

# **Human Geography through Merseyside - Quantitative Block: Seeing the world through numbers**

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# Welcome

This is the website for “Human Geography through Merseyside - Quantitative Block: Seeing the world through numbers” (module **ENVS162**) at the University of Liverpool. This block of the module is designed and delivered by Dr. Zi Ye and Dr. Ron Mahabir from the Geographic Data Science Lab at the University of Liverpool. The module seeks to provide hands-on experience and training in introductory statistics for human geographers.

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

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

## Contact

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# Overview

## Aim and Learning Objectives

This sub-module aims to provide training and skills on a set of basic quantitative skills for data collection, analysis, and interpretation and to enable you to link conceptual ideas with real world examples. **This block serves as the foundation for Year 2 BA field class and, optionally, for Year 3 dissertation.**

### Background

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

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

### Learning objectives:

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

## Module Structure

**Staff:** Dr Zi Ye and Dr Ron Mahabir

**Where and When**

**Week 1 - 5 Lecture:** Tuesday (12am – 1pm) @ Mathematical Sciences, Proudman Lecture Theatre

**Week 1 - 6 Practical PC session:** Friday (9 – 11 am) @ Central Teaching Lab: PC Teaching Centre

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

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

Week	Topic	Format	Staff
1	Introduction	Lecture	ZY/RM
	Getting Started in RStudio: Knowing Merseyside	Computer Lab Practical	
2	Exploratory Data Analysis: UK Election	Lecture and Computer Lab Practical	ZY
3	Sampling and data manipulation: Happiness around the world	Lecture and Computer Lab Practical	ZY
4	Correlation, data reliability and the issue of scale: Health	Lecture and Computer Lab Practical	RM
5	How robust are my findings	Lecture and Computer Lab Practical	RM
6	Online Assessment	Computer Lab	RM/ZY

## Software and Data

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

- R-4.2.2 (or later)
- RStudio 2022.12.0-353 (or later)

To install and update:

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

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

### **Data**

Example datasets could be accessed through [ENVS 162 Canvas module](#) every week.

# Assessment

## Week 6 Computer-based ‘open book’ multiple-choice exam

- The online assessment will be released at **4pm on Thursday 5th March** and should be completed by **4pm on Friday 6th March**.
- **Also available 06/03/2025 9:00 – 11:00 CTL PC Teaching Centre (1st Floor CTL)**
- Should take less **90 minutes**; c. 20 questions; 24 hours to complete
- Questions and answers randomised for each student (anti-cheating measure)
- Some questions of factual recall, more requiring data analysis to find answers

## *Preparation for assessment*

- Weekly lecture & weekly computer practical ‘clinic sessions’
- Weekly holding hands formative tasks at the last 20 mins of the practical session
- Week 5 mock online test

# 1 Lab: Getting Started in RStudio - Knowing Merseyside

## 1.1 Overview

This practical intend to prepare students who have limited experiences with R and RStudio. The content are adapted based on

- Brunsdon, Chris, and Lex Comber. 2018. *An Introduction to r for Spatial Analysis and Mapping* (2e). Sage.
- Comber, Lex, and Chris Brunsdon. 2021. *Geographical Data Science and Spatial Data Analysis: An Introduction in r*. Sage.

## 1.2 Getting set up with RStudio

### 1.2.1 Install R and RStudio (if necessary)

R is a free, open-source programming language used for statistical analysis, data visualization, and data science

RStudio is a free front-end to R, designed to make using R easier

All of the PCs in the University PC Teaching Centre used for this class come with R and RStudio pre-installed, as do the PCs in many other University PC Teaching Centres.

However, you may wish to install R and RStudio on your own computer, or on a University PC that lacks them.

**University computers:** Use the *Install University Applications* app on the computer to install the latest version of RStudio (this will also install the latest version of R)

**Your own computer:** R and RStudio can be downloaded from the CRAN website and installed your own computer - see below for details. A key point is that you should install R before you install RStudio.

The simplest way to get R installed on your computer is to go the download pages on the R website - a quick search for ‘download R’ should take you there, but if not you could try:

- Windows: <https://cran.r-project.org/bin/windows/base/>
- Mac: <https://cran.r-project.org/bin/macosx/>
- Linux: <http://cran.r-project.org/bin/linux/>

The Windows and Mac version come with installer packages and are easy to install whilst the Linux binaries require use of a command terminal.

RStudio can be downloaded from <https://www.rstudio.com/products/rstudio/download/> and the free version of RStudio Desktop is more than sufficient for this module and all the other things you will do at degree level.

If you experience any problems installing R or RStudio on your own computer, bring it to one of the class lab sessions where we will be able to provide advice.

### 1.2.2 File management

Before you start installing software or downloading data, create a folder on your M-Drive (if working on a University networked machine) or locally if working on your own device – name this ‘ENVS162’ and within this create a sub-folder for each practical session. For this session, create a sub-folder called Week1 in your ENVS162 folder on your M-Drive. Take care to ensure you do not delete any work you do complete in the practical sessions. It is imperative that you practice good file management!

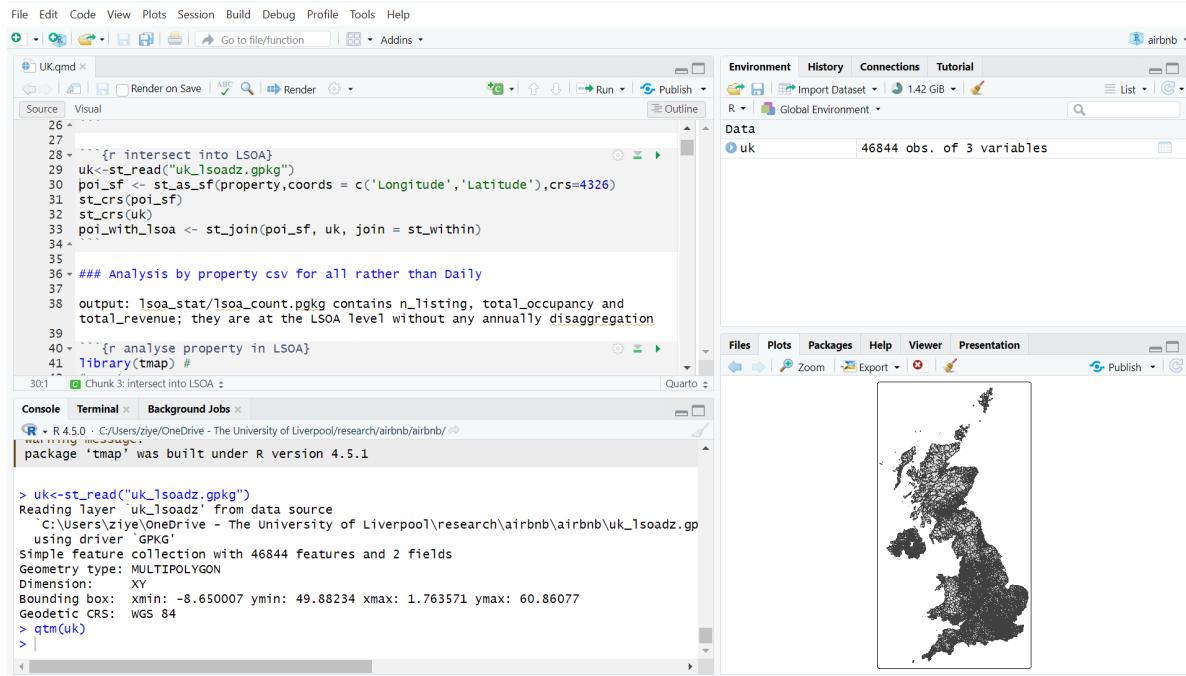
### 1.2.3 Open RStudio

RStudio provides an interface to the different things that R can do via the 4 panes: the Console where code is entered (bottom left), a Source pane with R scripts (top left), the variables in the working Environment (top right), Files, Plots, Help etc (bottom right) - see the RStudio environment in Figure below.

In the figure above of the RStudio interface, a new script has been opened, a line of code had been written and then run in the console. The code assigns a value of 100 to x. The file has been saved into the current working environment. You are expected to define a similar set up for each practical as you work through the code. Note that **in the script**, anything that follows a # is a comment and ignored by R.

Users can set up their personal preferences for how they like their RStudio interface. Similar to straight R, there are very few pull-down menus in R, and therefore you will type lines of code into your script and run these in what is termed a *command line interface* (the console). Like all command line interfaces, the learning curve is steep but the interaction with the software is more detailed which allows greater flexibility and precision in the specification of commands.

Beyond this there are further choices to be made. Commands can be entered in two forms: directly into the *R console* window or as a series of commands into a script window. We strongly advise that all code should be **written in a script** - (a .R file) and then **run from the script**. - To run code in a script, place the cursor on the line of code and then run by pressing the ‘Run’ icon at the top left of the script pane, or by pressing **Ctrl Enter** (PC) (or **Cmd Enter** on a Mac).



## 1.2.4 Ways of working

The first set of considerations relate to *how* you should work in R/RStudio. The key things to remember are:

- R is a learning curve if you have never done anything like this before. It can be scary. It can be intimidating. But once you have a bit of familiarity with how things work, it is incredibly powerful.
  - You will be working from practical worksheets which will have all the code you need. Your job is to try to **understand** what the code is doing and **not** to remember the code. Comments in your code really help.
  - To help you do this, the very strong suggestion is use the R scripts that are provided, and that you add your own comments to help you understand what is going on when you return to them. Comments are prefaced by a hash (#) that is ignored by R. Then

you can save your code (with comments), run it and return to it later and modify at your leisure.

The module places a strong emphasis placed on learning by doing, which means that you encouraged to unpick the code that you are given, adapt it and play with it. It is not about remembering or being able to recall each function used but about understanding what is being done. If you can remember what you did previously (i.e. the operations you undertook) and understand what you did, you will be able to return to your code the next time you want to do something similar. To help you with this you should:

1. Always run your code from an R script... **always!** These are provided for each practical;
2. Annotate your scripts with comments. These are prefixed by a hash (#) in the code;
3. Save your R script to your folder.

In Summary:

- You should always use a script (a text file containing code) for your code which can be saved and then re-run at a later date.
- You can write your own code into a script, copy and paste code into it or use an existing script (for example as provided for each of the R/RStudio practicals in this module).
- To open a new R script go to File > New File > R Script to open a new R file, and save it with a sensible name.
- To load an existing script file go to File > Open File and then navigate to your file. Or, if you have recently opened the file, go to File > Recent Files >.
- It is good practice to set the working directory at the beginning of your R session. This can be done via the menu in RStudio Session > Set Working Directory > .... This points the R session to the folder you choose and will ensure that any files you wish to read, write or save are placed in this directory.
- To run code in a script, place the cursor on the line of code and then run by pressing the ‘Run’ icon at the top left of the script pane, or by pressing Ctrl Enter (PC) or Cmd Enter (Mac).

### 1.2.5 Your first R code

In this section you will undertake a few generic operations. You will:

- undertake **assignment**: the allocation of values to an R object.
- use assignment to create a **vector** of elements and a **matrix** of elements.
- undertake **operations** on R objects.

- apply some **functions** to R objects (functions nearly always return a value).
- access some of R in-built data to examine a data table (or **data.frame** which is like an Excel spreadsheet).
- do some basic **plotting**, including scatter plots and histograms.
- create data summaries.

On the way you will also be introduced to **indexing**.

First, you should **create a new R script** (see above) and save it as **week1.R** in the working directory you are using for this practical. This should be the **Week1** sub-directory you created in the **ENVS162** folder. Note that you should create a separate folder for each week's practical.

### 1.2.5.1 Assignment

The command line prompt in the Console window, the **>**, is an invitation to start typing in your commands.

Write the following into your script: **3+5** and run it. Recall that code is run done by either by pressing the Run icon at the top left of the script pane, or by pressing **Ctrl Enter** (PC) or **Cmd Enter** (Mac).

```
3+5
```

```
[1] 8
```

Here the result is 8. The **[1]** that precedes the output formally indicates, *first requested element will follow*. In this case there is just one element. The **>** indicates that R is ready for another command.

Now type the following in to your script and run it:

```
y <- 3+5
y
```

```
[1] 8
```

Here the value of the `3+5` has been *assigned* to `y`. The syntax `y <- 3+5` can be read as `y gets 3+5`. When `y` is invoked its value is returned (8).

For the purposes of this module, in R the equals sign (`=`) is the same as `<-`, a left diamond bracket `<` followed by a minus sign `-`. This too is interpreted by R as *is assigned to* or *gets* when the code is read **right to left**.

Now copy and paste the following into your R script and run both lines:

```
x <- matrix(c(1,2,3,4,5,6,7,8), nrow = 4)
y = matrix(1:8, nrow = 4, byrow = T)
```

You should see the `x` appear with the `y` in the Environment pane. `y` has now been overwritten with a new assignment. If you click on the icon next to them, you will get a ‘spreadsheet’ view of the data you have created.

Of course you can also enter the following in the console and see what is returned:

```
x
```

```
[,1] [,2]
[1,]    1    5
[2,]    2    6
[3,]    3    7
[4,]    4    8
```

```
y
```

```
[,1] [,2]
[1,]    1    2
[2,]    3    4
[3,]    5    6
[4,]    7    8
```

**Note** In the code snippets above you have used **parentheses** - round brackets. Different kinds of brackets are used in different ways in R. Parentheses are used with **functions**, and contain the **arguments** that are passed to the function, separated by commas `(,)`.

In this case the functions are `c()` and `matrix()`. The function `c()` combines or concatenates elements into a vector, and `matrix()` creates a matrix of elements in a tabular format.

In the line of code `x = matrix(c(1,2,3,4,5,6,7,8), nrow = 4)`, the arguments passed to the `matrix()` function are the vector of values `c(1,2,3,4,5,6,7,8)` and `nrow = 4`. Other kinds of brackets are used in different ways as you will see later.

One final thing to note is that the matrix `y` has the numbers 1 to 8, but this is specified by `1:8`. Try entering `3:65`, `19:11`, and `1.5:5` to see how the colon (`:`) works in this context.

### 1.2.5.2 Operations

Now you can undertake *operations* on R objects and apply *functions* to them. Write the following code into your script and then run it:

```
# x is a matrix
x
```

```
[,1] [,2]
[1,]    1    5
[2,]    2    6
[3,]    3    7
[4,]    4    8
```

```
# multiplication
x*2
```

```
[,1] [,2]
[1,]    2   10
[2,]    4   12
[3,]    6   14
[4,]    8   16
```

```
# sum of x
sum(x)
```

```
[1] 36
```

```
# mean of x
mean(x)
```

```
[1] 4.5
```

Operations can be undertaken directly using mathematical notation like `*` for multiplication or using functions like `max` to find the maximum value in an R object.

### 1.2.5.3 Functions

Functions are always followed by parenthesis (round brackets) ( ). These are different from square and curly brackets [ ] and { }. Functions always return something, a result if you like, and have the generic form:

```
# don't run this or write this into your script!
result = function(value or R object, other parameters)
```

Do not run or enter this code in your script - it is an example!

### 1.2.5.4 Data Tables

Here we will load a data table in `data.frame` (like a spreadsheet) in R/RStudio. R has number of in-built datasets that we can use the code below loads one of these:

```
data(mtcars)
class(mtcars)
```

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

Have a look at what is loaded by listing the objects in the current R session

```
ls()
```

```
[1] "mtcars" "x"      "y"
```

You should see the `mtcars` object. You can examine this data in a number of ways

```
# the structure of mtcars
str(mtcars)
```

```
'data.frame': 32 obs. of 11 variables:
 $ mpg : num  21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
 $ cyl : num  6 6 4 6 8 6 8 4 4 6 ...
 $ disp: num  160 160 108 258 360 ...
 $ hp  : num  110 110 93 110 175 105 245 62 95 123 ...
 $ drat: num  3.9 3.9 3.85 3.08 3.15 2.76 3.21 3.69 3.92 3.92 ...
 $ wt  : num  2.62 2.88 2.32 3.21 3.44 ...
```

```
$ qsec: num 16.5 17 18.6 19.4 17 ...
$ vs : num 0 0 1 1 0 1 0 1 1 1 ...
$ am : num 1 1 1 0 0 0 0 0 0 ...
$ gear: num 4 4 4 3 3 3 3 4 4 4 ...
$ carb: num 4 4 1 1 2 1 4 2 2 4 ...
```

```
# the first six rows (or head) of mtcars
head(mtcars)
```

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Mazda RX4	21.0	6	160	110	3.90	2.620	16.46	0	1	4	4
Mazda RX4 Wag	21.0	6	160	110	3.90	2.875	17.02	0	1	4	4
Datsun 710	22.8	4	108	93	3.85	2.320	18.61	1	1	4	1
Hornet 4 Drive	21.4	6	258	110	3.08	3.215	19.44	1	0	3	1
Hornet Sportabout	18.7	8	360	175	3.15	3.440	17.02	0	0	3	2
Valiant	18.1	6	225	105	2.76	3.460	20.22	1	0	3	1

The `mtcars` object is a `data.frame`, a kind of data table, and it has a number of attributes which are all numeric. The code below prints it all out to the console:

```
mtcars
```

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4
Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4
Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1
Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3	2
Valiant	18.1	6	225.0	105	2.76	3.460	20.22	1	0	3	1
Duster 360	14.3	8	360.0	245	3.21	3.570	15.84	0	0	3	4
Merc 240D	24.4	4	146.7	62	3.69	3.190	20.00	1	0	4	2
Merc 230	22.8	4	140.8	95	3.92	3.150	22.90	1	0	4	2
Merc 280	19.2	6	167.6	123	3.92	3.440	18.30	1	0	4	4
Merc 280C	17.8	6	167.6	123	3.92	3.440	18.90	1	0	4	4
Merc 450SE	16.4	8	275.8	180	3.07	4.070	17.40	0	0	3	3
Merc 450SL	17.3	8	275.8	180	3.07	3.730	17.60	0	0	3	3
Merc 450SLC	15.2	8	275.8	180	3.07	3.780	18.00	0	0	3	3
Cadillac Fleetwood	10.4	8	472.0	205	2.93	5.250	17.98	0	0	3	4
Lincoln Continental	10.4	8	460.0	215	3.00	5.424	17.82	0	0	3	4
Chrysler Imperial	14.7	8	440.0	230	3.23	5.345	17.42	0	0	3	4
Fiat 128	32.4	4	78.7	66	4.08	2.200	19.47	1	1	4	1

Honda Civic	30.4	4	75.7	52	4.93	1.615	18.52	1	1	4	2
Toyota Corolla	33.9	4	71.1	65	4.22	1.835	19.90	1	1	4	1
Toyota Corona	21.5	4	120.1	97	3.70	2.465	20.01	1	0	3	1
Dodge Challenger	15.5	8	318.0	150	2.76	3.520	16.87	0	0	3	2
AMC Javelin	15.2	8	304.0	150	3.15	3.435	17.30	0	0	3	2
Camaro Z28	13.3	8	350.0	245	3.73	3.840	15.41	0	0	3	4
Pontiac Firebird	19.2	8	400.0	175	3.08	3.845	17.05	0	0	3	2
Fiat X1-9	27.3	4	79.0	66	4.08	1.935	18.90	1	1	4	1
Porsche 914-2	26.0	4	120.3	91	4.43	2.140	16.70	0	1	5	2
Lotus Europa	30.4	4	95.1	113	3.77	1.513	16.90	1	1	5	2
Ford Pantera L	15.8	8	351.0	264	4.22	3.170	14.50	0	1	5	4
Ferrari Dino	19.7	6	145.0	175	3.62	2.770	15.50	0	1	5	6
Maserati Bora	15.0	8	301.0	335	3.54	3.570	14.60	0	1	5	8
Volvo 142E	21.4	4	121.0	109	4.11	2.780	18.60	1	1	4	2

Data frames are ‘flat’ in that they typically have a rectangular layout like a spreadsheet, with rows typically relating to observations (individuals, areas, people, houses, etc) and columns relating to their properties or attributes (height, age, etc). The columns in data frames can be of different types: vectors of numbers, factors (classes) or text strings. In matrices all of the columns have to be of the same type. Data frames are central to what we will do in R.

### 1.2.5.5 Plotting the data: ‘Hello World!’

The code below creates a plot of 2 variables counts in the data: `mpg` and `disp`.

```
plot(disp ~ mpg, data = mtcars, pch=16)
```



The option `pch=16` sets the plotting character to a solid black dot. More plot characters are available - examine the help for `points()` to see these (For any command, if you are the first time use it, you can always ask R to explain to you by using `? as help`)

```
?points
```

This plot can be improved greatly. We can specify more informative axis labels, change size of the text and of the plotting symbol, and so on.

We can also specify the same plot by passing named variables to the `plot` function directly as well as other parameters, as in the figure. Notice how the syntax for this is different to the `plot` function above, and the different **parameters** that are passed to the `plot()` function:

```
plot(x = mtcars$mpg, y = mtcars$disp, pch = 1, col = "dodgerblue",
      cex = 1.5, xlab = "Miles per Gallon", ylab = "Displacement",
      main = "Hello World!")
```

## Hello World!



Notice how the dollar sign (\$) is used to access variables in the `mtcars` data table compared to the first plot command, which specified `data = mtcars`.

### 1.2.5.6 Data summaries and indexing

We may for example require information on variables in `mtcars`. The `summary` function is very useful:

```
summary(mtcars)
```

mpg	cyl	disp	hp
Min. :10.40	Min. :4.000	Min. : 71.1	Min. : 52.0
1st Qu.:15.43	1st Qu.:4.000	1st Qu.:120.8	1st Qu.: 96.5
Median :19.20	Median :6.000	Median :196.3	Median :123.0
Mean :20.09	Mean :6.188	Mean :230.7	Mean :146.7
3rd Qu.:22.80	3rd Qu.:8.000	3rd Qu.:326.0	3rd Qu.:180.0
Max. :33.90	Max. :8.000	Max. :472.0	Max. :335.0

drat	wt	qsec	vs
Min. :2.760	Min. :1.513	Min. :14.50	Min. :0.0000
1st Qu.:3.080	1st Qu.:2.581	1st Qu.:16.89	1st Qu.:0.0000
Median :3.695	Median :3.325	Median :17.71	Median :0.0000
Mean :3.597	Mean :3.217	Mean :17.85	Mean :0.4375

```

3rd Qu.:3.920   3rd Qu.:3.610   3rd Qu.:18.90   3rd Qu.:1.0000
Max.    :4.930   Max.    :5.424   Max.    :22.90   Max.    :1.0000
      am          gear          carb
Min.    :0.0000   Min.    :3.000   Min.    :1.000
1st Qu.:0.0000   1st Qu.:3.000   1st Qu.:2.000
Median  :0.0000   Median  :4.000   Median  :2.000
Mean    :0.4062   Mean    :3.688   Mean    :2.812
3rd Qu.:1.0000   3rd Qu.:4.000   3rd Qu.:4.000
Max.    :1.0000   Max.    :5.000   Max.    :8.000

```

This shows different summaries of the individual attributes in `mtcars`.

The main R graphics function is `plot()`. In addition to `plot()` there are functions for adding points and lines to existing graphs, for placing text at specified positions, for specifying tick marks and tick labels, for labelling axes, and so on.

There are various other alternative helpful forms of graphical summary. A helpful graphical summary for the `mtcars` data frame is the scatterplot matrix.

```
# return the names of the mtcars variables
names(mtcars)
```

```
[1] "mpg"   "cyl"   "disp"  "hp"    "drat"  "wt"    "qsec" "vs"    "am"    "gear"
[11] "carb"
```

```
# return the 3rd to 7th names
names(mtcars)[c(3:7)]
```

```
[1] "disp" "hp"   "drat" "wt"    "qsec"
```

```
# check what this does
c(3:7)
```

```
[1] 3 4 5 6 7
```

```
# plot the 3rd to 7th variables in mtcars
plot(mtcars[, c(3:7)], cex = 0.5,
     col = "red", upper.panel=panel.smooth)
```



The results show the correlations between the variables in the `mtcars` data frame, and the trend of their relationship is included with the `upper.panel=panel.smooth` parameter passed to `plot`.

There are number of things to notice here (as well as the figure). In particular note the use of the vector `c(2:7)` to subset the columns of `mtcars`:

- In the second line, this was used to subset the vector of column names created by `names(mtcars)`.
- In the third line, it was printed out. Notice how `3:7` printed out all the numbers between 3 and 7 - very useful.
- For the plot, the vector was passed to the second argument, after the comma, in the square brackets `[,]` to indicate which columns were to be plotted.

The referencing in this way (or *indexing*) is **very important**: the individual rows and columns of 2 dimensional data structures like data frames, matrices, tibbles etc can be accessed by passing references to them in the square brackets.

```
# 1st row
mtcars[1,]
```

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Mazda RX4	21	6	160	110	3.9	2.62	16.46	0	1	4	4

```
# 3rd column  
mtcars[,3]
```

```
[1] 160.0 160.0 108.0 258.0 360.0 225.0 360.0 146.7 140.8 167.6 167.6 275.8  
[13] 275.8 275.8 472.0 460.0 440.0 78.7 75.7 71.1 120.1 318.0 304.0 350.0  
[25] 400.0 79.0 120.3 95.1 351.0 145.0 301.0 121.0
```

```
# a selection of rows  
mtcars[c(3:5,8),]
```

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1
Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3	2
Merc 240D	24.4	4	146.7	62	3.69	3.190	20.00	1	0	4	2

Such indexing could of course have been assigned to a R object and used to do the subsetting:

```
x = c(3:7)  
names(mtcars)[x]
```

```
[1] "disp" "hp"   "drat" "wt"    "qsec"
```

Thus indexing allows specific rows and columns to be extracted from the data as required.

**Note** You have encountered a second type of brackets, square brackets [ ]. These are used to reference or **index** positions in a vector or a data table.

Consider the object `x` above. It contains a vector of values, 3,4,5,6,7. Entering `x[1]` would extract the first element of `x`, in this case 3. Similarly `x[4]` would return the 4th element and `x[c(1,4)]` would return the 1st and 4th elements of `x`.

However, in the examples above that index the 2-dimensional `mtcars` object, the square brackets are used to index **row** and **column** positions. The syntax for this is [rows, columns]. We will be using such indexing throughout this module.

You can ask R to return you specific rows and columns by different ways:

```
mtcars[c(2,9), 3:7]
```

```

      disp  hp drat    wt  qsec
Mazda RX4 Wag 160.0 110 3.90 2.875 17.02
Merc 230       140.8  95 3.92 3.150 22.90

```

```
mtcars[3:6, c("disp","hp","qsec")]
```

```

      disp  hp  qsec
Datsun 710     108  93 18.61
Hornet 4 Drive   258 110 19.44
Hornet Sportabout  360 175 17.02
Valiant        225 105 20.22

```

```
mtcars [, c("wt","gear","cyl")]
```

	wt	gear	cyl
Mazda RX4	2.620	4	6
Mazda RX4 Wag	2.875	4	6
Datsun 710	2.320	4	4
Hornet 4 Drive	3.215	3	6
Hornet Sportabout	3.440	3	8
Valiant	3.460	3	6
Duster 360	3.570	3	8
Merc 240D	3.190	4	4
Merc 230	3.150	4	4
Merc 280	3.440	4	6
Merc 280C	3.440	4	6
Merc 450SE	4.070	3	8
Merc 450SL	3.730	3	8
Merc 450SLC	3.780	3	8
Cadillac Fleetwood	5.250	3	8
Lincoln Continental	5.424	3	8
Chrysler Imperial	5.345	3	8
Fiat 128	2.200	4	4
Honda Civic	1.615	4	4
Toyota Corolla	1.835	4	4
Toyota Corona	2.465	3	4
Dodge Challenger	3.520	3	8
AMC Javelin	3.435	3	8
Camaro Z28	3.840	3	8
Pontiac Firebird	3.845	3	8
Fiat X1-9	1.935	4	4

Porsche 914-2	2.140	5	4
Lotus Europa	1.513	5	4
Ford Pantera L	3.170	5	8
Ferrari Dino	2.770	5	6
Maserati Bora	3.570	5	8
Volvo 142E	2.780	4	4

### 1.2.5.7 Packages

The **base** installation of R includes many functions and commands. However, more often we are interested in using some particular functionality, encoded into **packages** contributed by the R developer community. Installing packages for the first time can be done at the command line in the R console using the `install.packages` command as in the example below to install the `tmap` library or via the RStudio menu via **Tools > Install Packages**.

When you install these packages it is strongly suggested you also install the *dependencies*. These are other packages that are required by the package that is being installed. This can be done by selecting check the box in the menu or including `dep=TRUE` in the command line as below (don't run this yet!):

```
# don't run this!
install.packages("tidyverse", dep = TRUE)
```

You may have to set a **mirror** site from which the packages will be downloaded to your computer. Generally you should pick one that is nearby to you.

Further descriptions of packages, their installation and their data structures will be given as needed in the practicals. There are literally 1000s of packages that have been contributed to the R project by various researchers and organisations. These can be located by name at [http://cran.r-project.org/web/packages/available\\_packages\\_by\\_name.html](http://cran.r-project.org/web/packages/available_packages_by_name.html) if you know the package you wish to use. It is also possible to search the CRAN website to find packages to perform particular tasks at <http://www.r-project.org/search.html>. Additionally many packages include user guides and vignettes as well as a PDF document describing the package and listed at the top of the index page of the help files for the package.

As well as `tidyverse` you should install the `sf` package and dependencies. So we have 2 packages to install:

- `sf` for spatial data and spatial objects
- `tidyverse` for lots of lovely data science things - see <https://www.tidyverse.org>

You could do this in one go and this will take a bit of time:

```
install.packages(c("sf", "tidyverse"), dep = TRUE)
```

Remember: you will only have to install a package once!! So when the above code has run in your script you should comment it out. For example you might want to include something like the below in your R script.

```
# packages only need to be loaded once  
# install.packages(c("sf", "tidyverse"), dep = TRUE)
```

Once the package has been installed on your computer then the package can be called using the `library()` function into each of your R sessions as below.

```
library(tidyverse)  
library(sf)
```

## 1.3 Knowing Merseyside

### 1.3.1 Merseyside districts

Now we use these basic R command and newly installed packages to start our initial exploration by using some existing secondary dataset from the Census 2021.

In R we normally read in tabular dataset from .csv format. In your [ENVS162 Canvas page](#) find Week 1 -> Practical 1 Dataset, download the four datasets to your current working folder on your M drive (ENVS162 - Week 1). You may first identify one .csv dataset: **merseyside.csv**. You can open them in excel to have a look, but here we are using R instead of Excel to load and examine them.

#### 1.3.1.1 Loading tabular data

The survey data can be loaded into RStudio using the `read.csv` function.

However, you will need to tell R where to get the data from. The easiest way to do this is to use the menu if the R script file is open. Go to **Session > Set Working Directory > To Source File Location** to set the working directory to the location where your `week1.R` script is saved. When you do this you will see line of code print out in the Console (bottom left pane) similar to `setwd("SomeFilePath")`. You can copy this line of code to your script and paste into the line above the line calling the `read.csv` function.

```
# use read.csv to load a CSV file
# this is assignment to an object called `df`
df = read.csv(file = "merseyside.csv", stringsAsFactors = TRUE)
```

The `stringsAsFactors = TRUE` parameter tells R to read any character or text variables as classes or categories and not as just text.

You could inspect the help for the `read.csv` function to see the different parameters and their default values:

```
help(read.csv)
```

```
starting httpd help server ... done
```

```
# or
?read.csv
```

Functions always return something and in this case `read.csv()` function has returned a tabular R object with 5 records and 12 fields. This has been *assigned to df*.

Finally in this section, lets have a look at the data. This can be done in a number of ways.

- you could look at the `df` object by entering `df` in the Console. However this is not particular helpful as it simply prints out everything that is in `df` to the Console.
- you could click on the `df` object in the Environment pane and this shows the structure of the attributes in different fields.
- you could click on the little grid-like icon next `df` in the Environment pane to get a `View` of the data and remember to close the tab that opens!.
- or you could use some code as in the examples below.

First, let's have a look at the internal structure of the data using the `str` function:

```
str(df)
```

```
'data.frame': 5 obs. of 12 variables:
 $ LAD21CD      : Factor w/ 5 levels "E08000011","E08000012",...: 1 2 3 4 5
 $ District      : Factor w/ 5 levels "Knowsley","Liverpool",...: 1 2 4 3 5
 $ Population    : int 154519 486089 183248 279234 320196
 $ Households    : int 66073 207491 81011 123075 143253
 $ Working_population: int 69495 205749 82622 124596 139500
```

```

$ Students          : int 7050 59628 7582 12636 14642
$ Unemployed       : int 3852 13894 4076 6143 6542
$ Age_over_65       : int 26242 74322 37642 64763 70391
$ Disability        : int 34990 105962 40829 61134 73088
$ No_central_heating: int 1020 4822 1003 1965 2125
$ Overcrowding      : int 1892 7352 1888 2700 2355
$ Working_from_home : int 14880 53721 18973 34750 37299

```

There is other ways to get info about the number of rows and columns:

```
nrow(df)
```

```
[1] 5
```

```
ncol(df)
```

```
[1] 12
```

```
#or both row and col
dim(df)
```

```
[1] 5 12
```

The `head` function does this by printing out the first six records of the data table and you may need to scroll up and down in the Console pane to see all of what is returned.

```
head(df)
```

	LAD21CD	District	Population	Households	Working_population	Students
1	E08000011	Knowsley	154519	66073	69495	7050
2	E08000012	Liverpool	486089	207491	205749	59628
3	E08000013	St. Helens	183248	81011	82622	7582
4	E08000014	Sefton	279234	123075	124596	12636
5	E08000015	Wirral	320196	143253	139500	14642
	Unemployed	Age_over_65	Disability	No_central_heating	Overcrowding	
1	3852	26242	34990	1020	1892	
2	13894	74322	105962	4822	7352	
3	4076	37642	40829	1003	1888	
4	6143	64763	61134	1965	2700	

5	6542	70391	73088	2125	2355
	Working_from_home				
1		14880			
2		53721			
3		18973			
4		34750			
5		37299			

Another way to explore the data is through the `summary` function:

```
summary(df)
```

LAD21CD	District	Population	Households	
E08000011:1	Knowsley	:1 Min. :154519	Min. : 66073	
E08000012:1	Liverpool	:1 1st Qu.:183248	1st Qu.: 81011	
E08000013:1	Sefton	:1 Median :279234	Median :123075	
E08000014:1	St. Helens	:1 Mean :284657	Mean :124181	
E08000015:1	Wirral	:1 3rd Qu.:320196	3rd Qu.:143253	
		Max. :486089	Max. :207491	
	Working_population	Students	Unemployed	
	Min. : 69495	Min. : 7050	Min. : 3852	Min. :26242
	1st Qu.: 82622	1st Qu.: 7582	1st Qu.: 4076	1st Qu.:37642
	Median :124596	Median :12636	Median : 6143	Median :64763
	Mean :124392	Mean :20308	Mean : 6901	Mean :54672
	3rd Qu.:139500	3rd Qu.:14642	3rd Qu.: 6542	3rd Qu.:70391
	Max. :205749	Max. :59628	Max. :13894	Max. :74322
	Disability	No_central_heating	Overcrowding	Working_from_home
	Min. : 34990	Min. :1003	Min. :1888	Min. :14880
	1st Qu.: 40829	1st Qu.:1020	1st Qu.:1892	1st Qu.:18973
	Median : 61134	Median :1965	Median :2355	Median :34750
	Mean : 63201	Mean :2187	Mean :3237	Mean :31925
	3rd Qu.: 73088	3rd Qu.:2125	3rd Qu.:2700	3rd Qu.:37299
	Max. :105962	Max. :4822	Max. :7352	Max. :53721

Finally in this section, we come back to the dollar sign (\$). This is used to refer to or *extract* an individual named field or variable in an R object, like `df`.

The code below prints out the `Population` attribute and generates a summary of its values:

```
# extract an individual variable
df$Population
```

```
[1] 154519 486089 183248 279234 320196
```

```
# generate a summary of an individual variable  
summary(df$Population)
```

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
154519	183248	279234	284657	320196	486089	

And of course we can use such operations to *assign* the result to new R objects. The code below extracts three variables from df, assigns them to x, y and z, and then uses the `data.frame` function to convert these into a new `data.frame` object called `my_df`

```
# extract three variables, assigning them to temporary R objects  
x = df$District  
y = df$Working_population  
z = df$Students  
# create a data.frame from these, naming the new variables  
my_df = data.frame(district = x, worker = y, student = z)
```

You should have a look at what you have created:

```
head(my_df)
```

	district	worker	student
1	Knowsley	69495	7050
2	Liverpool	205749	59628
3	St. Helens	82622	7582
4	Sefton	124596	12636
5	Wirral	139500	14642

```
summary(my_df)
```

	district	worker	student
Knowsley	:1	Min. : 69495	Min. : 7050
Liverpool	:1	1st Qu.: 82622	1st Qu.: 7582
Sefton	:1	Median :124596	Median :12636
St. Helens	:1	Mean :124392	Mean :20308
Wirral	:1	3rd Qu.:139500	3rd Qu.:14642
		Max. :205749	Max. :59628

The temporary R objects can be removed from the Environment using the `rm` function and a *combine* vector function, `c()` that you encountered in Week 19, that takes a vector of object names (hence they are in quotes) as its arguments.

```
rm(list = c("x", "y", "z"))
```

### 1.3.1.2 Basic data manipulation

Now we can do some basic data manipulation to know Merseyside more from the data perspective.

What is the total population in Merseyside?

```
sum(df$Population)
```

```
[1] 1423286
```

What is the total number of full-time students in Merseyside?

```
sum(df$Students)
```

```
[1] 101538
```

Then, we can calculate the total number of workers that working from home:

```
sum(df$Working_from_home)
```

```
[1] 159623
```

What is the proportion of working population actually work from home in Merseyside? Yes, we need to use a division calculation of the total number of working from home vs. all the working population. R can do it by:

```
sum(df$Working_from_home) / sum(df$Working_population)
```

```
[1] 0.2566443
```

So the answer is 25.7% for the whole Merseyside - but which district has the highest proportion and which as the lowest? You may have your own guessing. But let R do the calculation:

```
df$Prop.WFH = df$Working_from_home / df$Working_population * 100 #add a new column called Prop.WFH
df #print out the df
```

	LAD21CD	District	Population	Households	Working_population	Students
1	E08000011	Knowsley	154519	66073	69495	7050
2	E08000012	Liverpool	486089	207491	205749	59628
3	E08000013	St. Helens	183248	81011	82622	7582
4	E08000014	Sefton	279234	123075	124596	12636
5	E08000015	Wirral	320196	143253	139500	14642
	Unemployed	Age_over_65	Disability	No_central_heating	Overcrowding	
1	3852	26242	34990		1020	1892
2	13894	74322	105962		4822	7352
3	4076	37642	40829		1003	1888
4	6143	64763	61134		1965	2700
5	6542	70391	73088		2125	2355
	Working_from_home	Prop.WFH				
1	14880	21.41161				
2	53721	26.10997				
3	18973	22.96362				
4	34750	27.89014				
5	37299	26.73763				

Here we ask R to add a new column named `Prop.WFH` which is the working from home proportion that calculated by the number of working from home people in each district divided by the total working population in that district. The `* 100` convert the rate in the percentage number. R will automatically do it row-by-row. We then print out the `df`, you may find at the very right end of the tabular, there is a new column called `Prop.WFH`.

For a very small dataframe like this, we can also using `View()` to open a new tab to review the data, where each column can be sorted from largest to smallest or vice versa. Try viewing it and find the newly created column `Prop.WFH`. Click on the column name, you should see it is sorted from highest to lowest, and click again, the ranking is reversed.

```
View(df)
```

### 1.3.1.3 Your first map for Merseyside

Now let's try to do our first map in R and allow yourself know more about Merseyside.

We will use the library `sf` and `tmap` to help us at here. Run the install codes if you haven't install them. Remember: you will only have to install a package once!!

```
install.packages("tmap", dep =TRUE)
```

Check the package version of tmap, as here we need to use tmap over 4.0 version.

```
packageVersion("tmap") # the version should over 4.0
```

```
[1] '4.1'
```

When they have been installed, we can start using them

```
library(tidyverse)
library(sf)
library(tmap)
```

You may find in Week 1 data, we have another file named *merseyside\_districts.gpkg*. A GeoPackage (GPKG) is a file-based format designed for storing geographic data. It supports the efficient storage and exchange of spatial datasets and can be readily used across GIS software such as QGIS and ArcGIS, as well as in programming environments including R and Python.

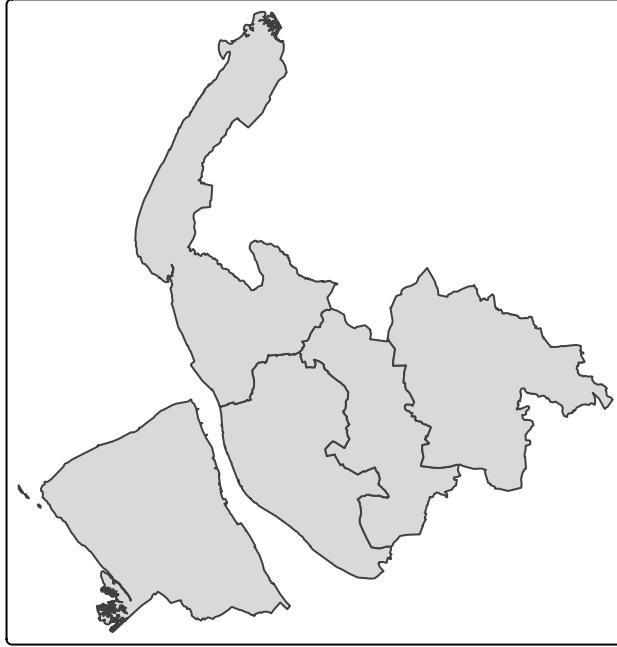
We first read it in by using the `st_read()` command in library sf.

```
sf <- st_read("merseyside_districts.gpkg")
```

```
Reading layer `lad_may_2025_uk_bgc_v2_4306843991635065087__lad_may_2025_uk_bgc_v2' from data
  using driver `GPKG'
Simple feature collection with 5 features and 8 fields
Geometry type: MULTIPOLYGON
Dimension:      XY
Bounding box:  xmin: 318351.7 ymin: 377515.4 xmax: 361796.3 ymax: 422866.5
Projected CRS: OSGB36 / British National Grid
```

The fastest way to map it is the `qtm()` function.

```
qtm(sf)
```



You can also add the district names on the map - which column in the sf contains district name? Use `names(sf)` to check for it.

Yes, the column should be `LAD25NM`. Now let's ask `qtm()` to also show the district names.

```
qtm(sf, text="LAD25NM")
```



But what if we want to make some meaningful maps, rather than just the boundaries of these five districts of Merseyside?

#### 1.3.1.4 Link tabular data to geographical boundaries

Recall that in our `df`, we have 14 columns, containing different information about the districts. We can get all their names by using `names()`.

```
names(df)
```

```
[1] "LAD21CD"           "District"          "Population"
[4] "Households"         "Working_population" "Students"
[7] "Unemployed"        "Age_over_65"       "Disability"
[10] "No_central_heating" "Overcrowding"      "Working_from_home"
[13] "Prop.WFH"
```

We can do the same thing for our geographical dataset `sf` to see what it includes:

```
names(sf)
```

```
[1] "LAD25CD"   "LAD25NM"   "LAD25NMW"  "BNG_E"     "BNG_N"     "LONG"      "LAT"
[8] "GlobalID"  "geom"
```

We can also show the whole `sf` as

```
sf
```

```
Simple feature collection with 5 features and 8 fields
Geometry type: MULTIPOINT
Dimension: XY
Bounding box: xmin: 318351.7 ymin: 377515.4 xmax: 361796.3 ymax: 422866.5
Projected CRS: OSGB36 / British National Grid
  LAD25CD  LAD25NM LAD25NMW  BNG_E  BNG_N      LONG      LAT
1 E08000011  Knowsley      344762 393778 -2.832979 53.43789
2 E08000012  Liverpool     339359 390556 -2.913680 53.40833
3 E08000013 St. Helens     353413 395992 -2.703093 53.45862
4 E08000014  Sefton       334282 398835 -2.991771 53.48213
5 E08000015  Wirral       329109 386965 -3.067034 53.37478
                           GlobalID               geom
1 {B4196BFE-EE90-4C31-ABD5-C7E743AE2F9B} MULTIPOINT (((341447.1 40...
2 {4FB47E7A-EF4E-4B9E-BF75-D4FC059CDE61} MULTIPOINT (((338860.9 39...
3 {943F0C6B-EB30-4C00-A42B-F6B3AEC3EFEE} MULTIPOINT (((349111.4 40...
4 {C6FD073B-CBEB-4E78-934A-A8FD11A20F0A} MULTIPOINT (((336374.5 42...
5 {88E9328B-371C-469C-91F1-3479C77D6950} MULTIPOINT (((331364.9 39...
```

Now we see that `sf` includes also the five districts, but also other geographical information. You may notice that although different column names, the first two columns of both `df` and `sf` are the district code and district name. This means what potentially we can link this two dataset together - appendix the `df` to `sf` to enrich the attributes of our geographical dataset.

```
merseyside <- left_join(sf, df, by=c("LAD25NM"="District"))
```

let's check out the new `sf2` by `View()` it:

```
View(merseyside)
```

In the open tab, we see all the `df` columns are now also attached to the `sf`, linking by the district names.

### 1.3.1.5 Choropleth map of Merseyside districts

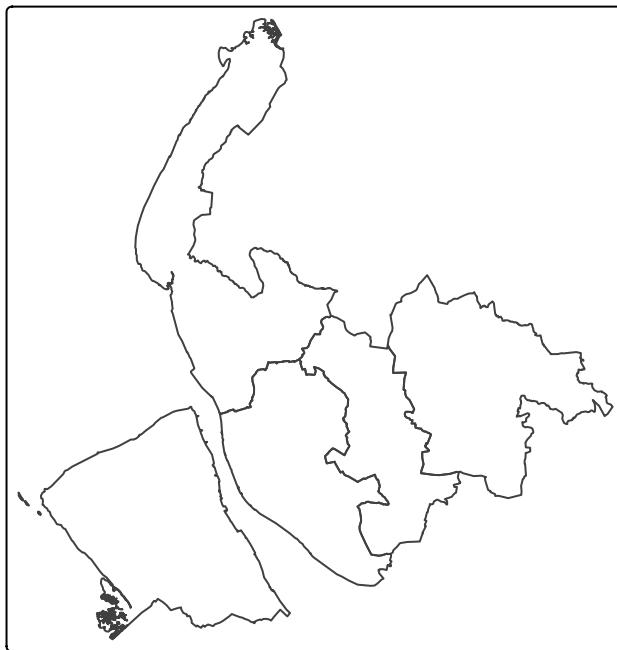
Now, we can use those new columns we attached from `df` to `sf2` to make some meaningful choropleth maps! Here we make use of the mapping functions in `tmap` (Remember to run `library(tmap)` if you haven't) to do the work for us.

`tmap` has a basic syntax (again, do not run this code - its is simply showing the syntax of `tmap`):

```
# don't run this or write this into your script!
tm_shape(data = <data>)+  
  tm_<function>(<variable to be mapped>)
```

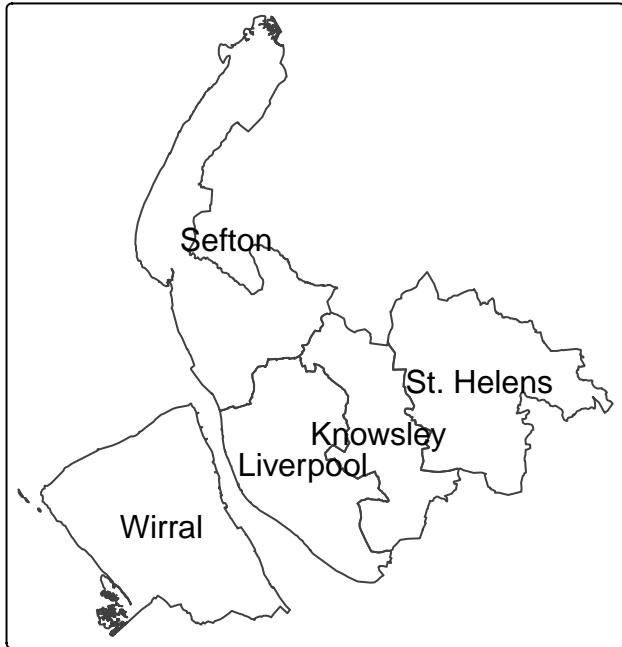
For example, to map the boundaries of `merseyside`:

```
tm_shape(merseyside) +  
  tm_borders()
```



To add label of district:

```
tm_shape(merseyside) +  
  tm_borders() +  
  tm_text("LAD25NM")
```



You might assume the quick mapping function `qtm()` can achieve the same result, but `tmap` provides far more flexibility when it comes to aesthetic customization. The easiest way to illustrate `tmap` is through some examples.

Let's start with a simple choropleth map, by using `tmap` to show the distribution of a continuous variable in different elements of the spatial data (here are the data Merseyside districts are polygons).

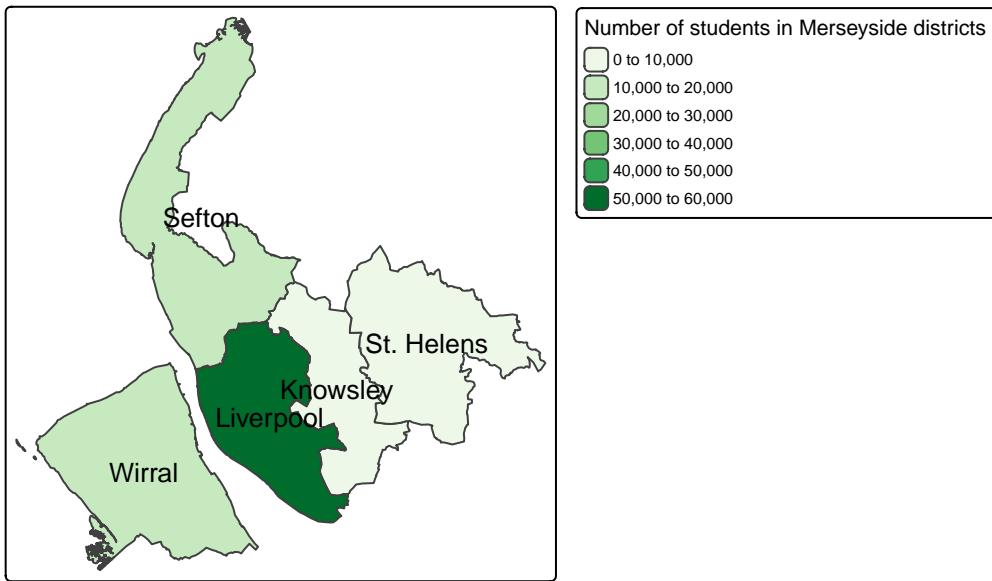
The code below maps 'Students' as in the Merseyside districts, and shows the district names of each polygon from 'LAD25NM' columns. The map below indicates that Liverpool has the highest number of full-time students while Knowsley and St.Helens have the least.

```
tm_shape(merseyside) +
  tm_polygons(fill = "Students") +    # Variable to map
  tm_text("LAD25NM")                  # Variable to label
```



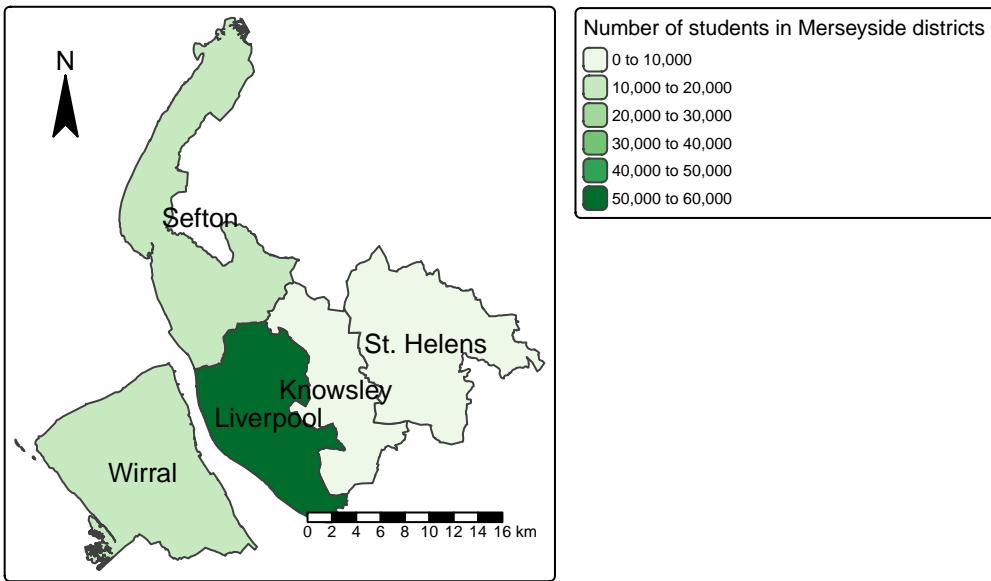
By default tmap picks a shading scheme, the class breaks and places a legend somewhere. All of these can be changed. The code below allocates the tmap plot to `map1` (Map 1), change the legend title as “Number of students in Merseyside districts”, and then prints it:

```
map1 = tm_shape(merseyside) +
  tm_polygons(fill="Students",
              fill.scale = tm_scale(values = "Greens"), # change palette to greens
              fill.legend = tm_legend(title = "Number of students in Merseyside districts")
  ) +# Legend title
  tm_text("LAD25NM",size=0.8) #size down the label slightly
map1
```



And of course many other elements included either by running the code snippet defining `map1` above with additional lines or by simply adding them as in the code below:

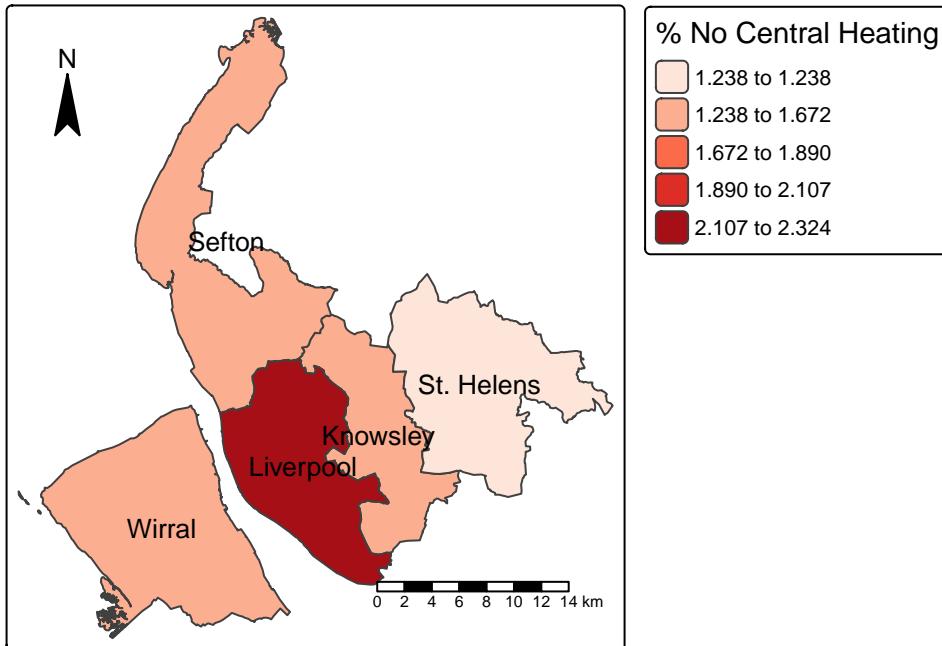
```
map1 +
  tm_scalebar(position = c("right", "bottom")) +
  tm_compass(position = c("left", "top")) # Use "top", "center", or "bottom"
```



We can also create new variable to the dataset and then map it. The below code chunk first creates a new column, “NoCentralHeating\_rate”, by dividing the number of households without access to central heating by the total number of households in each district; it then uses `tmap` to make a map of the proportion of households without central heating across districts in Merseyside:

```
merseyside$NoCentralHeating_rate = merseyside$No_central_heating / merseyside$Households * 100

map2 = tm_shape(merseyside) +
  tm_polygons(fill="NoCentralHeating_rate",
              fill.scale = tm_scale(values = "Reds", style = "jenks"), #use jenks classification
              fill.legend = tm_legend(title = "% No Central Heating")) +
  tm_text("LAD25NM",size=0.8) +
  tm_scalebar(position = c("right", "bottom")) + # Add a scale bar at the top-right corner
  tm_compass(position = c("left", "top")) # Add a compass rose at the top-right corner
map2
```



### 1.3.2 Merseyside neighbourhoods

Now let's read in the neighbourhood-level datasets, which include a .csv file of local statistics and the corresponding geographical boundaries.

```
lsoa_df <- read.csv("merseyside_lsoa.csv")
lsoa_sf <- st_read("LSOA_boundaries.gpkg")
```

```
Reading layer `merseyside_LSOA' from data source
`C:\Users\ziye\Documents\GitHub\quant\labs\LSOA_boundaries.gpkg'
using driver `GPKG'
Simple feature collection with 923 features and 4 fields
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: -3.200368 ymin: 53.2963 xmax: -2.576743 ymax: 53.6982
Geodetic CRS:  WGS 84
```

First, we take a look at the .csv dataset, which has been read into R as `lsoa_df`:

```
View(lsoa_df)
```

or check the structure of the dataset:

```
str(lsoa_df)
```

```
'data.frame': 923 obs. of 11 variables:  
 $ LSOA21CD      : chr  "E01006416" "E01006418" "E01006434" "E01006435" ...  
 $ Population    : int  1520 1315 1519 1524 1150 1654 1450 1581 1421 1373 ...  
 $ Households    : int  678 567 652 663 490 695 592 622 809 618 ...  
 $ Working_population: int  588 547 660 581 546 766 558 570 524 481 ...  
 $ Students      : int  59 64 69 82 51 66 65 89 52 72 ...  
 $ Unemployed    : num  3.57 2.74 5.11 3.43 1.62 ...  
 $ Age_over_65   : num  14.8 17.5 11.7 19.9 26.3 ...  
 $ Disability    : num  27.1 30 23.4 29 20.5 ...  
 $ No_central_heating: int  16 14 16 7 3 8 9 9 12 9 ...  
 $ Overcrowding   : int  24 24 35 28 13 21 29 23 31 22 ...  
 $ Working_from_home : int  91 84 102 96 165 171 101 64 66 48 ...
```

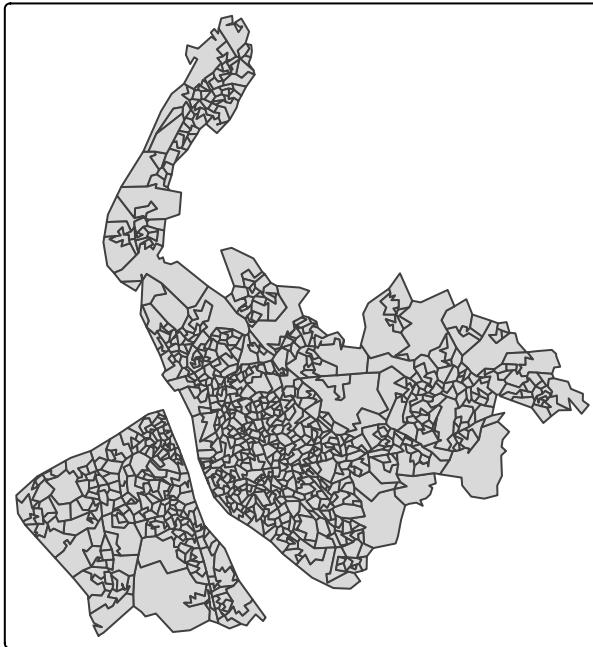
So now, you know how many LSOAs in Merseyside? Yes, there are 923 LSOAs. As we introduced in the Week 1 lecture, LSOA means Super Output Area Lower Area and is commonly used in the Census statistics. Each LSOA represents 1,000 to 3,000 people or 400 to 1,200 households in England and Wales.

```
dim(lsoa_df)
```

```
[1] 923 11
```

Use the quick mapping function `qtm()` to quickly inspect the geographical boundary dataset `lsoa_sf`.

```
qtm(lsoa_sf)
```



check how many LSOAs in the boundary dataset - there should also be 923.

```
nrow(lsoa_sf)
```

```
[1] 923
```

To familiarise yourself with the structures of both datasets, we can use the `names()` command

```
names(lsoa_df)
```

```
[1] "LSOA21CD"           "Population"          "Households"  
[4] "Working_population" "Students"            "Unemployed"  
[7] "Age_over_65"         "Disability"          "No_central_heating"  
[10] "Overcrowding"       "Working_from_home"
```

```
names(lsoa_sf)
```

```
[1] "LSOA21CD" "LSOA21NM" "LAD23CD"  "LAD23NM"  "geom"
```

You may find that both dataset are recorded at the LSOA level, with LSOA21CD as the key column. As we did with the district-level dataset, we can use `left_join()` to join these two dataset by their sharing field - LSOA21CD:

```
lsoa <- left_join(lsoa_sf,lsoa_df,by="LSOA21CD")
```

Now let's check the columns of new dataframe `lsoa`:

```
names(lsoa)
```

```
[1] "LSOA21CD"           "LSOA21NM"          "LAD23CD"  
[4] "LAD23NM"            "Population"         "Households"  
[7] "Working_population" "Students"           "Unemployed"  
[10] "Age_over_65"        "Disability"         "No_central_heating"  
[13] "Overcrowding"       "Working_from_home" "geom"
```

Or open a new tab to view the newly created dataset `lsoa` by

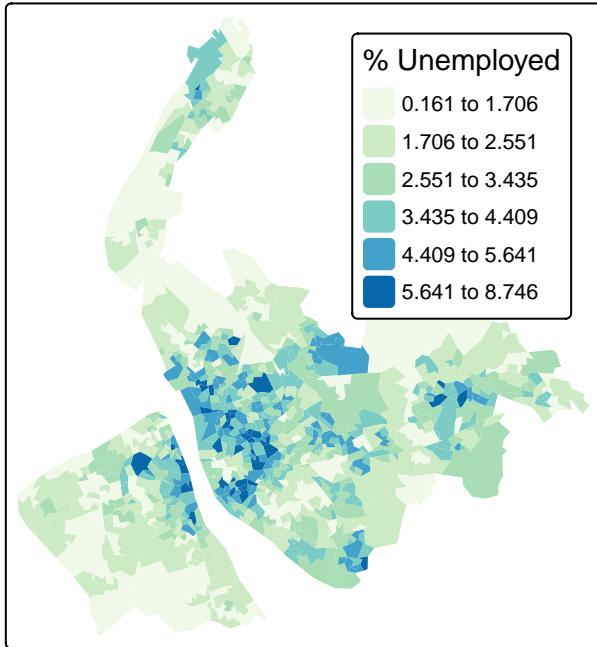
```
View(lsoa)
```

We can see that some columns contain counts, such as the number of residential population, number of households, number of working population, and number of students. Other columns are expressed as percentages, including unemployment, population aged 65 and over, disability, households without central heating, overcrowded households, and people working from home.

### 1.3.2.1 Making maps across LSOAs in Merseyside

Using the `Unemployed` column, we can create a map of the unemployment rate across neighbourhoods in Merseyside. Instead of using the default equal-interval breaks, this time we will use a jenks classification with six categories.

```
map3 = tm_shape(lsoa) +  
  tm_fill(  
    fill = "Unemployed",  
    fill.scale = tm_scale(values = "GnBu",  
                          style = "jenks",  
                          n = 6), #use jenks classification of 6 categories  
    fill.legend = tm_legend(title = "% Unemployed")  
  ) +  
  tm_layout(legend.position = c("right", "top"))  
map3
```



The above code uses `tm_layout(legend.position = c("right", "top"))` to move the legend inside the map frame, positioning it at the right-top corner.

Replace `tm_fill()` to `tm_polygons()` to see how the map changes?

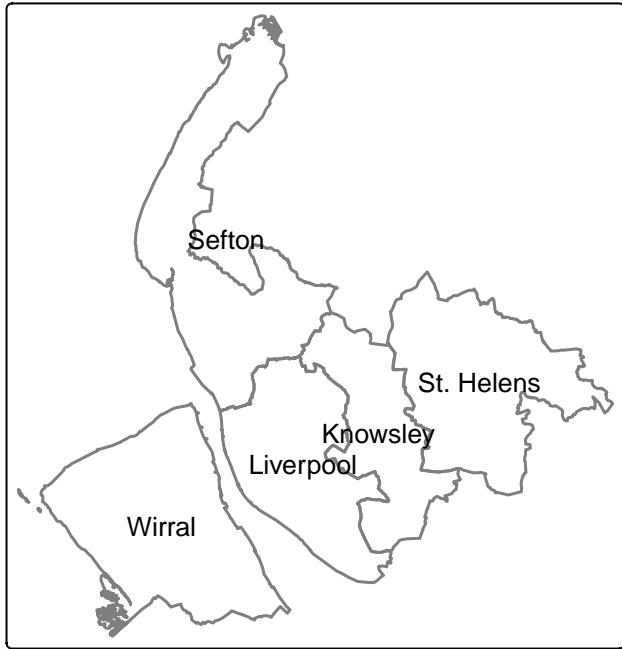
`tm_polygons()` is a condense version of `tm_fill() + tm_border()`. Here if you want show all the LSOA borders, use `tm_polygons()` instead of `tm_fill()`.

### 1.3.2.2 Overlapping tmap objects

`tmap` also supports adding or overlaying other data, such as boundaries. Because these are additional spatial data layers, they needs to be added with `tm_shape()` followed by the usual function.

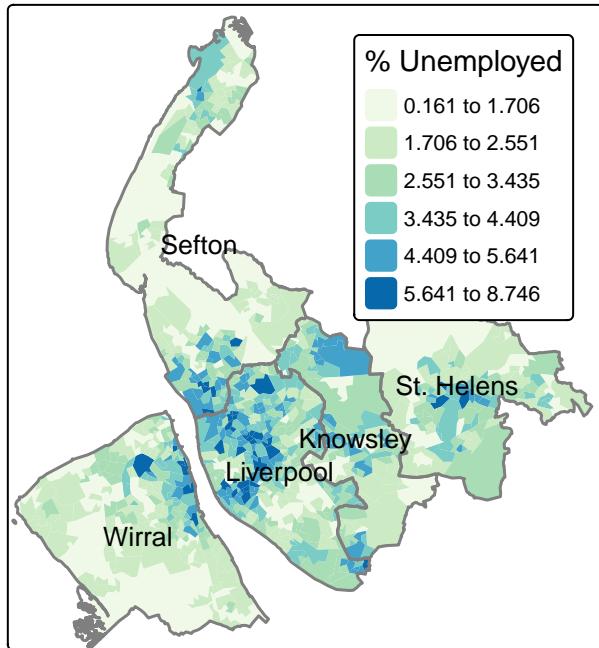
Remember we use the code chunk to make the district boundaries of Merseyside? This time let's change the aesthetic by using grey color as the border color and increase the line width, then we save it also as a `tmap` object called `map_district`:

```
map_district = tm_shape(merseyside) +
  tm_borders(col = "grey50", lwd=1.5) + #border color as grey, line width as 1.5
  tm_text("LAD25NM", size = 0.8)
map_district
```



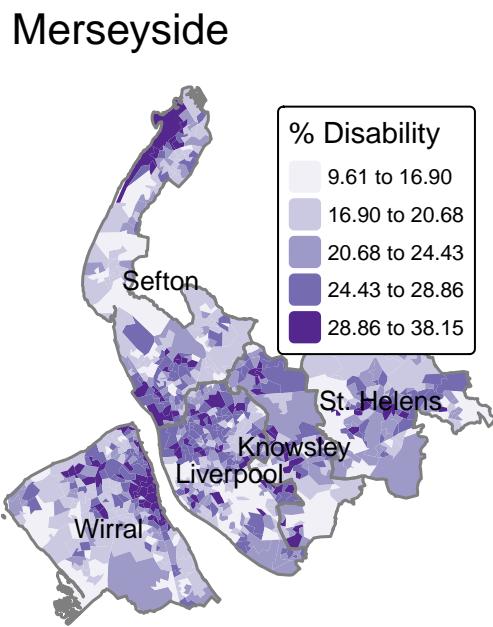
To display both `tmap` layers together, we can proceed as follows:

```
map3 + map_district
```



Now, let's move to making some more maps - this time showing the proportion of disability across neighbourhoods in Merseyside. Referring back to the columns in `lsoa`, this time we use the `Disability` variable. The code below applies a jenks classification and use a different color palette `Purples`. Also the map frame is removed by `frame = FALSE`.

```
tm_shape(lsoa) +
  tm_fill(fill = "Disability",
         fill.scale = tm_scale(values="Purples",
                               style = "jenks",
                               n=5),
         fill.legend = tm_legend(title = "% Disability")
  ) +
  tm_layout(main.title = "Merseyside",#add a main title
            legend.position = c("right", "top"),
            frame = FALSE)+  
map_district
```



### 1.3.2.3 Create new variables to make maps

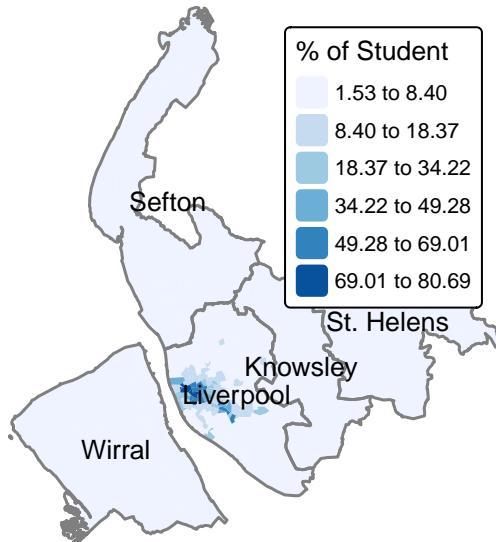
Similarly, we can make maps from new columns we made ourselves. For example, we can calculate the percentage of student by adding a new column to the dataframe:

```
lsoa$student.perc = lsoa$Students / lsoa$Population * 100
```

To make a map to visualisation the spatial distribution of student percentage. The code below uses `n=6` to increase the classification categories to 6 rather than default 5.

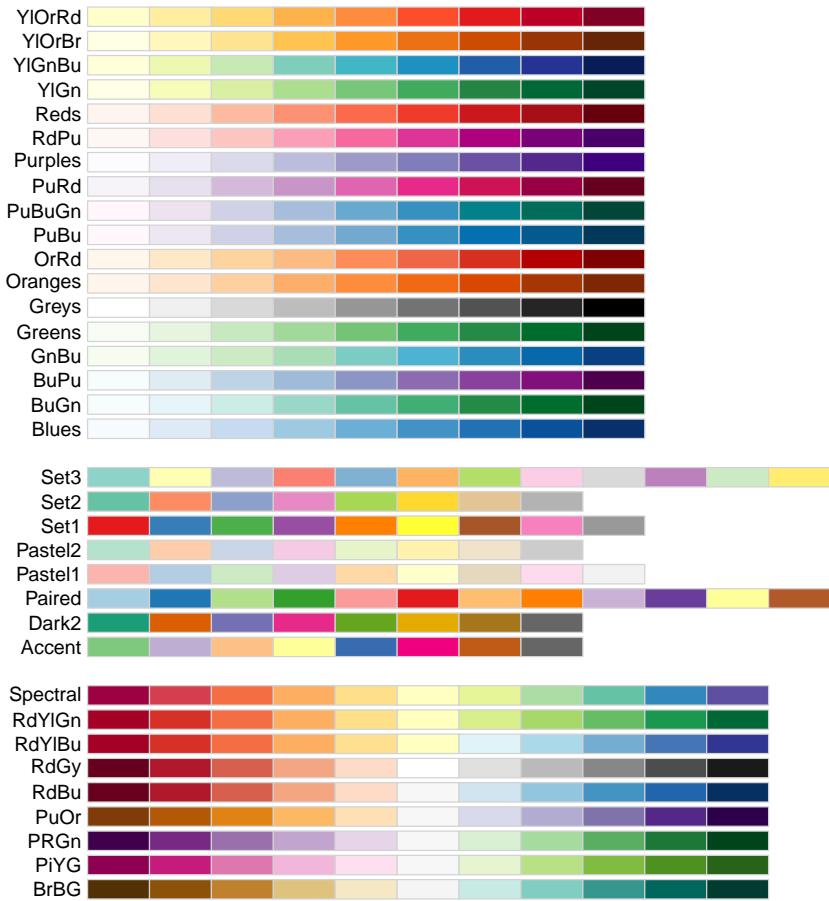
```
tm_shape(lsoa) +
  tm_fill(fill = "student.perc",
          fill.scale = tm_scale(values="Blues",
                                style = "jenks",
                                n=6),
          fill.legend = tm_legend(title = "% of Student",
                                  title.size = 0.8) #legend title change smaller font
  ) +
  tm_layout(main.title = "Merseyside",
            frame = FALSE,
            legend.position = c("right", "top"))+
  map_district
```

## Merseyside



To change the palette, RColorBrewer provides different palette choices:

```
RColorBrewer::display.brewer.all()
```



#### 1.3.2.4 In a nutshell

If we want to make a map to show the rate of no central heating households in all the neighbourhoods in Merseyside, we need to create a new variable `no.central.heating.perc` as the result of dividing households without central heating by total households in each LSOA. The code below combines all the cartographic elements together:

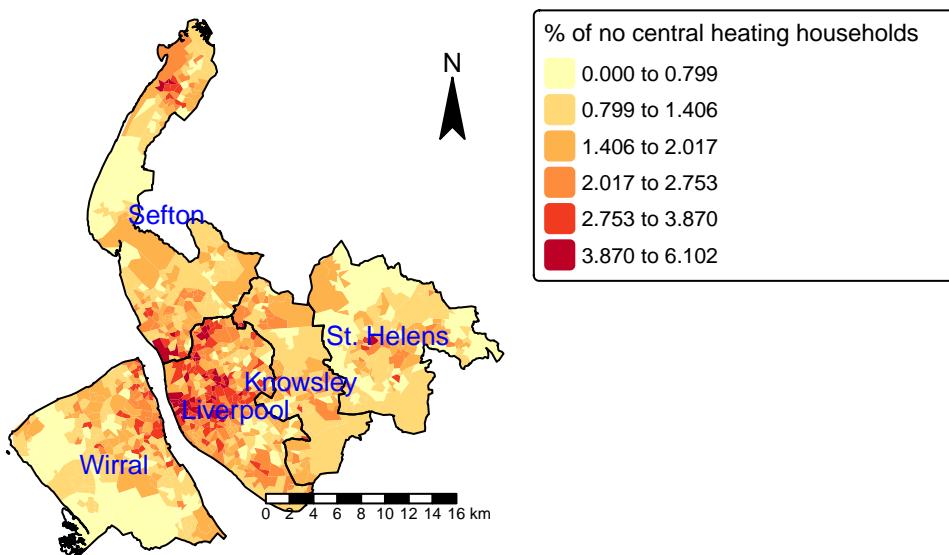
```

lsoa$no.central.heating.perc = lsoa$No_central_heating / lsoa$Households * 100

tm_shape(lsoa) +
  tm_fill(fill = "no.central.heating.perc",
         fill.scale = tm_scale(values="YlOrRd",
                               style = "jenks",n=6),
         fill.legend = tm_legend(title = "% of no central heating households",
                                 title.size = 0.8)
  ) +
  tm_layout(main.title = "Merseyside",
            main.title.size=1.2,
            frame = FALSE) +
  tm_compass(position = c("right", "top")) +
  tm_scalebar(position = c("right", "bottom")) +
  tm_shape(merseyside) +                      # Add another spatial layer (Merseyside boundary)
  tm_borders(col = "black", lwd = 1) +          # Draw the boundaries with black lines of width 1
  tm_text("LAD25NM",col = "blue",size = 0.8)

```

## Merseyside



## 1.4 Summary

The aim of this session has been to familiarise you with the R environment if you have not used R before. If you have but not for a while, then hopefully this has acted as a refresher. Some key things to take away are:

- R is a learning curve, and like driving the more your practice the better you become.
- Your job is to try to **understand** what the code is doing and **not** to remember the code.
- To help with this, you should add your own comments to the script to help you understand what is going on when you return to them. Comments are prefaced by a hash (#) that is ignored by R.
- Always set your working directory to the sub-folder containing your R script.
- Always run your code from an R script... **always!**

### 1.4.1 References

Brunsdon, Chris, and Lex Comber. 2018. *An Introduction to r for Spatial Analysis and Mapping* (2e). Sage.

Comber, Lex, and Chris Brunsdon. 2021. *Geographical Data Science and Spatial Data Analysis: An Introduction in r*. Sage.

Harris, Richard. 2016. *Quantitative Geography: The Basics*. Sage.

Other good on-line *get started in R* guides include:

- The Owen guide (only up to page 28) : <https://cran.r-project.org/doc/contrib/Owen-TheRGuide.pdf>
- An Introduction to R - [https://cran.r-project.org/doc/contrib/Lam-IntroductionToR\\_LHL.pdf](https://cran.r-project.org/doc/contrib/Lam-IntroductionToR_LHL.pdf)
- R for beginners [https://cran.r-project.org/doc/contrib/Paradis-rdebut\\_en.pdf](https://cran.r-project.org/doc/contrib/Paradis-rdebut_en.pdf)

## 1.5 Formative Tasks

**Task 1** From the district level dataset “merseyside.csv”, extract household information for the Liverpool and Wirral districts. The variables to be included are “Households”, “No\_central\_heating” and “Overcrowding”.

**Task 2** Use the dataset “merseyside\_lsoa.csv”, plot the **Disability** against **Age\_over\_65** from the data frame.

**Task 3** Use the district level dataset, how many households in total in Merseyside?

**Task 4** Use the district level dataset, what is the overall proportion of the ageing population (age over 65) in Merseyside?

**Task 5** Use the LSOA level dataset, what is the average proportion of the ageing population (age over 65) across all the neighbourhoods of Merseyside?

**Task 6** Create a map showing the spatial distribution of the proportion of ageing population (age over 65) over LSOAs in Merseyside? (use Jenks classification of 7 categories).