Getting Started with R for Economists

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Preface

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R is a free and powerful software environment for statistical computing and data visualization. It is widely used in academia and industry for data analysis and research. As one of the top programming languages for data science, R provides a variety of tools for statistical modeling, computing, and visualization.

Since empirical research is essential in economics, programming skills are crucial for conducting real-world data analysis. This textbook will introduce you to R and help you develop fundamental data science skills.

About This Book

This textbook is designed for beginners, providing a strong foundation in R for economic research. It focuses on **the tidyverse** ecosystem, a collection of R packages that provide a simple yet powerful approach to data analysis. You will learn how to use tidy tools to manage and analyze data efficiently, covering the entire lifecycle of a data science project.

Who Can Benefit from This Book

I wrote this textbook for two groups of readers. The first group is the participants of the workshop Getting Started with R for Economists: A Hands-On Workshop, which was organized for the 52nd Meeting of the Sri Lanka Forum of University Economists. This book serves as a companion to that workshop. Since the workshop lasts only one hour, the goal is to introduce participants to the tidyverse workflow and give them a strong foundation so they can continue learning on their own.

The second group is any economist who is new to programming and wants to start analyzing data using R. This book is a good starting point for your journey. However, to master each topic fully, I recommend reading more advanced textbooks on R, covering the different areas discussed here.

Share Your Thoughts!

This book is still a work in progress. If you have any suggestions to improve the content, feel free to open a GitHub issue here. I'd love to hear from you!

1 Introduction to R and RStudio

1.1 Installing R and Rstudio

- **Step 1:** First download R freely from the Comprehensive R Archive Network (CRAN) https://cran.r-project.org/. (At the moment of writing, R 4.4.2 is the latest version. Choose the most recent one.)
- **Step 2:** Then install R Studio's IDE (stands for integrated development environment), a powerful user interface for R from [https://posit.co/download/rstudio-desktop/](https://posit.co/download/rstudio-desktop/. Get the Open Source Edition of RStudio Desktop. RStudio allows you to run R in a more user-friendly environment.
  - You need to install **both** R and Rstudio to use RStudio.
  - If you have a pre-existing installation of R and/or RStudio, I highly recommend that you reinstall both and get as current as possible.
- **Step 3:** Then open **Rstudio**.

1.1.1 Posit Cloud

- In 2022, RStudio changed its corporate name to Posit with the aim of expanding its focus beyond R to include users of Python and Visual Studio Code.
- If you don't want to download or install R and R Studio, you can use RStudio on Posit Cloud for free.

1.2 RStudio layout

The RStudio interface consists of four panes: See Figure 1)

1. **Source pane**
2. **Console pane**
3. **Environment pane**, containing the Environment, History, Connections, Build, and Tutorial tabs

4. **Output pane**, containing the Files, Plots, Packages, Help, Viewer, and Presentation tabs

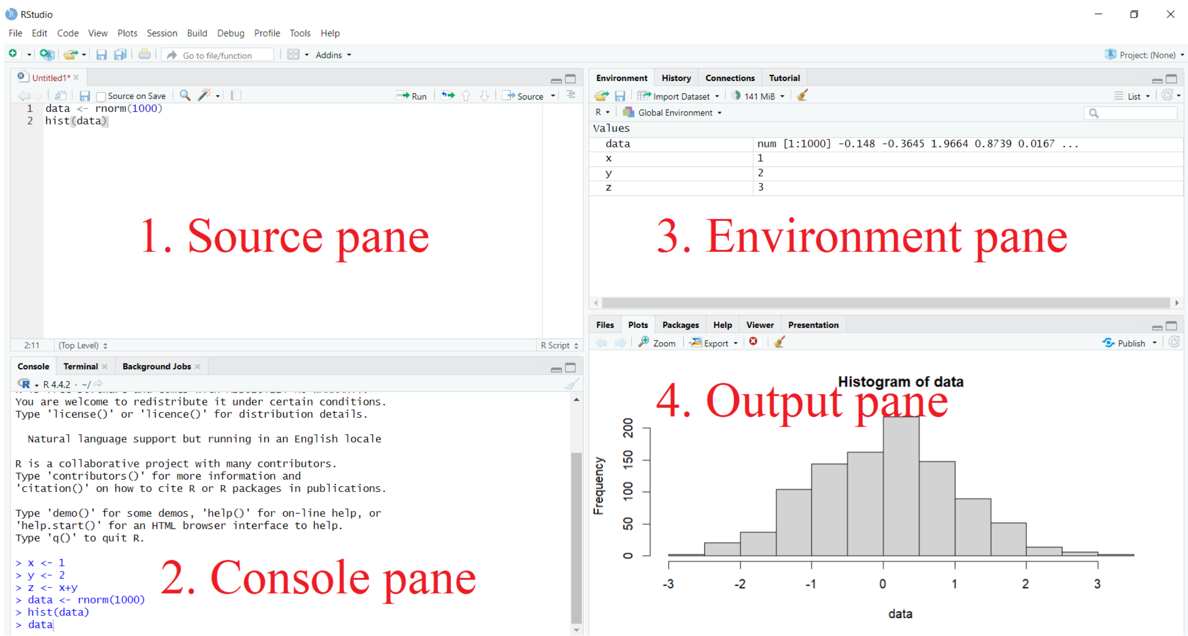


Figure 1.1: RStudio layout

1.2.1 Console Pane

- This is where you type and execute all your R commands.
- You can enter R commands after the '>' prompt, and R will process and execute them.
- This is the most essential window, as it is where R performs computations and executes your instructions.

1.2.2 Source pane

- In this window, a collection of commands (scripts) can be edited and saved.
- If this window is not visible, you can open it via File → New File → R Script.
- Simply typing a command in the Source pane is not enough; it must be sent to the Console before R executes it.
- To run a line from the Source pane, place your cursor on the desired line or select multiple lines to execute, then click Run or press CTRL + ENTER to send them to the Console pane.

- Make sure to save the 'Untitled1' file as a `*.R` script.

1.2.3 Environment pane

- This window contains multiple tabs: Environment, History, Connections, Build, and Tutorial.

The Environment tab displays all active objects.

- For data frames, clicking the grid symbol opens the full data frame in the Source pane.
- The History tab shows previously typed commands.
- To send a command in the history tab to the Source pane, select it and click the "To Source" icon, or click "To Console" to execute it in the Console.

1.2.4 Output Pane

- This window contains multiple tabs: Files, Plots, Packages, Help, Viewer, and Presentation.
- It allows you to open files, view plots (including previous ones), install and load packages, access help functions, and display web content such as Shiny apps and Quarto-generated web pages.

Now you are familiar with the layout. Let's begin with R basics.

1.3 Installing an R Package

- The primary source for R packages is CRAN (Comprehensive R Archive Network).
- Packages can be installed using the `install.packages()` function in R.
- To install a single package, pass its name as the first argument to `install.packages()`.
- The following code installs the tidyverse package from CRAN:

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

- This command downloads and installs the `tidyverse` package from CRAN.
- Any dependencies required by the package will also be downloaded and installed.

- Installing the tidyverse package may take several minutes, but you only need to do this once. Think of it like installing a mobile app—you install it once on your smartphone and can use its features until a new version is released, at which point you may need to update it

1.3.1 Alternative way to install R packages in Rstudio

- An alternative way to install R packages is through the Packages tab in the Output Pane.
- Navigate to the Packages tab in the Output Pane and click Install.
- Under "Install from," select "Repository (CRAN)".
- In the Packages field, enter the name of the package you want to install.
- To install multiple packages at once, separate the package names with commas.
- Finally, click Install.

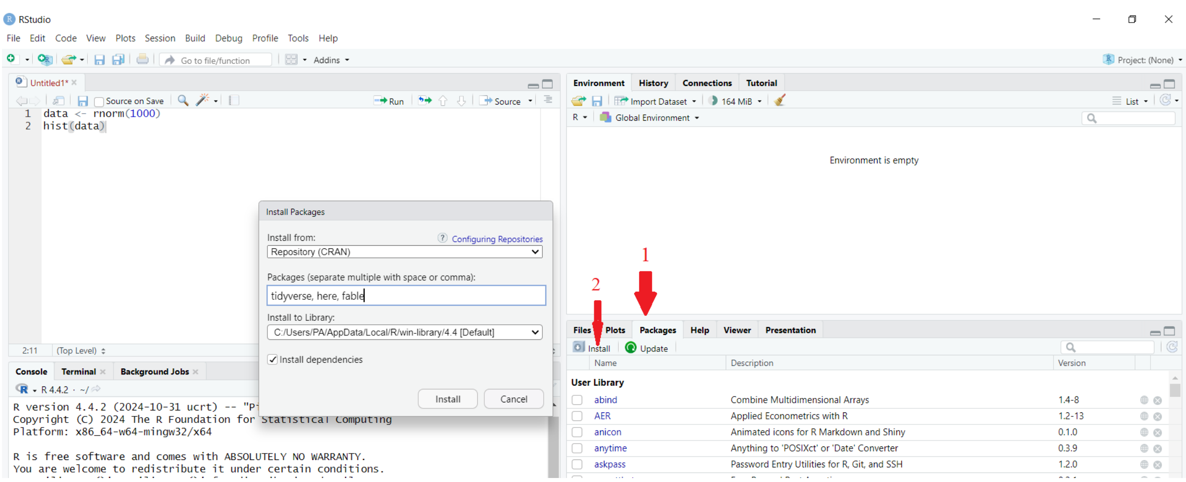


Figure 1.2: Alternative way to install R packages in Rstudio

1.4 Loading an R Package

- Installing a package does not automatically make it available for use; you must load it. It's like a mobile app—you need to open it to access its functionalities.
- The `library()` function is used to load installed packages into R.
- To load the tidyverse package, use:

```r
library(tidyverse)
```

```
-- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
v dplyr     1.1.4     v readr     2.1.5
v forcats   1.0.0     v stringr   1.5.1
v ggplot2   3.5.1     v tibble    3.2.1
v lubridate 1.9.3     v tidyr     1.3.1
v purrr     1.0.2
-- Conflicts ------------------------------------------ tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom
```

- **Note: Do not put the package name in quotes when using library().**
- Some packages display messages when loaded, while others do not.

1.5 Getting Started with R

For a detailed introduction to R, refer to:

An Introduction to R: https://cran.r-project.org/doc/manuals/R-intro.pdf

2 R Programming Basics

- R has two main parts: data structures and functions.
  - Data structures help store and organize data so it can be used efficiently.

```r
income <- c(1000, 4000, 3400, 9700, 9800)
income
```

```
[1] 1000 4000 3400 9700 9800
```

```
-   Functions tell R what to do.
```

```r
mean(income)
```

```
[1] 5580
```

```r
summary(income)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
   1000    3400    4000    5580    9700    9800 
```

2.1 Data structures

- R's basic data structures can be grouped by:
  - Their dimensions (1D, 2D, or multi-dimensional).
  - Whether they store one type of data (homogeneous) or different types of data (heterogeneous).
- This gives us five common data structures in R:
  - Homogeneous (same type of data): Vectors, Matrices, Arrays
  - Heterogeneous (different types of data): Data Frames, Lists

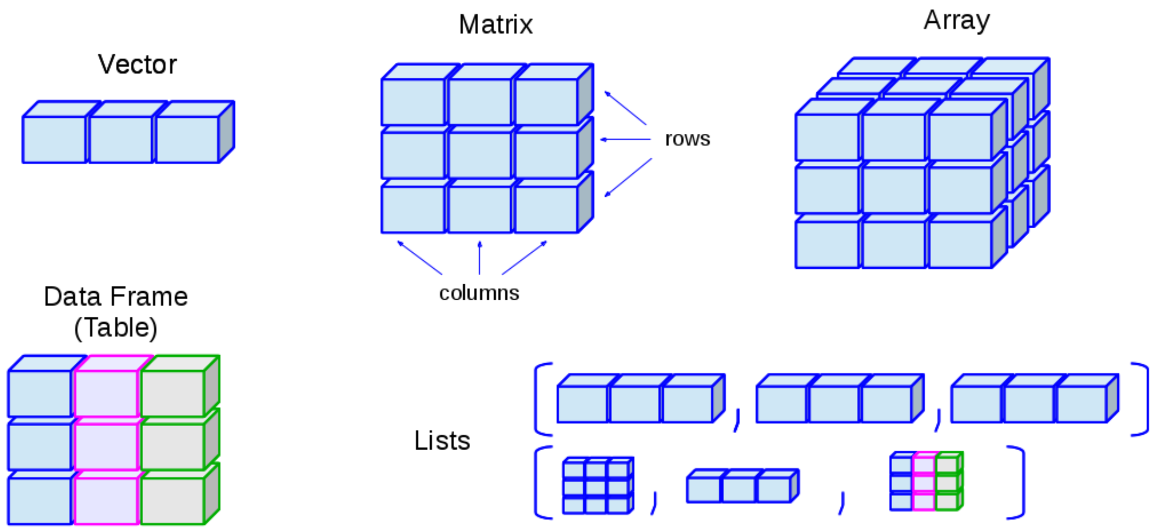


Figure 2.1: Data Structure Types. Image Source: http://venus.ifca.unican.es/Rintro/dataStruct.html

- Among these, vectors and data frames are the most commonly used data structures in practical applications.

2.1.1 Vectors

Creating vectors

Syntax

```
vector_name <- c(element1, element2, element3)
```

Example

```
x <- c(5, 6, 3, 1, 100)
x
```

```
[1]   5   6   3   1 100
```

Combine two vectors

```
p <- c(1, 2, 3)
p
```

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

```r
q <- c(10, 20, 30)
q
```

```
[1] 10 20 30
```

```r
r <- c(p, q)
r
```

```
[1]  1  2  3 10 20 30
```

Vector with charactor elements

```r
countries <- c("Sri Lanka", "Afghanistan", "Bangladesh", "Bhutan", "India", "Iran", "Maldives

countries
```

```
[1] "Sri Lanka"   "Afghanistan" "Bangladesh"  "Bhutan"      "India"
[6] "Iran"        "Maldives"    "Nepal"       "Pakistan"
```

Logical vector

```r
result <- c(TRUE, FALSE, FALSE, TRUE, FALSE)
result
```

```
[1]  TRUE FALSE FALSE  TRUE FALSE
```

Simplifying vector creation

- `rep` is a function in R that repeats the values in a vector

```r
id <- 1:10
id
```

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

```r
treatment <- rep(1:3, each=2)
treatment
```

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

Vector operations

```r
x <- c(1, 2, 3)
y <- c(10, 20, 30)
x+y
```

```
[1] 11 22 33
```

```r
p <- c(100, 1000)
x+p
```

```
Warning in x + p: longer object length is not a multiple of shorter object
length
```

```
[1]  101 1002  103
```

2.2 Data Frames

Required R package to deal with data frames

```r
library(tidyverse)
```

```
-- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
v dplyr     1.1.4     v readr     2.1.5
v forcats   1.0.0     v stringr   1.5.1
v ggplot2   3.5.1     v tibble    3.2.1
v lubridate 1.9.3     v tidyr     1.3.1
v purrr     1.0.2
-- Conflicts ------------------------------------------ tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom
```

Create a tibble

- A tibble is an improved version of a traditional data frame in R, designed to be more user-friendly and consistent.
- It is part of the `tidyverse` package and makes it easier to view and analyze data, especially when working with large datasets.

Lets consider the following example

GDP per capita (current US$) - South Asia

Data Source : https://data.worldbank.org/

Country	Most Recent Year	Most Recent Value
Afghanistan	2023	415.7
Bangladesh	2023	2,551.0
Bhutan	2023	NA
India	2023	2,480.8
Maldives	2023	12,530.4
Nepal	2023	1,377.6
Pakistan	2023	1,365.3
Sri Lanka	2023	3,828.0

```r
country <- c("Afghanistan", "Bangladesh", "Bhutan", "India", "Maldives",
             "Nepal", "Pakistan", "Sri Lanka")
year <- c(rep(2023,8))
value <- c(415.7, 2551.0, NA, 2480.8, 12530.4, 1377.6, 1365.3, 3828.0)

final <- tibble(Country = country, Recent_Year = year, Value = value )
final
```

```
# A tibble: 8 x 3
  Country     Recent_Year  Value
  <chr>             <dbl>  <dbl>
1 Afghanistan        2023   416.
2 Bangladesh         2023  2551
3 Bhutan             2023    NA
4 India              2023  2481.
5 Maldives           2023 12530.
6 Nepal              2023  1378.
7 Pakistan           2023  1365.
8 Sri Lanka          2023  3828
```

2.3 Functions in R

- In R, functions are blocks of code that perform specific tasks.
- They take input values (called arguments), process them, and return an output.
- Functions help automate repetitive tasks and make code more efficient.
- There are two main types of functions in R:
    - Built-in functions – Predefined in R (e.g., mean(), sum(), rep()).

```
summary(final$Value)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
  415.7  1371.5  2480.8  3507.0  3189.5 12530.4       1 
```

```
- User-defined functions - Created by users for specific needs using function().
```

2.4 Subsetting

```
final
```

```
# A tibble: 8 x 3
  Country     Recent_Year  Value
  <chr>             <dbl>  <dbl>
1 Afghanistan        2023   416.
2 Bangladesh         2023  2551 
3 Bhutan             2023    NA 
4 India              2023  2481.
5 Maldives           2023 12530.
6 Nepal              2023  1378.
7 Pakistan           2023  1365.
8 Sri Lanka          2023  3828 
```

```
final[1, 1]
```

```
# A tibble: 1 x 1
  Country    
  <chr>      
1 Afghanistan
```

```r
final[, 1]
```

```
# A tibble: 8 x 1
  Country
  <chr>
1 Afghanistan
2 Bangladesh
3 Bhutan
4 India
5 Maldives
6 Nepal
7 Pakistan
8 Sri Lanka
```

```r
final[1, ]
```

```
# A tibble: 1 x 3
  Country     Recent_Year Value
  <chr>             <dbl> <dbl>
1 Afghanistan        2023  416.
```

```r
final$Country
```

```
[1] "Afghanistan" "Bangladesh"  "Bhutan"      "India"       "Maldives"
[6] "Nepal"       "Pakistan"    "Sri Lanka"
```

2.5 Help file for Built-in functions

- To access the help file for a built-in function in R, you can use either `?` or the `help()` function.
- Running either of these commands will open the help page for the specified function.

= For example, using `?summary` or `help(summary)` will display the help file for the summary function, which is part of the base R package.

```r
?summary

# or

help(summary)
```

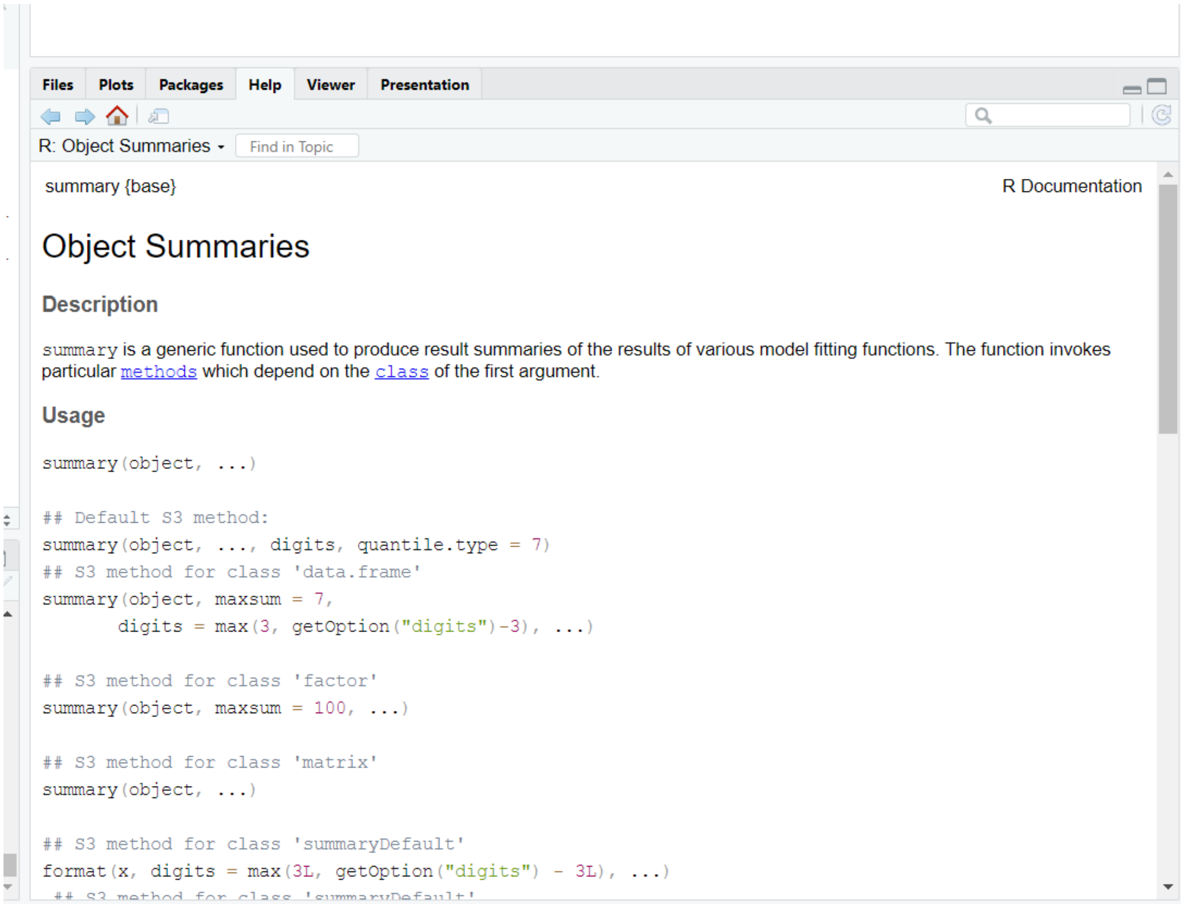


Figure 2.2: Help Page

2.6 Commenting

```
mean(final$Value) # Calculate the average GDP value
```

```
[1] NA
```

When you go to the help page for the `mean()` function, you'll find that by default, the `na.rm` argument is set to `FALSE`. This means that if the data contains missing values (NA), they will be included in the calculation, and the result will also be NA. To calculate the mean while ignoring missing values, you should set `na.rm = TRUE`.

```r
mean(final$Value, na.rm = TRUE) # Calculate the average GDP value
```

```
[1] 3506.971
```

2.7 Pipe operator (|>)

- The pipe operator (`|>`) in the base R package helps improve the readability of your code.
- It takes the output of one function and passes it directly into another function as an argument, making the steps in your data analysis more connected.
- Instead of using nested function calls like `function(first_input, other_inputs)`, you can write the same command in a simpler format: `first_input |> function(other_inputs)`.

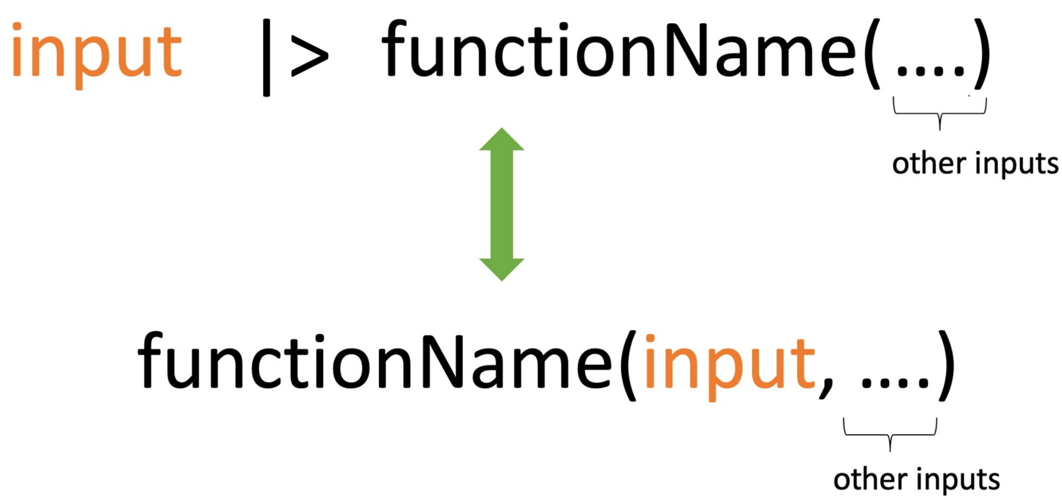


Figure 2.3: Pipe Operator

- Therefore, using the pipe operator allows you to chain multiple operations together in a way that is easier to read and understand compared to nested function calls.

```r
# Nested function call
mean(final$Value, na.rm = TRUE)
```

```
[1] 3506.971
```

```r
# Using pipe operator)
final$Value |> mean(na.rm=TRUE)
```

```
[1] 3506.971
```

3 Scripts and Rstudio Projects

So far, we've been using the console to run code. One problem with the R console is that once you close the project, you won't be able to access the previous code you ran unless you save the workspace. This is where the script editor comes in.

3.1 Working with R Scripts

- To open a script file, go to File -> New File -> R Script.
- You can use a script file to save your code so you don't have to re-type everything when you start a new R session.
- Just typing a command in the script file isn't enough. It must be sent to the Console before R can execute it.
- To run a line of code from the script, place your cursor on the line (or select multiple lines), then click Run or press CTRL + ENTER to send them to the Console.
- Remember to save your script with the *.R extension and give it a suitable name, not as 'Untitled1'.

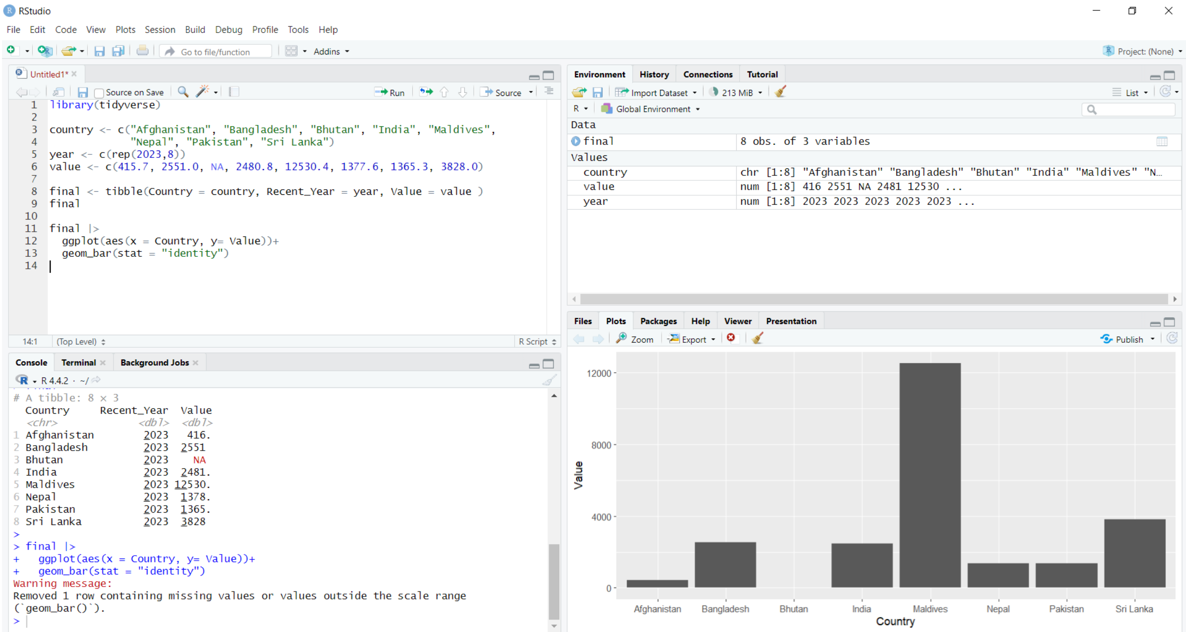


Figure 3.1: Working with R script files

3.2 Working with RStudio Projects

When you start working on large projects, you'll need to manage multiple files, such as input data, script files, and figures. Being organized is very important to manage your work efficiently. This is where RStudio projects help. RStudio projects allow you to keep all the documents related to a project in one folder.

To create an RStudio project, go to `File -> New Project -> New Directory -> New Project`, and then choose a suitable name for the folder to store your work. You also need to pick a location to save your project by setting the "Create project as subdirectory of" option. In the following example, I named my project "Test" and selected the Desktop to store it.

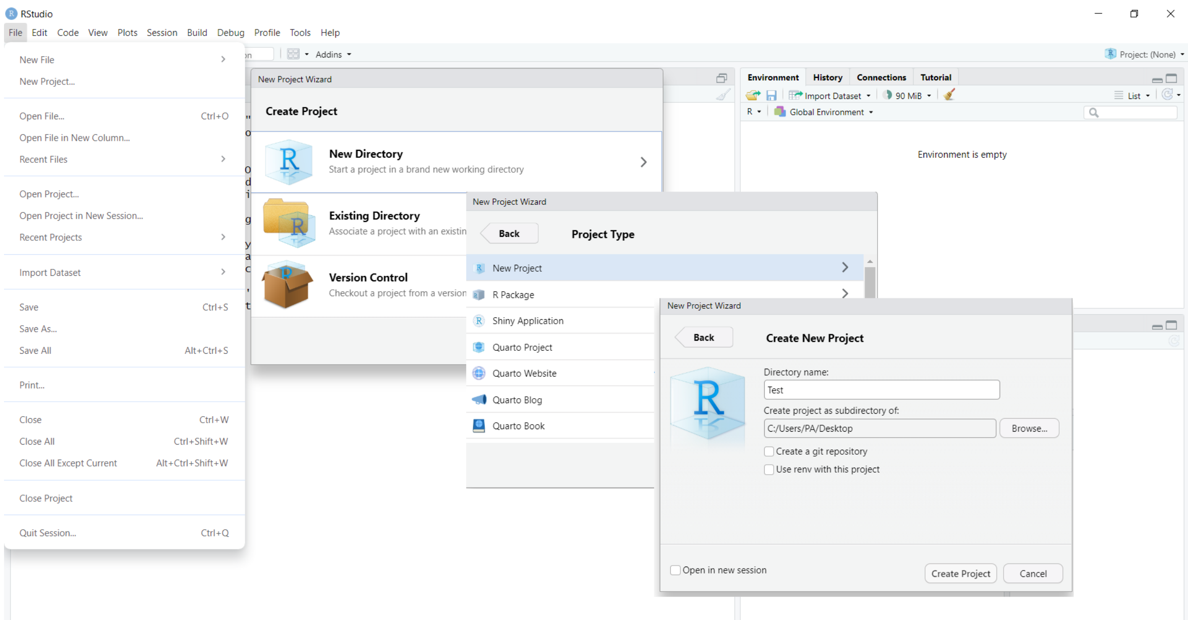


Figure 3.2: Working with RStudio Projects

Once this is done, I now have a new RStudio project called "Test" on my Desktop. This project looks like a regular folder where I can save all my work. If you open the folder, you will see a `.Rproj` file (R Project file). In my example, since I saved my project as "Test," the R project file is called "Test.Rproj." Inside this folder, you can create subfolders, like one for figures called `figures`, another for raw data files called `data`, and another for your R script files called `scripts`.

Let's say you're done working on the project for the day. Now, close the project and quit RStudio.

The next day, when you come back to the project, locate the folder (in my case, it's on the Desktop), open it, and double-click the .Rproj file. This will reopen the project, and you'll pick up right where you left off. You'll have access to all the files you've saved inside the RStudio Project.

The only things you can't retrieve are the commands you typed directly into the console and any unsaved outputs, like summary statistics or figures that were not saved.

But script files at least allow you to save time by preventing you from retyping commands or complex code you've already written in previous sessions. They're better than typing directly into the console.

4 Reproducible Reporting with Quarto

As an economist, you work with complex data and statistics to give businesses useful financial advice. Clear and effective data communication is essential for this role.

So far, we have learned how to perform our analysis by writing commands in a script file. The advantage of this approach is that you can save all your previous code, avoiding the need to retype it from scratch each time. However, one major drawback is that the generated outputs (such as tables and graphs) are not saved automatically—you must manually save each one.

Even if you make an effort to save the output, manually copying and pasting results can sometimes lead to human errors. Additionally, you may only notice errors in the original dataset after generating the outputs. When this happens, you have to rerun the code step by step, regenerate all the outputs, and manually replace the previous results based on incorrect data. This process is time-consuming and increases the risk of mistakes.

This is where reproducible reporting or dynamic documents become useful. Dynamic documents allow you to store text, code, and output (e.g., tables, graphs) all in a single file. Unlike R script files, dynamic documents make it easy to save both the code and its results together, ensuring everything is available for future use.

4.1 Dynamic documents

Dynamic documents are important because they:

- They let us add R code directly into the document, and the code runs automatically to include the results.
- They update analyses and visuals automatically when data changes, saving time and reducing mistakes.
- They help recreate results easily, making analyses more transparent and consistent.
- They make it simple to share analysis and results with team members, improving collaboration and communication.

4.2 Dynamic Documents with Quarto

Both R Markdown and Quarto allow you to create dynamic documents. Quarto is the next generation of R Markdown, so in this book, I will focus on Quarto. For those already familiar with R Markdown, you'll find the transition to Quarto very easy, as the syntax is very similar.

4.2.1 Installing Quarto

A stable release of Quarto is included with RStudio version 2022.07.1 and later. Upgrading to future versions of RStudio will also upgrade the bundled version of Quarto.

4.2.2 Why Quarto ?

- Quarto supports multiple programming languages (R, Python, Julia, and more) within the same document, allowing for a more versatile workflow.
- Quarto provides a wider range of output formats, including HTML, PDF, Word, and slides, all from a single document. This flexibility makes it easier to publish content in various formats without needing separate files.
- Quarto is designed with modern development practices in mind, making it easier to integrate with version control systems like Git.
- Quarto offers advanced features for customization, including the ability to create custom formats and templates, which can help in producing highly tailored outputs.
- Quarto is actively developed with a focus on modern data science practices, which means it benefits from ongoing improvements and a growing community.

4.3 Getting Started with Quarto

Let's get started with Quarto:

- First, go to `File -> New File -> Quarto Document...`

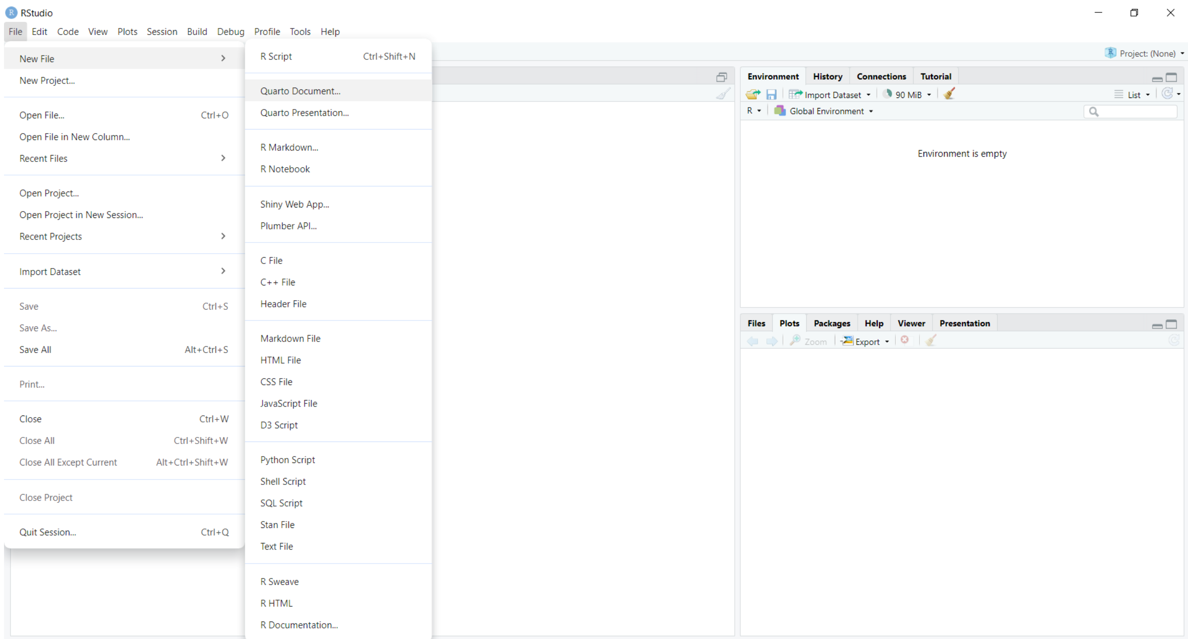


Figure 4.1: Getting Started with Quarto

- Assign a name for the document title. You can always change the title later.

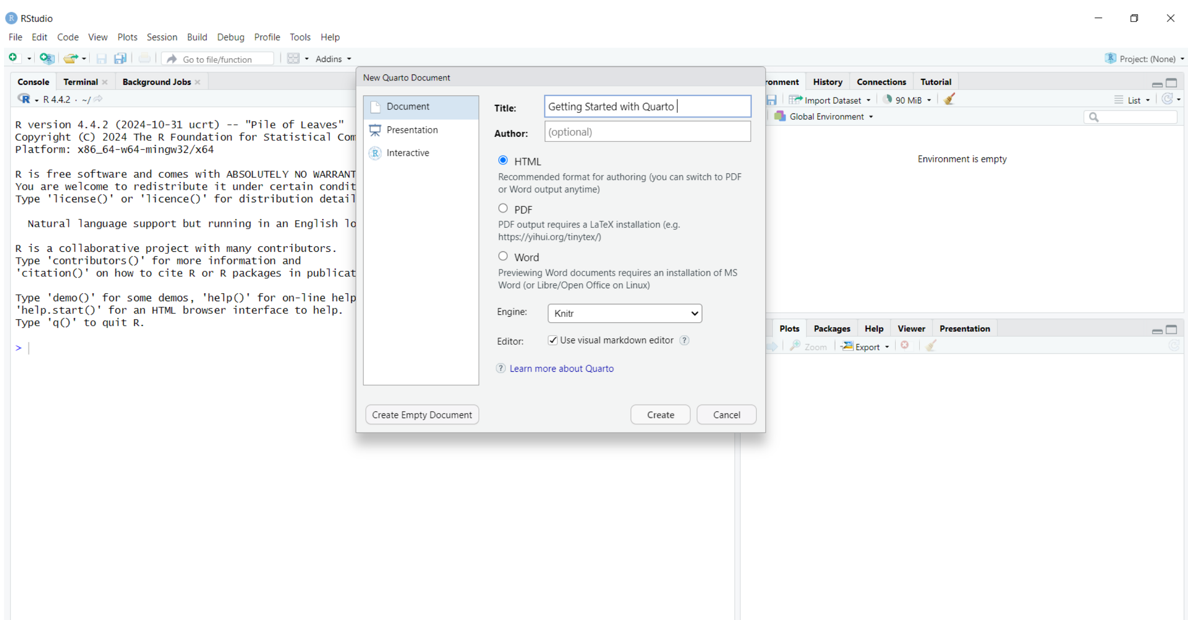


Figure 4.2: Assign a name for the document title

- Choose your preferred output format. In this example, I've selected HTML, which is the default setting. You can switch to PDF or Word output at any time using the same source file, with just minor changes to the output type.
- This will open a Quarto document called "Untitled1*" with example content. First, save the document with an appropriate file name.
- To get a feel for Quarto, let's render the example document and check the output.
- Use the Render button in the RStudio IDE to render the file and preview the output.
- To view the output in the Viewer Pane, click the settings button next to the Render button on the right side, and select the option "Preview in Viewer Pane".

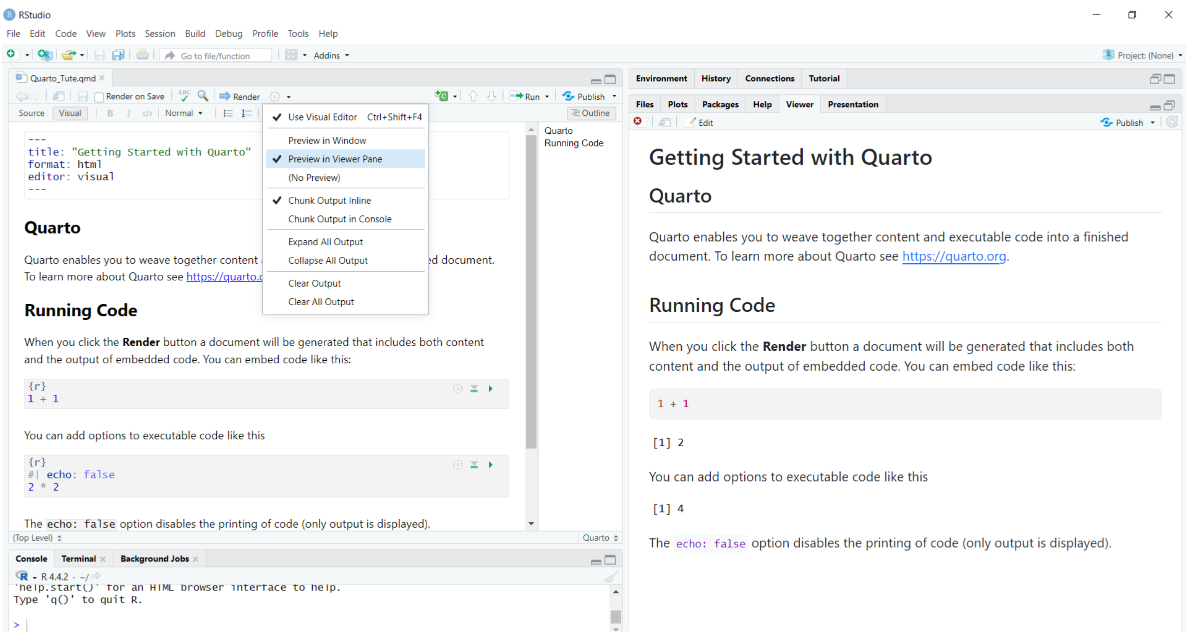


Figure 4.3: Save the document with an appropriate file name

- You will see the rendered output with both the code and the results in a single document.
- If you go to the directory where you saved the `.qmd` file (the Quarto source file), you will also find the generated HTML output with the same name in the same directory.

4.4 Anatomy of a Quarto document

Now that you know how to render a Quarto document, let's get familiar with the anatomy of a Quarto document. The file contains three types of content: a YAML header, code chunks, and markdown text.

In addition to that, we can view the same .qmd document in two modes of the RStudio editor: visual (on the left) and source (on the right). Open the source window so that you can easily identify the syntax..

4.4.1 YAML header

- In Quarto, YAML (which stands for YAML Ain't Markup Language) is used for setting up metadata and configurations for your document.
- It is placed at the top of the Quarto file within three dashes (—), and it allows you to specify document options such as the title, author, output format (HTML, PDF, Word), date, and more.
- In YAML, the basic format is `key: value`, where you assign a value to a key.

```
---
title: "Getting Started with Quarto"
subtitle: "Report 1"
author: "Priyanga Talagala"
date: "2025-01-31"
output: html_document
---
```

4.4.2 Code Chunks

- In Quarto, code chunks are sections of the document where you can write and run code. You can think of this part as a mini console window within the Quarto document.
- A code chunk in Quarto is enclosed between three backticks ("') to separate it from the rest of the text.
- The code inside these chunks is executed when you render the document, and the output (such as tables, plots, or results) is displayed directly in the final document.
- These chunks can contain code written in different programming languages, such as R, Python, or Julia. In the following example, {r} indicates that we are going to run R code inside this code chunk.
- If you want to run Python code, you just need to replace {r} with {python} in the code chunk.

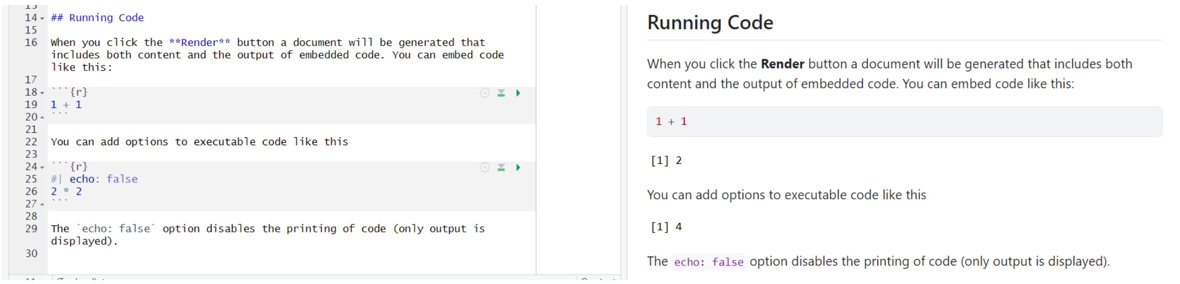


Figure 4.4: Code Chunks. LHS : Source file, RHS: Resulted output

4.4.3 Markdown text

- Markdown text includes formatted text, such as section headers, paragraphs, embedded images, and more. Quarto uses Markdown syntax for writing text, which is clear when you switch to the Source tab.
- To define section headings, you use the # symbol. The number of # symbols determines the level of the heading: one # for an H1 heading, two ## for an H2 heading, three ### for an H3 heading, and so on.
- In R Markdown syntax, you can format text as follows:
  - To make text bold, use `**bold**`.
  - To make text italic, use `*italic*`.

```
This is **bold** text and this is *italic* text.
```

This is **bold** text and this is *italic* text.

5 Data Import and Export

5.1 Tidy Workflow

As an economist, working with empirical research and data is crucial for making data-driven decisions, and data science helps transform raw data into understanding, knowledge, and insights to support this process. A **tidy workflow** focuses on the tools needed to carry out this process effectively.

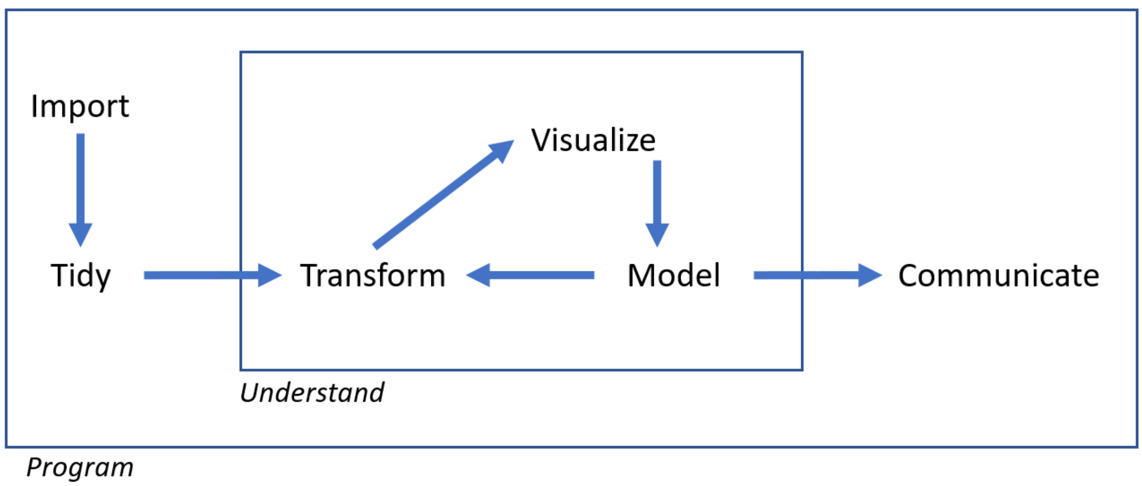


Figure 5.1: Tidy workflow, Image recreated from R for Data Science (2e) (https://r4ds.hadley.nz/intro.html)

When working with data, the first step is to import it into our data science environment. Next, we tidy up the data to make it clean and usable. Then, as data scientists, our main task is to understand the data using three key tools: transformation, visualization, and modeling. Finally, we communicate our results to the right people to support decision-making.

The `tidyverse` package is a collection of R packages that work together to make data analysis easier. When you load `tidyverse`, it also loads several useful packages, including: `dplyr`, `readr`, `forcats`, `stringr`, `ggplot2`, `tibble`, `lubridate`, `tidyr` and `purrr`

```
library(tidyverse)
```

Let's dive into each of these steps in the tidy workflow and explore the tools available in the R ecosystem.

5.2 Import data

When you work with data, you save your raw data in a separate file, like a CSV. You can easily load this external data into the data science environment using the `readr` package.

5.2.1 Read data files into a tibble

Download the dataset: touristsl.csv

```
data1 <- read_csv("touristsl.csv")
```

If the data file is in another folder within the **current working directory**, you can use the `here` function from the `here` package. With respect to the current working directory, the `here` function helps you define the file path starting from there.

For example, if you have a file called "touristsl.csv" inside a folder called "data" in the current working directory, and you are currently in the working directory, you would need to open the data folder to access the CSV file. In the `here` function, you define the path as `here("data", "touristsl.csv")`. Each folder you want to open is listed, and they are separated by commas.

```
library(here)
data <- read_csv(here("data", "touristsl.csv"))
```

5.3 Export data

Similarly, to save a data file, we can use the write_csv function.

```
weight <- c(50,44,60)
height <- c(150,160,163)
ds <- tibble(weight, height)
write_csv(ds, "ds.csv")
```

If you want to save the data file in another folder within the current working directory, use the `here` function to define the file path.

```
library(here)
write_csv(ds, here("data", "ds.csv"))
```

6 Data Wrangling

Data wrangling is the process of transforming and structuring raw data into a structured format to enhance its quality, making it easier to analyze. Data wrangling in the tidyverse workflow generally covers both tidy and transform steps int he tidy workflow.

6.1 Data Tidying

In this step you try to reshape messy data into a tidy format.

A tidy dataset follows these key principles:

- Each variable is placed in its own column.
- Each observation is placed in its own row.
- Each value is placed in its own cell.

The following examples are taken from published reports by various institutes and contains an untidy data structure. This is a common issue in real-world data. The problematic areas that make the data untidy are highlighted.

1. Image Source: Sri Lanka Export Development Board – Export Performance Indicators 2023

18. TOP 10 EXPORT SECTORS OF SRI LANKA - 2023

Table 18.1

	Sector	Export Value US$ Mn.	Share in World exports %	Ranking inWorld exports	Contribution to total exports %	Exports to major markets as % of total exports of the product	Top export markets
1.	Textiles & Garments	4,865	1.1 % [HS.61] 0.8 % [HS.61]	15[HS.61] 21 [HS.62]	32.21	80%	United States, United Kingdom, Italy, Germany, Netherlands, Canada, India, France, Belgium, Australia
2.	Transport & Logistics	1,550	N/A	N/A	10.26	N/A	N/A
3.	Tea	1,310	16.8 % [HS.0902]	5	8.67	70%	Turkey, Iraq, Russian Federation, United Arab Emirates, China, Saudi Arabia, Azerbaijan, Syrian Arab Republic, Libyan Arab Jamahiriya, United States
4.	ICT/ BPM	1,227	N/A	N/A	8.12	N/A	N/A
5.	Rubber & Rubber based products	930	0. 5%	29	6.16	70%	United States, Germany, Belgium, Italy, Brazil, France, Canada, United Kingdom, India, Australia
6.	Coconut & coconut-based products	709	0.85%	32	4.69	70%	United States, Germany, Netherlands, China, United Kingdom, India, United Arab Emirates, Canada, Mexico, Australia
7.	Electrical & electronics	487	0.01%	66	3.22	70%	Switzerland, India, United States, Bangladesh, Germany, Hong Kong, Singapore, United Kingdom, Mexico, Maldives
8.	Food & beverages	428	Since F&B is a vast sector comprising many HS chapters, unable to indicate World share & rank		2.83	70%	India, Maldives, Japan, United States, United Arab Emirates, Cyprus, Australia, Singapore, Malaysia, Netherlands
9.	Spices & Concentrates	398	2.42%	12	2.63	80%	India, Mexico, United States, Peru, Germany, Guatemala, Ecuador, Colombia, Bolivia, Spain
10.	Diamond, Gems & Jewelry	388			2.57	75%	Israel, Switzerland, United States, India, Thailand, Hong Kong, United Arab Emirates, Belgium, France, Italy

N/A – Not available
**- According to ITC Trade Map Data 2022,*
Sources: Central Bank of Sri Lanka, Sri Lanka Customs, ITC Trade map, EDB

Figure 6.1: Untidy Data, Image Source: Sri Lanka Export Development Board – Export Performance Indicators 2023

In this example, certain cells contain more than one value separated by a comma, making the dataset untidy.

2. Image Source: Central Bank of Sri Lanka – Annual Report 2022

NATIONAL OUTPUT, EXPENDITURE, INCOME AND EMPLOYMENT — TABLE 28

Performance of Selected State Owned Industrial Enterprises

Corporation/Enterprise and Products	Unit	2018			2019			2020			2021 (a)			2022 (b)		
		Capacity	Production	Sales	Capacity	Production	Sales	Capacity	Production	Sales	Capacity	Production	Sales	Capacity	Production	Sales
1. Lanka Salt Ltd																
Common Salt	mt	80,000	68,834	47,317	70,000	57,290	62,275	70,000	60,076	56,988	100,000	63,000	78,726	100,000	111,000	60,923
2. State Timber Corporation (c)																
Sawn Timber	m³ '000	5	4	250	4	5	295	7	3	222	8	4	309	9	3	373
Logs	"	127	130	3,249	109	123	3,445	101	107	3,299	104	128	4,929	108	103	3,624
Sleepers	Nos. '000	42	44	499	49	37	530	50	38	371	40	29	287	29	34	603
3. National Paper Co. Ltd (c)(d)																
Paper & Paper Products	mt	12,000	-	774	-	-	-	750	81	8.2	6,000	1,154	125	6,000	1,878	466
4. State Printing Corporation (c)																
80 pgs Exercise Books	mn	12	7	222	10	6	166	11	5	122	10	5	138	12	2	219
Text Books	"	13	3	289	13	10	979	20	14	1,096	20	15	1,030	22	15	-
Lottery Tickets	"	420	42[illegible]	360	525	503	427	756	537	332	756	495	270	760	585	490
Commercial Printing Jobs	Nos.	800	44[illegible]		1,200	448		1,200	306		1,200	306		1,200	280	
5. Sri Lanka Ayurvedic Drugs Corporation																
Syrup and Oil	mt	724	419	262	640	507	405	692	425	326	755	545	344	845	402	316
Other Ayurvedic Drugs	mt	90	69	39	146	102	61	123	86	63	107	170	63	128	64	48
6. Ceylon Petroleum Corporation (e)																
Petrol (92 Octane)	mt	162,400	165,428	1,172,540	180,500	185,915	1,148,482	187,790	164,416	1,025,126	168,889	124,092	1,102,737	187,790	38,666	964,996
Kerosene	"	56,760	35,195	203,604	62,610	38,345	202,841	69,300	109,165	175,568	60,102	98,284	185,330	66,780	25,289	98,377
Naphtha	"	118,500	140,661	137,123	130,600	162,019	161,960	157,720	156,953	164,649	143,485	106,956	10,624	158,044	30,835	32,259
Auto Diesel	"	500,300	567,577	1,793,763	570,900	624,462	1,998,724	629,953	537,645	1,574,490	568,544	370,594	1,706,155	608,253	128,165	1,475,628
Avtur	"	227,040	237,270	498,841	250,430	258,986	473,780	277,200	157,279	188,731	240,408	130,572	223,854	267,120	57,346	245,838

Figure 6.2: Untidy Data, Image Source: Central Bank of Sri Lanka – Annual Report 2022

In this example, certain cells are merged and presented as a common value using curly braces. This format makes the data untidy and difficult to analyze.

3. Image Source: Disaster Management Centre, Ministry of Defense – River Water Level and Flood Warning Report

වාරිමාර්ග දෙපාර්තමේන්තුව
நீர்ப்பாசனத் திணைக்களம்
IRRIGATION DEPARTMENT
(ජලවිද්‍යා හා ආපදා කළමනාකරණ අංශය)

Islandwide Water Level & Rainfall Situation in Major Rivers

DATE : 26-Jan-2025 TIME : 9:30 AM

River Basin	Tributary/River	Gauging Station					Water Level at 8:00 am	Water Level at 9:00 am	Remarks	Water Level Rising or Falling	24 Hr RF in mm at 8.30 am
		Station	Unit	Alert Level	Minor Flood Level	Major Flood Level					
Kelani Ganga (RB 01)	Kelani Ganga	Nagalagam Street	ft	4.00	5.00	7.00	1.50	1.50	Normal		-
	Kelani Ganga	Hanwella	m	7.00	8.00	10.00	0.60	0.58	Normal		6.5
	Kelani Ganga	Glencourse	m	15.00	16.50	19.00	8.68	8.65	Normal		14.8
	Kelani Ganga	Kithulgala	m	3.00	4.00	6.00	1.55	1.50	Normal		0.0
	Gurugoda Oya	Holombuwa	m	3.00	3.40	5.00	0.26	0.24	Normal		0.0
	Seethawaka Ganga	Deraniyagala	m	4.80	5.80	6.40	0.23	0.25	Normal		3.4
	Kehelgamu Oya	Norwood	m	1.50	3.00	4.50	0.69	0.68	Normal		0.5
Kalu Ganga (RB 03)	Kalu Ganga	Putupaula	m	3.00	4.00	5.00	0.55	0.46	Normal		0.0
	Kalu Ganga	Ellagawa	m	10.00	10.70	12.20	4.47	4.47	Normal		2.0
	Kalu Ganga	Rathnapura	m	5.20	7.50	9.50	1.04	1.03	Normal		4.1
	Maguru Ganga	Magura	m	4.00	6.00	7.50	1.16	1.16	Normal		0.0
	Kuda Ganga	Kalawellawa (Millakanda)	m	5.00	6.50	8.00	1.57	1.55	Normal		0.0
Gin Ganga (RB 09)	Gin Ganga	Baddegama	m	3.50	4.00	5.00	1.70	1.68	Normal		11.3
	Gin Ganga	Thawalama	m	4.00	6.00	7.50	1.25	1.23	Normal		1.1
Nilwala Ganga (RB 12)	Nilwala Ganga	Thalgahagoda	m	1.40	1.70	2.80	0.41	0.41	Normal		0.0
	Nilwala Ganga	Panadugama	m	5.00	6.00	7.50	2.68	2.68	Normal		0.0
	Nilwala Ganga	Pitabeddara	m	4.00	5.00	6.50	0.51	0.50	Normal		0.0

Figure 6.3: Untidy Data, Image Source: Disaster Management Centre, Ministry of Defense – River Water Level and Flood Warning Report

In this dataset, each cell in the last column contains both a value and a graphical representation, making the data untidy.

The tidy step in the tidy workflow ensures that the data adheres to the tidy principles of tidy data.

The `tidyr` package helps you structure data in a tidy format. This often involves:

- Pivoting: `pivot_longer()` and `pivot_wider()`
- Separating or uniting columns: `separate()` and `unite()`

For more details on its functionalities, refer to the `tidyr` package documentation:.

A well-organized dataset saves time and ensures accurate results!

6.2 Data Transformation

After tidying up the data, when you start analyzing it, especially with secondary data, it may not always be in the exact form you need. Sometimes, you may need to add new variables using data from other variables. Other times, you may need to filter specific rows or columns from the original dataset. You might also need to summarize the data or rename the columns properly.

This is where the data transformation step comes in.

The `dplyr` package provides powerful tools to transform your data into the desired format. Some of the most commonly used functions in `dplyr` include:

- `filter()` – Select specific rows based on conditions
- `select()` – Choose specific columns
- `mutate()` – Create or modify columns
- `summarise()` – Calculate summary statistics
- `arrange()` – Sort rows by a column
- `group_by()` – Group data for grouped operations
- `rename()` – Change column names

By performing these tasks, you change the structure of the original dataset as demontrated below, which is why it's called the data transformation step.

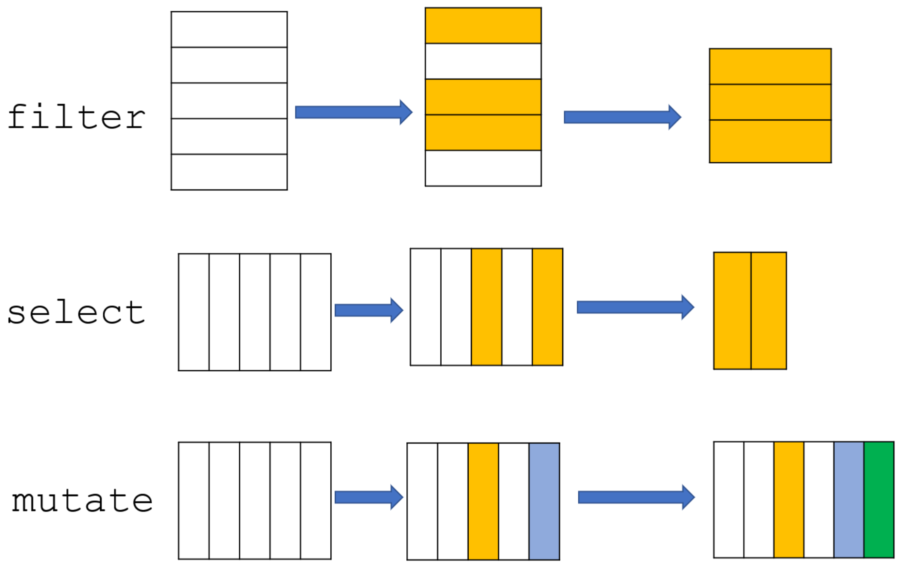


Figure 6.4: Data transformation, The original image, available here https://perso.ens-lyon.fr/lise.vaudor/dplyr/, has been updated with new additions.

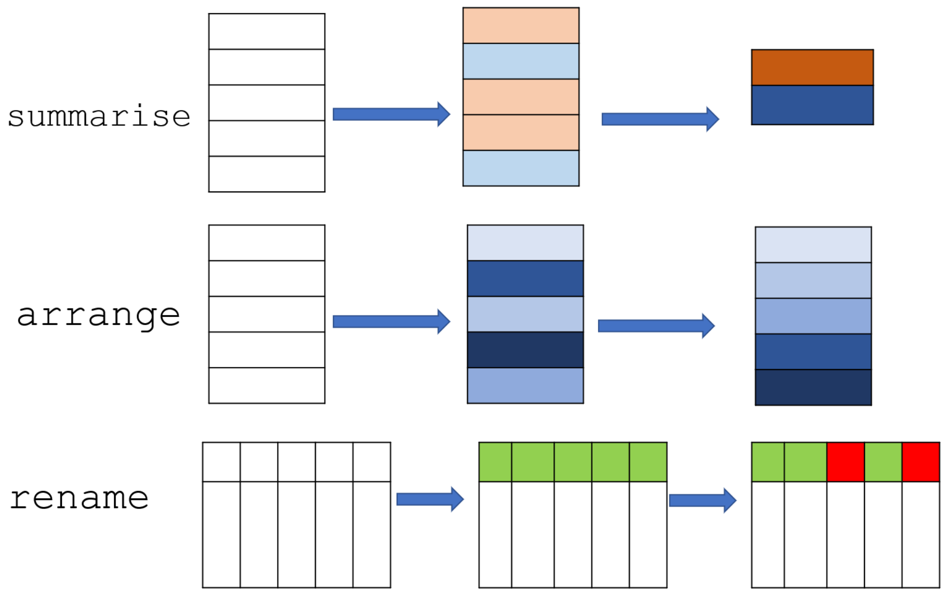


Figure 6.5: Data transformation, The original image, available here https://perso.ens-lyon.fr/lise.vaudor/dplyr/, has been updated with new additions.

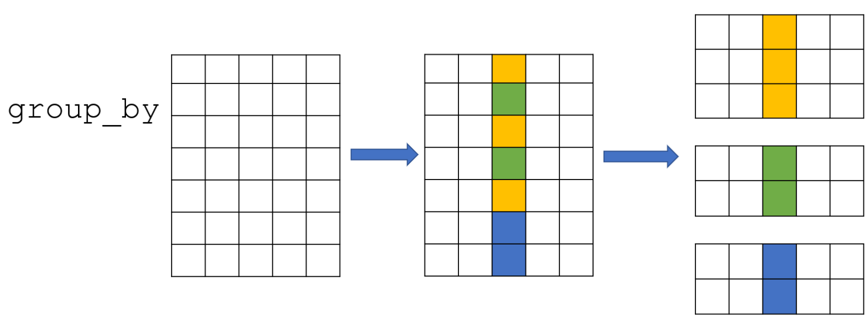


Figure 6.6: Data transformation, The original image, available here https://perso.ens-lyon.fr/lise.vaudor/dplyr/, has been updated with new additions.

6.2.1 Example

Let's consider the following dataset whihc contains synthetic airline data.

Download the dataset: airline_data.csv Data Source: https://www.kaggle.com/datasets/iamsouravbanerjee/air dataset/data

```r
library(tidyverse)
```

```
-- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
v dplyr     1.1.4     v readr     2.1.5
v forcats   1.0.0     v stringr   1.5.1
v ggplot2   3.5.1     v tibble    3.2.1
v lubridate 1.9.3     v tidyr     1.3.1
v purrr     1.0.2
-- Conflicts ------------------------------------------ tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom
```

```r
data <- read_csv(here::here("data", "airline_data.csv"))
```

```
Rows: 98619 Columns: 15
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (14): Passenger ID, First Name, Last Name, Gender, Nationality, Airport ...
dbl  (1): Age

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.
```

```r
dim(data)
```

```
[1] 98619    15
```

```r
colnames(data)
```

```
 [1] "Passenger ID"        "First Name"          "Last Name"
 [4] "Gender"              "Age"                 "Nationality"
 [7] "Airport Name"        "Airport Country Code" "Country Name"
[10] "Airport Continent"   "Continents"          "Departure Date"
[13] "Arrival Airport"     "Pilot Name"          "Flight Status"
```

Dataset Glossary (Column-wise)

Passenger ID - Unique identifier for each passenger

First Name - First name of the passenger

Last Name - Last name of the passenger

Gender - Gender of the passenger

Age - Age of the passenger

Nationality - Nationality of the passenger

Airport Name - Name of the airport where the passenger boarded

Airport Country Code - Country code of the airport's location

Country Name - Name of the country the airport is located in

Airport Continent - Continent where the airport is situated

Continents - Continents involved in the flight route

Departure Date - Date when the flight departed

Arrival Airport - Destination airport of the flight

Pilot Name - Name of the pilot operating the flight

Flight Status - Current status of the flight (e.g., on-time, delayed, canceled)

This synthetic dataset covers global airline operations. This dataset is useful for economists because it provides information on passenger travel patterns, flight routes, and airport locations. It helps analyze how air travel affects trade, tourism, and jobs. By looking at flight status and passenger details, economists can study the impact of aviation on the economy and make decisions about transportation policies and infrastructure development.

```r
data <- data |> as_tibble()
head(data)
```

```
# A tibble: 6 x 15
  `Passenger ID` `First Name` `Last Name` Gender   Age Nationality
  <chr>          <chr>        <chr>       <chr>  <dbl> <chr>
1 ABVWIg         Edithe       Leggis      Female    62 Japan
2 jkXXAX         Elwood       Catt        Male      62 Nicaragua
3 CdUz2g         Darby        Felgate     Male      67 Russia
4 BRS38V         Dominica     Pyle        Female    71 China
5 9kvTLo         Bay          Pencost     Male      21 China
6 nMJKVh         Lora         Durbann     Female    55 Brazil
# i 9 more variables: `Airport Name` <chr>, `Airport Country Code` <chr>,
#   `Country Name` <chr>, `Airport Continent` <chr>, Continents <chr>,
#   `Departure Date` <chr>, `Arrival Airport` <chr>, `Pilot Name` <chr>,
```

```
#   `Flight Status` <chr>
```

```r
summary(data)
```

```
 Passenger ID        First Name         Last Name            Gender         
 Length:98619       Length:98619       Length:98619       Length:98619      
 Class :character   Class :character   Class :character   Class :character  
 Mode  :character   Mode  :character   Mode  :character   Mode  :character  
                                                                            
                                                                            
                                                                            
      Age       Nationality        Airport Name       Airport Country Code
 Min.   : 1.0   Length:98619       Length:98619       Length:98619        
 1st Qu.:23.0   Class :character   Class :character   Class :character    
 Median :46.0   Mode  :character   Mode  :character   Mode  :character    
 Mean   :45.5                                                             
 3rd Qu.:68.0                                                             
 Max.   :90.0                                                             
 Country Name       Airport Continent   Continents        Departure Date    
 Length:98619       Length:98619       Length:98619       Length:98619      
 Class :character   Class :character   Class :character   Class :character  
 Mode  :character   Mode  :character   Mode  :character   Mode  :character  
                                                                            
                                                                            
                                                                            
 Arrival Airport     Pilot Name        Flight Status     
 Length:98619       Length:98619       Length:98619      
 Class :character   Class :character   Class :character  
 Mode  :character   Mode  :character   Mode  :character  
```

6.2.1.1 `filter`: Select specific rows based on conditions

- Takes logical expressions and returns the rows for which all are `TRUE`.

```r
filter(data, Age > 45)
```

```
# A tibble: 49,383 x 15
```

```
   `Passenger ID` `First Name` `Last Name` Gender   Age Nationality
   <chr>          <chr>        <chr>       <chr>  <dbl> <chr>
 1 ABVWIg         Edithe       Leggis      Female    62 Japan
 2 jkXXAX         Elwood       Catt        Male      62 Nicaragua
 3 CdUz2g         Darby        Felgate     Male      67 Russia
 4 BRS38V         Dominica     Pyle        Female    71 China
 5 nMJKVh         Lora         Durbann     Female    55 Brazil
 6 8IPFPE         Rand         Bram        Male      73 Ivory Coast
 7 sBf524         Briant       De La Haye  Male      71 Russia
 8 PlwJZT         Kalie        Scoble      Female    47 Sweden
 9 iU75x3         Catriona     Beaument    Female    77 Russia
10 eOH5LI         Jerrine      Peeters     Female    87 Philippines
# i 49,373 more rows
# i 9 more variables: `Airport Name` <chr>, `Airport Country Code` <chr>,
#   `Country Name` <chr>, `Airport Continent` <chr>, Continents <chr>,
#   `Departure Date` <chr>, `Arrival Airport` <chr>, `Pilot Name` <chr>,
#   `Flight Status` <chr>
```

```r
filter(data,  Nationality == "Sri Lanka")
```

```
# A tibble: 138 x 15
   `Passenger ID` `First Name` `Last Name` Gender   Age Nationality
   <chr>          <chr>        <chr>       <chr>  <dbl> <chr>
 1 fhD57Z         Jordan       Fierman     Female    11 Sri Lanka
 2 5joYmi         Valdemar     Marcone     Male       7 Sri Lanka
 3 2ROpnA         Jordon       Salloway e  Male      43 Sri Lanka
 4 eKkekT         Dael         Edlestone   Female    58 Sri Lanka
 5 5TxM24         Hiram        Memory      Male      21 Sri Lanka
 6 wQVX9G         Sherm        Kippie      Male      60 Sri Lanka
 7 fKtiLJ         Filippa      Prestige    Female    53 Sri Lanka
 8 q7uPji         Wainwright   Dunkerton   Male      47 Sri Lanka
 9 Tn9LGe         Matty        Alflat      Male       6 Sri Lanka
10 fZsoAD         Rowney       Messitt     Male      43 Sri Lanka
# i 128 more rows
# i 9 more variables: `Airport Name` <chr>, `Airport Country Code` <chr>,
#   `Country Name` <chr>, `Airport Continent` <chr>, Continents <chr>,
#   `Departure Date` <chr>, `Arrival Airport` <chr>, `Pilot Name` <chr>,
#   `Flight Status` <chr>
```

6.2.1.2 `select`: Choose specific columns by their names.

```r
select(data, `Passenger ID`:Gender)
```

```
# A tibble: 98,619 x 4
   `Passenger ID` `First Name` `Last Name` Gender
   <chr>          <chr>        <chr>       <chr>
 1 ABVWIg         Edithe       Leggis      Female
 2 jkXXAX         Elwood       Catt        Male
 3 CdUz2g         Darby        Felgate     Male
 4 BRS38V         Dominica     Pyle        Female
 5 9kvTLo         Bay          Pencost     Male
 6 nMJKVh         Lora         Durbann     Female
 7 8IPFPE         Rand         Bram        Male
 8 pqixbY         Perceval     Dallosso    Male
 9 QNAs2R         Aleda        Pigram      Female
10 3jmudz         Burlie       Schustl     Male
# i 98,609 more rows
```

```r
select(data, `Pilot Name`, `Flight Status`)
```

```
# A tibble: 98,619 x 2
   `Pilot Name`        `Flight Status`
   <chr>               <chr>
 1 Fransisco Hazeldine On Time
 2 Marla Parsonage     On Time
 3 Rhonda Amber        On Time
 4 Kacie Commucci      Delayed
 5 Ebonee Tree         On Time
 6 Inglis Dolley       On Time
 7 Stanislas Tiffin    Cancelled
 8 Sharyl Eastmead     Cancelled
 9 Daryn Bardsley      On Time
10 Alameda Carlyle     On Time
# i 98,609 more rows
```

When you pass a vector of column names with `-c()`, it omits the specified columns and returns the dataframe with the remaining columns. This option is very useful when working with large datasets that have many columns, and you only need to remove a few columns to finalize the dataset.

```r
select(data, -c(`Passenger ID`, `First Name`, `Last Name`))
```

```
# A tibble: 98,619 x 12
   Gender   Age Nationality `Airport Name` `Airport Country Code` `Country Name`
   <chr>  <dbl> <chr>       <chr>          <chr>                  <chr>
 1 Female    62 Japan       Coldfoot Airp~ US                     United States
 2 Male      62 Nicaragua   Kugluktuk Air~ CA                     Canada
 3 Male      67 Russia      Grenoble-Isèr~ FR                     France
 4 Female    71 China       Ottawa / Gati~ CA                     Canada
 5 Male      21 China       Gillespie Fie~ US                     United States
 6 Female    55 Brazil      Coronel Horác~ BR                     Brazil
 7 Male      73 Ivory Coast Duxford Aerod~ GB                     United Kingdom
 8 Male      36 Vietnam     Maestro Wilso~ BR                     Brazil
 9 Female    35 Palestinia~ Venice Marco ~ IT                     Italy
10 Male      13 Thailand    Vermilion Air~ CA                     Canada
# i 98,609 more rows
# i 6 more variables: `Airport Continent` <chr>, Continents <chr>,
#   `Departure Date` <chr>, `Arrival Airport` <chr>, `Pilot Name` <chr>,
#   `Flight Status` <chr>
```

6.2.1.3 `mutate`: Create or modify columns

- This function allows you to creates new variables from an existing variable.

```r
data_new <- data |> mutate(New_Age = Age + 2)
data_new
```

```
# A tibble: 98,619 x 16
   `Passenger ID` `First Name` `Last Name` Gender   Age Nationality
   <chr>          <chr>        <chr>       <chr>  <dbl> <chr>
 1 ABVWIg         Edithe       Leggis      Female    62 Japan
 2 jkXXAX         Elwood       Catt        Male      62 Nicaragua
 3 CdUz2g         Darby        Felgate     Male      67 Russia
 4 BRS38V         Dominica     Pyle        Female    71 China
 5 9kvTLo         Bay          Pencost     Male      21 China
 6 nMJKVh         Lora         Durbann     Female    55 Brazil
 7 8IPFPE         Rand         Bram        Male      73 Ivory Coast
 8 pqixbY         Perceval     Dallosso    Male      36 Vietnam
 9 QNAs2R         Aleda        Pigram      Female    35 Palestinian Territory
10 3jmudz         Burlie       Schustl     Male      13 Thailand
```

```
# i 98,609 more rows
# i 10 more variables: `Airport Name` <chr>, `Airport Country Code` <chr>,
#   `Country Name` <chr>, `Airport Continent` <chr>, Continents <chr>,
#   `Departure Date` <chr>, `Arrival Airport` <chr>, `Pilot Name` <chr>,
#   `Flight Status` <chr>, New_Age <dbl>
```

```
colnames(data_new)
```

```
 [1] "Passenger ID"         "First Name"           "Last Name"
 [4] "Gender"               "Age"                  "Nationality"
 [7] "Airport Name"         "Airport Country Code" "Country Name"
[10] "Airport Continent"    "Continents"           "Departure Date"
[13] "Arrival Airport"      "Pilot Name"           "Flight Status"
[16] "New_Age"
```

- The same mutate function also allows you to update an existing variables.

```
data_new <- data |> mutate(`Departure Date` =as.Date(`Departure Date`, format = "%m/%d/%Y"))
summary(data_new)
```

```
 Passenger ID        First Name          Last Name            Gender
 Length:98619       Length:98619       Length:98619       Length:98619
 Class :character   Class :character   Class :character   Class :character
 Mode  :character   Mode  :character   Mode  :character   Mode  :character



      Age        Nationality        Airport Name       Airport Country Code
 Min.   : 1.0   Length:98619       Length:98619       Length:98619
 1st Qu.:23.0   Class :character   Class :character   Class :character
 Median :46.0   Mode  :character   Mode  :character   Mode  :character
 Mean   :45.5
 3rd Qu.:68.0
 Max.   :90.0
 Country Name       Airport Continent   Continents         Departure Date
 Length:98619       Length:98619       Length:98619       Min.   :2022-01-01
 Class :character   Class :character   Class :character   1st Qu.:2022-04-01
 Mode  :character   Mode  :character   Mode  :character   Median :2022-07-01
                                                          Mean   :2022-07-01
                                                          3rd Qu.:2022-09-30
                                                          Max.   :2022-12-30
```

```
 Arrival Airport     Pilot Name        Flight Status
 Length:98619       Length:98619       Length:98619
 Class :character   Class :character   Class :character
 Mode  :character   Mode  :character   Mode  :character
```

6.2.1.4 `summarise`(British) or `summarize` (US) : Calculate summary statistics

- this function collapses many values down to a single summary.

```
data_new |>
  summarise(
    Departure_Date_start =min(`Departure Date`),
    Departure_Date_end =max(`Departure Date`),
    Age_median=median(Age),
    Age_mean=mean(Age))
```

```
# A tibble: 1 x 4
  Departure_Date_start Departure_Date_end Age_median Age_mean
  <date>               <date>                  <dbl>    <dbl>
1 2022-01-01           2022-12-30                 46     45.5
```

Since it contains missing values, they should be removed before calculating the summary statistics

```
data_new |>
  summarise(
    Departure_Date_start =min(`Departure Date`, na.rm = TRUE),
    Departure_Date_end =max(`Departure Date`, na.rm = TRUE),
    Age_median=median(Age, na.rm = TRUE),
    Age_mean=mean(Age, na.rm = TRUE))
```

```
# A tibble: 1 x 4
  Departure_Date_start Departure_Date_end Age_median Age_mean
  <date>               <date>                  <dbl>    <dbl>
1 2022-01-01           2022-12-30                 46     45.5
```

6.2.1.5 `arrange()` – Sort rows by a column

```r
arrange(data, desc(Age))
```

```
# A tibble: 98,619 x 15
   `Passenger ID` `First Name` `Last Name` Gender   Age Nationality
   <chr>          <chr>        <chr>       <chr>  <dbl> <chr>
 1 to75jW         Pamella      Eaden       Female    90 Indonesia
 2 Zlsjqw         Sydney       MacGhee     Male      90 Guatemala
 3 aogYWd         Vernen       Ivakhnov    Male      90 China
 4 X0basI         Mariann      Moogan      Female    90 Philippines
 5 N7DLfQ         Jermaine     Escott      Male      90 Portugal
 6 fZhPqR         Valdemar     Whate       Male      90 Brazil
 7 usnzLP         Raul         Mantha      Male      90 Argentina
 8 L49UDI         Neall        Zamudio     Male      90 Czech Republic
 9 L1ZBXS         Anthea       Blodget     Female    90 Indonesia
10 CjAY9o         Valene       Megarry     Female    90 Indonesia
# i 98,609 more rows
# i 9 more variables: `Airport Name` <chr>, `Airport Country Code` <chr>,
#   `Country Name` <chr>, `Airport Continent` <chr>, Continents <chr>,
#   `Departure Date` <chr>, `Arrival Airport` <chr>, `Pilot Name` <chr>,
#   `Flight Status` <chr>
```

6.2.1.6 `group_by()` – Group data for grouped operations

- This fucntion takes an existing tibble and converts it into a grouped tibble where operations are performed "by group". ungroup() removes grouping.

```r
customers_grouped <- data |> group_by(Continents )
customers_grouped
```

```
# A tibble: 98,619 x 15
# Groups:   Continents [6]
   `Passenger ID` `First Name` `Last Name` Gender   Age Nationality
   <chr>          <chr>        <chr>       <chr>  <dbl> <chr>
 1 ABVWIg         Edithe       Leggis      Female    62 Japan
 2 jkXXAX         Elwood       Catt        Male      62 Nicaragua
 3 CdUz2g         Darby        Felgate     Male      67 Russia
 4 BRS38V         Dominica     Pyle        Female    71 China
 5 9kvTLo         Bay          Pencost     Male      21 China
```

```
 6 nMJKVh         Lora         Durbann     Female     55 Brazil
 7 8IPFPE         Rand         Bram        Male       73 Ivory Coast
 8 pqixbY         Perceval     Dallosso    Male       36 Vietnam
 9 QNAs2R         Aleda        Pigram      Female     35 Palestinian Territory
10 3jmudz         Burlie       Schustl     Male       13 Thailand
# i 98,609 more rows
# i 9 more variables: `Airport Name` <chr>, `Airport Country Code` <chr>,
#   `Country Name` <chr>, `Airport Continent` <chr>, Continents <chr>,
#   `Departure Date` <chr>, `Arrival Airport` <chr>, `Pilot Name` <chr>,
#   `Flight Status` <chr>
```

```r
data |> summarise(age_mean=mean(Age, na.rm=TRUE))
```

```
# A tibble: 1 x 1
  age_mean
     <dbl>
1     45.5
```

```r
customers_grouped |> summarise(age_mean=mean(Age, na.rm=TRUE))
```

```
# A tibble: 6 x 2
  Continents    age_mean
  <chr>            <dbl>
1 Africa            45.6
2 Asia              45.7
3 Europe            45.2
4 North America     45.6
5 Oceania           45.4
6 South America     45.4
```

6.2.1.7 `rename()` – Change column names

```r
data <- rename(data,  Passenger_ID = `Passenger ID`,
       Airport_code = `Airport Country Code` ) # new_name = old_name
data
```

```
# A tibble: 98,619 x 15
   Passenger_ID `First Name` `Last Name` Gender   Age Nationality `Airport Name`
   <chr>        <chr>        <chr>       <chr>  <dbl> <chr>       <chr>
```

```
 1 ABVWIg       Edithe       Leggis      Female    62 Japan        Coldfoot Airp~
 2 jkXXAX       Elwood       Catt        Male      62 Nicaragua    Kugluktuk Air~
 3 CdUz2g       Darby        Felgate     Male      67 Russia       Grenoble-Isèr~
 4 BRS38V       Dominica     Pyle        Female    71 China        Ottawa / Gati~
 5 9kvTLo       Bay          Pencost     Male      21 China        Gillespie Fie~
 6 nMJKVh       Lora         Durbann     Female    55 Brazil       Coronel Horác~
 7 8IPFPE       Rand         Bram        Male      73 Ivory Coast Duxford Aerod~
 8 pqixbY       Perceval     Dallosso    Male      36 Vietnam      Maestro Wilso~
 9 QNAs2R       Aleda        Pigram      Female    35 Palestinia~ Venice Marco ~
10 3jmudz       Burlie       Schustl     Male      13 Thailand     Vermilion Air~
# i 98,609 more rows
# i 8 more variables: Airport_code <chr>, `Country Name` <chr>,
#   `Airport Continent` <chr>, Continents <chr>, `Departure Date` <chr>,
#   `Arrival Airport` <chr>, `Pilot Name` <chr>, `Flight Status` <chr>
```

6.2.1.8 Combine multiple operations

You can even combine multiple verbs at once to obtain the dataset in the desired structure. This is where the pipe operator becomes very handy.

```r
data |>
  filter(Nationality == "Sri Lanka") |>
  head(2)
```

```
# A tibble: 2 x 15
  Passenger_ID `First Name` `Last Name` Gender   Age Nationality `Airport Name`
  <chr>        <chr>        <chr>       <chr>  <dbl> <chr>       <chr>
1 fhD57Z       Jordan       Fierman     Female    11 Sri Lanka   Yoshkar-Ola Ai~
2 5joYmi       Valdemar     Marcone     Male       7 Sri Lanka   Mungeranie Air~
# i 8 more variables: Airport_code <chr>, `Country Name` <chr>,
#   `Airport Continent` <chr>, Continents <chr>, `Departure Date` <chr>,
#   `Arrival Airport` <chr>, `Pilot Name` <chr>, `Flight Status` <chr>
```

```r
data |>
  filter(Nationality == "Sri Lanka") |>
  summarise(Age_mean=mean(Age, na.rm=TRUE))
```

```
# A tibble: 1 x 1
  Age_mean
     <dbl>
1     43.9
```

```r
data_new |>
  filter(Nationality == "Sri Lanka") |>
  group_by(Gender) |>
  filter(Age > 45) |>
  arrange(desc(`Departure Date`))
```

```
# A tibble: 65 x 15
# Groups:   Gender [2]
   `Passenger ID` `First Name` `Last Name` Gender   Age Nationality
   <chr>          <chr>        <chr>       <chr>  <dbl> <chr>
 1 Garp7s         Elwood       Seczyk      Male      61 Sri Lanka
 2 bmMaNv         Mellie       Werrett     Female    76 Sri Lanka
 3 W9kjm9         Lewes        Gollard     Male      75 Sri Lanka
 4 C5sSaq         Jose         Duffit      Male      87 Sri Lanka
 5 YpH6kH         Xenos        McEntagart  Male      71 Sri Lanka
 6 lXSEsW         Ad           Fernihough  Male      48 Sri Lanka
 7 5OPpWn         Marieann     Strelitzki  Female    77 Sri Lanka
 8 oCZkZ2         Aaron        MacCaffery  Male      83 Sri Lanka
 9 L7ut1f         Dell         Shreenan    Male      62 Sri Lanka
10 soCbR1         Matthieu     Matches     Male      47 Sri Lanka
# i 55 more rows
# i 9 more variables: `Airport Name` <chr>, `Airport Country Code` <chr>,
#   `Country Name` <chr>, `Airport Continent` <chr>, Continents <chr>,
#   `Departure Date` <date>, `Arrival Airport` <chr>, `Pilot Name` <chr>,
#   `Flight Status` <chr>
```

7 Data Visualization

In R, there are many ways to create visualizations, as it provides various built-in functions for generating charts and graphics. . The graphics package, which comes with R by default, includes basic functions for creating different types of plots, such as line graphs, scatter plots, histograms, and bar charts. In this approach, each type of graph has its own dedicated function.

However, when there are too many plotting functions to remember, managing them becomes difficult. Every time you need a new type of graph, you have to learn a new function. This challenge is what visualization expert Leland Wilkinson aimed to address through the Grammar of Graphics.

Instead of treating plots as separate, unrelated charts, the Grammar of Graphics provides a unified framework for creating visualizations using a consistent set of rules. This approach moves beyond simply naming charts (e.g., pie chart, line chart, scatter plot) and focuses on understanding their structure or anatomy. By using layered components, we can build effective visualizations in a more systematic way.

The key idea behind the Grammar of Graphics is that any plot can be explained using eight layered components. This theoretical design system serves as the foundation for the ggplot2 package in R, which is an implementation of these principles.

7.1 The ggplot2 API

The ggplot2 package structures plots using eight key components (layers):

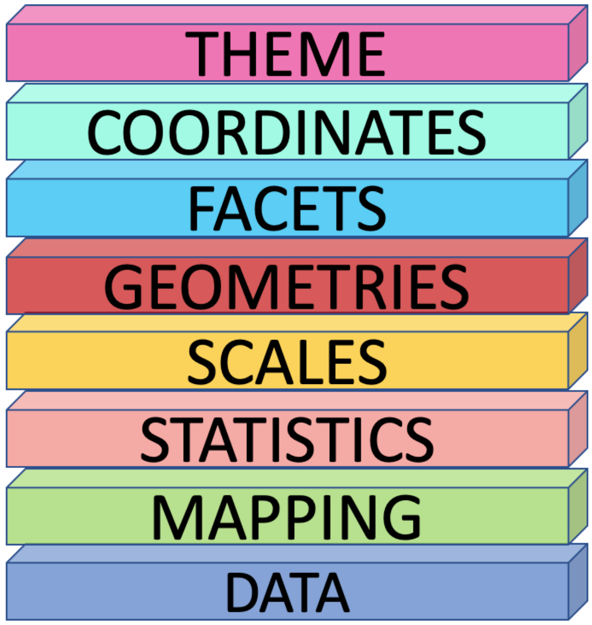


Figure 7.1: The ggplot2 API

In each layer, we aim to answer a specific question:

- **Data – What dataset should be used for the visualization?**
- **Mapping (Aesthetics - aes) – How should the data be mapped to visual properties? (e.g., x-axis, y-axis, color, size)***
- Statistics (stat) – Should any transformations or summaries be applied? (e.g., smoothing, binning, aggregation)
- Scales – How should data values be translated into visual properties? (e.g., color gradients, axis scales)
- **Geometries (geom) – What type of plot best represents the data? (e.g., points, lines, bars)**
- Facets – Should the data be divided into multiple panels for better comparison?
- Coordinates (coord) – Which coordinate system should be used? (e.g., Cartesian, polar)
- Theme – How should the overall appearance of the plot be styled? (e.g., fonts, background, gridlines)

By layering these components, ggplot2 provides a flexible and structured approach to building effective visualizations

Now, let's see how to create a plot using ggplot2.

Let's start with the foundational layer: the data layer

7.2 Data Layer

This layer asks the question: What dataset should be used for the visualization?

In this example, I am going to use South Asian economic indicators from the World Bank, covering the years 1960 to 2017.

Download the dataset: SAeconomy.csv

Dataset Glossary (Column-wise)

Country: The country or region of the series.

GDP: Gross domestic product (in $USD February 2019).

Growth: Annual percentage growth in GDP.

CPI: Consumer price index (base year 2010).

Imports: Imports of goods and services (% of GDP).

Exports: Exports of goods and services (% of GDP).

Population: Total population.

For the initial exploration, I am going to filter the economic health data specifically related to Sri Lanka and analyze the country's economic health .

```
library(tidyverse)
```

```
-- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
v dplyr     1.1.4     v readr     2.1.5
v forcats   1.0.0     v stringr   1.5.1
v ggplot2   3.5.1     v tibble    3.2.1
v lubridate 1.9.3     v tidyr     1.3.1
v purrr     1.0.2
-- Conflicts ------------------------------------------ tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom
```

```r
SAeconomy_data <- read_csv(here::here("data", "SAeconomy.csv" ))
```

```
Rows: 464 Columns: 9
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (2): Country, Code
dbl (7): Year, GDP, Growth, CPI, Imports, Exports, Population

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.
```

```r
SLeconomy <- SAeconomy_data |>
  filter(Country == "Sri Lanka")

SLeconomy
```

```
# A tibble: 58 x 9
   Country   Code   Year         GDP Growth   CPI Imports Exports Population
   <chr>     <chr> <dbl>       <dbl>  <dbl> <dbl>   <dbl>   <dbl>      <dbl>
 1 Sri Lanka LKA    1960 1409873950.  NA     1.49    32.9    30.0    9874481
 2 Sri Lanka LKA    1961 1444327731.  NA     1.50    28.5    27.5   10111646
 3 Sri Lanka LKA    1962 1434156379.   3.82  1.53    29.2    27.8   10352188
 4 Sri Lanka LKA    1963 1240672269.   2.52  1.56    27.5    25.8   10597520
 5 Sri Lanka LKA    1964 1309747899.   3.91  1.61    26.7    24.6   10849979
 6 Sri Lanka LKA    1965 1698319328.   2.54  1.62    25.5    25.9   11110828
 7 Sri Lanka LKA    1966 1751470588.   5.02  1.61    25.8    22.4   11380683
 8 Sri Lanka LKA    1967 1859465021.   6.44  1.65    23.3    20.5   11657660
 9 Sri Lanka LKA    1968 1801344538.   5.80  1.74    23.6    20.6   11937611
10 Sri Lanka LKA    1969 1965546218.   7.72  1.87    24.6    18.4   12214968
# i 48 more rows
```

A ggplot function call begins with the `ggplot()` function.

```r
ggplot()
```

This call is similar to taking a blank piece of paper to draw a plot, where you set the foundation for what will be visualized. In the data layer, you have to specify what dataset you want to use for the visualization. In this case, the dataset will be the economic health data for Sri Lanka.

```
ggplot(data =  SLeconomy)
```

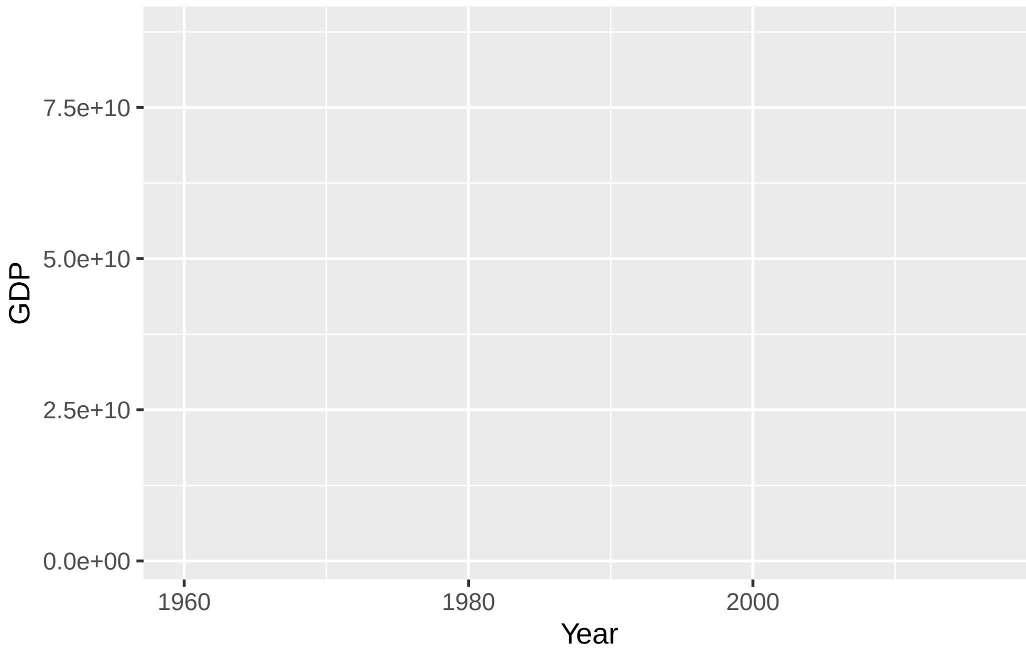
You're still getting the same result because ggplot() doesn't know how to work with the dataset until you tell it what to plot and how to map the data to the axes and visual elements.

This is done using the second layer, the Mapping layer.

7.3 Mapping Layer

In this layer you define how the data should be represented visually, such as which variables to map to the x-axis, y-axis, and other visual elements.

```
ggplot(data =  SLeconomy,
       mapping = aes(x = Year,
                     y = GDP))
```



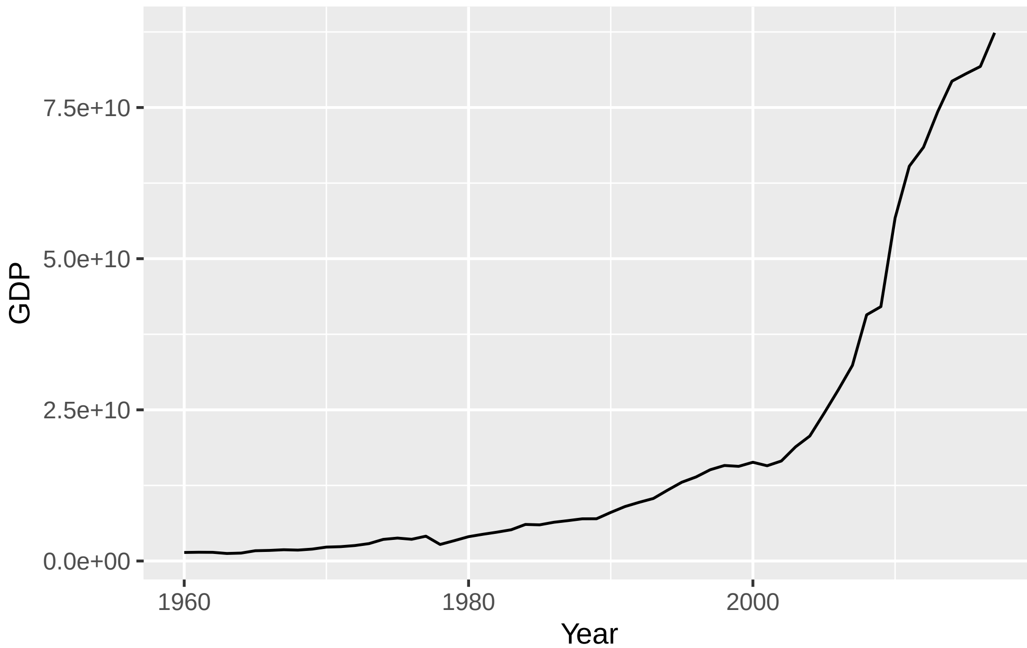
With the Mapping layer, we define what we want to see on the graph. For example, if I want to see the trend in the GDP series over the years, I select the relevant columns and map them to the x-axis and y-axis. This will label the axes with the selected variable names. However, you still can't see a visual representation in the plotting panel. That's because you need to specify how to draw the plot and what kind of geometry to use to represent the data values. This is where the Geometries layer comes in.

7.4 Geometries Layer

The Geometries layer is concerned with the shape of the data. In this case, since I have a time series, I can represent the data by using a line to show how the values change over the years.

We connect each layer with a plus sign (+), because it essentially "adds layers" to the existing plot, building on top of what was already defined.

```
ggplot(data =  SLeconomy,
       mapping = aes(x = Year,
                     y = GDP)) +
  geom_line()
```



Although the grammar of graphics framework has 8 layers, only 3 are necessary to create a meaningful plot. The other layers are optional.

7.5 Visualize Data Like a Pro in ggplot2 with `esquisse` package

When you install R, it automatically adds some packages. One important package is the Esquisse package, which helps you explore and visualize your data interactively.

In RStudio, you can use the Addins menu to launch the esquisse. Select ‘ggplot2’ builder under the ESQUISSE option.

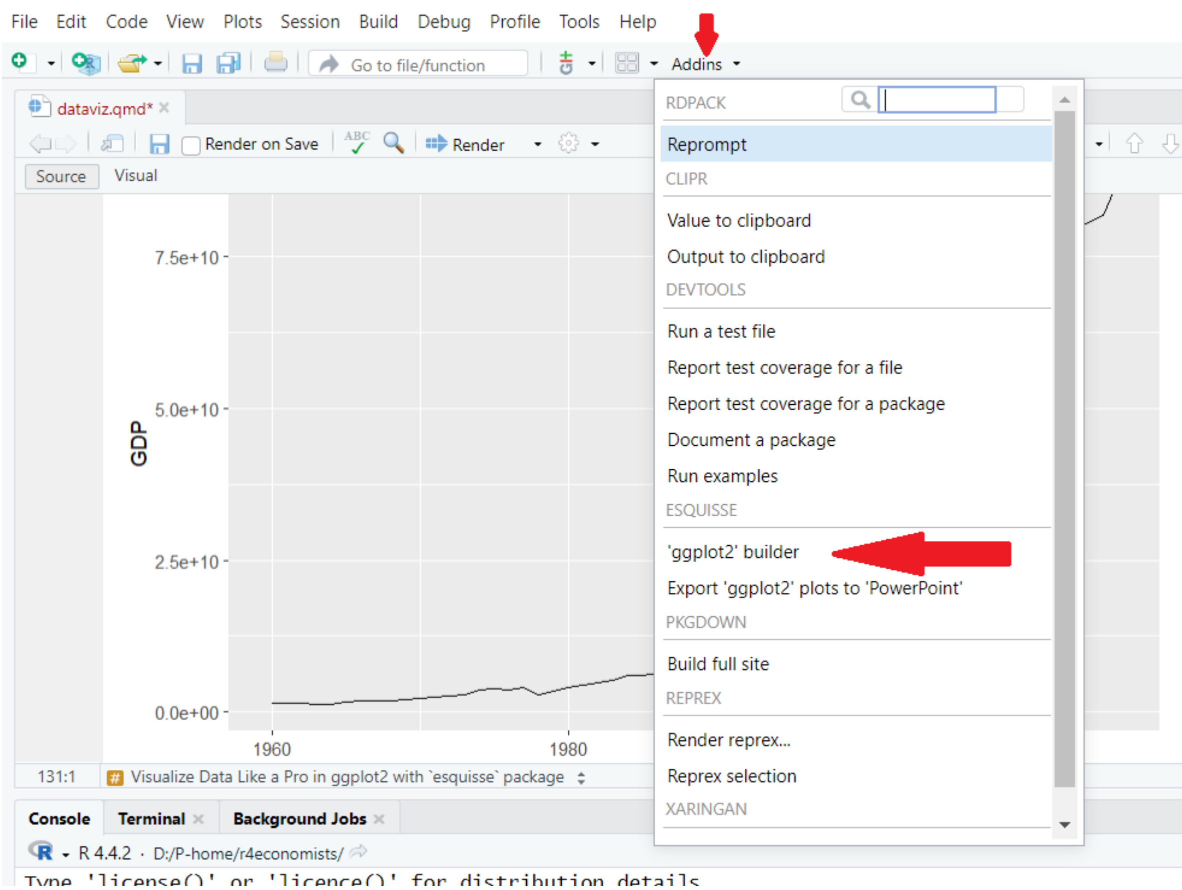


Figure 7.2: `esquisse` package

Or in the R console run:

```
esquisser()
```

A window will appear for importing data. If you have active datasets in your current working directory, you can select the required dataset from the 'Select a data.frame:' dropdown menu under the Environment panel.

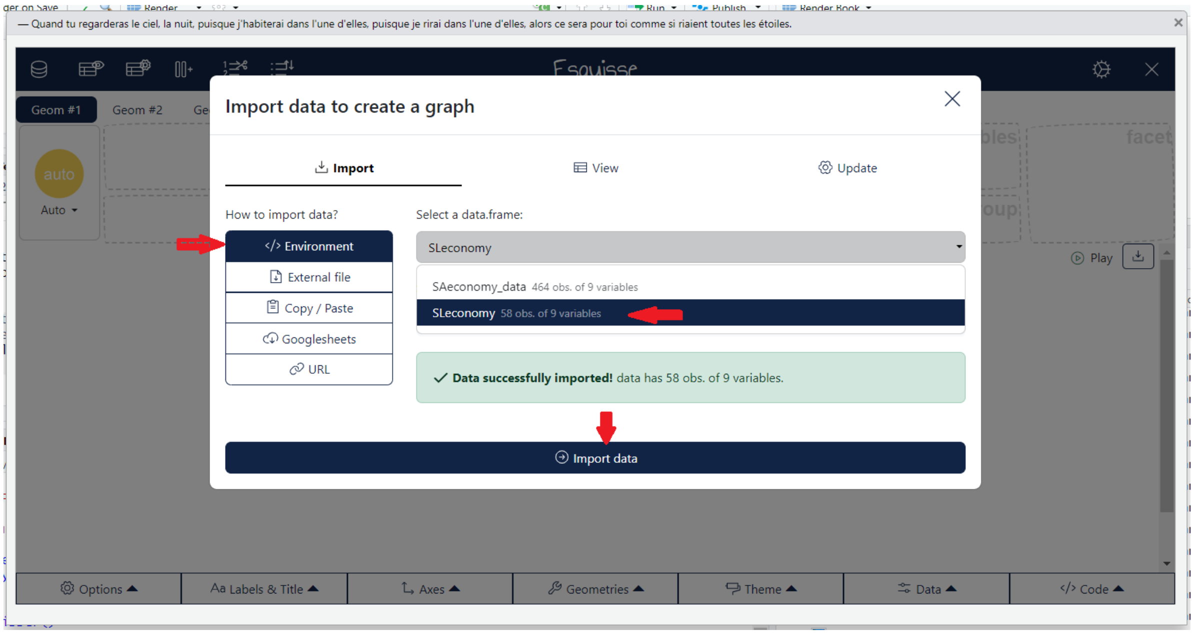


Figure 7.3: **esquisse** package: Import active dataframe

If you want to load an external file, go to the 'External File' panel, upload the file and select import.

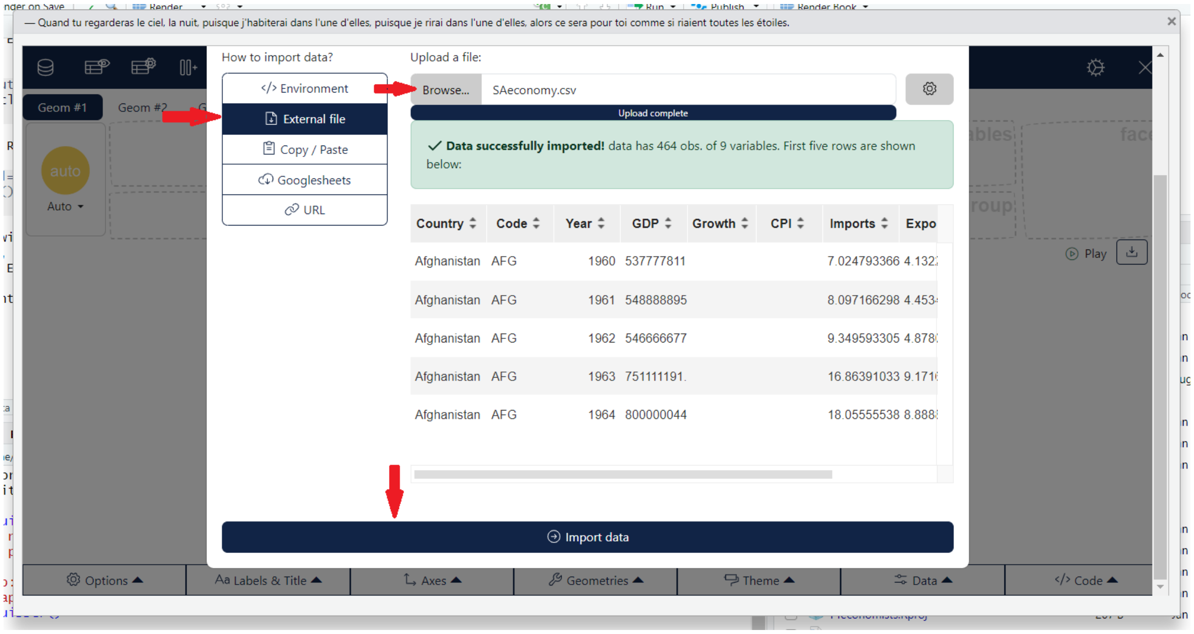


Figure 7.4: **esquisse** package: Import external datafile

Let's try to recreate the same plot we made earlier using the `esquisse` package.

To select aesthetics, click the gear icon in the top right corner, then drag and drop the options into the aesthetics boxes to create your plot.

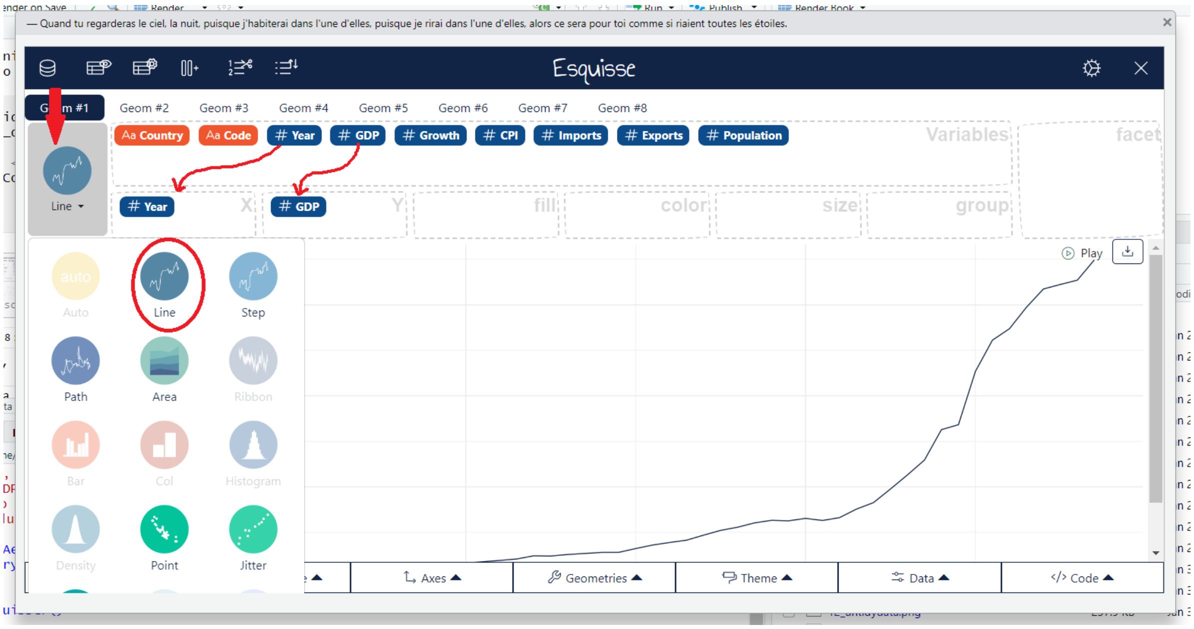


Figure 7.5: `esquisse` package: Create visual representation

Now you can get the code for this visualization by using the 'Reverse Engineer Your Visualizations' option. Just select 'Code' to see it.

Figure 7.6: `esquisse` package: Create visual representation

7.6 Statistics Layer

Sometimes, certain plots require the calculation of summary statistics. For example, to create a pie chart, you need percentages, or to produce a box plot, you need five summary statistics: the quartiles, minimum, and maximum. This is where the statistics layer comes in.

However, in practice, we rarely call the statistics layer directly. That's because most of the statistical calculations are done automatically behind the scenes when creating geometric shapes. As a result, we don't usually define them explicitly; the geom layer handles that for us. Each geom has a default stat.

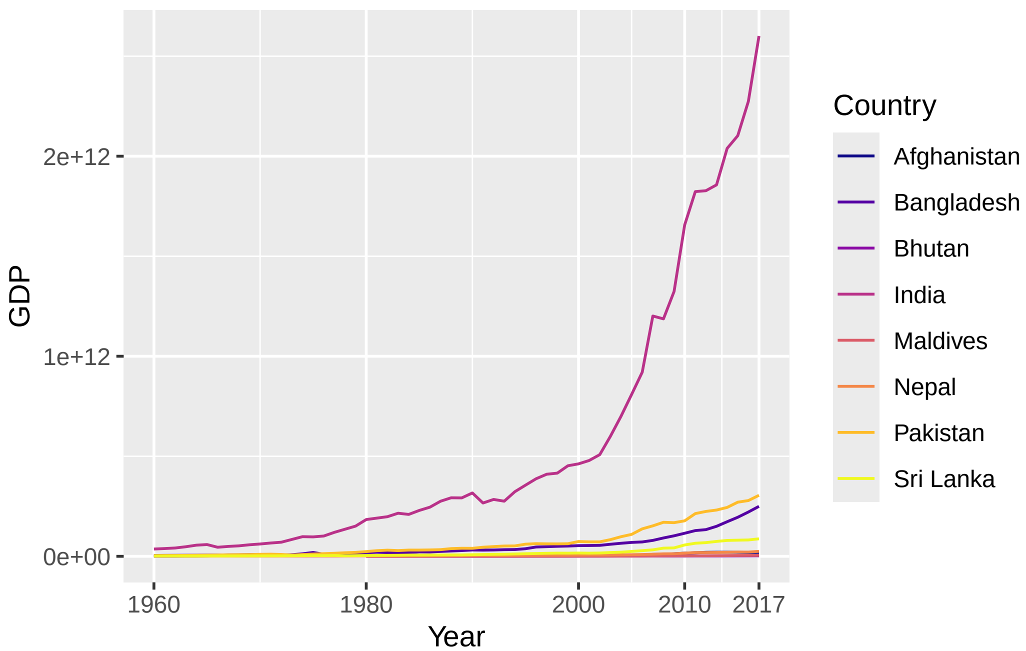
Statistics	Geometries
`stat_count`	`geom_bar`
`stat_boxplot`	`geom_boxplot`
`stat_identity`	`geom_col`
`stat_bin`	`geom_bar`, `geom_histogram`
`stat_density`	`geom_density`

7.7 Scales Layer

The scales layer in ggplot2 defines how the data values are mapped to visual properties, such as colors, sizes, and positions in the plot. For example, you can change the scale of the x or y-axis, adjust color gradients, or set custom limits for the data values using the scales layer.

```
ggplot(SAeconomy_data) +
  aes(x = Year,
      y = GDP,
      colour = Country,
      shape = Country) +
  geom_line() +
  scale_x_continuous( breaks = c(1960, 1980, 2000, 2010, 2017)) +
  scale_colour_viridis_d(direction = 1, option= 'plasma') +
  scale_shape_manual( values = 17:24)
```

```
Warning: Removed 40 rows containing missing values or values outside the scale range
(`geom_line()`).
```

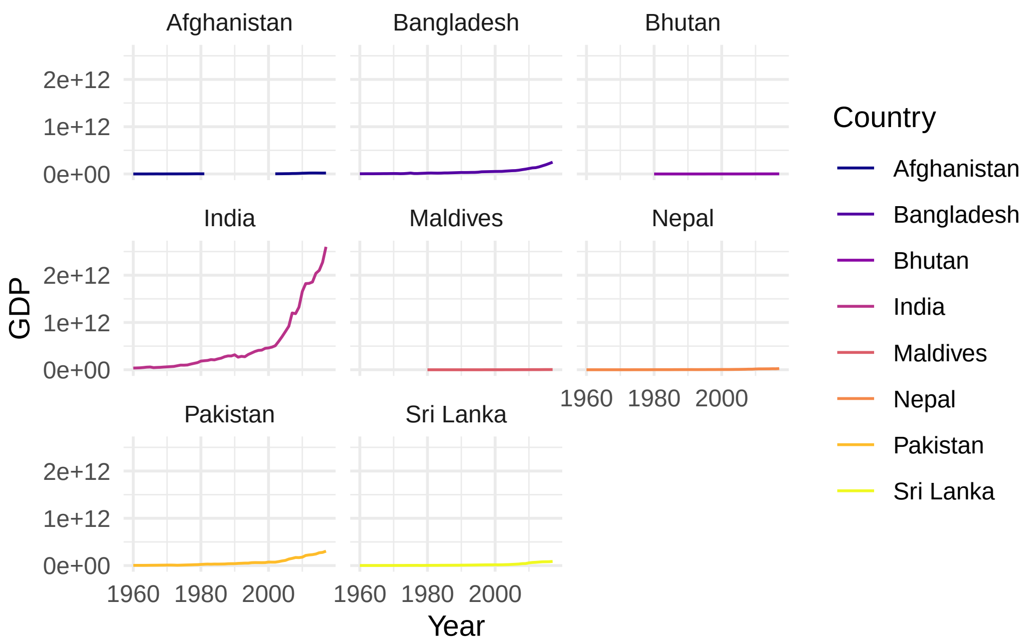


7.8 Facets Layer

The Facets layer answers the question: Should the data be split into multiple panels for easier comparison?

```r
ggplot(SAeconomy_data) +
 aes(x = Year, y = GDP, colour = Country) +
 geom_line() +
 scale_color_viridis_d(option = "plasma",
 direction = 1) +
 theme_minimal() +
 facet_wrap(vars(Country))
```

```
Warning: Removed 40 rows containing missing values or values outside the scale range
(`geom_line()`).
```



The code above was generated with the help of the `esquisse` package. I used 'country' as a facet variable to divide the data into multiple panels for better comparison.

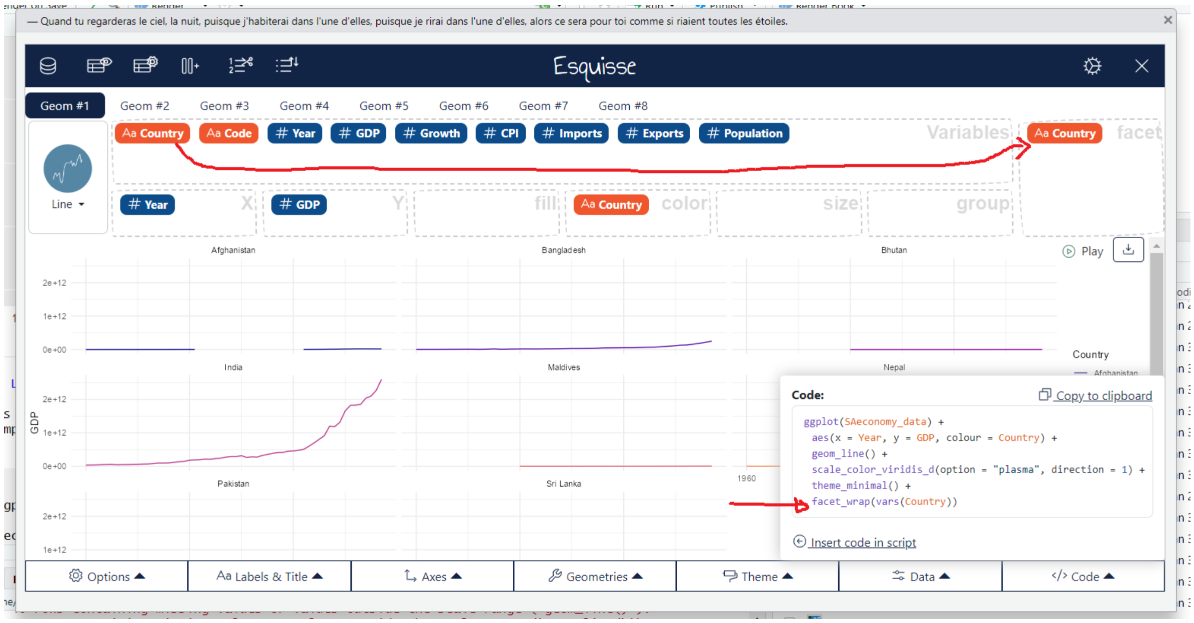
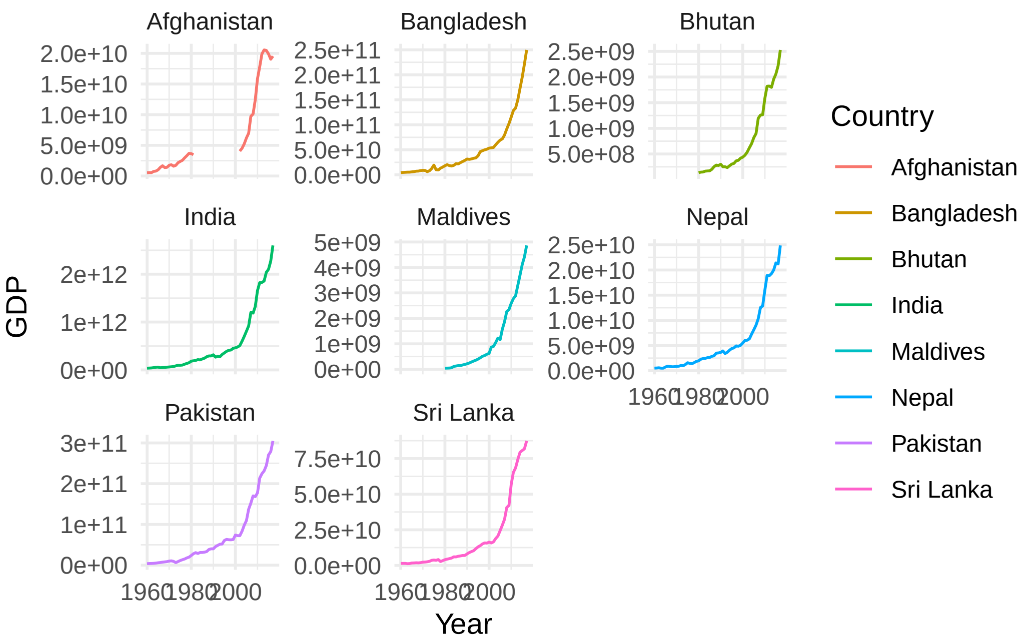


Figure 7.7: `esquisse` package: Create visual representation

Now we can see that the y-axis follows a common scale, which makes it difficult to observe the temporal pattern for low GDP levels, as the series with higher values dominate the visualization. To address this, we can set the scales argument in `facet_wrap` to 'free_y'.

```r
ggplot(SAeconomy_data) +
 aes(x = Year, y = GDP, colour = Country) +
 geom_line() +
 scale_color_hue(direction = 1) +
 theme_minimal() +
 facet_wrap(vars(Country), scales = "free_y")
```

```
Warning: Removed 40 rows containing missing values or values outside the scale range
(`geom_line()`).
```



The code above was generated with the help of the `esquisse` package.

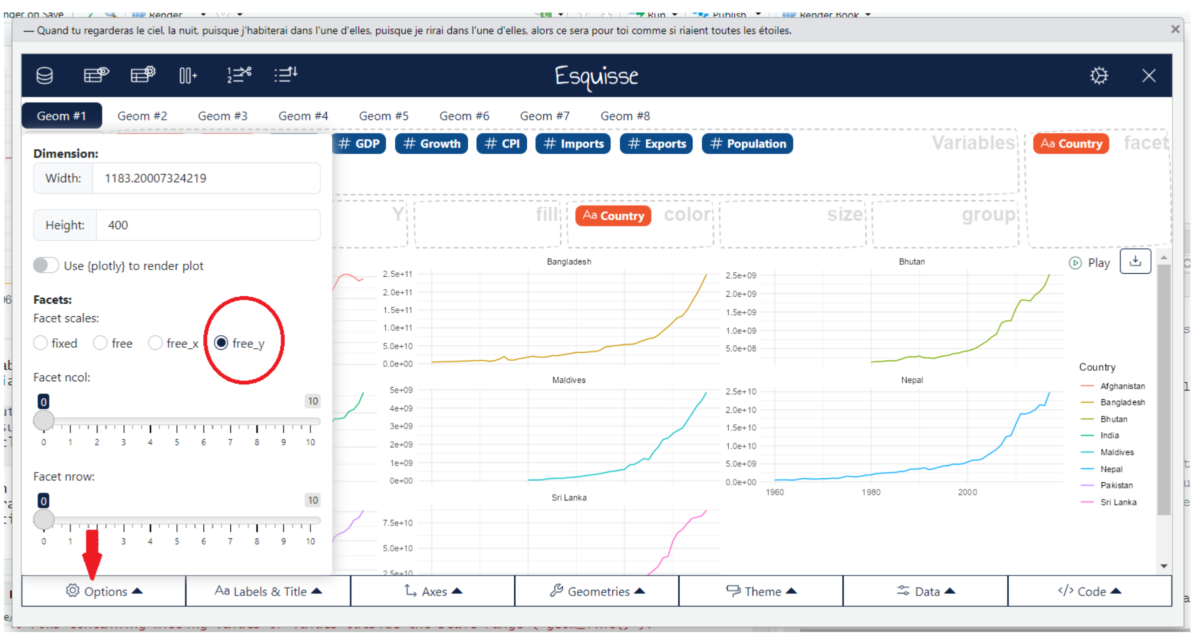


Figure 7.8: `esquisse` package: Create visual representation

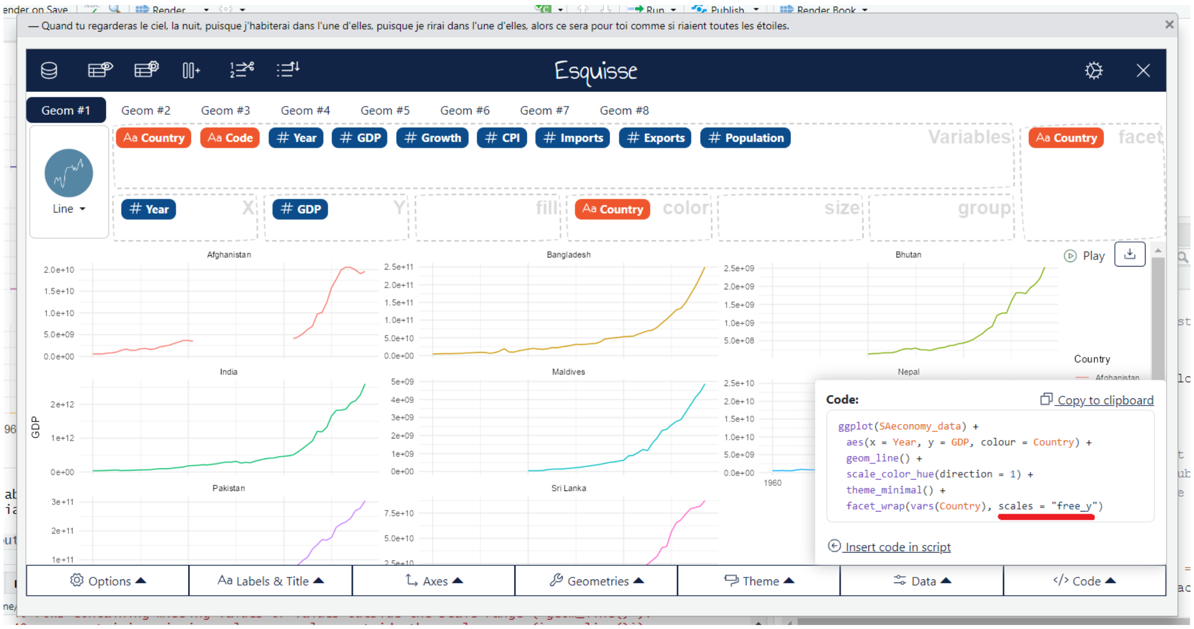


Figure 7.9: `esquisse` package: Create visual representation

7.9 Coordinates Layer

Coordinates (coord) layer answer the question: Which coordinate system should be used (e.g., Cartesian, polar)? In the above example, we've used the Cartesian coordinate system, which is the default.

There are two types of coordinate systems: - Linear coordinate systems : `coord_cartesian()`, `coord_flip()`, `coord_fixed()`

- Non-linear coordinate systems: `coord_map()`, `coord_quickmap()`, `coord_sf()`, `coord_polar()`, `coord_trans()`

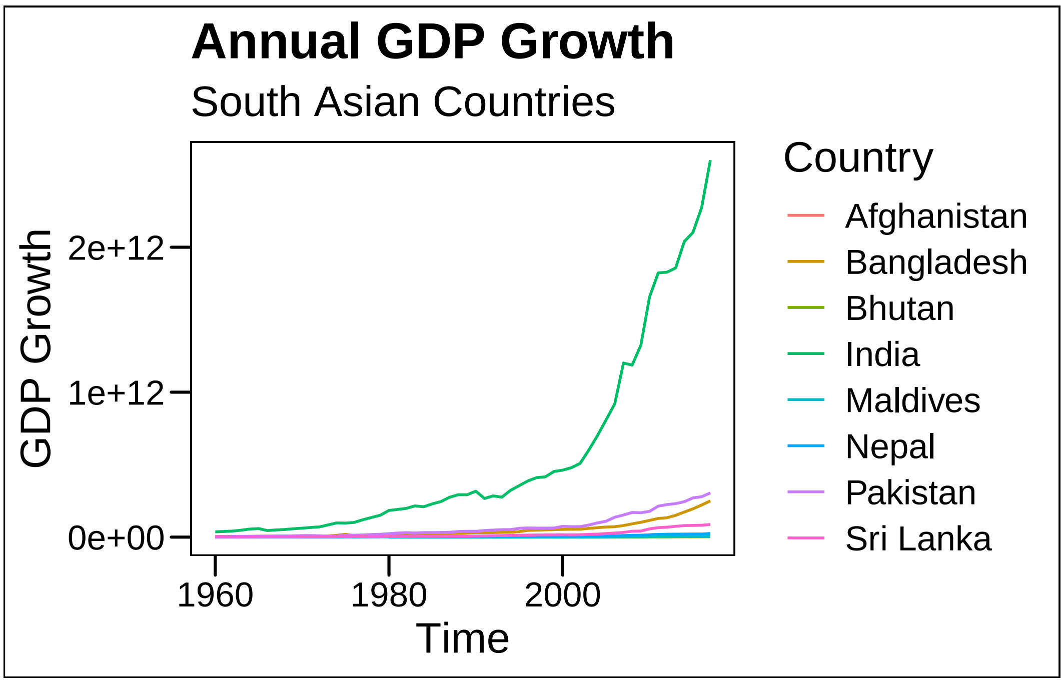
7.10 Theme Layer

Themes layer controls all the non-data elements of the plot, such as labels, titles, background, and grid lines.

```
ggplot(SAeconomy_data) +
  aes(x = Year, y = GDP, colour = Country) +
  geom_line() +
```

```
  scale_color_hue(direction = 1) +
  labs(
    x = "Time",
    y = "GDP Growth",
    title = "Annual GDP Growth ",
    subtitle = "South Asian Countries"
  ) +
  ggthemes::theme_base()
```

```
Warning: Removed 40 rows containing missing values or values outside the scale range
(`geom_line()`).
```



The code above was generated with the help of the `esquisse` package.

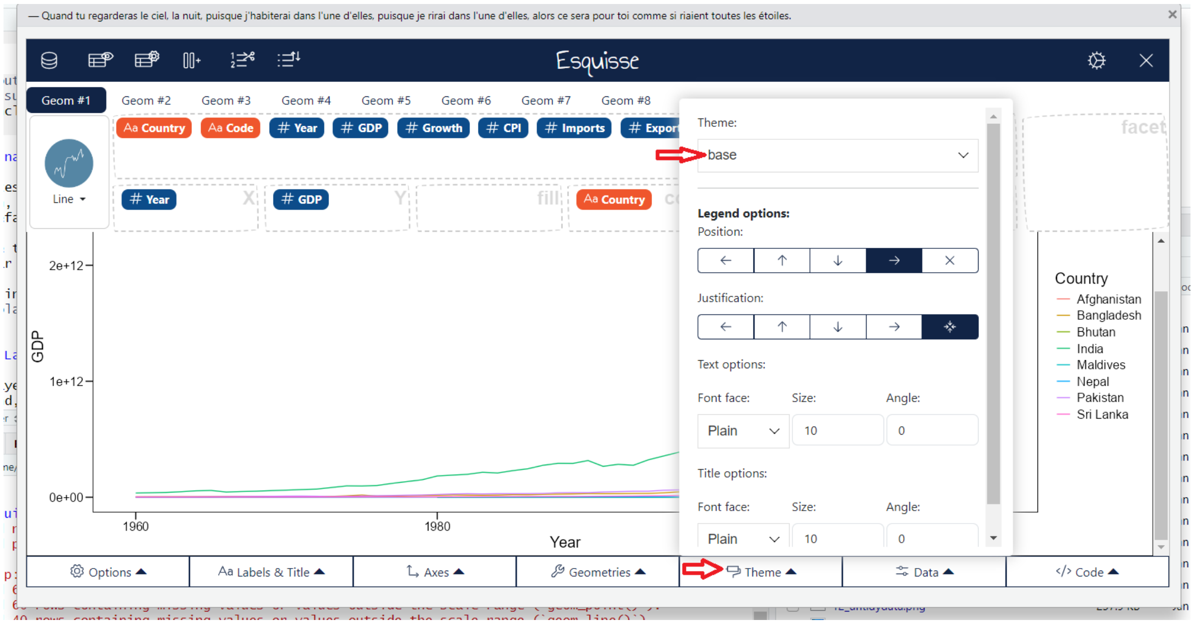


Figure 7.10: esquisse package: Create visual representation

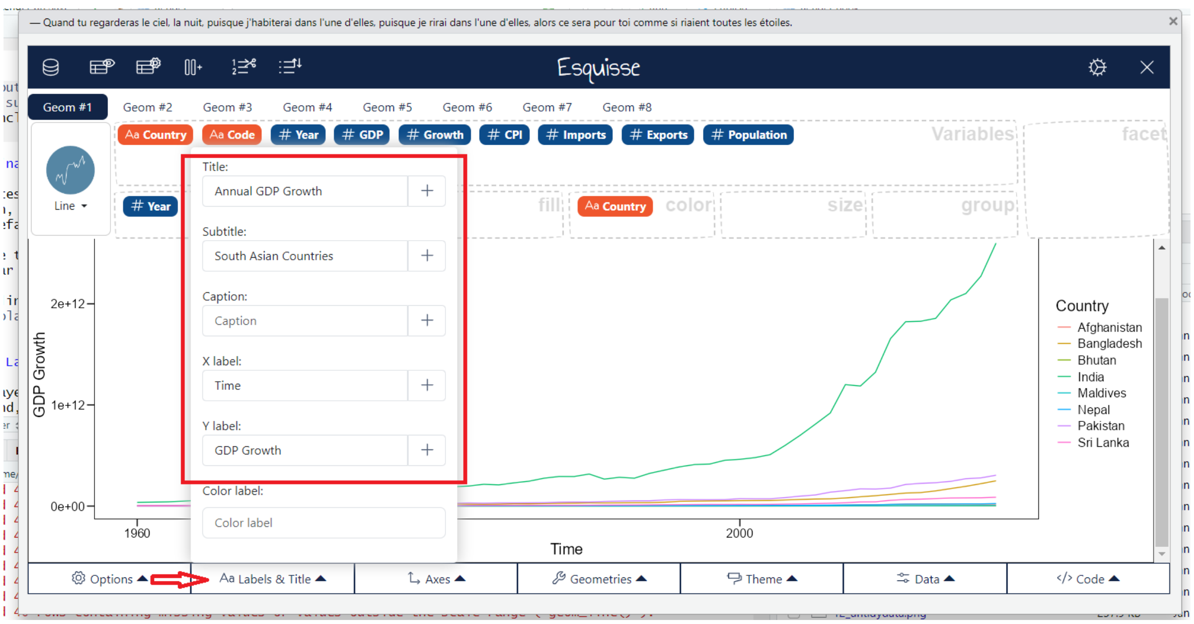


Figure 7.11: esquisse package: Create visual representation

8 Introduction to Statistical Modelling

R provides tools for everything from simple linear regression to complex machine learning algorithms.

Below are some key resources that will help you develop expertise in statistical modeling with R.

1. Data Visualisation Geometries Encyclopedia: Geoms in the Grammar of Graphics: All Types of Plots by Thiyanga Talagala

   This encyclopedia is a curated collection of geom available in different R programming software packages. This book can also be considered as an "Encyclopedia of Plots".

2. R for Data Science by by Hadley Wickham and Garrett Grolemund

   This is a great data science book for beginners interested in learning data science with R.

3. Advanced R by Hadley Wickham

   This book aimed at intermediate and advanced R users.

4. ggplot2: Elegant Graphics for Data Analysis by Hadley Wickham

   This book gives details on the basics of ggplot2 and Grammar of Graphics that ggplot2 uses.

5. An Introduction to Statistical Learning with Applications in R by Gareth M. James, Daniela Witten, Trevor Hastie, Robert Tibshirani

   This book covers topics, ranging from basic concepts to advanced machine learning techniques.

6. Forecasting: Principles and Practice by Rob J Hyndman and George Athanasopoulos

   This textbook provides a comprehensive introduction to time series analysis and forecasting method.

7. Introduction to Econometrics with R by Christoph Hanck, Martin Arnold, Alexander Gerber, and Martin Schmelzer

   This book is an empirical companion to Introduction to Econometrics by Stock and Watson (2020).

8. CRAN Task View: Econometrics

   The CRAN Task View offers a comprehensive list of R packages specifically for econometrics, providing useful tools for economic data analysis and modeling

9. Geocomputation with R by Robin Lovelace, Jakub Nowosad and Jannes Muenchow

   This book covers geographic data analysis, visualization, and modeling techniques

10. The `ceylon` R package by Thiyanga Talagala

The `ceylon` R package enables easy map visualization of Sri Lanka.

References

Wickham, H., Çetinkaya-Rundel, M., & Grolemund, G. (2023). *R for data science.* " O'Reilly Media, Inc.".

Wickham, H. (2019). *Advanced r.* chapman and hall/CRC.