

# Introduction to visualising spatial data in R

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## Preface

This tutorial is an introduction to analysing spatial data in R, specifically through map-making with R's 'base' graphics and various dedicated map-making packages for R including **tmap** and **leaflet**. It teaches the basics of using R as a fast, user-friendly and extremely powerful command-line Geographic Information System (GIS).

The tutorial is practical in nature: you will load-in, visualise and manipulate spatial data. We assume no prior knowledge of spatial data analysis but some experience with R will help. If you have not used R before, it may be worth following an introductory tutorial, such as “A (very) short introduction to R” (Torfs and Brauer, 2012). This is how the tutorial is organised:

1. Introduction: provides a guide to R's syntax and preparing for the tutorial
2. Spatial data in R: describes basic spatial functions in R
3. Creating and manipulating spatial data: includes changing projection, clipping and spatial joins
4. Map making with **tmap**, **ggplot2** and **leaflet**: this section demonstrates map making with more advanced visualisation tools
5. Taking spatial analysis in R further: a compilation of resources for furthering your skills

To distinguish between prose and code, please be aware of the following typographic conventions used in this document: R code (e.g. `plot(x, y)`) is written in a **monospace** font and package names (e.g. **rgdal**) are written in **bold**. A double hash (**##**) at the start of a line of code indicates that this is output from R. Lengthy outputs have been omitted from the document to save space, so do not be alarmed if R produces additional messages: you can always look up them up on-line.

As with any programming language, there are often many ways to produce the same output in R. The code presented in this document is not the only way to do things. We encourage you to play with the code to gain a deeper understanding of R. Do not worry, you cannot 'break' anything using R and all the input data can be re-loaded if things do go wrong. As with learning to skateboard, you learn by falling and getting an **Error**: message in R is much less painful than falling onto concrete! We encourage **Error**:s — it means you are trying new things.

## Part I: Introduction

### Prerequisites

For this tutorial you need a copy of R. The latest version can be downloaded from <http://cran.r-project.org/>.

We also suggest that you use an R editor, such as **RStudio**, as this will improve the user-experience and help with the learning process. This can be downloaded from <http://www.rstudio.com>. The R Studio interface is comprised of a number of windows, the most important being the console window and the script window. Anything you type directly into the console window will not be saved, so use the script window to create scripts which you can save for later use. There is also a Data Environment window which lists the dataframes and objects being used. Familiarise yourself with the R Studio interface before getting started on the tutorial.

When writing code in any language, it is good practice to use consistent and clear conventions, and R is no exception. Adding comments to your code is also useful; make these meaningful so you remember what the code is doing when you revisit it at a later date. You can add a comment by using the **#** symbol before or after a line of code, as illustrated in the block of code below. This code should create Figure 1 if typed correctly into the Console window:

This first line in this block of code creates a new *object* called **x** and assigns it to a range of integers between 1 and 400. The second line creates another object called **y** which is assigned to a mathematical formula, and the third line plots the two together to create the plot shown.

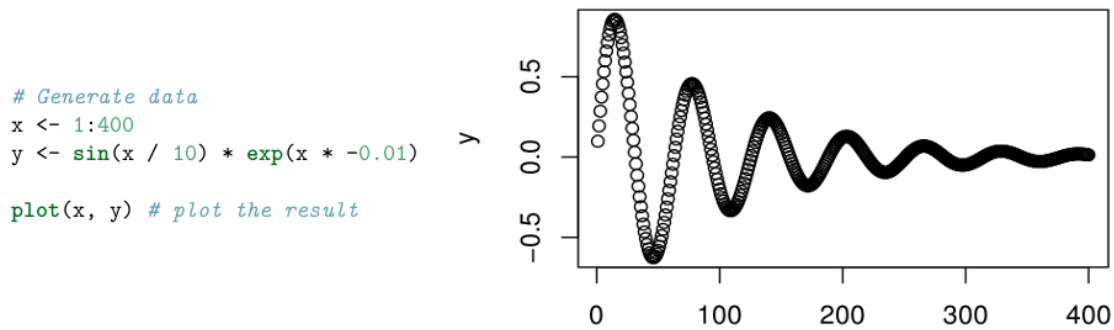


Figure 1: Basic plot of x and y (right) and code used to generate the plot (left).

Note `<-`, the directional “arrow” assignment symbol which creates a new object and assigns it to the value you have given.<sup>1</sup>

If you require help on any function, use the `help` command, e.g. `help(plot)`. Because R users love being concise, this can also be written as `?plot`. Feel free to use it at any point you would like more detail on a specific function (although R’s help files are famously cryptic for the un-initiated). Help on more general terms can be found using the `??` symbol. To test this, try typing `??regression`. For the most part, *learning by doing* is a good motto, so let’s crack on and download some packages and data.

## R Packages

R has a huge and growing number of spatial data packages. We recommend taking a quick browse on R’s main website to see the spatial packages available: <http://cran.r-project.org/web/views/Spatial.html>.

In this tutorial we will use the following packages:

- **ggmap**: extends the plotting package **ggplot2** for maps
- **rgdal**: R’s interface to the popular C/C++ spatial data processing library **gdal**
- **rgeos**: R’s interface to the powerful vector processing library **geos**
- **maptools**: provides various mapping functions
- **dplyr** and **tidyr**: fast and concise data manipulation packages
- **tmap**: a new packages for rapidly creating beautiful maps

Some packages may already be installed on your computer. To test if a package is installed, try to load it using the `library` function; for example, to test if **ggplot2** is installed, type `library(ggplot2)` into the console window. If there is no output from R, this is good news: it means that the library has already been installed on your computer.

If you get an error message, you will need to install the package using `install.packages("ggplot2")`. The package will download from the Comprehensive R Archive Network (CRAN); if you are prompted to select a ‘mirror’, select one that is close to current location. If you have not done so already, install these packages on your computer now. A [quick way](#) to do this in one go is to enter the following lines of code:

```
x <- c("ggmap", "rgdal", "rgeos", "maptools", "dplyr", "tidyr", "tmap")
# install.packages(x) # warning: uncommenting this may take a number of minutes
lapply(x, library, character.only = TRUE) # load the required packages
```

<sup>1</sup>Tip: typing `Alt -` on the keyboard will create the arrow in RStudio. The equals sign `=` also works but is rarely used.

## Part II: Spatial data in R

### Starting the tutorial and downloading the data

Now that we have looked at R's basic syntax and installed the necessary packages, let's load some real spatial data. The next part of the tutorial will focus on plotting and interrogating spatial objects.

The data used for this tutorial can be downloaded from: <https://github.com/Robinlovelace/Creating-maps-in-R>. Click on the “Download ZIP” button on the right hand side of the screen and once downloaded, unzip this to a new folder on your computer.

Open the existing ‘Creating-maps-in-R’ project using **File -> Open File...** on the top menu.

Alternatively, use the *project menu* to open the project or create a new one. It is *highly recommended* that you use RStudio's projects to organise your R work and that you organise your files into sub-folders (e.g. **code**, **input-data**, **figures**) to avoid digital clutter (Figure 2). The RStudio website contains an overview of the software: [rstudio.com/products/rstudio/](https://rstudio.com/products/rstudio/).

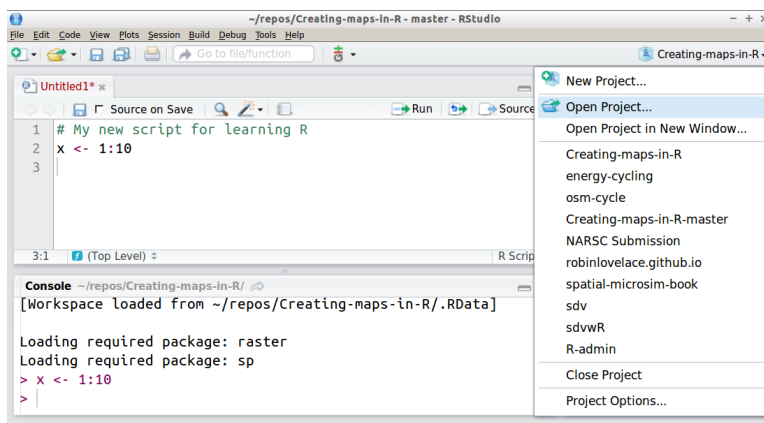


Figure 2: The RStudio environment with the project tab poised to open the Creating-maps-in-R project.

Opening a project sets the current working directory to the project's parent folder, the **Creating-maps-in-R** folder in this case. If you ever need to change your working directory, you can use the ‘Session’ menu at the top of the page or use the **setwd** command.

The first file we are going to load into R Studio is the “london\_sport” [shapefile](#) located in the ‘data’ folder of the project. It is worth looking at this input dataset in your file browser before opening it in R. You will notice that there are several files named “london\_sport”, all with different file extensions. This is because a shapefile is actually made up of a number of different files, such as .prj, .dbf and .shp.

You could also try opening the file “london\_sport.shp” file in a conventional GIS such as QGIS to see what a shapefile contains.

You should also open “london\_sport.dbf” in a spreadsheet program such as LibreOffice Calc. to see what this file contains. Once you think you understand the input data, it's time to open it in R. There are a number of ways to do this, the most commonly used and versatile of which is **readOGR**. This function, from the **rgdal** package, automatically extracts the information regarding the data.

**rgdal** is R's interface to the “Geospatial Abstraction Library (GDAL)” which is used by other open source GIS packages such as QGIS and enables R to handle a broader range of spatial data formats. If you've not already *installed* and loaded the **rgdal** package (see the ‘prerequisites and packages’ section) do so now:

```
library(rgdal)
lnd <- readOGR(dsn = "data", layer = "london_sport")
```

In the second line of code above the `readOGR` function is used to load a shapefile and assign it to a new spatial object called “lnd”; short for London. `readOGR` is a *function* which accepts two *arguments*: `dsn` which stands for “data source name” and specifies the directory in which the file is stored, and `layer` which specifies the file name (note that there is no need to include the file extension `.shp`). The *arguments* are separated by a comma and the order in which they are specified is important. You do not have to explicitly type `dsn=` or `layer=` as R knows which order they appear, so `readOGR("data", "london_sport")` would work just as well. For clarity, it is good practice to include argument names when learning new functions so we will continue to do so.

The file we assigned to the `lnd` object contains the population of London Boroughs in 2001 and the percentage of the population participating in sporting activities. This data originates from the [Active People Survey](#). The boundary data is from the [Ordnance Survey](#).

For information about how to load different types of spatial data, see the help documentation for `readOGR`. This can be accessed by typing `?readOGR`. For another worked example, in which a GPS trace is loaded, please see Cheshire and Lovelace (2014).

## The structure of spatial data in R

Spatial objects like the `lnd` object are made up of a number of different *slots*, the key *slots* being `@data` and `@polygons` (or `@lines` for line data). The data *slot* can be thought of as an attribute table and the geometry *slot* is the polygons that make up the physical boundaries. Specific *slots* are accessed using the `@` symbol. Let’s now analyse the sport object with some basic commands:

```
head(lnd@data, n = 2)

##      ons_label                name Partic_Per Pop_2001
## 0      00AF              Bromley      21.7   295535
## 1      00BD Richmond upon Thames      26.6   172330

mean(lnd$Partic_Per)

## [1] 20.05455
```

Take a look at the output created (note the table format of the data and the column names). There are two important symbols at work in the above block of code: the `@` symbol in the first line of code is used to refer to the data *slot* of the `lnd` object. The `$` symbol refers to the `Partic_Per` column (a variable within the table) in the `data` *slot*, which was identified from the result of running the first line of code.

The `head` function in the first line of the code above simply means “show the first few lines of data”, i.e. the head. It’s default is to output the first 6 rows of the dataset (try simply `head(lnd@data)`), but we can specify the number of lines with `n = 2` after the comma. The second line of the code above calculates the mean value of the variable `Partic_Per` (sports participation per 100 people) for each of the zones in the `lnd` object.

Type the function again but this time hit `tab` before completing the command. RStudio has auto-complete functionality which can save you a lot of time in the long run (see Figure 3).

To explore `lnd` object further, try typing `nrow(lnd)` (display number of rows) and record how many zones the dataset contains. You can also try `ncol(lnd)`.

## Basic plotting

Now we have seen something of the structure of spatial objects in R, let us look at plotting them. Note, that plots use the *geometry* data, contained primarily in the `@polygons` slot.

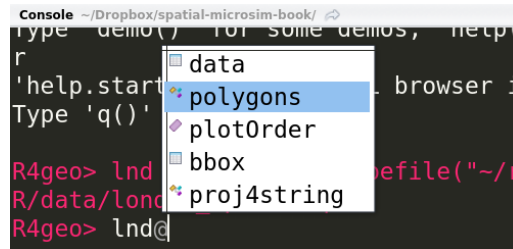


Figure 3: Tab-autocompletion in action: display from RStudio after typing `lnd@` then `tab` to see which slots are in `lnd`

```
plot(lnd) # not shown in tutorial - try it on your computer
```

`plot` is one of the most useful functions in R, as it changes its behaviour depending on the input data (this is called *polymorphism* by computer scientists). Inputting another object such as `plot(lnd@data)` will generate an entirely different type of plot. Thus R is intelligent at guessing what you want to do with the data you provide it with.

R has powerful subsetting capabilities that can be accessed very concisely using square brackets, as shown in the following example:

```
# select rows of lnd@data where sports participation is less than 15
lnd@data[lnd$Partic_Per < 15, ]
```

```
##      ons_label      name Partic_Per Pop_2001
## 17      00AQ      Harrow      14.8   206822
## 21      00BB      Newham      13.1   243884
## 32      00AA City of London      9.1    7181
```

The above line of code asked R to select only the rows from the `lnd` object, where sports participation is lower than 15, in this case rows 17, 21 and 32, which are Harrow, Newham and the city centre respectively. The square brackets work as follows: anything before the comma refers to the rows that will be selected, anything after the comma refers to the number of columns that should be returned. For example if the data frame had 1000 columns and you were only interested in the first two columns you could specify `1:2` after the comma. The “:” symbol simply means “to”, i.e. columns 1 to 2. Try experimenting with the square brackets notation (e.g. guess the result of `lnd@data[1:2, 1:3]` and test it).

So far we have been interrogating only the attribute data *slot* (`@data`) of the `lnd` object, but the square brackets can also be used to subset spatial objects, i.e. the geometry *slot*. Using the same logic as before try to plot a subset of zones with high sports participation.

```
# Select zones where sports participation is between 20 and 25%
sel <- lnd$Partic_Per > 20 & lnd$Partic_Per < 25
plot(lnd[sel, ]) # output not shown here
head(sel) # test output of previous selection (not shown)
```

This plot is quite useful, but it only displays the areas which meet the criteria. To see the sporty areas in context with the other areas of the map simply use the `add = TRUE` argument after the initial plot. (`add = T` would also work, but we like to spell things out in this tutorial for clarity). What do you think the `col` argument refers to in the below block? (see Figure 5).

If you wish to experiment with multiple criteria queries, use `&`.

```
plot(lnd, col = "lightgrey") # plot the london_sport object
sel <- lnd$Partic_Per > 25
plot(lnd[ sel, ], col = "turquoise", add = TRUE) # add selected zones to map
```

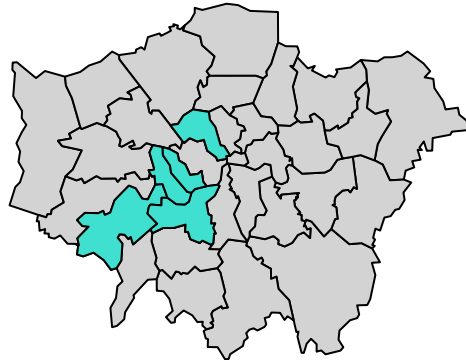


Figure 4: Simple plot of London with areas of high sports participation highlighted in blue

Congratulations! You have just interrogated and visualised a spatial object: where are areas with high levels of sports participation in London? The map tells us. Do not worry for now about the intricacies of how this was achieved: you have learned vital basics of how R works as a language; we will cover this in more detail in subsequent sections.

As a bonus stage, select and plot only zones that are close to the centre of London (see Fig. 6). Programming encourages rigorous thinking and it helps to define the problem more specifically:

**Challenge:** Select all zones whose geographic centroid lies within 10 km of the geographic centroid of inner London.<sup>2</sup>



Figure 5: Zones in London whose centroid lie within 10 km of the geographic centroid of the City of London. Note the distinction between zones which only touch or ‘intersect’ with the buffer (light blue) and zones whose centroid is within the buffer (darker blue).

## Attribute data

As we discovered in the previous section, shapefiles contain both attribute data and geometry data, both of which are automatically loaded into R when the `readOGR` function is used. Let’s look again at the attribute

<sup>2</sup>To see how this map was created, see the code in `intro-spatial.Rmd`. This may be loaded by typing `file.edit("intro-spatial.Rmd")` or online at [github.com/Robinlovelace/Creating-maps-in-R/blob/master/intro-spatial.Rmd](https://github.com/Robinlovelace/Creating-maps-in-R/blob/master/intro-spatial.Rmd).

data of the `lnd` object by looking at the headings contained within it: `names(lnd)` Remember, the attribute data is contained in the `data slot` that can be accessed using the `@` symbol: `lnd@data`. This is useful if you do not wish to work with the spatial components of the data at all times.

Type `summary(lnd)` to get some additional information about the data object. Spatial objects in R contain much additional information:

```
summary(lnd)

## Object of class SpatialPolygonsDataFrame
## Coordinates:
## min max
## x 503571.2 561941.1
## y 155850.8 200932.5
## Is projected: TRUE
## proj4string :
## [+proj=tmerc +lat_0=49 +lon_0=-2 +k=0.9996012717 ....]

...
```

The first line of the above output tells us that `lnd` is a special spatial class: a `SpatialPolygonsDataFrame`. This means it is composed of various polygons, each of which has a number of attributes. (Summaries of the attribute data are also provided, but are not printed above.) This is the ideal class of data to represent administrative zones. The coordinates tell us what the maximum and minimum x and y values are (the spatial extent of the data - useful for plotting). Finally, we are told something of the coordinate reference system with the `Is projected` and `proj4string` lines. In this case, we have a projected system, which means the data is relative to some point on the Earth's surface. We will cover reprojecting data in the next part of the tutorial.



## Part III: Creating and manipulating spatial data

Alongside visualisation and interrogation, a GIS must also be able to create and modify spatial data. R's spatial packages provide a very wide and powerful suite of functionality for processing and creating spatial data.

*Reprojecting* and *joining/clipping* are fundamental GIS operations, so in this section we will explore how these operations can be undertaken in R. Firstly We will join non-spatial data to spatial data so it can be mapped. Finally we will cover spatial joins, whereby information from two spatial objects is combined based on spatial location.

### Creating new spatial data

R objects can be created by entering the name of the class we want to make. `vector` and `data.frame` objects for example, can be created as follows:

```
vec <- vector(mode = "numeric", length = 3)
df <- data.frame(x = 1:3, y = c(1/2, 2/3, 3/4))
```

We can check the class of these new objects using `class()`:

```
class(vec)

## [1] "numeric"

class(df)

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

The same logic applies to spatial data, but the input requirements are stricter. To create a `SpatialPoints` object, for example, the input coordinates *must* be supplied in a matrix:

```
mat <- as.matrix(df) # create matrix object with as.matrix
sp1 <- SpatialPoints(coords = mat)
```

Note in the code above the use of `as.matrix()` to change the class of an existing object. We then create a spatial points object, one of the fundamental data types for spatial data. (The others are lines, polygons and pixels, which can be created by `SpatialLines`, `SpatialPolygons` and `SpatialPixels`, respectively.) Each type of spatial data has a corollary that can accept non-spatial data, created by adding `DataFrame`. `SpatialPointsDataFrame()`, for example, creates points with an associated `data.frame`. The number of rows in this dataset must equal the number of features in the spatial object, which in the case of `sp1` is 3.

```
class(sp1)

## [1] "SpatialPoints"
## attr(,"package")
## [1] "sp"

spdf <- SpatialPointsDataFrame(sp1, data = df)
class(spdf)
```

```
## [1] "SpatialPointsDataFrame"
## attr(,"package")
## [1] "sp"
```

The above code extends the pre-existing object `sp1` by adding data from `df`. To see how strict spatial classes are, try replacing `df` with `mat` in the above code: it causes an error. All spatial data classes can be created in a similar way, although `SpatialLines` and `SpatialPolygons` are much more complicated (Bivand et al. 2013). More frequently your spatial data will be read-in from an externally-created file, e.g. using `readOGR()`. Unlike the spatial objects we created above, most spatial data comes with an associate ‘CRS’.

## Projections: setting and transforming CRS in R

The *Coordinate Reference System* (CRS) of spatial objects defines where they are placed on the Earth’s surface. You may have noticed ‘proj4string’ in the summary of `lnd` above: the information that follows represents its CRS. Spatial data should always have a CRS. If no CRS information is provided, and the correct CRS is known, it can be set as follow:

```
proj4string(lnd) <- NA_character_ # remove CRS information from lnd
proj4string(lnd) <- CRS("+init=epsg:27700") # assign a new CRS
```

R issues a warning when the CRS is changed. This is so the user knows that they are simply changing the CRS, not *reprojecting* the data. An easy way to refer to different projections is via [EPSG codes](#).

Under this system 27700 represents the British National Grid. ‘WGS84’ (`epsg:4326`) is a very commonly used CRS worldwide. The following code shows how to search the list of available EPSG codes and create a new version of `lnd` in WGS84:<sup>3</sup>

```
EPSG <- make_EPSG() # create data frame of available EPSG codes
EPSG[grepl("WGS 84$", EPSG$note), ] # search for WGS 84 code
```

```
##      code      note                                prj4
## 249 4326 # WGS 84 +proj=longlat +datum=WGS84 +no_defs
```

```
lnd84 <- spTransform(lnd, CRS("+init=epsg:4326")) # reproject
```

Above, `spTransform` converts the coordinates of `lnd` into the widely used WGS84 CRS. Now we’ve transformed `lnd` into a more widely used CRS, it is worth saving it. R stores data efficiently in `.RData` or `.Rds` formats. The former is more restrictive and maintains the object’s name, so we use the latter.

```
# Save lnd84 object (we will use it in Part IV)
saveRDS(object = lnd84, file = "data/lnd84.Rds")
```

Now we can remove the `lnd84` object with the `rm` command. It will be useful later. (In RStudio, notice it also disappears from the Environment in the top right panel.)

```
rm(lnd84) # remove the lnd object
```

---

<sup>3</sup>Note: entering `projInfo()` provides additional CRS options. [spatialreference.org](http://spatialreference.org) provides more information about EPSG codes.

## Attribute joins

Attribute joins are used to link additional pieces of information to our polygons. In the `lnd` object, for example, we have 4 attribute variables — that can be found by typing `names(lnd)`. But what happens when we want to add more variables from an external source? We will use the example of recorded crimes by London boroughs to demonstrate this.

To reaffirm our starting point, let's re-load the “london\_sport” shapefile as a new object and plot it:

```
library(rgdal) # ensure rgdal is loaded
# Create new object called "lnd" from "london_sport" shapefile
lnd <- readOGR(dsn = "data", "london_sport")
plot(lnd) # plot the lnd object (not shown)
nrow(lnd) # return the number of rows (not shown)
```

The non-spatial data we are going to join to the `lnd` object contains records of crimes in London. This is stored in a comma separated values (`.csv`) file called “mps-recordedcrime-borough”. If you open the [file](#) in a separate spreadsheet application first, we can see each row represents a single reported crime. We are going to use a function called `aggregate` to aggregate the crimes at the borough level, ready to join to our spatial `lnd` dataset. A new object called `crime_data` is created to store this data.

```
# Create and look at new crime_data object
crime_data <- read.csv("data/mps-recordedcrime-borough.csv",
  stringsAsFactors = FALSE)

head(crime_data, 3) # display first 3 lines
head(crime_data$CrimeType) # information about crime type

# Extract "Theft & Handling" crimes and save
crime_theft <- crime_data[crime_data$CrimeType == "Theft & Handling", ]
head(crime_theft, 2) # take a look at the result (replace 2 with 10 to see more rows)

# Calculate the sum of the crime count for each district, save result
crime_ag <- aggregate(CrimeCount ~ Borough, FUN = sum, data = crime_theft)
# Show the first two rows of the aggregated crime data
head(crime_ag, 2)
```

You should not expect to understand all of this upon first try: simply typing the commands and thinking briefly about the outputs is all that is needed at this stage. Here are a few things that you may not have seen before that will likely be useful in the future:

- In the first line of code when we read in the file we specify its location (check in your file browser to be sure).
- The `==` function is used to select only those observations that meet a specific condition i.e. where it is equal to, in this case all crimes involving “Theft and Handling”.
- The `~` symbol means “by”: we aggregated the `CrimeCount` variable by the district name.

Now that we have crime data at the borough level, the challenge is to join it to the `lnd` object. We will base our join on the `Borough` variable from the `crime_ag` object and the `name` variable from the `lnd` object. It is not always straight-forward to join objects based on names as the names do not always match. Let's see which names in the `crime_ag` object match the spatial data object, `lnd`:

```
# Compare the name column in lnd to Borough column in crime_ag to see which rows match.
lnd$name %in% crime_ag$Borough
```

```
## [1] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## [13] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## [25] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE FALSE
```

```
# Return rows which do not match
lnd$name[!lnd$name %in% crime_ag$Borough]
```

```
## [1] City of London
## 33 Levels: Barking and Dagenham Barnet Bexley Brent Bromley ... Westminster
```

The first line of code above uses the `%in%` command to identify which values in `lnd$name` are also contained in the Borough names of the aggregated crime data. The results indicate that all but one of the borough names matches. The second line of code tells us that it is ‘City of London’. This does not exist in the crime data. This may be because the City of London has it’s own Police Force.<sup>4</sup> (The borough name in the crime data does not match `lnd$name` is ‘NULL’. Check this by typing `crime_ag$Borough[!crime_ag$Borough %in% lnd$name]`.)

**Challenge:** identify the number of crimes taking place in borough ‘NULL’, less than 4,000.

Having checked the data found that one borough does not match, we are now ready to join the spatial and non-spatial datasets. It is recommended to use the `left_join` function from the **dplyr** package but the `merge` function could equally be used. Note that when we ask for help for a function that is not loaded, nothing happens, indicating we need to load it:

```
?left_join # error flagged
??left_join
library(dplyr) # load the powerful dplyr package (use plyr if unavailable)
?left_join # should now be loaded (use join if unavailable)
```

The above code demonstrates how to search for functions that are not currently loaded in R, using the `??` notation (short for `help.search` in the same way that `?` is short for `help`). Note, you will need to have the **dplyr** package, which provides fast and intuitive functions for processing data, installed for this to work. After **dplyr** is loaded, a single question mark is sufficient to load the associated help.

The documentation for the `left_join` function will be displayed if the `plyr` package is available (if not, use `install.packages()` to install it). We use `left_join` because we want the length of the data frame to remain unchanged, with variables from new data appended in new columns. Or, in R’s rather terse documentation: “return all rows from `x`, and all columns from `x` and `y`.” The `*join` commands (including `inner_join` and `anti_join`) are more concise when joining variables have the same name across both datasets. **dplyr** is also helpful here as it contains a useful function to `rename` variables:

```
head(lnd$name) # dataset to add to (results not shown)
head(crime_ag$Borough) # the variables to join
crime_ag <- rename(crime_ag, name = Borough) # rename the 'Borough' heading to 'name'
# head(left_join(lnd@data, crime_ag)) # test it works
lnd@data <- left_join(lnd@data, crime_ag)
```

```
## Joining by: "name"
```

```
## Warning in left_join_impl(x, y, by$x, by$y): joining character vector and
## factor, coercing into character vector
```

---

<sup>4</sup>See [www.cityoflondon.police.uk/](http://www.cityoflondon.police.uk/).

Take a look at the new `lnd@data` object. You should see new variables added, meaning the attribute join was successful. Congratulations! You can now plot the rate of theft crimes in London by borough (see Fig 8).

```
library(tmap) # load tmap package (see Section IV)
qtm(lnd, "CrimeCount") # plot the basic map
```

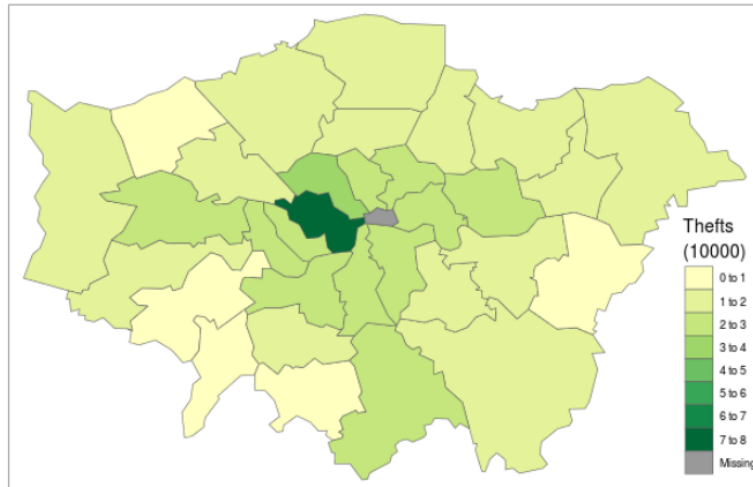


Figure 6: Number of thefts per borough.

**Optional challenge:** create a map of additional variables in London

With the attribute joining skills you have learned in this section, you should now be able to take datasets from many sources and join them to your geographical data. To test your skills, try to join additional borough-level variables to the `lnd` object. An excellent dataset on this can be found on the [data.london.gov.uk](http://data.london.gov.uk) website.

Using this dataset and the methods developed above, Figure 8 was created: the proportion of council seats won by the Conservatives in the 2014 local elections. The **challenge** is to create a similar map of a different variable (you may need to skip to Part IV to plot continuous variables).<sup>5</sup>

## Clipping and spatial joins

In addition to joining by attribute (e.g. Borough name), it is also possible to do [spatial joins](#) in R. There are three main types: many-to-one, where the values of many intersecting objects contribute to a new variable in the main table, one-to-many, or one-to-one. We will be conducting a many-to-one spatial join and using transport infrastructure points such as tube stations and roundabouts as the spatial data to join, with the aim of finding out about how many are found in each London borough.

```
library(rgdal)
# create new stations object using the "lnd-stns" shapefile.
stations <- readOGR(dsn = "data", layer = "lnd-stns")
proj4string(stations) # this is the full geographical detail.
proj4string(lnd) # what's the coordinate reference system (CRS)
bbox(stations) # the extent, 'bounding box' of stations
bbox(lnd) # return the bounding box of the lnd object
```

<sup>5</sup>Hint: the solution relies on the `rgeos` function `gCentroid()`. To see how this map was created, see the code in `intro-spatial.Rmd` at [github.com/Robinlovelace/Creating-maps-in-R/blob/master/intro-spatial.Rmd](https://github.com/Robinlovelace/Creating-maps-in-R/blob/master/intro-spatial.Rmd).

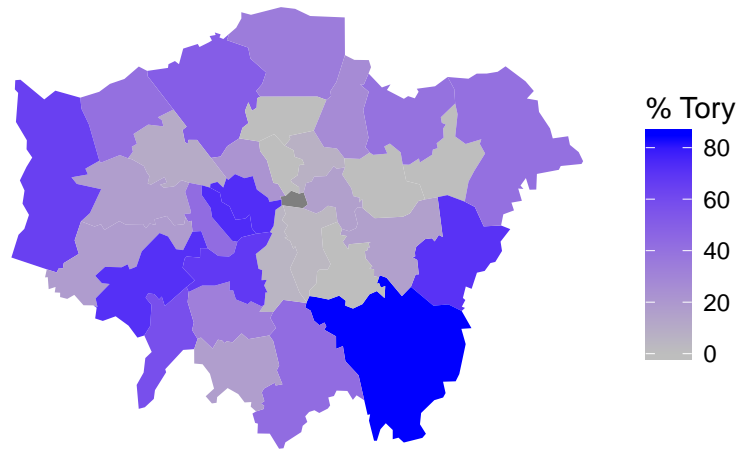


Figure 7: Proportion of council seats won by Conservatives in the 2014 local elections using data from `data.london.gov` and joined using the methods presented in this section

The above code loads the data correctly, but also shows that there are problems with it: the Coordinate Reference System (CRS) of `stations` differs from that of our `lnd` object. OSGB 1936 (or [EPSG 27700](#)) is the official CRS for the UK, so we will convert the ‘stations’ object to this:

```
# Create reprojected stations object
stations27700 <- spTransform(stations, CRSobj = CRS(proj4string(lnd)))
stations <- stations27700 # overwrite the stations object
rm(stations27700) # remove the stations27700 object to clear up
plot(lnd) # plot London for context (see Figure 9)
points(stations) # overlay the station points
```

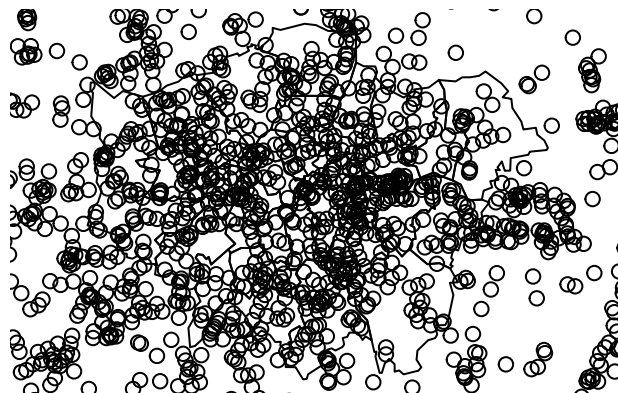


Figure 8: Sampling and plotting stations

Now we can clearly see that the `stations` points overlay the boroughs. The problem is that the spatial extent of `stations` is greater than that of `lnd`. We will create a spatially determined subset of the stations object that fall inside greater London. This is *clipping*.

Two functions can be used to clip `stations` so that only those falling within London boroughs are retained: `sp::over`, and `rgeos::gIntersects` (the word preceding the `::` symbol refers to the package which the function is from). Use `?` followed by the function to get help on each. Whether `gIntersects` or `over` is needed depends on the spatial data classes being compared (Bivand et al. 2013).

In this tutorial we will use the `over` function as it is easiest to use. In fact, it can be called just by using square brackets:

```
stations_backup <- stations # backup the stations object
stations <- stations_backup[lnd, ]
plot(stations) # test the clip succeeded (see Figure 10)
```

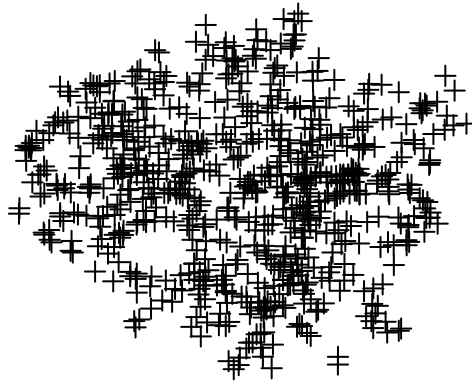


Figure 9: The clipped stations dataset

The above line of code says: “output all `stations` within the `lnd` object bounds”. This is an incredibly concise way of clipping and has the added advantage of being consistent with R’s syntax for non-spatial clipping. To prove it worked, only stations within the London boroughs appear in the plot.

`gIntersects` can achieve the same result, but with more lines of code (see [www.rpubs.com/RobinLovelace](http://www.rpubs.com/RobinLovelace) for more on this). It may seem confusing that two different functions can be used to generate the same result. However, this is a common issue in R; the question is finding the most appropriate solution.

In its less concise form (without use of square brackets), `over` takes two main input arguments: the target layer (the layer to be altered) and the source layer by which the target layer is to be clipped. The output of `over` is a data frame of the same dimensions as the original object (in this case `stations`), except that the points which fall outside the zone of interest are set to a value of `NA` (“no answer”). We can use this to make a subset of the original polygons, remembering the square bracket notation described in the first section. We create a new object, `sel` (short for “selection”), containing the indices of all relevant polygons:

```
sel <- over(stations_backup, lnd)
stations2 <- stations_backup[!is.na(sel[,1]),]
```

Typing `summary(sel)` should provide insight into how this worked: it is a data frame with 1801 `NA` values, representing zones outside of the London polygon. Note that the preceding two lines of code is equivalent to the single line of code, `stations <- stations[lnd, ]`. The next section demonstrates spatial aggregation, a more advanced version of spatial subsetting.

## Spatial aggregation

As with R’s very terse code for spatial subsetting, the base function `aggregate` (which provides summaries of variables based on some grouping variable) also behaves differently when the inputs are spatial objects.

```
stations_agg <- aggregate(x = stations["CODE"], by = lnd, FUN = length)
head(stations_agg@data)
```

```
## CODE
## 0 54
## 1 22
## 2 43
## 3 18
## 4 12
## 5 12
```

The above code performs a number of steps in just one line:

- `aggregate` identifies which `lnd` polygon (borough) each `station` is located in and groups them accordingly. The use of the syntax `stations["CODE"]` tells R that we are interested in the spatial data from `stations` and its `CODE` variable (any variable could have been used here as we are merely counting how many points exist).
- It counts the number of `stations` points in each borough, using the function `length`.
- A new spatial object is created, with the same geometry as `lnd`, and assigned the name `stations_agg`, the count of stations.

It may seem confusing that the result of the aggregated function is a new shape, not a list of numbers — this is because values are assigned to the elements within the `lnd` object. To extract the raw count data, one could enter `stations_agg$CODE`. This variable could be added to the original `lnd` object as a new field, as follows:

```
lnd$n_points <- stations_agg$CODE
```

As shown below, the spatial implementation of `aggregate` can provide summary statistics of variables, as well as simple counts. In this case we take the variable `NUMBER` and find its mean value for the stations in each ward.<sup>6</sup>

```
lnd_n <- aggregate(stations["NUMBER"], by = lnd, FUN = mean)
```

For an optional advanced task, let us analyse and plot the result.

```
brks <- quantile(lnd_n$NUMBER)
labs <- grey.colors(n = 4)
q <- cut(lnd_n$NUMBER, brks, labels = labs,
        include.lowest = T)
summary(q) # check what we've created

## #4C4C4C #969696 #C3C3C3 #E6E6E6
##      9      8      8      8

qc <- as.character(q) # convert to character class to plot
plot(lnd_n, col = qc) # plot (not shown in printed tutorial)
legend(legend = paste0("Q", 1:4), fill = levels(q), "topright")
areas <- sapply(lnd_n@polygons, function(x) x@area)
```

This results in a simple choropleth map and a new vector containing the area of each borough (the basis for Fig. 11). As an additional step, try comparing the mean area of each borough with the mean value of `stations` points within it: `plot(lnd_n$NUMBER, areas)`.

<sup>6</sup>See the miniature Vignette ‘Clipping and aggregating spatial data with `gIntersects`’ for more information on this: <http://rpubs.com/RobinLovelace/83834>.



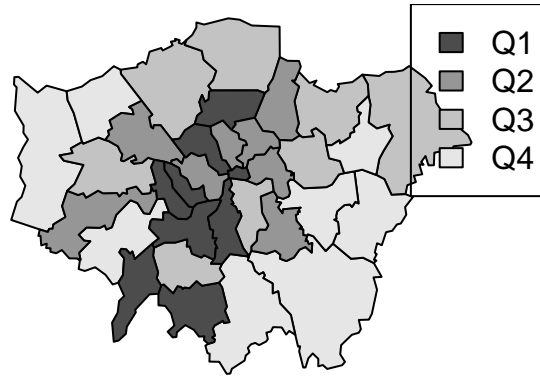


Figure 10: Choropleth map of mean values of stations in each borough

#### *Adding different symbols for tube stations and train stations*

Imagine now that we want to display all tube and train stations on top of the previously created choropleth map. How would we do this? The shape of points in R is determined by the `pch` argument, as demonstrated by the result of entering the following code: `plot(1:10, pch=1:10)`. To apply this knowledge to our map, try adding the following code to the chunk above (output not shown):

```
levels(stations$LEGEND) # see A roads and rapid transit stations (RTS) (not shown)
sel <- grepl("A Road Sing|Rapid", stations$LEGEND) # selection for plotting
sym <- as.integer(stations$LEGEND[sel]) # symbols
points(stations[sel,], pch = sym)
legend(legend = c("A Road", "RTS"), "bottomright", pch = unique(sym))
```

The above block of code first identifies which types of transport points are present in the map with `levels` (this command only works on factor data). Next we select a subset of `stations` using a new command, `grepl`, to determine which points we want to plot. Note that `grepl`'s first argument is a text string (hence the quote marks) and the second is a factor (try typing `class(stations$LEGEND)` to test this). `grepl` uses *regular expressions* to match whether each element in a vector of text or factor names match the text pattern we want. In this case, because we are only interested in roundabouts that are A roads and Rapid Transit systems (RTS). Note the use of the vertical separator `|` to indicate that we want to match `LEGEND` names that contain either "A Road" *or* "Rapid". Based on the positive matches (saved as `sel`, a vector of `TRUE` and `FALSE` values), we subset the stations. Finally we plot these as points, using the integer of their name to decide the symbol and add a legend. (See the documentation of `?legend` for detail on the complexities of legend creation in R's base graphics.)

This may seem a frustrating and unintuitive way of altering map graphics compared with something like QGIS. That's because it is! It may not be worth stressing too much about base graphics because there are intuitive alternatives for quickly creating beautiful maps in R, including **tmap**, **ggplot** and **leaflet**.

## Part IV: Making maps with tmap, ggplot2 and leaflet

This fourth part introduces alternative methods for creating maps with R that overcome some of the limitations and clunkiness of R's base graphics. Having worked hard to manipulate the spatial data, it is now time to display the results clearly, beautifully and, in the case of **leaflet**, interactively.

We try the newest of the three packages, **tmap**, first as it is the easiest to use. Then we progress to explore the powerful **ggplot2** paradigm before outlining **leaflet**.

### tmap

**tmap** was created to overcome some of the limitations of base graphics and **ggmap/ggplot2**. The focus is on generating 'thematic maps' (which show a variable change over space) quickly and easily. A concise introduction to **tmap** can be accessed (after the package is installed) by using the vignette function:

```
# install.packages("tmap") # install the CRAN version
# to download the development version, use the devtools package
# devtools::install_github("mtennekes/tmap", subdir = "pkg", build_vignette = TRUE)
library(tmap)

## Loading required package: raster
##
## Attaching package: 'raster'
##
## The following object is masked from 'package:dplyr':
##
##     select

vignette(package = "tmap") # available vignettes in tmap
vignette("tmap-nutshell")

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

A couple of basic plots show the package's intuitive syntax and attractive default parameters.

```
# Create our first tmap map (not shown)
qtm(shp = lnd, fill = "Partic_Per", fill.palette = "-Blues")

qtm(shp = lnd, fill = c("Partic_Per", "Pop_2001"), fill.palette = c("Blues"), ncol = 2)
```

The plot above shows the ease with which tmap can create maps next to each other for different variables. Figure 13 illustrates the power of the `tm_facets` command.

```
tm_shape(lnd) +
  tm_fill("Pop_2001", thres.poly = 0) +
tm_facets("name", free.coords=TRUE, drop.shapes=TRUE) +
  tm_layout(legend.show = FALSE, title.position = c("center", "center"), title.size = 20)
```

A more established plotting paradigm is **ggplot2** package. This has been subsequently adapted to maps thank to **ggmap**, as described below.

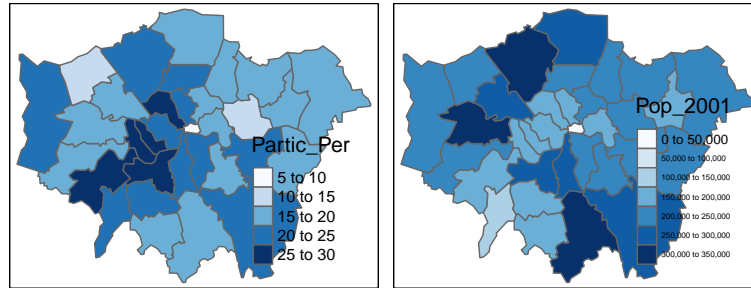


Figure 11: Side-by-side maps of crimes and % voting conservative

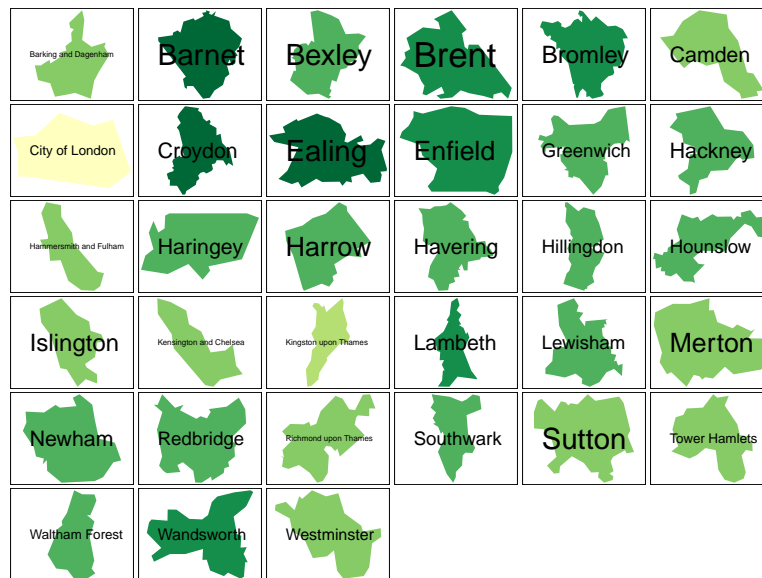


Figure 12: Facetted map of London Boroughs created by tmap

## ggmap

**ggmap** is based on the **ggplot2** package, an implementation of the Grammar of Graphics (Wilkinson 2005). This section focusses primarily on **ggplot2**. More on **ggmap** can be found in the vignettes accompanying this tutorial: <https://github.com/Robinlovelace/Creating-maps-in-R/tree/master/vignettes>

**ggplot2** can replace the base graphics in R (the functions you have been plotting with so far). It contains default options that match good visualisation practice.

**ggplot2** is one of the best documented packages in R. This documentation can be found on-line and it is recommended you test out the examples and play with them: <http://docs.ggplot2.org/current/>.

Good examples of graphs can also be found on the website [cookbook-r.com](http://cookbook-r.com).

Load the package with `library(ggplot2)`. It is worth noting that the base `plot()` function requires less data preparation but more effort in control of features. `qplot()` and `ggplot()` from **ggplot2** require some additional work to format the spatial data but select colours and legends automatically, with sensible defaults.

As a first attempt with **ggplot2** we can create a scatter plot with the attribute data in the `lnd` object created previously. Type:

```
p <- ggplot(lnd@data, aes(Partic_Per, Pop_2001))
```

What you have just done is set up a ggplot object where you say where you want the input data to come from. `lnd@data` is actually a data frame contained within the wider spatial object `lnd` (the `@` enables you to access the attribute table of the shapefile). The characters inside the `aes` argument refer to the parts of that data frame you wish to use (the variables `Partic_Per` and `Pop_2001`). This has to happen within the brackets of `aes()`, which means, roughly speaking ‘aesthetics that vary’.

If you just type `p` and hit enter you get the error `No layers in plot`. This is because you have not told **ggplot** what you want to do with the data. We do this by adding so-called “geoms”, in this case `geom_point()`.

```
p + geom_point()
```

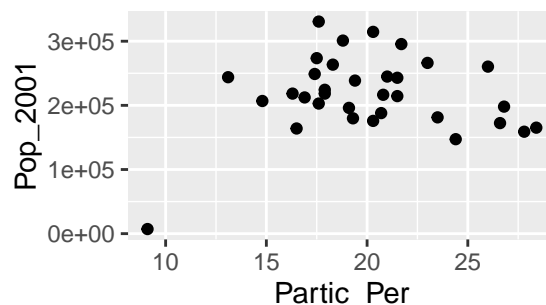


Figure 13: A simple graphic produced with **ggplot2**

Within the brackets you can alter the nature of the points. Try something like `p + geom_point(colour = "red", size=2)` and experiment.

If you want to scale the points by borough population and colour them by sports participation this is also fairly easy by adding another `aes()` argument.

```
p + geom_point(aes(colour=Partic_Per, size=Pop_2001)) # not shown
```

The real power of **ggplot2** lies in its ability to add layers to a plot. In this case we can add text to the plot.

```
p + geom_point(aes(colour = Partic_Per, size = Pop_2001)) +
  geom_text(size = 2, aes(label = name))
```

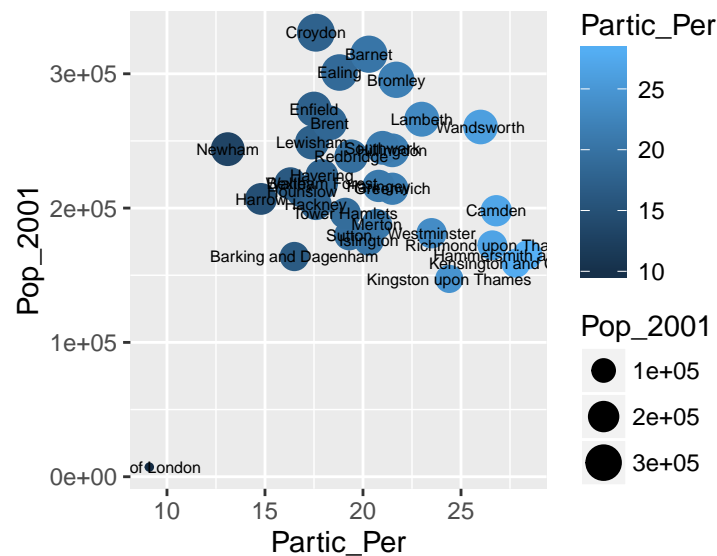


Figure 14: ggplot for text

This idea of layers (or geoms) is quite different from the standard plot functions in R, but you will find that each of the functions does a lot of clever stuff to make plotting much easier (see the documentation for a full list).

In the following steps we will create a map to show the percentage of the population in each London Borough who regularly participate in sports activities.

**ggmap** requires spatial data to be supplied as **data.frame**, using **fortify()**. The generic **plot()** function can use **Spatial\*** objects directly; **ggplot2** cannot. Therefore we need to extract them as a data frame. The **fortify** function was written specifically for this purpose. For this to work, either the **maptools** or **rgeos** packages must be installed.

```
library(rgeos)
lnd_f <- fortify(lnd) # you may need to load maptools
```

```
## Regions defined for each Polygons
```

This step has lost the attribute information associated with the **lnd** object. We can add it back using the **left\_join** function (this performs a data join). To use this function, ensure you have the **dplyr** package installed and loaded. To find out how it works look at the output of typing **?left\_join**. As usual the help documentation is a little sparse here, so let's consider what it means in more detail. The help document explains that **left\_join** retains all rows from the original dataset **x**, whereas **inner\_join** only retains rows in **x** which have a match in **y**. If there is no match in the joining variable, **inner\_join** simply adds **NA** values for the new variables for the affect rows.

```
head(lnd_f, n = 2) # peak at the fortified data
```

```
##      long      lat order  hole piece id group
## 1 541177.7 173555.7     1 FALSE     1  0  0.1
## 2 541872.2 173305.8     2 FALSE     1  0  0.1
```

```
lnd$id <- row.names(lnd) # allocate an id variable to the sp data
head(lnd@data, n = 2) # final check before join (requires shared variable name)
```

```
##   ons_label          name Partic_Per Pop_2001 CrimeCount conservative
## 1    00AF          Bromley      21.7  295535      15172           85
## 2    00BD Richmond upon Thames    26.6  172330      9715           72
##   n_points id
## 1      54  0
## 2      22  1
```

```
lnd_f <- left_join(lnd_f, lnd@data) # join the data
```

```
## Joining by: "id"
```

Take a look at the `lnd_f` object to see its contents (which stands for “London, fortified”). You should see a large data frame containing the coordinates (Easting and Northing points as the data are in British National Grid format) alongside the attribute information associated with each London Borough. If you type `print(lnd_f)` you will see just how many coordinate pairs are required! To keep the output to a minimum, take a peek at the first 2 lines of the object using just the `head` command:

```
lnd_f[1:2, 1:8]
```

```
##      long      lat order  hole piece id group ons_label
## 1 541177.7 173555.7     1 FALSE     1 0  0.1    00AF
## 2 541872.2 173305.8     2 FALSE     1 0  0.1    00AF
```

It is now straightforward to produce a map using all the built-in tools (such as setting the breaks in the data) that **ggplot2** has to offer. `coord_equal()` is the equivalent of `asp=T` in regular plots with R:

```
map <- ggplot(lnd_f, aes(long, lat, group = group, fill = Partic_Per)) +
  geom_polygon() +
  coord_equal() +
  labs(x = "Easting (m)", y = "Northing (m)",
       fill = "% Sports\nParticipation") +
  ggtitle("London Sports Participation")
```

Now, just typing `map` should result in your first ggplot-made map of London! There is a lot going on in the code above, so think about it line by line: what have each of the elements of code above been designed to do? Also note how the `aes()` components can be combined into one set of brackets after `ggplot`, that has relevance for all layers, rather than being broken into separate parts as we did above. The different plot functions still know what to do with these. The `group=group` points ggplot to the group column added by `fortify()` and it identifies the groups of coordinates that pertain to individual polygons (in this case London Boroughs).

The default colours are really nice but we may wish to produce the map in black and white, which should produce a map like the one shown below. Try changing the colours.

```
map + scale_fill_gradient(low = "white", high = "black")
```

To save a plot image you just need to use `ggsave` after each plot, e.g. `ggsave("my_map.pdf")` will save the map as a pdf, with default settings. For a larger map, you could try the following:

```
ggsave("large_plot.png", scale = 3, dpi = 400)
```

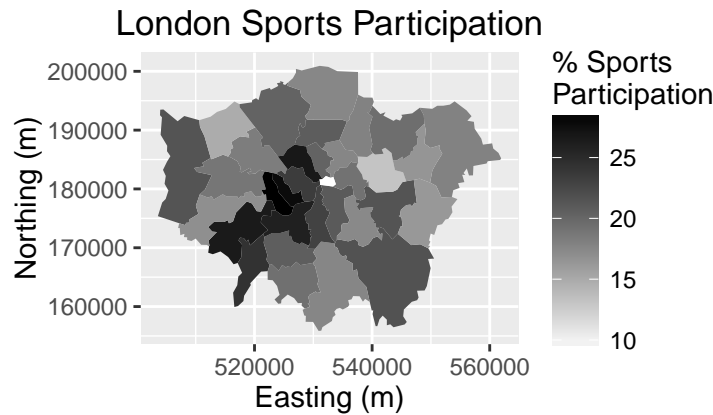


Figure 15: Greyscale map

## Creating interactive maps with leaflet

[Leaflet](#) is probably the world's premier web mapping system, serving hundreds of thousands of maps worldwide each day. The JavaScript library actively developed at [github.com/Leaflet/Leaflet](https://github.com/Leaflet/Leaflet), has a strong user community. It is fast, powerful and easy to learn.

A recent package developed by RStudio, called **leaflet**<sup>7</sup> provides R bindings to Leaflet. **rstudio/leaflet** allows the creation and deployment of interactive web maps in few lines of code. One of the exciting things about the package is its tight integration with the R package for interactive on-line visualisation, **shiny**. Used together, these allow R to act as a complete map-serving platform, to compete with the likes of GeoServer! For more information on **rstudio/leaflet**, see [rstudio.github.io/leaflet/](https://rstudio.github.io/leaflet/) and the following on-line tutorial: [robinlovelace.net/r/2015/02/01/leaflet-r-package.html](http://robinlovelace.net/r/2015/02/01/leaflet-r-package.html).

```
install.packages("leaflet")
library(leaflet)

leaflet() %>%
  addTiles() %>%
  addPolygons(data = lnd84)
```

## Advanced Task: Faceting for Maps

The below code demonstrates how to read in the necessary data for this task and ‘tidy’ it up. The data file contains historic population values between 1801 and 2001 for London, again from the London data store.

We tidy the data so that the columns become rows. In other words, we convert the data from ‘flat’ to ‘long’ format, which is the form required by **ggplot2** for faceting graphics: the date of the population survey becomes a variable in its own right, rather than being strung-out over many columns.

```
london_data <- read.csv("data/census-historic-population-borough.csv")
library(tidyr) # if not install it, or skip the next two steps

##
## Attaching package: 'tidyr'
```

<sup>7</sup>We also refer to this as **rstudio/leaflet**, after the project's on-line home at [github.com/rstudio/leaflet](https://github.com/rstudio/leaflet), to avoid confusion with the JavaScript library.

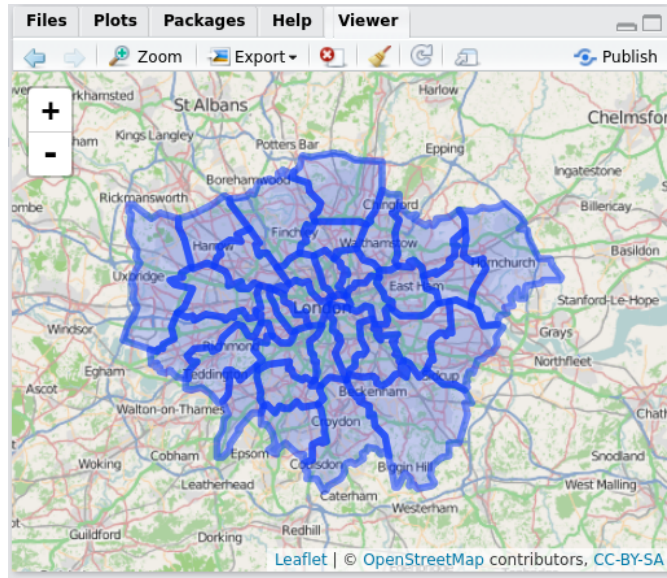


Figure 16: The `lnd84` object loaded in `rstudio` via the `leaflet` package

```
##
## The following object is masked from 'package:raster':
##
##      extract

ltidy <- gather(london_data, date, pop, -Area.Code, -Area.Name)
head(ltidy, 2) # check the output (not shown)
```

In the above code we take the `london_data` object and create the column names ‘date’ (the date of the record, previously spread over many columns) and ‘pop’ (the population which varies). The minus (-) symbol in this context tells `gather` not to include the `Area.Name` and `Area.Code` as columns to be removed. In other words, “leave these columns be”. Data tidying is an important subject: more can be read on the subject in Wickham (2014) or in a *vignette* about the package, accessed from within R by entering `vignette("tidy-data")`.

Merge the population data with the London borough geometry contained within our `lnd_f` object, using the `left_join` function from the `dplyr` package:

```
head(lnd_f, 2) # identify shared variables with ltidy

##      long      lat order  hole piece id group ons_label  name Partic_Per
## 1 541177.7 173555.7     1 FALSE     1 0 0.1      00AF Bromley      21.7
## 2 541872.2 173305.8     2 FALSE     1 0 0.1      00AF Bromley      21.7
##  Pop_2001 CrimeCount conservative n_points
## 1    295535      15172           85        54
## 2    295535      15172           85        54

ltidy <- rename(ltidy, ons_label = Area.Code) # rename Area.code variable
lnd_f <- left_join(lnd_f, ltidy)

## Joining by: "ons_label"
```



```
## Warning in left_join_impl(x, y, by$x, by$y): joining factor and character
## vector, coercing into character vector
```

Rename the date variable (use `?gsub` and Google ‘regex’ to find out more).

```
lnd_f$date <- gsub(pattern = "Pop_", replacement = "", lnd_f$date)
```

We can now use faceting to produce one map per year (Fig. 19).

```
ggplot(data = lnd_f, # the input data
  aes(x = long, y = lat, fill = pop/1000, group = group)) + # define variables
  geom_polygon() + # plot the boroughs
  geom_path(colour="black", lwd=0.05) + # borough borders
  coord_equal() + # fixed x and y scales
  facet_wrap(~ date) + # one plot per time slice
  scale_fill_gradient2(low = "blue", mid = "grey", high = "red", # colors
    midpoint = 150, name = "Population\n(thousands)") + # legend options
  theme(axis.text = element_blank(), # change the theme options
    axis.title = element_blank(), # remove axis titles
    axis.ticks = element_blank()) # remove axis ticks
# ggsave("figure/facet_london.png", width = 9, height = 9) # save figure
```

There is a lot going on here so explore the documentation to make sure you understand it. Try out different colour values as well.

Try experimenting with the above code block to see what effects you can produce.

**Challenge 1:** Try creating this plot for the % of population instead of the absolute population.

**Challenge 2:** For bonus points, try creating an animation of London’s evolving population over time using the excellent [animation](#) package.

## Part V: Taking spatial data analysis in R further

The skills taught in this tutorial are applicable to a very wide range of situations, spatial or not. Often experimentation is the most rewarding learning method, rather than just searching for the ‘best’ way of doing something (Kabakoff, 2011). We recommend you play around with your data.

If you enjoyed this tutorial, you may find the book chapter “Spatial Data Visualisation with R” of interest (Cheshire and Lovelace, 2014). The project’s repository can be found on its GitHub page: [github.com/geocomPP/sdvwR](https://github.com/geocomPP/sdvwR). There are also a number of bonus ‘vignettes’ associated with the present tutorial. These can be found on the [vignettes page](#) of the project’s repository.

Other advanced tutorials include

- “Using spatial data” from the [useR 2013 conference page](#)
- “Geographically Weighted PCA”, an in-depth and advanced tutorial by [Chris Brunsdon](#) - “The Spatial Autoregression Regression Model and Correlation”, another advanced tutorial, also by [Chris Brunsdon](#)
- “Using R as a GIS”, a long and detailed online tutorial by [Francisco Rodriguez-Sanchez](#).
- “solaR: Solar Radiation and Photovoltaic Systems with R”, a [technical academic paper](#) on the solaR package which contains a number of spatial function (.).

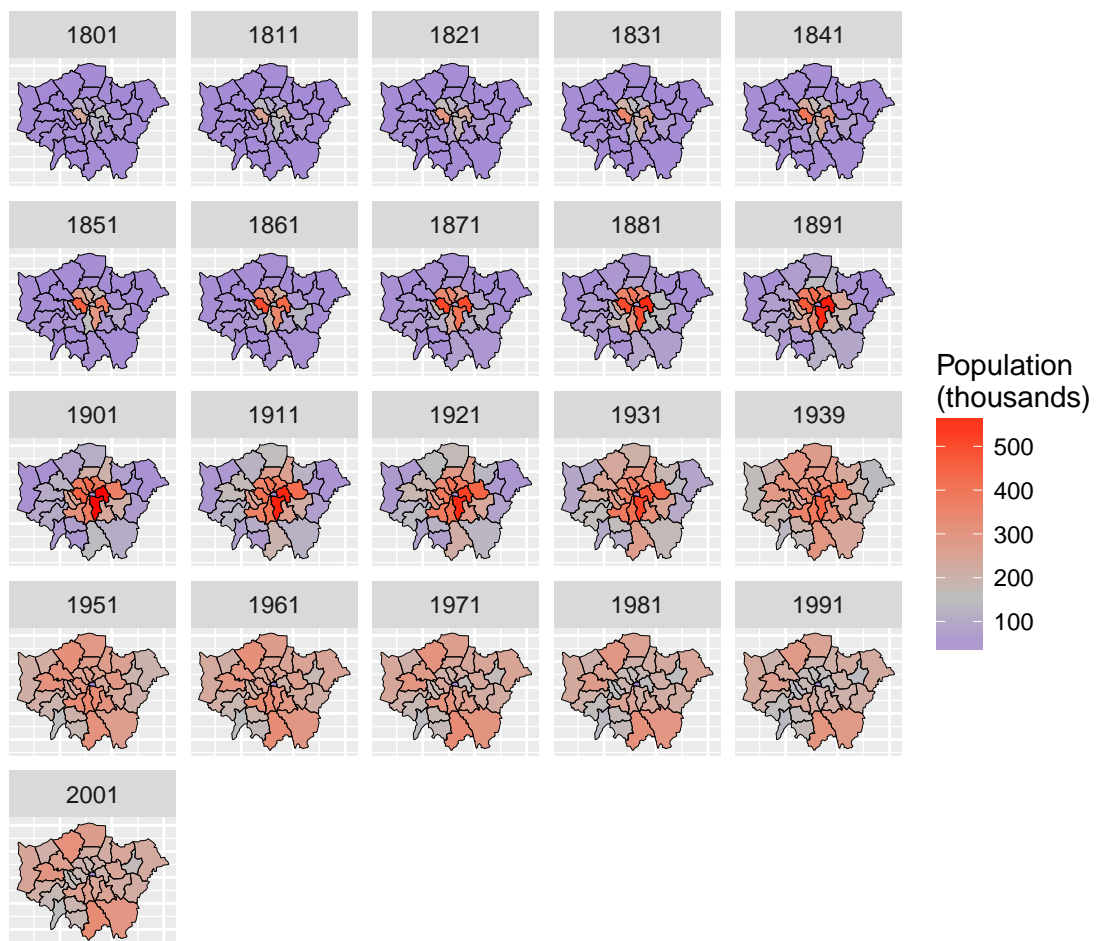


Figure 17: Faceted plot of the distribution of London's population over time

Such tutorials are worth doing as they will help you understand R’s spatial ‘ecosystem’ as a cohesive whole rather than as a collection of isolated functions. In R the whole is greater than the sum of its parts.

The supportive on-line communities surrounding large open source programs such as R are one of their greatest assets, so we recommend you become an active “[open source citizen](#)” rather than a passive consumer (Ramsey & Dubovsky, 2013).

This does not necessarily mean writing a new package or contributing to R’s ‘Core Team’ — it can simply involve helping others use R. We therefore conclude the tutorial with a list of resources that will help you further sharpen your R skills, find help and contribute to the growing on-line R community:

- R’s homepage hosts a wealth of [official](#) and [contributed](#) guides. <http://cran.r-project.org>
- [StackOverflow](#) and [GIS.StackExchange](#) groups (the “[R]” search term limits the results). If your question has not been answered yet, just ask, preferably with a reproducible example.
- R’s [mailing lists](#), especially [R-sig-geo](#). See [r-project.org/mail.html](http://r-project.org/mail.html).

Books: despite the strength of R’s on-line community, nothing beats a physical book for concentrated learning. We recommend the following:

- Everitt and Hothorn (updated 2015): This handbook of statistical analyses is available online as an [R package](#).
- Dorman (2014): detailed exposition of spatial data in R, with a focus on raster data. A [free sample](#) of this book is available online.
- Wickham (2009): ‘ggplot2: elegant graphics for data analysis’
- Bivand et al. (2013) : ‘Applied spatial data analysis with R’ - provides a dense and detailed overview of spatial data analysis.
- Kabacoff (2011): ‘R in action’ is a general R book with many fun worked examples.

## R quick reference

`#:` comments all text until line end

`df <- data.frame(x = 1:9, y = (1:9)^2):` create new object of class `data.frame`, called `df`, and assign values

`help(plot):` ask R for basic help on function, the same as `?plot`. Replace `plot` with any function (e.g. `spTransform`).

`library(ggplot2):` load a package (replace **ggplot2** with your package name)

`install.packages("ggplot2"):` install package — note quotation marks

`setwd("C:/Users/username/Desktop/"): set R's working directory (set it to your project's folder)`

`nrow(df):` count the number of rows in the object `df`

`summary(df):` summary statistics of the object `df`

`head(df):` display first 6 lines of object `df`

`plot(df):` plot object `df`

`save(df, "C:/Users/username/Desktop/" ):` save `df` object to specified location

`rm(df):` remove the `df` object

`proj4string(df):` query coordinate reference system of `df` object

`spTransform(df, CRS("+init=epsg:4326")):` reproject `df` object to WGS84

## Further information

An up-to-date version of this tutorial is maintained at <https://github.com/Robinlovelace/Creating-maps-in-R>. The source files used to create this tutorial, including the input data can be downloaded as a [zip file](#), as described below. The entire tutorial was written in [RMarkdown](#), which allows R code to run as the document compiles, ensuring reproducibility.

Any suggested improvements or new [vignettes](#) are welcome, via email to Robin or by [forking](#) the [master version](#) of this document.

The colourful syntax highlighting in this document is thanks to [RMarkdown](#). We try to follow best practice in terms of style, roughly following Google's style guide, an in-depth guide written by [Johnson \(2013\)](#) and a [chapter](#) from *Advanced R* (Wickham, in press).

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If you have found this tutorial useful in your work, please cite it:

Lovelace, R., & Cheshire, J. (2014). Introduction to visualising spatial data in R. National Centre for Research Methods Working Papers, 14(03). Retrieved from <https://github.com/Robinlovelace/Creating-maps-in-R>

The bibtext entry for this item can be downloaded from <https://raw.githubusercontent.com/Robinlovelace/Creating-maps-in-R/master/citation.bib> or [here](#).

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