MQAT

Exercises in R

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2025-11-25

Table of contents

1. Quantitative Methods of Analysis in Transportation course

Materials, exercises, data and tutorials for the **Quantitative Methods of Analysis in Transportation** course of the MSc in Transportation Systems at Instituto Superior Técnico - University of Lisbon.

This is not the official book for the course.

Please refer to Fénix: Quantitative Methods of Analysis in Transportation

2. Introduction

This book aims to provide tools to deal with transportation datasets using R programming, an open-source and widely used tool for data analytics in urban mobility.

It includes course sporting materials, exercises, and examples to explore with **R**, with a focus on modelling and spatial data analysis using GIS techniques.

Why R and GIS

Most academic programs focus on teaching modelling and deep analysis of data. However, there is a need to learn how to explore and prepare a dataset for modelling. The use of **programming and GIS** techniques have enormous advantages, including their flexibility; reproducibility; and transparency and understanding the step-by-step process.

The use of GIS techniques in transportation is of enormous relevance when doing accessibility analysis or reeling with georreferenced transportation data, such as bike sharing route trips' datasets, origin-destination flows datasets, home/work locations, GTFS public transit data, and so on. There is a need to learn how to locate these open datasets, how to explore them and how to integrate them into transportation and urban analysis. Additionally, the use of open source software and datasets allows researchers to perform methods that are reproducible and transparent.

TLDR

- Open-source tools widely used in data analytics and spatial analysis
- Flexibility and reproducibility in data manipulation and visualization
- Critical for urban mobility and transportation research, with spatial relevance
- Large transportation datasets are becoming increasingly common

Recommended readings

- Engel (2023) Introduction to R.
- Wickham, Çetinaka-Rundel, and Grolemund (2017) R for Data Science.
- Lovelace, Nowosad, and Muenchow (2024) Geocomputation with R.

3. Software

In this chapter we will guide you through the installation of R, RStudio and the packages you will need for this course.

R and **RStudio**[1] are separate downloads.

3.1. R

You will need **R** installed on your computer. **R stats** (how it is also known) is a programming language and free software environment for statistical computing and graphics supported by the R Foundation for Statistical Computing.

The download links live at The Comprehensive R Archive Network (aka CRAN). he most recent version is `4.5.1`, but you can use `>= 4.1.x` if you already have it installed.

3.1.1. Windows

Download R-4.5.1 for Windows and run the executable file.

> Important
>
> You will also need to install Rtools, which is a collection of tools necessary to build R packages in Windows.

3.1.2. Mac

Download R-4.5.1 for MacOX. You will have to choose between the *arm64* or the *x86-64* version.

Download the `.pkg` file and install it as usual.

[1] We will use RStudio, although if you already use other studio such as VScode, that's also fine.

3.1.3. Ubuntu

> ! These are instructions for Ubuntu. If you use other linux distribution, please follow the instructions on The Comprehensive R Archive Network - CRAN.

You can look for R in the Ubuntu **Software Center** or install it via the terminal:

```
# sudo apt update && sudo apt upgrade -y
sudo apt install r-base
```

Or, if you prefer, you can install the latest version of R from CRAN:

```
# update indices
sudo apt update -qq
# install two helper packages we need
sudo apt install --no-install-recommends software-properties-common
    dirmngr
# add the signing key (by Michael Rutter) for these repos
wget -qO- https://cloud.r-project.org/bin/linux/ubuntu/marutter_pubkey.asc
    | sudo tee -a /etc/apt/trusted.gpg.d/cran_ubuntu_key.asc
# add the R 4.0 repo from CRAN -- adjust 'focal' to 'groovy' or 'bionic'
    as needed
sudo add-apt-repository "deb https://cloud.r-project.org/bin/linux/ubuntu
    $(lsb_release -cs)-cran40/"
```

Then run:

```
sudo apt install r-base r-base-core r-recommended r-base-dev
```

> **Optional**
>
> To keep up-to-date R version and packages, you can follow the instructions at r2u.

After this installation, you don't need to open R base. Please proceed to install RStudio.

3.2. RStudio

RStudio Desktop is an integrated development environment (IDE) for R. It includes a console, syntax-highlighting editor that supports direct code execution, as well as tools for plotting, history, debugging and workspace management.

RStudio is available for free download from Posit RStudio.

3.2.1. Windows 10/11

Download RStudio 2025.09 and run the executable file.

3.2.2. MacOS

Download RStudio 2025.09 and install it as usual.

3.2.3. Ubuntu

> ! These are instructions for Ubuntu **24**. If you use other linux distribution, please follow the instructions on Posit RStudio.

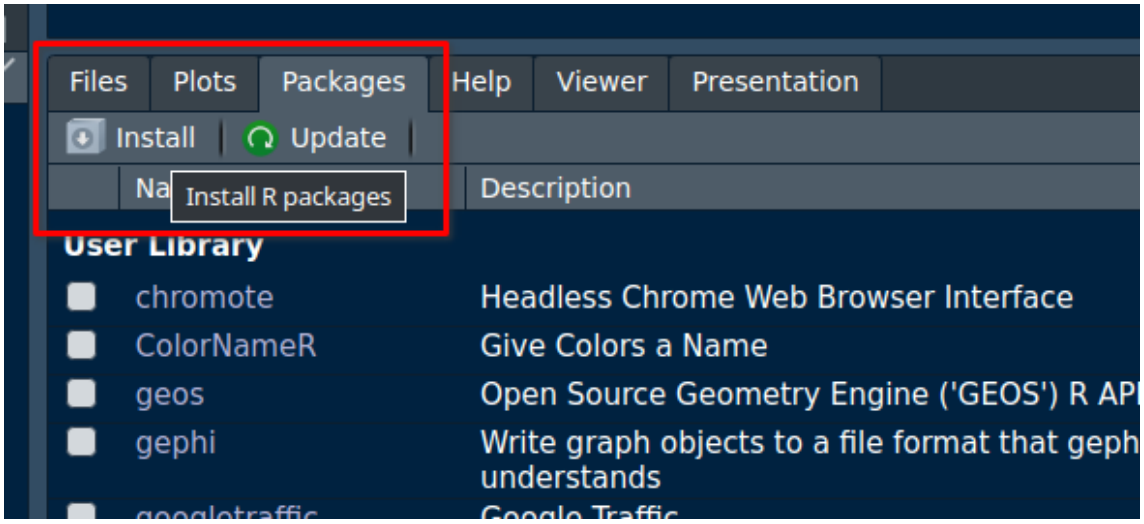
Install it via the terminal:

```
sudo apt install libssl-dev libclang-dev
wget
    https://download1.rstudio.org/electron/jammy/amd64/rstudio-2025.09.0-387-amd64.deb
sudo dpkg -i rstudio*
rm -v rstudio*
```

3.3. R packages

You will need to install some packages to work with the data and scripts in this course.

You can install them in RStudio by searching for them in the **Packages** tab:



or by running the following code in the console:

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

install.packages("sf")
install.packages("mapview")
install.packages("rmarkdown")
install.packages("centr")
install.packages("od")
install.packages("openrouteservice")

install.packages(c("remotes", "devtools", "usethis")) # optional
install.packages("osmextract") # optional
install.packages("stplanr") # optional
```

3.4. TinyTex

To be able to export your Rmakdown document to a **pdf** file, you will need a LaTeX processor. `tinytex` is a lightweight R package with the most used features of **LaTeX** that you can use with R.

You can install it from RStudio console by running:

```
# you need to run both lines
install.packages("tinytex")
tinytex::install_tinytex()
```

To use some LaTeX packages, you also need to install `tlmgr`.

```
tinytex::tlmgr_install()
tinytex::tlmgr_update() # updates all latex pkgs
```

3.5. Open Route Service

For some GIS exercises, we will use the Open Route Service to calculate routes and travel times.

In RStudio console, run:

```
# install.packages("openrouteservice")

# instructions to setup at the U-Shift server
options(openrouteservice.url = "https://...") # the server address
    provided to you
openrouteservice::ors_api_key("") # empty key
```

Part I.

Data and Models

4. R basics

In this chapter we will introduce to the R basics and some exercises to get familiar to how R works.

4.1. Math operations

4.1.1. Sum

```
1+1
```

```
[1] 2
```

4.1.2. Subtraction

```
5-2
```

```
[1] 3
```

4.1.3. Multiplication

```
2*2
```

```
[1] 4
```

4.1.4. Division

```
8/2
```

```
[1] 4
```

4.1.5. Round the number

```
round(3.14)
```

```
[1] 3
```

```
round(3.14, 1) # The "1" indicates to round it up to 1 decimal digit.
```

```
[1] 3.1
```

You can use help `?round` in the console to see the description of the function, and the default arguments.

4.2. Basics

4.2.1. Combinations

```
c(1, 2, 3)
```

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

```
c(1:3) # The ":" indicates a range between the first and second numbers.
```

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

> **Try it yourself**
>
> Try to write a combination with the numbers 10, 11, 56, 57, 58.

4.2.2. Create a comment with `ctrl + shift + c`

```
# Comments help you organize your code.
# A line with a comment will not be executed.
```

4.2.3. Create a table

A simple table with the number of trips by *car*, *PT*, *walking*, and *cycling* in a hypothetical street segment at a certain period.

Define variables

```
modes <- c("car", "PT", "walking", "cycling") # you can use "=" or "<-"
trips = c(200, 50, 300, 150) # key sensitive (uppercase and lowercase
    letters are different)
```

Join the variables to create a table

```
table_example = data.frame(modes, trips)
```

Take a look at the table

Visualize the table by clicking on the "Data" in the "Environment" page or use :

```
View(table_example)
```

Look at the first row

```
table_example[1,] #rows and columns start from 1 in R, differently from
    Python which starts from 0.
```

```
  modes trips
1   car   200
```

Look at first row and column

```
table_example[1,1]
```

```
[1] "car"
```

```
table_example[1,4]
```

```
NULL
```

4.3. Practical exercise

Dataset: the number of trips between all municipalities in the Lisbon Metropolitan Area, Portugal (INE 2018).

4.3.1. Import dataset

You can click directly in the file under the "Files" pan, or:

```
data = readRDS("data/TRIPSmode_mun.Rds")
```

> After you type " you can use `tab` to navigate between folders and files and `enter` to autocomplete.

4.3.2. Take a first look at the data

Summary statistics

```
summary(data)
```

```
 Origin_mun        Destination_mun        Total              Walk
Length:315         Length:315         Min.   :     7   Min.   :     0
Class :character   Class :character   1st Qu.:   330   1st Qu.:     0
Mode  :character   Mode  :character   Median :  1090   Median :     0
                                      Mean   : 16825   Mean   :  4033
                                      3rd Qu.:  5374   3rd Qu.:     0
                                      Max.   :875144   Max.   :306289
     Bike               Car             PTransit            Other
Min.   :   0.00   Min.   :     0   Min.   :     0.0   Min.   :    0.0
1st Qu.:   0.00   1st Qu.:   263   1st Qu.:     5.0   1st Qu.:    0.0
Median :   0.00   Median :   913   Median :   134.0   Median :    0.0
Mean   :  80.19   Mean   :  9956   Mean   :  2602.6   Mean   :  152.4
3rd Qu.:   0.00   3rd Qu.:  4408   3rd Qu.:   975.5   3rd Qu.:   62.5
Max.   :5362.00   Max.   :349815   Max.   :202428.0   Max.   :11647.0
```

Check the structure of the data

```
str(data)
```

```
Classes 'tbl_df', 'tbl' and 'data.frame':   315 obs. of  8 variables:
 $ Origin_mun     : chr  "Alcochete" "Alcochete" "Alcochete" "Alcochete" ...
 $ Destination_mun: chr  "Alcochete" "Almada" "Amadora" "Barreiro" ...
 $ Total          : num  20478 567 188 867 114 ...
 $ Walk           : num  6833 0 0 0 0 ...
 $ Bike           : num  320 0 0 0 0 0 0 0 91 0 ...
 $ Car            : num  12484 353 107 861 114 ...
 $ PTransit       : num  833 0 81 5 0 ...
 $ Other          : num  7 214 0 0 0 0 0 0 0 0 ...
```

Check the number of rows (observations) and columns (variables)

```
nrow(data)
```

```
[1] 315
```

```
ncol(data)
```

```
[1] 8
```

Open the dataset

```
View(data)
```

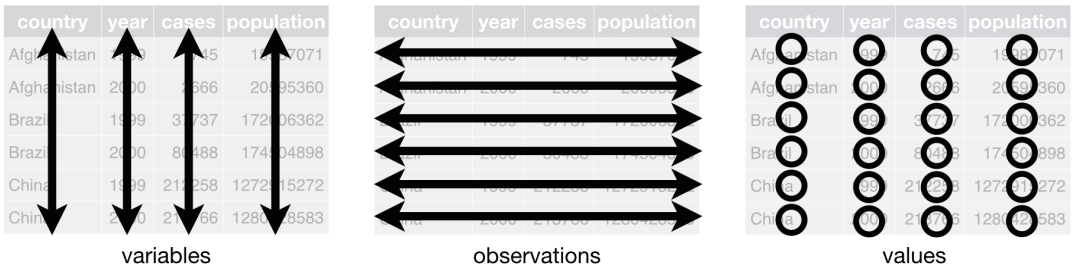


Figure 4.1.: The following three rules make a dataset tidy: variables are columns, observations are rows, and values are cells. [@wickham17r]

4.3.3. Explore the data

Check the total number of trips

Use `$` to select a variable of the data

```
sum(data$Total)
```

```
[1] 5299853
```

Percentage of car trips related to the total

```
sum(data$Car)/sum(data$Total) * 100
```

```
[1] 59.17638
```

Percentage of active trips related to the total

```
(sum(data$Walk) + sum(data$Bike)) / sum(data$Total) * 100
```

```
[1] 24.44883
```

4.3.4. Modify original data

Create a column with the sum of the number of trips for active modes

```
data$Active = data$Walk + data$Bike
```

Filter by condition (create new tables)

Filter trips only with origin from Lisbon

```
data_Lisbon = data[data$Origin == "Lisboa",]
```

Filter trips with origin **different** from Lisbon

```
data_out_Lisbon = data[data$Origin != "Lisboa",]
```

Filter trips with origin **and** destination in Lisbon

```
data_in_Out_Lisbon = data[data$Origin == "Lisboa" & data$Destination ==
    "Lisboa",]
```

Remove the first column

```
data = data[ ,-1] #first column
```

Create a table only with origin, destination and walking trips

There are many ways to do the same operation.

```
names(data)
```

```
[1] "Destination_mun" "Total"           "Walk"            "Bike"
[5] "Car"             "PTransit"        "Other"           "Active"
```

```
data_walk2 = data[ ,c(1,2,4)]
```

```
data_walk3 = data[ ,-c(3,5:9)]
```

4.3.5. Export data

Save data in **.csv** and **.Rds**

```
write.csv(data, 'data/dataset.csv', row.names = FALSE)
saveRDS(data, 'data/dataset.Rds') #Choose a different file.
```

4.3.6. Import data

```
csv_file = read.csv("data/dataset.csv")
rds_file = readRDS("data/dataset.Rds")
```

5. Data manipulation

In this chapter we will use some very useful `dplyr` functions to handle and manipulate data.

You can load the `dplyr` package directly, or load the entire tidy universe (`tidyverse`).

```
# library(tidyverse)
library(dplyr)
```

Using the same dataset as in R basics but with slightly differences[1].

We will do the same operations but in a simplified way.

```
TRIPS = readRDS("data/TRIPSorigin.Rds")
```

> **!** Important
>
> Note that it is very important to understand the R basics, that's why we started from there, even if the following functions will provide the same results.

You don't need to know everything! And you don't need to know by heart. The following functions are the ones you will probably use most of the time to handle data.

> There are several ways to reach the same solution. Here we present only one of them.

5.1. Select variables

Have a look at your dataset. You can open using `View()`, look at the information at the "Environment" panel, or even print the same information using `glimpse()`

```
glimpse(TRIPS)
```

We will create a new dataset with *Origin*, *Walk*, *Bike* and *Total*. This time we will use the `select()` function.

[1] This dataset includes the number of trips with origin in each neighborhood, divided by mode of transport, and inter or intra municipal trips.

```
TRIPS_new = select(TRIPS, Origin, Walk, Bike, Total) # the first argument
    is the dataset
```

The first argument, as usually in R, is the dataset, and the remaining ones are the columns to select.

With most of the `dplyr` functions you don't need to refer to `data$...` you can simply type the variable names (and even without the `"..."`!). This makes coding in R simpler :)

You can also remove columns that you don't need.

```
TRIPS_new = select(TRIPS_new, -Total) # dropping the Total column
```

5.1.1. Using pipes!

Now, let's introduce pipes. Pipes are a rule as: "**With this, do this.**"

This is useful to skip the first argument of the functions (usually the dataset to apply the function).

Applying a pipe to the `select()` function, we can write as:

```
TRIPS_new = TRIPS |> select(Origin, Walk, Bike, Total)
```

Two things to **note**:

1. The pipe symbol can be written as `|>` or `%>%`. [2] To write it you may also use the `ctrl+shift+m` shortcut.
2. After typing `select(` you can press `tab` and the list of available variables of that dataset will show up! `Enter` to select. With this you prevent typo errors.

5.2. Filter observations

You can filter observations based on a condition using the `filter()` function.

```
TRIPS2 = TRIPS[TRIPS$Total > 25000,] # using r-base, you cant forget the
    comma
TRIPS2 = TRIPS2 |> filter(Total > 25000) # using dplyr, it's easier
```

You can have other conditions inside the condition.

[2] You can change this in RStudio > Tools > Global Options > Code.

```
summary(TRIPS$Total)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
    361    5918   17474   22457   33378  112186
```

```
TRIPS3 = TRIPS |> filter(Total > median(Total))
```

Other filter conditions:

- `==` equal, `!=` different
- `<` smaller, `>` greater, `<=` smaller or equal, `>=` greater or equal
- `&` and, `|` or
- `is.na`, `!is.na` is not NA
- `%in%`, `!%in%` not in

5.3. Create new variables

You can also try again to create a variable of Car percentage using pipes! To create a new variable or change an existing one (overwriting), you can use the `mutate()` function.

```
TRIPS$Car_perc = TRIPS$Car/TRIPS$Total * 100 # using r-base

TRIPS = TRIPS |> mutate(Car_perc = Car/Total * 100) # using dplyr
```

5.4. Change data type

Data can be in different formats. For example, the variable *Origin* is a character, but we can convert it to a numeric variable.

```
class(TRIPS$Origin)
```

```
[1] "character"
```

```
TRIPS = TRIPS |>
  mutate(Origin_num = as.integer(Origin)) # you can use as.numeric() as
      well
class(TRIPS$Origin_num)
```

```
[1] "integer"
```

Most used data types are:

- integer (`int`)
- numeric (`num`)
- character (`chr`)
- logical (`logical`)
- date (`Date`)
- factor (`factor`)

5.4.1. Factors

Factors are useful to deal with categorical data. You can convert a character to a factor using `as.factor()`, and also use labels and levels for categorical ordinal data.

We can change the `Lisbon` variable to a factor, and `Internal` too.

```
TRIPS = TRIPS |>
  mutate(Lisbon_factor = factor(Lisbon, labels = c("No", "Yes")),
         Internal_factor = factor(Internal, labels = c("Inter", "Intra")))
```

But how do we know which levels come first? A simple way is to use `table()` or `unique()` functions.

```
unique(TRIPS$Lisbon) # this will show all the different values
```

```
[1] 0 1
```

```
table(TRIPS$Lisbon) # this will show the frequency of each value
```

```
  0   1
188  48
```

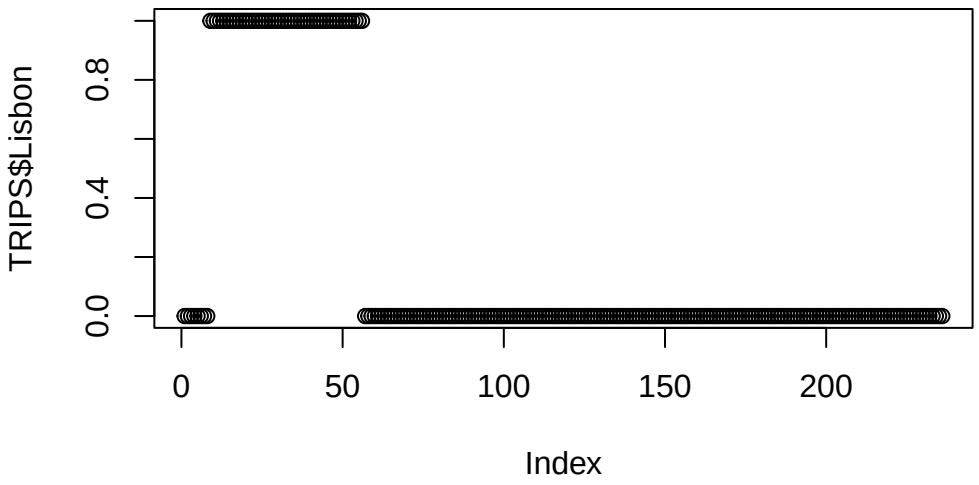
```
table(TRIPS$Lisbon_factor)
```

```
 No Yes
188  48
```

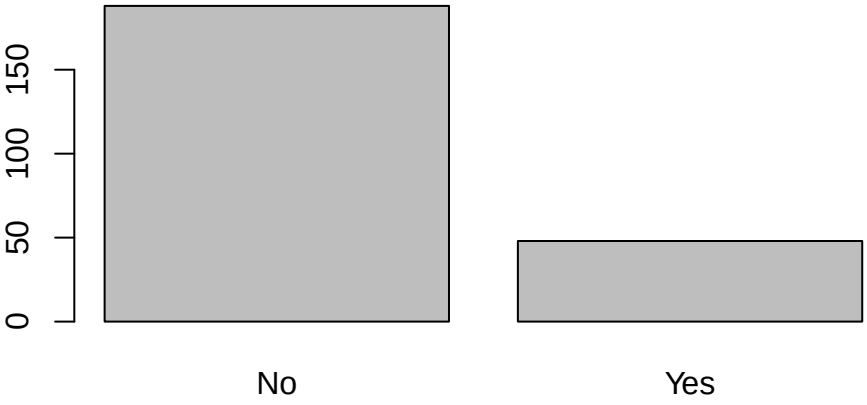
The first number to appear is the first level, and so on.

You can see the difference between using a continuous variable (in this case `Lisbon`‘ has 0 and 1) and a categorical variable (`Lisbon_factor`).

```
plot(TRIPS$Lisbon) # the values range between 0 and 1
```




```
plot(TRIPS$Lisbon_factor) # the values are categorical and labeled with
    Yes/No
```



5.5. Join data tables

When having relational tables - *i.e.* with a common identifier - it is useful to be able to join them in a very efficient way.

`left_join` is a function that joins two tables **by a common column**. The **first table is the one that will be kept**, and the **second one will be joined to** it. How `left_join` works:

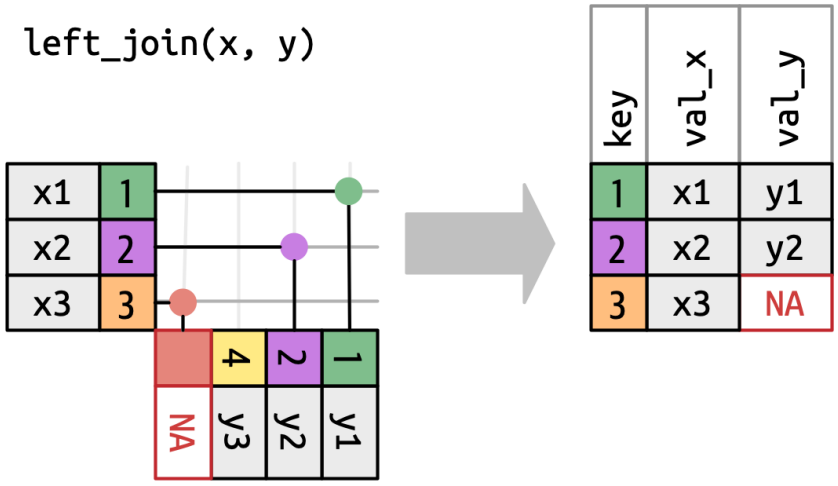


Figure 5.1.: A visual representation of the left join where every row in x appears in the output.Source: R for Data Science.

Let's **join the municipalities** to this table with a supporting table that includes all the **relation** between neighbourhoods and municipalities, and the respective names and codes.

```
Municipalities = readRDS("data/Municipalities_names.Rds")
```

```
head(TRIPS)
```

```
# A tibble: 6 x 13
  Origin Total  Walk  Bike   Car PTransit Other Internal Lisbon Car_perc
  <chr>  <dbl> <dbl> <dbl> <dbl>    <dbl> <dbl>    <dbl>  <dbl>    <dbl>
1 110501 35539 11325  1309 21446     1460     0        0      0     60.3
2 110501 47602  3502   416 37727     5519   437        1      0     79.3
3 110506 37183 12645    40 22379     2057    63        0      0     60.2
4 110506 42313  1418   163 37337     3285   106        1      0     88.2
5 110507 30725  9389  1481 19654      201     0        0      0     64.0
6 110507 54586  2630   168 44611     6963   215        1      0     81.7
# i 3 more variables: Origin_num <int>, Lisbon_factor <fct>,
#   Internal_factor <fct>
```

```
tail(Municipalities)
```

```
    Mun_code Neighborhood_code        Municipality
113     1109            110913              Mafra
114     1114            111409 Vila Franca de Xira
115     1109            110918              Mafra
116     1109            110904              Mafra
```

```
117     1502            150202           Alcochete
118     1109            110911               Mafra
                                          Neighborhood
113                                      Santo Isidoro
114                                  Vila Franca de Xira
115 União das freguesias de Azueira e Sobral da Abelheira
116                                        Encarnação
117                                           Samouco
118                                         Milharado
```

We can see that we have a common variable: `Origin` in `TRIPS` and `Neighborhood_code` in `Municipalities`.

To join these two tables we need to specify the common variable in each table, using the `by` argument.

```
TRIPSjoin = TRIPS |> left_join(Municipalities, by = c("Origin" =
    "Neighborhood_code"))
```

If you prefer, you can mutate or rename a variable so both tables have the same name. When **both tables have the same name**, you don't need to specify the `by` argument.

```
Municipalities = Municipalities |> rename(Origin = "Neighborhood_code") #
    change name
TRIPSjoin = TRIPS |> left_join(Municipalities) # automatic detects common
    variable
```

As you can see, both tables don't need to be the same length. The `left_join` function will keep all the observations from the first table, and join the second table to it. If there is no match, the variables from the second table will be filled with `NA`.

5.6. group_by and summarize

We have a very large table with all the neighbourhoods and their respective municipalities. We want to know the total number of trips with origin in each municipality.

To make it easier to understand, let's keep only the variables we need.

```
TRIPSredux = TRIPSjoin |> select(Origin, Municipality, Internal, Car,
    Total)
head(TRIPSredux)
```

```
# A tibble: 6 x 5
  Origin Municipality Internal   Car Total
  <chr>  <chr>           <dbl> <dbl> <dbl>
1 110501 Cascais             0 21446 35539
2 110501 Cascais             1 37727 47602
3 110506 Cascais             0 22379 37183
4 110506 Cascais             1 37337 42313
5 110507 Cascais             0 19654 30725
6 110507 Cascais             1 44611 54586
```

We can group this table by the `Municipality` variable and summarize the number of trips with origin in each municipality.

```
TRIPSsum = TRIPSredux |>
  group_by(Municipality) |> # you won't notice any chagne with only this
  summarize(Total = sum(Total))
head(TRIPSsum)
```

```
# A tibble: 6 x 2
  Municipality   Total
  <chr>          <dbl>
1 Alcochete      36789
2 Almada        289834
3 Amadora       344552
4 Barreiro      133658
5 Cascais       373579
6 Lisboa       1365111
```

We summed the total number of trips in each municipality.

If we want to group by more than one variable, we can add more `group_by()` functions.

```
TRIPSsum2 = TRIPSredux |>
  group_by(Municipality, Internal) |>
  summarize(Total = sum(Total),
            Car = sum(Car))
head(TRIPSsum2)
```

```
# A tibble: 6 x 4
# Groups:   Municipality [3]
  Municipality Internal  Total    Car
  <chr>           <dbl>  <dbl>  <dbl>
1 Alcochete           0  16954   9839
2 Alcochete           1  19835  15632
3 Almada              0 105841  49012
```

```
4 Almada                1 183993 125091
5 Amadora               0 117727  33818
6 Amadora               1 226825 142386
```

We summed the total number of trips and car trips in each municipality, **separated by** inter and intra municipal trips.

> It is a good practice to use the `ungroup()` function after the `group_by()` function. This will remove the grouping. If you don't do this, the grouping will be kept and you may have unexpected results in the next time you use that dataset.

5.7. Arrange data

You can **sort** a dataset by one or more variables.

For instance, `arrange()` by Total trips, ascending or descending order.

```
TRIPS2 = TRIPSsum2 |> arrange(Total)
TRIPS2 = TRIPSsum2 |> arrange(-Total) # descending

TRIPS2 = TRIPSsum2 |> arrange(Municipality) # alphabetic

TRIPS4 = TRIPS |> arrange(Lisbon_factor, Total) # more than one variable
```

This is not the same as opening the view table and click on the arrows. When you do that, the order is not saved in the dataset. If you want to save the order, you need to use the `arrange()` function.

5.8. All together now!

This is the pipes magic. It takes the last result and applies the next function to it. "With this, do this.". You can chain as many functions as you want.

```
TRIPS_pipes = TRIPS |>
  select(Origin, Internal, Car, Total) |>

  mutate(Origin_num = as.integer(Origin)) |>
  mutate(Internal_factor = factor(Internal, labels = c("Inter", "Intra"))) 
      |>

  filter(Internal_factor == "Inter")|>

  left_join(Municipalities) |>
```

```
  group_by(Municipality) |>
  summarize(Total = sum(Total),
            Car = sum(Car),
            Car_perc = Car/Total * 100) |>
  ungroup() |>

  arrange(desc(Car_perc))
```

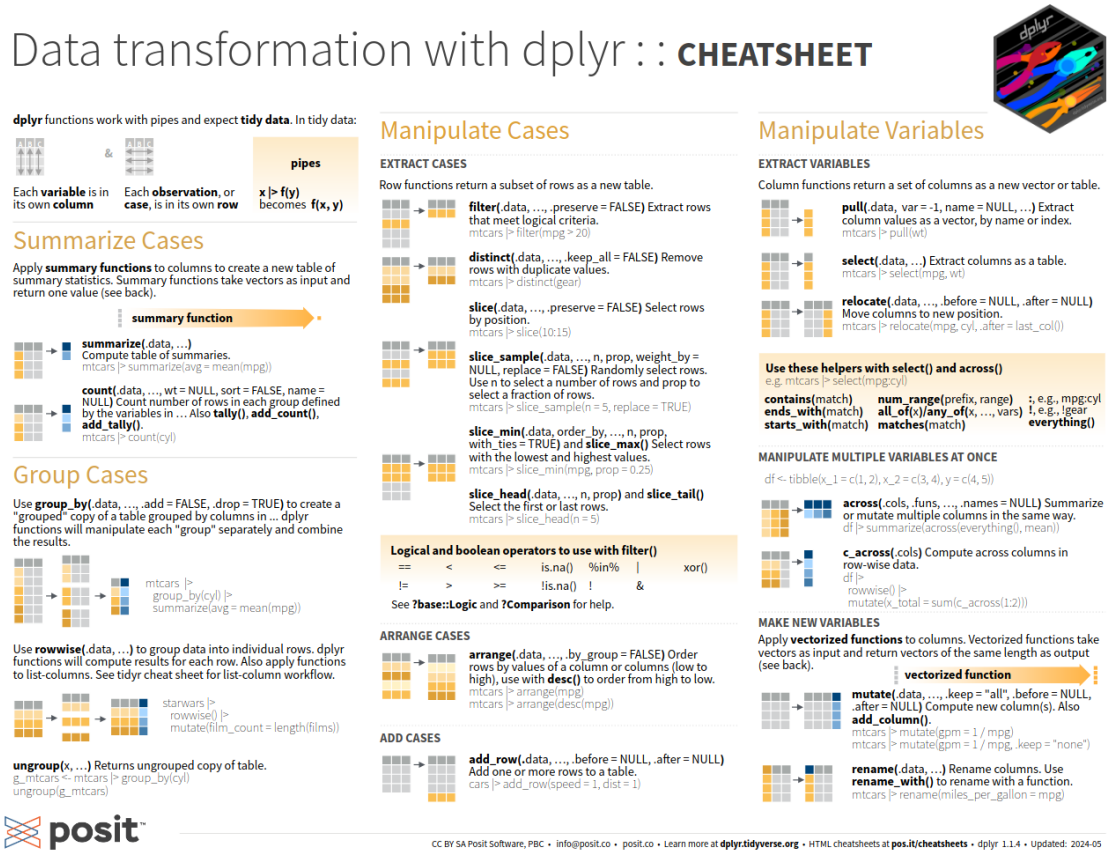
With this code we will have a table with the total number of intercity trips, by municipality, with their names instead of codes, arranged by the percentage of car trips.

```
TRIPS_pipes
```

```
# A tibble: 18 x 4
   Municipality         Total    Car Car_perc
   <chr>                <dbl>  <dbl>    <dbl>
 1 Mafra                65811  46329     70.4
 2 Sesimbra             49370  31975     64.8
 3 Cascais             161194  96523     59.9
 4 Palmela              66428  39688     59.7
 5 Alcochete            16954   9839     58.0
 6 Setúbal             129059  70318     54.5
 7 Montijo              57164  30900     54.1
 8 Seixal              120747  63070     52.2
 9 Sintra              237445 123408     52.0
10 Oeiras              134862  66972     49.7
11 Almada              105841  49012     46.3
12 Loures              132310  60478     45.7
13 Barreiro             52962  24160     45.6
14 Odivelas             93709  39151     41.8
15 Vila Franca de Xira 115152  47201     41.0
16 Moita                51040  17394     34.1
17 Amadora             117727  33818     28.7
18 Lisboa              280079  69038     24.6
```

5.9. Other dplyr functions

You can explore other `dplyr` functions and variations to manipulate data in the **dplyr cheat sheet**:



Take a particular attention to `pivot_wider` and `pivot_longer` (`tidyr` package) to transform **OD matrices** in **wide** and **long** formats.

Table 5.1.: OD matrix in long format

Origins	Destinations	Trips
A	B	20
A	C	45
B	A	10
C	C	5
C	A	30

Table 5.2.: OD matrix in wide format

Trips	A	B	C
A	NA	20	45
B	10	NA	NA
C	30	NA	5

6. Exploratory Data Analysis

6.1. Intro

This chapter will show you how to use visualization and transformation to explore your data in a systematic way, a task that statisticians call exploratory data analysis, or **EDA** for short. EDA is an iterative cycle, where you should feel free to "fall in love" with your data.

You:

1. Generate questions about your data.
2. Search for answers by visualizing, transforming, and modelling your data.
3. Use what you learn to refine your questions and/or generate new questions.

   Note: EDA is not a formal process with a strict set of rules!

See Wickham, Çetinaka-Rundel, and Grolemund (2017) for more, in particular the EDA chapter.

> **Do it yourself with R**
>
> Copy the script ExploratoryDataAnalysis.R and paste it in your session.
> Run each line using `CTRL` + `ENTER`

6.2. Load packages

```
library(tidyverse) # Pack of most used libraries for data science
library(skimr) # summary of the data
library(DataExplorer) # exploratory data analysis
library(corrplot) # correlation plots
```

6.3. Dataset

The database used in this example is a treated database from the Mobility Survey for the metropolitan areas of Lisbon and Porto in 2018 (INE 2018). We will only focus on trips within the metropolitan area of Lisbon.

Included **variables**:

- `Origin_dicofre16` - Code of Freguesia (district) as set by INE after 2016 (Distrito + Concelho + Freguesia), for trip origin
- `Total` - number of trips with origin at each district
- `Walk` - number of walking trips
- `Bike` - number of bike trips
- `Car` - number of car trips. Includes taxi and motorcycle.
- `PTransit` - number of Public Transit trips
- `Other` - number of other trips (truck, van, tractor, aviation)
- `Distance` - average trip distance (km)
- `Duration` - average trip duration (minutes)
- `Car_perc` - percentage of car trips
- `N_INDIVIDUOS` - number of residents (INE 2022)
- `Male_perc` - percentage of male residents (INE 2022)
- `IncomeHH` - average household income
- `Nvehicles` - average number of car/motorcycle vehicles in the household
- `DrivingLic` - percentage of car driving licence holders
- `CarParkFree_Work` - percentage of respondents with free car parking at the work location
- `PTpass` - percentage of public transit monthly pass holders
- `internal` - binary variable (factor). `Yes`: trip with same TAZ origin and destination, `No`: trips with different destination
- `Lisboa` - binary variable (factor). `Yes`: the district is part of Lisbon municipality, `No`: otherwise
- `Area_km2` - area of in `Origin_dicofre16`, in km^2

6.3.1. Import dataset

```
data = readRDS("../data/IMOBmodel.Rds")
```

Take a look at the dataset

```
View(data) # open in table
glimpse(data) # glimpse of the dataset
```

```
Rows: 236
Columns: 20
```

```
$ Origin_dicofre16 <chr> "110501", "110501", "110506", "110506", "110507", "11~
$ Total            <dbl> 35539, 47602, 37183, 42313, 30725, 54586, 57747, 6788~
$ Walk             <dbl> 11325, 3502, 12645, 1418, 9389, 2630, 20423, 3573, 62~
$ Bike             <dbl> 1309, 416, 40, 163, 1481, 168, 1406, 809, 13, 37, 3, ~
$ Car              <dbl> 21446, 37727, 22379, 37337, 19654, 44611, 33044, 5225~
$ PTransit         <dbl> 1460, 5519, 2057, 3285, 201, 6963, 2477, 10534, 110, ~
$ Other            <dbl> 0, 437, 63, 106, 0, 215, 396, 717, 2, 169, 3, 824, 0,~
$ Distance         <dbl> 11.779, 11.779, 9.868, 9.868, 9.600, 9.600, 12.875, 1~
$ Duration         <dbl> 23.96, 23.96, 22.78, 22.78, 23.39, 23.39, 26.89, 26.8~
$ Car_perc         <dbl> 60.34497, 79.25507, 60.18611, 88.24002, 63.96745, 81.~
$ N_INDIVIDUOS     <dbl> 44165, 44165, 59238, 59238, 46529, 46529, 64192, 6419~
$ Male_perc        <dbl> 47.66, 47.66, 47.12, 47.12, 45.54, 45.54, 46.14, 46.1~
$ IncomeHH         <dbl> 2204.32, 2204.32, 1896.05, 1896.05, 2430.43, 2430.43,~
$ Nvehicles        <dbl> 1.86, 1.86, 1.73, 1.73, 1.60, 1.60, 1.64, 1.64, 1.20,~
$ DrivingLic       <dbl> 63.03, 63.03, 65.42, 65.42, 67.05, 67.05, 72.75, 72.7~
$ CarParkFree_Work <dbl> 49.97, 49.97, 57.09, 57.09, 47.43, 47.43, 56.47, 56.4~
$ PTpass           <dbl> 11.14, 11.14, 17.12, 17.12, 18.25, 18.25, 19.73, 19.7~
$ internal         <fct> Yes, No, Yes, No, Yes, No, Yes, No, Yes, No, Yes, No,~
$ Lisboa           <fct> No, No, No, No, No, No, No, No, Yes, Yes, Yes, Yes, Y~
$ Area_km2         <dbl> 39.767414, 39.767414, 20.364310, 20.364310, 8.109861,~
```

```
str(data) # Structure of the dataset
```

```
'data.frame':   236 obs. of  20 variables:
 $ Origin_dicofre16: chr  "110501" "110501" "110506" "110506" ...
 $ Total           : num  35539 47602 37183 42313 30725 ...
 $ Walk            : num  11325 3502 12645 1418 9389 ...
 $ Bike            : num  1309 416 40 163 1481 ...
 $ Car             : num  21446 37727 22379 37337 19654 ...
 $ PTransit        : num  1460 5519 2057 3285 201 ...
 $ Other           : num  0 437 63 106 0 215 396 717 2 169 ...
 $ Distance        : num  11.78 11.78 9.87 9.87 9.6 ...
 $ Duration        : num  24 24 22.8 22.8 23.4 ...
 $ Car_perc        : num  60.3 79.3 60.2 88.2 64 ...
 $ N_INDIVIDUOS    : num  44165 44165 59238 59238 46529 ...
 $ Male_perc       : num  47.7 47.7 47.1 47.1 45.5 ...
 $ IncomeHH        : num  2204 2204 1896 1896 2430 ...
 $ Nvehicles       : num  1.86 1.86 1.73 1.73 1.6 1.6 1.64 1.64 1.2 1.2 ...
 $ DrivingLic      : num  63 63 65.4 65.4 67 ...
 $ CarParkFree_Work: num  50 50 57.1 57.1 47.4 ...
 $ PTpass          : num  11.1 11.1 17.1 17.1 18.2 ...
 $ internal        : Factor w/ 2 levels "Yes","No": 1 2 1 2 1 2 1 2 1 2 ...
 $ Lisboa          : Factor w/ 2 levels "No","Yes": 1 1 1 1 1 1 1 1 2 2 ...
 $ Area_km2        : num  39.77 39.77 20.36 20.36 8.11 ...
```

6.4. Summary statistics

Have an overview of the variables and their statistics' summary.

```
summary(data) # Check the summary statistics
```

```
 Origin_dicofre16       Total             Walk              Bike        
 Length:236         Min.   :   361   Min.   :    0.0   Min.   :   0.00  
 Class :character   1st Qu.:  5918   1st Qu.:  763.2   1st Qu.:   0.00  
 Mode  :character   Median : 17474   Median : 3125.0   Median :  13.50  
                    Mean   : 22457   Mean   : 5383.4   Mean   : 107.03  
                    3rd Qu.: 33378   3rd Qu.: 8298.5   3rd Qu.:  98.75  
                    Max.   :112186   Max.   :32646.0   Max.   :2040.00  
      Car            PTransit         Other           Distance      
 Min.   :    0   Min.   :    0   Min.   :   0.0   Min.   : 6.835  
 1st Qu.: 3243   1st Qu.:  249   1st Qu.:   2.0   1st Qu.: 9.539  
 Median : 9008   Median : 1057   Median :  44.0   Median :10.323  
 Mean   :13289   Mean   : 3474   Mean   : 203.4   Mean   :11.139  
 3rd Qu.:21249   3rd Qu.: 4853   3rd Qu.: 281.5   3rd Qu.:12.097  
 Max.   :52631   Max.   :41672   Max.   :2391.0   Max.   :22.660  
    Duration        Car_perc      N_INDIVIDUOS     Male_perc      
 Min.   :16.30   Min.   : 0.00   Min.   : 1566   Min.   :44.61  
 1st Qu.:23.00   1st Qu.:45.40   1st Qu.:11060   1st Qu.:46.58  
 Median :24.70   Median :62.62   Median :20855   Median :47.51  
 Mean   :25.42   Mean   :59.00   Mean   :24324   Mean   :47.54  
 3rd Qu.:27.73   3rd Qu.:75.72   3rd Qu.:36079   3rd Qu.:48.29  
 Max.   :37.42   Max.   :99.27   Max.   :68649   Max.   :55.94  
    IncomeHH        Nvehicles       DrivingLic    CarParkFree_Work 
 Min.   : 884.5   Min.   :1.020   Min.   :37.04   Min.   : 5.47  
 1st Qu.:1417.8   1st Qu.:1.350   1st Qu.:57.67   1st Qu.:40.39  
 Median :1594.7   Median :1.545   Median :63.00   Median :50.51  
 Mean   :1732.6   Mean   :1.530   Mean   :62.50   Mean   :49.30  
 3rd Qu.:1953.5   3rd Qu.:1.670   3rd Qu.:68.84   3rd Qu.:57.92  
 Max.   :3462.3   Max.   :2.420   Max.   :80.79   Max.   :87.60  
    PTpass      internal  Lisboa       Area_km2      
 Min.   : 0.00   Yes:118   No :188   Min.   :  1.494  
 1st Qu.:13.41   No :118   Yes: 48   1st Qu.:  5.044  
 Median :22.71                       Median : 11.598  
 Mean   :23.82                       Mean   : 25.553  
 3rd Qu.:32.94                       3rd Qu.: 28.511  
 Max.   :60.45                       Max.   :282.125  
```

```
skim(data) # In a more organized way
```

Table 6.1.: Data summary

Name	data
Number of rows	236
Number of columns	20
Column type frequency:	
character	1
factor	2
numeric	17
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
Origin_dicofre16	0	1	6	6	0	118	0

Variable type: factor

skim_variable	n_missing	complete_rate	ordered	n_unique	top_counts
internal	0	1	FALSE	2	Yes: 118, No: 118
Lisboa	0	1	FALSE	2	No: 188, Yes: 48

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
Total	0	1	22457.00	19084.45	361.00	5917.75	17474.00	33377.50	112186.00	
Walk	0	1	5383.44	6224.84	0.00	763.25	3125.00	8298.50	32646.00	
Bike	0	1	107.03	248.65	0.00	0.00	13.50	98.75	2040.00	
Car	0	1	13289.24	12351.61	0.00	3243.00	9008.00	21248.75	52631.00	
PTransit	0	1	3473.79	5467.82	0.00	249.00	1057.00	4853.00	41672.00	
Other	0	1	203.45	336.04	0.00	2.00	44.00	281.50	2391.00	
Distance	0	1	11.14	2.66	6.84	9.54	10.32	12.10	22.66	
Duration	0	1	25.42	3.91	16.30	23.00	24.70	27.73	37.42	
Car_perc	0	1	59.00	21.56	0.00	45.40	62.62	75.72	99.27	
N_INDIVIDUOS	0	1	24323.80	16438.04	1566.00	11060.00	20855.00	36079.00	68649.00	
Male_perc	0	1	47.54	1.57	44.61	46.58	47.50	48.29	55.94	
IncomeHH	0	1	1732.55	453.11	884.46	1417.76	1594.73	1953.50	3462.32	
Nvehicles	0	1	1.53	0.24	1.02	1.35	1.54	1.67	2.42	
DrivingLic	0	1	62.50	8.12	37.04	57.67	63.00	68.84	80.79	
CarParkFree_Work	0	1	49.30	14.30	5.47	40.39	50.51	57.92	87.60	
PTpass	0	1	23.82	12.87	0.00	13.41	22.72	32.94	60.45	
Area_km2	0	1	25.55	42.58	1.49	5.04	11.60	28.51	282.13	

6.5. Missing data

Is there missing data (`NA`)? How many?

```
table(is.na(data))
```

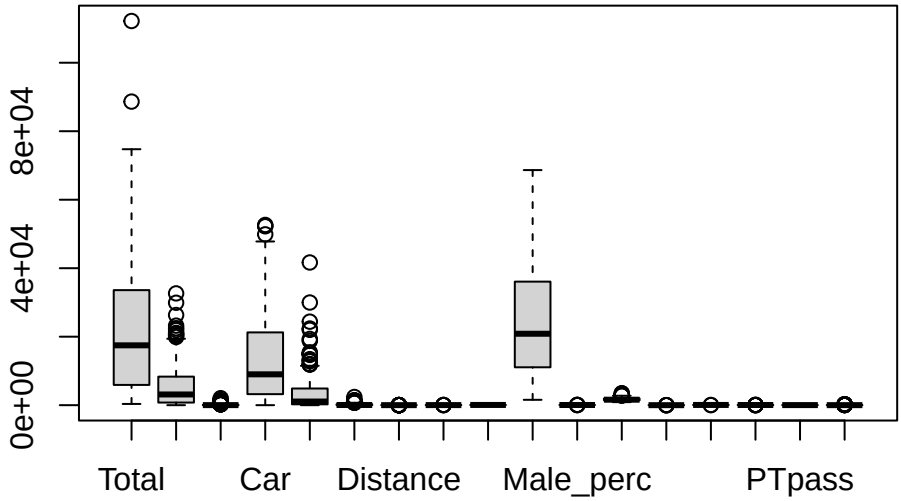
```
FALSE
 4720
```

6.6. Outliers

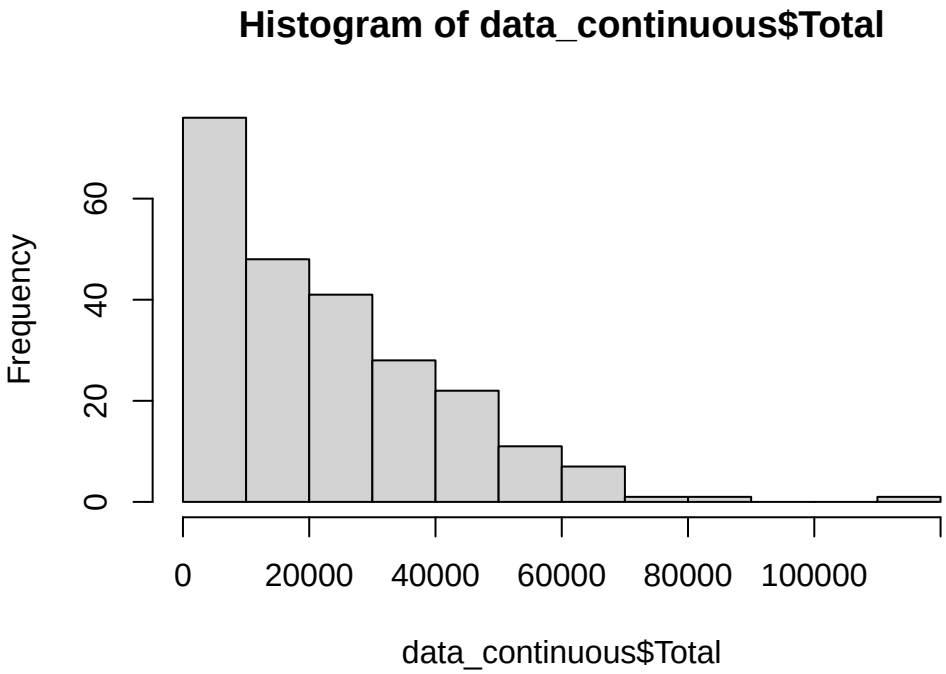
Inspect outliers and distributions

```
boxplot(data) # This does now work if variables are not all continuous
```

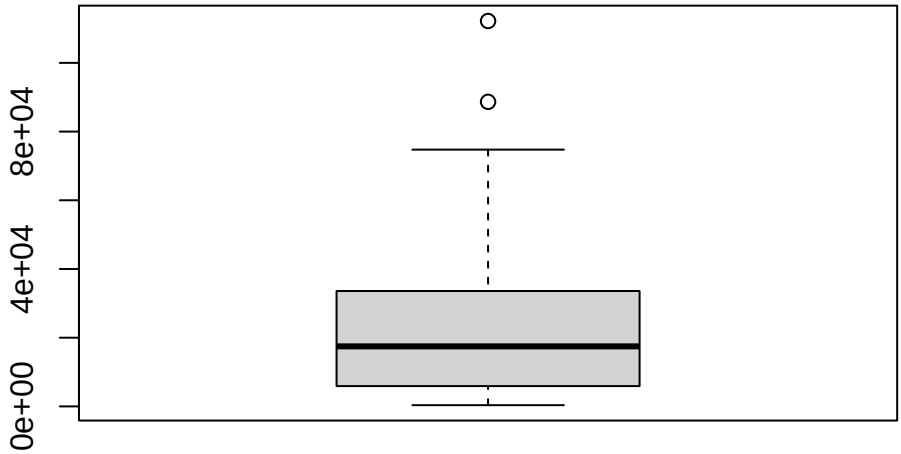
```
data_continuous = data |> select(-Origin_dicofre16, -internal, -Lisboa) #
    Exclude categorical variables
boxplot(data_continuous) # Exclude categorical variables
```




```
hist(data_continuous$Total) # histogram
```




```
boxplot(data_continuous$Total) # outliers detected
```



6.6.1. Treating outliers

Based on the theory, we can create a function to detect the outliers.

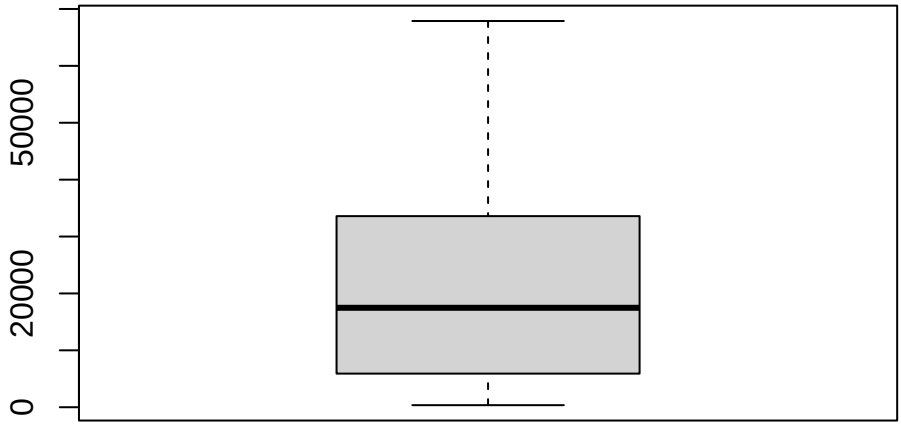
```
outlier = function(x) {
  q = quantile(x, probs = c(0.25, 0.75), na.rm = TRUE)  # Q1 and Q3
  caps = quantile(x, probs = c(0.05, 0.95), na.rm = TRUE) # 5th and 95th
    percentile
  H = 1.5 * IQR(x, na.rm = TRUE) # interquartile range

  case_when(
    x < (q[1] - H) ~ caps[1], # replace values that are LESS than
    Q1-1.5*IQR with the P5 value
    x > (q[2] + H) ~ caps[2], # replace values that are MORE than
    Q3+1.5*IQR with the P95 value
    TRUE ~ x # otherwise, return the original value
  )
}
```

Now, use it in a copy of the table

```
data_outliers = data_continuous # duplicate the table
data_outliers$Total = outlier(data_outliers$Total) # Use the function to
    the same variable
```

Take a look again at the boxplot

```
boxplot(data_outliers$Total)
```



Compare the variable with and without the outliers

```
# Mean
mean(data$Total)
```

```
[1] 22457
```

```
mean(data_outliers$Total)
```

```
[1] 22013.51
```

```
# Median
median(data$Total)
```

```
[1] 17474
```

```
median(data_outliers$Total)
```

```
[1] 17474
```

```
# Standard deviation
sd(data$Total)
```

```
[1] 19084.45
```

```
sd(data_outliers$Total)
```

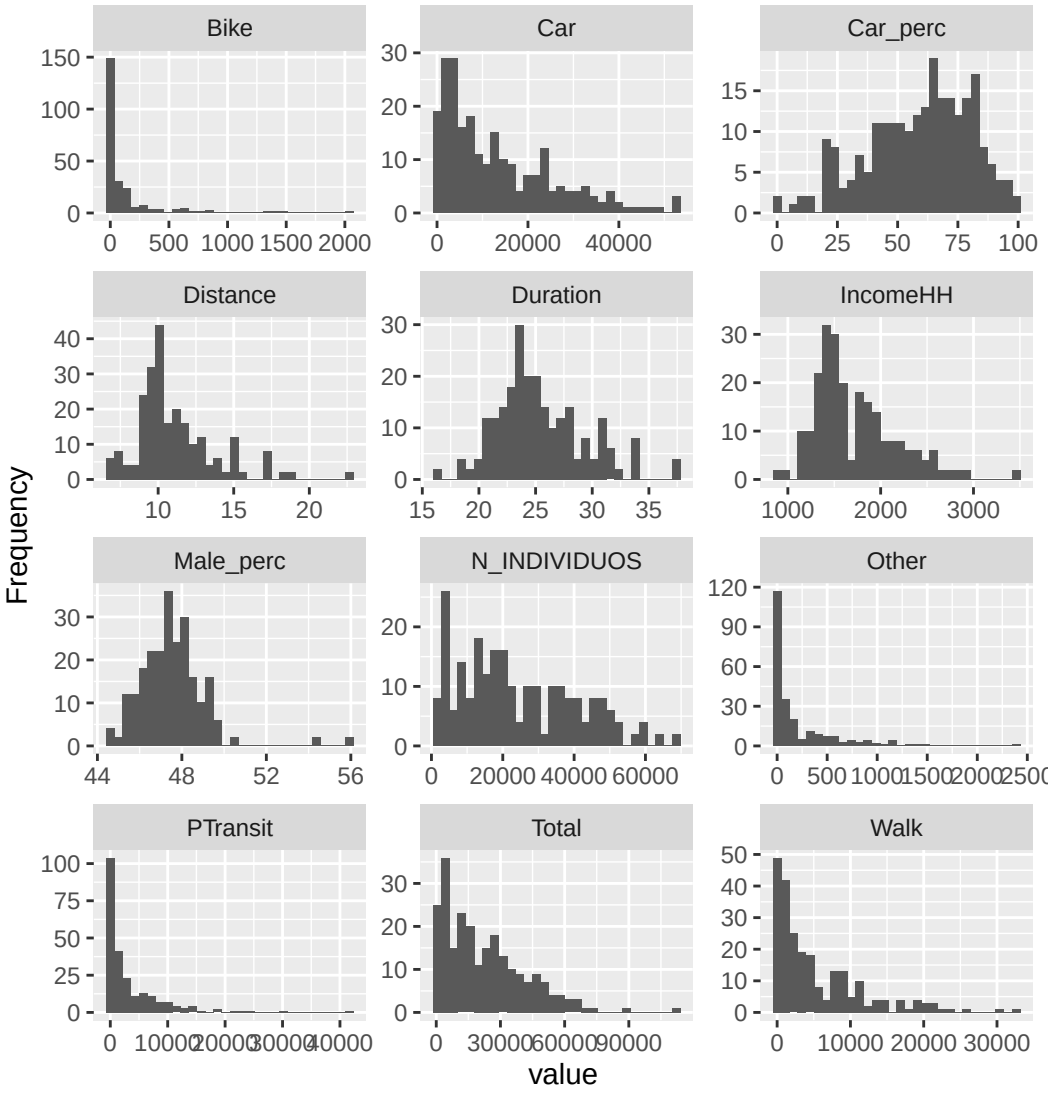
```
[1] 17739.39
```

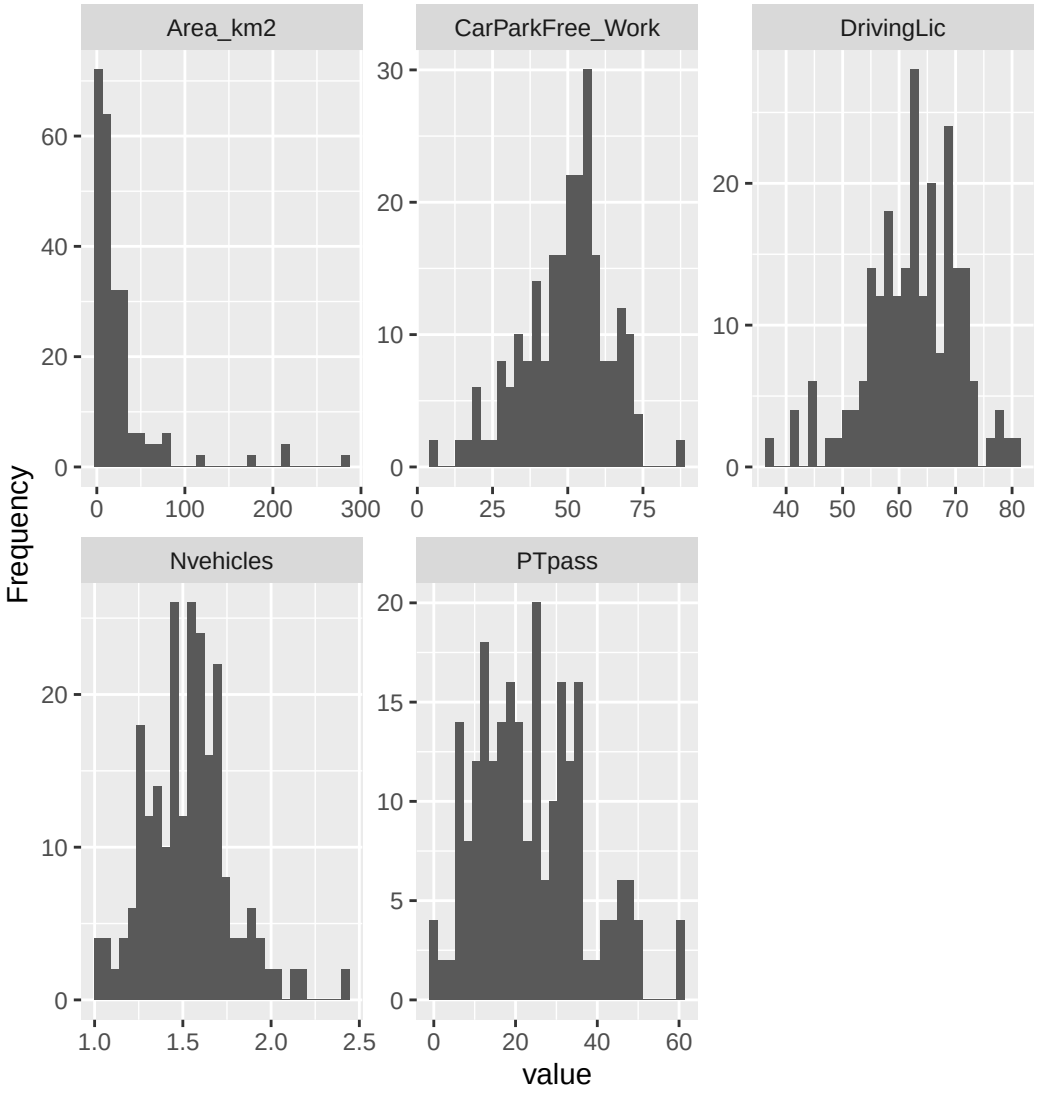
> **Note**
>
> There are many methods to treat outliers. This is just one of them.

6.7. Histograms

Plot histograms of all the continuous variables

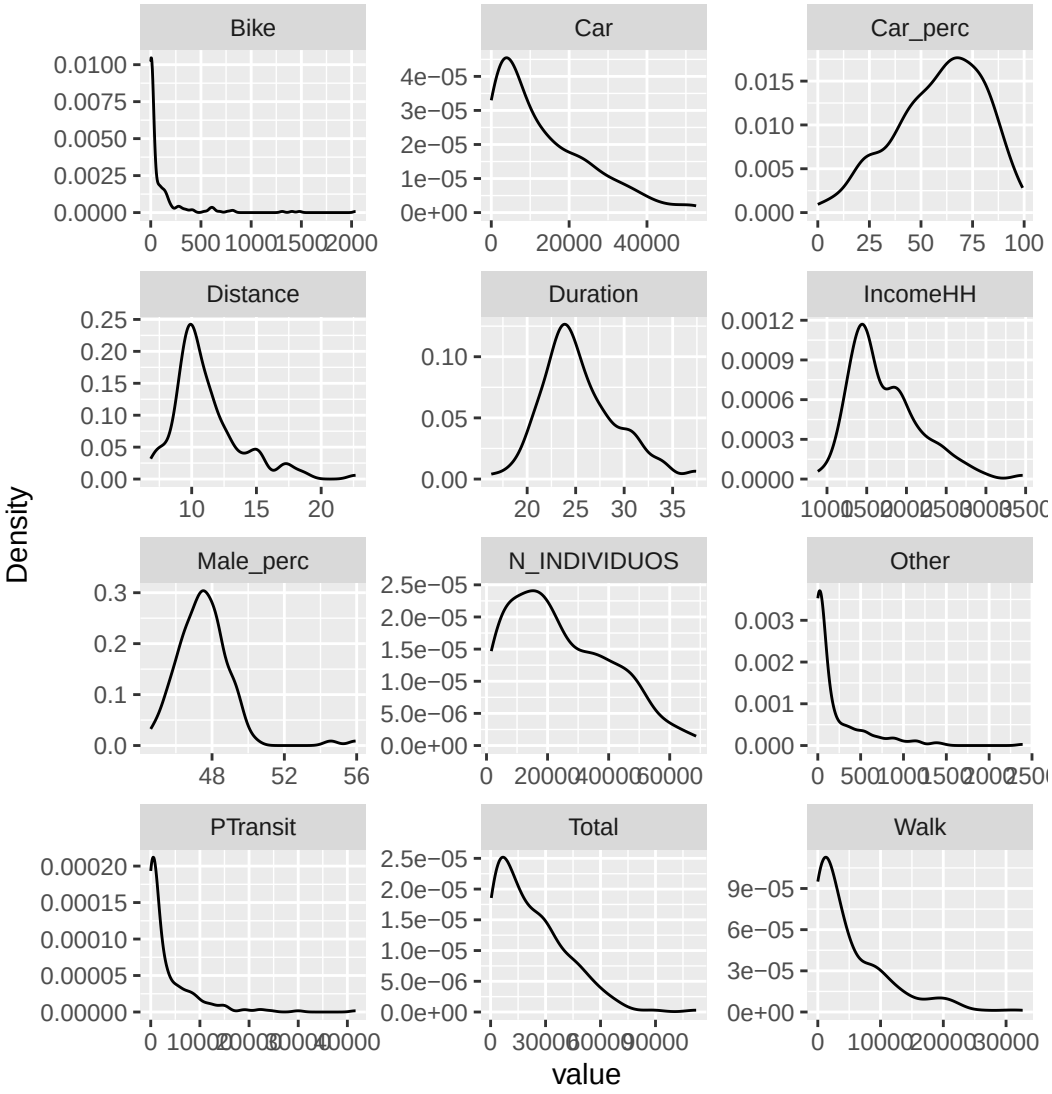
```
plot_histogram(data, ncol = 3) # histograms with 3 columns
```

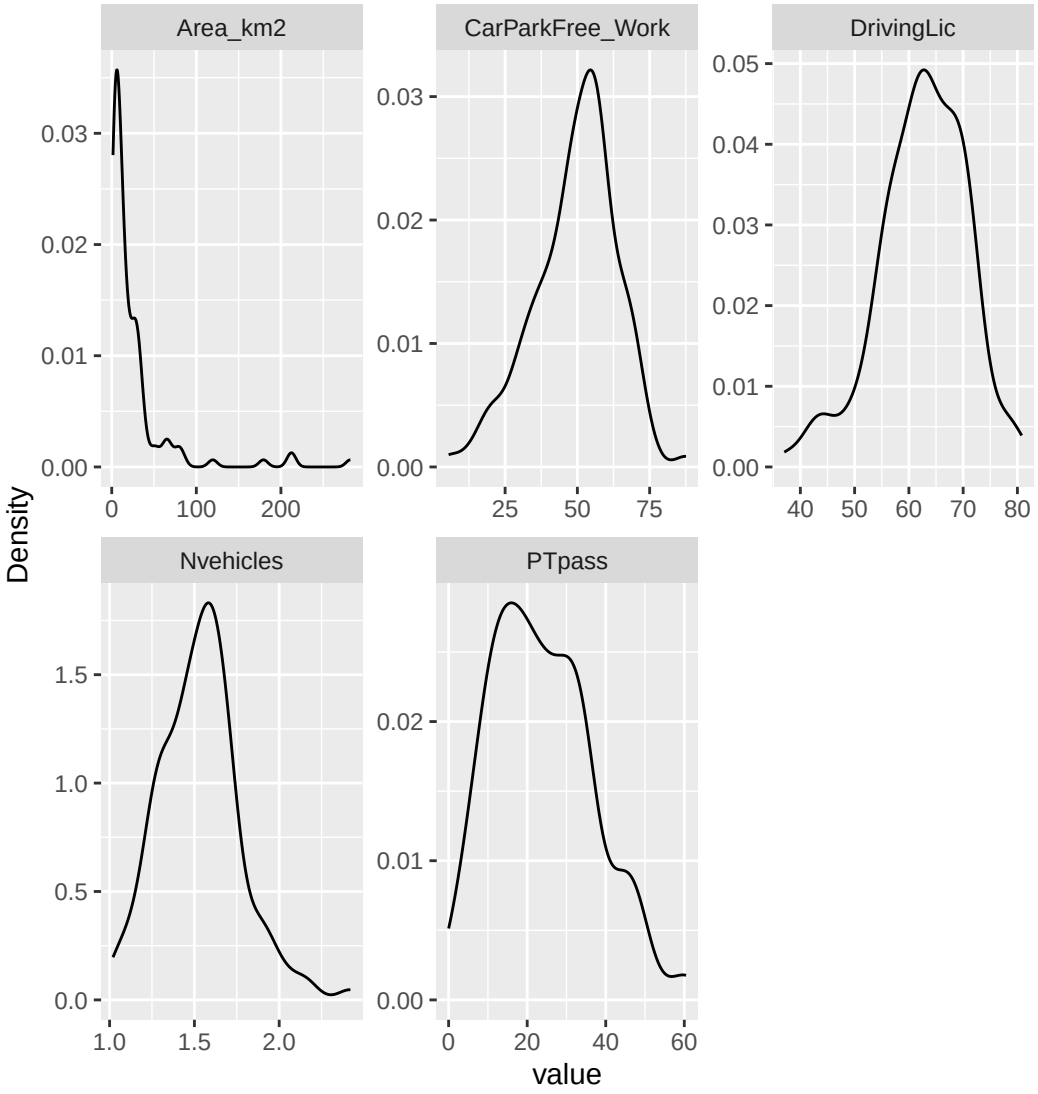




Page 2

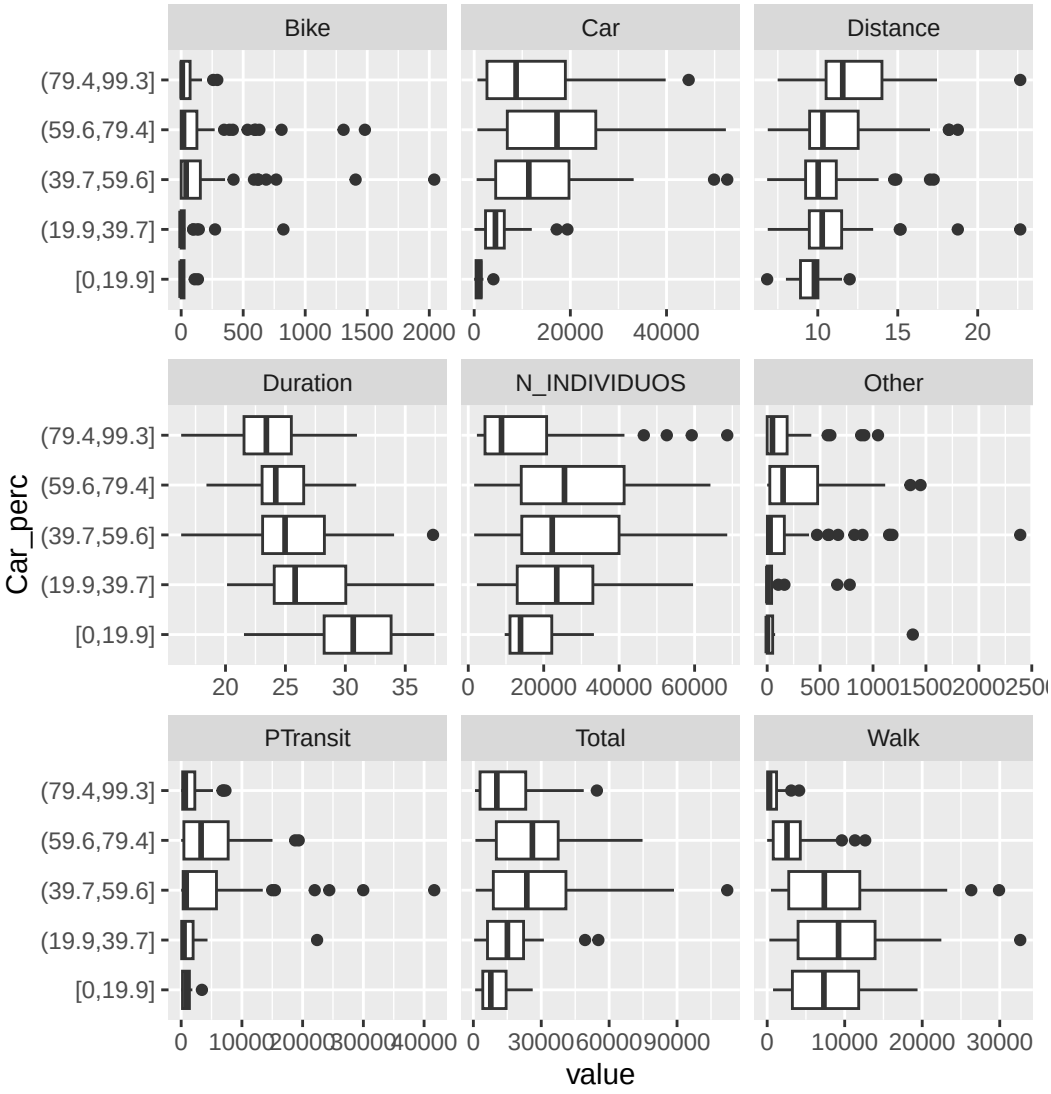
```
plot_density(data, ncol = 3) # density plots
```

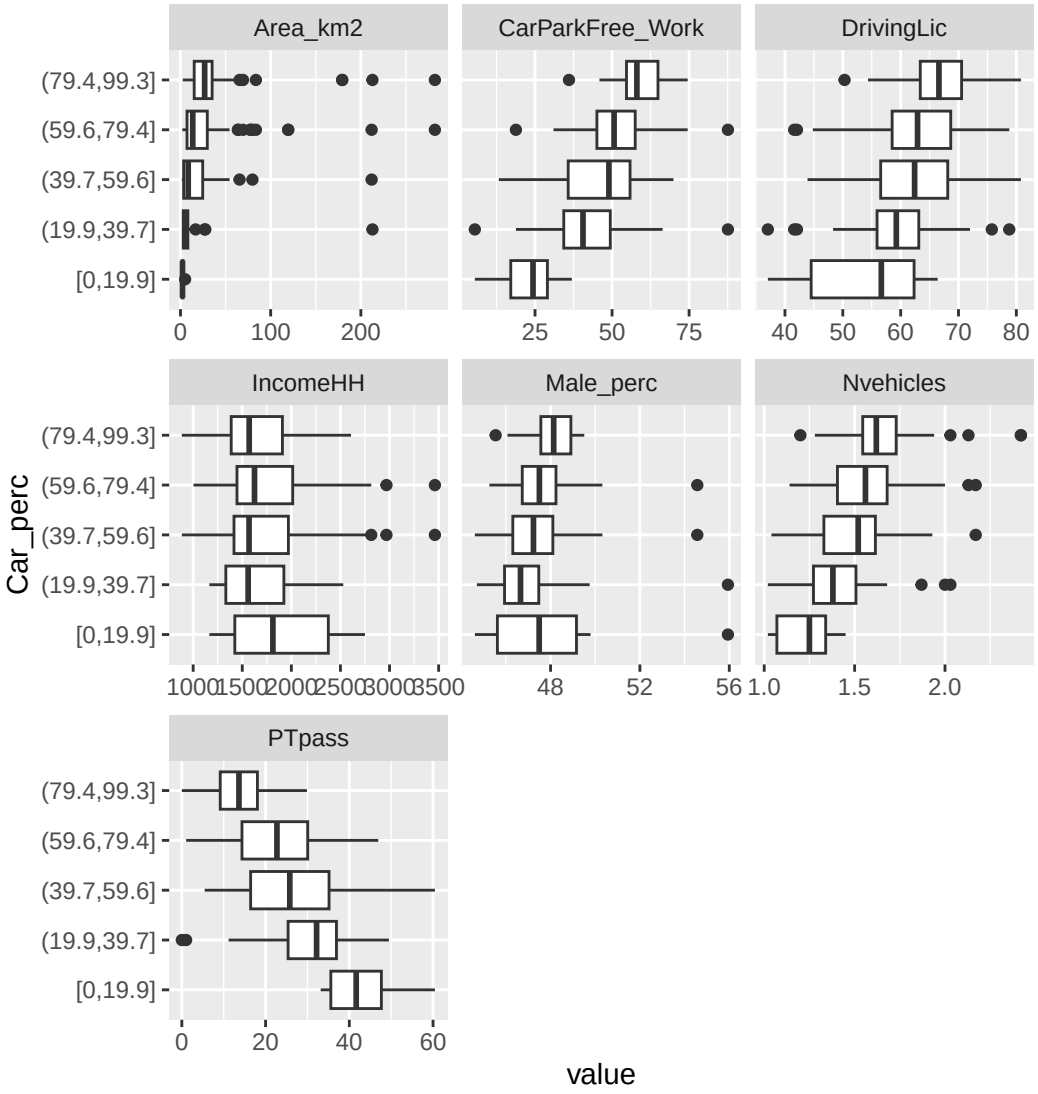

Bike
Car
Car_perc
Distance
Duration
IncomeHH
Male_perc
N_INDIVIDUOS
Other
PTransit
Total
Walk
Density
value
Page 1



Check how other variables are distributed regarding `Car_perc`

```
plot_boxplot(data, by = "Car_perc", ncol = 3)
```


Bike
Car
Distance
Duration
N_INDIVIDUOS
Other
PTransit
Total
Walk
Car_perc
(79.4,99.3]
(59.6,79.4]
(39.7,59.6]
(19.9,39.7]
[0,19.9]
value
Page 1



Note

When `Car_perc` increases, `PTpass` decreases.

Exercise

Try plotting the boxplots of each independent variable with `Car_perc`.

6.8. Correlations

Plot correlation heatmaps, between continuous variables.

```
# estimate correlation matrix
corrmat = cor(data_continuous, method = "pearson") |> round(2)
corrmat
```

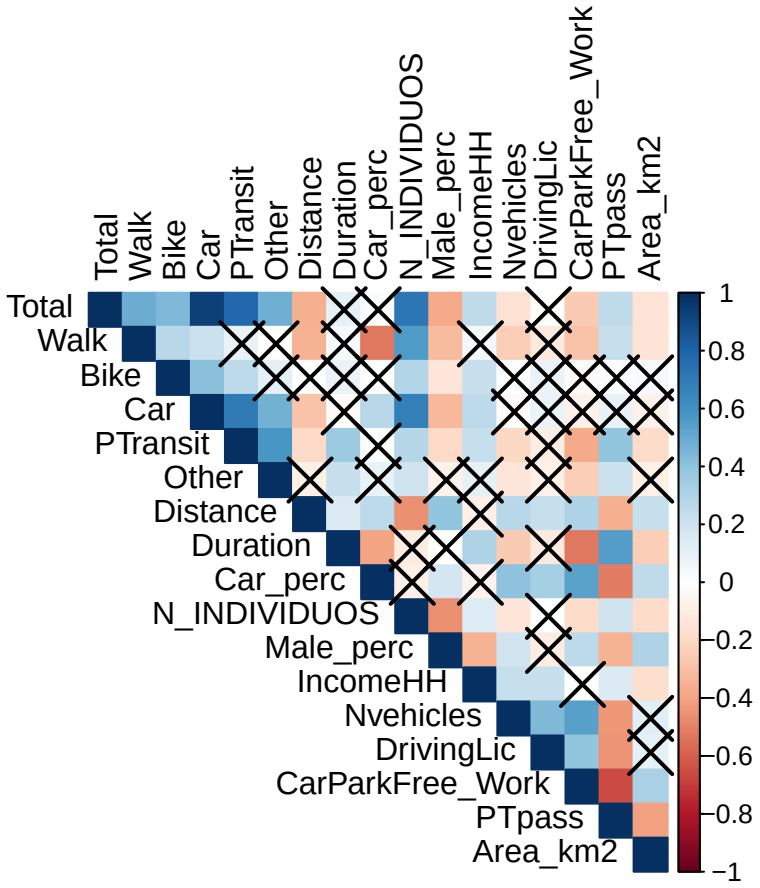
	Total	Walk	Bike	Car	PTransit	Other	Distance	Duration
Total	1.00	0.49	0.44	0.93	0.78	0.48	-0.36	0.10
Walk	0.49	1.00	0.27	0.21	0.09	-0.01	-0.34	0.03
Bike	0.44	0.27	1.00	0.41	0.26	0.11	0.00	0.08
Car	0.93	0.21	0.41	1.00	0.70	0.47	-0.29	-0.03
PTransit	0.78	0.09	0.26	0.70	1.00	0.58	-0.20	0.36
Other	0.48	-0.01	0.11	0.47	0.58	1.00	-0.09	0.22
Distance	-0.36	-0.34	0.00	-0.29	-0.20	-0.09	1.00	0.16
Duration	0.10	0.03	0.08	-0.03	0.36	0.22	0.16	1.00
Car_perc	0.01	-0.53	0.00	0.27	0.01	0.09	0.26	-0.40
N_INDIVIDUOS	0.72	0.56	0.29	0.68	0.28	0.20	-0.46	-0.11
Male_perc	-0.38	-0.32	-0.14	-0.33	-0.20	-0.08	0.39	-0.01
IncomeHH	0.25	0.04	0.22	0.26	0.23	0.10	-0.09	0.30
Nvehicles	-0.16	-0.25	0.00	-0.02	-0.21	-0.14	0.27	-0.26
DrivingLic	-0.01	-0.12	0.08	0.08	-0.10	-0.09	0.23	-0.12
CarParkFree_Work	-0.26	-0.29	-0.03	-0.08	-0.38	-0.25	0.30	-0.53
PTpass	0.25	0.23	0.01	0.09	0.39	0.21	-0.36	0.55
Area_km2	-0.15	-0.15	0.03	-0.08	-0.19	-0.09	0.23	-0.25

	Car_perc	N_INDIVIDUOS	Male_perc	IncomeHH	Nvehicles	DrivingLic
Total	0.01	0.72	-0.38	0.25	-0.16	-0.01
Walk	-0.53	0.56	-0.32	0.04	-0.25	-0.12
Bike	0.00	0.29	-0.14	0.22	0.00	0.08
Car	0.27	0.68	-0.33	0.26	-0.02	0.08
PTransit	0.01	0.28	-0.20	0.23	-0.21	-0.10
Other	0.09	0.20	-0.08	0.10	-0.14	-0.09
Distance	0.26	-0.46	0.39	-0.09	0.27	0.23
Duration	-0.40	-0.11	-0.01	0.30	-0.26	-0.12
Car_perc	1.00	-0.09	0.18	-0.07	0.40	0.33
N_INDIVIDUOS	-0.09	1.00	-0.46	0.14	-0.14	0.00
Male_perc	0.18	-0.46	1.00	-0.34	0.19	-0.11
IncomeHH	-0.07	0.14	-0.34	1.00	0.23	0.22
Nvehicles	0.40	-0.14	0.19	0.23	1.00	0.44
DrivingLic	0.33	0.00	-0.11	0.22	0.44	1.00
CarParkFree_Work	0.53	-0.19	0.26	-0.01	0.54	0.39
PTpass	-0.52	0.20	-0.34	0.16	-0.44	-0.45
Area_km2	0.25	-0.19	0.30	-0.18	0.12	0.10

	CarParkFree_Work	PTpass	Area_km2
Total	-0.26	0.25	-0.15
Walk	-0.29	0.23	-0.15
Bike	-0.03	0.01	0.03
Car	-0.08	0.09	-0.08
PTransit	-0.38	0.39	-0.19

```
Other                -0.25   0.21    -0.09
Distance              0.30  -0.36     0.23
Duration             -0.53   0.55    -0.25
Car_perc              0.53  -0.52     0.25
N_INDIVIDUOS         -0.19   0.20    -0.19
Male_perc             0.26  -0.34     0.30
IncomeHH             -0.01   0.16    -0.18
Nvehicles             0.54  -0.44     0.12
DrivingLic            0.39  -0.45     0.10
CarParkFree_Work      1.00  -0.66     0.32
PTpass               -0.66   1.00    -0.41
Area_km2              0.32  -0.41     1.00
```

```r
# store the results so you can call the p-value at the corrplot
res = cor.mtest(data_continuous, conf.level = .95)

corrplot(
  corrmat,
  method = "color", # or "circle"
  p.mat = res$p,
  sig.level = 0.05,
  type = "upper", # display only the upper triangular
  # order = "hclust", # order by hierarchical clustering
  tl.col = "black" # text label color
)
```

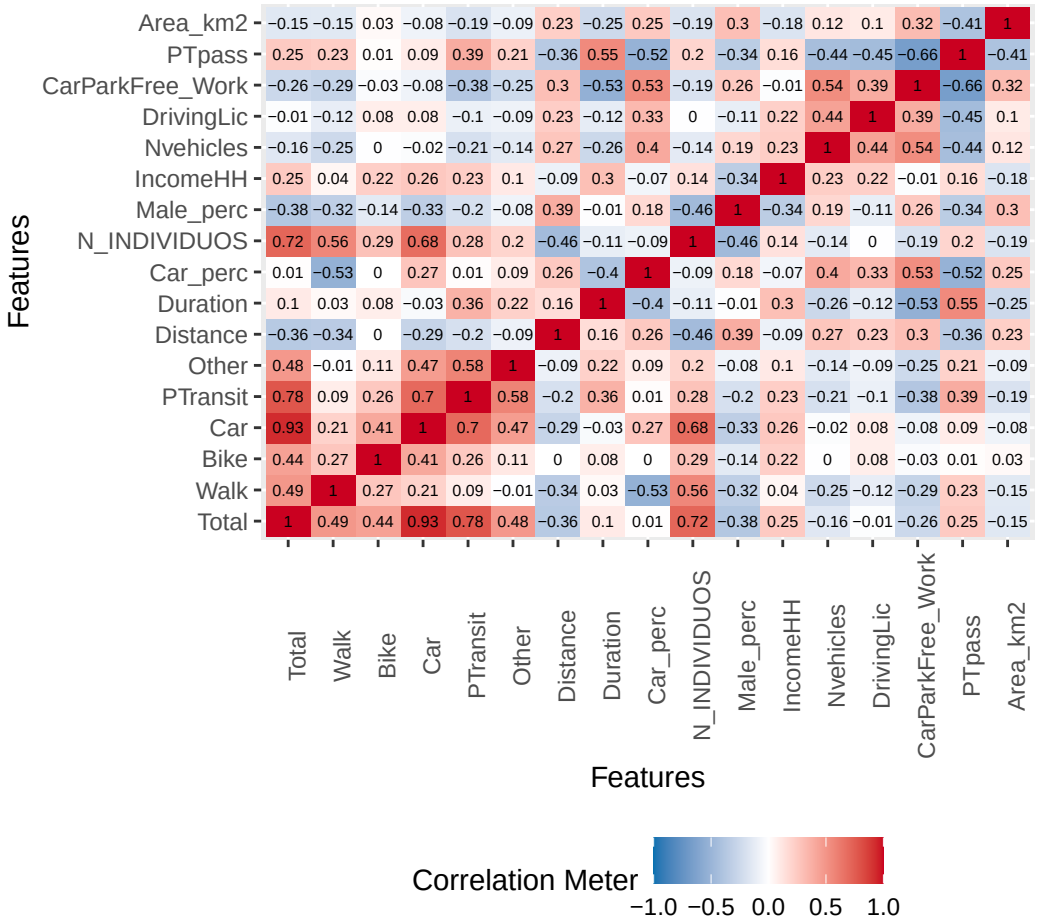


Note

The pairwise correlations that are crossed are statistically not significant. The null hypothesis (H_0) is that correlation is zero. The alternative hypothesis (H_A) is that correlation is not zero.
This means that the correlations are only significant when you reject the null hypothesis (p-value < 0.05).

Other method, using the `DataExplorer` package

```
plot_correlation(data_continuous)
```



Check the *p-value* of a crossed pair correlation:

```
cor.test(data$IncomeHH, data$Bike)
```

```
    Pearson's product-moment correlation

data:  data$IncomeHH and data$Bike
t = 3.5261, df = 234, p-value = 0.0005074
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.09977779 0.34249284
sample estimates:
      cor
0.2246163
```

```
cor.test(data$IncomeHH, data$Duration)
```

```
    Pearson's product-moment correlation

data:  data$IncomeHH and data$Duration
t = 4.817, df = 234, p-value = 2.62e-06
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.1795420 0.4122446
sample estimates:
     cor
0.300356
```

```
cor.test(data$Distance, data$Duration)
```

```
    Pearson's product-moment correlation

data:  data$Distance and data$Duration
t = 2.4605, df = 234, p-value = 0.0146
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.0317533 0.2808153
sample estimates:
      cor
0.1588098
```

The default for `cor.test` is Pearson, two-sided, with a 95% confident level. Check `?cor.test` for more options.

7. Multiple Linear Regression

Do it yourself with R

Copy the script MultipleLinarRegression.R and paste it in your session.
Run each line using `CTRL` + `ENTER`

! Your task

Estimate a linear regression model that predicts the car percentage per district.

7.1. Load packages

```
library(tidyverse) # Pack of most used libraries for data science
library(skimr) # summary of the data
library(DataExplorer) # exploratory data analysis
library(corrplot) # correlation plots

library(car) # Testing autocorrelation (Durbin Watson)
library(olsrr) # Testing multicollinearity (VIF, TOL, etc.)
```

7.2. Dataset

The database used in this example is a treated database from the Mobility Survey for the metropolitan areas of Lisbon in 2018 (INE 2018).

Included **variables**:

- `Origin_dicofre16` - Code of Freguesia (district) as set by INE after 2016 (Distrito + Concelho + Freguesia), for trip origin
- `Total` - number of trips with origin at each district
- `Walk` - number of walking trips
- `Bike` - number of bike trips
- `Car` - number of car trips. Includes taxi and motorcycle.
- `PTransit` - number of Public Transit trips
- `Other` - number of other trips (truck, van, tractor, aviation)
- `Distance` - average trip distance (km)

- `Duration` - average trip duration (minutes)
- `Car_perc` - percentage of car trips
- `N_INDIVIDUOS` - number of residents (INE 2022)
- `Male_perc` - percentage of male residents (INE 2022)
- `IncomeHH` - average household income
- `Nvehicles` - average number of car/motorcycle vehicles in the household
- `DrivingLic` - percentage of car driving licence holders
- `CarParkFree_Work` - percentage of respondents with free car parking at the work location
- `PTpass` - percentage of public transit monthly pass holders
- `internal` - binary variable (factor). `Yes`: trip with same TAZ origin and destination, `No`: trips with different destination
- `Lisboa` - binary variable (factor). `Yes`: the district is part of Lisbon municipality, `No`: otherwise
- `Area_km2` - area of in `Origin_dicofre16`, in km^2

7.2.1. Import dataset

```
data = readRDS("../data/IMOBmodel.Rds")
data_continuous = data |> select(-Origin_dicofre16, -internal, -Lisboa) #
    Exclude categorical variables
```

Show summary statistics

```
skim(data)
```

Table 7.1.: Data summary

Name	data
Number of rows	236
Number of columns	20
Column type frequency:	
character	1
factor	2
numeric	17
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
Origin_dicofre16	0	1	6	6	0	118	0

Variable type: factor

skim_variable	n_missing	complete_rate	ordered	n_unique	top_counts
internal	0	1	FALSE	2	Yes: 118, No: 118
Lisboa	0	1	FALSE	2	No: 188, Yes: 48

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
Total	0	1	22457.00	19084.45	361.00	5917.75	17474.00	33377.50	112186.00	
Walk	0	1	5383.44	6224.84	0.00	763.25	3125.00	8298.50	32646.00	
Bike	0	1	107.03	248.65	0.00	0.00	13.50	98.75	2040.00	
Car	0	1	13289.24	12351.61	0.00	3243.00	9008.00	21248.75	52631.00	
PTransit	0	1	3473.79	5467.82	0.00	249.00	1057.00	4853.00	41672.00	
Other	0	1	203.45	336.04	0.00	2.00	44.00	281.50	2391.00	
Distance	0	1	11.14	2.66	6.84	9.54	10.32	12.10	22.66	
Duration	0	1	25.42	3.91	16.30	23.00	24.70	27.73	37.42	
Car_perc	0	1	59.00	21.56	0.00	45.40	62.62	75.72	99.27	
N_INDIVIDUOS	0	1	24323.80	16438.04	1566.00	11060.00	20855.00	36079.00	68649.00	
Male_perc	0	1	47.54	1.57	44.61	46.58	47.50	48.29	55.94	
IncomeHH	0	1	1732.55	453.11	884.46	1417.76	1594.73	1953.50	3462.32	
Nvehicles	0	1	1.53	0.24	1.02	1.35	1.54	1.67	2.42	
DrivingLic	0	1	62.50	8.12	37.04	57.67	63.00	68.84	80.79	
CarParkFree_Work	0	1	49.30	14.30	5.47	40.39	50.51	57.92	87.60	
PTpass	0	1	23.82	12.87	0.00	13.41	22.72	32.94	60.45	
Area_km2	0	1	25.55	42.58	1.49	5.04	11.60	28.51	282.13	

The dependent variable is continuous.

7.3. Check the assumptions

Before running the model, you need to check if the assumptions are met.

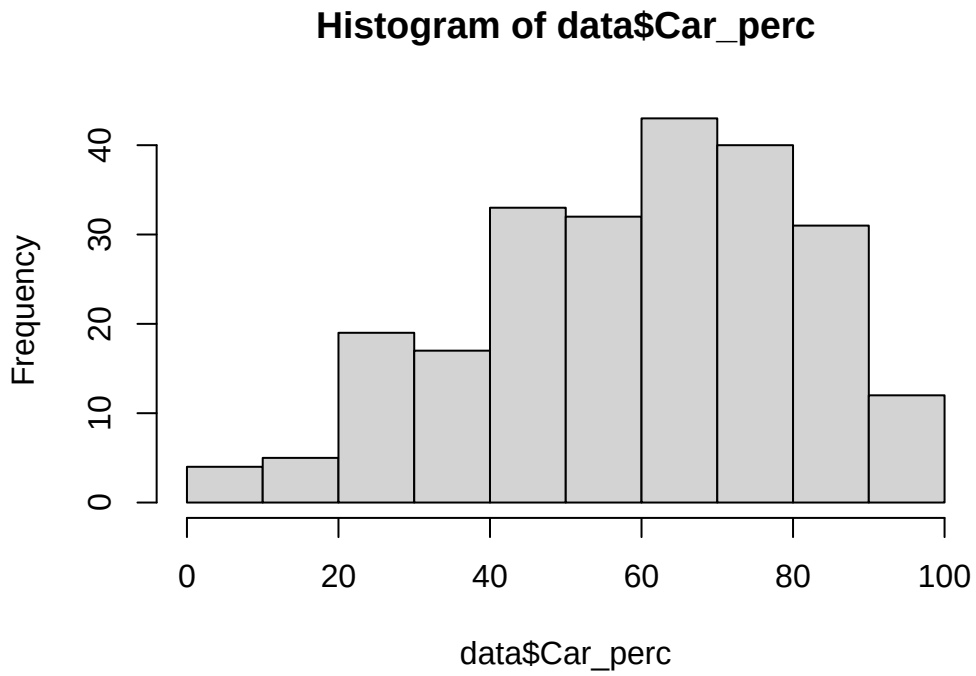
1. The dependent variable is normally distributed
2. Linear relationship between the dependent variable and the independent variables
3. No multicollinearity between independent variables (or only very little)
4. The observations are independent
5. Constant Variance (Assumption of Homoscedasticity)
6. Residuals are normally distributed

7.4. Assumption 1: Normal distribution

The Dependent Variable is be normally distributed.

Check the histogram of `Car_perc`:

```
hist(data$Car_perc)
```



If the sample is small (< 50 observations), we use **Shapiro-Wilk** test:

```
shapiro.test(data$Car_perc)
```

```
    Shapiro-Wilk normality test

data:  data$Car_perc
W = 0.97284, p-value = 0.0001709
```

If not, use the **Kolmogorov-Smirnov** test:

```
ks.test(
  data$Car_perc,
  "pnorm",
  mean = mean(data$Car_perc),
  sd = sd(data$Car_perc)
)
```

```
    Asymptotic one-sample Kolmogorov-Smirnov test

data:  data$Car_perc
D = 0.072477, p-value = 0.1675
alternative hypothesis: two-sided
```

The null hypothesis for both tests is that the distribution is normal. Therefore, for the distribution to be normal, the pvalue must be $>$ **0.05** and the null hypothesis is not rejected. From the output obtained we can assume normality.

7.5. Assumption 2: Linear relationship

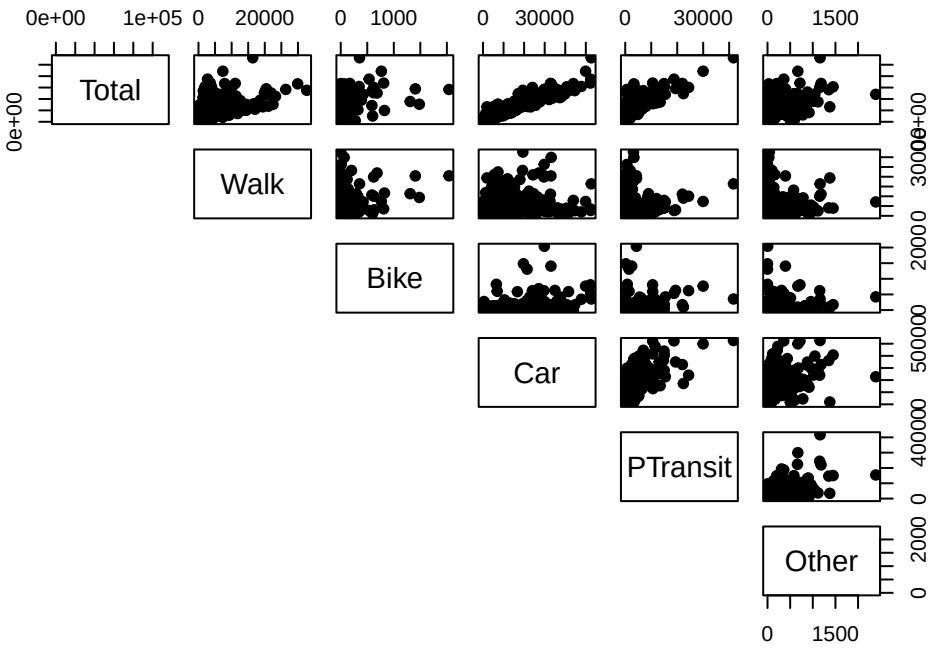
There is a linear relationship between dependent variable (DV) and independent variables (IV).

We can check this assumption by plotting scatterplots of the DV against each IV:

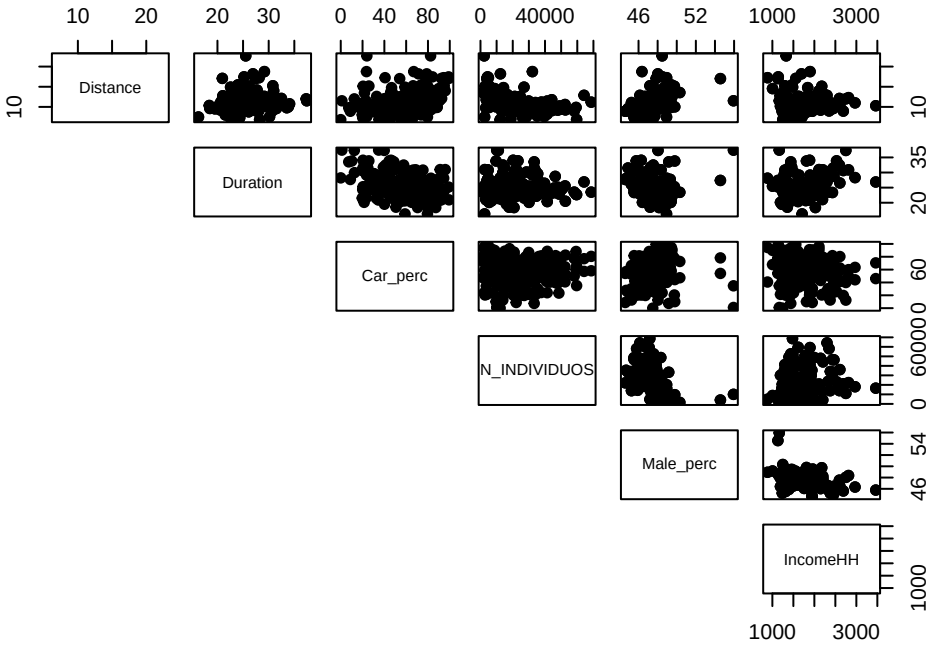
```
plot(x = data$Car_perc, y = data$Total, xlab = "Car_perc (%)", ylab =
    "Total (number of trips)")
plot(x = data$Car_perc, y = data$Walk, xlab = "Car_perc", ylab = "Walk")
plot(x = data$Car_perc, y = data$Bike, xlab = "Car_perc", ylab = "Bike")
plot(x = data$Car_perc, y = data$Car, xlab = "Car_perc", ylab = "Car")
plot(x = data$Car_perc, y = data$PTransit, xlab = "Car_perc", ylab =
    "PTransit")
plot(x = data$Car_perc, y = data$Other, xlab = "Car_perc", ylab = "Other")
plot(x = data$Car_perc, y = data$Distance, xlab = "Car_perc", ylab =
    "Distance")
plot(x = data$Car_perc, y = data$Duration, xlab = "Car_perc", ylab =
    "Duration")
plot(x = data$Car_perc, y = data$N_INDIVIDUOS, xlab = "Car_perc", ylab =
    "N_INDIVIDUOS")
plot(x = data$Car_perc, y = data$Male_perc, xlab = "Car_perc", ylab =
    "Male_perc")
plot(x = data$Car_perc, y = data$IncomeHH, xlab = "Car_perc", ylab =
    "IncomeHH")
plot(x = data$Car_perc, y = data$Nvehicles, xlab = "Car_perc", ylab =
    "Nvehicles")
plot(x = data$Car_perc, y = data$DrivingLic, xlab = "Car_perc", ylab =
    "Driving License")
plot(x = data$Car_perc, y = data$CarParkFree_Work, xlab = "Car_perc", ylab
    = "Free car parking at work")
plot(x = data$Car_perc, y = data$PTpass, xlab = "Car_perc", ylab =
    "PTpass")
plot(x = data$Car_perc, y = data$internal, xlab = "Car_perc", ylab =
    "internal trips")
plot(x = data$Car_perc, y = data$Lisboa, xlab = "Car_perc", ylab =
    "Lisboa")
plot(x = data$Car_perc, y = data$Area_km2, xlab = "Car_perc", ylab =
    "Area_km2")
```

Or you can make a pairwise scatterplot matrix, that compares every variable with each other:

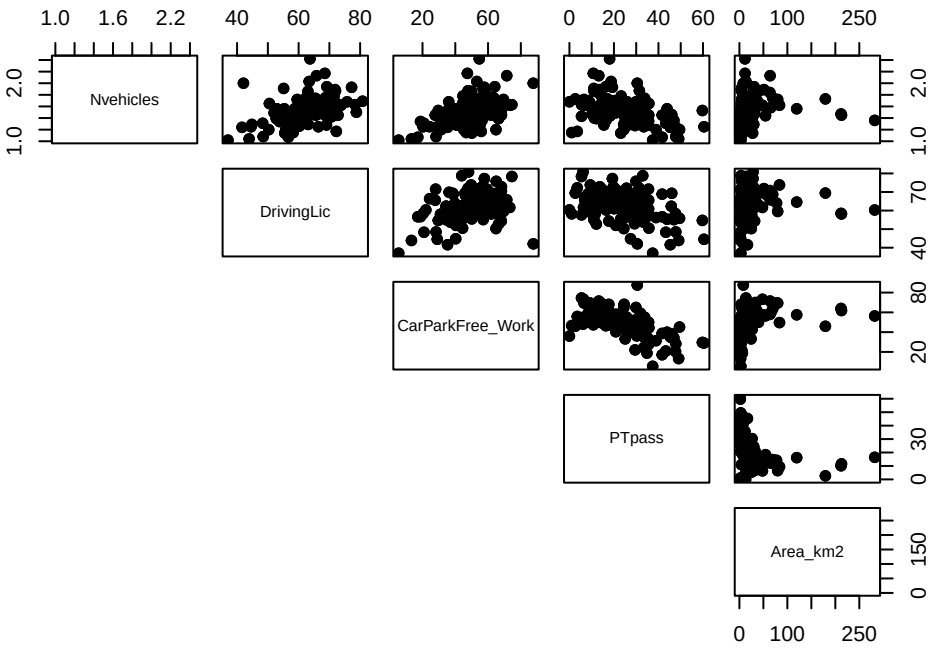
```
# pairs(data_continuous, pch = 19, lower.panel = NULL) # we have too many
    variables, let's split the plots
pairs(data_continuous[,1:6], pch = 19, lower.panel = NULL)
```




```
pairs(data_continuous[,7:12], pch = 19, lower.panel = NULL)
```



```
pairs(data_continuous[,13:17], pch = 19, lower.panel = NULL)
```



7.6. Assumption 3: No multicollinearity

Check the correlation plot before choosing the variables.

7.6.1. Declare the model

Use CTRL + SHIFT + C to comment/uncomment lines (variables)

```
# names(data) # to see the names of the variables

model = lm(
  Car_perc ~
    Total +
    Walk +
    Bike +
    Car +
    PTransit +
    Other +
    Distance +
    Duration +
    N_INDIVIDUOS +
    Male_perc +
```

```
    IncomeHH +
    Nvehicles +
    DrivingLic +
    CarParkFree_Work +
    PTpass +
    internal +
    Lisboa +
    Area_km2,
  data = data
)

summary(model)
```

```
Call:
lm(formula = Car_perc ~ Total + Walk + Bike + Car + PTransit +
    Other + Distance + Duration + N_INDIVIDUOS + Male_perc +
    IncomeHH + Nvehicles + DrivingLic + CarParkFree_Work + PTpass +
    internal + Lisboa + Area_km2, data = data)

Residuals:
    Min      1Q  Median      3Q     Max
-37.952  -4.907  -0.232   5.305  39.157

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)       4.047e+00  3.192e+01   0.127  0.89923
Total             1.633e-01  3.671e-01   0.445  0.65700
Walk             -1.640e-01  3.671e-01  -0.447  0.65552
Bike             -1.614e-01  3.669e-01  -0.440  0.66044
Car              -1.627e-01  3.671e-01  -0.443  0.65806
PTransit         -1.640e-01  3.672e-01  -0.447  0.65552
Other            -1.622e-01  3.671e-01  -0.442  0.65897
Distance          6.004e-01  3.629e-01   1.654  0.09948 .
Duration         -3.244e-01  3.325e-01  -0.976  0.33032
N_INDIVIDUOS     -6.627e-05  8.876e-05  -0.747  0.45612
Male_perc         2.723e-01  6.151e-01   0.443  0.65849
IncomeHH         -5.218e-04  2.199e-03  -0.237  0.81264
Nvehicles         7.301e+00  3.959e+00   1.844  0.06650 .
DrivingLic        2.910e-01  1.161e-01   2.506  0.01294 *
CarParkFree_Work  1.943e-01  7.882e-02   2.465  0.01449 *
PTpass           -8.254e-02  9.989e-02  -0.826  0.40956
internalNo        1.962e+01  2.136e+00   9.182  < 2e-16 ***
LisboaYes        -9.647e+00  3.182e+00  -3.031  0.00273 **
Area_km2          1.689e-02  1.860e-02   0.908  0.36486
---
```

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

Residual standard error: 10.59 on 217 degrees of freedom
Multiple R-squared:  0.7772,    Adjusted R-squared:  0.7587
F-statistic: 42.06 on 18 and 217 DF,  p-value: < 2.2e-16
```

7.6.2. Assessing the model

1. First check the **pvalue** and the **F statistics** of the model to see if there is any statistical relation between the dependent variable and the independent variables. If pvalue < 0.05 and the F statistics $>$ Fcritical $= 2.39$, then the model is statistically acceptable.
2. The **R-square** and **Adjusted R-square** evaluate the amount of variance that is explained by the model. The difference between one and another is that the R-square does not consider the number of variables. If you increase the number of variables in the model, the R-square will tend to increase which can lead to overfitting. On the other hand, the Adjusted R-square adjust to the number of independent variables.
3. Take a look at the **t-value** and the Pr(>|t|). If the t-value > 1.96 or Pr(>|t|) $<$ 0.05, then the IV is statistically significant to the model.
4. To analyse the **estimates** of the variables, you should first check the **signal** and assess if the independent variable has a direct or inverse relationship with the dependent variable. It is only possible to evaluate the **magnitude** of the estimate if all variables are continuous and standardized or by calculating the elasticities. Do not forget to access the **Intercept**...

We can see from the output that the R-squared value for the model (with ALL variables) is **0.7772**. We can also see that the overall F-statistic is **42.06** and the corresponding p-value is **<2.2e-16**, which indicates that the overall regression model is significant. Also, the predictor variables `DrivingLic` and `CarParkFree_Work`, `internal(No)` and `Lisboa(Yes)` are statistically significant at the 0.05 significance level.

> **Your turn**
>
> Now try to remove some variables from the model and assess it again. Elaborate a justification to exclude those variables.

7.6.3. Calculate the Variance Inflation Factor (VIF)

We use the `vif()` function from the car package to calculate the VIF for each predictor variable in the model:

```
car::vif(model)
```

```
       Total             Walk             Bike              Car
1.028324e+08     1.094004e+07     1.743544e+04     4.307486e+07
    PTransit            Other         Distance         Duration
8.443136e+06     3.186972e+04     1.957062e+00     3.544018e+00
N_INDIVIDUOS        Male_perc         IncomeHH        Nvehicles
4.459671e+00     1.961472e+00     2.079348e+00     1.882275e+00
  DrivingLic CarParkFree_Work           PTpass         internal
1.863227e+00     2.660375e+00     3.464699e+00     2.400178e+00
      Lisboa         Area_km2
3.451852e+00     1.313708e+00
```

A common rule of thumb is that a VIF value greater than 5 indicates a high level of multicollinearity among the predictor variables, which is potentially concerning.

7.6.4. Condition index

Condition index is another diagnostic tool for detecting multicollinearity, with values above 10 indicating moderate multicollinearity and values above 30 indicating severe multicollinearity. You will learn how to to that in the next class: Factor analysis.

7.7. Assumption 4: Independence of observations

Multiple linear regression assumes that each observation in the dataset is independent.

The error (E) is independent across observations and the error variance is constant across IV

The simplest way to determine if this assumption is met is to perform a Durbin-Watson test, which is a formal statistical test that tells us whether or not the **residuals** (and thus the **observations**) exhibit autocorrelation.

```
durbinWatsonTest(model)
```

```
 lag Autocorrelation D-W Statistic p-value
   1      0.07881007      1.840798   0.116
 Alternative hypothesis: rho != 0
```

> **Note**
>
> In the Durbin-Watson test, values of the D-W Statistic vary from 0 to 4.
> If the values are from 1.8 to 2.2 this means that there is **no autocorrelation** in the model.

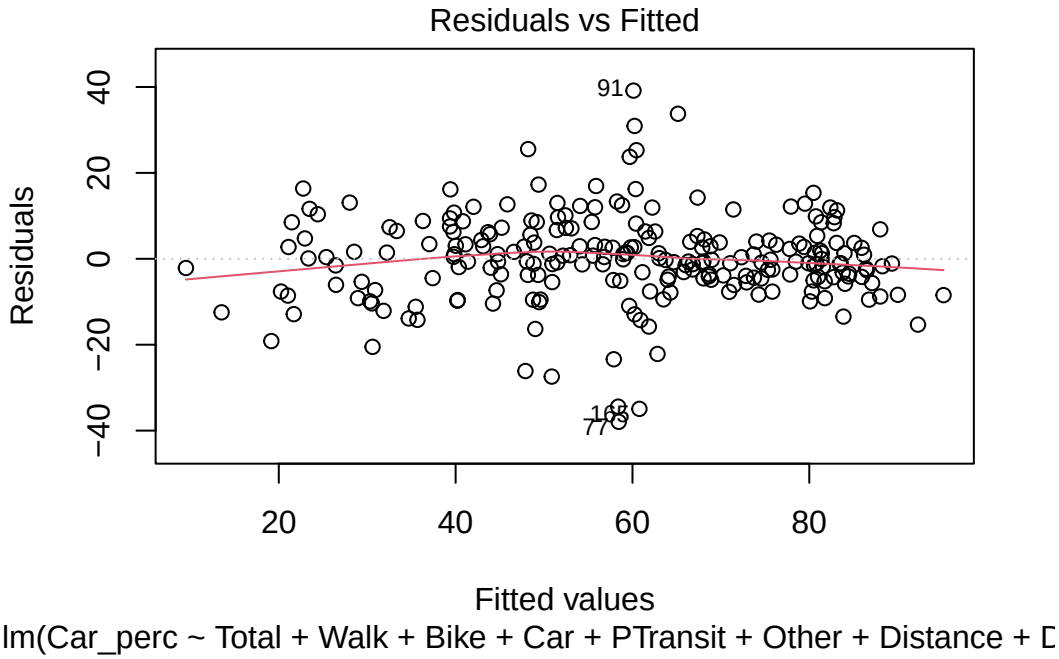
H_0 (null hypothesis): There is no correlation among the residuals. Since p-value > 0.05, we do not reject the null hypothesis and we can not discard that there is autocorrelation in the model.

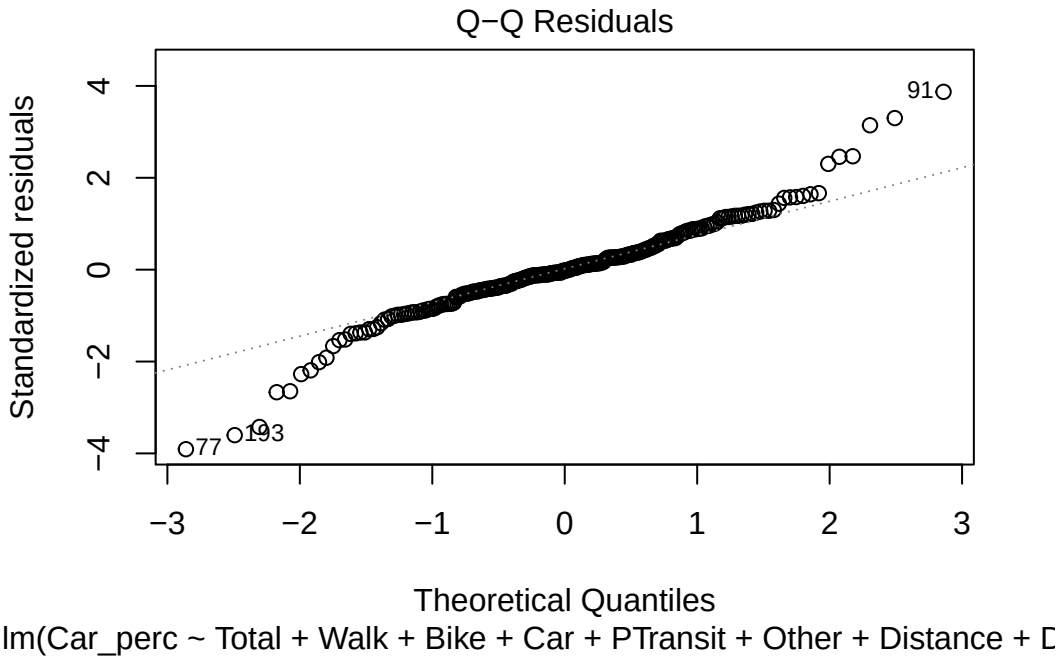
If the observations are not independent, you may consider to treat the observarions as a panel data.

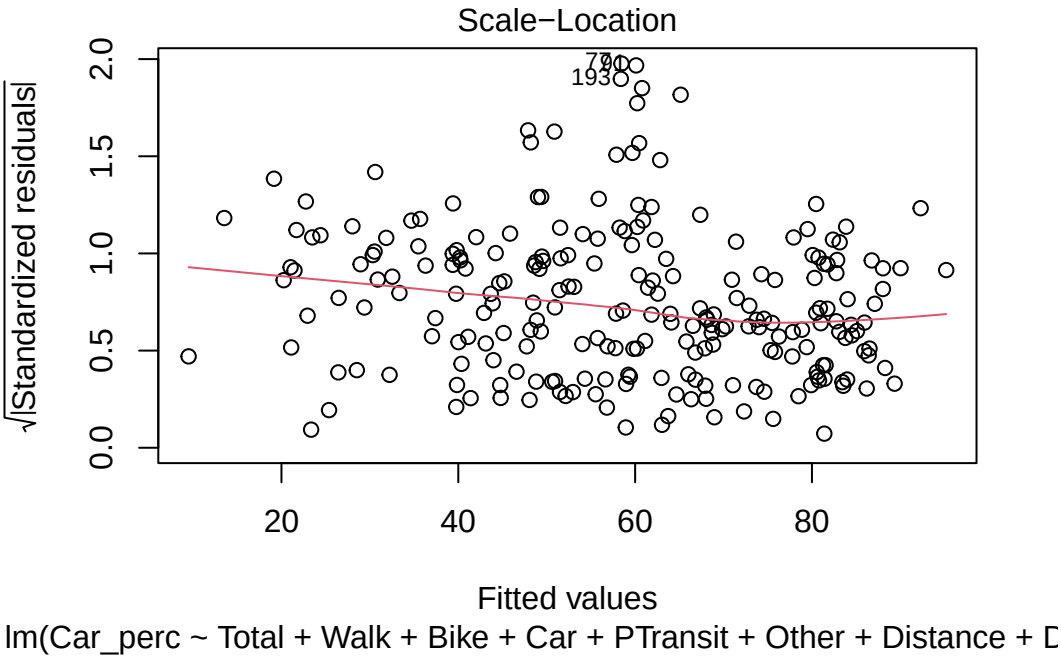
7.8. Assumption 5: Constant Variance (Homoscedasticity)

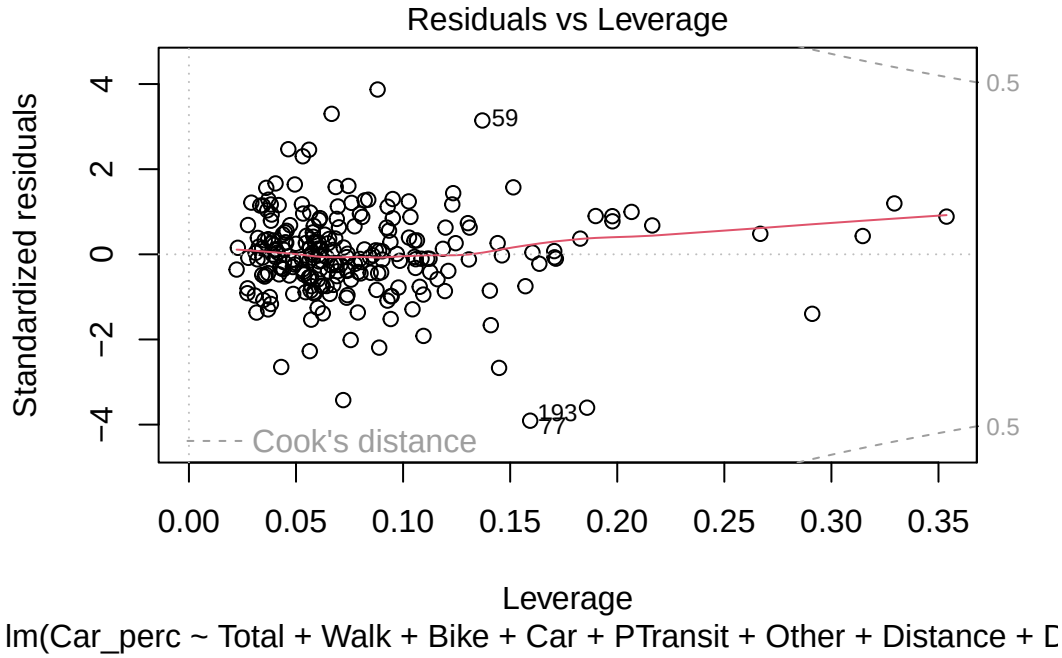
The simplest way to determine if this assumption is met is to create a plot of standardized residuals versus predicted values.

```
plot(model)
```




Q−Q Residuals
Standardized residuals
Theoretical Quantiles
lm(Car_perc ~ Total + Walk + Bike + Car + PTransit + Other + Distance + D
91
77
193


Scale−Location
√|Standardized residuals|
Fitted values
lm(Car_perc ~ Total + Walk + Bike + Car + PTransit + Other + Distance + D
193



For the Residuals, check the following **assumptions**:

- **Residuals vs Fitted:** This plot is used to detect non-linearity, heteroscedasticity, and outliers.
- **Normal Q-Q:** The quantile-quantile (Q-Q) plot is used to check if the disturbances follow a normal distribution
- **Scale-Location:** This plot is used to verify if the residuals are spread equally (homoscedasticity) or not (heteroscedasticity) through the sample.
- **Residuals vs Leverage:** This plot is used to detect the impact of the outliers in the model. If the outliers are outside the Cook-distance, this may lead to serious problems in the model.

Try analyzing the plots and check if the model meets the assumptions.

7.9. Assumption 6: Residuals are normally distributed

Assess the Q-Q Residuals plot above. When the residuals clearly depart from a straight diagonal line, it indicates that they do not follow a normal distribution.

Use a formal statistical test like Shapiro-Wilk or Kolmogorov-Smironov to validate those results.

8. Factor Analysis

Do it yourself with R

Copy the script `FactorAnalysis.R` and paste it in your session.
Run each line using `CTRL` + `ENTER`

This exercise is based on the paper "**Residential location satisfaction in the Lisbon metropolitan area**", by Martinez, Abreu e Silva, and Viegas (2010) .

The aim of this study was to examine the perception of households towards their residential location considering land use and accessibility factors, as well as household socio-economic and attitudinal characteristics.

! Your task

Create meaningful latent factors.

8.1. Load packages

```
library(tidyverse) # Pack of most used libraries for data science
library(summarytools) # Summary of the dataset
library(foreign) # Read SPSS files
library(nFactors) # Factor analysis
library(GPArotation) # GPA Rotation for Factor Analysis
library(psych) # Personality, psychometric, and psychological research
```

8.2. Dataset

Included **variables**:

- `RespondentID` - ID of the respondent
- `DWELCLAS` - Classification of the dwelling
- `INCOME` - Income of the household
- `CHILD13` - Number of children under 13 years old
- `H18` - Number of household members over 18 years old
- `HEMPLOY` - Number of household members employed

- `HSIZE` - Household size
- `IAGE` - Age of the respondent
- `ISEX` - Sex of the respondent
- `NCARS` - Number of cars in the household
- `AREA` - Area of the dwelling
- `BEDROOM` - Number of bedrooms in the dwelling
- `PARK` - Number of parking spaces in the dwelling
- `BEDSIZE` - BEDROOM/HSIZE
- `PARKSIZE` - PARK/NCARS
- `RAGE10` - 1 if Dwelling age <= 10
- `TCBD` - Private car distance in time to CBD
- `DISTTC` - Euclidean distance to heavy public transport system stops
- `TWCBD` - Private car distance in time of workplace to CBD
- `TDWWK` - Private car distance in time of dwelling to work place
- `HEADH` - 1 if Head of the Household
- `POPDENS` - Population density per hectare
- `EQUINDEX` - Number of undergraduate students/Population over 20 years old (500m)

8.2.1. Import dataset

```
data = read.spss("../data/example_fact.sav", to.data.frame = T)
```

8.2.2. Get to know your dataset

Take a look at the first values of the dataset

```
head(data, 5)
```

```
  RespondentID DWELCLAS INCOME CHILD13 H18 HEMPLOY HSIZE AVADUAGE IAGE ISEX
1    799161661        5   7500       1   2       2     3 32.00000   32    1
2    798399409        6   4750       0   1       1     1 31.00000   31    1
3    798374392        6   4750       2   2       2     4 41.50000   42    0
4    798275277        5   7500       0   3       2     4 44.66667   52    1
5    798264250        6   2750       1   1       1     2 33.00000   33    0
  NCARS AREA BEDROOM PARK   BEDSIZE PARKSIZE RAGE10      TCBD   DISTHTC
1     2  100       2    1 0.6666667      0.5      1 36.791237  629.1120
2     1   90       2    1 2.0000000      1.0      0 15.472989  550.5769
3     2  220       4    2 1.0000000      1.0      1 24.098125  547.8633
4     3  120       3    0 0.7500000      0.0      0 28.724796 2350.5782
5     1   90       2    0 1.0000000      0.0      0  7.283384  698.3000
      TWCBD    TDWWK HEADH   POPDENS   EDUINDEX   GRAVCPC   GRAVCPT  GRAVPCPT
1 10.003945 31.14282     1  85.70155 0.06406279 0.2492962 0.2492607 1.0001423
2 15.502989  0.00000     1 146.43494 0.26723192 0.3293831 0.3102800 1.0615674
```

```
3 12.709374 20.38427     1 106.60810 0.09996816 0.2396229 0.2899865 0.8263245
4  3.168599 32.94246     1  36.78380 0.08671065 0.2734539 0.2487830 1.0991661
5  5.364160 13.04013     1 181.62720 0.13091674 0.2854017 0.2913676 0.9795244
  NSTRTC    DISTHW    DIVIDX    ACTDENS   DISTCBD
1     38 2036.4661 0.3225354  0.6722406  9776.142
2     34  747.7683 0.3484588  2.4860345  3523.994
3     33 2279.0577 0.3237884  1.6249059 11036.407
4      6 1196.4665 0.3272149  1.7664923  6257.262
5     31 3507.2402 0.3545181 11.3249309  1265.239
```

```
View(data) # open in table
```

Make the `RespondentID` variable as **row names** or case number

```
data = data |> column_to_rownames(var = "RespondentID")
```

Take a look at the main characteristics of the dataset

```
str(data)
```

```
'data.frame':   470 obs. of  31 variables:
 $ DWELCLAS: num  5 6 6 5 6 6 4 2 6 5 ...
 $ INCOME  : num  7500 4750 4750 7500 2750 1500 12500 1500 1500 1500 ...
 $ CHILD13 : num  1 0 2 0 1 0 0 0 0 0 ...
 $ H18     : num  2 1 2 3 1 3 3 4 1 1 ...
 $ HEMPLOY : num  2 1 2 2 1 2 0 2 1 1 ...
 $ HSIZE   : num  3 1 4 4 2 3 3 4 1 1 ...
 $ AVADUAGE: num  32 31 41.5 44.7 33 ...
 $ IAGE    : num  32 31 42 52 33 47 62 21 34 25 ...
 $ ISEX    : num  1 1 0 1 0 1 1 0 0 0 ...
 $ NCARS   : num  2 1 2 3 1 1 2 3 1 1 ...
 $ AREA    : num  100 90 220 120 90 100 178 180 80 50 ...
 $ BEDROOM : num  2 2 4 3 2 2 5 3 2 1 ...
 $ PARK    : num  1 1 2 0 0 0 2 0 0 1 ...
 $ BEDSIZE : num  0.667 2 1 0.75 1 ...
 $ PARKSIZE: num  0.5 1 1 0 0 0 1 0 0 1 ...
 $ RAGE10  : num  1 0 1 0 0 0 0 0 1 1 ...
 $ TCBD    : num  36.79 15.47 24.1 28.72 7.28 ...
 $ DISTHTC : num  629 551 548 2351 698 ...
 $ TWCBD   : num  10 15.5 12.71 3.17 5.36 ...
 $ TDWWK   : num  31.1 0 20.4 32.9 13 ...
 $ HEADH   : num  1 1 1 1 1 1 1 0 1 1 ...
 $ POPDENS : num  85.7 146.4 106.6 36.8 181.6 ...
 $ EDUINDEX: num  0.0641 0.2672 0.1 0.0867 0.1309 ...
 $ GRAVCPC : num  0.249 0.329 0.24 0.273 0.285 ...
```

```
$ GRAVCPT : num  0.249 0.31 0.29 0.249 0.291 ...
$ GRAVPCPT: num  1 1.062 0.826 1.099 0.98 ...
$ NSTRTC  : num  38 34 33 6 31 45 12 6 4 22 ...
$ DISTHW  : num  2036 748 2279 1196 3507 ...
$ DIVIDX  : num  0.323 0.348 0.324 0.327 0.355 ...
$ ACTDENS : num  0.672 2.486 1.625 1.766 11.325 ...
$ DISTCBD : num  9776 3524 11036 6257 1265 ...
- attr(*, "variable.labels")= Named chr(0)
 ..- attr(*, "names")= chr(0)
- attr(*, "codepage")= int 1252
```

Check summary statistics of variables

```
skimr::skim(data)
```

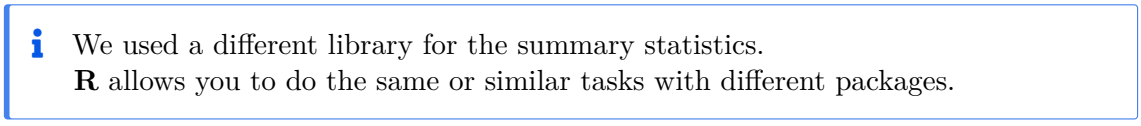
Table 8.1.: Data summary

Name	data
Number of rows	470
Number of columns	31
Column type frequency:	
numeric	31
Group variables	None

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
DWELCLAS	0	1	5.15	1.28	1.00	4.00	5.00	6.00	7.00	
INCOME	0	1	4259.57	3001.82	700.00	2750.00	2750.00	4750.00	12500.00	
CHILD13	0	1	0.40	0.78	0.00	0.00	0.00	0.00	4.00	
H18	0	1	2.11	0.93	0.00	2.00	2.00	2.75	6.00	
HEMPLOY	0	1	1.53	0.74	0.00	1.00	2.00	2.00	5.00	
HSIZE	0	1	2.58	1.25	1.00	2.00	2.00	4.00	7.00	
AVADUAGE	0	1	37.79	9.94	0.00	30.33	36.00	43.00	78.00	
IAGE	0	1	36.89	11.59	0.00	28.00	34.00	43.00	78.00	
ISEX	0	1	0.54	0.50	0.00	0.00	1.00	1.00	1.00	
NCARS	0	1	1.71	0.89	0.00	1.00	2.00	2.00	5.00	
AREA	0	1	132.96	121.54	30.00	90.00	110.00	150.00	2250.00	
BEDROOM	0	1	2.88	1.07	0.00	2.00	3.00	3.00	7.00	
PARK	0	1	0.83	0.97	0.00	0.00	1.00	1.00	4.00	
BEDSIZE	0	1	1.35	0.80	0.00	0.80	1.00	1.50	5.00	
PARKSIZE	0	1	0.47	0.57	0.00	0.00	0.25	1.00	3.00	
RAGE10	0	1	0.24	0.43	0.00	0.00	0.00	0.00	1.00	
TCBD	0	1	24.70	16.24	0.78	9.95	23.81	35.70	73.28	
DISTHTC	0	1	1346.98	1815.78	49.05	400.47	719.04	1525.45	17732.68	
TWCBD	0	1	17.00	16.24	0.31	5.25	9.86	25.27	67.82	
TDWWK	0	1	23.53	17.09	0.00	10.14	22.18	33.72	80.72	
HEADH	0	1	0.86	0.34	0.00	1.00	1.00	1.00	1.00	
POPDENS	0	1	92.00	58.20	0.00	45.86	83.17	135.01	255.55	
EDUINDEX	0	1	0.20	0.12	0.00	0.10	0.17	0.28	0.66	
GRAVCPC	0	1	0.29	0.07	0.07	0.25	0.31	0.34	0.39	
GRAVCPT	0	1	0.26	0.06	0.03	0.22	0.28	0.31	0.37	
GRAVPCPT	0	1	1.15	0.32	0.45	1.00	1.09	1.22	2.88	
NSTRTC	0	1	22.22	12.62	0.00	14.00	22.00	30.00	84.00	
DISTHW	0	1	1883.41	1748.30	74.67	712.79	1338.74	2533.30	16590.06	
DIVIDX	0	1	0.38	0.08	0.26	0.32	0.35	0.40	0.65	
ACTDENS	0	1	5.78	8.51	0.02	1.32	2.49	4.85	63.18	
DISTCBD	0	1	7967.41	7442.86	148.93	2025.26	5542.34	11803.20	44004.60	

```
# print(dfSummary(data), method = "render")
```



We used a different library for the summary statistics.
R allows you to do the same or similar tasks with different packages.

8.3. Assumptions for factoral analysis

There are some rules of thumb and assumptions that should be checked before performing a factor analysis.

Rules of thumb:

- At least 10 variables
- n $<$ 50 (Unacceptable); n $>$ 200 (recommended)
- It is recommended to use continuous variables. If your data contains categorical variables, you should transform them to dummy variables.

As we have 31 variables (none categorical) and more than 200 observations, we can proceed to check the assumptions.

Assumptions:

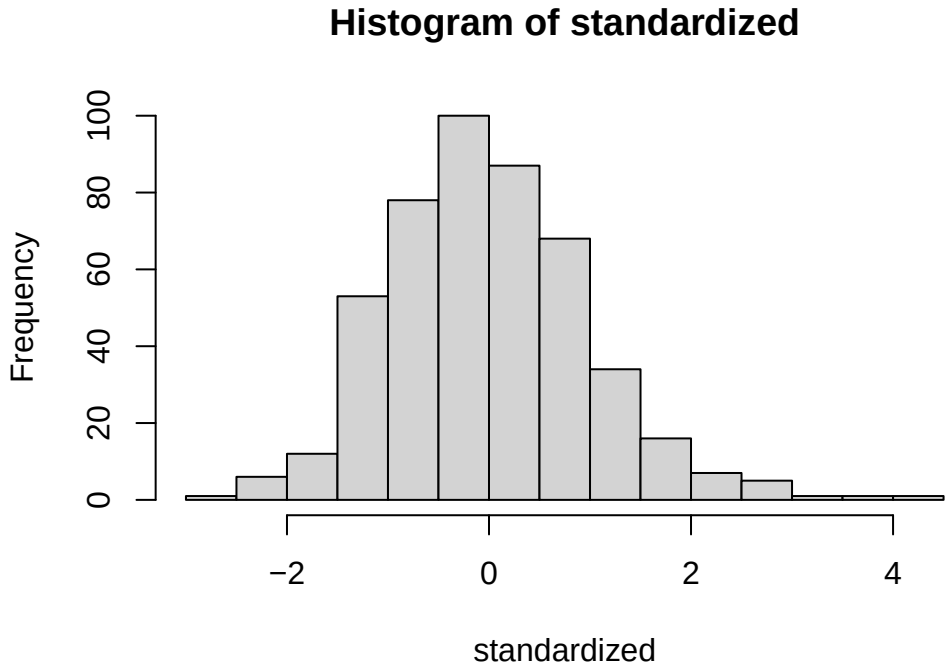
- Normality;
- Linearity;
- Homogeneity;
- Homoscedasticity (some multicollinearity is desirable);
- Correlations between variables $<$ 0.3 are not appropriate to use Factor Analysis

Let's run a random regression model in order to evaluate some of the assumptions.

```
# random regression model
random = rchisq(nrow(data), ncol(data))
fake = lm(random ~ ., data = data)
standardized = rstudent(fake)
fitted = scale(fake$fitted.values)
```

8.3.1. Normality

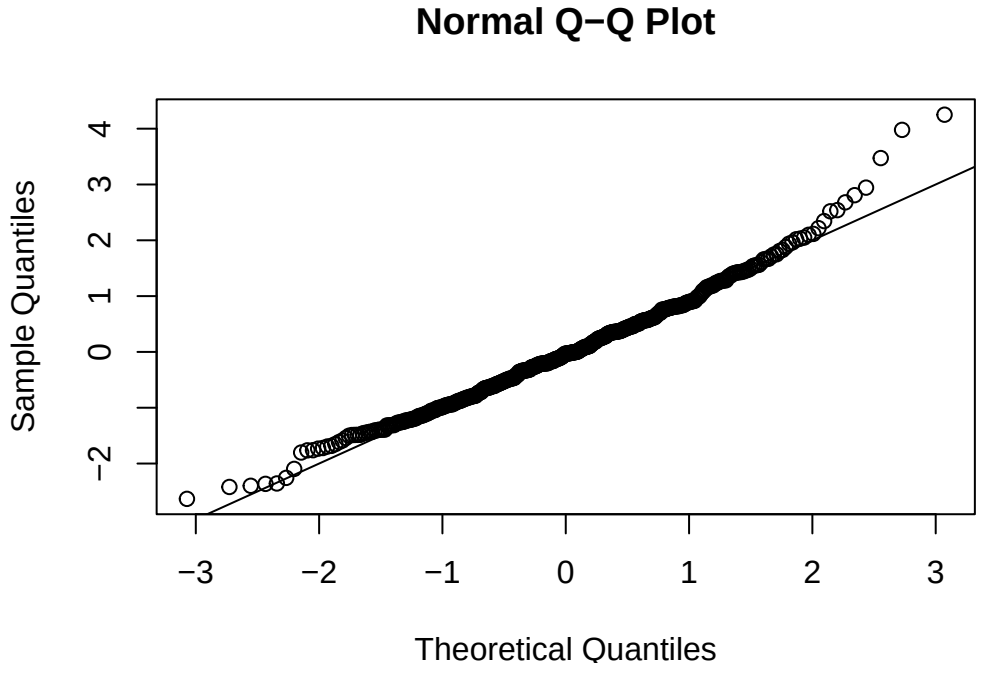
```
hist(standardized)
```



The histogram looks like a normal distribution.

8.3.2. Linearity

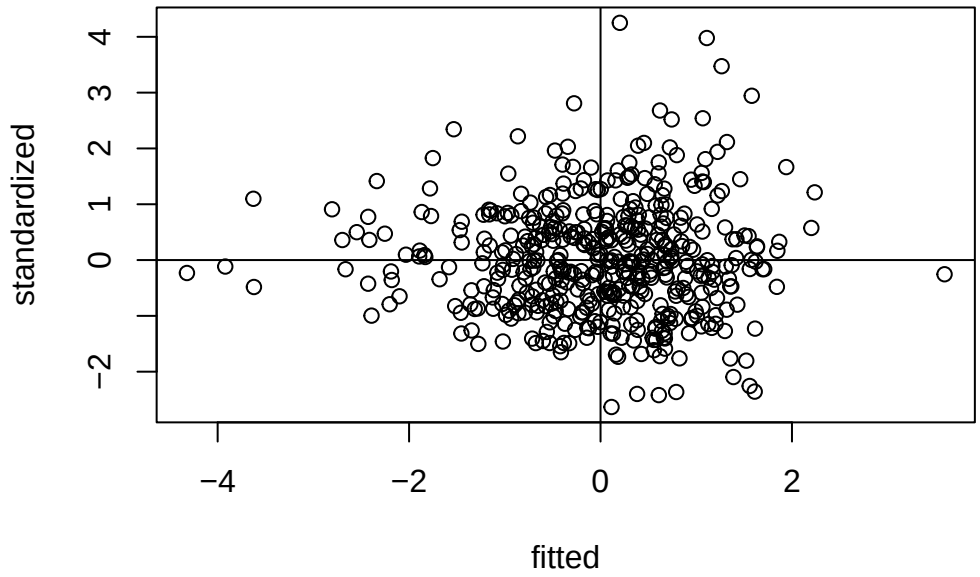
```
qqnorm(standardized)
abline(0, 1)
```



The QQ plot shows that the points are close to the diagonal line, indicating linearity.

8.3.3. Homogeneity

```
plot(fitted, standardized)
abline(h=0, v=0)
```



The residuals are randomly distributed around zero, indicating homogeneity.

8.3.4. Correlations between variables

Correlation matrix

```
corr_matrix = cor(data, method = "pearson")
```

The **Bartlett's test** examines if there is equal variance (homogeneity) between variables. Thus, it evaluates if there is any pattern between variables.

8.3.4.1. Correlation adequacy

Check for correlation adequacy - Bartlett's Test

```
cortest.bartlett(corr_matrix, n = nrow(data))
```

```
$chisq
[1] 9880.074

$p.value
[1] 0

$df
[1] 465
```

The null hypothesis is that there is no correlation between variables. Therefore, you want to **reject** the null hypothesis.

> **Note:** A p-value < 0.05 indicates that there are correlations between variables, and that **factor analysis** may be useful with your data.

8.3.4.2. Sampling adequacy

Check for sampling adequacy - KMO test

```
KMO(corr_matrix)
```

```
Kaiser-Meyer-Olkin factor adequacy
Call: KMO(r = corr_matrix)
Overall MSA =  0.68
MSA for each item =
DWELCLAS   INCOME  CHILD13      H18  HEMPLOY    HSIZE AVADUAGE     IAGE
    0.70     0.85     0.33     0.58     0.88     0.59     0.38     0.40
    ISEX    NCARS     AREA  BEDROOM     PARK  BEDSIZE PARKSIZE   RAGE10
    0.71     0.74     0.60     0.53     0.62     0.58     0.57     0.84
    TCBD  DISTHTC    TWCBD    TDWWK    HEADH  POPDENS EDUINDEX  GRAVCPC
    0.88     0.88     0.82     0.89     0.47     0.82     0.85     0.76
 GRAVCPT GRAVPCPT   NSTRTC   DISTHW   DIVIDX  ACTDENS  DISTCBD
    0.71     0.31     0.83     0.76     0.63     0.70     0.86
```

We want at least **0.7** of the overall Mean Sample Adequacy (MSA). If, $0.6 < \text{MSA} < 0.7$, it is not a good value, but acceptable in some cases.

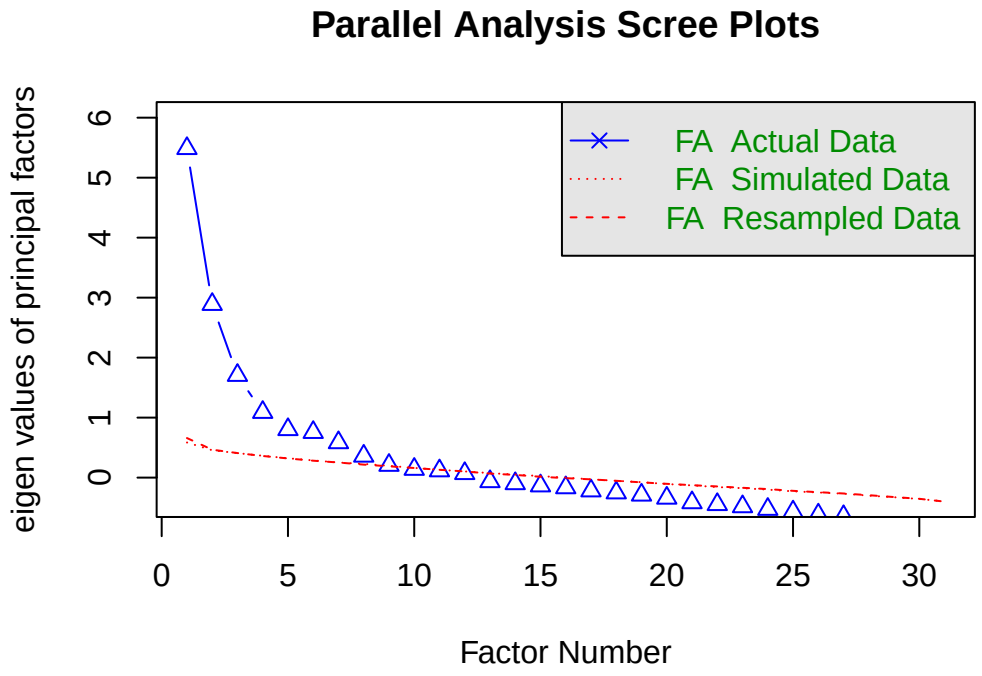
8.4. Determine the number of factors to extract

There are several ways to determine the number of factors to extract. Here we will use three different methods:

- Parallel Analysis
- Kaiser Criterion
- Principal Component Analysis (PCA)

8.4.1. Parallel Analysis

```
num_factors = fa.parallel(
  x = data,
  fm = "ml", # factor mathod = maximum likelihood
  fa = "fa") # factor analysis
```




```
Parallel analysis suggests that the number of factors =  8  and the number of components
```

The selection of the number of factors in the Parallel analysis can be threefold:

- Detect where there is an "elbow" in the graph;
- Detect the intersection between the "FA Actual Data" and the "FA Simulated Data";
- Consider the number of factors with eigenvalue > 1.

8.4.2. Kaiser Criterion

```
sum(num_factors$fa.values > 1) # Number of factors with eigenvalue > 1
```

```
[1] 4
```

```
sum(num_factors$fa.values > 0.7) # Number of factors with eigenvalue > 0.7
```

```
[1] 6
```

You can also consider factors with eigenvalue > 0.7, since some of the literature indicate that this value does not overestimate the number of factors as much as considering an eigenvalue $= 1$.

8.4.3. Principal Component Analysis (PCA)

PCA is not the same thing as Factor Analysis

PCA only considers the common information (variance) of the variables, while factor analysis takes into account also the unique variance of the variable. Both approaches are often mixed up. In this example we use PCA as only a first criteria for choosing the number of factors. PCA is usually used in image recognition and data reduction of big data.

8.4.3.1. Variance explained by components

Print variance that explains the components

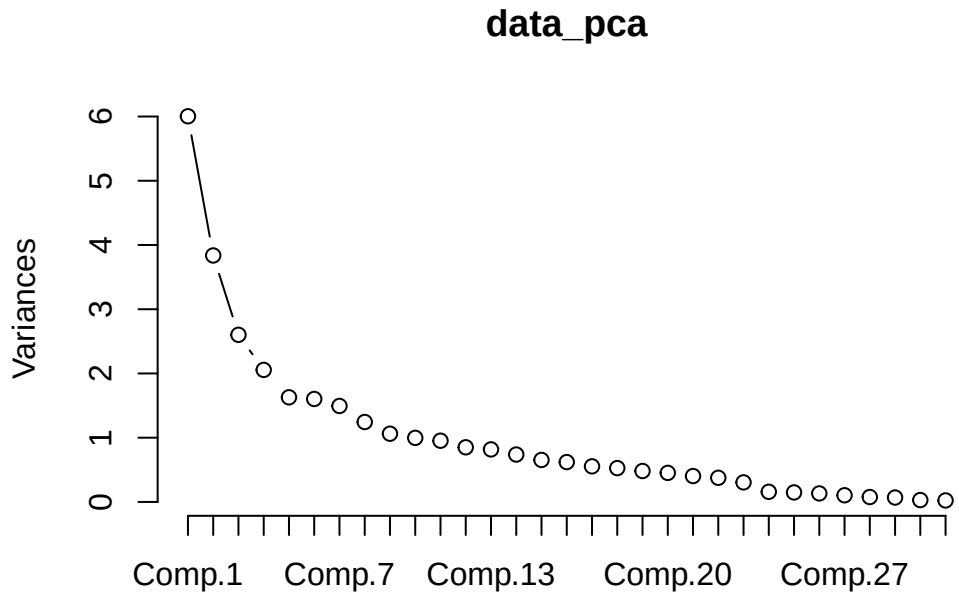
```
data_pca = princomp(data,
                    cor = TRUE) # standardizes your dataset before running
                       a PCA
summary(data_pca)
```

```
Importance of components:
                          Comp.1    Comp.2     Comp.3     Comp.4     Comp.5
Standard deviation     2.450253 1.9587909 1.61305418 1.43367870 1.27628545
Proportion of Variance 0.193669 0.1237697 0.08393367 0.06630434 0.05254531
Cumulative Proportion  0.193669 0.3174388 0.40137245 0.46767679 0.52022210
                           Comp.6     Comp.7     Comp.8    Comp.9    Comp.10
Standard deviation     1.26612033 1.22242045 1.11550534 1.0304937 0.99888665
Proportion of Variance 0.05171164 0.04820361 0.04014039 0.0342554 0.03218628
Cumulative Proportion  0.57193374 0.62013734 0.66027774 0.6945331 0.72671941
                          Comp.11    Comp.12   Comp.13    Comp.14    Comp.15
Standard deviation     0.97639701 0.92221635 0.9042314 0.85909928 0.80853555
Proportion of Variance 0.03075326 0.02743494 0.0263753 0.02380812 0.02108806
Cumulative Proportion  0.75747267 0.78490761 0.8112829 0.83509102 0.85617908
                          Comp.16    Comp.17    Comp.18    Comp.19    Comp.20
Standard deviation     0.7877571 0.74436225 0.72574751 0.69380677 0.67269732
Proportion of Variance 0.0200181 0.01787339 0.01699063 0.01552799 0.01459747
```

```
Cumulative Proportion  0.8761972 0.89407058 0.91106120 0.92658920 0.94118667
                          Comp.21    Comp.22    Comp.23     Comp.24     Comp.25
Standard deviation     0.63466979 0.61328635 0.55192724 0.397467153 0.384354087
Proportion of Variance 0.01299373 0.01213291 0.00982657 0.005096133 0.004765421
Cumulative Proportion  0.95418041 0.96631331 0.97613988 0.981236017 0.986001438
                           Comp.26     Comp.27     Comp.28     Comp.29
Standard deviation     0.364232811 0.322026864 0.276201256 0.262018088
Proportion of Variance 0.004279534 0.003345203 0.002460875 0.002214628
Cumulative Proportion  0.990280972 0.993626175 0.996087050 0.998301679
                            Comp.30      Comp.31
Standard deviation     0.1712372644 0.1527277294
Proportion of Variance 0.0009458774 0.0007524438
Cumulative Proportion  0.9992475562 1.0000000000
```

8.4.3.2. Scree Plot

```r
plot(data_pca, type = "lines", npcs = 31)
```



Check the cumulative variance of the first components and the scree plot, and see if the PCA is a good approach to detect the number of factors in this case.

8.5. Exploratory Factor Analysis (EFA)

8.5.1. Rotational indeterminacy

We can rotate the factors, so that the loadings will be as close as possible to a desired structure.

There are two types of rotation methods.

8.5.1.1. Orthogonal

Orthogonal rotation clarifies factor structure **while preserving independence between factors** - assumes the factors are independent from each other (i.e., their correlation is zero).
The underlying factors after rotation will be **uncorrelated**.

The method rotates the factor axes while **keeping them perpendicular**, so the factors remain uncorrelated.

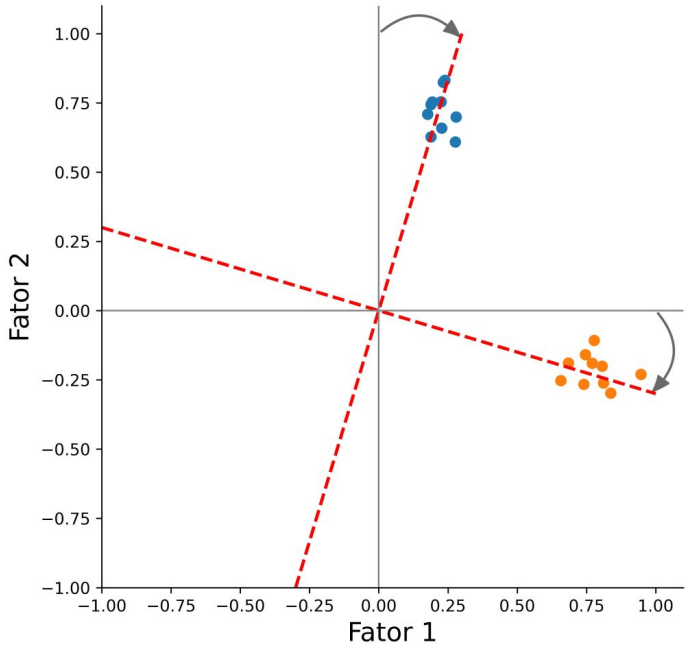


Figure 8.1.: Based in Field (2024)

The goal is to **increase** each item's loading on **one main factor**, and **reduce** its loadings on the other factors, which makes the factors **easier to interpret**.

Methods include:

- Varimax
- Quartimax
- Equimax

8.5.1.2. Oblique

Oblique rotation improves factor interpretability while allowing the factors to be **correlated** with each other. Unlike orthogonal rotation, it does **not** force the factors to remain independent.

Because of this, oblique methods are often more suitable for complex and interrelated constructs, where some degree of relationship between factors is expected.

Oblique rotation does **not** require the factor axes to stay perpendicular. As a result, the rotated factors can **correlate**, allowing a more realistic representation of how variables relate to multiple underlying dimensions.

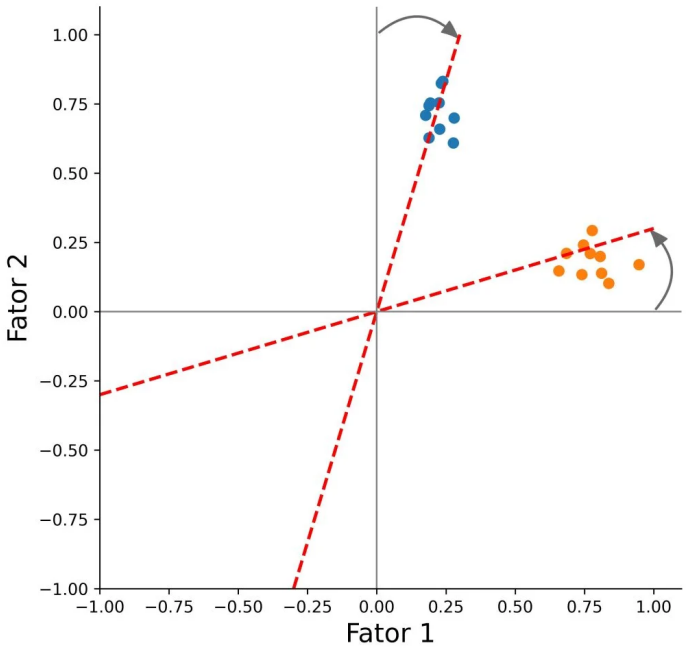


Figure 8.2.: Based in Field (2024)

Methods include:

- Oblimin
- Qaurtimin
- Promax

Let's run three different factor analysis models with different rotation methods:

- **Model 1**: No rotation
- **Model 2**: Rotation Varimax
- **Model 3**: Rotation Oblimin

```
# No rotation
data_factor = factanal(
  data,
  factors = 4, # change here the number of facotrs based on the EFA
  rotation = "none",
  scores = "regression",
  fm = "ml"
)

# Rotation Varimax
data_factor_var = factanal(
  data,
  factors = 4,
  rotation = "varimax", # orthogonal rotation (default)
  scores = "regression",
  fm = "ml"
)

# Rotation Oblimin
data_factor_obl = factanal(
  data,
  factors = 4,
  rotation = "oblimin", # oblique rotation
  scores = "regression",
  fm = "ml"
)
```

Print out the results of `data_factor_obl`, and have a look.

```
print(data_factor_obl,
      digits = 2,
      cutoff = 0.3, # > 0.3 due to the sample size is higher than 350
          observations.
      sort = TRUE)
```

```
Call:
factanal(x = data, factors = 4, scores = "regression", rotation = "oblimin",     fm = "ml

Uniquenesses:
DWELCLAS   INCOME  CHILD13      H18  HEMPLOY    HSIZE AVADUAGE     IAGE
    0.98     0.82     0.09     0.01     0.73     0.01     0.98     0.99
    ISEX    NCARS     AREA  BEDROOM     PARK  BEDSIZE PARKSIZE   RAGE10
    0.98     0.64     0.93     0.79     0.89     0.62     0.92     0.91
    TCBD  DISTHTC    TWCBD    TDWWK    HEADH  POPDENS EDUINDEX  GRAVCPC
    0.14     0.54     0.80     0.74     0.67     0.78     0.71     0.04
```

```
 GRAVCPT GRAVPCPT   NSTRTC   DISTHW   DIVIDX  ACTDENS  DISTCBD
    0.05     0.01     0.85     0.66     0.84     0.80     0.31

Loadings:
         Factor1 Factor2 Factor3 Factor4
TCBD      0.93
DISTHTC   0.62
EDUINDEX -0.53
GRAVCPC  -0.98
GRAVCPT  -0.74           -0.55
DISTHW    0.56
DISTCBD   0.81
H18               1.02
HSIZE             0.74            0.54
NCARS             0.57
BEDSIZE          -0.52
HEADH            -0.56
GRAVPCPT                  1.00
CHILD13                           0.97
DWELCLAS
INCOME            0.38
HEMPLOY           0.47
AVADUAGE
IAGE
ISEX
AREA
BEDROOM           0.37
PARK
PARKSIZE
RAGE10
TWCBD     0.43
TDWWK     0.49
POPDENS  -0.41
NSTRTC   -0.37
DIVIDX   -0.40
ACTDENS  -0.42

               Factor1 Factor2 Factor3 Factor4
SS loadings      5.24    3.13    1.66    1.57

Factor Correlations:
        Factor1 Factor2 Factor3 Factor4
Factor1   1.000   0.062   0.117   0.021
Factor2   0.062   1.000   0.011   0.199
Factor3   0.117   0.011   1.000   0.054
Factor4   0.021   0.199   0.054   1.000
```

```
Test of the hypothesis that 4 factors are sufficient.
The chi square statistic is 3628.43 on 347 degrees of freedom.
The p-value is 0
```

The variability contained in the factors is equal to `Communality` + `Uniqueness`.

8.5.2. Factor scores and factor loadings

In addition to the loading structure, you may also want to know the factor scores of each observation.

We can extract the factor scores with

```
View(data_factor_obl$scores)
# write.csv(data_factor_obl$scores, "data/data_factor_obl_scores.csv", sep
    = "\t")
head(data_factor_obl$scores)
```

```
            Factor1     Factor2    Factor3    Factor4
799161661  0.5269517 -0.01526867 -0.4212963  0.6723761
798399409 -0.6999716 -1.28451045 -0.3425305 -0.5906694
798374392  0.3140942  0.17925007 -1.0077065  1.8899099
798275277  0.2576954  1.09054593 -0.1178061  0.3756358
798264250 -0.3366206 -1.08082681 -0.5807561  0.6090050
798235878 -0.5993148  0.84250056  1.2619817 -0.5142385
```

The individual indicator/subtest scores would be the **weighted sum of the factor scores**, where the weights are the determined by **factor loadings**.

```
View(data_factor_obl$loadings)
# write.csv(data_factor_obl$loadings, "data/data_factor_obl_loadings.csv",
    sep = "\t")
head(data_factor_obl$loadings)
```

```
               Factor1     Factor2     Factor3     Factor4
DWELCLAS -0.0333847085 -0.04628588  0.13740126  0.03391240
INCOME   -0.1309767372  0.37518984  0.04293329  0.10335426
CHILD13   0.0041194104 -0.06692967  0.00769277  0.96689496
H18       0.0008958126  1.01553559 -0.01668507 -0.17758151
HEMPLOY   0.0638121517  0.47320725  0.07699066  0.09956475
HSIZE    -0.0081682615  0.73984312 -0.01057724  0.53609771
```

8.5.3. Visualize Rotation

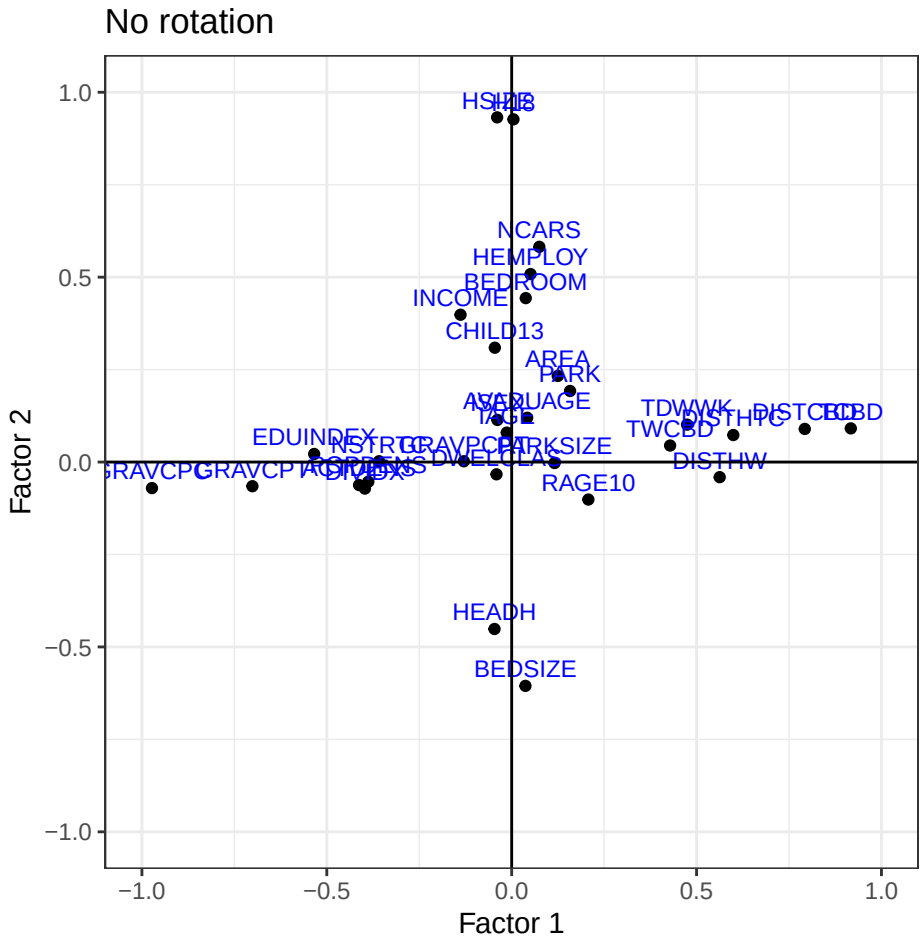
We will define a plot function to make it easier to visualize several factor pairs.

```
# define a plot function
plot_factor_loading <- function(data_factor,
                                f1 = 1,
                                f2 = 2,
                                method = "No rotation",
                                color = "blue") {

  # Convert to numeric matrix (works for psych loadings objects)
  L <- as.matrix(data_factor$loadings)

  # Extract selected factors
  df <- data.frame(item = rownames(L), x = L[, f1], y = L[, f2])

  ggplot(df, aes(x = x, y = y, label = item)) +
    geom_point() +
    geom_text(color = color,
              vjust = -0.5,
              size = 3) +
    geom_hline(yintercept = 0) +
    geom_vline(xintercept = 0) +
    coord_equal(xlim = c(-1, 1), ylim = c(-1, 1)) +
    labs(
      x = paste0("Factor ", f1),
      y = paste0("Factor ", f2),
      title = method
    ) +
    theme_bw()
}
```

8.5.3.1. No Rotation

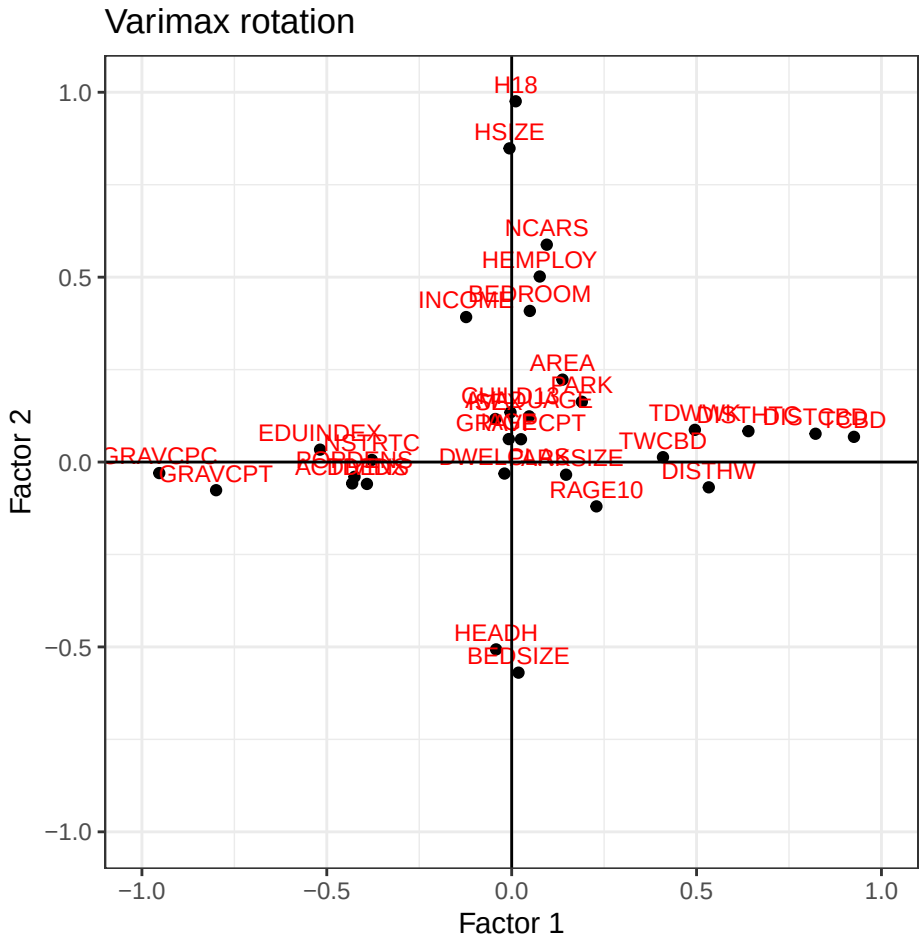
Plot factor 1 against factor 2, and compare the results

```
plot_factor_loading(
  data_factor = data_factor, # model no rotation
  f1 = 1, # Factor 1
  f2 = 2, # Factor 2
  method = "No rotation", # plot title
  color = "blue"
)
```



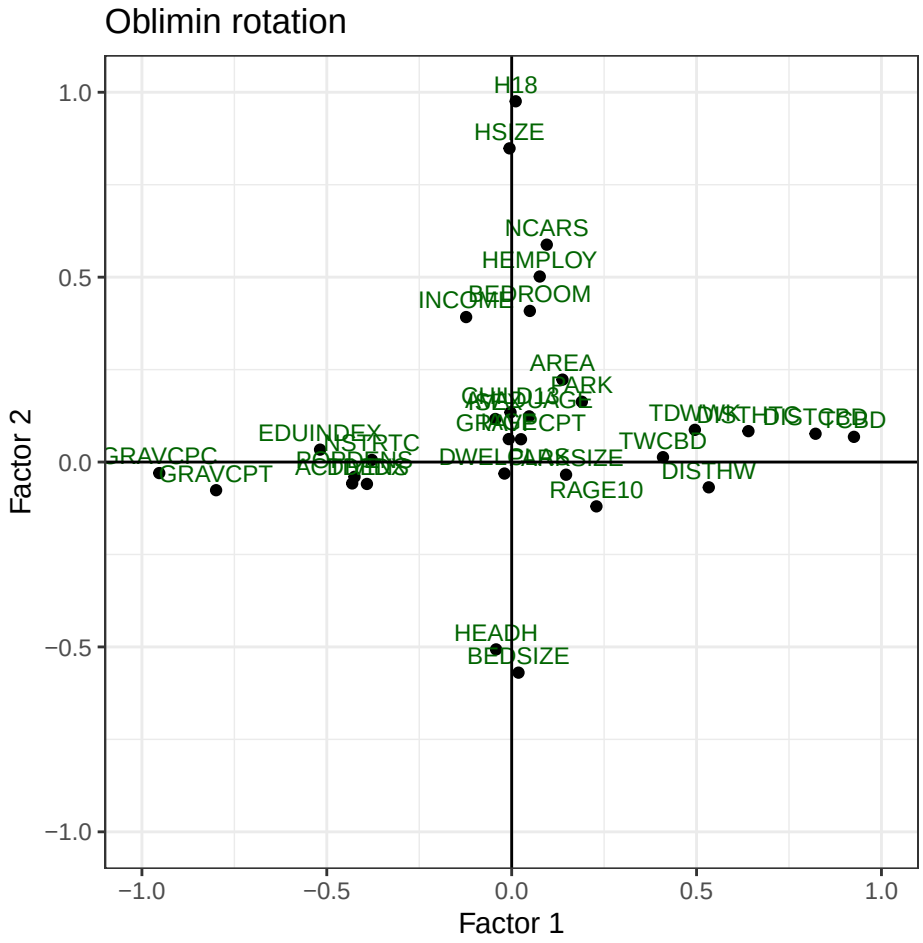
8.5.3.2. Varimax Rotation

```
plot_factor_loading(
  data_factor = data_factor_var, # model varimax
  f1 = 1, # Factor 1
  f2 = 2, # Factor 2
  method = "Varimax rotation",
  color = "red"
)
```



8.5.3.3. Oblimin Rotation

```
plot_factor_loading(
  data_factor = data_factor_var, # model oblimn
  f1 = 1, # Factor 1
  f2 = 2, # Factor 2
  method = "Oblimin rotation",
  color = "darkgreen"
)
```



When we have more than two factors it is difficult to analyse the factors by the plots.

Variables that have low explaining variance in the two factors analysed, could be highly explained by the other factors not present in the graph.

> **Your turn**
>
> Try comparing the plots with the factor loadings and plot the other factor pairs (replace `f1` and `f2`) to get more familiar with exploratory factor analysis. Interpret the factors and try to give them a name.

For instance, we can plot all the factors against each other as follows:

```
# create all combinations
plot_factor_loading(data_factor, 1, 2, method = "No rotation")
plot_factor_loading(data_factor, 1, 3, method = "No rotation")
plot_factor_loading(data_factor, 1, 4, method = "No rotation")
plot_factor_loading(data_factor, 2, 3, method = "No rotation")
plot_factor_loading(data_factor, 2, 4, method = "No rotation")
plot_factor_loading(data_factor, 3, 4, method = "No rotation")
```

9. Cluster Analysis

Do it yourself with R

Copy the script ClusterAnalysis.R and paste it in your session.
Run each line using `CTRL` + `ENTER`

Based on a dataset of European **Airports**, we will create **clusters** based on the observations.

Your task

Create and assess the many types of clustering methods.

9.1. Load packages

```
library(tidyverse) # Pack of most used libraries for data science
library(readxl) # Import excel files
library(skimr) # Summary statistics
library(mclust) # Model based clustering
library(cluster) # Cluster analysis
library(factoextra) # Visualizing distances
```

9.2. Dataset

Included **variables**:

- `Code` - Code of the airport
- `Airport` - Name of the airport
- `Ordem` - ID of the observations
- `Passengers` - Number of passengers
- `Movements` - Number of flights
- `Numberofairlines` - Number of airlines at each airport
- `Mainairlineflightspercentage` - Percentage of flights of the main airline of each airport
- `Maximumpercentageoftrafficpercountry` - Maximum percentage of flights per country

- `NumberofLCCflightsweekly` - Number of weekly low cost flights
- `NumberofLowCostAirlines` - Number of low cost airlines of each airport
- `LowCostAirlinespercentage` - Percentage of the number of low cost airlines in each airport
- `Destinations` - Number of flights arriving at each airport
- `Average_route_Distance` - Average route distance in km
- `DistancetoclosestAirport` - Distance to closest airport in km
- `DistancetoclosestSimilarAirport` - Distance to closest similar airport in km
- `AirportRegionalRelevance` - Relevance of the airport in a regional scale (0 - 1)
- `Distancetocitykm` - Distance between the airport and the city in km
- `Inhabitantscorrected` - Population of the city
- `numberofvisitorscorrected` - Number of visitors arrived in the airport
- `GDPcorrected` - Corrected value of the Gross Domestic Product
- `Cargoton` - The total number of cargo [ton] transported in a certain period multiplied by the number of flights.

9.2.1. Import dataset

```
data = read_excel("../data/Data_Aeroports_Clustersv1.xlsx")
data = data.frame(data) # as data frame only
```

9.2.2. Get to know your dataset

Take a look at the first values of the dataset

```
head(data, 5)
```

```
  Code Ordem          Airport Passengers Movements Numberofairlines
1  NCE     1 Nice Côte d'Azur    9830987    119322               64
2  CGN     2     Cologne Bonn    9742300    132200               29
3  LPA     3     Gran Canaria    9155665    101557               47
4  ALC     4         Alicante    9139479     74281               35
5  LTN     5     London Luton    9129053     83013               11
  Mainairlineflightspercentage Maximumpercentageoftrafficpercountry
1                           18                                  20
2                           33                                  13
3                           17                                  26
4                           29                                  23
5                           37                                  22
  NumberofLCCflightsweekly NumberofLowCostAirlines LowCostAirlinespercentage
1                      256                      18                  28.12500
2                      351                      12                  41.37931
3                      259                      19                  40.42553
4                      300                      18                  51.42857
```

```
5                     227                     8                 72.72727
  Destinations Average_Route_Distance DistancetoclosestAirport
1          104                  1253                 23.66681
2          189                  1721                 63.45766
3          116                  3143                122.58936
4          160                  1701                 63.09924
5           87                  1582                 45.13247
  DistancetoclosestSimilarAirport AirportRegionalrelevance Distancetocitykm
1                       223.83824                0.8698581                6
2                        63.45766                0.5127419               15
3                       132.45082                0.7840877               19
4                       134.50558                0.8098081                9
5                        45.13247                0.1947903               55
  Inhanbitantscorrected numberofvisitorscorrected GDPcorrected Cargoton
1             3551805.0                  2152829.8         26300 11223.39
2             4180133.5                  1151381.6         30100   562.00
3              705807.8                  1678968.6         20700 25994.00
4             1508358.6                  1944196.8         25000  3199.73
5             1562709.8                   181063.5         32000 28698.00
```

Check summary statistics of variables

```
skim(data)
```

Table 9.1.: Data summary

Name	data
Number of rows	32
Number of columns	21
Column type frequency:	
character	2
numeric	19
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
Code	0	1	3	3	0	32	0
Airport	0	1	4	35	0	32	0

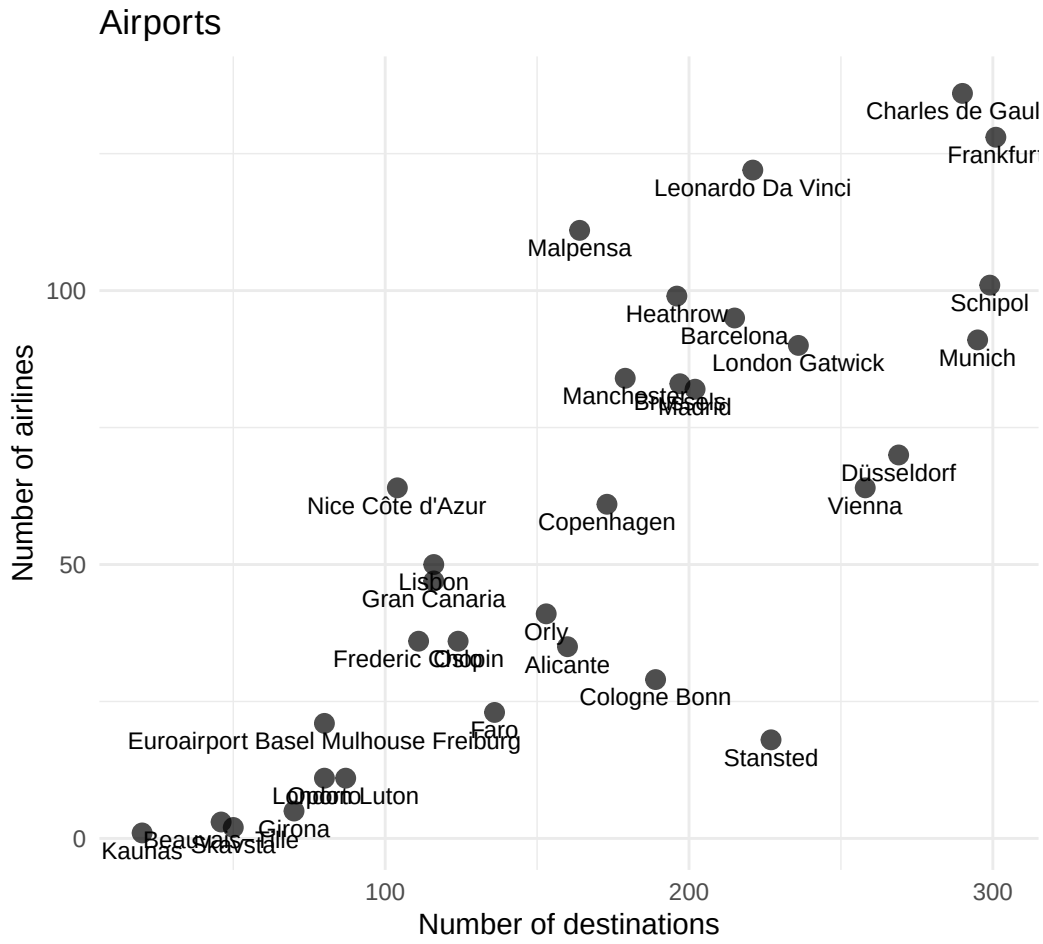
Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
Ordem	0	1	16.50	9.38	1.00	8.75	16.50	24.25	32.00	
Passengers	0	1	20750710.88	17601931.34	456698.00	8927021.50	17275317.50	28666511.50	67054745.00	
Movements	0	1	205111.16	143564.45	5698.00	82765.75	191742.50	258654.50	518018.00	
Numberofairlines	0	1	57.81	40.42	1.00	22.50	55.50	90.25	136.00	
Mainairlineflightspercentage	0	1	33.78	22.08	12.00	22.00	28.50	33.00	95.00	
Maximumpercentageoftrafficpercountry	0	1	17.47	7.31	9.00	12.00	15.00	22.25	35.00	
NumberofLCCflightsweekly	0	1	397.59	221.56	37.00	226.25	366.50	546.75	776.00	
NumberofLowCostAirlines	0	1	11.59	5.60	1.00	7.75	12.00	16.00	23.00	
LowCostAirlinespercentage	0	1	36.44	30.10	6.25	16.29	19.59	50.36	100.00	
Destinations	0	1	167.62	80.13	20.00	109.25	168.50	222.50	301.00	
Average_Route_Distance	0	1	2275.19	930.28	1225.00	1599.50	2152.00	2765.00	5635.00	
DistancetoclosestAirport	0	1	90.19	64.56	13.84	45.83	66.50	111.61	244.50	
DistancetoclosestSimilarAirport	0	1	248.64	183.60	38.16	97.74	206.12	376.15	635.05	

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
AirportRegionalrelevance	0	1	0.73	0.23	0.19	0.58	0.80	0.91	0.99	
Distancetocitykm	0	1	25.81	25.44	3.00	9.75	14.50	35.00	100.00	
Inhanbitantscorrected	0	1	4528561.95	2590542.88	329240.50	2856960.30	4532760.00	6733158.88	9870818.00	
numberofvisitorscorrected	0	1	2766002.58	2549773.72	80232.50	1018390.89	1896295.60	3450491.78	9732062.00	
GDPcorrected	0	1	30160.75	10510.93	8500.00	25000.00	31150.00	35550.00	56600.00	
Cargoton	0	1	236531.76	478310.12	0.00	10325.00	72749.85	153372.85	1819000.00	

As exploring the data, we can plot the `Numberofairlines` against the `Destinations` and observe.

```
ggplot(data, aes(x = Destinations, y = Numberofairlines)) +
  geom_point(size = 3, alpha = 0.7) +
  geom_text(aes(label = Airport), vjust = 1.5, size = 3, show.legend =
      FALSE) +
  labs(
    title = "Airports",
    x = "Number of destinations",
    y = "Number of airlines"
  ) +
  theme_minimal()
```



By looking at the plot, you may already have a clue on the number of clusters with this two variables. However, this is not clear and it does not consider the **other variables** in the analysis.

9.2.3. Prepare data

9.2.3.1. Row-names

Make the `Code` variable as **row names** or case number

```
data = data |> column_to_rownames(var = "Code")
```

9.2.3.2. Remove the non-continuous data

Leave only continuous variables and the ordered ID.

```
data_continuous = data |> select(-Ordem, -Airport) # remove chr and id
    variables
```

9.2.3.3. Standardize variables

Take a look at the scale of the variables. See how different they are!

```
head(data_continuous)
```

```
    Passengers Movements Numberofairlines Mainairlineflightspercentage
NCE    9830987    119322               64                           18
CGN    9742300    132200               29                           33
LPA    9155665    101557               47                           17
ALC    9139479     74281               35                           29
LTN    9129053     83013               11                           37
WAW    8320927    115934               36                           31
    Maximumpercentageoftrafficpercountry NumberofLCCflightsweekly
NCE                                   20                      256
CGN                                   13                      351
LPA                                   26                      259
ALC                                   23                      300
LTN                                   22                      227
WAW                                   14                      341
    NumberofLowCostAirlines LowCostAirlinespercentage Destinations
NCE                      18                  28.12500          104
CGN                      12                  41.37931          189
LPA                      19                  40.42553          116
```

```
ALC                      18                  51.42857          160
LTN                       8                  72.72727           87
WAW                       7                  19.44445          111
    Average_Route_Distance DistancetoclosestAirport
NCE                   1253                 23.66681
CGN                   1721                 63.45766
LPA                   3143                122.58936
ALC                   1701                 63.09924
LTN                   1582                 45.13247
WAW                   1460                244.49577
    DistancetoclosestSimilarAirport AirportRegionalrelevance Distancetocitykm
NCE                       223.83824                0.8698581                6
CGN                        63.45766                0.5127419               15
LPA                       132.45082                0.7840877               19
ALC                       134.50558                0.8098081                9
LTN                        45.13247                0.1947903               55
WAW                       559.31000                0.9810450               10
    Inhanbitantscorrected numberofvisitorscorrected GDPcorrected Cargoton
NCE             3551805.0                 2152829.8        26300 11223.39
CGN             4180133.5                 1151381.6        30100   562.00
LPA              705807.8                 1678968.6        20700 25994.00
ALC             1508358.6                 1944196.8        25000  3199.73
LTN             1562709.8                  181063.5        32000 28698.00
WAW             6626197.0                  770720.5        11200 82756.54
```

Z-score standardization:

$$Z = \frac{X - \mu}{\sigma}$$

```
data_scaled = data_continuous |>
  mutate(across(everything(), ~ ( . - mean(.) ) / sd(.)))
# Result = z-scores, same as scale()
```

9.3. Hierarchical Clustering

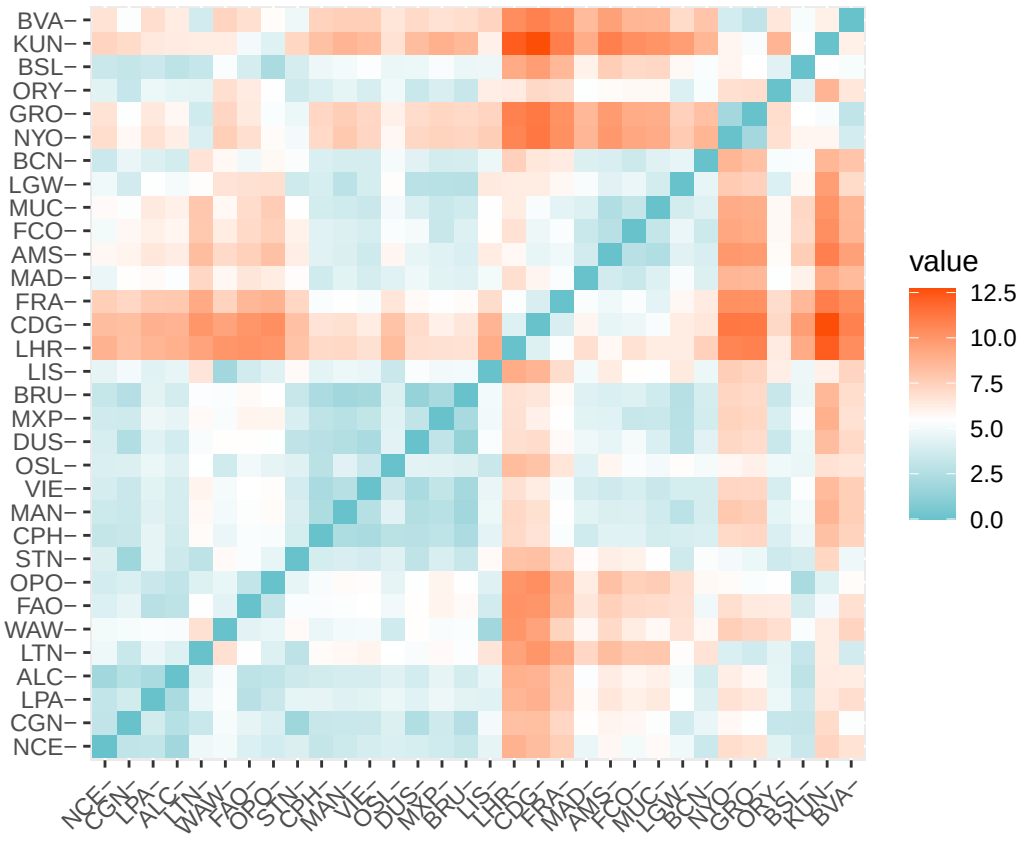
9.3.1. Distance measures

Similarity of observations can be measured through different **distance measures**, including:

- Euclidean distance
- Minkowski distance
- Manhattan distance
- Mahanalobis distance

Let's measure the **euclidean distances** of our standartize data and visualize them on a heatmap

```
# measure
distance = dist(data_scaled, method = "euclidean")

# heatmap
fviz_dist(
  distance,
  gradient = list(
    low = "#00AFBB",
    mid = "white",
    high = "#FC4E07"
  ),
  order = FALSE
)
```



By the color codes, you can have a clue of the airports that are more similar.

9.3.2. Types of hierarchical clustering

There are many types of hierarchical clustering. We will explore some of them:

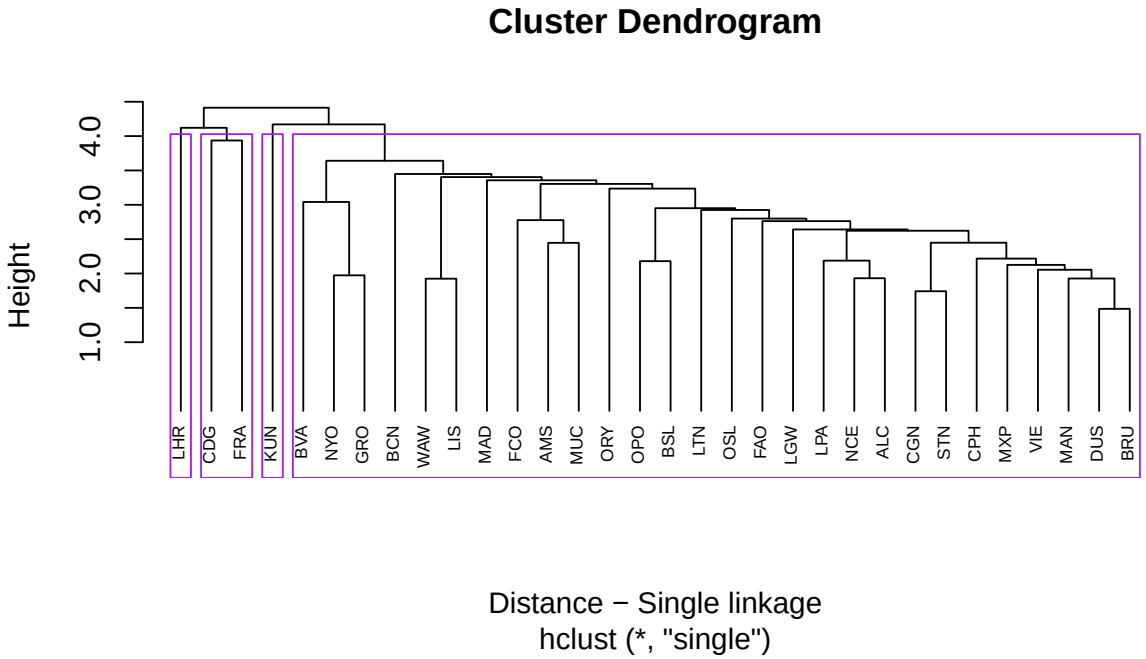
- Single linkage (nearest neighbour) clustering algorithm
- Complete linkage (Farthest neighbour) clustering algorithm
- Average linkage between groups
- Ward's method
- Centroid method

9.3.2.1. Single linkage

The *single linkage* method (which is closely related to the minimal spanning tree) adopts a 'friends of friends' clustering strategy.

This clustering algorithm is based on a bottom-up approach, by linking two clusters that have the **closest distance** between each other.

```
cluster_single = hclust(distance, "single")

# dendogram
plot(
  cluster_single,
    xlab = "Distance - Single linkage",
  hang = -1, # all to the bottom
  cex = 0.6 # label text size
)
rect.hclust(cluster_single, k = 4, border = "purple") # cut on the
    dendogram at 4 clusters
```



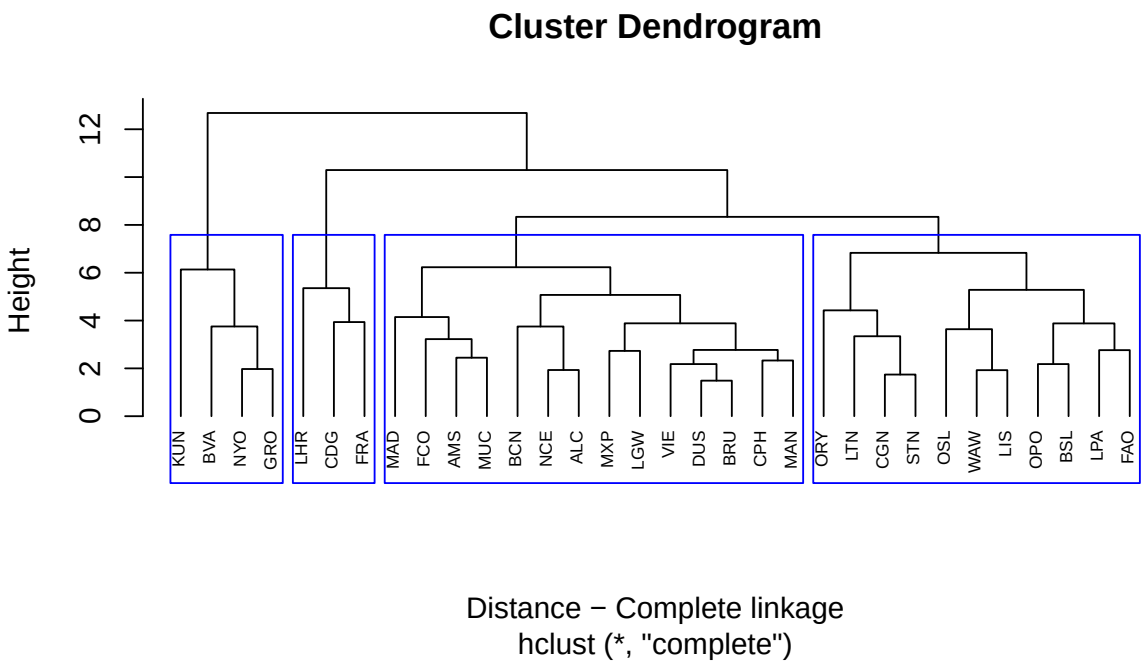
This results in 4 clusters, with *Heathrow Airport* and *Kaunas Airport* at their own cluster.

9.3.2.2. Complete linkage

The *complete linkage* method finds similar clusters.

Complete linkage is based on the **maximizing distance** between observations in each cluster.

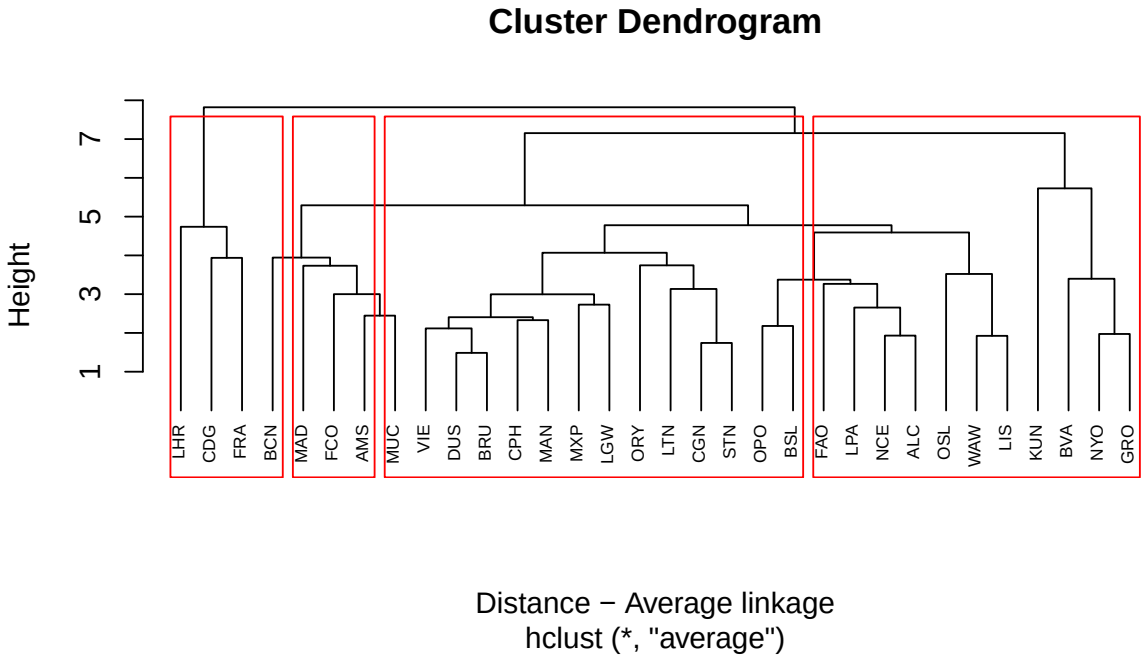
```
cluster_complete = hclust(distance, "complete")

# dendogram
plot(
  cluster_complete,
    xlab = "Distance - Complete linkage",
  hang = -1, # all to the bottom
  cex = 0.6 # label text size
)
rect.hclust(cluster_complete, k = 4, border = "blue") # cut on the
    dendogram at 4 clusters
```



9.3.2.3. Average linkage

The average linkage considers the distance between clusters to be the average of the **distances between observations in one cluster to all the members in the other cluster**.

```r
cluster_average = hclust(distance, "average")

# dendogram
plot(
  cluster_average,
  xlab = "Distance - Average linkage",
  hang = -1, # all to the bottom
  cex = 0.6 # label text size
)
rect.hclust(cluster_complete, k = 4, border = "red") # cut on the
    dendogram at 4 clusters
```



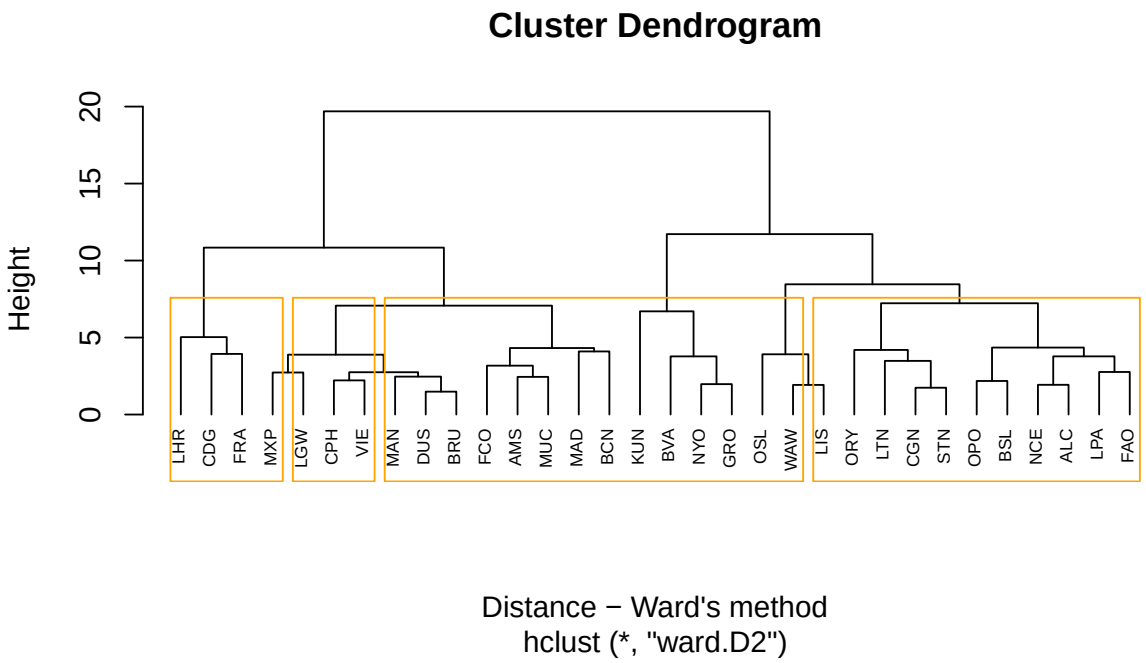
9.3.2.4. Ward‘s method

Ward's minimum variance method aims at finding compact, spherical clusters.

The Ward‘s method considers the measures of similarity as the **sum of squares within the cluster** summed over all variables.

```r
cluster_ward = hclust(distance, "ward.D2")

# dendogram
plot(
  cluster_ward,
  xlab = "Distance - Ward's method",
  hang = -1, # all to the bottom
  cex = 0.6 # label text size
```

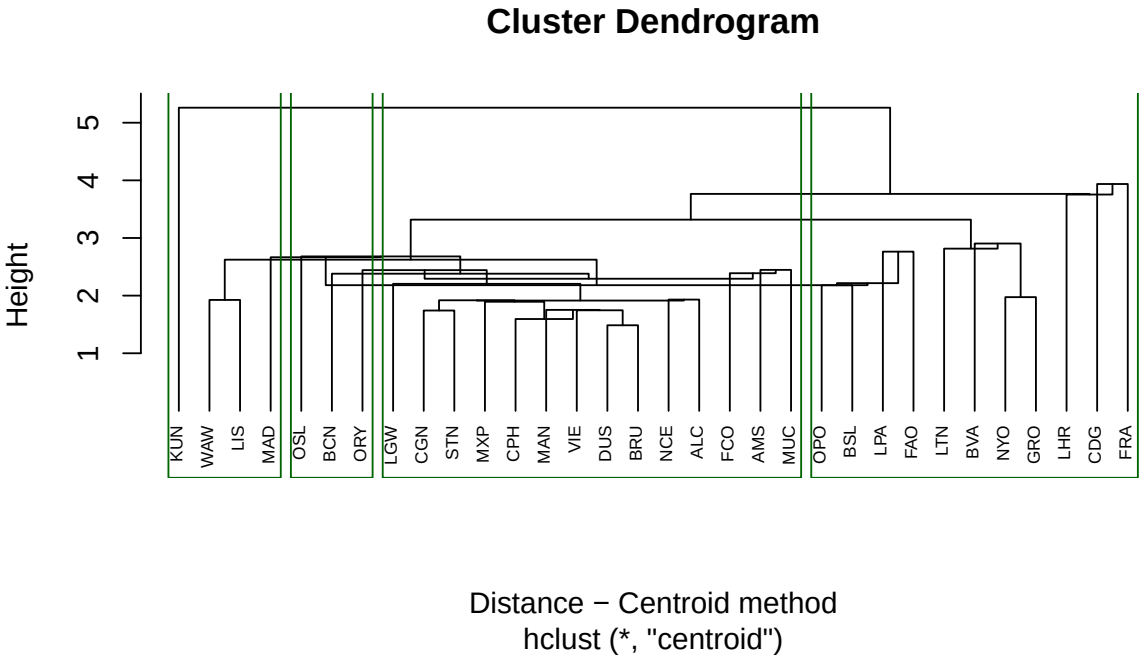
```
)
rect.hclust(cluster_complete, k = 4, border = "orange") # cut on the
    dendogram at 4 clusters
```



9.3.2.5. Centroid method

The centroid method considers the similarity between two clusters as the distance between its centroids.

```
cluster_centroid = hclust(distance, "centroid")

# dendogram
plot(
  cluster_centroid,
  xlab = "Distance - Centroid method",
  hang = -1, # all to the bottom
  cex = 0.6 # label text size
)
rect.hclust(cluster_complete, k = 4, border = "darkgreen") # cut on the
    dendogram at 4 clusters
```



As mentioned in R Core Team (2025), note however, that methods `centroid` are *not* leading to a *monotone distance* measure, or equivalently the resulting dendrograms can have so called *inversions* or *reversals* which **are hard to interpret**, but note the trichotomies in Legendre and Legendre (2012) .

9.3.3. Comparing results from different hierarchical methods

Now let's assess the **membership** of each observation with the `cutree` function for each method.

```
number_clusters = 4 # change here
member_single = cutree(cluster_single, k = number_clusters)
member_complete = cutree(cluster_complete, k = number_clusters)
member_average = cutree(cluster_average, k = number_clusters)
member_ward = cutree(cluster_ward, k = number_clusters)
member_centroid = cutree(cluster_centroid, k = number_clusters)
```

We can make a table of cluster **memberships for each observation** to each cluster method, and **compare them** with a color code.

```
# make a data frame
cluster_membership = data.frame(member_single,
                                member_complete,
                                member_average,
                                member_ward,
```

```
                                member_centroid
                                )
# manipulate data for plot
cluster_long = cluster_membership |>
  rownames_to_column(var = "airport") |>  # keep airport names
  pivot_longer(
    cols = starts_with("member_"),
    names_to = "method",
    values_to = "cluster") |>
  mutate(method = gsub("member_", "", method), # clean names
         method = factor(method, # preserve the label order
                         levels = c("single", "complete", "average",
                            "ward", "centroid")))
# plot
ggplot(cluster_long,
       aes(x = method,
           y = airport,
           fill = factor(cluster))) +
  geom_tile(color = "white") +
  scale_fill_brewer(palette = "Set3", name = "Cluster") +
  theme_minimal() +
  labs(title = "Cluster memberships by method",
    x = "Clustering method",
    y = "Airport") +
  theme(axis.text.y = element_text(size = 6))
```

Compare how common each method is to each other:

```
table(member_complete, member_average) # complete linkage vs. average
    linkage
```

```
                member_average
member_complete  1  2  3  4
              1 14  0  0  0
              2 11  0  0  0
              3  0  3  0  0
              4  0  0  3  1
```

```
table(member_complete, member_ward) # complete linkage vs. ward's method
```

```
                member_ward
member_complete  1  2  3  4
              1  2 12  0  0
              2 11  0  0  0
```

```
3  0  0  3  0
4  0  0  0  4
```

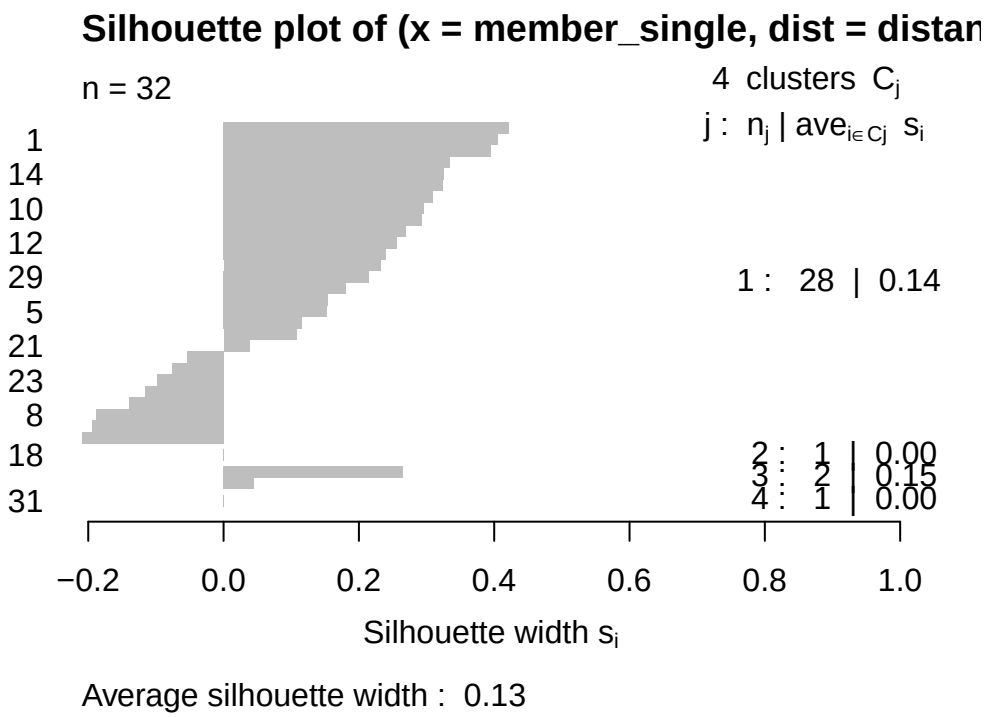
> **Your turn**
>
> Try comparing other methods, and evaluate how common they are.

9.3.4. Silhouette Plots

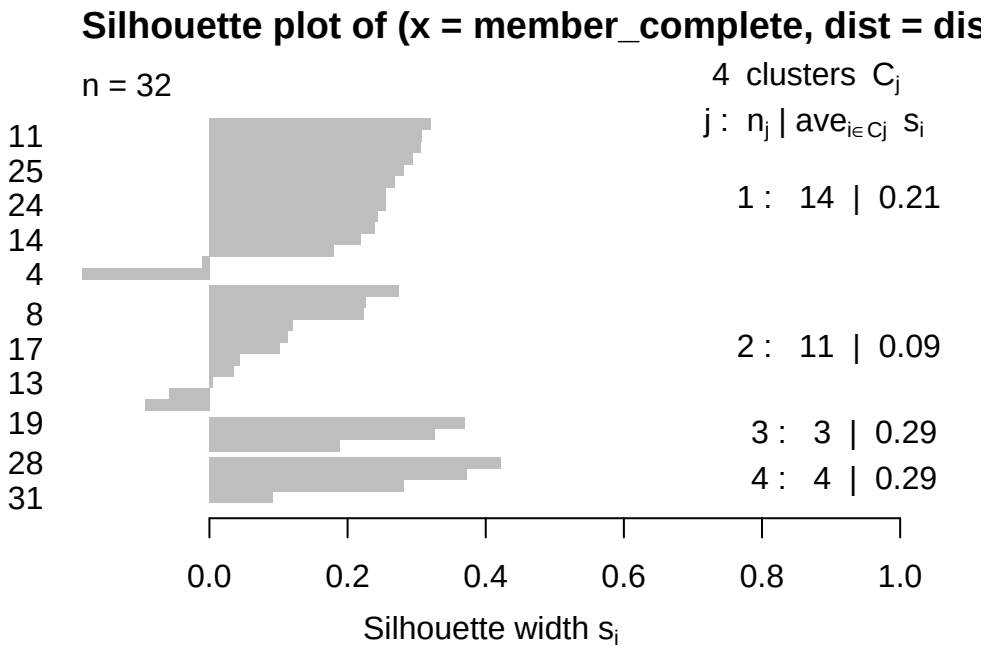
The silhouette plot evaluates how similar an observation is to its own cluster compared to other clusters.

The clustering configuration is appropriate when **most objects have high values**. **Low or negative values** indicate that the clustering method **is not appropriate** or the number of clusters **is not ideal**.

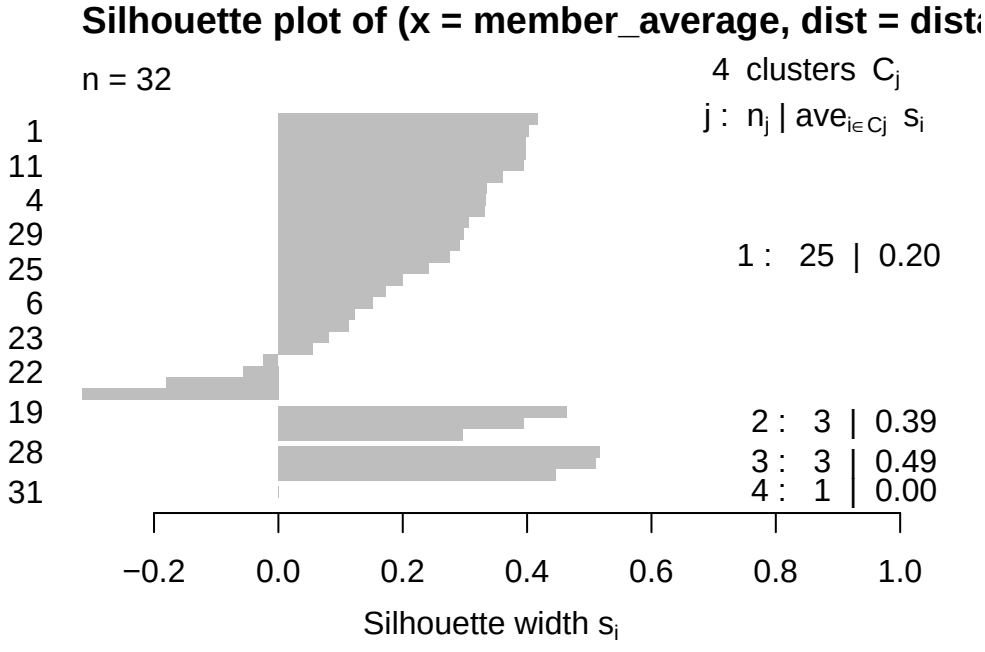
```
plot(silhouette(member_single, distance))
```



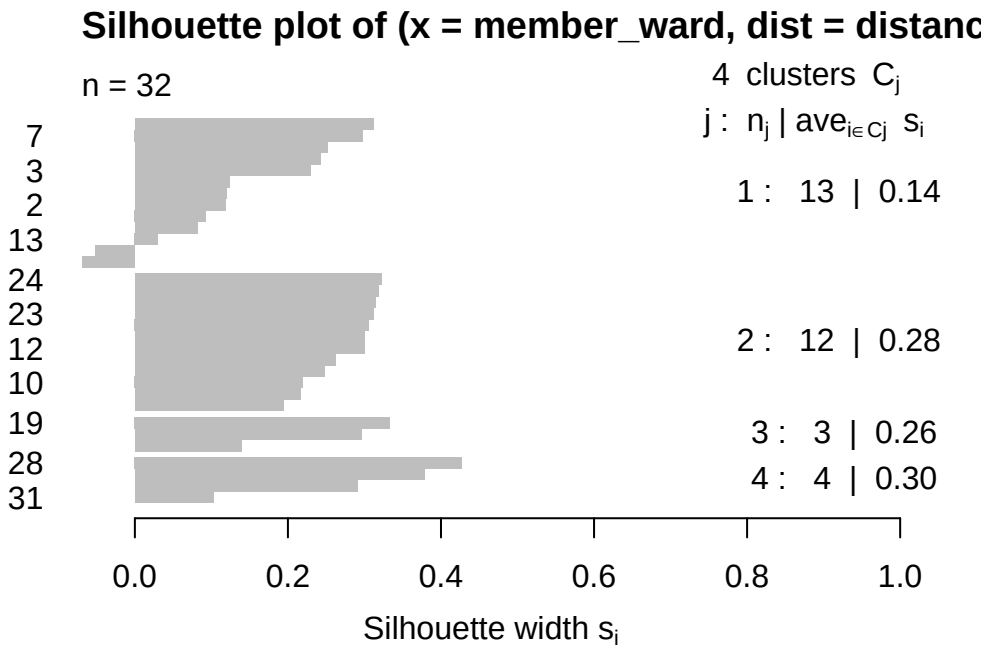

```
plot(silhouette(member_complete, distance))
```



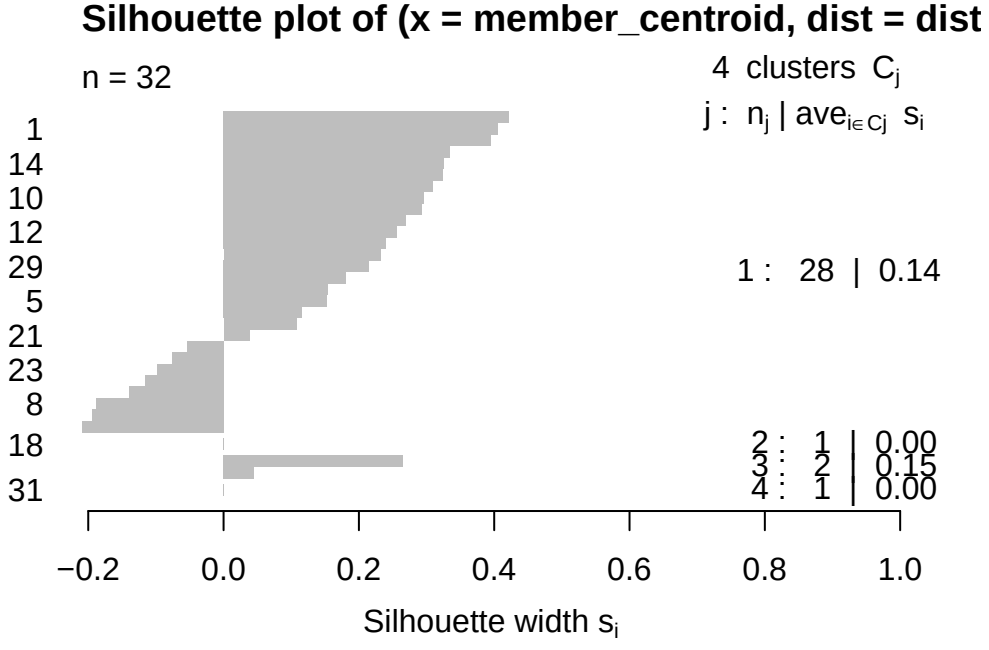

```
plot(silhouette(member_average, distance))
```




```
plot(silhouette(member_ward, distance))
```




```
plot(silhouette(member_centroid, distance))
```



9.4. Non-Hirarchical Clustering

Non-hierarchical clustering is a method that partitions data points into a **predetermined number of clusters**, denoted by , without creating a nested tree-like structure.

Unlike hierarchical clustering, it requires the user to **specify in advance** and uses an iterative algorithm to optimize a criterion, such as **minimizing the variance within each cluster**.

Popular examples include *K-Means* and *K-Medoids*, which assign points to the nearest cluster center (centroid or medoid) and repeat the process until the cluster assignments no longer change significantly.

In this exercise, we will use the **K-means clustering**.

9.4.1. Choose the number of clusters

We can observe a measure of the goodness of the classification for each k-means, using the following ratio:

$$\frac{Between_{SS}}{Total_{SS}}$$

`SS` stands for Sum of Squares, so it's the usual decomposition of deviance in deviance "Between" and deviance "Within". Ideally you want a clustering that has the properties of internal cohesion and external separation, i.e. the **BSS/TSS ratio** should approach **1**.

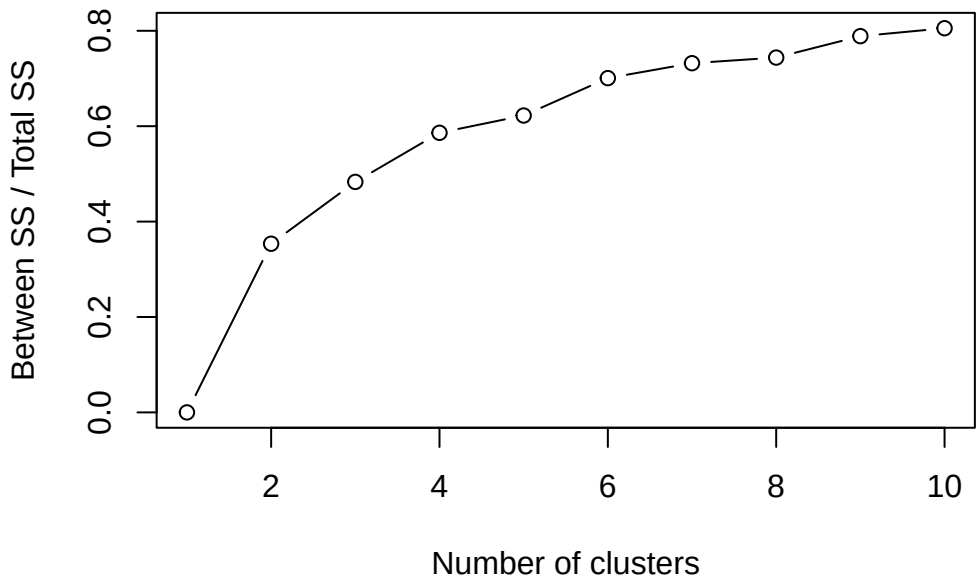
This algorithm will detect how many clusters, from 1 to 10, explains **more variance, with less clusters**:

```
# loop for the 10 cluster trials
kmeans_diagnostic = data.frame()

for (i in 1:10) {
  km = kmeans(data_scaled, centers = i)
  km_diagn = data.frame(
    k = i,
    between_ss = km$betweenss,
    tot_ss = km$totss,
    ratio = km$betweenss / km$totss
  )
  kmeans_diagnostic = rbind(kmeans_diagnostic, km_diagn)
}

# marginal improvements for each new cluster
kmeans_diagnostic = kmeans_diagnostic |>
  mutate(marginal = ratio - lag(ratio))

kmeans_diagnostic
```

```
    k   between_ss tot_ss        ratio   marginal
1   1 1.136868e-13    558 2.037399e-16         NA
2   2 1.972975e+02    558 3.535798e-01 0.35357981
3   3 2.696136e+02    558 4.831784e-01 0.12959861
4   4 3.270613e+02    558 5.861313e-01 0.10295287
5   5 3.472728e+02    558 6.223527e-01 0.03622144
6   6 3.910220e+02    558 7.007563e-01 0.07840355
7   7 4.084833e+02    558 7.320489e-01 0.03129260
8   8 4.150549e+02    558 7.438259e-01 0.01177703
9   9 4.401043e+02    558 7.887173e-01 0.04489142
10 10 4.493809e+02    558 8.053421e-01 0.01662481
```

Plot the ratio into a **scree plot**

```
plot(kmeans_diagnostic$k, kmeans_diagnostic$ratio,
     type = "b",
     ylab = "Between SS / Total SS",
     xlab = "Number of clusters")
```



9.4.2. Predetermined number of clusters

In this case we will use the **K-means clustering**, and define `k = 3` (3 clusters).

Here are the cluster results.

```
km_clust = kmeans(data_scaled, centers = 3) # k = 3
km_clust # print the results
```

```
K-means clustering with 3 clusters of sizes 18, 7, 7

Cluster means:
  Passengers  Movements Numberofairlines Mainairlineflightspercentage
1 -0.2469314 -0.2011272     -0.004982515                   -0.3699491
2 -0.9456035 -1.0500969     -1.239468064                    1.4006677
3  1.5805700  1.5672811      1.252280245                   -0.4493699
  Maximumpercentageoftrafficpercountry NumberofLCCflightsweekly
1                           -0.1629508               0.04370786
2                            0.9913460              -1.21033588
3                           -0.5723298               1.09794424
  NumberofLowCostAirlines LowCostAirlinespercentage Destinations
1               0.3305562                -0.2689855   0.07609389
2              -1.2287547                 1.4725164  -1.31999250
3               0.3787531                -0.7808392   1.12432250
  Average_Route_Distance DistancetoclosestAirport
1             -0.1062034               0.06631895
2             -0.8907198               0.20629602
3              1.1638144              -0.37683045
  DistancetoclosestSimilarAirport AirportRegionalrelevance Distancetocitykm
1                     -0.07737412                0.1407640       -0.3136475
2                     -0.67596963               -0.9617675        1.0125397
3                      0.87493166                0.5998030       -0.2060176
  Inhanbitantscorrected numberofvisitorscorrected GDPcorrected   Cargoton
1           -0.06258292                -0.2290652   -0.1117858 -0.3186842
2           -0.92990235                -0.7382133   -0.5168124 -0.4251367
3            1.09082987                 1.3272381    0.8042615  1.2446104

Clustering vector:
NCE CGN LPA ALC LTN WAW FAO OPO STN CPH MAN VIE OSL DUS MXP BRU LIS LHR CDG FRA
  1   1   1   1   2   1   1   2   1   1   1   1   1   1   1   1   1   3   3   3
MAD AMS FCO MUC LGW BCN NYO GRO ORY BSL KUN BVA
  3   3   3   3   1   1   2   2   1   2   2   2

Within cluster sum of squares by cluster:
[1] 150.32291  67.16167  70.90186
 (between_SS / total_SS =  48.3 %)

Available components:

[1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
[6] "betweenss"    "size"         "iter"         "ifault"
```

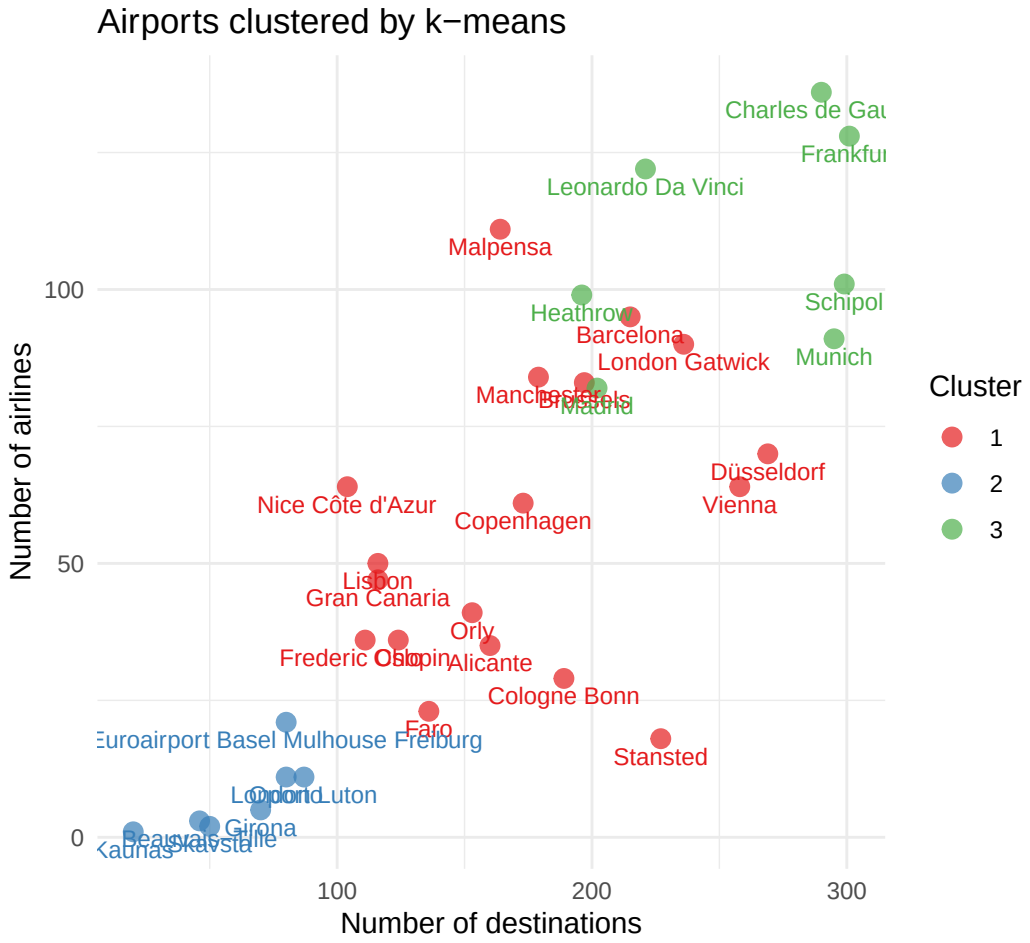
If we want to export the **cluster means for each variable** and the **cluster membership for each observation**:

```
# cluster means for each variable
var_cluster_means = data.frame(cluster = 1:nrow(km_clust$centers),
                               size = km_clust$size,
                               km_clust$centers)

# cluster membership for each observation
obs_cluster_member = data.frame(km_clust$cluster)
```

9.4.3. Plotting the clusters

Finally, plot again the `Numberofairlines` against the `Destinations` and observe the clusters results to check if they make sense.

```
# add cluster membership to original data
data_clust = data |>  mutate(cluster = factor(km_clust$cluster))

# plot
ggplot(data_clust, aes(x = Destinations, y = Numberofairlines, color =
    cluster)) +
  geom_point(size = 3, alpha = 0.7) +
  geom_text(aes(label = Airport), vjust = 1.5, size = 3, show.legend =
     FALSE) +
  scale_color_brewer(palette = "Set1") +
  labs(
    title = "Airports clustered by k-means",
    x = "Number of destinations",
    y = "Number of airlines",
    color = "Cluster"
  ) +
  theme_minimal()
```



What if... ?

Imagine that one of the airports was not operating any more.
Remove one airport from the data, at your choice, and **re-run the cluster analysis**.
How different are the results?

Part II.

GIS in R

10. Introduction to spatial data

Spatial data is **data that is associated with a geometry**. This geometry can be a point, a line, a polygon, or a grid.

Spatial data can be represented in many ways, such as vector data and raster data. In this tutorial, we will learn how to work with spatial data in R.

We will use the `sf` package to work with vector data, and the `dplyr` package to manipulate data.

```
library(sf)
library(dplyr)
```

The `sf` package is a powerful package for working with spatial data in R. It includes hundreds of functions to deal with spatial data (Pebesma and Bivand 2023).

10.1. Import vector data

Download and open `Municipalities_geo.gpkg` under EITcourse/data repository.

Within the `sf` package, we use the `st_read()` to read spatial features.

```
Municipalities_geo = st_read("data/Municipalities_geo.gpkg")
```

You can also open directly from url from github. Example:

```
url = "https://github.com/U-Shift/EITcourse/raw/main/data/Municipalities_geo.gpkg"
Municipalities_geo = st_read(url)
```

10.1.1. Projected vs Geographic Coordinate Systems

A **projected coordinate system** is a flat representation of the Earth's surface. A **geographic coordinate system** is a spherical representation of the Earth's surface.

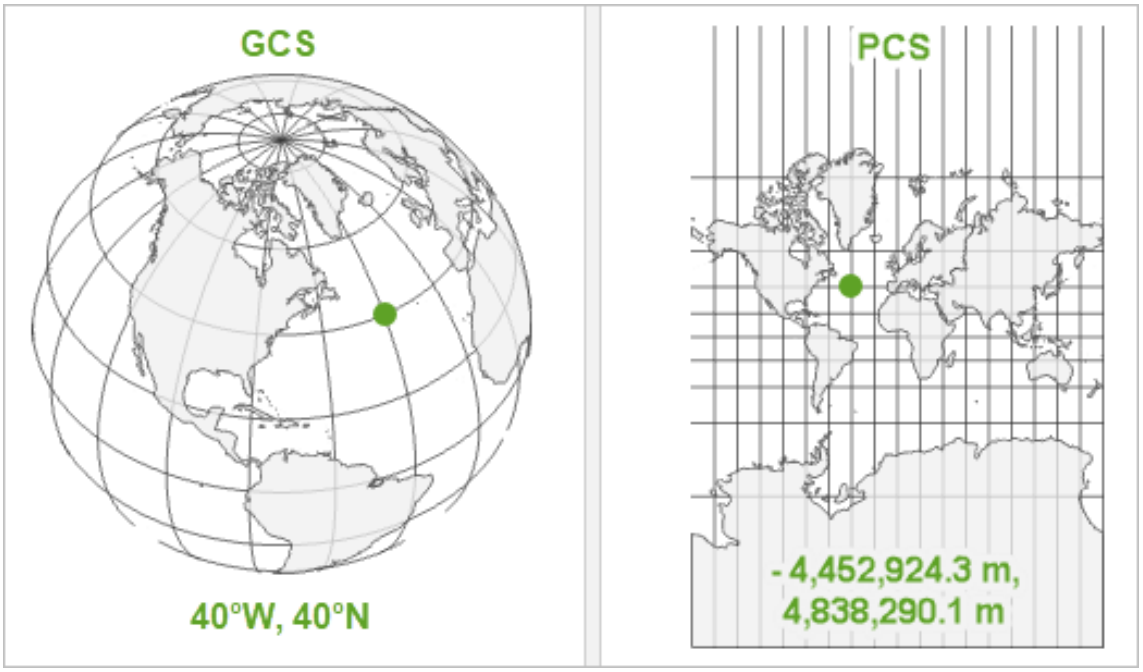


Figure 10.1.: Source: ESRI

The `st_crs()` function can be used to check the **coordinate reference system** of a spatial object.

```
st_crs(Municipalities_geo)
```

```
Coordinate Reference System:
  User input: WGS 84
  wkt:
GEOGCRS["WGS 84",
    ENSEMBLE["World Geodetic System 1984 ensemble",
        MEMBER["World Geodetic System 1984 (Transit)"],
        MEMBER["World Geodetic System 1984 (G730)"],
        MEMBER["World Geodetic System 1984 (G873)"],
        MEMBER["World Geodetic System 1984 (G1150)"],
        MEMBER["World Geodetic System 1984 (G1674)"],
        MEMBER["World Geodetic System 1984 (G1762)"],
        MEMBER["World Geodetic System 1984 (G2139)"],
        MEMBER["World Geodetic System 1984 (G2296)"],
        ELLIPSOID["WGS 84",6378137,298.257223563,
            LENGTHUNIT["metre",1]],
        ENSEMBLEACCURACY[2.0]],
    PRIMEM["Greenwich",0,
        ANGLEUNIT["degree",0.0174532925199433]],
    CS[ellipsoidal,2],
        AXIS["geodetic latitude (Lat)",north,
```

```
        ORDER[1],
        ANGLEUNIT["degree",0.0174532925199433]],
    AXIS["geodetic longitude (Lon)",east,
        ORDER[2],
        ANGLEUNIT["degree",0.0174532925199433]],
USAGE[
    SCOPE["Horizontal component of 3D system."],
    AREA["World."],
    BBOX[-90,-180,90,180]],
ID["EPSG",4326]]
```

WGS84 is the most common geographic coordinate system, used in GPS, and EPSG:**4326** is code for it.

If we want to project the data to a projected coordinate system, to use **metric units** instead of degrees, we can use the `st_transform()` function.

In this case, the EPGS:**3857** is the code for the Pseudo-Mercator coordinate system.

```
Municipalities_projected = st_transform(Municipalities_geo, crs = 3857)
```

Now see the differences when calling `Municipalities_geo` and `Municipalities_projected`.

10.2. Join geometries to data frames

Import `TRIPSmun.Rds` file and check data class

```
TRIPSmun = readRDS("../data/TRIPSmun.Rds")
class(TRIPSmun)
```

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

```
class(Municipalities_geo)
```

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

To join the geometries from the `Municipalities_geo` to the data frame, we can use the `left_join()` function from the `dplyr` package.

```
TRIPSgeo =
  TRIPSmun |>
  left_join(Municipalities_geo)

class(TRIPSgeo)
```

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

As you can see, this **does not make the object a spatial feature**. To do this, we need to use the `st_as_sf()` function.

```
TRIPSgeo = TRIPSgeo |> st_as_sf()
class(TRIPSgeo)
```

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

Now we have a spatial feature with the data frame.

10.3. Create spatial data from coordinates

The `st_as_sf()` function can also be used to create a spatial feature from a data frame with coordinates. In that case, we need to specify the columns with the coordinates.

We will use survey data (in `.txt`) with the participants' home latitude/longitude coordinates to create a spatial feature.

```
SURVEY = read.csv("../data/SURVEY.txt", sep = "\t") # tab delimiter
class(SURVEY)
```

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

```
SURVEYgeo = st_as_sf(SURVEY, coords = c("lon", "lat"), crs = 4326) #
    create spatial feature
class(SURVEYgeo)
```

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

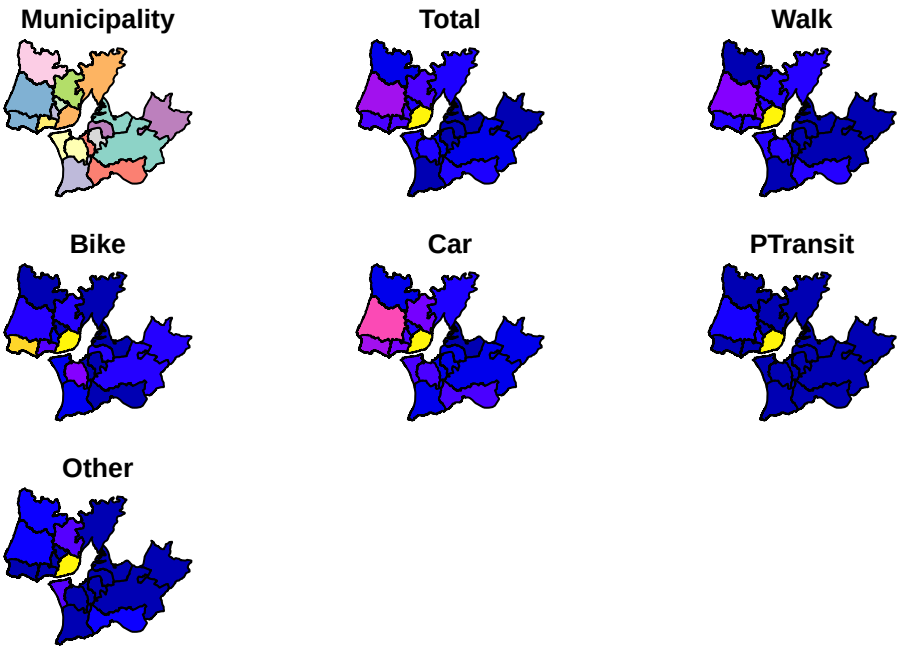
We can also set the **crs** of the spatial feature on the fly.

Check the differences between both data variables.

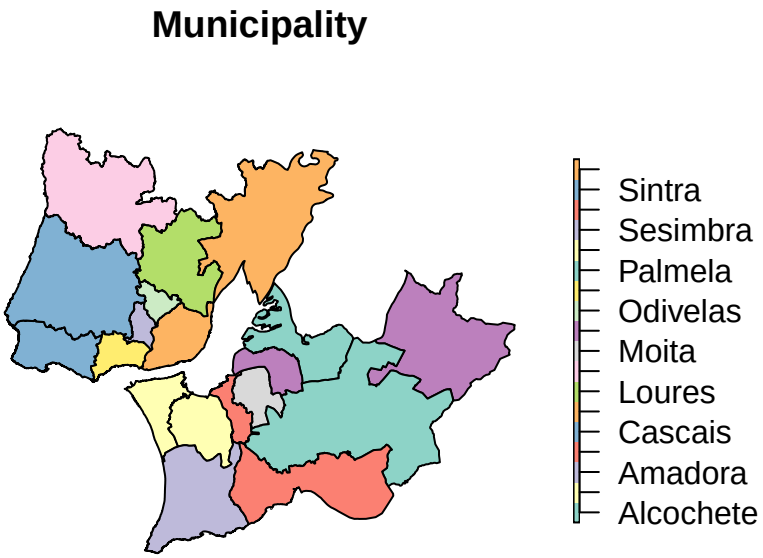
10.4. Visuzlize spatial data

Represent Transport Zones with Total and Car, using `plot()`.

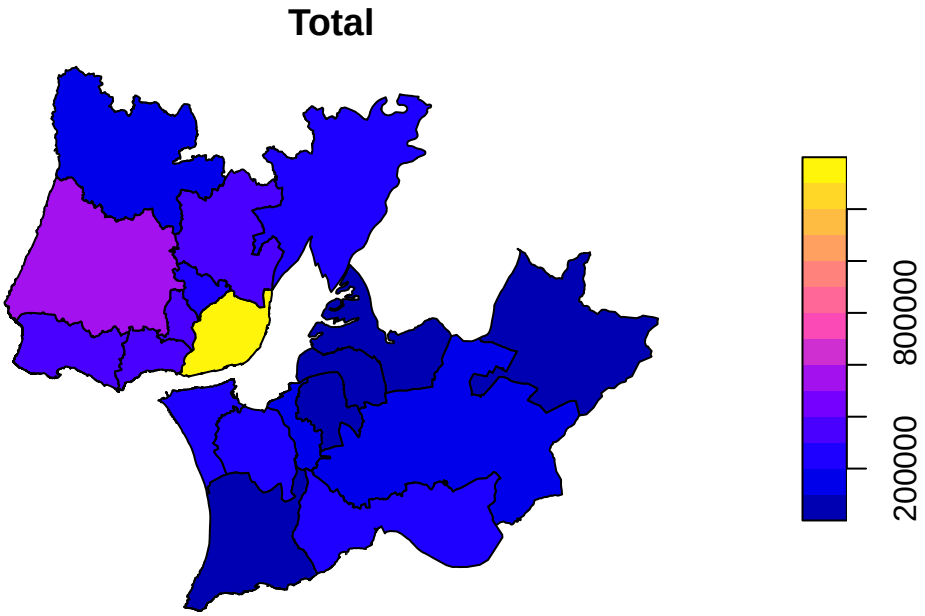
```
plot(TRIPSgeo) # all variables
```



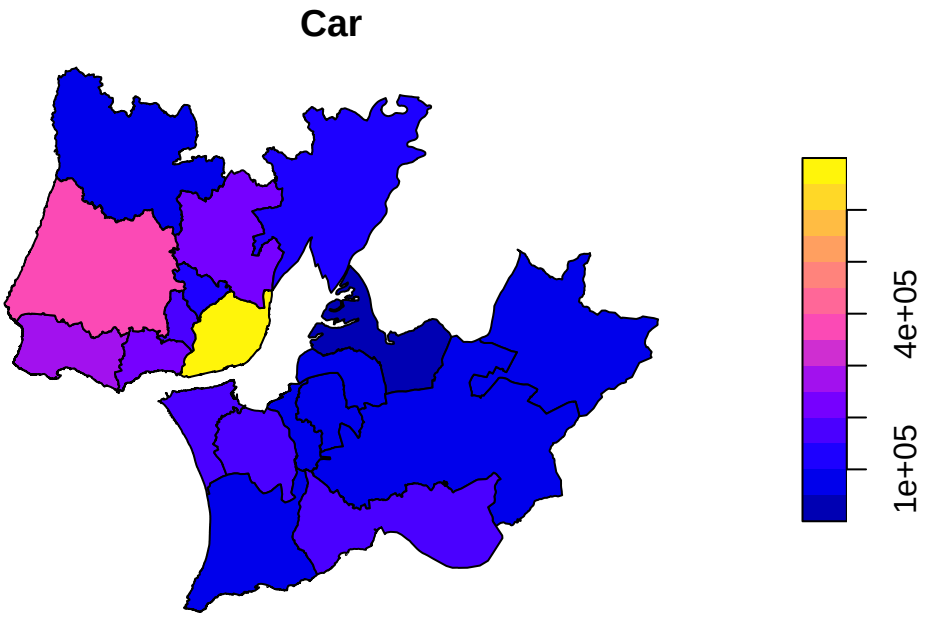

```
plot(TRIPSgeo["Municipality"])
```



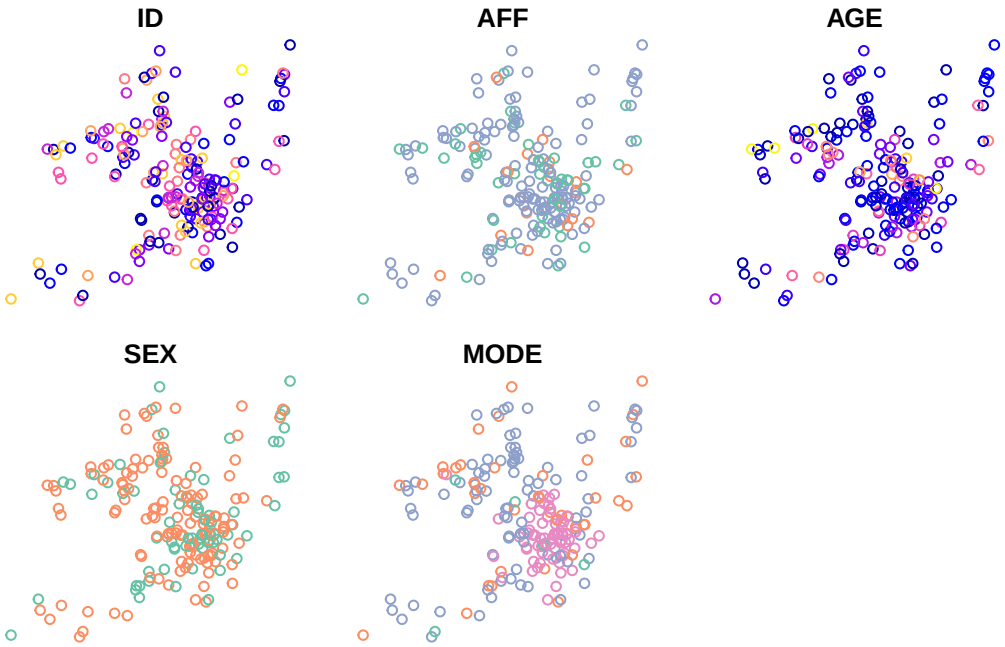

```
plot(TRIPSgeo["Total"])
```




```
plot(TRIPSgeo["Car"])
```




```
# plot pointy data
plot(SURVEYgeo)
```



In the next chapter we will learn how to create interactive maps.

10.5. Export spatial data

You can save your spatial data in different formats using the function `st_write()`, such as shapefiles (ESRI), GeoJSON, and GeoPackage.

This is also useful to convert spatial data between formats.

```
st_write(TRIPSgeo, "data/TRIPSgeo.gpkg") # as geopackage
st_write(TRIPSgeo, "data/TRIPSgeo.shp") # as shapefile
st_write(TRIPSgeo, "data/TRIPSgeo.geojson") # as geojson
st_write(TRIPSgeo, "data/TRIPSgeo.csv", layer_options = "GEOMETRY=AS_WKT")
    # as csv, with WKT geometry
```

If you already have a file with the same name, you can use the `delete_dns = TRUE` argument to overwrite it.

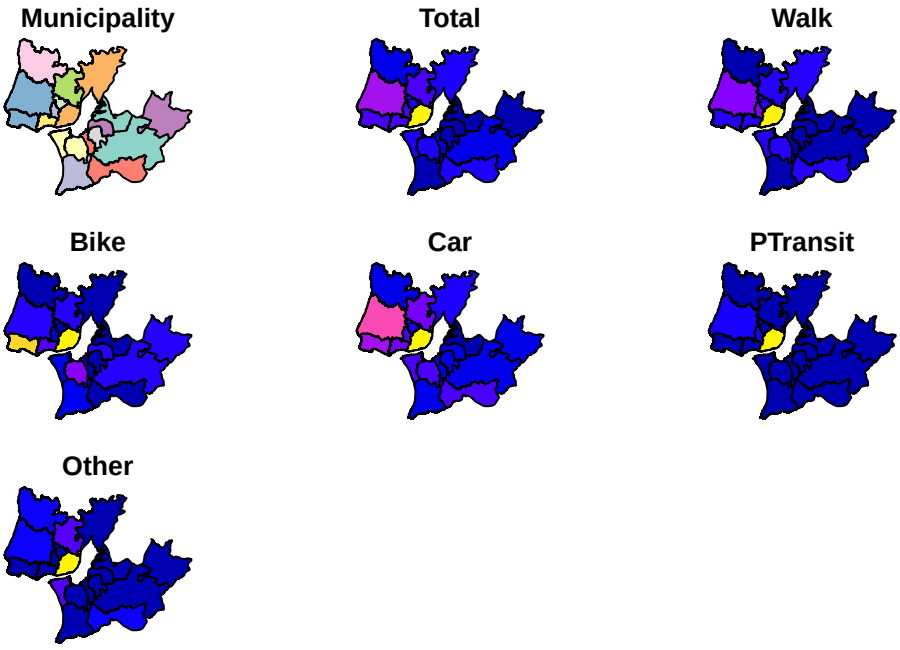
11. Interactive maps

You can plot a static map using `plof(sf)`, but you can also create interactive maps.

```
library(sf)
TRIPSgeo = st_read("../data/TRIPSgeo.gpkg")
```

```
Reading layer `TRIPSgeo' from data source
  `/media/rosa/Dados/GIS/MQAT/data/TRIPSgeo.gpkg' using driver `GPKG'
Simple feature collection with 18 features and 7 fields
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: -9.500527 ymin: 38.40907 xmax: -8.490972 ymax: 39.06472
Geodetic CRS:  WGS 84
```

```
plot(TRIPSgeo) # all variables
```




```
# one variable at a time
plot(TRIPSgeo["Municipality"])

plot(TRIPSgeo["Total"])
```

```
plot(TRIPSgeo["Car"])
```

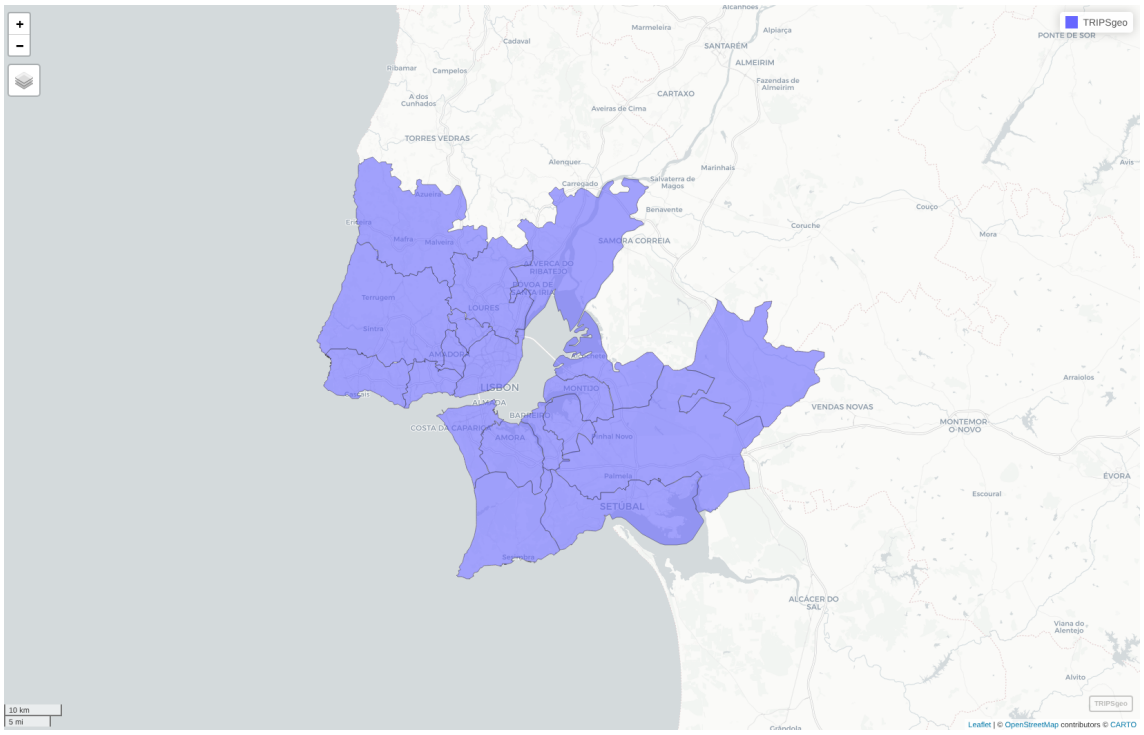
Interactive maps are useful to explore the data, as you can zoom in and out, and click on the points to see the data associated with them.

There are several R packages to create interactive maps. For instance, the `tmap` package, the `leaflet` package, and the `mapview` package.

11.1. Mapview

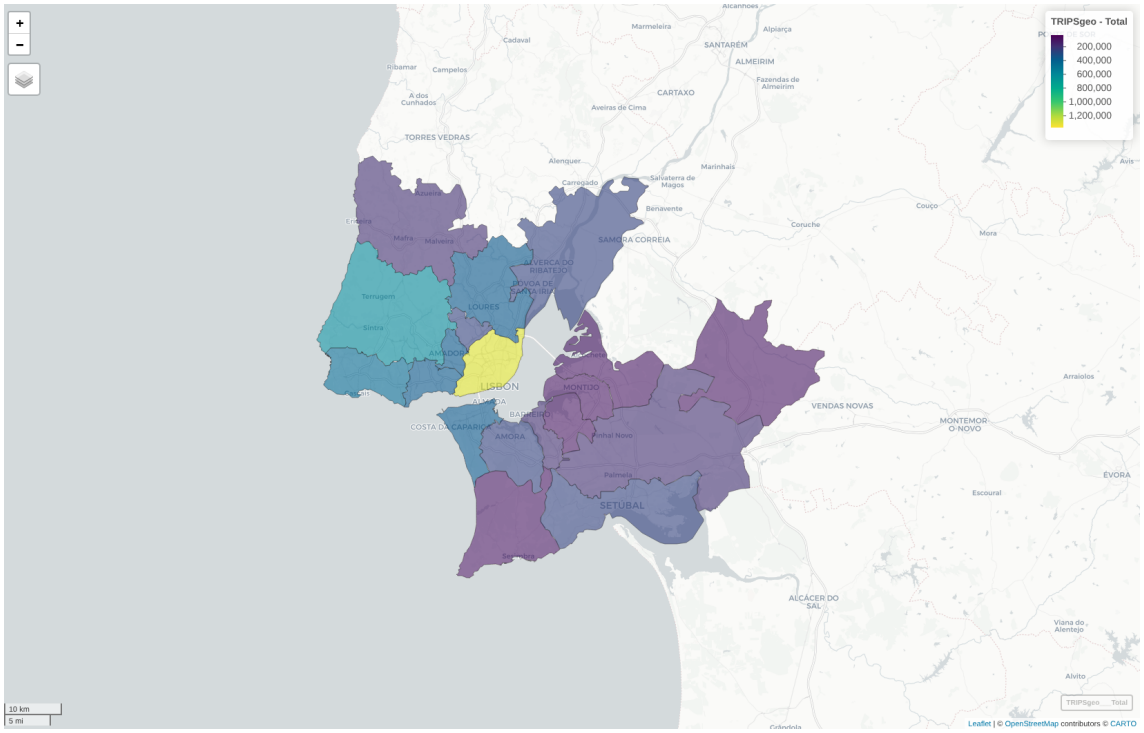
Mapview allows to create quick interactive maps, only by declaring the function `mapview()`.

```
library(mapview)
mapview(TRIPSgeo)
```



To color the points by a variable, you can use the `zcol` argument.

```
mapview(TRIPSgeo, zcol = "Total")
```

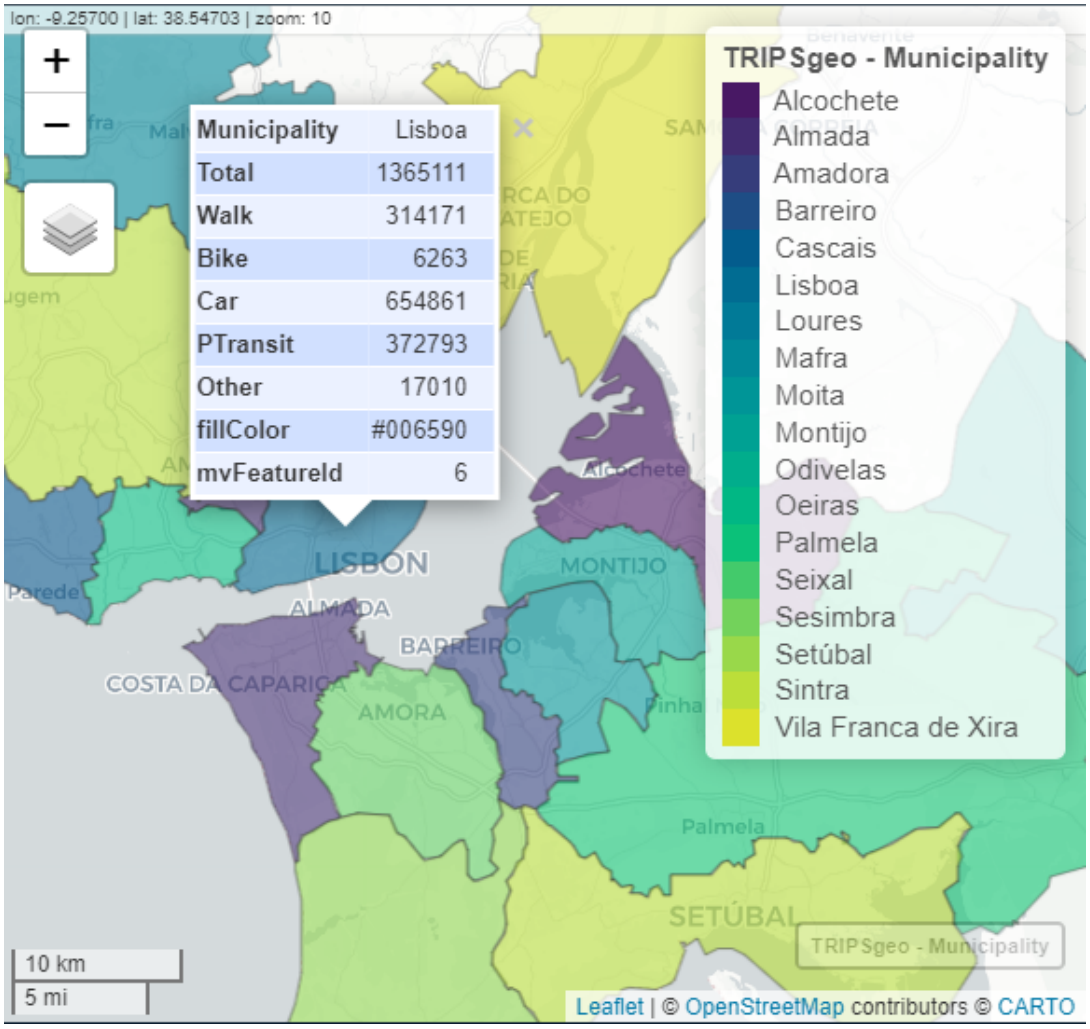


As you can see, a color palette is automatically assigned to the **continuous variable**.

Try to use a **categorical variable**.

```
mapview(TRIPSgeo,
        zcol = "Municipality", # depending on the variable
        alpha.regions = 0.4, # also add transparency
        color = "white" # border color
        )
```

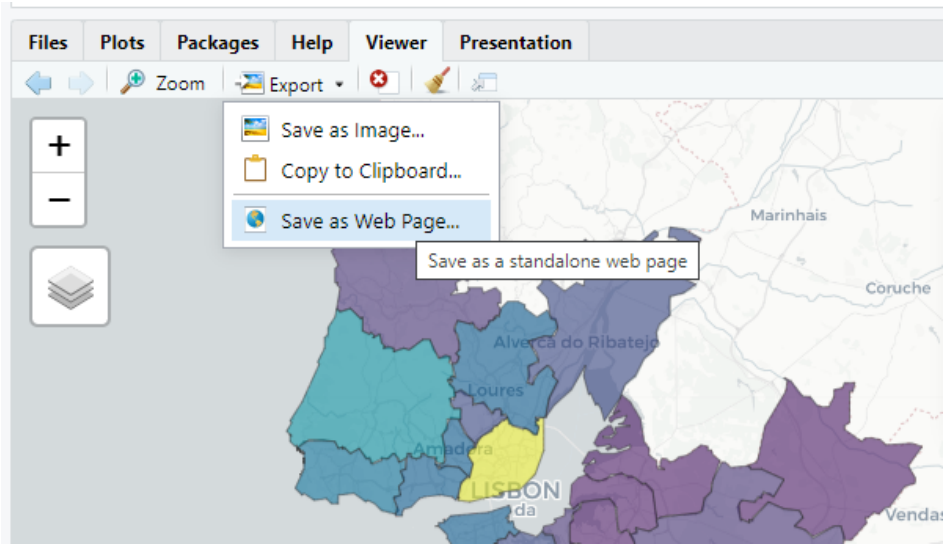
> Note that you can change the **basemap**, and click on the geometries to **see the data** associated with them.



You can go crazy with all the options that `mapview` offers. Please refer to the documentation to see all the options.

11.1.1. Export

You can directly export the map as an `html` file or image, using the Viewer panel.



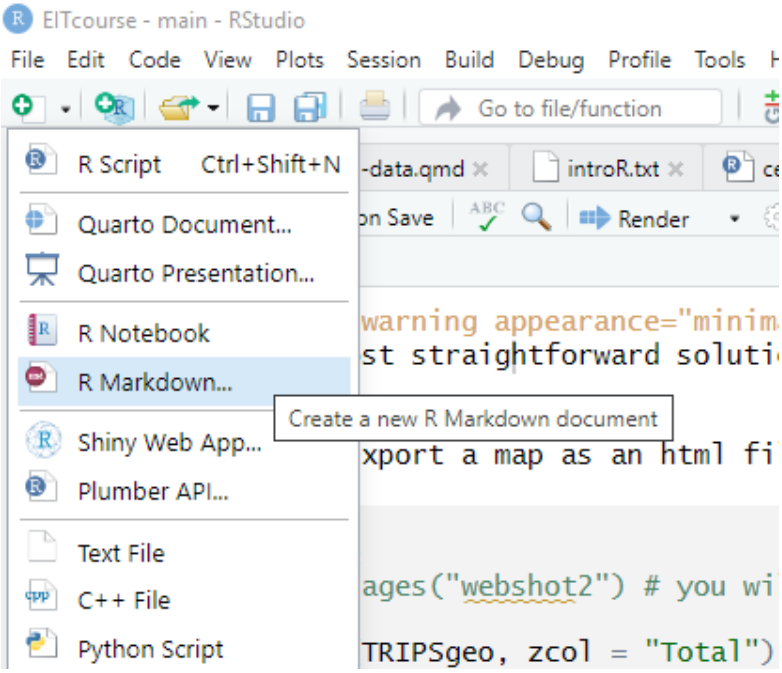
This is the most straightforward solution.

You can also export a map as an html file or image using code.

```
# install.packages("webshot2") # you will need this

map = mapview(TRIPSgeo, zcol = "Total") # first create an objet with the
    desired map

mapshot2(map, "data/map.html") # as webpage
mapshot2(map, file = "data/map.png") # as image
```

11.2. Rmarkdown

To include a map on a report, website, paper (any type), you can create an Rmarkdown file.



And include a R code chunk (`ctrl + alt + i`) with a map. If the output is html, you will get an interactive map on your document!

11.3. Flowmap blue

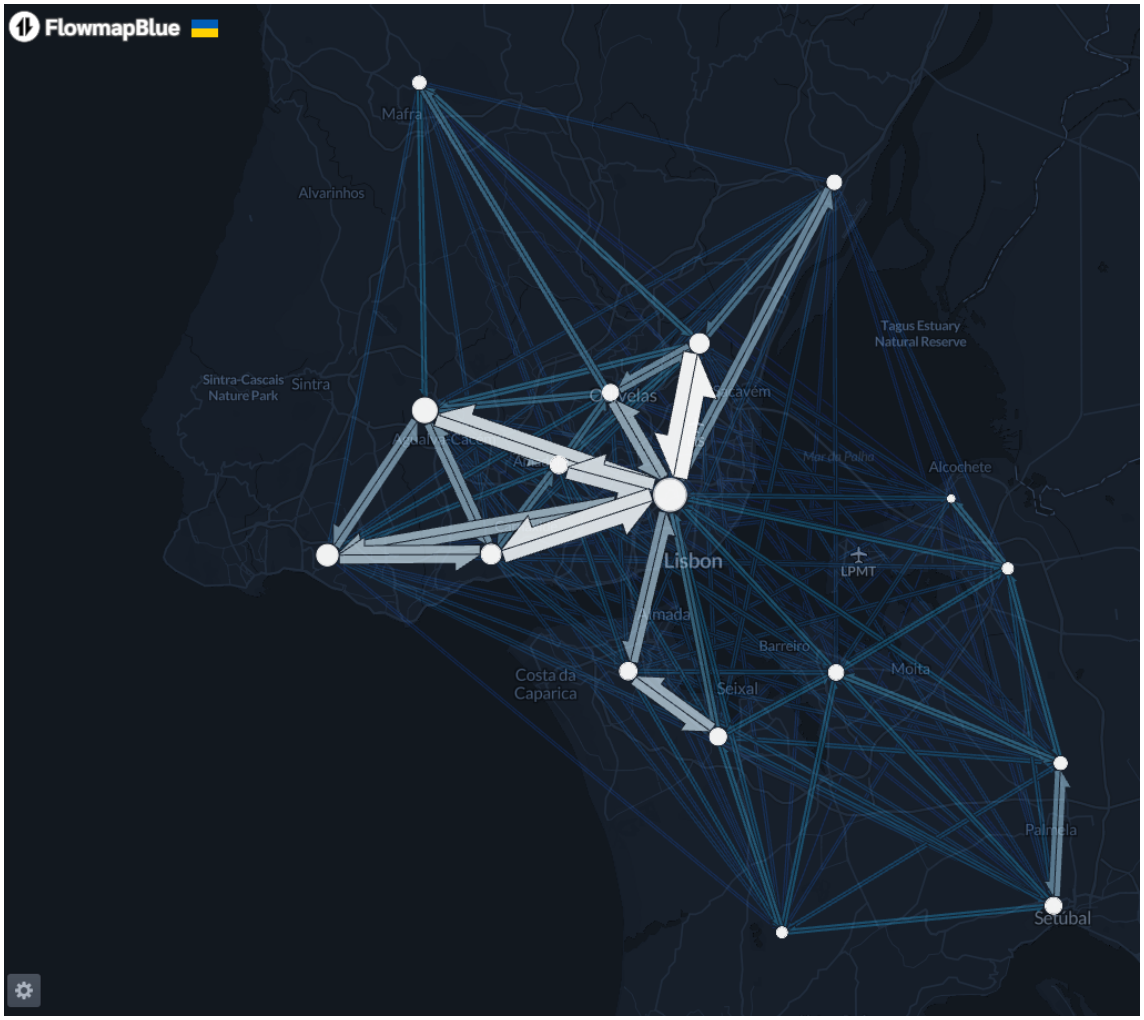
A way to visualize traffic or travel volumes between areas (OD pairs) is through the online tool flowmap.blue.

But you need to prepare the data so that they are exactly in the requested format. (See the used source code).

You need two files:

1. locations
2. flows

Try to copy and paste the content of these files in the corresponding fields the information about **car** trips in the Lisbon metropolitan area according to INE (2018).



Try it yourself

Visualize the **public transit** trips in the Lisbon metropolitan area. (flows_tp)

- Which differences do you see between car and public transit trips?
- How many trips are made daily in public transit with origin or destination in Sintra?

12. Centroids of transport zones

In this section we will calculate the geometric and the weighted centroids of transport zones.

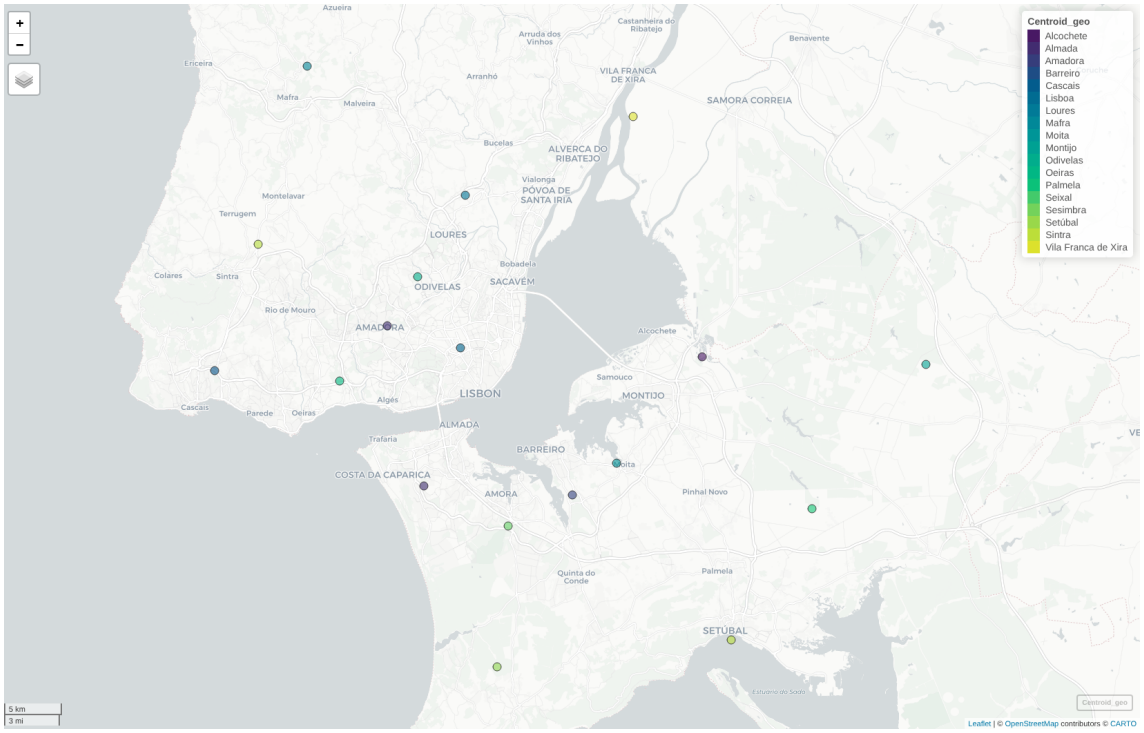
12.1. Geometric centroids

Taking the `Municipalities_geo` data from the previous section, we will calculate the geometric centroids, using the `st_centroid()` function.

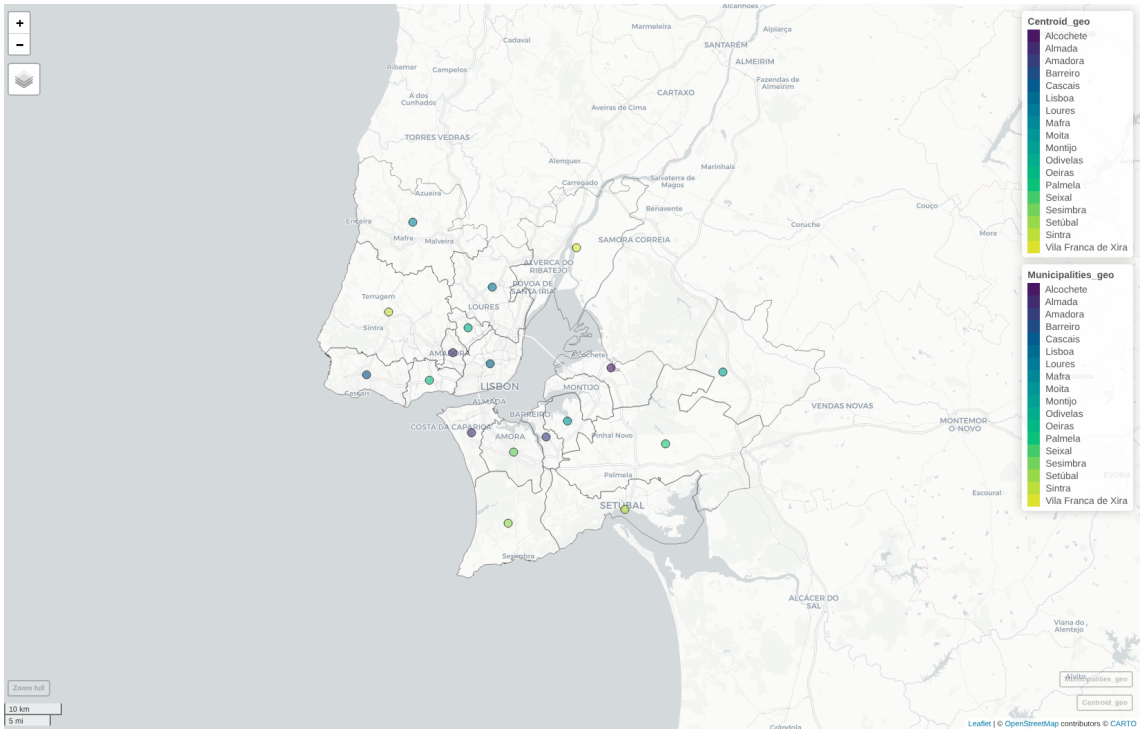
```
library(dplyr)
library(sf)
library(mapview)

Municipalities_geo = st_read("../data/Municipalities_geo.gpkg", quiet =
    TRUE)

Centroid_geo = st_centroid(Municipalities_geo)
```

This creates points at the geometric center of each polygon.

```
mapview(Centroid_geo)
```




```
mapview(Centroid_geo) + mapview(Municipalities_geo, alpha.regions = 0) #
    both maps, with full transparency in polygons
```



But… is this the best way to represent the center of a transport zone?

These results may be biased by the shape of the polygons, and not represent where activities are. Example: lakes, forests, etc.

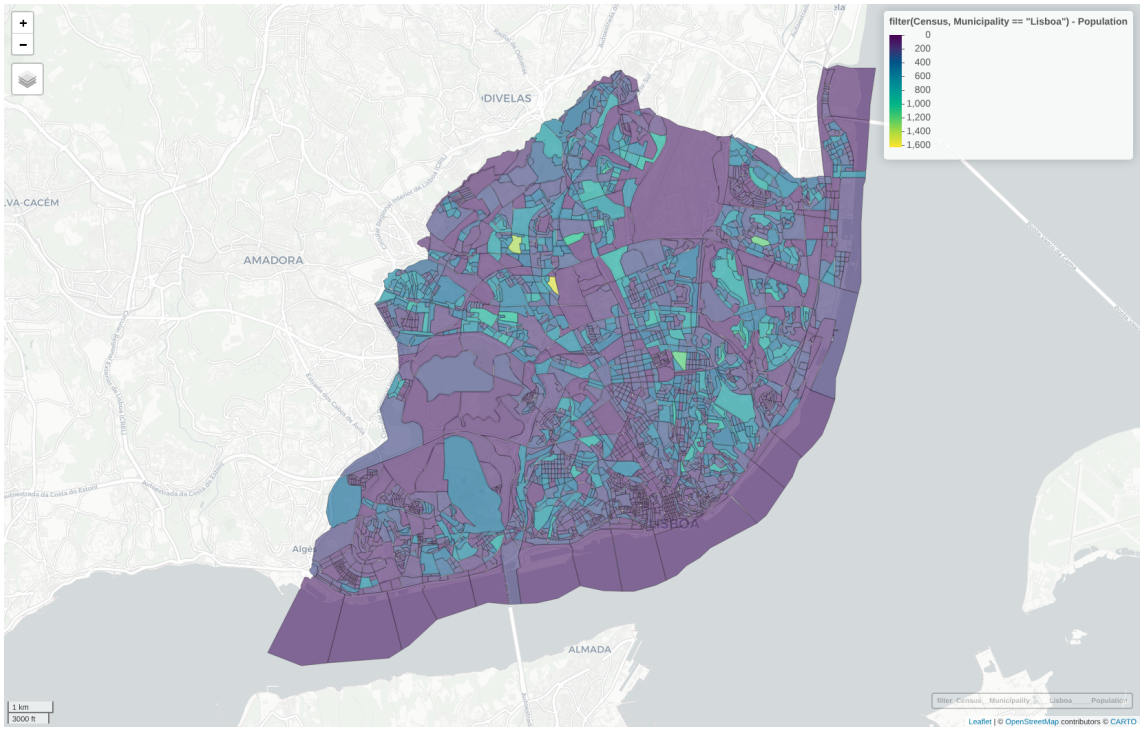
To overcome this, we can use **weighted centroids**.

12.2. Weighted centroids

We will weight centroids of transport zones by population and by number of buildings.

For this, we will need the census data (INE 2022).

```
Census = st_read("../data/census.gpkg", quiet = TRUE)

mapview(Census |> filter(Municipality == "Lisboa"), zcol = "Population")
```



It was not that easy to estimate weighted centroids with R, as it is with GIS software. But there is this new package `centr` that can help us (Zomorrodi 2024).

We need to specify the **group** we want to calculate the **mean centroids**, and the **weight variable** we want to use.

```
library(centr)
Centroid_pop = Census |>
  mean_center(group = "Municipality", weight = "Population")
```

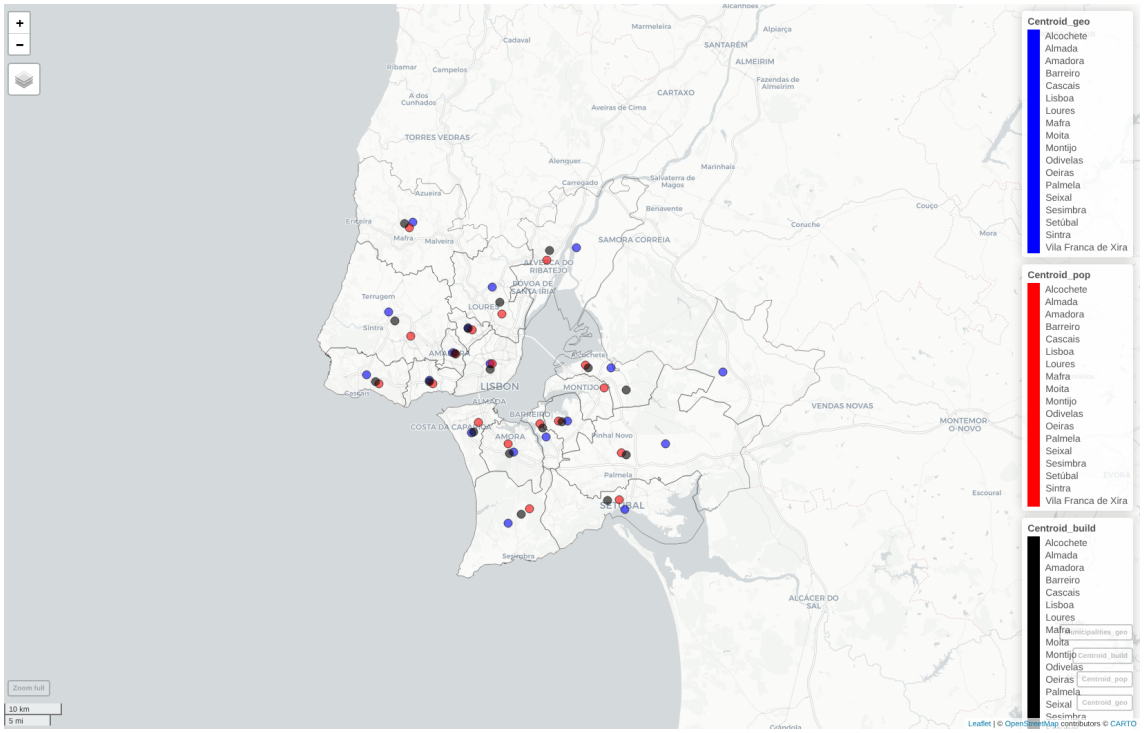
We can do the same for buildings.

```
Centroid_build = Census |>
  mean_center(group = "Municipality", weight = "Buildings")
```

12.3. Compare centroids in a map

12.3.1. Interactive map

```
mapview(Centroid_geo, col.region = "blue") +
  mapview(Centroid_pop, col.region = "red") +
  mapview(Centroid_build, col.region = "black") +
  mapview(Municipalities_geo, alpha.regions = 0) # polygon limits
```



See how the building, population and geometric centroids of Sintra are apart, from closer to Tagus, to the rural area.

12.3.2. Static map

To produce the same map, using only `plot()` and `st_geometry()`, we need to make sure that the geometries have the same crs.

```
st_crs(Centroid_geo) # 4326 WGS84
st_crs(Centroid_pop) # 3763 Portugal TM06
```

So, we need to transform the geometries to the same crs.

```
Centroid_pop = st_transform(Centroid_pop, crs = 4326)
Centroid_build = st_transform(Centroid_build, crs = 4326)
```

Now, to use `plot()` we incrementally add layers to the plot.

```
# Plot the Municipalities_geo polygons first (with no fill)
plot(st_geometry(Municipalities_geo), col = NA, border = "black")

# Add the Centroids_geo points in blue
plot(st_geometry(Centroid_geo), col = "blue", pch = 16, add = TRUE) # add!

# Add the Centroid_pop points in red
plot(st_geometry(Centroid_pop), col = "red", pch = 16, add = TRUE)

# Add the Centroid_build points in black
plot(st_geometry(Centroid_build), col = "black", pch = 16, add = TRUE)
```

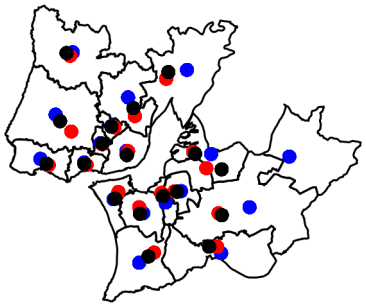


Figure 12.1.: Static map of different centroids of Municipalities

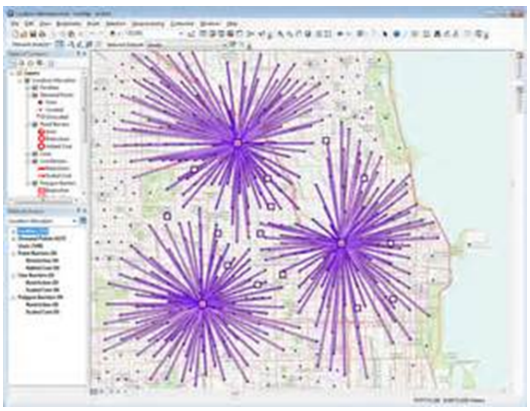
In the next section we will use these centroids to calculate the desire lines between them.

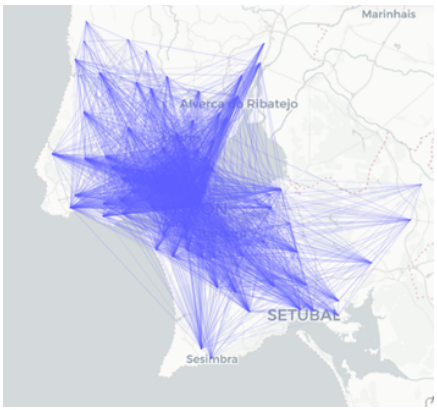
13. OD pairs and desire lines

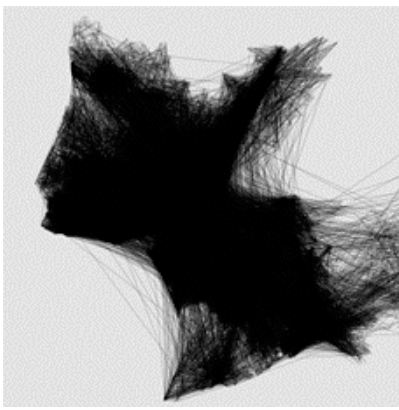
Desire lines are a way to represent the flow of people or goods between two points. They are often used in transport planning to represent the flow of trips between zones.

There are many ways to create desire lines, connecting origins and destinations. For instance:

- 1 origin to 1 destination
  - home work place
- multiple origins to a single destinations
  - students' homes 1 school
- origin zone to destination zone
  - for aggregated trips (macro representation)
- OD jittering[1]







The `stplanr` package is a collection of functions for sustainable transport planning with R, and it is built on top of the `sf` package (Lovelace and Ellison 2018).

In this workshop, we will use the `od` package, a lightweight package with a few functions from `stplanr`, namely the ones to create desire lines from origin-destination (OD) pairs (Lovelace and Morgan 2024).

[1] See (Lovelace, Félix, and Carlino 2022).

13.1. Desire lines with `od_to_sf`

To create desire lines, we need a dataset with OD pairs **and** other dataset with the corresponding transport zones (spatial data).

The `TRIPSmode.Rds` dataset includes origins, destinations and number of trips between municipalities.

```
TRIPSmode = readRDS("../data/TRIPSmode.Rds")
```

The `Municipalities_geo.gpkg` dataset includes the geometry of the transport zones.

```
library(sf)
Municipalities_geo = st_read("../data/Municipalities_geo.gpkg", quiet =
    TRUE) # supress mesage
```

Then, we need to load the `od` package. We will use the `od_to_sf()` function to create desire lines from OD pairs.

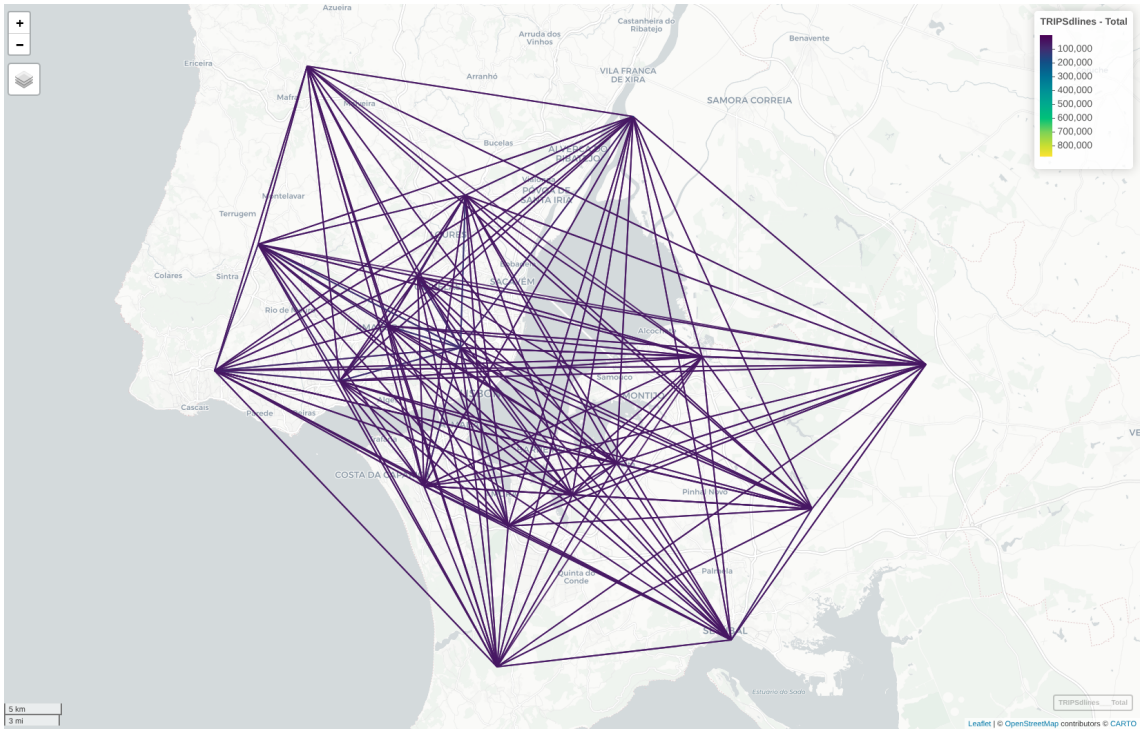
```
# install.packages("od")
library(od)

TRIPSdlines = od_to_sf(TRIPSmode, z = Municipalities_geo) # z for zones
```

For this magic to work smoothly, the first two columns of the `TRIPSmode` dataset must be the **origin** and **destination** zones, and these zones need to correspond to the first column of the `Municipalities_geo` dataset (with an associated geometry).

> See more options with the `?stplanr::od2line` function.

Now we can visualize the desire lines using the `mapview` function.

```
library(mapview)
mapview(TRIPSdlines, zcol = "Total")
```

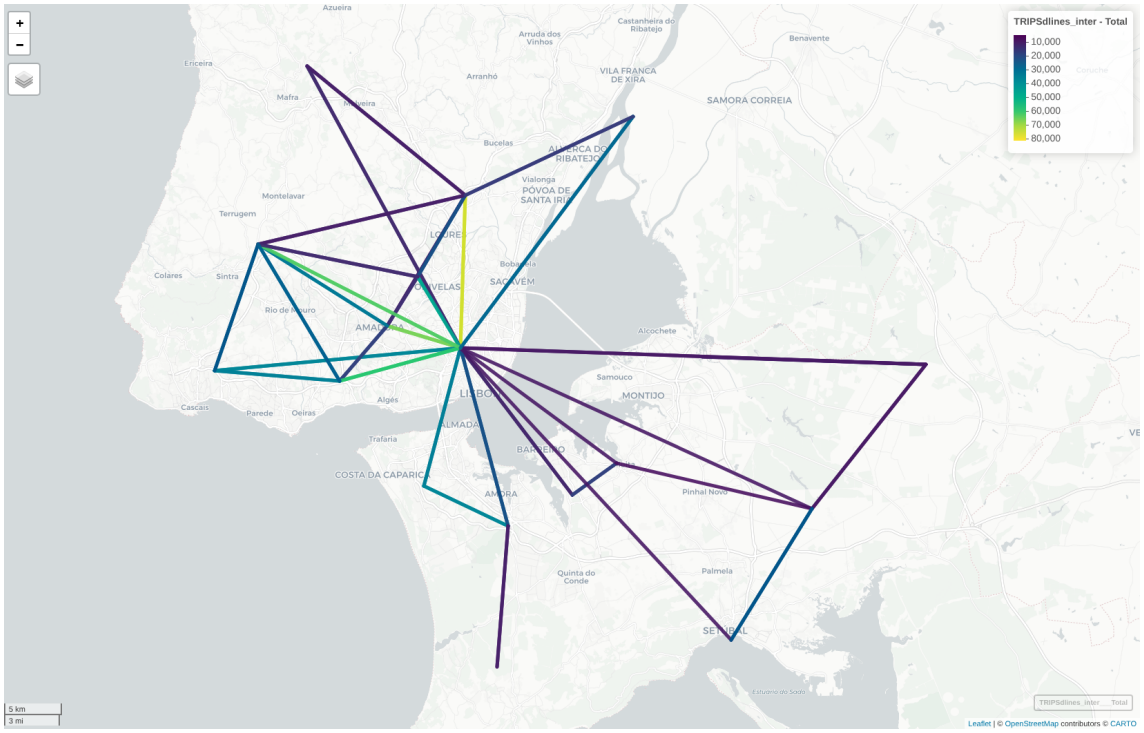


As you can see, this is too much information to be able to understand the flows.

13.1.1. Filtering desire lines

Filter **intrazonal** trips.

```
library(dplyr)

TRIPSdlines_inter = TRIPSdlines |>
  filter(Origin != Destination) |> # remove intrazonal trips
  filter(Total > 5000) # remove noise

mapview(TRIPSdlines_inter, zcol = "Total", lwd = 5)
```



Filter trips with origin or destination **not in** Lisbon.

```
TRIPSdl_noLX = TRIPSdlines_inter |>
  filter(Origin != "Lisboa", Destination != "Lisboa")

mapview(TRIPSdl_noLX, zcol = "Total", lwd = 8) # larger line width
```

Try to replace the `Total` with other variables, such as `Car`, `PTransit`, and see the differences.

13.2. Oneway desire lines

Note that the `od_to_sf()` function creates bidirectional desire lines. This can be not the ideal for visualization / representation purposes, as you will have 2 lines overlaping.

The function `od_oneway()` aggregates oneway lines to produce bidirectional flows.

By default, it returns the sum of each numeric column for each bidirectional origin-destination pair.

```
nrow(TRIPSdlines)
```

```
[1] 315
```

```
TRIPSdlines_oneway = od_oneway(TRIPSdlines) |>
  filter(o != d) # remove empty geometries
nrow(TRIPSdlines_oneway)
```

```
[1] 150
```

Note that for the last municipalities you have less combinations now. Nevertheless, all the possible combinations are represented.

```
head(TRIPSdlines_oneway[,c(1,2)]) # just the first 2 columns
```

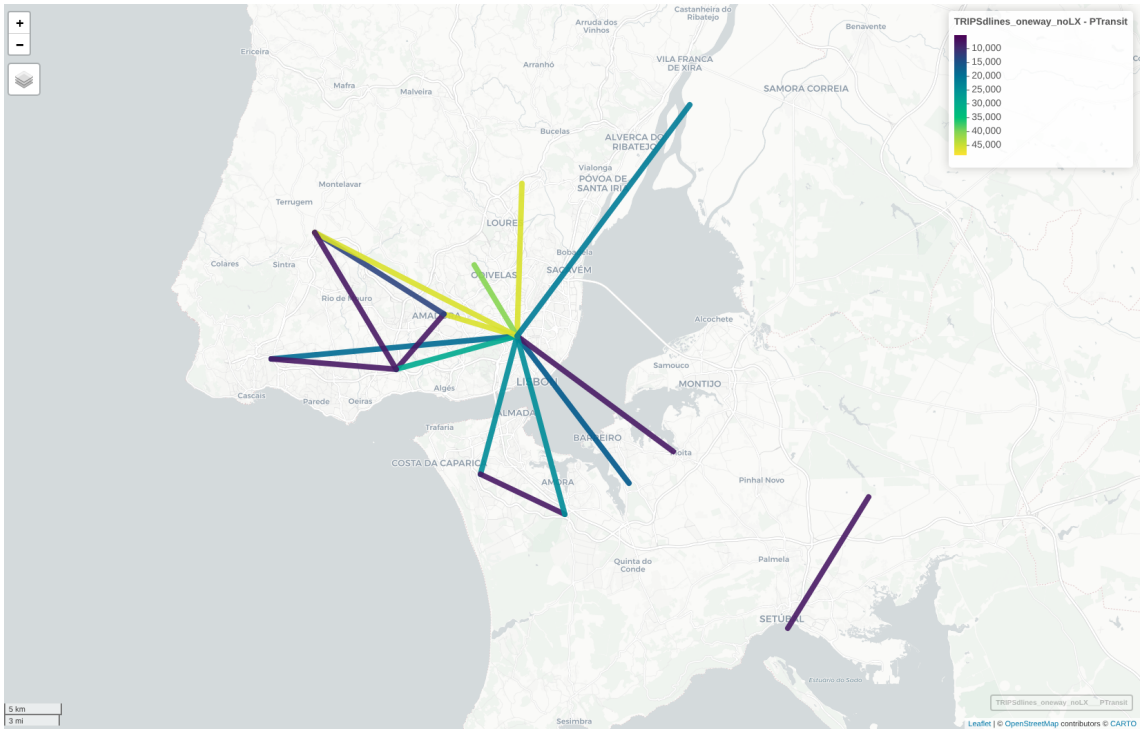
```
Simple feature collection with 6 features and 2 fields
Attribute-geometry relationships: identity (2)
Geometry type: LINESTRING
Dimension:     XY
Bounding box:  xmin: -9.229502 ymin: 38.62842 xmax: -8.915878 ymax: 38.75981
Geodetic CRS:  WGS 84
          o        d                        geometry
1 Alcochete   Almada LINESTRING (-8.915878 38.73...
2 Alcochete  Amadora LINESTRING (-8.915878 38.73...
3    Almada  Amadora LINESTRING (-9.193061 38.63...
4 Alcochete Barreiro LINESTRING (-8.915878 38.73...
5    Almada Barreiro LINESTRING (-9.193061 38.63...
6   Amadora Barreiro LINESTRING (-9.229502 38.75...
```

```
tail(TRIPSdlines_oneway[,c(1,2)])
```

```
Simple feature collection with 6 features and 2 fields
Attribute-geometry relationships: identity (2)
Geometry type: LINESTRING
Dimension:     XY
Bounding box:  xmin: -9.357651 ymin: 38.49491 xmax: -8.80664 ymax: 38.92208
Geodetic CRS:  WGS 84
           o                   d                        geometry
145   Oeiras Vila Franca de Xira LINESTRING (-9.276317 38.71...
146  Palmela Vila Franca de Xira LINESTRING (-8.80664 38.617...
147   Seixal Vila Franca de Xira LINESTRING (-9.108785 38.60...
148 Sesimbra Vila Franca de Xira LINESTRING (-9.120129 38.49...
149  Setúbal Vila Franca de Xira LINESTRING (-8.887489 38.51...
150   Sintra Vila Franca de Xira LINESTRING (-9.357651 38.82...
```

Example of visualization with Public Transit trips in both ways.

```
TRIPSdlines_oneway_noLX = TRIPSdlines_oneway |>
  filter(PTransit > 5000) # reduce noise

mapview(TRIPSdlines_oneway_noLX, zcol = "PTransit", lwd = 8)
```



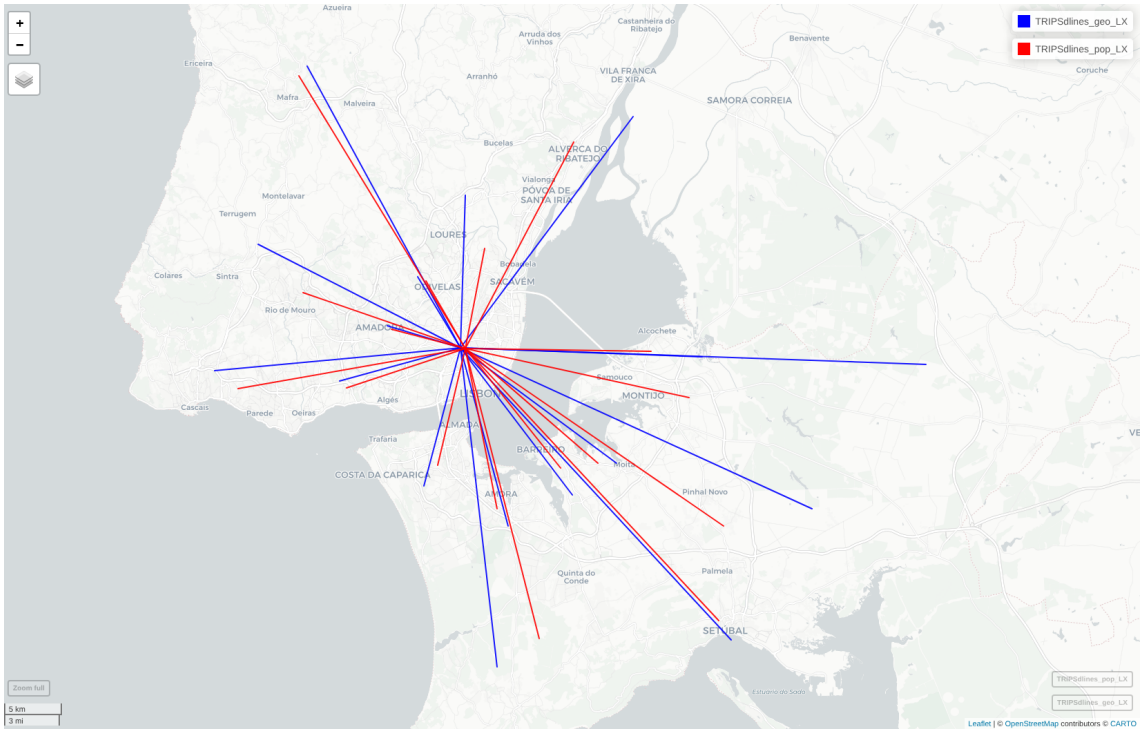
13.3. Using population centroids

The `od_to_sf()` function uses the geometric center of the zones to create the desire lines. But if we replace those zones by the weighted centroids, we can have a more realistic representation of the flows.

```
# Centroid_pop = st_read("data/Centroid_pop.gpkg")

TRIPSdlines_pop = od_to_sf(TRIPSmode, z = Centroid_pop) |>  # works the
    same way
  od_oneway() |> # oneway
  filter(o != d) # remove empty geometries
```

Check differences of lines with trips from/to Lisbon:

```
TRIPSdlines_geo_LX = TRIPSdlines_oneway |>
  filter(o == "Lisboa" | d == "Lisboa") # or condition
TRIPSdlines_pop_LX = TRIPSdlines_pop |>
  filter(o == "Lisboa" | d == "Lisboa")

mapview(TRIPSdlines_geo_LX, color = "blue") + mapview(TRIPSdlines_pop_LX,
    color = "red")
```



The next step will be estimating the **euclidean distances** between these centroids, and compare them with the **routing distances**.

14. Euclidean and routing distances

We will show how to estimate euclidean distances (*as crown flights*) using `sf` package, and the distances using a road network using `openrouteservice` package.

14.1. Euclidean distances

Taking the survey respondents' location, we will estimate the distance to the university (IST) using the `sf` package.

14.1.1. Import survey data frame convert to sf

We will use a survey dataset with 200 observations, with the following variables: ID, Affiliation, Age, Sex, Transport Mode to IST, and latitude and longitude coordinates.

```
library(dplyr)

SURVEY = read.csv("../data/SURVEY.txt", sep = "\t") # tab delimiter
names(SURVEY)
```

```
[1] "ID"   "AFF"  "AGE"  "SEX"  "MODE" "lat"  "lon"
```

As we have the coordinates, we can convert this data frame to a spatial feature, as explained in the Introduction to spatial data section.

```
library(sf)

SURVEYgeo = st_as_sf(SURVEY, coords = c("lon", "lat"), crs = 4326) #
    convert to as sf data
```

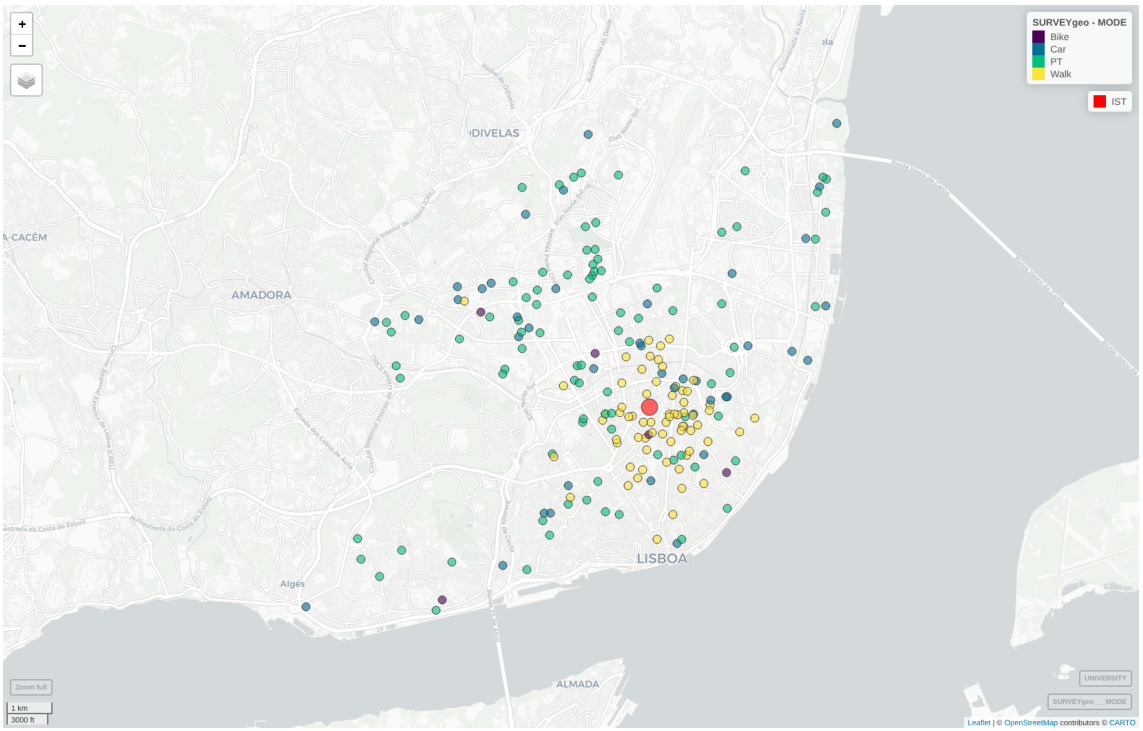
14.1.2. Create new point at the university

Using coordinates from Instituto Superior Técnico, we can directly create a simple feature and assign its crs.

```
UNIVERSITY = data.frame(place = "IST",
                        lon = -9.1397404,
                        lat = 38.7370168) |>  # first a dataframe
  st_as_sf(coords = c("lon", "lat"), # then a spacial feature
           crs = 4326)
```

Visualize in a map:

```
library(mapview)
mapview(SURVEYgeo, zcol = "MODE") + mapview(UNIVERSITY, col.region =
    "red", cex = 12)
```



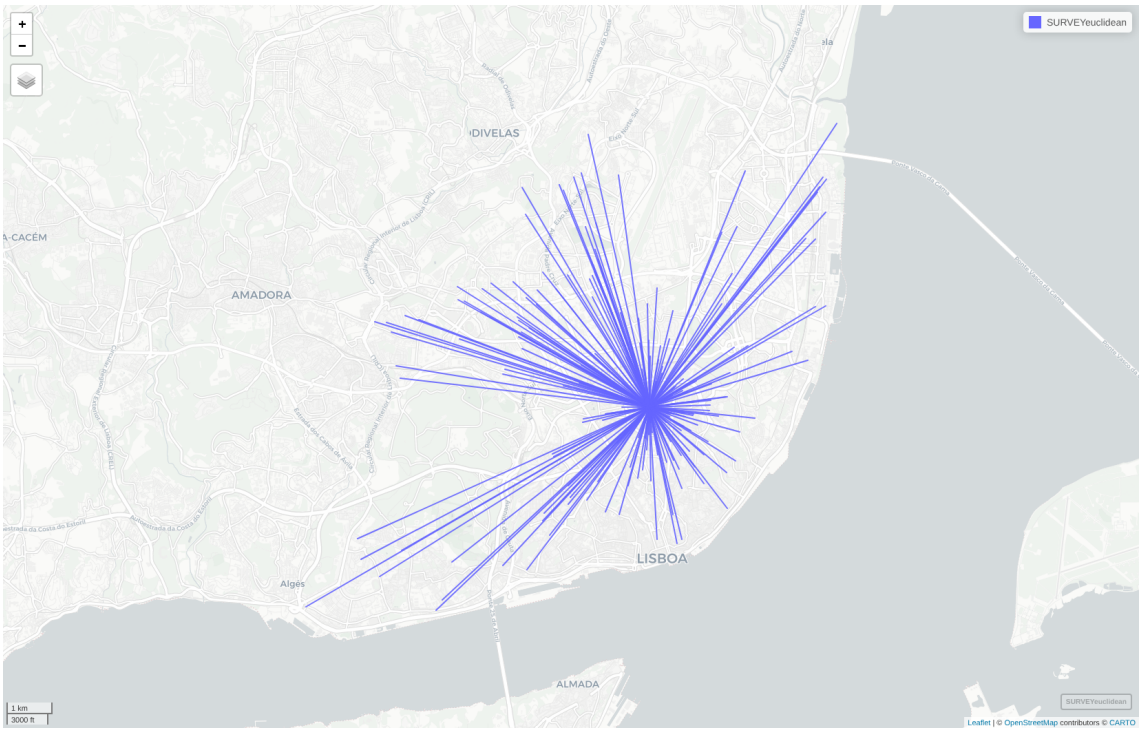
14.1.3. Straight lines

First we will create lines connecting the survey locations to the university, using the `st_nearest_points()` function.

This function finds returns the nearest points between two geometries, and creates a line between them. This can be useful to find the nearest train station to each point, for instance.

As we only have 1 point at UNIVERSITY layer, we will have the same number of lines as number of surveys = 200.

```
SURVEYeuclidean = st_nearest_points(SURVEYgeo, UNIVERSITY, pairwise =
    TRUE) |>
  st_as_sf() # this creates lines

mapview(SURVEYeuclidean)
```



Note that if we have more than one point in the second layer, the `pairwise = TRUE` will create a line for each combination of points. Set to `FALSE` if, for instance, you have the same number of points in both layers and want to create a line between the corresponding points.

14.1.4. Distance

Now we can estimate the distance using the `st_length()` function.

```
# compute the line length and add directly in the first survey layer
SURVEYgeo = SURVEYgeo |>
  mutate(distance = st_length(SURVEYeuclidean))

# remove the units - can be useful
SURVEYgeo$distance = units::drop_units(SURVEYgeo$distance)
```

We could also estimate the distance using the `st_distance()` function **directly**, although we would not get and sf with lines.

```
SURVEYgeo = SURVEYgeo |>
  mutate(distance = st_distance(SURVEYgeo, UNIVERSITY)[,1] |>  # in meters
           units::drop_units()) |>  # remove units
  mutate(distance = round(distance)) # round to integer

summary(SURVEYgeo$distance)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
    298    1106    2186    2658    3683    8600
```

`SURVEYgeo` is still a points' sf.

14.2. Routing Engines

There are different types of routing engines, regarding the type of network they use, the type of transportation they consider, and the type of data they need. We can have:

- Uni-modal vs. Multi-modal
  - One mode per trip vs. One trip with multiple legs that can be made with different modes
  - Multi-modal routing may require GTFS data (realistic Public Transit)
- Output level of the results
  - Routes (1 journey = 1 route)
  - Legs
  - Segments
- Routing profiles
  - Type of user
  - fastest / shortest path
  - avoid barriers / tolls, etc

Figure 14.1.: Routing options in OpenRouteService

- Local vs. Remote (service request - usually web API)
  - Speed vs. Quota limits / price
  - Hard vs. Easy set up

  - Hardware limitations in local routing
  - Global coverage in remote routing, with frequent updates

Examples: OSRM, Dodgr, r5r, Googleway, CycleStreets, HERE.

14.3. Routing distances with `openrouteservice`

We will use the `openrouteservice` r package to estimate the distances using a road network (Oleś 2025).

> ℹ To properly use the `openrouteservice` package, you need to setup the ORS provider. See the setup instructions for more details.

We will use only respondents with a distance to the university less than 2 km.

```
SURVEYsample = SURVEYgeo |> filter(distance <= 2000)
nrow(SURVEYsample)
```

```
[1] 95
```

We need an id (unique identifier) for each survey location, so we can compare them later.

Also, we need to extract the coordinates, from both datasets, to be used in the routing functions of `openrouteservice::directions()`.

```
# create id columns for both datasets
SURVEYsample = SURVEYsample |>
  mutate(id = c(1:nrow(SURVEYsample))) |>  # from 1 to the number of rows
  mutate(coordinates = st_coordinates(geometry)) # extract coordinates

UNIVERSITY = UNIVERSITY |>
  mutate(id = 1) |> # only one row
  mutate(coordinates = st_coordinates(geometry)) # extract coordinates
```

14.3.1. Distances by car

Estimate the routes with time and distance by car, from survey locations to University.

> ⚠ This one is not that easy to set-up because the function is prepared to retrieve only one result per request :(So we do a loop function.

```
library(openrouteservice)

SURVEYcar = data.frame() # initial empty data frame

# loop - the origin (i) is the survey location, and the UNIVERSITY is
    always the same destination
for (i in 1:nrow(SURVEYsample)) {
  ROUTES1 = ors_directions(
    data.frame(
      lon = c(SURVEYsample$coordinates[i, 1], UNIVERSITY$coordinates[1,
          1]),
      lat = c(SURVEYsample$coordinates[i, 2], UNIVERSITY$coordinates[1,
          2])
    ),
    profile = "driving-car", # or cycling-regular foot-walking
    preference = "fastest", # or shortest
    output = "sf"
  )
  ROUTES1$distance = ROUTES1$summary[[1]]$distance # extract these values
    from summary
  ROUTES1$duration = ROUTES1$summary[[1]]$duration

  SURVEYcar = rbind(SURVEYcar, ROUTES1) # to keep adding in the same df
}

SURVEYcar = SURVEYcar |>
  select(distance, duration, geometry) |> # discard unnecessary variables
  mutate(ID = SURVEYsample$ID) # cbind with syrvey ID
```

14.3.2. Distances by foot

Repeat the same for `foot-walking`.

```
SURVEYwalk = data.frame() # initial empty data frame

# loop - the origin (i) is the survey location, and the UNIVERSITY is
    always the same destination
for (i in 1:nrow(SURVEYsample)) {
  ROUTES1 = ors_directions(
    data.frame(
      lon = c(SURVEYsample$coordinates[i, 1], UNIVERSITY$coordinates[1,
          1]),
      lat = c(SURVEYsample$coordinates[i, 2], UNIVERSITY$coordinates[1,
          2])
    ),
    profile = "foot-walking", # or driving-car cycling-regular
        cycling-electric
```

```
    preference = "fastest", # or shortest
    output = "sf"
  )
  ROUTES1$distance = ROUTES1$summary[[1]]$distance # extract these values
    from summary
  ROUTES1$duration = ROUTES1$summary[[1]]$duration

  SURVEYwalk = rbind(SURVEYwalk, ROUTES1) # to keep adding in the same df
}

SURVEYwalk = SURVEYwalk |>
  select(distance, duration, geometry) |> # discard unnecessary variables
  mutate(ID = SURVEYsample$ID) # cbind with survey ID
```

14.3.3. Distances by bike

And for `cycling-regular`.

```
SURVEYbike = data.frame() # initial empty data frame

# loop - the origin (i) is the survey location, and the UNIVERSITY is
    always the same destination
for (i in 1:nrow(SURVEYsample)) {
  ROUTES1 = ors_directions(
    data.frame(
      lon = c(SURVEYsample$coordinates[i, 1], UNIVERSITY$coordinates[1,
          1]),
      lat = c(SURVEYsample$coordinates[i, 2], UNIVERSITY$coordinates[1,
          2])
    ),
    profile = "cycling-regular",
    preference = "fastest", # or shortest
    output = "sf"
  )
  ROUTES1$distance = ROUTES1$summary[[1]]$distance # extract these values
    from summary
  ROUTES1$duration = ROUTES1$summary[[1]]$duration

  SURVEYbike = rbind(SURVEYbike, ROUTES1) # to keep adding in the same df
}

SURVEYbike = SURVEYbike |>
  select(distance, duration, geometry) |> # discard unnecessary variables
  mutate(ID = SURVEYsample$ID) # cbind with survey ID
```

```
names(SURVEYcar)
```

```
[1] "distance" "duration" "ID"       "geometry"
```

> If we want to know only time and distance, and **not the route** itself, we can use the `ors_matrix()`.

14.4. Compare distances

We can now compare the euclidean and routing distances that we estimated for the survey locations under 2 km.

```
summary(SURVEYsample$distance) # Euclidean
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
    298     790    1046    1112    1470    1963
```

```
summary(SURVEYwalk$distance) # Walk
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  467.3  1009.0  1447.3  1471.8  1953.5  2769.4
```

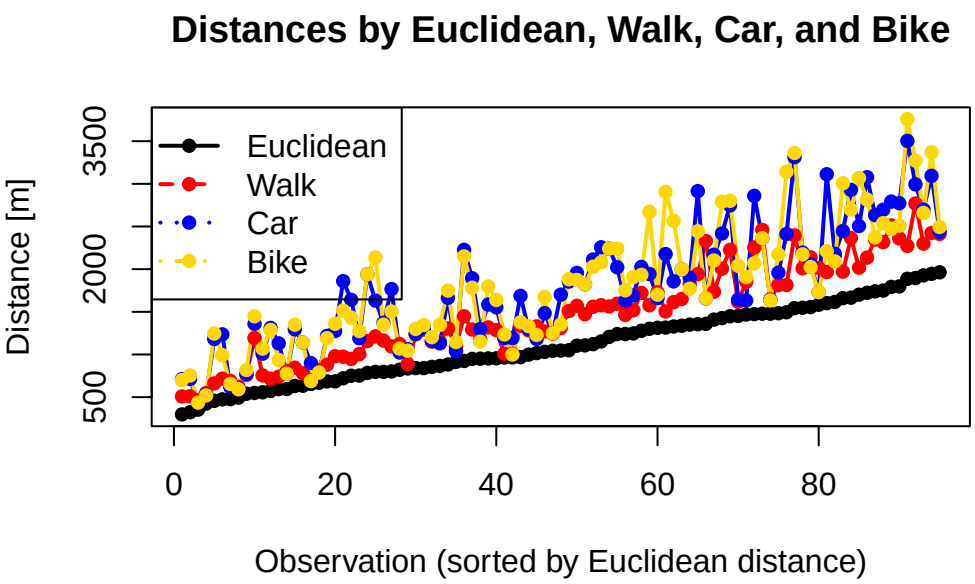
```
summary(SURVEYcar$distance) # Car
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  435.4  1227.0  1686.7  1771.4  2210.3  3503.2
```

```
summary(SURVEYbike$distance) # Bike
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
    436    1247    1752    1791    2225    3758
```

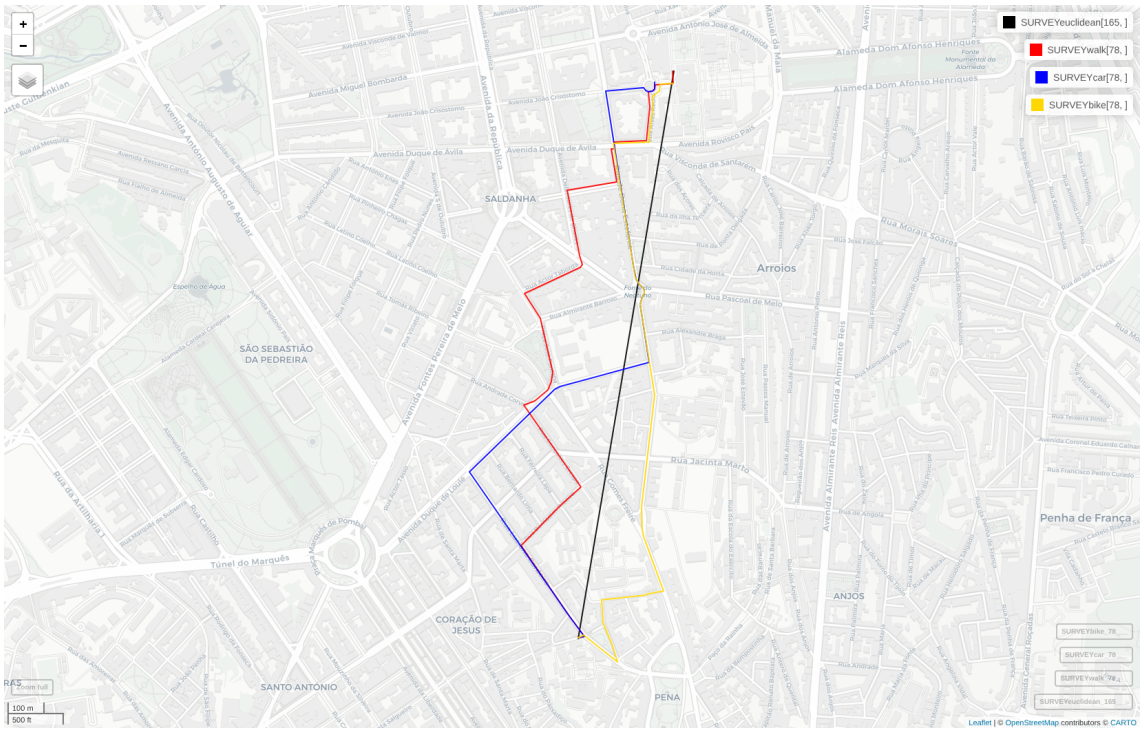
What can you understand from this results?



14.4.1. Circuity

Compare 1 single route.

```
mapview(SURVEYeuclidean[165,], color = "black") + # 1556 meters
  mapview(SURVEYwalk[78,], color = "red") + # 2126 meters
  mapview(SURVEYcar[78,], color = "blue") + # 2058 meters
  mapview(SURVEYbike[78,], color = "gold") # 2025 meters
```



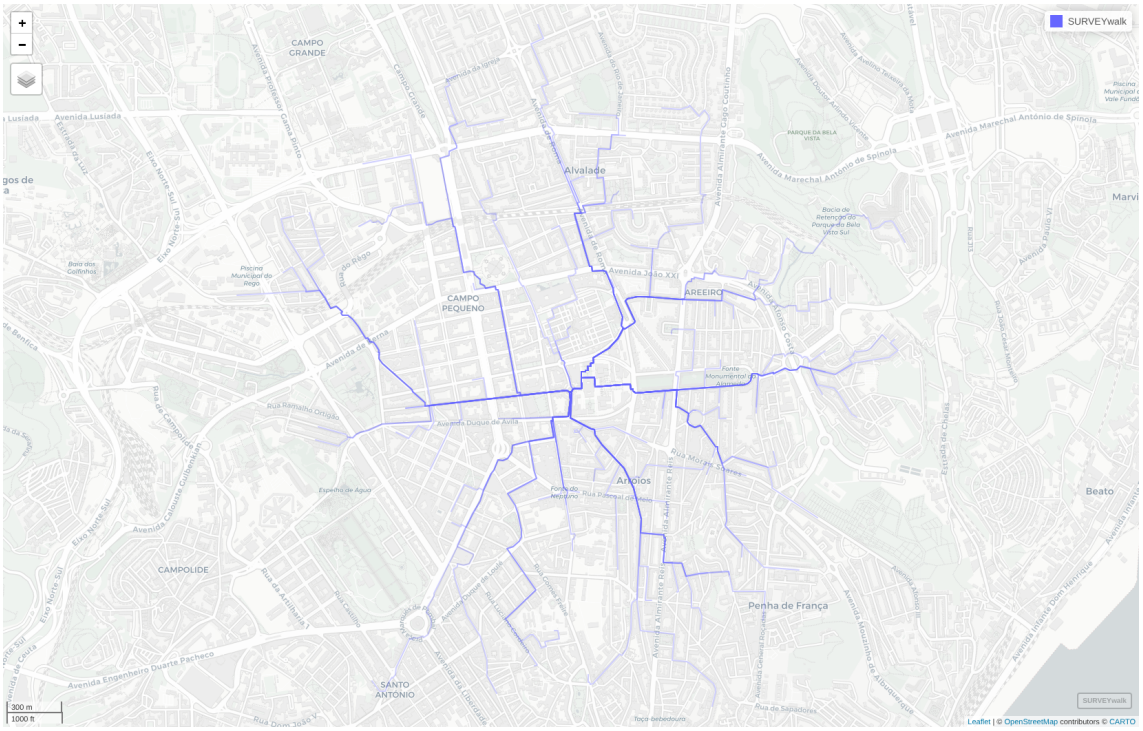
With this we can see the **circuity** of the routes, a measure of route / transportation efficiency, which is the ratio between the routing distance and the euclidean distance.

The circuity for car (1.32) is usually lower than for walking (1.37) or biking, for longer distances, and higher opposite for shorter distances.

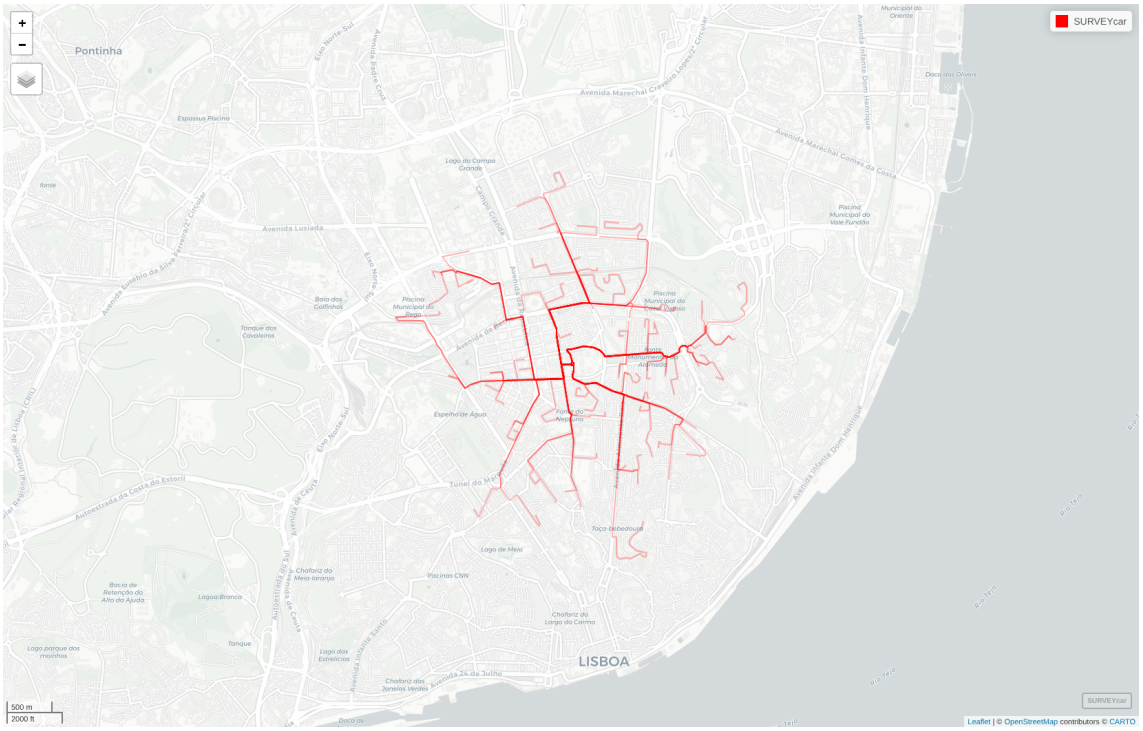
14.5. Visualize routes

Visualize with transparency of 30%, to get a clue when they overlay.

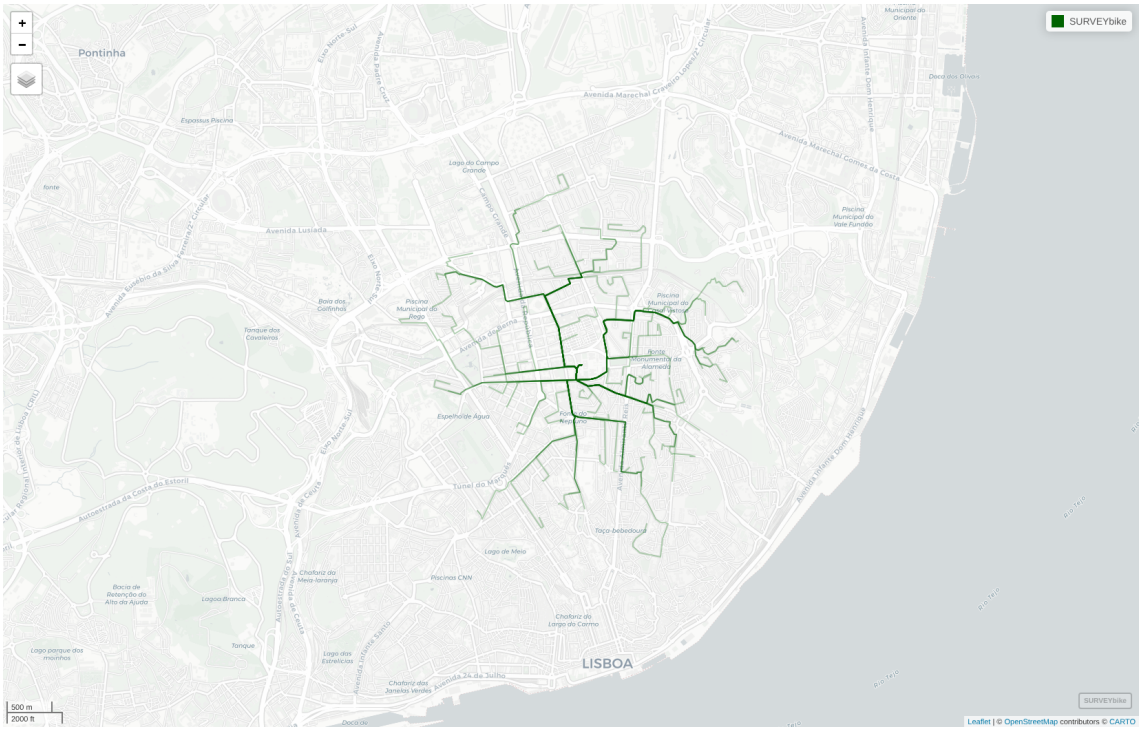
```
mapview(SURVEYwalk, alpha = 0.3)
```




```
mapview(SURVEYcar, alpha = 0.3, color = "red")
```

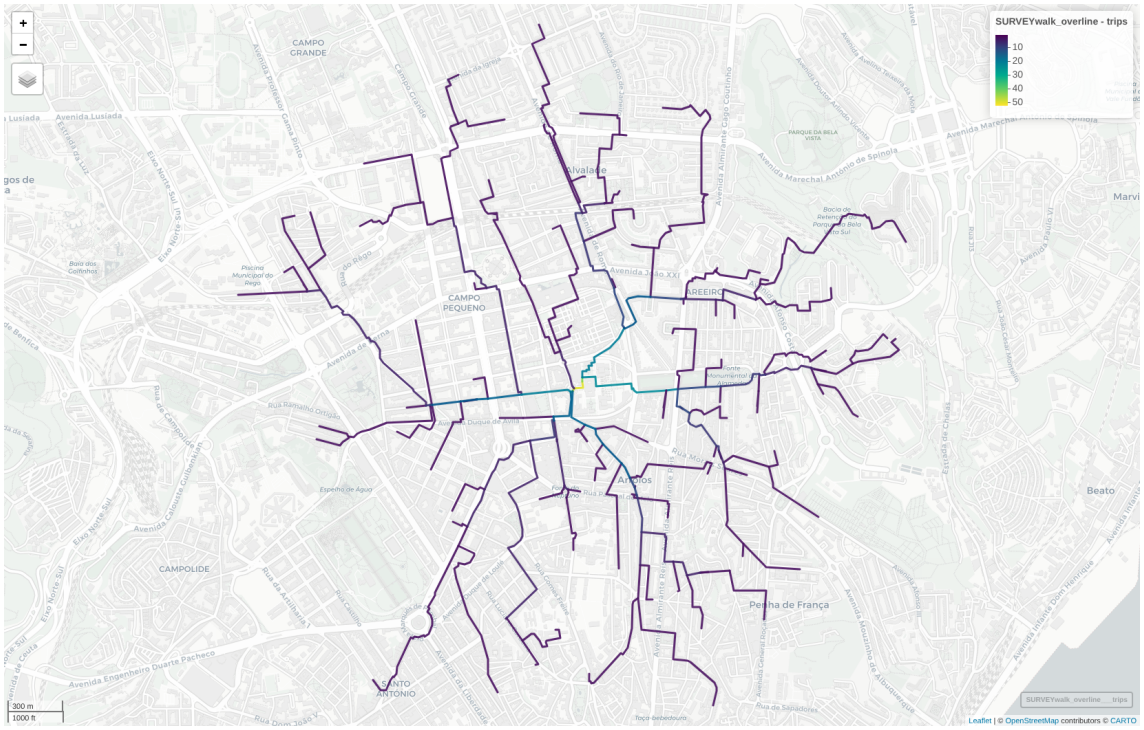



```
mapview(SURVEYbike, alpha = 0.3, color = "darkgreen")
```



We can also use the `overline()` function from `stplanr` package to break up the routes when they *overline*, and add them up.

```
# we create a value that we can later sum
# it can be the number of trips represented by this route
SURVEYwalk$trips = 1 # in this case is only one respondent per route

SURVEYwalk_overline = stplanr::overline(
  SURVEYwalk,
  attrib = "trips",
  fun = sum
)

mapview(SURVEYwalk_overline, zcol = "trips", lwd = 3)
```



With this we can visually inform on how many people travel along a route, from the survey dataset[1].

Questions

- How many people are entering IST by the stairs near *Bar de Civil*?
- And by the North gate?
- And from Alameda stairs?

[1] Assuming all travel by the shortest path.

15. Buffers vs. Isochones

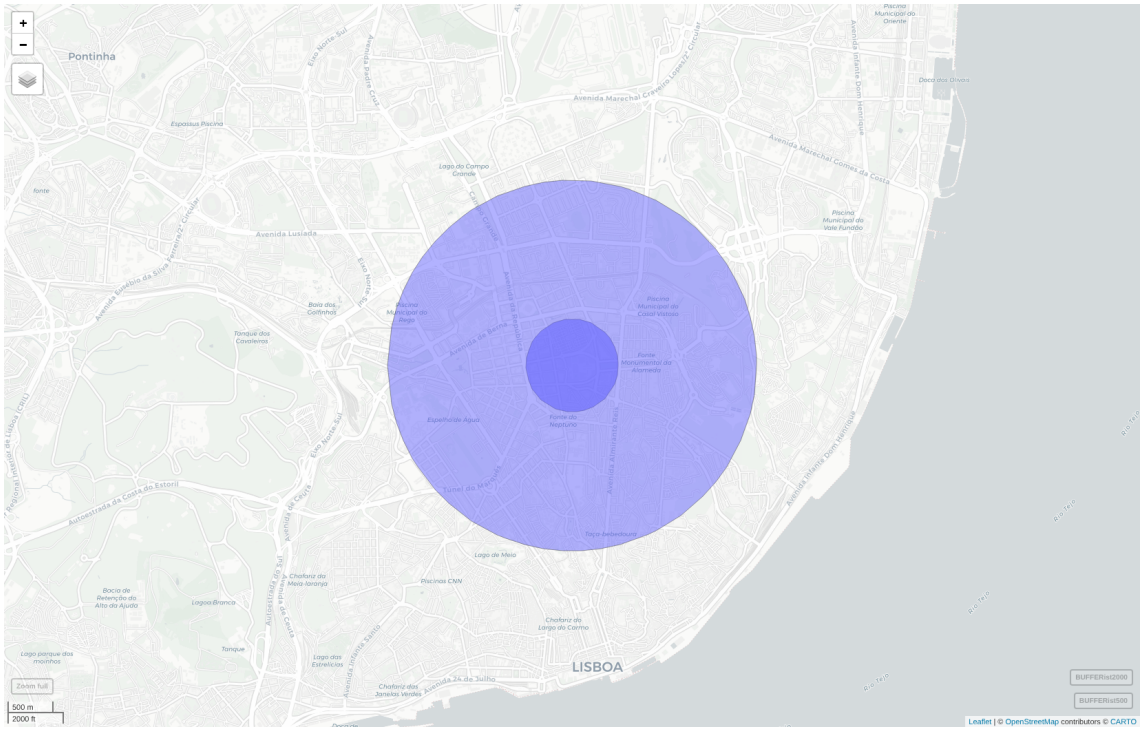
We will use the `stplnar` package to create buffers in meters, and the `openrouteservice` package to create isochrones.

15.1. Buffer

Represent a buffer of 500 m and 2000 m from IST[1].

```
IST = st_sfc(st_point(c(-9.1397404, 38.7370168)), crs = 4326) # create a
    point
IST$coordinates = st_coordinates(IST)

# BUFFERist500 = st_buffer(IST, dist = 500) # non  projected - results may
    be weird
BUFFERist500 = geo_buffer(IST[1], dist = 500) # from stplnar, to make sure
    it is in meters.
BUFFERist2000 = geo_buffer(IST[1], dist = 2000)

mapview(BUFFERist500) + mapview(BUFFERist2000, alpha.regions = 0.5)
```

[1] Here I selected only the first variable because now we also have the coordinates information (unecessary for this procedure)



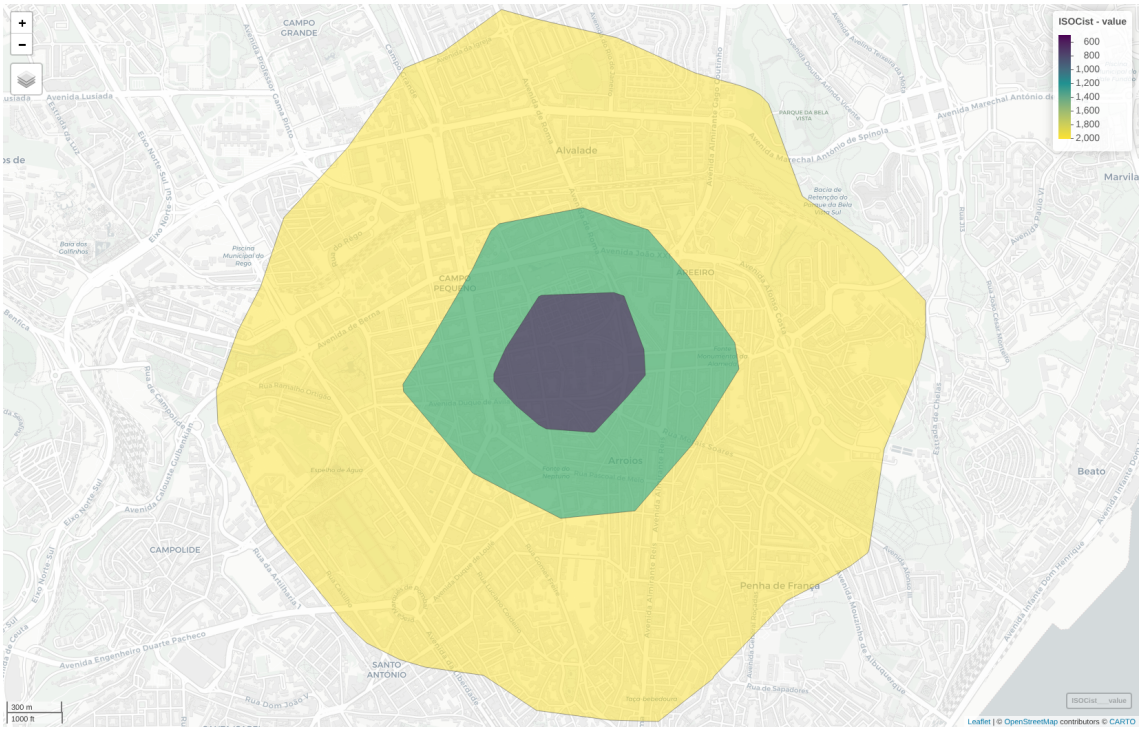
15.2. Isochrone

15.2.1. Isochrone from 1 point - distance

We use again the `openrouteservice` r package.

```
ISOCist = ors_isochrones(
  IST$coordinates,
  profile = "foot-walking",
  range_type = "distance", # or time
  range = c(500, 1000, 2000),
  output = "sf"
)

ISOCist = arrange(ISOCist, -value) |>  # to make the larger polygons on
    top of the table so the are displayed behind.
          select(-center) # unnecessary variable
```

```
mapview(ISOCist, zcol = "value", alpha.regions = 0.5)
```



As you can see, the distance buffer of 500m is larger than the isochrone of 500m. Actually we can measure their area of reach.

```
ISOCist$area = st_area(ISOCist)
BUFFERist500$area = st_area(BUFFERist500)
BUFFERist2000$area = st_area(BUFFERist2000)

ratio1 = BUFFERist500$area / ISOCist$area[ISOCist$value == 500] # 1.71
ratio2 = BUFFERist2000$area / ISOCist$area[ISOCist$value == 2000] # 1.22
```

The euclidean buffer of 500m is 1.7 times larger than its isochrone, and the buffer of 2000m is 1.23 times larger than its isochrone.

15.2.2. Isochrone from more than 1 point - time

For this purpose we will use the high schools dataset.

```
# import schools
SCHOOLS = st_read("../geo/SCHOOLS_basicsec.gpkg", quiet = TRUE)

SCHOOLS$coordinates = st_coordinates(SCHOOLS) # create coordinate variable

SCHOOLShigh = SCHOOLS |>
  filter(Nivel == "Secundario")  # filter the high schools
SCHOOLShigh = SCHOOLShigh |> mutate(id = 1:nrow(SCHOOLShigh)) # provide
    and id
```

```
# list of XY coordinates for ORS
coord_schools = data.frame(lon = SCHOOLShigh$coordinates[, 1],
                           lat = SCHOOLShigh$coordinates[, 2])
                           # id = SCHOOLShigh$id)
```

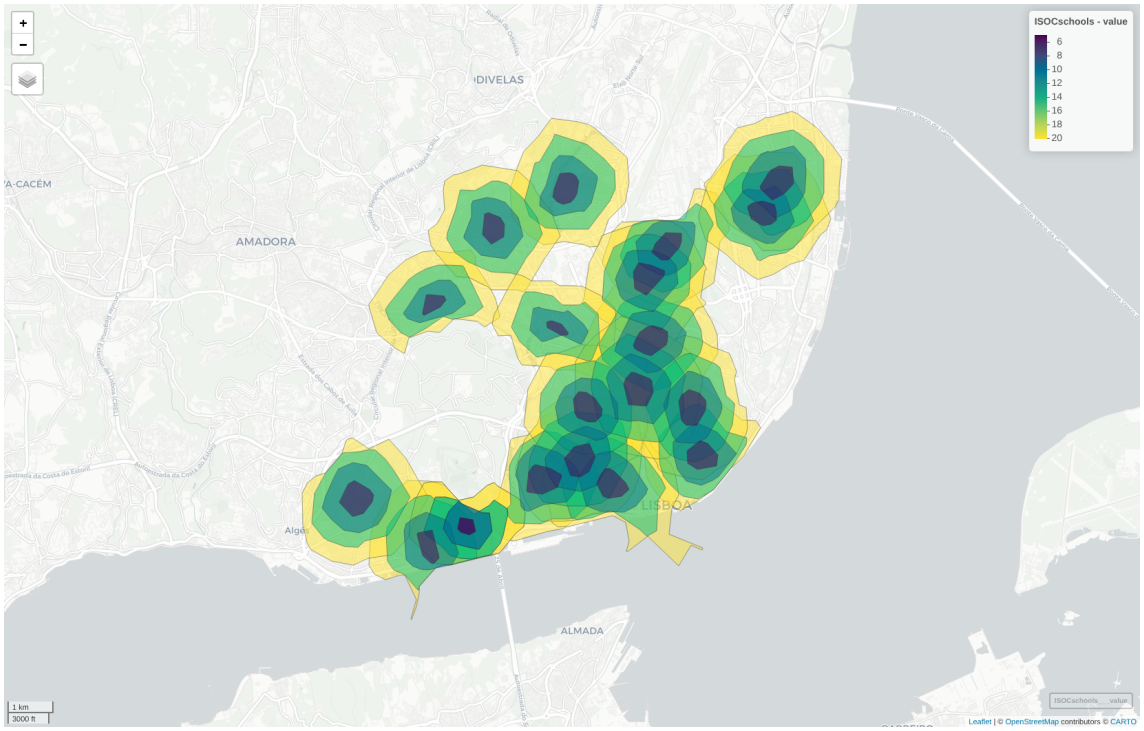
And proceed with the time isochrones, for a range of 20 min, with 5 min intervals.

```
ISOCschools = ors_isochrones(
  coord_schools,
  profile = "foot-walking",
  range_type = "time", # or distance
  range = 20*60, # 20 minutes in seconds
  interval = 5*60, # to have intervals of 5 minutes
  attributes = "area", #you can directly get area, population, and so on.
  output = "sf"
)

ISOCschools = arrange(ISOCschools, -value) |> # larger polygons on top of
    the table so the are displayed behind.
  select(-center)
```

And now merge this information with the schools' names.

```
ISOCschools = ISOCschools |>
  mutate(id = group_index + 1, # because group_index starts at 0
         value = value/60) |>
    left_join(SCHOOLShigh |>
                st_drop_geometry() |>
                select(id, INF_NOME, Alunos))
```

```
mapview(ISOCschools, zcol = "value", alpha.regions = 0.5)
```



And estimate areas for the 20min isochrones

```
summary(ISOCschools$area[ISOCschools$value==20])/1000000 # in km²
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  3.295   4.303   5.363   5.098   5.804   6.511 
```

16. Open transportation data

In this chapter we will guide you through sources of open data for transportation analysis: road networks and public transportation information.

16.1. Road Networks

16.1.1. OpenStreetMap

The OpenStreetMap is a collaborative online mapping project that creates a free editable map of the world.

This is the most used source of road network data for transportation analysis in academia, since it is available almost **everywhere in the world**, is open and free to use.

> Although it can be not 100% accurate, OSM is a good source of data for most of the cases.

You can access it's visualization tool at www.openstreetmap.org. To edit the map, you can use the Editor, once you register.

If you want to **download** the data, you can use the following tools.

- Overpass API
- Geofabrik

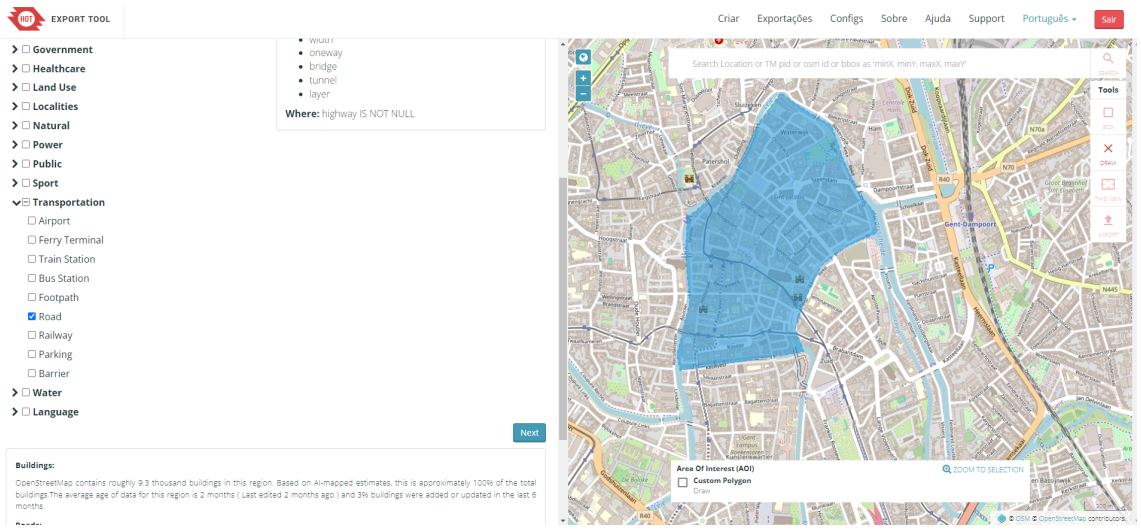
These websites include all the OSM data, with **much more information than you need**.

16.1.2. HOT Export Tool

This interactive tool helps you to select the **region** you want to extract, the type of **information** to include, and the output data **format**.

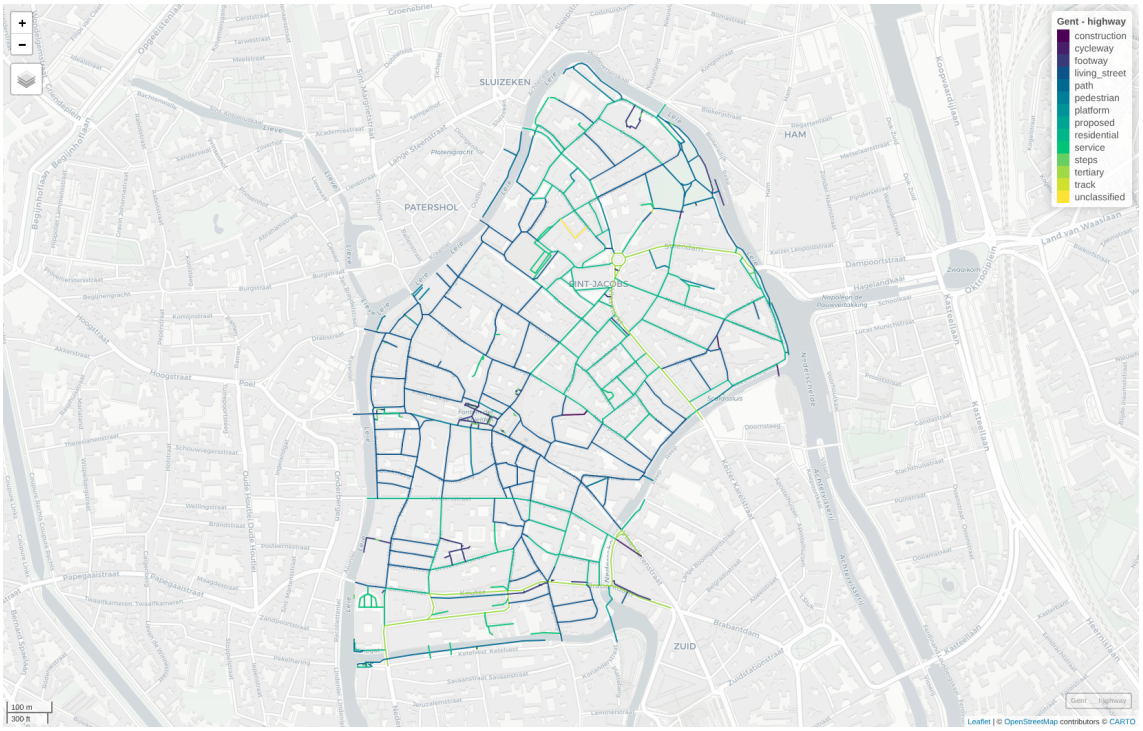
Access via export.hotosm.org[1].

[1] You need an OSM account to use it.



After the export, you can read in R using the `sf` package:

```
Gent = sf::st_read("../data/Gent_center.gpkg", quiet = TRUE)

mapview::mapview(Gent, zcol = "highway")
```



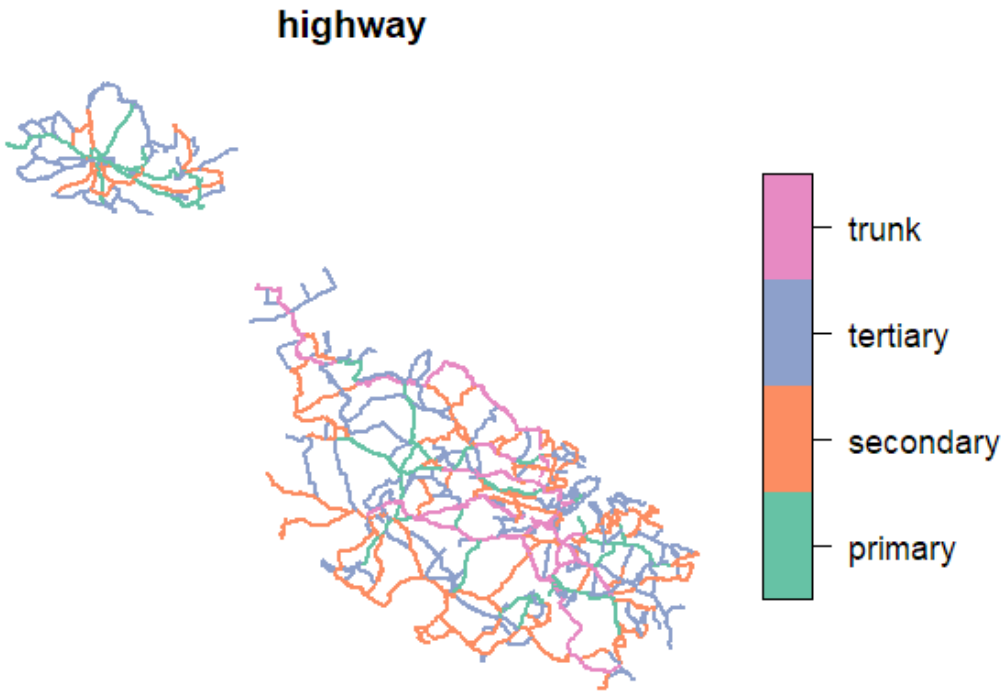
16.1.3. OSM in R

There are also some R packages that can help you to download and work with OpenStreetMap data, such as:

- osmdata
- osmextract

This is an example of how to download OpenStreetMap road network data using the `osmextract` package:

```
library(osmextract)
OSM_Malta = oe_get_network(place = "Malta") # it will geocode the place

Malta_main_roads = OSM_Malta |>
  filter(highway %in% c("primary", "secondary", "tertiary", "trunk"))

plot(Malta_main_roads["highway"])
```



16.2. Transportation Services' Data

16.2.1. GTFS

General Transit Feed Specification (GTFS) is standard format for documenting public transportation information, including: routes, schedules, stop locations, calendar patterns, trips, and possible transfers. Transit agencies are responsible for maintaining the data up-to-date.

This information is used in several applications, such as Google Maps, to provide public transportation directions. It can be offered for a city, a region, or even a whole country, depending on the PT agency.

The recent version 2 of the GTFS standard includes more information, such as **real-time data**.

The data is usually in a `.zip` file that includes several `.txt` files (one for each type of information) with tabular relations.

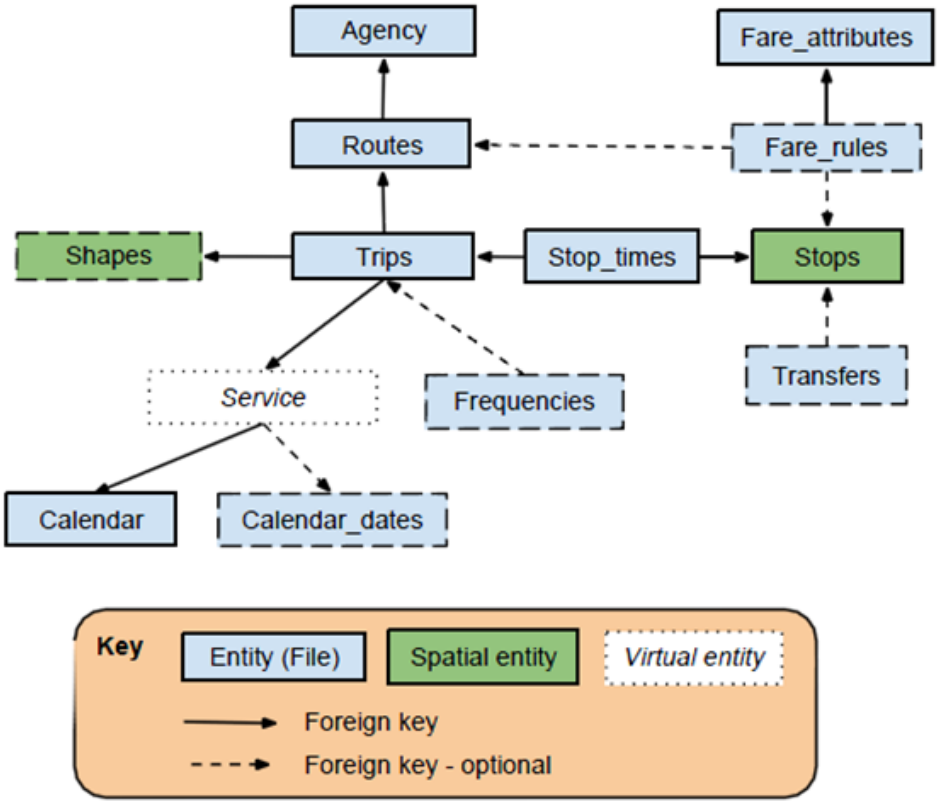


Figure 16.1.: Source: trilliumtransit.com

16.2.1.1. Online sources

You can find most GTFS data in the following websites:

- TransitLand
- TransitFeeds

Some PT agencies also provide their open-data in their websites.

16.2.1.2. R packages

There are some nice R packages to read and manipulate GTFS data, such as:

- `tidytransit`
- `gtfstools`

> Be aware that they may share the same function names, so it is important to use of of them at the time.

16.2.2. National Access Points

The European Union has a directive that requires the member states to provide access to transportation data. Data includes not only **Public Transportation** data, but also **road network**s, car **parking**, and other transportation-related information.

List of the European Union members states with National Access Points for Transportation data

Example of Bus services data in Belgium:

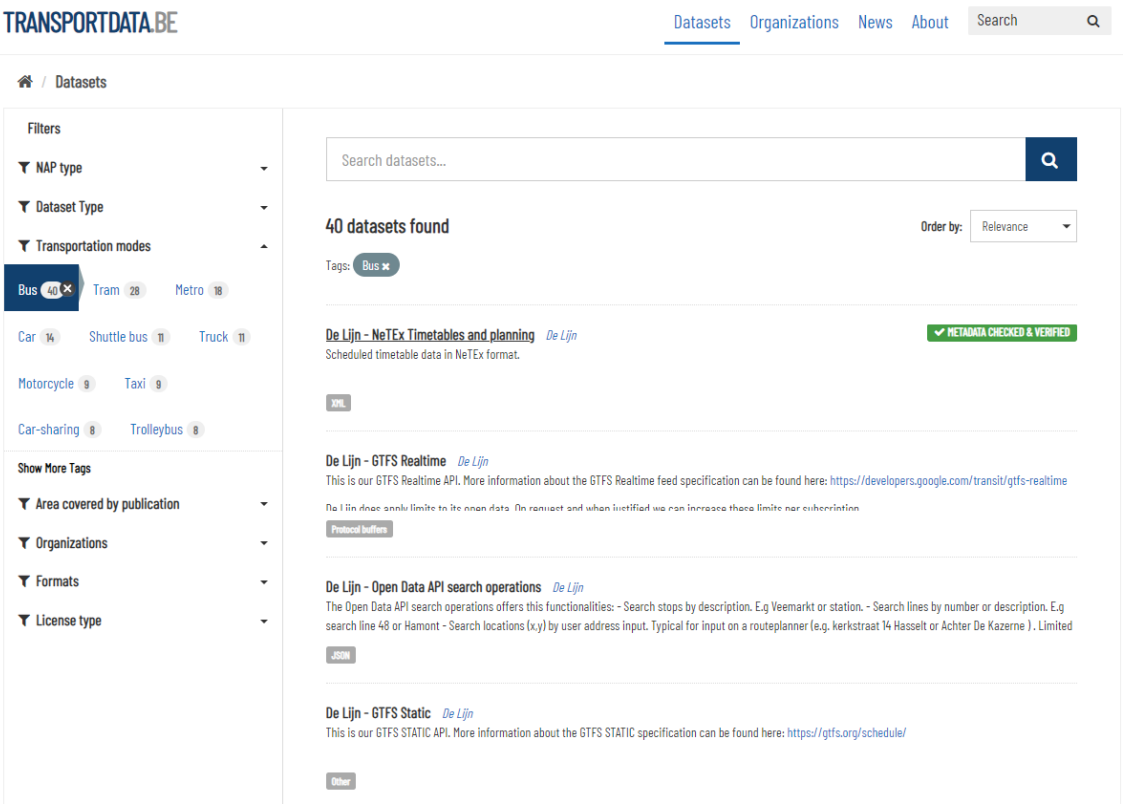


Figure 16.2.: Source: Transport Data Belgium

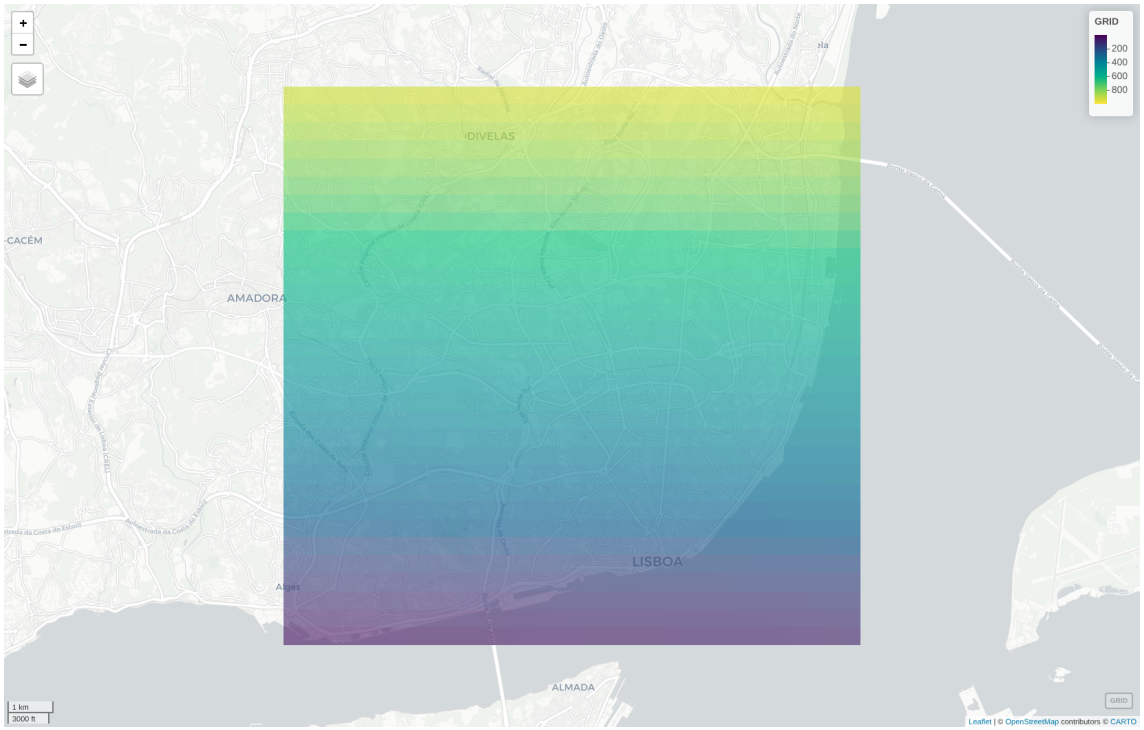
17. Grids

17.1. Make grid

```
library(sf)
library(dplyr)
library(mapview)

MUNICIPIOSgeo = st_read("../data/Municipalities_geo.gpkg", quiet = TRUE)
LISBON = MUNICIPIOSgeo |> filter(Municipality == "Lisboa") # filter only
    Lisbon
```

To make a grid we is the `st_make_grid()` function.

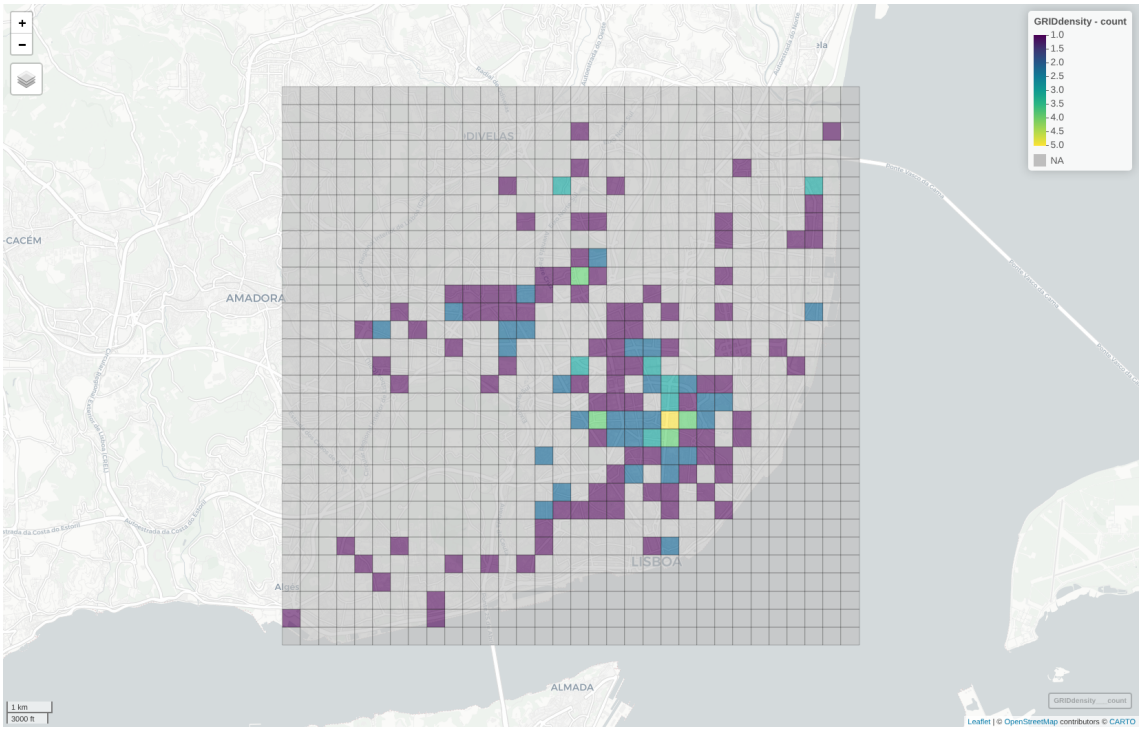
```
GRID = LISBON |>
  st_transform(crs = 3857) |> # to a projected crs
  st_make_grid(cellsize = 500, # meters, we are using a projected crs
               what = "polygons",
               square = TRUE) |> # if FALSE, hexagons
  st_sf() |> # from list to sf
  st_transform(crs = 4326) # to WGS84

GRID = GRID |>
  mutate(id = c(1:nrow(GRID)))  # just to give an ID to each cell

mapview(GRID, alpha = 0)
```



17.2. Count points in polygons

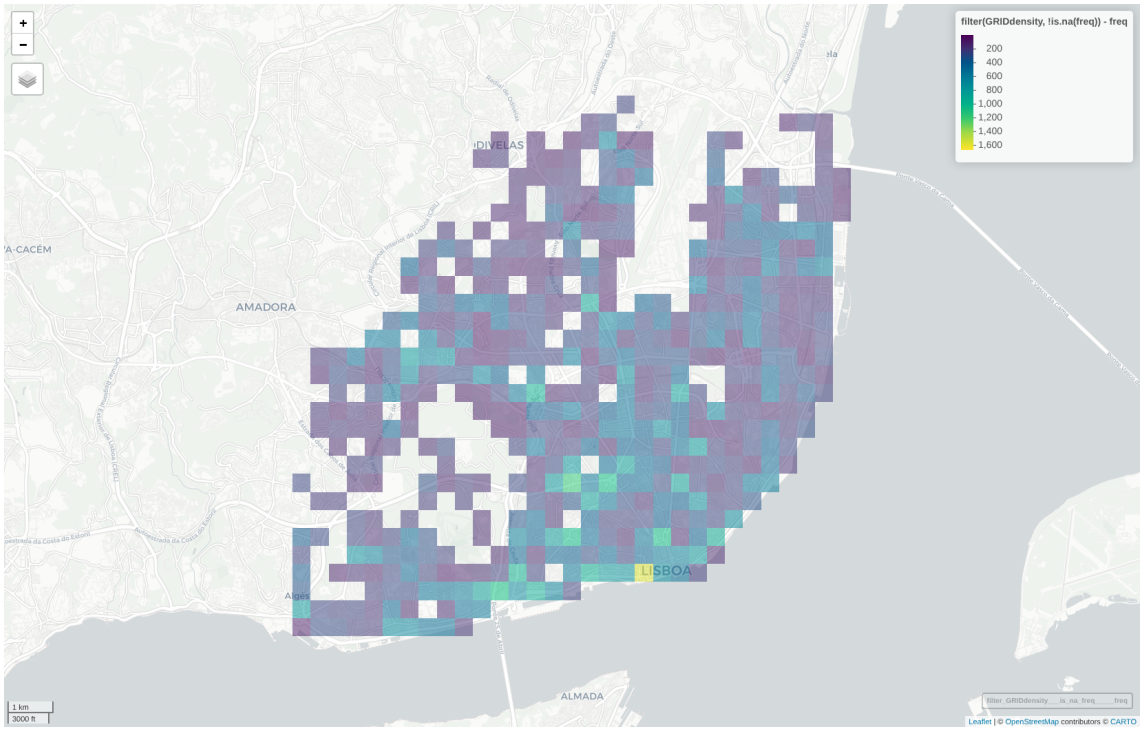
We can use the grid to count survey respondents in each cell.

```
SURVEY = read.csv("../data/SURVEY.txt", sep = "\t")
SURVEYgeo = SURVEY |> st_as_sf(coords = c("lon", "lat"), crs = 4326) #
    convert to sf from coordinates

SURVEY_with_GRIDid = SURVEYgeo |>
  st_join(GRID,
          join = st_intersects) |>
    st_drop_geometry() |>
    group_by(id) |>
    summarise(count = n()) |> # variable with the number of points
    ungroup()

# back to grid
GRIDdensity = GRID |> left_join(SURVEY_with_GRIDid)

mapview(GRIDdensity, zcol = "count")
```



Or to count bus stops in each cell.

```
BUSstops = st_read("../geo/Carris_stops.gpkg", quiet = TRUE)

BUS_with_GRIDid = BUSstops |>
  st_join(GRID,
          join = st_intersects) |>
    st_drop_geometry() |>
    group_by(id) |>
    summarise(freq = sum(frequency)) |>
    ungroup()

# back to grid
GRIDdensity = GRID |> left_join(BUS_with_GRIDid)

mapview(GRIDdensity |> filter(!is.na(freq)), # exclude NAs
        zcol = "freq",
        alpha.regions = 0.5, # area transparency
        alpha = 0) # hide cell limits
```


filter(GRIDdensity, !is.na(freq)) - freq
200
400
600
800
1,000
1,200
1,400
1,600
AMADORA
LISBOA
ALMADA
Leaflet | © OpenStreetMap contributors © CARTO

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