A Brief Introduction to Programming with R

MEcon & MiQE/F Introductory Week

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2025-09-05

Part I: Background / Tools

Schedule

Morning Sessions

09:15 - 10:00

Introduction, Background, Tools, First steps with R

10:00 - 10:15

Break, Support with Installations

10:15 - 11:00

Exercises, Basic Concepts

11:00 - 11:15

Break, Q&A

11:15 - 11:45

Exercises, Basic Concepts

Afternoon Sessions

11:45 - 13:15

Lunch (individually)

13:15 - 14:00

Working with Data

14:00 - 14:15

Break, Q&A

14:15 - 15:15

Exercises

Welcome

1. **Fire up** your notebooks!
2. **Download** (or clone) the course materials
    - GitHub Repository
    - Course slides available online
3. **Download and install R and R-studio** if you have not done so yet (https://cran.r-project.org/, https://posit.co/download/rstudio-desktop/)

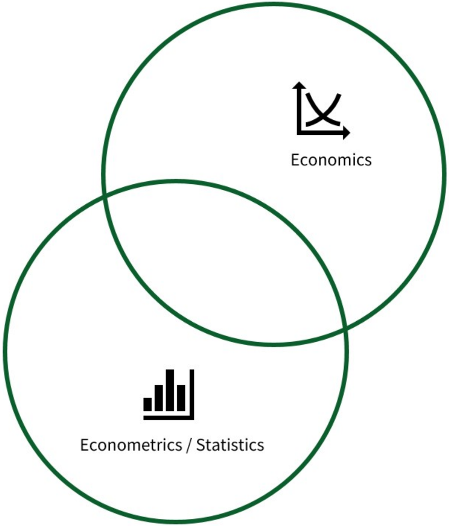
Why learn to program (now)?

Background: technological change

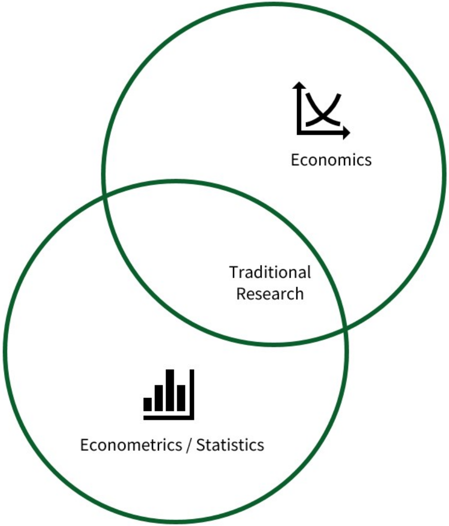
- Computers have become **omnipresent**
- Data is one of the world's most **valuable resources**
- **AI and machine learning** are reshaping every business and industry

Perspective: data science and economics

Perspective: data science and economics



Perspective: data science and economics



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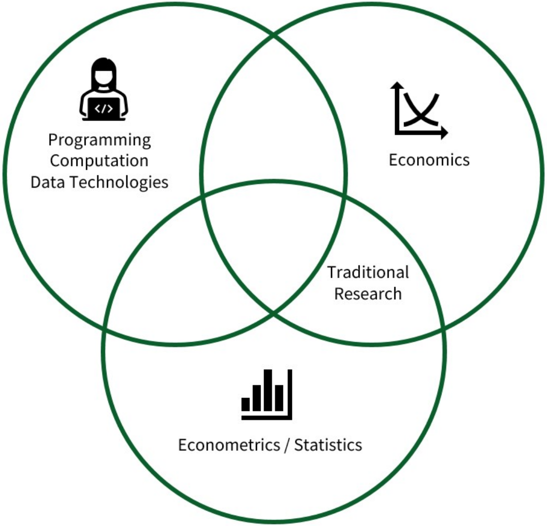
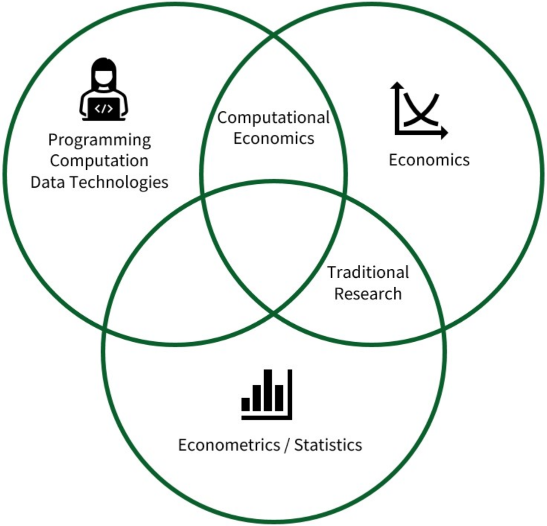


Perspective: data science and economics



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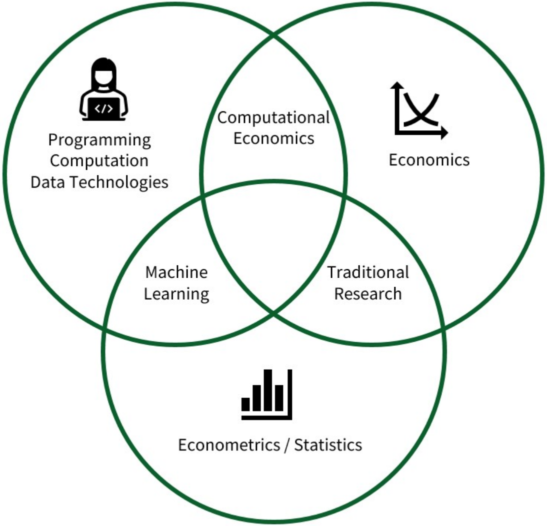
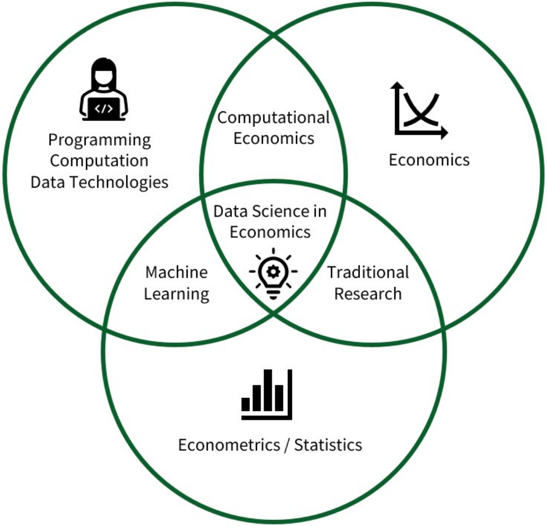


Perspective: data science and economics



Programming in the age of AI-assistance

AI assistants are powerful for many coding tasks, but might do ‘stupid’ hard to spot mistakes.

- **Understand code**: AI-usage requires coding skills to evaluate suggestions (bugs, efficiency, security)
- **Problem solving**: Structuring the analysis and adapting solutions are harder to automate.
- Blindly prompting AI for simple tasks hinders learning.

Recommendation: use **AI as a teacher** for programming

Why R?

A data language

- Widely used in **data science** jobs
- Particularly adapted to program with **data**
- Originally designed for **statistical analysis**
- Competing with Python as the **top data science language**

A high-level language

- **Relatively easy** to learn

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  - RStudio Cheatsheets

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  - DataCamp: Introduction to R
  - RStudio Cheatsheets
  - Stack Overflow

Tools for this workshop

R

R is the **programming language.**

You can download R from: https://cran.r-project.org/

Rstudio desktop

RStudio is the most popular **integrated development environment (IDE).** for R, giving a useful visual interface for key programming tasks.

You can download RStudio Desktop from: https://posit.co/download/rstudio-desktop/

Rstudio cloud

RStudio Cloud lets you use RStudio **without a local installation**

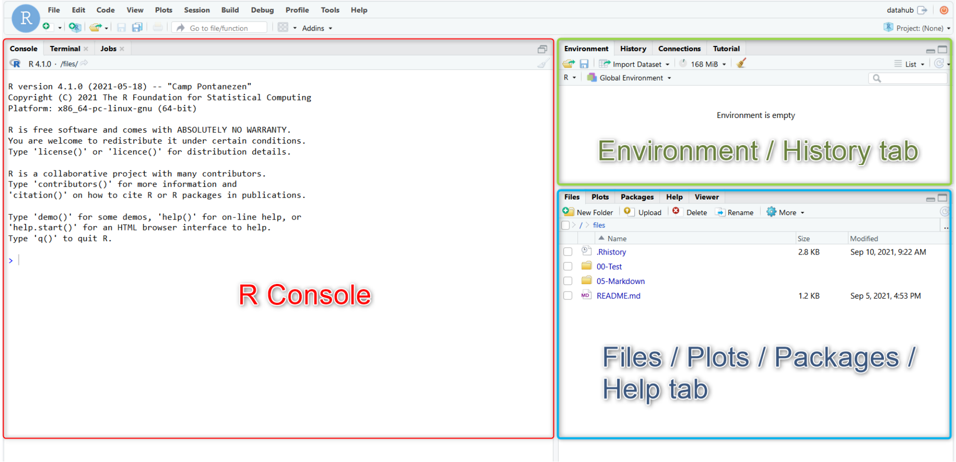
You can use RStudio (Posit) Cloud by registering here: https://posit.cloud/

An R-Studio Interface Tour

RStudio overview

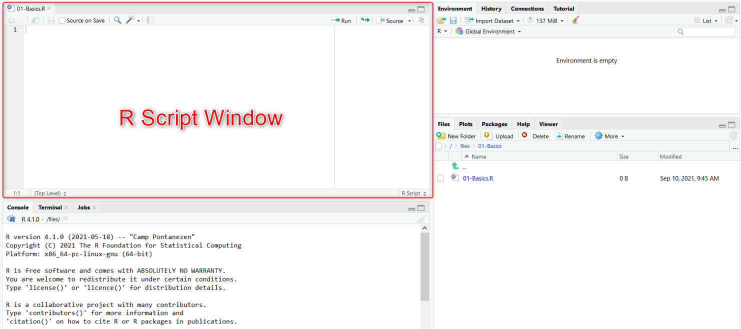
- **Console**: run R commands directly, quick testing
- **Environment / Files**: see variables, data, manage plots & files
- **Help / Viewer**: access documentation, view HTML output/plots

RStudio interface



Scripts in RStudio

- Write and save code in `.R` files
- Run selected lines (`Ctrl+Enter`)
- Keep work reproducible



Working directories & R projects

- **Working directory** = folder where R looks for files, e.g. data to load.
- Use `getwd()` and `setwd()`
- Better: **R Projects**
    - Define self-contained working environments
    - Save code, data, outputs together
    - Makes collaboration & reproducibility easier

Other tools in R-studio

- Help window for documentation
- Visual interfaces for file navigation, packages, exporting plots, loading data, ...
- Debugging, profiling, git for version control, AI integration (Copilot)

Exercises

Exercise a: setting up a working environment

1. Open **RStudio** and navigate to your desired working folder
2. Create a new folder called **r_course**
3. Set it as your **working directory**
4. Create subfolders: **data** and **code**

(*) Create a new **R Project** in the `r_course` folder

(*) Choose your favorite R-studio **appearance**: ‘Tools > Global Options > Appearance‘

Exercise b: r scripts

1. In the R console, type:

```r
print("Hello world")
```

2. Create a new **R script**: `File > New File > R Script` (or `Ctrl+Shift+N`)
3. Type the same code in the script and **run it** using `Ctrl+Enter` or `Ctrl+As+Enter`

Part II: First Steps and Basic Concepts

First steps in R

Variables and vectors

```r
a <- 2
a
```

```
[1] 2
```

Working with vectors

R easily allows to work with **vectors** of data!

```r
# Instantiate an integer vector 'a'
a <- c(10, 22, 33, 22, 40)
# Give names to the vector's elements
names(a) <- c("Andy", "Betty", "Claire",
              "Daniel", "Eva")
a  # Display the vector
```

```
  Andy  Betty Claire Daniel    Eva
    10     22     33     22     40
```

Indexing

We can access **single** (or **multiple**) elements of a vector:

```r
a[3]      # Access the 3rd element
```

```
Claire
    33
```

```r
a[3:5]    # Access the 3rd to 5th elements
```

```
Claire Daniel     Eva
    33     22      40
```

```r
a["Claire"]  # Access by name
```

```
Claire
```

Inspecting variables

```
class(a)  # Display the class
```

```
[1] "numeric"
```

```
str(a)    # Display the structure
```

```
 Named num [1:5] 10 22 33 22 40
 - attr(*, "names")= chr [1:5] "Andy" "Betty" "Claire" "Daniel" ...
```

Math operators

Basic operators:

- $+$: `+`
- $-$: `-`
- $\times$: `*`
- $\div$: `/`

More operators:

- a^n : `a^n`
- $\sqrt{a}$: `sqrt(a)`
- $\ln a$: `log(a)`
- e^n : `exp(n)`

Basic Programming Concepts

Loops

- **Repeatedly execute** a sequence of commands
- For a **known** or **unknown** number of iterations
  - **for-loop**: number of iterations typically known
  - **while-loop**: iterate until a condition is met

For-loops in r

```r
n_iter <- 5  # Define number of iterations
# Specify the loop
for (i in 1:n_iter) {
    print(i)  # Print the number 'i'
}
```

```
[1] 1
[1] 2
[1] 3
[1] 4
[1] 5
```

For-loops: summing numbers

```r
numbers <- c(72, 42, 150, 13, 36, 19)
total_sum <- 0  # Initialize sum

# Specify the loop
for (n in numbers) {
    total_sum <- total_sum + n
}
total_sum
```

```
[1] 332
```

Nested for-loops

```r
n_iter_inner <- 100
n_iter_outer <- 500

# Start outer loop
for (i in 1:n_iter_outer) {
    # Code for outer loop

    # Start inner loop
    for (j in 1:n_iter_inner) {
        # Code for inner loop
    }
}
```

How many iterations does this combination amount to?

While-loops in r

```r
# Instantiate starting value
total <- 0

# Loop while the condition is true
while (total <= 10) {
    total <- total + 3.14
}
total
```

```
[1] 12.6
```

Booleans and logical statements

```r
2 + 2 == 4  # Is 2+2 equal to 4?
```

```
[1] TRUE
```

```r
3 + 3 == 7  # Is 3+3 equal to 7?
```

```
[1] FALSE
```

```r
4 != 7      # Is 4 not equal to 7?
```

```
[1] TRUE
```

```r
!TRUE  # negation using '!'
```

Control flow with booleans

```r
condition <- TRUE

if (condition) {
    print("The condition is true!")
} else {
    print("The condition is false!")
}
```

```
[1] "The condition is true!"
```

R functions

- Functions take **parameter values** as input, process these values, and **return** results
- Many functions are **provided with R**
- Additional functions via **packages**

```
numbers <- c(13, 25, 39, 881)
mean(numbers)    # Compute the mean
```

```
[1] 240
```

```
sd(numbers)      # Standard deviation
```

```
[1] 428
```

```
median(numbers)   # Median
```

Creating custom functions

```r
# Define custom mean function
my_mean <- function(x) {
    x_bar <- sum(x) / length(x)
    return(x_bar)
}

# Test the function
my_mean(numbers)  # call the function with the input argument
```

```
[1] 240
```

```r
mean(numbers)  # Compare with built-in
```

```
[1] 240
```

Loading functions from packages

```r
install.packages("dplyr") # Install (from CRAN): run once
library(dplyr) # Load the package: run each session

# Example: call dplyr's summarise() to compute the mean
mean_tidyverse <- data.frame(x = numbers) |>
  summarise(avg = mean(x))
as.numeric(mean_tidyverse) # display mean as number
```

```
[1] 240
```

Note: use ‘package_name::function_name()’ when multiple packages have functions of the same name to avoid ambiguities.

Data Structures and Indices

Vectors and lists

```r
# Integer vector
integer_vector <- 9:20
integer_vector[2]     # Second element
```

```
[1] 10
```

```r
integer_vector[2:5]  # Second to fifth
```

```
[1] 10 11 12 13
```

```r
# String vector
string_vector <- c("a", "b", "c")
string_vector[-3]     # All except third
```

Lists

Lists can contain **different types** of elements:

```r
# Create a list
my_list <- list(
    numbers = integer_vector,
    letters = string_vector,
    condition = TRUE
)
str(my_list)
```

```
List of 3
 $ numbers  : int [1:12] 9 10 11 12 13 14 15 16 17 18 ...
 $ letters  : chr [1:3] "a" "b" "c"
 $ condition: logi TRUE
```

Accessing list elements

```r
# Access by name
my_list$numbers[1:3]
```

```
[1]  9 10 11
```

```r
my_list[["letters"]]
```

```
[1] "a" "b" "c"
```

```r
# Access by index
my_list[[1]][1:3]
```

```
[1]  9 10 11
```

Matrices

```r
# Create a matrix
my_matrix <- matrix(integer_vector, nrow = 4)
my_matrix
```

```
     [,1] [,2] [,3]
[1,]    9   13   17
[2,]   10   14   18
[3,]   11   15   19
[4,]   12   16   20
```

Matrices: extracting rows/columns

```r
my_matrix[2,]        # Second row
```

```
[1] 10 14 18
```

```r
my_matrix[, 1:2]    # First two columns
```

```
     [,1] [,2]
[1,]    9   13
[2,]   10   14
[3,]   11   15
[4,]   12   16
```

Data frames: creation

```r
# Create a dataframe
my_df <- data.frame(
    Name = c("Alice", "Betty", "Claire"),
    Age = c(20, 30, 45)
)

my_df
```

Name	Age
Alice	20
Betty	30
Claire	45

Data frames: access

```r
my_df$Age           # Access column
```

```
[1] 20 30 45
```

```r
my_df[2, ]          # Second row
```

	Name	Age
2	Betty	30

Exercises

Exercise a: write a sum function

Write a function that takes a **numeric vector** as input and returns the **sum** of the vector's elements.

```
my_sum <- function(x) {
    # Your code here
}
```

Test by comparing with built-in `sum()` function.

Exercise b: robustness and warnings

Test your `my_sum()` function with:

```r
numbers2 <- c("1", "2", "3")
```

Add **error checking** to make the function robust.

Exercise c: standard deviation function

Implement a function to compute the **standard deviation**:

$$\text{SD} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2}$$

Exercise d: standard error function

Building on Exercise C, implement:

$$\text{SE}_{\bar{x}} = \frac{\text{SD}}{\sqrt{N}}$$

Exercise e: t-test

Implement a **one-sample t-test** function:

$$t = \frac{\bar{x} - \mu_0}{\mathrm{SE}_{\bar{x}}}$$

Exercise f: fibonacci sequence

Generate the first 30 **Fibonacci numbers** where:

- $F_0 = 0$, $F_1 = 1$
- $F_n = F_{n-1} + F_{n-2}$ for $n > 1$

Exercise g: multiples of 3 and 5 (*)

Write a function that computes the sum of all **multiples of 3 or 5** up to a number N.

Hint: Multiples of both 3 and 5 should only be added once!

Exercise h: prime numbers (*)

Write a function that computes the sum of all **prime numbers** up to a number N.

Part III: Working with Data

Loading/Importing Data

Loading built-in r data sets

```r
# Load built-in dataset
data(swiss)

# Check if loaded
class(swiss)
```

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

The `data()` function loads **built-in R datasets** into your environment.

Inspect the data structure

```r
# Structure of the swiss dataset
str(swiss)
```

```
'data.frame':   47 obs. of  6 variables:
 $ Fertility       : num  80.2 83.1 92.5 85.8 76.9 76.1 83.8 92.4 82.
 $ Agriculture     : num  17 45.1 39.7 36.5 43.5 35.3 70.2 67.8 53.3
 $ Examination     : int  15 6 5 12 17 9 16 14 12 16 ...
 $ Education       : int  12 9 5 7 15 7 7 8 7 13 ...
 $ Catholic        : num  9.96 84.84 93.4 33.77 5.16 ...
 $ Infant.Mortality: num  22.2 22.2 20.2 20.3 20.6 26.6 23.6 24.9 21
```

First few rows of the data

```r
head(swiss, 4)
```

	Fertility	Agriculture	Examination	Education	Catholic	Infant.Mortality
Courtelary	80.2	17.0	15	12	9.96	22.2
Delemont	83.1	45.1	6	9	84.84	22.2
Franches-Mnt	92.5	39.7	5	5	93.40	20.2
Moutier	85.8	36.5	12	7	33.77	20.3

Comma separated values (csv)

Example of **CSV format**:

```
"","Fertility","Agriculture","Examination",...
"Courtelary",80.2,17,15,...
"Delemont",83.1,45.1,6,...
```

Importing data from different sources

```r
# Csv files
swiss_csv <- read.csv("./data/swiss.csv")

# Excel files (requires readxl)
library(readxl)
swiss_excel <- read_excel("./data/swiss.xlsx")

# Spss files (requires haven)
library(haven)
swiss_spss <- read_spss("./data/swiss.sav")
```

Introduction to the Tidyverse

What is the tidyverse?

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

To install and load:

```
install.packages("tidyverse") # Install once

library(tidyverse) # Load in each session
```

The pipe operator |>

Transform nested functions into **readable pipelines**:

```r
# Traditional approach
head(select(swiss, Fertility, Education), 3)

# With pipe operator
swiss |>
  select(Fertility, Education) |>
  head(3)
```

Note: |> is built into R (since version 4.1.0). %>% is from the `magrittr` package, which has additional features.

Select columns with `select()`

```r
# Select specific columns
swiss |>
  select(Fertility, Education, Catholic) |>
  head(3)
```

	Fertility	Education	Catholic
Courtelary	80.2	12	9.96
Delemont	83.1	9	84.84
Franches-Mnt	92.5	5	93.40

Select columns - advanced patterns

```r
# Select by pattern
swiss |>
  select(starts_with("E") | contains("Mort")) |>
  head(3)
```

	Examination	Education	Infant.Mortality
Courtelary	15	12	22.2
Delemont	6	9	22.2
Franches-Mnt	5	5	20.2

Filter rows with `filter()`

```r
# Keep rows meeting conditions
swiss |>
  filter(Education > 20) |>
  select(Fertility, Education, Catholic) |>
  head()
```

	Fertility	Education	Catholic
Lausanne	55.7	28	12.1
Neuchatel	64.4	32	16.9
V. De Geneve	35.0	53	42.3
Rive Droite	44.7	29	50.4
Rive Gauche	42.8	29	58.3

Create new variables with `mutate()`

```
swiss |>
  mutate(
    High_Education = Education > 15,
    Fert_per_100 = Fertility / 100
  ) |>
  select(Education, High_Education,
         Fertility, Fert_per_100) |>
  head(3)
```

	Education	High_Education	Fertility	Fert_per_100
Courtelary	12	FALSE	80.2	0.802
Delemont	9	FALSE	83.1	0.831
Franches-Mnt	5	FALSE	92.5	0.925

Arrange rows with `arrange()`

```
swiss |>
  arrange(desc(Education)) |>
  select(Education, Examination) |>
  head(4)
```

	Education	Examination
V. De Geneve	53	37
Neuchatel	32	35
Rive Droite	29	16
Rive Gauche	29	22

Summarize data with `summarize()`

```
swiss |>
  summarize(
    mean_edu = mean(Education),
    sd_edu = sd(Education),
    median_fert = median(Fertility),
    n = n()
  )
```

mean_edu	sd_edu	median_fert	n
11	9.62	70.4	47

Group operations with `group_by()`

```
# Group and summarize
swiss |>
  group_by(Catholic > 50) |>
  summarize(
    mean_education = mean(Education),
    mean_fertility = mean(Fertility),
    count = n()
  )
```

Catholic > 50	mean_education	mean_fertility	count
FALSE	12.14	66.2	29
TRUE	9.11	76.5	18

Combining multiple operations

```r
swiss |>
  filter(Agriculture < 50) |>
  group_by(Catholic > 50) |>
  summarize(
    avg_exam = mean(Examination),
    n = n(),
    .groups = "drop"
  ) |>
  arrange(desc(avg_exam))
```

Catholic > 50	avg_exam	n
FALSE	23.1	15
TRUE	12.3	6

Reshape data: wide to long

```
# Original wide format
swiss_subset <- swiss |>
  slice(1:2) |>
  select(Fertility, Agriculture)

swiss_subset
```

	Fertility	Agriculture
Courtelary	80.2	17.0
Delemont	83.1	45.1

Reshape data: `pivot_longer()`

```r
# Convert to long format
swiss_subset |>
  pivot_longer(
    cols = everything(),
    names_to = "Metric",
    values_to = "Value"
  )
```

Metric	Value
Fertility	80.2
Agriculture	17.0
Fertility	83.1
Agriculture	45.1

Join data frames (preparation)

```r
# Sample data
df1 <- data.frame(
  Student_ID = c(2501, 2502, 2503, 2504),
  Master = c("Mecon", "Mecon", "MiQE/F", "MiQE/F")
)

df2 <- data.frame(
  Student_ID = c(2501, 2502, 2503, 2504, 2505, 2506),
  Grades = c(6, 5, 5.5, 5.5, 4, 5)
)
```

Join data frames

```r
# Left join keeps all rows from df1
left_join(df1, df2, by = "Student_ID")
```

Student_ID	Master	Grades
2501	Mecon	6.0
2502	Mecon	5.0
2503	MiQE/F	5.5
2504	MiQE/F	5.5

Working with dates using lubridate (preparation)

```r
# Create and parse dates
dates <- c("2025-09-05", "2025-09-06")
parsed_dates <- ymd(dates)
```

Working with dates using lubridate

```
# Extract components
data.frame(
  date = parsed_dates,
  year = year(parsed_dates),
  month = month(parsed_dates),
  weekday = wday(parsed_dates, label = TRUE)
)
```

date	year	month	weekday
2025-09-05	2025	9	Fr
2025-09-06	2025	9	Sa

Purrr: map functions

```r
# Apply a function to multiple columns
swiss |>
  select(Fertility, Agriculture, Education) |>
  map_dbl(mean) |>
  round(2)
```

```
  Fertility Agriculture   Education
       70.1        50.7        11.0
```

String manipulation with stringr

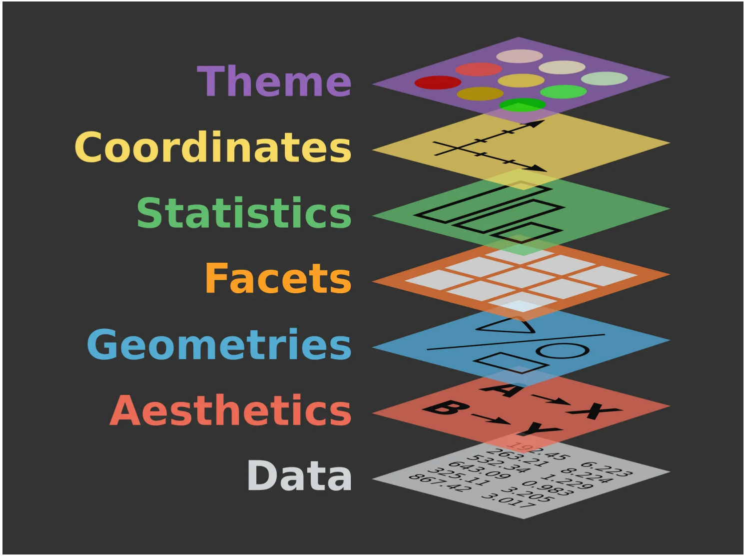
```r
masters <- c("Mecon", "MiQE/F", "MACFin")

# String operations
tibble(
  original = masters,
  lower = str_to_lower(masters),
  length = str_length(masters),
  contains_e = str_detect(masters, "e")
)
```

original	lower	length	contains_e
Mecon	mecon	5	TRUE
MiQE/F	miqe/f	6	FALSE
MACFin	macfin	6	FALSE

Visualization with R (ggplot2)

Grammar of graphics - layers



Ggplot2 basics

```
# Basic structure
ggplot(data = <DATA>,

       mapping = aes(x = <X>, y = <Y>)) +
  <GEOM_FUNCTION>() +
  <OPTIONAL_LAYERS>
```

Prepare the data

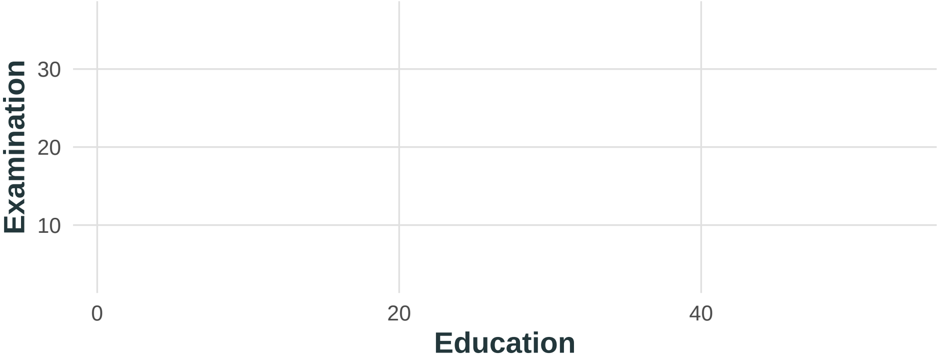
```r
# Add religion indicator
swiss <- swiss |>
  mutate(Religion = ifelse(Catholic > 50,
                           'Catholic', 'Protestant') |> factor())

# Check the data
table(swiss$Religion)
```

```
  Catholic Protestant
        18         29
```

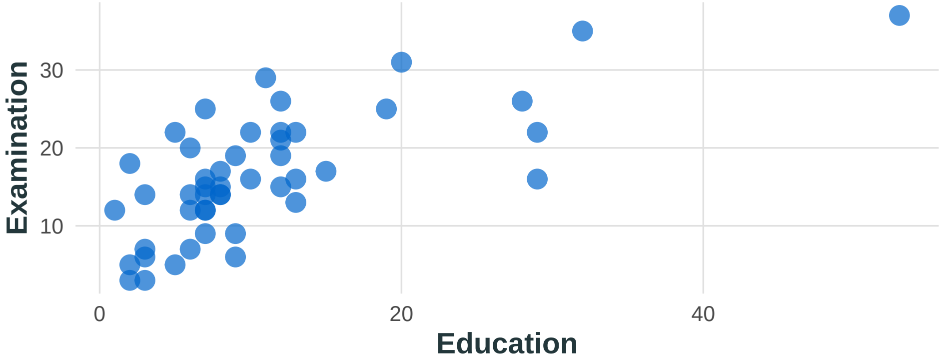
Building a plot: data + aesthetics

```
ggplot(data = swiss,
       aes(x = Education, y = Examination))
```



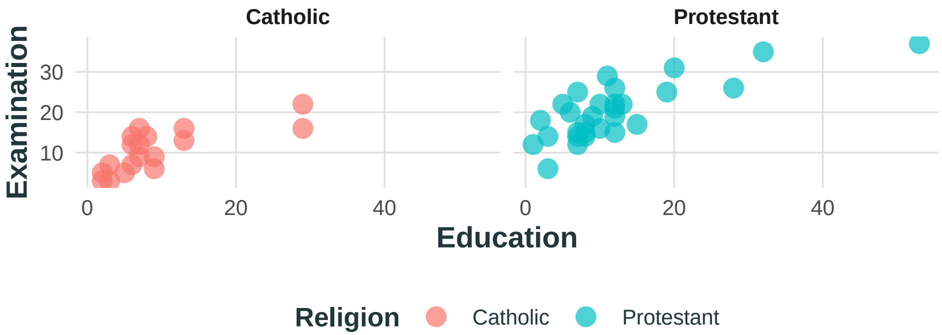
Adding geometries

```r
ggplot(data = swiss,
       aes(x = Education, y = Examination)) +
  geom_point(size = 3, alpha = 0.7, color = "#0066CC")
```



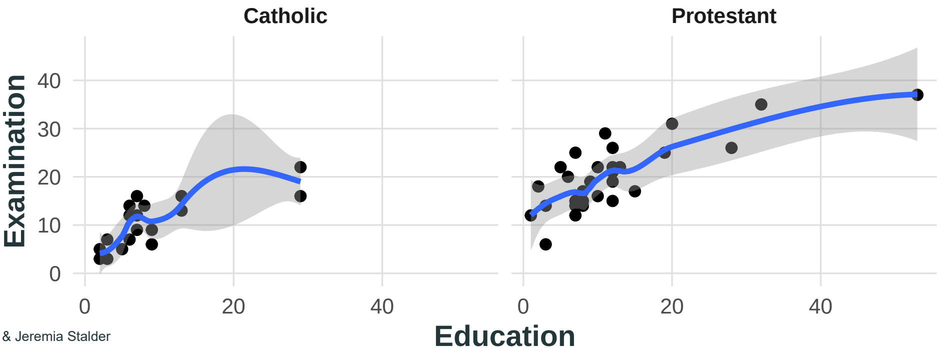
Using facets

```
ggplot(data = swiss,
       aes(x = Education, y = Examination)) +
  geom_point(size = 3, alpha = 0.7, aes(color = Religion)) +
  facet_wrap(~Religion)
```



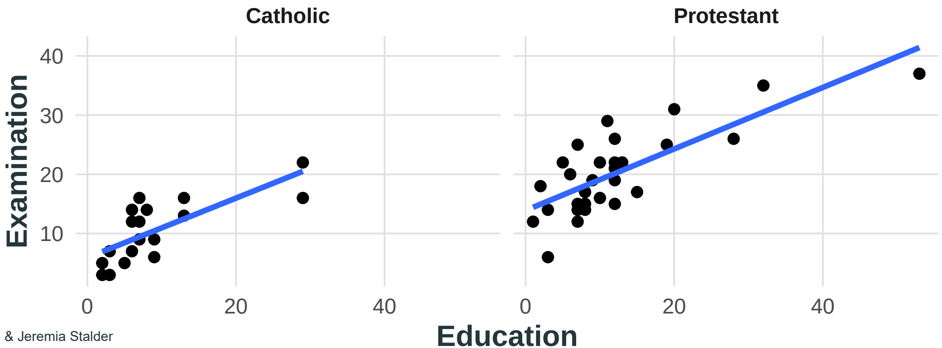
Adding statistics with loess

```r
ggplot(data = swiss,
       aes(x = Education, y = Examination)) +
  geom_point() +
  geom_smooth(method = 'loess') +
  facet_wrap(~Religion)
```



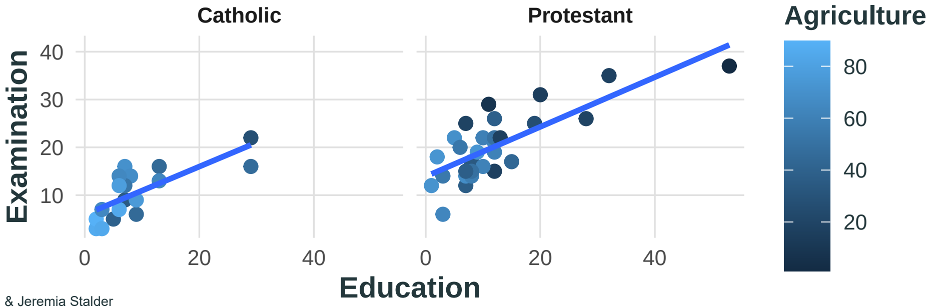
Adding statistics with lm

```r
ggplot(data = swiss,
       aes(x = Education, y = Examination)) +
  geom_point() +
  geom_smooth(method = 'lm', se = FALSE) +
  facet_wrap(~Religion)
```



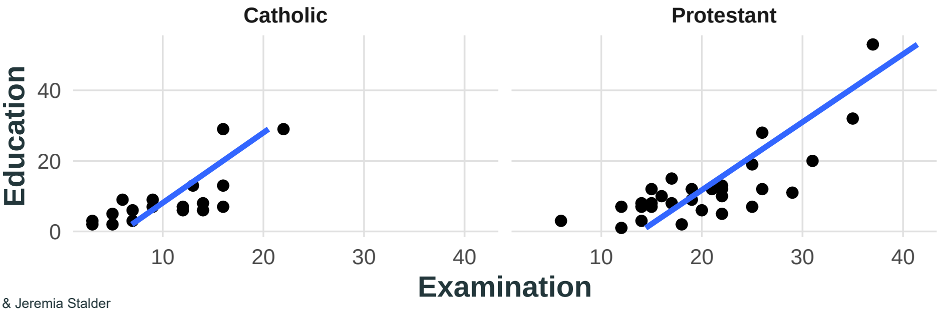
Multiple aesthetics

```
ggplot(data = swiss,
       aes(x = Education, y = Examination)) +
  geom_point(aes(color = Agriculture), size = 2) +
  geom_smooth(method = 'lm', se = FALSE) +
  facet_wrap(~Religion) +
  theme(legend.position = "right")
```



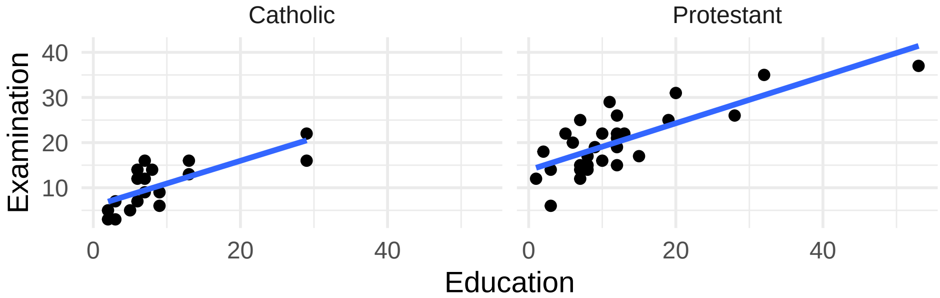
Change coordinates

```
ggplot(data = swiss,
       aes(x = Education, y = Examination)) +
  geom_point() +
  geom_smooth(method = 'lm', se = FALSE) +
  facet_wrap(~Religion) +
  coord_flip()
```



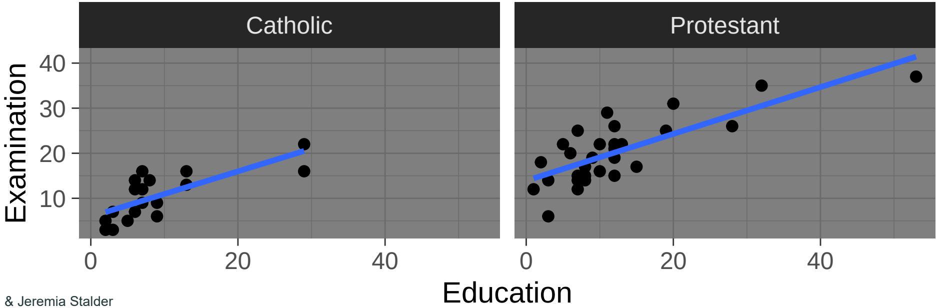
Customizing themes

```
ggplot(data = swiss,
       aes(x = Education, y = Examination)) +
  geom_point() +
  geom_smooth(method = 'lm', se = FALSE) +
  facet_wrap(~Religion) +
  theme_minimal()
```



Pre-built themes

```
ggplot(data = swiss,
       aes(x = Education, y = Examination)) +
  geom_point() +
  geom_smooth(method = 'lm', se = FALSE) +
  facet_wrap(~Religion) +
  theme_dark()
```



Save plots

```r
# Save the last plot
ggsave("my_plot.png",
       width = 8, height = 5,
       dpi = 300)

# Save a specific plot
p <- ggplot(swiss, aes(Education, Examination)) +
  geom_point()

ggsave("scatter.pdf", plot = p,
       width = 6, height = 4)
```

Basic Statistics with R

Descriptive statistics

```r
# Create sample data
x <- c(10, 22, 33, 22, 40)

# Basic statistics
tibble(
  mean = mean(x),
  median = median(x),
  sd = sd(x),
  min = min(x),
  max = max(x)
)
```

mean	median	sd	min	max
25.4	22	11.5	10	40

T-test example

```
# Generate sample data
set.seed(123)
sample <- rnorm(30, mean = 10, sd = 2)

# One-sample t-test
t_result <- t.test(sample, mu = 10)
t_result$p.value
```

```
[1] 0.794
```

```
t_result$conf.int
```

```
[1]  9.17 10.64
attr(,"conf.level")
[1] 0.95
```

Linear regression - setup

```r
# Define the model formula
model1 <- Examination ~ Education

# Fit the model
fit1 <- lm(model1, data = swiss)

# View coefficients
coef(fit1) # Use 'summary(fit1)' for more details
```

```
(Intercept)   Education
     10.127       0.579
```

Multiple linear regression

```r
# Fit model with multiple predictors
fit2 <- lm(Examination ~ Education + Catholic + Agriculture,
           data = swiss)

# Model fit statistics
tibble(
  R2 = summary(fit2)$r.squared,
  Adj_R2 = summary(fit2)$adj.r.squared,
  RMSE = sigma(fit2))
```

R2	Adj_R2	RMSE
0.728	0.709	4.3

Regression coefficients table

```
# Extract coefficient information
coef_summary <- summary(fit2)$coefficients
round(coef_summary, 3)
```

```
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   18.537      2.637    7.03    0.000
Education      0.424      0.087    4.89    0.000
Catholic      -0.080      0.017   -4.75    0.000
Agriculture   -0.068      0.040   -1.71    0.095
```

Other econometric models

```r
# Binary outcomes - logit
glm(y ~ x1 + x2,
    family = binomial(link = "logit"))

# Binary outcomes - probit
glm(y ~ x1 + x2,
    family = binomial(link = "probit"))

# Count data - poisson
glm(y ~ x1 + x2,
    family = poisson())

# Panel data - fixed effects
library(fixest) # install.packages("fixest")
feols(y ~ x1 + x2 | x3,
    data = panel_data)
```

Print regression results - console

```r
# Basic regression table
library(modelsummary)

models <- list(
  "Model 1" = lm(Examination ~ Education,
                 data = swiss),
  "Model 2" = lm(Examination ~ Education + Catholic + Agriculture,
                  data = swiss)
)

modelsummary(models,
             stars = TRUE,
             gof_omit = "AIC|BIC|Log.Lik.")
```

Save regression output

```r
# Save table directly to file
modelsummary(models, output = "table.docx")
modelsummary(models, output = "table.html")
modelsummary(models, output = "table.tex")
modelsummary(models, output = "table.md")
modelsummary(models, output = "table.txt")
modelsummary(models, output = "table.png")

# Raw table
modelsummary(models, output = "html")
modelsummary(models, output = "latex")
modelsummary(models, output = "markdown")
```

Exercise i: Working with Data using dplyr

Exercise i.1

- Load the dataset with `data(swiss)`
- Use `mutate()` to create two new variables:
  - `UrbanizationRate`: the inverse of Agriculture (100 – Agriculture)
  - `FertilityCategory`: a factor variable with levels:
    - 0–60: “Low”
    - 60–80: “Medium”
    - 80–100: “High”
- Hint: use `case_when()` for categorization

Exercise i.2

- Filter observations where Fertility > 70
- Arrange results by `Education` in descending order

Exercise i.3

- Group data by `FertilityCategory`
- Calculate average `Education` for each category using `group_by()` and `summarize()`

Exercise i.4

- Find the top 3 observations with highest Fertility values
- Display only `Fertility` and `Education` columns

Exercise i.5

- Create `EducationToFertilityRatio = Education / Fertility`
- Show all observations where the ratio is between 0.1 and 0.2

Exercise i.6

- Group by `FertilityCategory`
- Calculate:
  - Median Fertility
  - Standard deviation of Education
- Store the results in a new data frame

Exercise i.7

- Use `n_distinct()` to determine the number of distinct values in:
  - `Education`
  - `FertilityCategory`

Exercise j: Visualizing Data

Exercise j.1

- Load the dataset `swiss.csv` or call `data(swiss)`

Exercise j.2

- Print the last 3 observations of the dataset
- Create summary statistics for all variables

Exercise j.3

- Create new variables:
  - `UrbanizationRate` = 100 – Agriculture
  - `FertilityCategory`:
    - 0–60: “Low”
    - 60–80: “Medium”
    - 80–100: “High”
- Hint: use `cut()`

Exercise j.4

- Create a histogram of `Fertility`
  - Fill bars in dark blue
  - Add a minimal theme

Exercise j.5

- Create a boxplot of the variable `Education`

Exercise j.6

- Create a scatter plot of `Education` vs. `Fertility`
- Add a regression line (linear model)

Exercise j.7

- Create scatter plots of `Agriculture` vs. `Examination`
- Show them separately for each `FertilityCategory` using `facet_wrap()`

Final Remarks

Some best practices for R programming

1. **Organization**
    - Start scripts with `library()` calls
    - Use meaningful variable names
    - Comment your code with #

2. **Efficiency**
    - Use functions to avoid repetition
    - Vectorize operations when possible
    - Use the tidyverse for data manipulation

3. **Reproducibility**
    - Set seeds for random operations
    - Use relative paths (`./data/`)
    - Document package versions (or with with projects / environments)

Resources for learning R

Online Resources:

- Stack Overflow
- R for Data Science book
- Posit cheatsheets
- CRAN documentation

AI Assistance:

- ChatGPT
- GitHub Copilot
- Google Gemini
- Claude

Example prompts to use AI as programming teacher

Bad prompt

- *“Please solve this coding assignment.”*
- *“Here’s my code, please fix it.”*

Better prompt

“The code below yields a variable type error. Please correct it and explain my mistake.”

Good prompt:

- **System prompt**
  "I am learning to code in R and want to use you as a teacher.
  Please guide me to find the solution myself, not just give the answer."
- **Question prompt**
  "This code should do [A], but instead does [B].
  I think the issue is in line [X–Y], where I meant to do [C].
  Can you give me a hint?"

Upcoming courses

Next Week

R Programming Course

Instructor: Erik Senn

Dates: September 8-11, 2025

Time: 9:00-12:00 and 13:00-17:00

Location: Rosenbergstrasse 30, Room 61-152 Contents: Similar contents as today in slower pace. Automated reports using R-markdown on last day.

Thank you!

Thanks for joining our R workshop!

Happy Coding!

Survey - evaluation for introduction week

https://forms.office.com/e/Ki59zF84dY

Please take a moment to provide feedback on the introduction week.

Your input helps us improve future courses!