Crime Mapping and Spatial Data Analysis using R

Juanjo Medina and Reka Solymosi

2021-05-26

To my son,

without whom I should have finished this book two years earlier

Contents

Preamble: how to use this book

This book aims to provide the reader with an introduction to Crime Mapping and Spatial Data Analysis, using R as an engine for spatial data analysis and visualisation. Based on teaching materials developed by the authors, the book is a practical guide for those interested in crime analysis and criminology.

We imagine this to be useful for those teaching (or enrolled in) upper level undergraduate and graduate courses in higher education, as well as analysts in professional roles embarking on further training, or looking for a guide for their work, as well as criminologists interested in crime mapping. The material has been successful in our teaching both in higher education settings, and when training crime analysts working for the police or other law enforcement agencies.

Given the source material, this book may be used as a companion text for similar course units in crime mapping, the geography of crime, environmental criminology, or crime analysis. Equally, it can be used by students, practitioners, and academics alike interested in learning more about R and its GIS and spatial analysis capacity. It is not an advanced statistics textbook, but rather an applied textbook. Someone "self teaching" R for these purposes will find it helpful and, thus, unlike reference books, it is better to read and practice each chapter in sequence.

Crime mapping and analysis sits at the intersection of geocomputation, data visualisation and cartography, spatial statistics, environmental criminology, and crime analysis. In this book, environmental criminology, that focus on the analysis of the spatial and geographical distribution of crime, provides the substantive background.

This text cannot make justice to each of these bodies of inquiry, professional practice, and literature. We cannot offer a comprehensive and systematic treatment of each of these areas. What we do is provide a helpful introduction to R as a way to bring together these specialties and offer adequate references to our readers so that they can deepen their understanding of each of them. For a grounding in Environmental Criminology we recommend **?**, for debates and

issues in spatial criminology/crime analysis and crime and place research we suggest **?**, and for geocomputation and spatial data science **?** and **?** provide great foundations. For further topics for crime analysts **?** and more recently **?** are excellent as well. We also provide further resources at the end of each chapter for those who wish to delve deeper into each individual topic introduced.

Although all the examples we use concern the study of crime, there is fairly limited substantive criminology in the text. In fact, and despite the title, the volume could also be used, more generally, as a companion text for courses on social science spatial data analysis, since the techniques we cover are transferable to other substantive domains.

In the first part of this volume we introduce key concepts for geographic analysis and representation and provide the reader with the foundations needed to visualise spatial crime data. We then introduce a series of tools and techniques that are relevant to study spatial homogeneity and dependence of crime data. A key focus in this section is how to visualise and detect local clusters of crime and repeat victimisation. The final chapters introduce the use of spatial models, which account for the distribution of crime across space. In terms of spatial data analysis the focus of the book is on spatial point pattern analysis and lattice or area data analysis. Geostatistics have fewer applications in crime analysis and research and, therefore, we do not cover this topic here.

To follow along with the exercises we provide the data we use in a zip file. The best approach is to download this zip file into the working directory of your R project, and unzip it there. This way, you can follow our code. If you run the below code, this should do this for you automatically:

```
download.file(url = "https://osf.io/5u42g/download",
              destfile = "data.zip")
unzip("data.zip", exdir = "data")
```

From then on, you can read all files in from this downloaded data directory. In our code, we use the convention that all data are stored in a `"data/"` folder within our working directory.

We hope you enjoy this book and find it useful in your journey into crime mapping. The world of R and spatial analysis is ever-evolving, and we will try to stay updated. If you have ever suggestions, comments, concerns, or requests, do not hesitate to get in touch, or raise this as an issue in our GitHub repository: www.github.com/maczokni/crime_mapping[1].

[1] `https://github.com/maczokni/crime_mapping`

Producing your first crime map

0.1 Introduction

This chapter introduces some basic concepts and will get you started to make some maps using R. We will learn how we can take regular crime data, and assign the appropriate geometry for our chosen unit of analysis. Spatial or environmental criminologist most often work with data that are **discrete**. This may include data represented by points (e.g. locations of a crime incident) or counts and rates of crimes within a particular geographical unit (e.g. a neighbourhood, a census tract, or a municipality). In other scientific disciplines the mapped data may be **continuous** across the study surface (e.g. temperature).

In these first few chapters we will focus on ways to work with discrete data. Firstly, we introduce the spatial and non-spatial R packages used frequently throughout the book, and cover some key terms around projection and coordinate reference systems which will be essential for subsequent chapters. As we will discover throughout the book there are multiple R packages that have been developed to visualise spatial data. They all have advantages and disadvantages, but many offer similar functionality. Sometimes choosing one or the other is a matter of personal preference. We will introduce many different approaches throughout the book, to allow readers to select their own preferences. In this chapter we will focus on map-making with `ggplot2`, a general package for data visualisation (not just maps) based on the theory of the grammar of graphics. If you are not new to R, you may already be familiar with this package. Our intention in this chapter is to introduce enough background to let you to quickly produce your first map. In subsequent chapters we will further refine their look and aesthetic appeal, and discuss the many decisions that go into producing a crime map.

In this chapter we will use the following packages:

```
# Packages for reading data and data carpentry
library(readr)
library(tibble)
library(janitor)
library(dplyr)

# Packages for handling spatial data
library(sf)

# Packages for visualisation and mapping
library(ggplot2)
library(ggspatial)
```

If you are a little rusty on R packages, what they do, how to install them, how to load them, and so on, please refer to *Appendix A: LearnR* for a quick introduction and overview of R.

0.2 Geospatial Perspective: key terms and ideas

Geospatial analysis provides a distinct perspective on the world, a unique lens through which to examine events, patterns, and processes that operate on or near the surface of our planet. Ultimately geospatial analysis concerns what happens where, and makes use of geographic information that links features and phenomena on the Earth's surface to their locations.

We can talk about a few different concepts when it comes to spatial information. These are:

- Place
- Attributes
- Objects
- Networks

Let's discuss each in turn now.

0.2.1 Place

At the center of all spatial analysis is the concept of *place*. People identify with places of various sizes and shapes, from the parcel of land, to the neighbourhood, to the city, the country, the state or the nation state. Places often have names, and people use these to talk about and distinguish names. Names can be official or unofficial. Places also change continually as people move. In geospatial

analysis, the basis of rigorous and precise definition of place is a coordinate system. A **coordinate system** is a set of measurements that allows place to be specified unambiguously and in a way that is meaningful across different users, analysts, mappers, and researchers.

In Environmental Criminology, place has acquired different meanings through history. The first geographical studies of crime during the XIX century looked at variation across provinces in France (**?**), Belgium (**?**), and England (**?**). Later on, in the first decades of the XX century, the Chicago School of Sociology focused on the study of neighbourhoods (**?** , **?**). With the emergence of Environmental Criminology (**?**, **?**, **?**) a shift towards a greater interest in microplaces, such as street segments or particular addresses, can be seen (**?**). Although an interest in variation across large administrative units (as "place") remains within criminology, there has been a trend towards understanding place as particular locations, and focusing on risky places for crime .

However we define "place", it is the central concept to crime mapping, and spatial data analysis. Most human activity takes place in a specific location, and accounting for this spatial information is a key task for criminologists, crime analysts, and social and data scientists more broadly.

0.2.2 Attributes

Attribute has become the preferred term for any recorded characteristic or property of a place. It is what more generally in statistics we may call a variable and in data science a feature. A place's name is an obvious example of an attribute. But there can be other pieces of information, such as number of crimes in a neighbourhood, or the GDP of a country. Within geographic information science (GIS) the term 'attributes' usually refers to records in a data table associated with individual elements in a vector map, or cells in a grid in a raster or image file. These data behave exactly as data you may have encountered in past experience with non-spatial statistics. The rows represent observations, and the columns represent variables. The variables can be have different levels of measurement (like numeric (interval or ratio, discrete or continuous) or categorical (binary, nominal, ordinal)), and depending on what they are, you can apply different methods to making sense of them. The difference with other kind of data table is that the observations, your rows, correspond to places or locations and that the data necessarily will include elements that allow us to place it in a map.

0.2.3 Spatial objects

In spatial analysis it is customary to refer to places as objects. These objects can be a whole country, or a road. In forestry, the objects of interest might be trees, and their location will be represented as points. On the other hand, studies of

social or economic patterns may need to consider the two-dimensional extent of places, which will therefore be represented as areas. These representations of the world are part of what is called the **vector data model**: a representation of the world using points, lines, and polygons. Vector models are useful for storing data that have discrete boundaries, such as country borders, land parcels, and streets. This is made up of points, lines, and areas (polygons):

- *Points*: Points are pairs of coordinates, in latitude/longitude or some other standard system. In the context of crime analysis, the typical point we work with, though not the only one, represents the specific location of a criminal event. These points form patterns we explore and analyse.
- *Lines*: Lines are ordered sequences of points connected by straight lines.
- *Areas* (polygons): Areas are ordered rings of points, also connected by straight lines to form polygons. It can contain holes, or be linked with separate islands. Areas can represent neighbourhouds, police districts, municipal terms, etc. You may come across the term **lattice data** to denote the type of data we work with when we observed attributes of areas and want to explore and analyse this data.

Spatial objects may also be stored as **raster data**. Raster data are made up of pixels (or cells), and each cell has an associated value. Simplifying slightly, a digital photograph is an example of a raster dataset where each pixel value corresponds to a particular colour. In GIS, the pixel values usually represent continuous data such as elevation above sea level, or chemical concentrations, or rainfall, etc. The key point is that all of this data is represented as a grid of (usually square or hexagonal) cells.

0.2.4 Networks

We already mentioned lines that constitute objects of spatial data, such as streets, roads, railroads, etc. Networks constitute one-dimensional structures embedded in two or three dimensions. Discrete point objects may be distributed on the network, representing phenomena such as landmarks, or observation points. Mathematically, a network forms a graph, and many techniques developed for graphs have application to networks. These include various ways of measuring a network's connectivity, or of finding the shortest path between pairs of points on a network.

0.3 Maps and their types

Historically maps have been the primary means to store and communicate spatial data. Objects and their attributes can be readily depicted, and the human eye can quickly discern patterns and anomalies in a well-designed map.

In GIS we distinguish between reference and thematic maps. A **reference map** places the emphasis on the location of spatial objects such as cities, mountains, rivers, parks, etc. You use these maps to orient yourself in space and find out the location of particular places.

Thematic maps or statistical maps, on the other hand, are used to represent the spatial distribution of attributes or statistics. For example, the number of crimes across different neighbourhouds. Our focus in this book is on thematic maps, but often when producing thematic maps you may use a reference map as a backdrop, as a *basemap*, to help interpretation and to provide context. In this and subsequent chapters we will introduce different types of thematic maps.

Another useful distinction is between **static** and **interactive** maps. Your traditional printed road map is an example of a static map, whereas the web application Google maps is an example of an interactive map. In an interactive map you can zoom in and out, you can select and query information about objects in an interactive fashion, etc. In this chapter we introduce the R package `ggplot2`, which excels at static maps. In other chapters we will introduce another package called `leaflet`, which is particularly useful for interactive purposes, and the package `tmap`, in which we can shift our maps between static and interactive mode.

0.4 Map projections and geographic coordinate systems

Whenever we put something into a map we need some sort of system to pinpoint the location. A coordinate system allows you to integrate any dataset with other geographical datasets within a common framework. With the help of **coordinate reference systems** (CRS) every place on the Earth can be specified by a set of three numbers, called coordinates. In general CRS can be divided into **projected coordinate reference systems** (also called Cartesian or rectangular coordinate reference systems) and **geographic coordinate reference systems**.

A **geographic coordinate system** is a *three dimensional* reference system that enables you to locate any location on Earth. This coordinate system is round, and so records locations in angular units (usually degrees). The use of geographic coordinate reference systems is very common. The most popular is called the **World Geodetic System (WGS 84)** which refers to locations using "Longitude", "Latitude", and in some cases "Elevations". For example, to communicate where is the University of Manchester, I would say it is Longitude: -2.2360724 degrees and Latitude: 53.466853 degrees.

Projected coordinate systems or map projections, on the other hand, try to portray the surface of the Earth or a portion of the Earth on a *two dimensional* flat piece of paper or computer screen. Therefore location is recorded in linear

units (usually meters). Working, for example, with data in the UK, we will be using **British National Grid (BNG)**. In this case, points will be defined by "Easting" and "Northing" rather than "Longitude" and "Latitude". It basically divides the UK into a series of squares, and uses references to these to locate something. The most common usage is the six figure grid reference, employing three digits in each coordinate to determine a 100 m square. For example, the grid reference of the 100 m square containing the summit of Ben Nevis is NN 166 712.

All projections of a sphere like the Earth in a two-dimensional map involve some sort of distortion. You can't fit a three dimensional object into two dimensions without doing so. **Projections** differ to a large extent on the kind of distortion that they introduce. This will be important later on when we are linking data from different projections, or when you look at your map and you try to figure out why it might look "squished".

The decision as to which map projection and coordinate reference system to use, depends on the regional extent of the area you want to work in, on the analysis you want to do and often on the availability of data. Knowing the system you use would allow you to translate your data into other systems whenever this may be necessary. Often you may have to integrate data that is provided to you in different coordinate or projected systems. As long as you know the systems, you can do this, and we will be demonstrating this throughout the book.

You will often see the notation *epsg* when referring to different coordinate systems. This refers to the EPSG registry or **EPSG Geodetic Parameter Dataset**. It is a collection of geodetic datums, spatial reference systems, Earth ellipsoids, coordinate transformations, and related units of measurement. All standard coordinate systems will have one of these codes assigned to it. So, for example, the WGS84 coordinate system corresponds the epsg key 4326, whereas the British National Grid has the key 27700. Having this common framework to identify projections make things much easier when we want to change our data from one system to another. You can query the website `https://epsg.io/` for the different keys and information associated to each of them. This EPSG dataset was originally developed by the European Petroleum Survey Group (EPSG), thus the name.

0.5 Key terms summary

While the above was a whistlestop tour of some key terms, this should start you thinking about these concepts. For a deeper understanding, consult the further reading at the end of this chapter. For now, to progress, be sure that you are confident to know about:

- Spatial objects - what they are and how they are represented,

- Attributes - the bits of information that belong to your spatial objects,
- Maps and projections - especially what geographic versus projected coordinates mean, and why it's important that you know what CRS your data have.

0.6 Getting started with crime data

We live in a world awash with data and through this book we will use the different examples to show you some useful places and sources you can use to obtain your spatial data. Most geographically referenced crime data is based on crime reported to the police, although there are some notable exceptions (e.g., public health data on violence, geocoded victim survey data, etc.). Many police departments across the world make this data readily available to the public or researchers. This is more common in places like the United States, where crime mapping applications first got established, but increasingly we see publicly available crime data from other countries as well.

For our first map we will use data from the UK, which can be downloaded from the police.uk[2] website. We have downloaded some data for crime in Manchester, which is included in the data file you have downloaded to follow along (see the Preamble chapter for details). If you wanted to acquire the data yourself directly from the source, you could open the data.police.uk/data[3] website and then choose the data tab, in order to manually download some data.

So whether from the website, or the provided data file, you should have some police data ready. The next step is to read this into R. How can we do this? We say, "hello R, i would like to create a new object please and I will call this new object `my_data`." We do this by typing the name we are giving the object and the assignment operator `<-`. Then on the right hand side of the assignment operator, there is the value that we are assigning the variable. So it could be a bit of text, or it could be some function, for example when you read a csv file with the `read_csv()` function from the `readr` package.

When we read in this file, inside the function, we also need to specify *where* to read the csv from. Where should R look to find this data? This is where normally you are putting in the path to your file. Something like:

```
my_data <- read_csv("path to my file here")
```

If you downloaded the data following the steps in the Preamble chapter for this book, your data will be in your working directory, in a sub-folder called "data".

[2] https://data.police.uk/data/
[3] https://data.police.uk/data/

It is within this subfolder that you'll find all you need. In this case, let's look for the file `2019-06-greater-manchester-street.csv`. To read this into R we run:

```
library(readr)

crimes <- read_csv("data/2019-06-greater-manchester-street.csv")
```

If you look at the *Environment* window in the top right corner of RStudio you should see now a new object that contains a *tibble*, a particular format for dataframes, and that is called `crimes`. It will tell you how many observations (rows - and incidentally the number of recorded crimes in June 2019 within the GMP jurisdiction) and how many variables (columns) your data has.

Let's have a look at the crimes dataframe with the `View()` function. This will open the data browser in RStudio.

```
View(crimes)
```

If you rather just want your results in the console, you can use the `glimpse()` function from the `tibble` package. This function does just that, it gives you a quick glimpse of the first few cases in the dataframe. Notice that there are two columns (Longitude and Latitude) that provide the require geographical coordinates that we need to plot this data.

```
library(tibble)

glimpse(crimes)
```

```
## Rows: 32,058
## Columns: 12
## $ `Crime ID`          <chr> NA, "aa1cc4cb0c436f463635890bcb4ff2cba08f59925~
## $ Month                   <chr> "2019-06", "2019-06", "2019-06", "2019-
06", "2~
## $ `Reported by`        <chr> "Greater Manchester Police", "Greater Manchest~
## $ `Falls within`       <chr> "Greater Manchester Police", "Greater Manchest~
## $ Longitude                <dbl> -2.464422, -2.441166, -2.444807, -
2.444807, -2~
## $ Latitude            <dbl> 53.61250, 53.61604, 53.61151, 53.61151, 53.606~
## $ Location            <chr> "On or near Parking Area", "On or near Pitcomb~
## $ `LSOA code`         <chr> "E01004768", "E01004768", "E01004768", "E01004~
## $ `LSOA name`         <chr> "Bolton 001A", "Bolton 001A", "Bolton 001A", "~
```

```
## $ `Crime type`         <chr> "Anti-social behaviour", "Violence and sexual ~
## $ `Last outcome category` <chr> NA, "Unable to prosecute suspect", "Unable to ~
## $ Context             <lgl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA~
```

You may notice that a lot of the variable names are messy in that they have a space in them - this can cause issues, so before playing around too much with the data we want to clean this up. Luckily there is a very handy package you can use for this called `janitor` which contains the function `clean_names()`.

```
library(janitor)

crimes <- clean_names(crimes)
```

Now the names are much neater. You can print them all for a view using the `names()` function:

```
names(crimes)
```

```
##  [1] "crime_id"              "month"                 "reported_by"
##  [4] "falls_within"          "longitude"             "latitude"
##  [7] "location"              "lsoa_code"             "lsoa_name"
## [10] "crime_type"            "last_outcome_category" "context"
```

0.7 From dataframes to spatial objects

Having had a chance to inspect the data set you've downloaded, let's consider what sort of spatial information we might be able to use. If you have a look at the column names, what are some of the variables which you think might have some spatial component? Have a think about each column, and how you think it may help to put these crimes on the map.

There are a few answers here. In fact there are one each to map onto point, line, and polygon.

0.7.1 The point

First, and possibly most obvious, are the coordinates provided with each crime incident recorded. You can find this in the two columns - Longitude and Latitude. These two column help put each crime incident on a specific point on a map. For example, let's take the very first crime incident. Here we use the

`head()` function and specify that we want the first 1 rows only with `n=1` parameter.

```
head(crimes, n = 1)
```

You can see that the values are -2.464422 for Longitude and 53.612495 for Latitude. These two numbers allow us to put this point on a map.

0.7.2 The line

Another column which contains information about *where* the crime happened is the aptly named *location* variable. This shows you a list of locations related to where the crimes happened. You may see a few values such as on or near XYZ street. Let's look again at the first entry.

```
head(crimes, n = 1)
```

You can see that the value is On or near Parking Area this isn't great, as we might struggle to identify *which* parking area… Some other ones are more useful, let's look at the last entry for example with the `tail()` function.

```
tail(crimes, n = 1)
```

You can see that the value is On or near Fulwood Road. This makes our crime much easier to find, we just need to locate where is Fulwood Road. We might have a file of lines of all the roads of Manchester, and if we did, we can link the crime to that particular road, in order to map it.

0.7.3 The polygon

What more? You may also have seen the column "lsoa_name" and it seems to contain what looks like names for some sort of area or place. Let's have a look at the first crime again. You see the value for LSOA name is Bolton 001A - Bolton we know is a Borough of Greater Manchester, but what does the 001 mean?

Well, it denotes a particular geographical sub-unit within the municipality of Bolton called a **Lower Layer Super Output Area**. This is a unit of UK Census Geography[4]. The basic unit for Census Geography in the UK is an

[4] `https://www.ons.gov.uk/methodology/geography/ukgeographies/censusgeography`

'Output area' - this is the resolution at which we can access data from the UK Census. The Output Area (OA) is therefore the smallest unit we could use. The census in other countries use different names for the units for which they publish information, but the logic is similar.

There are 181,408 OAs, 34,753 lower layer super output areas (LSOA) and 7,201 middle layer super output areas (MSOA) in England and Wales. The neat thing about these Census geographies is the idea is that they don't change much from census to census (unlike other administrative boundaries) and in the UK case were created with statistical analysis in mind (they were designed to be as homogeneous as possible). The less neat thing is that although we use them to operationalise the concept of neighbourhood a lot, they may not bear much resemblance to what residents might think of as their neighbourhood. This is a common problem in the UK and elsewhere (that has been widely discussed in the literature - see **?** for example) when relying on census units as our proxy for community or neighbourhood, but one that is hard to escape from, for these units are those at which key demographic variable is typically sourced and published.

Looking back to our crime data, we find two columns that reference LSOAs, `lsoa_name` and `lsoa_code`. We can use these to *link* our crime data to a file containing the geometries needed to put the crime data on the map. In the next section we will illustrate how.

0.7.4 Choosing the ideal unit of analysis

The unit of analysis at which to consider approaching our research and analytical questions will depend most largely on what is the appropriate level at which addressing the question makes sense, and at what level can we get reliable data for the variables we wish to analyse. There is no simple answer to this. Questions around levels of measurement have formed a central part of discourse in the area of crime mapping (**?**). It is important that careful thought and consideration is given to this decision.

0.8 The simple features framework

We've established now that our crime data has spatial information, which we can use to put our crimes on the map. In this section, we will introduce the simple features framework as a way to do this using R. Our task is to specify a geometry for our data, which links each unit of analysis (whether that is the point, line, or polygon) to a relevant geographical representation, allowing us to put this thing on the map.

How you add geographical information will vary with the type of information we have, but in all of these, we will use the **simple features** framework. `sf`

package author Edzer Pebesma describes simple features as a standardized way of encoding spatial *vector data* (points, lines, polygons). The `sf` package is an R package for reading, writing, handling, and manipulating simple features in R, implementing the vector data handling functionality.

Traditionally spatial analysis in R were done using the `sp` package which creates a particular way of storing spatial objects in R. When most packages for spatial data analysis in R and for thematic cartography were first developed `sp` was the only way to work with spatial data in R. There are more than 450 packages that rely on `sp`, making it an important part of the R ecosystem. More recently `sf` is changing the way that R does spatial analysis. This package provides a new way of storing spatial objects in R and most recent R packages for spatial analysis and cartography are using it as the new default. It is easy to transform `sf` objects into `sp` objects and viceversa, so that those packages that still don't use this new format can be used. In this book we will emphasise the use of `sf` whenever possible. You can read more about the history of spatial packages and the `sf` package in the first two chapters of **?**.

Features can be thought of as "things" or objects that have a spatial location or extent; they may be physical objects like a building, or social conventions like a political state. Feature geometry refers to the spatial properties (location or extent) of a feature, and can be described by a point, a point set, a linestring, a set of linestrings, a polygon, a set of polygons, or a combination of these. The simple adjective of simple features refers to the property that linestrings and polygons are built from points connected by straight line segments. Features typically also have other properties (temporal properties, color, name, measured quantity), which are called feature attributes. For more detailed insight we recommend reading **?**.

Let's get started with making some maps using `sf`. First, make sure you install the package, and then load with `library()` function. We know that we have two columns one for longitude and one for latitude, which pinpoint each crime event to a specific point, close to where it happened. Not *quite* where it happened, as the data are anonymised (more on this later), but for our purposes here, we can assume this is the location of the crime. To map these points, we can transform our ordinary dataframe into a simple features object.

To do so, we can use the `st_as_sf()` function from `sf`, into which we need to specify what we are to transform (our dataframe), where the spatial data can be found (our columns which hold the latitude and longitude information), and also what coordinate reference system the object has (see above our discussion about projections and coordinate reference systems).

Latitude longitude coordinates specify location on the **WGS 84** CRS. We can tell R that this is our CRS of choice by including its EPSG identifier as a parameter in our function. It is handy to know the more common EPSG identifiers. For example, for WGS84 the EPSG identifier is *4326*. For British National Grid, the identifier is *27700*.

Putting it all together in practice, we can create a simple features object from our dataframe using the latitude and longitude columns:

```
library(sf)

crimes_sf <- st_as_sf(crimes,   #dataframe
                      #columns with coordinates:
                      coords = c("longitude", "latitude"),
                      crs = 4326)   #crs is WGS84
```

We can see that this is now a simple features object using the `class()` function to print the result "sf":

```
class(crimes_sf)
```

```
## [1] "sf"         "tbl_df"     "tbl"        "data.frame"
```

You might also notice something else that is different between "crimes" and "crimes_sf." Have a look at the dimension (hint: look in your 'Environment' tab). In the `sf` object you will see that the information provided by the longitude and latitude variables have been "merged" into a new variable called *geometry*, that `sf` uses to store the kind of object we have (a point in this case) and where to locate it.

0.9 Plotting data with ggplot2

Now that we have this `sf` object, how can we map it? We mentioned before about the graphical package `ggplot2`. We can use this, and its syntax, in order to map spatial data using the `geom_sf()` geometry.

First, a quick refresher on `ggplot2` and the grammar of graphics. The grammar of graphics upon which this package is based on defines various components of a graphic. Some of the most important are:

- **The data**: For using `ggplot2` the data has to be stored as a data frame or tibble (`sf` objects are of class tibble).
- **The geoms**: They describe the objects that represent the data (e.g., points, lines, polygons, etc..). This is what gets drawn. And you can have various different types layered over each other in the same visualisation.

- **The aesthetics**: They describe the visual characteristics that represent data (e.g., position, size, colour, shape, transparency).

- **Facets**: They describe how data is split into subsets and displayed as multiple small graphs.

-**Stats**: They describe statistical transformations that typically summarise data.

Let's take it one step at the time.

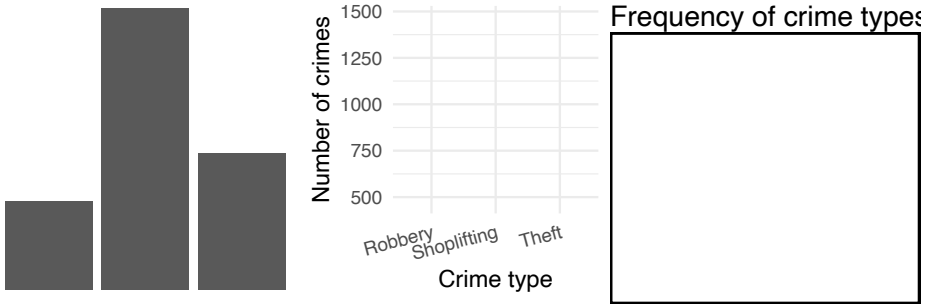
Essentially the philosophy behind this is that all graphics are made up of layers. You can build every graph from the same few components: a data set, a set of geoms—visual marks that represent data points, and a coordinate system.

Take this example from our crimes dataframe.

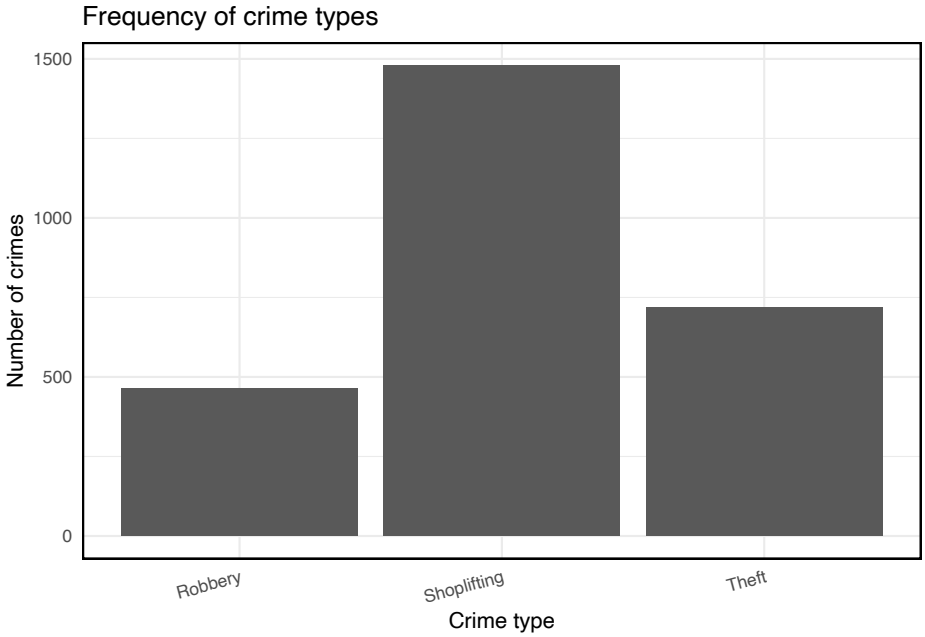
You have a table such as:

crime_type	n
Robbery	463
Shoplifting	1479
Theft from the person	718

You then want to plot this. To do so, you want to create a plot that combines the following layers:



This will result in a final plot:



Taking our crime data as an example, we would build up our plot as follows.

First let's create a small illustrative data set of only the crimes of "Robbery", "Shoplifting", and "Theft from the person".

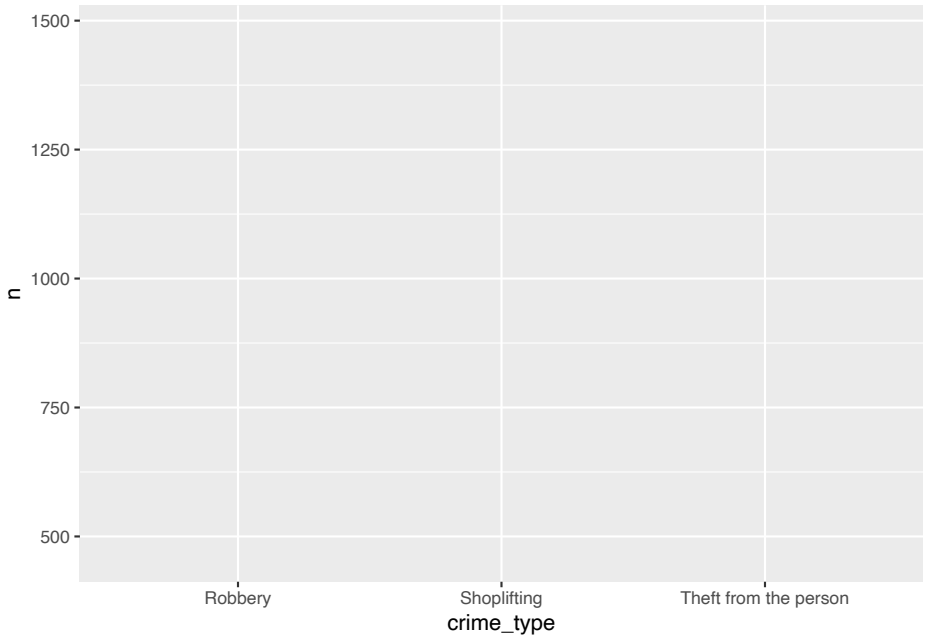
```
library(dplyr)

df <- crimes %>%
  filter(crime_type %in% c("Robbery",
                           "Shoplifting",
                           "Theft from the person")) %>%
  group_by(crime_type) %>%
  count()

df
```

```
## # A tibble: 3 x 2
## # Groups:   crime_type [3]
##   crime_type                n
##   <chr>                 <int>
## 1 Robbery                 463
## 2 Shoplifting            1479
## 3 Theft from the person   718
```

Now let us add the layers to our ggplot object.

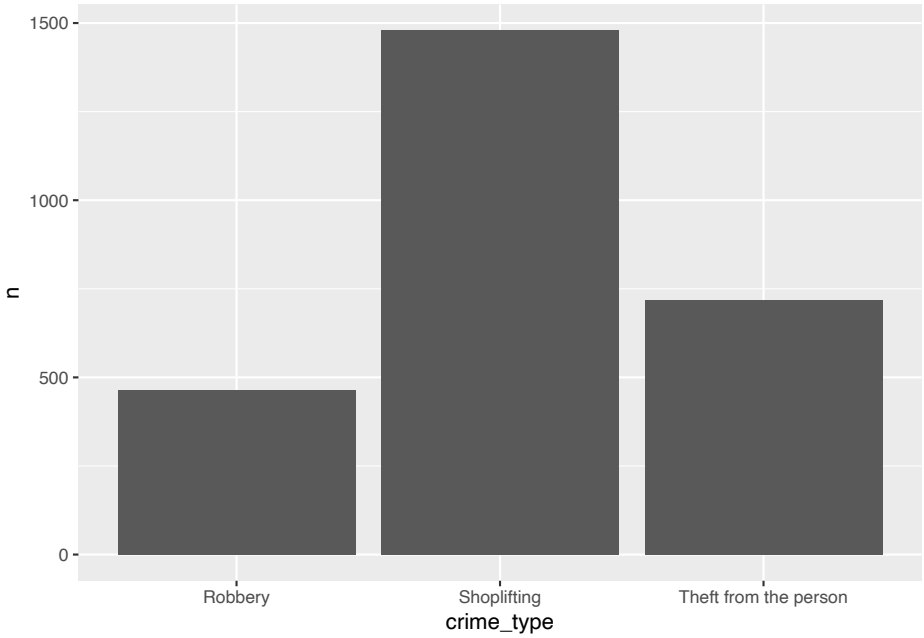
First, the data layer:

```
library(ggplot2)

ggplot(df, aes(x = crime_type, y = n))
```



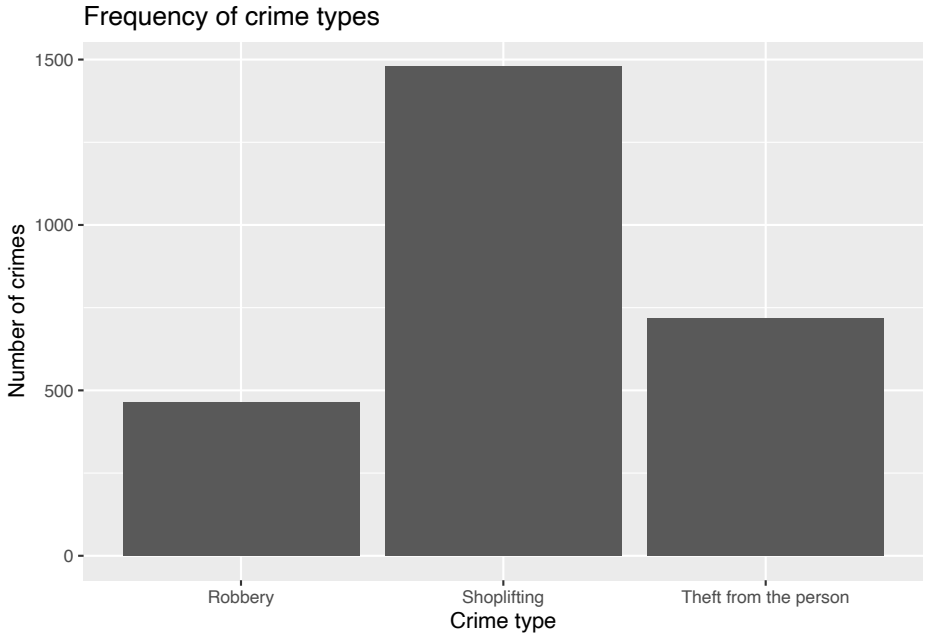
Then add the geometry (in this case, `geom_col()`):

```
ggplot(df, aes(x = crime_type, y = n)) +
  geom_col()
```



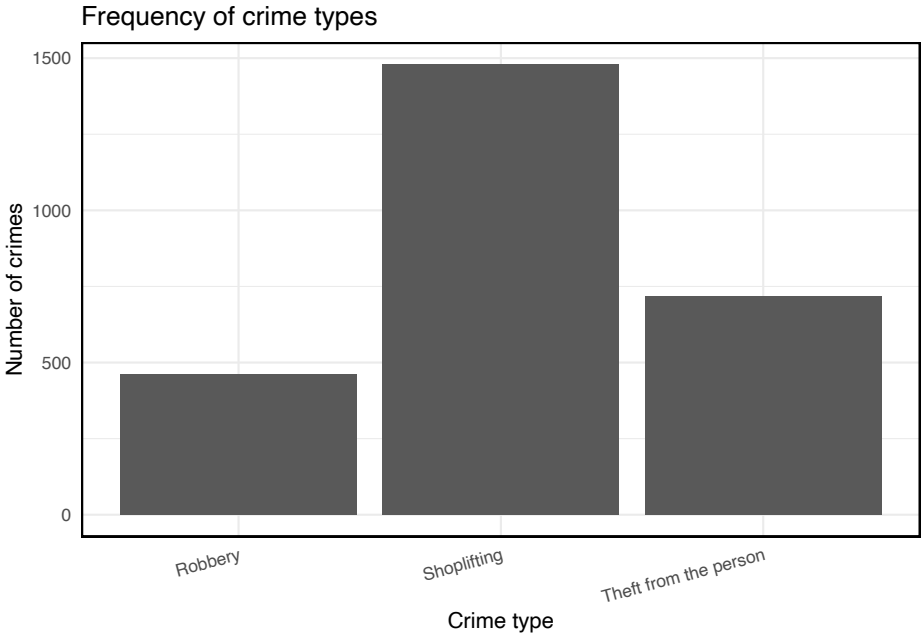
Then our annotations:

```
ggplot(df, aes(x = crime_type, y = n)) +
  geom_col() +
  labs(title = "Frequency of crime types") +
  xlab("Crime type") +
  ylab("Number of crimes")
```



We can also specify our themes, by using a custom theme such as `theme_minimal()`, and by adding our own specifications within an additional `theme()` function:

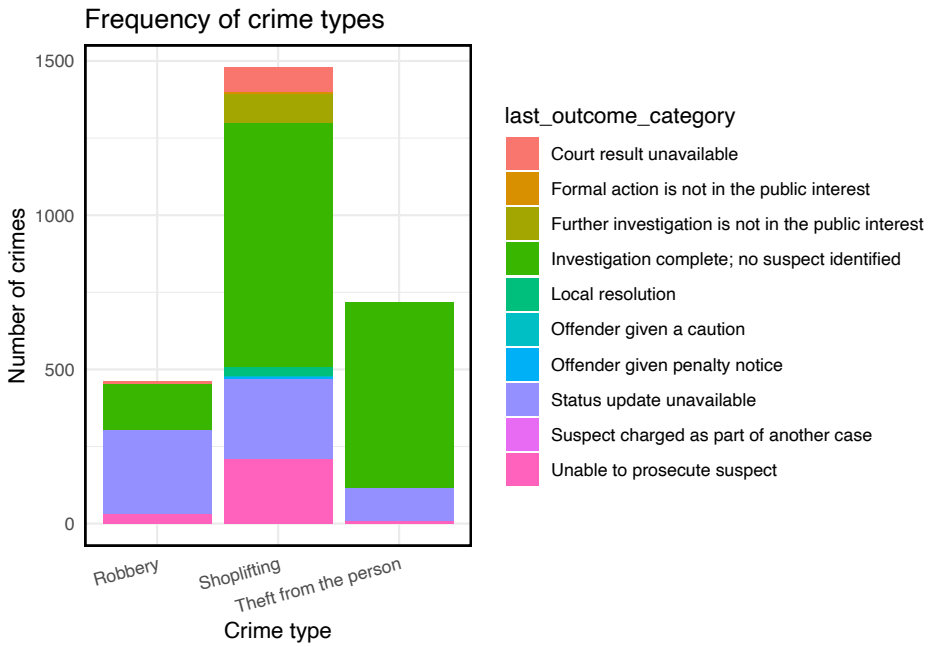
```
ggplot(df, aes(x = crime_type, y = n)) +
  geom_col() +
  labs(title = "Frequency of crime types") +
  xlab("Crime type") +
  ylab("Number of crimes") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 15, hjust = 1),
        panel.border = element_rect(colour = "black", fill=NA, size=1))
```



We can add further specifications within the `aes()` (aesthetics) function, where we add additional layers from our data, to represent even more information in our charts, for example the outcomes for each crime.

```
# create new dataframe (df) including last_outcome_category variable

df <- crimes %>%
  filter(crime_type %in% c("Robbery",
                           "Shoplifting",
                           "Theft from the person")
         ) %>%
  group_by(crime_type, last_outcome_category) %>%
  count()



# plot including new variable with fill= parameter in aes() function

ggplot(df, aes(x = crime_type,
               y = n,
               fill = last_outcome_category)) +
  geom_col() +
  labs(title = "Frequency of crime types") +
  xlab("Crime type") +
```

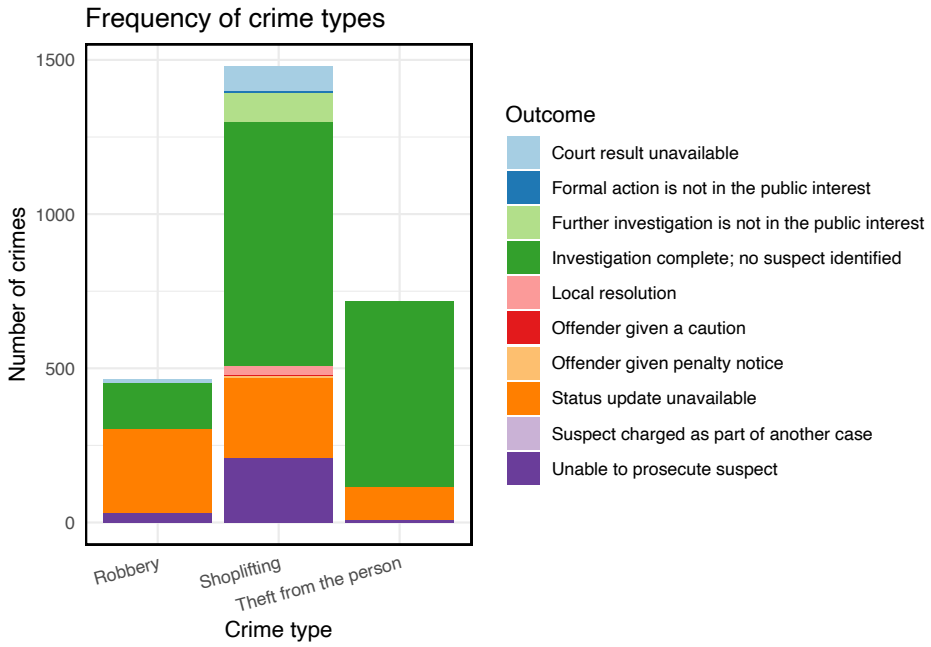
```
  ylab("Number of crimes") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 15,
                                   hjust = 1),
        panel.border = element_rect(colour = "black",
                                    fill=NA,
                                    size=1))
```



We can be explicit about the colours we want to use with the function `scale_fill_brewer()`, which we can also use to rename our legend. Don't worry too much at this point about where the palette comes from, in the chapter on cargography we will discuss colour in more detail.

```
ggplot(df, aes(x = crime_type,
               y = n,
               fill = last_outcome_category)) +
  geom_col() +
  labs(title = "Frequency of crime types") +
  xlab("Crime type") +
  ylab("Number of crimes") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 15,
```

```
                                  hjust = 1),
        panel.border = element_rect(colour = "black",
                                    fill=NA,
                                    size=1)
        ) +
scale_fill_brewer(type = "qual", palette = 3, name = "Outcome")
```

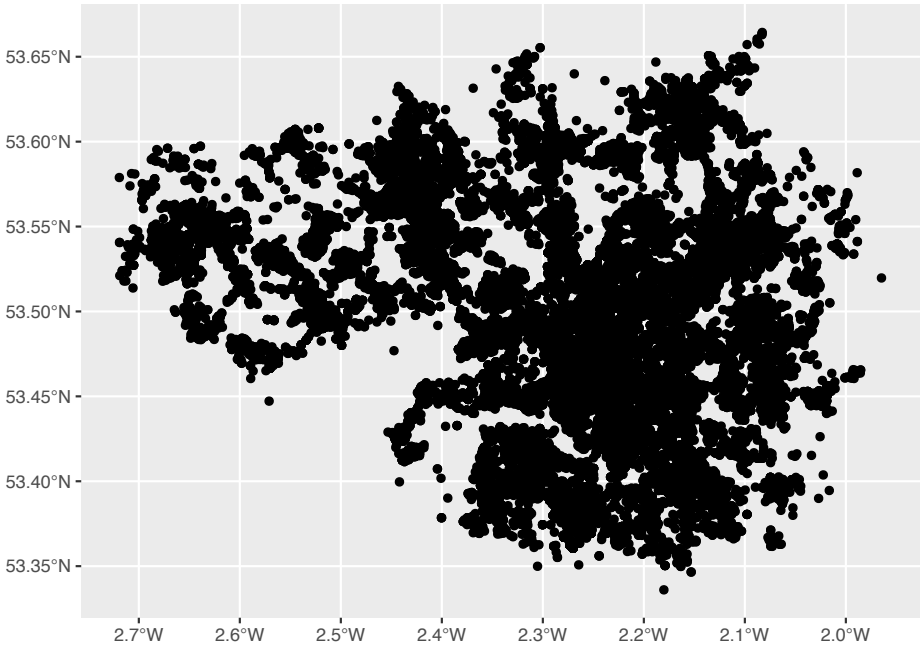


There are many many more options. While this here is not the greatest graph you'll ever see, it illustrates the process of building up your graphics the ggplot way. Do read up on `ggplot2` for example in **?**. In later chapters, we will talk more about visualisation, colour choice, and more!

0.10 Mapping crime data as points

So how can we use this for spatial data? We can use the `geom_sf()` function to do so. Using `geom_sf` is slightly different to other geometries, for example how we used `geom_col()` above. First we initiate the plot with the `ggplot()` function but don't include the data in there. Instead, it is in the geometry where we add the data. And second we don't need to specify the mapping of x and y. Since this is in the geometry column of our spatial object. Like so:

```
ggplot() +
  geom_sf(data = crimes_sf)
```



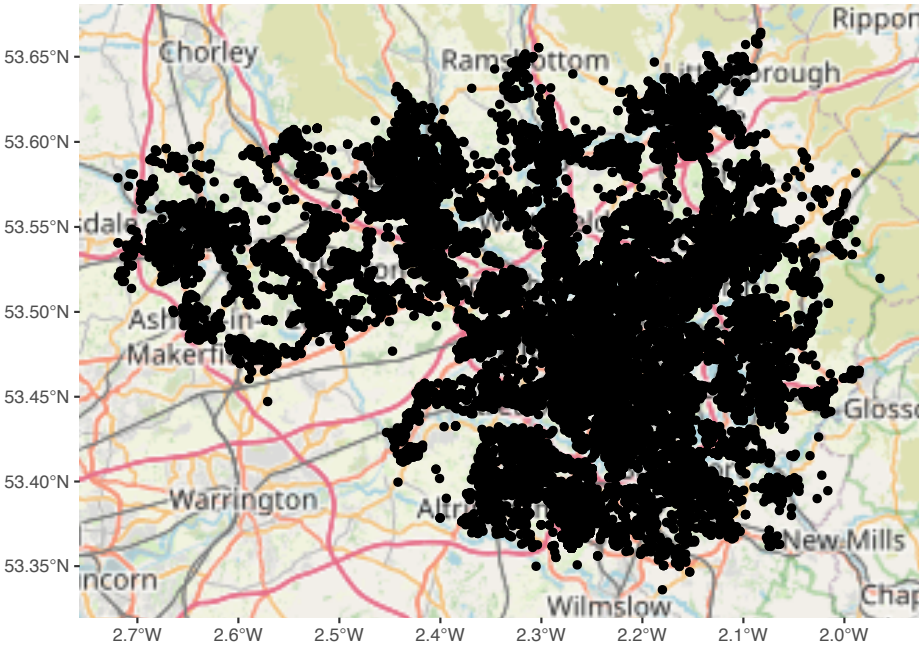
And here we have a map of each point in our data set, each recorded crime in June 2019 in Greater Manchester.

Would you call this a map though? While it is presenting spatial data, there is not a lot of meaning being communicated. Point maps generally can be messy and their uses are specific to certain situations and cases, usually when you have fewer points, but here, these points are especially devoid of any meaning, as they are floating in a graph grid. So let's give it a **basemap**.

We can do this by adding a layer to our graph object. Specifically we will use the `annotation_map_tile()` from the `ggspatial` package. This provides us with a static Open Street Map layer behind our data, giving it (some) more context. Remember to load the package (and install if you haven't already). And then use the `annotation_map_tile()` function, making sure to place it before the `geom_sf` points layer, so the background map is placed first, and the points on top of that:

```
library(ggspatial)

ggplot() +
```

```
annotation_map_tile() +
 geom_sf(data = crimes_sf)
```



So what you see above behind the points is what we can call a **basemap**. The term basemap is seen often in GIS and refers to a collection of GIS data and/or orthorectified imagery that form the background setting for a map. The function of the basemap is to provide background detail necessary to orient the location of the map. Basemaps also add to the aesthetic appeal of a map. **Basemaps** are essentially reference maps that may give us context and help with the interpretation. You can see above that you are seeing the *Open Street Map* Basemap. This is one option but there are others.

Let's leave the points for now, and move on to how we might map our lines and polygons.

0.11 Mapping crime data as polygons

What about our other two columns, location, and LSOAs? Well to put these on the map, we need a geometry representation of them. We need boundary data representing the areas we want to map. We will learn in this section where you may find, download and turn them into sf objects, and how to link our dataframe as attribute data in order to be able to map them.

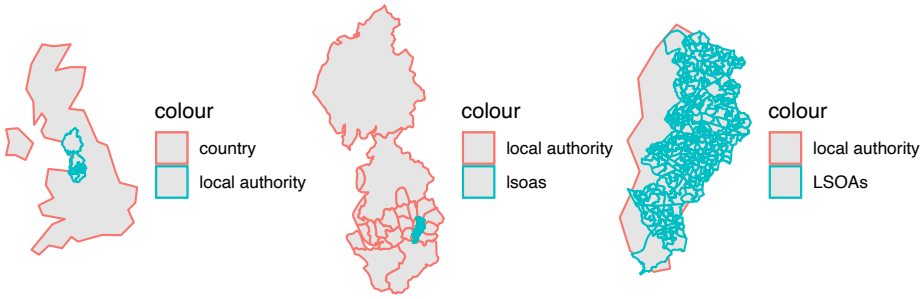
0.11.1 Finding boundary data

In this section you are going to learn how you take one of the most popular data formats for spatial objects, the **shapefile**, and read it into R. The shapefile was introduced by ESRI, the developers and vendors or ArcGIS. And although many other formats have developed since and ESRI no longer holds the same market position it once occupied (though they're still the player to beat), shapefiles continue to be one of the most popular formats you will encounter in your work.

We are going to obtain shapefiles for British census geographies. For this activity we will focus on the polygon (the LSOA) rather than the lines of the streets, but the logic is more or less the same.

Census boundary data are a digitised representation of the underlying geography of the census. Census Geography is often used in research and spatial analysis because it is divided into units based on population counts, created to form comparable units, rather than other administrative boundaries such as wards or police force areas. However depending on your research question and the context for your analysis, you might be using different units.

The hierarchy of the census geographies in the UK goes from Country to Local Authority to Middle Layer Super Output Area (MSOA) to Lower Layer Super Output Area (LSOA) to Output Area (in other countries you have similar levels in the census hierarchies):



Here we will get some boundaries for Manchester. We know that our crime data has a column for LSOA, so we can proceed with this as our appropriate unit of analysis.

To get some boundary data, you can use the UK Data Service website. There is a simple Boundary Data Selector[5] tool which you could use. Other countries also have such repositories, and in some cases where they do not, other resources, such as Open Street Map, or natural earth (and associated R package `rnaturalearth`) can be handy resources. In Appendix C "Sourcing geographical data for crime analysis" we elaborate more on these, with some examples.

For now, you can turn to the data folder which you have downloaded from this book's repository. (If unsure, refer to the Preamble section!).

[5] `https://borders.ukdataservice.ac.uk/bds.html`

Specifically, we're looking for a folder called `BoundaryData`. When we download a shapefile, we usually get many files, and a folder which contains them all. It is important for these files to be kept together, in the same folder. If you have a look inside thie BoundaryData folder, you will notice that there are 4 files with the same name "england_lsoa_2011".

NOTE: It is important that you keep all these files in the same location as each other!

They all contain different bits of information about your shapefile (and they are all needed):

- .shp — shape format; the feature geometry itself - this is what you see on the map
- .shx — shape index format; a positional index of the feature geometry to allow seeking forwards and backwards quickly
- .dbf — attribute format; columnar attributes for each shape, in dBase IV format.
- .prj — projection format; the coordinate system and projection information, a plain text file describing the projection using well-known text format

Sometimes there might be more files associated with your shapefile as well, but we will not cover them here. So unlike when you work with spreadsheets and data in tabular form, which typically is just all included in one file; when you work with shapefiles, you have to live with the required information living in separate files that need to be stored together. So, being tidy and organised is even more important when you carry out projects that involve spatial data.

0.11.2 Reading shapefiles into R

To read in your data into R, you will need to know the path to where you have saved it. Ideally this will be in your data folder in your project directory.

Let's create an object and assign it our shapefile's name:

```
# Remember to use the appropriate pathfile in your case
shp_name <- "data/BoundaryData/england_lsoa_2011.shp"
```

Make sure that this is saved in your working directory, and you have set your working directory.

Now use the `st_read()` function from the `sf` package to read in the shapefile:

```
manchester_lsoa <- st_read(shp_name)
```

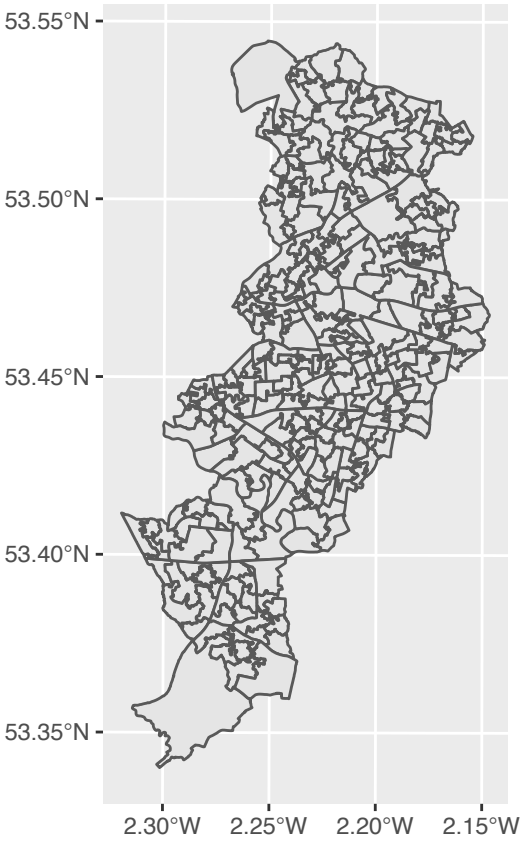
Now you have your spatial data file. Notice how running the function sends to the console some metadata about your data. You have a polygon, with 282 rows, and the CRS is the projected British National Grid. You can have a look at what sort of data it contains, the same way you would view a dataframe, with the `View()` function:

```
View(manchester_lsoa)
```

```
## Rows: 282
## Columns: 4
## $ label   <chr> "E08000003E02001062E01005066", "E08000003E02001092E01005073",~
## $ name    <chr> "Manchester 018E", "Manchester 048C", "Manchester 018A", "Man~
## $ code    <chr> "E01005066", "E01005073", "E01005061", "E01005062", "E0100506~
## $ geometry <POLYGON [m]> POLYGON ((384850 397432, 38..., POLYGON ((382221.1 38~
```

And of course, since it's spatial data, you can map it using the `geom_sf()` function, as we did with our points:

```
ggplot() +
  geom_sf(data = manchester_lsoa)
```



Great, we now have an outline of the LSOAs in Manchester. Notice how the shape is different to that of the points in our crime data since here we only obtained the data for the city of Manchester (Manchester Local Authority) rather than for the whole metropolitan area - and which includes all the other local authorities aside from Manchester city as well.

0.11.3 Data wrangling with dplyr

In order to map crimes to LSOAs we might want to take a step back and think about unit of analysis at which our data are collected. In our original dataframe of crimes, we saw that each crime incident is one row. So the unit of analysis is each crime. Since we were looking to map each crime at the location it happened, we used the latitude and longitude supplied with each one, and this supplied a geometry each for each crime type. However, when we are looking to map our data to LSOA level, we need to match the crime data to the geometry we wish to display.

Have a look at the "manchester_lsoa" object we mapped above. How many rows (observations) does it have? You can check this by looking in the Environment

pane, or by using the `nrow()` function.

```
nrow(manchester_lsoa)
```

You can see this has 282 rows. This means we have geometries for 282 LSOAs. On the other hand, our crimes dataframe has 32058 rows, one for each crime (observation). So how can we match these up? The answer lies in thinking about what it is that our map using LSOAs as our unit of analysis will be able to tell us. Think of other maps of areas - what are they usually telling you? Usually we expect to see crimes per neighbourhood - something like this. So our unit of analysis needs to be LSOA, and for each one we need to know how many crimes occurred in that area.

To achieve this, we will wrangle our data using functions from the `dplyr` package. This is a package for conducting all sorts of operations with data frames. We are not going to cover the full functionality of `dplyr` (which you can consult in the `dplyr` vignette (`https://cran.r-project.org/web/packages/dplyr/vignettes/dplyr.html`)), but we are going to cover three different very useful elements of dplyr: the `select` function, the `group_by` function, and the piping operator.

The `select()` function provides you with a simple way of subsetting columns from a data frame. So, say we just want to use one variable, "lsoa_code", from the "crimes" dataframe and store it in a new object we could write the following code. This variable tell us the LSOA in which the crime took place and it is essential if we want to group our crimes by LSOA (by using this standard method of merging information from datasets):

```
new_object <- select(crimes, lsoa_code)
```

We can also use the `group_by()` function for performing group operations. Essentially this function ask R to group cases within categories and then do something with those grouped cases. So, say, we want to count the number of cases within each LSOA, we could use the following code:

```
#First we group the cases by LSOA code and
# store this organised data into a new object
grouped_crimes <- group_by(new_object, lsoa_code)

#Then we count the number of cases within each category
# using the summarise function to print the results
summarise(grouped_crimes, count = n())
```

```
#We create a new dataframe with these results

crime_per_LSOA <- summarise(grouped_crimes, count = n())
```

As you can see we can do what we wanted, create a new dataframe with the required info, but if we do this we are creating many objects that we don't need, one at each step. Instead there is a more efficient way of doing this, without so many intermediate steps clogging up our environment with unnecessary objects. That's where the piping operator comes handy. The piping operator is written like `%>%` and it can be read as "and then". Look at the code below:

```
#First we say create a new object called crime_per_lsoa,
# and then select only the LSOA.code column to exist in this object,
# and then group this object by the LSOA.code,
# and then count the number of cases within each category.
# This is what I want in the new object.

crimes_per_lsoa <- crimes %>%
  group_by(lsoa_code) %>%
  summarise(count=n())
```

Essentially we obtain the same results but with more streamlined and elegant code, and not needing additional objects in our environment.

And now we have a new object, "crimes_per_lsoa" if we have a look at this one, we can now see what each row represents one LSOA, and next to it we have a variable for the number of crimes from each area. We created a new dataframe from a frequency table, and as each row of the crimes data was one crime, the frequency table tells us the number of crimes which occurred in each LSOA.

Those of you playing close attention might note that there are still more observations in this dataframe (1671) than in the "manchester_lsoas" one (282). Again, this is because "crimes_per_lsoa" also includes data from census areas in municipalities of the metropolitan area of Greater of Manchester other than Manchester city.

0.11.4 Join data to sf object

Our next task is to link our crimes data to our `sf` spatial object to help us map this. Notice anything similar between the data from the shapefile and the frequency table data we just created? Do they share a column?

Yes! You might notice that the "lsoa_code" field in the crimes data matches the values in the "code" field in the spatial data. In theory we could join these two data tables.

So how do we do this? Well what you can do is to link one data set with another. Data linking is used to bring together information from different sources in order to create a new, richer dataset. This involves identifying and combining information from corresponding records on each of the different source datasets. The records in the resulting linked dataset contain some data from each of the source datasets. Most linking techniques combine records from different datasets if they refer to the same entity (an entity may be a person, organisation, household or even a geographic region.)

You can merge (combine) rows from one table into another just by pasting them in the first empty cells below the target table—the table grows in size to include the new rows. And if the rows in both tables match up, you can merge columns from one table with another by pasting them in the first empty cells to the right of the table—again, the table grows, this time to include the new columns.

Merging rows is pretty straightforward, but merging columns can be tricky if the rows of one table don't always line up with the rows in the other table. By using `left_join()` from the `dplyr` package, you can avoid some of the alignment problems.

`left_join()` will return all rows from x, and all columns from x and y. Rows in x with no match in y will have NA values in the new columns. If there are multiple matches between x and y, all combinations of the matches are returned.

So we've already identified that both our crimes data, and the spatial data contain a column with matching values, the codes for the LSOA that each row represents.

You need a unique identifier to be present for each row in all the data sets that you wish to join. This is how R knows what values belong to what row. What you are doing is matching each value from one table to the next, using this unique identified column, that exists in both tables. For example, let's say we have two data sets from some people in Hawkins, Indiana. In one data set we collected information about their age. In another one, we collected information about their hair colour. If we collected some information that is unique to each observation, and this is the *same* in both sets of data, for example their names, then we can link them up, based on this information. Something like this:

	name	age
1	Barb	16
2	Steve	16
3	Mike	13

	name	hair_colour
1	Barb	Red
2	Steve	Brown
3	Mike	Black

And by doing so, we produce a final table that contains all values, lined up *correctly* for each individual observation, like this:

	name	age	hair_colour
1	Barb	16	Red
2	Steve	16	Brown
3	Mike	13	Black

This is all we are doing, when merging tables, is we are making use that we line up the correct value for all the variables, for all our observations.

Why are we using *left* join though? There is a whole family of join functions as part of dplyr (`http://stat545.com/bit001_dplyr-cheatsheet.html`) which join data sets. There is also a `right_join()`, and an `inner_join()` and an `outer_join()` and a `full_join()`. But here we use `left_join()`, because that way we keep all the rows in `x` (the left-hand side dataframe), and join to it all the matched columns in `y` (the right-hand side dataframe).

So let's join the crimes data to the spatial data, using `left_join()`. We have to tell the function what are the dataframes we want to join, as well as the names of the columns that contain the matching values in each one. This is "code" in the "manchester_lsoa" dataframe and "lsoa_code" in the "crimes_per_lsoa" dataframe. Like so:

```
manchester_lsoa <- left_join(manchester_lsoa, crimes_per_lsoa,
                             by = c("code"="lsoa_code"))
```

Now if you have a look at the data again, you will see that the column of number of crimes (`count`) has been added on.

You may not want to have to go through this process all the time you want to work with this data. One thing you could do is to save the "manchester_lsoa" object as a physical file in your machine. You can use the `st_write()` function from the `sf` package to do this. If we want to write into a shapefile format we would do as shown below. Make sure you save this file, for we will come back to it in subsequent chapters.

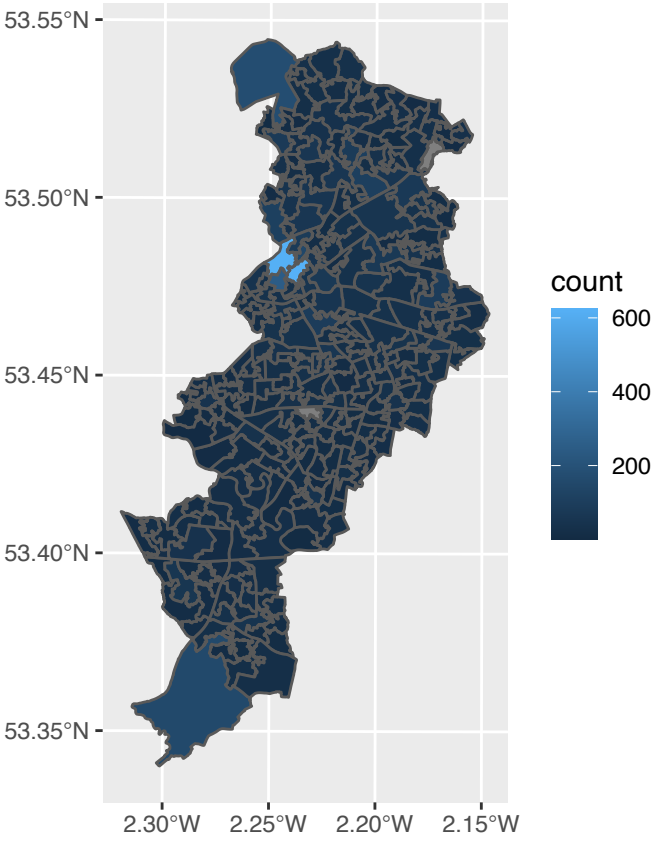
```
st_write(manchester_lsoa,
         "data/BoundaryData/manchester_crime_lsoa.shp")
```

0.11.5 Putting polygon data on the map

Now that we have joined the crimes data to the geometry, you can use this to make our map!

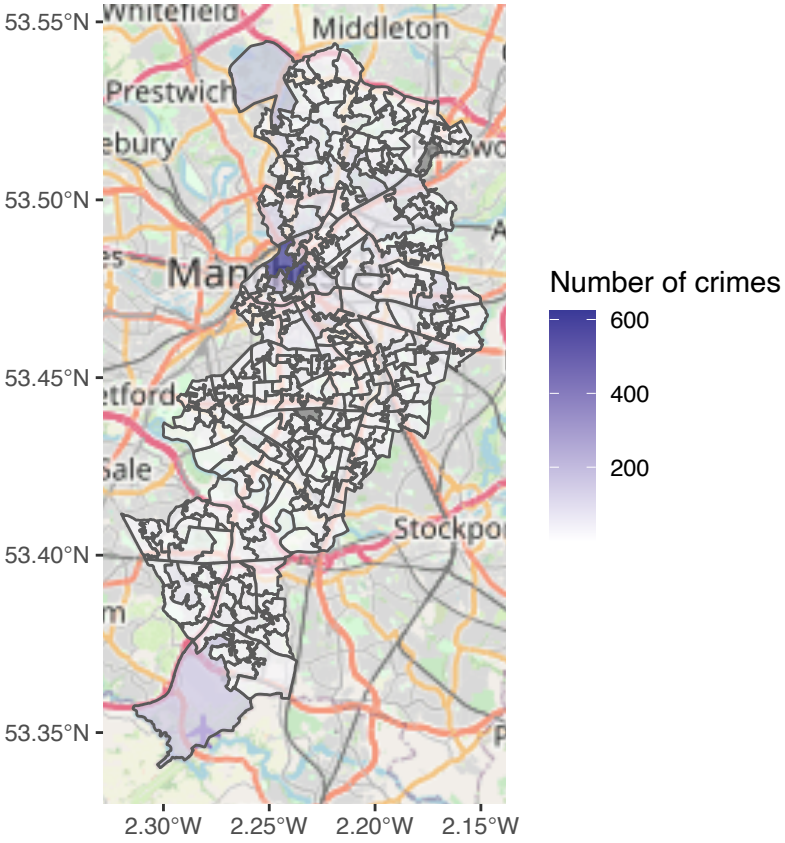
Remember our original empty map? Well now, since we have the column (variable) for number of crimes here, we can use that to share the polygons based on how many crimes there are in each LSOA. We can do this by specifying the `fill=` parameter of the `geom_sf` function.

```
ggplot() +
geom_sf(data = manchester_lsoa, aes(fill = count))
```



We can adjust the opacity of our thematic map, with the `alpha =` parameter, add a basemap, with the function `annotation_map_tile()` and adjust the colour scheme, with the `scale_fill_gradient2()` function.

```
ggplot() +
  annotation_map_tile() +  # add basemap
geom_sf(data = manchester_lsoa,
        aes(fill = count),
        alpha = 0.7) + # alpha sets the opacity
  #use scale_fill_gradient2() for a different palette
  # and name the variable on the legend
  scale_fill_gradient2(name ="Number of crimes")
```



In subsequent chapters we will play around with other packages in R that you can use to produce this kind of maps and gradually we will discuss the kind of choices you can make in order to select the adequate type of representation for the type of spatial data and question you have, and the aesthethic choices that are adequate depending on the purposes and medium in which you will publish your map. But for now, we can rejoice, here is our very first crime map of the book!

0.12 Summary and further reading

In this chapter we had a play around with some regular old crime data and discovered how we can use the `sf` package in R to assign it a geometry (both at point and polygon level), and how that can help us visualise our results. We covered some very important concepts such as projections and coordinate reference systems, and we had a play at acquiring shapefiles which can help us visualise our data. We had a think about units of analysis, and how that will affect how we visualise our data. In the next chapter we will spend a bit of more time discussing how to make good choices when producing maps.

There are a number of introductory texts to geographic information systems and analysis that provide adequate background to some of the key concepts we introduce in this chapter (**?**, **?**). The report by **?** produced for the National Institute of Justice still provides a good general introduction for basic ideas around crime mapping and CAN be accessed for free online. Chapter 3 of **?** offers invaluable observations on the nature of spatial and spatial-temporal attribute data, often using examples from crime research. From a more domain-knowledge point of view, the early chapters of **?** and **?** set the stage for the use of GIS as part of the crime analysis process, whereas **?** edited handbook provides an excellent introduction to environmental criminology (that provides the theoretical and empirical backbone to spatial analysis of crime). Finally, **?** provides a general introduction to data visualisation with R using the `ggplot2` package. Although Healy´s text is not just about mapping, it offers a very practical and helpful introduction to using `ggplot2` where you can learn how to further customise your maps and other charts.

This is a book about maps and spatial analysis, but clearly one of the first questions you need to ask yourself is whether producing a map is the right answer to your question. Just because your data is spatial doesn't mean you need a map for every question you pose to this data. There may be other forms of data visualisation that are more appropriate for exploring and summarising the story you want to tell with your data. If you are uncertain about whether you need a map or other kind of plot books such as **?**, **?**, or **?** provide useful guidance. For specifics of ggplot2 refer to **?**

Basic geospatial operations in R

0.13 Introduction

In this chapter we get our hands dirty with **spatial manipulation of data**. Thus far, our data manipulation exercises (using `dplyr`) were such that you might be familiar with, from any earlier exposures to data analysis. For example, linking datasets using a common column is a task which you can perform on spatial or non-spatial data. These are referred to as **attribute operations**. However today we will explore some exercises in data manipulation which are specific to *spatial* data analysis. We will be learning some key spatial operations, a set of functions that allow you to create new and manipulate spatial data.

The main objectives for this chapter are that by the end you will have:

- met a new format for accessing boundary data, called **geojson**.
- carried out **spatial operations** such as:
  - **subset** points that are within a certain area,
  - created new polygons by generating **buffers** around points,
  - counted the number of points that fall within a polygon (known as **points in polygon**),
  - finding the **nearest feature** in one data set to observations in another data set, and
  - **measured distance** between points in a map.
- made interactive point map with leaflet.
- used **geocoding** methods to translate text fields such as addresses into geographic coordinates.

These are all very useful tools for the spatial crime analyst, and we will hope to demonstrate this by working through an example project.

The packages we will use in this chapter are:

```
# Packages for reading data and data carpentry
library(readr)
library(dplyr)
library(janitor)
library(units)
library(purrr)

# Packages for handling spatial data and for geospatial carpentry
library(sf)
library(tidygeocoder)

# Packages for mapping and visualisation
library(leaflet)
library(RColorBrewer)

# Packages providing accesss to spatial data
library(osmdata)
```

0.14 Exploring the relationship between alcohol outlets and crime

The main example we will work through most of the chapter considers the assumption that licenced premises which serve alcohol are associated with increased crimes. We might have some hypotheses about why this may be.

One theory might be that some of these serve as *crime attractors*.

> Crime attractors are particular places, areas, neighbourhoods, districts which create well-known criminal opportunities to which strongly motivated, intending criminal offenders are attracted because of the known opportunities for particular types of crime. Examples might include bar districts; prostitution areas; drug markets; large shopping malls, particularly those near major public transit exchanges; large, insecure parking lots in business or commercial areas. The intending offender goes to rough bars looking for fights or other kinds of 'action'.

On the other hand, it is possible that these areas are *crime generators*.

> Crime generators are particular areas to which large numbers of people are attracted for reasons unrelated to any particular level of criminal motivation they might have or to any particular crime

> they might end up committing. Typical examples might include shopping precincts; entertainment districts; office concentrations; or sports stadiums.

It is possible that some licensed premises attract crimes, due to their reputation. However it is also possible that some of them are simply located in areas that are busy, attracts lots of people for lots of reasons, and crimes occur as a result of an abundance of opportunities instead.

In any case, what we want to do is to examine whether certain outlets have more crimes near them than others. We can do this using open data, some R code, and the spatial operations discussed above. We will return to data from Manchester, UK for this example, however as we will be using Open Street Map, you can easily replicate this for any other location where you have point-level crime data.

0.15 Get the data

We will be using three different sources of data in this chapter. First, we will acquire our crime data, which is what we used in the previous chapter, so this should be familiar. Then we will meet the new format for boundary data, geojson. And finally, we will look at Open Street Map for data on our points of interest.

0.15.1 Reading in crime data

```
crimes <- read_csv("data/2019-06-greater-manchester-street.csv")
```

If you replicate the exercises for getting to know the data set from the previous chapter, you might notice that in this case the column names are slightly different. For example, Latitude and Longitude are spelled with upper case "L". You should always familiarise yourself with your data set to make sure you are using the relevant column names. You can see just the column names using the `names()` function like so :

```
names(crimes)
```

```
##  [1] "Crime ID"              "Month"                 "Reported by"
##  [4] "Falls within"          "Longitude"             "Latitude"
##  [7] "Location"              "LSOA code"             "LSOA name"
## [10] "Crime type"            "Last outcome category" "Context"
```

This is because last time, we cleaned these names using the `clean_names()` function from the `janitor` package. Let's do this again, as these variable names are not ideal, with their capital letters and spacing...so messy!

```
crimes <- crimes %>%
  clean_names()
names(crimes)
```

```
##  [1] "crime_id"              "month"                 "reported_by"
##  [4] "falls_within"          "longitude"             "latitude"
##  [7] "location"              "lsoa_code"             "lsoa_name"
## [10] "crime_type"            "last_outcome_category" "context"
```

Much better! Now let's get some boundary data for Manchester.

0.15.2 Meet a new format: geojson

GeoJSON is an open standard format designed for representing simple geographical features, along with their non-spatial attributes. It is based on JSON, the JavaScript Object Notation. It is a format for encoding a variety of geographic data structures and is the most common format for geographical representation in the web. Unlike ESRI shapefiles, with GeoJSON data everything is stored in a single file.

Geometries are shapes. All simple geometries in GeoJSON consist of a type and a collection of coordinates. The features include points (therefore addresses and locations), line strings (therefore streets, highways and boundaries), polygons (countries, provinces, tracts of land), and multi-part collections of these types. GeoJSON features need not represent entities of the physical world only; mobile routing and navigation apps, for example, might describe their service coverage using GeoJSON.

To tinker with GeoJSON and see how it relates to geographical features, try `geojson.io`, a tool that shows code and visual representation in two panes.

Let's read in a geoJSON spatial file, again from the web. This particular geojson represents the wards of Greater Manchester.

```
manchester_ward <- st_read("data/wards.geojson")
```

```
## Reading layer `wards' from data source `/Users/reka/Desktop/crime_mapping/crime_mapping/data/w
## Simple feature collection with 215 features and 12 fields
```

```
## Geometry type: POLYGON
## Dimension:     XY
## Bounding box:  xmin: 351664 ymin: 381168.6 xmax: 406087.5 ymax: 421039.8
## Projected CRS: OSGB 1936 / British National Grid
```

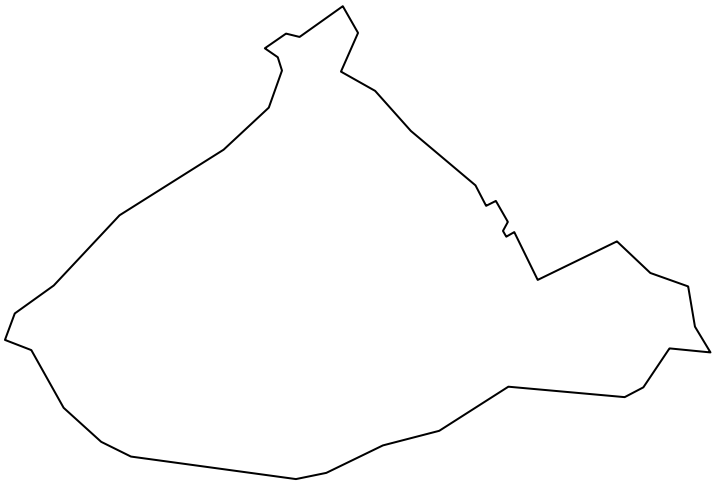
Let's select only the city centre ward, using the `filter()` function from the `dplyr` package.

```
city_centre <- manchester_ward %>%
  filter(wd16nm == "City Centre")
```

Let's see how this looks. In Chapter 1 we learned about plotting maps using the `ggplot()` function from the `ggplot2` package. Here, let's look at a different way, which can be useful for quick mapping - usually used when just checking in with our data to make sure it looks like what we were expecting.

With the `st_geometry()` function in the `sf` package, we can extract only the geometry of our object, stripping away the attributes. If we include this inside the `plot()` function, we get a quick, minimalist plot of the geometry of our object.

```
#extract geometry only
city_centre_geometry <- st_geometry(city_centre)

#plot geometry object
plot(city_centre_geometry)
```



Now we could use this to make sure that our points are in fact only licensed premises in the city centre. This will be your first spatial operation. Excited? Let's do this!

0.15.3 Open Street Map and points of interest

To map licenced premises we will be accessing data from Open Street Map, a database of geospatial information built by a community of mappers, enthusiasts and members of the public, who contribute and maintain data about all sorts of environmental features, such as roads, green spaces, restaurants and railway stations. You can see all about open street map on their online mapping platform (`https://www.openstreetmap.org/`). One feature of Open Street Map, unlike Google Map, is that the underlying data is openly available for download *for free*. In R, we can take advantage of a package written specifically for querying Open Street Map's API, called `osmdata`. For more detail on how to use this, see **?**.

If we load the package `osmdata` we can use its functions to query the Open Street Map API. To find out more about the capabilities of this package, see the package documentation and the associated vignette online: `https://cran.r-project.org/web/packages/osmdata/vignettes/osmdata.html`. While this is outside the scope of our chapter here, you may want to explore `osmdata` more, as it is an international database, and has lots of data may come in handy for research and analysis.

Here we focus specifically on Manchester. To retrieve data for a specific area, we must create a **bounding box**. You can think of the bounding box as a box drawn around the area that we are interested in (in this case, Manchester, UK) which tells the Open Street Map API that we want everything *inside* the box, but nothing *outside* the box.

So, how can we name a bounding box specification to define the study region? One way to do this is through a search term. Here, we want to select Greater Manchester, so we can use the search term "greater manchester united kingdom" within the `getbb()` function (stands for *get bounding box*). Using this function we can also specify what format we want the data to be in. In this case, we want a spatial object, specifically an `sf` polygon object (from the `sf` package), which we name `bb_sf`.

```
bb_sf <- getbb(place_name = "greater manchester united kingdom",
               format_out = "sf_polygon")
```

We can see what this bounding box looks like by plotting it (notice this time we combine the plot() and st_geometry() functions to save needing to create a new object):

```
plot(st_geometry(bb_sf))
```

We can see the bounding box takes the form of Greater Manchester. We can now use this to query data from the Open Street Map API using the `opq()` function. The function name is short for 'Overpass query', which is how users can query the Open Street Map API using search criteria.

Besides specifying what area we want to query with our bounding box object(s) in the `opq()` function, we must also define the feature which we want returned. Features in Open Street Map are defined through 'keys' and 'values'. Keys are used to describe a broad category of features (e.g. highway, amenity), and values are more specific descriptions (e.g. cycleway, bar). These are tags which contributors to Open Street Map have defined. A useful way to explore these is by using the comprehensive Open Street Map Wiki page on map features (`https://wiki.openstreetmap.org/wiki/Map_Features`).

We can select what features we want using the `add_osm_feature()` function, specifying our key as 'amenity' and our value as 'bar'. We also want to specify what sort of object (what class) to get our data into, and as we are still working with spatial data, we stick to the `sf` format, for which the function is `osmdata_sf()`. Here, we specify our bounding box as the `bb_sf` object we created above. If you use the bounding box obtained through `getbb()` one can subsequently trim down the outputs from `add_osm_feature()` using `trim_osmdata()`. For instance, we could add `trim_osmdata(bb_poly = bb_sf)` to our initial query.

```
osm_bar_sf <- opq(bbox = bb_sf) %>%    # select bounding box
  add_osm_feature(key = 'amenity', value = 'bar') %>% # select features
  osmdata_sf()          # specify class
```

The resulting object `osm_bar_sf` contains lots of information. We can view the contents of the object by simply executing the object name into the **Console**.

```
osm_bar_sf
```

This confirms details like the bounding box coordinates, but also provides information on the features collected from the query. As one might expect, most information relating to bar locations has been recorded using points (i.e. two-dimensional vertices, coordinates) of which we have 575 at the time of writing. We also have around fifty polygons. For now, let's extract the point information.

```
osm_bar_sf <- osm_bar_sf$osm_points
```

We now have an `sf` object with all the bars in our study region mapped by Open Street Map volunteers, along with ~90 variables of auxiliary data, such as characteristics of the bar (e.g.: `brewery`, or `cocktail`) or whether it offers `delivery` as well as address and contact information, amongst many others. Of course, it is up to the volunteers whether they collect all these data, and in many cases, they have not added information (you may see lots of missing values if you look at the data). Given the work relies on voluntaries there are unavoidably some accuracy issues (including how up to date the information may be). Nevertheless, when the details are recorded, they provide rich insight and local knowledge that we may otherwise be unable to obtain.

One column we should consider is the `name` which tells us the name of the bar. There are missing values here as well, and for this example, we will choose to exclude those lines where there is no name included, as we would like at least a little bit of context around our bars. To do this, perform an attribute operation using the`filter()` function:

```
osm_bar_sf <- osm_bar_sf %>% filter(!is.na(name))
```

We are still left with 259 bars in our data set.

0.16 Attribute operations

We mentioned above that we are using **attribute operations**. These are changes to the data which we make based on manipulation of elements in the attribute table. For example, the use of `filter()` is an attribute operation,

because we rely on the data in the attribute table in order to accomplish this task.

For example, let's say we want to focus only on violent crime. To do this, we use the information in the attribute table, namely the values for the `crime_type` variable for each observation (crime) in our data set.

```
crimes <- crimes %>%
  filter(crime_type == "Violence and sexual offences")
```

With the above, we select only those crimes (rows of the attribute table) where the crime_type variable meets a certain criteria (takes the value of "Violence and sexual offences"). **Spatial operations** on the other hand manipulate the *geometry* part of our data. We rely on the spatial information to accomplish the tasks of interest. In the next section, we will work through some examples of these.

0.17 Spatial operations

Spatial operations are a vital part of geocomputation. Spatial objects can be modified in a multitude of ways based on their location and shape. For a comprehensive overview of spatial operations in R I would recommend chapter 4 of **?**.

> "Spatial operations differ from non-spatial operations in some ways. To illustrate the point, imagine you are researching road safety. Spatial joins can be used to find road speed limits related with administrative zones, even when no zone ID is provided. But this raises the question: should the road completely fall inside a zone for its values to be joined? Or is simply crossing or being within a certain distance sufficent? When posing such questions it becomes apparent that spatial operations differ substantially from attribute operations on data frames: the type of spatial relationship between objects must be considered." (Lovelace & Nowosad, 2018)[6]

So you can see we can do exciting spatial operations with our spatial data, which we cannot with the non-spatial stuff.

[6] `https://geocompr.robinlovelace.net/spatial-operations.html`

0.17.1 Reprojecting coordinates

It is important to recall here some of the learning from the previous chapter on map projections and coordinate reference systems. We learned about ways of flattening out the earth, and ways of making sense of what that means for how to be able to point to specific locations in our maps. **Coordinate Reference System** or CRS is this method of how to refer to locations with our data. You might use a *Geographic Coordinate System*, which tells you where your data are located on the surface of the Earth. The most commonly used one (at least by us!) is the **WGS 84**, where we define our locations with latitude and longitude points. The other type is a *Projected Coordinate System* which tells the date how to draw on a flat, 2-dimensional surface (such as a computer screen). In our case here, we will often encounter the **British National Grid** when working with British data. Here our locations are defined with Eastings and Northings.

So why are we talking about this?

> It is important to note that spatial operations that use two spatial objects rely on both objects having the same coordinate reference system

If we are looking to carry out operations that involve two different spatial objects, they need to have the same CRS! Funky weird things happen when this condition is not met, so beware! So how do we know what CRS our spatial objects are? Well the `sf` package contains a handy function called `st_crs()` which let's us check. All you need to pass into the brackets of this function is the name of the object you want to know the CRS of.

So let's check what is the CRS of our crimes:

```
st_crs(crimes)
```

```
## Coordinate Reference System: NA
```

You can see that we get the CRS returned as `NA`. Can you think of why? Have we made this into a spatial object? Or is this merely a dataframe with a latitude and longitude column? The answer is really in the question here. So we need to convert this to a `sf` object, or a spatial object, and make sure that R knows that the latitude and the longitude columns are, in fact, coordinates.

In the `st_as_sf()` function we specify what we are transforming (the name of our dataframe), the column names that have the coordinates in them (longitude and latitude), the CRS we are using (4326 is the code for WGS 84, which is the CRS that uses latitude and longitude coordinates (remember BNG uses Easting and Northing)), and finally *agr*, the attribute-geometry-relationship,

specifies for each non-geometry attribute column how it relates to the geometry, and can have one of following values: "constant", "aggregate", "identity". Yhe option "constant" is used for attributes that are constant throughout the geometry (e.g. land use), "aggregate" where the attribute is an aggregate value over the geometry (e.g. population density or population count), "identity" when the attributes uniquely identifies the geometry of particular "thing", such as a building ID or a city name. The default value, NA_agr_, implies we don't know.

```
crimes <- st_as_sf(crimes, coords = c("longitude", "latitude"),
                 crs = 4326, agr = "constant", na.fail = FALSE)
```

Now let's check the CRS of this spatial version of our licensed premises:

```
st_crs(crimes)
```

```
## Coordinate Reference System:
##   User input: EPSG:4326
##   wkt:
## GEOGCRS["WGS 84",
##     DATUM["World Geodetic System 1984",
##         ELLIPSOID["WGS 84",6378137,298.257223563,
##             LENGTHUNIT["metre",1]]],
##     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["unknown"],
##         AREA["World"],
##         BBOX[-90,-180,90,180]],
##     ID["EPSG",4326]]
```

We can now see that we have this coordinate system as WGS 84. We need to then make sure that any other spatial object with which we want to perform spatial operations is also in the same CRS.

So let's look at our city centre ward boundary file:

```
st_crs(city_centre)
```

```
## Coordinate Reference System:
##   User input: OSGB 1936 / British National Grid
##   wkt:
## PROJCRS["OSGB 1936 / British National Grid",
##     BASEGEOGCRS["OSGB 1936",
##         DATUM["OSGB 1936",
##             ELLIPSOID["Airy 1830",6377563.396,299.3249646,
##                 LENGTHUNIT["metre",1]]],
##         PRIMEM["Greenwich",0,
##             ANGLEUNIT["degree",0.0174532925199433]],
##         ID["EPSG",4277]],
##     CONVERSION["British National Grid",
##         METHOD["Transverse Mercator",
##             ID["EPSG",9807]],
##         PARAMETER["Latitude of natural origin",49,
##             ANGLEUNIT["degree",0.0174532925199433],
##             ID["EPSG",8801]],
##         PARAMETER["Longitude of natural origin",-2,
##             ANGLEUNIT["degree",0.0174532925199433],
##             ID["EPSG",8802]],
##         PARAMETER["Scale factor at natural origin",0.9996012717,
##             SCALEUNIT["unity",1],
##             ID["EPSG",8805]],
##         PARAMETER["False easting",400000,
##             LENGTHUNIT["metre",1],
##             ID["EPSG",8806]],
##         PARAMETER["False northing",-100000,
##             LENGTHUNIT["metre",1],
##             ID["EPSG",8807]]],
##     CS[Cartesian,2],
##         AXIS["(E)",east,
##             ORDER[1],
##             LENGTHUNIT["metre",1]],
##         AXIS["(N)",north,
##             ORDER[2],
##             LENGTHUNIT["metre",1]],
##     USAGE[
##         SCOPE["unknown"],
##       AREA["UK - Britain and UKCS 49°46'N to 61°01'N, 7°33'W to 3°33'E"],
##         BBOX[49.75,-9.2,61.14,2.88]],
##     ID["EPSG",27700]]
```

We see that this is in fact in a projected coordinate system, namely the British National Grid we mentioned. To make them align, we can **re-project** this object into the *WGS84* geographic coordinate system. To do this, we can use the `st_transform()` function.

```
city_centre <- st_transform(city_centre, crs = 4326)
```

Now we can check the projection again:

```
st_crs(city_centre)
```

```
## Coordinate Reference System:
##   User input: EPSG:4326
##   wkt:
## GEOGCRS["WGS 84",
##     DATUM["World Geodetic System 1984",
##         ELLIPSOID["WGS 84",6378137,298.257223563,
##             LENGTHUNIT["metre",1]]],
##     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["unknown"],
##         AREA["World"],
##         BBOX[-90,-180,90,180]],
##     ID["EPSG",4326]]
```

And we can also check whether the CRS of the two objects match:

```
st_crs(crimes) == st_crs(city_centre)
```

```
## [1] TRUE
```

It is true! Finally, to check our bar data from Open Street Map:

```
st_crs(osm_bar_sf)
```

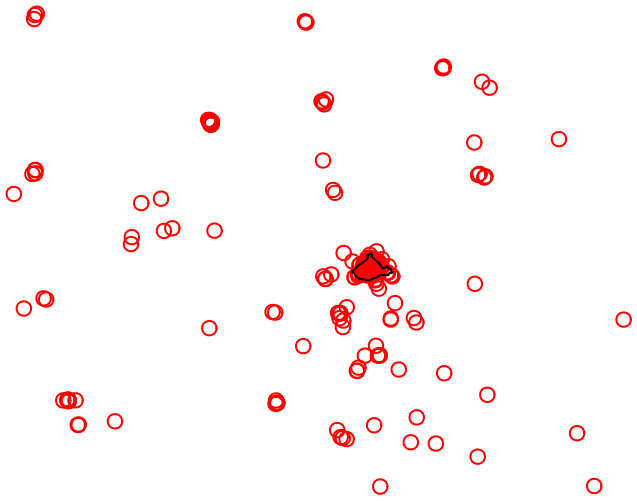
```
## Coordinate Reference System:
##   User input: EPSG:4326
##   wkt:
## GEOGCRS["WGS 84",
##     DATUM["World Geodetic System 1984",
##         ELLIPSOID["WGS 84",6378137,298.257223563,
##             LENGTHUNIT["metre",1]]],
##     PRIMEM["Greenwich",0,
##         ANGLEUNIT["degree",0.0174532925199433]],
##     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["unknown"],
##         AREA["World"],
##         BBOX[-90,-180,90,180]],
##     ID["EPSG",4326]]
```

Also in WGS84. We can now move on to carry out some spatial operations!

0.17.2 Subsetting points

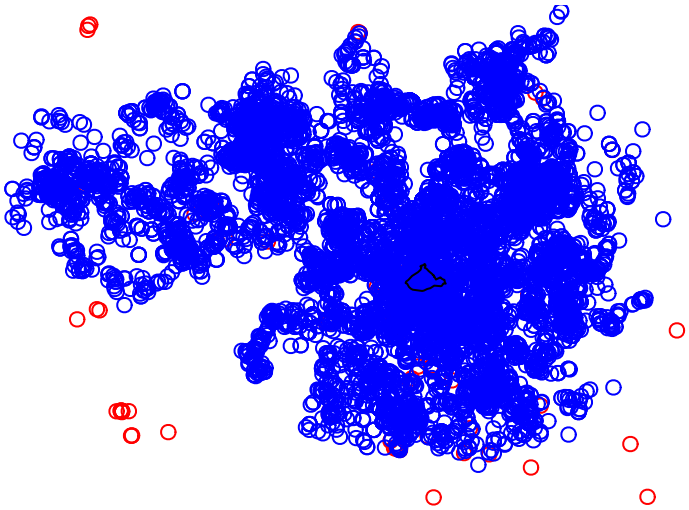
Recall above that we wanted to focus our efforts on the City Centre ward of Greater Manchester, however for our bounding box to download OSM data we used Greater Manchester. If we were to plot our bars, we would see that we have many which fall ourside of the City Centre ward:

```
plot(st_geometry(osm_bar_sf), col = 'red')
plot(st_geometry(city_centre),  add = TRUE)
```



This is also the case for our crimes data:

```
plot(st_geometry(osm_bar_sf), col = 'red')
plot(st_geometry(crimes), col = 'blue', add = TRUE)
plot(st_geometry(city_centre), add = TRUE)
```



So if we really want to focus on city centre, we should create spatial objects for the crimes and the bars which include only those which fall within the City Centre ward boundary.

First things first, we check whether they have the same CRS.

```
st_crs(city_centre) == st_crs(crimes)
```

```
## [1] TRUE
```

We do indeed, as we made sure in the previous section. Now we can move on to our spatial operation, where we select only those points within the city centre polygon. To do this, we first make a list of intersecting points to the polygon, using the `st_intersects()` function. This function takes two arguments, first the polygon which we want to subset our points within, and second, the points which we want to subset. We then use the resulting "cc_crimes" object to subset the crimes object to include only those which intersect (return `TRUE` for intersects):

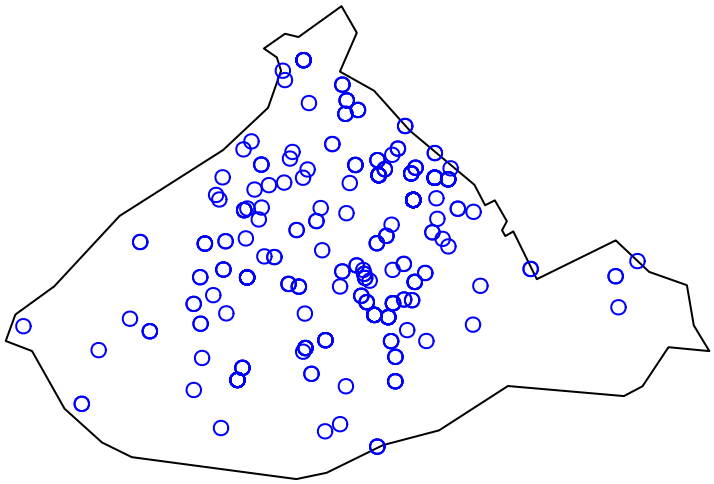
```
# intersection
cc_crimes <- st_intersects(city_centre, crimes)
# subsetting
cc_crimes <- crimes[unlist(cc_crimes),]
```

Have a look at this new "cc_crimes" object in your environment. How many observations does it have? Is this now fewer than the previous "crimes" object? Why do you think this is?

(hint: you're removing everything that is outside the city centre polygon)

We can plot this again to have a look:

```
plot(st_geometry(city_centre))
plot(st_geometry(cc_crimes), col = 'blue',  add = TRUE)
```



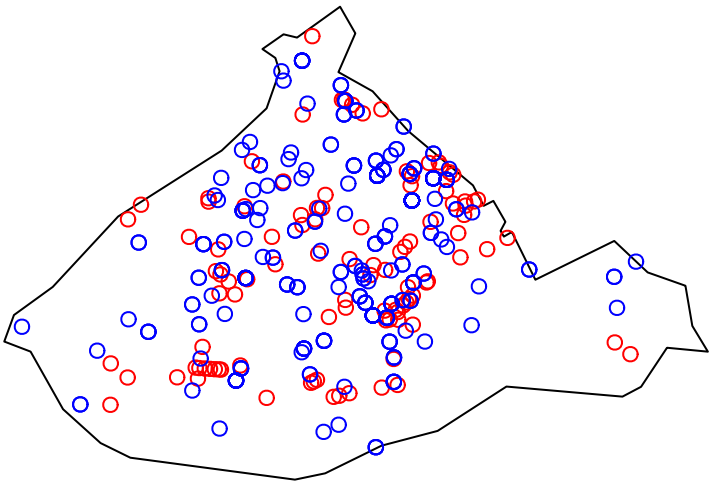
We have successfully performed our first spatial operation, we managed to subset our points data set or crimes to include only those crimes which are located inside the polygon for city centre.

We can do the same for the bars:

```
# intersection
cc_bars <- st_intersects(city_centre, osm_bar_sf)
# subsetting
cc_bars <- osm_bar_sf[unlist(cc_bars),]
```

We can see that of the previous 259 bars, 102 are within the City Centre ward. We can plot our data now:

```
plot(st_geometry(city_centre))
plot(st_geometry(cc_bars), col = 'red', add = TRUE)
plot(st_geometry(cc_crimes), col = 'blue', add = TRUE)
```



0.17.3 Building buffers

So we now have our bars and our violent crimes in Manchester City Centre. Let's go back to our original question. We want to know about crime in and around our areas of interest, in this case our bars. But how can we count this? We have our points that are crimes, right? Well… How do we connect them to our points that are licensed premises?

One approach is to build a buffer around our bars, and say that we will count all the crimes which fall within a specific radius of this bar. What should this radius be? Well this is where your domain knowledge as criminologist or crime analyst comes in. How far away would you consider a crime to still be related to this pub? 400 meters? 500 meters? 900 meters? 1 km? What do you think? This is one of them *it depends* questions, where there is no universal right answer, instead it will depend on the environment, the question, and contextual factors. Whatever buffer you choose you should justify, and make sure that you can defend when someone might ask about it, as the further your reach obviously the more crimes you will include, and these might alter your results.

So, let's say we are interested in all crimes that occur within 400 meters of each licensed premise. We chose 400m here as this is often the recommended distance for accessible bus stop guidance, so basically as far as people should walk to get to a bus stop. So in this case, we want to take our points, which represent the licensed premises, and build buffers of 400 meters around them.

You can do with the `st_buffer()` function. We pass two arguments to our function, the item which we want to buffer (the points in our 'cc_bars' object) and the size of this buffer.

Let's quickly illustrate:

```
prem_buffer <- st_buffer(cc_bars, 1)
```

You should get a warning here, saying *"st_buffer does not correctly buffer longitude/latitude datadist is assumed to be in decimal degrees (arc_degrees)."*. This message indicates that sf assumes a distance value (our size of the buffer, specified as '1' above) is given in degrees. This is because we have our data in a Geographic Coordinate System (lat/long data in WSG 48).

If we want to calculate the size of the size of our buffer in a meaningful distance on our 2D surfaces, we can transform to a Projected Coordinate System, such as British National Grid. Let's do this now:

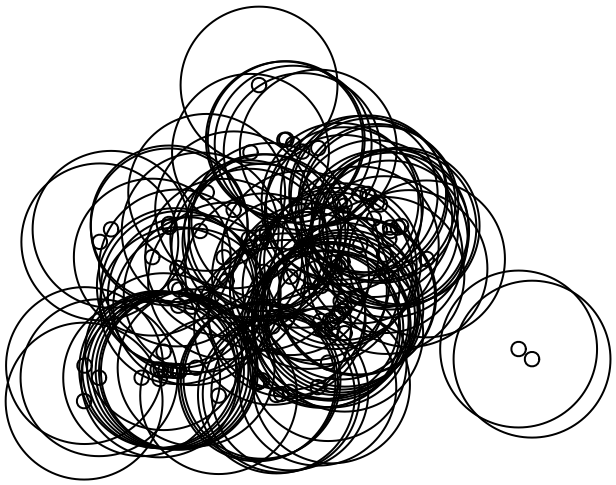
```
#The code for BNG is 27700
bars_bng <- st_transform(cc_bars, 27700)
```

Now we can try again, with meters, specifying our indicated 400m radius:

```
bars_buffer <- st_buffer(bars_bng, 400)
```

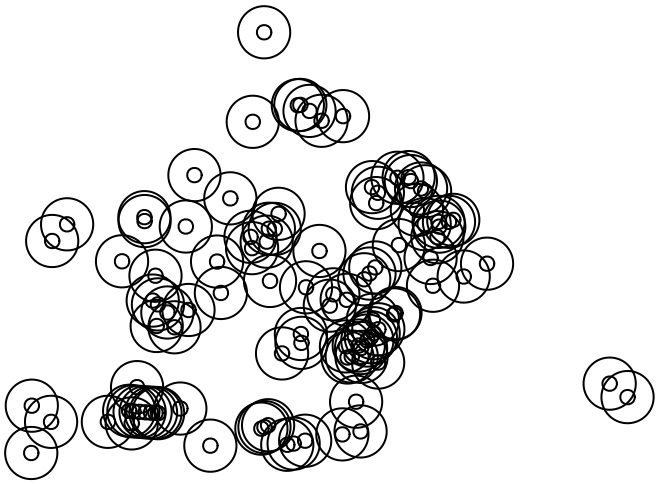
Let's see how that looks:

```
plot(st_geometry(bars_buffer))
plot(st_geometry(bars_bng), add = T)
```



That should look nice and squiggly. We can see it looks like there is *quite* a lot of overlap here. Should we maybe consider smaller buffers? Let's look at 100 meter buffers:

```
bar_buffer_100 <- st_buffer(bars_bng, 100) # create 100m buffer

# plot new buffers
plot(st_geometry(bar_buffer_100))
plot(st_geometry(bars_bng), add = T)
```



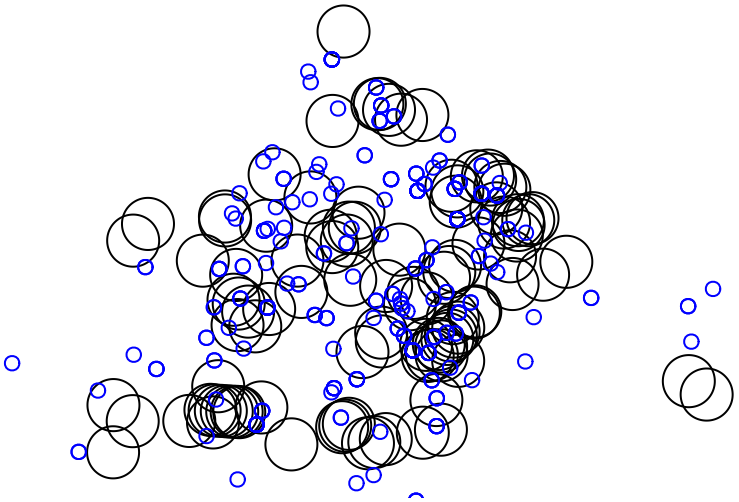
Still quite a bit of overlap, but this is possibly down to all the licensed premises being very densely close together in the city centre. We will discuss how to deal with this later on. For now, let's go with these 100m buffers, and where a crime falls into an area of overlap, we will count it towards both premises.

The next step will be to count the number of crimes which fall into each buffer. Before we move on though, remember the CRS for our crimes is WGS 48 here, so we will need to convert our buffer layer back to this:

```
buffer_WGS84 <- st_transform(bar_buffer_100, 4326)
```

Now let's just have a look:

```
plot(st_geometry(buffer_WGS84))
plot(st_geometry(cc_crimes), col = 'blue', add = T)
```



OKAY, so some crimes fall inside some buffers, others not so much. Well, let's get to our next spatial operation, to be able to determine how many crimes happened in the 100m radius of each bar in Manchester City Centre.

0.17.4 Counting Points within a Polygon

When you have a polygon layer and a point layer - and want to know how many or which of the points fall within the bounds of each polygon, you can use this method of analysis. In computational geometry, the point-in-polygon (PIP) problem asks whether a given point in the plane lies inside, outside, or

on the boundary of a polygon. As you can see, this is quite relevant to our problem, wanting to count how many crimes (points) fall within 100 meters of our licensed premises (our buffer polygons).

```
crimes_per_prem <- cc_crimes %>%
  st_join(buffer_WGS84, ., left = FALSE) %>%
  count(name)
```

You now have a new dataframe, `crimes_per_prem` which has a column for the name of the bars, a column for the number of violent crimes that fall within the buffer, and a column for the geometry.

Take a moment to look at this table. Use the `View()` function. Which premises have the most violent crimes? If you are perhaps familiar with Manchester bars - what do you think? Are you surprised? I was!

Let's see the bar with the most crimes:

```
crimes_per_prem %>%
  filter(n == max(n)) %>%
  select(name, n)
```

```
## Simple feature collection with 1 feature and 2 fields
## Geometry type: POLYGON
## Dimension:     XY
## Bounding box:  xmin: -2.237934 ymin: 53.48095 xmax: -2.234921 ymax: 53.48275
## Geodetic CRS:  WGS 84
##         name  n                       geometry
## 1 Crafty Pig 59 POLYGON ((-2.234921 53.4818...
```

The bar with the highest number of crimes is Crafty Pig with 59 crimes. Keep this in mind for the next section…!

So in this case, we used the point-in-polygon approach, and counted the number of points which fell into each polygon. We saw earlier, with the buffers, that they often overlapped with one another. This means that a crime may have been counted multiple times. This resulting data therefore tells us: *How many crimes happened within 100 meters of each bar.* This is one way to approach the problem, but not the only way. In our next spatial operation, we will calculate distances in order to explore another way.

0.17.5 Distances: Finding the nearest point

Another way to solve this problem is to assign each crime (point) to the closest possible bar (other point). That is, look at the distances for each crime between it's location and the locations of all the bars in Manchester, and then, from those, choose the bar which is the closest. Then, we can assign this bar as the location for that crime.

We can achieve this using the `st_nearest_feature()` function. This function takes our two sf objects, and for each row of the first one (x = cc_crimes), simply returns us the index of the nearest features from the second one (y = cc_bars). We combine with the `mutate()` function in order to create a new variable which contains this index for each crime. Let's illustrate:

```
crime_w_bars <- cc_crimes %>%
  mutate(nearest_bar = st_nearest_feature(cc_crimes, cc_bars))
```

If we now have a look at this new object "crime_w_bars", we can see it is our crimes data, but we have a new column, which contains the index of the closest bar in the cc_bars dataframe, right at the end. So for example, for me the first point there, the nearest bar is that in location 84 (vectors in R are 1-indexed, not 0-indexed like many other languages). If we wanted to look at what is on the 84th row we may call:

```
cc_bars[84]
```

However, this returns all the 90+ variables for this row. If we want only the name, we can query for the 84th row and the 2nd column (which is `name`):

```
cc_bars[84, 2]
```

```
## Simple feature collection with 1 feature and 1 field
## Geometry type: POINT
## Dimension:     XY
## Bounding box:  xmin: -2.236673 ymin: 53.4824 xmax: -2.236673 ymax: 53.4824
## Geodetic CRS:  WGS 84
##            name                  geometry
## 6404929536 Dive POINT (-2.236673 53.4824)
```

You can see the name is "Dive". For that first crime, in our data set, the nearest bar is "Dive" bar. Now, instead of going through this process manually for each point, we can use the index to subset within our `mutate()` function:

```
crime_w_bars  <- cc_crimes %>%
  mutate(nearest_bar = cc_bars[st_nearest_feature(cc_crimes, cc_bars),2])
```

Now we have new information in this `nearest_bar` column, the name of the nearest bar, and the geometry. We actually don't need the geometry for now, as we will simply be counting the frequency of each bar, which we can join back to our `cc_bars` object, which has a geometry, so we can extract the `$name` element only, and remove the geometry. Like so:

```
crimes_per_prem_2 <- crime_w_bars %>%  # create new crimes_per_prem_2 object
  st_drop_geometry() %>%               # drop (remove) the geometry
  group_by(nearest_bar$name) %>%       # group by to find frequency of each bar
  summarise(num_crimes = n()) %>%      # count number of crimes
  rename(name = `nearest_bar$name`)    # rename variable to 'name'
```

To tie this back to our spatial object "cc_bars" we can use the `left_join()` function:

```
crimes_per_prem_2 <- left_join(cc_bars, crimes_per_prem_2,
                               by = c("name" = "name"))
```

Let's see the bar with the most crimes with this approach:

```
crimes_per_prem_2 %>%
  filter(num_crimes == max(num_crimes, na.rm = TRUE)) %>%
  select(name, num_crimes)
```

```
## Simple feature collection with 1 feature and 2 fields
## Geometry type: POINT
## Dimension:     XY
## Bounding box:  xmin: -2.236427 ymin: 53.48185 xmax: -2.236427 ymax: 53.48185
## Geodetic CRS:  WGS 84
##         name num_crimes                   geometry
## 1 Crafty Pig         50 POINT (-2.236427 53.48185)
```

The bar with the highest number of crimes is still Crafty Pig, but now with 50 crimes. This means there is a difference in the number of crimes attributed to this bar bewteen the two approaches. Clearly there are 9 crimes which fell

within the buffer in the first approach, but were closer to another bar in the dataset, and were instead attributed to that one using this approach.

So which is better?

This is once again up to you as the researcher and analyst to decide. They do slightly different things, and so will answer slightly different questions. With the nearest feature approach, instead of talking about the number of crimes within some distance to the bar, we are instead talking about for each crime, the closest venue. This might mean that we could be attributing crimes that happen quite far from the venue to it, just because it's the closest within our data set. However, we are counting each crime only once. Pros and cons need to be weighed up, to make decisions.

0.17.6 Measuring distances

Let's have a look at the bar called "Night & Day". We can select this from the `cc_bars`, the buffers, and the crimes

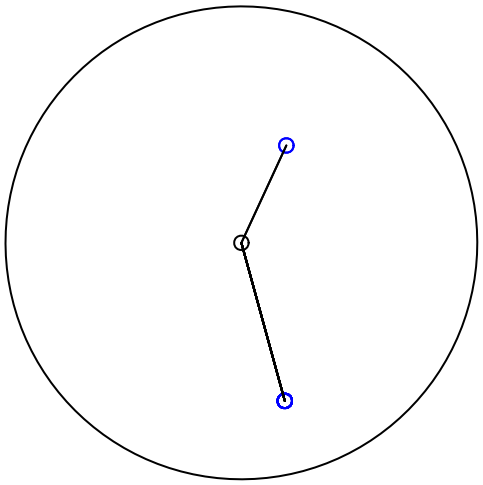
```
nd <- cc_bars %>%
  filter(name == "Night & Day")

nd_buffer <- bar_buffer_100 %>%
  filter(name == "Night & Day") %>%
  st_transform(4326)

nd_crimes <- crime_w_bars %>%
  filter(nearest_bar$name  == "Night & Day")
```

We can use `mapply()` and the `st_union()` function to draw a linestring between each crime and the closest bar (Night & Day in this case):

```
dist_lines <- st_sfc( # Create simple feature geometry list column
  mapply(   # apply function to multiple objects
    function(a,b){              # specify function parameters
      st_cast(st_union(a,b),"LINESTRING") # specify function
      },
    nd_crimes$geometry,  # input a for function
    nd_crimes$nearest_bar$geometry,  # input b for function
    SIMPLIFY=FALSE)) # don't attempt to reduce the result
```

We can then plot these to get an idea of what we're looking at:

```
plot(st_geometry(nd_buffer))
plot(st_geometry(nd), col = "black", add = TRUE)
plot(st_geometry(nd_crimes), col = "blue", add = TRUE)
plot(st_geometry(dist_lines), add = TRUE)
```



So we can see that the two locations where crimes occurred which were nearest to the Night & Day bar are both within the 100 meter buffer. But how far exactly are they?

You can use the `st_distance()` function to answer this question. We wrap this in the `mutate()` function in order to create a new column called *distance* which will contain for each row (each crime) the distance between that and its nearest bar (in this case Night & Day).

```
nd_crimes <- nd_crimes %>%
  mutate(distance = st_distance(geometry, nearest_bar$geometry))
```

Having a look at our newly created variable, we can see that the two crime locations are 69.3630151118733 and 45.3889988531455 away from Night & Day bar.

One thing you might find strange about the data is that why are all these crimes geocoded on top of one another? This is how the open data are released, using geo-masking by snapping crime locations to a geomask (a set of points). This is done to ensure anonymity in the data. In non-anonimysed data you might expect to see a little less overlap in your crime locations… Then with variation in distances between crimes and their nearest bars, we could use these distances to inform a buffer width for example. Anyway we will return to distances a little

later with a better data set. But now, let's move on to putting these outcomes on a map!

0.18 Plotting interactive maps with leaflet

In the first chapter, we introduced the `ggplot2` package for making maps in R. In this chapter, we are going to introduce `leaflet` (`http://leafletjs.com/`) as one way to easily make some neat maps. It is the leading open-source JavaScript library for mobile-friendly interactive maps. It is very popular, used by websites ranging from The New York Times and The Washington Post to GitHub and Flickr, as well as GIS specialists like OpenStreetMap, Mapbox, and CartoDB, some of who's names you'll recognise from the various basemaps we played with in previous labs.

In this section of the lab we will learn how to make really flashy looking maps using `leaflet`. If you haven't already, you will need to have installed the following packages to follow along:

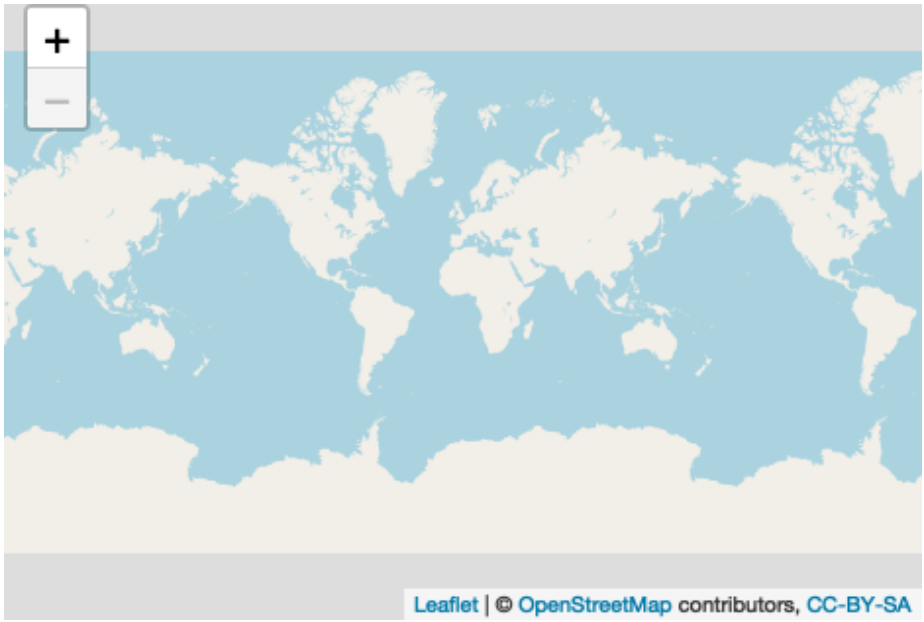
```
install.packages("leaflet") #for mapping
install.packages("RColorBrewer") #for getting nice colours for your maps
```

Once you have them installed, load them up with the `library()` function. To make a map, just load the leaflet library. You then create a map with this simple bit of code:

```
m <- leaflet() %>%
  addTiles()
```

And just print it:

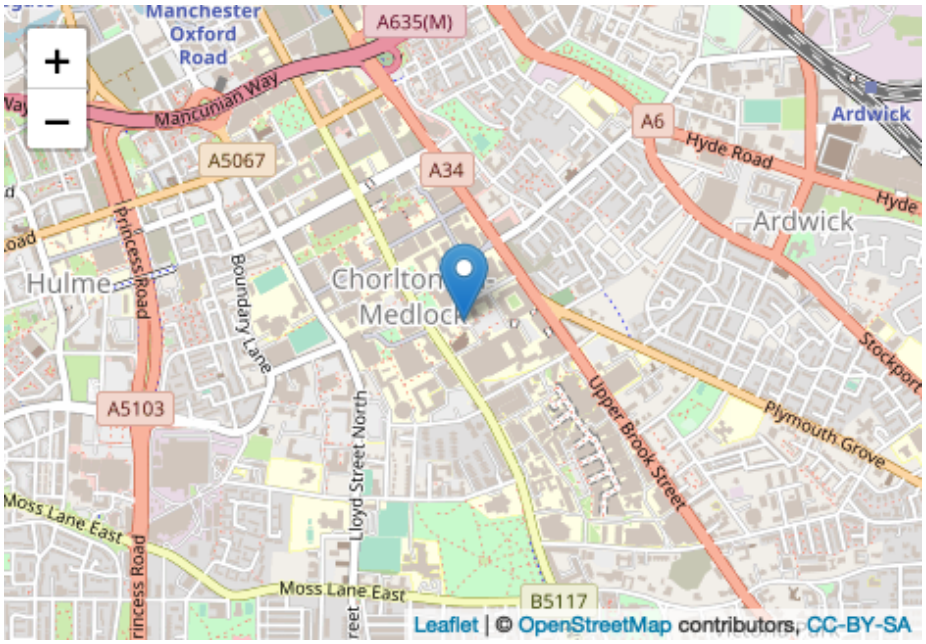
```
m
```



Not a super useful map, but it was really easy to make! You might of course want to add some content to your map.

You can add a point manually:

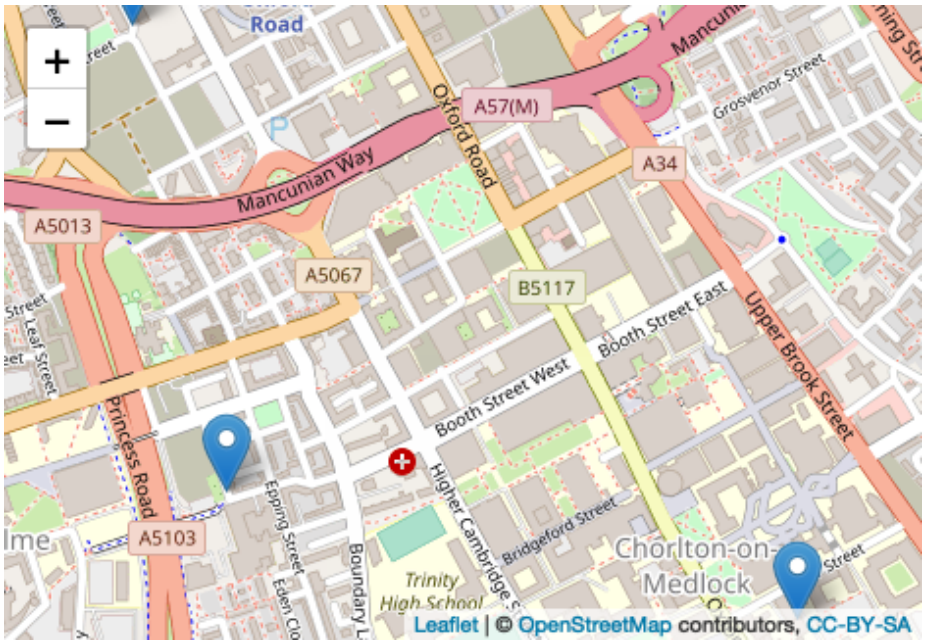
```
m <- leaflet() %>%
  addTiles()  %>%
  addMarkers(lng=-2.230899,  # longitude
             lat=53.464987,  # latitude
             popup="University of Manchester") # text for popup
m
```



If you click over the highlighted point you will read our input text "University of Manchester".

You can add many points manually, with some popup text as well:

```
# create dataframe of latitude, longitude, and popups
latitudes <- c(53.464987, 53.472726, 53.466649)
longitudes <- c(-2.230899, -2.245481, -2.243421)
popups <- c("You are here",
            "Here is another point",
            "Here is another point")
df <- data.frame(latitudes, longitudes, popups)

# create leaflet map
m <- leaflet(data = df) %>%
  addTiles()  %>%
  addMarkers(lng=~longitudes, lat=~latitudes, popup=~popups)

#print leaflet map
m
```



We can also map polygons, not just points. Let's plot our crimes on/near bars to illustrate. To do this, we can return to our buffers where we counted the number of crimes within 100m of each bar/ licensed premise (the "crimes_per_prem" object).

First, let's pick a colour palette. We do this with the `colorBin()` function. We will discuss colour choices in maps in Chapter 5, for now, let's just pick the *"RdPu"* palette. We should also specify the `domain =` parameter (what value to use for shading, in this case `n`, `bins = -` the number of crimes), the number of bins (in this case 5 - we will discuss this in detail in the coming chapters as well), and `pretty =` to use pretty breaks (this may actually mess with the number of bins specified in the bins parameter, but again, for now this is OK).

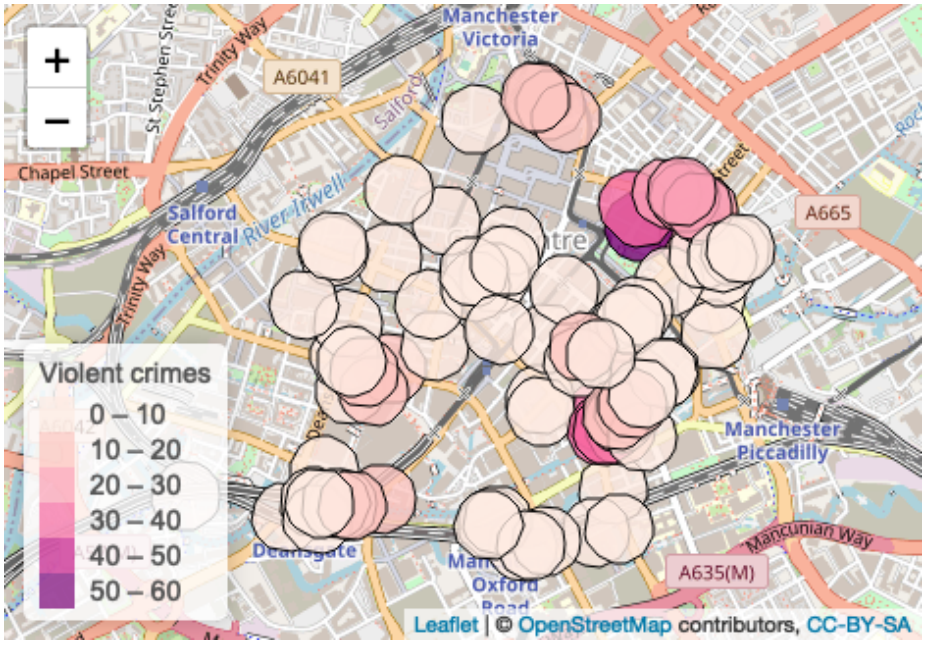
Let's create this palette and save in an object called `pal` for palette:

```
pal <- colorBin("RdPu",
                domain = crimes_per_prem$n,
                bins = 5,
                pretty = TRUE)
```

Now we can make a leaflet map, where we add these polygons (the buffers) with the `addPolygons()` function, and call our palette, specifying again the variable to use for shading, as well as some other parameters. One to highlight specifically is the `label` parameter. This allows us to use a variable as a label for when a user clicks on our polygon (buffer). Here we specify the name of the bar with

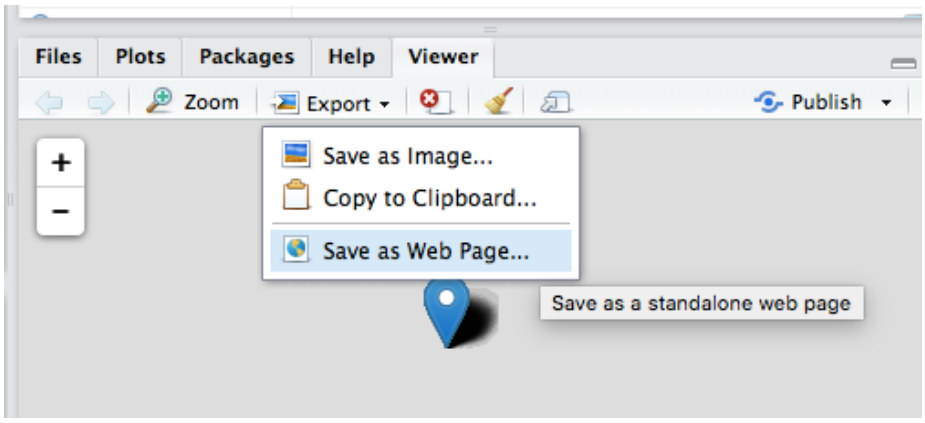
`label = ~as.character(name)`.This way we not only shade each buffer with the number of crimes which fall inside it, but also include a little popup label with the name of the establishment:

```
leaflet(crimes_per_prem) %>%
  addTiles() %>%
  addPolygons(fillColor = ~pal(n), fillOpacity = 0.8,
              weight = 1, opacity = 1, color = "black",
              label = ~as.character(name)) %>%
  addLegend(pal = pal, values = ~n, opacity = 0.7,
            title = 'Violent crimes', position = "bottomleft")
```



It's not the neatest of maps, with all these overlaps, but we will talk about prettifying maps further down the line.

Now let's say you wanted to save this map. You can do this by clicking on the export button at the top of the plot viewer, and choose the *Save as Webpage* option saving this as a .html file:



Then you can open this file with any type of web browser (safari, firefox, chrome) and share your map that way. You can send this to your friends, and make them jealous of your fancy map making skills.

0.19 Geocoding

We were making use of point of interest data from Open Street Map above, but it is possible that we have a data set of bars that are not geocoded. In this case, we may have a list of bars with an associated address, which is clearly *some* sort of spatial information, but how would you put this on a map?

One solution to this problem is to geocode these addresses. We can use the package `tidygeocoder` to achieve this. This package takes an address given as character values, for example "221B Baker Street, Marylebone, London NW1 6XE" and returns coordinates, geocoding this address. So let's say we have a dataframe of addresses (in this case only one observation):

```
addresses <- data.frame(name = "Sherlock Holmes",
                        address = "221B Baker Street, London, UK")
```

We can then use the `geocode()` function to get coordinates for this address. We have to specify the column which has the address (in this case *address*), and the method to use for geocoding. See the help file for the function for the many options. For example if you are in the USA you may use "census". Since we are global, we will use "osm", which uses nominatim (OSM) to provide worldwide coverage. So given the above example:

```
addresses %>%
  geocode(address, method = 'osm')
```

```
## # A tibble: 1 x 4
##   name            address                          lat   long
##   <chr>           <chr>                          <dbl>  <dbl>
## 1 Sherlock Holmes 221B Baker Street, London, UK  51.5 -0.158
```

To illustrate on scale, let's have a look at another source of data on bars in Manchester. Manchester City Council have an Open Data Catalogue (`http://open.manchester.gov.uk/open/homepage/3/manchester_open_data_catalogue`) on their website, which you can use to browse through what sorts of data they release to the public. Like in many city open data portals, there are a some more and some less interesting data sets made available here. It's not quite as impressive as the open data from some of the cities in the US such as New York (`https://opendata.cityofnewyork.us/`) or Dallas (`https://www.dallasopendata.com/`) but we'll take it.

One interesting data set, especially for our questions about the different alcohol outlets is the Licensed Premises (`http://www.manchester.gov.uk/open/downloads/file/169/licensed_premises`) data set. This details all the currently active licenced premises in Manchester. You can see there is a link to download.

As always, there are a few ways you can download this data set. On the manual side of things, you can simply right click on the download link from the website, save it to your computer, and read it in from there, by specifying the file path. Remember, if you save it in your R *working directory*, then you just need to specify the file name, as the working directory folder is where R will first look for this file.

So without dragging this on any further, let's read in the licensed premises data directly from the web using the URL `"http://www.manchester.gov.uk/open/download/downloads/id/169/l`

```
data_url <- "http://www.manchester.gov.uk/open/download/downloads/id/169/licensed_premises.csv"

lic_prem <- read_csv(data_url) %>%
  clean_names()
```

You will likely get some warnings when reading this data, but you can safely ignore those. You can always check if this worked by looking to your global environment on the righ hand side and seeing if this *lic_prem* object has appeared. If it has, you should see it has 65535 observations (rows), and 36 variables (columns).

Let's have a look at what this data set looks like. You can use the `View()` function for this:

```
View(lic_prem)
```

We see that there is a field for "premisesname" which is the name of the premise, and two fields, "locationtext" "postcode" which refer to address information. To geocode these, let's create a new column which combines the address and post code, and then use the `geocode()` function introduced above.

Note: this will take a while (like hours!) for the whole 65535 addresses data set, so just to illustrate for teaching purposes, we take the first 30

```
lic_prem <- lic_prem %>%
  slice(1:30) %>%    # Select first 30 venues
  # Create new complete_address column from locationtext and postcode using paste()
  mutate(complete_address = paste(locationtext,
                                  postcode,
                                  sep=", ")) %>%
  geocode(complete_address, method = 'osm')  # geocode with osm method
```

Now we have these licenced premises geocoded, with brand new latitude and longitude information! We can use this to make a leaflet map of our venues!

```
# make sure coordinates are numeric values
lic_prem$latitude <- as.numeric(lic_prem$lat)
lic_prem$longitude <- as.numeric(lic_prem$long)

# create map
leaflet(data = lic_prem) %>%
  addTiles() %>%
  addMarkers(lng=~longitude,
             lat=~latitude,
             popup=~as.character(premisesname),
             label = ~as.character(premisesname))
```

```
## Warning in validateCoords(lng, lat, funcName): Data contains 4 rows with either
## missing or invalid lat/lon values and will be ignored
```

Geocoding may come in handy when we have address data, or something similar but no geometry to use to map it.

0.20 Measuring distance more thoroughly

Before we end the chapter, we want to return to the spatial operation of measuring the distance between points. In crime science there is a whole area of research that, for example, focuses on studying the journey to crime by offenders and a common parameter studied is the average distance to crime from their home locations. In order to estimate these parameters, we first need to have a way to generate the distances. In this section, we will use another data set (this time from Madrid, Spain) to show a simpler example to look at the issue of geographical distance.

0.20.1 How far are police stations in Madrid?

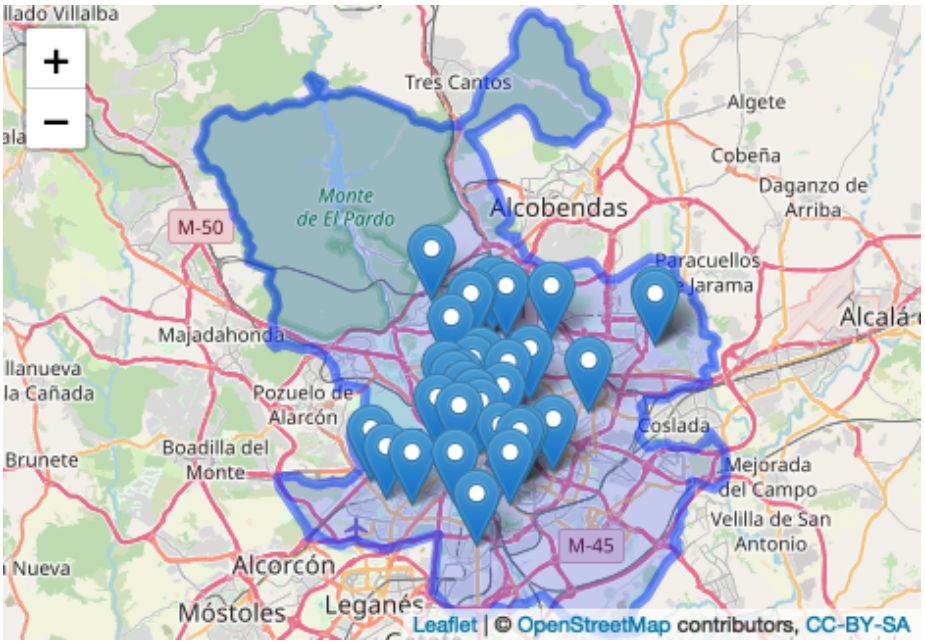
To illustrate how to measure distance we will download data from the city of Madrid in Spain. Specifically we will obtain a csv file with the latitude and longitude of the police stations and a geojson file with the administrative boundary for the city of Madrid. Both are stored in our GitHub repository and can be accessed with the code below. We will also turn the .csv into a `sf` object with the appropriate coordinate reference system for this data.

```
#read csv data
comisarias <- read_csv("data/nationalpolice.csv")
#set crs, read into sf object, and assign crs
polCRS <- st_crs(4326)
comisarias_sf <- st_as_sf(comisarias, coords = c("X", "Y"), crs = polCRS)

#create unique id for each row
comisarias_sf$id <- as.numeric(rownames(comisarias_sf))

#Read as sf boundary data for Madrid city
madrid <- st_read("data/madrid.geojson")
```

```
## Reading layer `madrid' from data source `/Users/reka/Desktop/crime_mapping/crime_mapping/data/madrid.geoj
## Simple feature collection with 1 feature and 4 fields
## Geometry type: MULTIPOLYGON
## Dimension:     XY
## Bounding box:  xmin: -3.888963 ymin: 40.31206 xmax: -3.518126 ymax: 40.64328
## Geodetic CRS:  WGS 84
```

We went through a lot of steps there, so it's worth to check in and plot our data, make sure that everything looks the way we expect. To practice with leaflet map some more, let's plot using `leaflet()` function:

```
leaflet(comisarias_sf) %>%
  addTiles() %>%
  addMarkers(data = comisarias_sf) %>%
  addPolygons(data = madrid)
```



We can clearly see here that there are areas of the municipal term that are far away from any national police station, the North West part of the city which you can see is a green area but noticeably also the South East, which is mostly urban and in fact is the location of a known shanty town and open drug market ("Cañada Real", you can read about it in the award-winning **?**).

0.20.2 Distance in geographical space

There are many definitions of distance in data science and spatial data science. A common definition of distance is the **Euclidean distance**, which simply is the length of a segment connecting two points in a two dimensional place. Because of the distortions caused by projections on a flat surface, a straight line on a map is not necessarily the shortest distance. Thus, another common definition used in geography is the **great circle distance**, which corresponds to an arc linking two points on a sphere and takes into account the spherical shape of the world.The great circle distance is useful, for example, to evaluate the shortest path when intercontinental distances are concerned.

We can compute both with the `st_distance` function of the `sf` package. This function can be used to measure the distance between two points, between one point and others or between all points. In the latter case we obtain a symmetric matrix of distances (NxN), taken pairwise between the points in our dataset. In the diagonal we find the combinations between the same points giving all null values.

Say we want to measure the distance between the main police headquarters ("Jefatura Superior de Policia", row 34) and three other stations (say row 1, row 10, and row 25 in our dataset). We could use the following code for that:

```
# calculate distance
dist_headquarters <- st_distance(slice(comisarias_sf, 34),
                                 slice(comisarias_sf, c(1, 10, 25)))

dist_headquarters # distance in meters
```

```
## Units: [m]
##          [,1]    [,2]     [,3]
## [1,] 8123.707 5096.02 8573.521
```

The result is a matrix with a single row or column (depending on the order of the spatial objects) with a class of *units*.

Often we may want to reexpress these distances in a different unit. For this purpose the `units` package offers useful functionality, through the `set_units()` function.

```
set_units(dist_headquarters, "km")
```

```
## Units: [km]
##          [,1]    [,2]     [,3]
## [1,] 8.123707 5.09602 8.573521
```

We can compute the distance between all police stations as well.

```
# calculate distance
m_distance <- st_distance(comisarias_sf)

# matrix dimensions
dim(m_distance)
```

```
## [1] 34 34
```

If you want to preview the top of the matrix you can use:

```
head(m_distance)
```

0.20.3 A practical example to evaluate distance

For this practical example we will look at the Madrid data.

```
plot(st_geometry(madrid))
```

We know this map is in EPSG 4326.

```
st_crs(madrid)
```

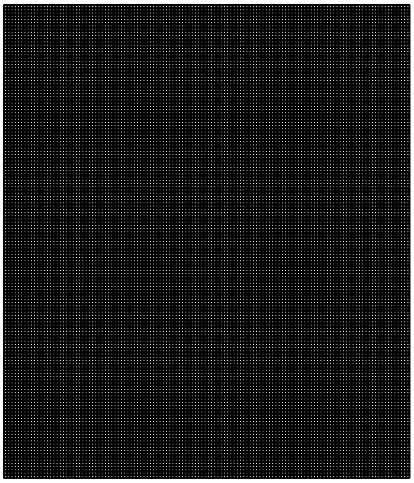
The distance here is expressed in degrees and we may prefer to evaluate distance in metrical system. Another way of saying this is that the current CRS uses geographic coordinates that account for earth's curvature, when we may prefer a flat surface to measure distances. For this we will transform and reproject to EPGS 2062, which is the appropriate projected coordinate system for Madrid (see here for details `https://epsg.io/?q=Spain%20kind%3APROJCRS`).

```
madrid_meters <- st_transform(madrid, crs = 2062)
```

Before we saw that some areas of Madrid are nowhere near a police station. Let´s say we want to get precise about this and we want to know how far

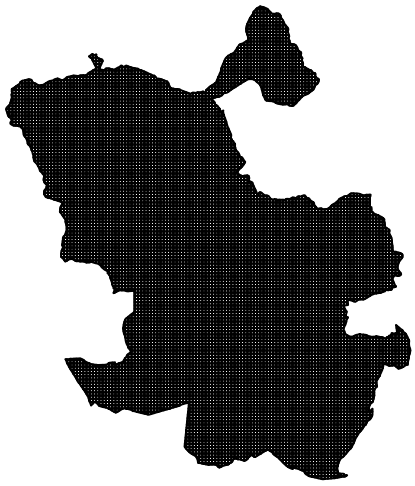
different parts of the city of Madrid are from a police station, and we want to be able to show this in a map. Solving this means we have to define "parts of the city". What we will do is to divide the city of Madrid into different cells of 250 meters within a grid using the `st_make_grid` function of the `sf` package. "

```
madrid_grid <- st_make_grid(madrid_meters,  cellsize = 250)
plot(madrid_grid)
```



We are now going to just extract the cells within the perimeter of Madrid:

```
#only extract the points in the limits of Madrid
madrid_grid <- st_intersection(madrid_grid, madrid_meters)

# plot this grid
plot(madrid_grid)
```



```
#Reproject to 4326 for later use
madrid_grid_wgs <- st_transform(madrid_grid, crs = 4326)
```

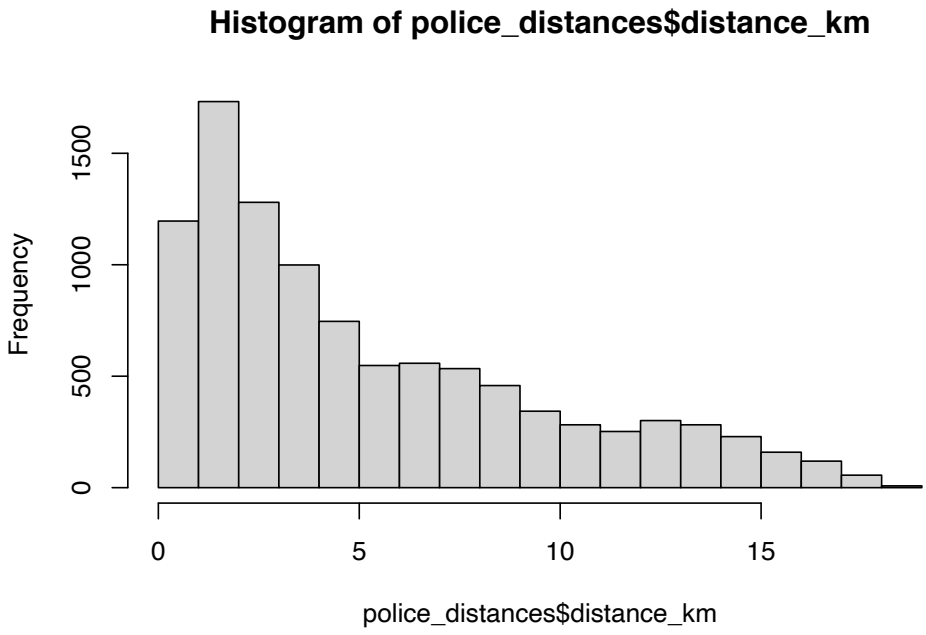
So how do we look at distance from police stations here? We will measure the distance between each grid cell to all 39 police stations. To estimate the distance to the nearest police station we will find the minimum distance value for each grid, i.e. the distance to the nearest station.

```
comisarias_sf_meters <- st_transform(comisarias_sf, crs = 2062)

distances <- st_distance(comisarias_sf_meters,
                         st_centroid(madrid_grid)) %>%
  as_tibble()
```

If you view the new object "distances" you will see there is a row for each police station and a column representing each of the 10082 cells in our grid. For using these distances in a leaflet map we will reproject back into 4326. And then will compute the shortest distance for each cell.

```
# Compute distances
police_distances <- data.frame(
  # We want grids in a WGS 84 CRS:
  us = st_transform(madrid_grid, crs = 4326),
  # Extract minimum distance for each grid
  distance_km = map_dbl(distances, min)/1000,
```

```
  # Extract the value's index for joining with the location info
  location_id = map_dbl(distances, function(x) match(min(x), x))) %>%
  # Join with the police station table
  left_join(comisarias_sf, by = c("location_id" = "id"))

# Plot and examine distances

hist(police_distances$distance_km)
```




```
quantile(police_distances$distance_km)
```

```
##          0%         25%         50%         75%        100%
##  0.01861606  1.73978931  3.81578329  7.95273442 18.17877100
```

Now we are ready to use this data to plot a map. We can get creative, and use the `makeIcon()` function from leaflet to assign an image as our icon, rather than thes regular pointer icon we've been seeing. First we will adjust some aesthetics.

```
# Create more appropriate icon, taking it from Wikepedia commons
icon_url <- "https://upload.wikimedia.org/wikipedia/commons/a/ad/189-woman-police-officer-1.svg"
```

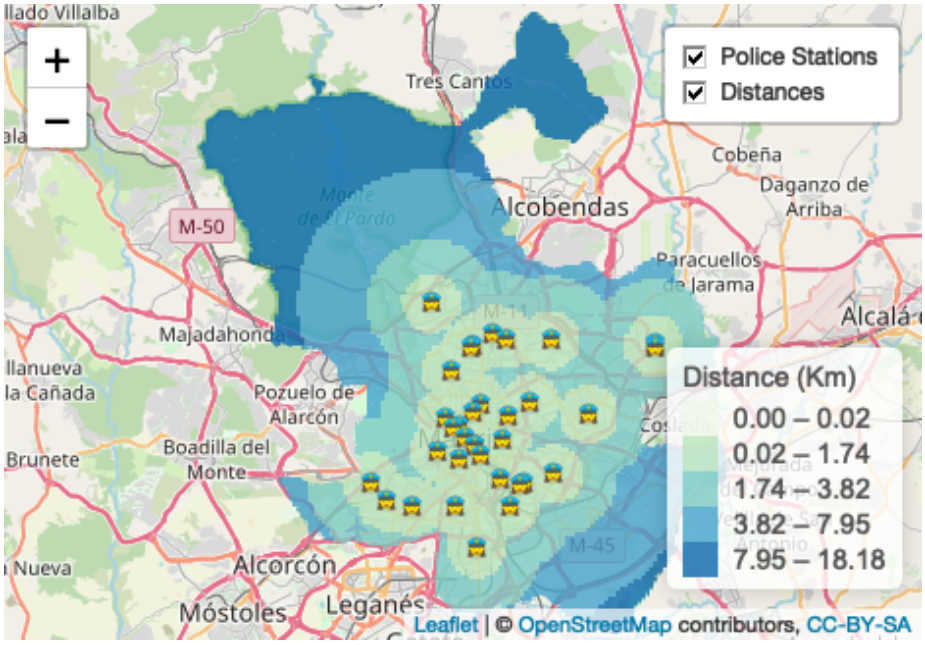
```
# create icon, adjusting size
police_icon <- makeIcon(icon_url,
                        iconWidth = 12,
                        iconHeight = 20)
```

```
# Bin ranges for a nicer color scale
bins <- c(0,0.02,1.74,3.82,7.95,18.18)
# Create a binned color palette
pal <- colorBin(c("#0868AC", "#43A2CA", "#7BCCC4",
                  "#BAE4BC", "#F0F9E8"),
                domain = police_distances$distance_km,
                bins = bins,
                reverse = TRUE)
```

Now let's create the map.

```
full_map <- leaflet() %>%
  addTiles() %>%
  addMarkers(data = comisarias_sf, icon = ~police_icon,
             group = "Police stations") %>%
  addPolygons(data = police_distances[[1]],
              fillColor = pal(police_distances$distance_km),
              fillOpacity = 0.8, weight =0,
              opacity = 1,
              color = "transparent",
              group = "Distances",
              highlight = highlightOptions(weight = 2.5,
                                           color = "#666",
                                           bringToFront = TRUE,
                                           opacity= 1),
              popupOptions = popupOptions(autoPan = FALSE,
                                          closeOnClick = TRUE,
                                          textOnly = T)) %>%
   addLegend(pal = pal,
             values = (police_distances$distance_km),
             opacity = 0.8,
             title = "Distance (Km)",
             position= "bottomright") %>%
  addLayersControl(overlayGroups = c("Police Stations", "Distances"),
                   options = layersControlOptions(collapsed = FALSE))
```

```
# print the map
full_map
```



And there you go. Just remember something. It is easy to misinterpret data and maps. You always need to care a great deal about measurement, quality of your data, and other potential issues affecting interpretation. When it comes to distance, and the movements of people and law enforcement personnel, for example, physical distance is not trivial, but time to arrival is also important and this is determined by factors other than Euclidean distance (e.g., availability and speed of transport, physical barriers, etc.). Our representation is always as good as the data we have. In Spain there are two other police forces (Guardia Civil, that patrols rural areas, and municipal civil, with jurisdiction for local administrative enforcement) that we are not representing here (that is, our data is incomplete). And we are not plotting the police stations in the nearby municipalities that are part of Madrid metropolitan area, around the edges.

0.21 Summary and further reading

In this chapter we explored the differences bweteen attribute and spatial operations, and made great use of the latter in practicing **spatial manipulation of data**. These spatial operations allow us to manipulate our data in a way that lets us study what is going on with crime at micro places. At the start of

the chapter we introduced the idea of different crime places. To read further in crime attractors vs crime generators turn to the recommended readings by **?** and **?**. There have since been more developments, for example about crime radiators and absorbers as well (watch this risky places lecture from Kate **?** to learn more!)

We covered how to subset points within an area, build buffers around geometries, count the number of points in a point layer that fall within each polygon in a polygon layer, find the nearest feature to a set of features, and turn non-spatial information such as an address into something we can map using geocoding. These spatial operations are just some of many, but we chose to cover them as they have the most frequent application in crime analysis.

For those interested to learn more, spatial operations are typically discussed in standard GIS textbooks, such as those we have recommended in previous chapters. You could see, for example, Chapter 9 of **?**. But probably the best follow up to what we discuss here is Chapter 4 and 5 of **?**, for it provides a systematic introduction to how to perform these spatial operations with R. There is an online book on development by two giants of the R spatial community, Edzer Pebesma and Roger Bivand, which at the time of writing is best cited as **?** . The first 5 chapters of the book provide a strong backbone to understand `sf` objects in greater detail, coordinate systems, and key concepts for spatial data science.

Mapping rates and counts

0.22 Introduction

In the first chapter we showed you fairly quickly how to create maps by understanding how data may have spatial elements, and how that can be linked to geometries.

In this chapter we will get to know how to think about thematic maps, and how to apply your learning to creating your own maps of this variety. In the process we will discuss various types of thematic maps and the various issues they raise.

Thematic maps focus on representing the spatial pattern of a variable of interest (e.g, crimes, trust in the police, etc.) and they can be used for exploration and analysis or for presentation and communication to others. There are different types of thematic maps depending on how the variable of interest is represented. In this and the next chapters we will introduce some of these types of particular interest for crime analysis, the different challenges they pose, and some ideas that may help you to choose the best representation for your data. Critically, we need to think about the quality of the data we work with, for adequate measurement is the basis of any data analysis.

In this chapter, we introduce in particular two types of thematic maps used for mapping quantitative variables: **choropleth maps** and **proportional symbol maps**. In previous chapters we introduced two separate packages for creating maps in R (`ggplot2` and `leaflet`). In this chapter we will introduce a third package for creating maps: `tmap`. The libraries we use in this chapter are as follow:

```
# Packages for reading data and data carpentry
library(readr)
library(dplyr)
library(janitor)

# Packages for data exploration
```

```
library(skimr)

# Packages for handling spatial data and for geospatial carpentry
library(sf)

# Packages for mapping and visualisation
library(tmap)
library(tmaptools)

# Packages for spatial analysis
library(DCluster)

# Packages with spatial datasets
library(geodaData)
```

0.23 Thematic maps: key terms and ideas

0.23.1 Choropleth maps

Choropleth maps display variation in areas (postal codes, police districts, census administrative units, municipal boundaries, regional areas, etc) through the use of the colour that fills each of these areas in the map. A simple case can be to use a light to dark color to represent less to more of the quantitative variable. They are appropriate to compare values across areas.

Most choropleth maps you encounter are classified choropleth maps. They group the values of the quantitative variable into a number of classes, typically between 5 and 7. We will return to this later in the chapter. It is one of the most common forms of statistical maps and like pie charts they are subject to ongoing criticism. **?** concluded they simply do not work. And there are indeed a number of known problems with choropleth maps:

1. They may not display variation within the geographical units being employed. You are imposing some degree of distortion by assuming all parts of an area display the same value. Our crime map may show a neighborhoud as secure, when there is a part of this neighbourhoud that has a high level of crime. And viceversa.

2. Boundaries of geographical areas are to a large extent arbitrary (and unlikely to be associated with major discontinuities in your variable of interest). In crime analysis we very often use census administrative units, but these rarely represent natural neighbourhoods.

3. They work better if areas are of similar size. Areas of greater size may be more heterogeneous internally than those of smaller size: that is, they potentially have the largest error of representation. Also, visual attention may be drawn by areas that are large in size (if size is not the variable use to create a ratio)

0.23.2 What do we use choropleth maps for?

0.23.2.1 Crime rates

In a choropleth map you "can" show raw totals (absolute values), for example number of crimes, or derived values (ratios), crime per 100,000 inhabitants. But as a general rule, you should restrict choropleth maps to show derived variables such as rates or percentages (**?**, **?**). This is because the areas we often use are of different size and this may introduce an element of confusion in the interpretation of choropleth maps. The size of say, a province or a county, "has a big effect on the amount of color shown on the map, but unit area may have little relationship, or even an inverse relationship, to base populations and related counts." (**?**: S30)

Mapping counts, mapping where a lot of the crime incidents concentrate is helpful, but we may want to understand as well if this is simply a function of the spatial distribution of the population at risk. As **?** suggests "practitioners often recognize that a substantial density of crime in a location is sufficient information to initiate a more detailed analysis of the problem", but equally we may want to know if "this clustering of crime is meaningfully non-random, and if the patterns observed are still present once the analysis has controlled for the population at risk." (p. 11-12).

A map of rates essentially aims to provide information into geographic variation of crime risk - understood as the probability that a crime may occur. Maps of rates are ultimately about communicating the risk of crime, with greater rates suggesting a higher probability of becoming a victim of crime.

In social science the denominator on mapped ratios is typically some form of population size, which typically we will want as current as possible. In other fields some measure of area size may be a preferred choice for the denominator.

However, a great deal of discussion in crime analysis has focused on the choice of the right denominator. Authors relate to this as the **denominator dilemma**: "the problem associated with identifying an appropriate target availability control that can overcome issues of spatial inequality in the areal units used to study crime" (Ratcliffe_2010). The best measure for your denominator is one which captures opportunities. If for example you are interested in residential burglary, it makes sense to use number of inhabited households as your denominator (rather than population size). Whatever denominator you choose, you

will usually want to make a case as to why that is the best representation of the opportunities for the crime type you're interested in.

As noted, population is a common choice, but it is not always the one that best captures crime opportunities. Population, on the other hand, is also highly mobile during the day. People do not stay in the areas where they live, they go to work, they go to school, they travel for tourism purposes, and in doing so they alter the population structure of any given area. As **?** highlights with an example "the residential population (as is usually available from the census) tells the researcher little about the real number of people outside nightclubs at 2 a.m" Geographers and criminologists, thus, distinguish between the standard measures of population (that relate to people that live in an area) provided by the census and government statistical authorities; and the so called **ambient population**, that relates to people that occupy an area at a given time, and which typically are a bit more difficult to source (see for example: **?**).

As we will see later, one of the key problems with mapping rates is that the estimated rates can be problematic if the enumeration areas we are studying have different population counts (or whatever it is we are counting in the denominator). When this happens, and those population counts produce small samples, we may have rates for some locations (those with more population) that are better estimated than others and, therefore, are less subject to noise.

Aside from problems with the denominator, we may also have problems with our numerator. In crime analysis, the key variable we map is geocoded crime, that is crime for which we know its exact location. The source for this variable tends to be crime reported to and recorded by the police. Yet, we know this is an imperfect source of data. A very large proportion of crime is not reported to the police. In England and Wales, for example, it is estimated that around 60% of crime is unknown to the police. And this is an average! The unknown figure of crime is larger for certain types of crime (e.g., interpersonal violence, sexual abuse, fraud, etc.). What is more, we know that there are community-level attributes that are associated with the level of crime *reporting* to the police (**?**).

Equally, not all police forces or units are equally adept at properly *recording* all crimes reported to the police. An in-depth study conducted in England and Wales concluded that over 800,000 crimes reported to the police were not properly recorded (an under-recording of 19%, which is higher for violence and sexual abuse, 33% and 26% respectively) (**?**). There are, indeed, institutional, economic, cultural and political factors that may shape the quality of crime recording across different parts of the area we want to map out.

Finally, the quality of the geocoding process, which varies across crime type, also comes into the equation. Sometimes there are issues with positional accuracy or the inability to geocode an address. Some authors suggest we need to be able to geocode at least 85% of the crime incidents to get accurate maps (**?**), otherwise geocoded crime records may be spatially biased. More recent studies offer a less conservative estimate depending on the level of analysis and number

of incidents (**?**). Although all this has been known for a while, criminologists and crime analysts are only now beginning to appreciate how this can affect the quality of crime mapping and the decision making based on this mapping (**?**; **?**).

Although most of the time crime analysts are primarily concerned with mapping crime incidence and those factors associated with it, increasingly we see interest in the spatial representation of other variables of interest to criminologists such as fear of crime, trust in the police, and more. In these cases, the data may come from surveys and the problem that may arise is whether we have a sample size large enough to derive estimates at the geographical level that we may want to work with. When this is not the case, methods for small area estimation are required (for details and criminological examples see **?**). There has also been recent work mapping perception of place and fear of crime at micro-levels (see **?** and **?**).

0.23.2.2 Prevalence vs incidence

There are many concepts in science that acquire multiple and confusing meanings. Two you surely will come across when thinking about rates are: incidence and prevalence. These are well defined in epidemiology. Criminology and epidemiology often use similar tools and concepts, but not in this regard. In criminological applications these terms often are understood differently and in, at least, two possible ways. Confused? You should be!

In public health and epidemiology prevalence refers to proportion of persons who have a condition at or during a particular time period, whereas incidence refers to the proportion or rate of persons who develop a condition during a particular time period. The numerator for prevalence is *all* cases during a given time period that have the condition, whereas the numerator for incidence is all *new* cases. What changes is the numerator and the key dimension in which it changes is time.

In criminology, on the other hand, you will find at least two ways of defining these terms. Those that focus on studying developmental criminology define prevalence as the percentage of a population that engages in crime during a specified period (number of offenders per population in a given time), while offending incidence refers to the frequency of offending among those criminally active during that period (number of offences per active offenders in a given time). For these criminologists the (total) crime rate in a population is the product of the prevalence and the incidence (**?**).

Confusingly, though, you will find authors and practitioners that consider incidence as equivalent to the (total) crime rate, as the number of crimes per population, and prevalence, as the number of victims per population. To make things more confusing, sometimes you see criminologists defining incidence as the number of crimes during a time period (say a year) and prevalence as the

number of victims during the lifetime. To avoid this confusion when producing maps *is probably best to avoid these terms and simply refer to crime rate or victimisation rate and be very clear in your legends about the time period covered for both.*

0.23.3 Proportional and graduate symbol maps: mapping crime counts

Proportional symbol maps, on the other hand, are used to represent quantitative variables for either areas or point locations. Each area get a symbol and the size represents the intensity of the variable. It is expected with this type of map that the reader could estimate the different quantities mapped out and to be able to detecting patterns across the map (**?**). The symbols typically will be squares or circles that are scaled "in proportion to the square root of each data value so that symbol areas visually represent the data values" (**?**: S29). Circles are generally used since they are considered to perform better in facilitating visual interpretation.

We often use proportional symbol maps to represent count data (e.g., number of crimes reported in a given area). A common problem with proportional symbol maps is symbol congestion/overlap, especially if there are large variations in the size of symbols or if numerous data locations are close together.

A similar type of map use graduated symbol maps. As with choropleth classing, the symbol size may represent data ranges. They are sometimes used when data ranges are too great to practically represent the full range on a small map.

0.24 Creating proportional symbol maps

Today we are going to introduce the `tmap` package. This package was developed to easily produce thematic maps. It is inspired by the `ggplot2` package and the layered grammar of graphics. It was written by Martjin Tennekes, a Dutch data scientist. It is fairly user friendly and intuitive.

There are a number of vignettes in the CRAN repository with helpful explanations (`https://cran.r-project.org/web/packages/tmap/index.html`) and also in the GitHub repo for this package (`https://github.com/mtennekes/tmap`) that you can explore.

In `tmap` each map can be plotted as a static map (*plot mode*) and shown interactively (*view mode*). We will start by focusing on static maps.

For the purpose of demonstrating some of the functionality of this package we will use the Manchester crime data generated in the first chapter. We have now added a few variables obtained from the Census that will be handy later on.

You can obtain the data in a GeoJSON format from the companion data to this book.

```
manchester <- st_read("data/manchester.geojson", quiet=TRUE)
```

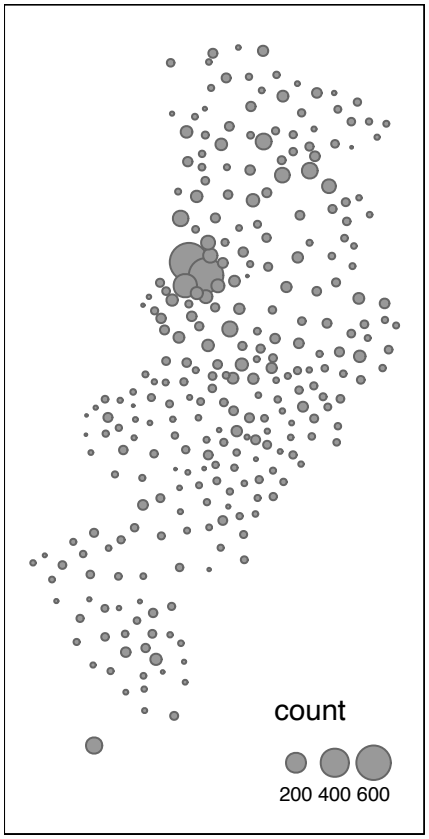
Every time you use this package you will need a line of code that specifies the spatial object you will be using. Although originally developed to handle `sp` objects only, it now also has support for `sf` objects. For specifying the spatial object we use the `tm_shape()` function and inside we specify the name of the spatial object we are using. Its key function is simply to do just that,to identify our spatial data. On its own, this will do nothing apparent. No map will be created. We need to add additional functions to specify what we are doing with that spatial object, how we want to represent it. If you try to run this line on its own, you'll get an error telling you you must "Specify at least one layer after each tm_shape".

```
tm_shape(manchester)
```

The main plotting method consists of elements that we can add. The first element is the `tm_shape()` function specifying the spatial object, and then we can add a series of elements specifying layers in the visualisation. They can include polygons, symbols, polylines, raster, and text labels as base layers.

In `tmap` you can use `tm_symbols` for this. As noted, with `tmap` you can produce both static and interactive maps. The interactive maps rely on `leaflet`. You can control whether the map is static or interactive with the `tmap_mode()` function. If you want a static map you pass `plot` as an argument, if you want an interactive map you pass `view` as an argument. Let's create a static map first:

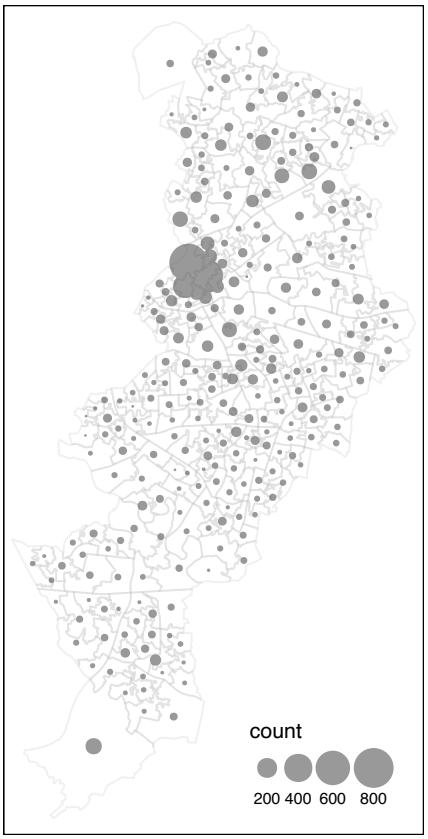
```
tmap_mode("plot")
tm_shape(manchester) +
  tm_bubbles("count")
```



Each bubble represents the number of crimes in each LSOA within the city of Manchester. We can add the borders of the census areas for better representation. The `border.lwd` argument set to NA in the `tm_bubbles()` is asking R not to draw a border to the circles. Whereas `tm_borders()` brings back a layer with the borders of the polygons representing the different LSOAs in Manchester city. Notice how we are modifying the transparency of the borders with the alpha parameter. In addition, we are adding a `tm_layout()` function that makes explicit where and how we want the legend.

```
 #use tm_shape function to specify spatial object
tm_shape(manchester) +
  #use tm_bubbles to add the bubble visualisation,
  # but set the 'border.lwd' parameter to NA,
  # meaning no symbol borders are drawn
  tm_bubbles("count", border.lwd=NA) +
  #add the LSOA border outlines using tm_borders,
  # but set their transparency using the alpha parameter
  # (0 is totally transparent, 1 is not at all)
```

```
  tm_borders(alpha=0.1) +
  #use tm_layout to make the legend look nice
  tm_layout(legend.position = c("right", "bottom"),
            legend.title.size = 0.8,
            legend.text.size = 0.5)
```

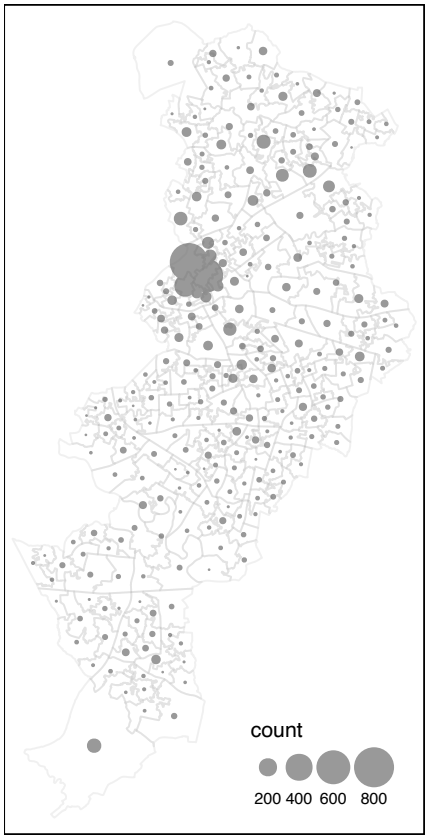


There are several arguments that you can pass within the `tm_bubble()` function that control the appearance of the symbols. The `scale` argument controls the symbol size multiplier number. Larger values will represent the largest bubble as larger. You can experiment with the value you find more appropriate. Another helpful parameter in `tm_bubble()` is `alpha`, which you can use to make the symbols more or less transparent as a possible way to deal with situations where you may have a significant degree of overlapping between the symbols. You can play around with this and modify the code we provide above with different values for these two arguments.

By default, the symbol area sizes are scaled proportionally to the data variable you are using. As noted above this is done by taking the square root of the

normalized data variable. This is called mathematical scaling. However, "it is well known that the perceived area of proportional symbols dose not match their mathematical area; rather, we are inclined to underestimate the area of larger symbols. As a solution to this problem, it is reasonable to modify the area of larger circles in order to match it with the perceived area." (**?**) The `perceptual = TRUE` option allows you to use a method that aims to compensate for how the default approach may underestimate the area of the larger symbols. Notice the difference between the map we produced and this new one.

```
tm_shape(manchester) +
  # add perceptual = TRUE
  tm_bubbles("count", border.lwd=NA, perceptual = TRUE) +
  tm_borders(alpha=0.1) +
  tm_layout(legend.position = c("right", "bottom"),
            legend.title.size = 0.8,
            legend.text.size = 0.5)
```



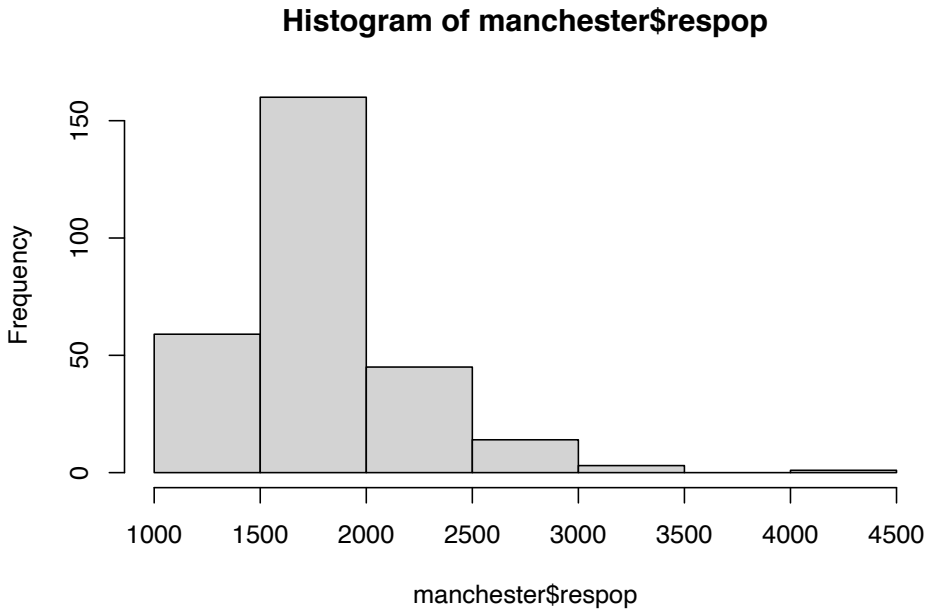
0.25 Mapping rates rather than counts

0.25.1 Generating the rates

We have now seen the importance to map rates rather than counts of things, and that is for the simple reason that population is not equally distributed in space. That means that if we do not account for how many people are somewhere, we end up mapping population size rather than our topic of interest.

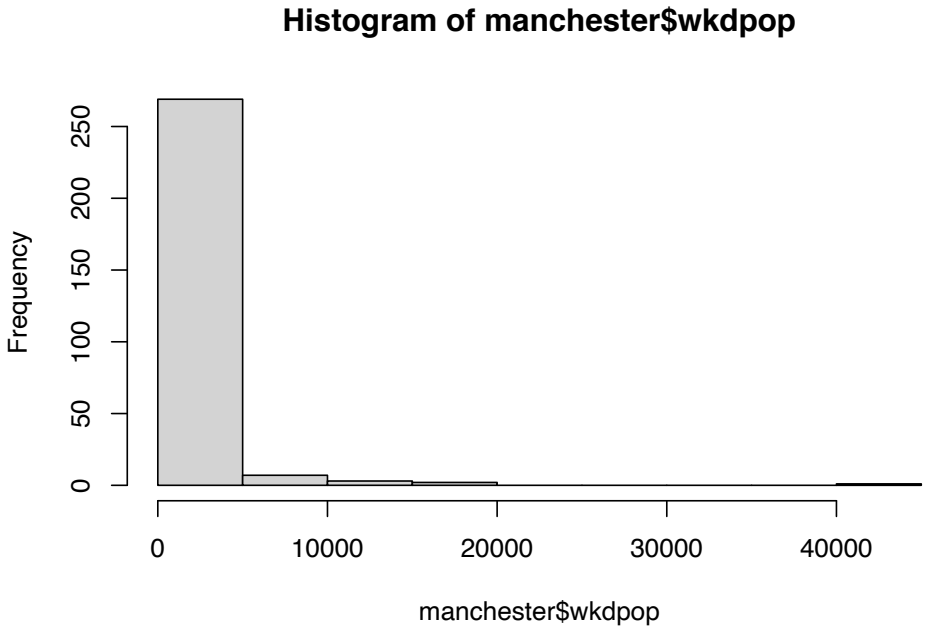
The *manchester* object we are working with has a column named "respop" that includes the residential population in each of the LSOA areas. These areas for the whole of the UK have an average population of around 1500 people. We can see a similar picture for Manchester city, with an average closer to 1700 here.

```
hist(manchester$respop)
```



We also have a variable "wkdpop" that represents the workday population. This variable re-distributes the usually resident population to their places of work, while those not in work are recorded at their usual residence. The picture it offers is much more diverse than the previous variable.

```
hist(manchester$wkdpop)
```



The distribution is much more skewed with some LSOAs in Manchester, with at least one LSOA attracting up to 42253 people during the working day. This gives an idea of the relevance of the "denominator dilemma" we mentioned earlier. In this section we will create rates of crime using both variables in the denominator to observe how the emerging picture varies.

First we need to create new variables. For this we can use the `mutate()` function from the `dplyr` package. This is a very helpful function to create new variables in a dataframe based on transformations or mathematical operations performed in other variables within the dataframe. In this function, the first argument is the name of the data frame, and then we can pass as arguments all new variables we want to create as well as the instructions as to how we are creating those variables.

First we want to create a rate using the usual residents, since crime rates are often expressed by 100,000 inhabitants we will multiply the division of the number of crimes by the number of usual residents by 100,000. We will then create another variable, "crimr2", using the workday population as the denominator. We will store this new variables in our existing "manchester" dataset. You can see that below then I specify the name of a new variable "crimr1" and then I tell the function I want that variable to equal (for each case) the division of the values in the variable "count" (number of crimes) by the variable "respop" (number of people residing in the area) and then we multiply the result of this division by 100,000 to obtain a rate expressed in those terms. Then we do likewise for the alternative measure of crime.

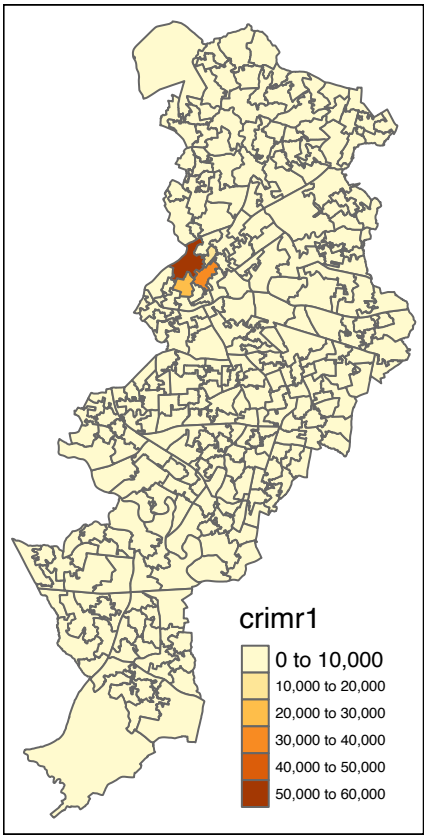
```
manchester <- mutate(manchester,
                     crimr1 = (count/respop)*100000,
                     crimr2 = (count/wkdpop)*100000)
```

And now we have two new variables, one for crime rate with residential population as a denominator, and another with workplace population as a denominator.

0.25.2 Creating a choropleth map with tmap

The structure of the grammar for producing a choropleth map is similar to what we use for proportional symbols. First we identify the object with `tm_shape()` and then we use a geometry to be represented. We will be using the `tm_fill()` passing as an argument the name of the variable with our crime rate.

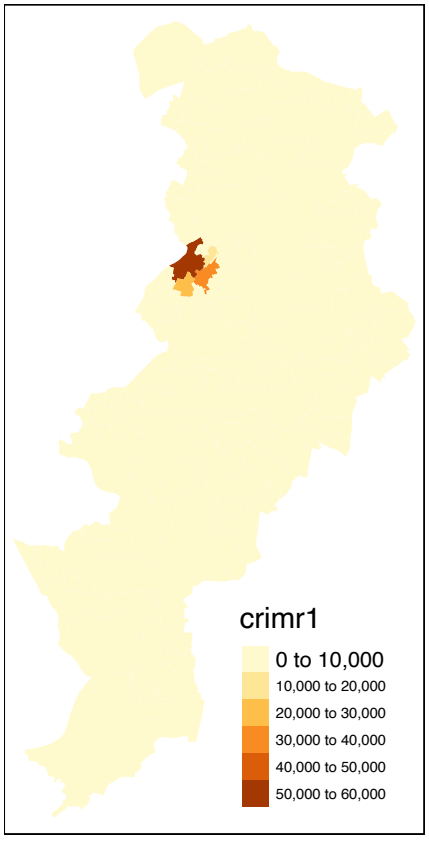
```
tm_shape(manchester) +
  tm_polygons("crimr1")
```



We have used `tm_polygons()` but we can also add the elements of a polygon map using different functions that break down what we represent here. In the map above you see the polygons have a dual representation, the borders are represented by lines and the colour is mapped to the intensity of the quantitative variable we are displaying. With darker colours representing more of the variable, the areas with more crimes.

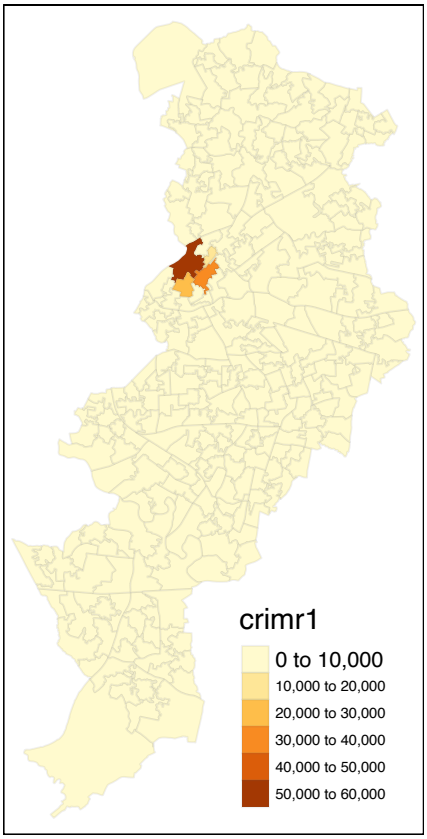
Instead of using `tm_polygon()` we can use the related functions `tm_fill()`, for the colour inside the polygons, and `tm_borders()`, for the aesthetics representing the border of the polygons. Say we find the borders distracting and we want to set them to be transparent. In that case we could just use `tm_fill()`.

```
tm_shape(manchester) +
  tm_fill("crimr1")
```



As you can see here, the look is a bit cleaner. However, we don't need to get rid of the borders completely. Perhaps we want to make them a bit more translucent. We could do that by adding the border element but making the drawing of the borders less pronounced.

```
tm_shape(manchester) +
  tm_fill("crimr1") +
  tm_borders(alpha = 0.1)
```

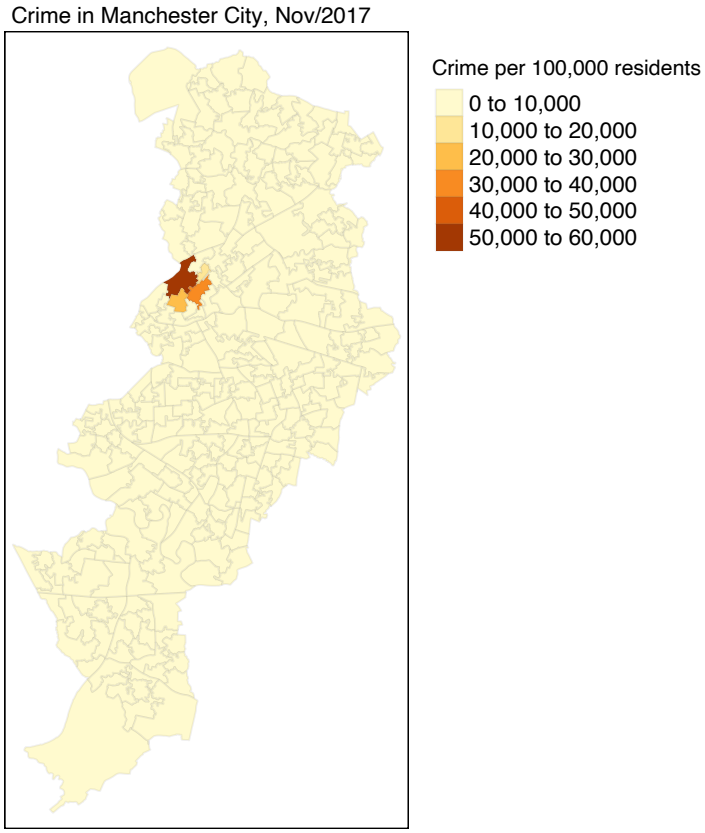


The alpha parameter that we are inserting within `tm_borders()` controls the transparency of the borders, we can go from 0 (totally transparent) to 1 (not transparent). You can play around with this value and see the results.

Notice as well that the legend in this map is not very informative and could be improved in terms of aesthetics. We can add a title within the `tm_fill` to clarify what count is and we can use the `tm_layout()` function to control the appearance of the legend. This later function `tm_layout` allows you to think about many of the more general cosmetics of the map.

```
tm_shape(manchester) +
  tm_fill("crimr1", title = "Crime per 100,000 residents") +
  tm_borders(alpha = 0.1) +
```

```
  tm_layout(main.title = "Crime in Manchester City, Nov/2017",
            main.title.size = 0.7 ,
            legend.outside = TRUE,  # Place legend outside of map
            legend.title.size = 0.8)
```



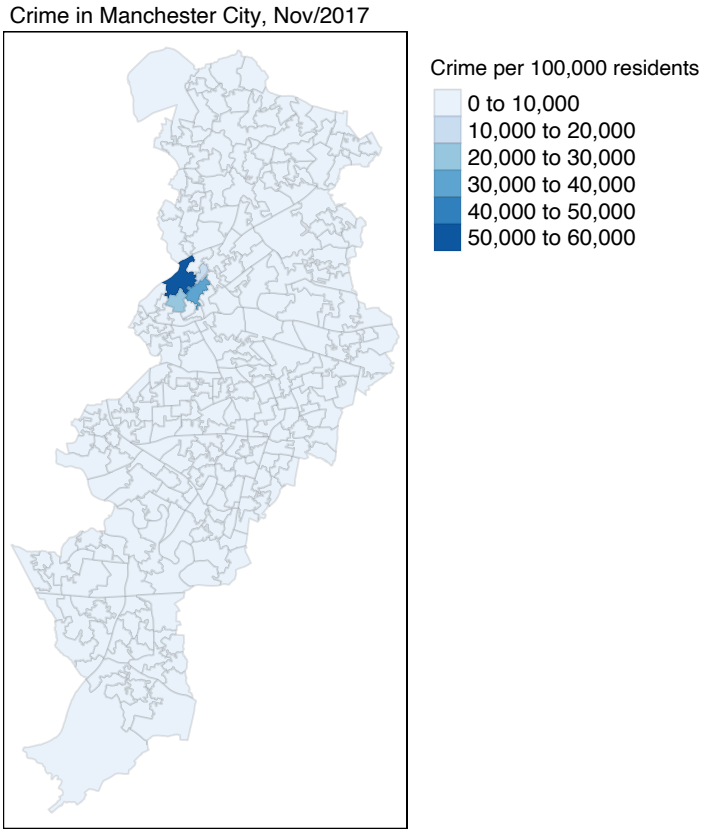
We are also going to change the current style of the maps by making them more friendly to colour blind people. We can use the `tmap_style()` function to do so.

```
current_style <- tmap_style("col_blind")
```

See how the map changes.

```
tm_shape(manchester) +
  tm_fill("crimr1", title = "Crime per 100,000 residents") +
  tm_borders(alpha = 0.1) +
```

```
tm_layout(main.title = "Crime in Manchester City, Nov/2017",
          main.title.size = 0.7 ,
          legend.outside = TRUE,  # Takes the legend outside the main map
          legend.title.size = 0.8,
          )
```



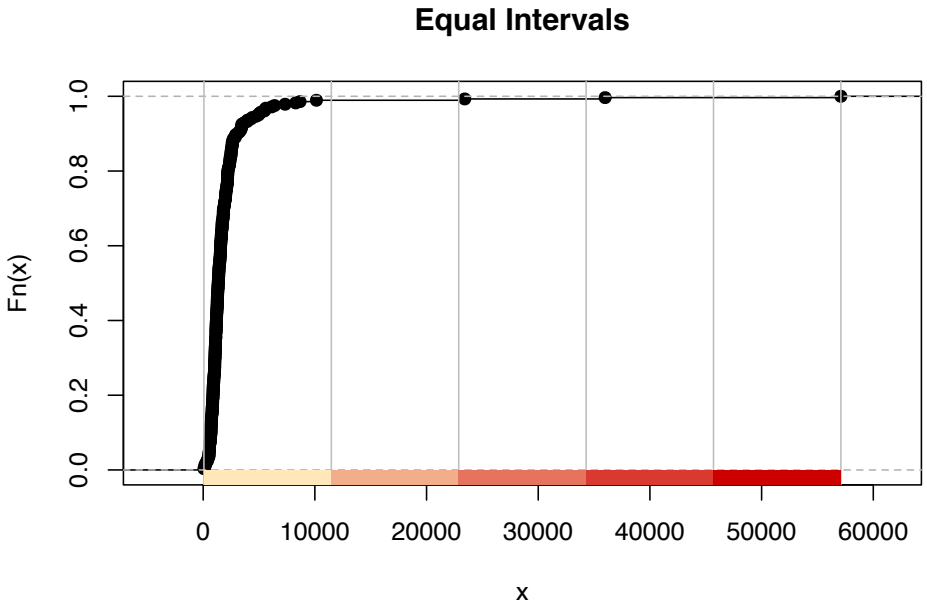
0.26 Classification systems for thematic maps

In thematic mapping, you have to make some key decisions, the most important one being how to display your data. When mapping a quantitative variable, we often have to "bin" this variable into groups. For example in the map we made below, the default binning applied was to display LSOAs grouped into those with a number of 0 to 10,000 crimes per 100,000 residents, then from 10,000 to 20,000, and so on. But why these? How were these groupings decided upon?

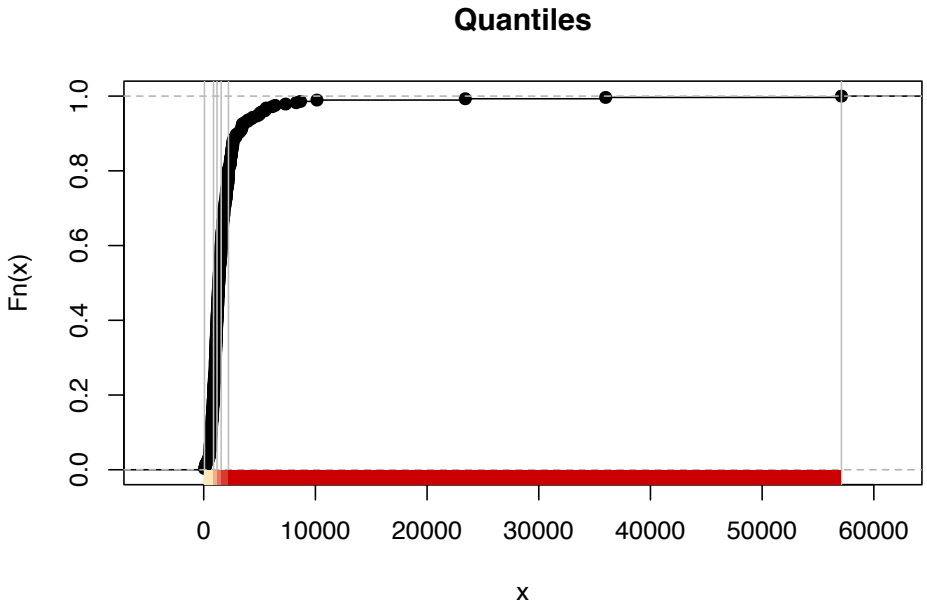
The quantitative information is usually classified before its symbolization in a thematic map. Theoretically, accurate classes that best reflect the distributional

character of the data set can be calculated. There are different ways of breaking down your data into classes:

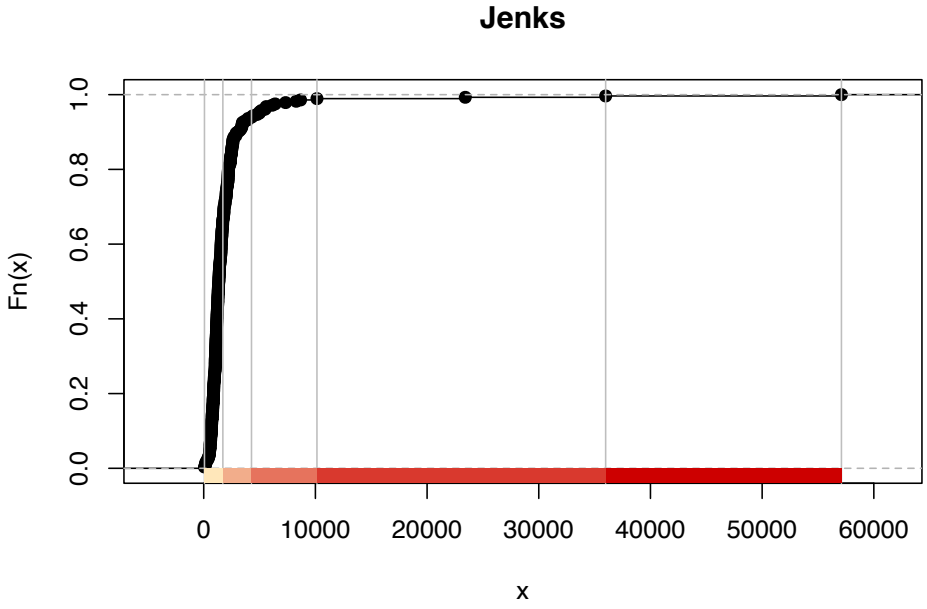
The equal interval (or equal step) classification method divides the range of attribute values into equally sized classes. What this means is that the values are divided into equal groups. Equal interval data classification subtracts the maximum value from minimum value in your plotted variable and then divides this by the number of classes to get the size of the intervals. This approach is best for continuous data. The range of the classes is structured so that it covers the same number of values in the plotted variable. With highly skewed variables this plotting method will focus our attention in areas with extreme values. When mapping crime it will create the impression that everywhere is safe, save a few locations. The graphic below shows five classes and the function shows the locations (represented by points) that fall within each class.



The quantile map bin the same count of features (areas) into each of its classes. This classification method places equal numbers of observations into each class. So, if you have five classes you will have 20 percent of the areas within each class. This method is best for data that is evenly distributed across its range. Here, given that our variable is highly skewed, notice how the top class includes areas with fairly different levels of crime, even if it does a better job at separating areas at the lower end of the crime rate continuum. Several authors consider that quantile maps are inappropriate to represent the skewed distributions of crime (**?**)

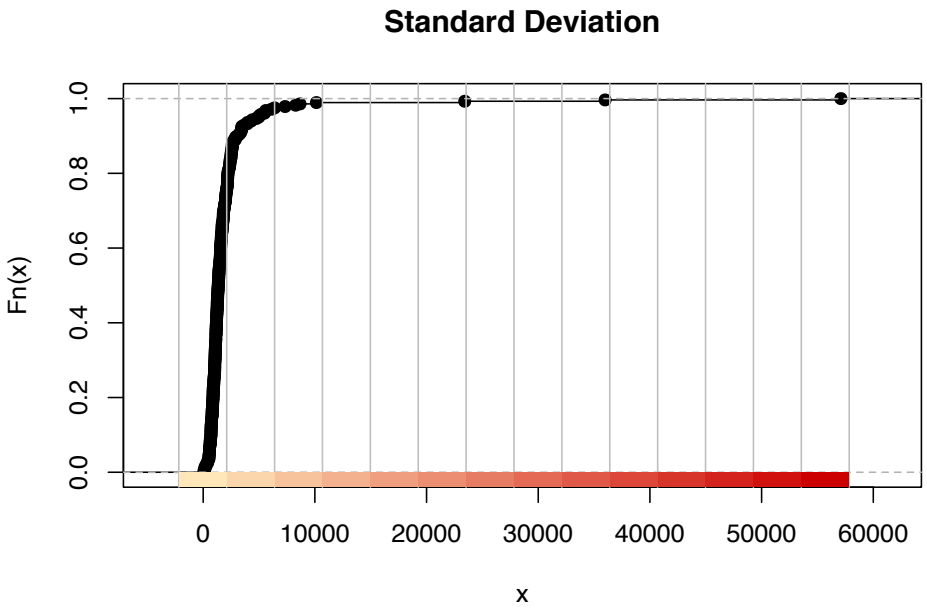


The natural breaks (or Jenks) classification method utilizes an algorithm to group values in classes that are separated by distinct break points. It is an optimisation method which takes an iterative approach to its groupings to achieve least variation within each class. Cartographers recommend to use this method with data that is unevenly distributed but not skewed toward either end of the distribution.

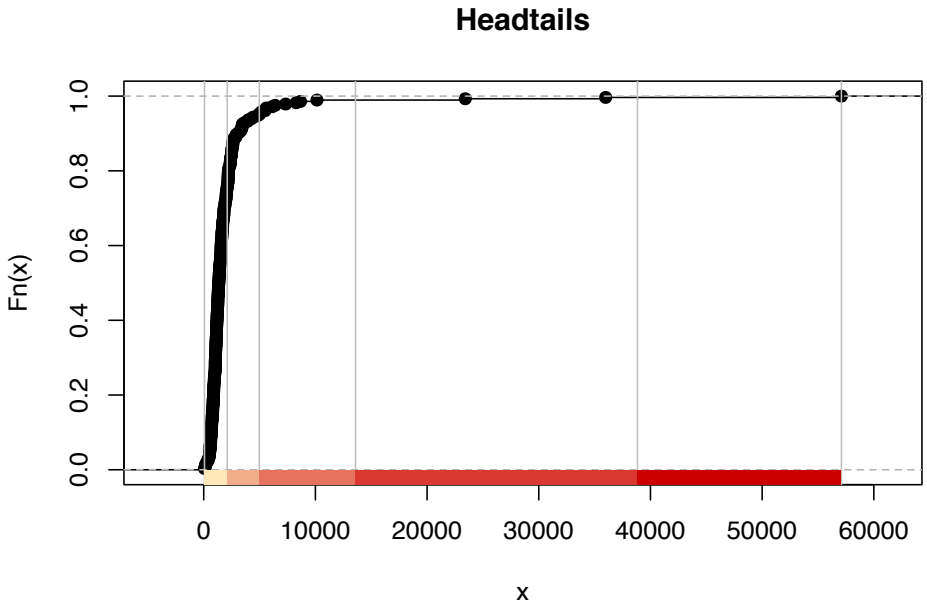


The standard deviation map uses the standard deviation (standardised mea-

sure of observations' deviation from the mean) to bin the observations into classes. This classification method forms each class by adding and subtracting the standard deviation from the mean of the dataset. It is best suited to be used with data that conforms to a normal distribution.



The headtails method This uses a method proposed by **?** as a solution for variables with a heavy tail distribution, like we often have with crime. "This new classification scheme partitions all of the data values around the mean into two parts and continues the process iteratively for the values (above the mean) in the head until the head part values are no longer heavy-tailed distributed. Thus, the number of classes and the class intervals are both naturally determined." (**?**, p. 482)



Not only you need to choose the classification method, you also need to decide on the number of classes. This is critical. The convention in cartography is to choose between 5 to 7 classes, although some authors would say 5 to 6 (**?**). Less than five and you loose detail, more than 6 or 7 and the audience looking at your map starts to have problems to perceive the differences in the symbology and to understand the spatial pattern displayed.

If you want to lie with a map, it would be very easy by using a data classification scheme that conveys the message that you want to get across. It is, thus, important that your decisions are based on good practice and are impartial.

For comparing the effects of using different methods we can use **small multiples**. Small multiples is simply a way of reproducing side by sides similar maps for comparative purposes. To be more precise small multiples are *sets of charts of the same type, with the same scale, presented together at a small size and with minimal detail, usually in a grid of some kind*. The term was at least popularized by Edward Tufte, appearing first in his *Visual Display of Quantitative Information* in 1983.

There are different ways of creating small multiples with `tmap` as you could see in the vignettes for the package, some of which are quicker but a bit more restricted. Here we are going to use `tmap_arrange()`. With `tmap_arrange()` first we need to create the maps we want and then we arrange them together.

Let's make five maps, each one using a different classification method: Equal interval, QUantile, Natural breaks (Jenks), Standard Deviation, and Headtails.

For each map, instead of visualising them one by one, just assign them to a new object. Let's call them *map1*, *map2*, *map3*, *map4*, *map5*.

So let's make *map1*. This will create a thematic map using equal intervals:

```
map1 <- tm_shape(manchester) +
  #Use tm_fill to specify variable, classification method,
  # and give the map a title
  tm_fill("crimr1", style="equal", title = "Equal") +
  tm_layout(legend.position = c("left", "top"),
            legend.title.size = 0.7,
            legend.text.size = 0.5)
```

Now create *map2*, with the jenks method often preferred by geographers:

```
map2 <- tm_shape(manchester) +
  tm_fill("crimr1", style="jenks", title = "Jenks") +
  tm_layout(legend.position = c("left", "top"),
            legend.title.size = 0.7,
            legend.text.size = 0.5)
```

Now create *map3*, with the quantile method often preferred by epidemiologists:

```
map3 <- tm_shape(manchester) +
  tm_fill("crimr1", style="quantile", title = "Quantile") +
  tm_layout(legend.position = c("left", "top"),
            legend.title.size = 0.7,
            legend.text.size = 0.5)
```

Let´s make *map4*, standard deviation map, which maps the values of our variable to distance to the mean value.

```
map4 <- tm_shape(manchester) +
  tm_fill("crimr1", style="sd", title = "Standard Deviation") +
  tm_layout(legend.position = c("left", "top"),
            legend.title.size = 0.7,
            legend.text.size = 0.5)
```

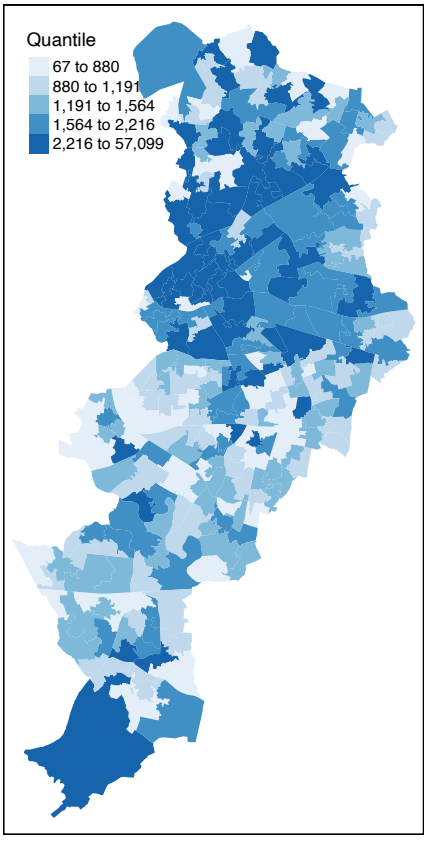
And finally let´s make *map5*, which is handy with skewed distributions.

```
map5 <- tm_shape(manchester) +
  tm_fill("crimr1", style="headtails", title = "Headtails") +
  tm_layout(legend.position = c("left", "top"),
            legend.title.size = 0.7,
            legend.text.size = 0.5)
```

Notice that we are not plotting the maps, we are storing them into R objects (map1 to map5). This way they are saved, and you can call them later, which is what we need in order to plot them together using the `tmap_arrange()` function.

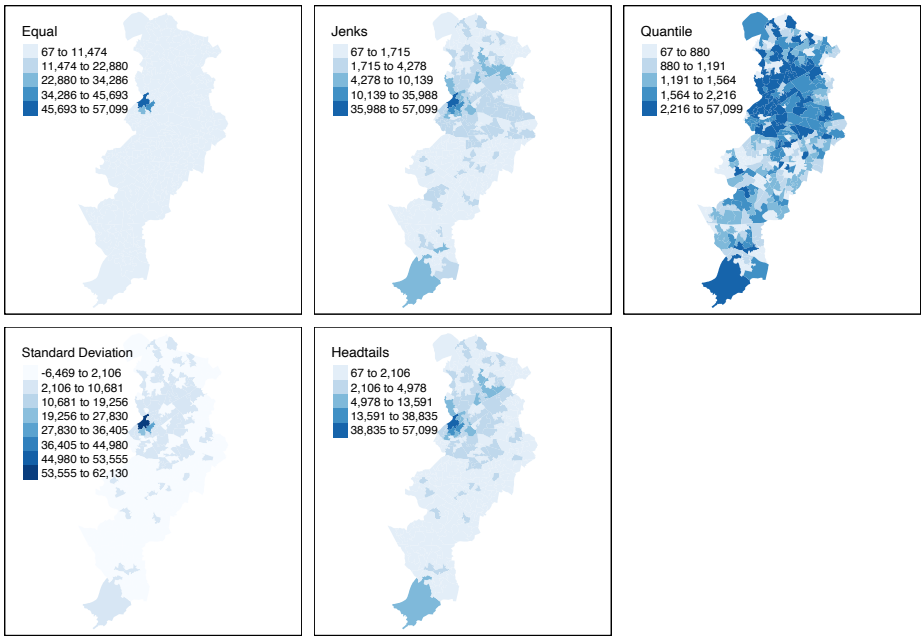
So if you wanted to map just *map3* for example, all you need to do, is call the map3 object. Like so:

```
map3
```



But now we will plot all 5 maps together, arranged using the `tmap_arrange()` function. Like so:

```
# deploy tmap_arrange to plot these maps together
tmap_arrange(map1, map2, map3, map4, map5)
```



As we can see using natural breaks (as the Jenks or Headtails method do, in different ways) to classify data is useful when mapping data values that are not evenly distributed, since it places value clusters in the same class. The disadvantage of using this approach is that it is often difficult to make comparisons between maps (for example of different crimes or for different time periods) since the classification scheme used is unique to each data set.

There are some other classification methods built into `tmap` which you can experiment with if you'd like. Your discrete gradient options are "cat", "fixed", "sd", "equal", "pretty", "quantile", "kmeans", "hclust", "bclust", "fisher", "jenks", "dpih", "headtails", and "log10_pretty". A numeric variable is processed as a categorical variable when using "cat", i.e. each unique value will correspond to a distinct category.

Taken from the help file we can find more information about these, for example the "kmeans" style uses kmeans clustering technique (a form of unsupervised statistical learning) to generate the breaks. The "hclust" style uses hclust to generate the breaks using hierarchical clustering and the "bclust" style uses bclust to generate the breaks using bagged clustering. These approaches are outisde the scope of what we cover, but just keep in mind that there are many different ways to classify your data, and you must think carefully about the choice you make, as it may affect your readers' conclusions from your map.

Imagine you were a consultant working for one of the political parties in the city of Manchester. Which map would you choose to represent to the electorate the situation of crime in the city if you were the party in control of the local government and which map you would choose if you were working for the opposition? As noted above, it is very easy to mislead with maps and, thus, this means the professional map maker has to abide by strict deontological criteria and take well justified impartial decisions when visualising data.

? suggests the following:

> "To know which classification scheme to use, an analyst needs to know how the data are distributed and the mapping objective. If the data are unevenly distributed, with large jumps in values or extreme outliers, and the analyst wants to emphasize clusters of observations that house similar values, use the natural breaks classification approach. If the data are evenly distributed and the analyst wants to emphasize the percentage of observations in a given classification category or group of categories, use the quantile classification approach. If the data are normally distributed and the analyst wants to represent the density of observations around the mean, use the equal interval approach. If the data are skewed and the analyst wants to identify extreme outliers or clusters of very high or low values, use the standard deviation classification approach."

0.27 Interactive mapping with tmap

So far we have been producing static maps with `tmap`. But this package also allows for interactive mapping by linking with leaflet. To change whether the plotted maps are static or interactive we need to use the `tmap_mode()` function. The default is `tmap_mode("plot")`, which corresponds to static maps. If we want to change to interactive display we need to change the argument we pass to `tmap_mode("view")`.

```
tmap_mode("view")
```

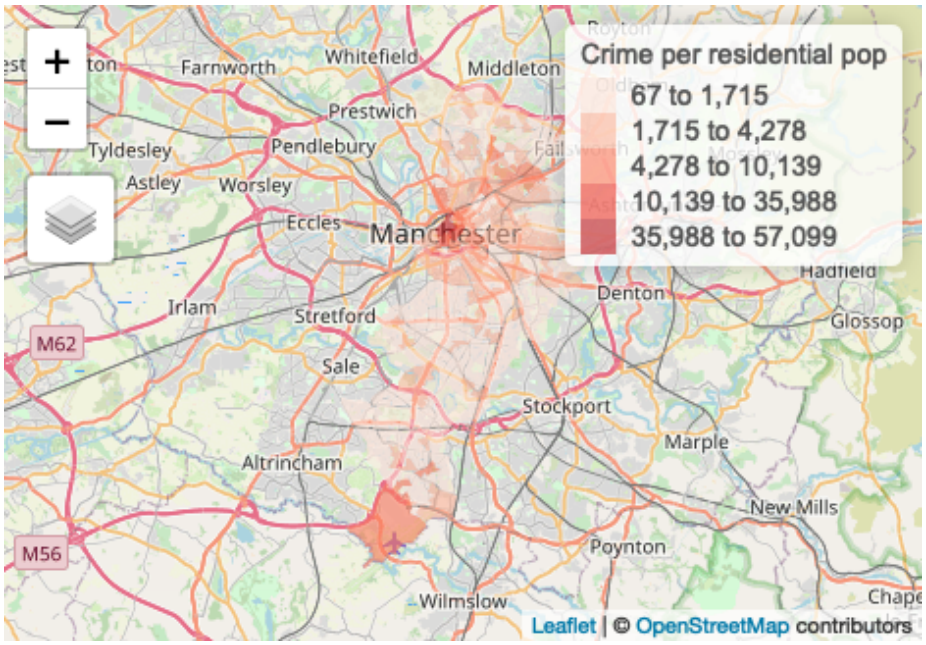
```
## tmap mode set to interactive viewing
```

When you use `tmap`, R will remember the mode you want to use. So once you specify `tmap_mode("view")`, all the subsequent maps will be interactive. It is only when you want to change this behaviour that you would need another `tmap_mode()` call. When using the interactive view we can also add a basemap with the `tm_basemap()` function and passing as an argument a particular source

for the basemap. Here we specify OpenStreetMap, but there are many other choices (for a complete listing and preview see `http://leaflet-extras.github.io/leaflet-providers/preview`).

Let´s explore the distribution of the two alternative definitions of crime rates with in an interactive way.

```
tm_shape(manchester) +
  tm_fill("crimr1", style="jenks", palette= "Reds",
          title = "Crime per residential pop", alpha = 0.6,
          ) +
  tm_basemap(leaflet::providers$OpenStreetMap)
```

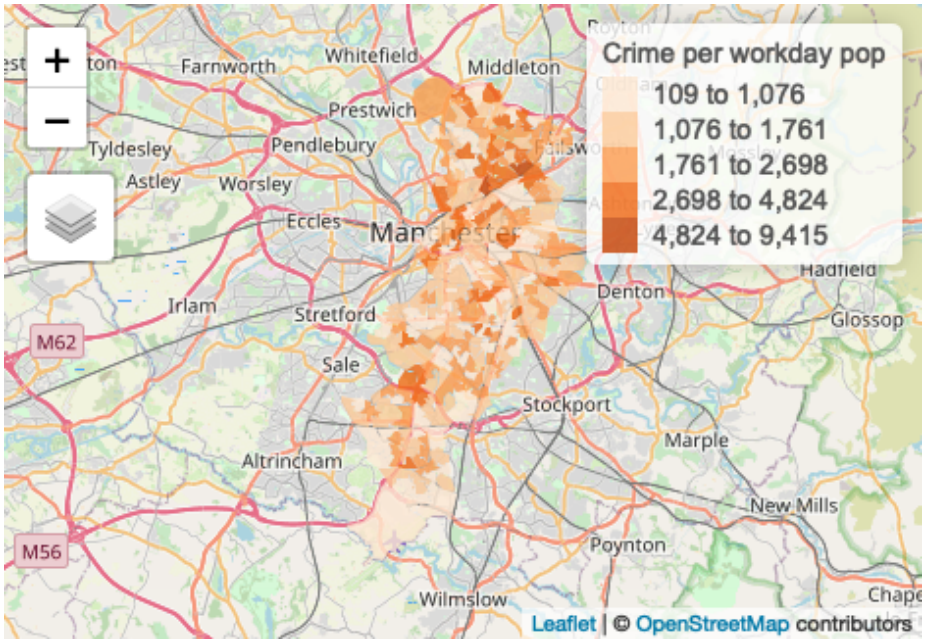


If we scroll down we can see that the crime rate is highest in the city centre of Manchester, but there are also pockets of high level of the crime rate in the North East of the city, Harpurhey and Moston (areas of high levels of deprivation) and in the LSOA farthest to the South (where the international airport is located).

What happens if we use the crime rate that uses the workday population?

```
tm_shape(manchester) +
  tm_fill("crimr2", style="jenks", palette= "Oranges",
          title = "Crime per workday pop", alpha = 0.8,
```

```
        ) +
  tm_basemap(leaflet::providers$OpenStreetMap)
```



Things look different, don´t they? For starters look at the values in the labels for the various classes. They are much less extreme. One of the reasons why we see such extreme rates in the first map is linked to the very large discrepancy between the residential population and the workday population in some parts of Manchester, like the international airport and the city centre (that attract very large volume of visitors). The LSOA with the highest crime rate (when using the residential population as the denominator) is E01033658.

```
filter(manchester, code=="E01033658")
```

```
## Simple feature collection with 1 feature and 7 fields
## Geometry type: POLYGON
## Dimension:     XY
## Bounding box:  xmin: 383304.1 ymin: 397889 xmax: 384344.6 ymax: 399194.4
## Projected CRS: OSGB 1936 / British National Grid
##       code count tothouse respop wkdpop                    geometry crimr1
## 1 E01033658   744     711   1303  42253 POLYGON ((384273.9 398999.7...  57099
##     crimr2
## 1 1760.822
```

We can see in this area there were 744 crime incidents for a residential population of 1303, but the workday population is as high as 42253 people. So, of course, using these different denominators is bound to have an impact in the resulting rate. As noted in criminology, using as a denominator some measure of the population at risk is most appropriate.

As noted by **?**: >"In the final analysis, although choropleth maps are very useful for visualizing spatial distributions, using them for hot spot analyses of crime has certain disadvantages. First, attention is often focused on the relative size of an area, so large areas tend to dominate the map. Second, choropleth maps involve the aggregation of data within statistical or administrative areas that may not correspond to the actual underlying spatial distribution of the data."

0.28 Smoothing rates: adjusting for small sample noise

In previous sections we discussed how to map rates. It seems a fairly straightforward issue, you calculate a rate by dividing your numerator (eg: number of crimes) by an appropriately selected denominator (eg: daytime population). You get your variable with the relevant rate and you map it using a choropleth map. However, things are not always that simple.

Rates are funny animals. **?** goes so far as to suggest that all maps of rates are misleading. The problem at hand is well known in spatial epidemiology: " plotting observed rates can have serious drawbacks when sample sizes vary by area, since very high (and low) observed rates are found disproportionately in poorly-sampled areas" (**?**, p. 3221). There is associated noise for those areas where the denominators give us a small sample size. And it is hard to solve this problem.

Let's illustrate with an example. We are going to use historic data on homicide across US counties. The dataset was used as the basis for the study by **?**. It contains data on homicide counts and rates for various decades across the US as well as information on structural factors often thought to be associated with violence. The data is freely available through the webpage of Geoda, a clever point-and-click interface developed by Luc Anselin (a spatial econometrician and coauthor of the above paper) and his team, to make spatial analysis accessible. It is also available as one of the packages in the `geodaData` package.

To read a data available in a library we have loaded we can use the `data()` function. If we check the `class()` of this object we will see it was already stored in `geodaData` as a `sf` object.

```
data("ncovr")
class(ncovr)
```

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

Let's look at the ncvor data. We can start by looking ath the homicide rate for 1960.

```
summary(ncovr$HR60)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   0.000   2.783   4.504   6.885  92.937
```

We can see that the county with the highest homicide rate in the 1960s had a rate of 92.937 homicides per 100,000 individuals. That is very high. Just to put it into context in the UK is about 0.92. Where is that place? I can tell you is a place called Borden. Check it out:

```
borden <- filter(ncovr, NAME == "Borden")
borden$HR60
```

```
## [1] 92.9368
```

Borden county (`https://en.wikipedia.org/wiki/Borden_County,_Texas`) in Texas. You may be thinking… "Texas Chainsaw Massacre" perhaps? No, not really. Ed Gein, who inspired the film, was based and operated in Wisconsin. Borden claim to fame is rather more prosaic: it was named after Gail Borden, the inventor of condensed milk. So, what's going on here? Why do we have a homicide rate in Borden that makes it look like a war zone? Is is that it is only one of the six counties where alcohol is banned in Texas (and people are consequently going nuts?).

Check this out too:

```
borden$HC60
```

```
## [1] 1
```

What? A total homicide count of 1. How can a county with just one homicide have a rate that makes it look like the most dangerous place in the US?

```
borden$PO60
```

```
## [1] 1076
```

Well, there were about 1076 people living there.

```
summary(ncovr$PO60)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     208    9417   18408   57845   39165 7781984
```

If you contrast that population count with the population of the average county in the US, that's tiny. One homicide in such a small place can end up producing a big rate. Remember that the rate is simply dividing the number of relevant events by the exposure variable (in this case population) and multiplying by a constant (in this case 100,000 since we expressed crime rates in those terms). Most times Borden looks like a very peaceful place:

```
borden$HR70
```

```
## [1] 0
```

```
borden$HR80
```

```
## [1] 0
```

```
borden$HR90
```

```
## [1] 0
```

It has a homicide rate of 0 in most decades. But it only takes one homicide and, bang, it goes top of the league. So a standard map of rates is bound to be noisy. There is the instability that is introduced by virtue of having areas that may be sparsely populated and in which one single event, like in this case, will produce a very noticeable change in the rate.

In fact, if you look at the counties with the highest homicide rate in the "ncovr" dataset you will notice all of them are places like Borden, areas that are sparsely populated, not because they are that dangerous, but because of the instability of rates. Conversely the same happens with those places with the lowest rate. They tend to be areas with a very small sample size.

This is a problem that was first noted by epidemiologists doing disease mapping. But a number of other disciplines have now noted this and used some of the approaches developed by public health researchers that confronted this problem when producing maps of disease (PRO TIP: techniques and approaches used by spatial epidemiologists are very similar to those used by criminologists -in case you ever think of changing careers or need inspiration for how to solve a crime analysis problem).

One way of dealing with this is by **smoothing** or **shrinking** the rates. This basically as the word implies aims for a smoother representation that avoids hard spikes associated with random noise. There are different ways of doing that. Some ways use a non-spatial approach to smoothing, using something called a **empirical bayesian smoother**. How does this work? This approach takes the raw rates and tries to "shrunk" them towards the overall average. What does this mean? Essentially, we compute a weighted average between the raw rate for each area and the global average across all areas, with weights proportional to the underlying population at risk. What this procedure does is to have the rates of smaller areas (those with a small population at risk) to have their rates adjusted considerably (brought closer to the global average), whereas the rates for the larger areas will barely change.

Here we are going to introduce the approach implemented in `DCluster`, a package developed for epidemiological research and detection of [clusters of disease.

```
res <- empbaysmooth(ncovr$HC60, ncovr$PO60)
```

In the new object we generate, which is a list, you have an element which contains the computed rates. We can add those to our dataset:

```
ncovr$HR60EBS <- res$smthrr * 100000
```

Instead of shrinking to the global rate, we can shrink to a rate based on the neighbours of each county. Shrinking to the global rate ignores the spatial dimension of the phenomenon being mapped out and may mask existing heterogeneity. If instead of shrinking to a global rate, we shrink to a local rate, we may be able to take unobserved heterogeneity into account. **?** proposed a local smoother estimator in which the crude rate is shrunk towards a loca, "neighbourhood", rate. To compute this we need the list of neighbours that surround

each county (we will discuss this code in the Chapter on Spatial Dependence, so for now just trust us we are computing the rate of the areas that surround each country):

```
ncovr_sp <- as(ncovr, "Spatial")
w_nb <- poly2nb(ncovr_sp, row.names=ncovr_sp$FIPSNO)
eb2 <- EBlocal(ncovr$HC60, ncovr$PO60, w_nb)
ncovr$HR60EBSL <- eb2$est * 100000
```

We can now plot the maps and compare them:

```
tmap_mode("plot")
```

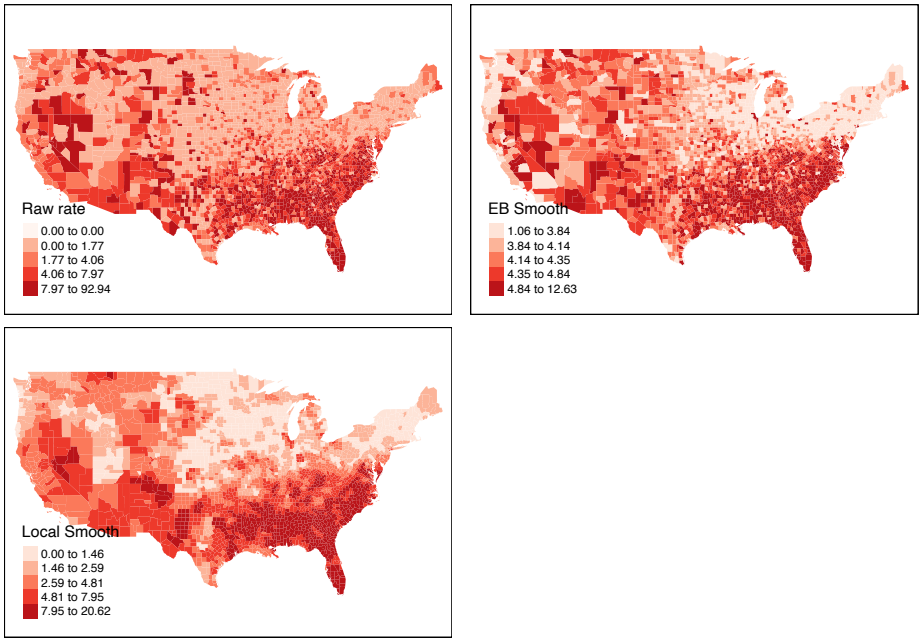
```
## tmap mode set to plotting
```

```
current_style <- tmap_style("col_blind")
```

```
## tmap style set to "col_blind"

## other available styles are: "white", "gray", "natural", "cobalt", "albatross", "beaver", "bw", '
```

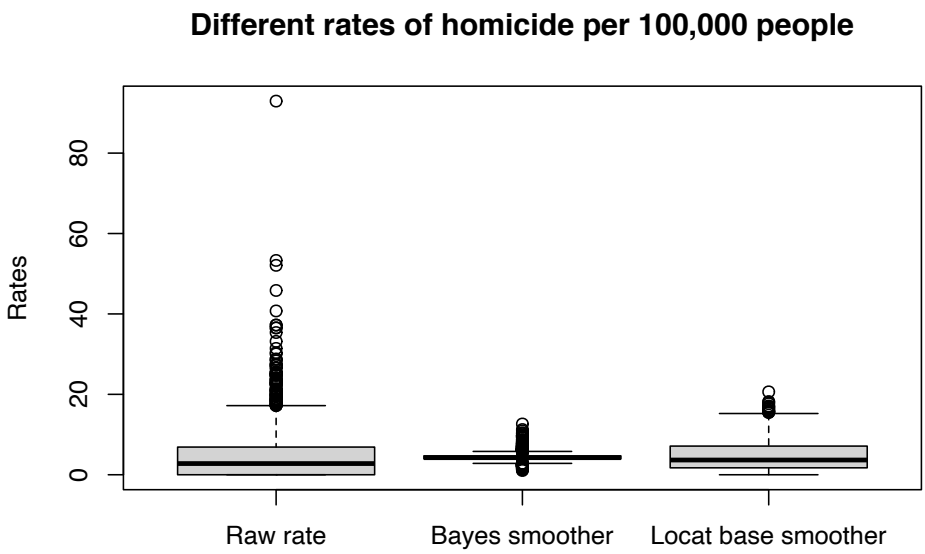
```
map1<- tm_shape(ncovr) +
  tm_fill("HR60", style="quantile",
          title = "Raw rate",
          palette = "Reds") +
  tm_layout(legend.position = c("left", "bottom"),
            legend.title.size = 0.8,
            legend.text.size = 0.5)

map2<- tm_shape(ncovr) +
  tm_fill("HR60EBS", style="quantile",
          title = "EB Smooth",
          palette = "Reds") +
  tm_layout(legend.position = c("left", "bottom"),
            legend.title.size = 0.8,
            legend.text.size = 0.5)
```

```
map3<- tm_shape(ncovr) +
  tm_fill("HR60EBSL", style="quantile",
          title = "Local Smooth",
          palette = "Reds") +
  tm_layout(legend.position = c("left", "bottom"),
            legend.title.size = 0.8,
            legend.text.size = 0.5)

tmap_arrange(map1, map2, map3)
```



Notice that the quantiles are not the same, so that will make your comparison difficult. Let´s look at a boxplot of these variables. In the map of raw rates we have the most variation.

```
#Boxplots with base R graphics
boxplot(ncovr$HR60, ncovr$HR60EBS, ncovr$HR60EBSL,
        main = "Different rates of homicide per 100,000 people",
        names = c("Raw rate",
                  "Bayes smoother",
                  "Locat base smoother"),
        ylab = "Rates")
```



The range for the raw rates is nearly 93. Much of the variation in observed homicide rates by county is attributable to statistical noise due to the small number of (observed and expected) homicides in low-population counties. Because of this noise, a disproportionate fraction of low-population counties are observed to have extremely high (or low) homicide rates when compared to typical counties in the United States. The second distribution shows that everything has been brought closer to the main mean, whereas the local smoother allows for a bit more variation. The general Bayes smoother has the opposite problem of mapping out the raw rates, it likely hides existing spatial variation. If you contrast the maps you will see how this results in a clearer and smoother spatial pattern for the rate that is estimated borrowing information from their neighbours.

So to smooth or not too smooth? Clearly we can see how smoothing stabilises the rates and removes noise. But as **?** suggests this introduces other artifacts and autocorrelation into our estimates. Some people are also not too keen on maps of statistically adjusted estimates. Yet, the conclusions one can derive from mapping raw rates (*when* the denominator varies significantly and we have areas with small sample size) means that smoothing is often a preferable alternative (**?**). The problem we have with maps of estimates is that we need information about the variability and it is hard to map this out in a convenient way (**?**). **?** (p. 38), in relation to the similar problem of disease mapping, suggests that "at the minimum any map of relative risk for a disease should be accompanied with information pertaining to estimates of rates within each region as well as estimates of variability within each region" whereas "at the other extreme it could be recommended that such maps be only used as a presentational aid, and not as a fundamental decision-making tool".

0.29 Summary and further reading

This chapter introduced some basic principles of thematic maps. We learned how to make them using the `tmap` package, we learned about the importance of classification schemes, and how each one may produce a different looking map, which may tell a different story. For further reading, **?** provides a brief condensed introduction to thematic mapping for epidemiologists but that can be generally extrapolated for crime mapping purposes. We have talked about the potential to develop misleading maps and **?** "How to lie with maps" provides good guidance to avoid that our negligent choices when producing a map confuse the readers. **?** offers a more detailed treatment of small multiples and micromaps.

Mapping rates has been more thoroughly discussed within spatial epidemiology than in criminology. There is ample literature on disease mapping that address in more sophisticated ways some of the issues we introduce here (see **?**, **?**, **?**, or **?**). Much of this work on spatial epidemiology adopts a Bayesian framework. We will talk a bit more about this later on, but if you want a friendly introduction to Bayesian data analysis there is no better introduction than **?**.

Variations of thematic mapping

0.30 Introduction

In this chapter are going to discuss some additional features around thematic maps. Specifically, we will address some of the problems we confront when we are trying to use use choropleth maps, as well as some alternatives to point based maps. We will also briefly introduce the modifiable area unit problem.

The main objectives for this chapter are that by the end you will have:

- Explored **binning** as an alternative to point maps.
- Been introduced to alternative visualisations of polygon-level data such as
  - **cartograms**, and
  - **bi-variate** thematic maps.
- Gained an insight into the **Modifiable Areal Unit Problem**

In this chapter, we will be making use of the following libraries:

```
# Packages for reading data and data carpentry
library(readr)
library(dplyr)
library(tidyr)

# Packages for handling spatial data and for geospatial carpentry
library(sf)

# Packages for mapping and visualisation
library(ggplot2)
library(ggspatial)
library(cartogram)
```

0.31 Binning points

In GIS it is often difficult to present point-based data because in many instances there are several different points and data symbologies that need to be shown. As the number of different data points grows they can become complicated to interpret and manage which can result in convoluted and sometimes inaccurate maps. This becomes an even larger problem in web maps that are able to be depicted at different scales because smaller scale maps need to show more area and more data. This makes the maps convoluted if multiple data points are included.

In many maps there are so many data points included that little can be interpreted from them. In order to reduce congestion on maps many GIS users and cartographers have turned to a process known as binning.

> **Binning** is defined as the process of grouping pairs of locations based on their distance from one another. These points can then be grouped as categories to make less complex and more meaningful maps.

Researchers and practitioners often require a way to systematically divide a region into equal-sized portions. As well as making maps with many points easier to read, binning data into regions can help identify spatial influence of neighbourhoods, and can be an essential step in developing systematic sampling designs.

This approach to binning generates an array of repeating shapes over a user-specified area. These shapes can be hexagons, squares, rectangles, triangles, circles or points, and they can be generated with any directional orientation.

0.31.1 The Binning Process

Binning is a data modification technique that changes the way data is shown at small scales. It is done in the pre-processing stage of data analysis to convert the original data values into a range of small intervals, known as a bin. These bins are then replaced by a value that is representative of the interval to reduce the number of data points.

Spatial binning (also called *spatial discretization*) discretizes the location values into a small number of groups associated with geographical areas or shapes. The assignment of a location to a group can be done by any of the following methods: - Using the coordinates of the point to identify which “bin” it belongs to. - Using a common variable in the attribute table of the bin and the point layers.

0.31.2 Different Binning Techniques

Binning itself is a general term used to describe the grouping of a dataset's values into smaller groups (Johnson, 2011[7]). The bins can be based on a variety of factors and attributes such as spatial and temporal and can thus be used for many different projects.

0.31.2.1 Choropleth maps

You might be thinking, "grouping points into a larger spatial unit, haven't we already done this when making choropleth maps?". In a way you are right. Choropleth maps are another type of map to that uses binning. Proportional symbol and choropleth maps group similar data points together to show a range of data instead of many individual points. We've covered this extensively, and is often the best approach to consider spatial grouping of your point variables, because the polygons (shapes) to which you are aggregating your points are *meaningful*. You can group into LSOAs because you want to show variation in neighbourhoods. Or you can group into police force areas because you want to look at differences between those units of analysis. But sometimes there is just not a geography present to meet your needs.

Let's say you are conducting some days of action in Manchester city centre, focusing on antisocial behaviour. You are going to put up some information booths and staff them with officers to engage with the local population about antisocial behaviour. For these to be most effective, as an analyst you decide that they should go into the areas with the highest *count* of antisocial behaviour. You want to be very specific about where you put these as well, and so LSOA level would be too broad, you want to zoom in more. One approach can be to split central Manchester into some smaller polygons, and just calculate the number of antisocial behaviour incidents recorded in each. That way you can then decide to put your information booths somewhere inside the top 5 highest count bins.

0.31.2.2 Rectangular binning

The aggregation of incident point data to regularly shaped grids is used for many reasons such as normalizing geography for mapping or to mitigate the issues of using irregularly shaped polygons created arbitrarily (such as county boundaries or block groups that have been created from a political process). Regularly shaped grids can only be comprised of equilateral triangles, squares, or hexagons, as these three polygon shapes are the only three that can tessellate (repeating the same shape over and over again, edge to edge, to cover an area without gaps or overlaps) to create an evenly spaced grid.

[7] http://indiemaps.com/blog/2011/10/hexbins/

Rectangular binning is the simplest binning method and as such it heavily used. However, there are some reasons why rectangular bins are less preferable over hexagonal bins. Before we cover this, let's have a look at hexagonal bins.

0.31.2.3 Hexagonal binning

In many applications binning is done using a technique called **hexagonal binning**. This technique uses hexagon shapes to create a grid of points and develops a spatial histogram that shows different data points as a range or group of pairs with common distances and directions. In hexagonal binning the number of points falling within a particular rectangular or hexagon in a gridded surface is what makes the different colors to easily visualize data (Smith, 2012)[8]. Hexagonnal binning was first developed in 1987 and today "hexbinning" is conducted by laying a hexagonal grid on top of 2-dimensional data (Johnson, 2011)[9]. Once this is done users can conduct data point counts to determine the number of points for each hexagon (Johnson, 2011)[10]. The bins are then symbolized differently to show meaningful patterns in the data.

So how can we use hexbinning to solve our antisocial behaviour days of action task? Well let's say we split Manchester city centre into hexagons, and count the number of antisocial behaviour instances in these. We can then identify the top hexagons, and locate our booths somewhere within these.

First make sure you have the appropriate packages loaded. Also let's get some data. You could go and get this data yourself from police.uk, we've been through all the steps for downloading data from there a few times now. But for now, we have a tidied set of data ready for you. This data is one year's worth of antisocial behaviour from the police.uk[11] data, from May 2016 to May 2017, for the borough of Manchester.

The data are included in the supplementary material, and also available on our GitHub page.

```
manchester_asb <- read_csv("data/manchester_asb.csv")
```

This is currently just a text dataframe, so we need to let R know that actually this is a spatial object, who's geometry can be find in its longitude and latitude coordinates. As we have long/lat we can assure it's in WGS 84 projection.

[8] https://www.mapbox.com/blog/binning-alternative-point-maps/
[9] http://indiemaps.com/blog/2011/10/hexbins/
[10] http://indiemaps.com/blog/2011/10/hexbins/
[11] data.police.uk

```
ma_spatial <- st_as_sf(manchester_asb,
                       coords = c("Longitude", "Latitude"),
                       crs = 4326,
                       agr = "constant")
```

Now one thing that this does is it consumes our Long and Lat columns into a geometry attribute. This is generally OK, but for the binning we will do, we would like to have them as separate coordinates. To do this, we can use the `st_coordinates()` function from the `sf` package. This function extracts the longitude and latitude from the geometry within the sf object, in this case "ma_spatial" object. For example, if we look at the first row:

```
ma_spatial %>%
  slice(1) %>%
  st_coordinates()
```

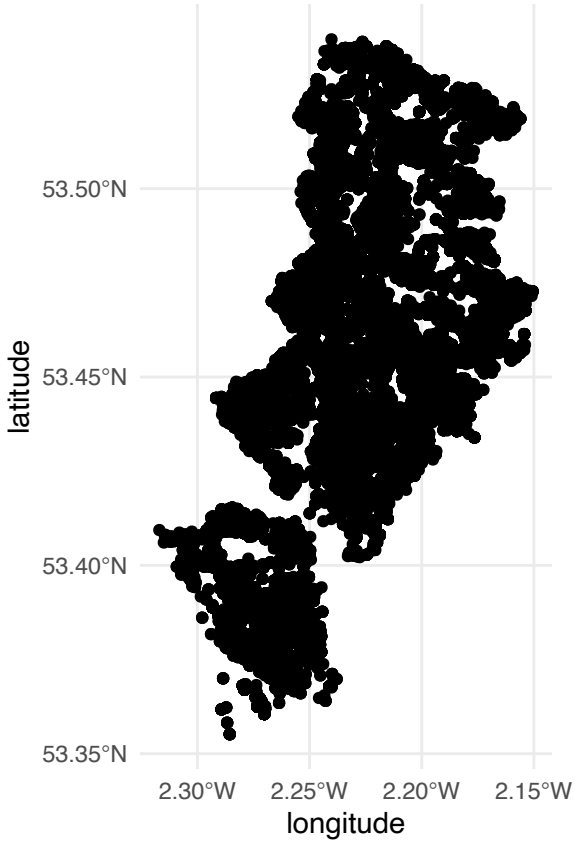
```
##           X        Y
## 1 -2.228809 53.53493
```

We have our longitude (X) and latitude (Y). We can select the first and second element of this to get only one or the other. To go through our whole dataframe, we can use the `mutate()` function, and assign each element to a longitude and latitude column respectively:

```
ma_spatial <- ma_spatial %>%
  mutate(longitude = st_coordinates(.)[,1],
         latitude = st_coordinates(.)[,2])
```

As a first step, we can plot asb in the borough of Manchester using simple ggplot, as demonstrated in Chapter 1. We can plot our points first:

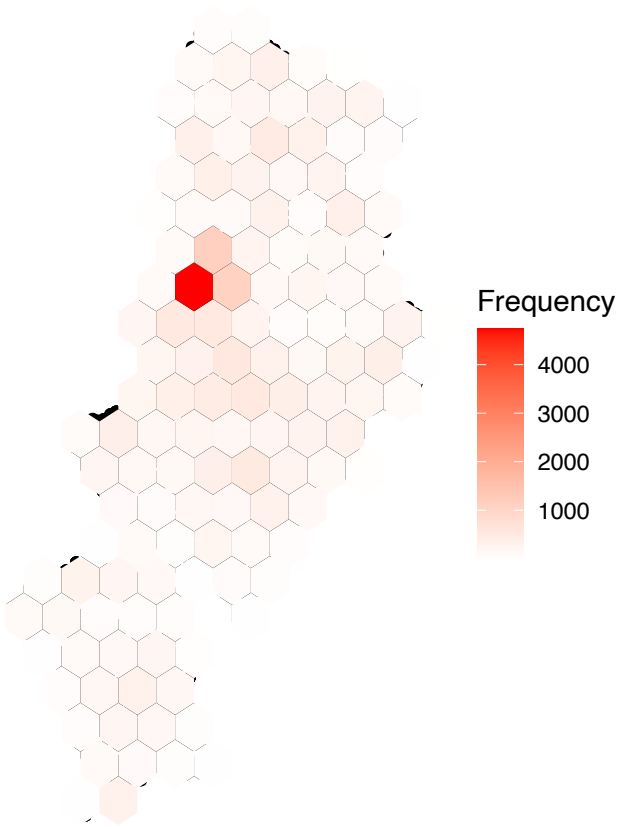
```
ggplot(ma_spatial, aes(x = longitude, y = latitude)) +
  geom_sf() +
  theme_minimal()
```



We see our nice map of Manchester, as outlined by ASB across the Local Authority. To create a bin of this map, what we do, is generate a grid of tessellating map of our desired shape, and then count the number of points which fall into each one of these shapes. We can use 'ggplot for this. It is such a great tool for building visualisations, because you can apply whatever geometry best suits your data. So for us to just have a look at the hexbinned version of our point data of antisocial behaviour, we can use the `stat_binhex()` function as a layer on our ggplot object. We can also recreate the thematic map element, as we can use the frequency of points in each hex to shade each hexbin from white (least number of incidents) to red (most number of incidents). So let's have a go:

```
#define data and variables for x and y axes
ggplot(ma_spatial, aes(longitude, latitude)) +
  # plot geometry with geom_sf()
  geom_sf() +
  #add binhex layer (hexbin) set bin size (in degrees)
  stat_binhex(binwidth = c(.015, .01)) +
  #add shading based on number of ASB incidents
```

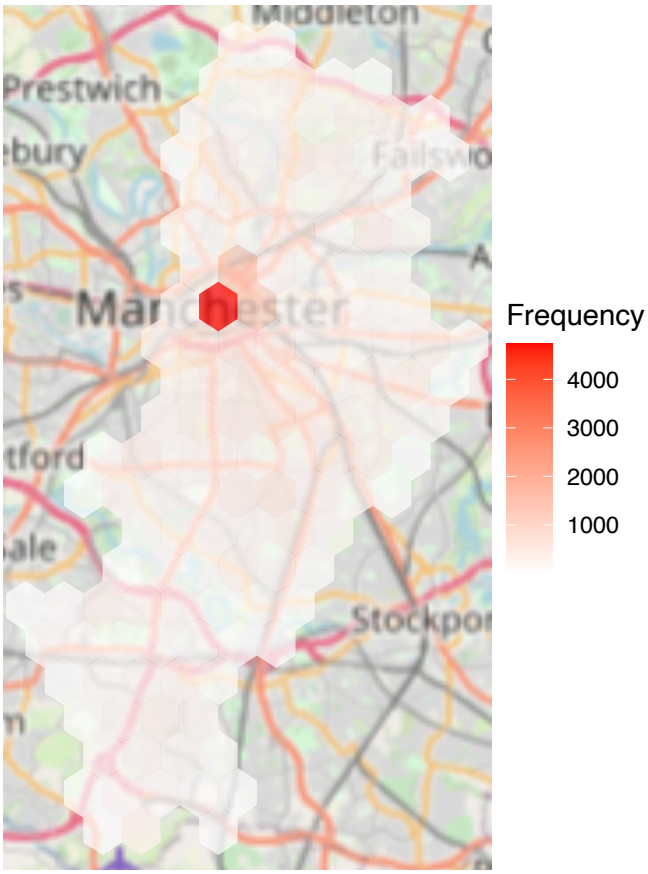
```
  scale_fill_gradientn(colours = c("white","red"),
                       name = "Frequency")  +
  theme_void()
```



Neat, but doesn't quite tell us *where* that really dark hexbon actually is. So it would be much better if we could do this with a basemap as the background. For this we use the function `annotation_map_tile()` from the `ggspatial` package. We can also set the opacity of the binhex layer, so we can see our basemap, with the `alpha` parameter.

```
ggplot(ma_spatial, aes(x = longitude, y = latitude)) +
  annotation_map_tile() +
  stat_binhex(binwidth = c(.015, .01), alpha=0.7) +   # set opacity
  scale_fill_gradientn(colours = c("white","red"),
                       name = "Frequency")   +
  theme_void()
```

```
## Zoom: 10
```

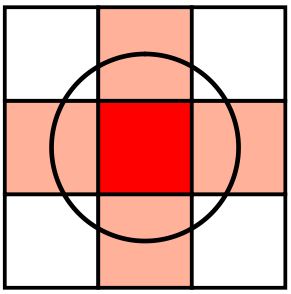


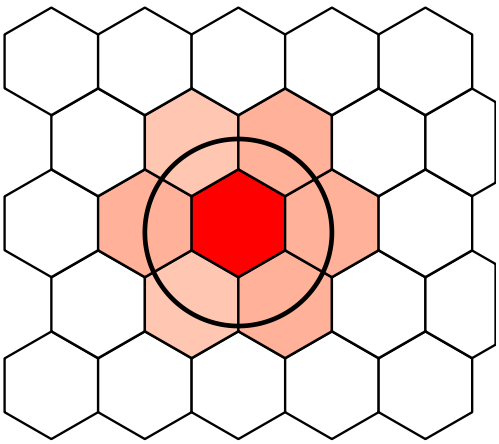
Adding this basemap provides us with a bit more context. And combined with the hexbin map, it is much easier to see where in Manchester borough Antisocial Behaviour concentrates (as opposed to with the point map!). Above we used a hexagon shape for our binning, however you might choose other shapes as well. I will illustrate in a moment the approach to use rectangular binning, but first, I want to highlight why hexagon might still be your ideal choice. Here are some thoughts:

- Hexagons reduce sampling bias due to edge effects[12] of the grid shape. The edge effects of bounded space refers to the problem of truncated data that can skew the results of subsequent analyses (we'll get to this in the next section). This is related to the low perimeter-to-area ratio of the shape of the hexagon. A circle has the lowest ratio but cannot tessellate to form a continuous grid. Hexagons are the most circular-shaped polygon that can tessellate to form an evenly spaced grid.

[12] https://link.springer.com/chapter/10.1007/978-0-387-09688-9_5

- This circularity of a hexagon grid allows it to represent curves in the patterns of your data more naturally than square grids.
- When comparing polygons with equal areas, the more similar to a circle the polygon is, the closer to the centroid the points near the border are (especially points near the vertices). This means that any point inside a hexagon is closer to the centroid of the hexagon than any given point in an equal-area square or triangle would be (this is due to the more acute angles of the square and triangle versus the hexagon).
- Hexagons are preferable when your analysis includes aspects of connectivity or movement paths. Due to the linear nature of rectangles, fishnet grids can draw our eyes to the straight, unbroken, parallel lines which may inhibit the underlying patterns in the data. Hexagons tend to break up the lines and allow any curvature of the patterns in the data to be seen more clearly and easily. This breakup of artificial linear patterns also diminishes any orientation bias that can be perceived in fishnet grids.
- If you are working over a large area, a hexagon grid will suffer less distortion due to the curvature of the earth than the shape of a fishnet grid.
- Finding neighbors is more straightforward with a hexagon grid. Since the edge or length of contact is the same on each side, the centroid of each neighbor is equidistant. However, with a fishnet grid, the Queen's Case (above/below/right/left) neighbor's centroids are N units away, while the centroids of the diagonal (Rook) neighbors are farther away (exactly the square root of 2 times N units away).
- Since the distance between centroids is the same in all six directions with hexagons, if you are using a distance band to find neighbors or are using the Optimized Hot Spot Analysis, Optimized Outlier Analysis or Create Space Time Cube By Aggregating Points tools, you will have more neighbors included in the calculations for each feature if you are using hexagonal grid as opposed to a fishnet grid.





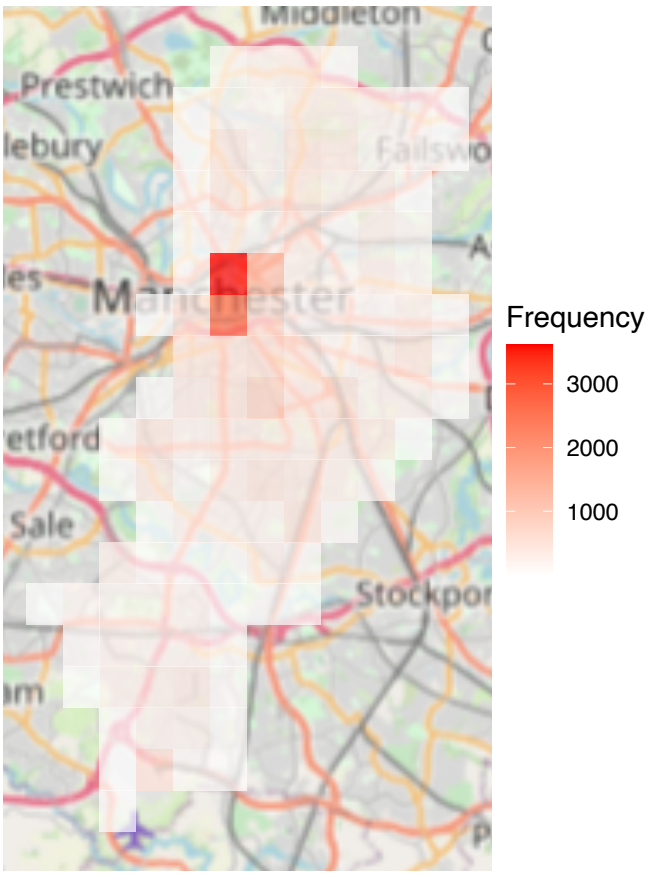
To illustrate the differences of different approaches, let's see what this map

would look like with:

a) rectangular binning:

```
ggplot(ma_spatial, aes(x = longitude, y = latitude)) +
  annotation_map_tile() +
  stat_bin2d(binwidth = c(.015, .01), alpha=0.7) +
  scale_fill_gradientn(colours = c("white","red"),
                       name = "Frequency") +
  theme_void()
```

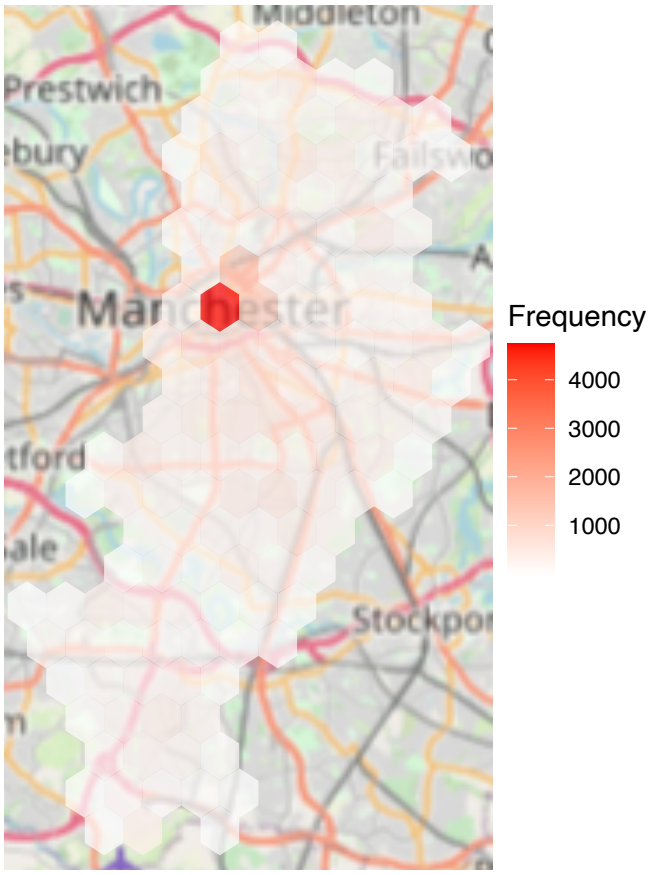
```
## Zoom: 10
```



b) hexagonal binning:

```
ggplot(ma_spatial, aes(x = longitude, y = latitude)) +
  annotation_map_tile() +
  stat_binhex(binwidth = c(.015, .01), alpha=0.7) +
  scale_fill_gradientn(colours = c("white","red"),
                       name = "Frequency") +
  theme_void()
```

```
## Zoom: 10
```

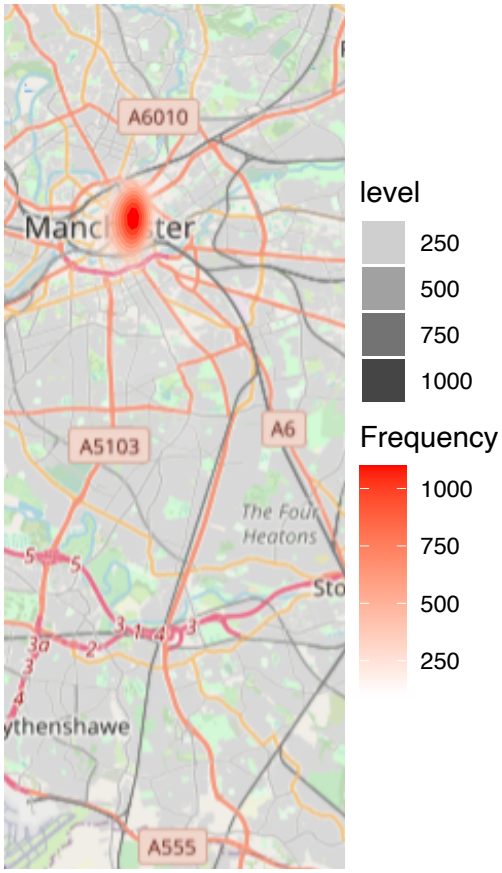


c) a simple "heatmap" (we will discuss these more thoroughly in Chapter 6):

```
ggplot(ma_spatial, aes(x = longitude, y = latitude)) +
  annotation_map_tile() +
```

```
  stat_density2d(aes(fill = ..level.., # value corresponding to
                                       # discretized density estimates
                     alpha = ..level..),
                 geom = "polygon") +  # creates the bands of
                                      # different colours
  ## Configure the colours, transparency and panel
  scale_fill_gradientn(colours = c("white","red"),
                       name = "Frequency") +
  theme_void()
```

```
## Zoom: 11
```



0.31.3 Benefits of Binning

Because of the plethora of data types available and the wide variety of projects being done in GIS, binning is a popular method for mapping complex data and

making it meaningful. Binning is a good option for map makers as well as users because it makes data easy to understand and it can be both static and interactive on many different map scales. If every different point were shown on a map it would have to be a very large scale map to ensure that the data points did not overlap and were easily understood by people using the maps. According to Kenneth Field, an Esri Research Cartographer:

> "Data binning is a great alternative for mapping large point-based data sets which allows us to tell a better story without interpolation. Binning is a way of converting point-based data into a regular grid of polygons so that each polygon represents the aggregation of points that fall within it."

By using binning to create categories of data maps are easier to understand, more accurate and more visually appealing. Hexbin plots can be viewed as an alternative to scatter plots. The hexagon-shaped bins were introduced to plot densely packed sunflower plots. They can be used to plot scatter plots with high-density data.

0.32 Transforming polygons

When you have meaningful spatial units of analysis in your polygons, for example you are interested specifically in Local Autorities, it might make sense to stick with what we did last week, and aggregate the points into these polygons to create thematic maps. However, while thematic maps are an accessible and visually appealing method for displaying spatial information, they can also be highly misleading. Irregularly shaped polygons and large differences in the size of areas being mapped can introduce misrepresentation. The message researchers want to get across might be lost, or even worse, misdirect the viewers to erroneous conclusions. **?** provide a helpful discussion of the problem illustrating the case with UK election maps. It is worth reading.

Fortunately, there are many methods in R to enhance the legibility of geographic information and the interpretability of what it is trying to be communicated. Selecting the appropriate method might depend on the research question being posed (e.g. clustering) and the data itself. Even once a method has been selected, there are different ways of operationalising them. Here we focus on **cartograms**. A cartogram is is "a thematic map of a set of features (countries, provinces, etc.), in which their geographic size is altered to be directly proportional to a selected ratio-level variable, such as travel time, population, or GNP" (Wikipedia).

Let's explore this using the example of the results of the 2016 EU referendum at Local Authority level, where remain areas clustered in London. A simple thematic map does not necessarily communicate this well because Local Authorities are both small and densely populated in London.

You can download the full set of EU referendum result data as a csv from the Electoral Commission webside[13]. We've already done this and included in our data folder. Let's read it straight into R:

```
eu_ref <- read_csv("data/EU-referendum-result-data.csv")
```

We also need a spatial object to join this to. See the appendix on how to source boundary data for more detail on how we can find relevant boundary data for our analyses. For now, we can use the data which comes with this book from the supplementary materials. Specifically the shapefile for English Local Authorities. This file is called `england_lad_2011_gen.shp` and is found in the `England_lad_2011_gen` subfolder.

```
las <- st_read("data/England_lad_2011_gen/england_lad_2011_gen.shp")
```

```
## Reading layer `england_lad_2011_gen' from data source `/Users/reka/Desktop/crime_mapping/crime
## Simple feature collection with 326 features and 4 fields
## Geometry type: MULTIPOLYGON
## Dimension:     XY
## Bounding box:  xmin: 82644.8 ymin: 5349.399 xmax: 655976.9 ymax: 657599.5
## Projected CRS: OSGB 1936 / British National Grid
```

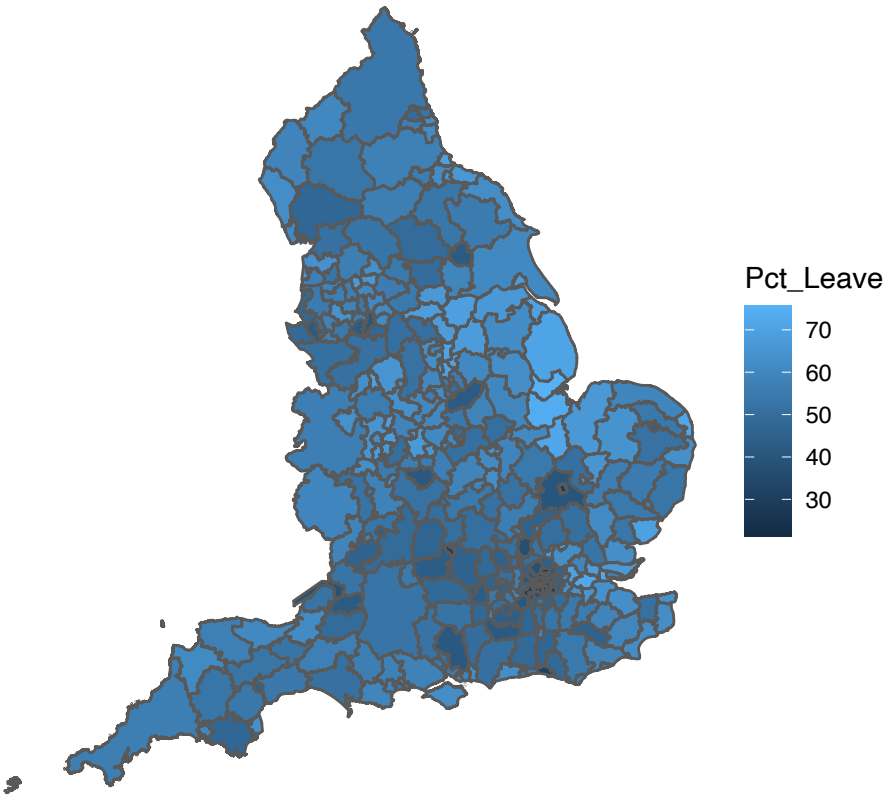
We can now join the EU referendum data using the attribute operation `left_join()`, as we have illustrated in detail in Chapter 1.

```
eu_sf <- left_join(las, eu_ref, by = c("name" = "Area"))

#make sure we are in British National Grid Projection
eu_sf <- st_transform(eu_sf, 27700)
```

Now we can have a look at these data:

```
ggplot() +
  geom_sf(data = eu_sf, aes(fill = Pct_Leave)) +
  theme_void()
```

[13] https://www.electoralcommission.org.uk/find-information-by-subject/elections-and-referendums/past-elections-and-referendums/eu-referendum/eu-referendum-result-visualisations



The Local Authorities vary greatly in their shape and size, and in the case of smaller LAs the result is barely visible. In this case, we cannot really see what was happening with the EU referendum in London, for example. This is the sort of situationwhere augmenting our polygons may be handy. Cartograms offer one way to achieve this.

There are different types of cartograms. **Density-equalizing (contiguous) cartograms** are your traditional cartograms. In density-equalizing cartograms, map features bulge out a specific variable. Even though it distorts each feature, it remains connected during its creation. On the other hand, you can have **Non-Contiguous Cartograms**, where features in non-contiguous cartograms don't have to stay connected. Finally, **Dorling Cartograms** (named after professor Danny Dorling[14]) use shapes like circles and rectangles to depict area. These types of cartograms make it easy to recognize patterns.

We can explore cartograms using the `cartogram` package. Within that we will use the `cartogram()` function. In this function, we will specify two parameters: 1 - `shp =`, which asks for the shape file (it can be a SpatialPolygonDataFrame or an sf object), and 2 - `weight =`, which asks for the variable which it should use to distort the polygon by.

[14] `https://www.geog.ox.ac.uk/staff/ddorling.html`

In our data set we have a variable "Electorate" which refers to the total number of registered electors in that Local Authority. It serves to give an indicator of the total number of people who were eligible to vote in the referendum. We can use this variable to distort our polygons and create our cartogram.

```
eu_cartogram <- cartogram(eu_sf, "Electorate")
```

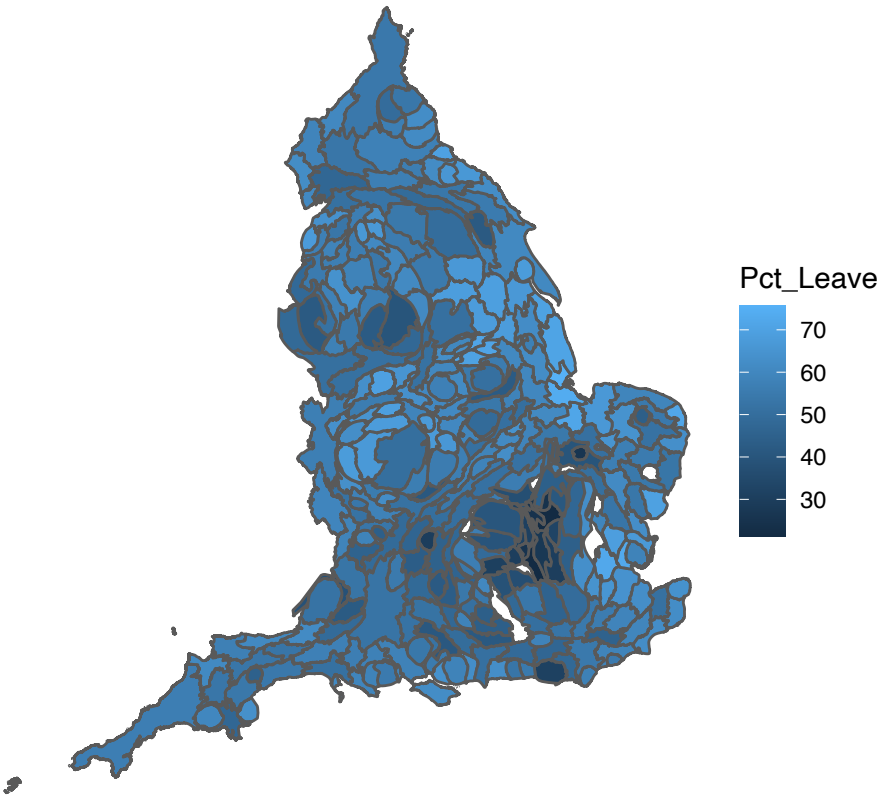
If you run this, it might take a long time. This function, while it looks nice and simple, is actually very computationally taxing for your computer. For those interested, you may like to take the time while R works this out for you to read up on the maths behind this transformation in **?** (it's got a fun name: a rubber sheet distortion algorithm!).

I do have a tip for you if you want to make sure the process does not take too long. You can set another parameter in the cartogram function which is the `itermax=` parameter. This specifies the maximum number of iterations we are happy to sit through for our cartogram. If you do not specify it's set to 15. Let's set to 5 for the sake of speed:

```
# construct a cartogram using the percentage voting leave
eu_cartogram <- cartogram_cont(eu_sf, "Electorate", itermax = 5)
```

This will be faster (but may not result in the best possible cartogram output). Once your cartogram has been created, you can now plot again the referendum results, but using the electorate to change the size of the Local Authority:

```
ggplot() +
  geom_sf(data = eu_cartogram, aes(fill = Pct_Leave)) +
  theme_void()
```



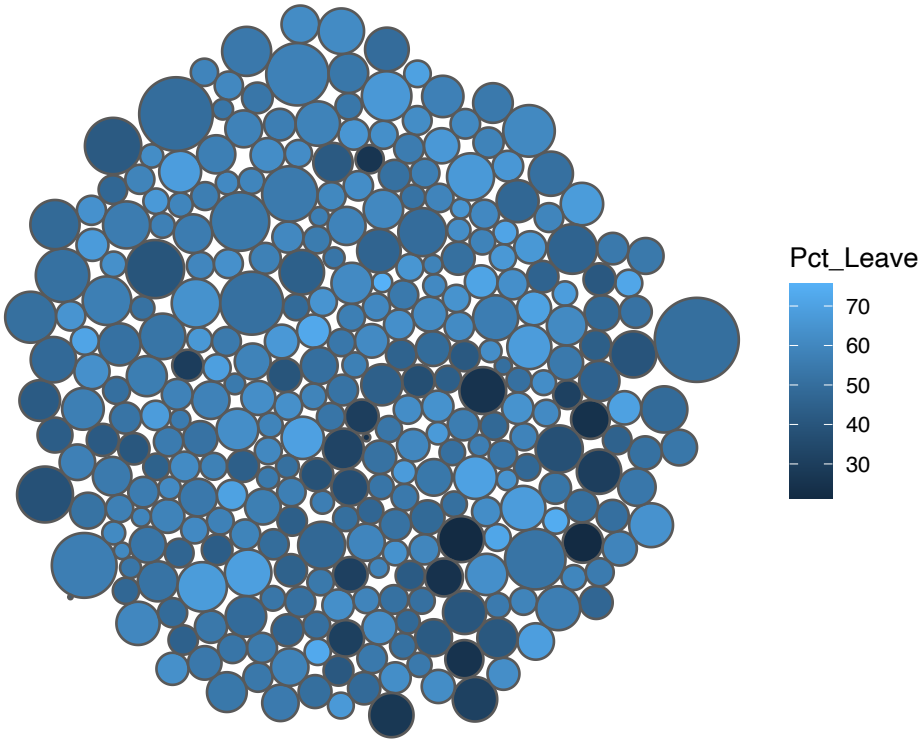
We can now see London much better, and see that darker coloured cluster where much smaller percentage of people voted leave. We can eye-ball where London may be, as this continuous area cartogram tries to maintain some fidelity to our original shapes, while weighting them by some variable of interest, in our case the electorate in each Local Authority.

0.32.1 Dorling Cartogram

While the continuous area cartogram we created above tries to maintain some fidelity to our original shapes, other approaches take more freedom when applyign transformations. Sometimes, maintaining a resemblance to the original geometry of each polygon may not be important. In that case, you might be interested in creating a **Dorling cartogram**.

```
# construct a Dorling cartogram using the percentage voting leave
eu_dorling_cartogram <- cartogram_dorling(eu_sf, "Electorate")
```

```
ggplot() +
  geom_sf(data = eu_dorling_cartogram, aes(fill = Pct_Leave)) +
  theme_void()
```



This map has transformet each Local Authority's shape into a circle, where the radius is determined as a function of the variable we supplied, which is our Electorate in each LA. The shading here is again provided by the percentage of people who voted to leave in each area, with lighter values indicating more people voting to leave, and darker values indicating fewer people voting to leave the EU. However, the relations of these Local Authorities is tough to maintain here, and I may be hard-pressed to identify London's boroughs out of this collection. However, Dorling cartograms may have their use and place. You may read up more about them in **?** .

0.33 Bivariate Maps

Usually in your thematic maps you are mapping one variable. For example in the maps above, we mapped the distribution of the percepntage who voted to leave the European Union (the `Pct_Leave` variable). But occasionally, you might

want to use your map to illustrate the relationship between *two* variables. In this case, you may want to create a **Bivariate Choropleth Map**. Bivariate choropleths follow the same concept as the univariate ones (which display only one variable), except they show two variables at once. This is achieved through the creative use of colour.

We first came across the idea of bivariate choropleth maps from the blog of **?**. I recommend having a read as he discusses in great detail how to develop the colour schemes necessary for these maps. The idea is that there are two main colours, each one representing gradual change in one of our two variables of interest. Then, these two colours are combined to create an overlapping colour scheme.

The process itself is not too complicated. We start with binning our two variables into classes. If we bin variable 1 into n classes, and then again variable 2 into n classes, then when we compare them across one another to create our bivariate map, we will end up with n^2 classes. For example, if we bin both variables into 3 classes (low, medium, high), then when displaying them together, we will have 9 classes to visualise. **?** blog illustrates with nice visuals, so I recommend having a look. However the practical example is in QGIS, and here we are working in R. There had been adaptations into R (eg see **?**) which we can borrow from here too.

Creating the map boils down to 5 key steps. First, we take our two variables of interest, and create bins. Second, we create a new variable, which we will use for the shading. Third we create our colour scheme. Fourth, we join this to our sf object. And, finally we map! Let's go through these steps now. Using the example of voting to leave the EU.

It may be an interesting question to look into not only how the voting outcome was distributed (`Pct_Leave`) but how this varies with voter turnout (`Pct_Turnout`). We might be interested in areas with high turnout and high or percentage on voting to leave, as these may be areas where people felt passionately. On the other hand, other areas may have had low turnout, which may have influenced the result, and in those places, were people who did turn out voting to leave or remain? These are the kinds of questions we can answer with a bivariate map.

0.33.1 Step 1: Bin our variables of interest

We are interested in two key variables, `Pct_Leave` - the percentage of people who voted to leave the EU, and `Pct_Turnout` - the percentage of the electorate who actually voted. These are both numeric continuous variables. In order to create our bivariate choropleth map, we have to bin these values into n discrete categories. Here let's go with $n = 3$.

We can use the `cut()` and the `quantile()` functions in base R to class our variable into three quantiles. The `quantile()` function identifies the sample

quantiles in a continuous variable. We need to include the parameters `x=`: the numeric vector whose sample quantiles are wanted (in this case our variables `Pct_Leave` and `Pct_Turnout`), and `probs=`: numeric vector of probabilities with values in [0,1]. We can use the sequence generator function `seq()` to generate these from 0 to 1, by the increment of $\frac{1}{3}$ for 3 groups.

So first, let's create the breaks first for the `Pct_Leave` variable.

```
leave_breaks <- quantile(eu_sf$Pct_Leave,
                         probs = seq(0,1, by = 1/3), # probabilities
                         na.rm=TRUE, # remove NAs
                         names=TRUE, # keep names attribute
                         include.lowest=TRUE) # include value equal to
                                              # lowest 'breaks' value
```

And then the same again but for the turnout variable `Pct_Turnout`.

```
tunrout_breaks <- quantile(eu_sf$Pct_Turnout,
                           probs = seq(0,1, by = 1/3),
                           na.rm=TRUE,
                           names=TRUE,
                           include.lowest=TRUE)
```

We can have a look at the output:

```
leave_breaks
```

```
##        0% 33.33333% 66.66667%      100%
##  21.38000  51.72000  59.12333  75.56000
```

The results are the cutoff values which we want to use to "cut" our numeric variable. We do this with the `cut()` function, where we specify again what to cut (the variables `Pct_Leave` and `Pct_Turnout`), and the breaks at which to cut (the objects we created above, `leave_breaks` and `tunrout_breaks`):

```
eu_sf <- eu_sf %>%
  mutate(leave_quantiles = cut(Pct_Leave,
                               breaks = leave_breaks),
         turnout_quantiles = cut(Pct_Turnout,
                                 breaks = tunrout_breaks))
```

We have two resulting variables, `leave_quantiles` and `turnout_quantiles` which classify each one of our observations into one of these quartiles for both the variables. In the next step, we use these to create a new variable.

0.33.2 Step 2: New variable

This step is really quite easy. What we want to do is create a new variable, this time let's call it `group`, which tells us which quartile the specific Local Authority (each row) falls into. By applying the `as.numeric()` function we translate the ranges of the quartile into their label (i.e. 1, 2, or 3rd quartile). We do this for both variables, and paste them together using the `paste()` function, and the separator "-":

```
eu_sf <- eu_sf %>%
  mutate(group = paste(
      as.numeric(turnout_quantiles), "-",
      as.numeric(leave_quantiles))
    )
```

We now have a new column, called group, which tells us for each Local Authority, which quartile it falls into for each variable. For example, a value of "1 - 1" means the Local Authority belongs to the first quartile in both variables. This area would be considered to have low percent voting leave, and also low turnout. On the other hand, "3 - 1" means that there was high turnout, but a low percentage voted to leave. We use this variable to assign the appropriate colour for our colour scheme for each of the 3^2 (9) combinations.

0.33.3 Step 3: Create colour scheme

Picking a colour scheme which reflects both gradual change in each individual variable, and the combined change in both is not an easy task! Luckily **?** has created some scale recommendations for us to choose from. I copy two of them below, but you can see the blog for another 2 options.

In this code below, I simply specify for each of the 9 values of the variable created in the previous step ("1 - 1", "1 - 2", "1 - 3", "2 - 1", … "3 - 3") an associated colour using the relevant hex code.

```
library(tibble)

bivariate_color_scale_1 <- tibble(
```

```
  "3 - 3" = "#574249", # high - high
  "2 - 3" = "#985356",
  "1 - 3" = "#c85a5a", # low - high
  "3 - 2" = "#627f8c",
  "2 - 2" = "#ad9ea5", # medium - medium
  "1 - 2" = "#e4acac",
  "3 - 1" = "#64acbe", # high - low
  "2 - 1" = "#b0d5df",
  "1 - 1" = "#e8e8e8" # low - low
) %>%
  gather("group", "fill_col")

bivariate_color_scale_2 <- tibble(
  "3 - 3" = "#3b4994", # high - high
  "2 - 3" = "#5698b9",
  "1 - 3" = "#5ac8c8", # low - high
  "3 - 2" = "#8c62aa",
  "2 - 2" = "#a5add3", # medium - medium
  "1 - 2" = "#ace4e4",
  "3 - 1" = "#be64ac", # high - low
  "2 - 1" = "#dfb0d6",
  "1 - 1" = "#e8e8e8" # low - low
) %>%
  gather("group", "fill_col")
```

You can have a look at both these, and see which one you like. Feel free to use either in your future bivariate mapping adventures. Or construct your own, perhaps following the two additional ones provided by **?**, or some entirely news ones you may have constructued.

0.33.4 Step 4: Join colour scheme

Now that we have a colour scheme, we can join to the spatial object, using `left_join()`. The common element is the `group` variable, so with this approach, we join the relevant colour to each value of group in that column. Let's join `bivariate_color_scale_2`, the second of the two we created above.

```
eu_sf <- left_join(eu_sf, bivariate_color_scale_2, by = "group")
```

We now have an additional column in our `eu_sf` dataframe which

0.33.5 Step 5: Create legend

The legend is a little tricky, as we need to separate out the values into separate Leave and Turnout columns. We can achieve this with the `separate()` function

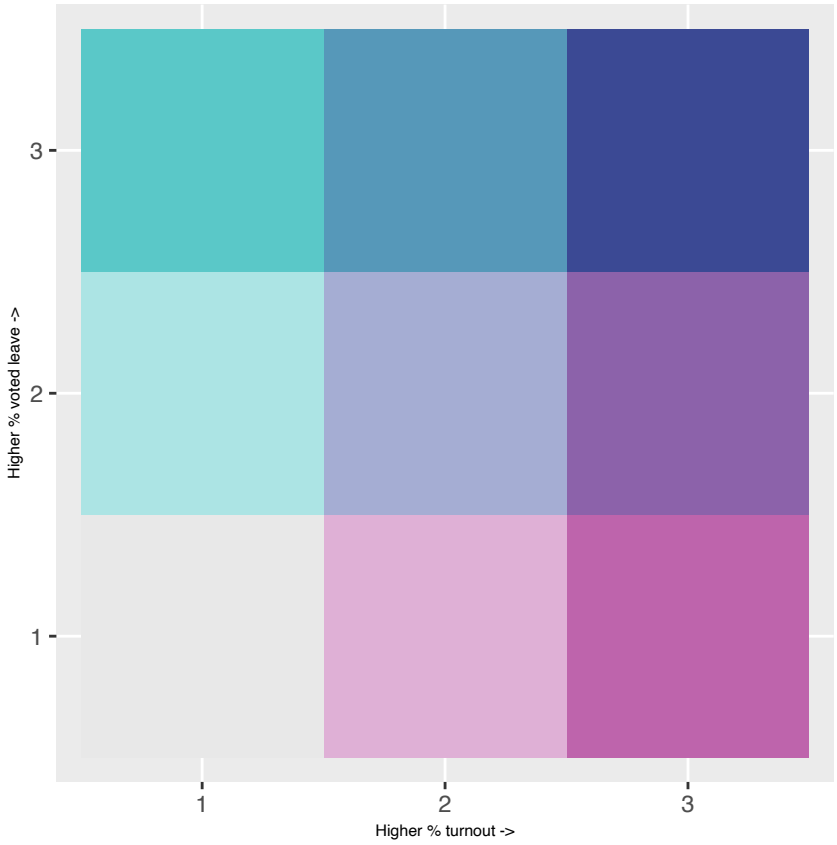
```
# separate the groups
bivariate_color_scale <- bivariate_color_scale_2 %>%
  separate(group,
           into = c("Pct_Turnout", "Pct_Leave"), sep = " - ")
```

Then to create the legend, we actually build a `ggplot()` object. This genius bit of code is borrowed from **?** implementation of bivariate choropleth maps.

```
legend <- ggplot() +
  geom_tile( data = bivariate_color_scale,
             aes(x = Pct_Turnout, y = Pct_Leave, fill = fill_col)) +
  scale_fill_identity() +
  labs(x = "Higher % turnout ->",
       y = "Higher % voted leave ->") +
  theme(axis.title = element_text(size = 6)) + # makes text small for
                                               # adding legend to map
  coord_fixed()  # forces a specified ratio to create quadratic tiles
```

This code returns the legend as a chart itself. Have a look what it looks like:

```
legend
```



0.33.6 Step 6: Map

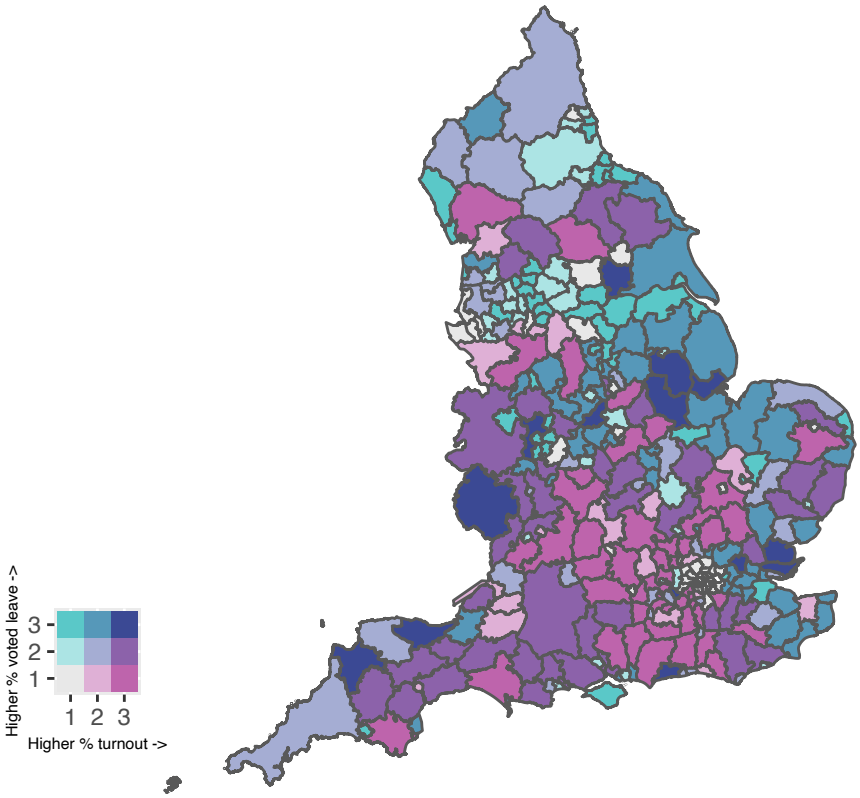
Now finally we put it all on the map. For the choropleth map, we use our variable `fill_col` which contains the matched colour to the group that each observation belongs to. We pass this in the familiar `geom_sf()` geometry and use the `fill=` parameter to colour the Local Authorities according to their turnout / voted leave combination. We also have to add the `scale_fill_identity()` function, as the values in the `fill_col` variable are actually the hex codes for the colour which we use to shade the Local Authorities.

```
map <- ggplot(eu_sf) +
  geom_sf(aes( fill = fill_col)) +
  scale_fill_identity() +
  theme_void()
```

Finally, to display the legend and the map together, we can use the `ggdraw()`

and `draw_plot()` functions from the `cowplot` package.

```
library(cowplot)
ggdraw() +
  draw_plot(map, 0, 0, 1, 1) +
  draw_plot(legend, 0.05, 0.075, 0.2, 0.2)
```



This map may now be able to provide insight into spatial patterns in turnout and voting to leave. For example, in the South you can see lots of pink, representing areas of high turnout and low % voting to leave the EU. You can also spot the dark blue areas, these are Local Authorities which saw high voter turnout and a high proportion voting to leave.

Overall these maps can help visualise two variables on one map, and motivate discussion about relationships between variables in different places.

0.34 A note of caution: MAUP

Now that we've shown you how to do a lot of spatial crime analysis, we wanted to close with some words of caution. Remember that everything you've learned here are just tools that you will be applying to data you are working with, but it's up to you, the researcher, the analyst, the domain expert, to apply and use these with careful consideration and cautions. This discussion is very much part of spatial crime analysis, and an important field of thought.

We borrow here from George Renghert and Brian Lockwood:

> When spatial analysis of crime is conducted, the analyst should not ignore the spatial units that data are aggregated into and the impact of this choice on the interpretation of findings. Just as several independent variables are considered to determine whether they have statistical significance, a consideration of multiple spatial units of analysis should be made as well, in order to determine whether the choice of aggregation level used in a spatial analysis can result in biased findings. **?**

In particular, they highlight four main issues inherent in most studies of space:

- issues associated with politically bounded units of aggregation,
- edge effects of bounded space
- the modifiable aerial unit problem (MAUP)
- and ways in which the results of statistical analyses can be manipulated by changes in the level of aggregation.

0.34.0.1 Scale

The scale problem involves results that change based on data that are analyzed at higher or lower levels of aggregation (Changing the number of units). For example, evaluating data at the state level vs. Census tract level.

The scale problem has moved to the forefront of geographical criminology as a result of the recent interest in small-scale geographical units of analysis. It has been suggested that smaller is better since small areas can be directly perceived by individuals and are likely to be more homogenous than larger areas. - Gerell, Manne. "Smallest is better? The spatial distribution of arson and the modifiable areal unit problem." Journal of quantitative criminology 33.2 (2017): 293-318.[15]

[15] https://link.springer.com/article/10.1007/s10940-016-9297-6

0.34.0.2 Zone

The zonal problem involves keeping the same scale of research (say, at the state level) but changing the actual shape and size of those areas.

The basic issue with the MAUP is that aggregate units of analysis are often arbitrarily produced by whom ever is in charge of creating the aggregate units. A classic example of this problem is known as Gerrymandering. Gerrymandering involves shaping and re-shaping voting districts based on the political affiliations of the resident citizenry.

The inherent problem with the MAUP and with situations such as Gerrymandering is that units of analysis are not based on geographic principles, and instead are based on political and social biases. For researchers and practitioners the MAUP has very important implications for research findings because it is possible that as arbitrarily defined units of analysis change shape findings based on these units will change as well.

When spatial data are derived from counting or averaging data within areal units, the form of those areal units affects the data recorded, and any statistical measures derived from the data. Modifying the areal units therefore changes the data. Two effects are involved: a zoning effect arising from the particular choice of areas at a given scale; and an aggregation effect arising from the extent to which data are aggregated over smaller or larger areas. The modifiable areal unit problem arises in part from edge effect. If you're interested, in particular about politics and voting, you can read this interesting piece to learn more about gerrymandering[16]

0.34.1 Why does MAUP matter?

The practical implications of MAUP are immense for almost all decision-making processes involving GIS technology, since with the availability of aggregated maps, policy could easily focus on issues and problems which might look different if the aggregation scheme used were changed.

All studies based on geographical areas are susceptible to MAUP. The implications of the MAUP affect potentially any area level data, whether direct measures or complex model-based estimates. Here are a few examples of situations where the MAUP is expected to make a difference, taken from **?**.

- The special case of the ecological fallacy is always present when Census area data are used to formulate and evaluate policies that address problems at individual level, such as deprivation. Also, it is recognised that a potential source of error in the analysis of Census data is 'the arrangement of continuous space into defined regions for purposes of data reporting'

[16] https://projects.fivethirtyeight.com/redistricting-maps/

- The MAUP has an impact on indices derived from areal data, such as measures of segregation, which can change significantly as a result of using different geographical levels of analysis to derive composite measures .
- The choice of boundaries for reporting mortality ratios is not without consequences: when the areas are too small, the values estimated are unstable, while when the areas are too large, the values reported may be over-smoothed, i.e. meaningful variation may be lost.

0.34.2 What can we do?

Most often you will just have to remain aware of the MAUP and its possible effects. There are some techniques, that can help you address these issues, and the chapter pointed out at the beginning of this section is a great place to start to explore these. It is possible to use also an alternative, zone-free approach to mapping these crime patterns, perhaps by using kernel density estimation. Here we model the relative density of the points as a density surface - essentially a function of location (x,y) representing the relative likelihood of occurrence of an event at that point. We have covered KDE elsewhere in this course.

For now, it's enough that you know of, and understand the MAUP and its implications. Always be smart when choosing your appropriate spatial unit of analysis, and when you use binning of any form, make sure you consider how and if your conclusions might change compared to another possible approach.

0.35 Summary and further reading

In this chapter we explored the use of binning points into hexbins and rectangular grids, as well as transforming polygons in order to enhanche the legibility of your maps. For some more information on binning see **?**. For transforming polygons, read **?** and **?**. We can also suggest a read of **?** and check out this video from SAGE methods **?**.

To read up more on the Modifiable Areal Unit Problem (MAUP) in general, we recommend the original **?**. For some criminology/ crime mapping specific reading try **?** and **?**.

Visualisation: good cartographic design

0.36 Introduction

This chapter aims to focus on introducing good practice in map design and presentation. When putting a map together you need to think about its intended audience (their level of expertise, whether you want them to interact with the map), purpose, and format of delivery (e.g., printed, web, projected in a screen, etc). There are many design decisions you need to consider: fonts, labels, colour, legends, layout, etc. In this chapter we provide a general introduction to some basic design principles for map production. These themes, and the appropriate election of symbol representation, are the subject matter of cartography, the art and science of map making. Within cartography a considerable body of research and scholarship has focused on studying the visual and psychological implications of our mapping choices. As noted on previous chapters one of the problems with maps is that powerful as a tool as they, they can lead to misunderstanding. What the mapmaker chooses to emphasise and what the map reader see may not be the same thing. We will work you through an example of a fairly basic map and the process of taking to a point where it could be ready for presentation to an audience other that yourself.

In this chapter we will be working with some data published by Hungarian police available online `http://www.police.hu/hu/a-rendorsegrol/statisztikak/kozrendvedelem`. Specifically we will be looking at some statistics related to drink driving. Drunk driving is one of a number of problems police confront that relate to impaired and dangerous driving. Hungary has a strict drink driving policy, with the maximum drink diving limit being 0.0 BAC. Most European countries are at 0.5 BAC, while the UK is 0.8 (except 0.5 for Scotland). We have record for each county the number of brethalyser checks carried out, and the number of these which returned a positive result. Let's read in this data from January 2020 (taken from here[17]),

[17] `http://www.police.hu/sites/default/files/Kozrendvedelem%20SK%202021_01.pdf`

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


# read in geojson polygon for Hungary
hungary <- st_read("data/hungary.geojson")

#read in drink driving data
drink_driving <- read_csv("data/drink_driving.csv")

#join the csv (attribute) data to the polygons
hu_dd <- left_join(hungary, drink_driving, by = c("name" = "name"))
```

We can now use this example to talk through the important principles of good visualisation of spatial data. We draw specifically from two areas of research: cartography and data visualisation.

Cartographers have always been concerned about the appearance of maps and how the display marries form with function **?**. As there is no definitive definition for what is meant by *cartographic design* it can be challenging to evaluate what makes *good* design. However there are themes and elements which can be used to guide the map maker, and offer points of reflection to encourage thoughtful designs.

The primary aim of maps is the communication of information in an honest and ethical way. This means each map should have a clear goal and know its audience, show all relevant data and not use the data to lie or mislead **?**. It should also be reproducible, transparent, cite all data sources, and consider diversity in its audience **?**. So what does that mean for specifically implementing these into practice. While a good amount of critical thought from the map maker will be required, there are aids we can rely upon. For example, **?** developed a map evaluation checklist which you can access here: `http://downloads.esri.com/MappingCenter2007/arcGISResources/more/MapEvaluationGuidelines.pdf`. The questions fall into three broad categories:

- *Cartographic Requirements*: such as what is the rationale for the map, who are the audience?
- *Cartographic Complication and Design* such as are all the relevant features included and do the colours, symbold, and other features legible and appropriate to achieve the map's objectives? And finally,
- *Map Elements and Page Layout* which tackle some specific features such as orientation indicator, scale indicator, legend, titles and subtitles, and production notes.

We will discuss these elements in this chapter to some degree, and the recommended reading will guide the reader to further advice on these topics.

Data visualisation is a somewhat newer field, however, it seems to encompass the same guiding principles when consdiering what makes good design. According to **?** three principles offer a guide when deciding what makes a *good* data visualisation. It must be:

- Trustworthy
- Accessible, and
- Elegant

The first principle, of trust speaks to the integrity, accuracy, and legitimacy of any data visualisation we produce. **?** suggests this principle to be held above all else, as our primary goal is to communicate truth (as far as we know it) and avoid at all cost to present what we know to be misleading content. Accessibility refers to our visualisation being useful, understandable, and unobtrusive, as well as accessible for all users. There are many things to consider in your audience such as *dynamic of need* (do they have to engage with your visualisation, or is it voluntary?), *subject-matter knowledge* are they experts in the area, are they lay people to whom you must communicate a complex message?, and many other factors (see **?**). Finally, elegance refers to aesthetics, attention to detail, and an element of *doing as little design as possible* - meaning a certain invisibility whereby the viewer of your visualisation focussed on the content, rather than the design - that is the main point is the message that you are trying to communicate with your data! There are various schools of though within data visualisation research. For example, the work of **?** emphasises clean, minimalist approaches to data visualisation, emphasising a low *data-to-ink-ratio*, which means all the ink needed to print the visualisation should contribute data to the graph. However, other research has explored the usefulness of additional embellishments on charts (which Tufte calls "chart junk") - finding there may be value to these sorts of approaches as well (e.g. see **?**).

In this chapter, we will aim to bring together the above principles, and work through a practical example of how to apply these to the maps we make. Specifically we will cover:

- data representation
- colour
- text
  - titles and subtitles
  - legend
  - annotation
  - production notes
- composition

  - orientation indicator
  - scale indicator
  - borders

- inset maps

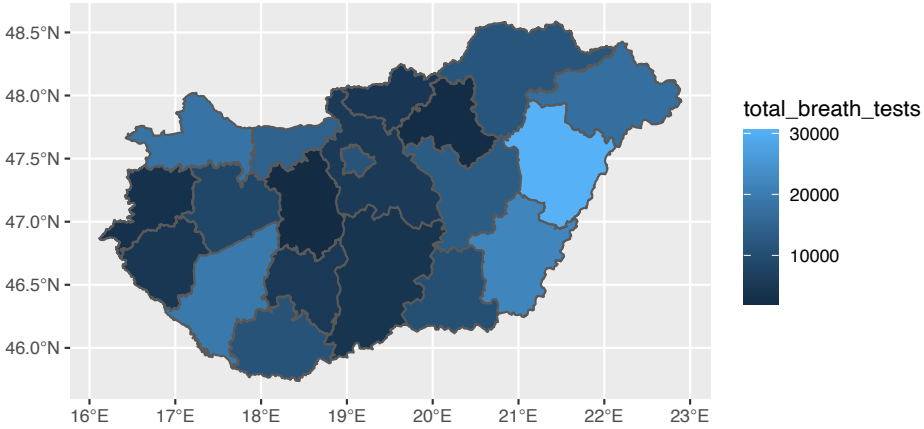
0.37 Data representation

0.37.1 Thematic maps

We've been working with thematic maps thus far. There are many decisions that go into making a thematic map, which we have explored at length in the previous chapters, such as how (and whether) to bin your data (Chapter 3) and how (or whether) to transform your polygons (Chapter 4). These are important considerations on how to represent your data to your audience, and require a technical understanding, not only an aesthetic one. So please do read over those chapters carefully when thinking about how to represent your data.

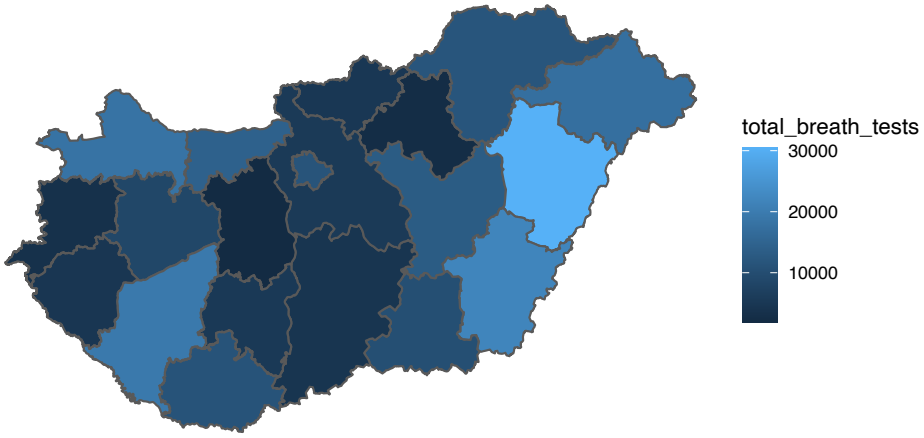
We can use the `ggplot2` package to plot our thematic map, using the `geom_sf()` function. To shade each polygon with the values of a specific variable, we use the `fill =` argument within the `aes()` (aesthetics) function. Most simply:

```
library(ggplot2)

ggplot(data = hu_dd) + # specify data to use
  geom_sf(aes(fill = total_breath_tests)) # specify aestetics
```



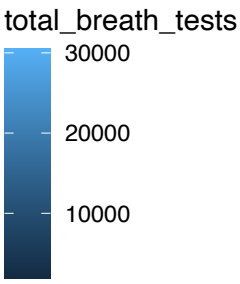
Ggplot plots automatically add a grid reference to our data (see Chapter 1). To remove this, we can use the `theme_void()` theme, which will strip this away.

```
ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_breath_tests)) +
  theme_void()  # remove grid
```



We can change the colour and size of the borders of our polygons with arguments inside the `geom_sf()` function, but outside the `aes()` function, as long as we're not using our data to define these. For example we can change the line width (`lwd =`) to 0, eliminating bordering lines between our polygons:

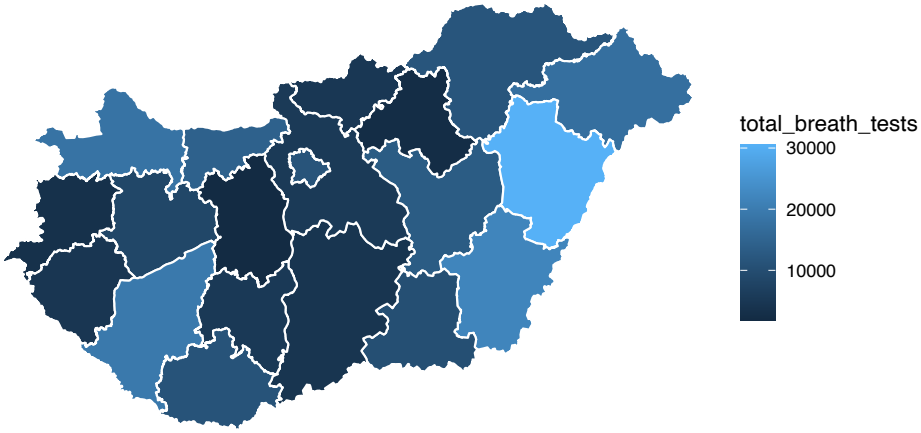
```
ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_breath_tests),
          lwd = 0) +  # specify line width
  theme_void()
```



Or we can change the colour of the borders with the `col =` argument:

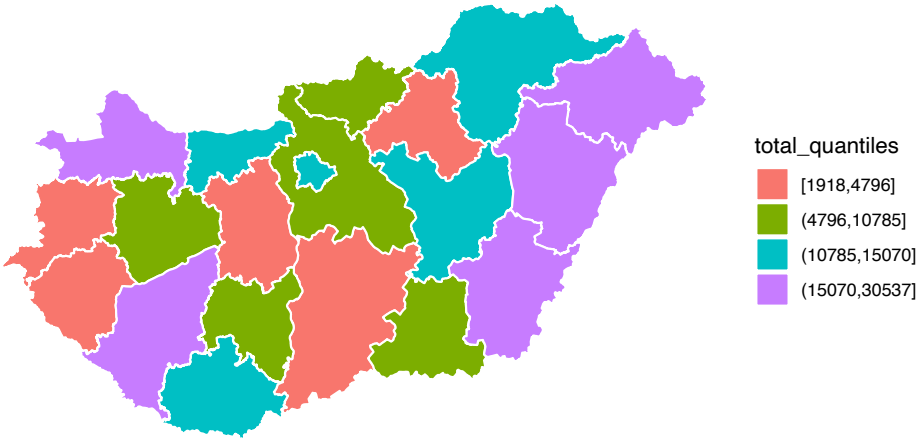
```
ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_breath_tests),
```

```
          lwd = 0.5,
          col = "white") + # specify border colour
  theme_void()
```



Here we have a continuous fill for our values, however we can employ our learning from Chapter 3 and apply a classification system, such as quantiles. To do this we might create a new variable which contains the quantiles of our numeric variable, and then use that as our `fill =`.

```
# create new variable for quantiles
hu_dd <- hu_dd %>%
  mutate(total_quantiles = cut(total_breath_tests, breaks = round(quantile(total_breath_tests),

# plot this new variable
ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_quantiles),
          lwd = 0.5,
          col = "white") +
  theme_void()
```

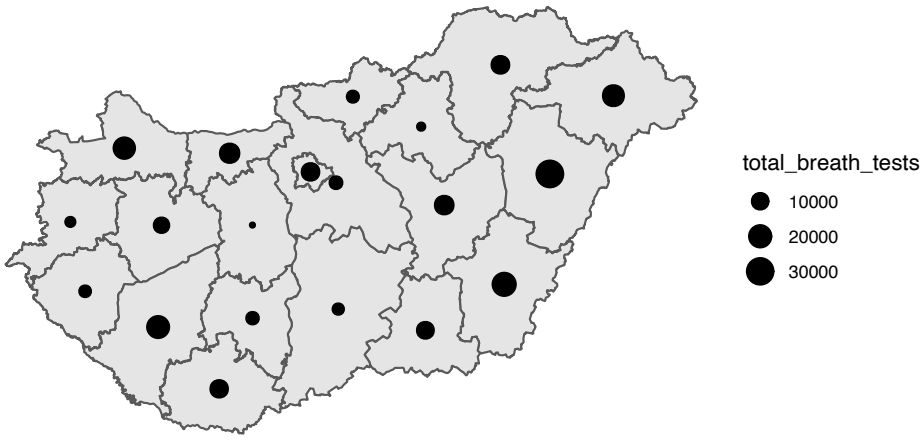


The colour scheme is terrible, but we will talk about colour in the next section, so we can forgive that for now...

0.37.2 Symbols

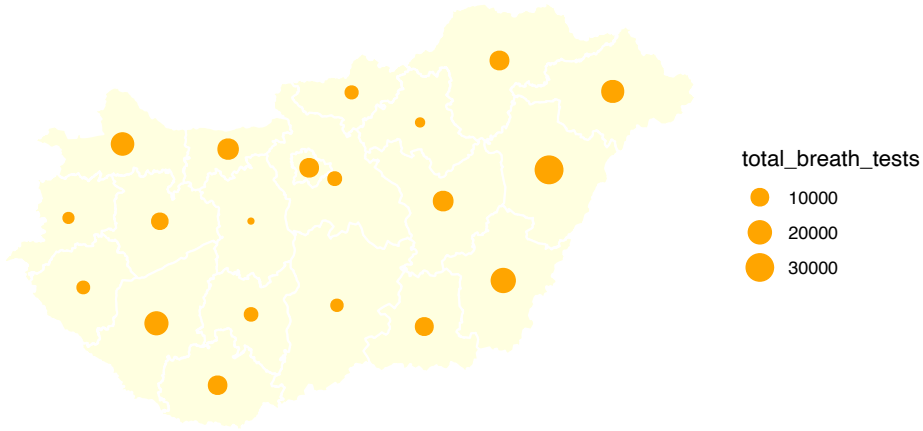
You might not want to display your map as thematic map, you may want to use symbols. Again we explored this in Chapter 3 where you used the `tmap` package for this. Here is another way you can use graduated symbol map with `ggplot()`. You can take the centroid of each county polygon using the `st_centroid()` function from the `sf` package, and then when mapping with `geom_sf()`, within the `aes()` function specity the `size =` argument to the variable you wish to visualise:

```
ggplot(data = hu_dd) +
  geom_sf() +
  geom_sf(data = st_centroid(hu_dd),  #get centroids
          aes(size = total_breath_tests)) +  # variable for size
  theme_void()
```



Like with the thematic map you can play around with colour and shape:

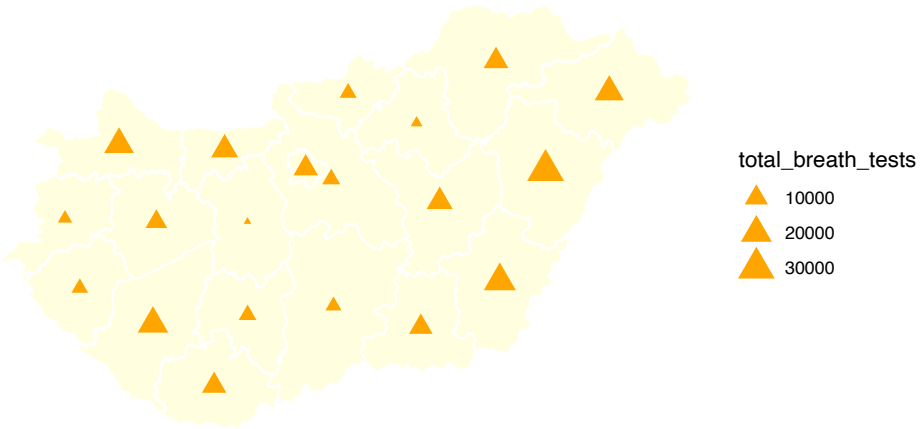
```
ggplot(data = hu_dd) +
  geom_sf(fill = "light yellow",   # specify polygon fill colour
          col = "white") +    # specify border colour
  geom_sf(data = st_centroid(hu_dd),
          aes(size = total_breath_tests),
          col = "orange") +  # specify symbol colour
  theme_void()
```



You can also change the symbol itself with the `shape =` parameter. For example you could use a triangle:

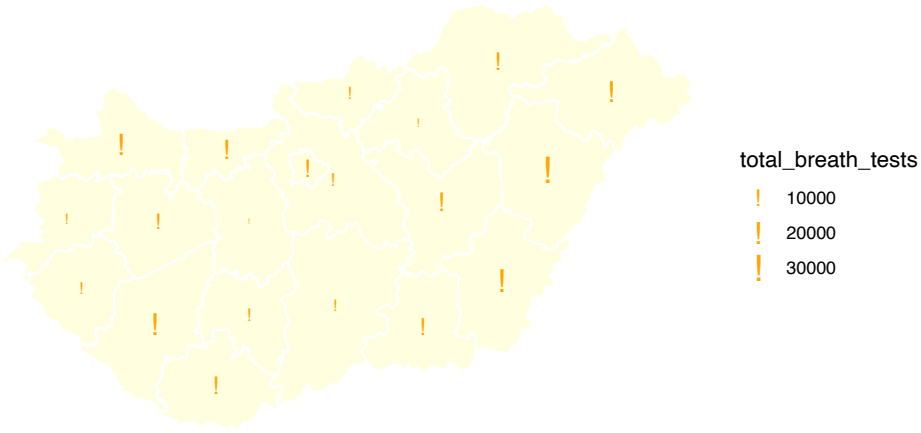
```
ggplot(data = hu_dd) +
  geom_sf(fill = "light yellow",
```

```
        col = "white") +
  geom_sf(data = st_centroid(hu_dd),
        aes(size = total_breath_tests),
        col = "orange",
        shape = 17) + # set shape to be a triangle
  theme_void()
```



Or to any other symbol. The possible values that you can use for the shape argument are the numbers 0 to 25, and the numbers 32 to 127. Only shapes 21 to 25 are filled (and thus are affected by the fill color), the rest are just drawn in the outline color. Shapes 32 to 127 correspond to the corresponding ASCII characters. For example, if we wanted to use the exclamation mark, the corresponding value is 33:

```
ggplot(data = hu_dd) +
  geom_sf(fill = "light yellow",
        col = "white") +
  geom_sf(data = st_centroid(hu_dd),
        aes(size = total_breath_tests),
        col = "orange",
        shape = 33) + # specify shape as "!"
  theme_void()
```



How you choose to represent your data will depend on your decisions to the questions asked above about audience, message, integrity, and so on.

0.37.3 Rate vs count

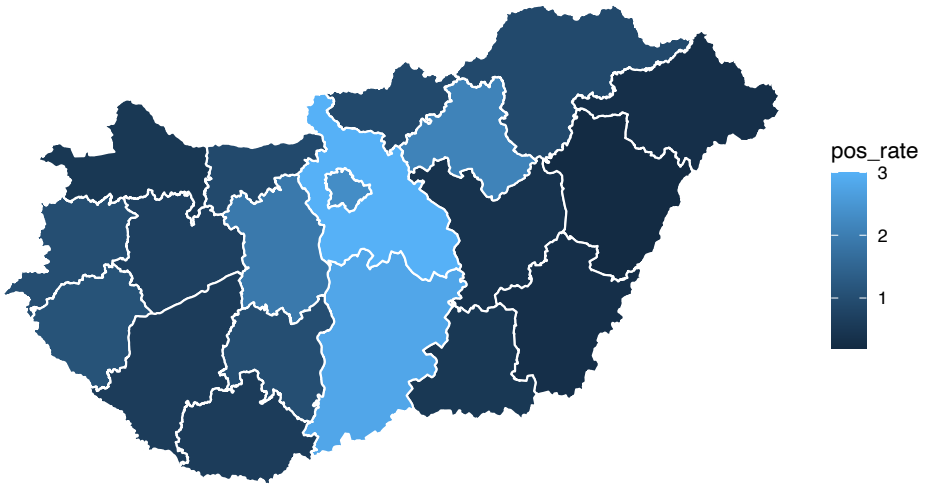
In chapter 3 we have discussed this already in great detail, so again I will not dwell on this, but it is important that your data are meaningful and easy to interpret. We might, in this case for example, want to consider the rate of positive breath tests per test carried out in each county. To compute this, we might want to consider the proportion of positive results on the breatalyser tests (where the person had been drinking and their result is over the limit). To compute this, we can simply divide the positive results by the total test, and multiply by 100. We also include the `round()` function in there

```
hu_dd <- hu_dd %>%
  mutate(pos_rate = round(positive_breath_tests/total_breath_tests*100,1))
```

We can see the county with the highers proportion of test yielding drink drivers is Pest megye with 3 %, while the county with the lowest is Hajdú-Bihar with 0.2 %.

We can visualise this rate on our thematic map in exactly the same way as the count data, but using our new variable in the `fill =` argument:

```
ggplot(data = hu_dd) +
  geom_sf(aes(fill = pos_rate), lwd = 0.5, col = "white") +
  theme_void()
```



But with a graduated symbol map we can get a little more creative. Sure, one approach may be to once again change the size of the symbol, but we could get a little more creative and use charts. For example there is the library `scatterpie` which has the function `geom_scatterpie()` which allows us to present our ratios in pie charts.

To use this function, we need our data to be in a dataframe which has separate columns for latitude and longitude (rather than a geometry object), where each observation has a unique id, and where we have a separate column for each proportion we wish to visualise.

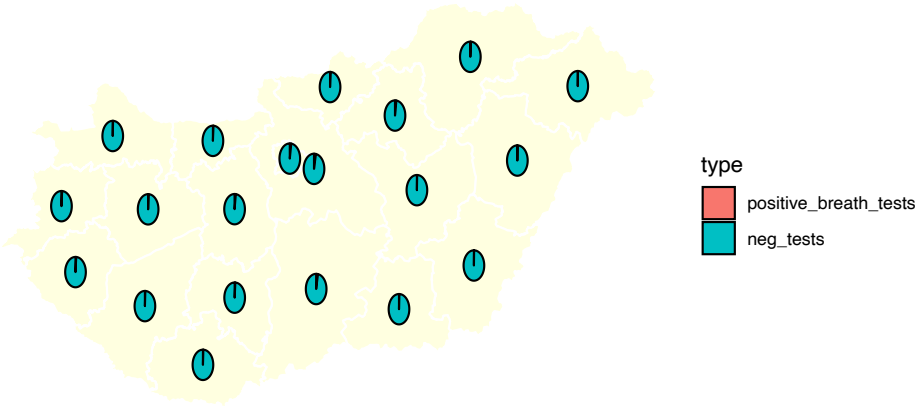
To create this, we first need to get the centroid of each polygon to get our longitude and latitude. We also need to calculate the number of negative breath tests. We then need to extract the coordinates into longitude and latitude columns, and finally we can drop the geometry and keep only the columns we need for this new dataframe.

```
scatter_map_df <- hu_dd %>%
  mutate(# extract centroid longitude
         cent_lng = st_coordinates(st_centroid(.))[,1],
         # extract centroid latitude
         cent_lat = st_coordinates(st_centroid(.))[,2],
         # calculate negative tests
         neg_tests = total_breath_tests - positive_breath_tests) %>%
  st_drop_geometry() %>%     # remove the geometry column
  dplyr::select(cent_lng, cent_lat, osm_id,   # select only necessary columns
                positive_breath_tests, neg_tests)
```

We now have this new dataframe which has coordinates for the centroid of each polygon, and we can use the `geom_scatterpie()` function from the `scatterpie`

package to plot a pie chart of the proportion of positive to negative breath tests in each county in Hungary:

```
library(scatterpie)

ggplot(data = hu_dd) +
  geom_sf(data = hu_dd,
          fill = "light yellow",
          col = "white") +
  geom_scatterpie(data=scatter_map_df,   # specify new df
                  aes(x=cent_lng,        # longitude
                      y=cent_lat,        # latitude
                      group=osm_id),     # ID for polygons
                  # specify the columns of pos and neg tests
                  cols=c("positive_breath_tests", "neg_tests")) +
  theme_void()
```



In this case, it's not super informative to visualise this, as discussed above our positive rates range between 0.2 %, and 3 %. However with more evenly distributed proportions this may be something to try.

0.38 Colour

When choosing a colour palette, the first thing to consider is what kind of colour scheme we need. This will depend on the variable we are trying to visualise. We go back, once again, to the first week of the course, where we discussed *Levels of Measurement*. Remember those? Still important!

Depending on the kind of varaible we want to visualise, we might want a Qualitative colour scheme (for categorical nominal variables), a Sequential colour

scheme (for categorial ordinal, or for numeric variables) or a Diverging colour scheme (for categorial ordinal, or for numeric variables).

For qualitative colour schemes, we want each category (each value for the variable) to have a perceptible difference in colour. For sequential and diverging color schemes, we will want mappings from data to color that are not just numerically but also perceptually uniform.

- **sequential scales** (also called gradients) go from low to high saturation of a colour.
- **diverging scales** represent a scale with a neutral mid-point (as when we are showing temperatures, for instance, or variance in either direction from a zero point or a mean value), where the steps away from the midpoint are perceptually even in both directions.
- **qualitative scales** identify as different the different values of your categorical nominal variable from each other.

For your sequetial and diverging scales, the goal in each case is to generate a perceptually uniform scheme, where hops from one level to the next are seen as having the same magnitude.

Of course, perceptual uniformity matters for your qualitative scales for your unordered categorical variables as well. We often use color to represent data for different countries, or political parties, or types of people, and so on. In those cases we want the colors in our qualitative palette to be easily distinguishable, but also have the same valence for the viewer. Unless we are doing it deliberately, we do not want one color to perceptually dominate the others.

The main message here is that you should generally not put together your color palettes in an ad hoc way. It is too easy to go astray. In addition to the considerations we have been discussing, there we might also want to avoid producing plots that confuse people who are colour blind, for example, and color blindness comes in a variety of forms. Fortunately for us, almost all of the work has been done for us already. Different color spaces have been defined and standardized in ways that account for these uneven or nonlinear aspects of human color perception.

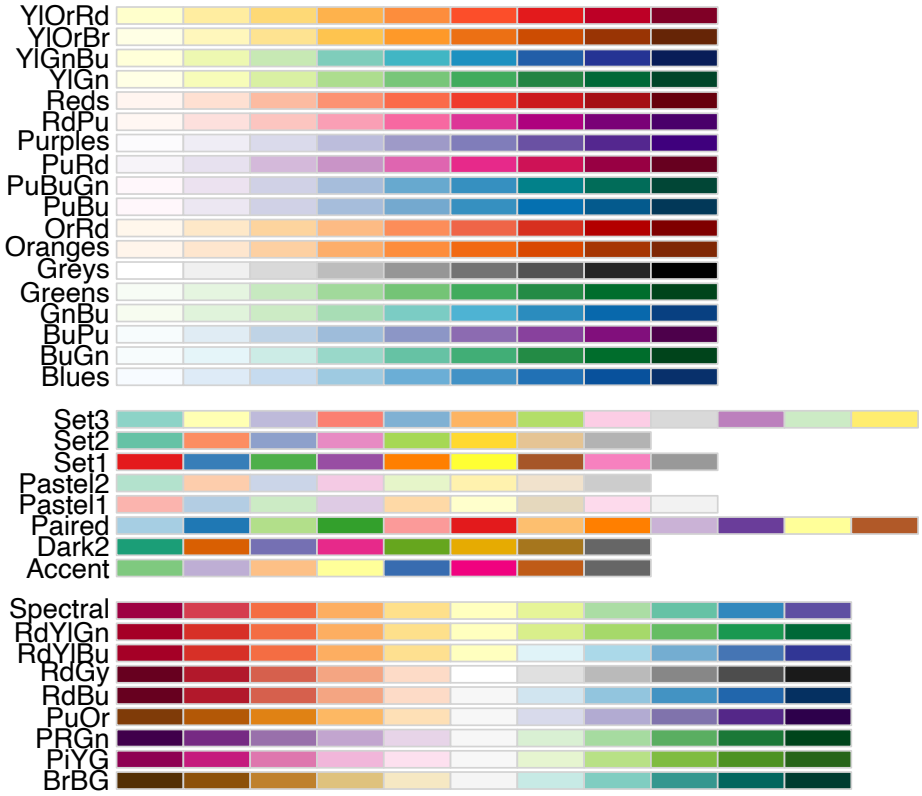
A good resource is colorbrewer[18]. We have come across **?** in Chapter 3. Colorbrewer is a resource developed by Cynthia Brewer and colleagues in order to help implement good colour practice in data visualisation and cartography **?**. This site offers many colour schemes we can make use of for our maps, which are easily integrated into R using the `Rcolorbrewer` package.

```
library(RColorBrewer)
```

[18] `http://colorbrewer2.org/`

Once you have the package loaded, we can look at all the associated palettes with the function `display.brewer.all()`.

```
display.brewer.all()
```



The above gives a wide choice of pallettes, and while they are applicable to all sorts of data visualisations, they were created especially for the case of thematic maps.

We might use the above code to pick a palette we like. We might then want to examine the colours more closely. To do this we can use the `display.brewer.pal()` function, and specify `n=` - the number of colours we need, as well as the palette name with `name =`:

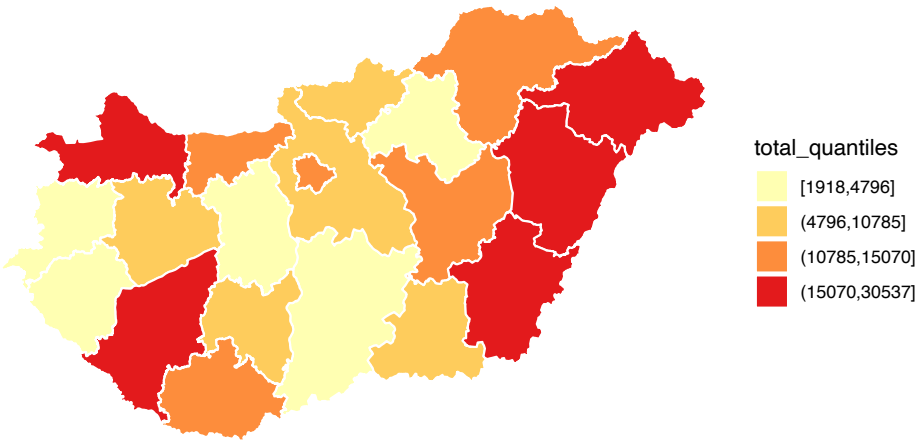
```
display.brewer.pal(n = 5, "Spectral")
```

Spectral (divergent)

Let's go back to our thematic map of the quantiles of total breath tests per county. We might be interested in this map to show distribution of policing activity for example. We made this map earlier with the default colour scheme, which didn't really communicate to use the graduated nature of our data we were visualising. To properly do this, we may imagine using a *seqantial* scale. We can use one of the sequential scales available within `RColorBrewer` with adding the `scale_fill_brewer()` function to our ggplot. In this function we can specify the `type=` parameter, i.e. if we want to use sequential, divergining, or qualitative colour schemes (specified as either "seq" (sequential), "div" (diverging) or "qual" (qualitative)). We can then specify our preferred palette with the `palette =` argument.

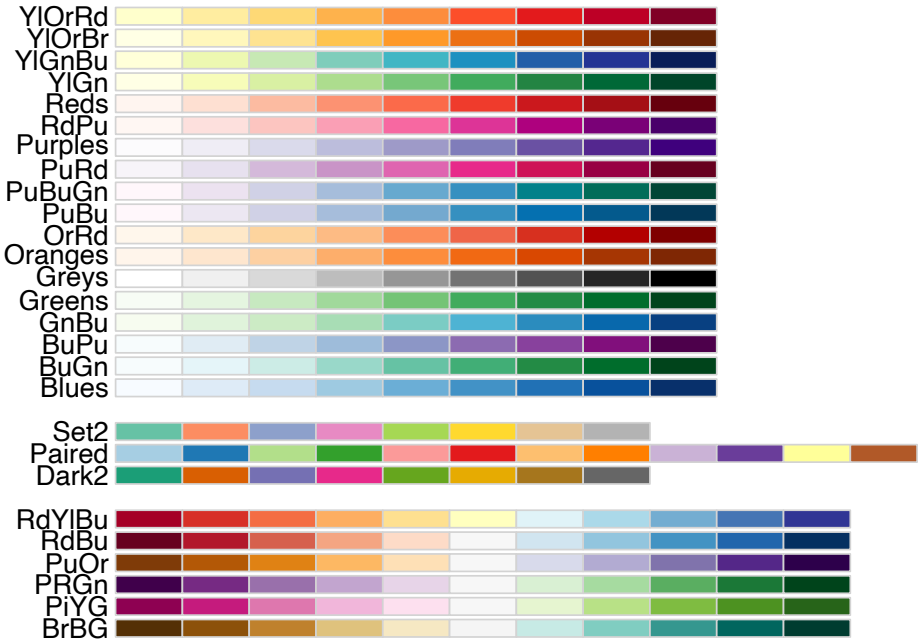
Let's demonstrate here with the "YlOrRd" sequential palette:

```
ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_quantiles),
          lwd = 0.5,
          col = "white") +
  scale_fill_brewer(type = "seq",   # pick pallette type
                    palette = "YlOrRd") +  # specify pallette by name
  theme_void()
```



This looks much better, and communicates our message much more clearly. Is this accessible to our colourblind colleagues? Earlier, when we asked to view all the palettes with the `display.brewer.all()` function, we did not specify any arguments. However, we can do so in order to filter only those palettes which are accessible for all audiences. We can include the parameter `colorblindFriendly = ` to do so:

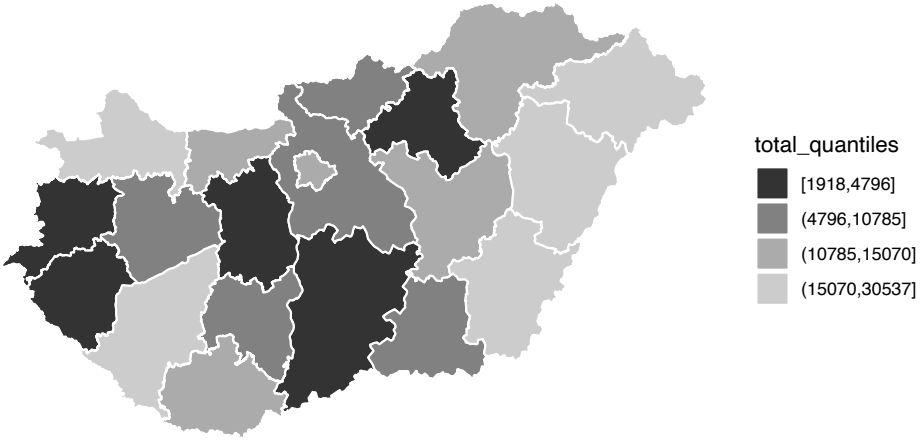
```
display.brewer.all(colorblindFriendly = TRUE)
```



You can see there are a few palettes missing from our earlier results, when we did not specify this requirement. My recommendation is to always use one of these palettes.

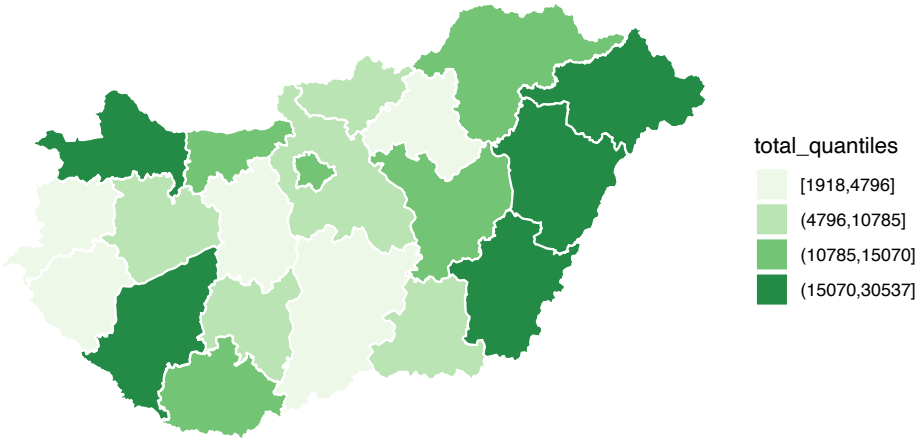
Another way to ensure that we are making accessible maps is to use greyscale (if your map is being printed, this may also save some money). To introduce a greyscale palette, you can use the function `scale_fill_grey()` from the `ggplot2` package:

```
ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_quantiles), lwd = 0.5, col = "white") +
  scale_fill_grey() +
  theme_void()
```



Sometimes you might prefer such a map. However, do keep in mind, a number of studies have shown the desirability of monochrome colour (over greyscale) thematic maps, as they are linked to less observer variability in interpretation (**?**). So you might want to use something like this instead:

```
ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_quantiles), lwd = 0.5, col = "white") +
  scale_fill_brewer(type = "seq", palette = "Greens") +
  theme_void()
```



Overall, the key thing is to be conscious with the colours you choose to represent your data. Make sure that they are accessible for all audiences, and best represent the patterns in your data which you want to communicate to your audiences.

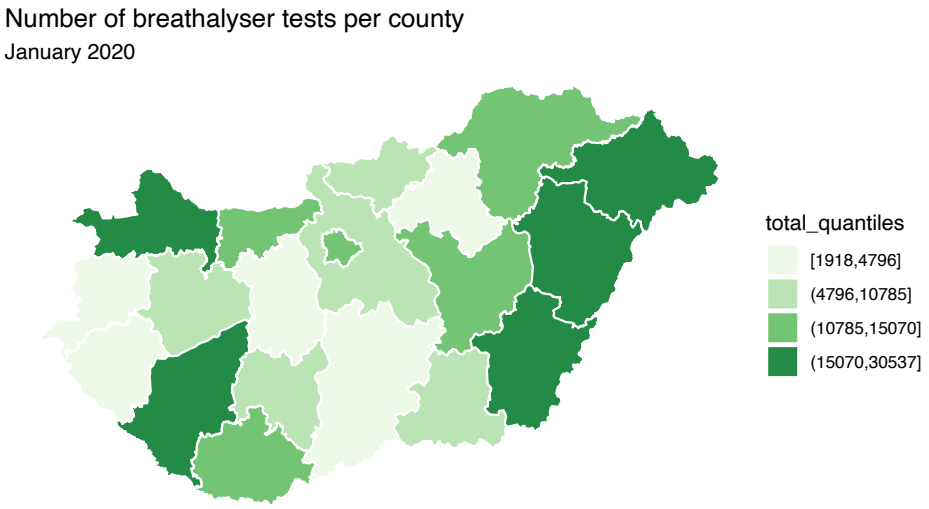
0.39 Text

There are important pieces of information with every map which are represented by text. Titles, subtitles, legend labels, and annotations all help to make the message communicated by your map more clear and obvious to your readers. Further, important information about the underlying data can be communicated through product notes. You want to acknowledge the sources of your data (both attribute data and geometry data), as well as leave some information about yourself as the map maker, so consumers of your map can understand who is behind this map, and leave some contact information get in touch with any questions. In this section we go through how to add such text information to your maps.

0.39.1 Titles and subtitles

To give your map a title and subtitle, you can use the appropriate functions from the `ggplot2()` package. In this case we can add both within the `ggtitle` function. Make sure that your title is short and specific, so it is clear what your map is about. You can include a subtitle to elaborate on this, or you can add additional information such as the period for which your map represents data (in this case January 2020).

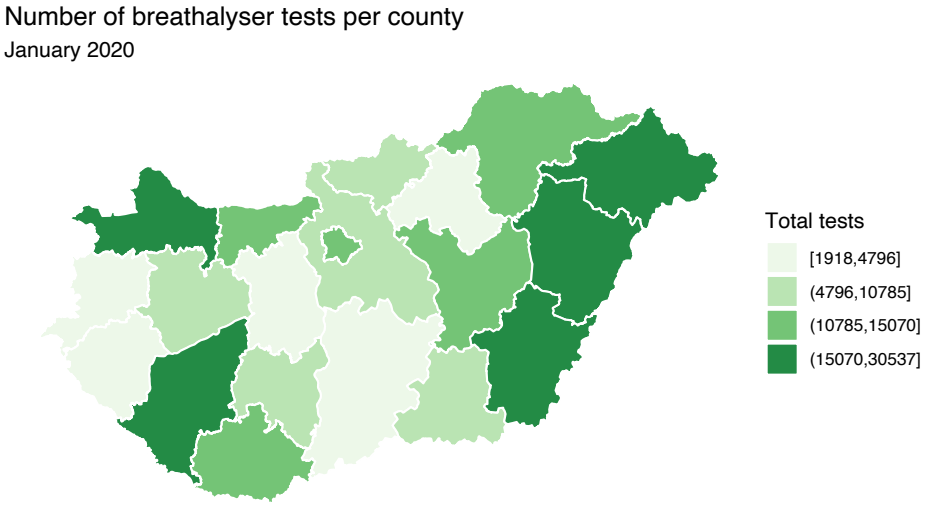
```
ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_quantiles),
          lwd = 0.5, col = "white") +
  scale_fill_brewer(type = "seq", palette = "Greens") +
  theme_void() +
  # specify both title and subtitle:
  ggtitle(label = "Number of breathalyser tests per county",
          subtitle = "January 2020")
```



0.39.2 Legend

Besides an informative title/subtitle you need your legend to be clear to your reades as well. To modify the title to your legend, you can use the `name =` parameter in your `scale_fill_brewer()` function, where we specified the colour palette.

```
ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_quantiles),
          lwd = 0.5, col = "white") +
  scale_fill_brewer(type = "seq", palette = "Greens",
                    name = "Total tests") + # desired legend title
  theme_void() +
  ggtitle(label = "Number of breathalyser tests per county",
          subtitle = "January 2020")
```

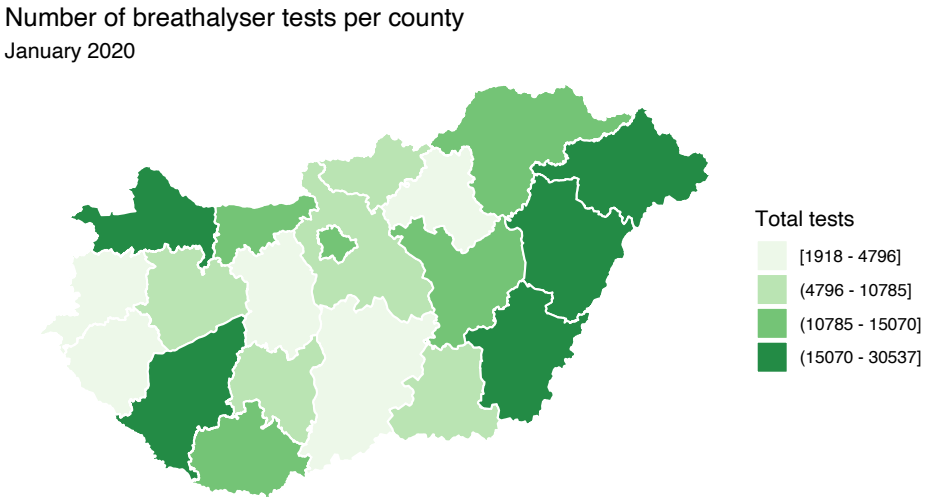


Besides the legend title, we can also change how the levels are labeled. For this, we can use text manipulation functions, such as `gsub()` which substitutes one string for another. For example, we can replace the "," with a " - " if we'd like using the `gsub()` function. We can create a new object, here `new_levels`, which has the desired labels:

```
# create object new_levels with desired labels
new_levels <- gsub(","," - ",levels(hu_dd$total_quantiles))
```

We can then assign this new levels object in the `labels =` parameter of the `scale_fill_brewer()` function:

```
ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_quantiles),
          lwd = 0.5, col = "white") +
  scale_fill_brewer(type = "seq", palette = "Greens",
                    name = "Total tests",
                    labels = new_levels) +  # specify our new labels
  theme_void() +
  ggtitle(label = "Number of breathalyser tests per county",
          subtitle = "January 2020")
```

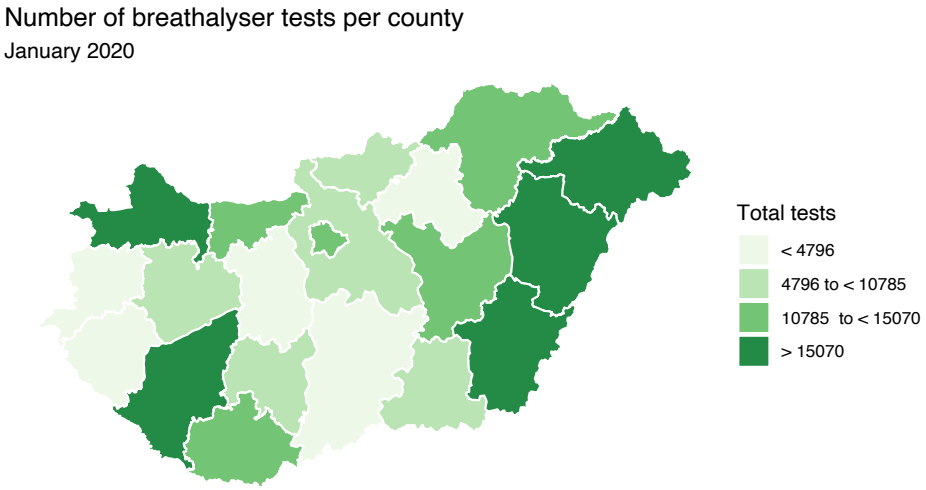


Of course it is possible that we want to completely re-write the levels, rather than just swap out one character for another. In this case, we can completely rename the levels if we liked, by passing the new, desired labels into this `new_levels` object

```
new_levels <- c("< 4796", "4796 to < 10785", "10785  to < 15070", "> 15070")
```

And once again, we specify to use these labels in the `labels =` parameter of the `scale_fill_brewer()` function:

```
ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_quantiles),
          lwd = 0.5, col = "white") +
  scale_fill_brewer(type = "seq", palette = "Greens",
                    name = "Total tests",
                    labels = new_levels) + # again specify labels object
  theme_void() +
  ggtitle(label = "Number of breathalyser tests per county",
          subtitle = "January 2020")
```



You can change the labels however you would like, but do keep in mind any loss of information you may introduce. For example with this second version, we no longer know what are the minimum and maximum values on our map, as we've removed that information with our new levels. Again, no wrong answers here, but whatever best fits the data and the purpose of the map.

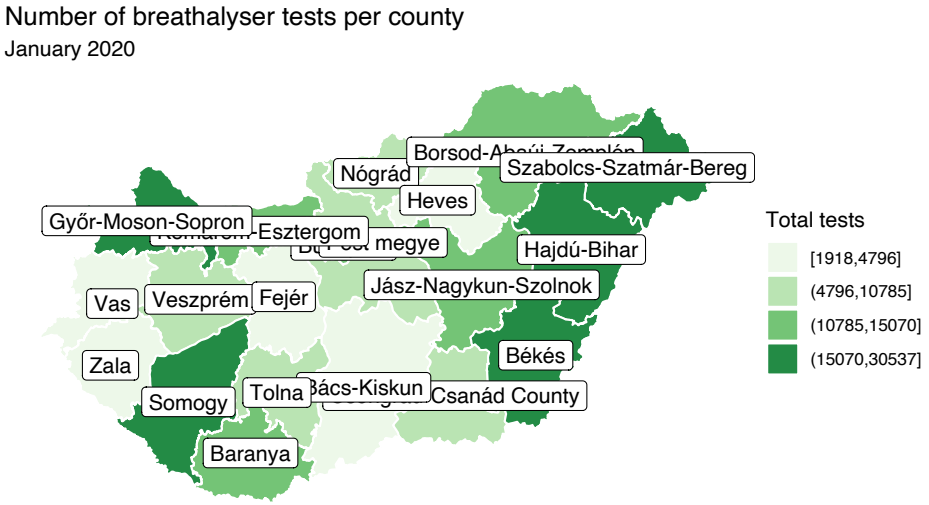
0.39.3 Annotation

In certain cases, it might be that we want to point out something specific on our map. This would be the case if we imagine showing someone the map in person, and pointing to a specific region, or area, to highlight it. Or we might just want to label all polygons, for clarity. If we are not present to discuss our map, we might want to include some text annotation instead, which will do this for us. From `ggplot2` versions v.3.1.0 the functions `geom_sf_text()` and `geom_sf_label()` make it very smooth for us to do this.

In the below example, let's say we want to label each polygon with the name of the county which it represents. In this case, we use the `geom_sf_label()` geometry, and inside it we use `aes()` to point to which column in our dataframe we want to use (in this case the column is called *name*).

```
ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_quantiles),
          lwd = 0.5, col = "white") +
  scale_fill_brewer(type = "seq",
                    palette = "Greens",
                    name = "Total tests") +
  geom_sf_label(aes(label = name)) +  # add layer of labels from the name column
```

```
  theme_void() +
  ggtitle(label = "Number of breathalyser tests per county",
          subtitle = "January 2020")
```



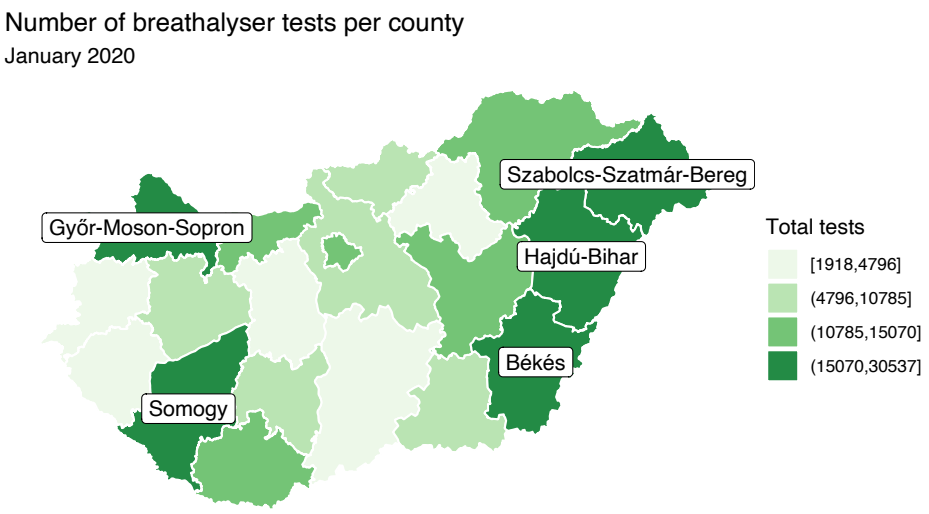
You may notice there is some overlapping here which renders some names unreadable. Well while there is work in this space to develop the function geom_sf_label_repel()[19] at the time of writing this is not yet available. However this application of the `geom_label_repel()` function from the `ggrepel` package advised by **?** achieves the same outcome:

```
library(ggrepel)

ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_quantiles),
          lwd = 0.5, col = "white") +
  scale_fill_brewer(type = "seq",
                    palette = "Greens",
                    name = "Total tests") +
  geom_label_repel(data = hu_dd,       # add repel layer, specify dataframe
                   aes(label = name,   # specify where to find label (name column)
                       geometry = geometry),  # specify geometry
                   stat = "sf_coordinates",  # transformation to use on the data
                   min.segment.length = 0) + # don't draw segments shorter than this
  theme_void() +
  ggtitle(label = "Number of breathalyser tests per county",
          subtitle = "January 2020")
```

[19] https://github.com/slowkow/ggrepel/issues/111

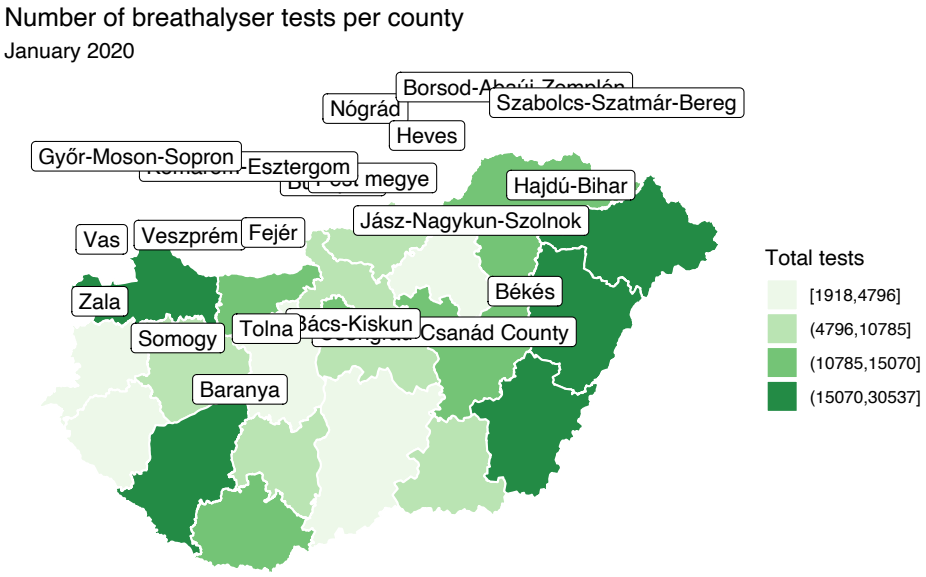
This way we can display the names of all the counties without overlap, so they all become legible. While this is achievable, think back to the principles of good design. This seems busy, and like it may overwhelm the reader. Not to mention - is it important that all polygons are labelled here? It might be - remember this depends on the message the map is intended to communicate! But here let's consider a different scenario, where we want to use annotation to label only those counties which meet some specific criteria. For example, you might want to label only those which are in the top quartile. One way to achieve this is to create a separate dataframe, which only includes the desired polygons, and pass this into the `geom_sf_label()` function.

```
#create new dataframe with only top counties
labs_df <- hu_dd %>% filter(total_breath_tests >= 15070)

#add to map
ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_quantiles),
          lwd = 0.5, col = "white") +
  scale_fill_brewer(type = "seq",
                    palette = "Greens",
                    name = "Total tests") +
  geom_sf_label(data = labs_df, # specify to use the labels df
                aes(label = name)) +
  theme_void() +
  ggtitle(label = "Number of breathalyser tests per county",
          subtitle = "January 2020")
```



In another scenario, you might want to label only one region of interest. In this case, we might actually want to keep our annotation off the map, and draw an arrow onto the map pointing to where this annotation refers to. We can do this by using the `nudge_x` and `nudge_y` parameters of the `geom_sf_label()` function. In this case, let's label only Budapest.

```
#create new labels dataframe
labs_df <- hu_dd %>% filter(name == "Budapest")

ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_quantiles),
          lwd = 0.5, col = "white") +
  scale_fill_brewer(type = "seq",
                    palette = "Greens",
                    name = "Total tests") +
  geom_sf_label(data = , aes(label = name), # label from name column
                nudge_y = 0.9,  # move label on y axis
                nudge_x = -0.1) + # move label on x axis
  theme_void() +
  ggtitle(label = "Number of breathalyser tests per county",
          subtitle = "January 2020")
```



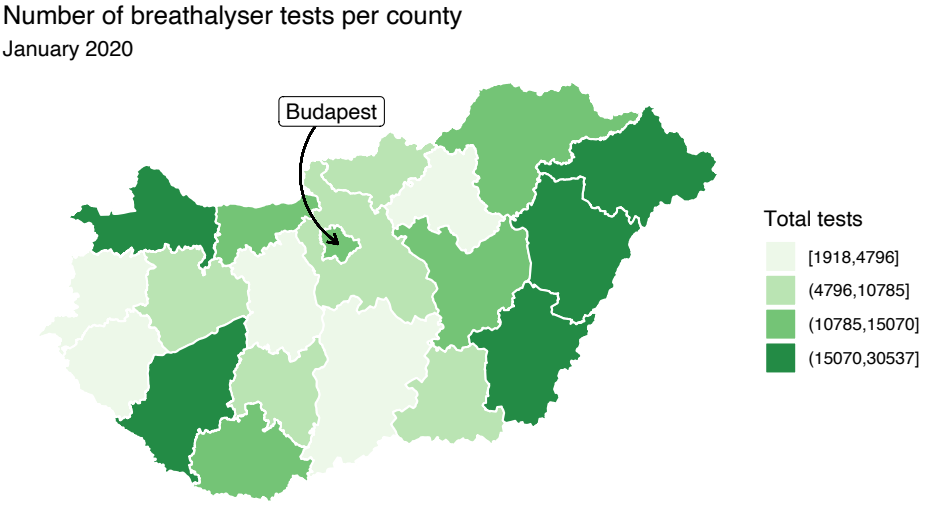
But this floating label is a little ambiguous, and needs to be more explicitly connected to the map. To achieve this, we might want to use an arrow to point out Budapest on the map. To do this, we can use `geom_curve()` within `ggplot2`. We will need two sets of x and y values for this segment, the start point (`x` and `y`) and the end point (`xend` and `yend`). The end point will be the coordinates where we want the arrow pointing to. This would be some x,y pair within Budapest. We can use the `st_coordinates()` function once again the extract the centroid, this time of the Budapest polygon. Let's extract the longitude of the centroid into an object called `bp_x` for our x value, and the latitude of the centroid into an object called `bp_y` for our y value.

```
# get x coordinate
bp_x <- labs_df %>%
  mutate(cent_lng = st_coordinates(st_centroid(.))[,1]) %>%
  pull(cent_lng)

# get y coordinate
bp_y <- labs_df %>%
  mutate(cent_lat = st_coordinates(st_centroid(.))[,2]) %>%
  pull(cent_lat)
```

Great, so we have the end point for our segment, but where should it start. Well we want it pointing from our label, so we can think back to how we adjusted this label with the `nudge_x` and `nudge_y` parameters inside the `geom_sf_label()` function earlier. We can add (or subtract) these values to our bp_x and bp_y objects to determine the start points for our curve. Finally, we can also specify

some characteristics of the arrow head on our curve with the `arrow =` parameter. Here we specify we want 2 millimeter size.

```
ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_quantiles),
          lwd = 0.5, col = "white") +
  scale_fill_brewer(type = "seq",
                    palette = "Greens",
                    name = "Total tests") +
  geom_curve(x = bp_x - 0.1,  # starting x coordinate (the label)
             y = bp_y + 0.9, # starting y coordinate (the label)
             xend = bp_x , # ending x coordinate (BP centroid)
             yend = bp_y,  # ending y coordinate (BP centroid)
             arrow = arrow(length = unit(2, "mm"))) +
  geom_sf_label(data = labs_df,
                aes(label = name),
                nudge_y = 0.9,
                nudge_x = -0.1) +
  theme_void() +
  ggtitle(label = "Number of breathalyser tests per county",
          subtitle = "January 2020")
```



This is one way to include annotation while keeping the map clear, but still using the geographic information to reference. Annotations can be useful, but think carefully about whether you need them for your map, as they can also be distracting if not used appropriately.

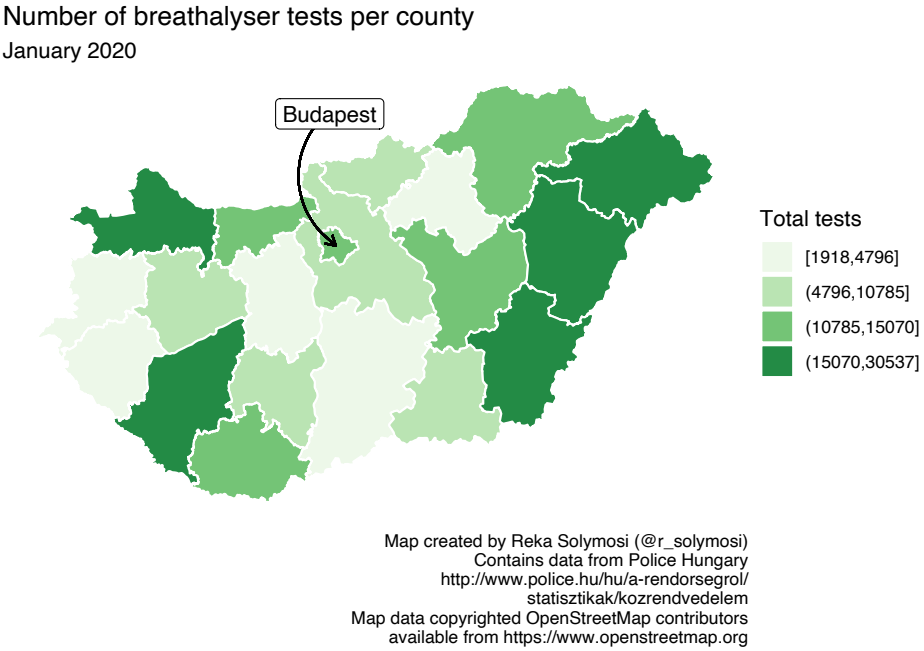
0.39.4 Production notes

Something that should be a key feature of all maps is the inclusion of production notes. This includes some information about you who made it, as well as any attributions for data. Here we can string together a series of information we want to include, appended with a newline character (`\n`), in order to keep our notes nice and legible. We save this into a new object called `caption_text`.

```
caption_text <- paste("Map created by Reka Solymosi (@r_solymosi)",
                      "Contains data from Police Hungary",
                      "http://www.police.hu/hu/a-rendorsegrol/",
                      "statisztikak/kozrendvedelem",
                      "Map data copyrighted OpenStreetMap contributors",
                      "available from https://www.openstreetmap.org",
                      sep = "\n")
```

Then we can include this `caption_text` object as a caption in the function `labs()`.

```
ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_quantiles),
          lwd = 0.5, col = "white") +
  scale_fill_brewer(type = "seq",
                    palette = "Greens",
                    name = "Total tests") +
  geom_curve(x = bp_x - 0.1,
             y = bp_y + 0.9,
             xend = bp_x ,
             yend = bp_y,
             arrow = arrow(length = unit(2, "mm"))) +
  geom_sf_label(data = labs_df,
                aes(label = name),
                nudge_y = 0.9,
                nudge_x = -0.1) +
  theme_void() +
  ggtitle(label = "Number of breathalyser tests per county",
          subtitle = "January 2020") +
  labs(caption = caption_text) # include production notes here
```



In this way we give credibility to our map, and we also make the proper attributions to where our data come from.

0.40 Composition

Composition of the map is the process of bringing all its elements together in order that they portray a complete image of what you are representing. Composition includes considerations of size, proportions, generalisation, simplification, and similar topics. We do not address these here, as they rely so much on the specific purpose of the map being created. Is it for the web? Is it for print? Are having detailed outlines of coasts and waterways important, or is a generalised representation of the underlying geography enough? These are questions the map maker should answer early on, and pick geometry data, and specify output sizes and resolutions accordingly. In this section instead, we will docus on the element of composition which is concerned with the inclusion of basic map elements - information required by the map readers to make sense of our data, specifically orientation and scale indicators

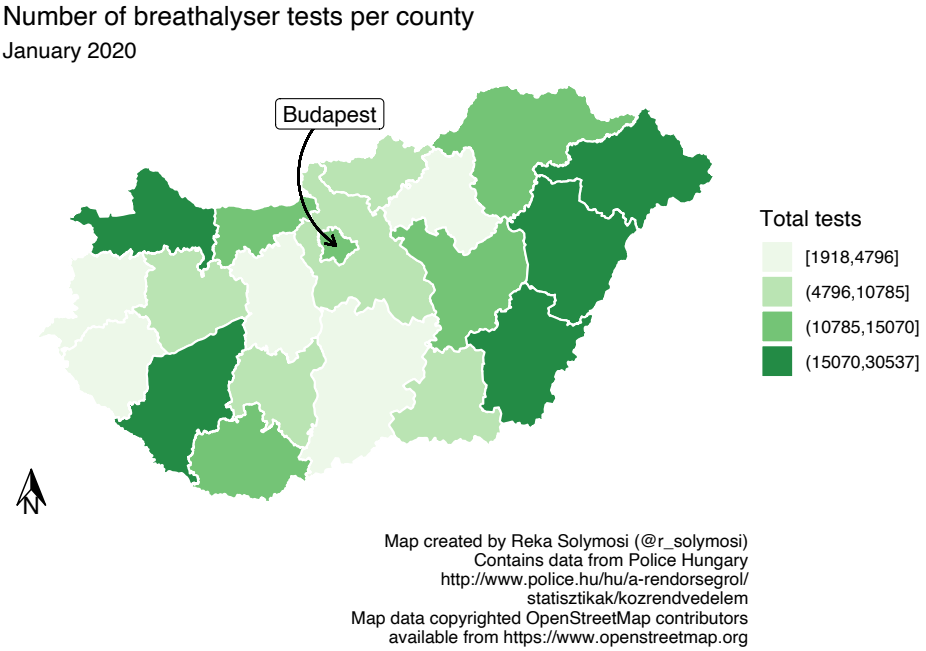
0.40.1 Orientation indicators

It used to be that no map was complete without the inclusion of an orientation indicator (known colloquially as the “North Arrow”). Readers who are geography fans may know that the issue of where is North is maybe not so straight

forward - true north (the direction to the North Pole) differs from magnetic north, and the latter actually moves around as the Earth's geophysical conditions change. There are reference maps which include both, however for most crime mapping applications we can conclude that this is overkill. Most maps are oriented to true north, anyway, so we are not being very deviant with choosing this approach.

So how to include this in our mapping in R? Well we can turn to the `ggspatial` library, and employ the function `annotation_north_arrow()`. In this function we can specify some aesthetic properties of our arrow, such as the height and width. Here we do so using millimeters as units.

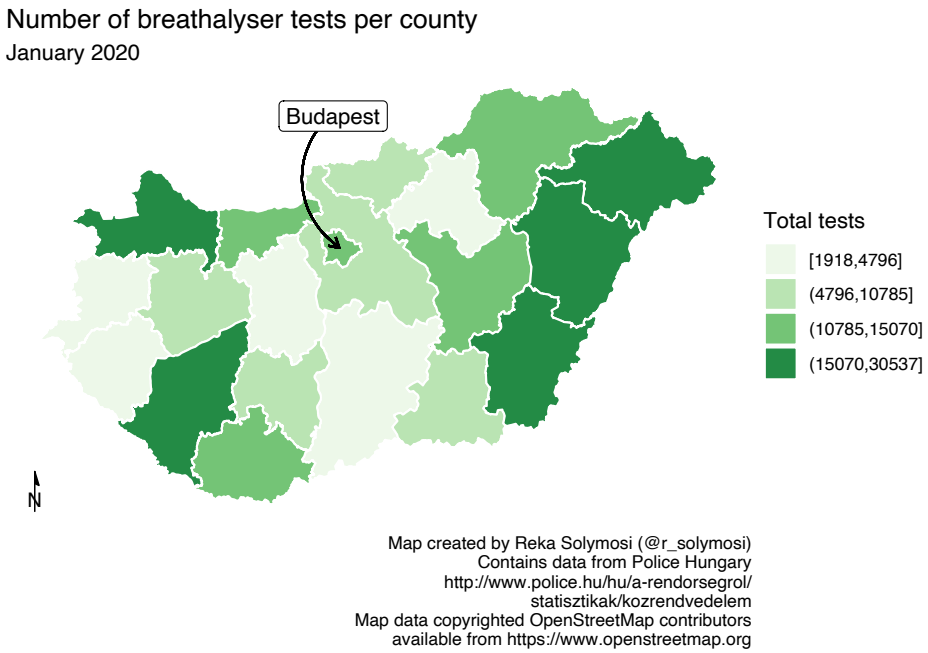
```
library(ggspatial)

ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_quantiles),
          lwd = 0.5, col = "white") +
  scale_fill_brewer(type = "seq",
                    palette = "Greens",
                    name = "Total tests") +
  geom_curve(x = bp_x - 0.1,
             y = bp_y + 0.9,
             xend = bp_x ,
             yend = bp_y,
             arrow = arrow(length = unit(2, "mm"))) +
  geom_sf_label(data = labs_df,
                aes(label = name),
                nudge_y = 0.9,
                nudge_x = -0.1) +
  theme_void() +
  ggtitle(label = "Number of breathalyser tests per county",
          subtitle = "January 2020") +
  labs(caption = caption_text) +
  annotation_north_arrow(height = unit(7, "mm"), # specify arrow height
                         width = unit(5, "mm")) # specify arrow width
```



You can also change the style with the `style =` parameter, and choose from styles such as `north_arrow_fancy_orienteering()` or `north_arrow_minimal()`:

```
ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_quantiles),
          lwd = 0.5, col = "white") +
  scale_fill_brewer(type = "seq",
                    palette = "Greens",
                    name = "Total tests") +
  geom_curve(x = bp_x - 0.1,
             y = bp_y + 0.9,
             xend = bp_x ,
             yend = bp_y,
             arrow = arrow(length = unit(2, "mm"))) +
  geom_sf_label(data = labs_df,
                aes(label = name),
                nudge_y = 0.9,
                nudge_x = -0.1) +
  theme_void() +
  ggtitle(label = "Number of breathalyser tests per county",
          subtitle = "January 2020") +
  labs(caption = caption_text) +
  annotation_north_arrow(height = unit(7, "mm"), # specify arrow height
                         width = unit(5, "mm"),
```

```
                        style = north_arrow_minimal()) # specify arrow style
```

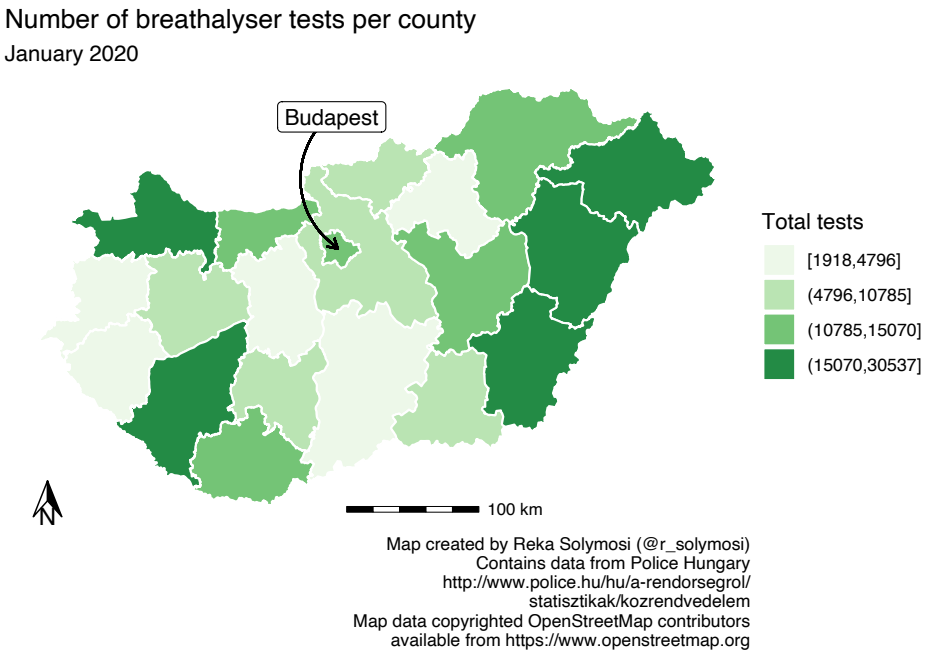


0.40.2 Scale indicators

Besides the North Arrow another key feature of maps is the scale indicator, which helps to understand distances we are presenting in our maps. Generally, scale should always be indicated or implied, unless the audience is so familiar with the map area or distance of such little relative importance that it can be assumed by the audience. You could use text to indicate scale. For example you could write "One centimeter is equal to one kilometer, or you could write 1:10000. But a common, graphical representation is to use a scale bar. Also in the `ggspatial` library, there is the function `annotation_scale()`, which helps us achieve this. To plot both the north arrow, and the scale indicator, you want to think about where you place these. You can move them along the x-axis using the using the `pad_x` parameter, and along the y-axis with the `pad_y` parameter.

```
ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_quantiles),
          lwd = 0.5, col = "white") +
  scale_fill_brewer(type = "seq",
                    palette = "Greens",
```

```
                  name = "Total tests") +
geom_curve(x = bp_x - 0.1,
           y = bp_y + 0.9,
           xend = bp_x ,
           yend = bp_y,
           arrow = arrow(length = unit(2, "mm"))) +
geom_sf_label(data = labs_df,
              aes(label = name),
              nudge_y = 0.9,
              nudge_x = -0.1) +
theme_void() +
ggtitle(label = "Number of breathalyser tests per county",
        subtitle = "January 2020") +
labs(caption = caption_text) +
annotation_north_arrow(height = unit(7, "mm"),
                       width = unit(5, "mm"),
                       pad_x = unit(5, "mm"),   # adjust on x axis
                       pad_y = unit(1, "mm")) + # adjust on y axis
annotation_scale(line_width = 0.5,      # add scale and specify width
                 height = unit(1, "mm"), # specify height
                 pad_x = unit(6, "cm"))  # adjust on x axis
```



You can move these elements about however you like to achieve your desired composition.

0.41 Context

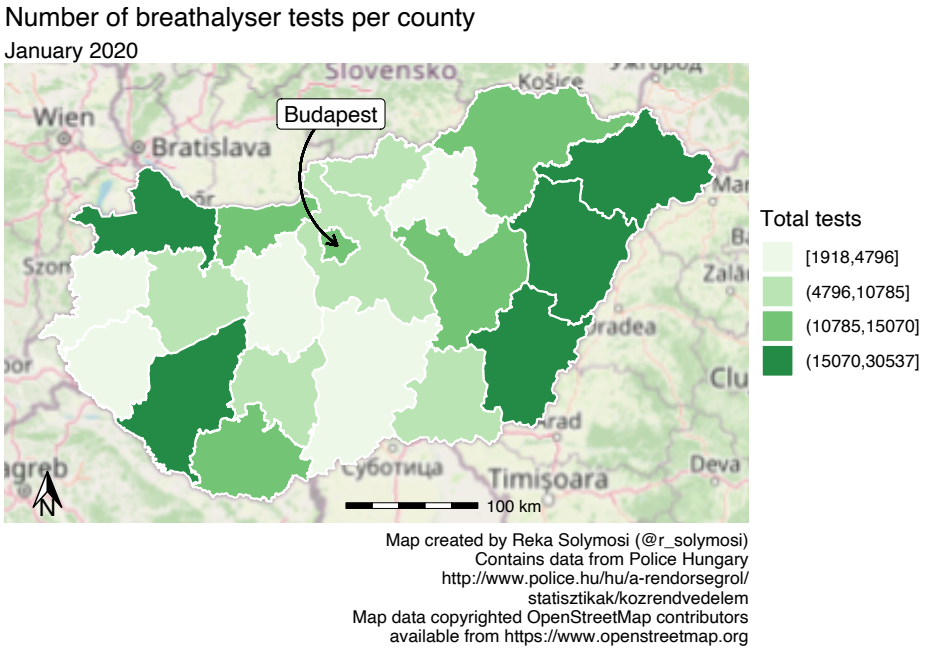
Besides the orientation and scale indicators, there are other ways to give context to your map, that is situate it within the wider environment, and put things into perspective for your map readers. In this section we will touch on basemaps, although this is something we have already encountered in great detail in earlier chapters, we illustrate how to add basemaps in ggplot. We also introduce inset maps, as a way of highlighting where your map sits in the wider context.

0.41.1 Basemap

As mentioned above, we have encountered and included basemaps in previous exercises in previous chapters. For the sake of illustration, we can add a basemap now using the the `annotation_map_tile()` function also from the `ggspatial` package (like the orientation and scale indicators). Make sure that the basemap is the first layer added to the map, so that all subsequent layers are drawn on top of it. If we were to add `annotation_map_tile()` last, it would cover all the other layers.

```
ggplot(data = hu_dd) +
  annotation_map_tile() +  # add basemap layer first
  geom_sf(aes(fill = total_quantiles),
          lwd = 0.5, col = "white") +
  scale_fill_brewer(type = "seq",
                    palette = "Greens",
                    name = "Total tests") +
  geom_curve(x = bp_x - 0.1,
             y = bp_y + 0.9,
             xend = bp_x ,
             yend = bp_y,
             arrow = arrow(length = unit(2, "mm"))) +
  geom_sf_label(data = labs_df,
                aes(label = name),
                nudge_y = 0.9,
                nudge_x = -0.1) +
  theme_void() +
  ggtitle(label = "Number of breathalyser tests per county",
          subtitle = "January 2020") +
  labs(caption = caption_text) +
  annotation_north_arrow(height = unit(7, "mm"),
                         width = unit(5, "mm"),
                         pad_x = unit(5, "mm"),
                         pad_y = unit(2, "mm")) +
```

```
  annotation_scale(line_width = 0.5,
                   height = unit(1, "mm"),
                   pad_x = unit(6, "cm"))
```



This provides one way to add context. In previous iterations, we have adjusted the opacity of our other layers, in order to aid visibility of the basemap underneath them, so this might be something to consider.

0.41.2 Inset maps

Inset maps provide another approach to situating your map in context. You might use this to show where your main map fits into the context of a larger area, for example, here we might illustrate how Hungary is situated within Europe. You might also use an inset map in another situation, where you have additional areas which you want to show which may be geographically far but politically related to your region. For example, we might want to portray a map of the United States of America, and make sure to include Hawaii and Alaska on the map. The basic principles behind these maps is the same. Essentially we must create two map objects, and then bring these together. Let's illustrate how.

First, we need to create the map we will be displaying in the inset map. In this case, let's highlight the location of Hungary on the map. We can do this by

creating a map of Europe (let's use the `rnaturalearth` package for this). We create a list of the countries from the world map 'countries110', and filter only Europe (we also exclude Russia because it is so big it makes the rest of Europe hard do see on a smaller map, and Iceland as it's far, also making the map bigger than we need).

```
library(rnaturalearth)

europe_countries <- st_as_sf(countries110) %>%  # get geom for all countries
  filter(region_un=="Europe" & # select Europe
           name != "Russia" &   # remove Russia
           name != "Iceland") %>% # remove Iceland
  pull(name) # get only the names in a list

europe <- ne_countries(geounit = europe_countries, # get geoms for countries in list
                       type = 'map_units',  # country type as map_units
                       returnclass = "sf") # return sf object (not sp)
```

Now we can use the returned sf object `europe` to create a map of Europe. But this isn't necessarily enough context. We also want the inset map to highlight Hungary within this map. We can do this by creating another layer, with only Hungary, and making its border red and a use thicker line width. By layering this on top of the Europe map, we are essentially highlighting our study region.

```
inset_map <- ggplot() +  # create new ggplot
  geom_sf(data = europe,  # add europe map as first layer
          fill = "white") + # white fill
  geom_sf(data = europe %>% filter(name == "Hungary"), # new layer only Hungary
          fill = "white" ,  # white fill
          col = "red",   # make the border red
          lwd = 2) +   # make border line thick
  theme_void() +  # strip grid elements
  theme(panel.border = element_rect(colour = "black", # draw border around map
                                    fill=NA))
```

We now have this separate map, which highlights where Hungary can be found, right there in Central Europe. To display this jointly with our map of breathalyser test, we must join the two maps. For this, we will need both as separate objects. We've already assigned out inset map to the object `inset_map` but we must take our main map, and also assign it to an object. Let's call this `main_map`.

```
main_map <- ggplot(data = hu_dd) +
  geom_sf(aes(fill = total_quantiles),
          lwd = 0.5,
          col = "white") +
  scale_fill_brewer(type = "seq",
                    palette = "Greens",
                    name = "Total tests") +
  geom_curve(x = bp_x - 0.1,
             y = bp_y + 0.9,
             xend = bp_x ,
             yend = bp_y,
             arrow = arrow(length = unit(2, "mm"))) +
  geom_sf_label(data = labs_df,
                aes(label = name),
                nudge_y = 0.9,
                nudge_x = -0.1) +
  theme_void() +
  ggtitle(label = "Number of breathalyser tests per county",
          subtitle = "January 2020") +
  labs(caption = caption_text) +
  annotation_north_arrow(height = unit(7, "mm"),
                         width = unit(5, "mm"),
                         pad_x = unit(5, "mm"),
                         pad_y = unit(1, "mm")) +
  annotation_scale(line_width = 0.5,
                   height = unit(1, "mm"),
                   pad_x = unit(6, "cm"))
```

So now we have our inset map and main map stored as two map objects. To display them together we can use the `ggdraw()` and `draw_plot()` functions from the `cowplot` package. Let's load this package.

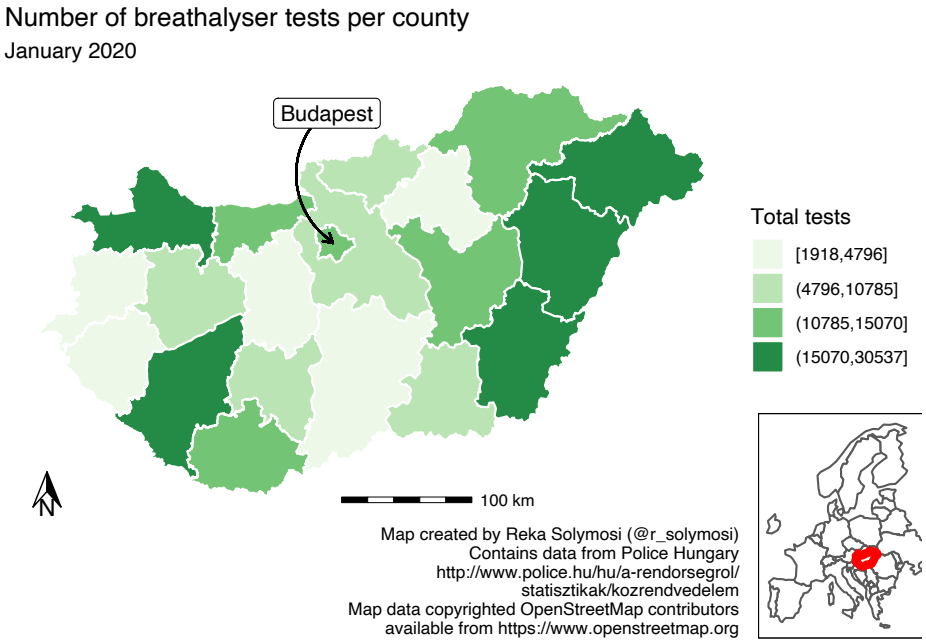
```
library(cowplot)
```

First, we set up an empty drawing layer for our ggplot using the `ggdraw()` function. Then we layer on the two maps both using the `draw_plot()` function. This allows us to draw plots and sub plots. This function places a plot (which we specify as the first parameter of this function) somewhere onto the drawing canvas. By default, coordinates run from 0 to 1, and the point (0, 0) is in the lower left corner of the canvas. We want to therefore specify where the plots go on our canvas explicitly. Alongside position, we can also specify size. This is important, we usually make the inset map smaller.

```
hu_dd_with_inset <- ggdraw() +  # set layer
  draw_plot(main_map) +  # draw the main map
  draw_plot(inset_map,   # draw inset map
            x = 0.75,    # specify location on x axis
            y = 0,    # specify location on y axis
            width = 0.35,    # specify width
            height = 0.35)   # specify height
```

We now have our final map, which we can check out now:

```
hu_dd_with_inset
```



You can play around with where you position your inset map by adjusting the x and y coordinates. You can also play around with the size of it by adjusting the parameters for height and width. And like mentioned above, you can use inset maps not only for context, but also to include geographically far away regions which belong to the same political unity, for example to include Alaska and Hawaii in maps of the United States.

0.42 Summary and further reading

In this chapter we covered some principles of data visualisation and good map design, specifically how to implement some of these using `ggplot2` library in R. We talked about symbols, about colour, about text, and about adding context. GGplot2 is an incredibly flexible framework, and through the use of layers you can achieve a very beautiful and meaningful map output. We could for example consider adding topography, such as rivers, lakes, and mountains to our maps, and it would be only a case of adding another layer. To get more familiar with this I recommend **?** and **?**.

For general readings on cartography, the work of Kenneth Field privudes (eg: **?** or **?**) thorough and engaging guidance. For data visualisation, while **?** is a classic text, those looking for practical instruction may wish to turn to **?** or **?** for more guidance.

Time matters

0.43 Introduction

In this chapter we provide a brief introduction into spatio-temporal visualisation. The importance of place in criminology and crime analysis is widely recognised, and is the central topic of this book. However, taking into consideration **time** is just as important as place. We often hear that crime is "going up" or "going down" over time. These variations on the levels of crime along time also vary across space. These variations across both time and place are called **spatio-temporal variations**, and are of crucial importance for crime analysis, explanation, and prevention.

Traditionally the temporal and spatial analysis of crime are not introduced in a combined manner. Although a great deal of energy has been devoted to produce accessible training material for crime analysts on geographic information systems and spatial analysis, most criminology degrees (even at postgraduate level) and training packages for crime analysis devote a very limited (if any) content to the appropriate visualisation and analysis of temporal and spatio-temporal data. Therefore, before we discuss the spatio-temporal, we have to introduce a few key ideas and concepts about temporal crime analysis.

In this chapter, we will therefore give a very high-level overview of **temporal crime analysis**, before moving on to ways in which we can display spatio-temporal variation in our data using maps. The key concepts covered in this chapter are:

- an introduction to temporal data in crime analysis,
- cleaning and wrangling temporal data,
- visualising time data,
- time series and its three components: trend, seasonality, and random variation,
- visualising spatio-temporal variation.

We will be making use of the following R packages:

```
# Basic reading and data carpentry
library(readr)
library(dplyr)
library(lubridate) # adds functionality for better handling of temporal data

# Packages for handling spatial data
library(sf)
library(spacetime)
library(sp)

# General visualisation and ggplot plugins for temporal data
library(ggplot2)
library(ggfortify)
library(ggTimeSeries)
library(ggseas)
library(gganimate)
library(tmap)
```

0.44 Temporal data in crime analysis

In this book so far we have really emphasised the role of place in presenting opportunities for crimes to occur. However we cannot consider space without also considering time. An area might look very different during the day and during the night, on a weekend or on a weekday, and in the summer or in the winter.

On a macro-scale, the relationship between crime and the seasons is something that had been a topic of concern for researchers as long as space has (**?**). Zooming into a micro-scale, changes in routine activities with time of day or day of week will affect the profile of a place, and linking back to the idea of crime places such as *generators* or *attractors*, will have significant effect on crime rates. In conceptualising these crime places, **?** emphasised the importance to consider the measure of busyness of a place by time of day in order to understand its role as an attractor, generator, or other crime place. For example, at transit stations during school days there is a morning peak time of work and school users combined, an afternoon school closing peak, and a secondary and slightly later end-of-workday peak time. Any calculation of crime rates needs to account for these micro-level temporal variations.

At whatever unit of analysis, time is a vital variable to include in our crime analysis and criminological research. To quote **?**

> "[I]t is important to disaggregate data into sensible temporal categories to have a real understanding of the relationship between the

variables under scrutiny. (**?**, p.627)

Returning to the importance of the role of place, we can introduce **spatio-temporal data** analysis. Spatio-temporal analysis is the process of utilising geo-and-time-referenced data in order to extract meaning and patterns from our data. In the earlier days, crime pattern analysis has tended to focus on identifying areas with higher densities of criminal activity, but not so much the monitoring of change in crime patterns over time (**?**). However, crime hotspots display significant spatio-temporal variance, and the identification of spatio-temporal patterns of hot streets provides significant 'actionable intelligence' for police departments (**?**). Evidently, we cannot ignore time as a variable in our analyses. And while the main focus of this book is space, we must take at least one chapter to introduce some key concepts, and provide additional resources for readers to follow up with.

0.45 Temporal data wrangling

Temporal data means that we can perform all sorts of exciting operations in our data wrangling processes. Just how we learned about spatial operations with spatial data, there are some things we can do only with temporal data. In this section we will introduce some of these.

A key R package that will help with temporal data wrangling is `lubridate`. Date-time data can be frustrating to work with and many base R commands for date-times can be unintuitive. The package `lubridate` was created to address such issues, and make it easier to do the things R does with date-times.

Specifically, we will be using crime data from New York City made available by **?** which is also accessible through the R package `crimedata` **?**. You can refer to these citations to learn more about acquiring data from this fantastic resource! However for now, let's make use of the data provided with the book, where we selected a specific subset of aggravated assault in New York for a period of five years.

```
agassault_ny<-read_csv("data/agassault.csv")
```

When you read the data into R, you will see that there is a column for date called **date_single**. Let's have a look at the first value in this column:

```
agassault_ny %>%
  select(date_single) %>%
  head(1)
```

```
## # A tibble: 1 x 1
##   date_single
##   <dttm>
## 1 2014-01-01 00:03:00
```

We can see that the date is stored in the following format: year-month-day hour-minute-second. So the first date on there you can see is *2014-01-01 00:03:00*. What kind of variable is this?

```
class(agassault_ny$date_single)
```

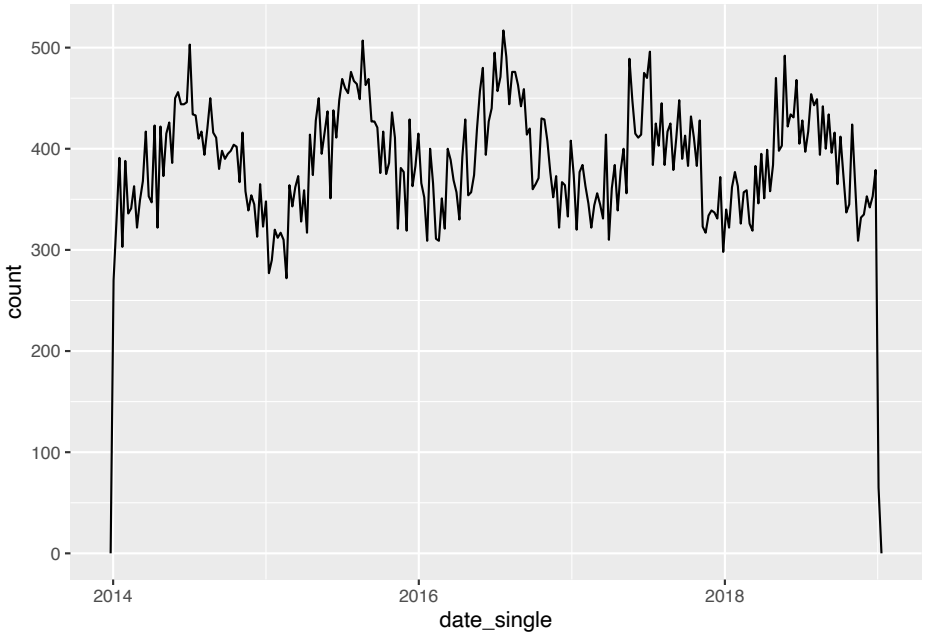
```
## [1] "POSIXct" "POSIXt"
```

Our date and time variables are of class `POSIXct` and `POSIXt`. These are the two basic classes of date/times. Class "POSIXct" represents the (signed) number of seconds since the beginning of 1970[20] as a numeric vector. Class "POSIXt" is a named list of vectors representing seconds (0–61), minutes (0–59), hours (0–23), day of the month (1–31), months after the first of the year (0–11), years since 1900, day of the week, starting on Sunday (0–6), and a flag for whether it is daylight savings time or not (positive if in force, zero if not, negative if unknown).

Let's plot this data:

```
agassault_ny %>%
  ggplot(aes(date_single)) +
  geom_freqpoly(binwidth = 7*24*60*60) # 7 days in seconds
```

[20] https://en.wikipedia.org/wiki/Unix_time

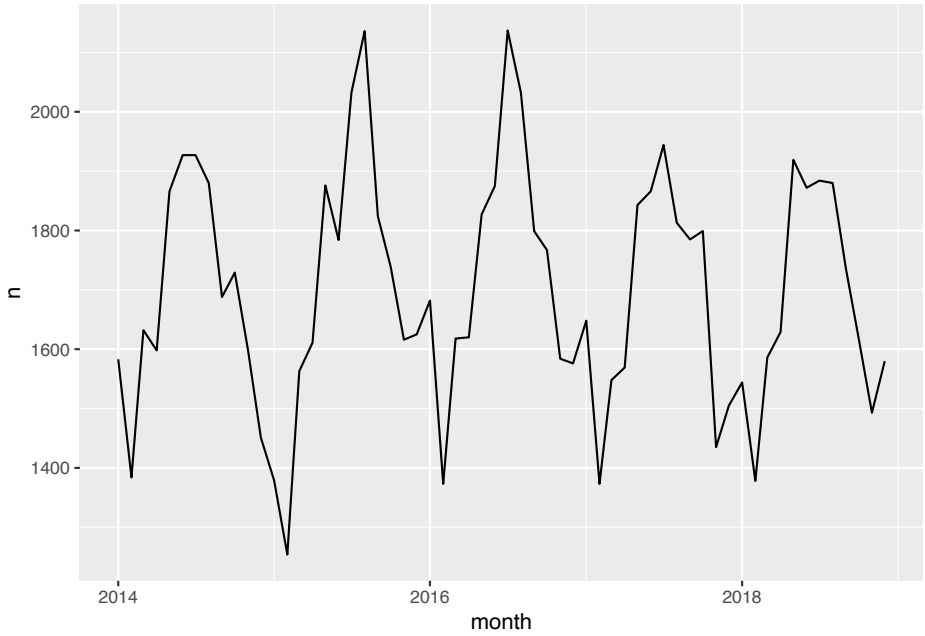


Notice what `geom_freqpoly()` is doing. We have a dataframe with rows for each case. The data is not aggregated in any form. But this function counts on the fly the number of cases (of rows) for each of the bins as we define them. It is, thus, a convenient function that saves us from having to first do that aggregation ourselves when we want to plot it.

An alternative approach to plotting individual components is to round the date to a nearby unit of time, with `floor_date()`, `round_date()`, and `ceiling_date()`. These functions live inside the lubridate package.

Each function takes a vector of dates to adjust and then the name of the unit round down (floor), round up (ceiling), or round to. So to aggregate per month we will code as:

```
library(lubridate)

agassault_ny %>%
  count(month = floor_date(date_single, "month")) %>% # use floor date function
  ggplot(aes(month, n)) +
    geom_line()
```



What if I asked you the question: which year had the most aggravated assaults? Or what if I want to know if aggravated assaults happen more in the weekday, when people are at work, or in the weekends, maybe when people are away for a holiday? You have the date, so you should be able to answer these questions, right?

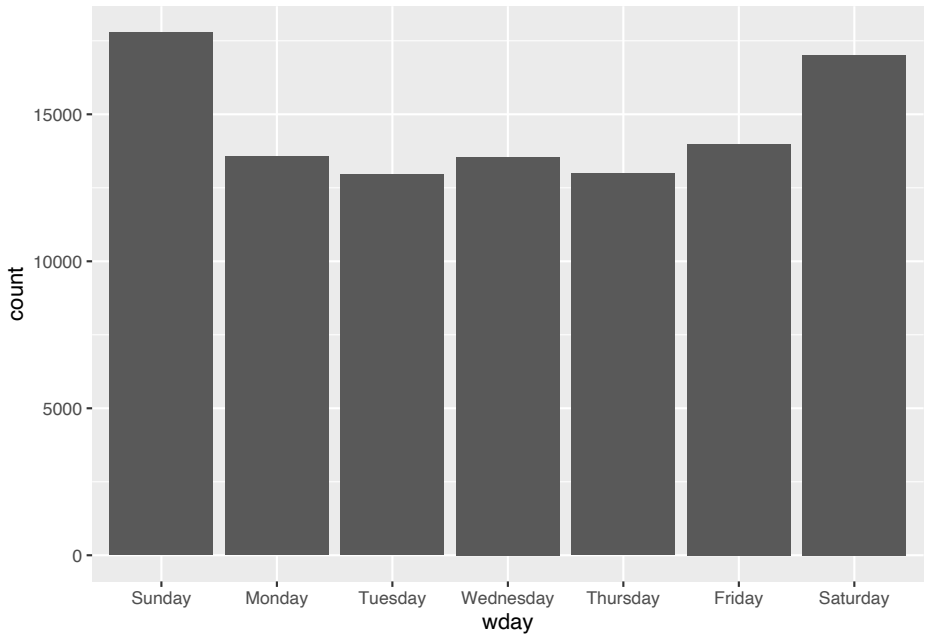
Well you need to be able to have the right variables to answer these questions. To know what year saw the most aggravated assaults, you need to have a variable for year. To know what day of the week has the most aggravated assaults, you need to have a variable for day of the week. So how can we extract these variables from your date column? Well luckily the `lubridate` package can help us do this. We can use the `year()`, `month()`, `day()`, and `wday()` to extract these components of a date-time.

```
agassault_ny <- agassault_ny %>%
  mutate(year = year(date_single),
         month = month(date_single, label = TRUE, abbr=FALSE),
         day = day(date_single),
         wday = wday(date_single, label = TRUE, abbr=FALSE)
         )
```

We have now created a set of additional variables that have extracted information from your original time of occurrence variable.

Let's consider distribution of events per day of the week.

```
agassault_ny %>%
  ggplot(aes(x = wday)) +
    geom_bar()
```



In order to extract such date-time information from variables, we need these to be date-time objects. We saw above that in this case this assumption was met. However if it is not, you can turn text column of dates into a date-time object using lubridate's functions. For example if you have a data set of day-month-year separated with "/", you can use the `dmy()` function (stands for day month year) to parse it as a date-time object. On the other hand, if you have some US data, and it is actually written as month-day-year, separated by "/", you can simply shuffle the order of the letters in the function, and use the function `mdy()`. They will translate into the same item. See for yourself:

```
dmy("15/3/2021") == mdy("3/15/2021")
```

```
## [1] TRUE
```

In fact, `lubridate` is so good, it can even parse text representations of months. Look at this for example:

```
dmy("15/3/2021") == mdy("March/15/2021")
```

```
## [1] TRUE
```

Amazing stuff, which will definitely come in handy, especially if you might be a crime analyst working with some messy messy data. Lubridate should most definitely form part of your data wrangling toolkit in this case!

0.46 Visualising time data

Once we have parsed and cleaned the temporal information that is available in our date variable, we can make use of this to visualise trends in other ways, not just using time series. For example, we might want to show where hotspots in time occur, within a year, or within a week, or some other set interval.

One approach for this is to use a calendar heatmap.

First, we create a column for date, removing the time (hour minute and second). We can achieve this easily by using the `date()` function in `lubridate`:

```
agassault_ny$date <- date(agassault_ny$date_single)
```

If we have a look we can now see that the time component has been stripped away, and we have this date object. Let's look at the value for the first row.

```
agassault_ny$date[1]
```

```
## [1] "2014-01-01"
```

That looks like what we are expecting. Now let's see the class of this variable.

```
class(agassault_ny$date)
```

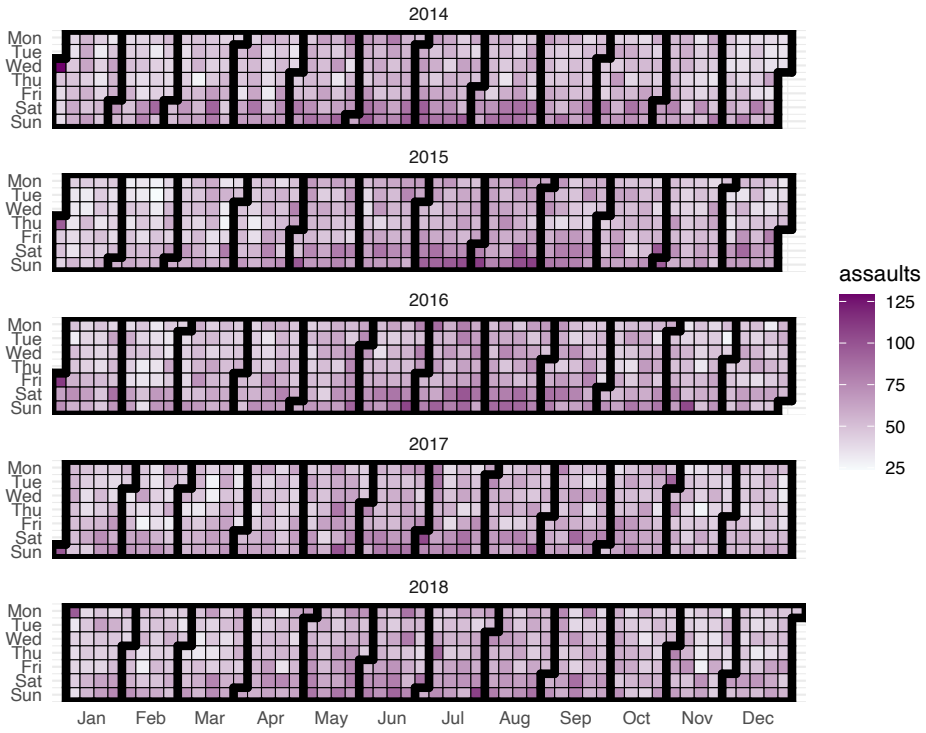
```
## [1] "Date"
```

It is a date object, so we will be able to do date-time operations to it. Good stuff. Now what we want to do is create a heatmap, a sort of calendar, of the number of aggrevated assault incidents per date. We can use our well known attribute operations here, specifically the `group_by()` function in the `dplyr` packate to count the events per day.

```
agassault_ny_d <- agassault_ny %>%
                    group_by(date) %>%
                    summarise(assaults = n())
```

Now we hav e this new dataframe, the number of aggravated assaults per day. To make our temporal heatmap calendar, we will now use a `ggplot2` extension, `ggTimeSeries`, that allows us to produce calendar heat visualisations. In this package, we can use the `ggplot_calendar_heatmap()` function, which creates a calendar heatmap. This approach provides context for weeks, and day of week which makes it a better way to visualise daily data than line charts.

```
library(ggTimeSeries)

ggplot_calendar_heatmap(
   agassault_ny_d,  # our dataset of dates and number of crimes
   cDateColumnName = 'date', # column name of the dates
   cValueColumnName = 'assaults') + # column name of the data
   xlab(NULL) + # x axis lable
   ylab(NULL) + # y axis lable
   scale_fill_continuous(low = '#f7fcfd',  # set colour for low count
                         high = '#6e016b') +   # set colour for high count
  facet_wrap(~Year, ncol = 1) +  # separate out by each year
  theme_minimal()
```



This sort of visualisation might be useful for example to see if certain days of the week see more incidents than others, possibly due to differences in the underlying routine activities that predominate for example weekends versus weekdays. For a bit of fun, you can read **?** for a safety rating on each day of the week.

0.46.1 How (not) to present time

In our calendar heatmap above we presented count of crimes on each day. But there are other approaches to visualise change over time as well. One such approach is to present **percentage change** from one point in time to the next. There are many issues with this approach, which lead to misinterpreting the data, which are explored in detail by **?**. For example, he mentions that percent change is not symmetric.

> For example, an increase from 4 to 5 crimes is a 25% increase, whereas a decrease from 5 to 4 crimes is only a 20% decrease. (p.x).

He presents an alternative metric in Poisson z-scores.

Another issue is with the very popular approach of showing changes as **year-to-date**. In the post "Why you can't identify changes in crime by comparing this month to last month" **?** presents some great arguments for why at-

tempts to identify changes in crime frequency that involve simply comparing the number of crimes this week/month/year to the number that occurred last week/month/year, or comparing this week, month etc to the same period last year is not an appropriate way to analyse change over time. For example, doing this means throwing away useful information, ignoring trends and seasonality, and leaves results vulnerable to noise. As an alternative, he promotes the use of creating a forecast based on historic data, and comparing observed values against this.

It is important that when presenting temporal data, we keep in mind these notes of caution, and follow good practice recommendations such as those notes here.

0.47 Time series analysis

A key way to ensure we are analysing our time data appropriately is to deal with time series data, and treat them accordingly. **Time series analysis** looks at trends in crime or incidents. A crime or incident trend is a broad direction or pattern that specific types or general crime and/or incidents are following. Three types of trend can be identified:

- **overall trend** – highlights if the problem is getting worse, better or staying the same over a period of time
- **seasonal, monthly, weekly or daily cycles of offences** – identified by comparing previous time periods with the same period being analysed
- **random fluctuations** – caused by a large number of minor influences, or a one-off event, and can include displacement of crime from neighbouring areas due to partnership activity or crime initiatives.

Decomposing these trends is an important part of what time series analysis is all about. We will see some examples.

0.47.1 Plotting time series data

Let's get some fresh data by travelling about three and a half thousand miles to Spain. The data we will work with now is called `femicidos.csv` in the companion data, and is a collection of intimate partner femicides from Spain.

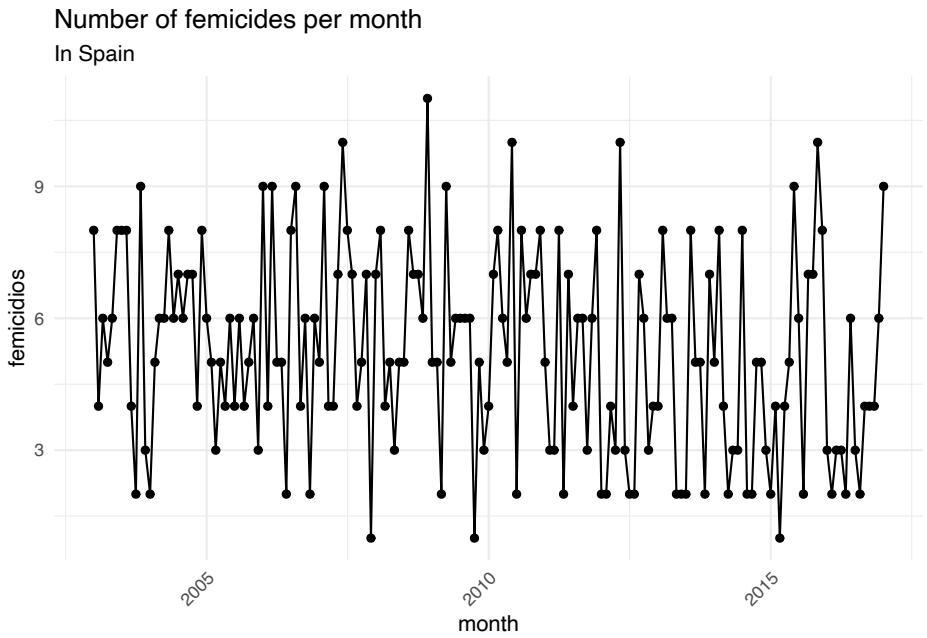
```
femicidos <- read_csv("data/femicidos.csv")
```

This dataframe has only two columns, `femicidos`, which is a monthly observation of the number of intimate partner femicides per month, starting in January 2003,

and `month`, which is the date for each observation. So, each row represents a monthly count of these crimes.

We could do something like plot the number of crimes over each month using `ggplot2`.

```
library(ggplot2)

ggplot(femicidos, aes(x = month, y = femicidios, group = 1)) +
  geom_point() +
  geom_line() +
  theme_minimal() +
  ggtitle(label = "Number of femicides per month", subtitle = "In Spain") +
  theme(axis.text.x = element_text(hjust = 1, angle = 45))
```



This visualisation gives us an insight into how the count of crimes varies between observations, but it subsumes in itself the three elements mentioned above (the overal trend, seasonal fluctuation, and random noise). This makes it difficult to isolate and discuss any one of these, making it difficult to answer the question about whether crime is going up or down, or whether there are any seasonal fluctuations present. In order to achieve this, we want to **decompose** the data into these components.

To look into decomposing into these components, we can use the many functionality within R to deal with time series data. To take advantage of many of

these, we will need our dataframe to be stored as a **time series** object. This enables us to apply R's many functions for analysing time series data. To store the data in a time series object, we use the `ts()` function. Inside this function, we pass only the column which contains the number of crimes for each month (we filter with the `select()` function)

```
library(dplyr)

fem_timeseries <- ts(femicidos %>%
                       select(femicidios))
```

We have taken our dataframe of observed values in our time series (montly observations of crime counts in this case) and tranformed it into a matric with class of "ts" - essentially representing our data as having been sampled at set intervals (in this case every month). Once we have the result stored in our `fem_timeseries` object, we can auto print to see some details:

```
fem_timeseries
```

We can see that each observation point has been numbered in order, and we have a value for each observation (the number of femicides recorded in each month). Sometimes the time series data set that you have may have been collected at regular intervals that were less than one year, for example, monthly or quarterly. In this case, you can specify the number of times that data was collected per year by using the `frequency` parameter in the `ts()` function. For monthly time series data, you set `frequency = 12`, while for quarterly time series data, you set `frequency = 4`

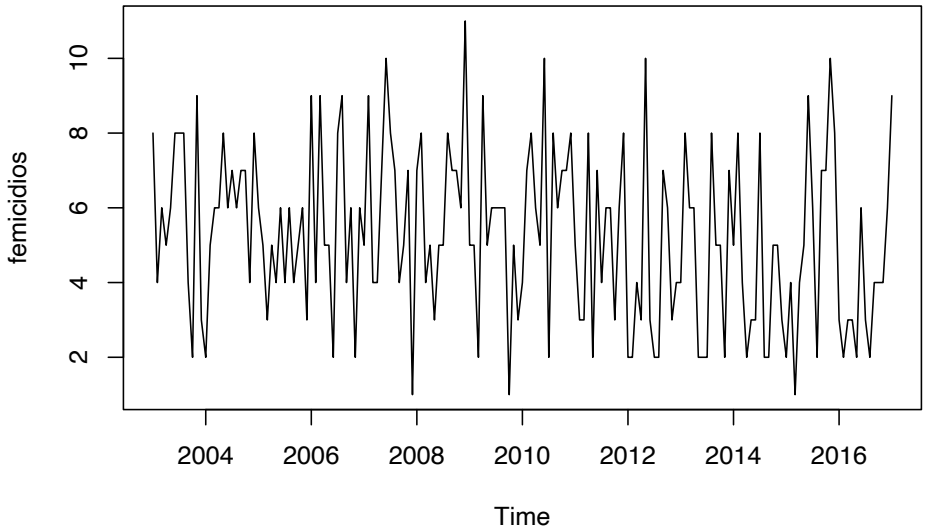
You can also specify the first year that the data was collected, and the first interval in that year by using the `start` parameter in the `ts()` function. So, in our case, we would do as follows:

```
# transform into time series
fem_timeseries <- ts(femicidos %>%
                       select(femicidios), # specify dataframe selecting column
                     frequency=12,  # specify monthly frequency
                     start=c(2003,1) # specify start time (January 2003)
                     )
```

Now that we have created this timeseries object, we can use the timeseries specific functions in order to extract meaning and insight. For example, going

back to plotting our data so that we can see what sort of trends might be going on with crime, we can make use of the `plot.ts()` function, the basic plotting method for objects that are of class "ts".

```
plot.ts(fem_timeseries)
```



This plot should look similar to the one we created using ggplot2 above, however our observations are now treated as a continuous variable, labeled "Time". We can of course also use `ggplot2`to plot a time series like the one we just did but here we would need a variable encoding the date (and preferably a full date, not just month and year as here).

As you can see it is very noisy. Fortunately, the annual count for intimate partner femicides is low in Spain. There seems to be some seasonality too. But what more can we do with plotting time series objects? Well we can use the function `decompose()` in order to break down our plot into the three constituent parts discussed above. This function will decompose a time series into the trend, seasonal, and the noise (also called irregular component) using moving averages.

A seasonal time series consists of a trend component, a seasonal component and an irregular component. Decomposing the time series means separating the time series into these three components: that is, using statistics to estimate these three components.

To estimate the trend component and seasonal component of a seasonal time series that can be described using an additive model, we can use the `decompose()` function in R. This function estimates the trend, seasonal, and irregular components of a time series using moving averages. It deals with additive or multiplicative seasonal components (the default is additive).

The function `decompose()` returns a list object as its result, where the estimates of the seasonal component, trend component and irregular component are stored in named elements of that list objects, called "seasonal", "trend", and "random" respectively.

Let's now decompose this time series to estimate the trend, seasonal and irregular components.

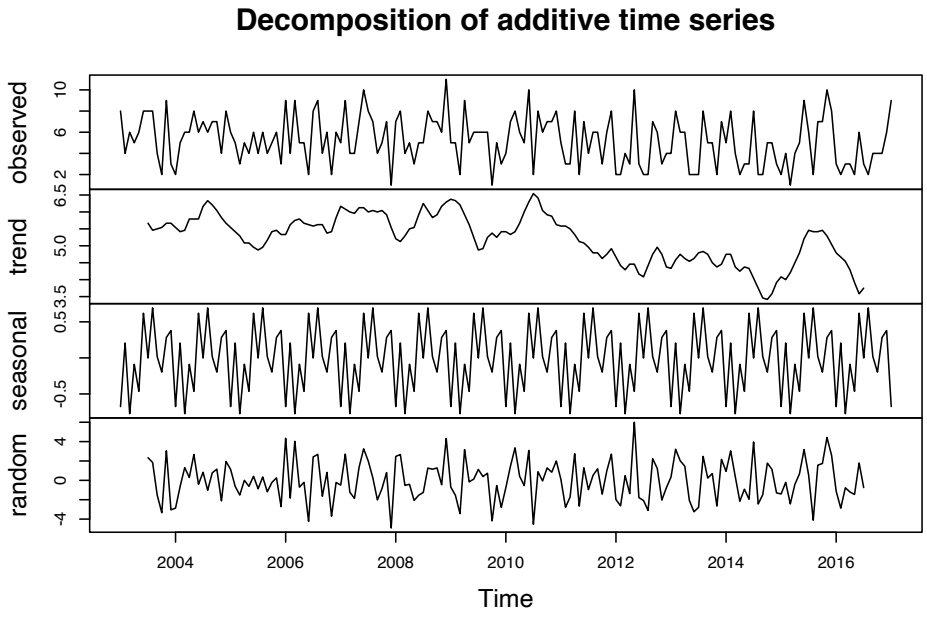
```
fem_timeseriescomponents <- decompose(fem_timeseries)
```

The estimated values of the seasonal, trend and irregular components are now stored in variables `fem_timeseriescomponents$seasonal`, `fem_timeseriescomponents$trend` and `fem_timeseriescomponents$random`. For example, we can print out the estimated values of the seasonal component by typing:

```
fem_timeseriescomponents$seasonal
```

The estimated seasonal factors are given for the months January-December, and are the same for each year. The largest seasonal factor is for July (about 0.70), and the lowest is for February (about -0.76), indicating that there seems to be a peak in femicides in July and a trough in femicides in February each year. We can plot the estimated trend, seasonal, and irregular components of the time series by using the `plot()` function, for example:

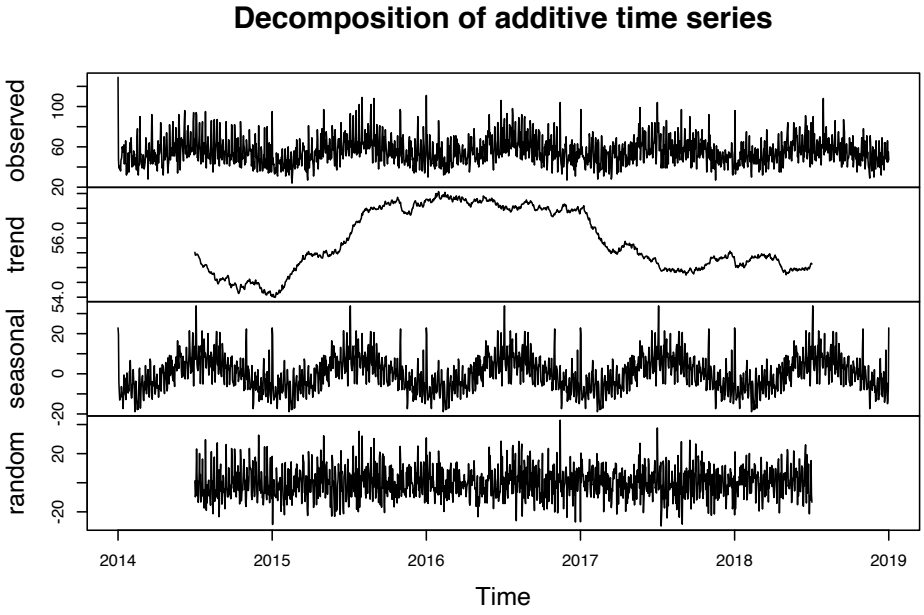
```
plot(fem_timeseriescomponents)
```



Once we remove the noise and the seasonal components, it becomes easier to see the estimated trend. Notice that while random and seasonal components still look messy, their scales are different and centred around zero.

We can adapt this code to decompose and estimate the trends for the aggravated assault data for NYC that we used earlier in the chapter too.

```
# select relevant column (assaults)
agassault_ny_d2 <- dplyr::select(agassault_ny_d, assaults)

#use ts() to transform to time series object
ny_timeseries <- ts(agassault_ny_d2,
                    frequency=365,
                    start=c(2014,1,1))

# decompose time series
ny_timeseriescomponents <- decompose(ny_timeseries)

#plot results
plot(ny_timeseriescomponents)
```

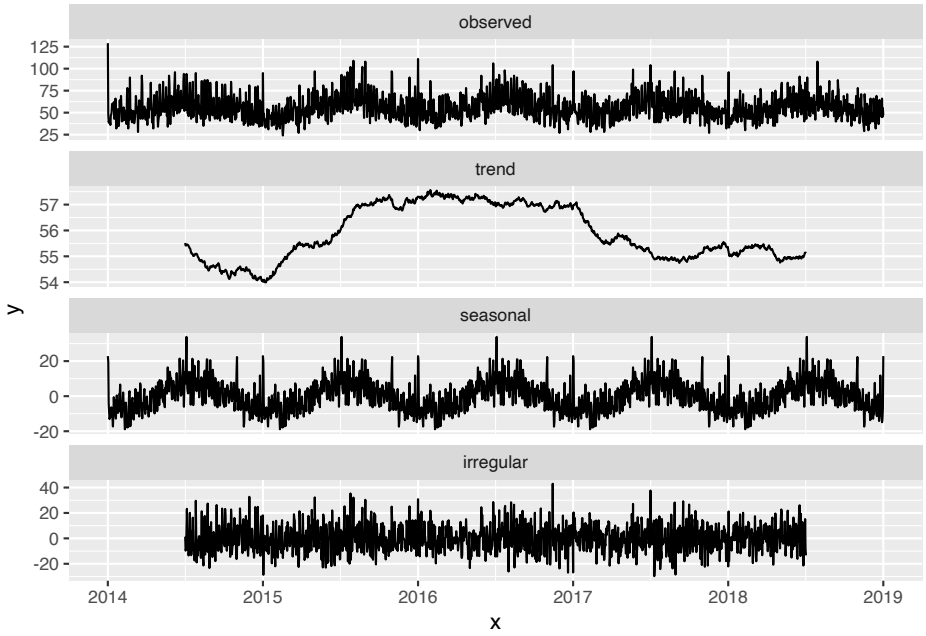


We can also use `ggplot2` for these purposes. In particular we can use the `ggseas` extension which allows for seasonal decomposition within `ggplot` (see **?** for details). First we can use the `tsdf()` function from the `ggseas` package. This turns the `ts` object we just created into a dataframe and then plot the series.

```
library(ggseas)

ny_df <- tsdf(ny_timeseries)
```

Then we can use the `ggsdc()` function in order to create a four-facet plot of seasonal decomposition showing observed, trend, seasonal and random components

```
ggsdc(ny_df, aes(x = x, y = y),
      method = "decompose") +
   geom_line()
```



The resulting graph similarly presents the 4 components, the observe data, the trend, the seasonal component and the random fluctuation.

We have now covered a quick overview of ways of making sense of temporal data. Of course there is a lot more out there, and we urge interested readers to make use of the recommended reading section in this chapter to explore further the topic of temporal data analysis. But now let's return to the spatial focus of our book.

0.48 Spatio-temporal data visualisation

For the next set of exercises we are going to look at temporal variations on burglary across Greater Manchester. We are going to focus on wards as the unit of analysis. Accordingly, we will need to import another data set, this time a geojson which contains the wards (administrative boundaries) for Manchester, and the montly burglary count for each ward in 2018.

To load the ward shapefiles for Manchester into a `sf` object we use code we had already used in a previous session.

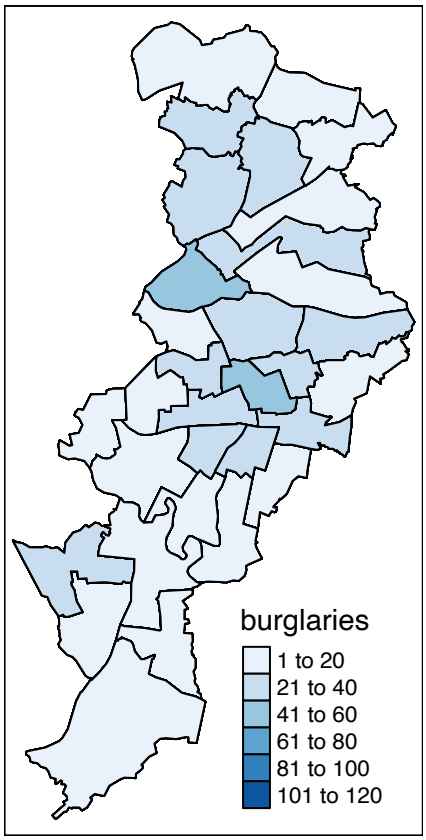
```
mcr_burglary <- st_read("data/mcr_burglary.geojson")
```

```
## Reading layer `mcr_burglary' from data source `/Users/reka/Desktop/crime_mapping/crime_mapping
```

```
## Simple feature collection with 384 features and 3 fields
## Geometry type: POLYGON
## Dimension:     XY
## Bounding box:  xmin: -2.319906 ymin: 53.34013 xmax: -2.146819 ymax: 53.54462
## Geodetic CRS:  WGS 84
```

With this data in our environment we can plot a map using `tmap`.

```
library(tmap)

tm_shape(mcr_burglary) +
  tm_fill("burglaries") +
  tm_borders()
```



So this is something we're already familiar with. But how can we map the temporal information? We will now cover two approaches.

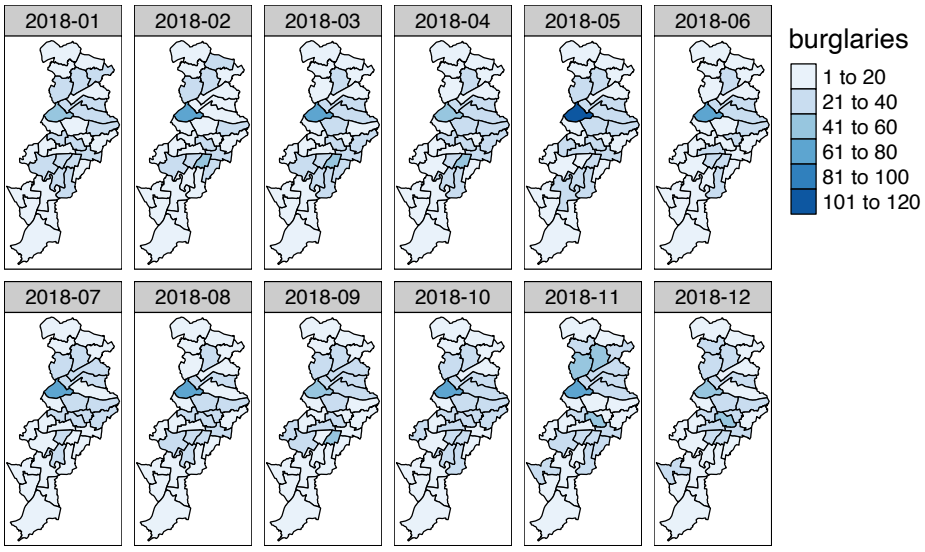
0.48.1 Small multiples to show temporal variation

As noted by **?**, spatio-temporal data often come in the form of single tables expressed in one of the three following formats:

- *time-wide* where different columns reflect different moments in time,
- *space-wide* where different columns reflect different measurement locations or areas, or
- *long formats* where each record reflects a single time and space combination.

What we have in the `mcr_burglary` object if we view the data frame is a table expressed in the long format, where each row represents a single month and ward combination. We can see as well this is not simple a data table but a `sf` object which embeds the geographical information that allow us to place it in a map. We can now try to produce the small multiples with the `tm_facets()` function. (Note: if you wanted to use `ggplot2` instead of `tmap` you can look up the function `facet_wrap()` to achieve the same result).

```
tm_shape(mcr_burglary) +
  tm_fill("burglaries") +
  tm_borders() +
  tm_facets("month", free.coords=FALSE)
```



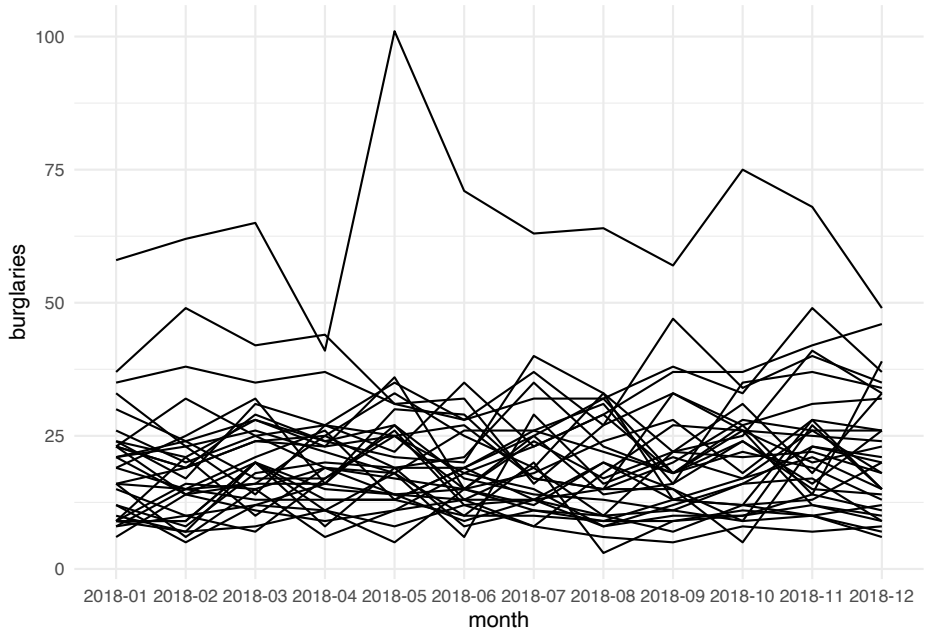
So this is one way to visualise temporal variation. What are some more?

0.48.2 Spaghetti plots

In longitudinal studies and in studies looking at areas over time, sometimes researchers use spaghetti plots. On their own they are not great, but they can used when one wants to put a trajectory within a broader context or when comparing different trajectories. You can read more about how to not use them in **?**.

While we will include the ward name as a spatial component in a way, this isn't technically spatio-temporal data visualisation, as we are stripping away any sort of spatial element, and keeping ward name only as a nominal variable. It is not great, but let's show you why you might use it. The basic concept is just the same line chart we saw earlier, but with the trajectories grouped within the wards. So instead of one line, we will get 32, one for each ward in our data.

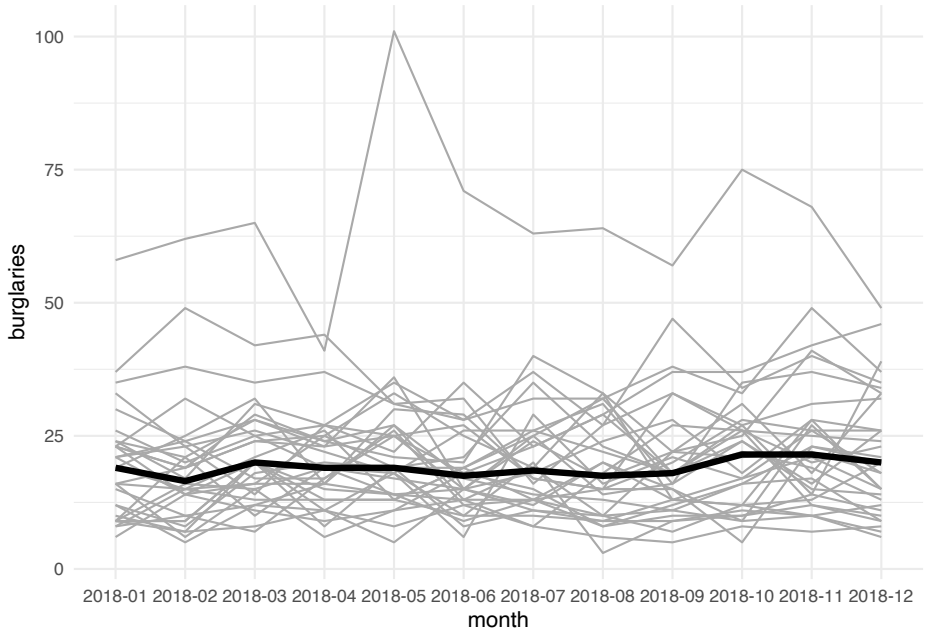
```
ggplot(mcr_burglary,
       aes(x = month,
           y = burglaries,
           group = ward_name)) +
  geom_line() +
  theme_minimal()
```



This is quite the mess. So in what situation may this be useful? Well maybe you want to compare the variation here with some central tendency. For this

we can "grey out" the lines (by chanhing the colour) and add some summary such as the median let's say, by using the `stat_summary()` function.

```
ggplot(mcr_burglary,
       aes(x = month,
           y = burglaries,
           group = ward_name)) +
  geom_line(color="darkgrey") +
  stat_summary(aes(group = 1), # we want to summarise all the data together
               geom = "line",  # geometry to display the summary
               fun.y = median, # function to apply
              lwd = 1.5) +   # specifying thick line for attention
  theme_minimal()
```

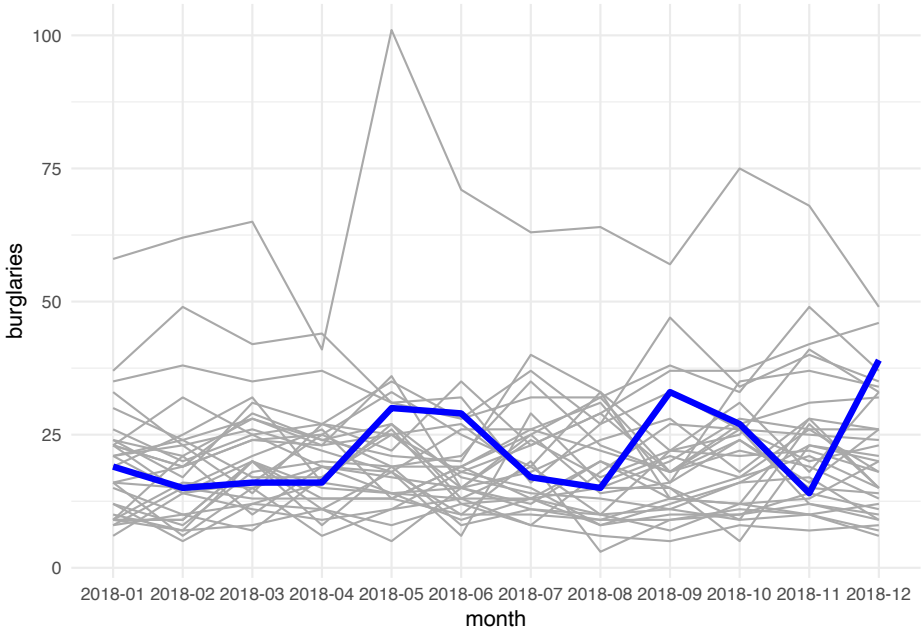


This way we can show something like the median trajectory compared with the individual observations' trajectories.

We could also use colour to highlight a specific area compared to the rest of the wards. For example, if we are interested in Fallowfield ward, we might highlight that as an additional layer in our spaghetti pile:

```
ggplot(mcr_burglary,
       aes(x = month,
```

```
          y = burglaries,
          group = ward_name)) +
geom_line(color="darkgrey") +
geom_line(data = mcr_burglary %>%    # pass new data in this layer
            filter(ward_name == "Fallowfield"),  #filter only Fallowfield
           aes(x = month,
          y = burglaries),
          colour = "blue",  # change colour for emphasis
          lwd = 1.5) + # change line width for emphasis
theme_minimal()
```



We can now maybe draw some conclusions about Fallowfield's burglary trajectory compared with the other wards in our data set. But let's move on now to the final approach, where we again make use of our spatial component.

0.48.3 Animations

The final way we will present here to visualise time and place together is through the use of animations. This feature is brought to `ggplot2` thanks to the `gganimate` extension.

The idea behind this display is really similar to that behind the small multiples, introduced earlier. A separate map is created for each month, and these are displayed near one another in order to show the change over time. However,

instead of side by side, these maps are sequential - they appear in the same place but one after another, in order to present change.

So first thing we do is to load the `gganimate` package:

```
library(gganimate)
```

Also, to apply `gganimate` to `sf` objects, you need to have a package called `transformr` installed. You don't need to load this, but make sure it is installed! If not, install with `install.packages(transformr)`.

Then, we need to make sure that our temporal variable is a date object. We can use the `ymd()` function, from the fantastic `lubridate` package (really I cannot praise this package enough, it makes handling dates so easy…!) to make sure that our month variable is a date object.

One thing you might notice looking at this data is that there is no date associated with each observation, only month and year. How can we use `ymd()` which clearly requires *y*ear *m*onth and *day*! Well, one approach is to make this up, and just say that everything in our data happened on the 1st of the month. We can use the `paste0()` function to do this:

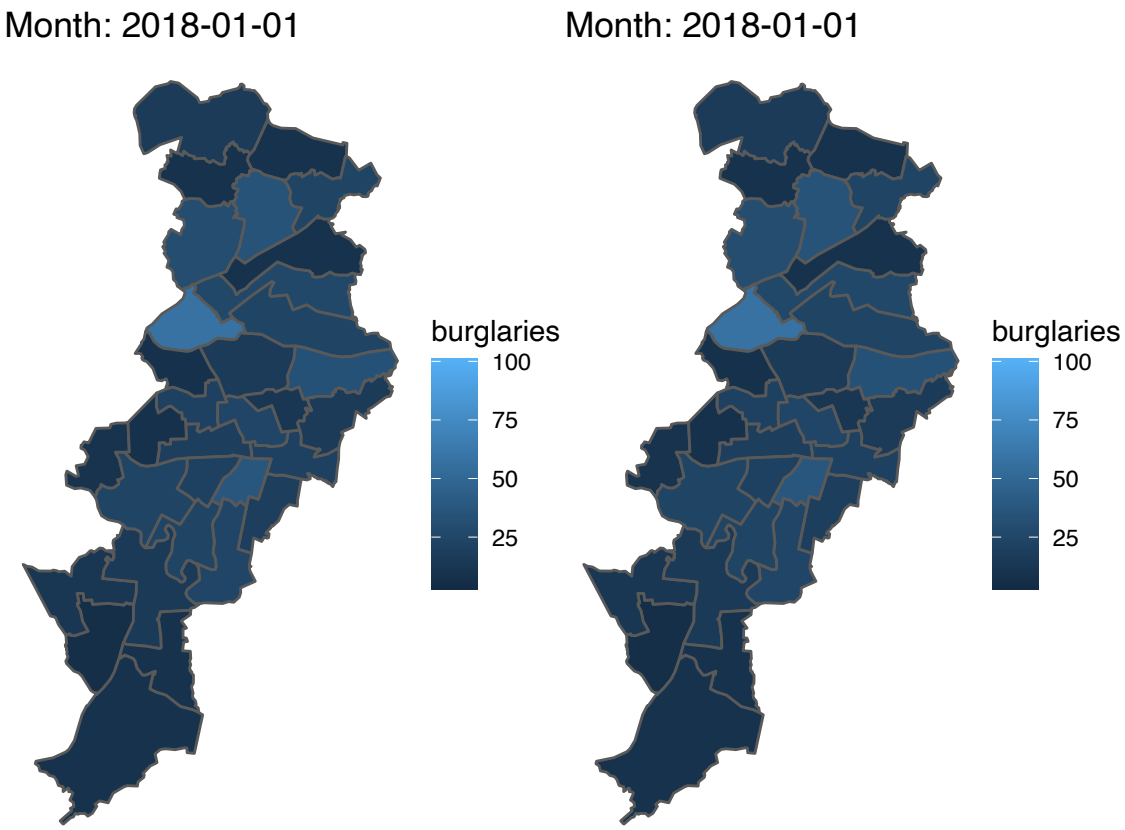
```
mcr_burglary$date_month <- ymd(paste0(mcr_burglary$month, "-01"))
```

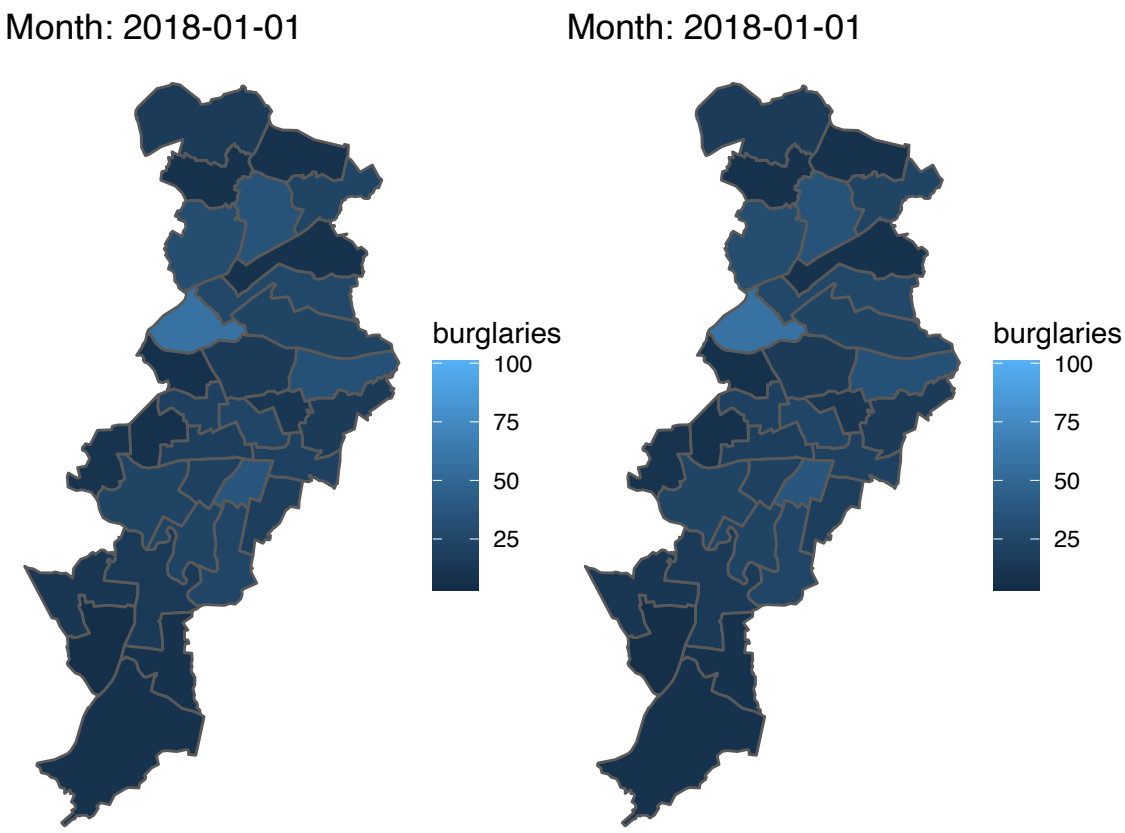
Now, we can create a simple static plot, the way we already know how. Let's plot the number of burglary incidents per ward, and save this in an object called `anim`:

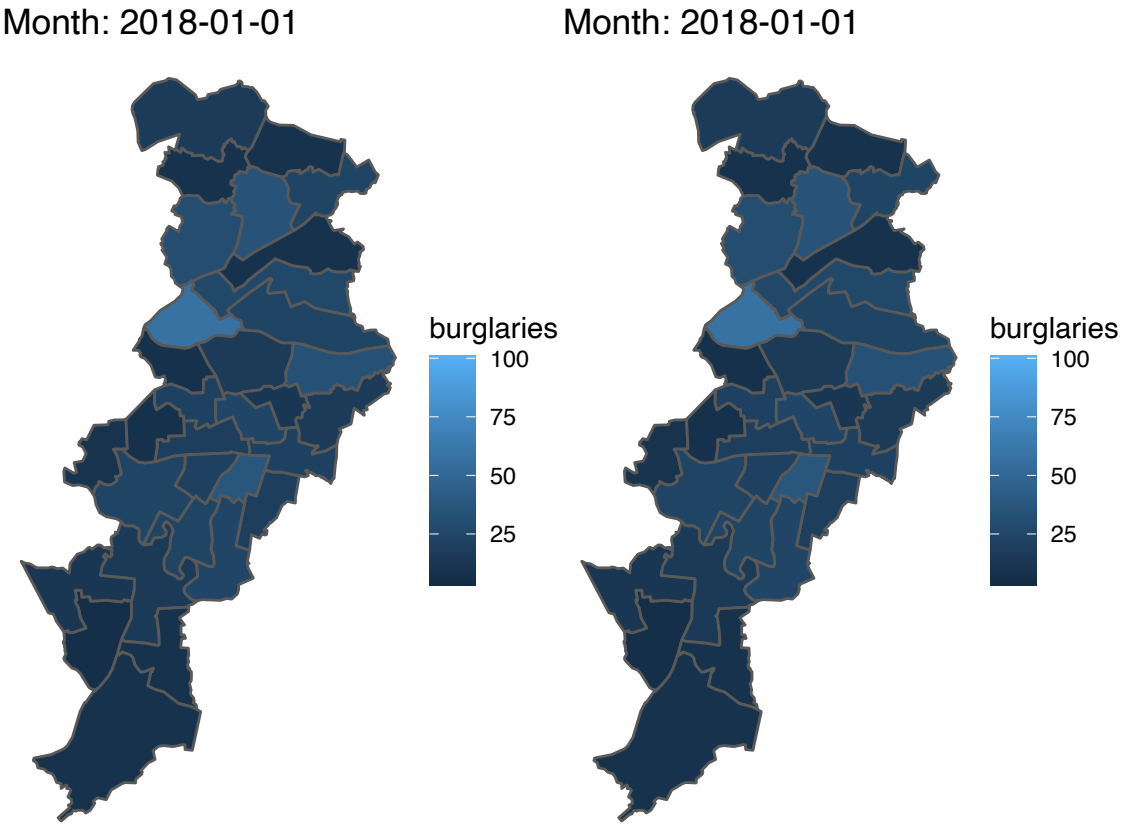
```
anim <- ggplot() +
  geom_sf(data = mcr_burglary,
          aes(fill = burglaries)) +
  theme_void()
```

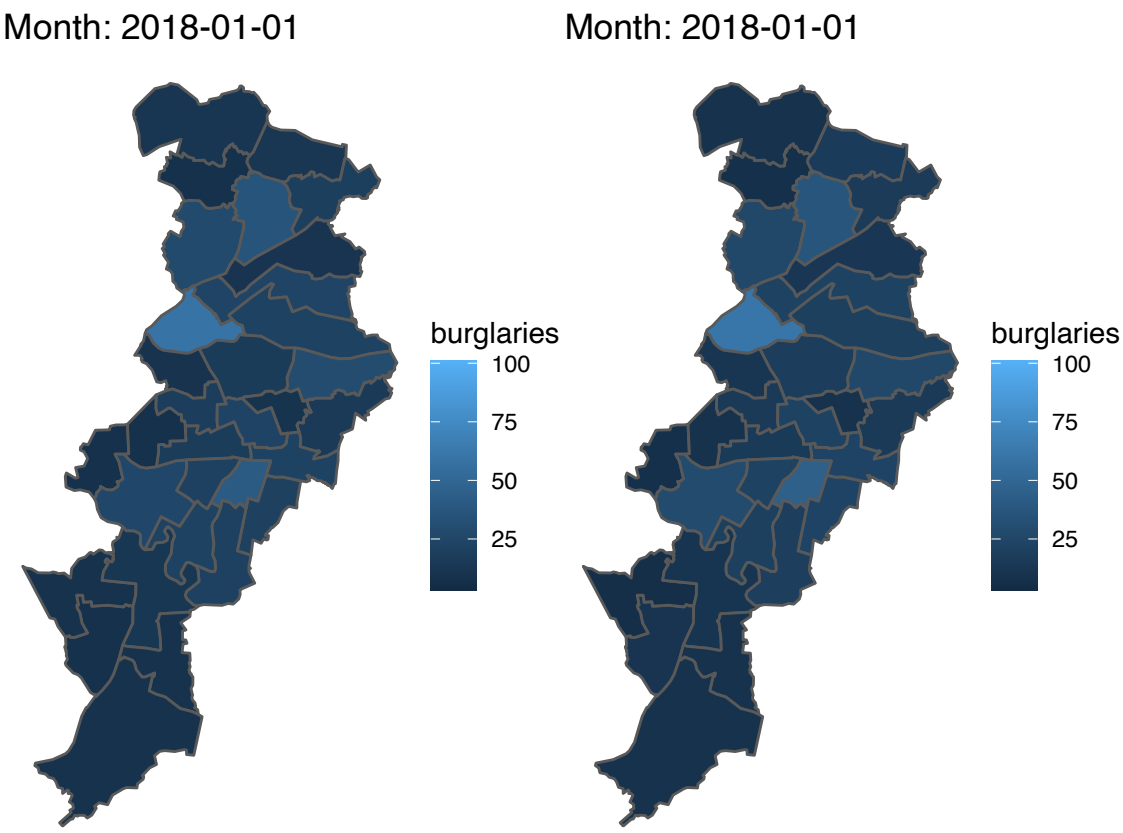
Now, finally, we can animate this graph. Take the object of the static graph (`anim`) and add a form of transition, which will be used to animate the graph. In this case, we can use `transition_states()`. This transition splits your data into multiple states based on the levels in a given column, much like how faceting splits up the data in multiple panels. It then shifts between the defined states and pauses at each state. Layers with data without the specified column will be kept constant during the animation (again, mimicking facet_wrap). States are the unquoted name of the column holding the state levels in the data. You can then use `closest_state` to dynamically label the graph:

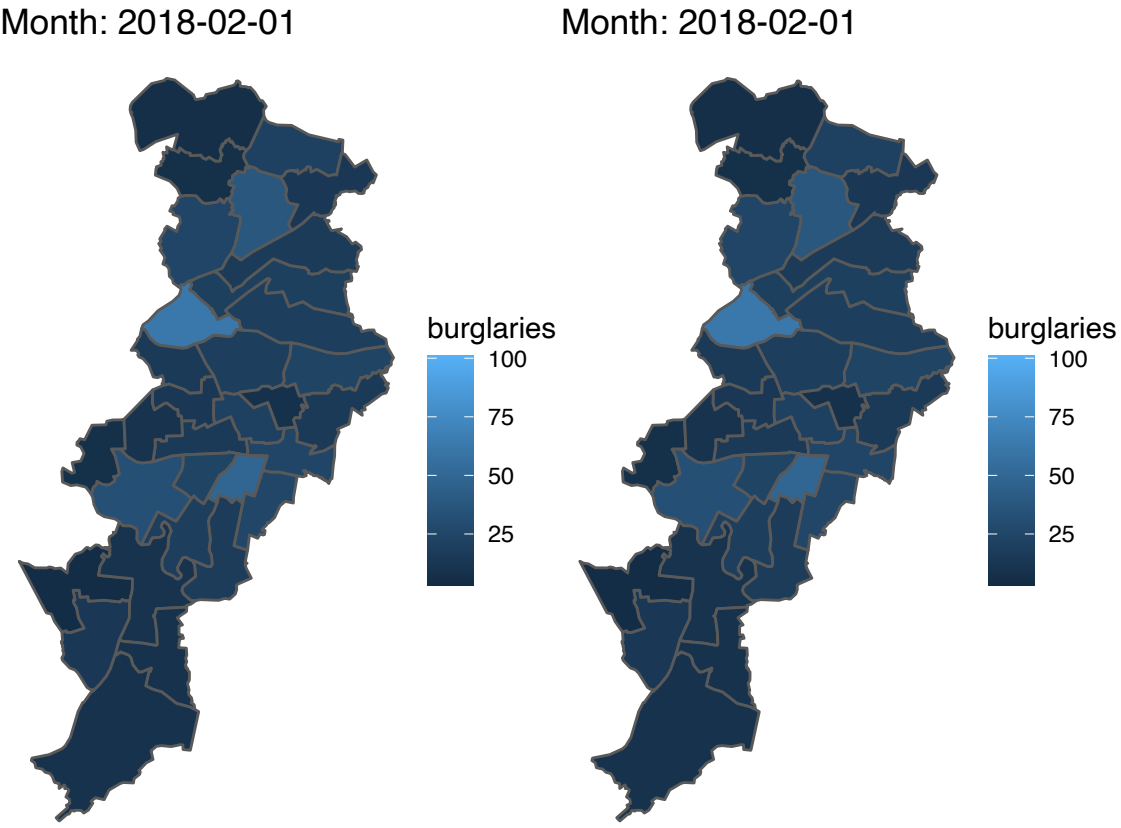
```
anim +
  transition_states(date_month,  # column holding the state levels in the data
                    transition_length = 1, # relative length of the transition
                    state_length = 2) + # elative length of the pause
  labs(title = "Month: {closest_state}")
```

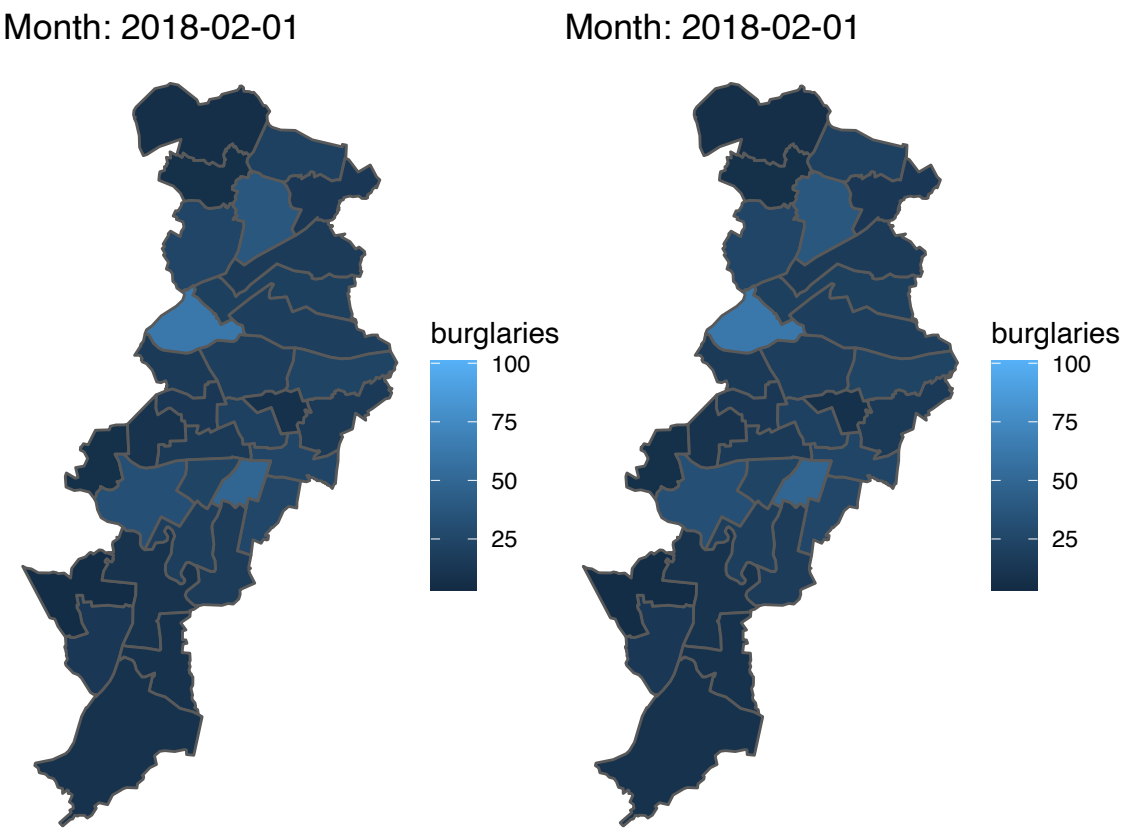


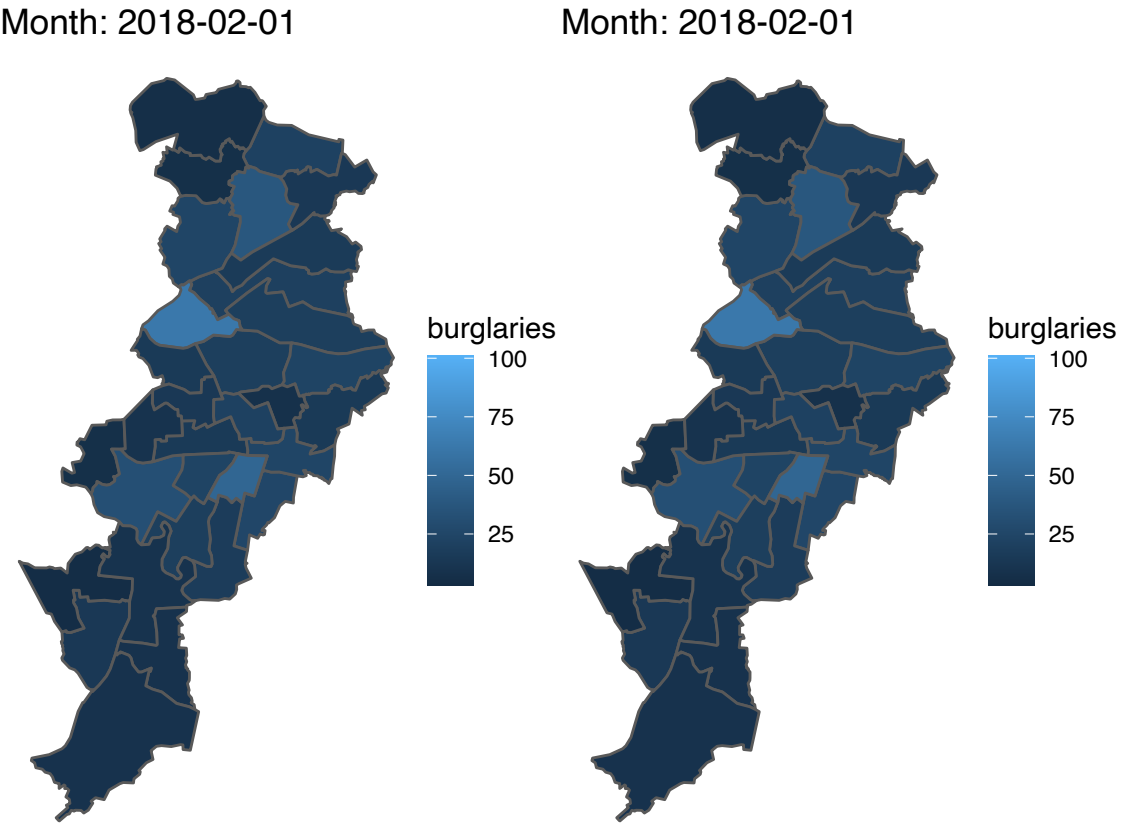

Month: 2018-01-01
burglaries
100
75
50
25
Month: 2018-01-01
burglaries
100
75
50
25

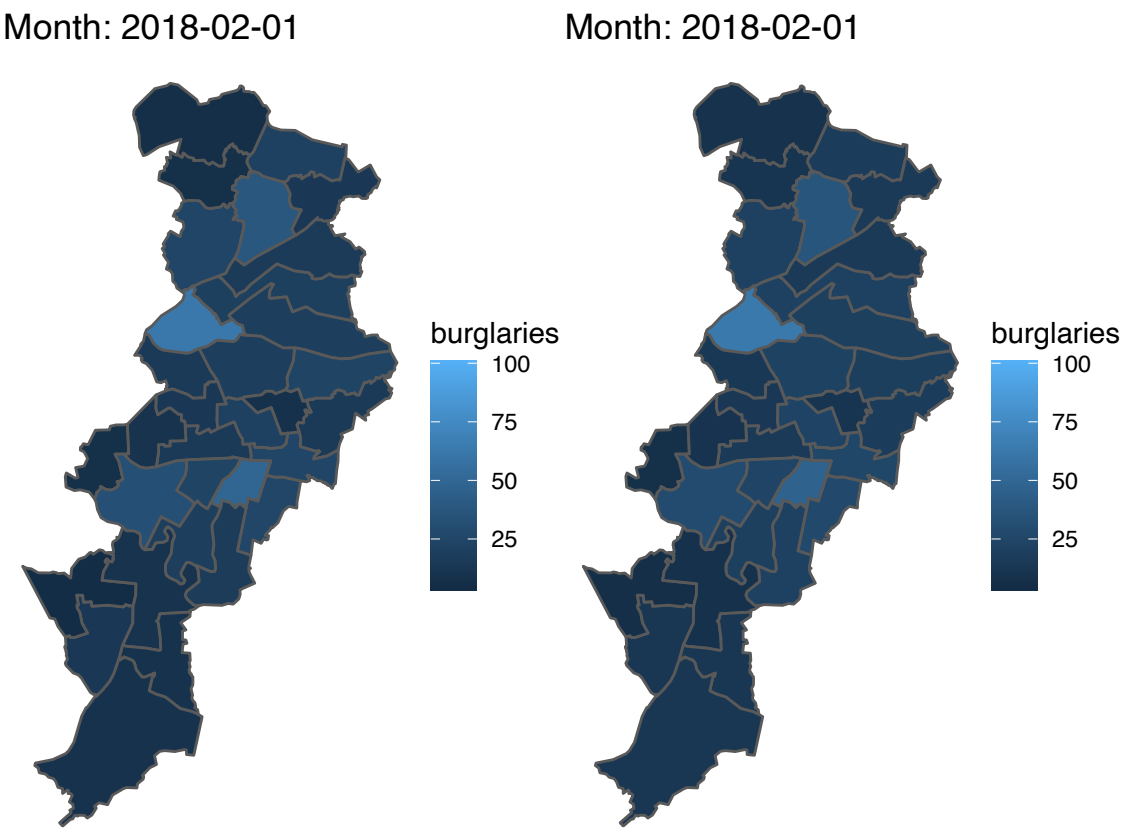

Month: 2018-01-01
burglaries
100
75
50
25
Month: 2018-01-01
burglaries
100
75
50
25

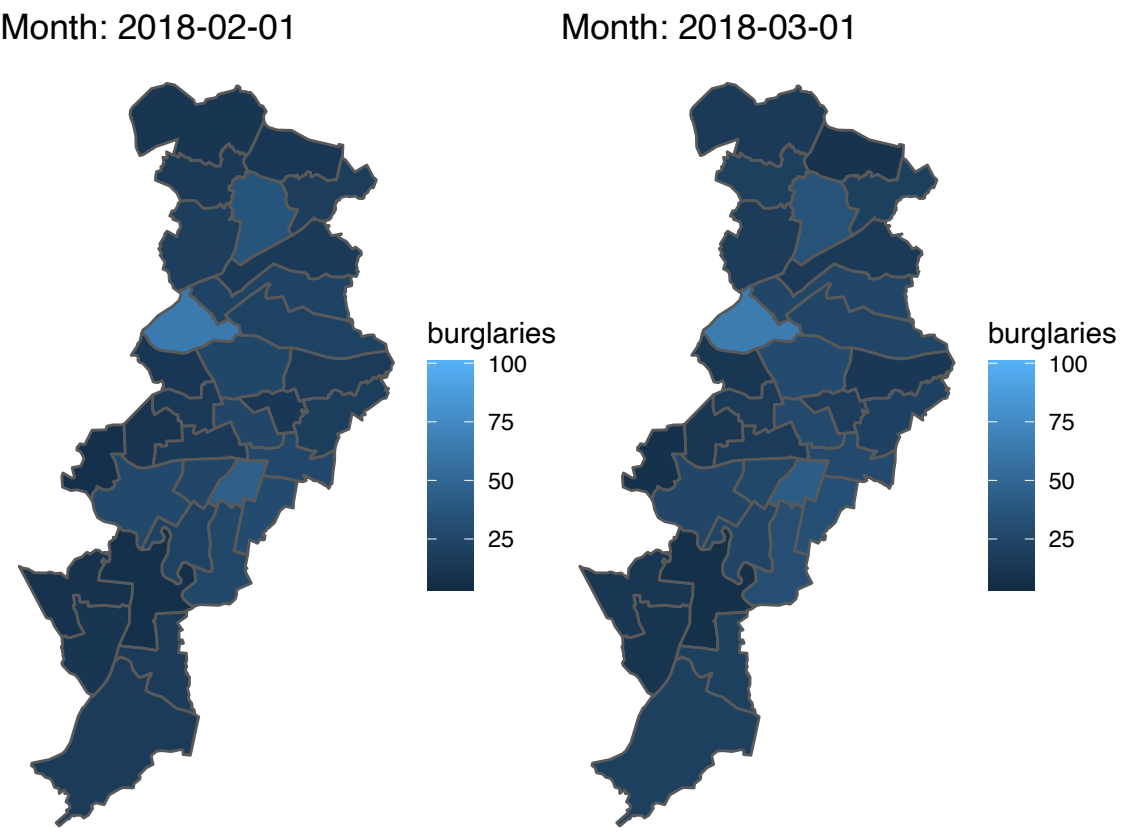

Month: 2018-01-01
burglaries
100
75
50
25
Month: 2018-01-01
burglaries
100
75
50
25

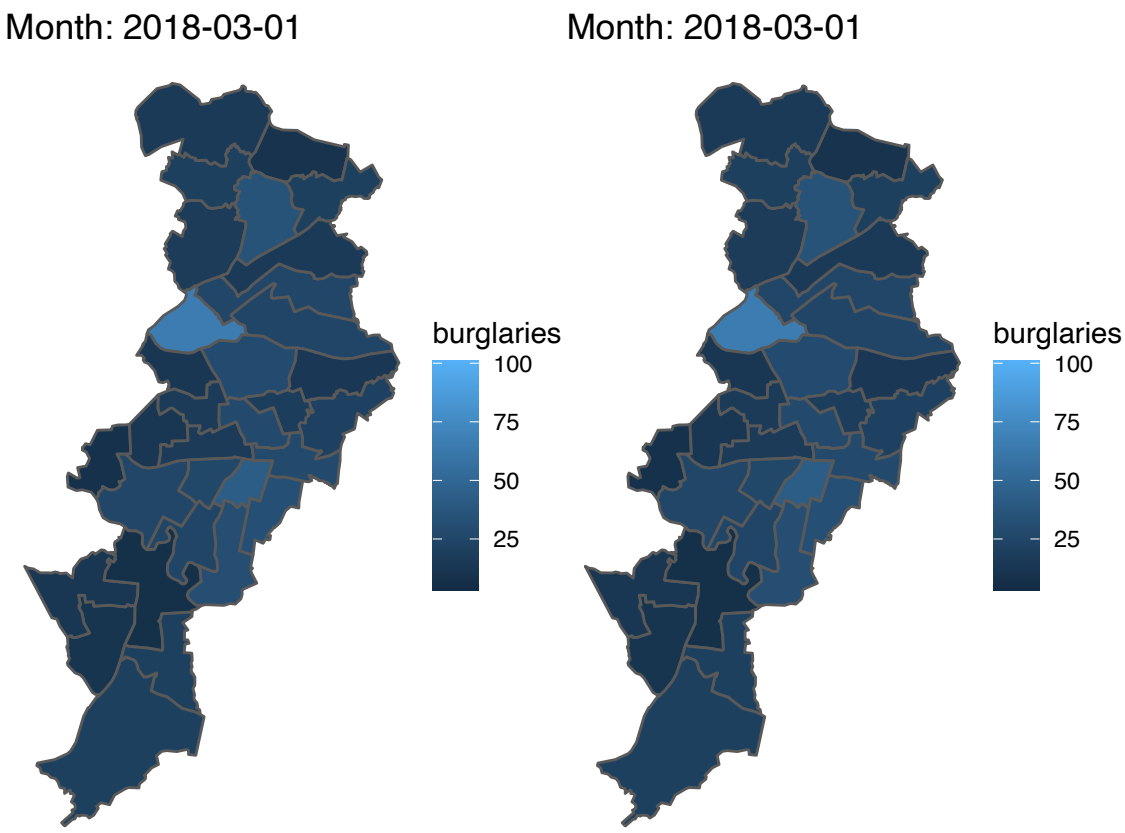

Month: 2018-02-01
burglaries
100
75
50
25
Month: 2018-02-01
burglaries
100
75
50
25

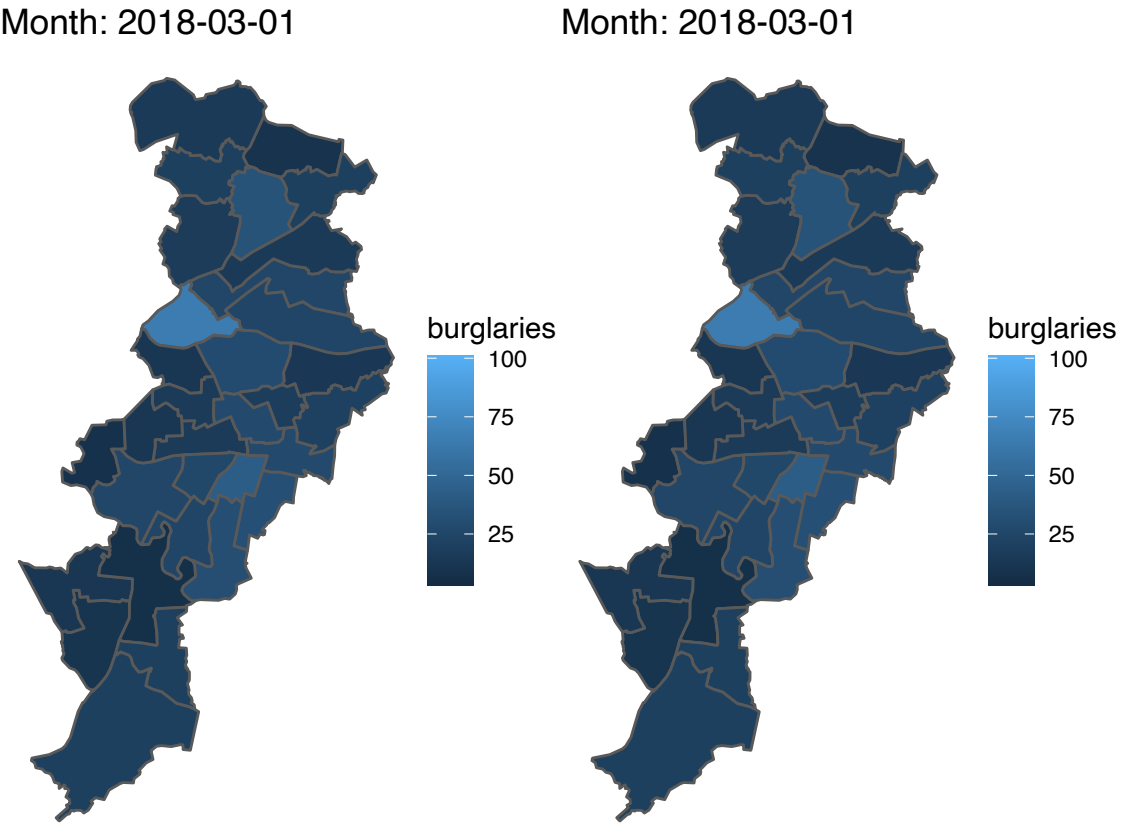

Month: 2018-02-01
burglaries
100
75
50
25
Month: 2018-02-01
burglaries
100
75
50
25

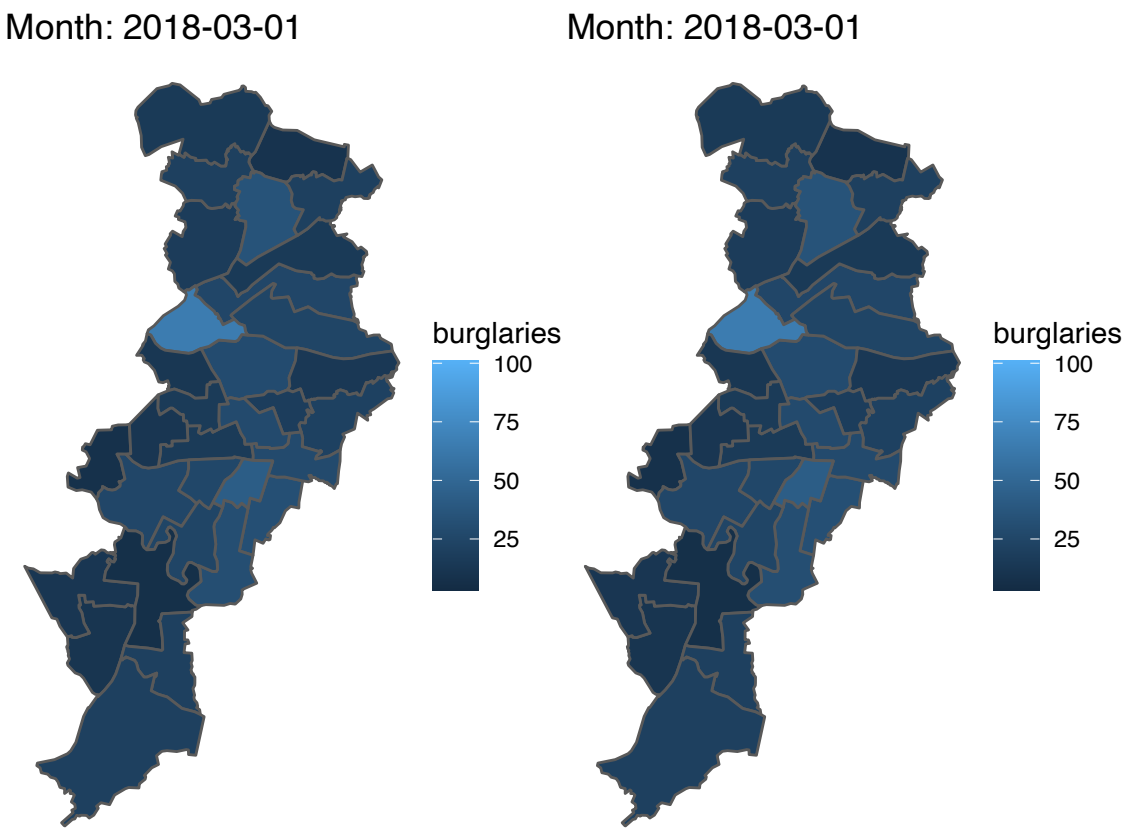

Month: 2018-02-01
burglaries
100
75
50
25
Month: 2018-02-01
burglaries
100
75
50
25

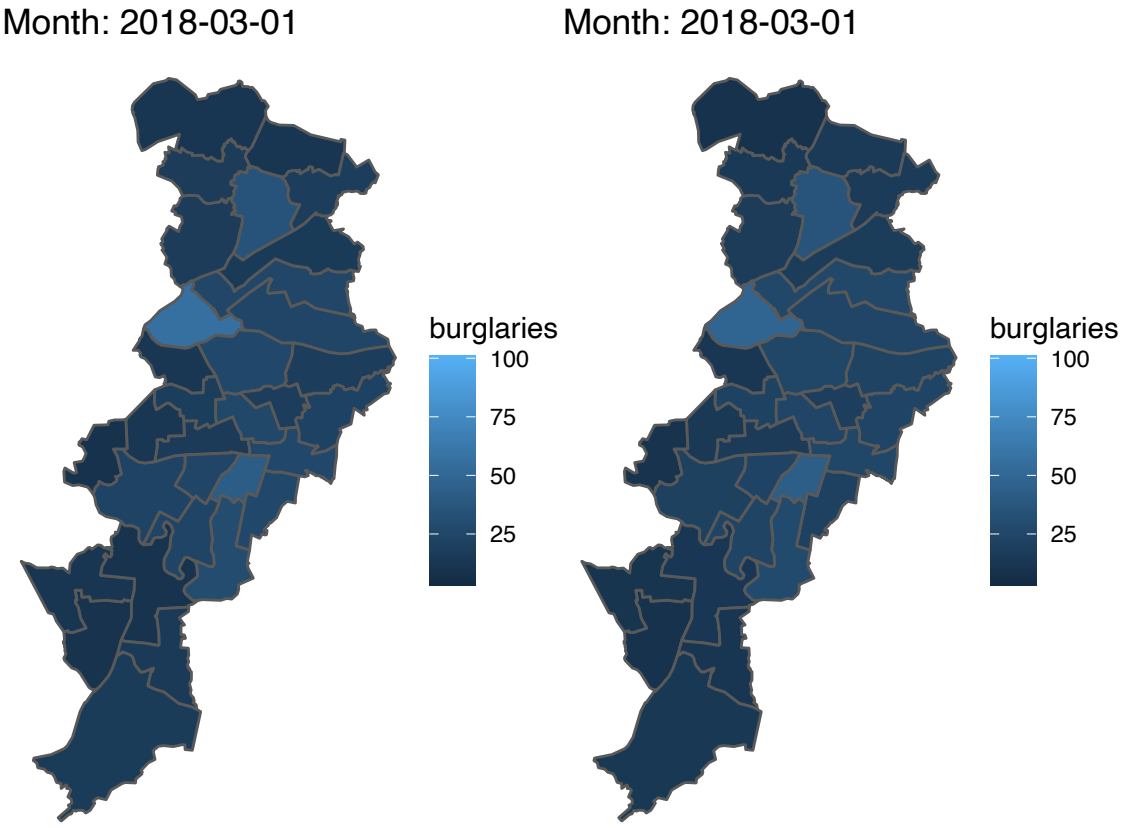

Month: 2018-02-01
burglaries
100
75
50
25
Month: 2018-02-01
burglaries
100
75
50
25

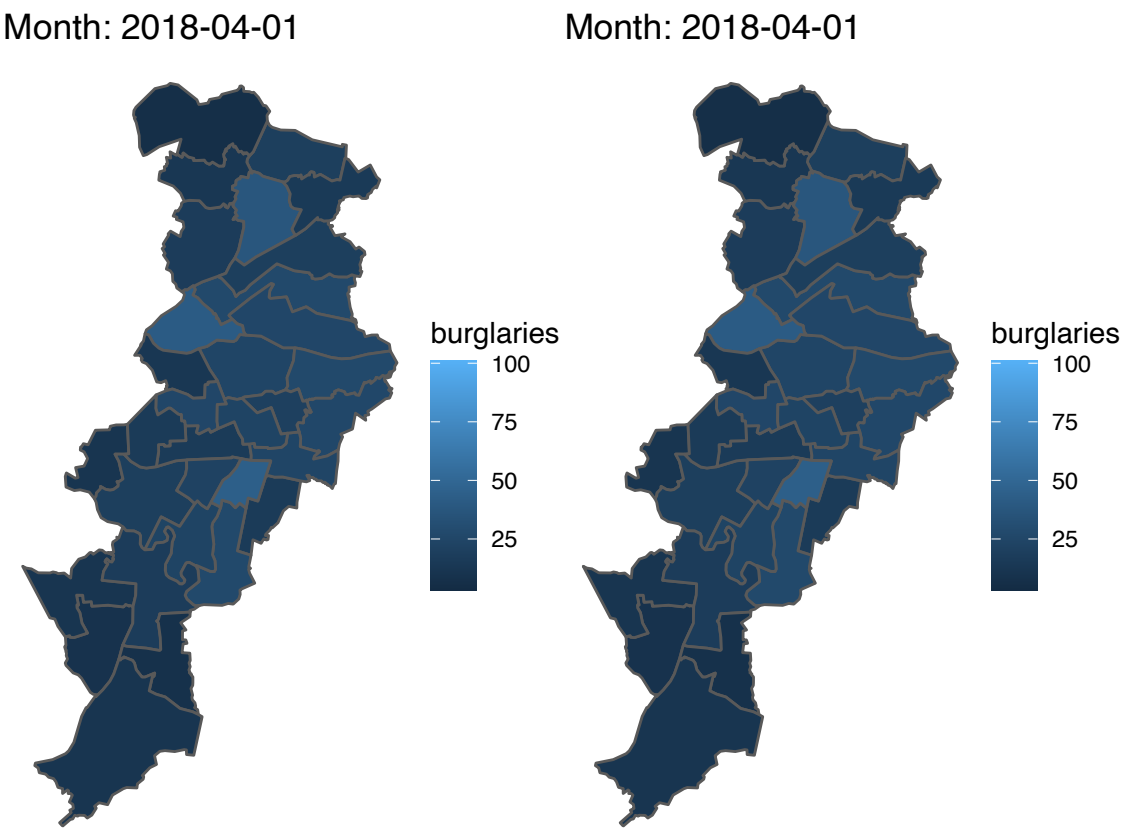

Month: 2018-02-01
burglaries
100
75
50
25
Month: 2018-03-01
burglaries
100
75
50
25

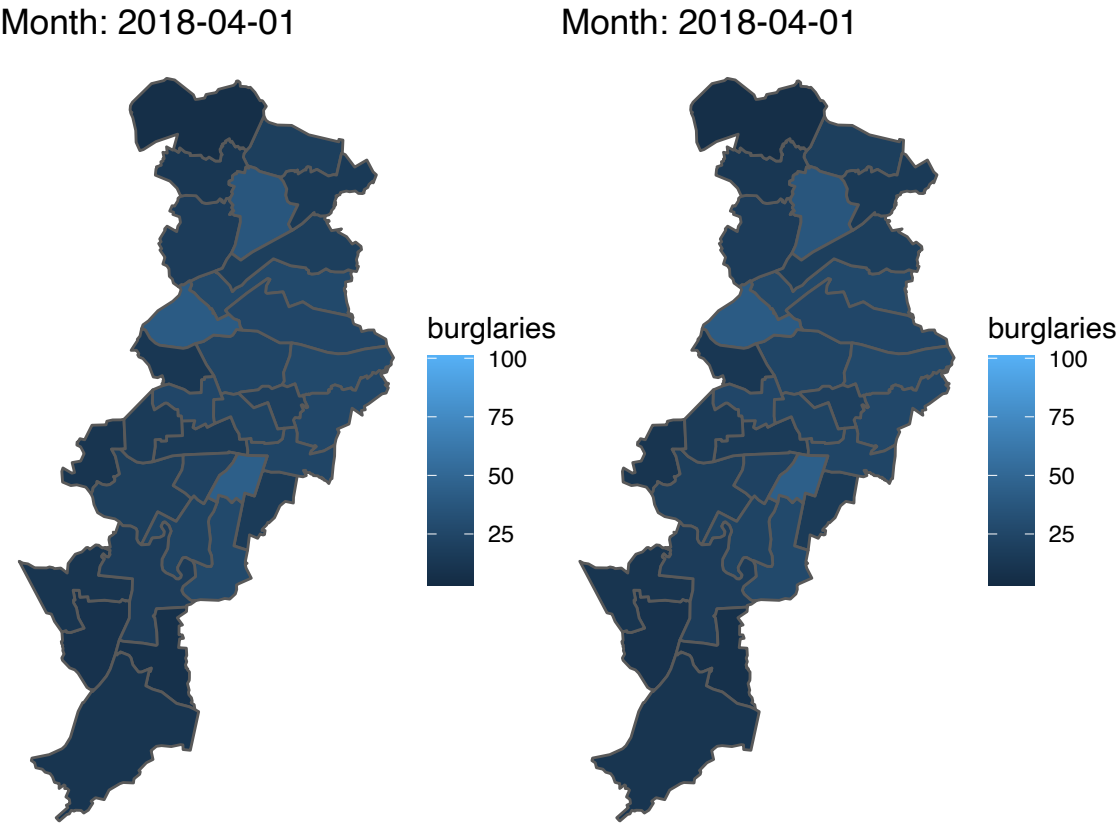

Month: 2018-03-01
burglaries
100
75
50
25
Month: 2018-03-01
burglaries
100
75
50
25

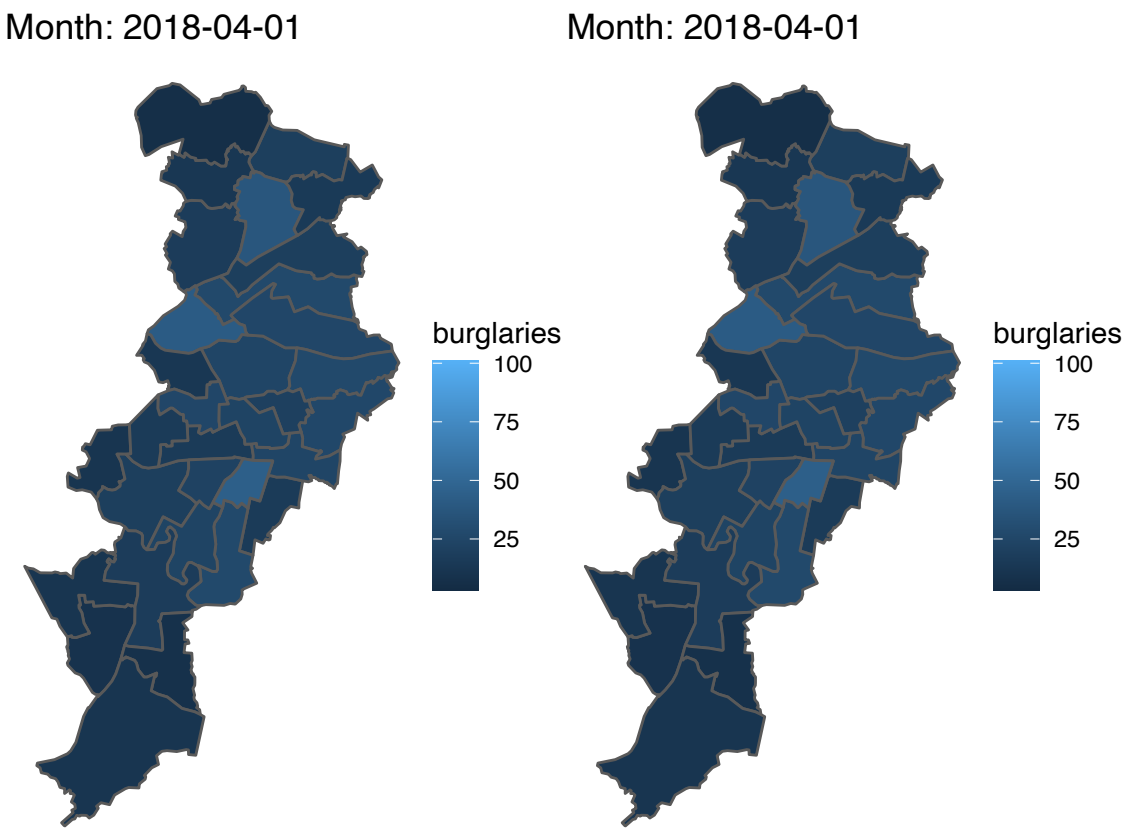

Month: 2018-03-01
burglaries
100
75
50
25
Month: 2018-03-01
burglaries
100
75
50
25

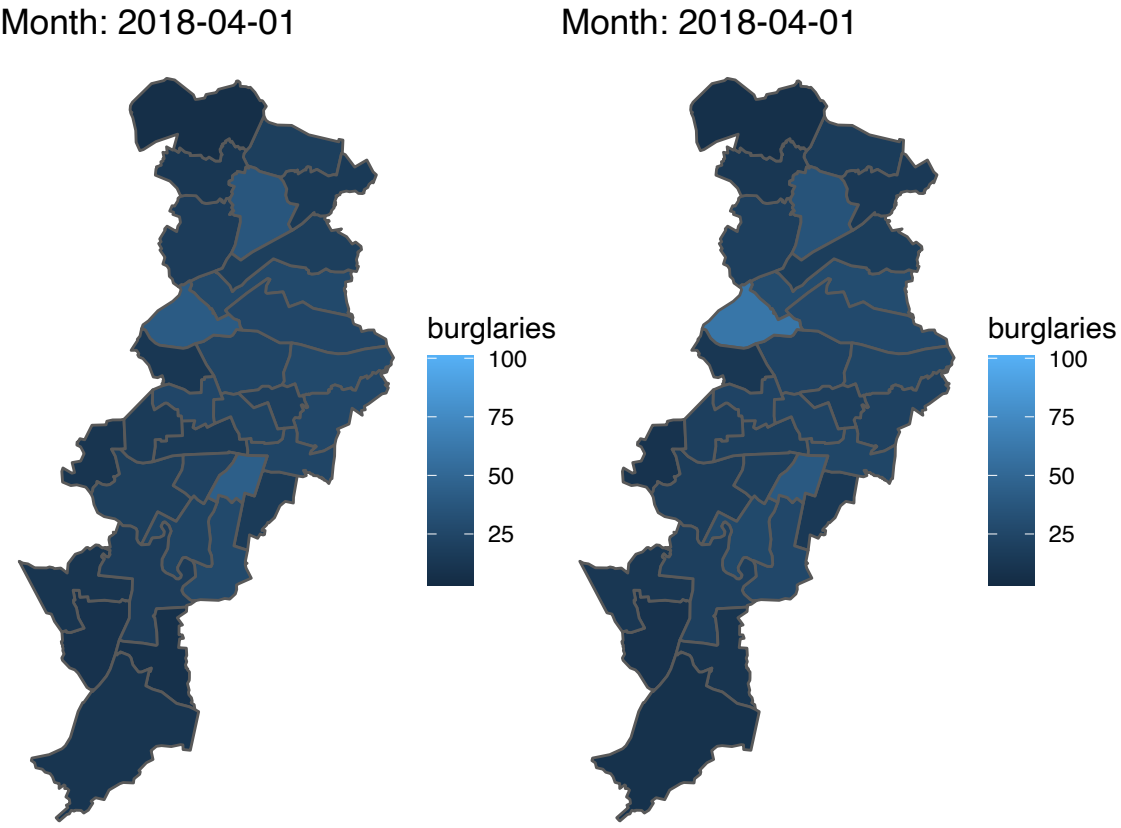

Month: 2018-03-01
burglaries
100
75
50
25
Month: 2018-03-01
burglaries
100
75
50
25


Month: 2018-03-01
burglaries
100
75
50
25
Month: 2018-03-01
burglaries
100
75
50
25

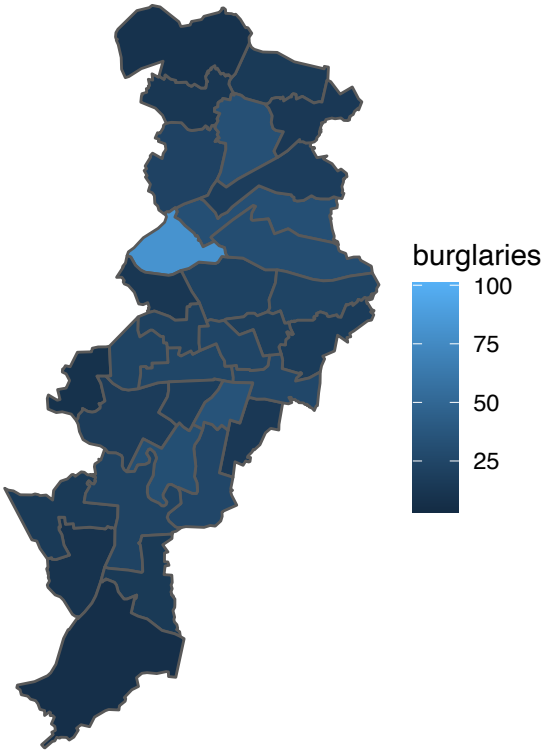

Month: 2018-04-01
burglaries
100
75
50
25
Month: 2018-04-01
burglaries
100
75
50
25


Month: 2018-04-01
burglaries
100
75
50
25
Month: 2018-04-01
burglaries
100
75
50
25

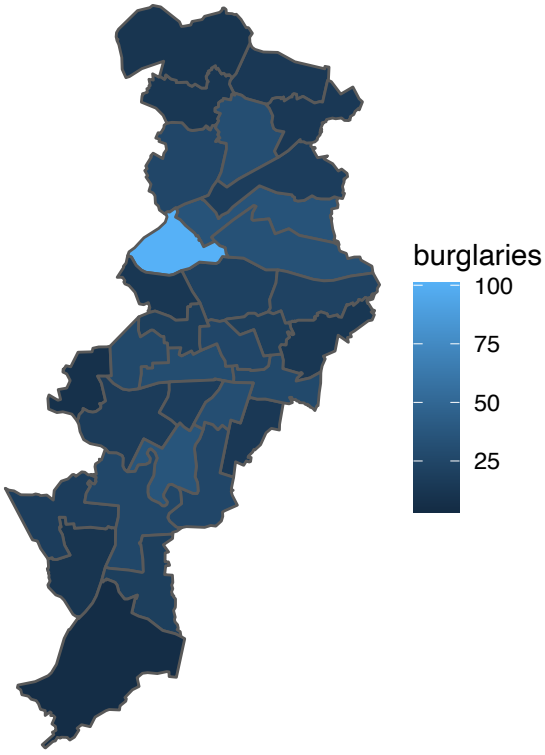

Month: 2018-04-01
burglaries
100
75
50
25
Month: 2018-04-01
burglaries
100
75
50
25

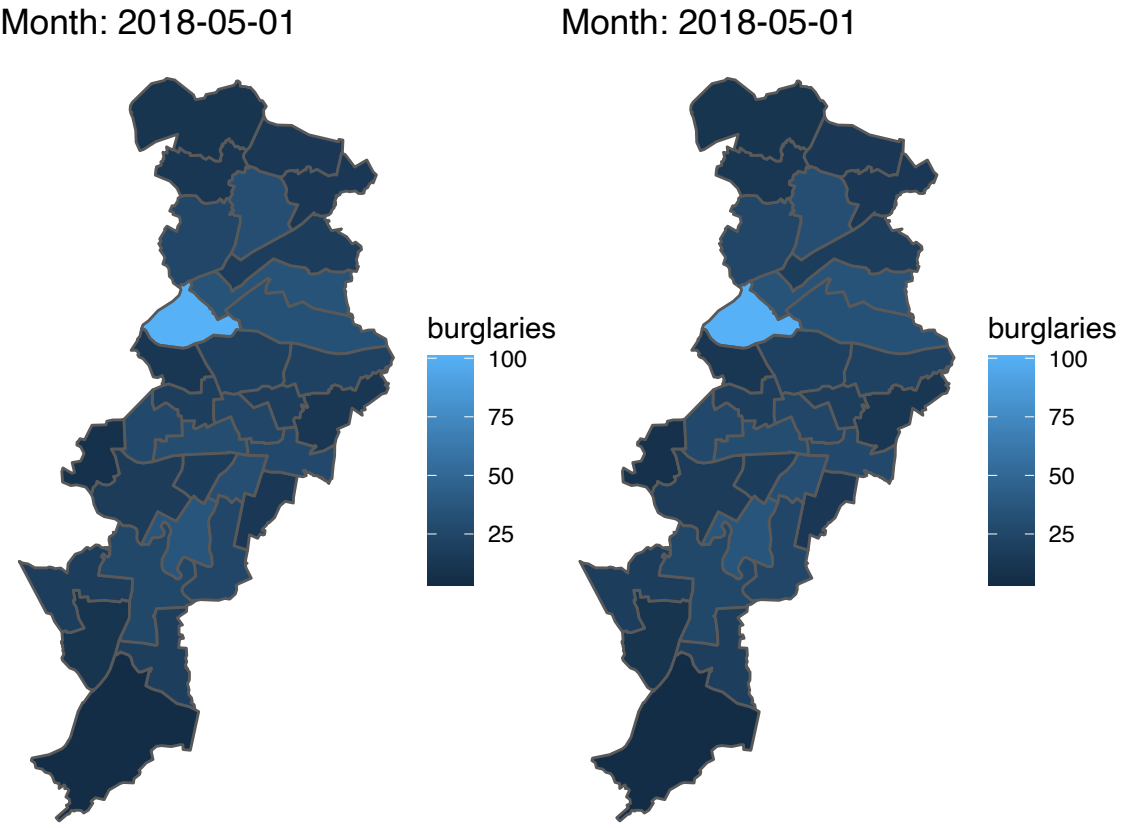

Month: 2018-04-01
burglaries
100
75
50
25
Month: 2018-04-01
burglaries
100
75
50
25

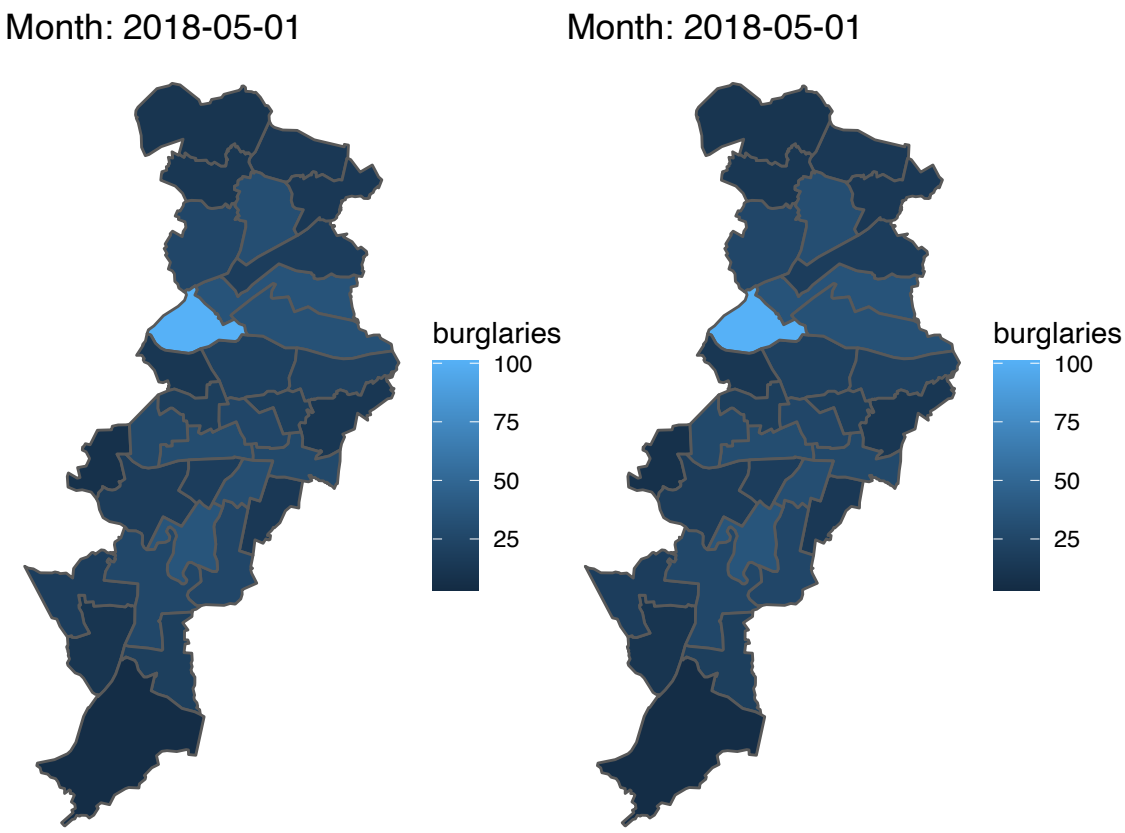
Month: 2018-04-01

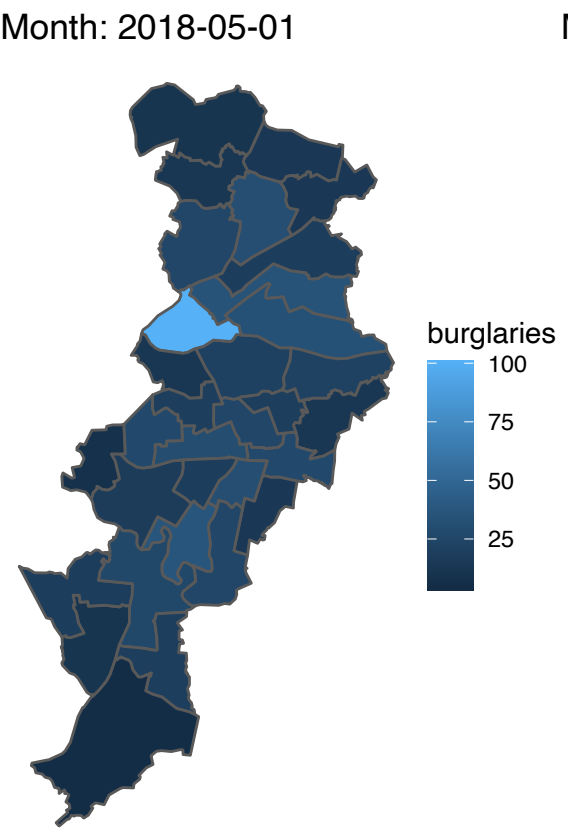


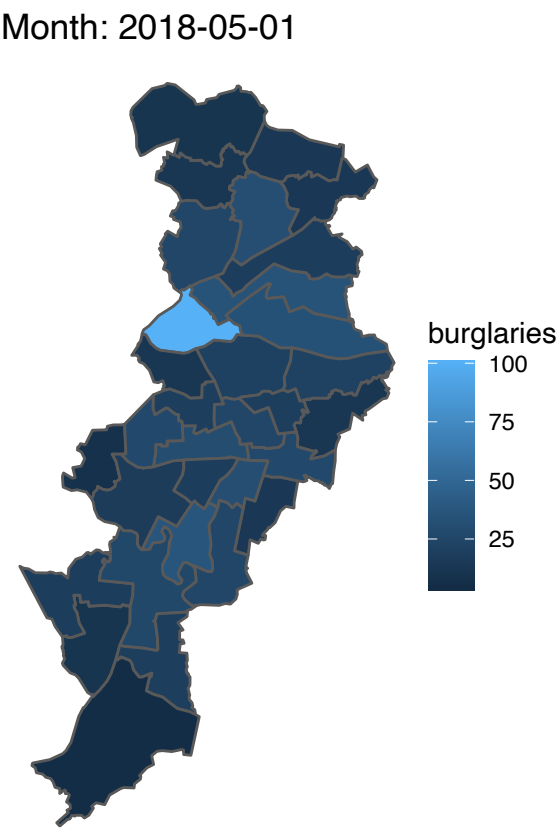
Month: 2018-05-01

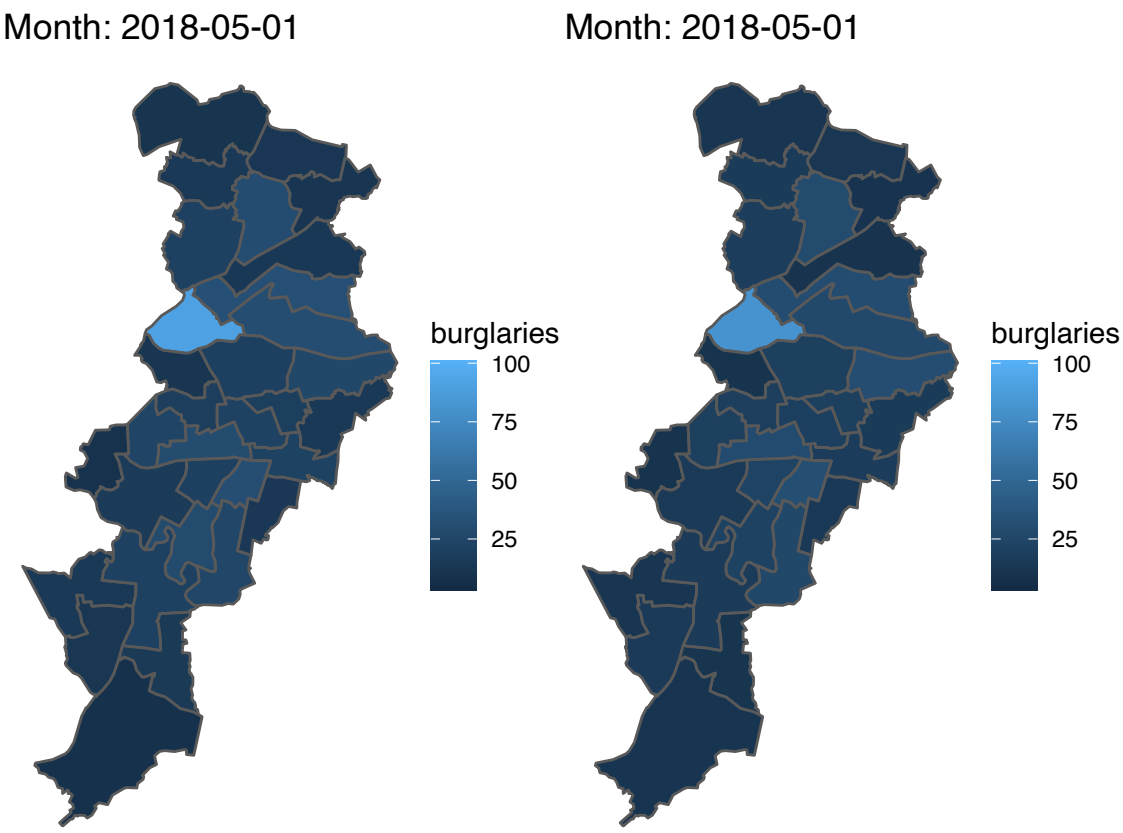


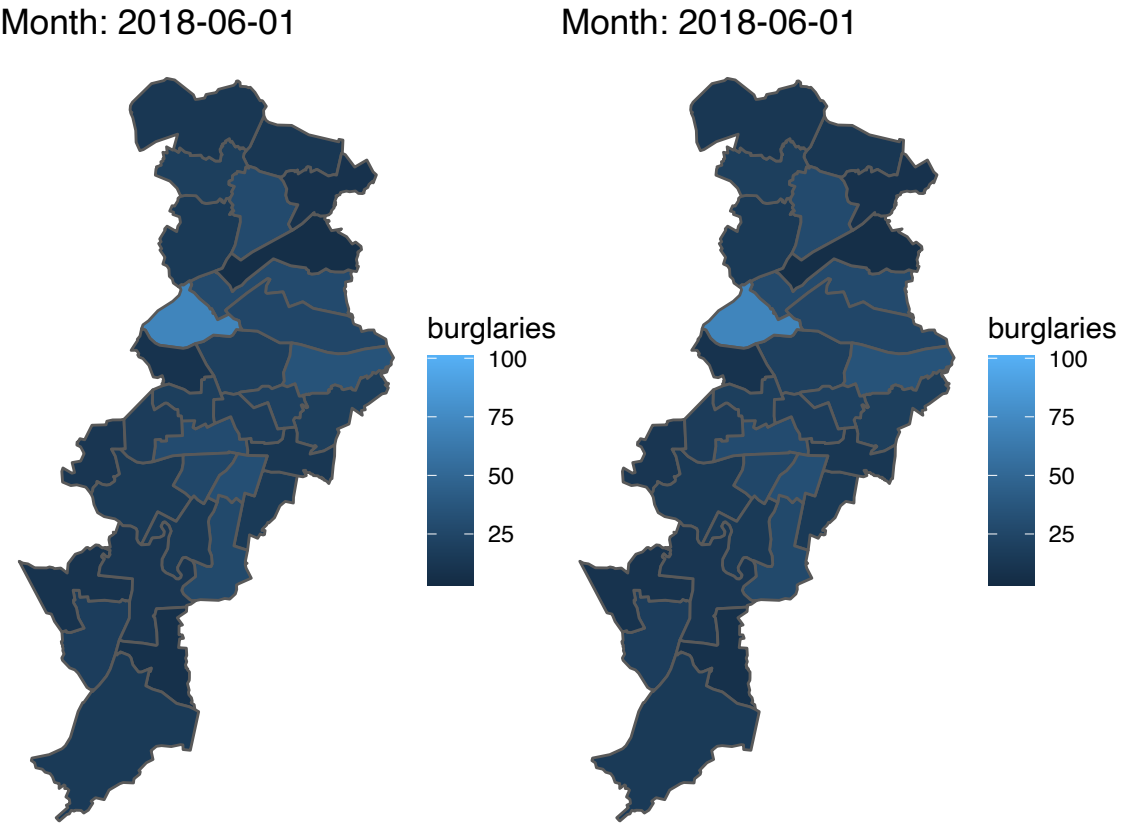

Month: 2018-05-01
burglaries
100
75
50
25
Month: 2018-05-01
burglaries
100
75
50
25

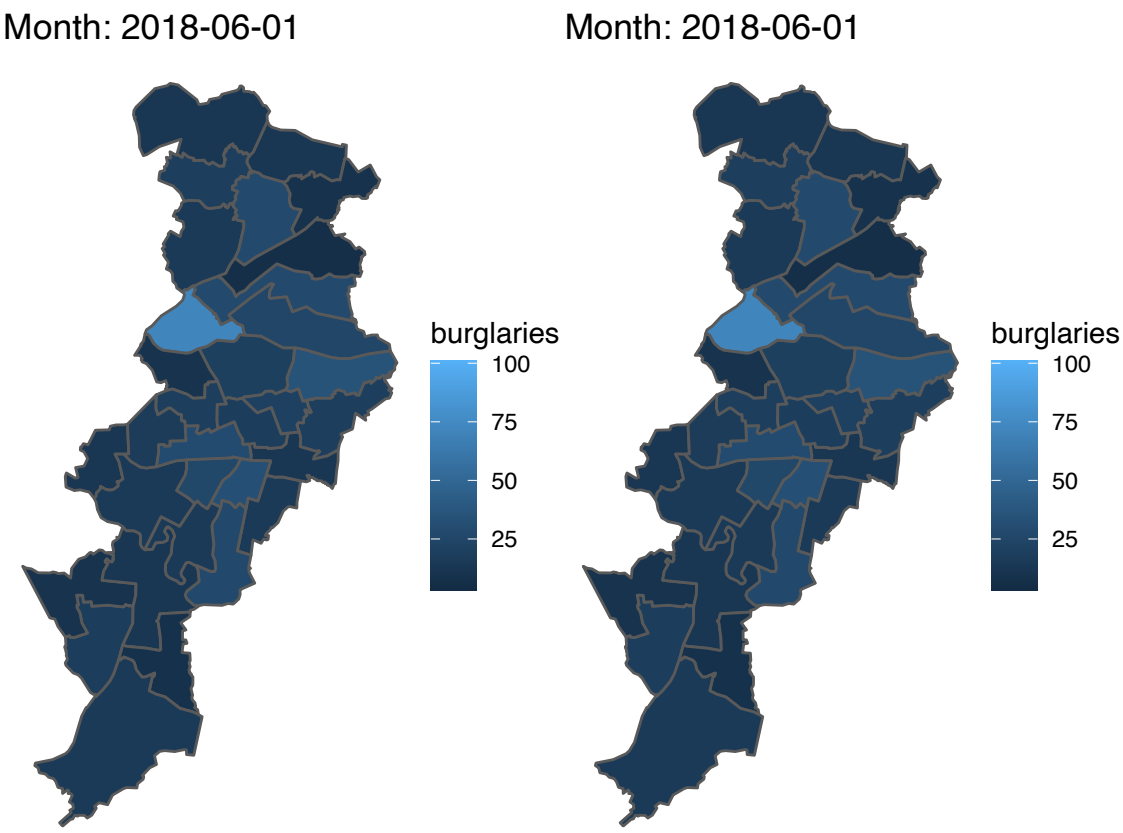

Month: 2018-05-01
burglaries
100
75
50
25
Month: 2018-05-01
burglaries
100
75
50
25

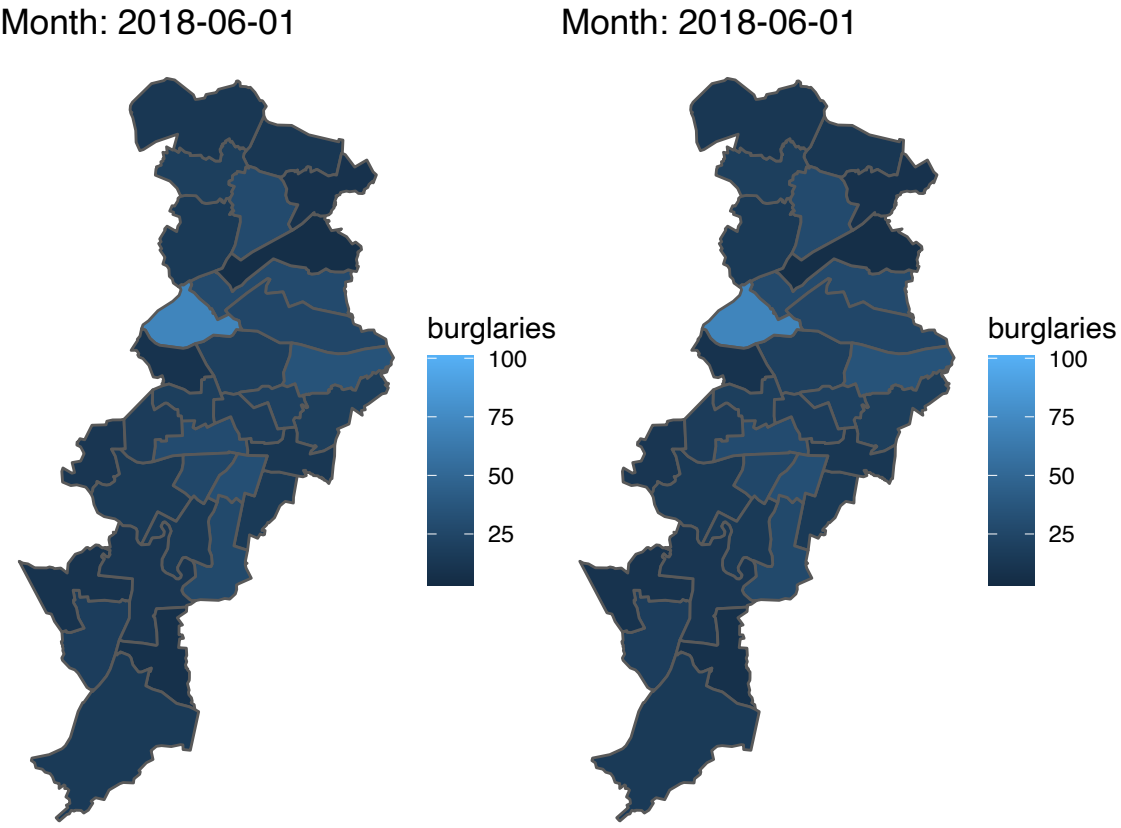

Month: 2018-05-01
burglaries
100
75
50
25

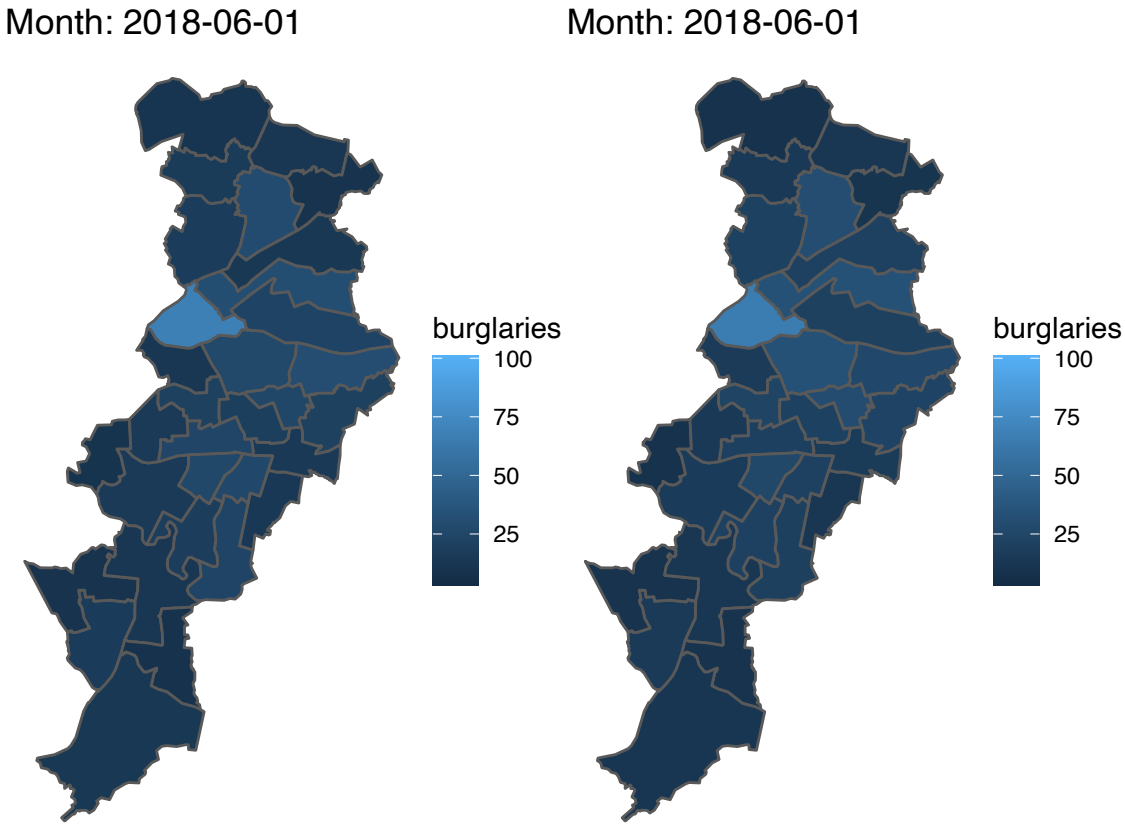

Month: 2018-05-01
burglaries
100
75
50
25

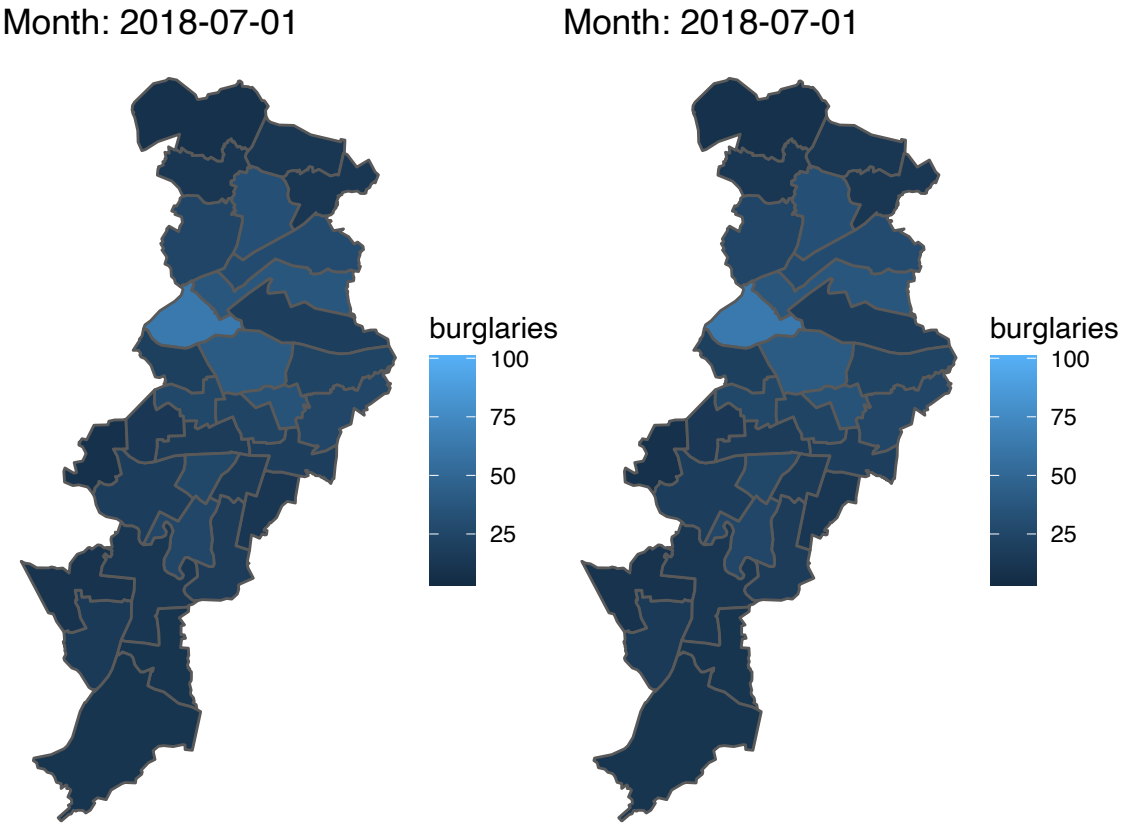

Month: 2018-05-01
burglaries
100
75
50
25
Month: 2018-05-01
burglaries
100
75
50
25

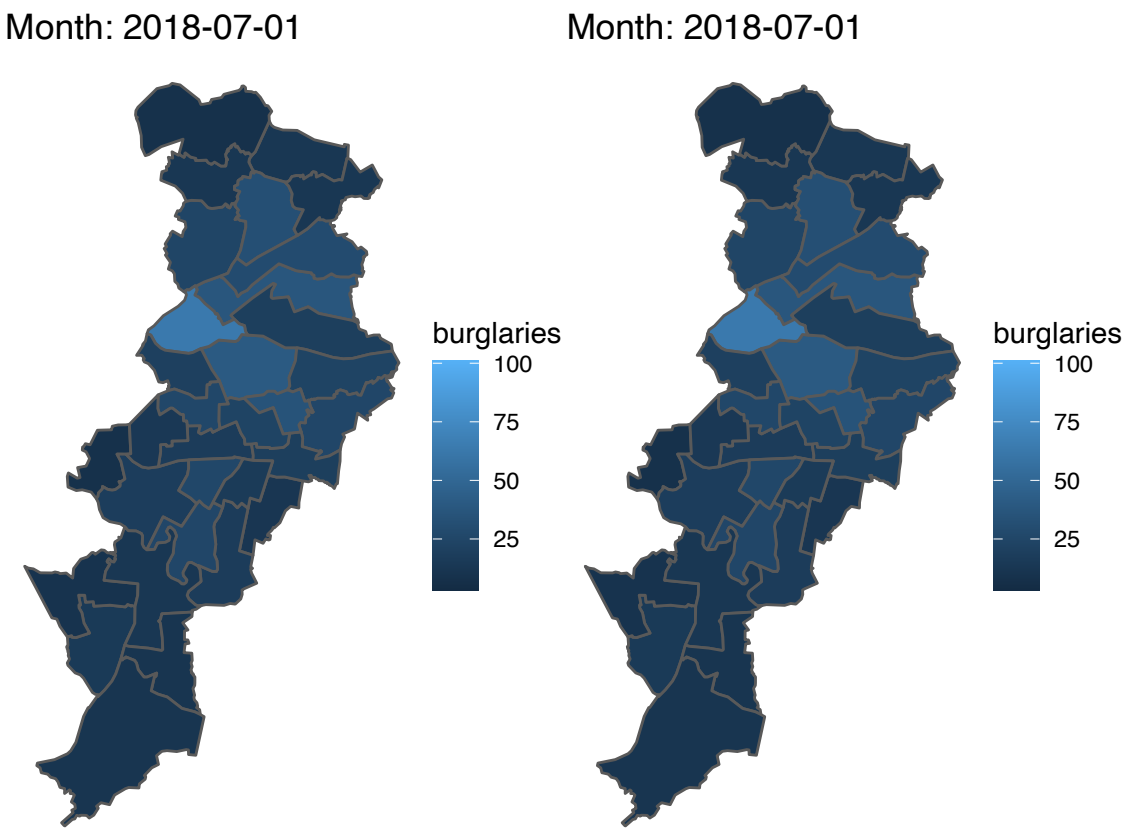

Month: 2018-06-01
burglaries
100
75
50
25
Month: 2018-06-01
burglaries
100
75
50
25

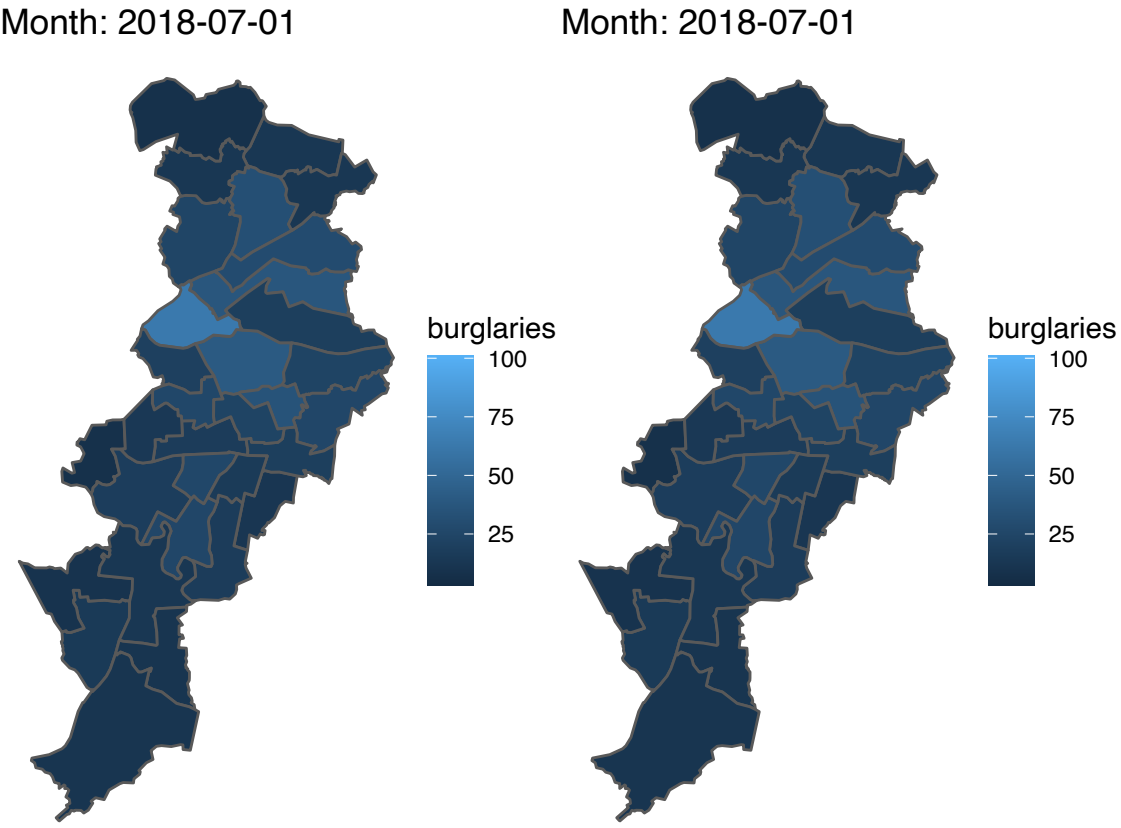

Month: 2018-06-01
burglaries
100
75
50
25
Month: 2018-06-01
burglaries
100
75
50
25

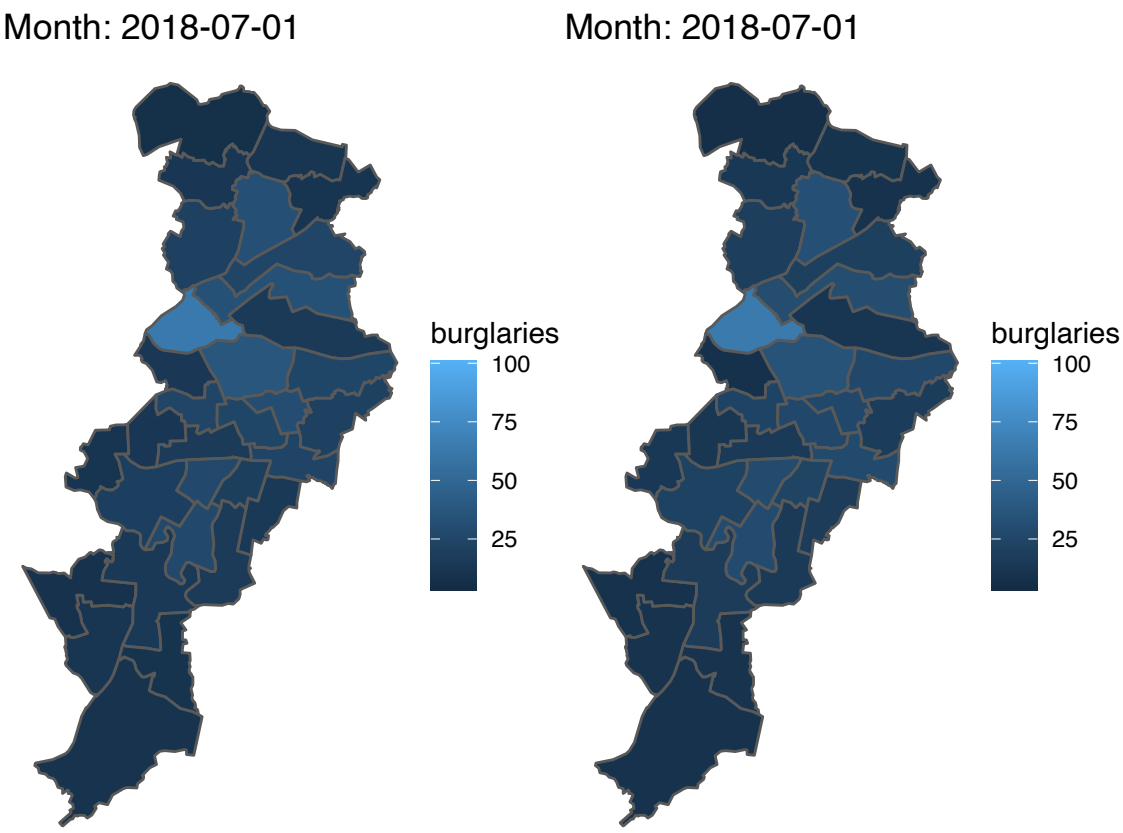

Month: 2018-06-01
burglaries
100
75
50
25
Month: 2018-06-01
burglaries
100
75
50
25

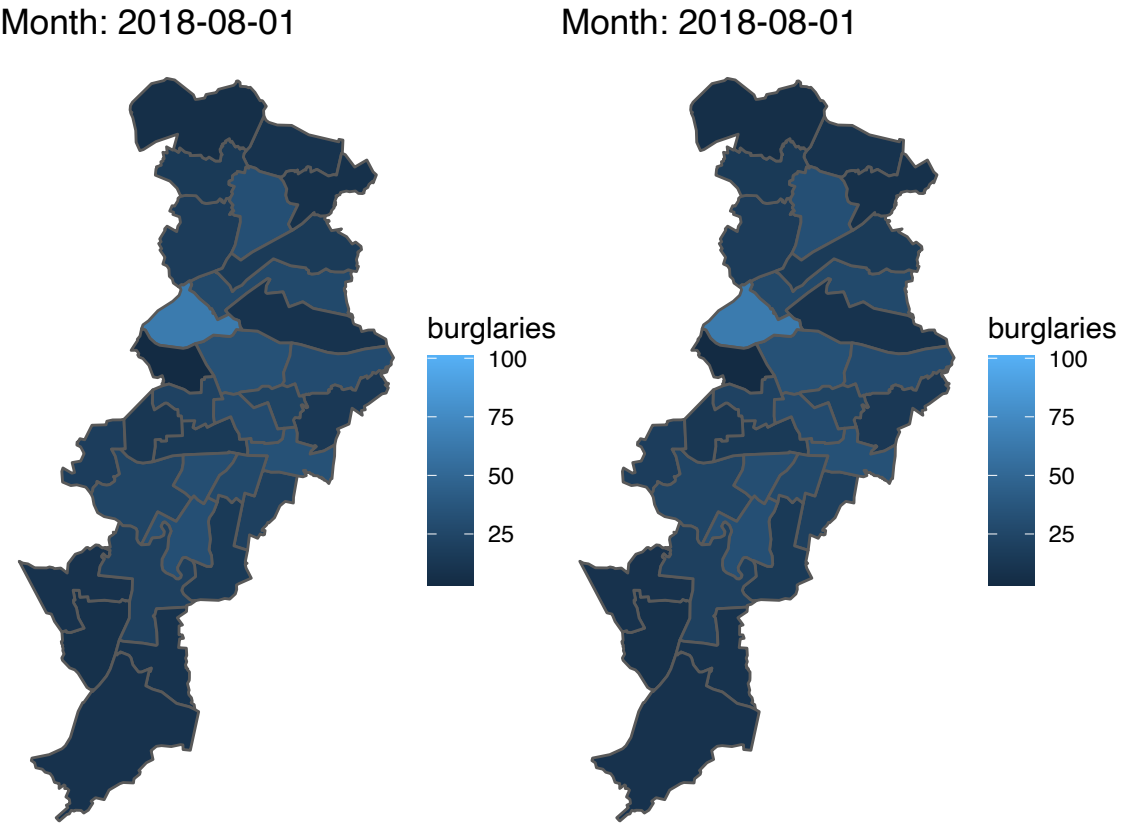

Month: 2018-06-01
burglaries
100
75
50
25
Month: 2018-06-01
burglaries
100
75
50
25

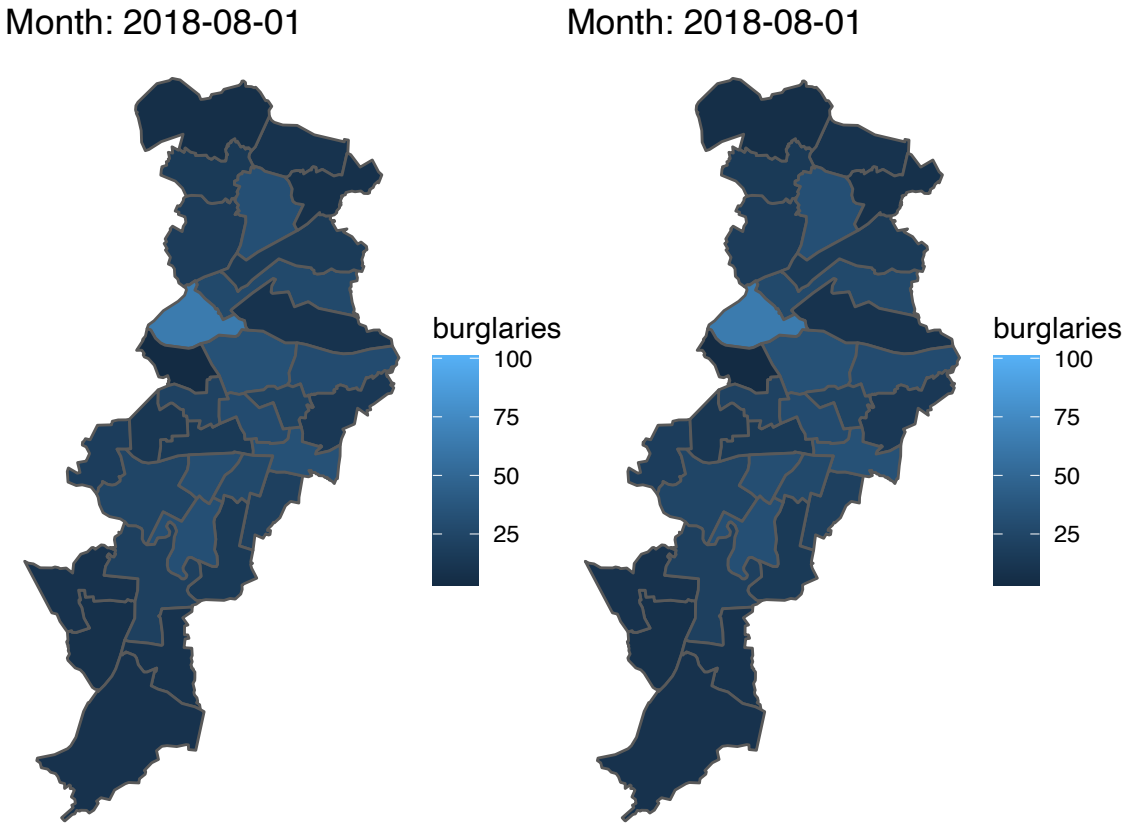

Month: 2018-07-01
burglaries
100
75
50
25
Month: 2018-07-01
burglaries
100
75
50
25

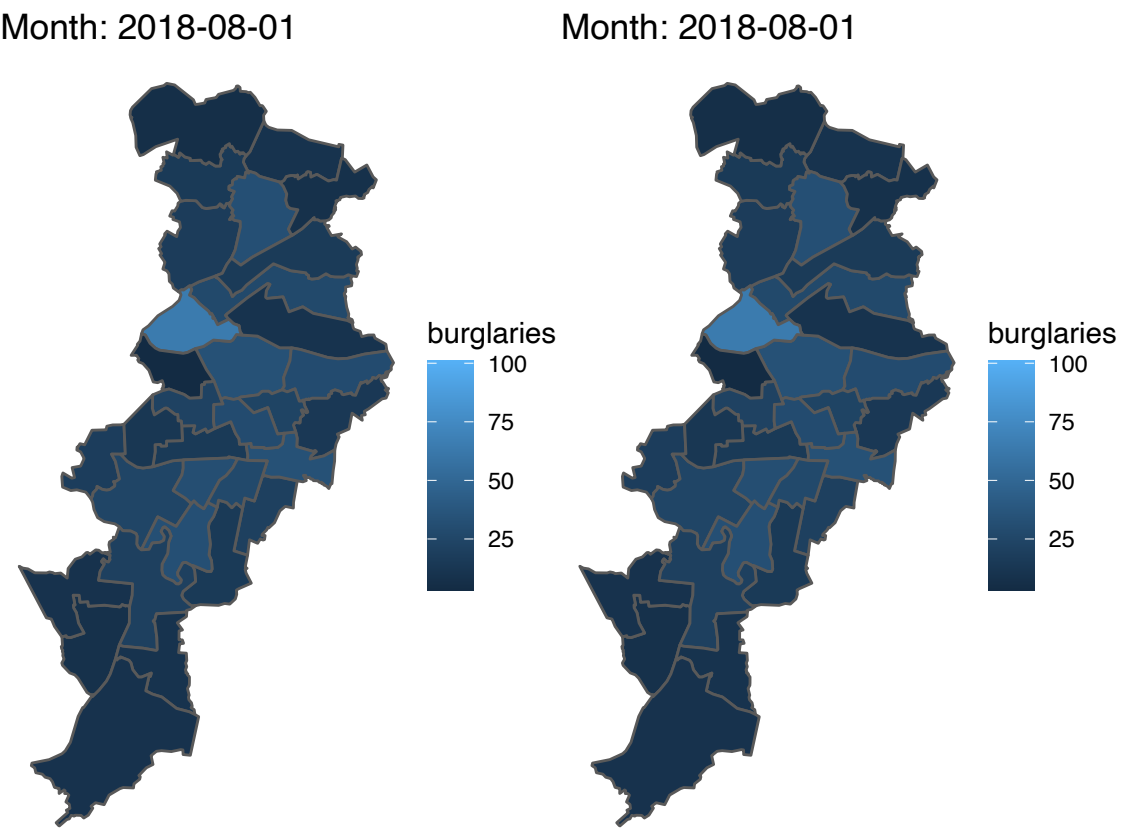

Month: 2018-07-01
burglaries
100
75
50
25
Month: 2018-07-01
burglaries
100
75
50
25

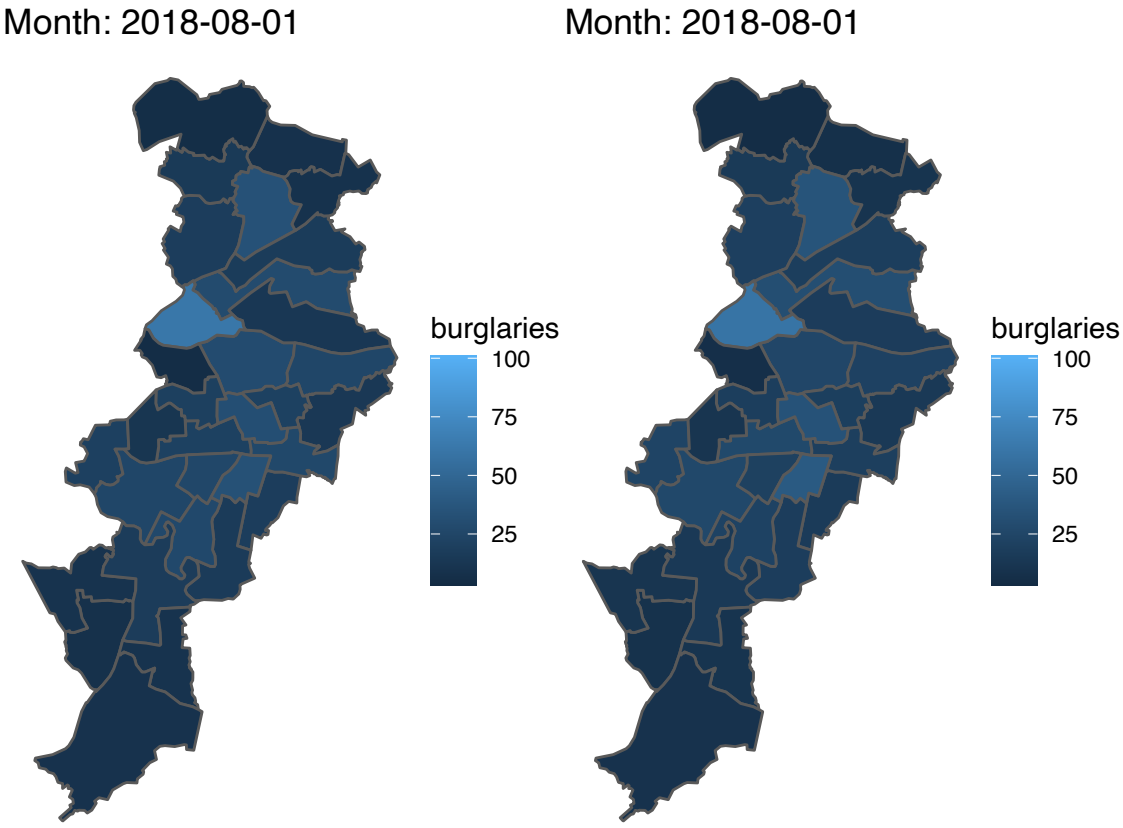

Month: 2018-07-01
burglaries
100
75
50
25
Month: 2018-07-01
burglaries
100
75
50
25

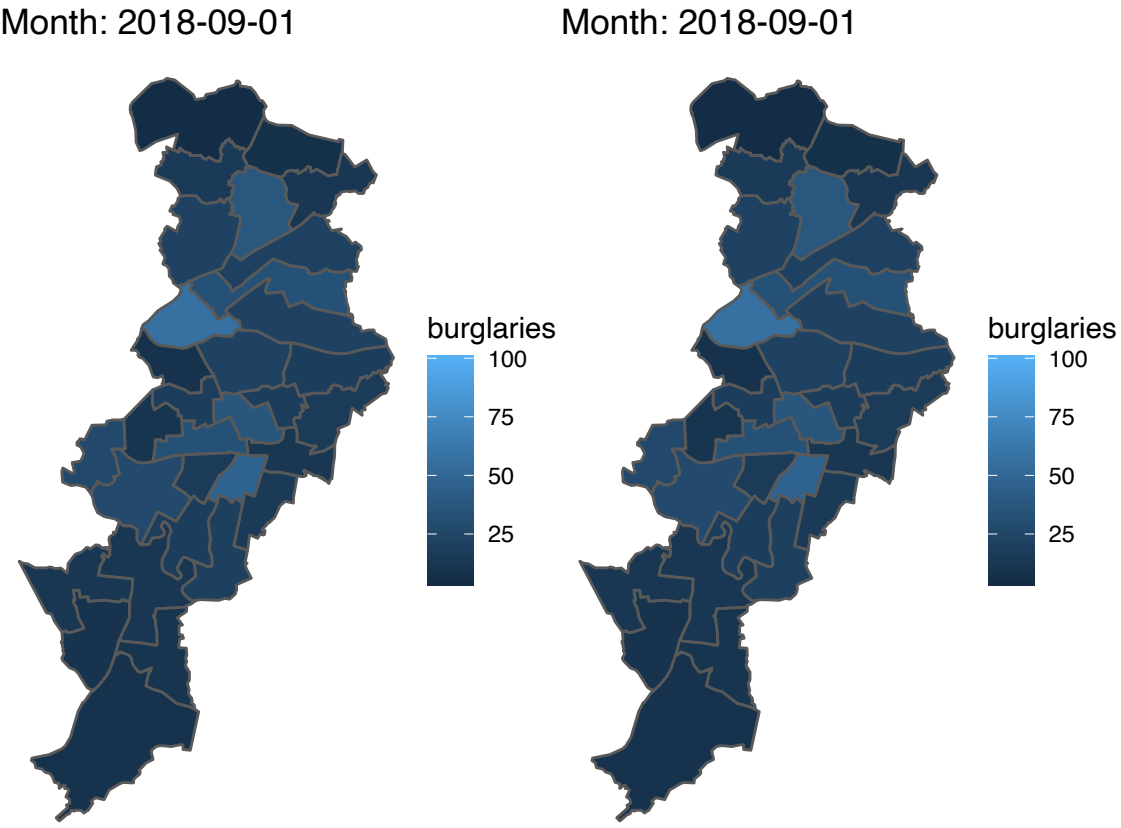

Month: 2018-07-01
burglaries
100
75
50
25
Month: 2018-07-01
burglaries
100
75
50
25

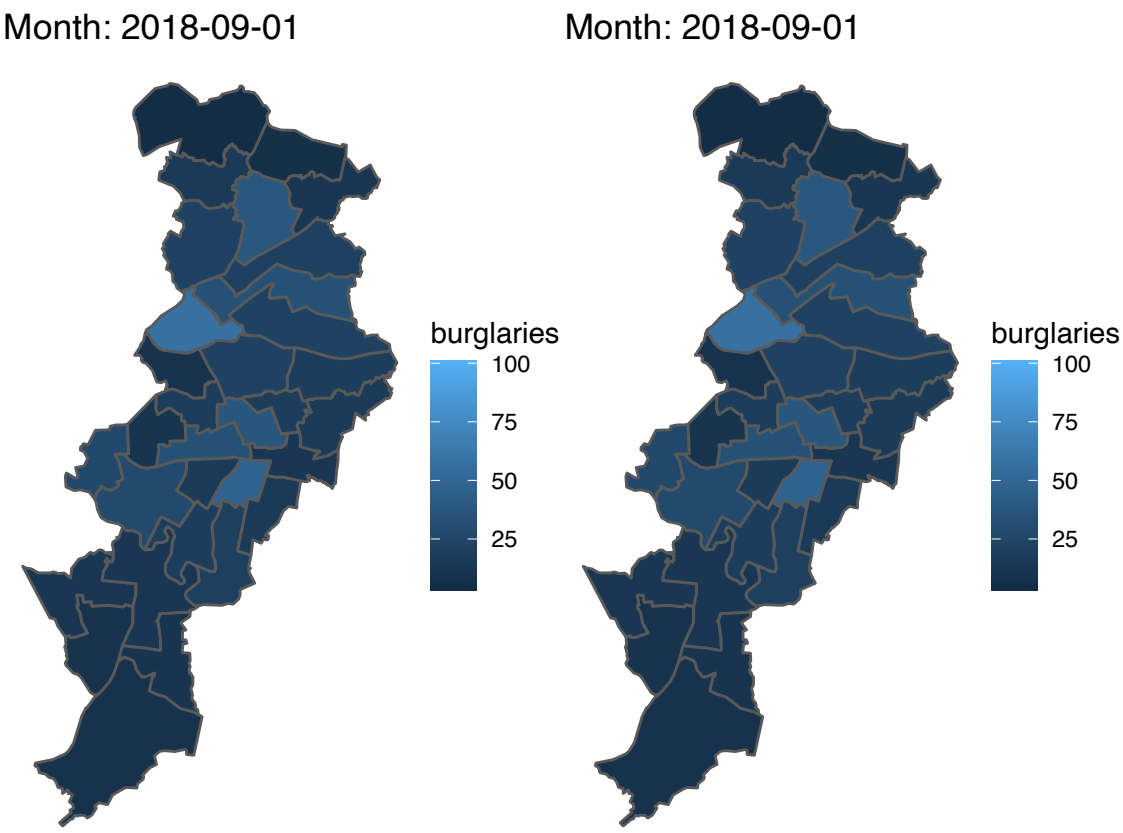

Month: 2018-08-01
burglaries
100
75
50
25
Month: 2018-08-01
burglaries
100
75
50
25

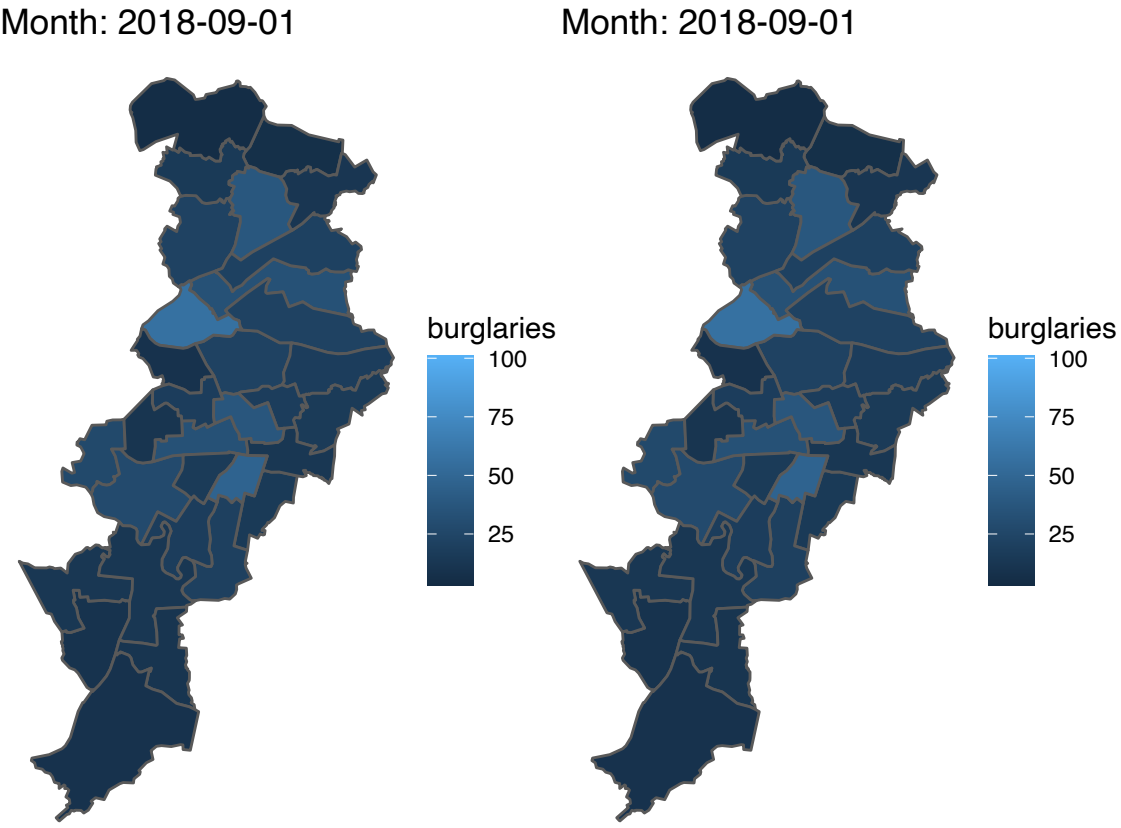

Month: 2018-08-01
burglaries
100
75
50
25
Month: 2018-08-01
burglaries
100
75
50
25

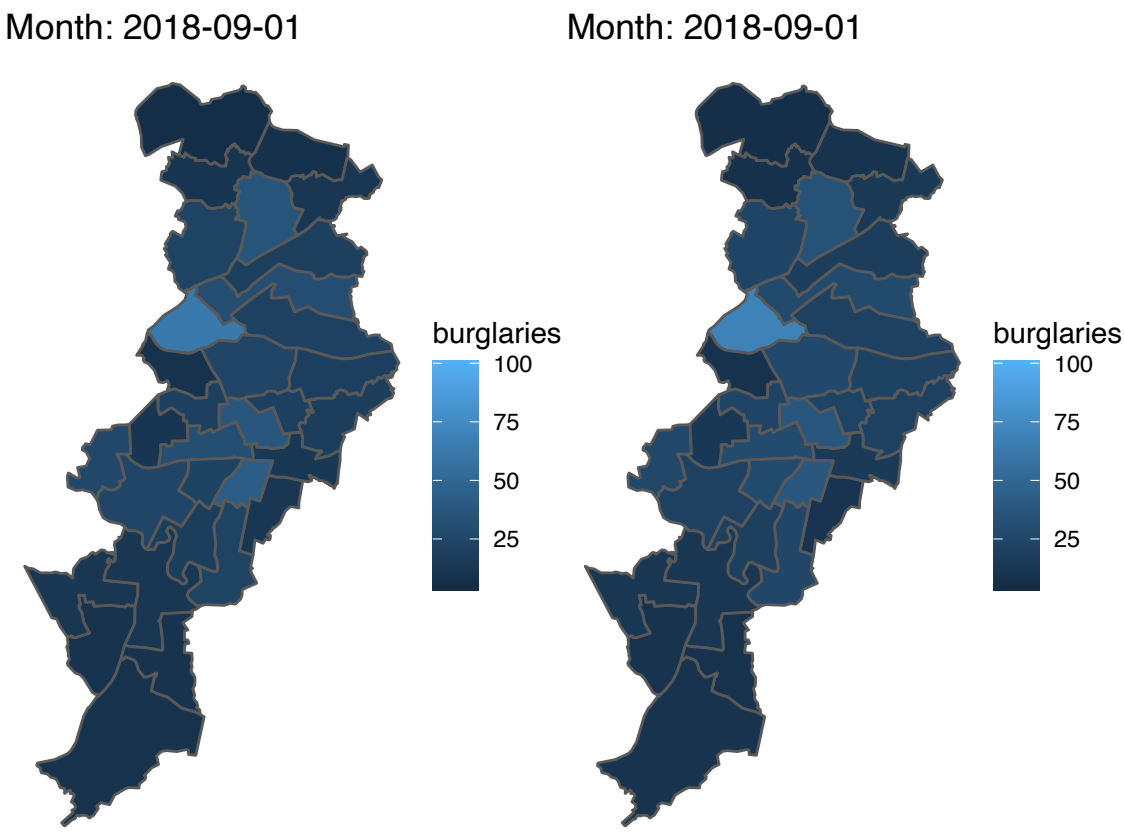

Month: 2018-08-01
burglaries
100
75
50
25
Month: 2018-08-01
burglaries
100
75
50
25

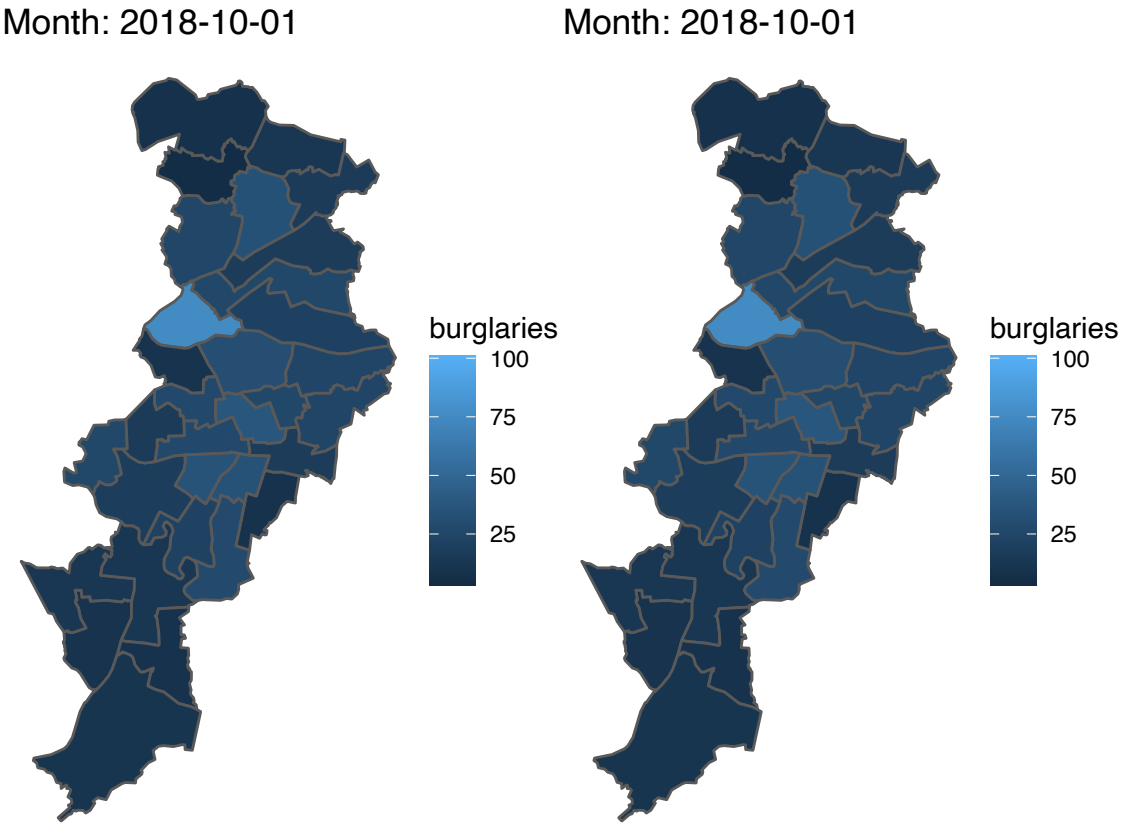

Month: 2018-08-01
burglaries
100
75
50
25
Month: 2018-08-01
burglaries
100
75
50
25

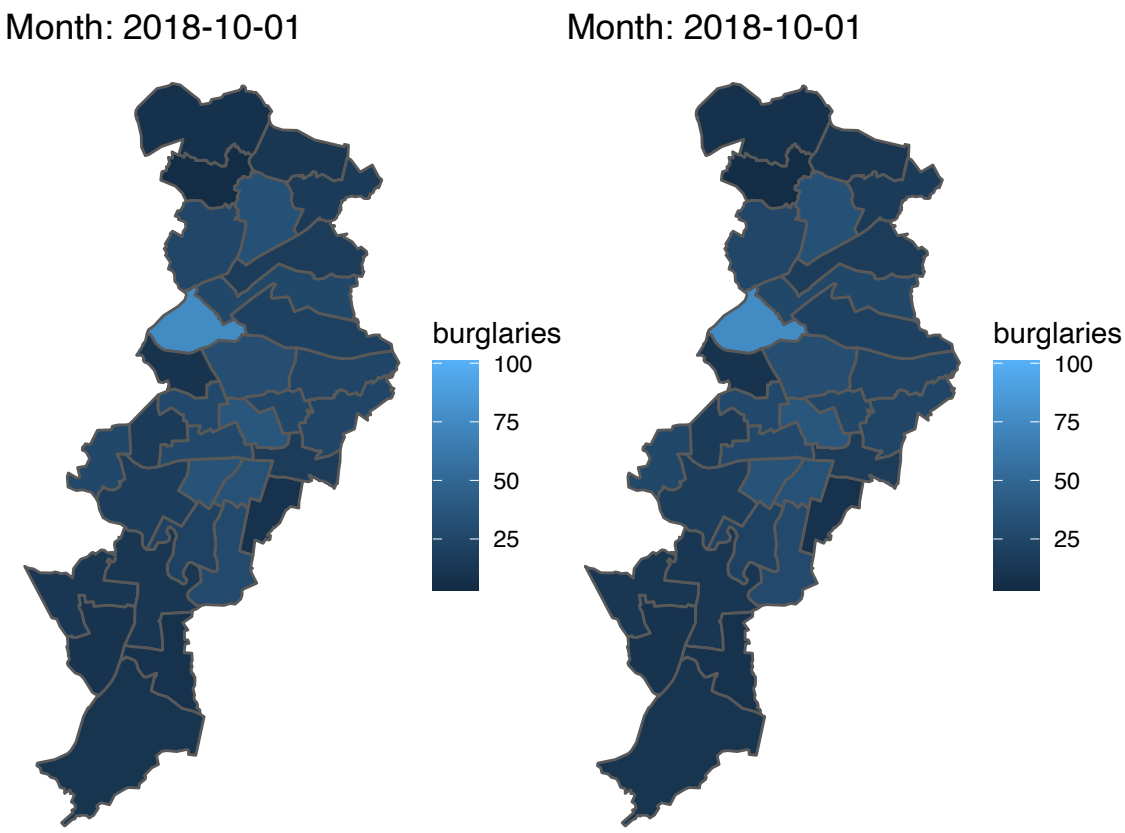

Month: 2018-09-01
burglaries
100
75
50
25
Month: 2018-09-01
burglaries
100
75
50
25

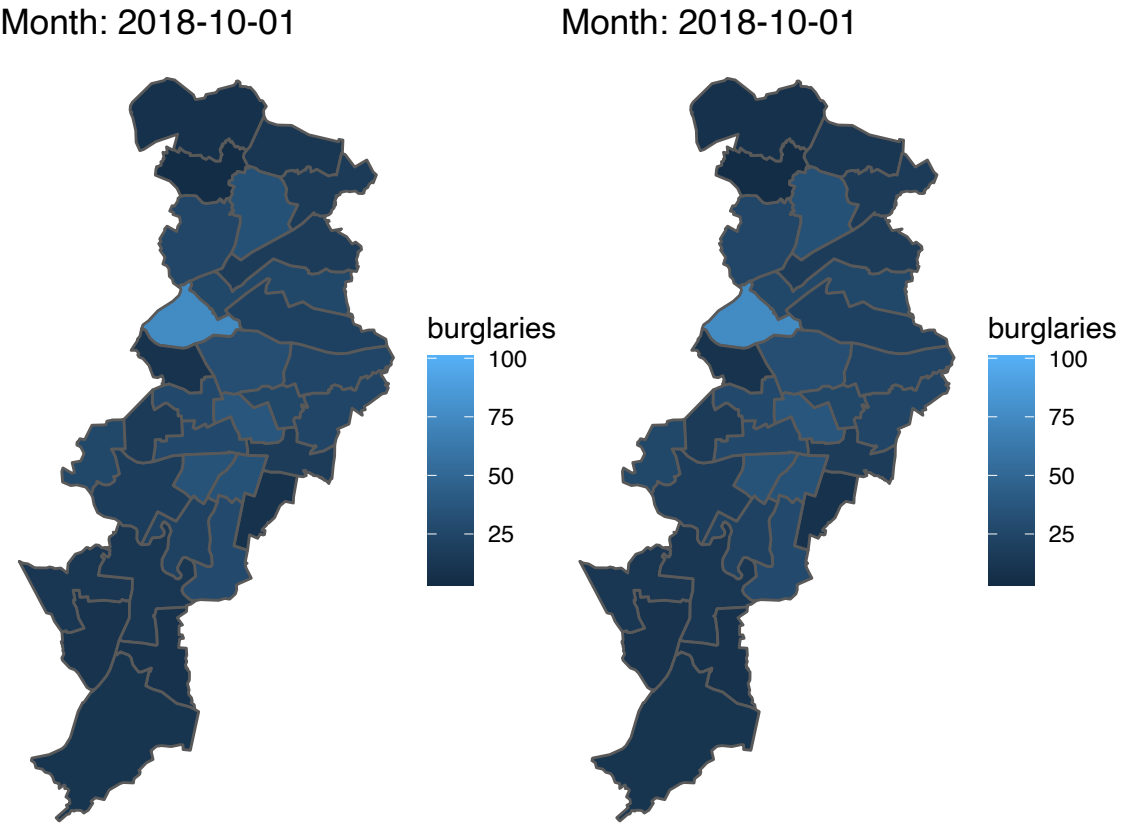

Month: 2018-09-01
burglaries
100
75
50
25
Month: 2018-09-01
burglaries
100
75
50
25


Month: 2018-09-01
burglaries
100
75
50
25
Month: 2018-09-01
burglaries
100
75
50
25

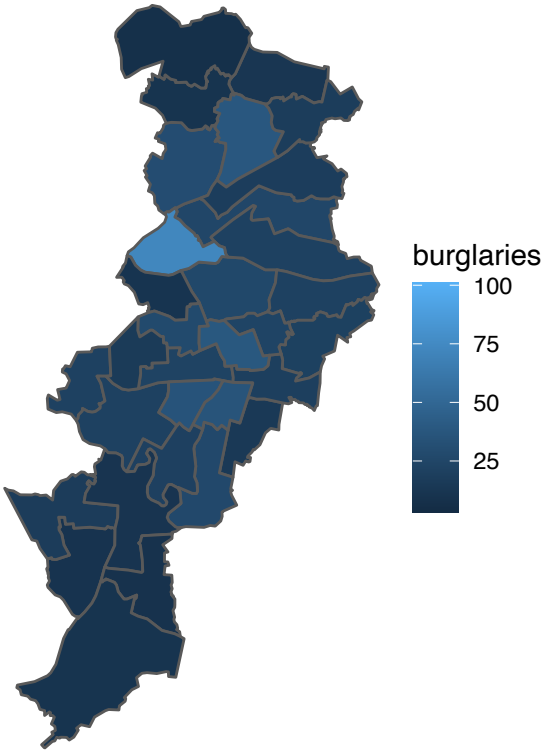

Month: 2018-09-01
burglaries
100
75
50
25
Month: 2018-09-01
burglaries
100
75
50
25


Month: 2018-10-01
burglaries
100
75
50
25
Month: 2018-10-01
burglaries
100
75
50
25

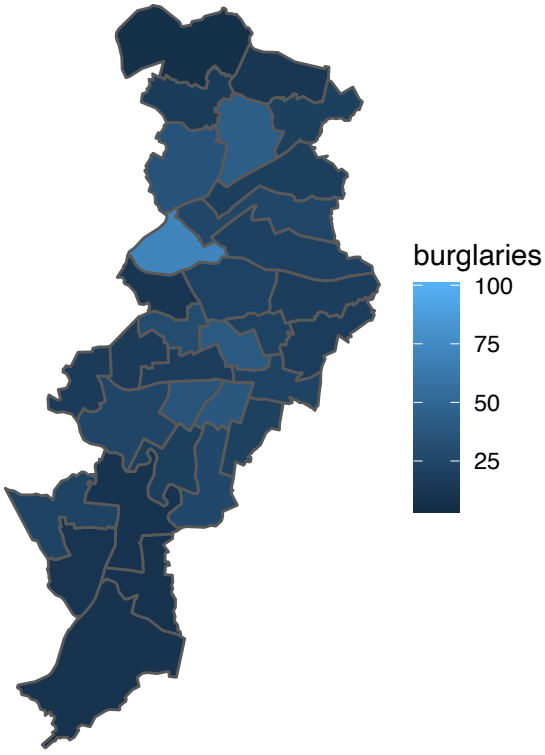

Month: 2018-10-01
burglaries
100
75
50
25
Month: 2018-10-01
burglaries
100
75
50
25

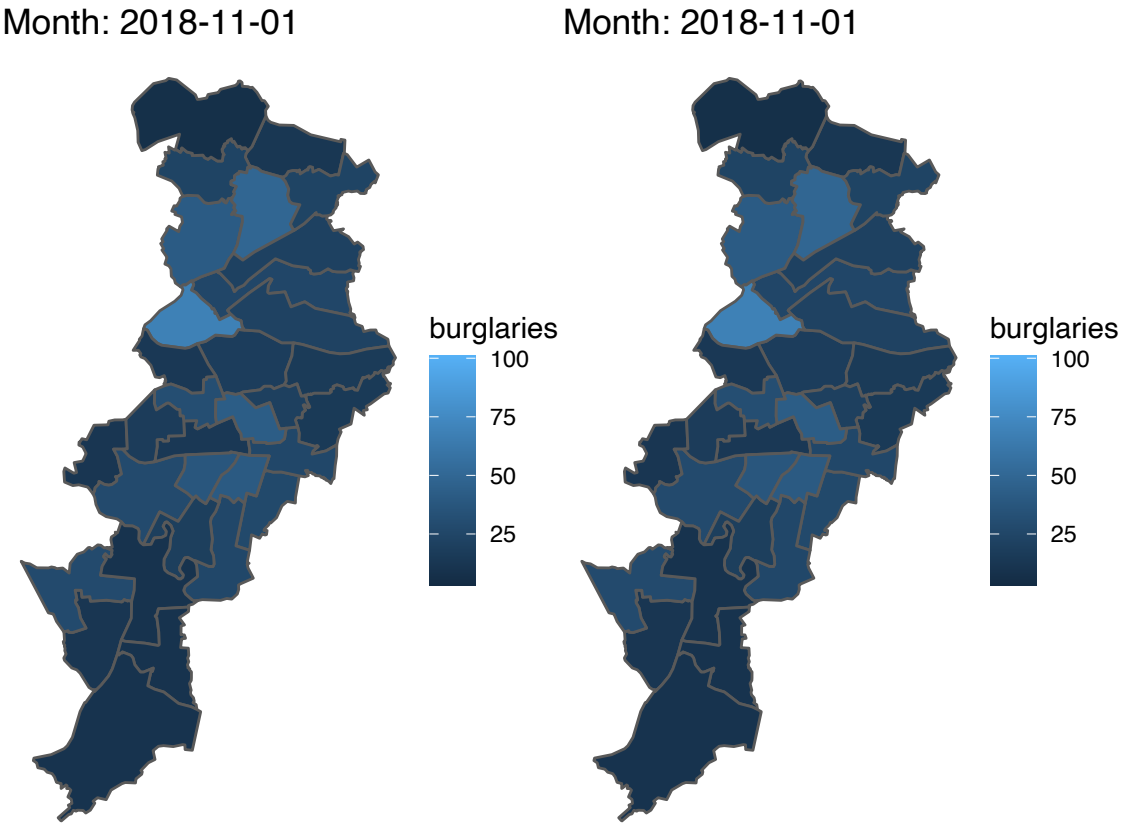

Month: 2018-10-01
burglaries
100
75
50
25
Month: 2018-10-01
burglaries
100
75
50
25

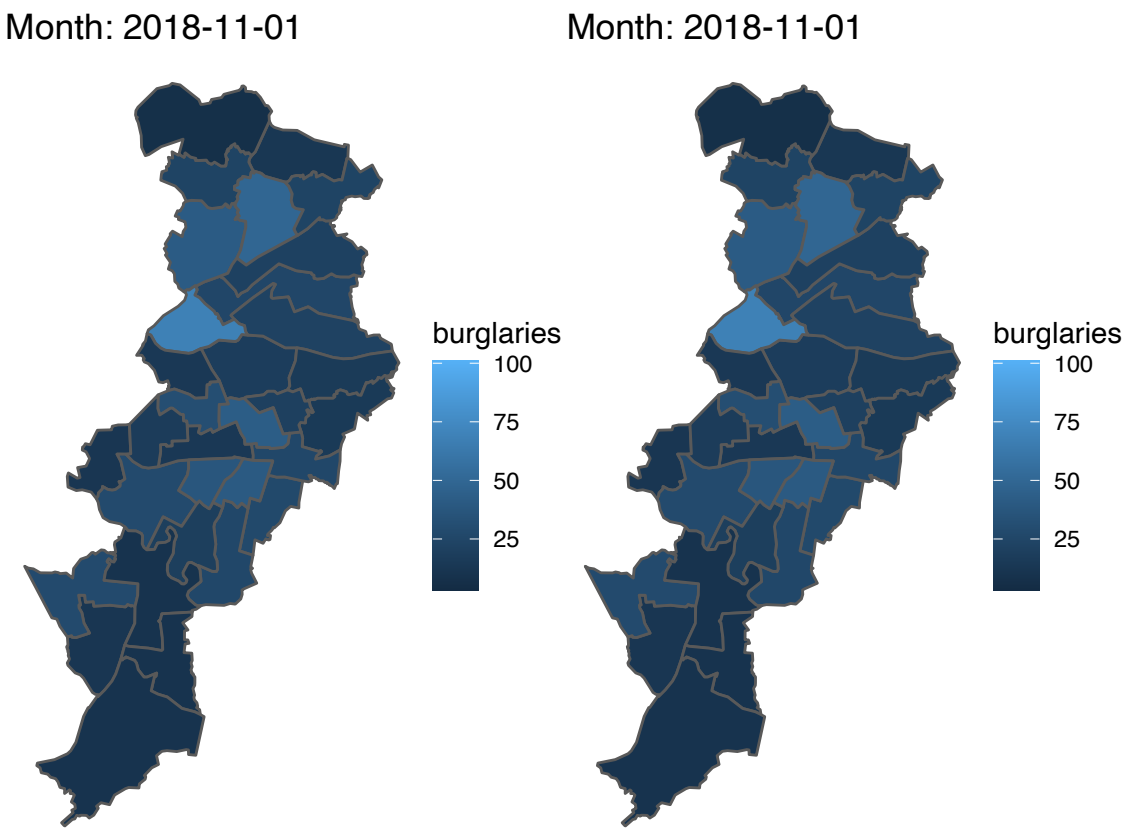
Month: 2018-10-01

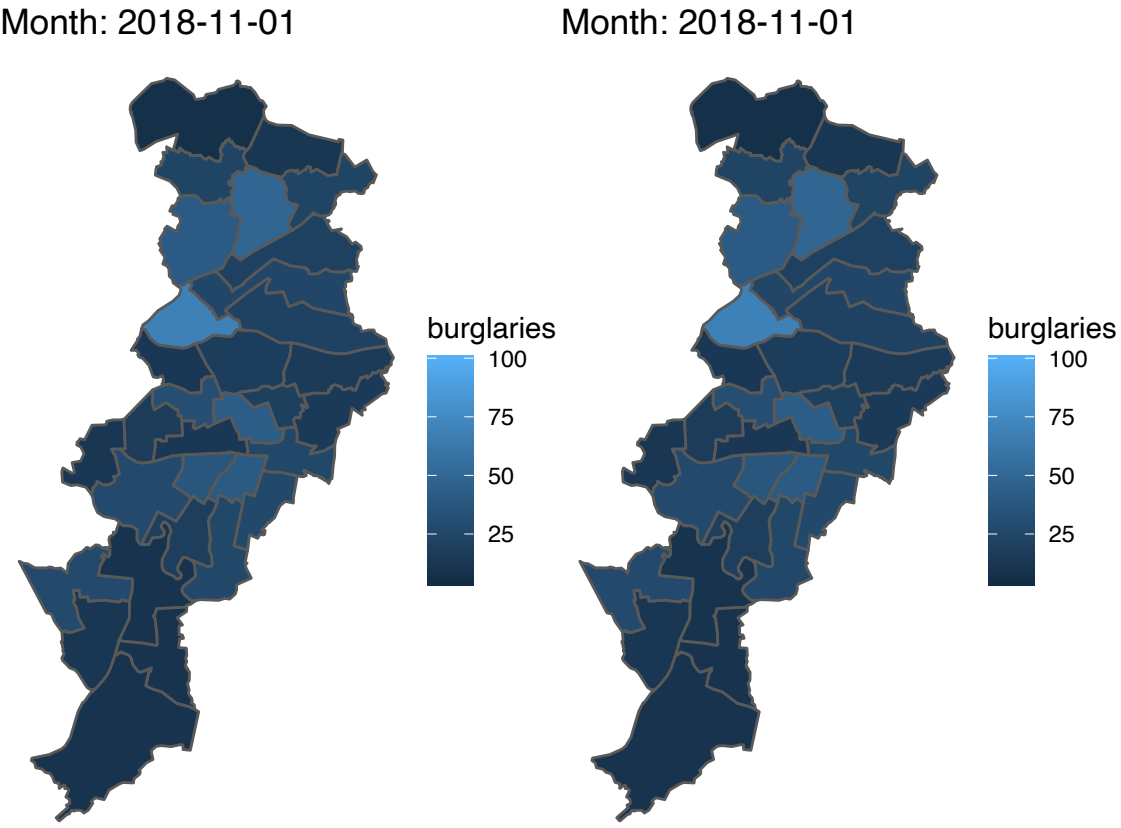


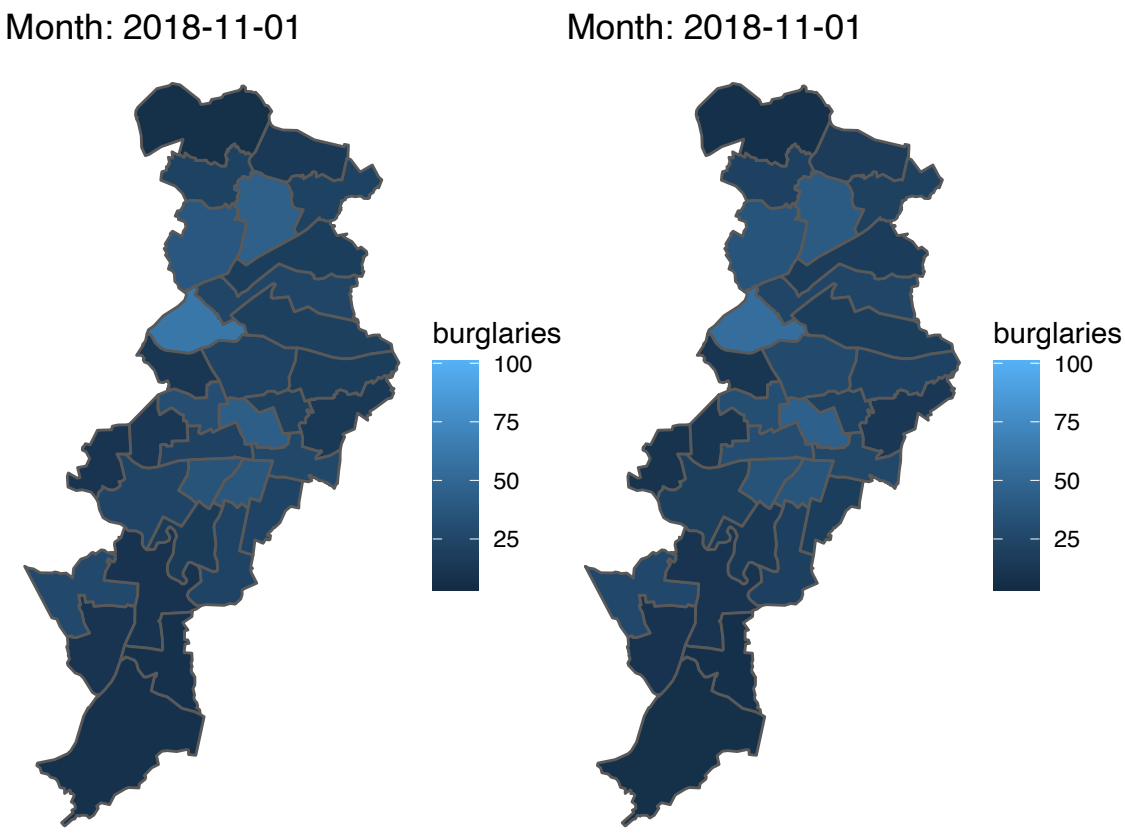
Month: 2018-10-01

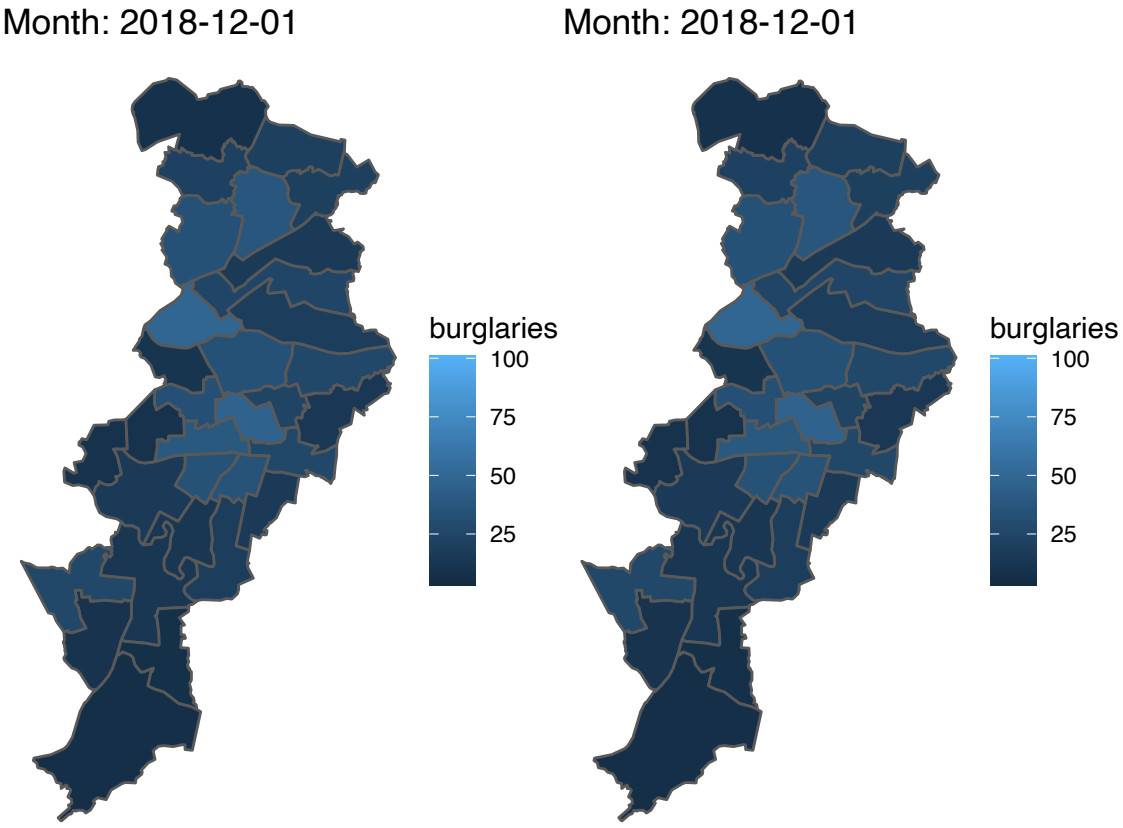


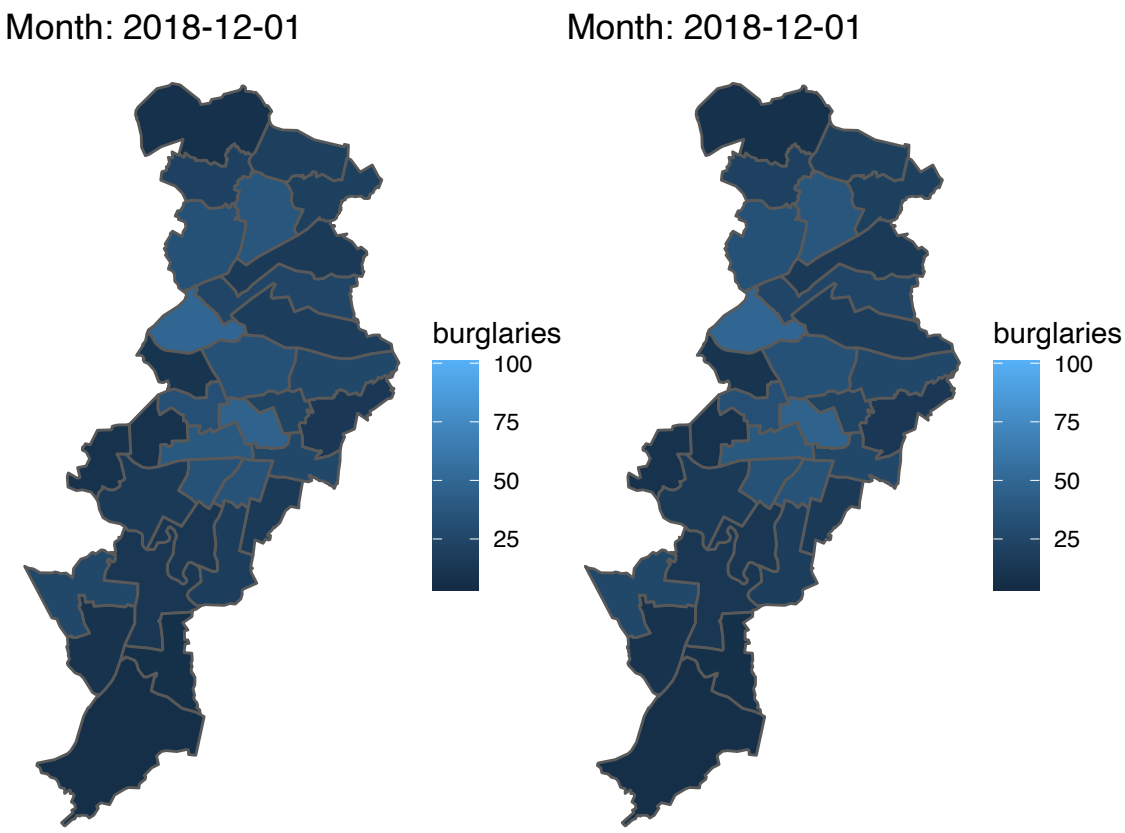

Month: 2018-11-01
burglaries
100
75
50
25
Month: 2018-11-01
burglaries
100
75
50
25

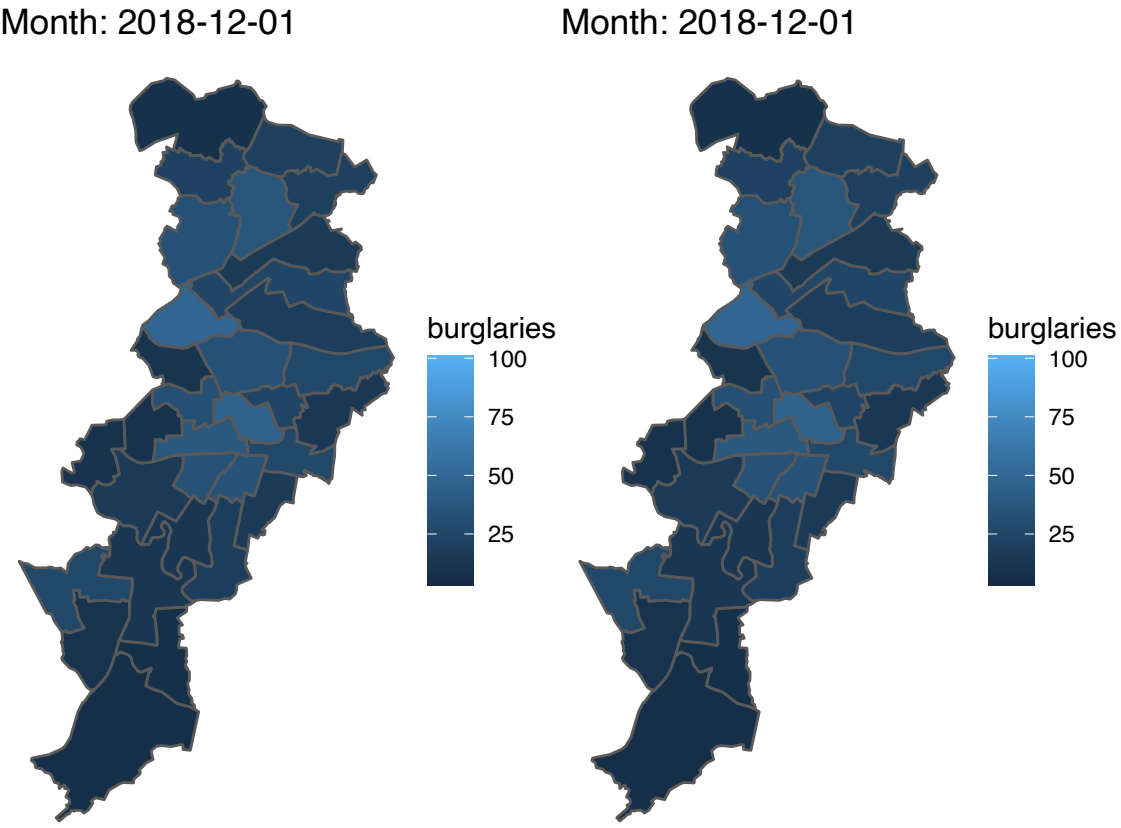

Month: 2018-11-01
burglaries
100
75
50
25
Month: 2018-11-01
burglaries
100
75
50
25

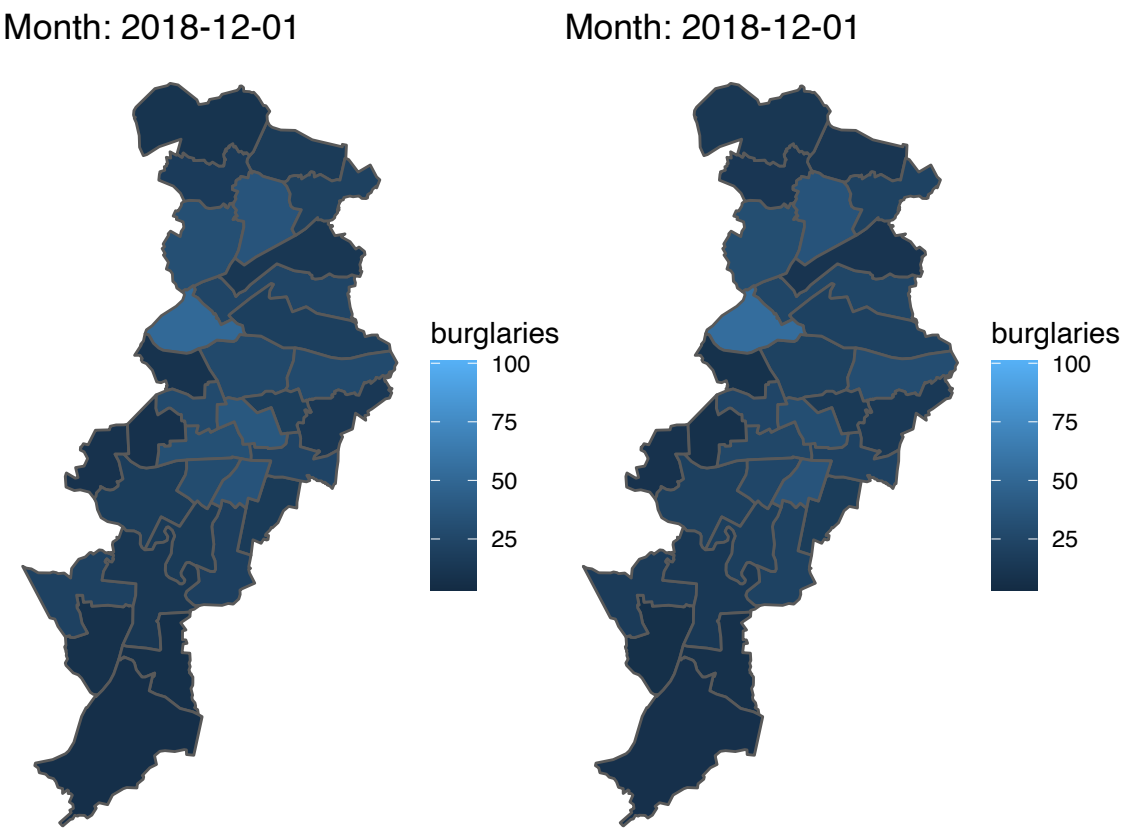

Month: 2018-11-01
burglaries
100
75
50
25
Month: 2018-11-01
burglaries
100
75
50
25


Month: 2018-11-01
burglaries
100
75
50
25
Month: 2018-11-01
burglaries
100
75
50
25


Month: 2018-12-01
burglaries
100
75
50
25
Month: 2018-12-01
burglaries
100
75
50
25


Month: 2018-12-01
burglaries
100
75
50
25
Month: 2018-12-01
burglaries
100
75
50
25


Month: 2018-12-01
burglaries
100
75
50
25
Month: 2018-12-01
burglaries
100
75
50
25



In the print book, this will not look very exciting, but hopefull you are following along, and now are looking at a very smooth animation of how burglary changed over the months of 2018 in Manchester.

0.49 Summary and further reading

In this chapter we had a very brief introduction to temporal data, and considered how we can manipulate and wrangle this new type of data using packages such as `lubridate`. We then introduced some approaches to visualising temporal data, and finally, ways to visualise spatio-temporal variation as well. To read up on the importance of time, and specifically spatio-temporal crime analysis, we recommend **?**, **?**, and **?**.

While we did not get to go into any spatio-temporal analysis at this stage, visualisation is a good starting point to begin to engage with this important element of crime data. To move into spatio-temporal analysis would require a more thorough training in temporal data analysis first, and so we do not cover here. But we provide some resources for those interested. Notably **?** is

an excellent resource for this, and we can also recommend **?**. For those already comfortable with this, **?** also offers a very thoughtful introduction to how spatio-temporal data layouts appear and useful graphs for spatio-temporal data. **?** also introduces the R package `spacetime`, for handling such analyses. At the time of writing, functions in `spacetime` take as inputs older `sp` objects, but work in `sftime`, to work with `sf` objects is ongoing. For additional details in how to visualise space-time data with R we suggest **?** and Chapter 2 of **?**.

As noted there are packages that provide functionality for better handling of dates and time. It is worth to go over the details of ´lubridate´ in the official page and the relevant chapter in **?** is also very helpful. There is a brand new package `clock` that aims to improve on `lubridate` and that is also worth exploring (for details see **?**).