

Exploring the Social World - Quantitative Block: Statistics

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Table of contents

Welcome	4
Contact	4
Overview	5
Aim and Learning Objectives	5
Module Structure	6
Software and Data	6
Assessment	8
Required Report Structure	8
How to get there?	9
How to submit	10
1 Lab: Introduction to R for Statistics	12
1.1 R?	12
1.2 R(Studio) Basics	13
1.2.1 Starting a session in RStudio	13
1.2.2 Using the console	16
1.2.3 R as a simple calculator	16
1.2.4 Variables Assignment	18
1.2.5 Working with Scripts	18
1.2.6 R Packages	20
1.3 Practice: Dataset and Dataframes	20
1.3.1 Datasets in R	22
1.3.2 Importing Data in R	23
1.4 Practice: Descriptive Statistics	25
1.4.1 Summarizing Data	25
1.4.2 Understanding the Structure of the FRS Datafile	32
1.4.3 Explore the Distribution of Your Outcome Variable	34
2 Lab: Correlation, Single, and Multiple Linear Regression	40
2.1 Part I. Correlation	40
2.1.1 Data Overview: Descriptive Statistics:	40
2.1.2 Simple visualisation for continuous data	42
2.1.3 Part. 2: Implementing a Linear Regression Model	47
2.1.4 Model fit	48

2.1.5	Interpreting the Results	50
2.1.6	Interpretation of regression coefficients or covariate effects	51
2.1.7	Identify factors of % bad health	52
2.2	Part C: Practice and Extension	52

Welcome

This is the website for “Exploring the Social World - Quantitative Block: Statistics” (module **ENVS225**) at the University of Liverpool. This block of the module is designed and delivered by Dr. Gabriele Filomena and Dr. Zi Ye from the Geographic Data Science Lab at the University of Liverpool. The module seeks to provide hands-on experience and training in introductory statistics for human geographers.

The website is **free to use** and is licensed under the [Attribution-NonCommercial-NoDerivatives 4.0 International](#). A compilation of this web course is hosted as a GitHub repository that you can access:

- As an [html website](#).
- As a [GitHub repository](#).

Contact

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Overview

Aim and Learning Objectives

This sub-module aims to provide training and skills on a set of basic quantitative research methods for data collection, analysis, and interpretation. You will learn how to define coherent, relevant research questions, utilise various research quantitative methods, and identify appropriate methodologies to tackle your research questions. **This block serves as the foundation for the dissertation and fieldwork modules.**

Background

Data and research are key pillars of the global economy and society today. We need rigorous approaches to collecting and analysing both the statistics that can tell us ‘how much’ and if there are observable relationships between phenomena; and the information gives us a nuanced understanding of cultural contexts and human dynamics. Quantitative skills enable us to explore and measure socio-economic activities and processes at large scales, while qualitative skills enable understanding of social, cultural, and political contexts and diverse lived experiences. Rather than being in opposition, qualitative and quantitative research can complement one another in the investigation of today’s pressing research questions.

To these ends, this block will help you develop your quantitative (statistical) skills, as critical tools. This course will help you understand what quantitative statistical researchers use and develop a set of research techniques that can be used in your field classes and dissertations.

Learning objectives:

- Understand how to explore a dataset, containing a number of observations described by a set of variables.
- Demonstrate an understanding in the application and interpretation of commonly used quantitative research methods.
- Demonstrate an understanding of how to work with quantitative data to address real-world research questions.

Module Structure

Staff: Dr Zi Ye and Dr Gabriele Filomena

Where and When

Quantitative Block (Weeks 7-12):

- **Lecture:** 10 am – 10.45 am Fridays
- **PC Practical sessions:** 11am – 1 pm, following the Lecture

Week 7: Central Teaching Hub: PC Teaching Centre BLUE+GREEN+ORANGE ZONES

Week 8 -12: Central Teaching Hub, PCTC

Lectures will introduce and explain the fundamentals of quantitative methods, with the opportunity to apply the method introduced in the labs later in the week.

The computer practical sessions, will give you the chance to use and apply quantitative methods to real-world data. These are primarily self-directed sessions, but with support on hand if you get stuck. Support and training in R will be provided through these sessions. Weekly sessions will be driven by empirical research questions.

Week	Topic	Format	Staff
7	Introduction & Review	Lecture and Computer Lab Practical	GF
8	Single & Multiple Linear Regression	Lecture and Computer Lab Practical	GF
9	Multiple Linear Regression with Categorical Variables	Lecture and Computer Lab Practical	ZY
10	Logistic Regression	Lecture and Computer Lab Practical	ZY
11	Data Visualisation	Lecture and Computer Lab Practical	GF
12	Summary and Assessment Support	Lecture and Computer Lab Practical	ZY

Software and Data

For quantitative training sessions, ensure you have installed and/or have access to **RStudio**. To run the analysis and reproduce the code in R, you need the following software installed on your machine:

- R-4.2.2
- RStudio 2022.12.0-353

To install and update:

- R, download the appropriate version from [The Comprehensive R Archive Network \(CRAN\)](#).
- RStudio, download the appropriate version from [here](#).

This software is already installed on University Machines. But you will need it to run the analysis on your personal devices.

Data

Example datasets could be accessed through Canvas or the [GitHub](#) Repository of the module. These include:

- 2021 UK Census Data.
- 2021 Annulation Population Survey.
- 2016 Family Resource Survey.

Note: The Annual Population Survey requires the completion of a form prior to its usage, as it is licensed.

Assessment

Deadline: Tuesday 7th January 2025.

The assignment **Data Exploration and Analysis** consists of writing a research report using one of the regression techniques learned during the module. The basic idea is to put in practice the methods learned during the quantitative block of the module. You are required to apply a linear or logistic regression model to the data provided for the module. The report needs to include the following sections (in brackets, % of the whole length):

- Introduction (5%).
- Literature Review (20%).
- Methods and data (30%).
- Results and discussion (40%).
- Conclusion (5%).
- Reference List.

Required Report Structure

1. Introduction

- Context: Why is the topic relevant or worth being investigated?
- Brief discussion of existing literature.
- Knowledge gap and Aim.
- Research questions.

2. Literature review

- More detailed Literature review, i.e. what do we already know about this subject
- Rationale for including certain predictor variables in the model.
- What knowledge gap remains that this article will address? (includes “not studied before in this area”). *Note: there is no expectation on totally original research. The focus is on a clean, sensible, data analysis situated in existing ideas.*

3. Methodology:

- A brief introduction to the dataset being analysed (who collected it? When? How many responses? etc.)
- A description of the variables chosen to be analysed.

- A description of any transformation made to the original data, i.e. turning a continuous variable of income into intervals, or reducing the number of age groups from 11 to 3.
- A description and justification of the statistical techniques in the subsequent analysis.

4. Results and Discussion

- Descriptive statistics and summary of the variables employed.
- Results and interpretation, including links and contrasts to existing literature.
- Selective illustrations (graphs and tables) to make your findings as clear as possible.

5. Conclusion

- Summary of main findings.
- Limitations of study (self-critique).
- Potential future directions.

Follow this structure and include **ALL** these points, do not make your life harder.

How to get there?

The first stage is to identify **ONE** a relevant research question to be addressed. Based on the chosen question, you will need to identify a dependent (or outcome) variable which you want to explain, and at least two relevant independent variables that you can use to explain the chosen dependent variable. The selection of variables should be informed by the literature and empirical evidence.

To detail in the Methods Section: Once the variables have been chosen, you will need to describe the data and **appropriate** type of regression to be used for the analysis. You need to explain any transformation done to the original data source, such as reclassifying variables, or changing variables from continuous to nominal scales. You also need to briefly describe the data use: source of data, year of data collection, indicate the number of records used, state if you are using individual records or geographical units, explain if you are selecting a sample, and any relevant details. You also need to identify type of regression to be used and why.

To detail in the Results and Discussion Section: Firstly, you need to provide two types of analyses. First, you need to provide a descriptive analysis of the data. Here you could use tables and/or plots reporting relevant descriptive statistics, such as the mean, median and standard deviation; variable distributions using histograms; and relationships between variables using correlation matrices or scatter plots. Secondly, you need to present an estimated regression model or models and the interpretation of the estimated coefficients. You need a careful and critical analysis of the regression estimates. You should think that you intend to use your regression models to advice your boss who is expecting to make some decisions based

on the information you will provide. As part of this process, you need to discuss the model assessment results for the overall model and regression coefficients. Remember to substantiate your arguments using relevant literature and evidence, and present results clearly in tables and graphs.

How to submit

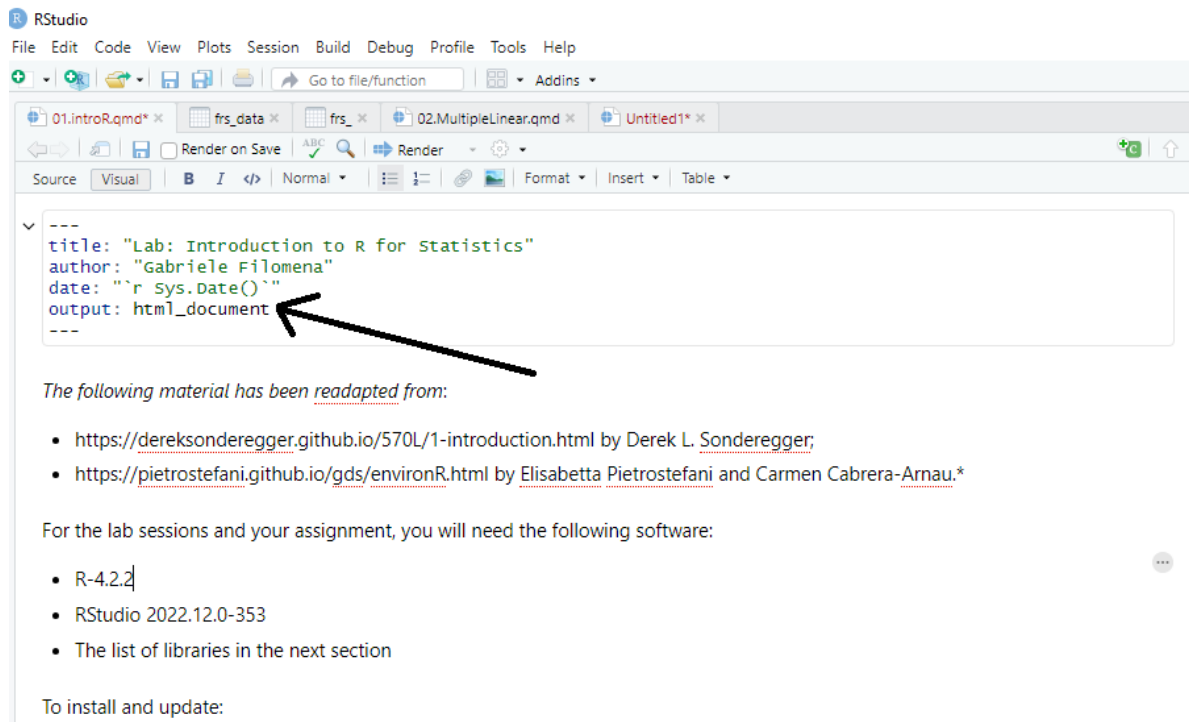
You should submit a `.pdf` file, that is a rendered version of a Quarto Markdown file (`qmd` file). This will allow you to write a research paper that also includes your working code, without the need of including the data (rendered `.qmd` files are executed before being converted to R).

How to get a PDF?

1. **Install Quarto:** Make sure you have Quarto installed. You can download it from quarto.org.
2. **LaTeX Installation:** For PDF output, you'll need a LaTeX distribution like **TinyTeX** from R, by executing this in the R console:

```
install.packages("tinytex")
tinytex::install_tinytex()
```

3. **Open the Quarto File:** Open your `.qmd` file in RStudio.
4. **Set Output Format:** In the YAML header at the top of your Quarto file, specify `pdf` under `format`:



```
title: "Your Document Title"
author: "Anonymous" # do not change
format: pdf
```

5. Click the **Render** button in the RStudio toolbar (next to the Knit button).

1 Lab: Introduction to R for Statistics

The following material has been readapted from:

- <https://dereksonderegger.github.io/570L/1-introduction.html> by Derek L. Sonderegger;
- <https://pietrostefani.github.io/gds/envIRON.html> by Elisabetta Pietrostefani and Carmen Cabrera-Arnau.*

The lecture's slides can be found [here](#).

For the lab sessions and your assignment, you will need the following software:

- R-4.2.2
- RStudio 2022.12.0-353
- The list of libraries in the next section

To install and update:

- R, download the appropriate version from [The Comprehensive R Archive Network \(CRAN\)](#)
- RStudio, download the appropriate version from [Posit](#)

1.1 R?

R is an open-source program that is commonly used in Statistics. It runs on almost every platform and is completely free and is available at www.r-project.org. Most of the cutting-edge statistical research is first available on R.

R is a script based language, so there is no point and click interface. While the initial learning curve will be steeper, understanding how to write scripts will be valuable because it leaves a clear description of what steps you performed in your data analysis. Typically you will want to write a script in a separate file and then run individual lines. This saves you from having to retype a bunch of commands and speeds up the debugging process.

1.2 R(Studio) Basics

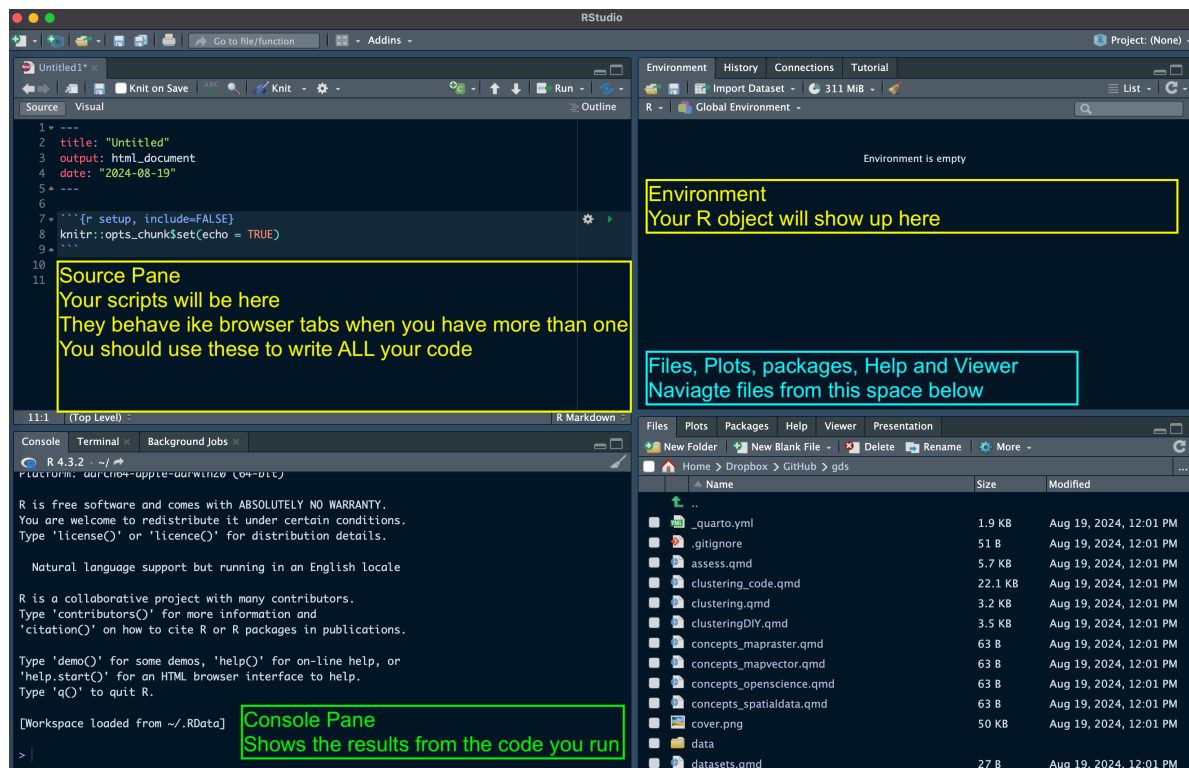
We will be running R through the program RStudio which is located at rstudio.com. When you first open up RStudio the console window gives you some information about the version of R you are running and then it gives the prompt `>`. This prompt is waiting for you to input a command. The prompt `+` tells you that the current command is spanning multiple lines. In a script file you might have typed something like this:

```
for( i in 1:5 ){  
  print(i)  
}
```

Finding help about a certain function is very easy. At the prompt, just type `help(function.name)` or `?function.name`. If you don't know the name of the function, your best bet is to go to the web page www.rseek.org which will search various R resources for your keyword(s). Another great resource is the coding question and answer site [stackoverflow](https://stackoverflow.com).

1.2.1 Starting a session in RStudio

Upon startup, RStudio will look something like this.



Note: the **Pane Layout** and **Appearance** settings can be altered:

- on Windows by clicking RStudio>Tools>Global Options>Appearance or Pane Layout
- on Mac OS by clicking RStudio>Preferences>Appearance or Pane Layout.

You will also have a standard white background; but you can choose specific [themes](#).

Source Panel (Top-Left)

This is where you write, edit, and view scripts, R Markdown/Quarto documents, or R scripts. It allows:

- Editing Scripts: Write and edit R scripts or documents (`.R`, `.Rmd`, `.qmd`).
- Executing the Code: Run lines, blocks, or the entire script directly from the editor.

Console Panel (Bottom-Left)

The Console is the main place to run R commands interactively. It allows:

- Executing the Code: Type and run R commands directly.
- Viewing outputs, warnings, and errors for immediate feedback.
- Browsing and reusing past commands (History Tab).
- Toggling between the R Console, and the Terminal (you don't really need the latter).

Environment Panel (Top-Right)

This panel helps track variables, functions, and the history of commands used. It contains:

- Environment Tab: Shows all current variables, datasets, and objects in your session, including their structure and values.
- History Tab: Provides a record of past commands. You can re-run or move commands to the console or script.

Files / Plots / Packages / Help Panel (Bottom-Right)

This multifunctional panel is for file navigation, plotting, managing packages, viewing help, and managing jobs. It contains:

- Files Tab: Navigate, open, and manage files and directories within your project.
- Plots Tab: Displays plots generated in your session. You can export or navigate through multiple plots here.
- Packages Tab: Lists installed packages and allows you to install, load, and update packages.
- Help Tab: Displays help documentation for R functions, packages, and other resources. You can search for documentation by typing a function or package name.

Important: Unless you are working with a script, you will be likely writing code on the console.

At the start of a session, it's good practice clearing your R environment (console):

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

In R, we are going to be working with **relative paths**. With the command `getwd()`, you can see where your working directory is currently set.

```
getwd()
```

For ENVS225, download the [material](#) of the module and unzip it wherever you like.

The folder structure should look like:

```
stats/  
  data/  
  labs_img/  
  labs/
```

You can delete other sub-folders (e.g. docs).

This should be on your personal computer or if on a local machine, I suggest using the directory M: to store the folder, it can be accessed from every computer.

Then, in R Studio - on Windows by clicking RStudio>Tools>Global Options>General.. - on Mac OS by clicking RStudio>Preferences>Appearance or Pane Layout...

browse and set the folder you just created as your working directory.

Check if that has been applied.

```
getwd()
```

File paths in R work like this:

File Path	Description
MyFile.csv	Look in the working directory for MyFile.csv.
MyFolder/MyFile.csv	Is the working directory, there is a subdirectory called MyFolder and inside that folder is MyFile.csv.

You do not need to set your working directory if you are using an R-markdown or Quarto document and you have it saved in the right location. The pathway will start from where your document is saved.

1.2.2 Using the console

Try to use the console to perform a few operations. For example type in:

```
1+1
```

```
[1] 2
```

Slightly more complicated:

```
print("hello world")
```

```
[1] "hello world"
```

If you are unsure about what a command does, use the “Help” panel in your Files pane or type `?function` in the console. For example, to see how the `dplyr::rename()` function works, type in `?dplyr::rename`. When you see the double colon syntax like in the previous command, it’s a call to a package without loading its library.

1.2.3 R as a simple calculator

You can use R as a simple calculator. At the prompt, type `2+3` and hit enter. What you should see is the following

```
# Some simple addition  
2+3
```

```
[1] 5
```

In this fashion you can use R as a very capable calculator.

```
6*8
```

```
[1] 48
```

```
4^3
```

```
[1] 64
```



```
exp(1)    # exp() is the exponential function
```

```
[1] 2.718282
```

R has most constants and common mathematical functions you could ever want. For example, the absolute value of a number is given by `abs()`, and `round()` will round a value to the nearest integer.

```
pi        # the constant 3.14159265...
```

```
[1] 3.141593
```

```
abs(1.77)
```

```
[1] 1.77
```

Whenever you call a function, there will be some arguments that are mandatory, and some that are optional and the arguments are separated by a comma. In the above statements the function `abs()` requires at least one argument, and that is the number you want the absolute value of.

When functions require more than one argument, arguments can be specified via the order in which they are passed or by naming the arguments. So for the `log()` function, for example, which calculates the logarithm of a number, one can specify the arguments using the named values; the order wouldn't matter:

```
# Demonstrating order does not matter if you specify  
# which argument is which  
log(x=5, base=10)
```

```
[1] 0.69897
```

```
log(base=10, x=5)
```

```
[1] 0.69897
```

When we don't specify which argument is which, R will decide that `x` is the first argument, and `base` is the second.

```
# If not specified, R will assume the second value is the base...  
log(5, 10)
```

```
[1] 0.69897
```

```
log(10, 5)
```

```
[1] 1.430677
```

When we want to specify the arguments, we can do so using the `name=value` notation.

1.2.4 Variables Assignment

We need to be able to assign a value to a variable to be able to use it later. R does this by using an arrow `<-` or an equal sign `=`. While R supports either, for readability, I suggest people pick one assignment operator and stick with it.

Variable names cannot start with a number, may not include spaces, and are case sensitive.

```
var <- 2*7.5      # create two variables  
another_var = 5   # notice they show up in 'Environment' tab in RStudio!  
var
```

```
[1] 15
```

```
var * another_var
```

```
[1] 75
```

As your analysis gets more complicated, you'll want to save the results to a variable so that you can access the results later. *If you don't assign the result to a variable, you have no way of accessing the result.*

1.2.5 Working with Scripts

R Scripts (.R files)

Traditional script files look like this:

```

# Problem 1
# Calculate the log of a couple of values and make a plot
# of the log function from 0 to 3
log(0)
log(1)
log(2)
x <- seq(.1,3, length=1000)
plot(x, log(x))

# Problem 2
# Calculate the exponential function of a couple of values
# and make a plot of the function from -2 to 2
exp(-2)
exp(0)
exp(2)
x <- seq(-2, 2, length=1000)
plot(x, exp(x))

```

In RStudio you can create a new script by going to **File -> New File -> R Script**. This opens a new window in RStudio where you can type commands and functions as a common text editor.

This looks perfectly acceptable as a way of documenting what one does, but this script file doesn't contain the actual results of commands you ran, nor does it show you the plots. Also anytime you want to comment on some output, it needs to be offset with the commenting character `#`. It would be nice to have both the commands and the results merged into one document. This is what the R Markdown file does for us.

R Markdown (.Rmd and .qmd files)

The R Markdown is an implementation of the Markdown syntax that makes it extremely easy to write webpages or scientific documents that include code. This syntax was extended to allow users to embed R code directly into more complex documents. Perhaps the easiest way to understand the syntax is to look at an at the [RMarkdown website](#).

The R code in a R Markdown document (.rmd file extension) can be nicely separated from regular text using the three backticks (3 times `'`, see below) and an instruction that it is R code that needs to be evaluated. A code chunk will look like:

```
for (i in 1:5) {print(i)}
```

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

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

In ENVS225: In this module we will be using .qmd a more flexible development of .rmd files.

Markdown files present several advantages compared to writing your code in the console or just using scripts. You'll save yourself a huge amount of work by embracing Markdown files from the beginning; you will keep track of your code and your steps, be able to document and present how you did your analysis (helpful when writing the methods section of a paper), and it will make it easier to re-run an analysis after a change in the data (such as additional data values, transformed data, or removal of outliers) or once you spot an error. Finally, it makes the script more readable.

1.2.6 R Packages

One of the greatest strengths about R is that so many people have developed add-on packages to do some additional function. To download and install the package from the Comprehensive R Archive Network (CRAN), you just need to ask RStudio it to install it via the menu **Tools -> Install Packages...** Once there, you just need to give the name of the package and RStudio will download and install the package on your computer.

Once a package is downloaded and installed on your computer, it is available, but it is not loaded into your current R session by default. To improve overall performance only a few packages are loaded by default and the you must explicitly load packages whenever you want to use them. You only need to load them once per session/script.

```
library(dplyr) # load the dplyr library, will be useful later
```

1.3 Practice: Dataset and Dataframes

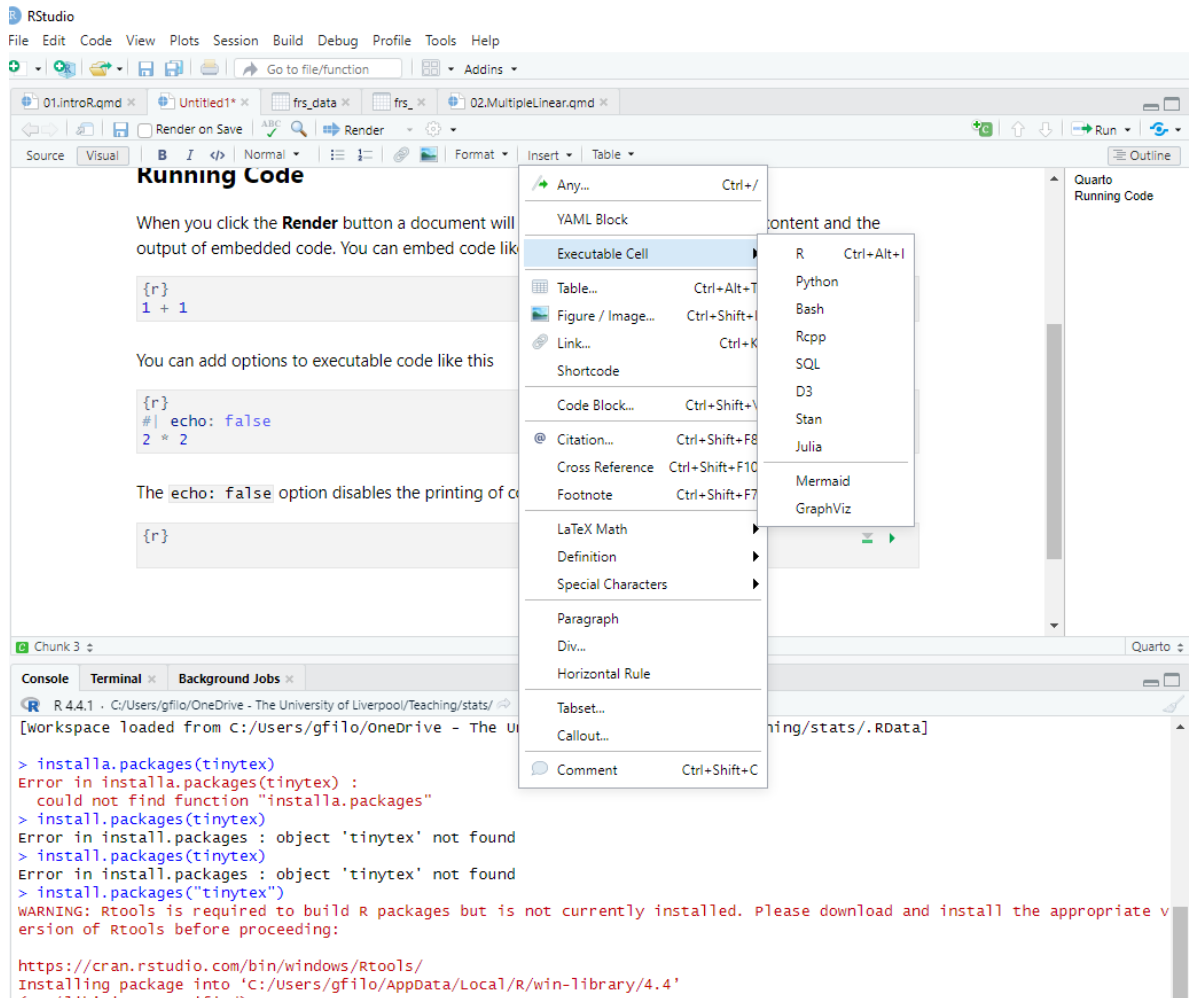
First of all, create a new Markdown document. We use the **File -> New File -> Quarto Document...** dropdown option, and a menu will appear asking you for the document title, author, and preferred output type. You can select HTML, but you will need your assignment to be submitted in PDF; more on that later.

Follow the practical below. You can describe what you are doing in normal text. See [here](#) for how to format normal text in Markdown documents

Remember, when you want to write code in a markdown document you have to enclose it like this:



or you can insert it manually:



Within this module we will be working with data stored in so-called datasets. A dataset is a structured collection of data points that represent various measurements or observations, often organized in a tabular format with rows and columns. A dataset might contain information about different locations, such as neighborhoods or cities, with each row representing a place and each column detailing characteristics like population density, average income, or number of green parks. For example, a dataset could be compiled to study patterns in urban mobility, where the data includes the number of daily commuters, the distance they travel, and the mode of transport they use. Datasets provide the essential building blocks for statistical

analysis; they enable exploring relationships, identifying patterns, and drawing conclusions about certain phenomena.

Examples of everyday datasets:

- **Premier League Standings:** Each row represents a team, with columns for points, games played, wins, draws, and losses.
- **Movie Dataset:** Each row represents a movie, with columns showing its title, genre, release year, director, and rating.
- **Weather Dataset:** Each row shows a day's weather in a city, with columns for temperature, humidity, wind speed, and precipitation.

Usually, data is organized in

- **Columns** of data representing some trait or variable that we might be interested in. In general, we might wish to investigate the relationship between variables.
- **Rows** represent a single object on which the column traits are measured.

For example, in a grade book for recording students scores throughout the semester, there is one row for every student and columns for each assignment. A greenhouse experiment dataset will have a row for every plant and columns for treatment type and biomass.

1.3.1 Datasets in R

In R, we want a way of storing data where it feels just as if we had an Excel Spreadsheet where each row represents an observation and each column represents some information about that observation. We will call this object a `data.frame`, an R representation of a data set. The easiest way to understand data frames is to create one.

Task: Copy the code below in your markdown. Create a `data.frame` that represents an instructor's grade book, where each row is a student, and each column represents some sort of assessment.

```
Grades <- data.frame(
  Name   = c('Bob', 'Jeff', 'Mary', 'Valerie'),
  Exam.1 = c(90, 75, 92, 85),
  Exam.2 = c(87, 71, 95, 81)
)
# Show the data.frame
# View(Grades) # show the data in an Excel-like tab. Doesn't work when knitting
Grades        # show the output in the console. This works when knitting
```

	Name	Exam.1	Exam.2
1	Bob	90	87
2	Jeff	75	71
3	Mary	92	95
4	Valerie	85	81

To execute just one chunk of code press the green arrow top-right of the chunk:

✓ `{r}`
`1 + 1`

R allows two different ways to access elements of the `data.frame`. First is a matrix-like notation for accessing particular values.

Format	Result
[a,b]	Element in row a and column b
[a,]	All of row a
[,b]	All of column b

Because the columns have meaning and we have given them column names, it is desirable to want to access an element by the name of the column as opposed to the column number.

Task: Copy and Run:

```
Grades[, 2]      # print out all of column 2
```

```
[1] 90 75 92 85
```

```
Grades$Name      # The $-sign means to reference a column by its label
```

```
[1] "Bob"      "Jeff"     "Mary"     "Valerie"
```

1.3.2 Importing Data in R

From: https://raw.githubusercontent.com/dereksonderegger/570L/master/07_DataImport.Rmd

Usually we won't type the data in by hand, but rather load the data from some package. Reading data from external sources is a necessary skill.

Comma Separated Values Data

To consider how data might be stored, we first consider the simplest file format: the comma separated values file (`.csv`). In this file type, each of the “cells” of data are separated by a comma. For example, the data file storing scores for three students might be as follows:

```
Able, Dave, 98, 92, 94
Bowles, Jason, 85, 89, 91
Carr, Jasmine, 81, 96, 97
```

Typically when you open up such a file on a computer with MS Excel installed, Excel will open up the file assuming it is a spreadsheet and put each element in its own cell. However, you can also open the file using a more primitive program (say Notepad in Windows, TextEdit on a Mac) you’ll see the raw form of the data.

Having just the raw data without any sort of column header is problematic (which of the three exams was the final??). Ideally we would have column headers that store the name of the column.

```
LastName, FirstName, Exam1, Exam2, FinalExam
Able, Dave, 98, 92, 94
Bowles, Jason, 85, 89, 91
Carr, Jasmine, 81, 96, 97
```

Reading (`.csv`) files

To make R read in the data arranged in this format, we need to tell R three things:

1. Where does the data live? Often this will be the name of a file on your computer, but the file could just as easily live on the internet (provided your computer has internet access).
2. Is the first row data or is it the column names?
3. What character separates the data? Some programs store data using tabs to distinguish between elements, some others use white space. R’s mechanism for reading in data is flexible enough to allow you to specify what the separator is.

The primary function that we’ll use to read data from a file and into R is the function `read.csv()`. This function has many optional arguments but the most commonly used ones are outlined in the table below.

Argument	Default	Description
<code>file</code>	Required	A character string denoting the file location.
<code>header</code>	<code>TRUE</code>	Specifies whether the first line contains column headers.

Argument	Default	Description
<code>sep</code>	<code>","</code>	Specifies the character that separates columns. For <code>read.csv()</code> , this is usually a comma.
<code>skip</code>	<code>0</code>	The number of lines to skip before reading data; useful for files with descriptive text before the actual data.
<code>na.strings</code>	<code>"NA"</code>	Values that represent missing data; multiple values can be specified, e.g., <code>c("NA", "-9999")</code> .
<code>quote</code>	<code>"</code>	Specifies the character used to quote character strings, typically <code>"</code> or <code>'</code> .
<code>stringsAsFactors</code>	<code>FALSE</code>	Controls whether character strings are converted to factors; <code>FALSE</code> means they remain as character data.
<code>row.names</code>	<code>NULL</code>	Allows specifying a column as row names, or assigning <code>NULL</code> to use default indexing for rows.
<code>colClasses</code>	<code>NULL</code>	Specifies the data type for each column to speed up reading for large files, e.g., <code>c("character", "numeric")</code> .
<code>encoding</code>	<code>"unknown"</code>	Sets the text encoding of the file, which can be useful for files with special or international characters.

Most of the time you just need to specify the file. |

Task: Let's read in a dataset of terrorist attacks that have taken place in the UK:

```
attacks <- read.csv(file = '../data/attacksUK.csv') # where the data lives
View(attacks)
```

1.4 Practice: Descriptive Statistics

1.4.1 Summarizing Data

It is very important to be able to take a data set and produce summary statistics such as the mean and standard deviation of a column. For this sort of manipulation, we use the package `dplyr`. This package allows chaining together many common actions to form a particular task.

The foundational operations to perform on a data set are:

- Subsetting - Returns a with only particular columns or rows
 - `select` - Selecting a subset of columns by name or column number.
 - `filter` - Selecting a subset of rows from a data frame based on logical expressions.
 - `slice` - Selecting a subset of rows by row number.

- **arrange** - Re-ordering the rows of a data frame.
- **mutate** - Add a new column that is some function of other columns.
- **summarise** - calculate some summary statistic of a column of data. This collapses a set of rows into a single row.

Each of these operations is a function in the package **dplyr**. These functions all have a similar calling syntax,:- The first argument is a data set,;- Subsequent arguments describe what to do with the input data frame and you can refer to the columns without using the **df\$column** notation.

All of these functions will return a data set.

The **dplyr** package also includes a function that “pipes” commands together. The idea is that the **%>%** operator works by translating the command **a %>% f(b)** to the expression **f(a,b)**. This operator works on any function **f**. The beauty of this comes when you have a suite of functions that takes input arguments of the same type as their output. For example if we wanted to start with **x**, and first apply function **f()**, then **g()**, and then **h()**, the usual R command would be **h(g(f(x)))** which is hard to read because you have to start reading at the innermost set of parentheses. Using the pipe command **%>%**, this sequence of operations becomes **x %>% f() %>% g() %>% h()**. For example:

```
Grades # Recall the Grades data
```

	Name	Exam.1	Exam.2
1	Bob	90	87
2	Jeff	75	71
3	Mary	92	95
4	Valerie	85	81

```
# The following code takes the Grades data.frame and calculates
# a column for the average exam score, and then sorts the data
# according to the that average score
```

```
Grades %>%
  mutate( Avg.Score = (Exam.1 + Exam.2) / 2 ) %>%
  arrange( Avg.Score )
```

	Name	Exam.1	Exam.2	Avg.Score
1	Jeff	75	71	73.0
2	Valerie	85	81	83.0
3	Bob	90	87	88.5
4	Mary	92	95	93.5

Keep it in mind, it is not necessary to memorise this.

Let's consider the `summarize` function to calculate the mean score for `Exam.1`. Notice that this takes a data frame of four rows, and summarizes it down to just one row that represents the summarized data for all four students.

```
library(dplyr) # load the library
Grades %>%
  summarize( Exam.1.mean = mean( Exam.1 ) )
```

```
Exam.1.mean
1      85.5
```

Similarly you could calculate the **standard deviation** for the exam as well.

```
Grades %>%
  summarize( Exam.1.mean = mean( Exam.1 ),
            Exam.1.sd    = sd( Exam.1 ) )
```

```
Exam.1.mean Exam.1.sd
1      85.5    7.593857
```

Task: Write the code above in your markdown file and run it. Do not to copy it this time.

Let's go back to the terrorist attacks. There are attacks perpetrated by several different groups. Each record is a single attack and contains information about who perpetrated the attack, what year, how many were killed and how many were wounded. You can get a glimpse of the dataframe with the function `head`

```
head(attacks, n = 10)
```

	nrKilled	nrWound	year	country	group
1	0	0	2005	United Kingdom	Abu Hafs al-Masri Brigades
2	0	0	2005	United Kingdom	Abu Hafs al-Masri Brigades
3	0	0	2005	United Kingdom	Abu Hafs al-Masri Brigades
4	0	0	2005	United Kingdom	Abu Hafs al-Masri Brigades
5	0	1	1982	United Kingdom	Abu Nidal Organization (ANO)
6	0	0	2014	United Kingdom	Anarchists
7	0	0	2014	United Kingdom	Anarchists
8	0	0	2014	United Kingdom	Anarchists
9	0	0	2014	United Kingdom	Anarchists

10	0	0	2014	United Kingdom	Anarchists
				attack	target
1				Bombing/Explosion	Transportation
2				Bombing/Explosion	Transportation
3				Bombing/Explosion	Transportation
4				Bombing/Explosion	Transportation
5				Assassination	Government (Diplomatic)
6	Facility/Infrastructure	Attack			Business
7	Facility/Infrastructure	Attack			Business
8	Facility/Infrastructure	Attack			Business
9	Facility/Infrastructure	Attack	Private	Citizens & Property	
10	Facility/Infrastructure	Attack			Police
				weapon	
1	Explosives/Bombs/Dynamite				
2	Explosives/Bombs/Dynamite				
3	Explosives/Bombs/Dynamite				
4	Explosives/Bombs/Dynamite				
5		Firearms			
6		Incendiary			
7		Incendiary			
8		Incendiary			
9		Incendiary			
10		Incendiary			

We might want to compare different actors and see the mean and standard deviation of the number of people wound, by each group's attack, across time. To do this, we are still going to use the `summarize`, but we will precede that with `group_by(group)` to tell the subsequent `dplyr` functions to perform the actions separately for each breed.

```
attacks %>%
  group_by( group) %>%
  summarise( Mean = mean(attacks$nrWound),
             Std.Dev = sd(attacks$nrWound))
```

```
# A tibble: 38 x 3
```

group	Mean	Std.Dev
<chr>	<dbl>	<dbl>
1 Abu Hafs al-Masri Brigades	0.963	7.22
2 Abu Nidal Organization (ANO)	0.963	7.22
3 Anarchists	0.963	7.22
4 Animal Liberation Front (ALF)	0.963	7.22
5 Animal Rights Activists	0.963	7.22

```

6 Armenian Secret Army for the Liberation of Armenia 0.963 7.22
7 Black September 0.963 7.22
8 Continuity Irish Republican Army (CIRA) 0.963 7.22
9 Dissident Republicans 0.963 7.22
10 Informal Anarchist Federation 0.963 7.22
# i 28 more rows

```

Task: Write the code above in your markdown file and run it. Try out another categorical variable instead of `group` (e.g. `year`) and `nrKilled` instead of `nrWound`.

Let's now move to another dataset to address a research question. For illustration purposes, we will use the **Family Resources Survey (FRS)**. The FRS is an annual survey conducted by the UK government that collects detailed information about the income, living conditions, and resources of private households across the United Kingdom. Managed by the Department for Work and Pensions (DWP), the FRS provides data that is essential for understanding the economic and social conditions of households and informing public policy.

Consider questions such as:

- How many respondents (persons) are there in the 2016-17 FRS?
- How many variables (population attributes) are there?
- What types of variables are present in the FRS?
- What is the most detailed geography available in the FRS?

Task: To answer these questions, load and inspect the dataset.

```

# the FRS dataset should be already loaded, otherwise
frs_data <- read.csv("../data/FamilyResourceSurvey/FRS16-17.csv")

# Display basic structure
glimpse(frs_data)

```

```

Rows: 44,145
Columns: 45
$ household    <int> 1, 1, 1, 1, 1, 2, 3, 3, 3, 3, 4, 4, 4, 5, 6, 6, 7, 7, ~
$ family       <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, ~
$ person       <int> 1, 2, 3, 4, 5, 1, 1, 2, 3, 4, 1, 2, 3, 1, 1, 2, 1, 2, ~
$ country      <int> 1, 1, 1, 1, 1, 3, 1, 1, 1, 1, 1, 2, 2, 2, 1, 1, 1, 1, ~
$ region       <int> 8, 8, 8, 8, 8, 12, 4, 4, 4, 4, 11, 11, 11, 6, 8, 8, 4, ~
$ age_group    <int> 9, 9, 2, 2, 4, 8, 8, 8, 2, 1, 13, 12, 7, 14, 7, 8, 15, ~
$ sex          <int> 2, 1, 1, 2, 1, 1, 1, 2, 1, 1, 1, 2, 2, 2, 1, 1, 2, 1, ~
$ marital_status <int> 3, 3, 1, 1, 1, 1, 3, 3, 1, 1, 3, 3, 1, 1, 3, 3, 3, 3, ~
$ ethnicity    <int> 8, 8, 8, 8, 8, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, ~

```

```

$ hrp <int> 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, ~
$ rel_to_hrp <int> 1, 0, 3, 3, 4, 0, 0, 1, 4, 3, 0, 1, 3, 0, 1, 0, 1, 0, ~
$ lifestage <int> 1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, ~
$ dependent <int> 2, 2, 1, 1, 1, 2, 2, 2, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, ~
$ arrival_year <int> 1995, 1995, -9, -9, -9, -9, -9, -9, -9, -9, -9, -9, -9, -9, ~
$ birth_country <int> 8, 8, -9, -9, -9, 3, 1, 1, -9, -9, 2, 2, 2, 1, 4, 8, ~
$ care_hours <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ educ_age <int> 17, 17, -9, -9, -9, 30, 21, 18, -9, -9, 19, 18, 17, 2, ~
$ educ_type <int> 10, 0, 1, 1, 1, 4, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ fam_youngest <int> 6, 6, 6, 6, 6, -1, 4, 4, 4, 4, -1, -1, -1, -1, -1, -1, ~
$ fam_toddlers <int> 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, ~
$ fam_size <int> 5, 5, 5, 5, 5, 1, 4, 4, 4, 4, 2, 2, 1, 1, 2, 2, 2, 2, ~
$ happy <int> 1, 6, -9, -9, -9, 4, 4, -1, -9, -9, 7, 7, 7, 10, 8, -9, ~
$ health <int> 1, 1, -1, -1, 1, 2, 3, -1, -1, -1, 2, 2, 2, 3, 2, -1, ~
$ hh_accom_type <int> 3, 3, 3, 3, 3, 4, 1, 1, 1, 1, 1, 1, 1, 2, 4, 4, 2, 2, ~
$ hh_benefits <int> 2496, 2496, 2496, 2496, 2496, 0, 1768, 1768, 1768, 17~
$ hh_composition <int> 6, 6, 6, 6, 6, 2, 6, 6, 6, 6, 9, 9, 9, 1, 7, 7, 5, 5, ~
$ hh_ctax_band <int> 4, 4, 4, 4, 4, 8, 4, 4, 4, 4, 7, 7, 7, 4, 4, 4, 2, 2, ~
$ hh_housing_costs <int> 8060, 8060, 8060, 8060, 8060, 6604, 4108, 4108, 4108, ~
$ hh_income_gross <int> 29640, 29640, 29640, 29640, 29640, 17264, 78520, 7852~
$ hh_income_net <int> 26884, 26884, 26884, 26884, 26884, 17264, 60112, 6011~
$ hh_size <int> 5, 5, 5, 5, 5, 1, 4, 4, 4, 4, 3, 3, 3, 1, 2, 2, 2, 2, ~
$ hh_tenure <int> 3, 3, 3, 3, 3, 4, 2, 2, 2, 2, 1, 1, 1, 1, 2, 2, 1, 1, ~
$ highest_qual <int> 2, 3, -9, -9, -9, 2, 1, 1, -9, -9, 3, 3, 3, 1, 1, 1, ~
$ income_gross <dbl> 2496, 27144, 0, 0, 0, 17264, 40924, 37596, 0, 0, -301~
$ income_net <dbl> 2496, 24388, 0, 0, 0, 17264, 31772, 28340, 0, 0, -317~
$ jobs <int> 0, 1, -9, -9, -9, 1, 1, 1, -9, -9, 1, 1, 1, 1, 1, 1, ~
$ life_satisf <int> 8, 5, -9, -9, -9, 6, 8, -1, -9, -9, 7, 7, 7, 9, 9, -1~
$ nssec <int> 7, 7, 12, 12, 12, 10, 1, 3, 12, 12, 5, 3, 3, 7, 5, 3, ~
$ sic_chapter <int> 17, 14, -9, -9, -9, 7, 13, 13, -9, -9, 1, 17, 3, 7, 1~
$ sic_division <int> 87, 80, -9, -9, -9, 47, 72, 72, -9, -9, 1, 88, 28, 47~
$ soc2010 <int> 6, 6, -9, -9, -9, 9, 1, 3, -9, -9, 5, 2, 3, 7, 1, 4, ~
$ work_hours <dbl> -2.0, 48.0, -9.0, -9.0, -9.0, 12.0, 40.0, 37.0, -9.0, ~
$ workstatus <int> 8, 1, -9, -9, -9, 1, 1, 1, -9, -9, 3, 1, 1, 2, 3, 1, ~
$ years_ft_work <int> 16, 25, -9, -9, -9, 8, 18, 15, -9, -9, 41, 30, 15, 10~
$ survey_weight <int> 1870, 1870, 1870, 1870, 1870, 1083, 1571, 1571, 1571, ~

```

and summary:

```
summary(frs_data)
```

household	family	person	country	region
-----------	--------	--------	---------	--------

Min. : 1	Min. :1.000	Min. :1.00	Min. :1.000	Min. : 1.0
1st Qu.: 4816	1st Qu.:1.000	1st Qu.:1.00	1st Qu.:1.000	1st Qu.: 5.0
Median : 9673	Median :1.000	Median :2.00	Median :1.000	Median : 8.0
Mean : 9677	Mean :1.106	Mean :1.98	Mean :1.618	Mean : 7.8
3rd Qu.:14553	3rd Qu.:1.000	3rd Qu.:3.00	3rd Qu.:2.000	3rd Qu.:11.0
Max. :19380	Max. :6.000	Max. :9.00	Max. :4.000	Max. :13.0
age_group	sex	marital_status	ethnicity	
Min. : 1.000	Min. :1.000	Min. :1.000	Min. :1.000	
1st Qu.: 5.000	1st Qu.:1.000	1st Qu.:1.000	1st Qu.:1.000	
Median : 9.000	Median :2.000	Median :3.000	Median :1.000	
Mean : 8.707	Mean :1.519	Mean :2.429	Mean :1.462	
3rd Qu.:13.000	3rd Qu.:2.000	3rd Qu.:3.000	3rd Qu.:1.000	
Max. :16.000	Max. :2.000	Max. :6.000	Max. :9.000	
hrp	rel_to_hrp	lifestage	dependent	
Min. :0.000	Min. : 0.000	Min. :0.000	Min. :1.000	
1st Qu.:0.000	1st Qu.: 0.000	1st Qu.:1.000	1st Qu.:2.000	
Median :0.000	Median : 1.000	Median :1.000	Median :2.000	
Mean :0.439	Mean : 1.553	Mean :0.773	Mean :1.766	
3rd Qu.:1.000	3rd Qu.: 3.000	3rd Qu.:1.000	3rd Qu.:2.000	
Max. :1.000	Max. :20.000	Max. :1.000	Max. :2.000	
arrival_year	birth_country	care_hours	educ_age	
Min. : -9.0	Min. : -9.0000	Min. :0.0000	Min. : -9.00	
1st Qu.: -9.0	1st Qu.: 1.0000	1st Qu.:0.0000	1st Qu.: -1.00	
Median : -9.0	Median : 1.0000	Median :0.0000	Median :16.00	
Mean : 207.4	Mean : -0.1686	Mean :0.2819	Mean :11.14	
3rd Qu.: -9.0	3rd Qu.: 3.0000	3rd Qu.:0.0000	3rd Qu.:18.00	
Max. :2017.0	Max. : 8.0000	Max. :7.0000	Max. :55.00	
educ_type	fam_youngest	fam_toddlers	fam_size	
Min. : 0.000	Min. : -1.000	Min. :0.0000	Min. :1.000	
1st Qu.: 0.000	1st Qu.: -1.000	1st Qu.:0.0000	1st Qu.:2.000	
Median : 0.000	Median : -1.000	Median :0.0000	Median :2.000	
Mean : 0.392	Mean : 2.466	Mean :0.2557	Mean :2.599	
3rd Qu.: 0.000	3rd Qu.: 5.000	3rd Qu.:0.0000	3rd Qu.:4.000	
Max. :10.000	Max. :19.000	Max. :4.0000	Max. :9.000	
happy	health	hh_accom_type	hh_benefits	
Min. : -9.000	Min. : -1.0000	Min. : -1.000	Min. : 0	
1st Qu.: -1.000	1st Qu.: -1.0000	1st Qu.: 1.000	1st Qu.: 0	
Median : 5.000	Median : 1.0000	Median : 2.000	Median : 1768	
Mean : 2.197	Mean : 0.9781	Mean : 2.326	Mean : 5670	
3rd Qu.: 8.000	3rd Qu.: 2.0000	3rd Qu.: 3.000	3rd Qu.:10192	
Max. :10.000	Max. : 5.0000	Max. : 7.000	Max. :54080	
hh_composition	hh_ctax_band	hh_housing_costs	hh_income_gross	
Min. : 1.000	Min. :1.000	Min. : -1	Min. : -326092	

1st Qu.: 5.000	1st Qu.:2.000	1st Qu.: 572	1st Qu.: 22256
Median : 6.000	Median :3.000	Median : 2704	Median : 35984
Mean : 5.474	Mean :3.198	Mean : 3820	Mean : 46076
3rd Qu.: 6.000	3rd Qu.:4.000	3rd Qu.: 5616	3rd Qu.: 57252
Max. :10.000	Max. :8.000	Max. :135720	Max. :1165216
hh_income_net	hh_size	hh_tenure	highest_qual
Min. : -334776	Min. :1.00	Min. :1.000	Min. : -9.00000
1st Qu.: 20748	1st Qu.:2.00	1st Qu.:1.000	1st Qu.: 1.00000
Median : 31512	Median :3.00	Median :2.000	Median : 2.00000
Mean : 37447	Mean :2.96	Mean :2.369	Mean : 0.04098
3rd Qu.: 47008	3rd Qu.:4.00	3rd Qu.:3.000	3rd Qu.: 3.00000
Max. :1116596	Max. :9.00	Max. :5.000	Max. : 5.00000
income_gross	income_net	jobs	life_satisf
Min. : -354848	Min. : -358592	Min. : -9.000	Min. : -9.00
1st Qu.: 52	1st Qu.: 0	1st Qu.: 0.000	1st Qu.: -1.00
Median : 12740	Median : 12012	Median : 0.000	Median : 6.00
Mean : 17305	Mean : 14204	Mean : -1.644	Mean : 2.23
3rd Qu.: 23712	3rd Qu.: 20384	3rd Qu.: 1.000	3rd Qu.: 8.00
Max. :1127360	Max. :1110928	Max. : 4.000	Max. :10.00
nssec	sic_chapter	sic_division	soc2010
Min. : 1.000	Min. : -9.000	Min. : -9.00	Min. : -9.000
1st Qu.: 3.000	1st Qu.: -2.000	1st Qu.: -2.00	1st Qu.: -2.000
Median : 7.000	Median : 7.000	Median :47.00	Median : 3.000
Mean : 6.707	Mean : 5.351	Mean :40.85	Mean : 1.229
3rd Qu.:10.000	3rd Qu.:15.000	3rd Qu.:84.00	3rd Qu.: 6.000
Max. :12.000	Max. :21.000	Max. :99.00	Max. : 9.000
work_hours	workstatus	years_ft_work	survey_weight
Min. : -9.00	Min. : -9.0000	Min. : -9.00	Min. : 221
1st Qu.: -2.00	1st Qu.: 1.0000	1st Qu.: -1.00	1st Qu.: 1097
Median : -2.00	Median : 1.0000	Median :11.00	Median : 1380
Mean : 12.75	Mean : 0.8902	Mean :14.15	Mean : 1459
3rd Qu.: 37.00	3rd Qu.: 6.0000	3rd Qu.:30.00	3rd Qu.: 1742
Max. :150.00	Max. :11.0000	Max. :73.00	Max. :39675

1.4.2 Understanding the Structure of the FRS Datafile

In the FRS data structure, each row represents a person, but:

- Each person is nested within a family.
- Each family is nested within a household.

Below is an example dataset structure:

household	family	person	region	age_group	sex	marital_status	rel_to_hrp
1	1	1	London	40-44	Female	Married/Civil partnership	Spouse
1	1	2	London	40-44	Male	Married/Civil partnership	Household Representative
1	1	3	London	5-10	Male	Single	Son/daughter (incl. adopted)
1	1	4	London	5-10	Female	Single	Son/daughter (incl. adopted)
1	1	5	London	16-19	Male	Single	Step-son/daughter
2	1	1	Scotland	35-39	Male	Single	Household Representative
3	1	1	Yorks and the Humber	35-39	Female	Married/Civil partnership	Household Representative
3	1	2	Yorks and the Humber	35-39	Male	Married/Civil partnership	Spouse
3	1	3	Yorks and the Humber	5-10	Male	Single	Step-son/daughter
4	1	1	Wales	0-4	Male	Single	Son/daughter (incl. adopted)
4	1	2	Wales	60-64	Male	Married/Civil partnership	Household Representative
4	1	3	Wales	55-59	Female	Married/Civil partnership	Spouse
4	2	3	Wales	30-34	Female	Single	Son/daughter (incl. adopted)

The first five people in the FRS all belong to the same household (household 1); they also all belong to the same family. This family comprises a married middle-aged couple plus their three children, one of whom is a stepson.

The second household (household 2) comprises only one person – a single middle-aged male. The third household comprises another married couple, this time with two children.

Superficially the fourth household looks similar to households 1 and 2: a married couple plus their daughter. The difference is that this particular married couple is nearing retirement age, and their daughter is middle-aged. Consequently, despite being a child of the married couple, the middle-aged daughter is treated as a separate ‘family’ (family 2 in the household). This is because the FRS (and Census) define a ‘family’ as a couple plus any ‘dependent’ children. A dependent child is defined as a child who is either ‘aged 0-15 or aged 16-19, unmarried and in full-time education. All children aged 16-19 who are married or no longer in full-time education

are regarded as ‘independent’ adults who form their own family unit, as are all children aged 20+.

The inclusion of all persons in a household allows us more flexibility in the types of research question we can answer. For example, we could explore how the likelihood of a woman being in paid employment `WorkStatus` is influenced by the age of the youngest child still living in her family (if any) `fam_youngest`.

In the FRS (and Census), a “family” is defined as a couple and any “dependent” children. Dependent children are defined as those aged 0–15, or aged 16–19 if unmarried and in full-time education.

1.4.3 Explore the Distribution of Your Outcome Variable

Before starting your analysis, it is critical to know the type of scale used to measure your outcome variable: is it categorical or continuous? Here we will start off by exploring a continuous variable which can then turn into a categorical variable (e.g. top earners: yes or no). We explore the income distribution in the UK by first looking at the low and high end of the distribution ie. What sorts of people have high (or low) incomes?

In the FRS each person’s annual income is recorded, both gross (pre-tax) and net (post-tax). This income includes all income sources, including earnings, profits, investment returns, state benefits, occupational pensions etc. As it is possible to make a loss on some of these activities, it is also possible (although unusual) for someone’s gross or net annual income in a given year to be negative (representing an overall loss).

Task: Load the FRS dataset into your R environment, if it’s not already loaded, and inspect the data.

```
# Load the dataset (replace 'frs_data.csv' with the actual file path)
frs_data <- read.csv("../data/FamilyResourceSurvey/FRS16-17.csv")
```

Open the dataset in RStudio’s **Data Viewer** to explore its structure, including the `income_gross` and `income_net` variables.

```
# Open the data in the RStudio Viewer
View(frs_data)
```

in the **Data Viewer** tab, scroll horizontally to locate the `income_gross` and `income_net` columns. If columns are listed alphabetically, they will appear near other attributes that start with “income.”

You should notice two things:

- Incomes are recorded to the nearest £, NOT in income bands.
- Dependent children almost all have a recorded income of £0.

This second observation highlights the somewhat loose wording of our question above (*What sorts of people have high (or low) incomes?*). To avoid reaching the somewhat banal conclusion that those with the lowest of all incomes are almost all children, we should re-frame the question more precisely as *What sorts of people (excluding dependent children) have low incomes?*

Task: Determine the Scale of the Outcome Variable.

**

```
# Summarize income variables
summary(frs_data$income_gross)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-354848	52	12740	17305	23712	1127360

```
# Summarize income variables
summary(frs_data$income_net)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-358592	0	12012	14204	20384	1110928

Task: Exclude Dependent Children.

**

You need to select all cases (persons) that are independent, that is where the variable dependent has value 2 (1 = dependent, 2 = independent).

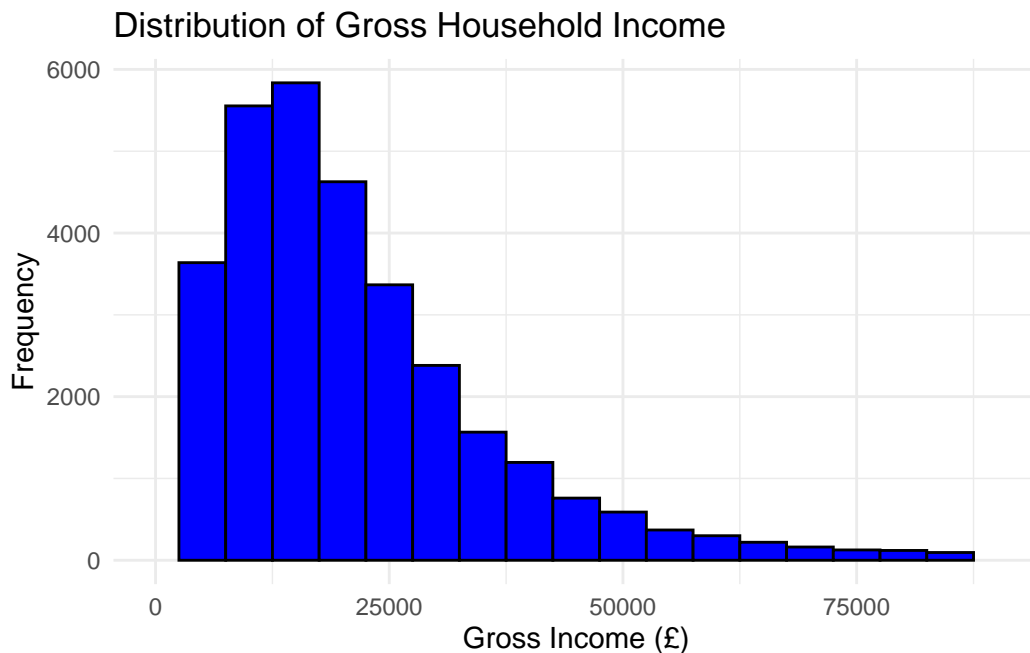
```
# Filter to include only independent persons
frs_independent <- frs_data %>% filter(dependent == "2")
```

Task: Create a basic histogram (a visualisation lecture is scheduled later on).

The income variables in the FRS are all scale variables so a good starting point is to examine its distribution looking at a histogram of `income_gross`.

```
library(ggplot2)

ggplot(frs_independent, aes(x = income_gross)) +
  geom_histogram(binwidth = 5000, fill = "blue", color = "black") +
  labs(
    title = "Distribution of Gross Household Income",
    x = "Gross Income (£)",
    y = "Frequency"
  ) +
  xlim(0, 90000) +
  theme_minimal()
```



You should see the histogram below. It reveals that the income distribution is very skewed with few people earning high salaries and the majority earning just over or less 35,000 annually.

Task: Adopt a regrouping strategy.

**

You can also cross-tabulate gross (or net) income with any of the other variables in the FRS to your heart's content – or can you?

Again, here is important to recall that the income variables in the FRS are all 'scale' variables; in other words, they are precise measures rather than broad categories. Consequently, every single person in the FRS potentially has their own unique income value. That could make for

a table c. 44,000 rows long (one row per person) if each person has their own unique value. The solution is to create a categorical version of the original income variable by assigning each person to one of a set of income categories (income bands). Having done this, cross-tabulation then becomes possible.

But which strategy to use? Equal intervals, percentiles or ‘ad hoc’. Here I would suggest that ‘ad hoc’ is best: all you want to do is to allocate each independent adult to one of three arbitrarily defined groups: ‘low’, ‘middle’ and ‘high’ income. **Define Low and High Income Thresholds**

Define thresholds for income categories:

- Low-income threshold: £_____
- High-income threshold: £_____

Task: Create a New Variable Based on Regrouping of Original Variable.

Recode `income_gross` into categories based on the chosen thresholds.

```
# Define thresholds for income categories
LOW_THRESHOLD <- 10000 # Replace with the upper limit for low income
HIGH_THRESHOLD <- 50000 # Replace with the lower limit for high income

# Define income categories based on thresholds
frs_independent <- frs_independent %>%
  mutate(income_category = case_when(
    income_gross <= LOW_THRESHOLD ~ "Low",
    income_gross >= HIGH_THRESHOLD ~ "High",
    TRUE ~ "Middle" ))
```

The `mutate()` function in R, from the **dplyr** package, is used to add or modify columns in a data frame. It allows you to create new variables or transform existing ones by applying calculations or conditional statements directly within the function.

Explanation of the code

- `frs_independent %>%`: The pipe operator `%>%` sends `frs_independent` into `mutate()`, allowing us to apply transformations without reassigning it repeatedly.
- `mutate()`: Starts the transformation process by defining new or modified columns.
- `income_category = case_when(...)`:
 - This creates a new column named `income_category`.
 - The `case_when()` function defines conditions for assigning values to this new column.
- `case_when()`:

- `case_when()` is used here to assign categorical labels based on conditions.
- `income_gross <= LOW_THRESHOLD ~ "Low"`: If `income_gross` is less than or equal to `LOW_THRESHOLD`, `income_category` will be labeled “Low.”
- `income_gross >= HIGH_THRESHOLD ~ "High"`: If `income_gross` is greater than or equal to `HIGH_THRESHOLD`, `income_category` will be labeled “High.”
- `TRUE ~ "Middle"`: Any values not meeting the previous conditions are labeled “Middle.”

Task: Add some Metadata.

Define metadata for the new variable by labeling income categories.

```
# Add metadata by converting to a factor and defining labels

frs_independent$income_category <- factor(frs_independent$income_category,
                                           levels = c("Low", "Middle", "High"), labels = c("<= £10,000", "£10,001 - £49,999", ">= £50,000"))
```

Task: Check your work.

Examine the frequency distribution of the variable you have just created. Both variables should have the same number of missing cases, unless:

- Missing cases in the old variable have been intentionally converted into valid cases in the new variable.
- You forgot to allocate a new value to one of the old variable categories, in which case the new variable will have more missing cases than the old variable.

```
# Frequency distribution of income categories
table(frs_independent$income_category)
```

<= £10,000	£10,001 - £49,999	>= £50,000
8584	22981	2271

After preparing the data, use cross-tabulations to compare income levels across demographic groups.

```
# Cross-tabulate income category by age group, nationality, etc.
table(frs_independent$income_category, frs_independent$age_group)
```

	4	5	6	7	8	9	10	11	12	13	14	15
<= £10,000	373	680	492	558	474	511	554	652	781	826	773	744
£10,001 - £49,999	263	1241	1802	2056	2052	1948	1995	1967	1749	1772	2073	1554
>= £50,000	1	8	59	186	314	331	334	356	237	177	144	56

	16
<= £10,000	1166
£10,001 - £49,999	2509
>= £50,000	68

Explore income distribution across different regions.

```
# Cross-tabulate income category by region
table(frs_independent$income_category, frs_independent$region)
```

	1	2	4	5	6	7	8	9	10	11	12	13
<= £10,000	357	878	670	562	744	665	740	895	588	399	1212	874
£10,001 - £49,999	979	2347	1728	1550	1892	1855	1850	2563	1707	971	3234	2305
>= £50,000	48	174	114	135	164	245	367	367	149	63	322	123

Tips for Cross-Tabulation

- Place the income variable in the columns.
- Add multiple variables in the rows to create simultaneous cross-tabulations.

2 Lab: Correlation, Single, and Multiple Linear Regression

In this week's practical we are going to review how to calculate and visualise correlation coefficients between variables. This practical is split into two parts. The first part focuses on measuring the correlation between and visualising the relationship between **continuous variables**. The second part goes through the implementation of a Linear Regression Model, again between **continuous variables**.

Learning Objectives:

- Visualise the association between two continuous variables using a scatterplot.
- Measure the strength of the association between two variables by calculating their correlation coefficient.
- Build a formal regression model.
- Understand how to estimate and interpret a multiple linear regression model.

Note for the practical: copy/editor/document the code in your own .qmd file. The code is supposed to be run as if the script was placed in the course folder, containing the dataset. That should be the working directory of RStudio.

2.1 Part I. Correlation

2.1.1 Data Overview: Descriptive Statistics:

Let's start by picking **one dataset derived from the UK 2021 Census data**. You can choose one dataset that aggregates data either at a) county, b) district, or c) ward-level. Lower Tier Local Authority-, Region-, and Country-level data is also available in the data folder.

see also: <https://canvas.liverpool.ac.uk/courses/77895/pages/census-data-2021>

```
# Load necessary libraries
library(ggplot2)
library(dplyr)
```


Attaching package: 'dplyr'

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

filter, lag

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

intersect, setdiff, setequal, union

```
# load data
census <- read.csv("../data/Census2021/EW_DistrictPercentages.csv") # County level
```

We're using a (district/ward/etc.)-level census dataset that includes:

- % of population with poor health (variable name: `pct_Very_bad_health`).
- % of population with no qualifications (`pct_No_qualifications`).
- % of male population (`pct_Males`).
- % of population in a higher managerial/professional occupation (`pct_Higher_manager_prof`).

Let's first get some descriptive statistics that help identify general trends and distributions in the data.

```
# Summary statistics
summary_data <- census %>%
  select(pct_Very_bad_health, pct_No_qualifications, pct_Males, pct_Higher_manager_prof) %>%
  summarise_all(list(mean = mean, sd = sd))
summary_data
```

	pct_Very_bad_health_mean	pct_No_qualifications_mean	pct_Males_mean			
1	1.173198	17.89878	48.96817			
	pct_Higher_manager_prof_mean	pct_Very_bad_health_sd	pct_No_qualifications_sd			
1	13.21677	0.3401808	3.959094			
	pct_Males_sd	pct_Higher_manager_prof_sd				
1	0.660313	4.730412				

Q1. Complete the table by specifying the type (continuous or categorical) and reporting the mean and standard deviation for each variable.

Variable Name	Type (Continuous or Categorical)	Mean	Standard Deviation
pct_Very_bad_health			
pct_No_qualifications			
pct_Males			
pct_Higher_manager_prof			

2.1.2 Simple visualisation for continuous data

The relationship between two continuous variables may be visualised graphically using a scatter-plot. Using the chosen census datasets, visualise the association between the % of population with bad health (`pct_Very_bad_health`) and each of the following:

- the % of population with no qualifications (`pct_No_qualifications`);
- the % of population aged 65 to 84 (`pct_Age_65_to_84`);
- the % of population in a married couple (`pct_Married_couple`);
- the % of population in a Higher Managerial or Professional occupation (`pct_Higher_manager_prof`).

```
# Scatterplot for each variable variables
variables <- c("pct_No_qualifications", "pct_Age_65_to_84", "pct_Married_couple", "pct_Higher_manager_prof")

# Loop to create scatterplots and calculate correlations

for (var in variables) {
  # Scatterplot
  ggplot(census, aes_string(x = var, y = "pct_Very_bad_health")) +
    geom_point() +
    labs(title = paste("Scatterplot of pct_Very_bad_health vs", var),
         x = var, y = "pct_Very_bad_health") +
    theme_minimal()
}
```

Warning: `aes_string()` was deprecated in ggplot2 3.0.0.
 i Please use tidy evaluation idioms with `aes()`.
 i See also `vignette("ggplot2-in-packages")` for more information.

Q2. Which of the associations do you think is strongest, which one is the weakest?

As noted, before, an observed association between two variables is no guarantee of causation. It could be that the observed association is:

- simply a chance one due to sampling uncertainty;
- caused by some third underlying variable which explains the spatial variation of both of the variables in the scatterplot;
- due to the inherent arbitrariness of the boundaries used to define the areas being analysed (the ‘Modifiable Area Unit Problem’).

Q3. Setting these caveats to one side, are the associations observed in the scatter-plots suggestive of any causative mechanisms of bad health?

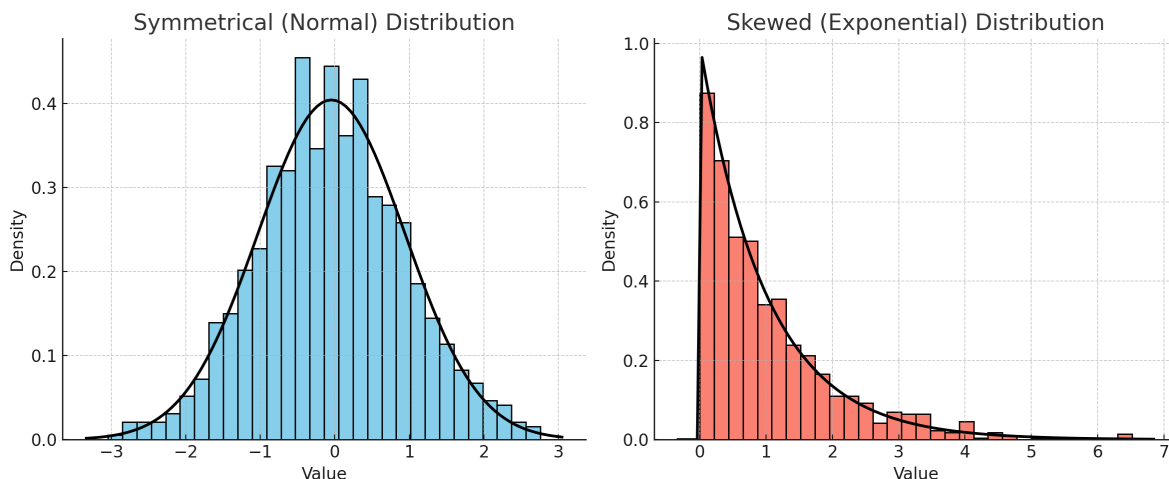
Rather than relying upon an impressionistic view of the strength of the association between two variables, we can measure that association by calculating the relevant correlation coefficient. The Table below identifies the statistically appropriate measure of correlation to use between two continuous variables.

Variable Data Type	Measure of Correlation	Range
Both symmetrically distributed	Pearson’s	-1 to +1
One or both with a skewed distribution	Spearman’s Rank	-1 to +1

Different Calculation Methods: Pearson’s correlation assumes linear relationships and is suitable for symmetrically distributed (normally distributed) variables, measuring the strength of the linear relationship. Spearman’s rank correlation, however, works on ranked data, so it’s more suitable for skewed data or variables with non-linear relationships, measuring the strength and direction of a monotonic relationship.

If you’re calculating the correlation for a single pair of variables, pick the method that best matches the data distribution for that specific pair:

- Use **Pearson’s** if both variables are symmetrically distributed.
- Use **Spearman’s** if one or both variables are skewed.

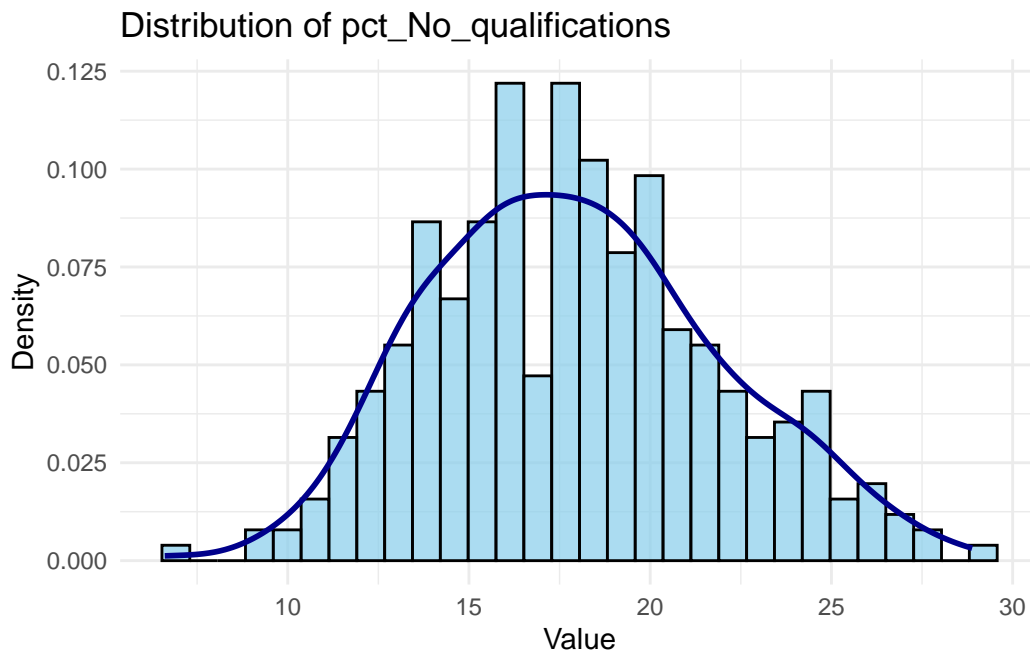


You can check the distribution of a variable (e.g. `pct_No_qualifications` like this):

```
# Plot histogram with density overlay for a chosen variable (e.g., 'pct_No_qualifications')
ggplot(census, aes(x = pct_No_qualifications)) +
  geom_histogram(aes(y = ..density..), bins = 30, color = "black", fill = "skyblue", alpha = 0.5) +
  geom_density(color = "darkblue", size = 1) +
  labs(title = "Distribution of pct_No_qualifications", x = "Value", y = "Density") +
  theme_minimal()
```

Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
i Please use `linewidth` instead.

Warning: The dot-dot notation (`..density..`) was deprecated in ggplot2 3.4.0.
i Please use `after_stat(density)` instead.



When analyzing multiple pairs of variables, using different measures (Pearson for some pairs, Spearman for others) creates inconsistencies since Pearson and Spearman values aren't directly comparable in size due to their different calculation methods. To maintain consistency across comparisons, calculate **both Pearson's and Spearman's correlations** for each pair. Check if the trends align (both showing strong, weak, or moderate correlation in the same direction). This consistency check can give confidence that the relationships observed are not dependent on the correlation method chosen. While in a report, you'd typically include only one set of

correlations (usually Pearson's if the relationships appear linear), calculating both can validate that your observations aren't an artifact of the correlation method.

Research Question 1: Which of our selected variables are most strongly correlated with % of population with bad health?

To answer this question, complete the Table below by editing/running this code:.

Pearson correlations

```
pearson_correlation <- cor(census$pct_Very_bad_health,
  census$pct_No_qualifications, use = "complete.obs", method = "pearson")

# Display the results
cat("Pearson Correlation:", pearson_correlation, "\n")
```

Pearson Correlation: 0.7620569

Spearman correlations:

```
spearman_correlation <- cor(census$pct_Very_bad_health,
  census$pct_No_qualifications, use = "complete.obs", method = "spearman")

cat("Spearman Correlation:", spearman_correlation, "\n")
```

Spearman Correlation: 0.7785197

Covariates	Pearson	Spearman
pct_Very_bad_health - pct_No_qualifications		
pct_Very_bad_health - pct_Age_65_to_84		
pct_Very_bad_health - pct_Married_couple		
pct_Very_bad_health - pct_Higher_manager_prof		

What can you make of this numbers?

If you think you have found a correlation between two variables in our dataset, this doesn't mean that an association exists between these two variables in the population at large. The uncertainty arises because, by chance, the random sample included in our dataset might not be fully representative of the wider population.

For this reason, we need to verify whether the correlation is statistically significant,

```
# significance test for pearson, for example
pearson_test <- cor.test(census$pct_Very_bad_health,
  census$pct_No_qualifications, method = "pearson", use = "complete.obs")
pearson_test
```

Pearson's product-moment correlation

```
data: census$pct_Very_bad_health and census$pct_No_qualifications
t = 21.347, df = 329, p-value < 2.2e-16
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.7128142 0.8038232
sample estimates:
      cor
0.7620569
```

Look at <https://www.rdocumentation.org/packages/stats/versions/3.6.2/topics/cor.test> for details about the function. But in general, when calculating the correlation between two variables, a **p-value** accompanies the correlation coefficient to indicate the statistical significance of the observed association. This p-value tests the null hypothesis that there is no association between the two variables (i.e., that the correlation is zero).

In interpreting p-values, certain thresholds denote different levels of confidence. A p-value less than 0.05 is generally considered statistically significant at the 95% confidence level, suggesting that we can be 95% confident there is an association between the variables in the broader population. When the p-value is below 0.01, the result is significant at the 99% confidence level, meaning we have even greater confidence (99%) that an association exists. Sometimes, on research papers or tables significance levels are denoted with asterisks: one asterisk (*) typically indicates significance at the 95% level ($p < 0.05$), while two asterisks (**) denote significance at the 99% level ($p < 0.01$).

Typically, p-values are reported under labels such as “Sig (2-tailed),” where “2-tailed” refers to the fact that the test considers both directions (positive and negative correlations). Reporting the exact p-value (e.g., $p = 0.001$) is more informative than using thresholds alone, as it gives a clearer picture of how strongly the data contradicts the null hypothesis of no association.

In a nutshell, lower p-values suggest a stronger statistical basis for believing that an observed correlation is not due to random chance. A statistically significant p-value reinforces confidence that an association likely exists in the wider population, though it does not imply causation.

2.1.3 Part. 2: Implementing a Linear Regression Model

A key goal of data analysis is to explore the potential factors of health at the local district level. So far, we have used cross-tabulations and various bivariate correlation analysis methods to explore the relationships between variables. One key limitation of standard correlation analysis is that it remains hard to look at the associations of an outcome/dependent variable to multiple independent/predictor variables at the same time. Regression analysis provides a very useful and flexible methodological framework for such a purpose. Therefore, we will investigate how various local factors impact residents' health by building a multiple linear regression model in R.

We use `pct_Very_bad_health` as a proxy for residents' health.

Research Question 2: How do local factors affect residents' health?

Dependent (or Outcome) Variable:

- % of population with bad health (`pct_Very_bad_health`).

Independent (or Predictor) Variables:

- % of population with no qualifications (`pct_No_qualifications`).
- % of male population (`pct_Males`).
- % of population in a higher managerial/professional occupation (`pct_Higher_manager_prof`).

Load some other Libraries

```
library(tidyverse)
```

```
-- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
v forcats   1.0.0      v stringr   1.5.1
v lubridate 1.9.3      v tibble    3.2.1
v purrr     1.0.2      v tidyr     1.3.1
v readr     2.1.5
-- 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 become
```

```
library(broom)
```

and the data (if not loaded):

```
# Load dataset
census <- read.csv("../data/Census2021/EW_DistrictPercentages.csv")
```

Regression models are the standard method for constructing predictive and explanatory models. They tell us how changes in one variable (the target variable or independent variable, y) are *associated with* changes in explanatory variables, or dependent variables, x_1, x_2, x_3 , etc. Classic linear regression is referred to *Ordinary least squares* (OLS) regression because they estimate the relationship between one or more independent variables and a dependent variable y using a hyperplane (i.e. a multi-dimensional line) that minimises the sum of the squared difference between the observed values of y and the values predicted by the model (denoted as \hat{y} , y -hat).

Having seen **Single Linear Regression** in class - where the relationship between one independent variable and a dependent variable is modeled - we can extend this concept to situations where more than one predictor might influence the outcome. While single linear regression helps us understand the effect of **ONE** variable in isolation, real-world phenomena are often influenced by multiple factors simultaneously. Multiple linear regression addresses this complexity by allowing us to model the relationship between a dependent variable and multiple independent variables, providing a more comprehensive view of how various predictors contribute to changes in the outcome.

Here, regression allows us to examine the relationship between people's health rates and multiple predictors.

2.1.4 Model fit

```
# Linear regression model
model <- lm(pct_Very_bad_health ~ pct_No_qualifications + pct_Males + pct_Higher_manager_prof, data = census)
summary(model)
```

Call:

```
lm(formula = pct_Very_bad_health ~ pct_No_qualifications + pct_Males +
    pct_Higher_manager_prof, data = census)
```

Residuals:

Min	1Q	Median	3Q	Max
-0.49028	-0.13686	-0.03516	0.09834	0.76575

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	4.017987	0.880039	4.566	7.06e-06 ***


```
pct_No_qualifications    0.052959    0.005911    8.959 < 2e-16 ***
pct_Males                -0.073920    0.017850   -4.141 4.40e-05 ***
pct_Higher_manager_prof -0.013088    0.004938   -2.650 0.00843 **
---
```

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

Residual standard error: 0.2133 on 327 degrees of freedom

Multiple R-squared: 0.6105, Adjusted R-squared: 0.6069

F-statistic: 170.8 on 3 and 327 DF, p-value: < 2.2e-16

Code explanation

lm() Function:

- `lm()` stands for “linear model” and is used to fit a linear regression model in R.
- The formula syntax `pct_Very_bad_health ~ pct_No_qualifications + pct_Males + pct_Higher_manager_prof` specifies a relationship between:
 - **Dependent Variable:** `pct_Very_bad_health`.
 - **Independent Variables:** `pct_No_qualifications`, `pct_Males`, and `pct_Higher_manager_prof`. The model is trained on the data dataset.

Storing the Model: The `model <-` syntax stores the fitted model in an object called `model`.

`summary(model)` provides a detailed output of the model’s results, including:

- **Coefficients:** Estimates of the regression slopes (i.e., how each predictor affects `pct_Very_bad_health`).
- **Standard Errors:** The variability of each coefficient estimate.
- **t-values** and **p-values:** Indicate the statistical significance of each predictor.
- **R-squared** and **Adjusted R-squared:** Show how well the independent variables explain the variance in the dependent variable.
- **F-statistic:** Tests the overall significance of the model.

Regression Coefficients

```
# Regression coefficients
coefficients <- tidy(model)
coefficients
```

A tibble: 4 x 5

term	estimate	std.error	statistic	p.value
<chr>	<dbl>	<dbl>	<dbl>	<dbl>

1 (Intercept)	4.02	0.880	4.57	7.06e- 6
2 pct_No_qualifications	0.0530	0.00591	8.96	2.54e-17
3 pct_Males	-0.0739	0.0179	-4.14	4.40e- 5
4 pct_Higher_manager_prof	-0.0131	0.00494	-2.65	8.43e- 3

We focus on key output metrics:

- **Adjusted R-squared:** Indicates how well the model explains the variance in the outcome variable.
- **Coefficients:** Estimate the average change in bad health rates for a one-unit increase in each predictor, assuming other variables are held constant.

2.1.5 Interpreting the Results

The *t tests* of regression coefficients are used to judge the statistical inferences on regression coefficients, i.e. associations between independent variables and the outcome variable. For a t-statistic of a predictor variable there is a corresponding *p-value*. It is much easier to judge the statistical inference on regression coefficient by comparing the p value to the conventional level of significance of **0.05**; as discussed above:

- If the *p-value* of a coefficient is smaller than 0.05, the coefficient is statistically significant. In this case, you can say that the relationship between this independent variable and the outcome variable is *statistically* significant.
- If the *p-value* of a coefficient is larger than 0.05, the coefficient is not statistically significant. In this case, you can say or conclude that there is no evidence of an association or relationship between this independent variable and the outcome variable.

```
# Format regression results for reporting
results_table <- coefficients %>%
  select(term, estimate, statistic, p.value)
results_table
```

```
# A tibble: 4 x 4
  term                estimate statistic  p.value
<chr>                <dbl>    <dbl>    <dbl>
1 (Intercept)         4.02        4.57 7.06e- 6
2 pct_No_qualifications 0.0530        8.96 2.54e-17
3 pct_Males          -0.0739       -4.14 4.40e- 5
4 pct_Higher_manager_prof -0.0131       -2.65 8.43e- 3
```

Q4. Complete the table above by filling in the coefficients, t-values, p-values, and indicating if each variable is statistically significant.

Variable Name	Coefficients	t-values	p-values	Significant?
pct_No_qualifications				
pct_Males				
pct_Higher_manager_prof				

2.1.6 Interpretation of regression coefficients or covariate effects

2.1.6.1 Interpretation of the Intercept or Constant term

From the lecture notes, you know that the Intercept or Constant represents the estimated average value of the outcome variable when the values of all independent variables are equal to zero.

Q5. When values of `pct_Males`, `pct_No_qualifications` and `pct_Higher_manager_prof` are all *zero*, what is the % of population with very bad health? Is the intercept term meaningful? Think about whether there are districts with zero percentages of persons with no qualification. Are there any districts (or units, depending on the dataset you chose) with zero percentages of persons with no qualification in your data set?

2.1.6.2 Interpretation of regression slopes

The regression coefficient of an independent variable is the estimated average change in Y for a one unit change in X , when all other explanatory variables are held constant. There are two key points worth mentioning:

- **The unit of X and Y :** you need to know what the units are of the independent and dependent variables. For instance, one unit could be one year if you have an age variable, or a one percentage point if the variable is measured in percentages (all the variables in this week's practical).
- **All the other explanatory variables are held constant.** It means that the coefficient of an explanatory variable x_1 (e.g. b_1) should be interpreted as: a one unit change in x_1 is associated with b_1 units change in Y , keeping other values of explanatory variables (e.g. x_2 , x_3) constant – for instance, $x_2 = 0.1$ or $x_3 = 0.4$.

Q6. Interpret the regression coefficients of `pct_Males`, `pct_No_qualifications` and `pct_Higher_manager_prof`. Do they make sense?

2.1.7 Identify factors of % bad health

Now combine the above two sections and identify factors affecting the percentage of population with very bad health. Fill in each row for the direction (positive or negative) and significance level of each variable.

Variable Name	Positive or Negative	Statistical Significance
pct_No_qualifications		
pct_Higher_manager_prof		
pct_Males		

Q5. Think about the potential conclusions that can be drawn from the above analyses. Try to answer the research question of this practical: How do local factors affect residents' health?

2.2 Part C: Practice and Extension

If you haven't understood something, if you have doubts, even if they seem silly, ask.

1. Finish working through the practical.
2. Revise the material.
3. Extension activities (optional): Think about other potential factors of long-term illness and test your ideas with new linear regression models.