 196, 222, 218, 170, 200, 207, 200, 221, 20~
$ turn             <dbl> 40, 40, 35, 40, 43, 43, 34, 42, 43, 42, 44, 43, 45, 34, 4~
$ displacement    <dbl> 121, 258, 121, 196, 350, 231, 304, 196, 231, 231, 425, 35~
$ gear_ratio      <dbl> 3.58, 2.53, 3.08, 2.93, 2.41, 2.73, 2.87, 2.93, 2.93, 3.0~
$ foreign         <dbl+lbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~

```

```
print(auto, n = Inf) # Print all rows of the dataset
```

```

# A tibble: 74 x 12
  make      price   mpg rep78 headroom trunk weight length turn displacement
  <chr>     <dbl> <dbl> <dbl>    <dbl> <dbl> <dbl> <dbl> <dbl>    <dbl>
1 AMC Concord 4099    22     3     2.5     11    2930    186     40      121
2 AMC Pacer   4749    17     3     3      11    3350    173     40      258
3 AMC Spirit   3799    22    NA     3      12    2640    168     35      121

```


2. Kickstart

```

55 BMW 320i    9735    25     4     2.5    12   2650    177    34    121
56 Datsun 200   6229    23     4     1.5     6   2370    170    35    119
57 Datsun 210   4589    35     5     2      8   2020    165    32     85
58 Datsun 510   5079    24     4     2.5     8   2280    170    34    119
59 Datsun 810   8129    21     4     2.5     8   2750    184    38    146
60 Fiat Strada  4296    21     3     2.5    16   2130    161    36    105
61 Honda Acco~  5799    25     5     3      10   2240    172    36    107
62 Honda Civic   4499    28     4     2.5     5   1760    149    34     91
63 Mazda GLC    3995    30     4     3.5    11   1980    154    33     86
64 Peugeot 604   12990   14     NA    3.5    14   3420    192    38    163
65 Renault Le~   3895    26     3     3      10   1830    142    34     79
66 Subaru        3798    35     5     2.5    11   2050    164    36     97
67 Toyota Cel~   5899    18     5     2.5    14   2410    174    36    134
68 Toyota Cor~   3748    31     5     3      9    2200    165    35     97
69 Toyota Cor~   5719    18     5     2      11   2670    175    36    134
70 VW Dasher    7140    23     4     2.5    12   2160    172    36     97
71 VW Diesel    5397    41     5     3      15   2040    155    35     90
72 VW Rabbit    4697    25     4     3      15   1930    155    35     89
73 VW Scirocco  6850    25     4     2      16   1990    156    36     97
74 Volvo 260    11995   17     5     2.5    14   3170    193    37    163
# i 2 more variables: gear_ratio <dbl>, foreign <dbl+lbl>

```

The data seems to be a cross-section of cars. Let us check if the variable `make` identifies each line uniquely:

```

# Check for duplicate entries based on the 'make' variable
auto |>
  get_dupes(make)

```

No duplicate combinations found of: make

```

# A tibble: 0 x 13
# i 13 variables: make <chr>, dupe_count <int>, price <dbl>, mpg <dbl>,
#   rep78 <dbl>, headroom <dbl>, trunk <dbl>, weight <dbl>, length <dbl>,
#   turn <dbl>, displacement <dbl>, gear_ratio <dbl>, foreign <dbl+lbl>

```

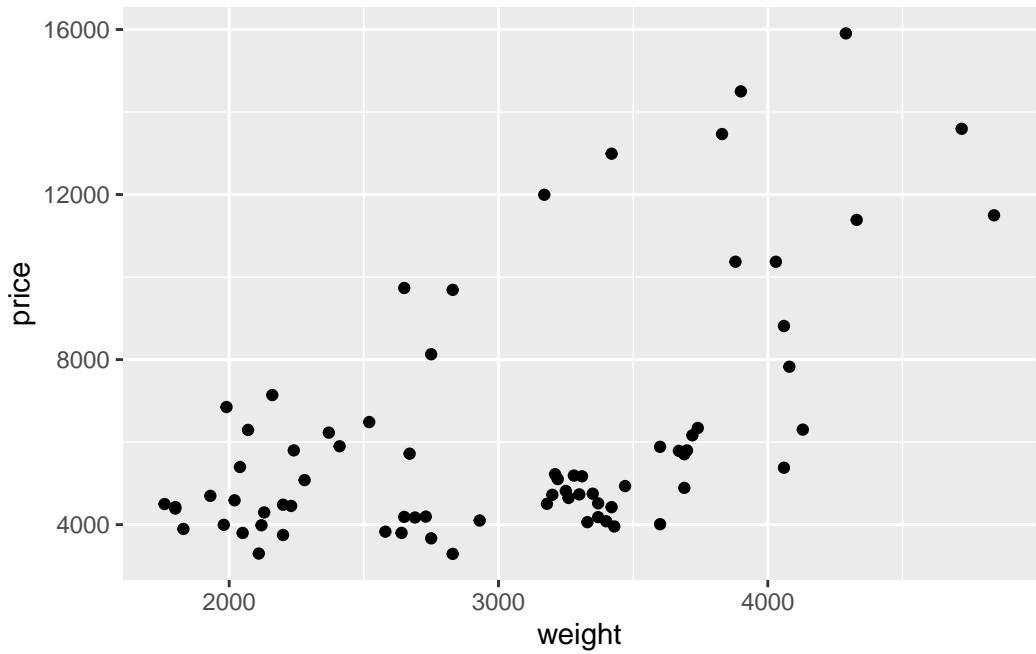
Indeed, the variable `make` has no duplicates. Now, let's make and save some graphical visualizations:

```

# Create and display a scatter plot of car price versus weight
plot_weight_price <- ggplot(auto, aes(x = weight, y = price)) +
  geom_point()
plot_weight_price

```

2. Kickstart

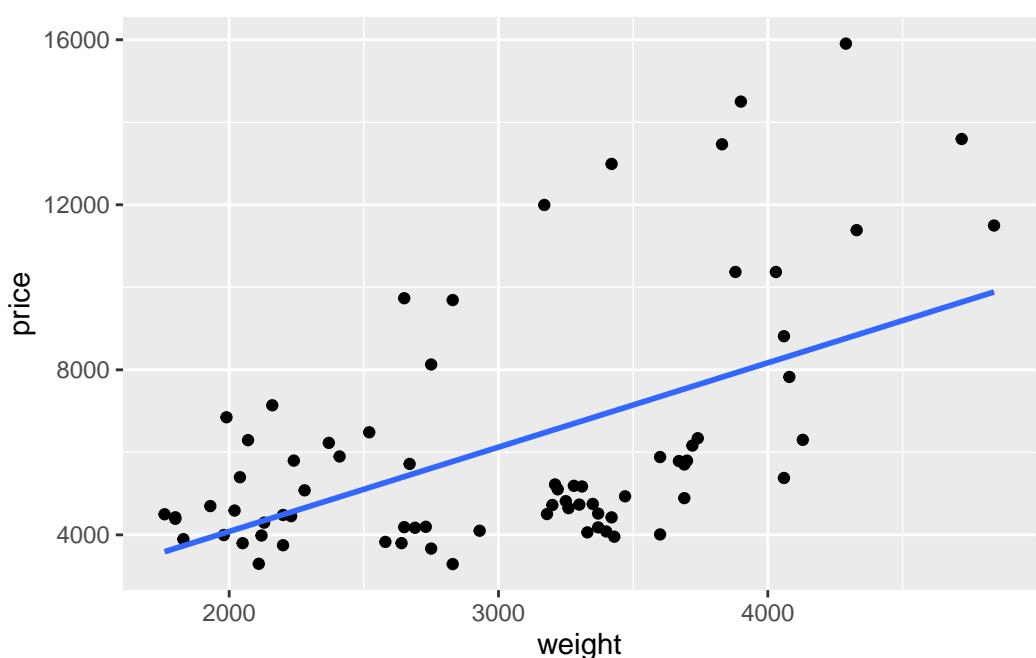


```
# Save the plot to a file
ggsave("fig/plot_weight_price.png", plot = plot_weight_price, dpi = 300)
```

Saving 5.5 x 3.5 in image

```
# Create a scatter plot with a linear regression line of price vs weight
plot_weight_price_fit <- ggplot(auto, aes(x = weight, y = price)) +
  geom_point() +
  geom_smooth(method = lm, se = FALSE) # 'lm' denotes linear model, 'se' is standard error
plot_weight_price_fit
```

`geom_smooth()` using formula = 'y ~ x'



2. Kickstart

```
# Save the plot to a file
ggsave("fig/plot_weight_price_fit.png", plot = plot_weight_price_fit, dpi = 300)
```

```
Saving 5.5 x 3.5 in image
`geom_smooth()` using formula = 'y ~ x'
```

Let us perform a linear regression to quantify the impact of `weight` on `price`:

```
# Perform a linear regression to analyze the relationship between weight and price
reg_result <- lm(price ~ weight , data = auto)
summary(reg_result) # Display the regression results
```

Call:

```
lm(formula = price ~ weight, data = auto)
```

Residuals:

Min	1Q	Median	3Q	Max
-3341.9	-1828.3	-624.1	1232.1	7143.7

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-6.7074	1174.4296	-0.006	0.995
weight	2.0441	0.3768	5.424	7.42e-07 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2502 on 72 degrees of freedom

Multiple R-squared: 0.2901, Adjusted R-squared: 0.2802

F-statistic: 29.42 on 1 and 72 DF, p-value: 7.416e-07

2.2. Accessing World Bank's *World Development Indicators*

The World Wide Web is a treasure trove of data, and most major databases offer researchers direct download options. Numerous user-supplied packages are available for seamless access to such data. In this section, I present two popular packages that facilitate the downloading of data from the World Bank's *World Development Indicators*:

WDI (World Development Indicators) Package - Official CRAN package documentation: [WDI on CRAN](#) - Source code on GitHub: [WDI GitHub Repository](#)

wbstats (World Bank Statistics) Package - Official CRAN package documentation: [wbstats on CRAN](#) - Source code on GitHub: [wbstats GitHub Repository](#)

Now, let's download some GDP data and explore how to manipulate it. This exercise will demonstrate practical applications of the tools.

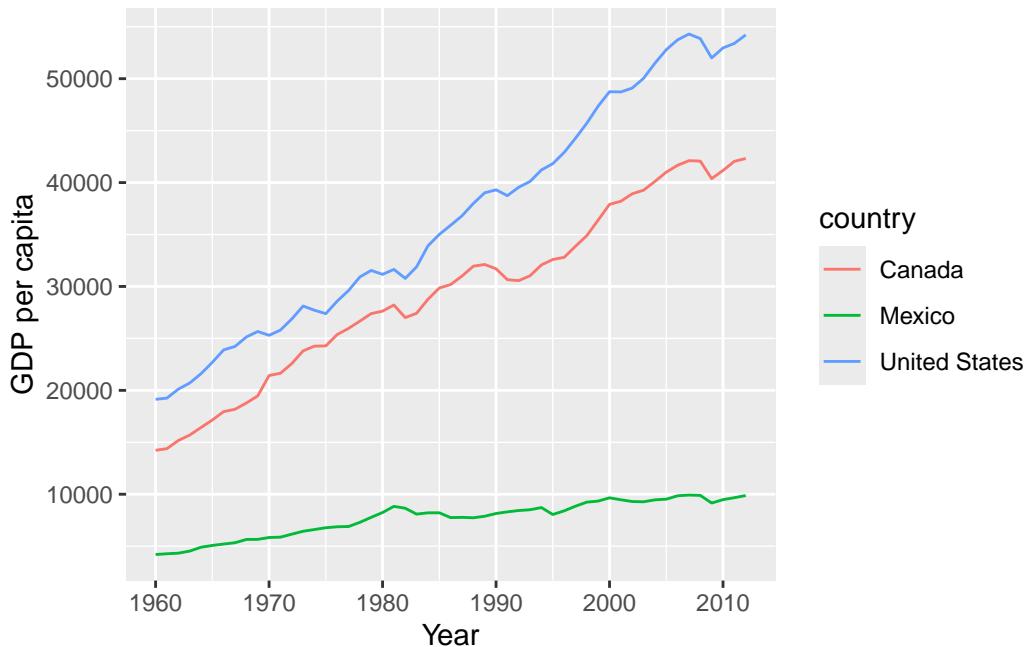
```
# Search for GDP indicators and display the first 10
WDIsearch("gdp") [1:10, ]
```

2. Kickstart

	indicator	name
712	5.51.01.10.gdp	Per capita GDP growth
714	6.0.GDP_current	GDP (current \$)
715	6.0.GDP_growth	GDP growth (annual %)
716	6.0.GDP_usd	GDP (constant 2005 \$)
717	6.0.GDPpc_constant	GDP per capita, PPP (constant 2011 international \$)
1557	BG.GSR.NFSV.GD.ZS	Trade in services (% of GDP)
1558	BG.KAC.FNEI.GD.PP.ZS	Gross private capital flows (% of GDP, PPP)
1559	BG.KAC.FNEI.GD.ZS	Gross private capital flows (% of GDP)
1560	BG.KLT.DINV.GD.PP.ZS	Gross foreign direct investment (% of GDP, PPP)
1561	BG.KLT.DINV.GD.ZS	Gross foreign direct investment (% of GDP)

```
# Retrieve GDP per capita data for specified countries and years
df_WDI <- WDI(
  indicator = "NY.GDP.PCAP.KD",
  country = c("MX", "CA", "US"),
  start = 1960,
  end = 2012
)

# Plot GDP per capita over time for the specified countries
ggplot(df_WDI, aes(year, NY.GDP.PCAP.KD, color = country)) +
  geom_line() +
  xlab("Year") +
  ylab("GDP per capita")
```



```
# Retrieve GDP per capita data for specified countries and years using the wbstats package
df_wb <- wb(
  indicator = "NY.GDP.PCAP.KD",
  country = c("MX", "CA", "US"),
  start = 1960,
  end = 2012,
```

2. Kickstart

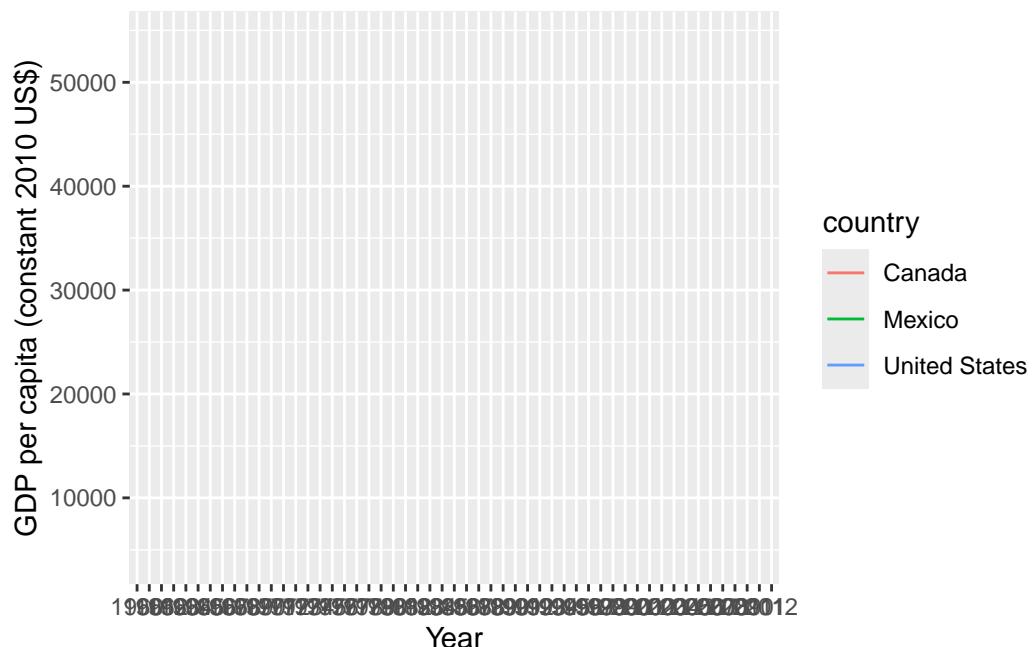
```
  return_wide = TRUE  
)
```

Warning: `wb()` was deprecated in wbstats 1.0.0.
i Please use `wb_data()` instead.

Warning: `spread_()` was deprecated in tidyr 1.2.0.
i Please use `spread()` instead.
i The deprecated feature was likely used in the wbstats package.
Please report the issue at <<https://github.com/nset-ornl/wbstats/issues>>.

```
# Plot GDP per capita over time for the specified countries  
ggplot(df_wb, aes(date, NY.GDP.PCAP.KD, color = country)) +  
  geom_line() +  
  xlab("Year") +  
  ylab("GDP per capita (constant 2010 US$)")
```

`geom_line()`: Each group consists of only one observation.
i Do you need to adjust the group aesthetic?



The latter graph appears empty. Why? Let's take a closer look at the data to identify any discrepancies that might explain this issue:

```
# Look at the data types year and date are different:  
glimpse(df_WDI)
```

```
Rows: 159  
Columns: 5  
$ country      <chr> "Canada", "Canada", "Canada", "Canada", "Canada", "Can~  
$ iso2c        <chr> "CA", ~
```

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```
$ iso3c      <chr> "CAN", "CAN", "CAN", "CAN", "CAN", "CAN", "CAN", "CAN", ~  
$ year       <int> 2012, 2011, 2010, 2009, 2008, 2007, 2006, 2005, 2004, 2~  
$ NY.GDP.PCAP.KD <dbl> 42319.63, 42043.51, 41165.57, 40377.82, 42067.80, 42106~
```

```
glimpse(df_wb)
```

```
Rows: 159  
Columns: 5  
$ iso3c      <chr> "CAN", "CAN", "CAN", "CAN", "CAN", "CAN", "CAN", "CAN", ~  
$ date       <chr> "1960", "1961", "1962", "1963", "1964", "1965", "1966", ~  
$ iso2c      <chr> "CA", "CA", "CA", "CA", "CA", "CA", "CA", "CA", "CA", ~  
$ country    <chr> "Canada", "Canada", "Canada", "Canada", "Canada", "Canada", ~  
$ NY.GDP.PCAP.KD <dbl> 14229.83, 14389.40, 15173.02, 15689.70, 16419.39, 17143~
```

The answer is: A lineplot with a character variable (date is `<chr>`) on the x-axis does not work!

Now, let us manipulate the `df_wb` data so that the two dataset are equal:

```
df_wb_cln <- df_wb |>  
  # Convert 'date' in df_wb from character to integer  
  mutate(year = as.integer(date)) |>  
  # Since 'year' has been created, remove the original 'date' column  
  select(-date) |>  
  # Relocate columns to organize the data frame  
  relocate(country, iso2c, iso3c, year, NY.GDP.PCAP.KD)  
  
glimpse(df_WDI)
```

```
Rows: 159  
Columns: 5  
$ country    <chr> "Canada", "Canada", "Canada", "Canada", "Canada", "Canada", ~  
$ iso2c      <chr> "CA", "CA", "CA", "CA", "CA", "CA", "CA", "CA", "CA", ~  
$ iso3c      <chr> "CAN", "CAN", "CAN", "CAN", "CAN", "CAN", "CAN", "CAN", "CAN", ~  
$ year       <int> 2012, 2011, 2010, 2009, 2008, 2007, 2006, 2005, 2004, 2~  
$ NY.GDP.PCAP.KD <dbl> 42319.63, 42043.51, 41165.57, 40377.82, 42067.80, 42106~
```

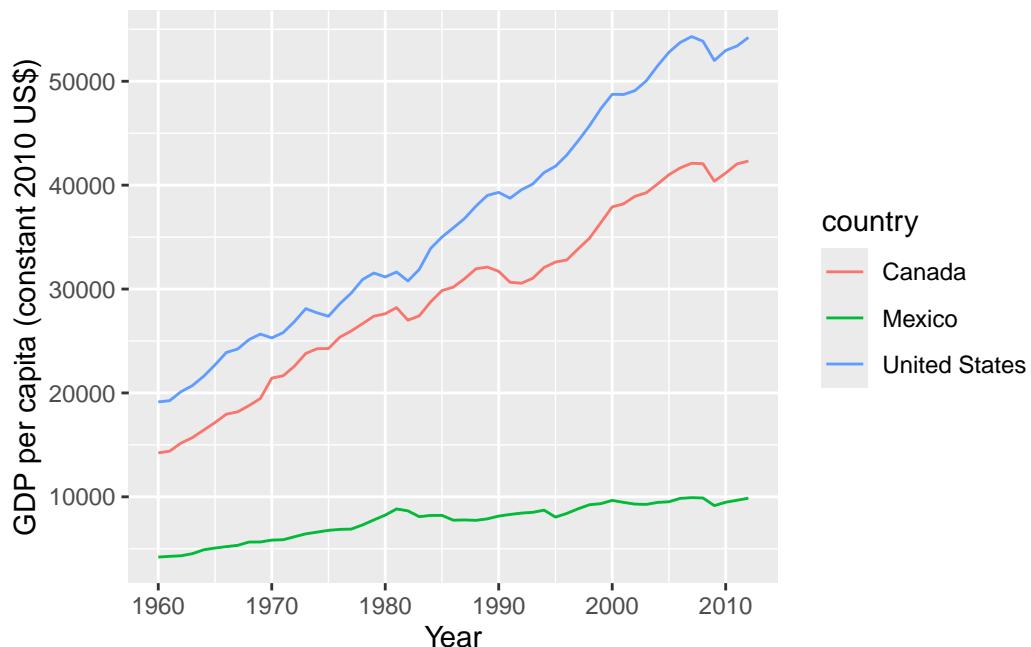
```
glimpse(df_wb_cln)
```

```
Rows: 159  
Columns: 5  
$ country    <chr> "Canada", "Canada", "Canada", "Canada", "Canada", "Canada", ~  
$ iso2c      <chr> "CA", "CA", "CA", "CA", "CA", "CA", "CA", "CA", "CA", ~  
$ iso3c      <chr> "CAN", "CAN", "CAN", "CAN", "CAN", "CAN", "CAN", "CAN", "CAN", ~  
$ year       <int> 1960, 1961, 1962, 1963, 1964, 1965, 1966, 1967, 1968, 1~  
$ NY.GDP.PCAP.KD <dbl> 14229.83, 14389.40, 15173.02, 15689.70, 16419.39, 17143~
```

Now it works:

2. Kickstart

```
# Plot GDP per capita over time for the specified countries
ggplot(df_wb_cln, aes(year, NY.GDP.PCAP.KD, color = country)) +
  geom_line() +
  xlab("Year") +
  ylab("GDP per capita (constant 2010 US$)")
```



Loading required package: funcuse

Loading required package: pacman

Solution

The script uses the following functions: `aes`, `as.integer`, `c`, `dim`, `geom_line`, `geom_point`, `geom_smooth`, `get_dupes`, `ggplot`, `ggsave`, `glimpse`, `head`, `lm`, `mutate`, `names`, `ncol`, `nrow`, `print`, `read_dta`, `relocate`, `select`, `setwd`, `summary`, `tail`, `wb`, `WDI`, `WDIsearch`, `xlab`, `ylab`.

R script

```

# This script demonstrates a typical data analysis workflow in R
# ----

# Install and load required libraries
# Installs 'pacman' if not already available, which is used for package management
if (!require(pacman)) install.packages("pacman")

# Unload all previously loaded packages to start fresh
suppressMessages(pacman::p_unload(all))

# Load necessary packages for data manipulation, cleaning, and visualization
pacman::p_load(
  tidyverse, # A suite of packages designed for data science that includes tools for data
  haven, # Used for importing and exporting data with SPSS, Stata, and SAS formats.
  janitor, # Provides functions for examining and cleaning data, such as `clean_names()`
  WDI, # Facilitates downloading data from the World Bank's World Development Indicators
  wbstats # Provides an interface to the World Bank's APIs for a comprehensive range of
)

# Set the working directory to a project-specific folder
setwd("~/Dropbox/hsf/courses/dsr")

# Clear the current environment of any objects
rm(list = ls())

# ----

# Load data from a Stata file available online
auto <- read_dta("http://www.stata-press.com/data/r8/auto.dta")
# 'auto': Dataset contains information about different car models

# Display basic information about the dataset
ncol(auto) # Number of columns
nrow(auto) # Number of rows
dim(auto) # Dimensions of the dataset
names(auto) # Names of variables
head(auto) # First few rows
tail(auto) # Last few rows
summary(auto) # Summary statistics for each column
glimpse(auto) # Compact display of the structure of the dataset
print(auto, n = Inf) # Print all rows of the dataset

# Check for duplicate entries based on the 'make' variable
auto |>
  get_dupes(make)

# Create and display a scatter plot of car price versus weight
plot_weight_price <- ggplot(auto, aes(x = weight, y = price)) +
  geom_point()
plot_weight_price

# Save the plot to a file
ggsave("fig/plot_weight_price.png", plot = plot_weight_price, dpi = 300)

```

2. Kickstart

3. Pitfalls

R newbies often make the same small mistakes that can lead to major confusion, frustration and inefficiency. Some of them can be easily avoided. In this section, I will outline common pitfalls that I have repeatedly observed as an R instructor and offer practical solutions to avoid them.

3.1. No clue about the “working directory”

Problem: Students start their R sessions unaware of their current working directory. This can lead to difficulties when reading and writing files.

Solution: At the beginning of your R script set a working directory using `setwd()`. Consider using R Studio projects, see Section A.4. For more information, see Appendix A: *Navigating the file system* and *Workflow: scripts and projects* of Wickham and Grolemund [2023].

3.2. No consistent directory structure

Problem: Students save files in different directories without a clear scheme. This disorganization often leads to problems: Scripts and data gets lost and code breaks.

Solution: Organize your project into a clear directory structure from the beginning. Here is my suggestion for a directory structure but feel free to come up with your own:

Table 3.1.: Typical folder structure

Sub-Directory	What to save here
doc/	documentation
dta/	processed data
fig/	figures
lit/	literature and pdfs
ori/	original raw data that you should never change
qmd/	reports
scr/	R scripts
tab/	tables
tmp/	temporary files

This structure will save time and headaches when navigating projects.

💡 Tip 1: Do not save processed data unless necessary

It may seem reasonable to save data after editing, but this often isn't necessary if you're using scripts to create your data. These scripts can be rerun whenever needed, regenerating

the dataset each time. To avoid wasting disk space and maintain an organized project folder, it's advisable to save processed datasets only when the preprocessing steps are time-consuming. This way, you can keep your project folder more organized and ensure that your data analyses are always reproducible with the latest updates to your code.

3.3. Working manually outside R

Problem: Students want to get their work done quickly. This sometimes leads to them relying on manual processes that they have already mastered for their data work. This approach can lead to serious problems when it comes to the reproducibility of their data work.

Consider a typical three-step process for loading data: (1) downloading the data, (2) unpacking the data, and finally (3) importing the data into R. Many students often take a manual approach by using their Internet browser to download the data, then using their operating system's unpacking application, and finally importing the data into an R script. While this method is not inherently wrong, there is a risk that students will forget to unpack the downloaded data, resulting in them accidentally working with outdated data. In the kickstart example provided by Section 2.2, I show that all three steps can be performed seamlessly in R. This way you ensure that you are always working with the most up-to-date data.

Solution: Do as much as possible in the script. Invest some time to find out how to download and manipulate the data within R. If it is not possible or if alternatives are superior, describe what you do outside of R explicitly and write a warning note at the top of your script.

3.4. No active R Packages management

Problem: Students often forget to install and/or load the packages correctly at the beginning of a script. Some unnecessarily install packages repeatedly when running a script. All this can lead to errors and interruptions.

Solution: At the beginning of each script, make sure that all required packages are loaded correctly. Use the `pacman` package, which provides the `p_load()` function to load and, if necessary, install packages and the `p_unload(all)` function to unload all packages.

💡 Tip 2: Start your script with

```
if (!require(pacman)) install.packages("pacman")
pacman::p_unload(all)
pacman::p_load(tidyverse, janitor)
setwd("~/your-directory/")
rm(list = ls())
```

3.5. Confusion between console and script

Problem: Alternating between running code in the console and from the script without a systematic approach can lead to untracked changes and confusion about the current state of objects in the workspace. Additionally, students often borrow code snippets from others and run

3. Pitfalls

only the sections that seem immediately relevant. This practice can lead to errors or unexpected results, as such code often relies on previous commands or setups.

Solution: Develop the habit of testing small blocks of code in the console but run the complete script regularly to ensure everything works in sequence. Use shortcuts like **Ctrl + Alt + R** to source the entire script or **Ctrl + Alt + B/E** to execute it up to a specific point.

3.6. Misunderstanding data types and formats

Problem: Misusing or misunderstanding R’s data types and structures can lead to errors in data manipulation and analysis. Many functions require certain types of data. For example, the `tidyverse` packages required data to be “tidy”. Moreover, data often comes with errors and/or missings (`NA`). Beginners overlook data cleaning and considering missings.

Solution: Familiarize yourself with basic data types and structures like vectors, lists, data frames/tibbles, and factors. For more information, see Section 6.2 and [Data tidying of Wickham and Grolemund \[2023\]](#). Moreover, spend adequate time on data cleaning and preprocessing. Techniques such as handling missing values, normalizing data, and correcting data types are critical. For more information, see [Missing values of Wickham and Grolemund \[2023\]](#).

3.7. Lack of knowledge about data identification

Problem: Students often handle data without understanding which variables uniquely identify the information contained in other variables. It is crucial to recognize these identifying variables and verify their uniqueness to ensure data integrity.

Solution: Perform checks for uniqueness at the beginning of their data analysis process. See exercise *Names and duplicates* in Section 8.15 and the `get_dupes` function introduced in Section 6.4.3.2.

 Tip 3: Always check your data with `get_dupes`

For example, you expect that your dataframe `df` is a panel dataset. With

```
get_dupes(df, country, year)
```

you can check whether the two variables `country` and `year` indeed identify each row uniquely.

3.8. Losing track of data due to excessive overwriting

Problem: Students often manipulate their data by repeatedly overwriting the same object. This can lead to confusion about the data’s current state and the transformations applied.

Solution: Minimize the number of assignments to a single object. Instead, create a new object with a descriptive and concise name each time you alter the data. This practice helps maintain clarity about each stage of data manipulation.

For example, if you're working with data `df`, you might store the cleanded data as `df_cln`, then after filtering for specific criteria, you could use `df_cln_flt`, and finally, if you aggregate the data, name it `df_cln_flt_agg`. Having some clear naming convention makes it clear what each dataset represents and the transformations it has undergone.

 Tip 4: Do clear the environment at the beginning of a script with

```
rm(list = ls())
```

3.9. No documentation

Problem: Students do not comment code. This makes it hard to remember the purpose of various lines of code and difficult for other people to read and understand the code.

Solution: Regularly comment your code, explaining why something is done, not just what is done. Use clear, concise comments to improve readability and maintainability.

3.10. Ignoring error messages and warnings

Problem: Students see that their code doesn't work but do not read the error message which often contains hints for solving the problem.

Solution: Read and follow error messages. Do not ignore warnings or errors unless you know what they mean. Study what the error message might mean. Use online resources such as Google and ChatGPT, see Figure 3.1. Finally, have the confidence to implement the suggested solution. Don't be frustrated if the first attempt does not work: Try again and play around.

 Tip 5: Common error messages

Students often come to me with error messages suggesting that they install the `tinytex` package or the `RTools` compiler for Windows. Since they are not familiar with these R and software packages, they wonder if it is safe to proceed with the installation. My answer here is: yes, it is recommendable to install it.

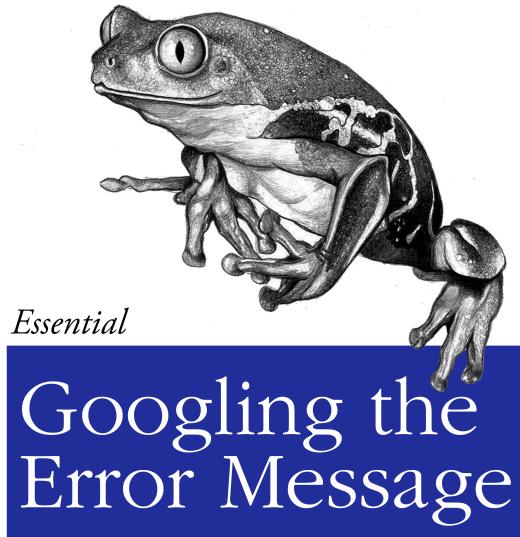
Based the [report of Noam Ross](#) who examine roughly 10,000 R error messages, the most frequently encountered error messages of R are shown in Table 3.2 with some ideas of mine what to do.

Table 3.2.: Most frequent errors

Error Type	Some suggestions on what to do
Could not find function	Check spelling of the function and whether the respective packages are loaded properly.
Error in if	This suggests an issue with non-logical or missing values in a conditional statement. Check syntax and spelling. Maybe use ChatGPT to debug the code.
Error in eval	Points to references to non-existent objects.
Cannot open	Check if the files exist at the place you try to call them.
No applicable method	Check your data type and whether it fits to the requirements of the functions you're trying to use.

Figure 3.1.: Googling the error message

The internet will make those bad words go away



O RLY?

*The Practical Developer
@ThePracticalDev*

Source: DEV Community on GitHub

Package errors

This can stem from issues with installing, compiling, or loading a package. Maybe you try to re-install the package and their dependencies, or update the packages.

3.11. No attempt to identify the problem and troubleshoot

Problem: Students often do not fully understand the problems they encounter, which can lead to difficulties in seeking solutions. It's common for students to feel overwhelmed and seek help without attempting to find the source of the problem and without attempting to work out possible solutions first.

Solution: When you encounter an issue in your R code, it's crucial to methodically dissect the problem. Here's how you can effectively *troubleshoot*, that is, a problem-solving skill that is essential for becoming proficient in programming:

- **Identify the problem:** Attempt to identify the issue to better understand its nature. Once you know which line of code is causing some trouble, you are often close to a solution. Commenting out parts of your script or going back until there is no error can help here.
- **Active solution search:** Once you've identified the problem, actively look for solutions. This can include consulting the R documentation, searching for similar issues online, or asking others for help.
- **Trial and error process:** Don't hesitate to experiment with different solutions to see what works best.

3. Pitfalls

- **Seek Help:** If you're stuck, ask for help from more experienced R users or communities.
- **Minimal Reproducible Example (MRE):** When asking for help, explain your problem precisely and provide a MRE. That is the simplest version of the code that still produces the error, including only essential data and code. This practice not only aids in self-troubleshooting but also makes it easier for others to help by providing a clear, concise context.
- **Additional information:** Sometime the interplay of your the packages loaded, your operating system, the version of R, and/or the RStudio version may play a role in your problem. Thus, 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/libopenblas-p0.3.21.so

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   base

loaded via a namespace (and not attached):
[1] compiler_4.2.2    fastmap_1.1.1    cli_3.6.2      tools_4.2.2
[5] htmltools_0.5.7   rstudioapi_0.15.0  rmarkdown_2.25  knitr_1.45
[9] jsonlite_1.8.8    xfun_0.41       digest_0.6.33   rlang_1.1.2
[13] evaluate_0.23
```

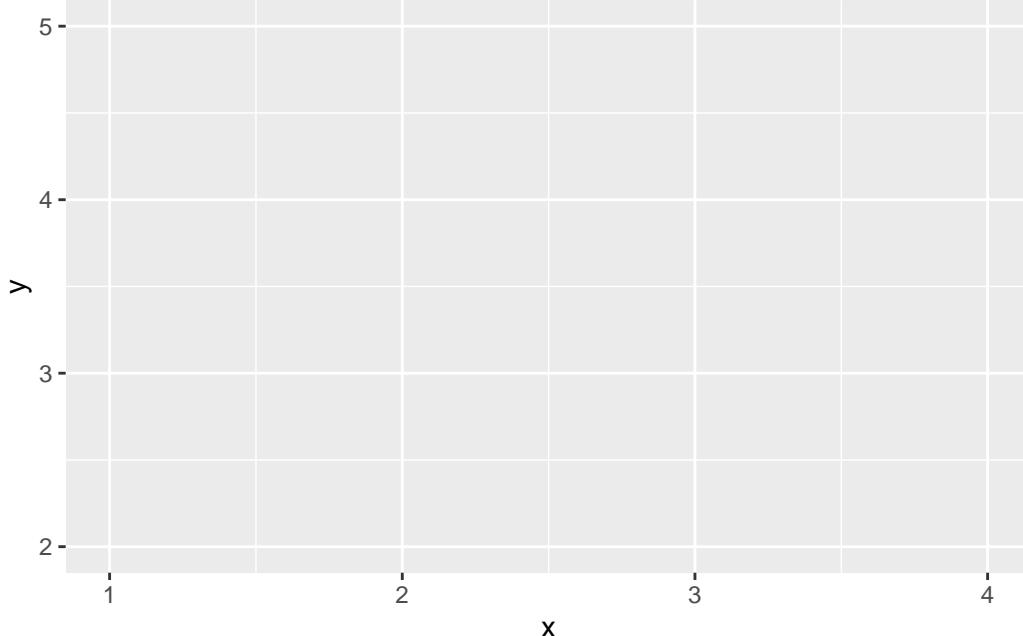
For more information, see [Workflow: getting help](#) of [Wickham and Grolemund \[2023\]](#).

Example of a minimal reproducible example

For example, the following script is a MRE:

```
library(ggplot2)
data <- data.frame(x = 1:4, y = c(2, 3, 5, 3.4))
ggplot(data, aes(x, y))
```

3. Pitfalls



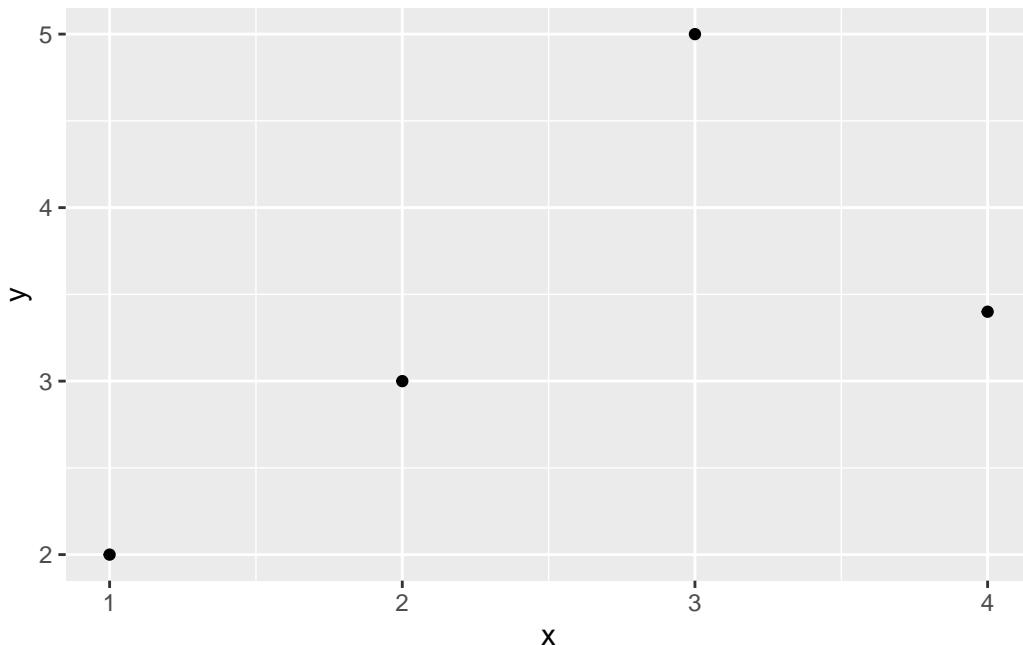
```
+geom_point()
```

Error:

```
! Cannot use `+` with a single argument.  
i Did you accidentally put `+` on a new line?
```

Everybody who copies these few lines of code can reproduce the shown error message and hence can work on a solution. Obviously, the + was set falsely. It must be placed in the line of `ggplot`:

```
library(ggplot2)  
data <- data.frame(x = 1:4, y = c(2, 3, 5, 3.4))  
ggplot(data, aes(x, y)) +  
  geom_point()
```



3.12. Unstylish code

To avoid issues while programming in R, it's essential to understand and adhere to various conventions, rules, and best practices specific to the language. Following these conventions makes your code more readable and simplifies your own experience with R. Below, you will find a non-exhaustive list of these guidelines.

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 (see Appendix A).
6. Do not use whitespace and indentation for naming files, directories, or objects.
7. Do define objects to represent hard-coded values instead of using them directly in code.
8. Do remember to (install and) load packages that contain functions you want to use.
9. Do use <- instead of = for assignment.

 Tip 6

There are two packages, `styler` and `lintr`, that support you writing code according to the *The tidyverse style guide* of Wickham [2024].

4. An interactive introduction using `swirl`

This section is designed to kickstart your journey into data science with R through the R package `swirl` that offers an interactive learning platform. `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.

For those seeking additional or alternative resources beyond `swirl`, exploring other introductory textbooks and resources on R is highly recommended. Please consider the resources I discuss in Section 1.3. One notable example is [Irizarry \[2022\]](#) who provides a comprehensive and conservative approach to understanding R.

4.1. Set up `swirl`

To install `swirl` and my learning modules, 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 four lines of code do the following:

- Install the `swirl` package, ensuring it's available for use in R.
- Load the `swirl` package, making its functions accessible.
- Install my `swirl` course that is hosted on GitHub, making its functions accessible.
- By entering `swirl` into the Console (located at the bottom-left in RStudio) and pressing the Enter key, you initiate `swirl`. This begins your interactive learning experience with the package.

 Tip 7: If the course has failed to install,

you can try to download the file `swirl-it.swc` from github.com/hubchev/swirl-it and install the course with loading the `swirl` package and typing `install_course()` into the console.

After initiating the `swirl` environment, follow the instructions displayed in the Console. Specifically, select the *swirl-it* course and the *huber-intro-1* learning module to begin. You can exit `swirl` at any moment by typing `bye()` into the Console or pressing the *Esc* key on your keyboard.

4.2. swirl-it: huber-intro-1

i Click to see the full content of the module

Welcome to this swirl course. If you find any errors or if you have suggestions for improvement, please let me know via stephan.huber@hs-fresenius.de.

The RStudio interface consists of several windows. You can change the size of the windows by dragging the grey bars between the windows. We'll go through the most important windows now.

Bottom left is the Console window (also called command window/line). Here you can type commands after the > prompt and R will then execute your command. This is the most important window, because this is where R actually does stuff.

Top left is the Editor window (also called script window). Here collections of commands (scripts) can be edited and saved. When you do not get this window, you can open it with 'File' > 'New' > 'R script'.

Just typing a command in the editor window is not enough, it has to be send to the Console before R executes the command. If you want to run a line from the script window (or the whole script), you can click 'Run' or press 'CTRL+ENTER' to send it to the command window.

The shortcut to send the current line to the console and run it there is _____.

- a) CTRL+SHIFT
- b) CTRL+ENTER
- c) CTRL+SPACE
- d) SHIFT+ENTER

Hint: You find all shortcuts in the menu at Tools > Keyboard Shortcuts Help or click ALT+SHIFT+K. If you are a Mac user, your shortcut is 'Cmd+Return' instead of 'SHIFT+ENTER'. To move on type skip().

i Solution

answer: b

Top right is the environment window (a.k.a workspace). Here you can see which data R has in its memory. You can view and edit the values by clicking on them.

Bottom right is the plots / packages / help window. Here you can view plots, install and load packages or use the help function.

The first thing you should do whenever you start Rstudio is to check if you are happy with your working directory. That directory is the folder on your computer in which you are currently working. That means, when you ask R to open a certain file, it will look in the working directory for this file, and when you tell R to save a data file or figure, it will save it in the working directory.

You can check your working directory with the function `getwd()`. So let's do that. Type in the command window `getwd()` .

```
getwd()
```

```
[1] "/home/sthu/Dropbox/hsf/courses/dsr"
```

Are you happy with that place? if not, you should set your working directory to where all your data and script files are (or will be). Within RStudio you can go to 'Session' > 'Set working directory' > 'Choose directory'. Please do this now.

4. An interactive introduction using swirl

Instead of clicking, you can use the function `setwd("/YOURPATH")`. For example, `setwd("/Users/MYNAME/MYFOLDER")` or `setwd("C:/Users/jenny/myrstuff")`. Make sure that the slashes are forward slashes and that you do not forget the apostrophes. R is case sensitive, so make sure you write capitals where necessary.

Whenever you want R to do something you need to use a function. It is like a command. All functions of R are organized in so-called packages or libraries. With the standard installation many packages are already installed. However, many more exist and some of them are really cool. For example, with `installed.packages()` all installed packages are listed. Or, with `swirl()`, you started swirl.

Of course, you can also go to the Packages window at the bottom right. If the box in front of the package name is ticked, the package is loaded (activated) and can be used. To see via Console which packages are loaded type in the console (`.packages()`)

```
(.packages())
```

```
[1] "stats"      "graphics"   "grDevices"  "utils"       "datasets"   "methods"  
[7] "base"
```

There are many more packages available on the R website. If you want to install and use a package (for example, the package called `geometry`) you should first install the package. Type `install.packages("geometry")` in the console. Don't be afraid about the many messages. Depending on your PC and your internet connection this may take some time.

```
install.packages("geometry")
```

After having installed a package, you need to load the package. That is a bit annoying but essential. Type in `library("geometry")` in the Console. You also did this for the swirl package (otherwise you couldn't have been doing these exercises).

```
library("geometry")
```

Check if the package is loaded typing `(.packages())`

```
(.packages())
```

Now, let's get started with the real programming.

R can be used as a calculator. You can just type your equation in the command window after the `>`. Type `10^2 + 36`.

```
10^2 + 36
```

```
[1] 136
```

And R gave the answer directly. By the way, spaces do not matter.

If you use brackets and forget to add the closing bracket, the `>` on the command line changes into a `+`. The `+` can also mean that R is still busy with some heavy computation. If you want R to quit what it was doing and give back the `>`, press ESC.

You can also give numbers a name. By doing so, they become so-called variables which can be used later. For example, you can type in the command window `A <- 4`.

```
A <- 4
```

4. An interactive introduction using swirl

The `<-` is the so-called assignment operator. It allows you to assign data to a named object in order to store the data.

Don't be confused about the term object. All sorts of data are stored in so-called objects in R. All objects of a session are shown in the Environment window. In the second part of this course, I will introduce different data types.

You can see that `A` appeared in the environment window in the top right corner, which means that R now remembers what `A` is.

You can also ask R what `A` is. Just type `A` in the command window.

```
A
```

```
[1] 4
```

You can also do calculations with `A`. Type `A * 5`.

```
A * 5
```

```
[1] 20
```

If you specify `A` again, it will forget what value it had before. You can also assign a new value to `A` using the old one. Type `A <- A + 10`.

```
A <- A + 10
```

You can see that the value in the environment window changed.

To remove all variables from R's memory, type `rm(list=ls())`.

```
rm(list = ls())
```

You see that the environment window is now empty. You can also click the broom icon (`clear all`) in the environment window. You can see that RStudio then empties the environment window. If you only want to remove the variable `A`, you can type `rm(A)`.

Like in many other programs, R organizes numbers in scalars (a single number, 0-dimensional), vectors (a row of numbers, also called arrays, 1-dimensional) and matrices (like a table, 2-dimensional).

The `A` you defined before was a scalar. To define a vector with the numbers 3, 4 and 5, you need the function `c()`, which is short for concatenate (paste together). Type `B=c(3,4,5)`.

```
B <- c(3, 4, 5)
```

If you would like to compute the mean of all the elements in the vector `B` from the example above, you could type `(3+4+5)/3`. Try this

```
(3 + 4 + 5) / 3
```

```
[1] 4
```

But when the vector is very long, this is very boring and time-consuming work. This is why things you do often are automated in so-called functions. For example, type `mean(x=B)` and guess what this function `mean()` can do for you.

```
mean(x = B)
```

```
[1] 4
```

Within the brackets you specify the arguments. Arguments give extra information to the function. In this case, the argument `x` says of which set of numbers (vector) the mean should be computed (namely of `B`). Sometimes, the name of the argument is not necessary; `mean(B)` works as well. Try it.

```
mean(B)
```

```
[1] 4
```

Compute the sum of 4, 5, 8 and 11 by first combining them into a vector and then using the function `sum`. Use the function `c` inside the function `sum`.

```
sum(c(4, 5, 8, 11))
```

```
[1] 28
```

The function `rnorm`, as another example, is a standard R function which creates random samples from a normal distribution. Type `rnorm(10)` and you will see 10 random numbers

```
rnorm(10)
```

```
[1] 0.5111290 1.0020289 -0.7123098 0.4674057 -0.4165985 -1.8162489
[7] 0.9808822 -0.1434794 0.9210288 -0.3844244
```

Here `rnorm` is the function and the 10 is an argument specifying how many random numbers you want - in this case 10 numbers (typing `n=10` instead of just 10 would also work). The result is 10 random numbers organised in a vector with length 10.

If you want 10 random numbers out of normal distribution with mean 1.2 and standard deviation 3.4 you can type `rnorm(10, mean=1.2, sd=3.4)`. Try this.

```
rnorm(10, mean = 1.2, sd = 3.4)
```

```
[1] -6.6141733 2.2778909 4.1786512 4.4708194 2.2553746 4.8408788
[7] -1.0572970 -4.9919843 -0.3948916 -5.0949526
```

This shows that the same function (`rnorm()`) may have different interfaces and that R has so called named arguments (in this case `mean` and `sd`).

Comparing this example to the previous one also shows that for the function `rnorm` only the first argument (the number 10) is compulsory, and that R gives default values to the other so-called optional arguments. Use the help function to see which values are used as default by typing `?rnorm`.

```
?rnorm
```

You see the help page for this function in the help window on the right. RStudio has a nice features such as autocompletion and snapshots of the R documentation. For example, when you type `rnorm(` in the command window and press TAB, RStudio will show the possible arguments.

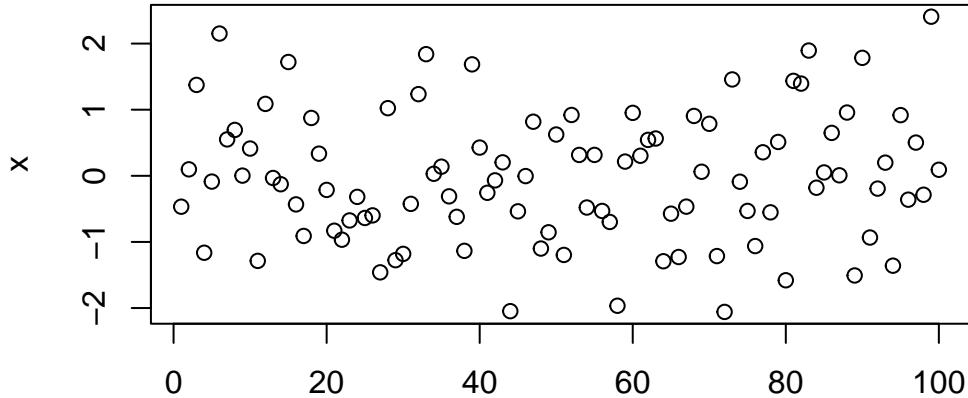
You can also store the output of the function in a variable. Type `x=rnorm(100)`.

```
x <- rnorm(100)
```

Now 100 random numbers are assigned to the variable x, which becomes a vector by this operation. You can see it appears in the Environment window.

R can also make graphs. Type `plot(x)` for a very simple example.

```
plot(x)
```



Index

The 100 random numbers are now plotted in the plots window on the right.

You now are more familiar to RStudio and you know some basic R stuff. In particular, you know...

- ...that everything in R is said with functions,
- ...that functions can but don't have to have arguments,
- ...that you can install packages which contain functions,
- ...that you must load the installed packages every time you start a session in RStudio, and
- ...that this is just the beginning. Thus, please continue with the second module of this introduction.

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*.

4.3. swirl-it: huber-intro-2

i Click to see the full content of the module

Welcome to the second module. Again, if you find any errors or if you have suggestions for improvement, please let me know via stephan.huber@hs-fresenius.de.

Before you start working, you should set your working directory to where all your data and script files are or should be stored. Within RStudio you can go to 'Session' > 'Set working directory', or you can type in `setwd(YOURPATH)`. Please do this now.

```
setwd("/home/sthu/Documents/mydir")
```

Hint: Instead of clicking, you can also type `setwd("path")`, where you replace "path" with the location of your folder, for example `setwd("D:/R/swirl")`.

R is an interpreter that uses a command line based environment. This means that you

4. An interactive introduction using swirl

have to type commands, rather than use the mouse and menus. This has many advantages. Foremost, it is easy to get a full transcript of everything you did and you can replicate your work easy.

As already mentioned, all commands in R are functions where arguments come (or do not come) in round brackets after the function name.

You can store your workflow in files, the so-called scripts. These scripts have typically file names with the extension, e.g., foo.R .

You can open an editor window to edit these files by clicking ‘File’ and ‘New’. Try this. Under ‘File’ you also find the options ‘Open file...’, ‘Save’ and ‘Save as’. Alternatively, just type CTRL+SHIFT+N.

You can run (send to the Console window) part of the code by selecting lines and pressing CTRL+ENTER or click ‘Run’ in the editor window. If you do not select anything, R will run the line your cursor is on.

You can always run the whole script with the console command source, so e.g. for the script in the file foo.R you type source('foo.R'). You can also click ‘Run all’ in the editor window or type CTRL+SHIFT+S to run the whole script at once.

Make a script called firstscript.R. Therefore, open the editor window with ‘File’ > ‘New’. Type `plot(rnorm(100))` in the script, save it as `firstscript.R` in the working directory. Then type `source("firstscript.R")` on the command line.

```
source("firstscript.R")
```

Run your script again with `source("firstscript.R")`. The plot will change because new numbers are generated.

```
source("firstscript.R")
```

Hint: Type `source("firstscript.R")` again or type `skip()` if you are not interested.

Vectors were already introduced, but they can do more. Make a vector with numbers 1, 4, 6, 8, 10 and call it `vec1`.

Hint: Type `vec1 <- c(1,4,6,8,10)`.

```
vec1 <- c(1, 4, 6, 8, 10)
```

Elements in vectors can be addressed by standard [i] indexing. Select the 5th element of this vector by typing `vec1[5]`.

```
vec1[5]
```

Replace the 3rd element with a new number by typing `vec1[3]=12`.

```
vec1[3] <- 12
```

Ask R what the new version is of `vec1`.

```
vec1
```

You can also see the numbers of `vec1` in the environment window. Make a new vector `vec2` using the `seq()` (sequence) function by typing `seq(from=0, to=1, by=0.25)` and check its values in the environment window.

Hint: Type `vec2 <- seq(from=0, to=1, by=0.25)`.

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```
vec2 <- seq(from = 0, to = 1, by = 0.25)
```

Type `sum(vec1)`.

```
sum(vec1)
```

The function `sum` sums up the elements within a vector, leading to one number (a scalar). Now use `+` to add the two vectors.

Hint: Type `vec1 + vec2`.

```
vec1 + vec2
```

If you add two vectors of the same length, the first elements of both vectors are summed, and the second elements, etc., leading to a new vector of length 5 (just like in regular vector calculus).

Matrices are nothing more than 2-dimensional vectors. To define a matrix, use the function `matrix`. Make a matrix with `matrix(data=c(9,2,3,4,5,6),ncol=3)` and call it `mat`.

Hint: Type `mat <- matrix(data=c(9,2,3,4,5,6),ncol=3)` or type `skip()` if you are not interested.

```
mat <- matrix(data = c(9, 2, 3, 4, 5, 6), ncol = 3)
```

The third type of data structure treated here is the data frame. Time series are often ordered in data frames. A data frame is a matrix with names above the columns. This is nice, because you can call and use one of the columns without knowing in which position it is. Make a data frame with `t = data.frame(x = c(11,12,14), y = c(19,20,21), z = c(10,9,7))`.

```
t <- data.frame(x = c(11, 12, 14), y = c(19, 20, 21), z = c(10, 9, 7))
```

Ask R what `t` is.

Hint: Type `t` or `skip()` if you are not interested.

```
t
```

The data frame is called `t` and the columns have the names `x`, `y` and `z`. You can select one column by typing `t$z`. Try this.

```
t$z
```

Another option is to type `t[["z"]]`. Try this as well.

```
t[["z"]]
```

Compute the mean of column `z` in data frame `t`.

Hint: Use function `mean` or type `skip()` if you are not interested.

```
mean(t$z)
```

In the following question you will be asked to modify a script that will appear as soon as you move on from this question. When you have finished modifying the script, save your

4. An interactive introduction using swirl

changes to the script and type `submit()` and the script will be evaluated. There will be some comments in the script that opens up. Be sure to read them!

Make a script file which constructs three random normal vectors of length 100. Call these vectors `x1`, `x2` and `x3`. Make a data frame called `t` with three columns (called `a`, `b` and `c`) containing respectively `x1`, `x1+x2` and `x1+x2+x3`. Call `plot(t)` for this data frame. Then, save it and type `submit()` on the command line.

Hint: Type `plot(rnorm(100))` in the script, save it and type `submit()` on the command line.

```
# Text behind the #-sign is not evaluated as code by R.  
# This is useful, because it allows you to add comments explaining what the script does.  
  
# In this script, replace the ... with the appropriate commands.  
  
x1 <- ...  
x2 <- ...  
x3 <- ...  
t <- ...  
plot(...)
```

i Result

```
# Text behind the #-sign is not evaluated as code by R.  
# This is useful, because it allows you to add comments explaining what the script does.  
  
# In this script, replace the ... with the appropriate commands.  
  
x1 <- rnorm(100)  
x2 <- rnorm(100)  
x3 <- rnorm(100)  
t <- data.frame(a = x1, b = x1 + x2, c = x1 + x2 + x3)  
plot(t)
```

Do you understand the results?

Another basic structure in R is a list. The main advantage of lists is that the `columns` (they are not really ordered in columns any more, but are more a collection of vectors) don't have to be of the same length, unlike matrices and data frames. Make this list `L <- list(one=1, two=c(1,2), five=seq(0, 1, length=5))`.

```
L <- list(one = 1, two = c(1, 2), five = seq(0, 1, length = 5))
```

The list `L` has names and values. You can type `L` to see the contents.

```
L
```

`L` also appeared in the environment window. To find out what's in the list, type `names(L)`.

```
names(L)
```

Add 10 to the column called `five`.

Hint: Type `L$five + 10`

4. An interactive introduction using swirl

```
L$five + 10
```

Plotting is an important statistical activity. So it should not come as a surprise that R has many plotting facilities. Type `plot(rnorm(100), type="l", col="gold")`.

Hint: The symbol between quotes after the `type=`, is the letter `l`, not the number 1. To see the result you can also just type `skip()`.

```
plot(rnorm(100), type = "l", col = "gold")
```

Hundred random numbers are plotted by connecting the points by lines in a gold color. Another very simple example is the classical statistical histogram plot, generated by the simple command `hist`. Make a histogram of 100 random numbers.

Hint: Type `hist(rnorm(100))`

```
hist(rnorm(100))
```

The script that opens up is the same as the script you made before, but with more plotting commands. Type `submit()` on the command line to run it (you don't have to change anything yet).

Hint: Change plotting parameters in the script, save it and type `submit()` on the command line.

```
# Text behind the #-sign is not evaluated as code by R.  
# This is useful, because it allows you to add comments explaining what the script does.  
  
# Make data frame  
x1 <- rnorm(100)  
x2 <- rnorm(100)  
x3 <- rnorm(100)  
t <- data.frame(a = x1, b = x1 + x2, c = x1 + x2 + x3)  
  
# Plot data frame  
plot(t$a, type = "l", ylim = range(t), lwd = 3, col = rgb(1, 0, 0, 0.3))  
lines(t$b, type = "s", lwd = 2, col = rgb(0.3, 0.4, 0.3, 0.9))  
points(t$c, pch = 20, cex = 4, col = rgb(0, 0, 1, 0.3))  
  
# Note that with plot you get a new plot window while points and lines add to the previous
```

Try to find out by experimenting what the meaning is of `rgb`, the last argument of `rgb`, `lwd`, `pch`, `cex`. Type `play()` on the command line to experiment. Modify lines 11, 12 and 13 of the script by putting your cursor there and pressing CTRL+ENTER. When you are finished, type `nxt()` and then `?par`.

Hint: Type `?par` or type `skip()` if you are not interested.

```
?par
```

You searched for `par` in the R help. This is a useful page to learn more about formatting plots. Google 'R color chart' for a pdf file with a wealth of color options.

To copy your plot to a document, go to the plots window, click the 'Export' button, choose the nicest width and height and click 'Copy' or 'Save'.

4. An interactive introduction using `swirl`

After having almost completed the second learning module, you are getting closer to become a nerd as you know...

...that everything in R is stored in objects (values, vectors, matrices, lists, or data frames),
...that you should always work in scripts and send code from scripts to the Console,
...that you can do it if you don't give up.

Please continue choosing another `swirl` learning module.

4.4. `swirl-it`: 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.

4.5. `swirl-it`: 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.

4.6. 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()
```

5. Work with R scripts

5.1. The limitations of no-code applications

No-Code Applications (NCA) such as [Microsoft Excel](#), [RapidMiner](#), [KNIME](#), [DataRobot](#), [Tableau](#), [Microsoft Power BI](#), and [Google AutoML](#) are popular for good reasons. They enable the application of advanced empirical methods with no or minimal programming effort. Their intuitive graphical user interfaces come with pre-built templates and drag-and-drop functionality which helps to get things done quick, without having to study the program documentation for hours. Despite their apparent ease of use and efficiency, these platforms come with several disadvantages compared to traditional ways of working with computer by scripting and coding. Understanding these weaknesses helps to see why professional researchers, especially those actively publishing in academic journals, tend to rely on scripting languages like R and Python. These programming languages offer full control, are customizable and extendable, offer extensive opportunities for automation and reproducibility, and are often better suited for demanding data science tasks.

Disadvantages of No-Code Applications (NCA)

- NCA lack flexibility and are limited in their adaptability.
- NCA often have problems scaling with increasing data volumes or user requirements.
- NCA are often closed systems that make it difficult to integrate other systems or applications.
- NCA often bind a company to a specific ecosystem. This can lead to dependencies and vendor lock-in.
- NCA can obscure the underlying logic of how applications work, which can make troubleshooting more difficult.
- NCA abstracts the coding process and prevents users from understanding fundamental concepts that could be beneficial to their professional growth and ability to tackle more complex problems.

In summary, while low-code and no-code platforms offer quick deployment and ease of use, they can lack the depth, flexibility, and control provided by traditional scripting. Researchers and businesses must consider these trade-offs, especially when planning for long-term scalability, complex customizations, or in-depth integrations.

A hypothetical but realistic example with Excel

Suppose you work with a spreadsheet software like Excel. You import a CSV file using the implemented import tool, you save the converted file. You notice that Excel has messed up the dates during the import, so you spend a few minutes cleaning that manually. Then, you visualize the data and you save the visualizations in various tabs. Maybe, you can spot some outliers and you document in footnote that these outliers are the result of some issues with the raw data. As these errors cannot be solved, you delete the observations and variables that contain a significant amount of errors. Finally, you use filters to calculate

some summary statistics. All your results are written in a new tab. You're convinced that you've done a great job. However, you send the file to your supervisor and you ask him for her opinion.

- She probably asks you what you have done to the data. How can you efficiently and completely communicate that?
- She comes back to you some time later and asks you to do the same analysis with an updated version of the data. How can you exactly redo the analysis and how long do you think it will take you to complete the job?
- She finds an error in your work or she has an idea to improve your analysis by making a few adjustments. Can you implement the adjustments easily, or do you have to redo everything from scratch?
- She sends you back the file with the comment that she has worked out some things in the file and now everything should be fine. How do you know what she has done to the data?

To say it in the words of [Stephenson \[2023\]](#), sec. 5.1]:

“Spreadsheets are a nightmare for quality control and reproducibility, and you should always think twice before using one. Spreadsheets will always be a handy way to manipulate tabular datasets, and you’ll probably find them useful for data collection and quick back-of-the-envelope calculations, but they’re often more trouble than they’re worth.”

5.2. R Scripts: Why they are useful

I have already discussed in Section 1.7 that you can run code either directly by typing your code into the console of R or by writing a script and then sending the code with **Ctrl+Enter** or with the **Run** button to the console of R. 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 just plain text that is interpreted as code or as a comment if the text follows a hastag **#**. A script comes with important advantages.

Scripts...

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

5.3. Create, write, and run R scripts

5.3.1. Create

i 3 equivalent ways to create a script

1. Use the menu: **File > New File > R Script**
2. Use the keyboard shortcut: **Ctrl+Shift+N** (Windows/Linux) or **Cmd+Shift+N** (Mac) or
3. Type the following 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/Linux) or **Cmd+S** (Mac). If you go for the third way, you need to open it manually.

5.3.2. Write

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

```
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:

- With the assignment operator `<-` we create an object that stores the words “hello world” in an object entitled `x`. In Section 6.1.1 the assignment operator is further explained.
- With the third input we print the content of the object `x`.

5.3.3. Run

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")
```

5. Work with R scripts

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.

Exercise 5.1. Run a script and round numbers

Please copy and paste the following lines of code into an R script, run it on your computer, and try to understand how it works.

```
# Create a vector that contains the sales data
sales_by_month <- c(0, 100, 200, 50, 3, 4, 8, 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()
```

Solution

```
round(revenue_per_day, digits = 4)
```

6. Manage data

6.1. Import and generate data

6.1.1. Assigning data to an object using the assignment operator <-

Suppose I'm trying to calculate how much money I'm going to make from selling an item. Let's assume you sell 350 units. To create a variable called `sales` and assigns a value to it, we need to use the assignment operator of R, that is, `<-`:

```
sales <- 350
```

When you send that line of code to the console, it doesn't print out any output but it creates the object `sales`. In Rstudio, you can see the object in the *environment panel* at the top right. Alternatively, you can call the object in the console:

```
sales
```

```
[1] 350
```

R also allows to use `->` and `=` for the assignment. For example, the following ways of assigning data are equivalent:

```
350 -> sales
sales = 350
sales <- 350
```

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

6.1.2. 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
```

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```
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
```

6. Manage data

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 [Section 6.2](#).

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

Exercise

See exercise in [Section 8.1: Import data with `c\(\)`.](#)

6.1.3. 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.

6.1.4. 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
```

6.1.5. 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 example, `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:

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```
# 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")
```

Warning: `wb()` was deprecated in wbstats 1.0.0.
i Please use `wb_data()` instead.

```
head(df_gdp, 3)
```

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

```
glimpse(df_gdp)
```

```
Rows: 13,198
Columns: 7
$ iso3c      <chr> "AFE", "AFE", "AFE", "AFE", "AFE", "AFE", "AFE", "A~
$ date       <chr> "2022", "2021", "2020", "2019", "2018", "2017", "2016", "2~
$ value      <dbl> 1.185138e+12, 1.086531e+12, 9.288802e+11, 1.006191e+12, 1.~
$ indicatorID <chr> "NY.GDP.MKTP.CD", "NY.GDP.MKTP.CD", "NY.GDP.MKTP.CD", "NY.~
$ indicator    <chr> "GDP (current US$)", "GDP (current US$)", "GDP (current US~
$ iso2c      <chr> "ZH", "ZH", "ZH", "ZH", "ZH", "ZH", "ZH", "ZH", "ZH"~
$ country     <chr> "Africa Eastern and Southern", "Africa Eastern and Souther~
```

```
summary(df_gdp)
```

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

Figure 6.1.: The logo of the packages `readr`, `haven`, and `readxl`

6.1.6. 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.

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

6.1.7. Examples

Flat files such as CSV (Comma-Separated Values) are among the most common and straightforward data formats to work with.

```
data_csv <- read_csv("https://github.com/hubchev/courses/raw/main/dta/classdata.csv")
```

Excel files, due to their wide use in business and research, require a specific approach specifying sheets and cell ranges.

```
BWL_Zeitschriftenliste <-
  read_excel(
    "https://www.forschungsmonitoring.org/VWL_Zeitschriftenliste%202023.xlsx",
    sheet = "SJR main",
    range = "A1:D1977"
  )
```

6.2. Data

6.2.1. Data frames and tibbles

Figure 6.2.: 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).

6.2.2. 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 Figure 6.3. 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.

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

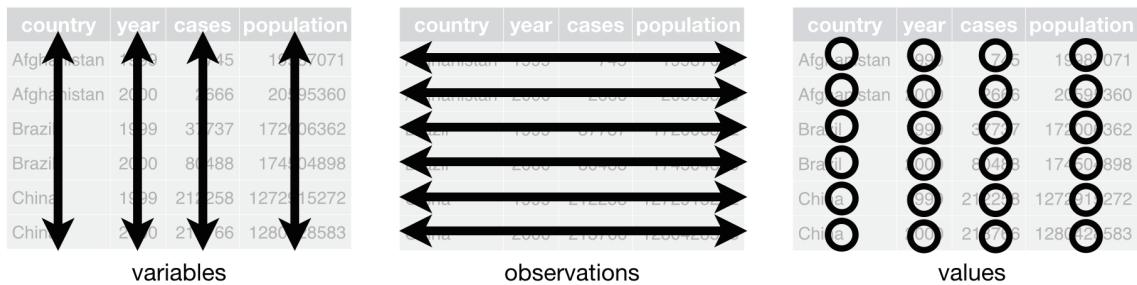
One difference between data frames and tibbles is that dataframes store the row names. For example, take the `mtcars` dataset which consists of 32 different cars and the names of the cars are not stored as rownames:

```
class(mtcars) # mtcars is a data frame
```

```
[1] "data.frame"
```

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Figure 6.3.: Features of a tidy dataset: variables are columns, observations are rows, and values are cells



Source: *Wickham and Grolemund [2023]*.

```
rownames(mtcars)
```

```
[1] "Mazda RX4"           "Mazda RX4 Wag"      "Datsun 710"
[4] "Hornet 4 Drive"      "Hornet Sportabout" "Valiant"
[7] "Duster 360"          "Merc 240D"        "Merc 230"
[10] "Merc 280"            "Merc 280C"        "Merc 450SE"
[13] "Merc 450SL"          "Merc 450SLC"      "Cadillac Fleetwood"
[16] "Lincoln Continental" "Chrysler Imperial" "Fiat 128"
[19] "Honda Civic"         "Toyota Corolla"   "Toyota Corona"
[22] "Dodge Challenger"    "AMC Javelin"     "Camaro Z28"
[25] "Pontiac Firebird"    "Fiat X1-9"       "Porsche 914-2"
[28] "Lotus Europa"        "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> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <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
```

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When we look at the data, we've lost the names of the cars. To store 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  carb
  <chr>     <dbl> <dbl>
1 Mazda RX4    21      6   160   110   3.9   2.62  16.5     0     1     4     4
2 Mazda RX4 W~  21      6   160   110   3.9   2.88  17.0     0     1     4     4
3 Datsun 710   22.8     4   108    93   3.85  2.32  18.6     1     1     4     1
```

6.2.3. 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.

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- `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.

6.3. Operators

An overview of the most important operators of R is provided in Appendix B.

6.3.1. Algebraic operators

R can perform any kind of arithmetic calculation using the operators listed in Table 6.1.

Table 6.1.: Basic algebraic operators

Operation	Operator	Example input	Example output
addition	<code>+</code>	<code>10+2</code>	12
subtraction	<code>-</code>	<code>9-3</code>	6
multiplication	<code>*</code>	<code>5*5</code>	25
division	<code>/</code>	<code>10/3</code>	3
power	<code>^</code>	<code>5^2</code>	25

6.3.2. 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.

 Tip 8: Set the native pipe in RStudio

With the keyboard shortcut `Ctrl+Shift+M`, RStudio inserts `%>%`. To change that behavior, simply check the box labeled “Use native pipe operator, `|>`” in the Global Options, see: `Tools > Global Options > Code > Editing`.

Consider the following example of code to explain the usage of the pipe operator:

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```
# 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.
```

Exercise

See exercise in Section 8.3: *Base R, %in% operator, and the pipe />*.

6.3.3. 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()`.

Exercise

See exercise in Section 8.3: *Base R, %in% operator, and the pipe />*.

6.3.4. 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,

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```
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"]].

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6.3.5. 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 6.2.

Table 6.2.: 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	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
Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1
Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3	2
Valiant	18.1	6	225.0	105	2.76	3.460	20.22	1	0	3	1
Duster 360	14.3	8	360.0	245	3.21	3.570	15.84	0	0	3	4
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
Merc 450SE	16.4	8	275.8	180	3.07	4.070	17.40	0	0	3	3
Merc 450SL	17.3	8	275.8	180	3.07	3.730	17.60	0	0	3	3
Merc 450SLC	15.2	8	275.8	180	3.07	3.780	18.00	0	0	3	3
Cadillac Fleetwood	10.4	8	472.0	205	2.93	5.250	17.98	0	0	3	4
Lincoln Continental	10.4	8	460.0	215	3.00	5.424	17.82	0	0	3	4
Chrysler Imperial	14.7	8	440.0	230	3.23	5.345	17.42	0	0	3	4
Dodge Challenger	15.5	8	318.0	150	2.76	3.520	16.87	0	0	3	2
AMC Javelin	15.2	8	304.0	150	3.15	3.435	17.30	0	0	3	2
Camaro Z28	13.3	8	350.0	245	3.73	3.840	15.41	0	0	3	4
Pontiac Firebird	19.2	8	400.0	175	3.08	3.845	17.05	0	0	3	2
Ford Pantera L	15.8	8	351.0	264	4.22	3.170	14.50	0	1	5	4
Ferrari Dino	19.7	6	145.0	175	3.62	2.770	15.50	0	1	5	6
Maserati Bora	15.0	8	301.0	335	3.54	3.570	14.60	0	1	5	8

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

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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
AMC Javelin	15.2	8	304.0	150	3.15	3.435	17.30	0	0	3	2
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
Ford Pantera L	15.8	8	351.0	264	4.22	3.170	14.50	0	1	5	4
Ferrari Dino	19.7	6	145.0	175	3.62	2.770	15.50	0	1	5	6
Maserati Bora	15.0	8	301.0	335	3.54	3.570	14.60	0	1	5	8
Volvo 142E	21.4	4	121.0	109	4.11	2.780	18.60	1	1	4	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

6.4. Data manipulation

6.4.1. dplyr: A human readable grammar of data manipulation

Figure 6.4.: The logo of the dplyr package



The **dplyr** package is part of tidyverse and makes data manipulation easy as it works well with the pipe operator `|>`. The most important function are the following:

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

These functions can be used in conjunction with `group_by()` and/or `rowwise()`, which changes the scope of each function from operating on the entire dataset to operating on it group-by-group or by rows. Moreover, you can check for conditions and take action with, for example, `if_else()` and `case_when()`.

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.

Read the vignette of `dplyr` that you find [here](#) or with:

```
vignette("dplyr")
```

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

```
library(tidyverse)

# load mtcars dataset
data(mtcars)

# filter only cars with four gears
mtcars_gear_4 <- mtcars |>
  filter(carb == 4)

# arrange rows by mpg in descending order
mtcars_gear_4 |>
  arrange(desc(mpg))
```

	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
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
Ford Pantera L	15.8	8	351.0	264	4.22	3.170	14.50	0	1	5	4
Chrysler Imperial	14.7	8	440.0	230	3.23	5.345	17.42	0	0	3	4
Duster 360	14.3	8	360.0	245	3.21	3.570	15.84	0	0	3	4
Camaro Z28	13.3	8	350.0	245	3.73	3.840	15.41	0	0	3	4
Cadillac Fleetwood	10.4	8	472.0	205	2.93	5.250	17.98	0	0	3	4
Lincoln Continental	10.4	8	460.0	215	3.00	5.424	17.82	0	0	3	4

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```
# Change the order of the variables  
glimpse(mtcars_gear_4)
```

```
Rows: 10  
Columns: 11  
$ mpg <dbl> 21.0, 21.0, 14.3, 19.2, 17.8, 10.4, 10.4, 14.7, 13.3, 15.8  
$ cyl <dbl> 6, 6, 8, 6, 6, 8, 8, 8, 8, 8  
$ disp <dbl> 160.0, 160.0, 360.0, 167.6, 167.6, 472.0, 460.0, 440.0, 350.0, 35~  
$ hp <dbl> 110, 110, 245, 123, 123, 205, 215, 230, 245, 264  
$ drat <dbl> 3.90, 3.90, 3.21, 3.92, 3.92, 2.93, 3.00, 3.23, 3.73, 4.22  
$ wt <dbl> 2.620, 2.875, 3.570, 3.440, 3.440, 5.250, 5.424, 5.345, 3.840, 3.~  
$ qsec <dbl> 16.46, 17.02, 15.84, 18.30, 18.90, 17.98, 17.82, 17.42, 15.41, 14~  
$ vs <dbl> 0, 0, 0, 1, 1, 0, 0, 0, 0, 0  
$ am <dbl> 1, 1, 0, 0, 0, 0, 0, 0, 0, 1  
$ gear <dbl> 4, 4, 3, 4, 4, 3, 3, 3, 3, 5  
$ carb <dbl> 4, 4, 4, 4, 4, 4, 4, 4, 4, 4
```

```
mtcars_gear_4 |>  
  relocate(cyl, disp, carb) |>  
  glimpse()
```

```
Rows: 10  
Columns: 11  
$ cyl <dbl> 6, 6, 8, 6, 6, 8, 8, 8, 8, 8  
$ disp <dbl> 160.0, 160.0, 360.0, 167.6, 167.6, 472.0, 460.0, 440.0, 350.0, 35~  
$ carb <dbl> 4, 4, 4, 4, 4, 4, 4, 4, 4, 4  
$ mpg <dbl> 21.0, 21.0, 14.3, 19.2, 17.8, 10.4, 10.4, 14.7, 13.3, 15.8  
$ hp <dbl> 110, 110, 245, 123, 123, 205, 215, 230, 245, 264  
$ drat <dbl> 3.90, 3.90, 3.21, 3.92, 3.92, 2.93, 3.00, 3.23, 3.73, 4.22  
$ wt <dbl> 2.620, 2.875, 3.570, 3.440, 3.440, 5.250, 5.424, 5.345, 3.840, 3.~  
$ qsec <dbl> 16.46, 17.02, 15.84, 18.30, 18.90, 17.98, 17.82, 17.42, 15.41, 14~  
$ vs <dbl> 0, 0, 0, 1, 1, 0, 0, 0, 0, 0  
$ am <dbl> 1, 1, 0, 0, 0, 0, 0, 0, 0, 1  
$ gear <dbl> 4, 4, 3, 4, 4, 3, 3, 3, 3, 5
```

```
mtcars_gear_4 |>  
  relocate(sort(names(mtcars_gear_4))) |>  
  glimpse()
```

```
Rows: 10  
Columns: 11  
$ am <dbl> 1, 1, 0, 0, 0, 0, 0, 0, 0, 1  
$ carb <dbl> 4, 4, 4, 4, 4, 4, 4, 4, 4, 4  
$ cyl <dbl> 6, 6, 8, 6, 6, 8, 8, 8, 8, 8  
$ disp <dbl> 160.0, 160.0, 360.0, 167.6, 167.6, 472.0, 460.0, 440.0, 350.0, 35~  
$ drat <dbl> 3.90, 3.90, 3.21, 3.92, 3.92, 2.93, 3.00, 3.23, 3.73, 4.22  
$ gear <dbl> 4, 4, 3, 4, 4, 3, 3, 3, 3, 5  
$ hp <dbl> 110, 110, 245, 123, 123, 205, 215, 230, 245, 264  
$ mpg <dbl> 21.0, 21.0, 14.3, 19.2, 17.8, 10.4, 10.4, 14.7, 13.3, 15.8
```

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```
$ qsec <dbl> 16.46, 17.02, 15.84, 18.30, 18.90, 17.98, 17.82, 17.42, 15.41, 14~  
$ vs    <dbl> 0, 0, 0, 1, 1, 0, 0, 0, 0  
$ wt    <dbl> 2.620, 2.875, 3.570, 3.440, 3.440, 5.250, 5.424, 5.345, 3.840, 3.~
```

```
# filter rows where cyl = 4  
mtcars_gear_4 |>  
  filter(cyl == 4)
```

```
[1] mpg cyl disp hp drat wt qsec vs am gear carb  
<0 rows> (or 0-length row.names)
```

```
# select columns mpg, cyl, and hp  
mtcars_gear_4 |>  
  select(mpg, cyl, hp) |>  
  head()
```

	mpg	cyl	hp
Mazda RX4	21.0	6	110
Mazda RX4 Wag	21.0	6	110
Duster 360	14.3	8	245
Merc 280	19.2	6	123
Merc 280C	17.8	6	123
Cadillac Fleetwood	10.4	8	205

```
# select columns all variables except wt and hp  
mtcars_gear_4 |>  
  select(-wt, -hp) |>  
  head()
```

	mpg	cyl	disp	drat	qsec	vs	am	gear	carb
Mazda RX4	21.0	6	160.0	3.90	16.46	0	1	4	4
Mazda RX4 Wag	21.0	6	160.0	3.90	17.02	0	1	4	4
Duster 360	14.3	8	360.0	3.21	15.84	0	0	3	4
Merc 280	19.2	6	167.6	3.92	18.30	1	0	4	4
Merc 280C	17.8	6	167.6	3.92	18.90	1	0	4	4
Cadillac Fleetwood	10.4	8	472.0	2.93	17.98	0	0	3	4

```
# select only variables starting with `c`  
mtcars_gear_4 |>  
  select(starts_with("c"))
```

	cyl	carb
Mazda RX4	6	4
Mazda RX4 Wag	6	4
Duster 360	8	4
Merc 280	6	4
Merc 280C	6	4
Cadillac Fleetwood	8	4

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```
Lincoln Continental    8     4
Chrysler Imperial     8     4
Camaro Z28             8     4
Ford Pantera L         8     4
```

```
# summarize avg mpg by number of cylinders
mtcars_gear_4 |>
  group_by(cyl) |>
  summarize(avg_mpg = mean(mpg))
```

```
# A tibble: 2 x 2
  cyl   avg_mpg
  <dbl>   <dbl>
1     6     19.8
2     8     13.2
```

```
# create new column wt_kg, which is wt in kg
mtcars_gear_4 |>
  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
Duster 360	3.570	1.619048
Merc 280	3.440	1.560091
Merc 280C	3.440	1.560091
Cadillac Fleetwood	5.250	2.380952

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

# Print the first few rows of the updated dataset
head(mtcars_new)
```

	wt	hp	hp_per_t
Mazda RX4	2.620	110	41.98473
Mazda RX4 Wag	2.875	110	38.26087
Datsun 710	2.320	93	40.08621
Hornet 4 Drive	3.215	110	34.21462
Hornet Sportabout	3.440	175	50.87209
Valiant	3.460	105	30.34682

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```
# Rename hp to horsepower
mtcars_gear_4 |>
  rename(horsepower = hp) |>
  glimpse()
```

Rows: 10
Columns: 11

	mpg	cyl	disp	horsepower	drat	wt	qsec	vs	am	gear	carb
	<dbl> 21.0, 21.0, 14.3, 19.2, 17.8, 10.4, 10.4, 14.7, 13.3, 15.8	<dbl> 6, 6, 8, 6, 6, 8, 8, 8, 8, 8	<dbl> 160.0, 160.0, 360.0, 167.6, 167.6, 472.0, 460.0, 440.0, 350~	<dbl> 110, 110, 245, 123, 123, 205, 215, 230, 245, 264	<dbl> 3.90, 3.90, 3.21, 3.92, 3.92, 2.93, 3.00, 3.23, 3.73, 4.22	<dbl> 2.620, 2.875, 3.570, 3.440, 3.440, 5.250, 5.424, 5.345, 3.8~	<dbl> 16.46, 17.02, 15.84, 18.30, 18.90, 17.98, 17.82, 17.42, 15.~	<dbl> 0, 0, 0, 1, 1, 0, 0, 0, 0, 0	<dbl> 1, 1, 0, 0, 0, 0, 0, 0, 1	<dbl> 4, 4, 3, 4, 4, 3, 3, 3, 3, 5	<dbl> 4, 4, 4, 4, 4, 4, 4, 4, 4, 4

Exercise

See exercise:

- Section 8.4: *Generate and drop variables*
- Section 8.5: *Subsetting*

6.4.2. 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 `if_else()` 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."
```

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```
# 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$mpg_category <- if_else(mtcars_2$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 Section 6.4.1).

6.4.3. Examining and cleaning data with the `janitor` package

The `janitor` package follows the principles of the tidyverse and works well with the pipe operator `|>`. The `janitor` functions expedite the initial data exploration and cleaning that comes with any new data set.

First, make sure the `janitor` package is loaded:

```
library("janitor")
```

```
Attaching package: 'janitor'
```

The following objects are masked from 'package:stats':

```
chisq.test, fisher.test
```

6.4.3.1. Clean data.frame names with `clean_names()`

Call this function every time you read data.

It works in a `|>` pipeline and handles problematic variable names, especially those that are so well-preserved by `readxl::read_excel()` and `readr::read_csv()`.

- Parses letter cases and separators to a consistent format.
 - Default is to snake_case, but other cases like camelCase are available
- Handles special characters and spaces, including transliterating characters like `æ` to `oe`.
- Appends numbers to duplicated names
- Converts “%” to “percent” and “#” to “number” to retain meaning
- Spacing (or lack thereof) around numbers is preserved

```
# Create a data.frame with dirty names
test_df <- as.data.frame(matrix(ncol = 6))
names(test_df) <- c(
  "firstName", "ábc@!*", "% successful (2009)",
  "REPEAT VALUE", "REPEAT VALUE", ""
)
```

Clean the variable names, returning a data.frame:

```
test_df |>
  clean_names()
```

	first_name	abc	percent_successful_2009	repeat_value	repeat_value_2	x
1	NA	NA		NA	NA	NA NA

Compare to what base R produces:

```
make.names(names(test_df))
```

	[1] "firstName"	"ábc..."	"X..successful..2009."
[4]	"REPEAT.VALUE"	"REPEAT.VALUE"	"X"

This function is powered by the underlying exported function `make_clean_names()`, which accepts and returns a character vector of names (see below). This allows for cleaning the names of *any* object, not just a data.frame. `clean_names()` is retained for its convenience in piped workflows, and can be called on an `sf` simple features object or a `tbl_graph` tidygraph object in addition to a data.frame.

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6.4.3.2. Find duplicated values for specific combinations of variables with `get_dups()`

`get_dups` allows you to check for the identifying variable. In other words, it shows you duplicates for specific combinations of variables.

For example, consider the following tibble:

```
df_panel <- tibble(
  country = c(rep("a", 3), rep("b", 3), rep("c", 3)),
  year = rep(1:3, 3),
  GDP = c(1000, 2000, 3000, 4000, 5000, 6000, 7000, 8000, 9000)
)
df_panel
```

```
# A tibble: 9 x 3
  country   year   GDP
  <chr>     <int> <dbl>
1 a          1    1000
2 a          2    2000
3 a          3    3000
4 b          1    4000
5 b          2    5000
6 b          3    6000
7 c          1    7000
8 c          2    8000
9 c          3    9000
```

with

```
get_dups(df_panel, country, year)
```

No duplicate combinations found of: country, year

```
# A tibble: 0 x 4
# i 4 variables: country <chr>, year <int>, dupe_count <int>, GDP <dbl>
```

we see that this is a panel dataset identified by a combination of `country` and `year`. Now let us introduce a duplicate and check again:

```
new_obs <- tibble(country = "b", year = 2, GDP = 5000)
df_panel_dup <- bind_rows(df_panel, new_obs)
get_dups(df_panel_dup, country, year)
```

```
# A tibble: 2 x 4
  country   year dupe_count   GDP
  <chr>     <dbl>      <int> <dbl>
1 b          2        2    5000
2 b          2        2    5000
```

 Tip 9: The `plm` package

Speaking of panel datasets, it's worth mentioning the `plm` package, which is excellent for managing such data. For example, you can use `is.pbalanced` to verify whether a panel is balanced, meaning it has the same years for all countries.

```
pacman::p_load(plm)
is.pbalanced(df_panel)
```

```
[1] TRUE
```

If your panel is unbalanced, you can use `make.pbalanced` to rectify it:

```
df_unbal <- df_panel |>
  filter(row_number() != 7)
df_unbal
```

```
# A tibble: 8 x 3
  country year   GDP
  <chr>   <int> <dbl>
1 a         1 1000
2 a         2 2000
3 a         3 3000
4 b         1 4000
5 b         2 5000
6 b         3 6000
7 c         2 8000
8 c         3 9000
```

```
is.pbalanced(df_unbal)
```

```
[1] FALSE
```

```
df_unbal_balanced <- make.pbalanced(df_unbal)
df_unbal_balanced
```

```
country year   GDP
1       a    1 1000
2       a    2 2000
3       a    3 3000
4       b    1 4000
5       b    2 5000
6       b    3 6000
7       c    1   NA
8       c    2 8000
9       c    3 9000
```

6.4.3.3. `remove_empty()` rows and columns

For cleaning Excel files that contain empty rows and columns after being read into R, `remove_empty` can be very helpful:

```
q <- data.frame(
  v1 = c(1, NA, 3),
  v2 = c(NA, NA, NA),
  v3 = c("a", NA, "b")
)
q |>
  remove_empty(c("rows", "cols"))
```

```
v1 v3
1 1 a
3 3 b
```

6.4.3.4. `remove_constant()` columns

Removes variables from data that contain only a single constant value (with an `na.rm` option to control whether NAs should be considered as different values from the constant).

```
a <- data.frame(good = 1:3, boring = "the same")
a
```

```
good  boring
1     1 the same
2     2 the same
3     3 the same
```

```
a |>
  remove_constant()
```

```
good
1     1
2     2
3     3
```

6.4.4. `tabyl()` - a better version of `table()`

`tabyl()` is a tidyverse-oriented replacement for `table()`. It counts combinations of one, two, or three variables, and then can be formatted with a suite of `adorn_*` functions to look just how you want. For example:

```
mtcars |>
  tabyl(gear, cyl) |>
  adorn_totals("col") |>
  adorn_percentages("row") |>
  adorn_pct_formatting(digits = 2) |>
  adorn_ns() |>
  adorn_title()
```

	cyl			Total	
gear	4	6	8		
3	6.67% (1)	13.33% (2)	80.00% (12)	100.00	(15)
4	66.67% (8)	33.33% (4)	0.00% (0)	100.00	(12)
5	40.00% (2)	20.00% (1)	40.00% (2)	100.00% (5)	

Learn more in the [tabyls vignette](#).

6.5. User-defined functions and conflicts

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`:

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```
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'
```

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The following objects are masked from 'package:plm':

between, lag, lead

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. This is one example of why I highly recommend to unload all packages at the beginning of a script and then to use `p_load` to install and load the packages that should be used in the upcoming script:

```
pacman::p_unload(all)
pacman::p_load(dplyr)
```

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()`.

6.6. Example: 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 date_var
    <dbl>        <dbl>      <chr>     <fct>      <lgl>     <date>
1       1        1.1 apple     red       TRUE     2022-01-01
2       2        2.2 banana   yellow    red       TRUE     2022-02-01
3       3        NA orange   red       TRUE     2022-03-01
4       4        4.4 cherry  blue      FALSE    2022-04-01
5       5        5.5 grape   green    TRUE     2022-05-01
```

```
summary(df)
```

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

date_var
Min.   :2022-01-01
1st Qu.:2022-02-01
Median :2022-03-01
Mean   :2022-03-02
3rd Qu.:2022-04-01
Max.   :2022-05-01
```

```
glimpse(df)
```

```
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, 2022-04-01, 2022-05--
```

6. Manage data

```
# 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))
```

6. Manage data

```
# 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 97 105 109 110 113 123 150 175 180 205 215 230 245
  4  1  1  1  2  1  1  1  1   0   1   0   1   0   0   0   0   0   0   0   0   0
```

6. Manage data

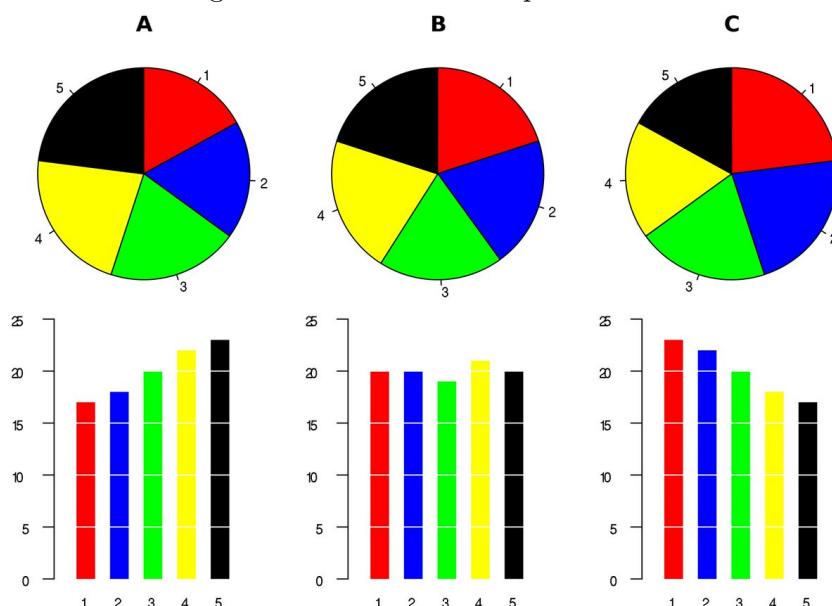
6	0	0	0	0	0	0	0	0	1	0	3	0	2	0	1	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	3	1	1	1
264	335																		
0	0																		
0	0																		
1	1																		

7. Visualize 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 Figure 7.1 may proof this.

Figure 7.1.: Pie charts are problematic



Source: https://en.wikipedia.org/wiki/Pie_chart

💡 More tips

- [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 [From Data to Viz](#) website leads you to the most appropriate graph for your data. It links to the code to build it and lists common caveats you should avoid.
- The [R Graph Gallery](#) and [R CHARTS by R CODER](#) 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.

A great resource to learn how to visualize data is [Wickham and Grolemund \[2023\]](#). As I cannot do that any better, I refer to that source and refrain from writing section myself. 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 the chapter ([Data visualization](#)) of [Wickham and Grolemund \[2023\]](#). Another good resource on modern data visualization is [Kabacoff \[2024\]](#).

💡 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.

8. Collection of exercises

8.1. Import data with `c()`

Table 8.1 shows COVID for three states in Germany:

Table 8.1.: 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`.

Loading required package: pacman

Solution

The script uses the following functions: `c`, `data.frame`, `tibble`.

R script

```
# Solution to excercise "Import data":\n\n# load packages\nif (!require(pacman)) install.packages("pacman")\npacman::p_load(tibble)\n\nstate <- c("BY", "NRW", "BW")\ndeaths <- c(4.92, 5.32, 3.69)\ncases <- c(24111, 25466, 16145)\ndf_covid <- data.frame(state, deaths)\ntbl_covid <- tibble(state, deaths)\n\nsuppressMessages(pacman::p_unload(tibble))
```

Output of the R script

```
# Solution to excercise "Import data":

# load packages
if (!require(pacman)) install.packages("pacman")
pacman::p_load(tibble)

state <- c("BY", "NRW", "BW")
deaths <- c(4.92, 5.32, 3.69)
cases <- c(24111, 25466, 16145)
df_covid <- data.frame(state, deaths)
tbl_covid <- tibble(state, deaths)

suppressMessages(pacman::p_unload(tibble))
```

8.2. Filter and select observations

Set up R, RStudio, and R packages

Open [this interactive tutorial](#) and work through it.

The script uses among others the following functions: `filter`, `is.na`, `select`.

8.3. Base R,%in% operator, and the pipe |>

- a) 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.

 Solution

The script uses the following functions: `c`, `filter`, `identical`, `if_else`, `mutate`, `subset`, `transform`, `with`.

R script

```

# Base R or pipe
# exe_base_pipe.R
# Stephan Huber; 2023-05-08

# setwd("/home/sthu/Dropbox/hsf/test")
rm(list=ls())

# load packages
if (!require(pacman)) install.packages("pacman")
pacman::p_load(datasets, tidyverse)

# a)
# Using the pipe |>
# Select rows where cyl is 4 or 6 and wt is less than 3.5
df1 <- mtcars |>
  filter(cyl %in% c(4, 6) & wt < 3.5)
df1

# Without the pipe |>
# Select rows where cyl is 4 or 6 and wt is less than 3.5
df2 <- subset(mtcars, cyl %in% c(4, 6) & wt < 3.5)
df2

# Check if the resulting dataframe is identical to the expected output
identical(df1, df2)

# b)
# Using the pipe |> and tidyverse (mutate)
df3 <- mtcars |>
  mutate(cyl_4_or_6 =
    if_else(cyl %in% c(4, 6) & wt < 3.5, TRUE, FALSE))
df3

# without pipe and with base R (transform)
df4 <- mtcars
df4$cyl_4_or_6 <- with(mtcars, cyl %in% c(4, 6) & wt < 3.5)

# Alternatively in one line:
df5 <- transform(mtcars, cyl_4_or_6 = cyl %in% c(4,6) & wt < 3.5)

# Check if the resulting dataframe is identical to the expected output
identical(df3, df4)
identical(df3, df5)

# unload packages
suppressMessages(pacman::p_unload(datasets, tidyverse))

```

8. Collection of exercises

8.4. Generate and drop variables

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

```
mtcars
```

- a) 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.
- b) 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`.
- c) Remove the variable `d_cyl_6to8` from the data frame.

Solution

The script uses the following functions: `as_tibble`, `if_else`, `mutate`, `rownames_to_column`, `select`.

R script

```
# Generate and drop variables
# exe_genanddrop.R
# Stephan Huber; 2023-05-09

# setwd("/home/sthu/Dropbox/hsf/test")
rm(list = ls())

# load packages
if (!require(pacman)) install.packages("pacman")
pacman::p_load(datasets, tidyverse)

# a)
mtcars_new <- mtcars |>
  rownames_to_column(var = "car") |>
  as_tibble() |>
  mutate(d_cyl_6to8 = if_else(cyl > 6, 1, 0))
mtcars_new

# b)
mtcars_new <- mtcars_new |>
  mutate(posercar = if_else(cyl > 6 & mpg < 18, 1, 0))
mtcars_new

# c)
mtcars_new <- mtcars_new |>
  select(-d_cyl_6to8)
mtcars_new

# unload packages
suppressMessages(pacman::p_unload(datasets, tidyverse))
```

Output of the R script

```
# Generate and drop variables
# exe_genanddrop.R
# Stephan Huber; 2023-05-09

# setwd("/home/sthu/Dropbox/hsf/test")
rm(list = ls())

# load packages
if (!require(pacman)) install.packages("pacman")
pacman::p_load(datasets, tidyverse)

# a)
mtcars_new <- mtcars |>
  rownames_to_column(var = "car") |>
  as_tibble() |>
  mutate(d_cyl_6to8 = if_else(cyl > 6, 1, 0))
mtcars_new

# A tibble: 32 x 13
  car       mpg   cyl  disp    hp  drat    wt  qsec    vs    am  gear carb
  <chr>     <dbl> <dbl>
1 Mazda RX4    21      6   160    110   3.9   2.62  16.5     0     1     4     4
2 Mazda RX4 ~   21      6   160    110   3.9   2.88  17.0     0     1     4     4
3 Datsun 710   22.8     4   108     93   3.85  2.32  18.6     1     1     4     1
4 Hornet 4 D~   21.4     6   258    110   3.08  3.22  19.4     1     0     3     1
5 Hornet Spo~   18.7     8   360    175   3.15  3.44  17.0     0     0     3     2
6 Valiant      18.1     6   225    105   2.76  3.46  20.2     1     0     3     1
7 Duster 360   14.3     8   360    245   3.21  3.57  15.8     0     0     3     4
8 Merc 240D    24.4     4   147.    62    3.69  3.19   20        1     0     4     2
9 Merc 230     22.8     4   141.    95    3.92  3.15  22.9     1     0     4     2
10 Merc 280    19.2     6   168.   123    3.92  3.44  18.3     1     0     4     4
# i 22 more rows
# i 1 more variable: d_cyl_6to8 <dbl>

# b)
mtcars_new <- mtcars_new |>
  mutate(posercar = if_else(cyl > 6 & mpg < 18, 1, 0))
mtcars_new

# A tibble: 32 x 14
  car       mpg   cyl  disp    hp  drat    wt  qsec    vs    am  gear carb posercar
  <chr>     <dbl> <dbl>
1 Mazda RX4    21      6   160    110   3.9   2.62  16.5     0     1     4     4     0
2 Mazda RX4 ~   21      6   160    110   3.9   2.88  17.0     0     1     4     4     0
3 Datsun 710   22.8     4   108     93   3.85  2.32  18.6     1     1     4     1     0
4 Hornet 4 D~   21.4     6   258    110   3.08  3.22  19.4     1     0     3     1     0
5 Hornet Spo~   18.7     8   360    175   3.15  3.44  17.0     0     0     3     2     0
6 Valiant      18.1     6   225    105   2.76  3.46  20.2     1     0     3     1     0
7 Duster 360   14.3     8   360    245   3.21  3.57  15.8     0     0     3     4     0
8 Merc 240D    24.4     4   147.    62    3.69  3.19   20        1     0     4     2     0
9 Merc 230     22.8     4   141.    95    3.92  3.15  22.9     1     0     4     2     0
10 Merc 280    19.2     6   168.   123    3.92  3.44  18.3     1     0     4     4     0
# i 22 more rows
```

8.5. 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 `|>`.

 Solution

The script uses the following functions: `arrange`, `class`, `dim`, `ends_with`, `filter`, `mutate`, `ncol`, `nrow`, `rename`, `rename_all`, `rownames_to_column`, `select`.

R script

```
# Subsetting with \R
# exe_subset.R
# Stephan Huber; 2022-06-07
```

```
# setwd("/home/sthu/Dropbox/hsf/22-ss/dsda/work/")
rm(list = ls())
```

```
# 0
```

```
# load packages
```

```
if (!require(pacman)) install.packages("pacman")
pacman::p_load(tidyverse, dplyr, tibble)
```

```
# 1
```

```
mtcars
```

```
# 2
```

```
cars <- mtcars
```

```
# 3
```

```
class(cars)
```

```
# 4
```

```
dim(cars)
```

```
# Alternative
```

```
ncol(cars)
```

```
nrow(cars)
```

```
# 5
```

```
cars <- rename(cars, MPG = mpg)
```

```
# 6
```

```
cars <- rename_all(cars, toupper)
```

```
# if you like lower cases:
```

```
# cars <- rename_all(cars, tolower)
```

```
# 7
```

```
cars <- rownames_to_column(mtcars, var = "car")
```

```
# 8
```

```
pvars <- select(cars, car, ends_with("p"))
```

```
# 9
```

```
carsSub <- select(cars, car, wt, qsec, hp)
```

```
# 10
```

```
dim(carsSub)
```

```
# 11
```

```
carsSub <- rename_all(carsSub, toupper)
```

```
# 12
```

```
cars_mpg <- filter(cars, mpg > 20)
```

```
dim(cars_mpg)
```

Output of the R script

```
# Subsetting with \R
# exe_subset.R
# Stephan Huber; 2022-06-07

# setwd("/home/sthu/Dropbox/hsf/22-ss/dsda/work/")
rm(list = ls())

# 0
# load packages
if (!require(pacman)) install.packages("pacman")
pacman::p_load(tidyverse, dplyr, tibble)

# 1
mtcars
```

8.6. 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.

Solution

The script uses the following functions: aes, arrange, desc, dir.create, dir.exists, filter, geom_point, geom_text_repel, ggplot, head, ifelse, max, min, min_max_norm, mutate, na.omit, read_dta, select, tail, theme_minimal, xlab, ylab.

R script

```

# Load the required libraries
if (!require(pacman)) install.packages("pacman")
pacman::p_load(tidyverse, haven, ggrepel)

# setwd("~/Dropbox/hsf/23-ws/R_begin")

rm(list = ls())

# Read the Stata dataset
auto <- read_dta("http://www.stata-press.com/data/r8/auto.dta")

# Create a scatter plot of price vs. weight
scatter_plot <- ggplot(auto, aes(x = mpg, y = price, label = make)) +
  geom_point() +
  geom_text_repel() +
  xlab("Miles per Gallon") +
  ylab("Price in Dollar") +
  theme_minimal()

scatter_plot

# Create "fig" directory if it doesn't already exist
if (!dir.exists("fig")) {
  dir.create("fig")
}

# Save the scatter plot in different formats
# ggsave("fig/scatter_plot.png", plot = scatter_plot, device = "png")
# ggsave("fig/scatter_plot.pdf", plot = scatter_plot, device = "pdf")

# Create 'lp100km' variable for fuel consumption
n_auto <- auto |>
  mutate(lp100km = (1 / (mpg * 1.6 / 3.8)) * 100)

# Create 'larger6000' dummy variable
n_auto <- n_auto |>
  mutate(larger6000 = ifelse(price > 6000, 1, 0))

# Normalize variables

## Do it slowly
n_auto <- n_auto |>
  mutate(sprice = (price - min(auto$price)) / (max(auto$price) - min(auto$price)))

n_auto <- n_auto |>
  filter(larger6000 == 0)

## Do it with a self-written function
min_max_norm <- function(x) {
  100
  (x - min(x, na.rm = TRUE)) / (max(x, na.rm = TRUE) - min(x, na.rm = TRUE))
}

```

8. Collection of exercises

8.7. DatasauRus

Figure 8.1.: The logo of the DatasauRus package



Source: <https://github.com/jumpingrivers/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.
- j) Create a loop that generates separate scatter plots for each unique datatset 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.

Solution

The script uses the following functions: `aes`, `cor`, `dim`, `dir.create`, `dir.exists`, `facet_wrap`, `filter`, `geom_point`, `ggplot`, `ggsave`, `glimpse`, `group_by`, `head`, `labs`, `length`, `mean`, `median`, `paste`, `paste0`, `round`, `sd`, `select`, `summarise`, `summary`, `theme`, `theme_bw`, `unique`, `view`.

R script

```

# setwd("/home/sthu/Dropbox/hsf/23-ws/ds_mim/")
rm(list = ls())

# Load the packages datasauRus and tidyverse. If necessary, install these packages.

# load packages
if (!require(pacman)) install.packages("pacman")
pacman::p_load(datasauRus, tidyverse)

# The packagedatasauRus comes with a dataset in two different formats:
#   datasaurus_dozen and datasaurus_dozen_wide. Store them as ds and ds_wide.

ds <- datasaurus_dozen
ds_wide <- datasaurus_dozen_wide

# Open and read the R vignette of the datasauRus package.
#   Also open the R documentation of the dataset datasaurus_dozen.

??datasaurus

# Explore the dataset: What are the dimensions of this dataset? Look at the descriptive

ds
dim(ds)
head(ds)
glimpse(ds)
view(ds)
summary(ds)

# 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.

unique(ds$dataset)

unique(ds$dataset) |>
  length()

# 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.

ds |>
  group_by(dataset) |>
  summarise(
    mean_x = mean(x),
    mean_y = mean(y)
  )

# Compute the standard deviation, the correlation, and the median in the same way. Round

ds |>
  group_by(dataset) |>
  summarise(
    stdev_x = sd(x),
    cor_xy = cor(x, y),
    median_y = median(y)
  )

```

8. Collection of exercises

8.8. 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.

Solution

The script uses the following functions: `aes`, `as.numeric`, `c`, `cor`, `describe`, `diff`, `filter`, `gather`, `geom_point`, `geom_text`, `ggarrange`, `ggplot`, `ggtitle`, `group_by`, `head`, `ifelse`, `lag`, `list`, `lm`, `log`, `mean`, `mutate`, `names`, `read_dta`, `select`, `set_label`, `starts_with`, `stat_smooth`, `stat_desc`, `str`, `subset`, `substr`, `summarise`, `summarise_all`, `summarise_at`, `summary`, `tab_model`, `tail`, `tbl_summary`, `vars`, `view`.

R script

```

# Convergence

# set working directory
# setwd("/home/sthu/Dropbox/hsf/github/courses/")

# clear the environment
rm(list = ls())

# load packages
if (!require(pacman)) install.packages("pacman")
pacman::p_load(
  haven, tidyverse, vtable, gtsummary, pastecs, Hmisc,
  sjlabelled, tis, ggpubr, sjPlot, psych
)

# import data
data <- read_dta("https://github.com/hubchev/courses/raw/main/dta/convergence.dta")

# inspect data
names(data)
str(data)
data
head(data)
tail(data)
summary(data)
view(data)

# library(vtable)
# vtable(data, missing=TRUE)

# library(pastecs)
stat.desc(data)

# library(Hmisc)
describe(data)

# library(gtsummary)
tbl_summary(data)

# check the assignments of countries to continents
data |>
  select(country, africa, asia, weurope) |>
  view()

data <- mutate(data, x_1 = africa + asia + weurope)

data |>
  filter(x_1 == 0) |>
  select(africa, asia, weurope, country) |>
  view()

# correct the assignment manually 106
data$weurope[data$country == "Austria"] <- 1
data$weurope[data$country == "Greece"] <- 1

```

8. Collection of exercises

8.9. 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 in 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.)

8. Collection of exercises

- (14) For the upcoming analysis you are only interested in 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.)

8. Collection of exercises

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

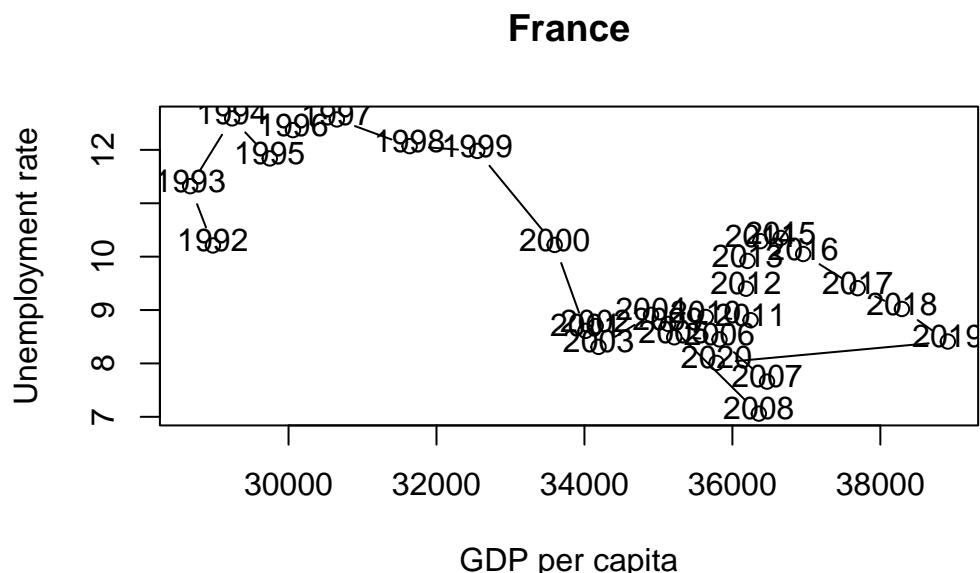
- (20) Write down the R code to calculate the coefficient of variation (COV) for the **GDP per capita** in Germany and France. (Hint: See below for what your result should look like.)

```
# 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**.

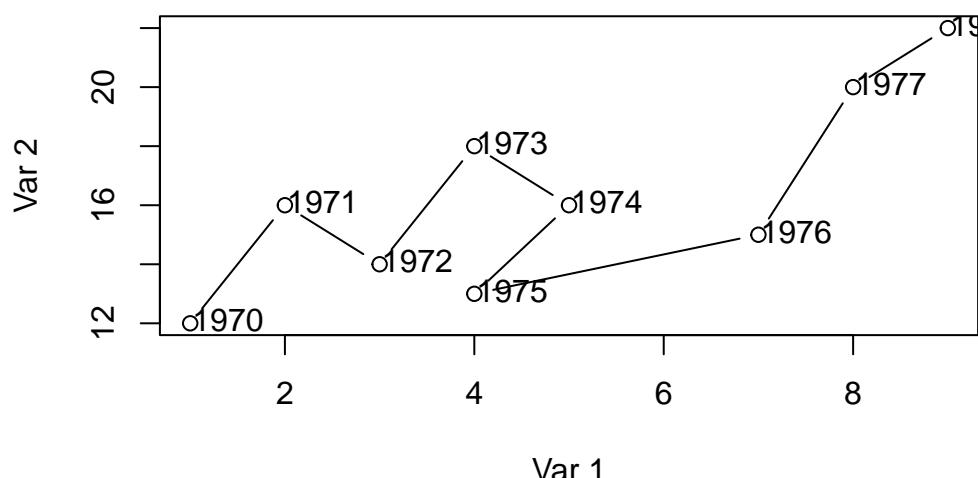


Suppose you want to visualize the simultaneous evolution of the unemployment rate and GDP per capita over time for Germany as well.

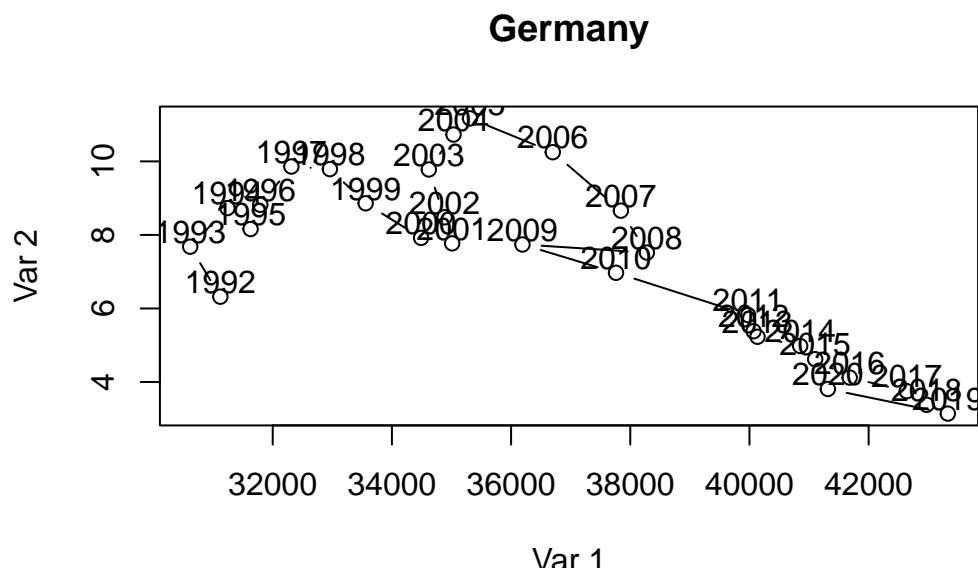
Suppose further that you have found the following lines of code that create the kind of chart you are looking for.

```
# 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, labels)
```



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.

Solution

The script uses the following functions: `aes`, `c`, `dim`, `filter`, `geom_line`, `ggplot`, `ggtitle`, `group_by`, `head`, `load`, `max`, `mean`, `mutate`, `plot`, `rename`, `sd`, `select`, `summarise`, `tail`, `text`, `title`, `url`.

R script

```

# setwd("/home/sthu/Dropbox/hsf/exams/22-11/scr/")

rm(list = ls())

if (!require(pacman)) install.packages("pacman")
pacman::p_load(tidyverse, ggpibr, sjPlot)

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

head(df, 8)

tail(df, 1)

# panel data set
# date and country.x

observations_df <- dim(df)

df <- rename(df, nation = country.x)
df <- rename(df, year = date)

df <- df |>
  select(nation, year, gdp, pop, gdppc, unemployment)

df <- df |>
  mutate(gdp_pc = gdp / pop)

df <- df |> filter(nation == "Germany" | nation == "France")

df |>
  group_by(nation) |>
  summarise(mean(unemployment), mean(gdppc))

df |>
  filter(year == 2020) |>
  group_by(nation) |>
  summarise(mean(unemployment), mean(gdppc))

df |>
  group_by(nation) |>
  summarise(max(unemployment), max(gdppc))

df |>
  group_by(nation) |>
  summarise(sd(gdppc), sd(unemployment))

df |>
  group_by(nation) |>
  summarise(sd(unemployment), mean(unemployment), cov = sd(unemployment) / mean(unemployment))

df |>
  group_by(nation) |>
  summarise(sd(gdppc), mean(gdppc), cov = sd(gdppc) / mean(gdppc))

```

8. Collection of exercises

8.10. 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()`.

Solution

The script uses the following functions: `aes`, `download.file`, `geom_line`, `ggplot`, `pivot_longer`, `read_excel`, `unzip`.

R script

```

# setwd("~/Dropbox/hsf/courses/Rlang/hortacsu")

rm(list = ls())


# install and load packages
if (!require(pacman)) install.packages("pacman")
pacman::p_load(tidyverse, readxl)

# Define the URL of the ZIP file
zipF <- "https://github.com/hubchev/courses/raw/main/dta/113962-V1.zip"

# Download the ZIP file
download.file(zipF, destfile = "113962-V1.zip")

# Unzip the contents
unzip("113962-V1.zip")

df_curves <- read_excel("Hortacsu_Syverson_JEP_Retail/diffusion_curves_figure.xlsx",
  sheet = "Data and Predictions", range = "N3:Y60"
)

df <- df_curves |>
  pivot_longer(
    cols = "Music and Video":"Food and Beverages",
    names_to = "industry",
    values_to = "value"
  )

# Plot
df |>
  ggplot(aes(x = Year, y = value, group = industry, color = industry)) +
  geom_line()

# unload packages
suppressMessages(pacman::p_unload(tidyverse, readxl))

```

Output of the R script

```
# setwd("~/Dropbox/hsf/courses/Rlang/hortacsu")

rm(list = ls())

# install and load packages
if (!require(pacman)) install.packages("pacman")
pacman::p_load(tidyverse, readxl)

# Define the URL of the ZIP file
zipF <- "https://github.com/hubchev/courses/raw/main/dta/113962-V1.zip"

# Download the ZIP file
download.file(zipF, destfile = "113962-V1.zip")

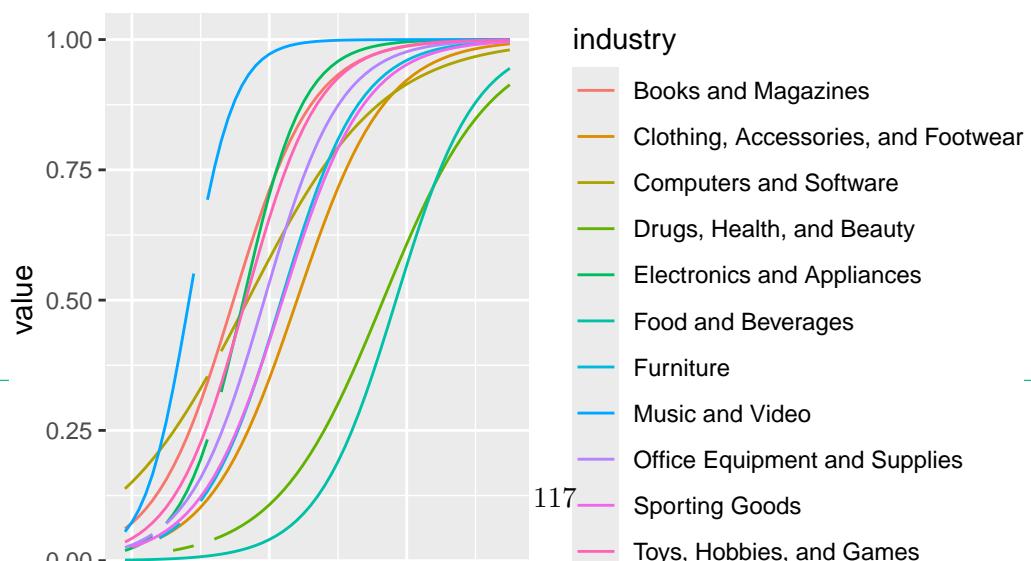
# Unzip the contents
unzip("113962-V1.zip")

df_curves <- read_excel("Hortacsu_Syverson_JEP_Retail/diffusion_curves_figure.xlsx",
  sheet = "Data and Predictions", range = "N3:Y60"
)

df <- df_curves |>
  pivot_longer(
    cols = "Music and Video": "Food and Beverages",
    names_to = "industry",
    values_to = "value"
  )

# Plot
df |>
  ggplot(aes(x = Year, y = value, group = industry, color = industry)) +
  geom_line()
```

Warning: Removed 18 rows containing missing values or values outside the scale range (`geom_line()`).



8.11. Explain the weight of students

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/classdata.csv")
```

💡 Solution

The script uses the following functions: `aes`, `c`, `coef`, `fitted`, `geom_abline`, `geom_point`, `ggplot`, `head`, `library`, `lm`, `plot`, `read.csv`, `residuals`, `show`, `stat_smooth`, `subset`, `summary`, `tab_model`.

R script

```

## ---- echo = TRUE-----
# install and load packages
if (!require(pacman)) install.packages("pacman")
pacman::p_load(tidyverse, haven)

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

head(classdata)

## ---- echo = TRUE-----

summary(classdata)

## ----pressure, echo=TRUE-----
library("ggplot2")
ggplot(classdata, aes(x = height, y = weight)) +
  geom_point()

## ---- echo=TRUE-----
ggplot(classdata, aes(x = height, y = weight)) +
  geom_point() +
  stat_smooth(formula = y ~ x, method = "lm", se = FALSE, colour = "red", linetype = 1)

## ---- echo=TRUE-----
## baseline regression model
model <- lm(weight ~ height + sex, data = classdata)
show(model)
intercept <- model$coefficients[1]
slope <- model$coefficients[2]
intercept_w <- model$coefficients[1] + model$coefficients[3]

## ---- echo=TRUE-----
summary(model)

## ---- echo=TRUE-----
ggplot(classdata, aes(x = height, y = weight, shape = sex)) +
  geom_point() +
  geom_abline(slope = slope, intercept = intercept_w, linetype = 2, size = 1.5) +
  geom_abline(slope = slope, intercept = intercept, linetype = 2, size = 1.5) +
  geom_abline(slope = coef(model)[[2]], intercept = coef(model)[[1]])

## ---- echo=TRUE-----

ggplot(classdata, aes(x = height, y = weight, shape = sex)) +
  geom_point(aes(size = 2)) +
  stat_smooth(
    formula = y ~ x, method = "lm",
    se = FALSE, colour = "red", linetype = 1
)

```

8. Collection of exercises

8.12. Calories and weight

- Write down your name, your matriculation number, and the date.
- Set your working directory.
- Clear your global environment.
- 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 dataframe 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.

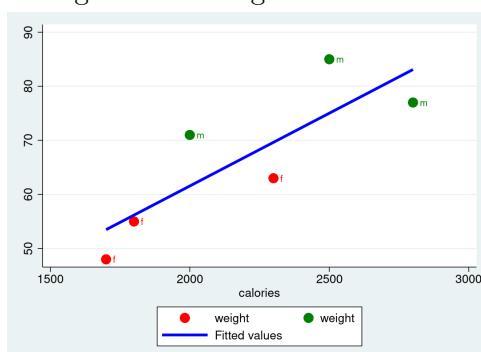
i Specify the column types or set `show_col_types = FALSE` to quiet this message.

- 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.

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- i) 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.
- j) The following plot visualizes the two variables weight and calories. Discuss what can be improved in the graphical visualization.

Figure 8.2.: Weight vs. Calories



- k) Make a scatterplot matrix containing all numerical variables.
- l) Calculate the Pearson Correlation Coefficient of the two variables
 1. `calories` and `sport`
 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: `[weight_i = _0 + _1 calories_i + _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

8. Collection of exercises

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*?

Solution

The script uses the following functions: `aes`, `c`, `cor`, `data.frame`, `geom_point`, `geom_text`, `ggplot`, `group_by`, `lm`, `mean`, `plot`, `read_csv`, `sd`, `stat_smooth`, `summarise`, `summary`.

R script

```

# 1
# Stephan Huber, 000, 2020-May-30

# 2
# setwd("/home/sthu/Dropbox/hsf/22-ss/dsb_bac/work/")

# 3
rm(list = ls())

# 4
if (!require(pacman)) install.packages("pacman")
pacman::p_load(tidyverse, haven)

# 5
# cross-section

# 6
sex <- c("f", "f", "f", "m", "m", "m")
age <- c(21, 19, 23, 18, 20, 61)
weight <- c(48, 55, 63, 71, 77, 85)
calories <- c(1700, 1800, 2300, 2000, 2800, 2500)
sport <- c(60, 120, 180, 60, 240, 30)
df <- data.frame(sex, age, weight, calories, sport)

# write_csv(df, file = "/home/sthu/Dropbox/hsf/exams/21-04/stuff/df.csv")
# write_csv(df, file = "/home/sthu/Dropbox/hsf/github/courses/dta/df-calories.csv")
df <- read_csv("https://raw.githubusercontent.com/hubchev/courses/main/dta/df-calories.csv")

# 7
summary(df)

# 8
df |>
  group_by(sex) |>
  summarise(
    mcal = mean(calories),
    sdcal = sd(calories),
    mweight = mean(weight),
    sdweight = sd(weight)
  )

# 9
# discussed in class

# 10
# Many things can be mentioned here such as the use of colors
# (red/blue is not a good choice for color blind people),
# the legend makes no sense as red and green both refer to \textit{sport},
# the label of 'f' and 'm' is not explained in the legend,
# rotating the labels of the y-axis would increase readability, and
# both axes do not start at zero which is hard to see.
# Also, it is a common to draw the variable you want to explain
# (here: calories) on the y-axis.

```

8. Collection of exercises

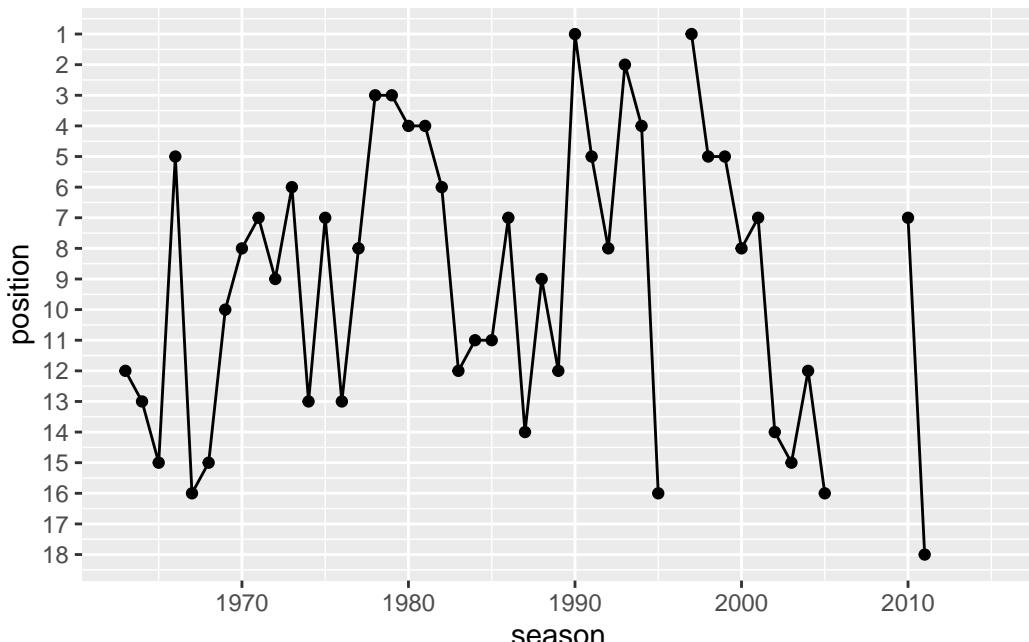
8.13. Bundesliga

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

1. Set your working directory.
2. Clear the 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 Figure 8.3, the ranking history of 1. FC Kaiserslautern is shown. Replicate that plot.

Figure 8.3.: Ranking history: 1. FC Kaiserslautern

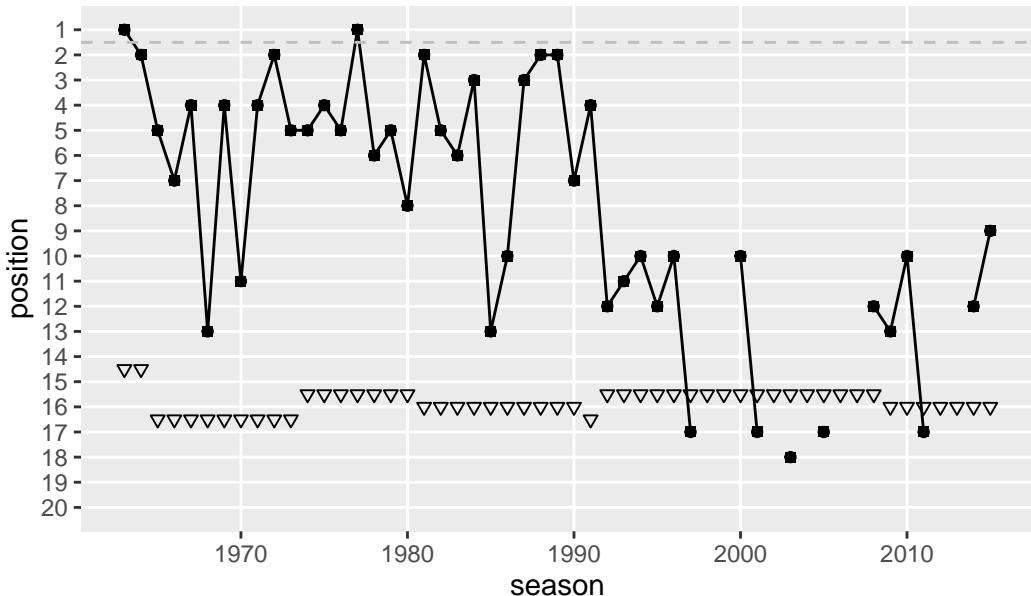


34. In Figure Figure 8.4, I made the graph a bit nicer. Can you spot all differences and can you guess what the dashed line and the triangles mean? How could the visualization be improved further? Reproduce the plot.
35. Try to make the ranking history for each club ever played the league and export the graph as a `.png` file.

Solution

The script uses the following functions: `aes`, `arrange`, `as_tibble`, `as.numeric`, `between`, `c`, `case_when`, `class`, `complete`, `desc`, `dir.create`, `dir.exists`, `element_blank`, `facet_wrap`, `factor`, `filter`, `geom_hline`, `geom_line`, `geom_point`, `geom_vline`, `ggplot`, `ggsave`, `glimpse`, `group_by`, `head`, `ifelse`, `is.na`, `labs`, `list`, `max`, `mutate`, `n_distinct`, `paste`, `print`, `rename`, `rename_all`, `row_number`, `scale_x_continuous`, `scale_y_continuous`, `scale_y_reverse`, `select`, `seq`, `setdiff`, `slice_head`, `subset`, `sum`, `summarise`, `summary`, `table`, `tail`, `theme`, `theme_classic`, `theme_minimal`, `unique`, `unlink`, `view`, `xlim`.

Figure 8.4.: Ranking history: 1. FC Köln
Ranking History: 1. FC Koeln



R script

```
# In dfb.R I analyze German soccer results

# set working directory
# setwd("~/Dropbox/hsf/23-ws/dsda/scripts")

# clear environment
rm(list = ls())

# (Install and) load packages
if (!require(pacman)) install.packages("pacman")
pacman::p_load(
  bundesligR,
  tidyverse
)

# Read in the data as tibble
liga <- as_tibble(bundesligR)

# -----
# !!! ERRORS / ISSUES:
# "Borussia Moenchengladbach" is also entitled "Bor. Moenchengladbach"!
# Leverkusen is falsely entitled "SV Bayer 04 Leverkusen"
# Uerdingen has changed its name several times
# Stuttgarter Kickers are named differently

# How often is "Bor. Moenchengladbach" in the data?
sum(liga$Team == "Bor. Moenchengladbach")

# show the entries
liga |>
  filter(Team == "Bor. Moenchengladbach")

# Replace "Bor. Moenchengladbach" with "Borussia Moenchengladbach"
```

8. Collection of exercises

8.14. 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.)

8. Collection of exercises

```
# 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.)

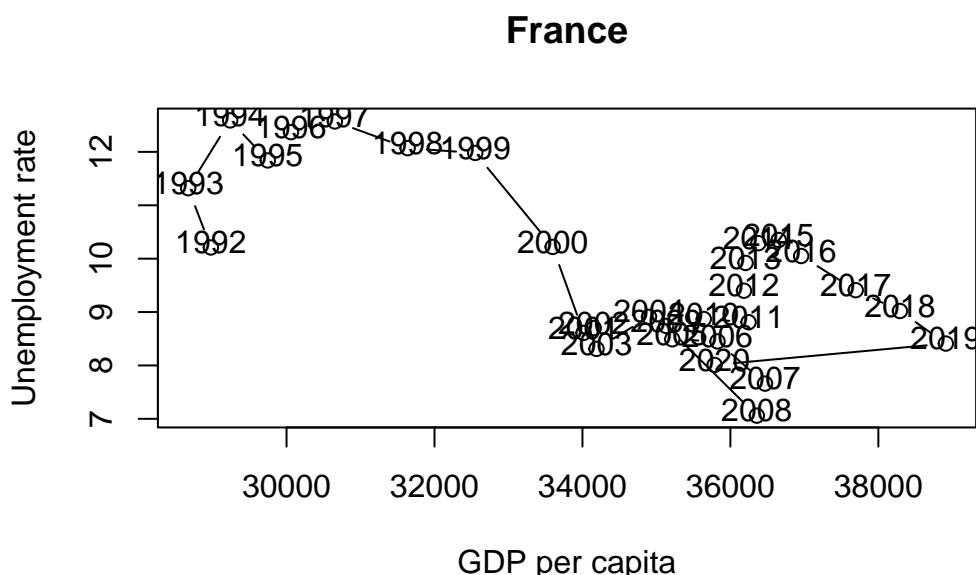
look like.)

```
# 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 simultaneous development of the unemployment rate and GDP per capita over time for **France**.



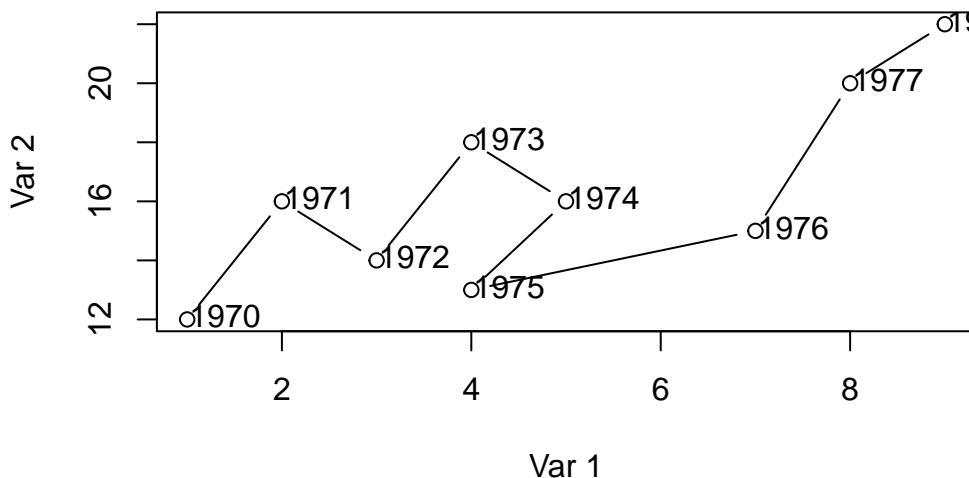
8. Collection of exercises

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

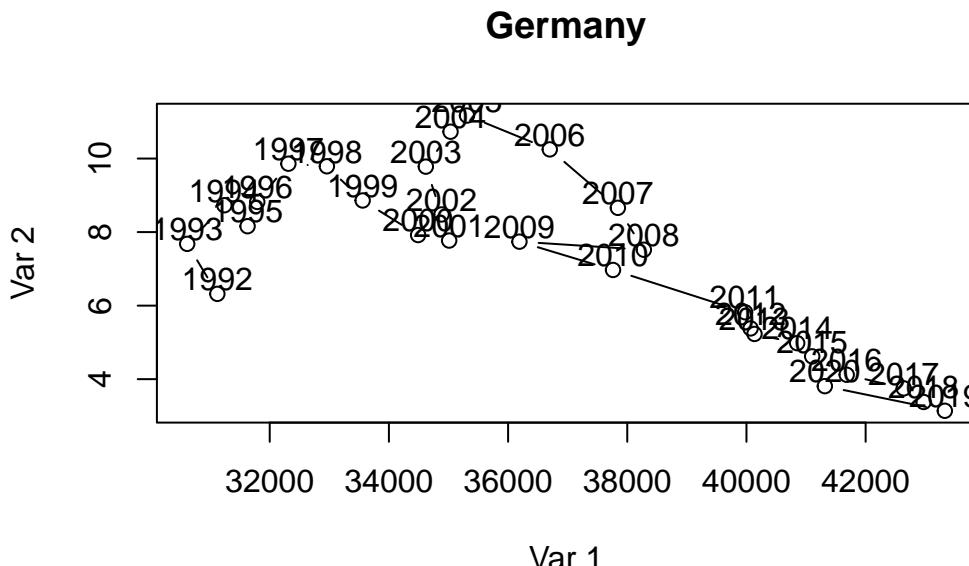
Suppose further that you have found the following lines of code that create the kind of chart you are looking for.

```
# 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, labels)
```



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.

 Solution

The script uses the following functions: `aes`, `c`, `dim`, `filter`, `geom_line`, `ggplot`, `ggtitle`, `group_by`, `head`, `load`, `max`, `mean`, `mutate`, `plot`, `rename`, `sd`, `select`, `summarise`, `tail`, `text`, `title`, `url`.

R script

```

# setwd("/home/sthu/Dropbox/hsf/exams/22-11/scr/")

rm(list = ls())

# load packages
if (!require(pacman)) install.packages("pacman")
pacman::p_load(tidyverse, ggpubr, sjPlot)

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

head(df, 8)

tail(df, 1)

# panel data set
# date and country.x

observations_df <- dim(df)

df <- rename(df, nation = country.x)
df <- rename(df, year = date)

df <- df |>
  select(nation, year, gdp, pop, gdppc, unemployment)

df <- df |>
  mutate(gdp_pc = gdp / pop)

df <- df |>
  filter(nation == "Germany" | nation == "France")

df |>
  group_by(nation) |>
  summarise(mean(unemployment), mean(gdppc))

df |>
  filter(year == 2020) |>
  group_by(nation) |>
  summarise(mean(unemployment), mean(gdppc))

df |>
  group_by(nation) |>
  summarise(max(unemployment), max(gdppc))

df |>
  group_by(nation) |>
  summarise(sd(gdppc), sd(unemployment))

df |>
  group_by(nation) |>
  summarise(sd(unemployment), mean(unemployment), cov = sd(unemployment) / mean(unemployment))

df |>
  group_by(nation) |>
  summarise(sd(gdppc), mean(gdppc), cov = sd(gdppc) / mean(gdppc))

```

8. Collection of exercises

8.15. 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?

Solution

The script uses the following functions: `anti_join`, `arrange`, `c`, `cur_group_id`, `desc`, `dim`, `distinct`, `filter`, `get_dupes`, `glimpse`, `group_by`, `head`, `load`, `max`, `mutate`, `n`, `paste`, `relocate`, `row_number`, `setdiff`, `summary`, `tail`, `ungroup`, `url`.

R script

```

# Find duplicates

# set working directory
# setwd("~/Dropbox/hsf/test/initial_script")

# clear environment
rm(list = ls())

# load packages
if (!require(pacman)) install.packages("pacman")
pacman::p_load(tidyverse, janitor, babynames, stringr)

load(url("https://github.com/hubchev/courses/raw/main/dta/df_names.RData"))

# Remove all objects except df_2022 and df_2022_error
rm(list = setdiff(ls(), c("df_2022_error", "df_2022")))

# Re-order the data so that surname, name, and age appears first.
# Save the changed data in a tibble called `df`.
df <- df_2022 |>
  relocate(surname, name, age)

# Sort the data according to surname, name, and age.
df <- df |>
  arrange(surname, name, age)

# Inspect df_2022 and df_2022_error
df
dim(df)
head(df)
tail(df)
glimpse(df)
summary(df)

df_2022_error

# Make a variable that contains the year of birth. Name the variable `born`
# and new dataframe `df`.
df <- df_2022 |>
  mutate(born = time - age)

# Make a new variable that identifies each person by surname, name,
# and their birth born. Name the variable `id`.
df <- df |>
  mutate(id = paste(surname, name, born, sep = "_"))

# How many different groups do exist?
df <- df |>
  group_by(id) |>
  mutate(id_num = cur_group_id()) |>
  ungroup()

max(df$id_num)

```

8. Collection of exercises

8.16. 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.

	<code>mean(pop2011)</code>	<code>sum(pop2011)</code>
<code>state</code>	<code><dbl></code>	<code><dbl></code>
1 Baden-Württemberg	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

8. Collection of exercises

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 `NA`s 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

8. Collection of exercises

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 Perl      NA          NA        NA           43
2 Perl      NA          NA        NA           43
3 Ahrweiler Commune    Saarland  11107       1390
4 Kleinblittersdorf Commune  Saarland  11396       1354
5 Überherrn  Commune    Saarland  11655       1317
6 Mettlach   Commune    Saarland  12180       1241
7 Tholey    Commune    Saarland  12385       1217
8 Saarwellingen Commune  Saarland  13348       1104
9 Quierschied Commune  Saarland  13506       1088
10 Spiesen-Elversberg Commune  Saarland  13509       1086
11 Rehlingen-Siersburg Commune  Saarland  14526       996
12 Riegelsberg Commune  Saarland  14763       982
13 Ottweiler   City      Saarland  14934       969
14 Beckingen  Commune    Saarland  15355       931
15 Losheim am See Commune  Saarland  15906       887
16 Schiffweiler Commune  Saarland  15993       882
17 Wadern     City      Saarland  16181       874
18 Schmelz    Commune    Saarland  16435       857
19 Sulzbach/Saar City      Saarland  16591       849
20 Illingen   Commune    Saarland  16978       827
21 Schwalbach Commune    Saarland  17320       812
22 Eppelborn   Commune    Saarland  17726       793
23 Wadgassen  Commune    Saarland  17885       785
24 Bexbach    City      Saarland  18038       777
25 Heusweiler Commune    Saarland  18201       762
26 Püttlingen  City      Saarland  19134       718
27 Lebach     City      Saarland  19484       701
28 Dillingen/Saar City      Saarland  20253       654
29 Blieskastel City      Saarland  21255       601
30 St. Wendel City      Saarland  26220       460
31 Merzig     City      Saarland  29727       392
32 Saarlouis   City      Saarland  34479       323
33 St. Ingbert City      Saarland  36645       299
34 Völklingen City      Saarland  38809       279
35 Homburg    City      Saarland  41502       247
36 Neunkirchen City      Saarland  46172       206
37 Saarbrücken City      Saarland  175853      43
```

8. Collection of exercises

1	Bonn	City with County Rights	Nordrhein-Westfalen	305765	3
2	Bonn	City with County Rights	Nordrhein-Westfalen	305765	3
3	Bonn	City with County Rights	Nordrhein-Westfalen	305765	3
4	Brühl	Commune	Baden-Württemberg	13805	2
5	Brühl	City	Nordrhein-Westfalen	43568	2
6	Erbach	City	Baden-Württemberg	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	Nordrhein-Westfalen	10473	2
11	Lichtenau	Commune	Sachsen	7544	2
12	Münster	Commune	Hessen	14071	2
13	Münster	City with County Rights	Nordrhein-Westfalen	289576	2
14	Neunkirchen	Commune	Nordrhein-Westfalen	13930	2
15	Neunkirchen	City	Saarland	46172	2
16	Neuried	Commune	Baden-Württemberg	9383	2
17	Neuried	Commune	Bayern	8277	2
18	Petersberg	Commune	Hessen	14766	2
19	Petersberg	Commune	Sachsen-Anhalt	10097	2
20	Senden	City	Bayern	21560	2
21	Senden	Commune	Nordrhein-Westfalen	19976	2
22	Staufenberg	City	Hessen	8114	2
23	Staufenberg	Commune	Niedersachsen	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.

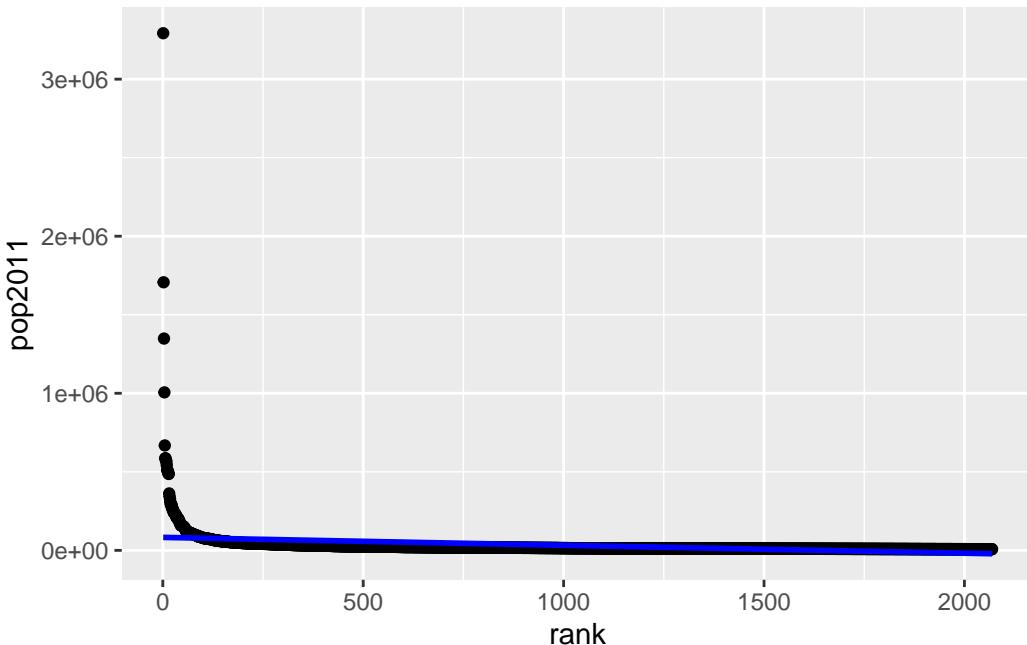
8. Collection of exercises

```
# 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:

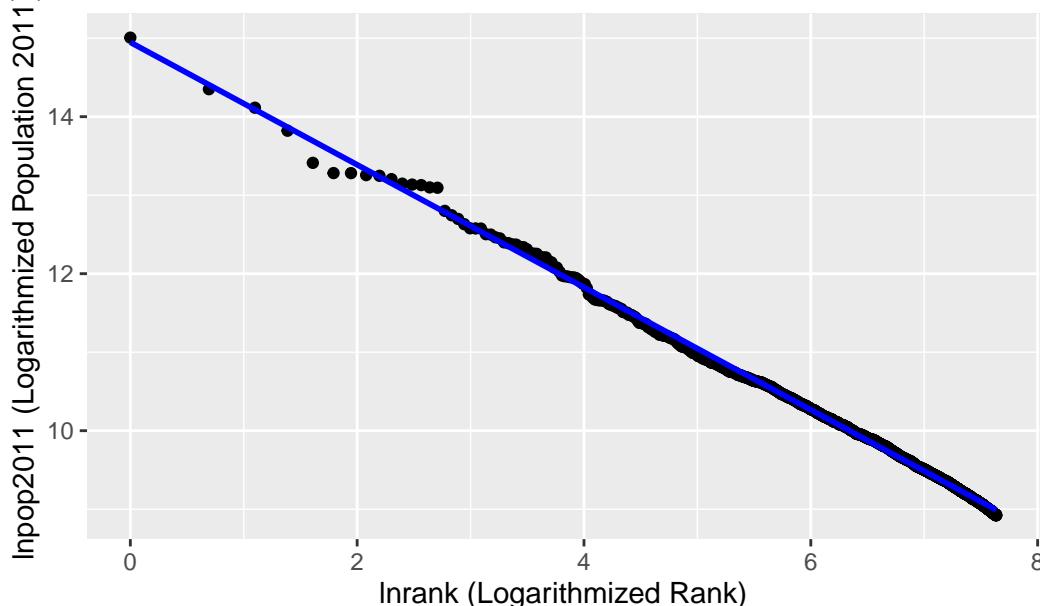
```
# A tibble: 6 x 5
  city          rank  lnrank pop2011  lnpop2011
  <chr>        <int>   <dbl>   <dbl>      <dbl>
1 Berlin         1     0.0 3292365  15.0
2 Hamburg        2     0.693 1706696  14.4
3 München [Munich] 3     1.10 1348335  14.1
4 Köln [Cologne] 4     1.39 1005775  13.8
5 Frankfurt am 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 logarithmic city size in the year 2011 on the logarithmic 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.
```

💡 Solution

The script uses the following functions: `aes`, `arrange`, `as_tibble`, `c`, `case_when`, `cor`, `desc`, `dim`, `exp`, `filter`, `geom_point`, `geom_smooth`, `ggplot`, `group_by`, `head`, `is.na`, `labs`, `lm`, `log`, `mean`, `mutate`, `n`, `predict`, `print`, `read_dta`, `rename`, `row_number`, `save`, `select`, `starts_with`, `sum`, `summarise`, `summary`, `tail`, `ungroup`.

R script

```

# load packages
if (!require(pacman)) install.packages("pacman")
suppressMessages(pacman::p_unload(all))
# setwd("~/Dropbox/hsf/exams/24-01/Rmd")

rm(list = ls())

pacman::p_load(tidyverse, haven, janitor, jtools)

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

head(df)
tail(df)

dim(df)

summary(df)

df <- df |>
  rename(city = stadt)

df <- df |>
  select(-pop1970, -pop1987)

df |>
  group_by(state) |>
  summarise(
    mean(pop2011),
    sum(pop2011)
  )

df <- df |>
  mutate(state = case_when(
    state == "Baden-Wrttemberg" ~ "Baden-Württemberg",
    state == "Th_ringen" ~ "Thüringen",
    TRUE ~ state
  ))

df |>
  group_by(state) |>
  summarise(
    mean(pop2011),
    sum(pop2011)
  )

df |>
  filter(state == "Saarland") |>
  print(n = 100)

```

8. Collection of exercises

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A. 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.

A.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.

A.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

A. Navigating the file system

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/dsr"
```

A.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 Section A.5. Let’s check the current active working directory:

A. Navigating the file system

```
getwd()
```

```
[1] "/home/sthu/Dropbox/hsf/courses/dsr"
```

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()
```

A.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.

A.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" )
```

B. Operators

B.1. Assignment:

- `<-` (assignment operator)

B.2. Arithmetic:

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

B.3. Relational:

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

B.4. Logical:

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

B.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.

C. Popular functions

C.1. Help

- `?:` Search R documentation for a specific term.
- `??` Search R help files for a word or phrase.
- `RSiteSearch`: Search search.r-project.org
- `help.start`: Access to html manuals and documentations implemented in R
- `browseVignettes`: view a list of all vignettes associated with your installed packages
- `vignette`: View a specified package vignette, that is, supporting material such as introductions.

C.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.

C.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.

C.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.

C.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.

C.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.
- `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 last n elements.
- `unique`: Extracts unique elements from a vector.
- `view`: Opens a viewer for data frames.

C.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.

C.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.

C. Popular functions

- `rownames`: Get or set the row names of a matrix-like object.
- `tibble`: Creates a tibble, a modern and tidy data frame.

C.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.

C.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.

C.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.

C. Popular functions

- `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.

D. Helpful shortcuts

Table D.1.: Table 1: Different OS, different keys

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

Table D.2.: 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.
	Alt + (-)	Inserts the assignment operator (<-) with spaces surrounding it.
Write code	Ctrl + Shift + M	Inserts the magrittr/pipe operator (%>%) with spaces surrounding it.
	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.
Navigating in RStudio	Ctrl+Tab and Ctrl+Shift+Tab	to switch between tabs.
	Ctrl + Shift + N	Open a new R script.
	Ctrl + w	Close a tab.