

The Open Science Manual
Make Your Scientific Research Accessible and Reproducible

Claudio Zandonella Callegher and Davide Massidda

04 May, 2022 [last-updated]



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Preface

Science is one of humanity’s greatest inventions. Academia, on the other hand, is not. It is remarkable how successful science has been, given the often chaotic habits of scientists. In contrast to other fields, like say landscaping or software engineering, science as a profession is largely *unprofessional* - apprentice scientists are taught less about how to work responsibly than about how to earn promotions. This results in ubiquitous and costly errors. Software development has become indispensable to scientific work. I want to playfully ask how it can become even more useful by transferring some aspects of its professionalism, the day-to-day tracking and back-tracking and testing that is especially part of distributed, open-source software development. Science, after all, aspires to be distributed, open-source knowledge development.

“Science as Amateur Software Development” Richard McElreath (2020)

https://youtu.be/zwRdO9_GGhY

Inspired by McElreath’s words, this book aims to describe programming good practices and introduce common tools used in software development to guarantee the reproducibility of analysis results. We want to make scientific research an open-source knowledge development.

The book is available online at <https://arca-dpss.github.io/manual-open-science/>.

A PDF copy is available at <https://arca-dpss.github.io/manual-open-science/manual-open-science.pdf>.

Book Summary

In the book, we will learn to:

- Share our materials using the **Open Science Framework**
- Organize project files and data in a well structured and documented **Repository**
- Write readable and maintainable code using a **Functional Style** approach
- Use **Git** and **GitHub** for tracking changes and managing collaboration during the development

- Use dedicated tools for managing the **Analysis Workflow** pipeline
- Use dedicated tools for creating **Dynamic Documents**
- Manage project requirements and dependencies using **Docker**

As most researchers have no formal training in programming and software development, we provide a very gentle introduction to many programming concepts and tools without assuming any previous knowledge.

Examples and specific applications are based on the R programming language. However, this book provides recommendations and guidelines useful for any programming language.

About the Authors

During our careers, we both moved into the field of Data Science after a PhD in Psychological Sciences. This book is our attempt to bring back into scientific research what we have learned outside of academia.

- Claudio Zandonella Callegher (claudiozandonella@gmail.com). During my PhD, I fell in love with data science. Understanding the complex phenomena that affect our lives by exploring data, formulating hypotheses, building models, and validating them. I find this whole process extremely challenging and motivating. Moreover, I am excited about new tools and solutions to enhance the replicability and transparency of scientific results.
- Davide Massidda (d.massidda@kode-solutions.net).

ARCA

ARCA courses are advanced and highly applicable courses on modern tools for research in Psychology. They are organised by the Department of Developmental and Social Psychology at the University of Padua.

Contribute

If you think there is something missing, something should be described better, or something is wrong, please, feel free to contribute to this book. Anyone is welcome to contribute to this book.

This is the heart of open-source: contribution. We will understand the real value of this book not by the number of people that will read it but by the number of people who will invest their own time trying to improve it.

For typos (the probability of typos per page is always above 1) just send a pull request with all the corrections. Instead, if you like to add new chapters or paragraphs to include new arguments or discuss more in detail some aspects, open an issue so we can find together the best way to organize the structure of the book.

View book source at GitHub repository <https://github.com/arca-dpss/manual-open-science>.

Cite

For attribution, please cite this work as:

Zandonella Callegher, C., & Massidda, D. (2022). The Open Science Manual: Make Your Scientific Research Accessible and Reproducible. <https://arca-dpss.github.io/manual-open-science/>

BibTeX citation:

```
@book{zandonellaMassiddaOpenScience2022,
  title = {The Open Science Manual: Make Your Scientific Research Accessible and Reproducible},
  author = {Zandonella Callegher, Claudio and Massidda, Davide},
  date = {2022},
  url = {https://arca-dpss.github.io/manual-open-science/}
}
```

License



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Contents

1

Introduction

Science is one of humanity's greatest inventions. Academia, on the other hand, is not. It is remarkable how successful science has been, given the often chaotic habits of scientists. In contrast to other fields, like say landscaping or software engineering, science as a profession is largely *unprofessional* - apprentice scientists are taught less about how to work responsibly than about how to earn promotions. This results in ubiquitous and costly errors. Software development has become indispensable to scientific work. I want to playfully ask how it can become even more useful by transferring some aspects of its professionalism, the day-to-day tracking and back-tracking and testing that is especially part of distributed, open-source software development. Science, after all, aspires to be distributed, open-source knowledge development.

“Science as Amateur Software Development” Richard McElreath (2020)

https://youtu.be/zwRdO9_GGhY

McElreath’s words are as enlightening as always. Usually, researchers start their academic careers led by their great interest in a specific scientific area. They want to answer some specific research question, but these questions quickly turn into data, statistical analysis, and lines of code, hundreds of lines of code. Most researchers, however, receive essentially no training about programming and software development good practices resulting in very chaotic habits that can lead to costly errors. Moreover, bad practices may

hinder the transparency and reproducibility of the analysis results.

Thanks to the Open Science movement, transparency and reproducibility are recognized as fundamental requirements of modern scientific research. In fact, openly sharing study materials and analyses code are prerequisites for allowing results replicability by new studies. Note the difference between replicability and reproducibility (Nosek & Errington, 2020):

- **Reproducibility**, obtaining the results reported in the original study using the *same data* and the *same analysis*.
- **Replicability**, obtaining the results reported in the original study using *new data* but the *same analysis* (a new study with the same experimental design).

So, reproducibility simply means re-running someone else's code on the same data to obtain the same result. At first, this may seem a very simple task, but actually, it requires properly organising and managing all the analysis material. Without adequate programming and software development skills, it is very difficult to guarantee the reproducibility of the analysis results.

The present book aims to describe programming good practices and introduce common tools used in software development to guarantee the reproducibility of analysis results. Inspired by Richard McElreath's talk, we want to make scientific research an open-source knowledge development.

1.1 Book Structure

The book is structured as follows.

- In Chapter 2, we introduce the Open Science Framework (OSF), a free, open-source web application that allows researchers to collaborate, document, archive, share, and register research projects, materials, and data.
- In Chapter ??, we describe recommended practices to organize all the materials and files of our projects and which are the advantages of creating a well structured, documented, and licensed repository.
- In Chapter ??, we discuss the main guidelines regarding organizing, documenting, and sharing data.
- In Chapter ??, we provide general good practices to create readable and maintainable code and we describe the functional style approach.
- In Chapter ??, we provide a basic tutorial about the use of the terminal.
- In Chapter ??, we introduce Git software for tracking changes in any file during the development of our project.
- In Chapter ??, we introduce GitHub for managing collaboration using remote repositories.
- In Chapter 3, we discuss how to manage the analysis workflow to enhance results reproducibility and code maintainability.

- In Chapter ??, we introduce the main tools to create dynamic documents that integrate narrative text and code describing the advantages.
- In Chapter ??, we discuss how to manage our project requirements and dependencies (software and package versions) to enhance results reproducibility.
- In Chapter ??, we introduce Docker and the container technology that allows us to create and share an isolated, controlled, standardized environment for our project.
- In Chapter ??, we introduce the Rocker Project which provides Docker Containers for the R Environment.

1.2 Instructions

Let's discuss some useful tips about how to get the best out of this book.

1.2.1 Programming Language

This book provides useful recommendations and guidelines that can be applied independently of the specific programming language used. However, examples and specific applications are based on the R programming languages.

In particular, each chapter first provides general recommendations and guidelines that apply to most programming languages. Subsequently, we discuss specific tools and applications available in R.

In this way, readers working with programming languages other than R can still find valuable guidelines and information and can later apply the same workflow and ideas using dedicated tools specific to their preferred programming language.

1.2.2 Long Journey

To guarantee results replicability and project maintainability, we need to follow all the guidelines and apply all the tools covered in this book. However, if we are not already familiar with all these arguments, it could be incredibly overwhelming at first.

Do not try to apply all guidelines and tools all at once. Our recommendation is to build our reproducible workflow gradually, introducing new guidelines and new tools step by step at any new project. In this way, we have the time to learn and familiarize ourselves with a specific part of the workflow before introducing a new step.

The book is structured to facilitate this process, as each chapter is an independent step to build our reproducible workflow:

- Share our materials using online repositories services
- Learn how to structure and organize our materials in a repository
- Follow recommendations about data organization and data sharing
- Improve code readability and maintainability using a Functional Style
- Learn version control and collaboration using Git and Github
- Manage analysis workflow with dedicated tools
- Create dynamic documents

- Manage project requirements and dependencies using dedicated tools
- Create a container to guarantee reproducibility using Docker

Learning advanced tools such as Git, pipeline tools, and Docker still requires a lot of time and practice. They may even seem excessively complex at first. However, we should consider them as an investment. As soon as our analyses will become more complex than a few lines of code, these tools will allow us to safely develop and manage our project.

1.2.3 Non-Programmer Friendly

Most of the arguments discussed in this book are the A-B-C of the daily workflow of many programmers. The problem is that most researchers lack any kind of formal training in programming and software development.

The aim of the book is exactly that: to introduce popular tools and common guidelines of software development into scientific research. We try to provide a very gentle introduction to many programming concepts and tools without assuming any previous knowledge. Note, however, that we assume the reader is already familiar with the R programming language for specific examples and applications.

1.2.4 Info Boxes

Inside the book, there are special Info-Boxes that provide further details.



Tip-Box:

Tip-Boxes are used to provide insight into specific topics.



Warning-Box:

Warning-Boxes are used to provide important warnings.



Instructions-Box:

Instructions-Boxes are used to provide detailed instructions.



Details-Box:

Details-Boxes are used to provide further details about advanced topics.



Trick-Box:

Trick-Boxes are used to describe special useful tricks.



Command Cheatsheet:

Command Cheatsheets are used to summarize commands of a specific software.

Moreover, at the end of each chapter, we list all useful links to external documentation in a dedicated box.



Documentation-Box

Documentation-Boxes are used to collect all useful links to external documentation.

1.2. Instructions

2

The Open Science Framework

In this chapter, we introduce the Open Science Framework (OSF), an open-source project that enhances open collaboration in scientific research.

2.1 OSF Introduction

The OSF is a free, open-source web application that connects and supports the research workflow, enabling scientists to increase the efficiency and effectiveness of their research (Elliott et al., 2021). Researchers can use OSF to collaborate, document, archive, share, and register research projects, materials, and data.



Although the OSF was initially used to work on a project in the reproducibility of psychology research, it has subsequently become multidisciplinary (from Wikipedia https://en.wikipedia.org/wiki/Center_for_Open_Science). The OSF can help us during any part of the research lifecycle (Elliott et al., 2021):

- **Store research materials.** The OSF allows us to store all research materials in a manageable, secure cloud environment. The OSF ensures we and our colleagues can access materials, when needed, reducing the likelihood of losing study materials.
- **Collaborate with colleagues.** With the OSF, our work is preserved and easily accessible to only those people that should have access. By sharing materials via OSF, we ensure that everyone is working with the correct, up-to-date file versions and we never lose files again.

- **Cite research materials.** The OSF can be used to share manuscripts, unpublished findings, materials, and in-progress work. The OSF makes all of it citable so that our impact is measured and we get credit for our work.
- **Measure research impact.** The OSF provides tools to help us measure our impact (e.g., download and visit counts).

In Sections 2.2, we provide a guide on how to create an account and start a project on the OSF. In Section 2.3, we describe further features useful to researchers.

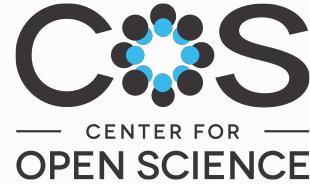
Details-Box: Title

Center for Open Science

The OSF is released by the Center for Open Science.

The Center for Open Science (COS; <https://www.cos.io>) is a non-profit technology startup founded in 2013 with a mission to increase the openness, integrity, and reproducibility of scientific research (Elliott et al., 2021).

COS pursues this mission by building communities around open science practices, supporting metascience research, and developing and maintaining free, open-source software tools.



2.2 Getting Started

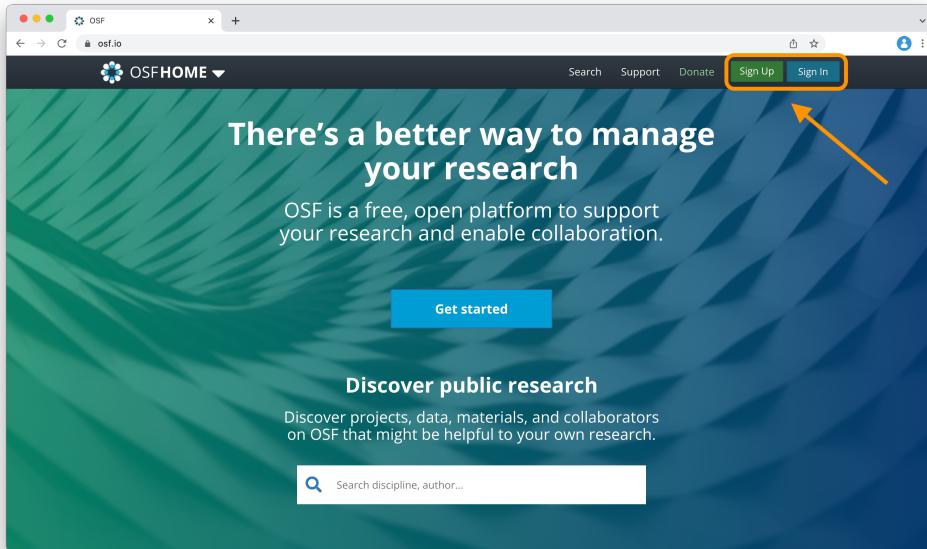
This is an introductory tutorial. For a complete guide of the OSF and a description of all features, see:

- **OSF Support** <https://help.osf.io/>
- **OSF Wiki** <https://osf.io/4znzp/wiki/home/>

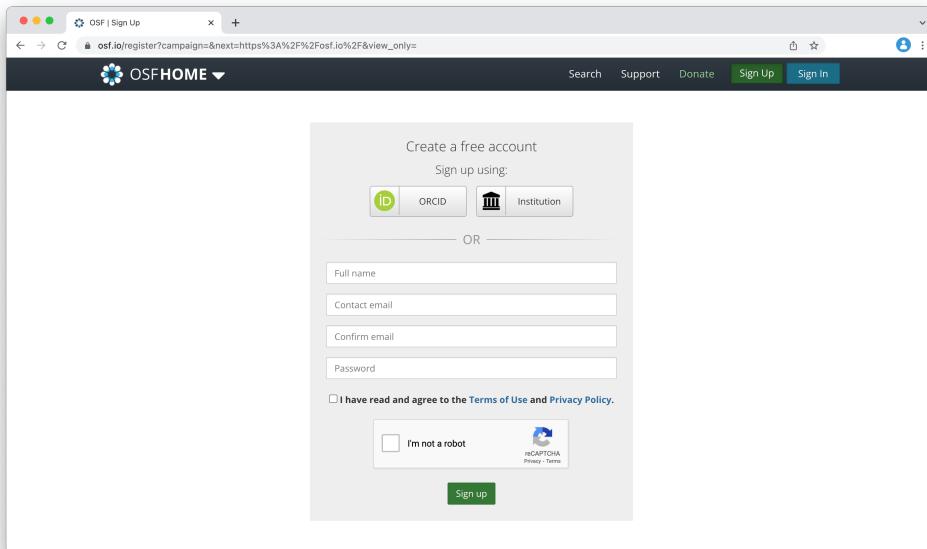
2.2.1 Subscribe

To subscribe to the OSF:

- Go to the OSF homepage (<https://osf.io>) and click the “Sign Up” (or “Sign In”) button in the top right corner.



- Create a new account or use the ORCID or Institution credential to register.

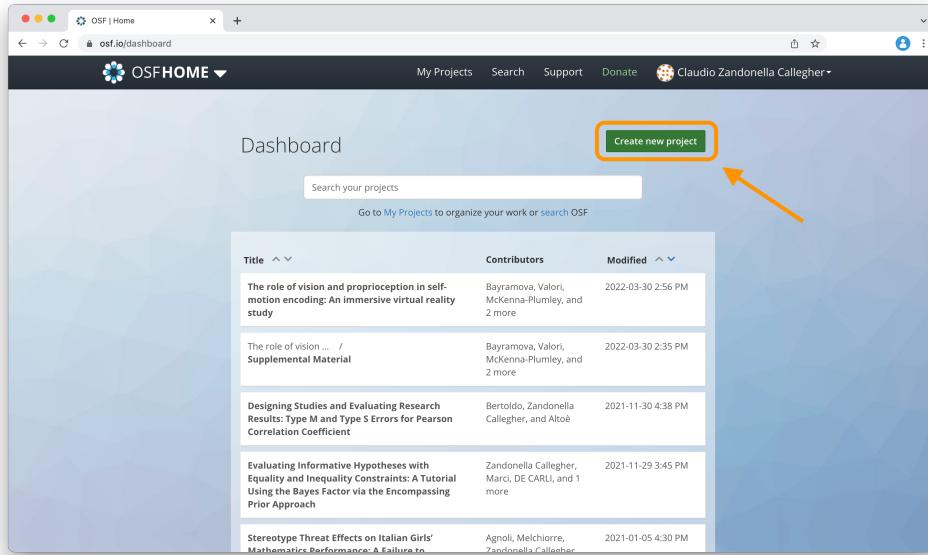


2.2.2 Create a Project

To create a new project:

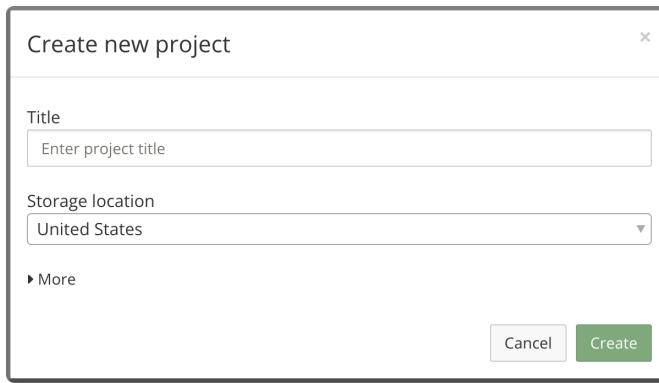
- From the user Dashboard, click the “Create new project” button.

2.2. Getting Started



The screenshot shows the OSF Home dashboard. At the top right, there is a blue button labeled "Create new project". An orange arrow points from the left towards this button. Below the button is a search bar with the placeholder "Search your projects" and a link "Go to My Projects to organize your work or search OSF". The main area displays a list of projects with columns for "Title", "Contributors", and "Modified". The first project in the list is titled "The role of vision and proprioception in self-motion encoding: An immersive virtual reality study". Other projects listed include "The role of vision ... / Supplemental Material", "Designing Studies and Evaluating Research Results: Type M and Type S Errors for Pearson Correlation Coefficient", "Evaluating Informative Hypotheses with Equality and Inequality Constraints: A Tutorial Using the Bayes Factor via the Encompassing Prior Approach", and "Stereotype Threat Effects on Italian Girls' Mathematics Performance: A Culture to ...".

- Specify the project title and store location. Next, press the “*Create*” button. Note that institutions may require that data be stored in the EU to comply with storage regulations.



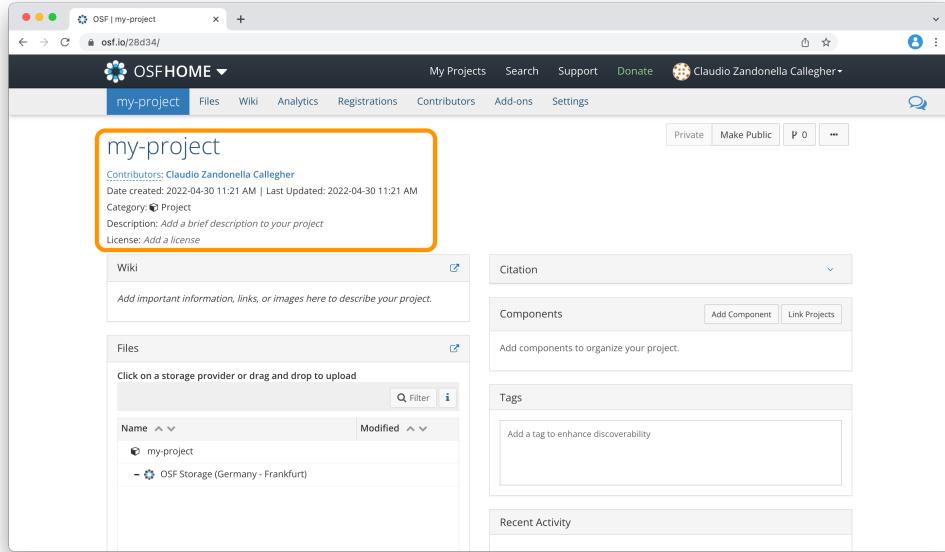
The dialog box is titled "Create new project". It has two main sections: "Title" and "Storage location". The "Title" section contains a text input field with the placeholder "Enter project title". The "Storage location" section contains a dropdown menu set to "United States". Below these sections is a "More" link. At the bottom right are "Cancel" and "Create" buttons, with "Create" being green and bold.

2.2.3 Project Homepage

The project homepage provides summary information about the project. In particular,

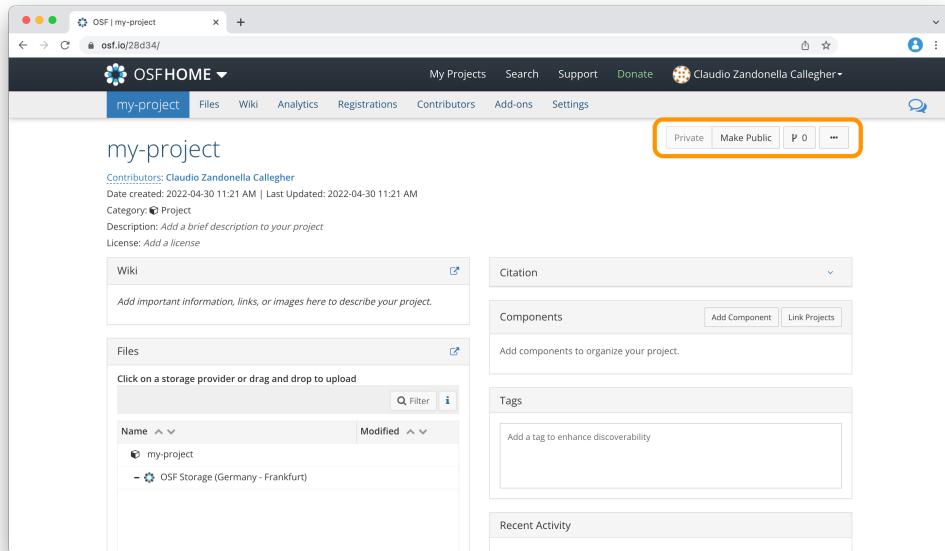
- **Project title.** The project title.
- **Contributors.** List of all contributors. See Section 2.3.2, to add new contributors to the project.
- **Date created.** Date of creation and last updated.
- **Category.** Specify the type of project.

- **Description.** Provide a brief description of the project
- **License.** Specify the project license. To know more about licenses, see Chapter ??.



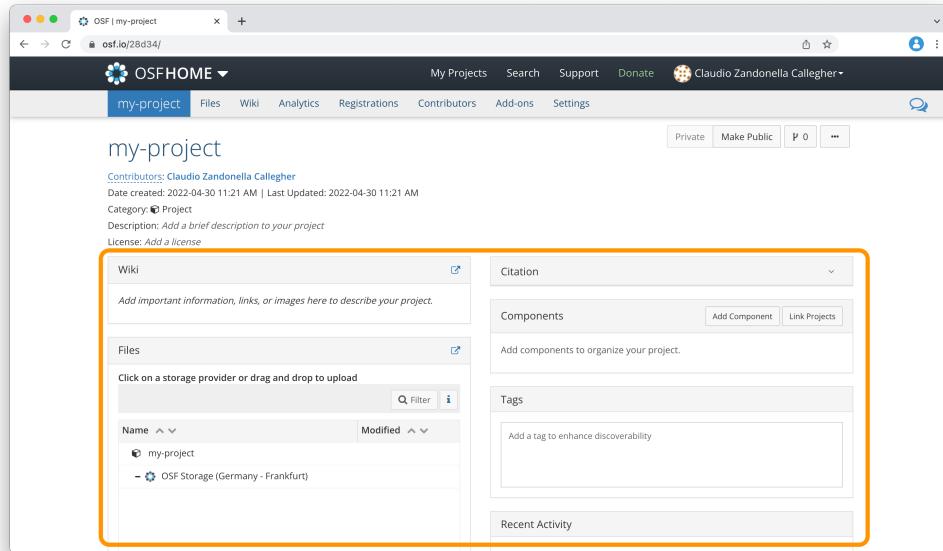
On the top right corner, we find further options about,

- **Visibility.** Check and modify the project visibility (public or private).
- **Fork.** Created copies of the project.
- Share or add a bookmark to the project.

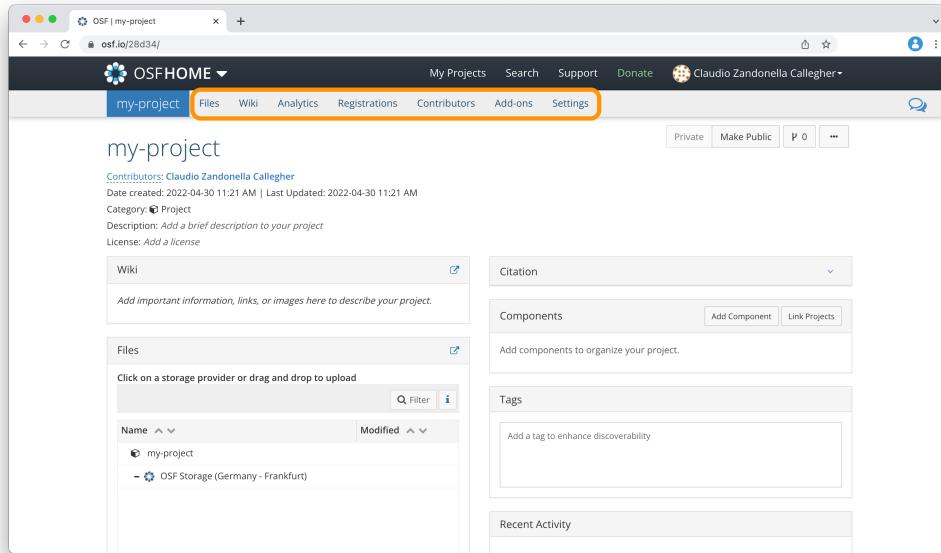


Moreover, multiple panels provide detailed information about the project. In particular,

- **Wiki.** Provide a detailed description of the project.
- **Files.** List all project files and materials.
- **Citation.** Specify how other colleagues should cite the project.
- **Components.** Add sub-projects to create a hierarchy structure.
- **Tags.** Add tags to the project to facilitate discoverability.
- **Recent Activity.** History of the project activity.



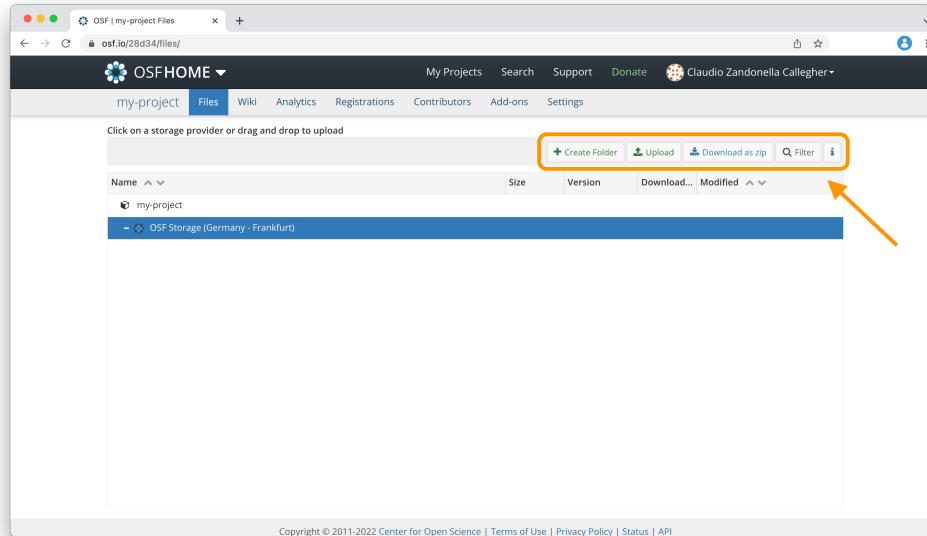
Finally, on the top of the project homepage, we find all the menu tabs to modify and manage our project.



2.2.4 Adding Files

To add a file,

- From the “*Files*” tab, select the desired OSF Storage.
- Use the buttons at the top to create folders, upload/download files.

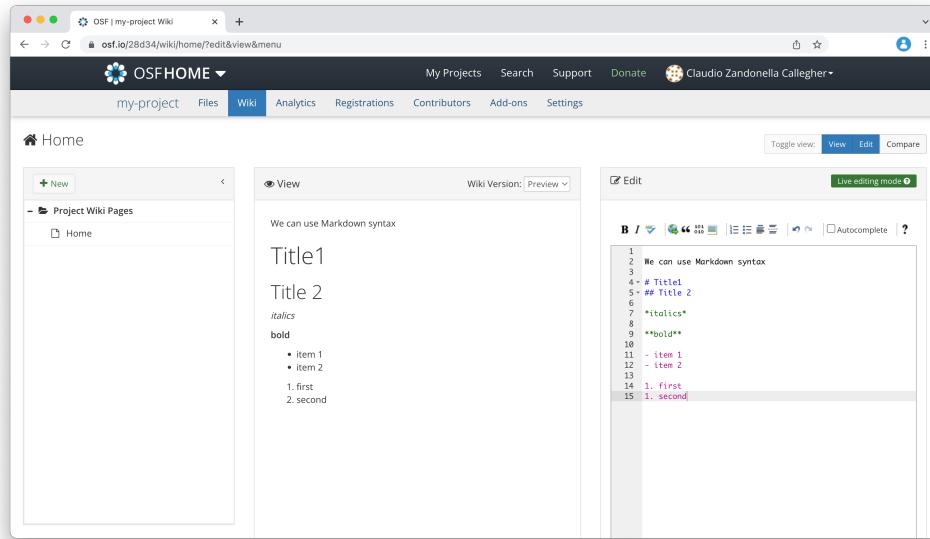


Note that we can add files also directly from the “*Files*” panel on the project homepage.

2.2.5 Documentation

To create a detailed description of the project,

- Open the “*Wiki*” tab from the top menu.
- Edit the wiki document. Note that Markdown syntax is supported (for an introduction to the Markdown syntax, consider the “*Markdown Guide*” available at <https://www.markdownguide.org>).



- Save the changes (button at the bottom) to update the project homepage.

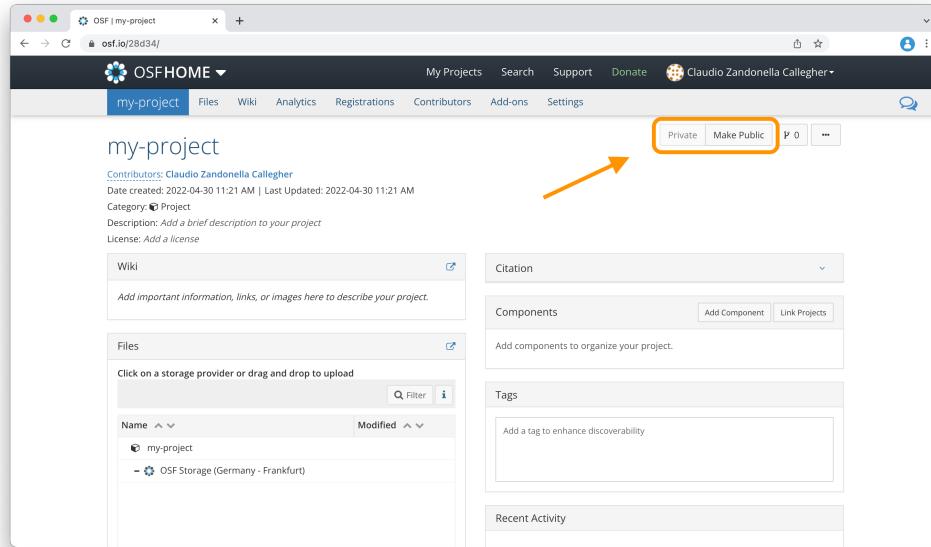
2.3 Research Features

In this section, we describe further features useful to researchers.

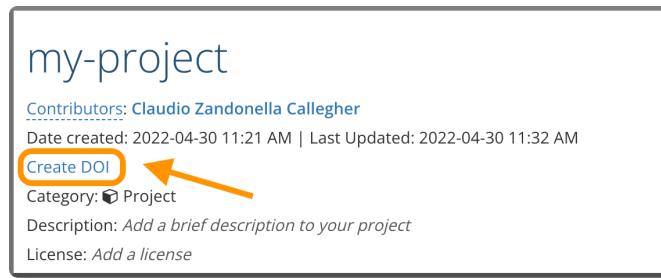
2.3.1 DOI

To obtain a DOI for the project,

- From the project homepage, change project visibility to public by pressing the “*Make Public*” button.



- Now the option “*Create DOI*” will be available.



2.3.2 Contributors

To add new contributors to the project,

- Open the “*Contributors*” tab from the top menu.
- Click the “+ Add” button in the “*Contributors*” section.

2.3. Research Features

The screenshot shows the OSF Contributor page for a project titled "my-project". The "Contributors" tab is selected, and a new contributor, "Claudio Zandonella Callegher", has been added. The "View-only Links" section is visible at the bottom, with a "+ Add" button highlighted by a red arrow.

- Search users by name and add them as contributors.

2.3.3 Sharable Anonymized Links

We can share anonymized links (hide contributor names in the project). A particularly useful feature for blinded peer review. To create an anonymized link,

- Open the “*Contributors*” tab from the top menu.
- Click the “+ Add” button in the “*View-only Links*” section.

The screenshot shows the OSF Contributor page for a project titled "my-project". The "View-only Links" section is highlighted, showing a "+ Add" button. This section allows users to create a link to share the project without revealing the contributor names.

- Provide a name to identify the link and select the “*Anonymize*” option.

Create a new link to share your project

Link name	<input type="text" value="reviewers"/>
<input checked="" type="checkbox"/> Anonymize contributor list for this link (e.g., for blind peer review). <i>Ensure the wiki pages, files, registration forms and add-ons do not contain identifying information.</i>	
Which components would you like to associate with this link? Anyone with the private link can view—but not edit—the components associated with the link.	
<input checked="" type="checkbox"/> my-project (current component)	Select all De-select all
Cancel Create	

- The link is created and listed in the “*View-only Links*” section.

View-only Links [+ Add](#)

Create a link to share this project so those who have the link can view—but not edit—the project.

Link Name	Shared Components	Created Date	Created By	Anonymous
reviewers	my-project	2022-04-30 11:27 AM	Claudio Zandonella Callegher	Yes 

Warning-Box: Anonymization

In a blinded peer review process, we are required to remove any information about the authors.

Anonymized Links hide contributor names in the project, but it is our responsibility to check that project files contain no references to the authors.

Moreover, we need to keep private project visibility. Anonymized links are of type `https://osf.io/<id-project>/?view_only=<token>`. If the project is public, reviewers can still retrieve the original repository using the link

<https://osf.io/<id-project>> obtained by simply removing the last part of the anonymized link (i.e., ?view_only=<token>).

2.3.4 Preprints

We can share preprints using the OSF Preprints service (<https://osf.io/preprints/>). The OSF Preprints is an aggregator of various preprint servers (e.g., PsyArXiv, and ArXiv).

To create a preprint, follow instructions at <https://help.osf.io/article/376-preprints-home-page>.

2.3.5 Add-ons and API

The OSF provides Add-ons and APIs that allow us to integrate third-party services. These include citation software (e.g., Zotero and Mendeley), storage services (e.g., Dropbox and Google Drive), Git repository-hosting services (e.g., GitHub and GitLab, see Chapter ??), and API services to access files and project info.

For all details about Add-ons and API, see <https://help.osf.io/article/377-add-ons-api-home-page>



Details-Box: The osfr R Package

The **osfr** R Package (Wolen & Hartgerink, 2020) provides a suite of functions for interacting R with the Open Science Framework. In particular, using the **osfr** R Package, we can:

- *Access Open Research Materials.* Explore publicly accessible projects and download the associated files and materials
- *Manage Projects.* Create projects, add components, and manage directories and files.



Package documentation with all details is available at <https://docs.ropensci.org/osfr/>.



Documentation-Box

The OSF

- Homepage
<https://osf.io/>
- Support
<https://help.osf.io/>
- Wiki
<https://osf.io/4znzp/wiki/home/>
- Preprints Service
<https://osf.io/preprints/>
- Preprint Guide
<https://help.osf.io/article/376-preprints-home-page>
- Add-ons and API
<https://help.osf.io/article/377-add-ons-api-home-page>
- osfr R Package
<https://docs.ropensci.org/osfr/>

Extra

- The Center for Open Science
<https://www.cos.io>
- Markdown Guide
<https://www.markdownguide.org>

2.3. Research Features

3

Workflow Analysis

In the previous chapters, we learned to organize all our files and data in a well structured and documented repository. Moreover, we learned how to write readable and maintainable code and to use Git and GitHub for tracking changes and managing collaboration during the development of our project.

At this point, we have everything we need to run our analysis. In this chapter, we discuss how to manage the analysis workflow to enhance results reproducibility and code maintainability.

3.1 Reproducible Workflow

To enhance results reproducibility we need to establish a workflow that will allow other colleagues to easily run the analysis. First, we describe how to organize the code used to run the analysis. Next, we discuss the importance of appropriate documentation and common issues related to results reproducibility. Finally, we discuss workflow management tools used to create specific pipelines for running our analysis. These tools allow us to improve the analysis maintainability during the project development.

3.1.1 Run the Analysis

In Chapter ??, we introduced the functional style approach that allows us to organize and develop the code required for the analysis very efficiently. In summary, instead of having a unique script, we define functions to execute each analysis step breaking down the code into small pieces. These functions are defined in separate scripts and subsequently used in another script to run the analysis.

Therefore, in our project we can organize our scripts into two different directories:

- **analysis/**: A directory with the scripts needed to run all the steps of the analysis.
- **code/**: A directory with all the scripts in which we defined the functions used in the analysis.

But how can we organize the scripts used to run the analysis? Well, of course, this will depend on the complexity of the analysis and its specific characteristics. However, let's see some general advice:

- **Single Script.** If the analysis is relatively short and straightforward, we can simply collect everything in a single script. Using the functions defined elsewhere, we specify all the analysis steps in the required order. To run the analysis, we execute the script line by line in the given order (from top to bottom).
- **Multiple Scripts.** When the analysis is very long or composed of different distinct steps, it is preferable to break down the analysis into different scripts. In this way, each script is used to run a specific part of the analysis. A good idea is to name each script with an auto-descriptive name preceded by a **progressive number** (e.g., `xx-<script-goal>`). Auto-descriptive names allow us to easily understand the aim of each script, whereas progressive numbers indicate the required order in which scripts should be executed. As later scripts may rely on results obtained in previous ones, it is necessary to run each script in the required order one at a time.
- **Main Script.** In the case of complex analysis with multiple scripts, it may be helpful to define an extra script to manage the whole analysis run. We can name this special script `main` and use it to manage the analysis by running the other scripts in the required order and dealing with other workflow aspects (e.g., settings and options). By doing this, we can run complex analyses following a simple and organized process.

Following these general recommendations, we obtain a well-structured project that allows us to easily move between the different analysis parts and reproduce the results. As a hypothetical example, we could end up having a project with the following structure.

```
- my-project/
  |
  |-- analysis/
  |   |-- 01-data-preparation
  |   |-- 02-experiment-A
  |   |-- 03-experiment-B
  |   |-- 04-comparison-experiments
  |   |-- 05-sensitivity-analysis
  |   |-- main
  |-- code/
      |-- data-munging
```

```
|   |-- models  
|   |-- plots-tables  
|   |-- utils
```

3.1.2 Documentation

Independently of the way we organize the scripts used to run the analysis, it is important to always provide appropriate documentation. This includes both comments within the scripts to describe all the analysis steps and step-by-step instructions on how to reproduce the analysis results.

- **Comments Analysis Steps.** In Chapter ??, we described general advice on how to write informative comments for the code. In summary, comments should explain “*why*” rather than “*what*”. However, as we are commenting on the analysis steps rather than the code itself, in this case, it is also important to clearly describe “*what*” we are doing in the different analysis steps.

Of course, we still need to provide information about the “*why*” of particular choices. However, specific choices during the analysis usually have theoretical reasons and implications that could be better addressed in a report (supplemental material or paper) used to present the results. Ideally, comments should describe the analysis steps to allow colleagues (not familiar with the project) to follow and understand the whole process while reading the analysis scripts.

- **Instructions Analysis Run.** Step-by-step instructions on how to run the analysis are usually provided in the README file. We need to provide enough details to allow colleagues (not familiar with the project) to reproduce the results.

Documenting the analysis workflow is time-consuming and therefore an often overlooked aspect. However, documentation is extremely important as it allows other colleagues to easily navigate around all the files and reproduce the analysis. Remember, this could be the future us!

3.1.3 Reproducibility Issues

A well structured and documented analysis workflow is a big step toward results reproducibility. However, it is not guaranteed that everyone will obtain the exact same results. Let’s discuss some aspects that could hinder result reproducibility.

- **Random Number Generator.** During the analysis, some processes may require the generation of random numbers. As these numbers are (pseudo-) random, they will be different at each analysis run. For this reason, we could obtain slightly different values when reproducing the results. Fortunately, programming languages provide ad-hoc functions to allow reproducibility of random numbers generation. We should look at the specific functions documentation and adopt the suggested

solutions. Usually, we need to set the seed for initializing the state for random number generation.

- **Session Settings.** Other global settings related to the specific programming language may affect the final results. We need to ensure that the analysis is run using the same settings each time. To do that we can specify the required options directly in the analysis script as code lines to be executed.
- **Project Requirements.** Other elements such as operating system, specific software version, and installed libraries could affect the analysis results. In Chapter ?? and Chapter ??, we discuss how to manage project requirements to guarantee results reproducibility.

3.1.4 Workflow Manager

At this point, we would like something to help us manage the workflow. In particular, we need a tool that allows us to:

- **Automatically Run the Analysis.** Ideally, we should be able to run the whole analysis in a single click (or better a single command line), following a pre-defined analysis pipeline.
- **Discover Dependencies.** Tracking the dependencies between the different analysis parts allows for identifying the objects that are affected by changes or modifications in the code.
- **Update the Analysis.** Following changes in the analysis (or when new analysis parts are added), results should be updated computing only the outdated dependencies (or the new objects) that were affected by the changes made. In this way, we avoid re-running unnecessary analysis parts, optimizing the required time.
- **Caching System.** Saving copies of the intermediate and final analysis objects so they can be used later avoiding to re-run the analysis at each session.

A manager tool with these characteristics is particularly useful during the project development, allowing a very smooth workflow. In Section 3.1.4.1, we introduce Make, a Unix utility that allows us to automate tasks execution for general purposes. In Section 3.3, we present specific solutions for the R programming language.

3.1.4.1 Make

Make is a Unix utility that manages the execution of general tasks. It is commonly used to automatize packages and programs installation, however, it can be also used to manage any project workflow. In Windows, an analogous tool is NMake (see <https://docs.microsoft.com/en-us/cpp/build/reference/nmake-reference>)

Make has several powerful features. In particular, it allows us to define dependencies between the different project parts and it automatically figures out which files to update following changes or modifications. Moreover, Make is not limited to a particular language

but it can be used for any purpose. See official documentation for more details <https://www.gnu.org/software/make/>.

Make requires a **Makefile** (or **makefile**) where all the tasks to be executed are defined. **Makefile** has its own syntax that is beyond the aim of the present book. Interested readers can refer to this tutorial for a general introduction to Make <https://opensource.com/article/18/8/what-how-makefile>.

Ideally, we could create a **Makefile** with all the details and use Make to automatize the analysis workflow. This would be very useful but it requires some extra programming skills. In Section 3.3, we introduce alternative tools specific to the R programming language. However, Make may still be the choice to go if we need to integrate multiple programs into the workflow or for more general purposes.

3.2 R

Now we discuss how to manage the analysis workflow specifically when using the R programming language. First, we consider some general recommendations and how to solve possible reproducibility issues. Next, we describe the main R-packages available to manage the analysis workflow.

3.2.1 Analysis Workflow

In Chapter ??, we discussed how to create our custom functions to execute specific parts of the analysis. Following the R-packages convention, we store all the .R scripts with our custom functions in the **R/** directory at the root of our project.

Now, we can use our custom functions to run the analysis. We do that in separate .R scripts saved in a different directory named, for example, **analysis/**. Of course, during the actual analysis development, this is an iterative process. We continuously switch between defining functions and adding analysis steps. It is important, however, to always keep the scripts used to run the analysis in a separate directory from the scripts with our custom functions:

- **analysis/**: Scripts to run the analysis.
- **R/**: Scripts with function definitions.

Considering the previous example, we would have a project with the following structure.

```
- my-project/
  |
  |-- analysis/
    |   |-- 01-data-preparation.R
    |   |-- 02-experiment-A.R
    |   |-- 03-experiment-B.R
```

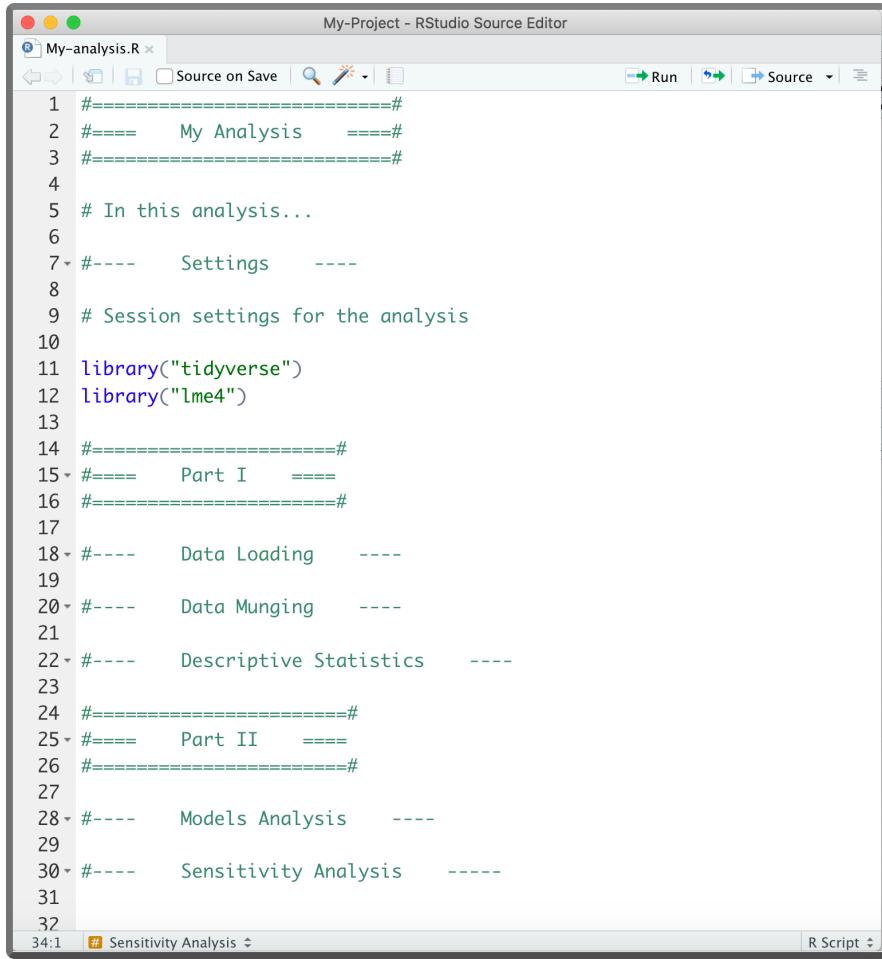
```
|      |-- 04-comparison-experiments.R  
|      |-- 05-sensitivity-analysis.R  
|      |-- main.R  
|-- R/  
|      |-- data-munging.R  
|      |-- models.R  
|      |-- plots-tables.R  
|      |-- utils.R
```

3.2.1.1 Script Sections

To enhance the readability of the analysis scripts, we can divide the code into sections. In RStudio, it is possible to create sections adding at the end of a comment line four (or more) consecutive symbols ##### (alternatively, ---- or =====).

```
# Section 1 #####  
  
# Section 2 ----  
  
#----    Section 3    ----  
  
#####  Not Valid Section  --##
```

Using the available characters, it is possible to create different styles. The important thing is to finish the line with four (or more) identical symbols. As an example, we could organize our script as presented below



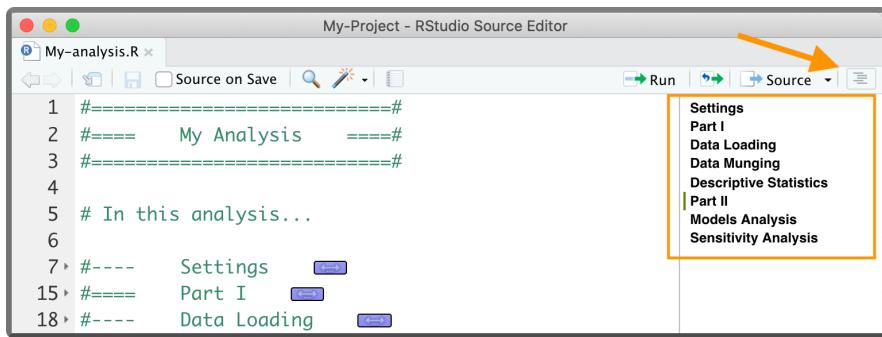
```

1 #=====
2 ##### My Analysis #####
3 #=====
4
5 # In this analysis...
6
7 #---- Settings ----
8
9 # Session settings for the analysis
10
11 library("tidyverse")
12 library("lme4")
13
14 #=====
15 ##### Part I #####
16 #=====
17
18 #---- Data Loading ----
19
20 #---- Data Munging ----
21
22 #---- Descriptive Statistics ----
23
24 #=====
25 ##### Part II #####
26 #=====
27
28 #---- Models Analysis ----
29
30 #---- Sensitivity Analysis ----
31
32

```

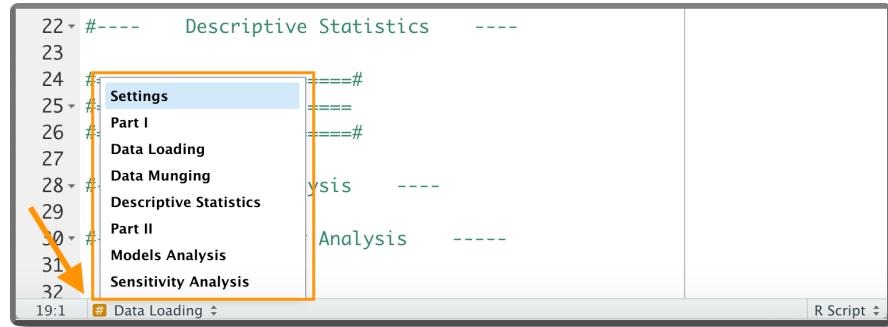
The screenshot shows the RStudio Source Editor window with a script titled "My-analysis.R". The script is organized into sections using multi-line comments. At the top right, there is a navigation menu with a dropdown arrow pointing to a list of section titles: "Settings", "Part I", "Data Loading", "Data Munging", "Descriptive Statistics", "Part II", "Models Analysis", and "Sensitivity Analysis". The "Source" button in the toolbar is also highlighted with a red arrow.

One of the advantages of organizing our script into sections is that at the top right corner we can find a navigation menu with the document outline. Section titles are given by the comment text.



The screenshot shows the RStudio Source Editor window with the same "My-analysis.R" script. A navigation bar is visible at the bottom left corner, containing icons for "Settings", "Part I", "Data Loading", "Data Munging", "Descriptive Statistics", "Part II", "Models Analysis", and "Sensitivity Analysis". An orange arrow points from the text above to this navigation bar.

Another navigation bar is also available at the bottom left corner.



A screenshot of an R script editor window. The code is organized into sections:

```
22 #---- Descriptive Statistics ----
23
24 #----#
25 #---- Settings ----#
26 #---- Part I ----#
27 #---- Data Loading
28 #---- Data Munging
29 #---- Descriptive Statistics
30 #----#
31 #---- Part II ----#
32 #---- Models Analysis
#---- Sensitivity Analysis
```

The section from line 25 to line 32 is highlighted with a yellow box and has a small orange arrow pointing towards it, indicating it is a collapsible section. The status bar at the bottom shows "Data Loading".

Dividing the code into sections enhances readability and helps us to navigate between the different analysis parts. However, we should avoid creating too long scripts as they are more difficult to maintain.



Trick-Box: Collapsing Sections

Note that next to the code line number, small arrows are now displayed. These arrows allow us to expand/collapse code sections.

```

My-Project - RStudio Source Editor
My-analysis.R
Source on Save | Run | Source | 
1 #=====
2 ##### My Analysis #####
3 #=====
4
5 # In this analysis...
6
7 ##### Settings #####
8
9 # Session settings for the analysis
10
11 library("tidyverse")
12 library("lme4")
13
14 #=====
15 ##### Part I #####
16 #=====
17
18 ##### Data Loading #####
19 ##### Data Munging #####
20 ##### Descriptive Statistics #####
21
22 ##### Part II #####
23
24 ##### Models Analysis #####
25 ##### Sensitivity Analysis #####
26
27
28
29
30
31
32
33
34 |

```

34:1 Sensitivity Analysis R Script

3.2.1.2 Loading Functions

As we have defined our custom functions in separate scripts, before we can use them, we need to load them in our session environment. To do that we have two different solutions:

- **source()**. This function allows us to read code from R scripts, see `?source()` for options and details. Assuming all the required scripts are in the `R/` directory in the project root, we can use the following code lines to list all available scripts and source them:

```

# List all scripts in R/
script_list <- list.files("R", full.names = TRUE)

# Source scripts
invisible(sapply(script_list, source))

```

- `devtools::load_all()`. We briefly introduced the `devtools` R package in Chapter ???. This package provides many useful functions that facilitate our workflow when using the R-package project template (remember that the `DESCRIPTION` file is required). The function `devtools::load_all()` allows us to automatically source all scripts in the `R/` directory. See `?devtools::load_all()` for options and details. We can use `devtools::load_all()` in our analysis script specifying as argument the path to the project root where the `DESCRIPTION` file is present.

```
# Load functions
devtools::load_all(path = "<path-to-the-project-root>")
```

The keyboard shortcut `Ctrl/Cmd + Shift + L` is also available. This is very handy during the analysis development as it facilitates the common workflow:

1. *Write a new function*
2. *Save the script*
3. *Load all functions with `Ctrl/Cmd + Shift + L`*
4. *keep working on the analysis*

We should include the code snippet used to load our custom functions at the beginning of the analysis scripts. Alternatively, we can include it in the `.Rprofile` to automatically load all functions at the beginning of each session. The latter approach, however, may lead to some problems. In particular, it limits the code readability as colleagues not familiar with the `.Rprofile` could not understand what is going on. Moreover, `.Rprofile` is not always automatically sourced when compiling dynamic documents. When compiling a document using the `Knit` button in Rstudio, a separate R session is launched using as working directory the document location. If this is not the project root (where the `.Rprofile` is located), the `.Rprofile` is not sourced.

Therefore, declaring the code snippet used to load our custom functions in the analysis scripts (or in the Rmarkdown file) following a more explicit approach is preferable (see “*Trick-Box: Using `.Rprofile`*” below for a good tip).



Trick-Box: Using `.Rprofile`

A good tip is to use the `.Rprofile` to run all commands and set options required to work on the analysis development. By doing this we can automate all those processes routinely done at the beginning of each session allowing us to jump straight into the development workflow without wasting time.

Common routine processes are loading our custom functions, loading required packages, and specifying preferred settings. For example, a possible `.Rprofile` may look like,

```
#---- .Rprofile ----#
# Load custom functions
devtools::load_all()

# Load packages
library("tidyverse")
library("lme4")

# Settings ggplot
theme_set(theme_bw())
```

The actual analysis run, however, should rely only on the code declared explicitly in the analysis script. This would facilitate the analysis readability for colleagues not familiar with more advanced R features and avoid possible problems related to the creation of new R sessions (as in the case of dynamic documents compilation).

Note, however, that if we run the analysis script in our current session, the commands specified in the `.Rprofile` are still valid. To manage separately the session where we develop the analysis from the session where the analysis is run, we can evaluate whether the session is interactive or not. By specifying,

```
#---- .Rprofile ----#
# Commands for interactive and non-interactive sessions
...
# Commands only for interactive sessions
if(interactive()){
  # Load custom functions
  devtools::load_all()

  # Load packages
  library("tidyverse")
  library("lme4")

  # Settings ggplot
  theme_set(theme_bw())
}
```

commands defined inside the `if(interactive()){}` block are executed only in interactive sessions (usually when we develop the code). Note that commands defined outside the `if(interactive()){}` block will be always executed.

To run the analysis in a non-interactive session, we can run the script directly from the terminal (**not the R console!**) using the command,

```
$ Rscript <path-to/script.R>
```

For further details about running R in non-interactive mode, see <https://github.com/gastonstat/tutorial-R-noninteractive>. Note that using the Knit button in Rstudio (or using the `targets` workflow to run the analysis; see Section 3.3) automatically runs the code in a new, non-interactive session.

3.2.1.3 Loading R-packages

During our analysis, we will likely need to load several R packages. To do that, we can use different approaches:

- **Analysis Scripts.** We can declare the required packages directly at the beginning of the analysis scripts. The packages will be loaded when running the code.
- **.Rprofile.** Declaring the required packages in the `.Rprofile`, we can automatically load them at the beginning of each session.
- **DESCRIPTION.** When using the R-package project template, we can specify the required packages in the `DESCRIPTION` file. In particular, packages listed in the `Depends` field are automatically loaded at the beginning of each session. See <https://r-pkgs.org/namespac.html?q=depends#imports> for further details.

As in the case of loading custom functions (see Section 3.2.1.2), it is preferable to explicitly declare the required packages in the analysis scripts. This facilitates the analysis readability for colleagues not familiar with the `.Rprofile` and the `DESCRIPTION` file functioning. However, the `.Rprofile` (and the `DESCRIPTION` file) can still be used to facilitate the workflow during the analysis development (see “*Trick-Box: Using .Rprofile*” above).



Details-Box: Conflicts

Another aspect to take into account is the presence of **conflicts among packages**. Conflicts happen when two loaded packages have functions with the same name. In R, the default conflict resolution system is to give precedence to the

most recently loaded package. However, this makes it difficult to detect conflicts and can waste a lot of time debugging. To avoid package conflicts, we can:

- **conflicted.** The R package `conflicted` (Wickham, 2021) adopts a different approach making every conflict an error. This forces us to solve conflicts by explicitly defining the function to use. See <https://conflicted.r-lib.org/> for more information.
- `<package>::<function>`. We can refer to a specific function by using the syntax `<package>::<function>`. In this case, we are no longer required to load the package with the `library("<package>")` command avoiding possible conflicts. This approach is particularly useful if only a few functions are required from a package. However, note that not loading the package prevents also package-specific classes and methods from being available. This aspect could lead to possible errors or unexpected results. See <http://adv-r.had.co.nz/OO-essentials.html> for more details on classes and methods.

Common conflicts to be aware of are:

- `dplyr::select()` vs `MASS::select()`
- `dplyr::filter()` vs `stats::filter()`

3.2.1.4 Reproducibility

Finally, let's discuss some details that may hinder result reproducibility:

- **Random Number Generator.** In R, using the function `set.seed()` we can specify the seed to allow reproducibility of random numbers generation. See `?set.seed()` for options and details. Ideally, we specify the seed at the beginning of the script used to run the analysis. Note that functions that call other software (e.g., `brms::brm()` or `rstan::stan()` which are based on Stan) may have their own `seed` argument that is independent of the seed in the R session. In this case, we need to specify both seeds to obtain reproducible results.
- **Global Options.** If our project relies on some specific global options (e.g., `stringsAsFactors` or `contrasts`), we should define them explicitly at the beginning of the script used to run the analysis. See `?options()` for further details. Note that we could also specify global options in the `.Rprofile` to facilitate our workflow during the analysis development (see “*Trick-Box: Using .Rprofile*” above).
- **Project Requirements.** To enhance results reproducibility, we should use the same R and R packages versions as in the original analysis. In Chapter ??, we discuss how to manage project requirements.



Tip-Box: Settings Section

We recommend creating a section “*Settings*” at the top of the main script where to collect the code used to define the setup of our analysis session. This includes:

- Loading required **packages**
- Setting required **session options**
- Defining the **random seed**
- Defining **global variables**
- Loading custom functions

3.2.2 Workflow Manager

In R, two main packages are used to create pipelines and manage the analysis workflow facilitating the project maintainability and enhancing result reproducibility. These packages are:

- **targets** (<https://github.com/ropensci/targets>). The **targets** package (Landau, 2022b) creates a Make-like pipeline. **targets** identifies dependencies between the analysis targets, skips targets that are already up to date, and runs only the necessary outdated targets. This package enables an optimal, maintainable and reproducible workflow.
- **workflowr** (<https://github.com/workflowr/workflowr>). The **workflowr** package (Blischak et al., 2021) organizes the project to enhance management, reproducibility, and sharing of analysis results. In particular, **workflowr** also allows us to create a website to document the results via GitHub Pages or GitLab Pages.

Between the two packages, **targets** serves more general purposes and has more advanced features. Therefore, it can be applied in many different scenarios. On the other hand, **workflowr** offers the interesting possibility of creating a website to document the results. However, we can create a website using other packages with lots more customizable options, such as **bookdown** (<https://github.com/rstudio/bookdown>), **blogdown** (<https://github.com/rstudio/blogdown>), or **pkgdown** (<https://github.com/r-lib/pkgdown>). Moreover, using **targets** does not exclude that we can also use **workflowr** to create the website. For more details see <https://books.ropensci.org/targets/markdown.html>.

In the next section, we discuss in more detail the **targets** workflow.

3.3 Targets

The `targets` package (successor of `drake`) creates a Make-like pipeline to enable an optimal, maintainable and reproducible workflow. Similar to Make, `targets` identifies dependencies between the analysis targets, skips targets that are already up to date, and runs only the necessary outdated targets. Moreover, `targets` support high-performance computing allowing us to run multiple tasks in parallel on our local machine or a computing cluster. Finally, `targets` also provide an efficient cache system to easily access all intermediate and final analysis results.



In the next sections, we introduce the `targets` workflow and its main features. This should be enough to get started, however, we highly encourage everyone to take a tour of `targets` official documentation available at <https://books.ropensci.org/targets/>. There are many more aspects to learn and solutions for possible issues.

3.3.1 Project Structure

To manage the analysis using `targets`, some specific files are required. As an example of a minimal workflow, consider the following project structure.

```
- my-project/
  |
  |-- _targets.R
  |-- _targets/
  |-- data/
    |-- raw-data.csv
  |-- R/
    |-- my-functions.R
  |-- ...
```

In line with the common project structure, we have a fictional data set (`Data/raw-data.csv`) to analyse,

ID	x	y
1	A	2.583
2	A	2.499
3	A	-0.625
...

and `R/My-functions.R` with our custom functions to run the analysis. In addition, we need a special R script `_targets.R` and a new directory `_targets/`.

3.3.1.1 The `_targets.R` Script

The `_targets.R` script is a special file used to define the workflow pipeline. By default, this file is in the root directory (however, we can indicate the path to the `_targets.R` script and also specify a different name; see Section 3.3.3.1 and `?tarconfig_set()` for special custom settings). In this case, the `_targets.R` script looks like,

```
#=====#
#==== _targets.R =====#
#=====#

library("targets")

#---- Settings ----

# Load packages
library("tidyverse")
library("lme4")

# Source custom functions
source("R/my-functions.R")

# Options
options(tidyverse.quiet = TRUE)

#---- Workflow ----

list(
  # Get data
  tar_target(raw_data_file, "data/raw-data.csv", format = "file"),
  tar_target(my_data, get_my_data(raw_data_file)),

  # Descriptive statistics
  tar_target(plot_obs, get_plot_obs(my_data)),

  # Inferential statistics
  tar_target(lm_fit, get_lm_fit(my_data))
)
```

Let's discuss the different parts:

- `library("targets")`. It is **required** to load the `targets` R package itself at the beginning of the script (it is only required before the workflow definition, but it is common to specify it at the top).

- **Settings.** Next, we specify required R packages (also by `tar_option_set(packages = c("<packages>"))`; see <https://books.ropensci.org/targets/packages.html>), load custom functions, and set the required options.
- **Workflow.** Finally, we define inside a list each target of the workflow. In the example, we indicate the file with the raw data and we load the data in R. Next, we get a plot of the data and, finally, we fit a linear model.

3.3.1.2 Defining Targets

Each individual target is defined using the function `tar_target()` specifying the target name and the R expression used to compute the target. Note that all targets are collected within a list.

Specifying `format = "file"`, we indicate that the specified target is a dynamic file (i.e., an external file). In this way, `targets` tracks the file to evaluate whether it is changed. For more details see `?tar_target()`

Each target is an intermediate step of the workflow and their results are saved to be used later. `targets` automatically identifies the dependency relations between targets and updates single targets that are invalidated due to changes made. Ideally, each target should represent a meaningful step of the analysis. However, in case of changes to the code they depend on, large targets are required to be recomputed entirely even for small changes. Breaking down a large target into smaller ones allows skipping those parts that are not invalidated by changes.

3.3.1.3 The `_targets/` Directory

`targets` stores the results and all files required to run the pipeline in the `_targets/` directory. In particular, inside we can find:

- `meta/.` It contains metadata regarding the targets, runtimes and processes.
- `objects/.` It contains all the targets results.
- `users/.` It is used to store custom files

This directory is automatically created the first time we run the pipeline. Therefore, we do not have to care about this directory as everything is managed by `targets`. Moreover, the entire `_targets/` directory should not be tracked by git. Only the file `_targets/meta/meta` is important. A `.gitignore` file is automatically added to track only relevant files.

Note that we can also specify a location other than `_targets/` where to store the data (see `?tarconfig_set()` for special custom settings).

3.3.2 The `targets` Workflow

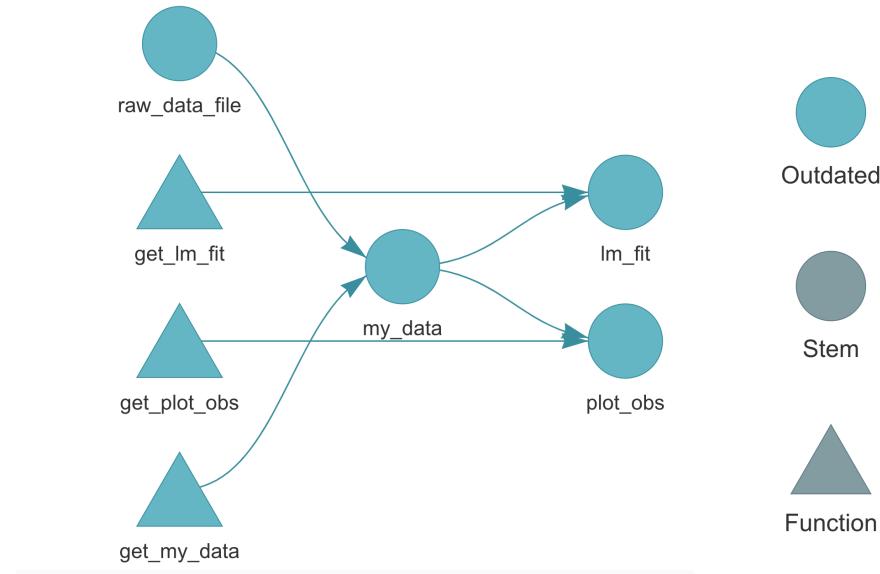
At this point, we have everything we need to run the analysis. Let's start the `targets` workflow.

3.3.2.1 Check the Pipeline

Before running the pipeline, we can inspect it to evaluate the possible presence of errors. Using the function `targets::tar_manifest()`, we obtain a data frame with all the targets and information about them. Note that targets are ordered according to their topological order (i.e., the expected order of execution without considering parallelization and priorities). See `?targets::tar_manifest()` for further details and options.

```
tar_manifest(fields = "command")
## # A tibble: 4 x 2
##   name      command
##   <chr>    <chr>
## 1 raw_data_file  "\"data/raw-data.csv\""
## 2 my_data      "get_my_data(raw_data_file)"
## 3 plot_obs     "get_plot_obs(data = my_data)"
## 4 lm_fit       "get_lm_fit(data = my_data)"
```

We can also use the function `targets::tar_visnetwork()`, to visualize the pipeline and the dependency relationship between targets. The actual graph we obtain is made by the `visNetwork` package (we need to install it separately) and it is interactive (try it in RStudio). See `?targets::tar_visnetwork()` for further details and options. At the moment, all our targets are outdated.



3.3.2.2 Run the Pipeline

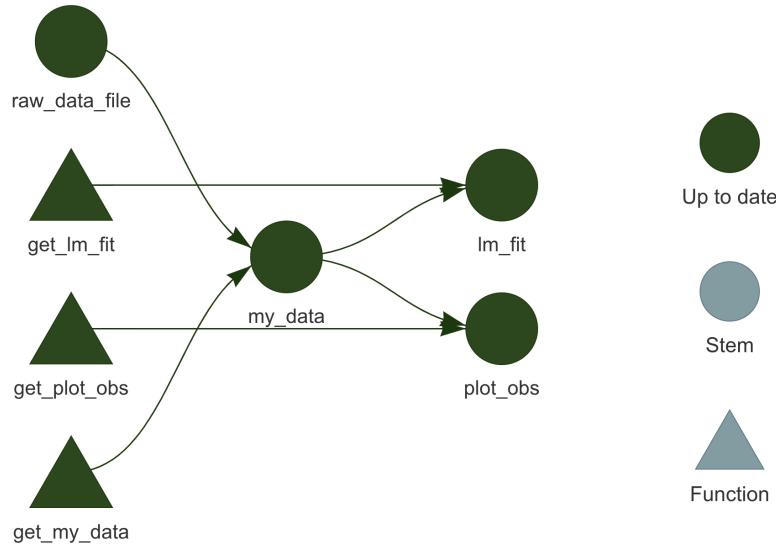
Using the function `targets::tar_make()`, we can run the pipeline. All targets are evaluated in a new external session in the correct order and results are saved in the `_targets/` directory. See `?targets::tar_make()` for further details and options.

```

tar_make()
## * start target raw_data_file
## * built target raw_data_file
## * start target my_data
## * built target my_data
## * start target plot_obs
## * built target plot_obs
## * start target lm_fit
## * built target lm_fit
## * end pipeline

```

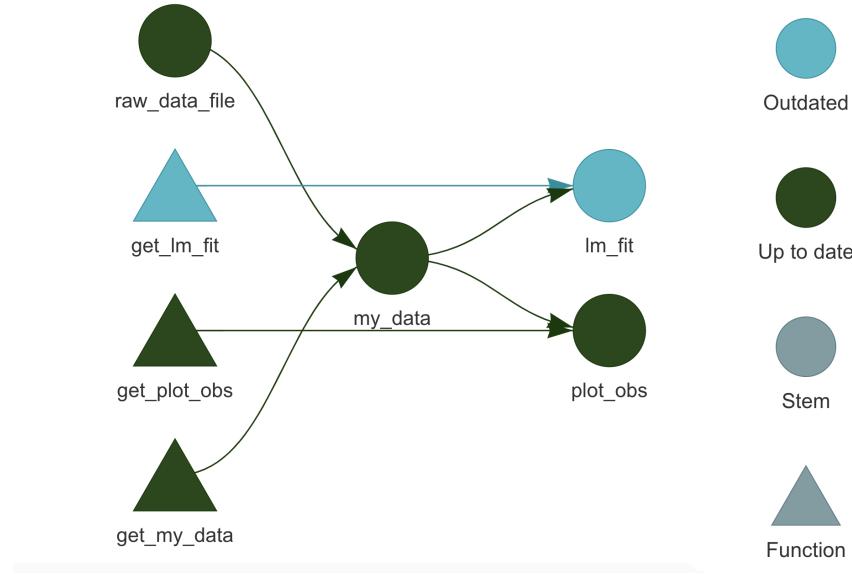
If we look again at `targets::tar_visnetwork()` graph, we can see that now all targets are up to date.



3.3.2.3 Make Changes

Let's say we make some changes to the function used to fit the linear model. `targets` will notice that and it will identify the invalidated targets that require to be updated. Looking at the `targets::tar_visnetwork()` graph, we can see which targets are affected by the changes made.

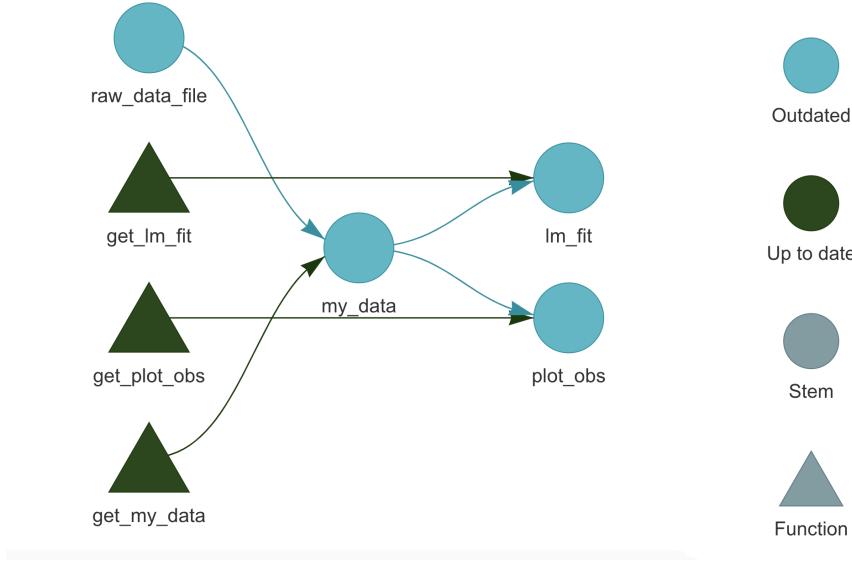
3.3. Targets



Running `targets::tar_make()` a second time, we see that up-to-date targets are skipped and only outdated targets are computed again, potentially saving us a lot of time.

```
tar_make()
## v skip target raw_data_file
## v skip target my_data
## v skip target plot_obs
## * start target lm_fit
## * built target lm_fit
## * end pipeline
```

Suppose, instead, that we made some changes to the raw data (e.g., adding new observations). `targets` will detect that as well and in this case, the whole pipeline will be invalidated.



3.3.2.4 Get the Results

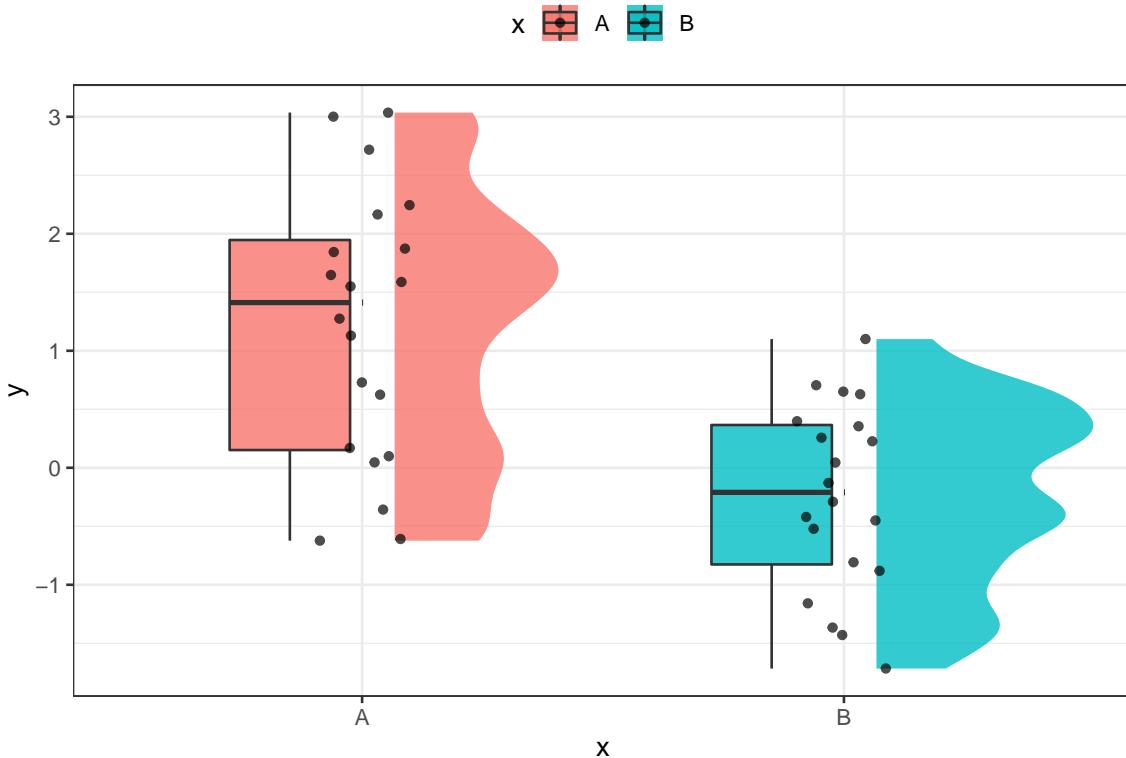
To access the targets results, we have two functions:

- **targets::tar_read()**. Read the target from the `_targets/` directory and return its value.
- **targets::tar_load()**. Load the target directly into the current environment (NULL is returned).

For example, we can use `targets::tar_read()` to obtain the created plot,

```
targets::tar_read(plot_obs)
```

3.3. Targets



or we can use `targets::tar_load()` to load a target in the current environment so we can use it subsequently with other functions.

```
targets::tar_load(lm_fit)
summary(lm_fit)
##
## Call:
## lm(formula = y ~ x, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max 
## -1.83060 -0.70935  0.08828  0.64521  1.82840 
## 
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept)  1.2076    0.2225  5.428 3.47e-06 ***
## xB          -1.4477    0.3146 -4.601 4.58e-05 ***
## ---        
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 0.995 on 38 degrees of freedom
```

```
## Multiple R-squared:  0.3578, Adjusted R-squared:  0.3409
## F-statistic: 21.17 on 1 and 38 DF,  p-value: 4.575e-05
```

Again, we stress the difference between the two functions: `tar_read()` returns the target's value, whereas `tar_load()` loads the target in the current environment. Therefore, to subsequently use the target, we need to assign its value when using `tar_read()` or simply use the target after loading it with `tar_load()`. For example,

```
# Assign the target's value for later use
obs <- targets::tar_read(my_data)
head(obs)
##   ID x      y
## 1  1 A  1.274
## 2  2 A  0.169
## 3  3 A  2.718
## 4  4 A  1.588
## 5  5 A  3.001
## 6  6 A -0.609

# my_data is not available
my_data
## Error in eval(expr, envir, enclos): object 'my_data' not found

# Load target in the current environment
targets::tar_load(my_data)
head(my_data)
##   ID x      y
## 1  1 A  1.274
## 2  2 A  0.169
## 3  3 A  2.718
## 4  4 A  1.588
## 5  5 A  3.001
## 6  6 A -0.609
```

3.3.3 Advanced Features

Now we discuss some other more advanced features of `targets`. Again, `targets` is a complex package with many features and options to account for any needs. Therefore, we highly encourage everyone to take a tour of `targets` official documentation available at <https://books.ropensci.org/targets/>. There are many more aspects to learn and solutions for possible issues.

3.3.3.1 Project Structure

Let's see how we can optimize our project organization when using the `targets` workflow. A possible solution is to collect all directories and files related to `targets` in the `analysis/` directory.

```
- my-project/
  |
  |-- _targets.yaml
  |-- analysis/
  |   |-- targets-workflow.R
  |   |-- targets-analysis.R
  |   |-- _targets/
  |-- data/
  |   |-- raw-data.csv
  |-- R/
  |   |-- my-functions.R
  |   |-- ...
```

In particular, we have:

- `analysis/targets-workflow.R`. The R script with the definition of the workflow pipeline. This is the same as the `_targets.R` scripts described in Section 3.3.1.1.
- `analysis/_targets/`. The directory where `targets` stores all the results and pipeline information. See Section 3.3.1.3.
- `analysis/targets-analysis.R`. In this script we can collect all the functions required to manage and run the workflow.

As we are no longer using the default `targets` project structure, it is required to modify `targets` global settings by specifying the path to the R script with the workflow pipeline (i.e., `analysis/targets-workflow.R`) and the path to the storing directory (i.e., `analysis/_targets/`). To do that, we can use the function `targets::tar_config_set()` (see the help page for more details). In our case, the `targets-analysis.R` script looks like this

```
#=====
#==== Targets Analysis ===#
#=====

# Targets settings
targets::tar_config_set(script = "analysis/targets-workflow.R",
                        store = "analysis/_targets/")
```

```
#----  Analysis  ----

# Check workflow
targets::tar_manifest(fields = "command")
targets::tar_visnetwork()

# Run analysis
targets::tar_make()

# End
targets::tar_visnetwork()

#----  Results  ----

# Aim of the study is ...
targets::tar_load(my_data)

# Descriptive statistics
summary(data)
targets::tar_read(plot_obs)

# Inferential statistics
targets::tar_load(lm_fit)
summary(lm_fit)
...
#----
```

After the code used to run the analysis, we can also include a section where results are loaded and briefly presented. This will allow colleagues to explore analysis results immediately. Note that appropriate documentation is required to facilitate results interpretation.

- `_targets.yaml`. A YAML file with the custom `targets` settings. This file is automatically created when `targets` global settings are modified using the `targets::tar_config_set()` function (see help page for more information about custom settings). In our case, the `_targets.yaml` file looks like this

```
#---- _targets.yaml ----#
main:
  script: analysis/targets-workflow.R
  store: analysis/_targets/
```

3.3.3.2 targets and R Markdown

To integrate the `targets` workflow with dynamic documents created by R Markdown, there are two main approaches

- **R Markdown as Primary Script.** The R Markdown document is used as the primary script to manage the `targets` workflow. Following this approach, the whole pipeline is defined and managed within one or more R Markdown documents. To learn how to implement this approach, see <https://books.ropensci.org/targets/markdown.html>.
- **R Markdown as Target.** The R Markdown document is considered as a new target in the pipeline. Following this approach, the whole pipeline is defined and managed outside of the R Markdown document. R Markdown documents should be lightweight with minimal code used simply to present the targets' results retrieved with `targets::tar_read()` or `targets::tar_load()`. Targets should not be computed within the R Markdown documents. To learn how to implement this approach, see <https://books.ropensci.org/targets/files.html#literate-programming>.

Among the two approaches, we recommend the second one. Using R Markdown documents as primary scripts to manage the analysis is fine in the case of simple projects. However, in the case of more complex projects, it is better to keep the actual analysis and the presentation of the results separate. In this way, the project can be maintained and developed more easily.

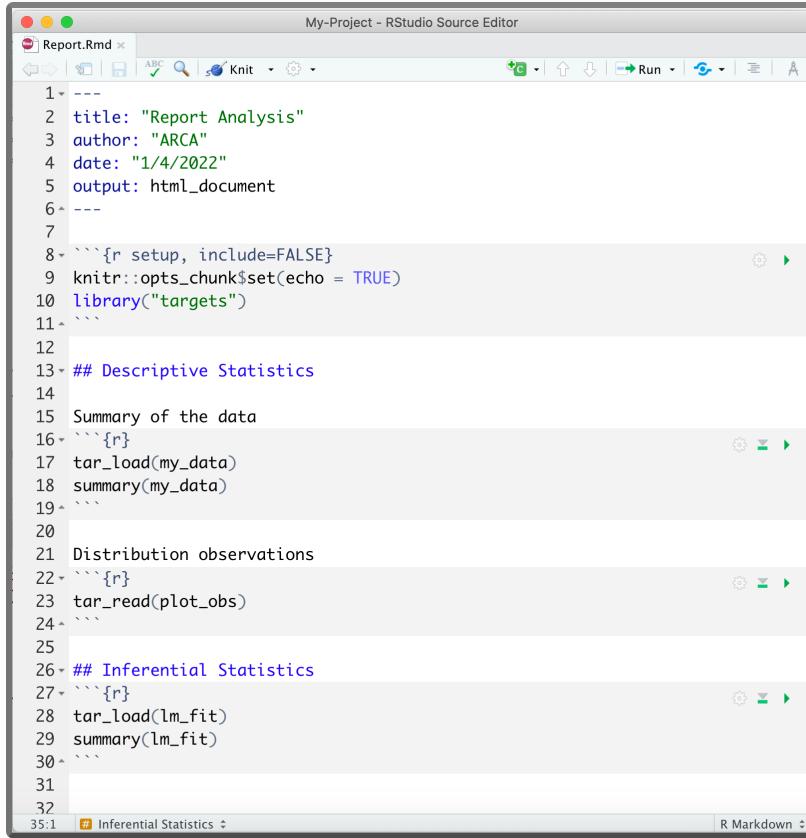


Details-Box: R Markdown as Target

Following this approach, the `target` workflow is defined and managed following the usual approach and R Markdown documents are considered as targets in the pipeline.

To add an R Markdown document to the pipeline, we have to define the target using `tarchetypes::tar_render()` instead of the common `targets::tar_target()` function. Note that we need to install the `tarchetypes` package (Landau, 2022a). See the help page for function arguments and details.

Suppose we created the following report saved as `documents/report.Rmd`.



```

1 ---  

2 title: "Report Analysis"  

3 author: "ARCA"  

4 date: "1/4/2022"  

5 output: html_document  

6 ---  

7  

8 ``{r setup, include=FALSE}  

9 knitr::opts_chunk$set(echo = TRUE)  

10 library("targets")  

11 ```  

12  

13 ## Descriptive Statistics  

14  

15 Summary of the data  

16 ``{r}  

17 tar_load(my_data)  

18 summary(my_data)  

19 ```  

20  

21 Distribution observations  

22 ``{r}  

23 tar_read(plot_obs)  

24 ```  

25  

26 ## Inferential Statistics  

27 ``{r}  

28 tar_load(lm_fit)  

29 summary(lm_fit)  

30 ```  

31  

32

```

Next, we add it to the workflow pipeline,

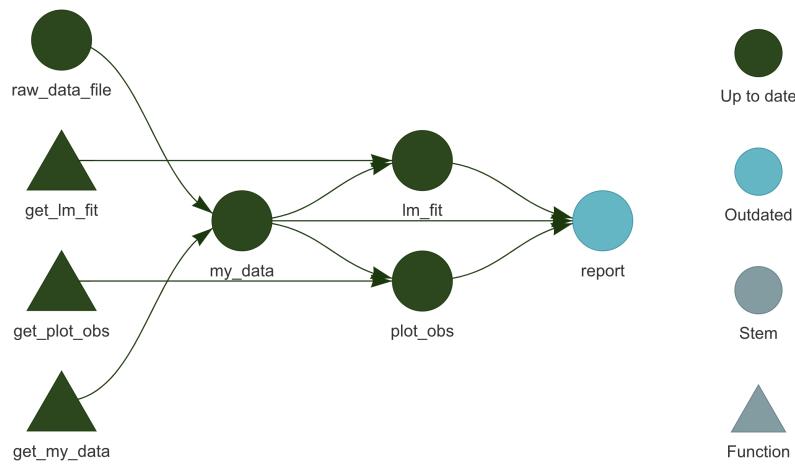
```

#---- Targets-workflow.R ----#
...
list(
  ...
  # Report
  tarchetypes::tar_render(report, "documents/report.Rmd"),
  ...
)

```

Now, `targets` will automatically recognize the dependencies our report is based on and will add the report to the workflow pipeline. Note that to

allow dependency identification, targets have to be explicitly retrieved with `targets::tar_read()` or `targets::tar_load()`.



Running `targets::tar_make()`, we can update the pipeline compiling the report as well.

Alternatively, we can also compile the report outside the pipeline as usual by clicking the Knit button in RStudio. However, unless the report is in the root directory, we need to specify the position of the directory `_targets/` (i.e., the directory with all the targets' results and information) relative to the report position. To do that do not use the `targets::tar_config_set()` function as this would overwrite global settings for the whole `targets` workflow. Instead, create manually a `_targets.yaml` file in the same directory as the report specifying the store location. Considering the report in the example above, we would define

```

#---- documents/_targets.yaml ----#
main:
  store: ../analysis/_targets/
  
```

3.3.3.3 Reproducibility

`targets` enhance the reproducibility of the results by automatically running the pipeline in a reproducible background process. This procedure avoids that our current environment or other temporary settings affect the results.

Let's discuss some other details relevant for results reproducibility:

- **Random Number Generator.** When running the pipeline, each target is built

using a unique seed determined by the target’s name (no two targets share the same seed). In this way, each target runs with a reproducible seed and we always obtain the same results. See `targets::tar_meta()` for a list of targets’ metadata including each target specific seed. See function documentation for further details.

- **Global Settings.** Global settings are usually defined explicitly in the script used to specify the workflow pipeline (see Section 3.3.1.1). However, commands defined in the `.Rprofile` are also evaluated when running the pipeline. This is not a problem for reproducibility but it may limit the code understanding of colleagues not familiar with more advanced features of R. To overcome this issue, note that `targets` runs the analysis in a non-interactive session. Therefore, we can avoid that the `.Rprofile` code is evaluated following the suggestion described in “*Trick-Box: Using .Rprofile*”.
- **Project Requirements.** `targets` does not track changes in the R or R-packages versions. To enhance reproducibility, it is good practice to use the `renv` package for package management (see Chapter ??). `targets` and `renv` can be used together in the same project workflow without problems.

3.3.3.4 Branching

A very interesting feature of `targets` is branching. When defining the analysis pipeline, many targets may be obtained iteratively from very similar tasks. If we are already used to functional style, we will always aim to write concise code without repetitions. Here is where branching comes into play as it allows to define multiple targets concisely.

Conceptually branching is similar to the `purr::map()` function used to apply the same code over multiple elements. In `targets` there are two types of branching:

- **Dynamic Branching.** The new targets are defined dynamically while the pipeline is running. The number of new targets is not necessarily known in advance. Dynamic branching is better suited for creating a large number of very similar targets. For further details on dynamic branching, see <https://books.ropensci.org/targets/dynamic.html>.
- **Static Branching.** The new targets are defined in bulk before the pipeline starts. The exact number of new targets is known in advance and they can be visualized with `targets::tar_visnetwork()`. Static branching is better suited for creating a small number of heterogeneous targets. For further details on static branching, see <https://books.ropensci.org/targets/static.html>.

Branching increases a little bit the pipeline complexity as it has its own specific code syntax. However, branching allows obtaining a more concise and easier to maintain and read pipeline (once familiar with the syntax).

3.3.3.5 High-Performance Computing

`targets` supports high-performance computing allowing us to run multiple tasks in parallel on our local machine or a computing cluster. To do that, `targets` integrates in

its workflow the `Clustermq` (<https://mschubert.github.io/clustermq>) and the `future` (<https://future.futureverse.org/>) R packages.

In the case of large, computationally expensive projects, we can obtain valuable gains in performance by parallelizing our code execution. However, configuration details and instructions on how to integrate high-performance computing in the `targets` workflow are beyond the aim of this chapter. For further details on high-performance computing, see <https://books.ropensci.org/targets/hpc.html>.

3.3.3.6 Load All Targets

We have seen how targets' results can be retrieved with `targets::tar_read()` or `targets::tar_load()`. However, it may be useful to have a function that allows us to load all required targets at once. To do that, we can define the following functions in a script named `R/targets-utils.R`.

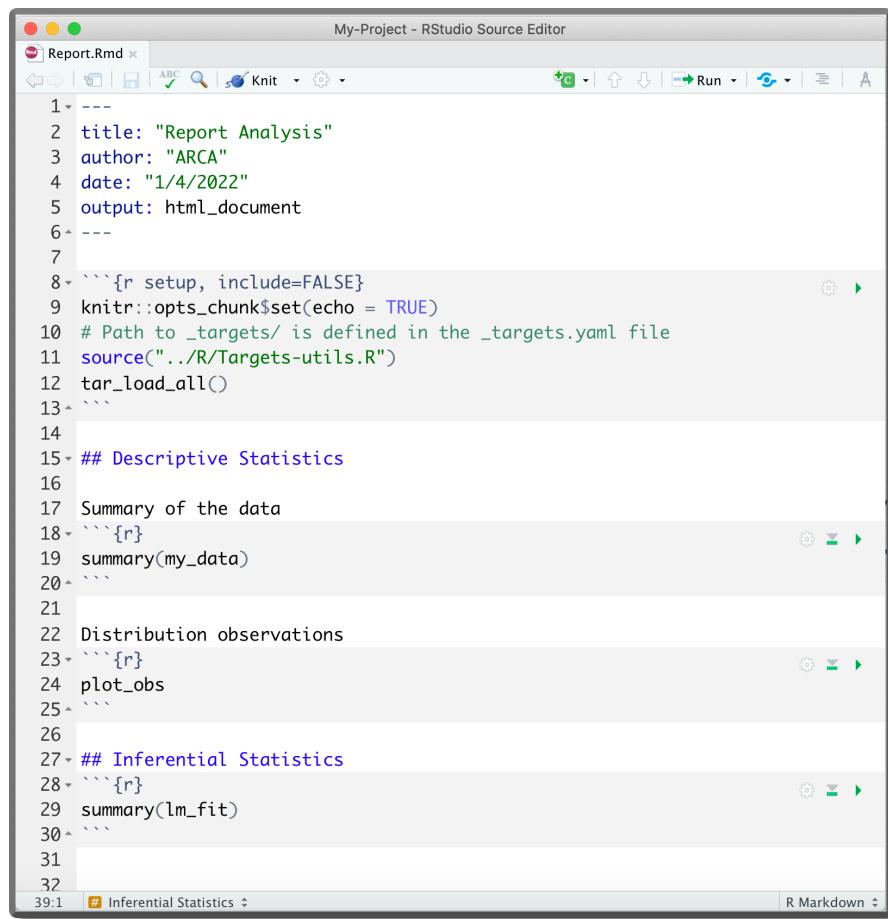
```
##### R/Targets-utils.R #####
##### load_glob_env #####
# Load targets in the global environment
load_glob_env <- function(..., store = targets::tar_config_get("store")){
  targets::tar_load(..., envir = globalenv(), store = store)
}

##### tar_load_all #####
# Load listed targets
tar_load_all <- function(store = targets::tar_config_get("store")){
  targets <- c("my_data", "lm_fit", "plot_obs", "<other-targets>", "...")
  # load
  sapply(targets, load_glob_env, store = store)
  return(cat("Targets loaded!\n"))
}
```

Where:

- `load_glob_env()` is used to load the targets directly in the global environment (otherwise targets would be loaded only in the function environment and we could not use them).
- `tar_load_all()` is used to create a list of the targets of interest and subsequently load them into the global environment.

Now we can use the function `tar_load_all()` to directly load all specified targets. Note, however, that loading the targets in this way in an RMarkdown document would not allow `targets` to detect dependencies correctly.

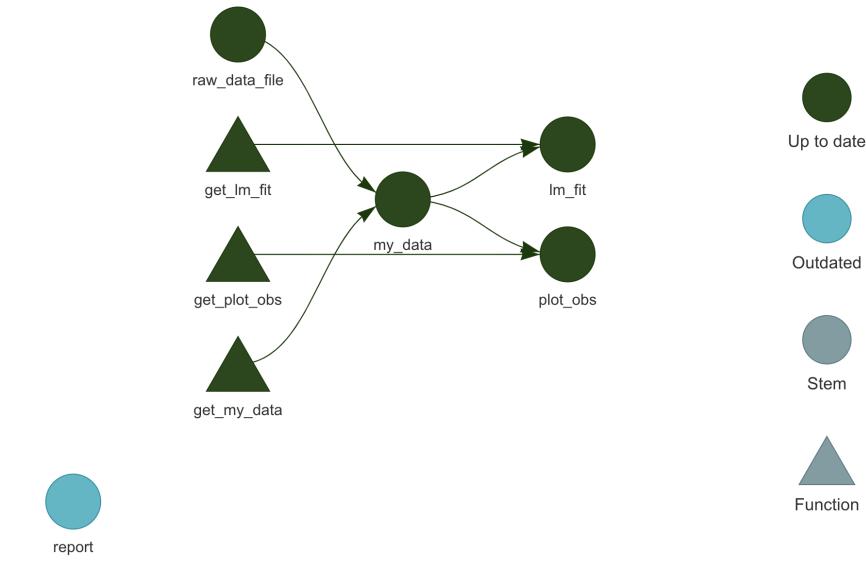


The screenshot shows the RStudio Source Editor interface with the title bar "My-Project - RStudio Source Editor". The file tab shows "Report.Rmd". The editor window displays the following R Markdown code:

```
1 ---  
2 title: "Report Analysis"  
3 author: "ARCA"  
4 date: "1/4/2022"  
5 output: html_document  
6 ---  
7  
8 ```{r setup, include=FALSE}  
9 knitr::opts_chunk$set(echo = TRUE)  
10 # Path to _targets/ is defined in the _targets.yaml file  
11 source("../R/Targets-utils.R")  
12 tar_load_all()  
13```  
14  
15 ## Descriptive Statistics  
16  
17 Summary of the data  
18 ```{r}  
19 summary(my_data)  
20```  
21  
22 Distribution observations  
23 ```{r}  
24 plot_obs  
25```  
26  
27 ## Inferential Statistics  
28 ```{r}  
29 summary(lm_fit)  
30```  
31  
32
```

The status bar at the bottom shows "39:1" and "Inferential Statistics". The bottom right corner shows "R Markdown".

3.3. Targets



Trick-Box: Load Targets Using .Rprofile

We could automatically load targets into the environment by including the function `tar_load_all()` in the `.Rprofile`.

```
#---- .Rprofile ----#
...
# Commands only for interactive sessions
if(interactive()){

    ...
    # Load custom function
    source("R/targets-utils.R")

    # alternatively devtools::load_all()

    # Load targets
    tar_load_all()

    ...
}
```

In this way, each time we restart the R session all targets are loaded in the environment and we can go back straight into the analysis development.



Documentation-Box

Make

- make official documentation
<https://www.gnu.org/software/make/>.
- NMake
<https://docs.microsoft.com/en-us/cpp/build/reference/nmake-reference>
- makefile
<https://opensource.com/article/18/8/what-how-makefile>

R

- Run R non-interactive
<https://github.com/gastonstat/tutorial-R-noninteractive>
- DESCRIPTION load packages
<https://r-pkgs.org/namespace.html?q=depends#imports>
- conflicted R package
<https://conflicted.r-lib.org/>
- Object Oriented
<http://adv-r.had.co.nz/OO-essentials.html>
- workflowr R package
<https://github.com/workflowr/workflowr>

Targets

- Official documentation
<https://books.ropensci.org/targets/>
- Load packages
<https://books.ropensci.org/targets/packages.html>
- Literate programming
<https://books.ropensci.org/targets/files.html#literate-programming>
- Dynamic branching
<https://books.ropensci.org/targets/dynamic.html>
- Static branching
<https://books.ropensci.org/targets/static.html>
- High-performance computing
<https://books.ropensci.org/targets/hpc.html>

References

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