Hacking Religion: TRS & Data Science in Action

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Introduction: Hacking Religion

Why this book?

Data science is quickly consolidating as a new field, with new tools and user communities emerging seemingly every week! At the same time the field of academic research has opened up into new interdisciplinary vistas, with experts crossing over into new fields, transgressing disciplinary boundaries and deploying tools in new and unexpected ways to develop knowledge. There are many gaps yet to be filled, but one which I found to be particularly glaring is the lack of applied data science documentation around the subject of religion. On one hand, scholars who are working with cutting edge theory seldom pick up the emerging tools of data science. On the other hand, data scientists rarely go beyond dabbling in religious themes. This book aims to bring these two things together: introducing the tools of data science in an applied way, whilst introducing some of the complexities and cutting edge theories which help us to conceptualise and frame our understanding of this knowledge.

The hacker way

It's worth emphasising at the outset that this isn't meant to be a generic data science book. My own training as a researcher lies in the field of religious ethics, and my engagement with digital technology has, from the very start, been a context for exploring matters of personal values, and social action. A fair bit of ink has been spilled in books, magazines, blogs, zines, and tweets unpacking what exactly it means to be a "hacker". Pressing beyond some of the more superficial cultural stereotypes, I want to explain a bit here about how hacking can be

a much more substantial vision for ethical engagement with technology and social transformation.

Back in the 1980s Steven Levy tried to capture some of this in his book "Hackers: Heroes of the Computer Revolution". As Levy put it, the "hacker ethic" included: (1) sharing, (2) openness, (3) decentralisation, (4) free access to computers and (5) world improvement. The key point here is that hacking isn't just about writing and breaking code, or testing and finding weaknesses in computer systems and networks. It can be a more substantial ethical code.

This emphasis on ethics is especially important when we're doing data science because this kind of research work will put you in positions of influence and grant you power over others. You might think this seems a bit overstated, but it never ceases to amaze me how much bringing a bar chart which succinctly shows some sort of social trend can sway a conversation or decision making process. There is something unusually persuasive that comes with the combination of aesthetics, data and storytelling. I've met many people who have come to data science out of a desire to bring about social transformation in some sphere of life. People want to use technology and communication to make the world better. However, it's possible that this can quickly get out of hand. It's important to have a clear sense of what sorts of convictions guide your work in this field, a "hacker code" of sorts. With this in mind, I'd like to share with you my own set of principles:

It never ceases to amaze me how often people think that, when they're working for something they think is important it is acceptable to conceal bad news or amplify good or compelling information beyond its real scope. There are always consequences, eventually. When people realise you've been misleading or manipulating them your platform and credibility will evaporate. Good work mixed with bad will all get tossed out. And sometimes, our convictions can lead us beyond our true apprehension of a situation.

Presenting through "facts" an argument can become unnaturally compelling. Wrapping those facts up in something that uses colour, line and shape in a way that is aesthetically pleasing, even beautiful, enhances this allure even further. As you

take up the hacker way, it's vitally important that you always strive to tell the truth. This includes a willingness to acknowledge the limits of your information, and to share the whole set of information. The easiest way to do this is to work with visualation in a responsible way (I'll get into this a bit more in Chapter 1) and to open up your data and code to scrutiny. By allowing others to try, criticise, edit, and reappropriate your code and data in their own ways, you contribute to knowledge help to build up a community of accountability. The upside of this is that it's also a lot more fun and interesting to work alongside others.

Far too often, scholarly research (and theology) has been criticised for being disconnected from reality, making abstract pie-in-the-sky claims about how life should be lived. When exposed to the uncomfortable pressures of reality, these claims can crumble, or even turn sinister. One of the upsides of working with empirical research is that you have a chance to engage with the real world. For this reason, I love to do ethics in a way that arises - bottom-up - from real world experiences and relationships. There's also the potential that when we make choices based on reliable information drawn from everyday reality like this our policy and culture can be more resilient and accountable. This also works well with the hacker ethos of "learning by doing" and it's this approach that guides my approach in this book. This isn't just a book about data analysis, I'm proposing an approach which might be thought of as research-as-code, where you write out instructions to execute the various steps of work. The upside of this is that other researchers can learn from your work, correct and build on it as part of the commons. It takes a bit more time to learn and set things up, but the upside is that you'll gain access to a set of tools and a research philosophy which is much more powerful.

Here's a quick summary of these principles, which I'll return to periodically as we work through the coding and data in this book:

1. Tell the truth: Be candid about your limits, use visualisation responsibly
2. Work transparently: Open data, open code

3. Work in community, draw others in by producing reproducible research
4. Work with reality, learn by doing

Learning to code: my way

This guide is a little different from other textbooks targetting learning to code. I remember when I was first starting out, I went through a fair few guides, and they all tended to spend about 200 pages on various theoretical bits, how you form an integer, or data structures, subroutines, the logical structure of algorithms or whatever. It was usuallyweeks of reading before I got to actually *do* anything. I know some people may prefer this approach, but I prefer a problem-focussed approach to learning. Give me something that is broken, or a problem to solve, which engages the things I want to figure out and the motivation for learning just comes much more naturally. And we know from research in cognitive science that these kinds of problem-focussed approaches can tend to faciliate faster learning and better retention, so it's not just my personal preference, but also justified! It will be helpful for you to be aware of this approach when you get into the book as it explains some of the editorial choices I've made and the way I've structured things. Each chapter focusses on a *problem* which is particularly salient for the use of data science to conduct research into religion. That problem will be my focal point, guiding choices of specific aspects of programming to introduce to you as we work our way around that data set and some of the crucial questions that arise in terms of how we handle it. If you find this approach unsatisfying, luckily there are a number of really terrific guides which lay things out slowly and methodically and I will explicitly signpost some of these along the way so that you can do a "deep dive" when you feel like it. Otherwise, I'll take an accelerated approach to this introduction to data science in R. I expect that you will identify adjacent resources and perhaps even come up with your own creative approaches along the way, which incidentally is how real data science tends to work in practice.

There are a range of terrific textbooks out there which cover all

these elements in greater depth and more slowly. In particular, I'd recommend that many readers will want to check out Hadley Wickham's "R For Data Science" book. I'll include marginal notes in this guide pointing to sections of that book, and a few others which unpack the basic mechanics of R in more detail.

Getting set up

Every single tool, programming language and data set we refer to in this book is free and open source. These tools have been produced by professionals and volunteers who are passionate about data science and research and want to share it with the world, and in order to do this (and following the "hacker way") they've made these tools freely available. This also means that you aren't restricted to a specific proprietary, expensive, or unavailable piece of software to do this work. I'll make a few opinionated recommendations here based on my own preferences and experience, but it's really up to your own style and approach. In fact, given that this is an open source textbook, you can even propose additions to this chapter explaining other tools you've found that you want to share with others.

There are, right now, primarily two languages that statisticians and data scientists use for this kind of programmatic data science: python and R. Each language has its merits and I won't rehash the debates between various factions. For this book, we'll be using the R language. This is, in part, because the R user community and libraries tend to scale a bit better for the work that I'm commending in this book. However, it's entirely possible that one could use python for all these exercises, and perhaps in the future we'll have volume two of this book outlining python approaches to the same operations.

Bearing this in mind, the first step you'll need to take is to download and install R. You can find instructions and install packages for a wide range of hardware on the The Comprehensive R Archive Network (or "CRAN"): https://cran.rstudio.com. Once you've installed R, you've got some choices to make about the kind of programming environment you'd like to use. You can just use a plain text

editor like `textedit` to write your code and then execute your programs using the R software you've just installed. However, most users, myself included, tend to use an integrated development environment (or "IDE"). This is usually another software package with a guided user interface and some visual elements that make it faster to write and test your code. Some IDE packages, will have built-in reference tools so you can look up options for libraries you use in your code, they will allow you to visualise the results of your code execution, and perhaps most important of all, will enable you to execute your programs line by line so you can spot errors more quickly (we call this "debugging"). The two most popular IDE platforms for R coding at the time of writing this textbook are RStudio and Visual Studio. You should download and try out both and stick with your favourite, as the differences are largely aesthetic. I use a combination of RStudio and an enhanced plain text editor Sublime Text for my coding.

Once you have R and your pick of an IDE, you are ready to go! Proceed to the next chapter and we'll dive right in and get started!

1 The 2021 UK Census

1.1 Your first project: the UK Census

Let's start by importing some data into R. Because R is what is called an object-oriented programming language, we'll always take our information and give it a home inside a named object. There are many different kinds of objects, which you can specify, but usually R will assign a type that seems to fit best.

In the example below, we're going to read in data from a comma separated value file ("csv") which has rows of information on separate lines in a text file with each column separated by a comma. This is one of the standard plain text file formats. R has a function you can use to import this efficiently called "read.csv". Each line of code in R usually starts with the object, and then follows with instructions on what we're going to put inside it, where that comes from, and how to format it:

If you'd like to explore this all in a bit more depth, you can find a very helpful summary in R for Data Science, chapter 8, "data import".

```
setwd("/Users/kidwellj/gits/hacking_religion_textbook/hacking_religion")
library(here)  |> suppressPackageStartupMessages()
library(tidyverse)  |> suppressPackageStartupMessages()
here::i_am("chapter_1.qmd")
```

```
here() starts at /Users/kidwellj/gits/hacking_religion_textbook/hacking_religion
```

```
# Set up local workspace:
if (dir.exists("data") == FALSE) {
  dir.create("data")
}
if (dir.exists("figures") == FALSE) {
  dir.create("figures")
}
```

```
if (dir.exists("derivedData") == FALSE) {
  dir.create("derivedData")
}

uk_census_2021_religion <- read.csv(here("example_data", "census2021-ts030-rgn.csv"))
```

1.2 Examining data:

What's in the table? You can take a quick look at either the top of the data frame, or the bottom using one of the following commands:

```
head(uk_census_2021_religion)
```

```
                 geography   total no_religion christian buddhist  hindu jewish
1               North East 2647012     1058122   1343948     7026  10924   4389
2               North West 7417397     2419624   3895779    23028  49749  33285
3 Yorkshire and The Humber 5480774     2161185   2461519    15803  29243   9355
4            East Midlands 4880054     1950354   2214151    14521 120345   4313
5            West Midlands 5950756     1955003   2770559    18804  88116   4394
6                     East 6335072     2544509   2955071    26814  86631  42012
  muslim   sikh other no_response
1  72102   7206  9950      133345
2 563105  11862 28103      392862
3 442533  24034 23618      313484
4 210766  53950 24813      286841
5 569963 172398 31805      339714
6 234744  24284 36380      384627
```

This is actually a fairly ugly table, so I'll use an R tool called kable to give you prettier tables in the future, like this:

```
knitr::kable(head(uk_census_2021_religion))
```

geography	total	no_religion	christian	buddhist	hindu	jewish	muslim	sikh	other	no_response
North East	2647012	1258122	1234394	8826	10924	4389	72107	7206	99501	33345
North West	7417334	3471962	3489572	30284	97493	33285	563101	51862	281039	2862
Yorkshire and The Humber	5480774	2611824	2461519	19803	29243	9355	442532	24034	236181	3484
East Midlands	4880019	2303524	2214151	14521	12034	5313	210766	6395	248128	6841
West Midlands	5950756	2765002	2770551	18804	8811	6394	569963	17239	318053	9714
East	6335027	3024502	2955072	16814	8663	14201	234742	14284	363808	4627

You can see how I've nested the previous command inside the `kable` command. For reference, in some cases when you're working with really complex scripts with many different libraries and functions, they may end up with functions that have the same name. You can specify the library where the function is meant to come from by preceding it with :: as we've done `knitr::` above. The same kind of output can be gotten using `tail`:

```
knitr::kable(tail(uk_census_2021_religion))
```

	geography	total	no_religion	christian	buddhist	hindu	jewish	muslim	sikh	other	no_response
5	West Midlands	5950756	2765002	2770551	18804	8811	6394	569963	17239	318053	9714
6	East	6335027	3024502	2955072	16814	8663	14201	234742	14284	363808	4627
7	London	8799728	3804040	3577687	37425	45303	145466	618754	144548	367501	5662
8	South East	9278066	4330943	4313359	19433	15474	18682	309067	7434	540985	6279
9	South West	5701327	2613362	2635872	12579	2774	7387	80152	7465	368844	7732
10	Wales	3107494	1446398	1354770	7507	1224	2044	66947	4048	159269	5041

1.3 Parsing and Exploring your data

The first thing you're going to want to do is to take a smaller subset of a large data set, either by filtering out certain columns or rows. Now let's say we want to just work with the data from the West Midlands, and we'd like to omit some of the columns. We can choose a specific range of columns using `select`, like this:

You can use the `filter` command to do this. To give an example, `filter` can pick a single row in the following way:

```
uk_census_2021_religion_wmids <- uk_census_2021_religion %>% filter(geography=="West Midland
```

Now we'll use select in a different way to narrow our data to specific columns that are needed (no totals!).

In keeping with my goal to demonstrate data science through examples, we're going to move on to producing some snappy looking charts for this data.

Some readers will want to pause here and check out Hadley Wickham's "R For Data Science" book, in the section, "Data visualisation" to get a fuller explanation of how to explore your data.

1.4 Making your first data visulation: the humble bar chart

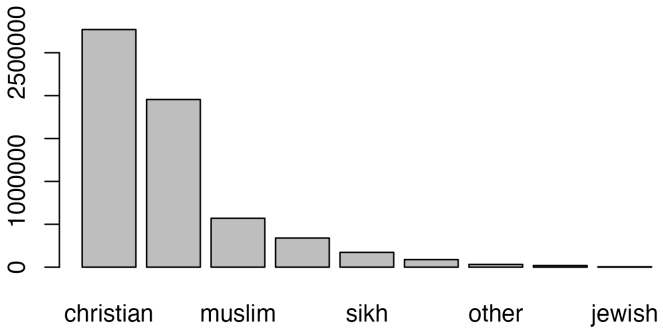
We've got a nice lean set of data, so now it's time to visualise this. We'll start by making a pie chart:

```
uk_census_2021_religion_wmids <- uk_census_2021_religion_wmids %>% select(no_religion:no_res
uk_census_2021_religion_wmids <- gather(uk_census_2021_religion_wmids)
```

There are two basic ways to do visualisations in R. You can work with basic functions in R, often called "base R" or you can work with an alternative library called ggplot:

1.4.1 Base R

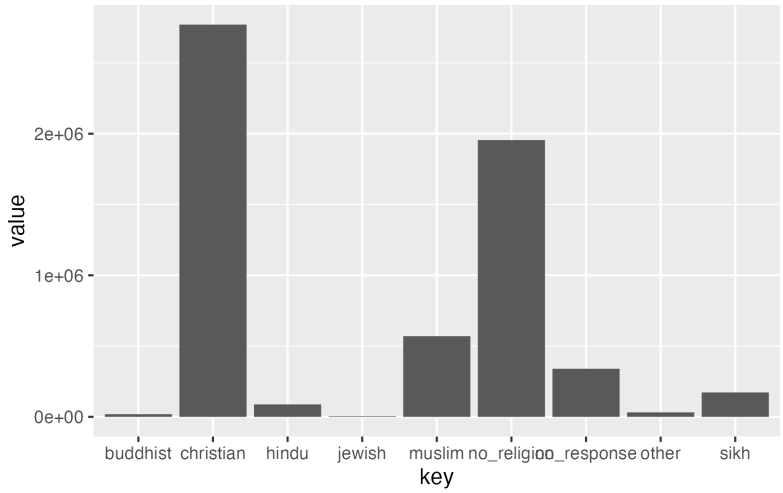
```
df <- uk_census_2021_religion_wmids[order(uk_census_2021_religion_wmids$value,decreasing = T
barplot(height=df$value, names=df$key)
```



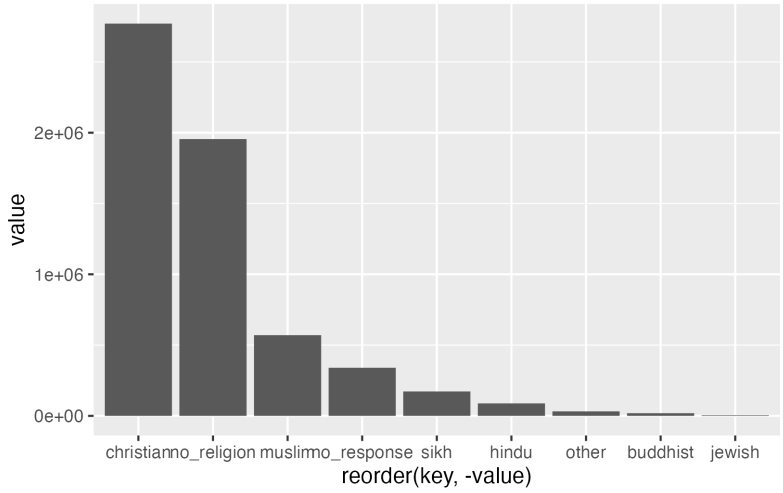
1.4.2 GGPlot

```
ggplot(uk_census_2021_religion_wmids, aes(x = key, y = value)) + ①
  geom_bar(stat = "identity")
```

② We'll re-order the column by size.




```
ggplot(uk_census_2021_religion_wmids, aes(x= reorder(key,-value),value)) + geom_bar(stat ="i
```



Let's assume we're working with a data set that doesn't include a "totals" column and that we might want to get sums for each column. This is pretty easy to do in R:

```
uk_census_2021_religion_totals <- uk_census_2021_religion %>% select(no_religion:no_response
uk_census_2021_religion_totals <- uk_census_2021_religion_totals %>%
```

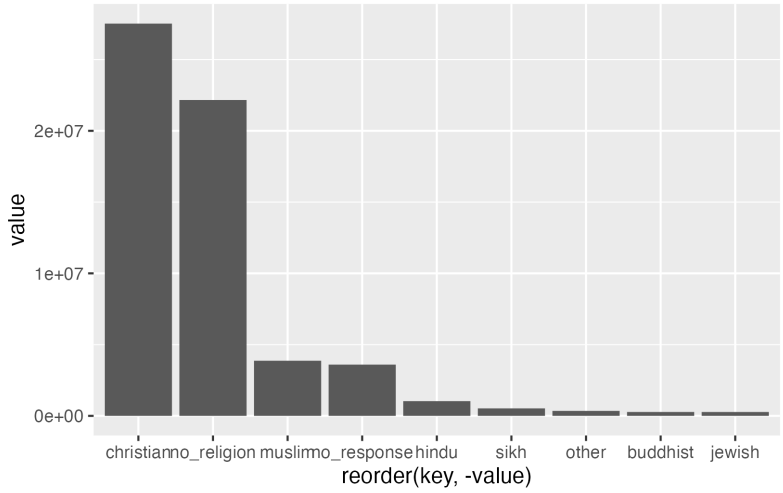
```
   summarise(across(everything(), ~ sum(., na.rm = TRUE)))  ②
uk_census_2021_religion_totals <- gather(uk_census_2021_religion_totals) ③
ggplot(uk_census_2021_religion_totals, aes(x= reorder(key,-value),value)) + geom_bar(stat ="
```

① First, remove the column with region names and the totals for the regions as we want just integer data.

② Second calculate the totals. In this example we use the tidyverse library `dplyr()`, but you can also do this using base R with `colsums()` like this: `uk_census_2021_religion_totals <- colSums(uk_census_2021_religion_totals, na.rm = TRUE)`. The downside with base R is that you'll also need to convert the result into a dataframe for `ggplot` like this: `uk_census_2021_religion_totals <- as.data.frame(uk_census_2021_religion_totals)`

③ In order to visualise this data using ggplot, we need to shift this data from wide to long format. This is a quick job using gather()

④ Now plot it out and have a look!



You might have noticed that these two dataframes give us somewhat different results. But with data science, it's much more interesting to compare these two side-by-side in a visualisation. We can join these two dataframes and plot the bars side by side using `bind()` - which can be done by columns with cbind() and rows using rbind():

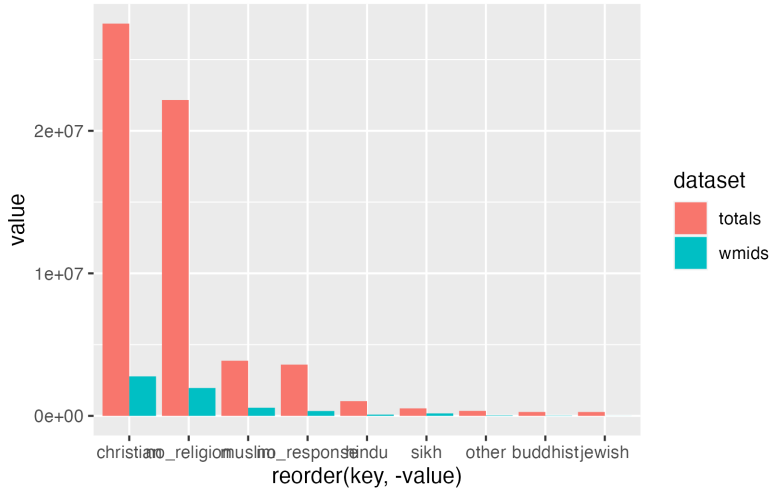
```
uk_census_2021_religion_merged <- rbind(uk_census_2021_religion_totals, uk_census_2021_relig
```

Do you notice there's going to be a problem here? How can we tell one set from the other? We need to add in something idenfiable first! This isn't too hard to do as we can simply create a new column for each with identifiable information before we bind them:

```
uk_census_2021_religion_totals$dataset <- c("totals")
uk_census_2021_religion_wmids$dataset <- c("wmids")
uk_census_2021_religion_merged <- rbind(uk_census_2021_religion_totals, uk_census_2021_relig
```

Now we're ready to plot out our data as a grouped barplot:

```
ggplot(uk_census_2021_religion_merged, aes(fill=dataset, x= reorder(key,-value), value)) + g
```

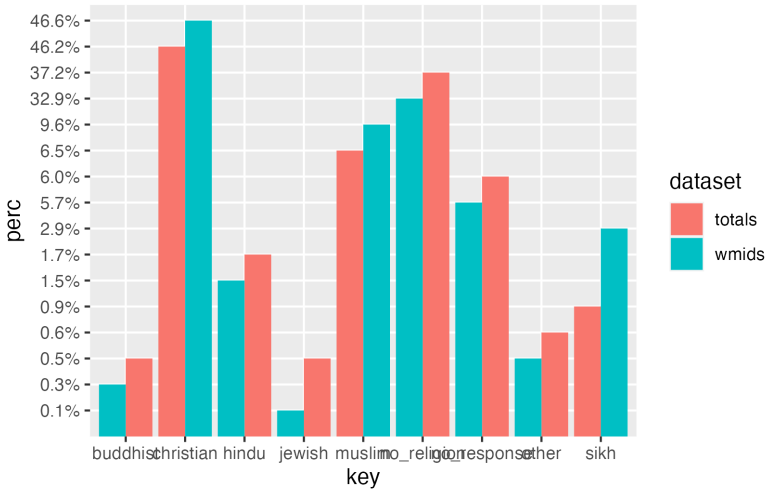


If you're looking closely, you will notice that I've added two elements to our previous ggplot. I've asked ggplot to fill in the columns with reference to the `dataset` column we've just created. Then I've also asked ggplot to alter the `position="dodge"` which places bars side by side rather than stacked on top of one another. You can give it a try without this instruction to see how this works. We will use stacked bars in a later chapter, so remember this feature.

If you inspect our chart, you can see that we're getting closer, but it's not really that helpful to compare the totals. What we need to do is get percentages that can be compared side by side. This is easy to do using another `dplyr` feature `mutate`:

```
uk_census_2021_religion_totals <- uk_census_2021_religion_totals %>%
  dplyr::mutate(perc = scales::percent(value / sum(value), accuracy = 0.1, trim = FALSE)) ③
uk_census_2021_religion_wmids <- uk_census_2021_religion_wmids %>%
  dplyr::mutate(perc = scales::percent(value / sum(value), accuracy = 0.1, trim = FALSE))
uk_census_2021_religion_merged <- rbind(uk_census_2021_religion_totals, uk_census_2021_religion_wmids)
ggplot(uk_census_2021_religion_merged, aes(fill=dataset, y=perc, x=key)) + geom_bar(position
```

It's worth noting that an alternative approach to take is to leave the numbers intact, and simply label them differently so they render as percentages on your charts. You can do this with the scales() library and the label_percent() function. The downside of this approach is that it won't transfer to tables if you make them.

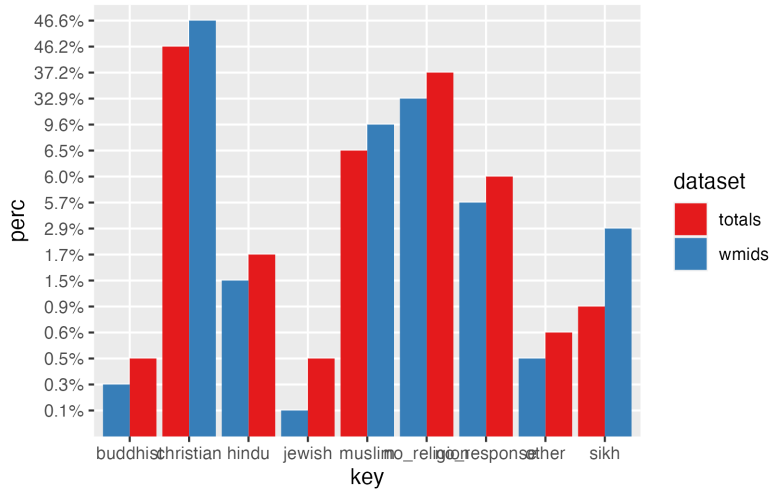


Now you can see a very rough comparison, which sets bars from the W Midlands data and overall data side by side for each category. The same principles that we've used here can be applied to draw in more data. You could, for example, compare census data from different years, e.g. 2001 2011 and 2021. Our use of `dplyr::mutate` above can be repeated to add an infinite number of further series' which can be plotted in bar groups.

We'll draw this data into comparison with later sets in the next chapter. But the one glaring issue which remains for our chart is that it's lacking in really any aesthetic refinements. This is where `ggplot` really shines as a tool as you can add all sorts of things.

These are basically just added to our `ggplot` code. So, for example, let's say we want to improve the colours used for our bars. You can specify the formatting for the fill on the `scale` using `scale_fill_brewer`. This uses a particular tool (and a personal favourite of mine) called `colorbrewer`. Part of my appreciation of this tool is that you can pick colours which are not just visually pleasing, and produce useful contrast / complementary schemes, but you can also work proactively to accommodate colourblindness. Working with colour schemes which can be divergent in a visually obvious way will be even more important when we work on geospatial data and maps in a later chapter.

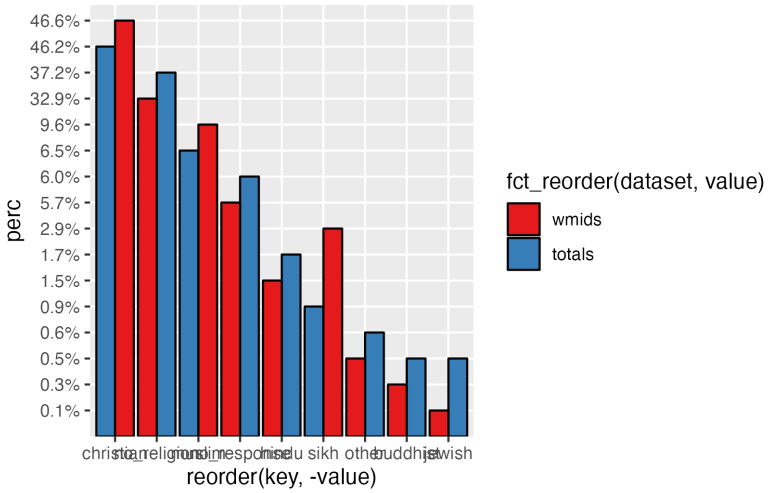
```
ggplot(uk_census_2021_religion_merged, aes(fill=dataset, x=key, y=perc)) + geom_bar(position
```



We might also want to add a border to our bars to make them more visually striking (notice the addition of `color` to the geom_bar below. I've also added `reorder()` to the x value to sort descending from the largest to smallest.

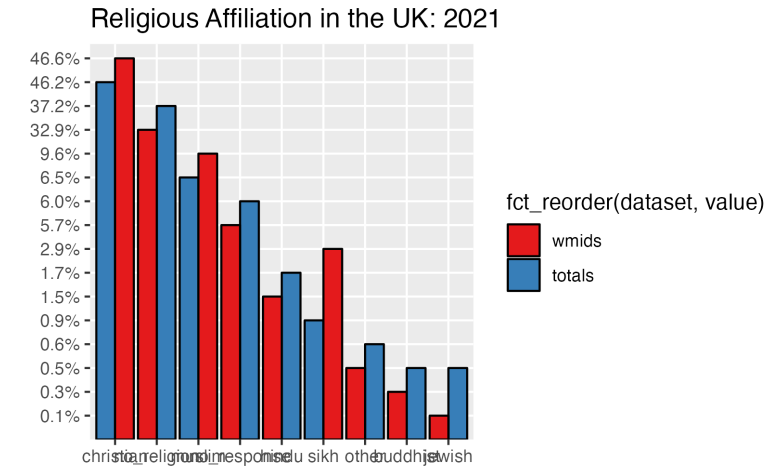
You can find more information about reordering ggplots on the R Graph Gallery.

```
uk_census_2021_religion_merged$dataset <- factor(uk_census_2021_religion_merged$dataset, lev
ggplot(uk_census_2021_religion_merged, aes(fill=fct_reorder(dataset, value), x=reorder(key,-
```



We can fine tune a few other visual features here as well, like adding a title with `ggtitle` and a them with some prettier fonts with `theme_ipsum()` (which requires the `hrbrthemes()` library). We can also remove the x and y axis labels (not the data labels, which are rather important).

```
ggplot(uk_census_2021_religion_merged, aes(fill=fct_reorder(dataset, value), x=reorder(key,-
```



1.5 Is your chart accurate? Telling the truth in data science

There is some technical work yet to be done fine-tuning the visualisation of our chart here. But I'd like to pause for a moment and consider an ethical question. Is the title of this chart truthful and accurate? On one hand, it is a straight-forward reference to the nature of the question asked on the 2021 census survey instrument. However, as you will see in the next chapter, large data sets from the same year which asked a fairly similar question yield different results. Part of this could be attributed to the amount of non-respose to this specific question which, in the 2021 census is between 5-6% across many demographics. It's possible (though perhaps unlikely) that all those non-responses were Sikh respondents who felt uncomfortable identifying themselves on such a survey. If even half of the non-responses were of this nature, this would dramatically shift the results especially in comparison to other minority groups. So there is some work for us to do here in representing non-response as a category on the census.

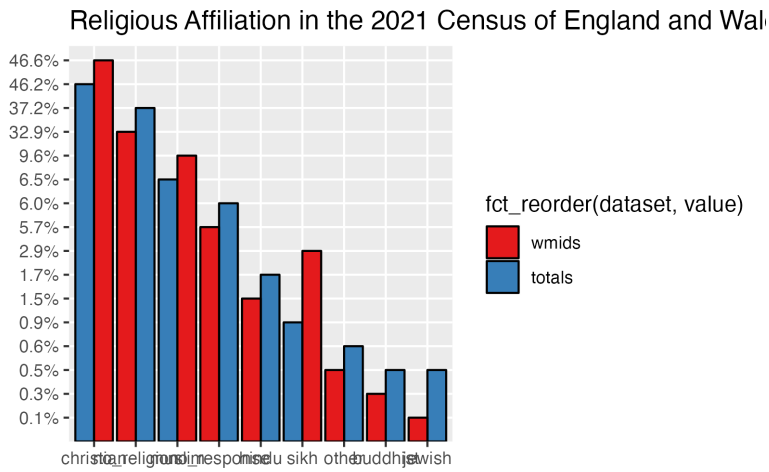
It's equally possible that someone might feel uncertain when answering, but nonetheless land on a particular decision marking "Christian" when they wondered if they should instead tick "no religion. Some surveys attempt to capture uncertainty in this way, asking respondents to mark how confident they are about their answers, but the census hasn't capture this so we simply don't know. If a large portion of respondents in the"Christian" category were hovering between this and another response, again, they might shift their answers when responding on a different day, perhaps having just had a conversation with a friend which shifted their thinking. Even the inertia of survey design can have an effect on this, so responding to other questions in a particular way, thinking about ethnic identity, for example, can prime a person to think about their religious identity in a different or more focussed way, altering their response to the question. For this reason, some survey instruments randomise the order of questions. This hasn't been done on the census (which would have been quite hard work given that most of the instruments were printed hard copies!),

so again, we can't really be sure if those answers given are stable.

Finally, researchers have also found that when people are asked to mark their religious affiliation, sometimes they can prefer to mark more than one answer. A person might consider themselves to be "Muslim" but also "Spiritual but not religious" preferring the combination of those identities. It is also the case that respondents can identify with more unexpected hybrid religious identities, such as "Christian" and "Hindu". The census only allows respondents to tick a single box for the religion category. It is worth noting that, in contrast, the responses for ethnicity allow for combinations. Given that this is the case, it's impossible to know which way a person went at the fork in the road as they were forced to choose just one half of this kind of hybrid identity. Finally, it is interesting to wonder exactly what it means for a person when they tick a box like this. Is it because they attend synagogue on a weekly basis? Some persons would consider weekly attendance at workship a prerequisite for membership in a group, but others would not. Indeed we can infer from surveys and research which aims to track rates of participation in weekly worship that many people who tick boxes for particular religious identities on the census have never attended a worship service at all.

What does this mean for our results? Are they completely unreliable and invalid? I don't think this is the case or that taking a clear-eyed look at the force and stability of our underlying data should be cause for despair. Instead, the most appropriate response is humility. Someone has made a statement which is recorded in the census, of this we can be sure. They felt it to be an accurate response on some level based on the information they had at the time. And with regard to the census, it is a massive, almost completely population level, sample so there is additional validity there. The easiest way to represent all this reality in the form of speaking truthfully about our data is to acknowledge that however valid it may seem, it is nonetheless a snapshot. For this reason, I would always advise that the best title for a chart is one which specifies the data set. We should also probably do something different with those non-responses:

```
ggplot(uk_census_2021_religion_merged, aes(fill=fct_reorder(dataset, value), x=reorder(key,-
```



Change orientation of X axis labels + theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))

Relabel fields Simplify y-axis labels Add percentage text to bars (or maybe save for next chapter?)

1.6 Making our script reproducible

Let's take a moment to review our hacker code. I've just spent some time addressing how we can be truthful in our data science work. We haven't done much yet to talk abour reproducibility.

1.7 Multifactor Visualisation

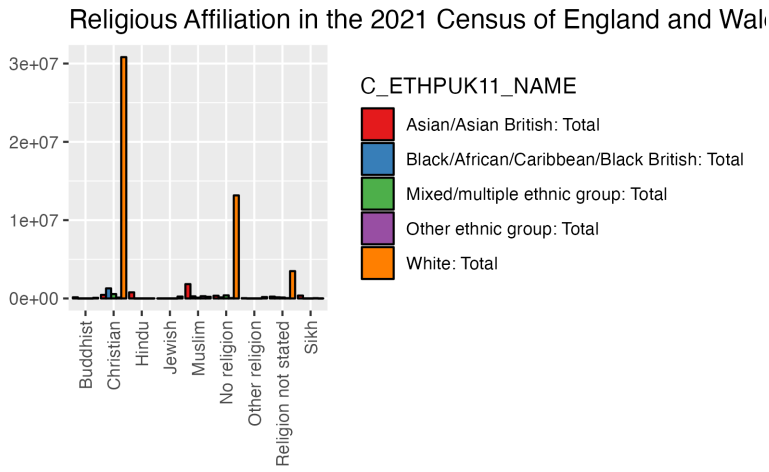
One element of R data analysis that can get really interesting is working with multiple variables. Above we've looked at the breakdown of religious affiliation across the whole of England and Wales (Scotland operates an independent census), and by placing this data alongside a specific region, we've already made

a basic entry into working with multiple variables but this can get much more interesting. Adding an additional quantative variable (also known as bivariate data) into the mix, however can also generate a lot more information and we have to think about visualising it in different ways which can still communicate with visual clarity in spite of the additional visual noise which is inevitable with enhanced complexity. Let's have a look at the way that religion in England and Wales breaks down by ethnicity.

> **What is Nomis?**
>
> For the UK, census data is made available for programmatic research like this via an organisation called NOMIS. Luckily for us, there is an R library you can use to access nomis directly which greatly simplifies the process of pulling data down from the platform. It's worth noting that if you're not in the UK, there are similar options for other countries. Nearly every R textbook I've ever seen works with USA census data, so you'll find plenty of documentation available on the tools you can use for US Census data. Similarly for the EU, Canada, Austrailia etc.
> If you want to draw some data from the nomis platform yourself in R, have a look at the companion cookbook repository.

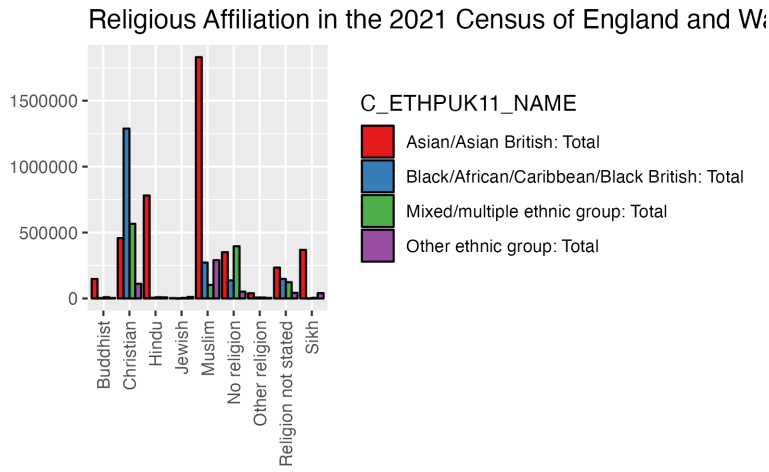
```
# Get table of Census 2011 religion data from nomis
z <- readRDS(file = (here("example_data", "z.rds")))

# Filter down to simplified dataset with England / Wales and percentages without totals
uk_census_2011_religion <- filter(z, GEOGRAPHY_NAME=="England and Wales" & RURAL_URBAN_NAME=
# Drop unnecessary columns
uk_census_2011_religion <- select(uk_census_2011_religion, C_RELPUK11_NAME, OBS_VALUE)
# Plot results
plot1 <- ggplot(uk_census_2011_religion, aes(x = C_RELPUK11_NAME, y = OBS_VALUE)) + geom_bar
# ggsave(filename = "plot.png", plot = plot1)

# grab daata from nomis for 2001 census religion / ethnicity
z0 <- readRDS(file = (here("example_data", "z0.rds")))
```

```r
# select relevant columns
uk_census_2001_religion_ethnicity <- select(z0, GEOGRAPHY_NAME, C_RELPUK11_NAME, C_ETHHUK11_
# Filter down to simplified dataset with England / Wales and percentages without totals
uk_census_2001_religion_ethnicity <- filter(uk_census_2001_religion_ethnicity, GEOGRAPHY_NAM
# Simplify data to only include general totals and omit subcategories
uk_census_2001_religion_ethnicity <- uk_census_2001_religion_ethnicity %>% filter(grepl('Tot

# grab data from nomis for 2011 census religion / ethnicity table
z1 <- readRDS(file = (here("example_data", "z1.rds")))

# select relevant columns
uk_census_2011_religion_ethnicity <- select(z1, GEOGRAPHY_NAME, C_RELPUK11_NAME, C_ETHPUK11_
# Filter down to simplified dataset with England / Wales and percentages without totals
uk_census_2011_religion_ethnicity <- filter(uk_census_2011_religion_ethnicity, GEOGRAPHY_NAM
# Simplify data to only include general totals and omit subcategories
uk_census_2011_religion_ethnicity <- uk_census_2011_religion_ethnicity %>% filter(grepl('Tot

# grab data from nomis for 2021 census religion / ethnicity table
z2 <- readRDS(file = (here("example_data", "z2.rds")))

# select relevant columns
uk_census_2021_religion_ethnicity <- select(z2, GEOGRAPHY_NAME, C2021_RELIGION_10_NAME, C202
# Filter down to simplified dataset with England / Wales and percentages without totals
uk_census_2021_religion_ethnicity <- filter(uk_census_2021_religion_ethnicity, GEOGRAPHY_NAM
# 2021 census includes white sub-groups so we need to omit those so we just have totals:
uk_census_2021_religion_ethnicity <- filter(uk_census_2021_religion_ethnicity, C2021_ETH_8_N

ggplot(uk_census_2011_religion_ethnicity, aes(fill=C_ETHPUK11_NAME, x=C_RELPUK11_NAME, y=OBS
```



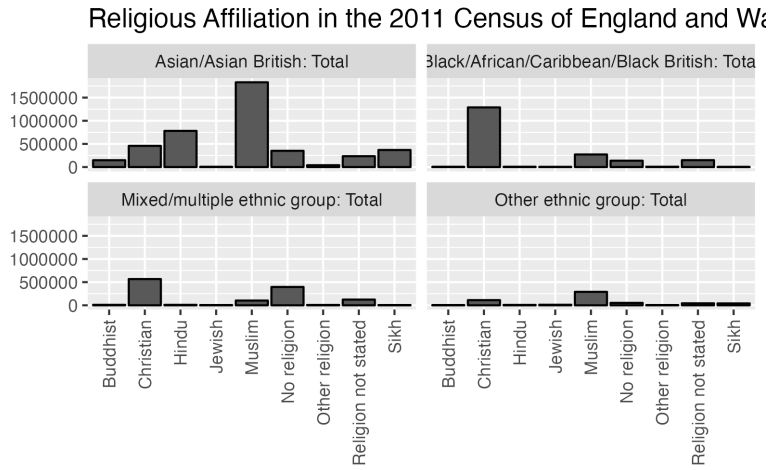
The trouble with using grouped bars here, as you can see, is that there are quite sharp disparities which make it hard to compare in meaningful ways. We could use logarithmic rather than linear scaling as an option, but this is hard for many general public audiences to apprecaite without guidance. One alternative quick fix is to extract data from "white" respondents which can then be placed in a separate chart with a different scale.

```
# Filter down to simplified dataset with England / Wales and percentages without totals
uk_census_2011_religion_ethnicity_white <- filter(uk_census_2011_religion_ethnicity, C_ETHPU
uk_census_2011_religion_ethnicity_nonwhite <- filter(uk_census_2011_religion_ethnicity, C_ET

ggplot(uk_census_2011_religion_ethnicity_nonwhite, aes(fill=C_ETHPUK11_NAME, x=C_RELPUK11_NA
```



This still doesn't quite render with as much visual clarity and communication as I'd like. For a better look, we can use a technique in R called "faceting" to create a series of small charts which can be viewed alongside one another.

```
ggplot(uk_census_2011_religion_ethnicity_nonwhite, aes(x=C_RELPUK11_NAME, y=OBS_VALUE)) + ge
```

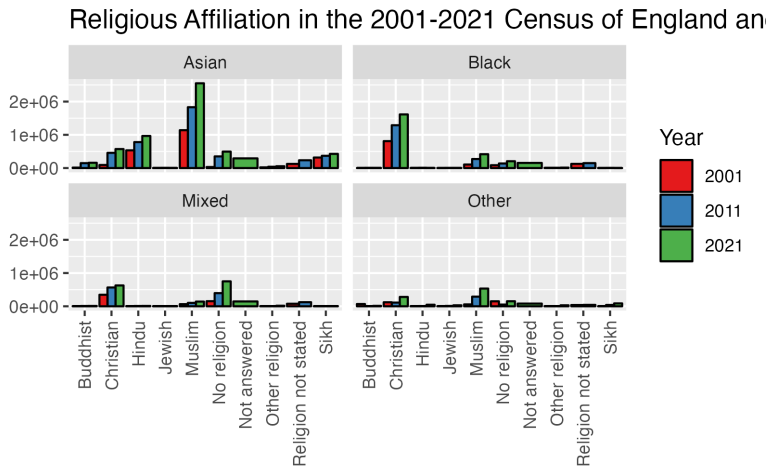


For our finale chart, I'd like to take the faceted chart we've just done, and add in totals for the previous two census years (2001

and 2011) so we can see how trends are changing in terms of religious affiliation within ethnic self-identification categories. We'll draw on some techniques we're already developed above using `rbind()` to connect up each of these charts (after we've added a column identifying each chart by the census year). We will also need to use one new technique to change the wording of ethnic categories as this isn't consistent from one census to the next and ggplot will struggle to chart things if the terms being used are exactly the same. We'll use `mutate()` again to accomplish this with some slightly different code.

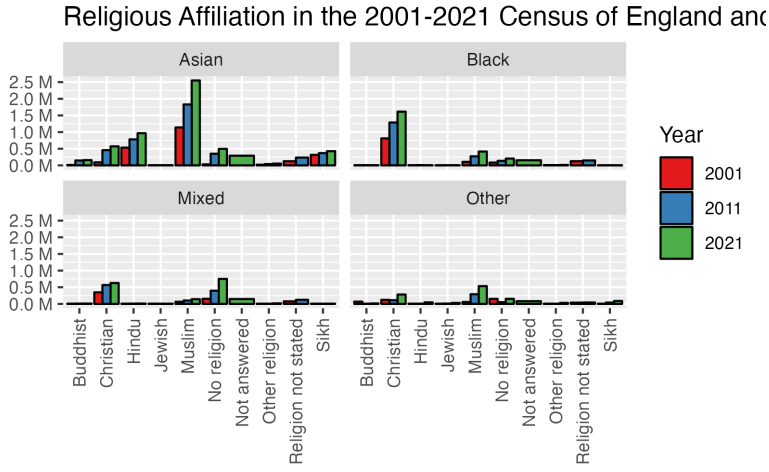
```
# First add column to each dataframe so we don't lose track of the census it comes from:
uk_census_2001_religion_ethnicity$dataset <- c("2001")
uk_census_2011_religion_ethnicity$dataset <- c("2011")
uk_census_2021_religion_ethnicity$dataset <- c("2021")

# Let's tidy the names of each column:

names(uk_census_2001_religion_ethnicity) <- c("Geography", "Religion", "Ethnicity", "Value",
names(uk_census_2011_religion_ethnicity) <- c("Geography", "Religion", "Ethnicity", "Value",
names(uk_census_2021_religion_ethnicity) <- c("Geography", "Religion", "Ethnicity", "Value",

# Next we need to change the terms using mutate()
uk_census_2001_religion_ethnicity <- uk_census_2001_religion_ethnicity %>%
  mutate(Ethnicity = str_replace_all(Ethnicity,
            pattern = "^White: Total$", replacement = "White")) %>%
  mutate(Ethnicity = str_replace_all(Ethnicity,
            pattern = "^Mixed: Total$", replacement = "Mixed")) %>%
  mutate(Ethnicity = str_replace_all(Ethnicity,
            pattern = "^Asian: Total$", replacement = "Asian")) %>%
  mutate(Ethnicity = str_replace_all(Ethnicity,
            pattern = "^Black or Black British: Total$", replacement = "Black")) %>%
  mutate(Ethnicity = str_replace_all(Ethnicity,
            pattern = "^Chinese or Other ethnic group: Total$", replacement = "Other"))

uk_census_2011_religion_ethnicity <- uk_census_2011_religion_ethnicity %>%
  mutate(Ethnicity = str_replace_all(Ethnicity,
            pattern = "^White: Total$", replacement = "White")) %>%
  mutate(Ethnicity = str_replace_all(Ethnicity,
            pattern = "^Mixed/multiple ethnic group: Total$", replacement = "Mixed")) %>%
```

```
  mutate(Ethnicity = str_replace_all(Ethnicity,
           pattern = "^Asian/Asian British: Total$", replacement = "Asian")) %>%
  mutate(Ethnicity = str_replace_all(Ethnicity,
           pattern = "^Black/African/Caribbean/Black British: Total$", replacement = "Black
  mutate(Ethnicity = str_replace_all(Ethnicity,
           pattern = "^Other ethnic group: Total$", replacement = "Other"))

uk_census_2021_religion_ethnicity <- uk_census_2021_religion_ethnicity %>%
  mutate(Ethnicity = str_replace_all(Ethnicity,
           pattern = "^White: Total$", replacement = "White")) %>%
  mutate(Ethnicity = str_replace_all(Ethnicity,
           pattern = "^Mixed or Multiple ethnic groups$", replacement = "Mixed")) %>%
  mutate(Ethnicity = str_replace_all(Ethnicity,
           pattern = "^Asian, Asian British or Asian Welsh$", replacement = "Asian")) %>%
  mutate(Ethnicity = str_replace_all(Ethnicity,
           pattern = "^Black, Black British, Black Welsh, Caribbean or African$", replaceme
  mutate(Ethnicity = str_replace_all(Ethnicity,
           pattern = "^Other ethnic group$", replacement = "Other"))

# Now let's merge the tables:

uk_census_merged_religion_ethnicity <- rbind(uk_census_2021_religion_ethnicity, uk_census_20

uk_census_merged_religion_ethnicity <- rbind(uk_census_merged_religion_ethnicity, uk_census_

# As above, we'll split out non-white and white:

uk_census_merged_religion_ethnicity_nonwhite <- filter(uk_census_merged_religion_ethnicity,

# Time to plot!

ggplot(uk_census_merged_religion_ethnicity_nonwhite, aes(fill=Year, x=Religion, y=Value)) +
```



There are a few formatting issues which remain. Our y-axis number labels are in scientific format which isn't really very easy to read. You can use the very powerful and flexible `scales()` library to bring in some more readable formatting of numbers in a variety of places in R including in ggplot visualizations.

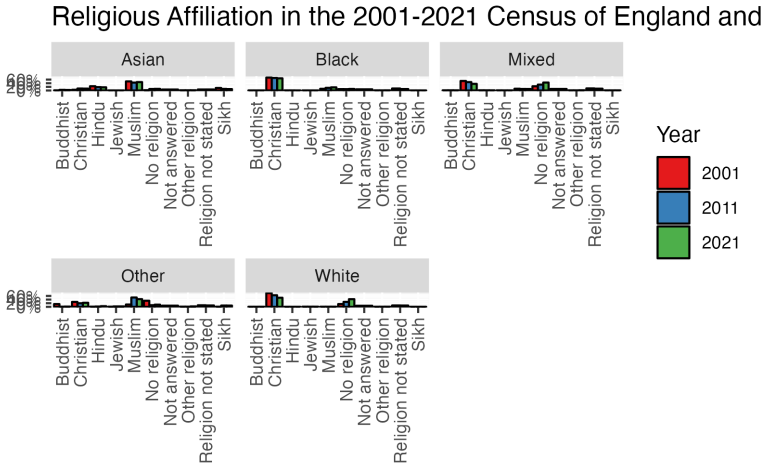
```
library(scales) |> suppressPackageStartupMessages()
ggplot(uk_census_merged_religion_ethnicity_nonwhite, aes(fill=Year, x=Religion, y=Value)) +
```



```
# https://ggplot2-book.org/scales-position#sec-position-continuous-breaks
```

This chart shows an increase in almost every category, though it's a bit hard to read in some cases. However, this information is based on the increase in raw numbers. It's possbile that numbers may be going up, but in some cases the percentage share for a particular category has actually gone down. Let's transform and visualise our data as percentages to see what kind of trends we can actually isolate:

```
uk_census_merged_religion_ethnicity <- uk_census_merged_religion_ethnicity %>%
  group_by(Ethnicity, Year) %>%
  dplyr::mutate(Percent = Value/sum(Value))

ggplot(uk_census_merged_religion_ethnicity, aes(fill=Year, x=Religion, y=Percent)) + geom_ba
```



Now you can see why this shift is important - the visualisation tells a completely different story in some cases across the two different charts. In the first, working off raw numbers we see a net increase in Christianity across all categories. But if we take into account the fact that the overall share of population is growing for each of these groups, their actual composition is changing in a different direction. The proportion of each group is declining across the three census periods (albeit with

an exception for the “Other” category from 2011 to 2021).

To highlight a few features of this final plot, I’ve used a specific feature within `facet_wrap scales = "free_x"` to let each of the individual facets adjust the total range on the x-axis. Since we’re looking at trends here and not absolute values, having correspondence across scales isn’t important and this makes for something a bit more visually tidy. I’ve also shifted the code for `scale_y_continuous` to render values as percentages (rather than millions).

In case you want to print this plot out and hang it on your wall, you can use the ggsave tool to render the chart as an image file:

```
plot1 <- ggplot(uk_census_merged_religion_ethnicity, aes(fill=Year, x=Religion, y=Percent))

ggsave("chart.png", plot=plot1, width = 8, height = 10, units=c("in"))
```

2 Survey Data: Spotlight Project

In the last chapter we explored some high level data about religion in the UK. This was a census sample, which usually refers to an attempt to get as comprehensive a sample as possible. But this is actually fairly unusual in practice. Depending on how complex a subject is, and how representative we want our data to be, it's much more common to use selective sampling, that is survey responses at n=100 or n=1000 at a maximum. The advantage of a census sample is that you can explore how a wide range of other factors - particularly demographics - intersect with your question. And this can be really valuable in the study of religion, particularly as you will see as we go along that responses to some questions are more strongly correlated to things like economic status or educational attainment than they are to religious affiliation. It can be hard to tell if this is the case unless you have enough of a sample to break down into a number of different kinds of subsets. But census samples are complex and expensive to gather, so they're quite rare in practice.

For this chapter, I'm going to walk you through a data set that a colleague (Charles Ogunbode) and I collected in 2021. Another problem with smaller, more selective samples is that researchers can often undersample minoritised ethnic groups. This is particularly the case with climate change research. Until the time we conducted this research, there had not been a single study investigating the specific experiences of people of colour in relation to climate change in the UK. Past researchers had been content to work with large samples, and assumed that if they had done 1000 surveys and 50 of these were completed by people of colour, they could "tick" the box. But 5% is actually well below levels of representation in the UK generally, and even more sharply the case for specific communities. And

if we bear in mind that non-white respondents are (of course!) a highly heterogenous group, we're even more behind in terms of collecting data that can improve our knowledge. Up until recently researchers just haven't been paying close enough attention to catch the significant neglect of the empirical field that this represents.

While I've framed my comments above in terms of climate change research, it is also the case that, especially in diverse societies like the USA, Canada, the UK etc., paying attention to non-majority groups and people and communities of colour automatically draws in a strongly religious sample. This is highlighted in one recent study done in the UK, the "Black British Voices Report" in which the researchers observed that "84% of respondents described themselves as religious and/or spiritual". My comments above in terms of controlling for other factors remains important here - these same researchers also note that "despire their significant important to the lives of Black Britons, only 7% of survey respondents reported that their religion was more defining of their identity than their race".

We've decided to open up access to our data and I'm highlighting it in this book because it's a unique opportunitiy to explore a dataset that emphasises diversity from the start, and by extension, provides some really interesting ways to use data science techniques to explore religion in the UK.

2.1 Loading in some data

```
# R Setup ------------------------------------------------------------------
setwd("/Users/kidwellj/gits/hacking_religion_textbook/hacking_religion")
library(here)  |> suppressPackageStartupMessages()
library(tidyverse)  |> suppressPackageStartupMessages()
# used for importing SPSS .sav files
library(haven)   |> suppressPackageStartupMessages()
here::i_am("chapter_2.qmd")
```

```
here() starts at /Users/kidwellj/gits/hacking_religion_textbook/hacking_religion
```

```
climate_experience_data <- read_sav(here("example_data", "climate_experience_data.sav"))
```

The first thing to note here is that we've drawn in a different type of data file, this time from an `.sav` file, usully produced by the statistics software package SPSS. This uses a different R Library (I use `haven` for this). The upside is that in some cases where you have survey data with both a code and a value like "1" is eqivalent to "very much agree" this will preserve both in the R dataframe that is created. Now that you've loaded in data, you have a new R dataframe called "climate_experience_data" with a lot of columns with just under 1000 survey responses.

2.2 How can you ask about religion?

One of the challenges we faced when running this study is how to gather responsible data from surveys regarding religious identity. We'll dive into this in depth as we do analysis and look at some of the agreements and conflicts in terms of respondent attribution. Just to set the stage, we used the following kinds of question to ask about religion and spirituality:

1. Question 56 asks respondents simply, "What is your religion?" and then provides a range of possible answers. We included follow-up questions regarding denomination for respondents who indicated they were "Christian" or "Muslim". For respondents who ticked "Christian" we asked, "What is your denomination?" nad for respondents who ticked "Muslim" we asked "Which of the following would you identify with?" and then left a range of possible options which could be ticked such as "Sunni," "Shia," "Sufi" etc.

This is one way of measuring religion, that is, to ask a person if they consider themselves formally affiliated with a particular group. This kind of question has some (serious) limitations, but we'll get to that in a moment.

We also asked respondents (Q57): "Regardless of whether you belong to a particular religion, how religious would you say you

are?" and then provided a slider from 0 (not religious at all) to 10 (very religious).

We included some classic indicators about how often respondents go to worship (Q58): Apart from weddings, funerals and other special occasions, how often do you attend religious services? and (Q59): "Q59 Apart from when you are at religious services, how often do you pray?"

- More than once a week (1)
- Once a week (2)
- At least once a month (3)
- Only on special holy days (4)
- Never (5)

Each of these measures a particular kind of dimension, and it is interesting to note that sometimes there are stronger correlations between how often a person attends worship services (weekly versus once a year) and a particular view, than there is between their affiliation (if they are Christian or Pagan). We'll do some exploratory work shortly to see how this is the case in our sample. We also included a series of questions about spirituality in Q52 and used a nature relatedness scale Q51.

You'll find that many surveys will only use one of these forms of question and ignore the rest. I think this is a really bad idea as religious belonging, identity, and spirituality are far too complex to work off a single form of response. We can also test out how these different attributions relate to other demographic features, like interest in politics, economic attainment, etc.

So *who's* religious?

As I've already hinted in the previous chapter, measuring religiosity is complicated. I suspect some readers may be wondering something like, "what's the right question to ask?" here. Do we get the most accurate representation by asking people to self-report their religious affiliation? Or is it more accurate to ask individuals to report on how religious they are? Is it, perhaps, better to assume that the indirect query about practice, e.g. how frequently one attends services at a place of worship may be the most

reliable proxy?
Highlight challenges of various approaches pointing to literature.

Let's dive into the data and see how this all works out. We'll start with the question 56 data, around religious affiliation:

```
religious_affiliation <- as_tibble(as_factor(climate_experience_data$Q56))        ①
names(religious_affiliation) <- c("response")  ②
religious_affiliation <- filter(religious_affiliation, !is.na(response)) ③
```

There are few things we need to do here to get the data into initial proper shape. This might be called "cleaning" the data:

1. Because we imported this data from an SPSS `.sav` file format using the R `haven()` library, we need to start by adapting the data into a format that our visualation engine ggplot can handle (a dataframe).
2. Next we'll rename the columns so these names are a bit more useful.
3. We need to omit non-responses so these don't mess with the counting (these are `NA` in R)

If we pause at this point to view the data, you'll see it's basically just a long list of survey responses. What we need is a count of each unique response (or `factor`). This will take a few more steps:

```
religious_affiliation_sums <- religious_affiliation %>%
  dplyr::count(response, sort = TRUE) %>%     ①
  dplyr::mutate(response = forcats::fct_rev(forcats::fct_inorder(response)))     ②
religious_affiliation_sums <- religious_affiliation_sums %>%
  dplyr::mutate(perc = scales::percent(n / sum(n), accuracy = .1, trim = FALSE)) ③
```

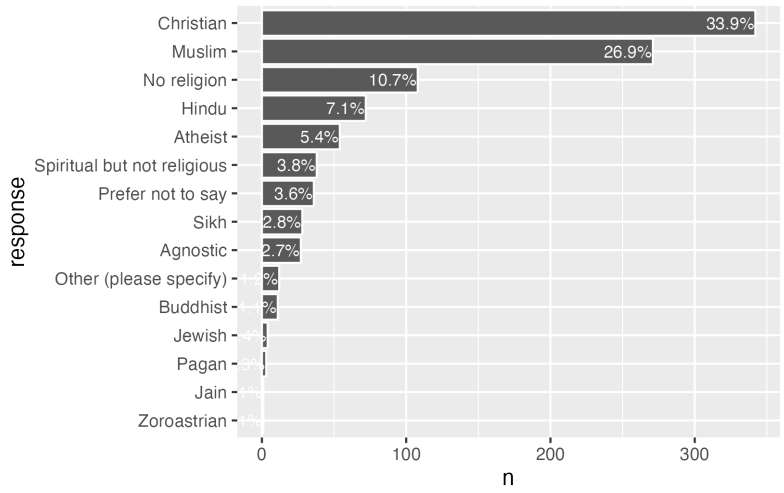
① First we generate new a dataframe with sums per category and
② …sort in descending order
③ Then we add new column with percentages based on the sums you've just generated

That should give us a tidy table of results, which you can see if you view the contents of our new `religious_affiliation_sums` dataframe:

```
head(religious_affiliation_sums)
```

```
# A tibble: 6 x 3
  response                      n perc
  <fct>                     <int> <chr>
1 Christian                   342 "33.9%"
2 Muslim                      271 "26.9%"
3 No religion                 108 "10.7%"
4 Hindu                        72 " 7.1%"
5 Atheist                      54 " 5.4%"
6 Spiritual but not religious  38 " 3.8%"
```

```
# make plot
ggplot(religious_affiliation_sums, aes(x = n, y = response)) +
  geom_col(colour = "white") +
  ## add percentage labels
  geom_text(aes(label = perc),
            ## make labels left-aligned and white
            hjust = 1, nudge_x = -.5, colour = "white", size=3)
```



I've added one feature to our chart that wasn't in the bar charts in chapter 1, text labels with the actual value on each bar.

You may be thinking about the plots we've just finished in chapter 1 and wondering how they compare. Let's use the same facet approach that we've just used to render this data in a subsetted way.

```
# First we need to add in data on ethnic self-identification from our respondents:
df <- select(climate_experience_data, Q56, Q0)
religious_affiliation_ethnicity <- as_tibble(as_factor(df))
names(religious_affiliation_ethnicity) <- c("Religion", "Ethnicity")

religious_affiliation_ethnicity_sums <- religious_affiliation_ethnicity %>%
  group_by(Ethnicity) %>%
  dplyr::count(Religion, sort = TRUE) %>%     ①
  dplyr::mutate(Religion = forcats::fct_rev(forcats::fct_inorder(Religion)))

plot1 <- ggplot(religious_affiliation_ethnicity_sums, aes(x = n, y = Religion)) +
  geom_col(colour = "white") + facet_wrap(~Ethnicity, scales="free_x")

ggsave("chart.png", plot=plot1, width = 8, height = 10, units=c("in"))
```

What is Religion?

Content tbd

Hybrid Religious Identity

Content tbd

What is Secularisation?

Content tbd

References

3 Mapping churches: geospatial data science

Until recently, most data science books didn't have a section on geospatial data. It was considered a specialist form of research best left to GIS technicians who tended to use proprietary tools like ArcGIS. This has changed significantly in the past five years, but you'll still be hard pressed to find an introduction to the subject which strays very far from a few simple data sets (mostly of the USA) and relatively uncomplicated geospatial operations. I actually first began learning R, back in 2013, right when open source geospatial research tools were beginning to be developed with quite a lot more energy and geospatial data is my personal favourite data science playground, so in this book we're going to go much deeper than is usual. There are also good reasons to take things a few steps further in the particular forms of data and inquiry that religion takes us into.

Recommend https://r-spatial.org/book/

Geospatial data is, in the most basic form, working with maps. This means that most of your data can be a quite simple dataframe, e.g. just a list of names or categories associated with a set of X and Y coordinates. Once you have a set of items, however, things get interesting very quickly, as you can layer data sets on top of one another. We're going to begin this chapter by developing a geolocated data set of churches in the UK. This information is readily and freely available online thanks to the UK Ordnance Survey, a quasi-governmental agency which maintains the various (now digital) maps of Britain. Lucky for us, the Ordnance Survey has an open data product that anyone can use!

Before we begin, there are some key things we should note about geospatial data. Geospatial data tends to fall into one

of two kinds: points and polygons. Points can be any kind of feature: a house, a church, a pub, someone's favourite ancient oak tree, or some kind of sacred relic. Polygons tend to be associated with wider areas, and as such can be used to describe large features, e.g. an Ocean, a local authority, or a mountain, or also demographic features, like a census Output Area with associated census summaries. Points are very simple data representations, an X and Y coordinate. Polygons are much more complex, often containing dozens or even thousands of points.

The most complex aspect of point data relates to the ways that coordinates are encoded, as they will aways need to be associated with a coordinate reference system (CRS) which describes how they are situated with respect to the planet earth. The most common CRS is the WGS, though for our data sets we'll also come into contact with the BGS, a specifically British coordinate reference system. There are dozens of CRS, usually mapping onto a specific geographical region. Bearing in mind the way that you need to use a CRS to understand how coordinates can be associated with specific parts of the earth, you can see how this is a bit like survey data, where you also need a "codebook" to understand what the specific response values map onto, e.g. a "1" means "strongly agree" and so on. We also saw, in a previous chapter, how some forms of data have the codebook already baked into the factor data, simplifying the process of interpreting the data. In a similar way, some types of geospatial data sets can also come with CRS "baked in" while we'll need to define CRS for other types. Here are some of the most common types of geospatial data files:

CSV: "comma separated values" a plain text file containing various coordinates Shapefile: a legacy file format, often still in use, but being replaced by others for a variety of good reasons. For more on this see [http://switchfromshapefile.org/] Geopackage: one of the more recent ways of packaging up geospatial data. Geopackages can contain a wide variety of different data and are easily portable. GeoJSON: a file format commonly used in other forms of coding, the "JSON" (an acronym for JavaScript Object Notation) is meant to be easily interchangeable across various platforms. GeoJSON is an augmented version of JSON data with coordinates added in.

Now that you have a sense of some of the basic aspects of geospatial data, let's dive in and do a bit of learning in action.

3.1 Administrative shapes - the UK

A good starting point is to aquire some adminstrative data. This is a way of referring to political boundaries, whether country borders or those of a local authority or some other administrative unit. For our purposes, we're going to import several different types of administrative boundary which will be used at different points in our visualisations below. It's worth noting that the data we use here was prepared to support the 2011 census, and make use of the shapefile format.

```
library(sf) |> suppressPackageStartupMessages()
library(here)  |> suppressPackageStartupMessages()
library(tidyverse)
```

```
-- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
v dplyr     1.1.3     v readr     2.1.4
v forcats   1.0.0     v stringr   1.5.0
v ggplot2   3.4.3     v tibble    3.2.1
v lubridate 1.9.3     v tidyr     1.3.0
v purrr     1.0.2
-- Conflicts ------------------------------------------ tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become
```

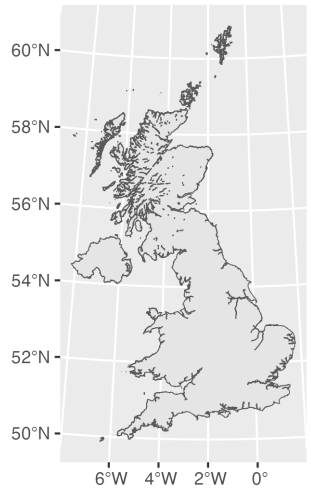
```
# better video device, more accurate and faster rendering, esp. on macos. Also should enable
library(ragg) |> suppressPackageStartupMessages()

setwd("/Users/kidwellj/gits/hacking_religion_textbook/hacking_religion")
here::i_am("chapter_3.qmd")
```

```
here() starts at /Users/kidwellj/gits/hacking_religion_textbook/hacking_religion
```

```
# Download administrative boundaries for whole UK at country level
if (file.exists(here("data", "infuse_uk_2011_clipped.shp")) == FALSE) {
download.file("https://borders.ukdataservice.ac.uk/ukborders/easy_download/prebuilt/shape/in
unzip("data/infuse_uk_2011_clipped.zip", exdir = "data")
}
uk_countries <- st_read(here("data", "infuse_uk_2011_clipped.shp"), quiet = TRUE)

# Download administrative boundaries for whole UK at regions level
if (file.exists(here("data", "infuse_rgn_2011_clipped.shp")) == FALSE) {
download.file("https://borders.ukdataservice.ac.uk/ukborders/easy_download/prebuilt/shape/in
unzip("data/infuse_rgn_2011_clipped.zip", exdir = "data")
}
uk_rgn <- st_read(here("data", "infuse_rgn_2011_clipped.shp"), quiet = TRUE)

# Download administrative boundaries for whole UK at local authority level
if (file.exists(here("data", "infuse_dist_lyr_2011_clipped.shp")) == FALSE) {
download.file("https://borders.ukdataservice.ac.uk/ukborders/easy_download/prebuilt/shape/in
unzip("data/infuse_dist_lyr_2011_clipped.zip", exdir = "data")
}
local_authorities <- st_read(here("data", "infuse_dist_lyr_2011_clipped.shp"), quiet = TRUE)

# Download building outlines for whole UK
if (file.exists(here("data", "infuse_dist_lyr_2011_simplified_100m_buildings_simplified.gpkg
  download.file("https://zenodo.org/record/6395804/files/infuse_dist_lyr_2011_simplified_100
local_authorities_buildings_clip <- st_read(here("data", "infuse_dist_lyr_2011_simplified_10
```

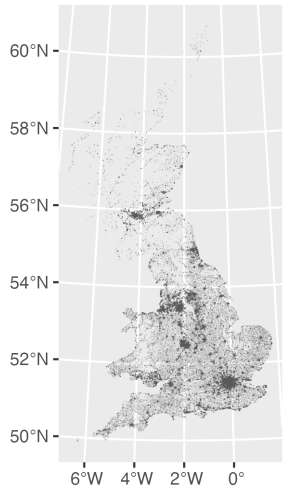
Before we move on, let's plot a simple map and have a look at one of our administrative layers. We can use ggplot with a new type of shape `geom_sf()` to plot the contents of a geospatial data file with polygons which is loaded as a `simplefeature` in R.

```
ggplot(uk_countries) + geom_sf()
```



3.2 Load in Ordnance Survey OpenMap Points Data

```
# Note: for more advanced reproducible scripts which demonstrate how these data surces have
# obtained, see the companion cookbook here: https://github.com/kidwellj/hacking_religion_co

os_openmap_pow <- st_read(here("data", "os_openmap_pow.gpkg"), quiet = TRUE)

ggplot(os_openmap_pow) + geom_sf()
```

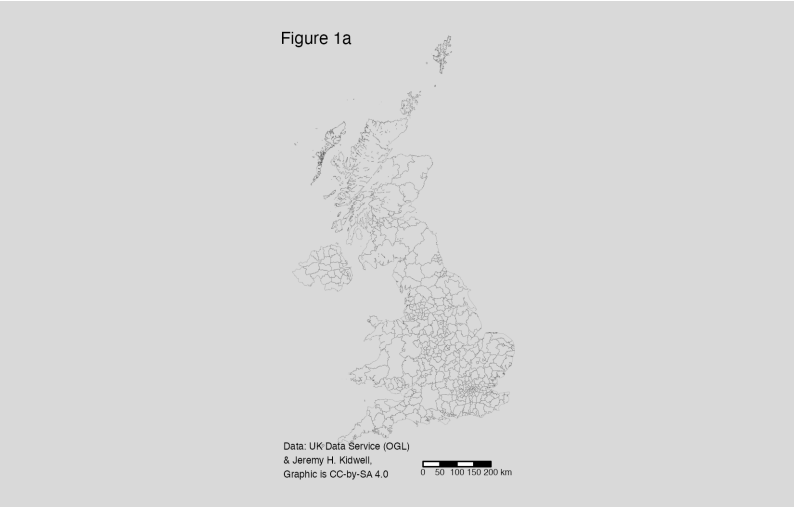


It's worth noting that the way that you load geospatial data in R has changed quite dramatically since 2020 with the introduction of the simplefeature class in R. Much of the documentation you will come across "out there" will make reference to a set of functions which are now deprecated.

Let's use that data we've just loaded to make our first map:

```
# Generate choropleth map of respondent locations
# using temporary palette here so that 0s are white
library(tmap) |> suppressPackageStartupMessages()
# palette <- c(white, "#a8ddb5", "#43a2ca")

map1 <- tm_shape(local_authorities) +
#  tm_fill(col = "surveys_count", , palette = palette, title = "Concentration of survey resp
  tm_borders(alpha=.5, lwd=0.1) +
  # for intermediate polygon geometries
  # tm_shape(local_authorities) +
  # tm_borders(lwd=0.6) +
  # for dots from original dataset
  # tm_dots("red", size = .05, alpha = .4) +
  tm_scale_bar(position = c("right", "bottom")) +
  tm_style("gray") +
  tm_credits("Data: UK Data Service (OGL)\n& Jeremy H. Kidwell,\nGraphic is CC-by-SA 4.0",
             size = 0.4,
```

```
              position = c("left", "bottom"),
              just = c("left", "bottom"),
              align = "left") +
  tm_layout(asp = NA,
            frame = FALSE,
            title = "Figure 1a",
            title.size = .7,
            legend.title.size = .7,
            inner.margins = c(0.1, 0.1, 0.05, 0.05)
  )

map1
```




```
# save image
tmap_save(map1, here("figures", "map.png"), width=1920, height=1080, asp=0)
```

```
Map saved to /Users/kidwellj/gits/hacking_religion_textbook/hacking_religion/figures/map.png

Resolution: 1920 by 1080 pixels

Size: 6.4 by 3.6 inches (300 dpi)
```

```
# subsetting ordnance survey openmap data for measuring clusters and proximity

os_openmap_important_buildings <- st_read(here("data", "os_openmap_important_buildings.gpkg"

# add pubs, check_cashing, pawnbrokers, SSSI
## subsets
```

1. Count the number of churches in Local Authorities

```
# OSM data

# Note: for more advanced reproducible scripts which demonstrate how these data surces have
# obtained, see the companion cookbook here: https://github.com/kidwellj/hacking_religion_co


# osm_uk_points <- st_read(system.file(here("data", "pow_osm.gpkg", package = "spData")))
# vector_filepath = system.file("data/osm-gb-2018Aug29_pow_osm.pbf", package = "sf")
# osm_uk_points = st_read(vector_filepath)
```

Guides to geographies: https://rconsortium.github.io/censusguide/
https://ocsi.uk/2019/03/18/lsoas-leps-and-lookups-a-beginners-guide-to-statistical-geographies/

Calculate proximity to pubs

References

4 Data scraping, corpus analysis and wordclouds

References

5 What's next?

5.1 How to get more data

Data can come from a wide variety of places

5.2 How to get help

Online forums Etiquette

References

6 Summary

An open textbook introducing data science to religious studies

References