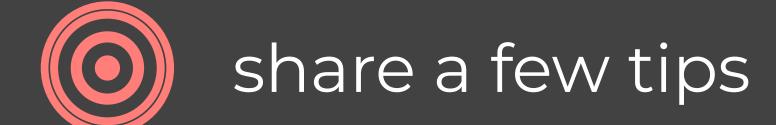


How can we effectively and efficiently teach data science to students with little to no background in computing and statistical thinking?

How can we equip them with the skills and tools for reasoning with various types of data and leave them wanting to learn more?

## goals





provide open-source teaching resources



data visualisation data wrangling, tidying, acquisition exploratory data analysis predictive modeling + uncertainty quantification effective communication of results



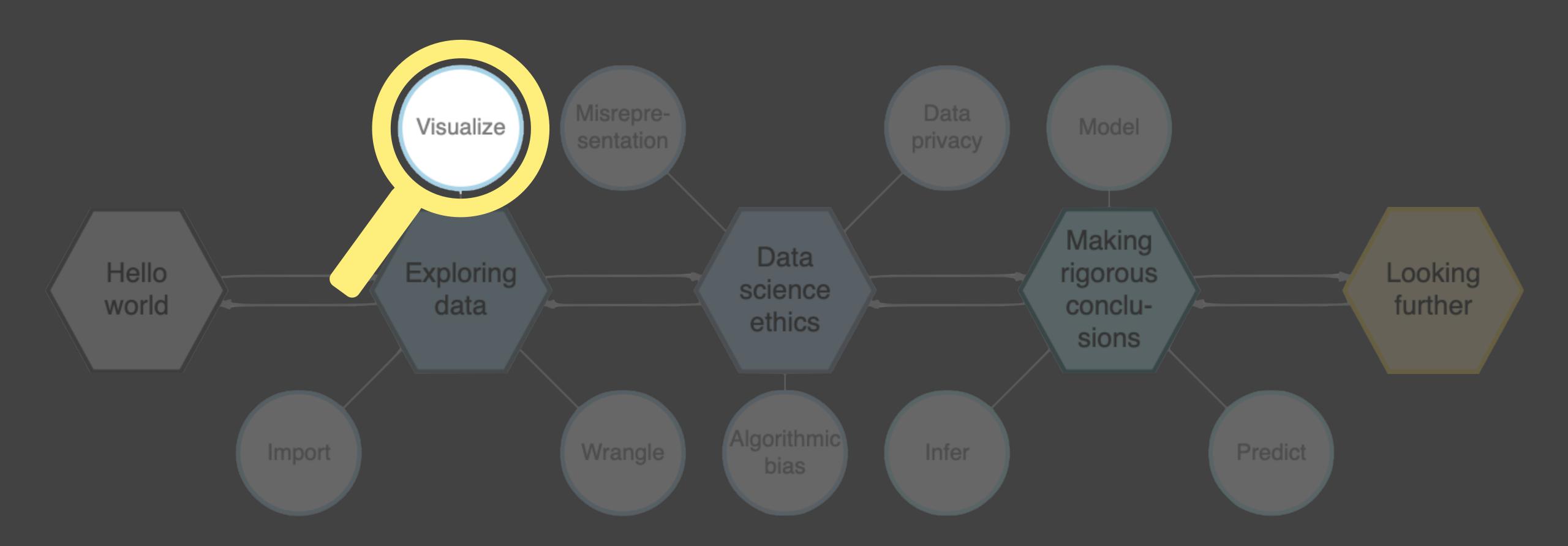
interactive visualizations text analysis machine learning Bayesian inference

• • •



consistent syntax | tidyverse reproducibility | R Markdown version control and collaboration | Git + GitHub

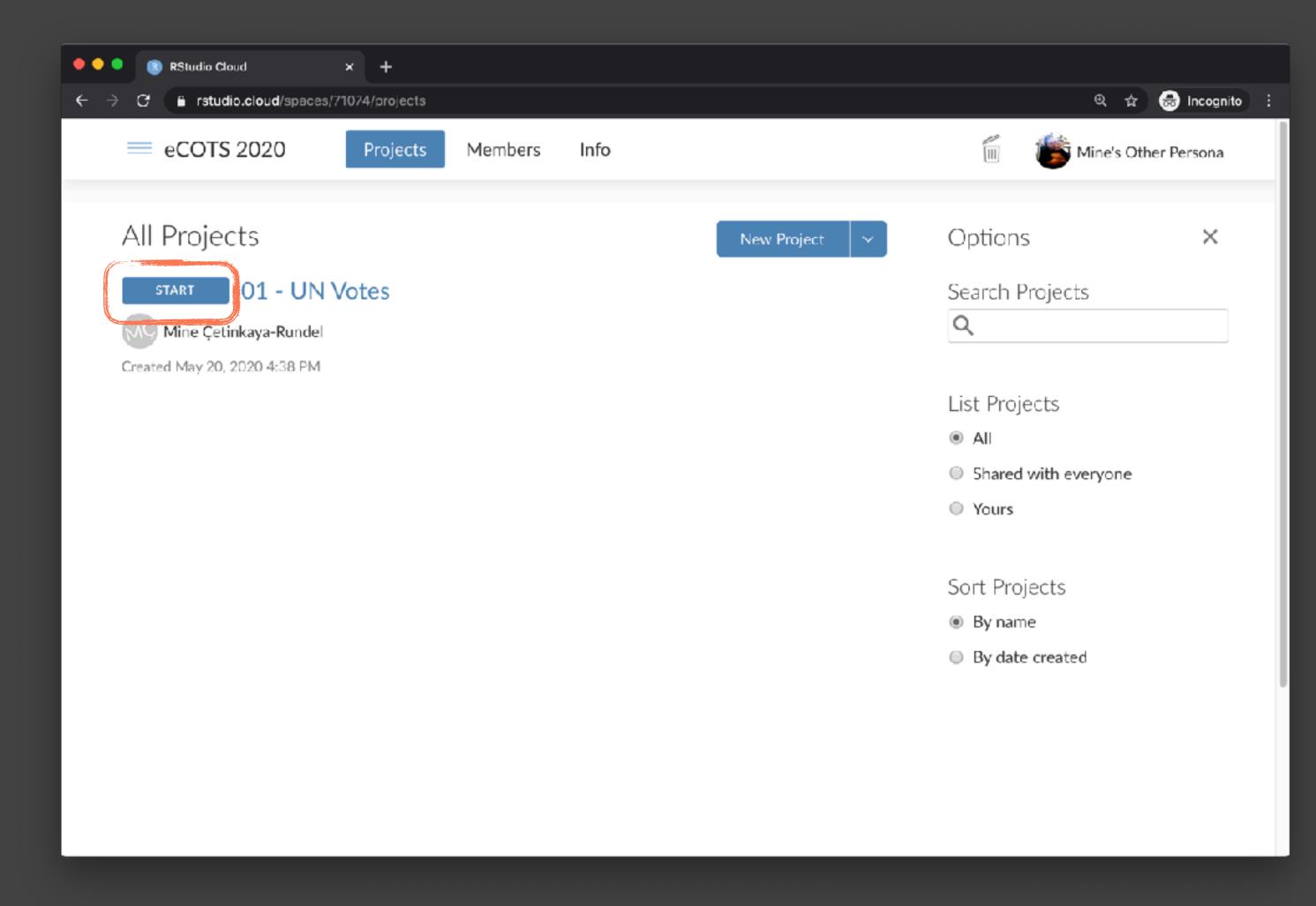






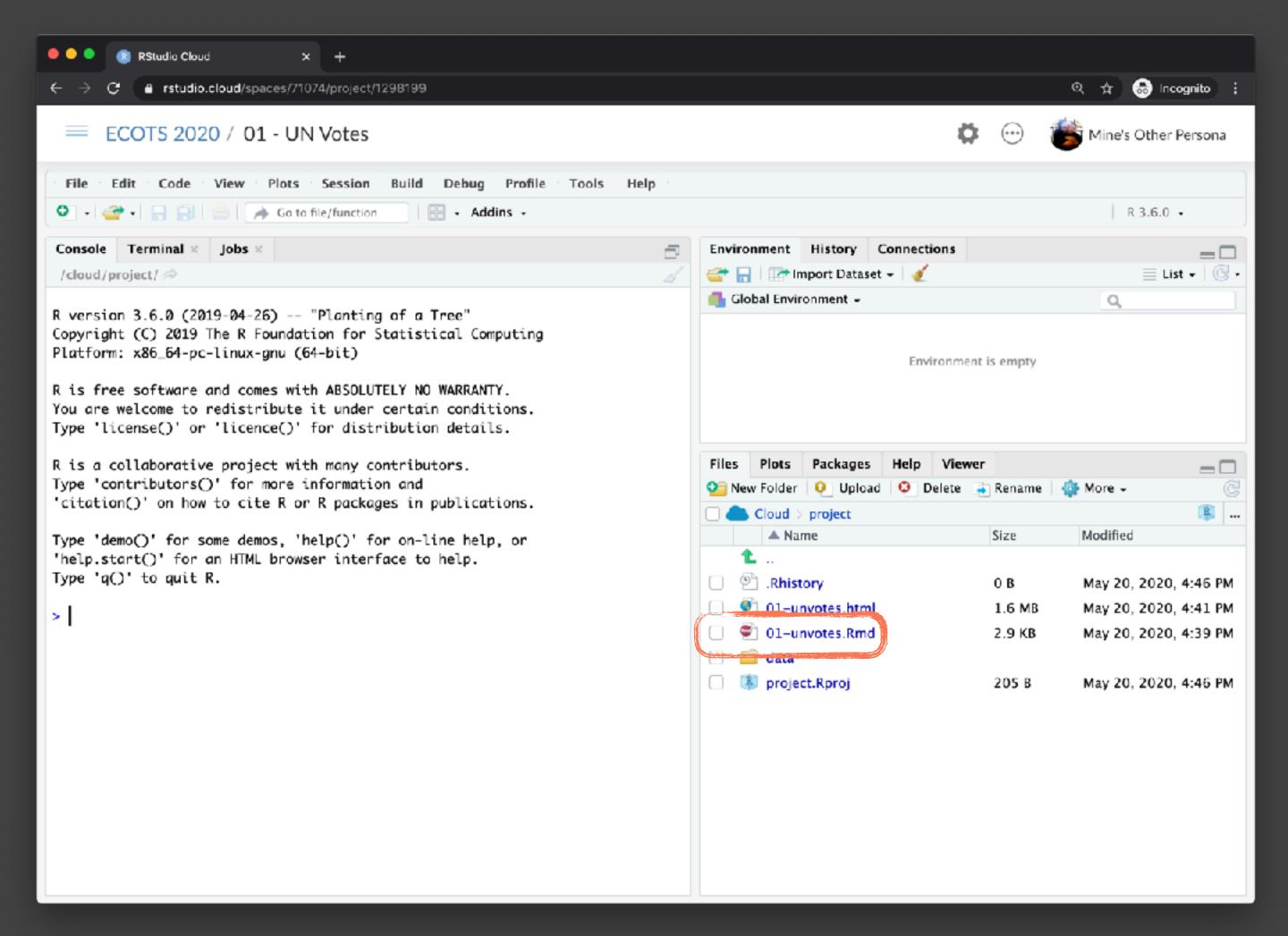
- Go to RStudio Cloud
- Start the project titled UN Votes

# rstd.io/dsbox-cloud



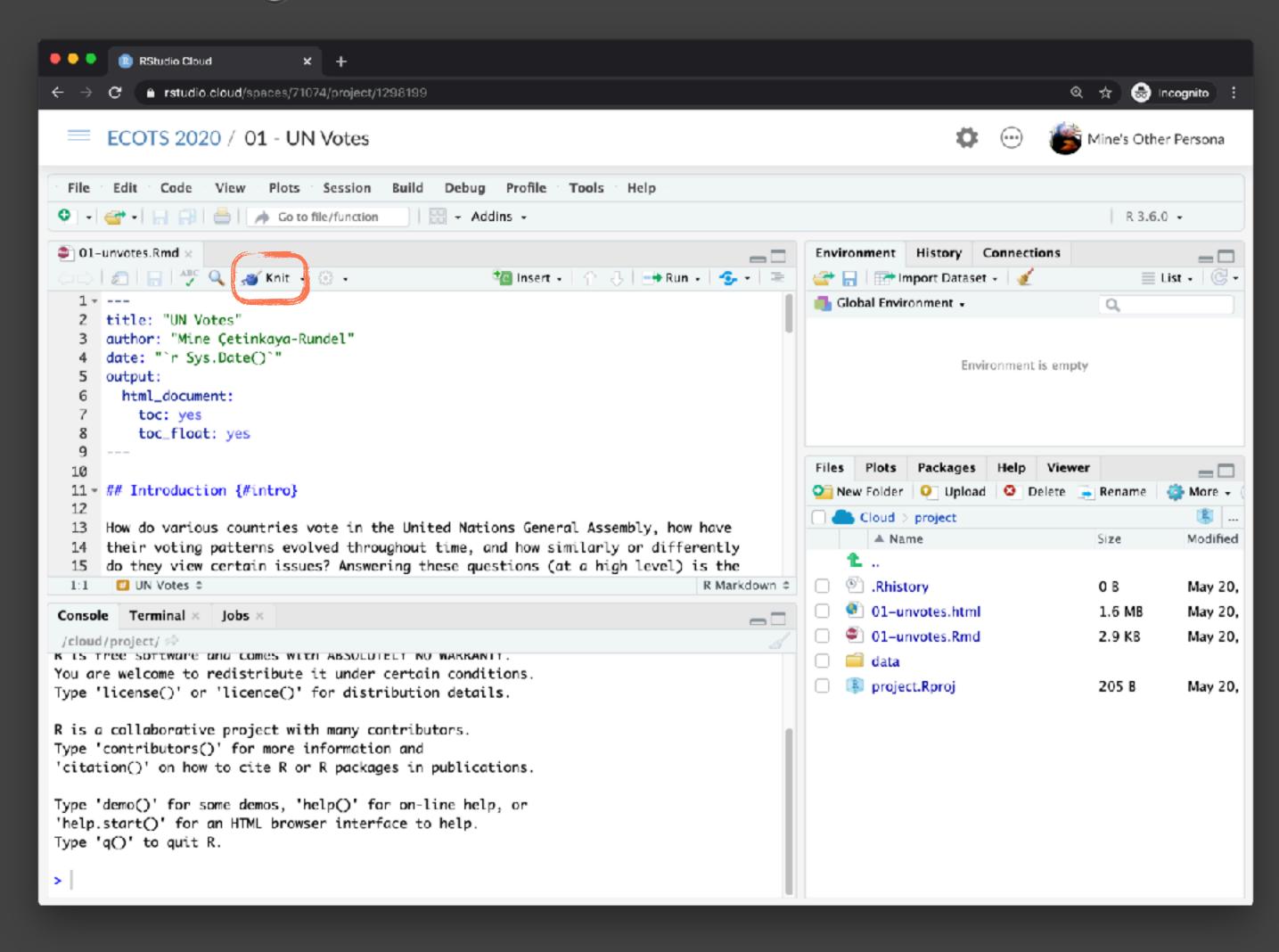
- Go to RStudio Cloud
- Start the project titled UN Votes
- Open the R Markdown
   document called unvotes.Rmd





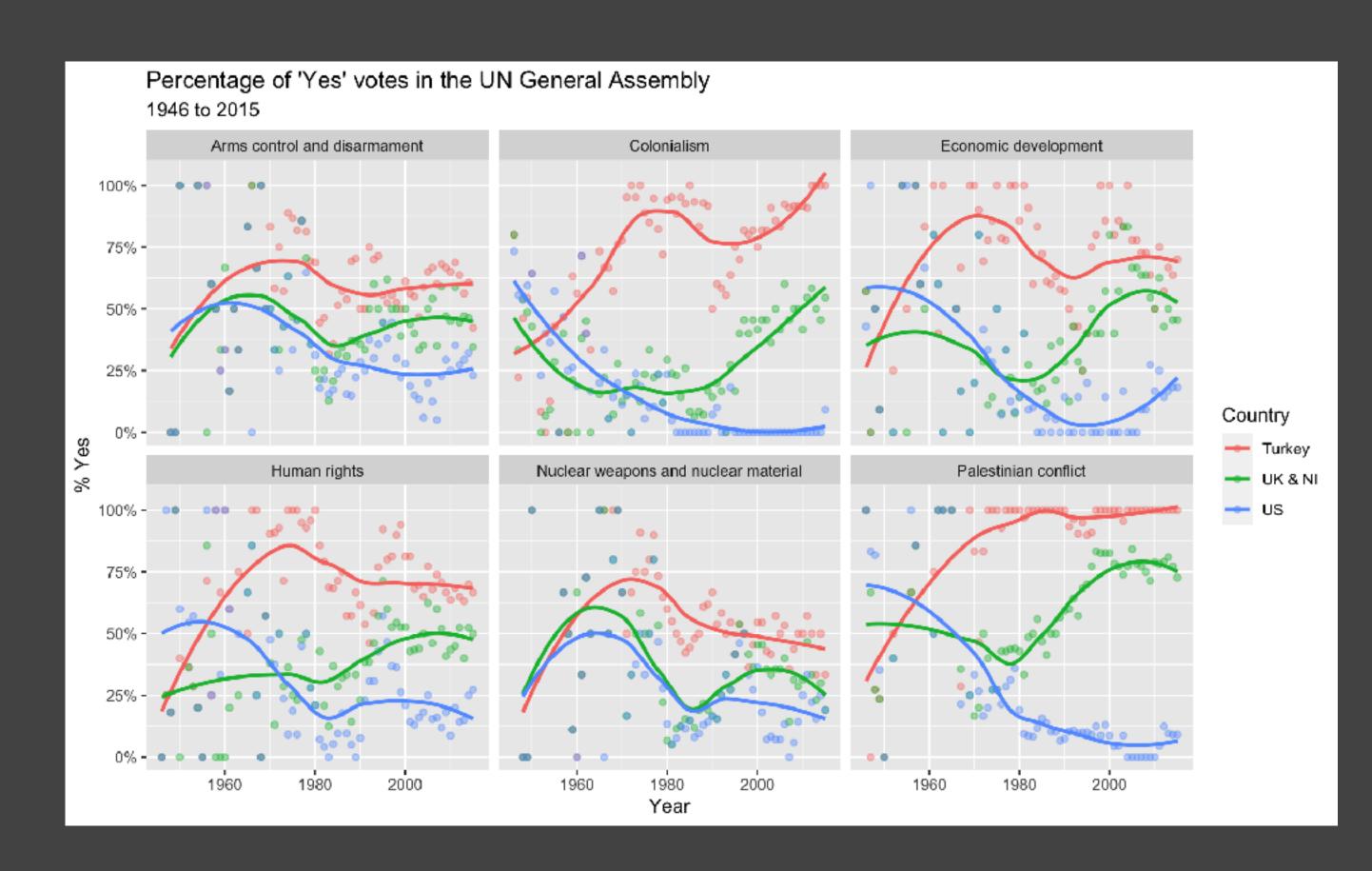
- Go to RStudio Cloud
- Start the project titled UN Votes
- Open the R Markdown
   document called unvotes.Rmd
- Knit the document and review the data visualisation you just produced

# rstd.io/dsbox-cloud



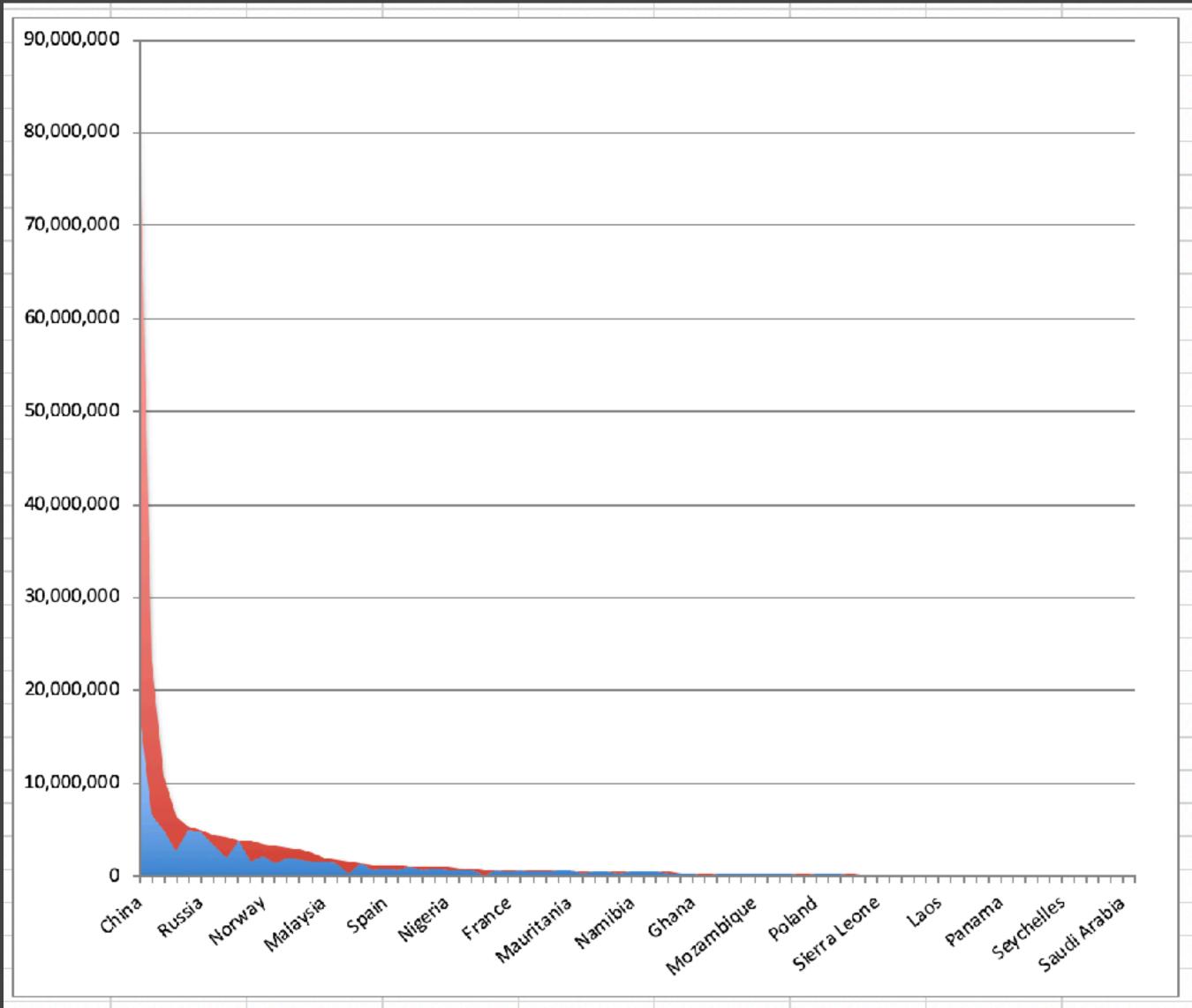
- Go to RStudio Cloud
- Start the project titled UN Votes
- Open the R Markdown
   document called unvotes. Rmd
- Knit the document and review the data visualisation you just produced
- Then, look for the character string "Turkey" in the code and replace it with another country of your choice
- Knit again, and review how the voting patterns of the country you picked compares to the United States and United Kingdom & Northern Ireland

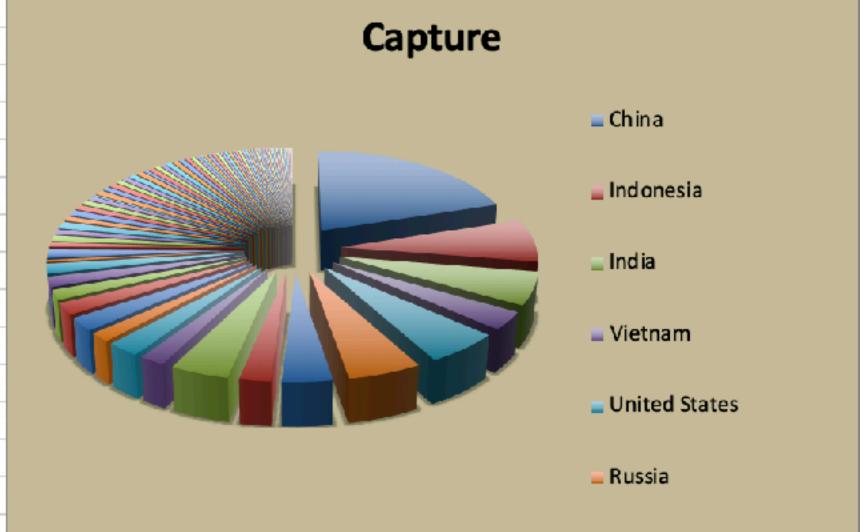


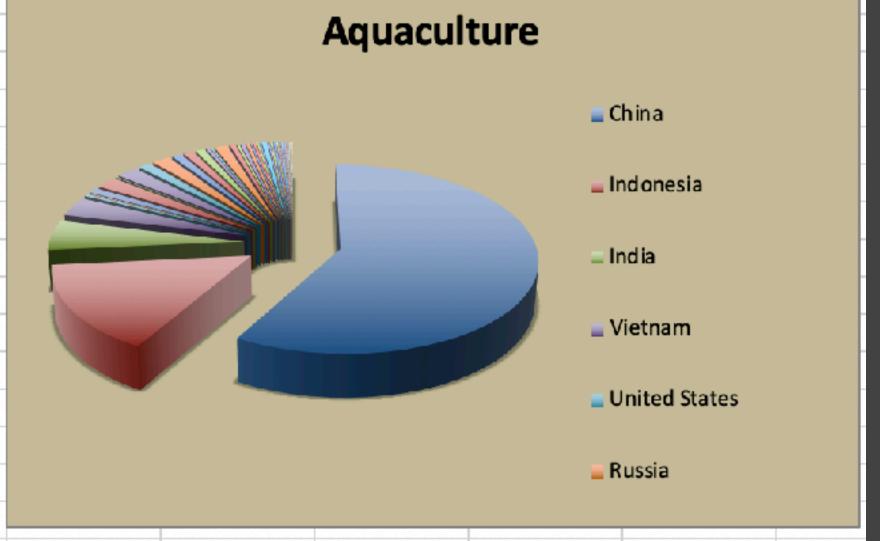












### fisheries %>% select(country)

```
#> # A tibble: 75 x 1
#>
      country
                             continents
      <chr>
#>
                             #> # A tibble: 245 x 2
    1 Algeria
#>
                             #>
                                   country
    2 Angola
#>
                             #>
                                   <chr>
                                                      <chr>
    3 Argentina
#>
                                 1 Afghanistan
                                                      Asia
    4 Australia
#>
```

#### #> 6 Brazil

#>

7 Cambodia #>

5 Bangladesh

- #> 8 Canada
- 9 Chile #>
- #> 10 Colombia
- #> # ... with 65 more rows

```
continent
   2 Åland Islands
                         Europe
   3 Albania
#>
                         Europe
    4 Algeria
                         Africa
    5 American Samoa
                        Oceania
    6 Andorra
                         Europe
                         Africa
   7 Angola
    8 Anguilla
                        Americas
    9 Antigua & Barbuda Americas
  10 Argentina
                         Americas
#> # ... with 235 more rows
```

√ data joins

### fisheries <- left\_join(fisheries, continents)

Joining, by = "country"

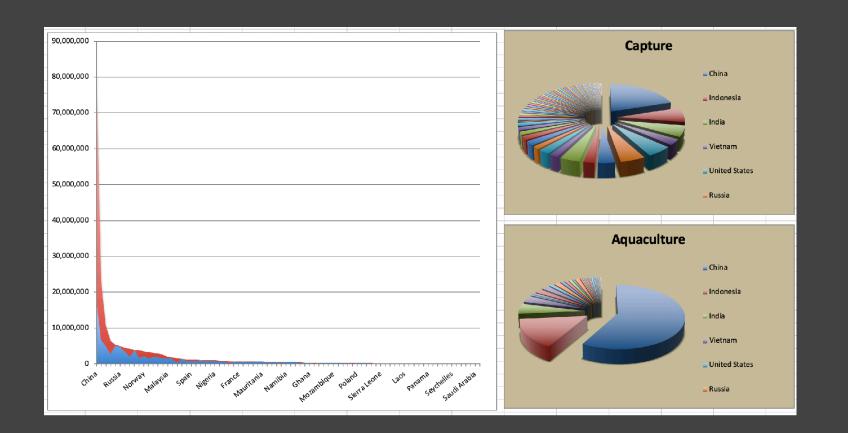
√ data joins

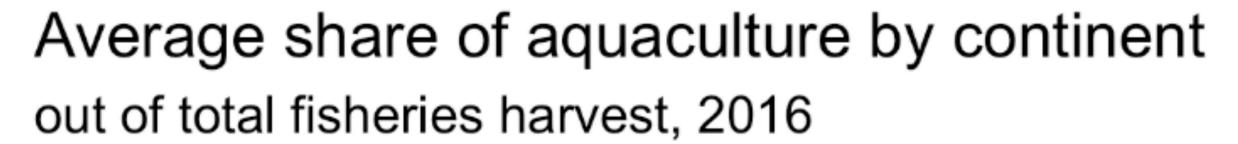
fisheries %>%

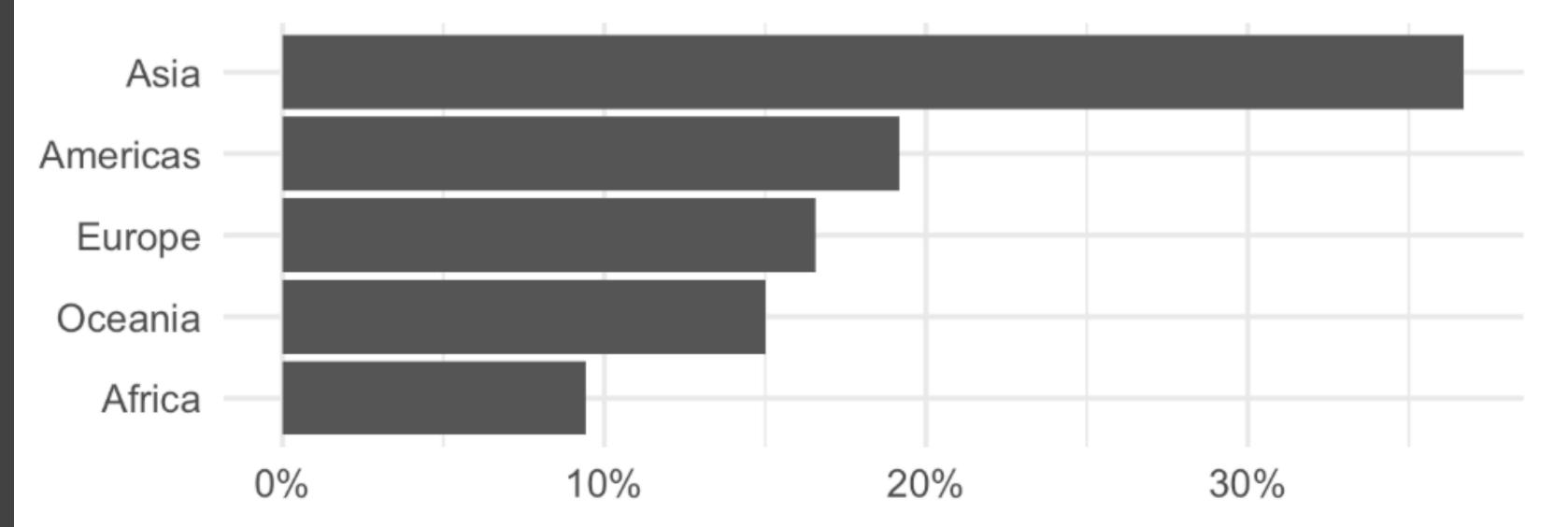
filter(is.na(continent))#> # A tibble: 75 x 1

✓ ethics

```
#> # A tibble: 5 x 4
                                        capture aquaculture continent
#>
     country
                                          <dbl>
     <chr>
                                                      <dbl> <chr>
#>
#> 1 Congo, Democratic Republic of the
                                         220000
                                                       2965 NA
                                         161964
                                                       4130 NA
#> 2 Hong Kong
  3 Myanmar
                                        1742956
                                                     474510 NA
#> 4 Other
                                                     786993 NA
                                        9685851
#> 5 Taiwan (Republic of China)
                                                     304756 NA
                                        1017243
```

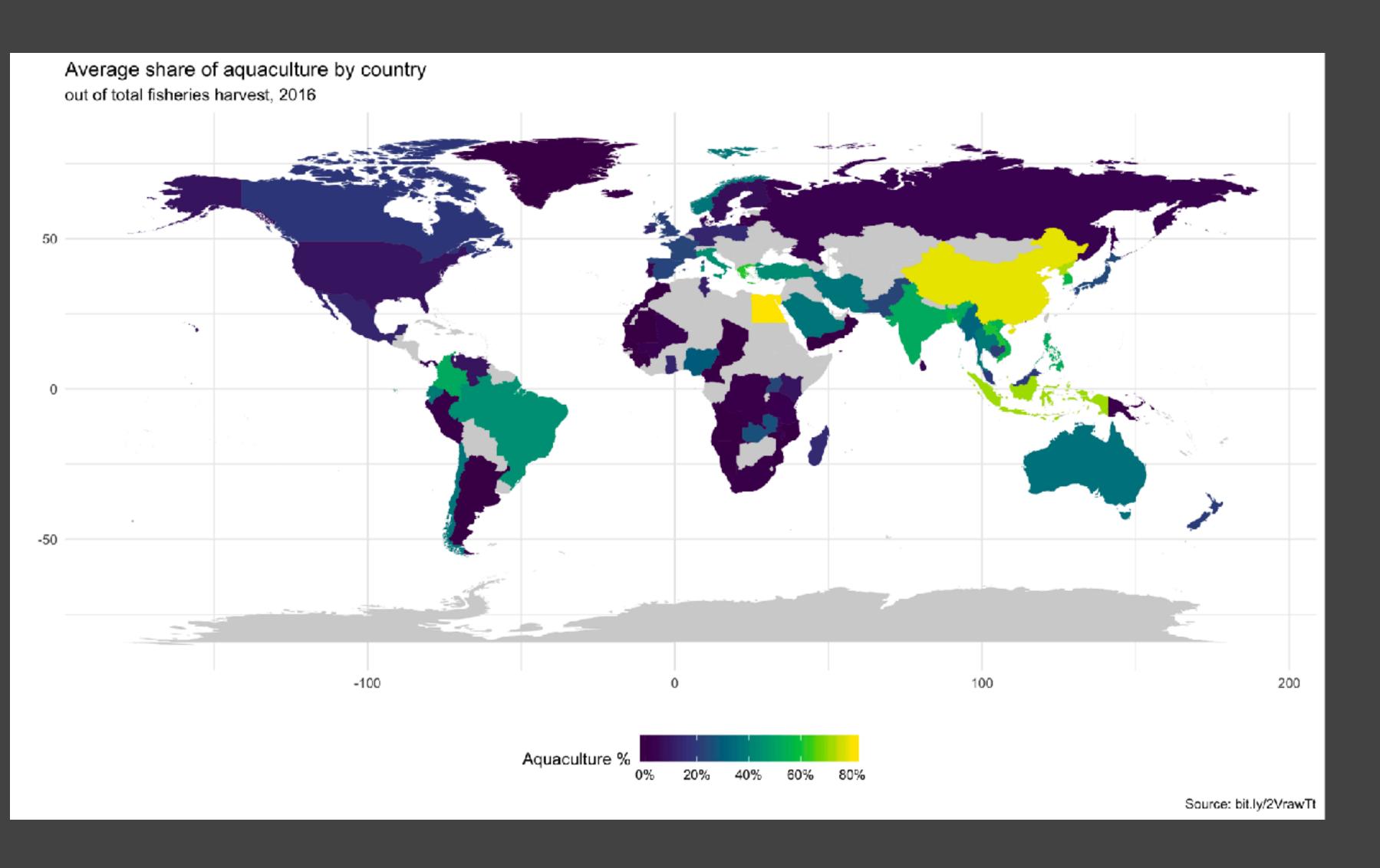






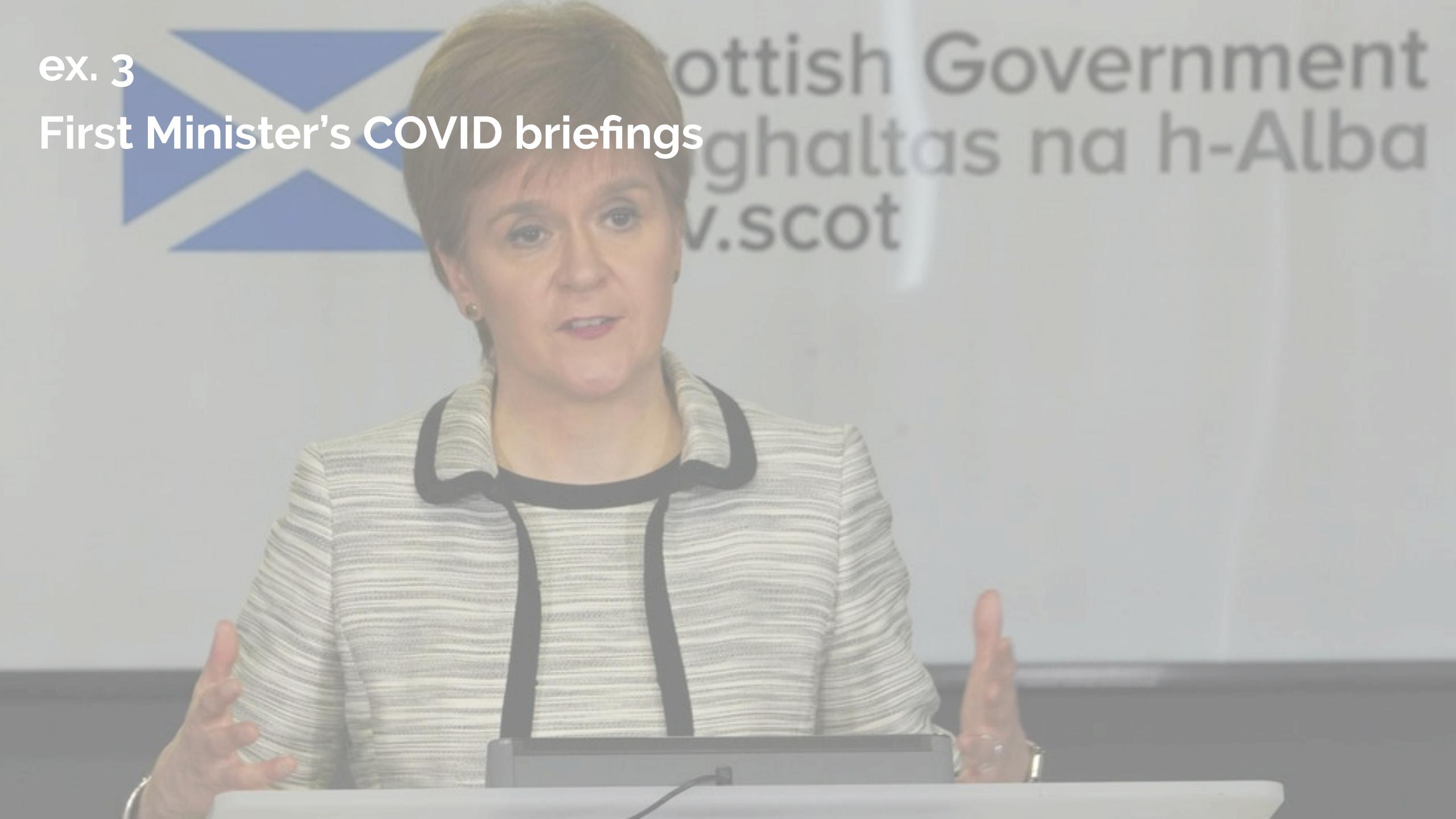
- ✓ data joins
- √ ethics
- ✓ critique
- improving
  visualisations

Source: bit.ly/2VrawTt



- ✓ data joins
- √ ethics
- ✓ critique
- ✓ improving
- √ visualisations
- mapping





# First Minister's speeches

From: First Minister

Speeches delivered by the First Minister Nicola Sturgeon.

#### On this page:

- 2020
- 2019
- 2018
- 2017
- 2016

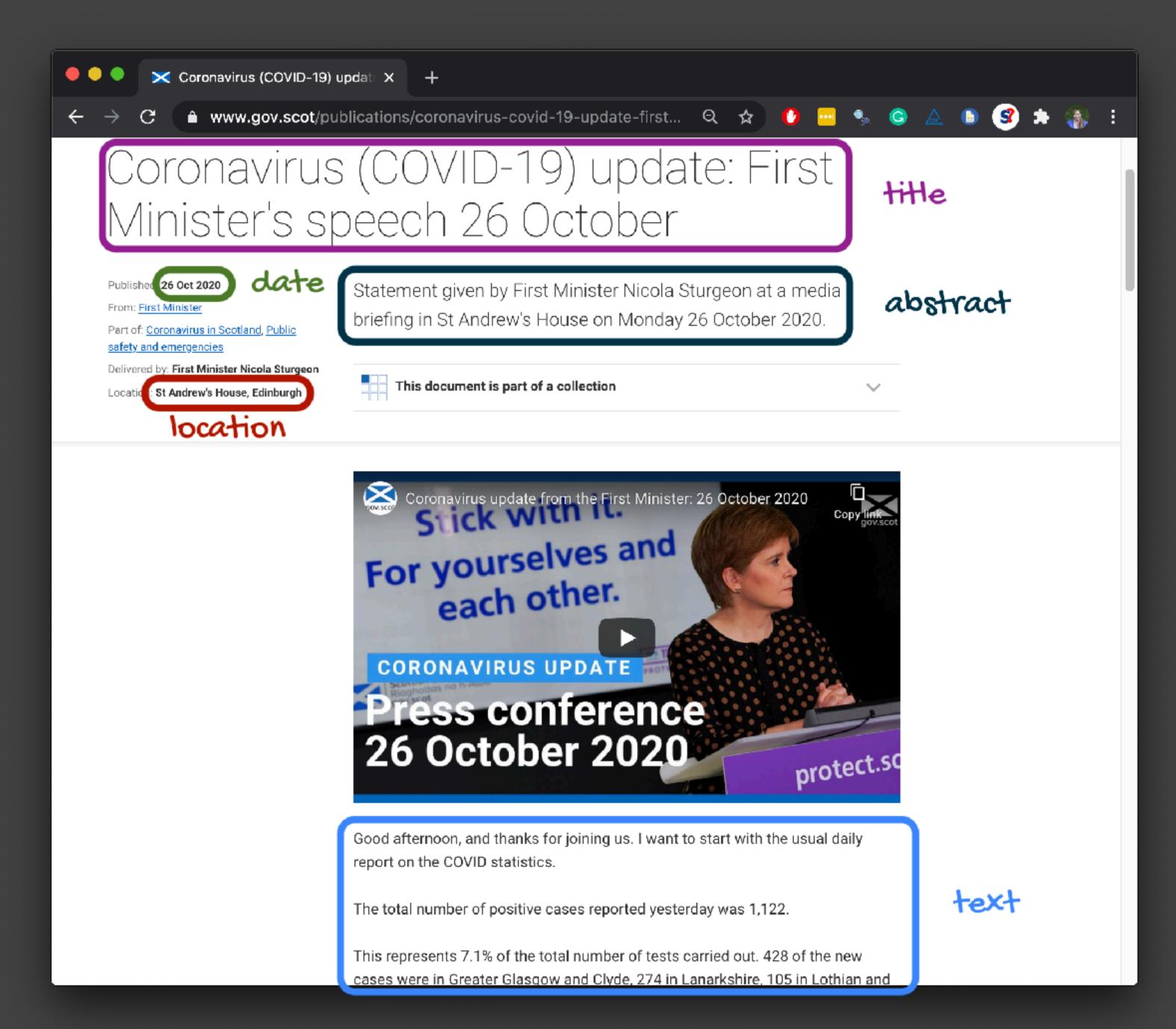
#### 2020

- Coronavirus (COVID-19) update: First Minister's speech 26 October
- Coronavirus (COVID-19) update: First Minister's speech 23 October
- Coronavirus (COVID-19) update: First Minister's speech 22 October 2020
- Coronavirus (COVID-19) update: First Minister's speech 21 October 2020
- Coronavirus (COVID-19) update: First Minister's speech 20 October 2020
- Coronavirus (COVID-19) update: First Minister's speech 19 October 2020
- Coronavirus (COVID-19) update: First Minister's speech 16 October 2020
- Coronavirus (COVID-19) update: First Minister's speech 15 October 2020
- Coronavirus (COVID-19) update: First Minister's speech 14 October 2020
- Coronavirus (COVID-19) update: First Minister's speech 13 October 2020
- Coronavirus (COVID-19) update: First Minister's speech 12 October 2020
- Coronavirus (COVID-19) update: First Minister's speech 9 October 2020

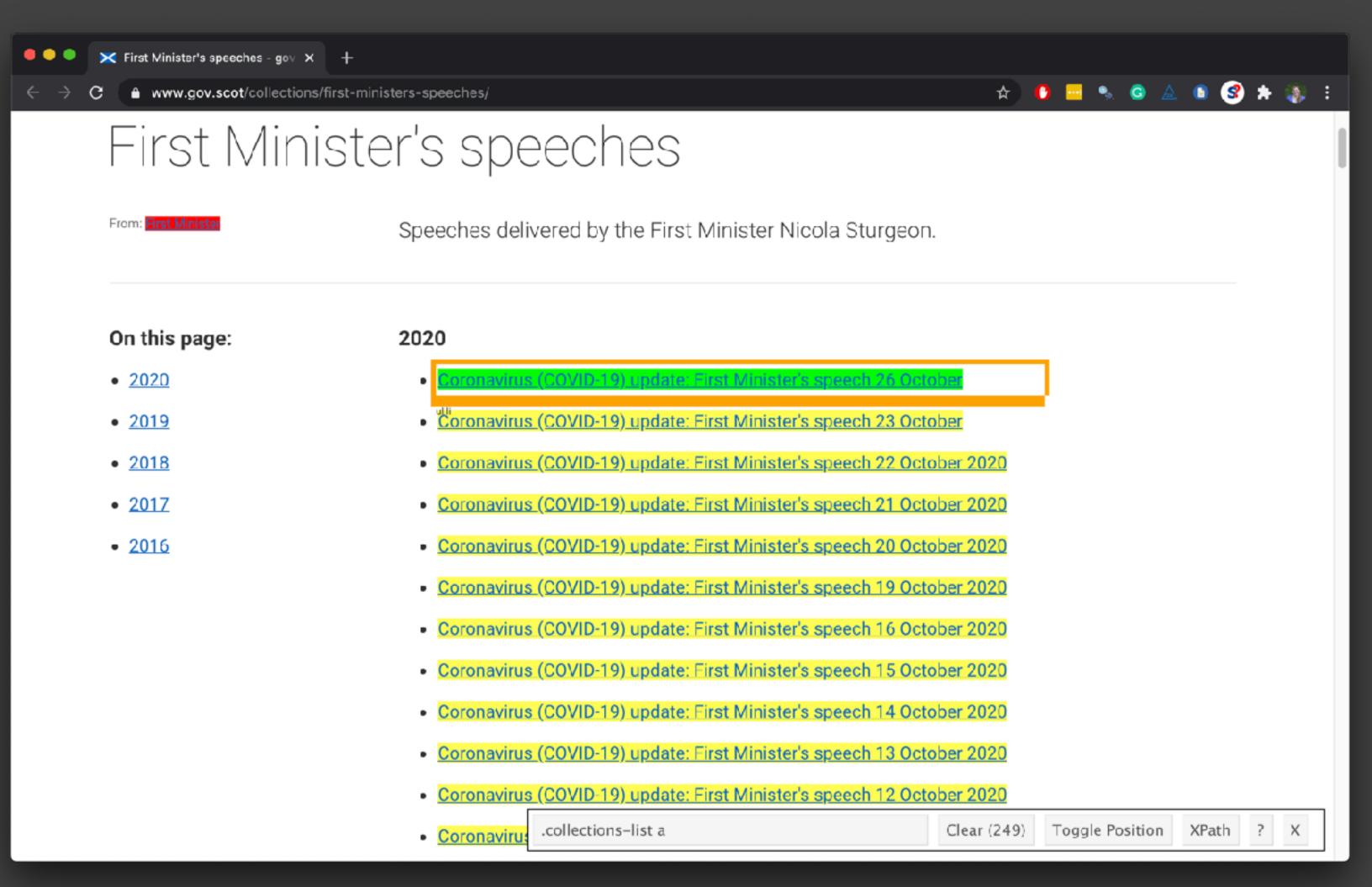


```
robotstxt::paths_allowed("https://www.gov.scot/")
www.gov.scot
```

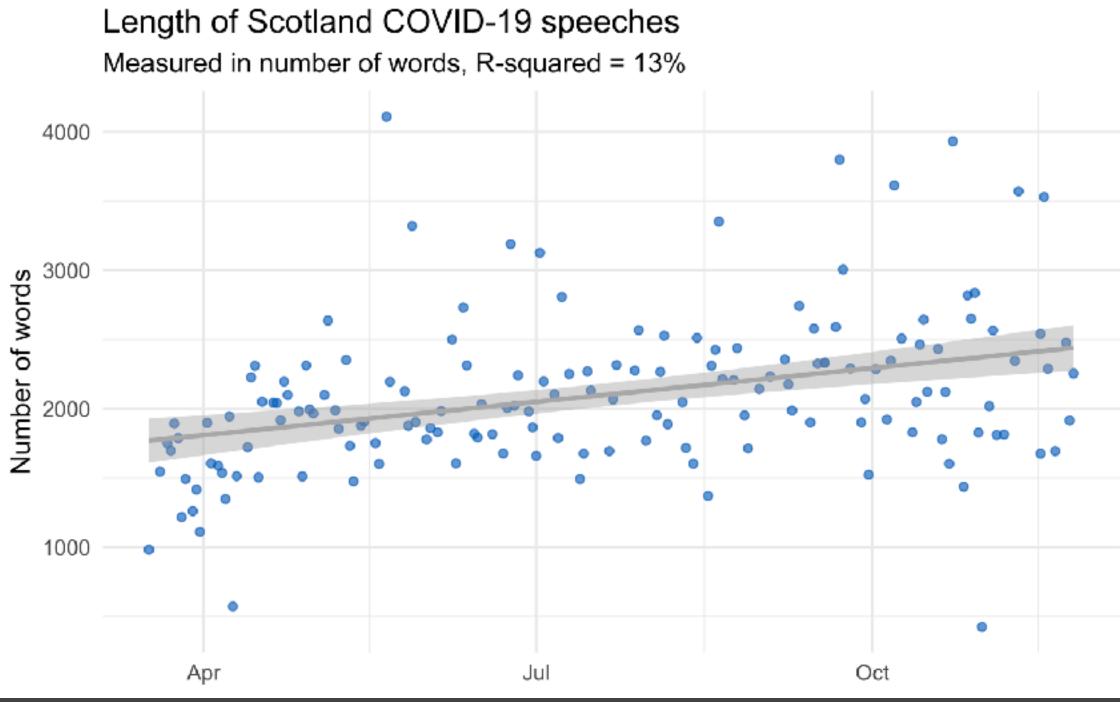
[1] TRUE

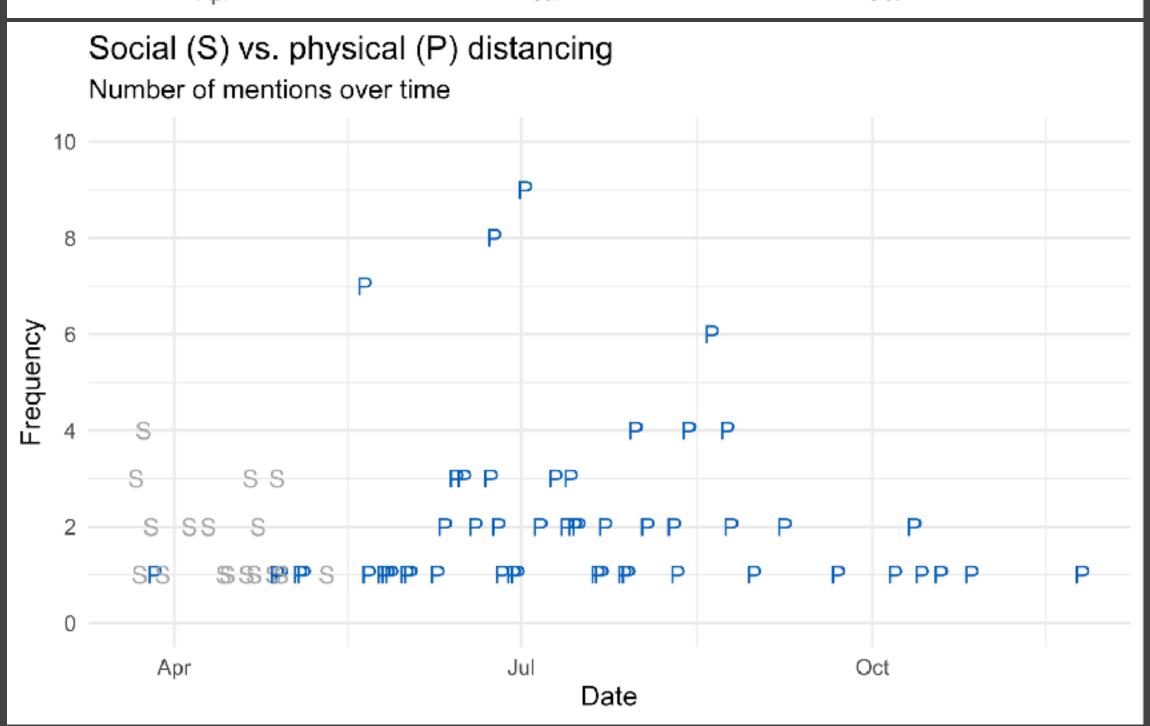


- √ ethics
- web scraping
- √ text parsing
- data types
- regular expressions

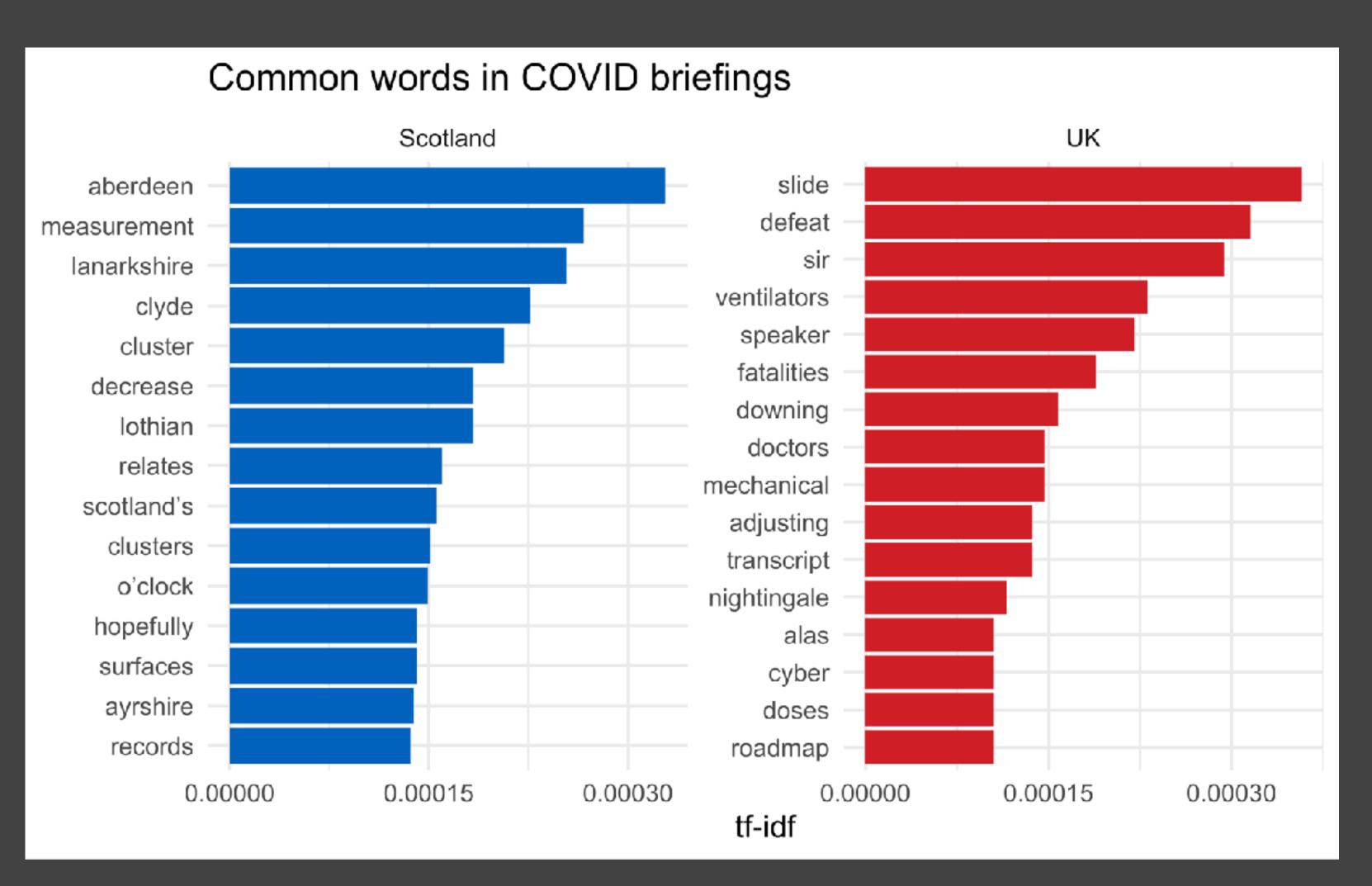


- √ ethics
- ✓ web scraping
- √ text parsing
- √ data types
- ✓ regular expressions
- ✓ functions
- ✓ iteration

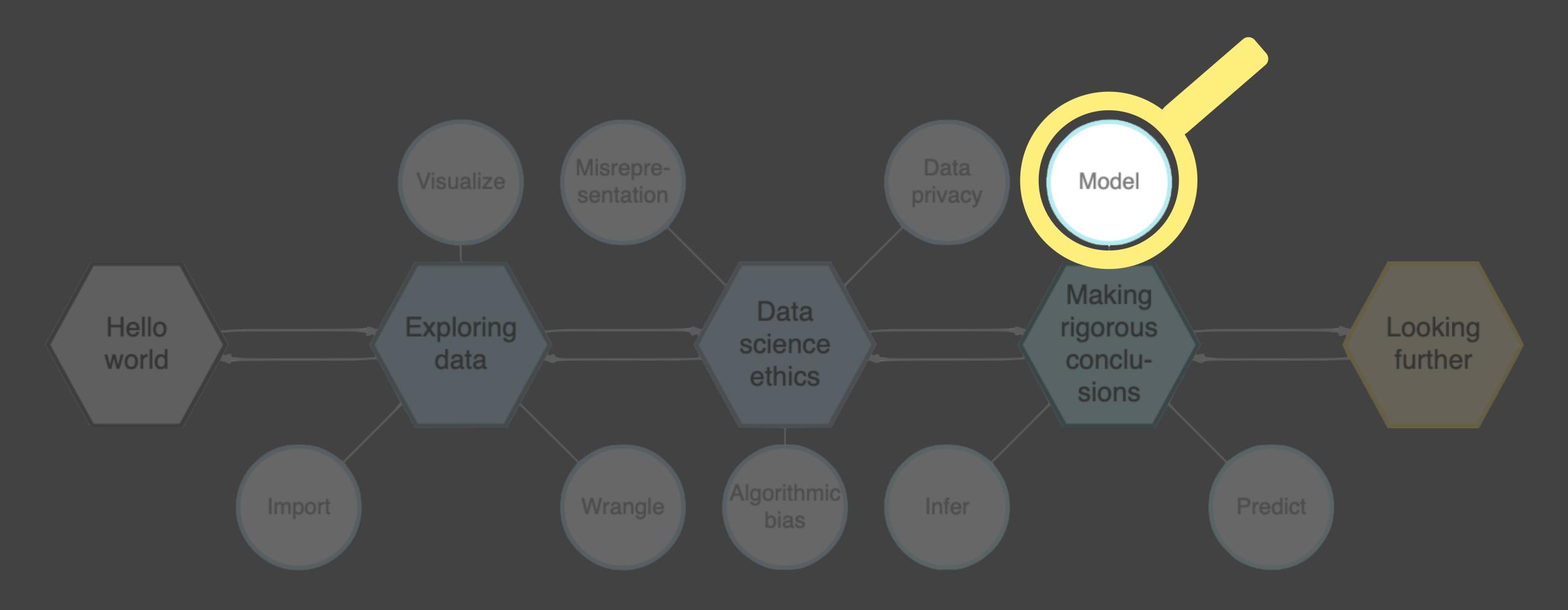




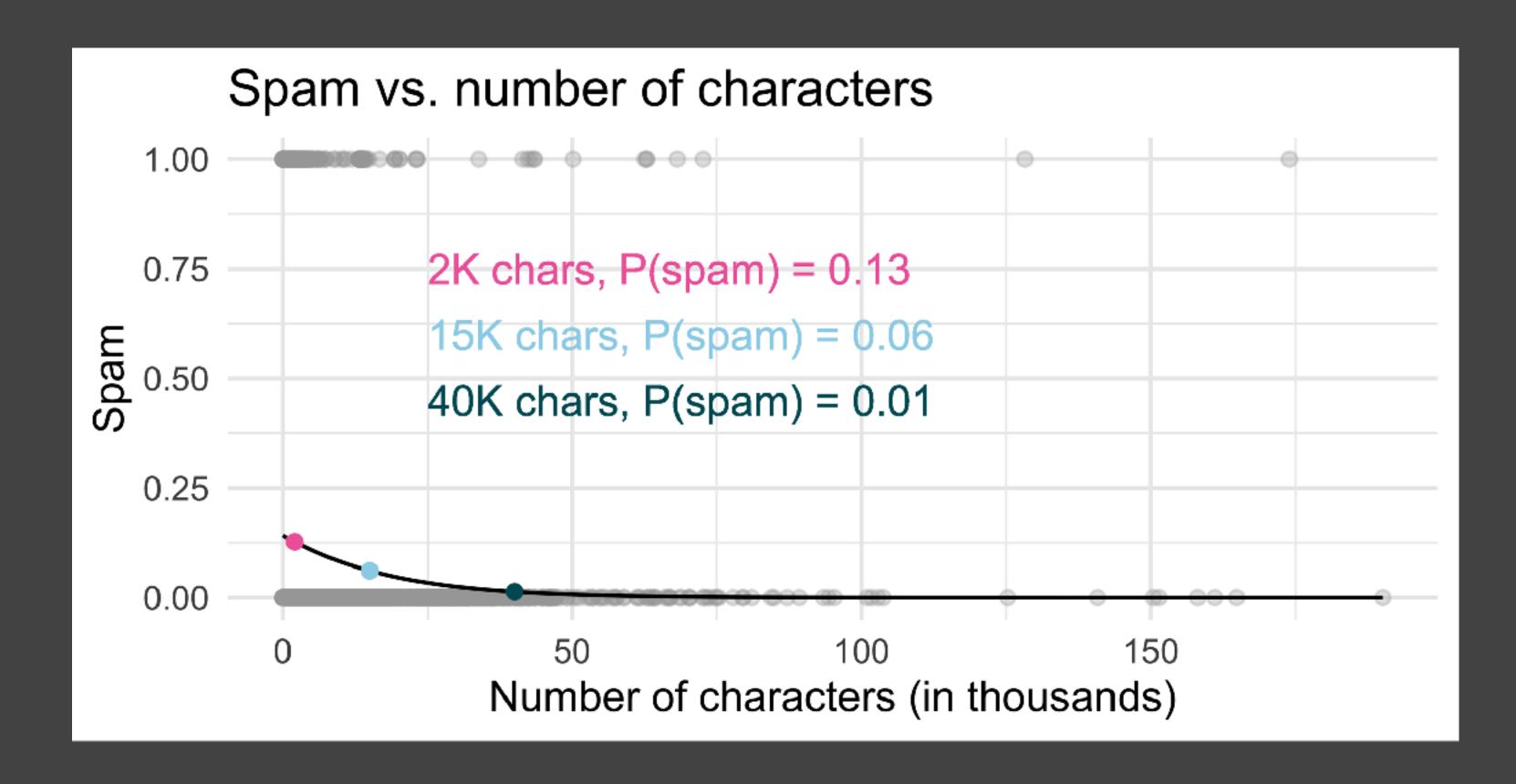
- √ ethics
- ✓ web scraping
- √ text parsing
- ✓ data types
- ✓ regular expressions
- √ functions
- ✓ iteration
- √ visualisation
- ✓ interpretation



- √ ethics
- ✓ web scraping
- √ text parsing
- ✓ data types
- ✓ regular expressions
- ✓ functions
- ✓ iteration
- √ visualisation
- ✓ interpretation
- √ text analysis



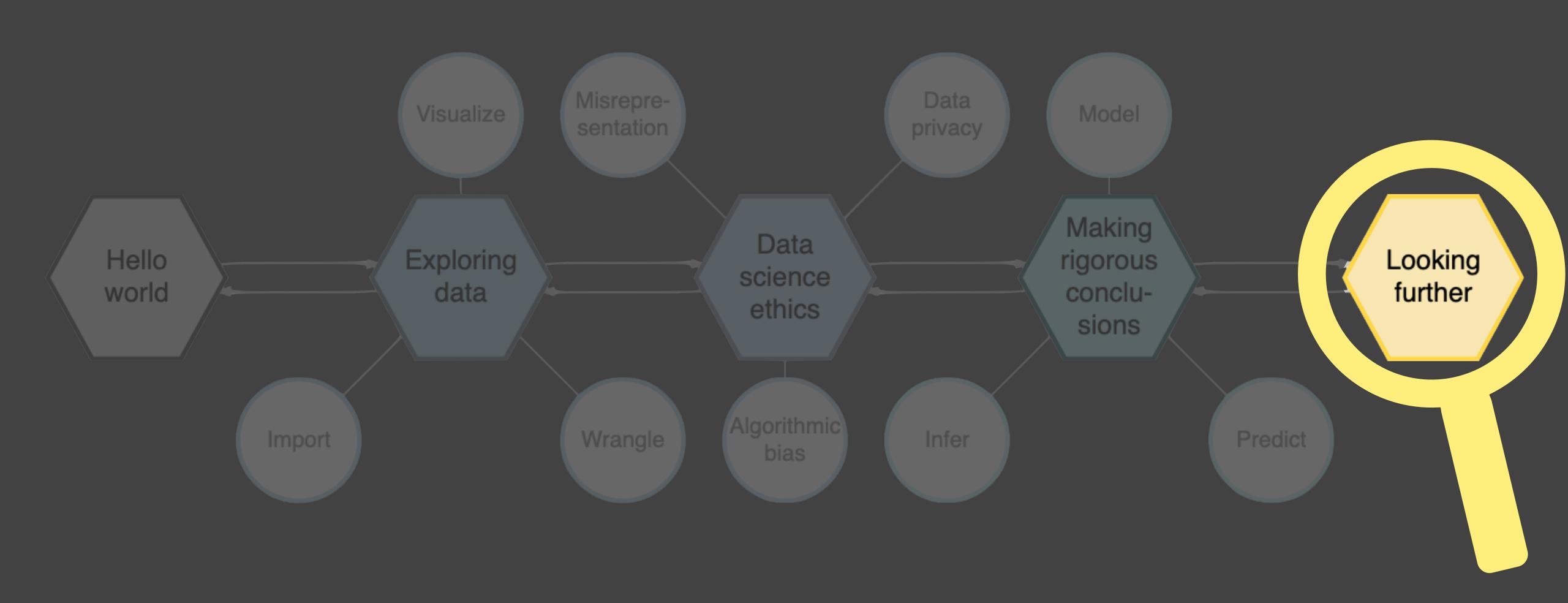


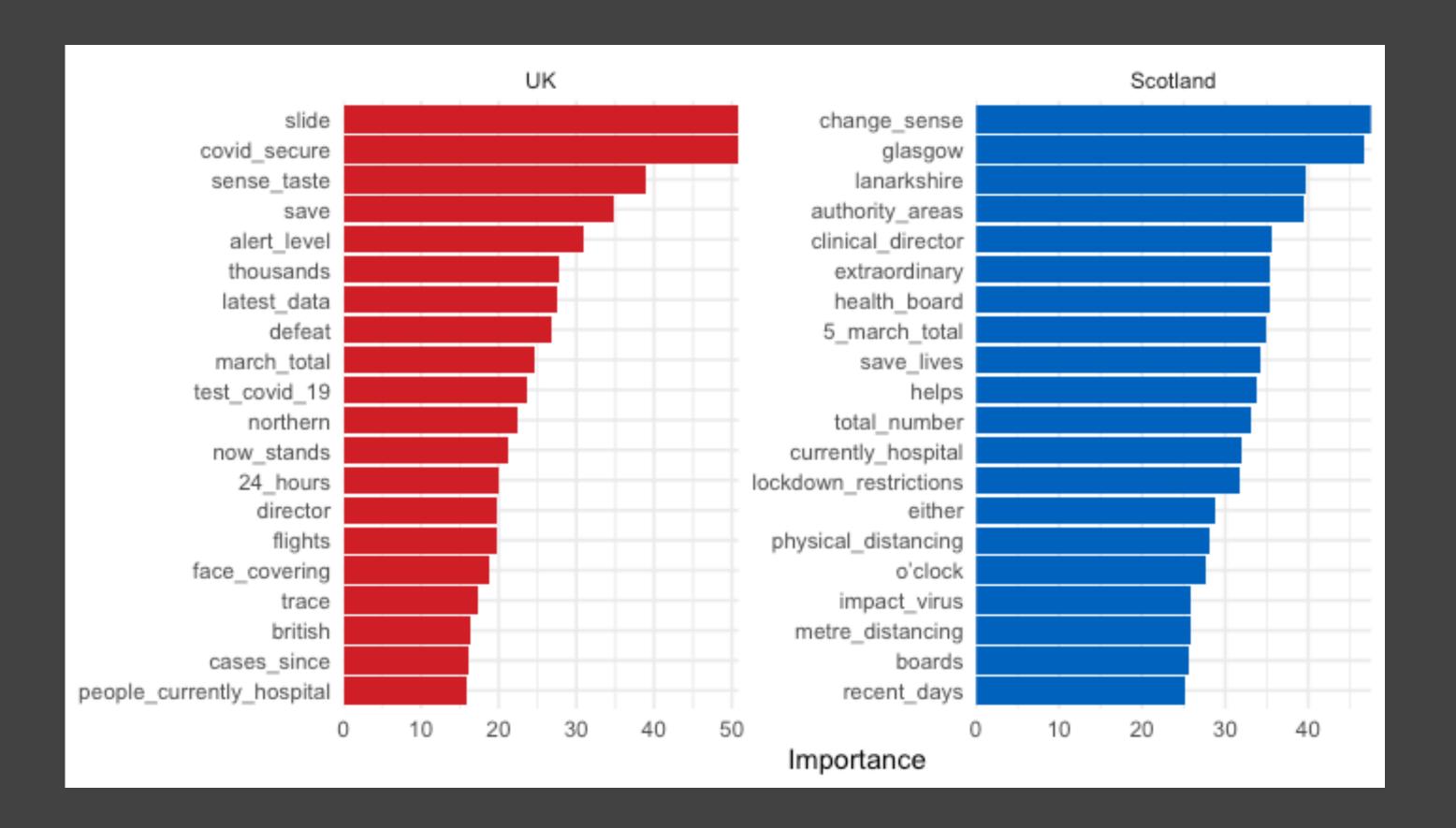


- ✓ logistic regression
- ✓ prediction

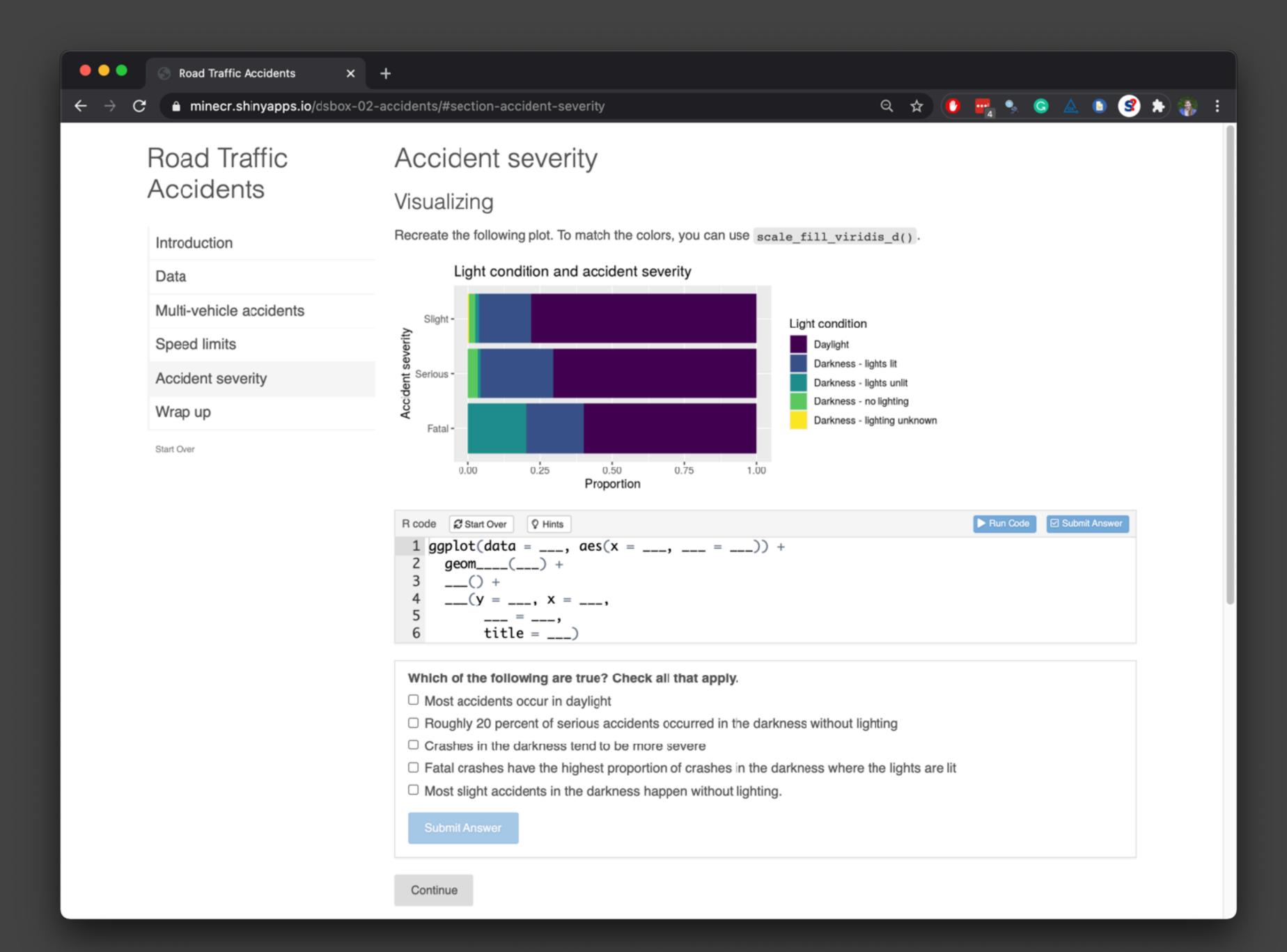
	Email is spam	Email is not spam
Email labelled spam	True positive	False positive (Type 1 error)
Email labelled not spam	False negative (Type 2 error)	True negative

- ✓ logistic regression
- ✓ prediction
- ✓ decision errors
- sensitivity/
  specificity
- ✓ intuition around loss functions



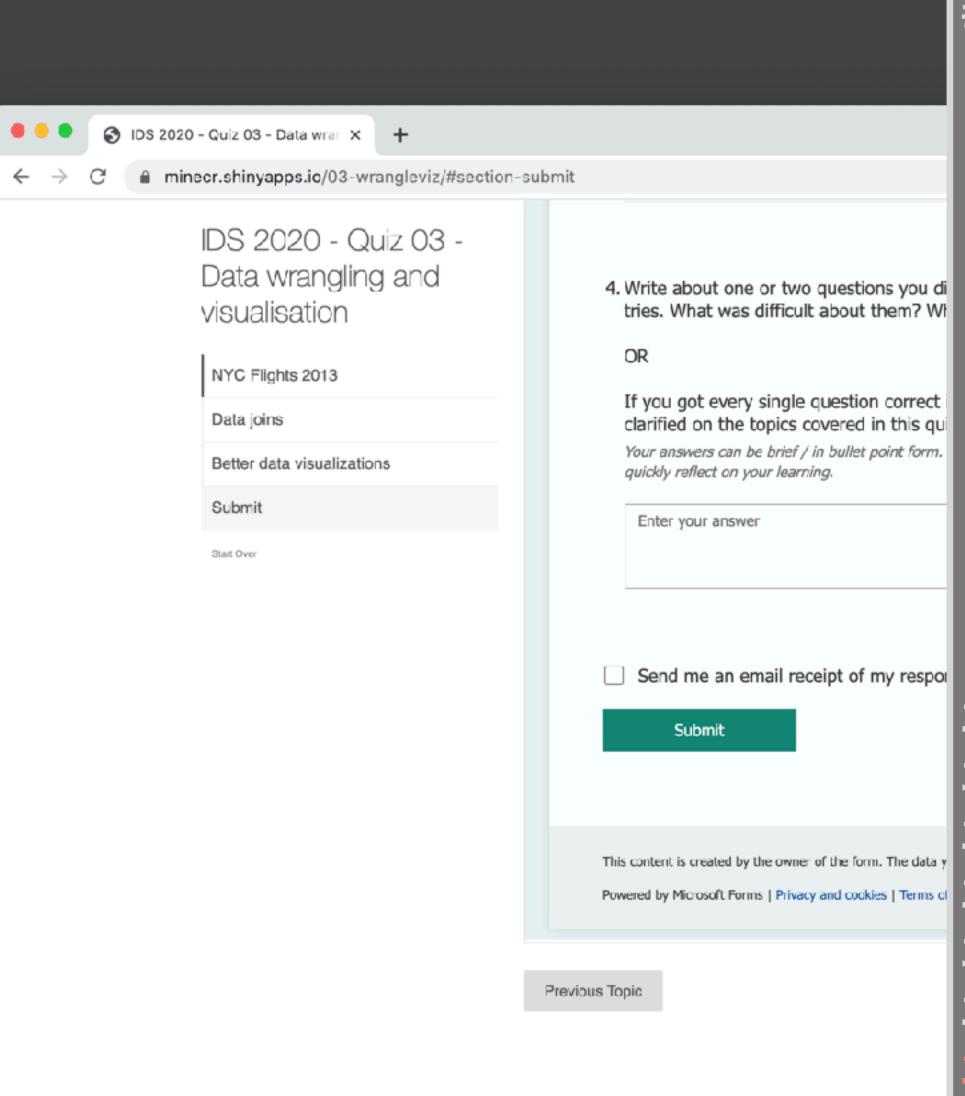


# machine learning for text data



# ✓ repetition

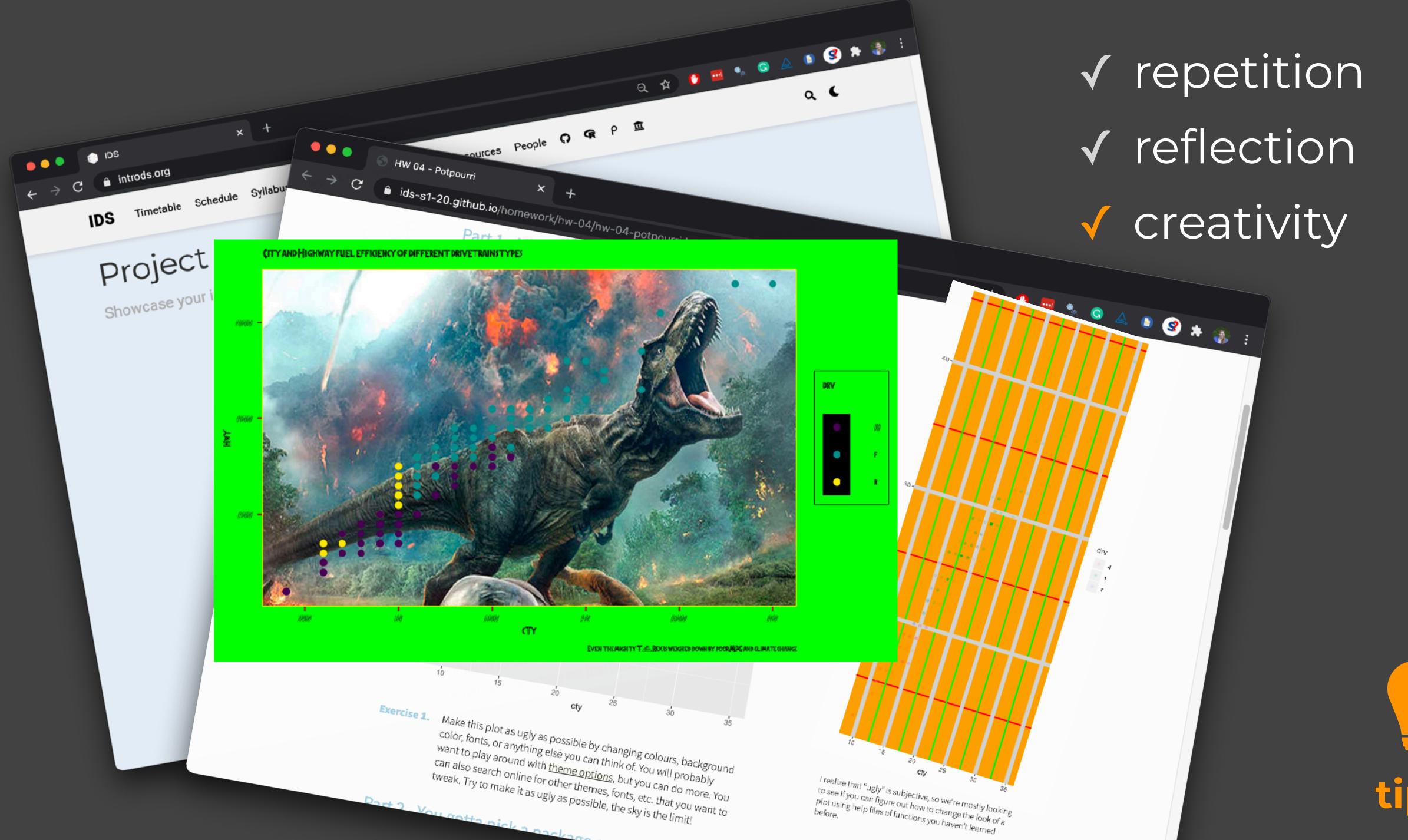




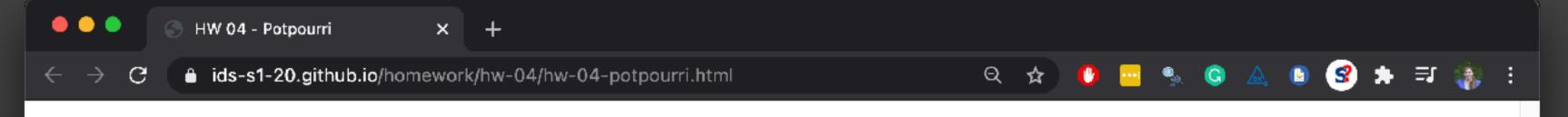
# #	A tibble: 19 x 2	
	bigram	n
	<chr></chr>	<int></int>
1	question 7	19
2	question 8	16
3	questions 7	12
4	join function	9
5	question 2	9
6	choice questions	7
7	first question	7
8	multiple choice	7
9	correct answer	6
10	necessarily improve	6
11	join functions	5
12	question 1	5
13	7 8	4
14	airline names	4
<b>15</b>	data frames	4
16	feel like	4
<b>17</b>	many options	4
18	right answer	4
19	x axis	4

- ✓ repetition✓ reflection









#### Part 3 - Peer review

For the last part of this assignment we're asking you to review **two** projects. You will get access to the two project repos you will review after the workshop on Friday, 20 November. To locate these repos go to the course organisation on GitHub and look for project repos that are not your own, with the name project-SOME-OTHER-TEAM-NAME.

You will have limited access to these repos. You can open issues but you can't make changes to them. To complete your review, go to the **Issues** tab and open a **New Issue**. Then, select the issue template titled **Peer review**, and answer the following questions for the project.

- Describe the goal of the project.
- Describe the data used or collected.
- Describe how the research question will be answered, e.g. what approaches / methods will be used.
- Is there anything that is unclear from the proposal?
- Provide constructive feedback on how the team might be able to improve their project.
- What aspect of this project are you most interested in and would like to see highlighted in the presentation.
- Provide constructive feedback on any issues with file and/or code organization.
- (Optional) Any further comments or feedback?

- √ reflection
- ✓ creativity
- peer review

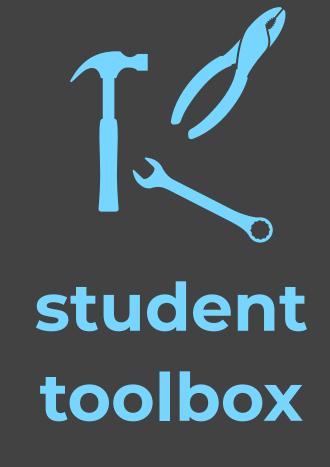


# Add references and info to codebook, fixes #2 committed yesterday Amend code book committed yesterday Removed redundant variable list committed yesterday Add raw data and R Script used for pre-processing, closes #3 committed 2 days ago Use nrow() instead of count() in EDA, fixes #4 committed 2 days ago Delete redundant README.html, closes #1 committed 2 days ago

- √ repetition
- ✓ reflection
- ✓ creativity
- ✓ peer review
- ✓ real workflows

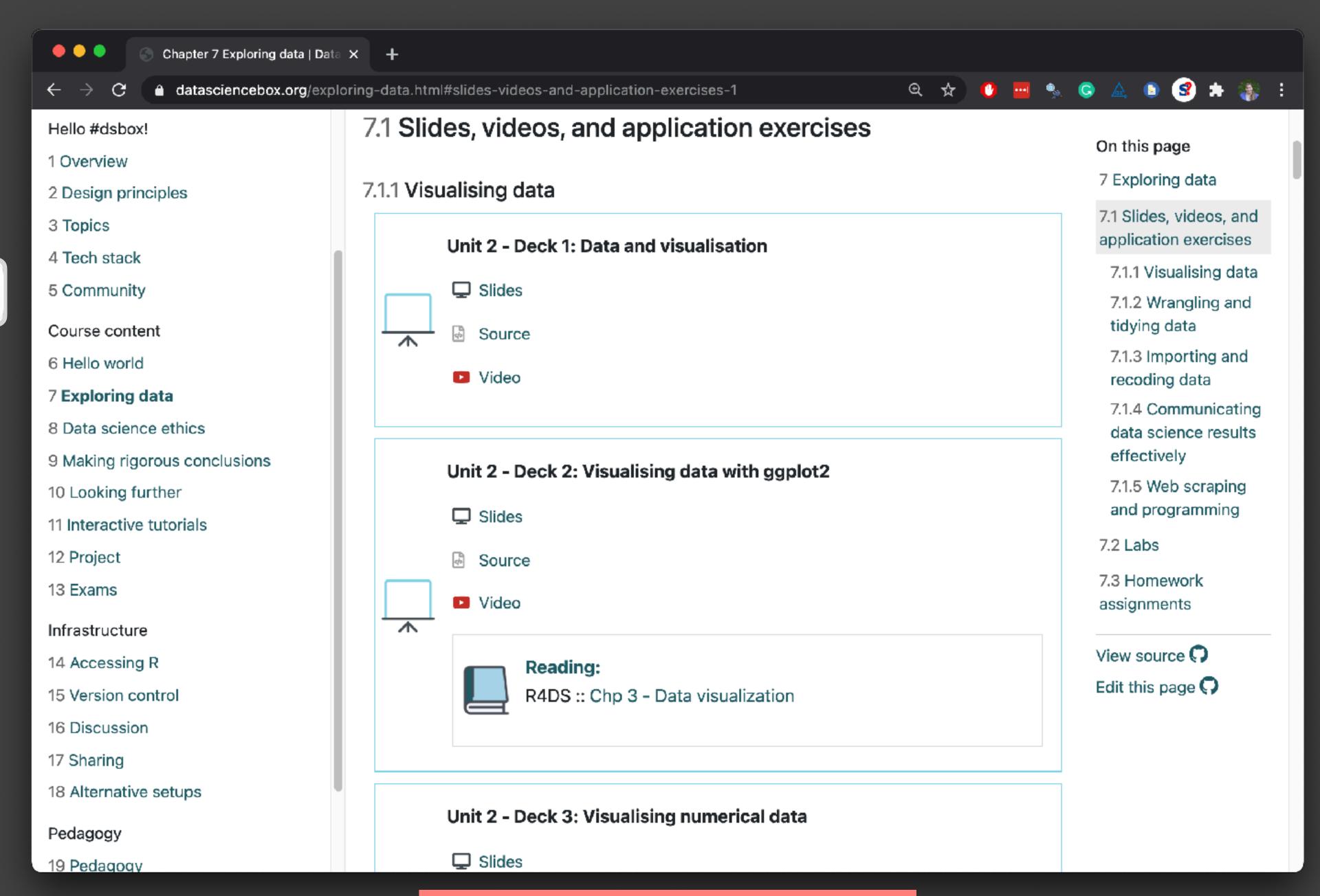


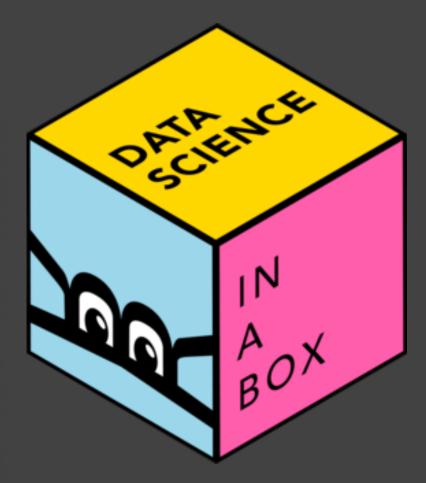














JOURNAL OF STATISTICS EDUCATION 2020, VOL. 00, NO. 0, 1-11 https://doi.org/10.1080/10691898.2020.1804497



බ OPEN ACCESS



#### A Fresh Look at Introductory Data Science

Mine Çetinkaya-Rundel<sup>a,b,c</sup> o and Victoria Ellison<sup>b</sup>

\*School of Mathematics, University of Edinburgh, Edinburgh, UK; Department of Statistical Science, Duke University, Durham, NC; RStudio, Boston, MA

The proliferation of vast quantities of available datasets that are large and complex in nature has challenged universities to keep up with the demand for graduates trained in both the statistical and the computational set of skills required to effectively plan, acquire, manage, analyze, and communicate the findings of such data. To keep up with this demand, attracting students early on to data science as well as providing them a solid foray into the field becomes increasingly important. We present a case study of an introductory undergraduate course in data science that is designed to address these needs. Offered at Duke University, this course has no prerequisites and serves a wide audience of aspiring statistics and data science majors as well as humanities, social sciences, and natural sciences students. We discuss the unique set of challenges. posed by offering such a course, and in light of these challenges, we present a detailed discussion into the pedagogical design elements, content, structure, computational infrastructure, and the assessment methodology of the course. We also offer a repository containing all teaching materials that are opensource, along with supplementary materials and the R code for reproducing the figures found in the article.

Data science curriculum; Data visualization: Exploratory data analysis; Modeling; Reproducibility; R.

#### 1. Introduction

How can we effectively and efficiently teach data science to students with little to no background in computing and statistical thinking? How can we equip them with the skills and tools for reasoning with various types of data and leave them wanting to learn more? This article describes an introductory data science course that is our (working) answer to these questions.

At its core, the course focuses on data acquisition and wrangling, exploratory data analysis, data visualization, inference, modeling, and effective communication of results. Time permitting, the course also provides very brief forays into additional tools and concepts such as interactive visualizations, text analysis, and Bayesian inference. A heavy emphasis is placed on a consistent syntax (with tools from the tidyverse), reproducibility (with R Markdown), and version control and collaboration (with Git and GitHub). The course design builds on the three key recommendations from Nolan and Temple Lang (2010): (1) broaden statistical computing to include emerging areas, (2) deepen computational reasoning skills, and (3) combine computational topics with data analysis. The goal of the course is to bring students from zero experience to being able to complete a fully reproducible data science project on a dataset of their choice and answer questions that they care about within the span

most recent curriculum guidelines for undergraduate programs — meant to encompass is still debated. However, in this article,

in data science, statistics, and computer science. In this section, we also present a synopsis of the course content and structure of introductory data science courses at four other institutions with the goal of providing a snapshot of the current state of affairs in undergraduate introductory data science curricula. In Section 3, we outline the overall design goals of the Duke University introductory data science course that is the focus of this article and discuss how this course addresses current undergraduate curriculum guidelines in statistics and data science. In Section 4, we expand on the course content, flow, and pacing, and present examples of case studies from the course. In Section 5, we detail the pedagogical methods employed by this course, specifically addressing how these methods can support a large class with students with a diverse range of previous experiences in statistics and programming. Section 6 presents the computing infrastructure of the course, Section 7 presents the methods of assessment, and finally in Section 8, we provide a synthesis of where this course sits in the landscape of introductory data science curriculum guidelines, future design plans for the course, and opportunities and challenges for faculty wanting to adopt this

#### 2. Background and Related Work

In Section 2 of this article, we start with a review of the An exact characterization of what the field of data science is

CONTACT Mine Cetinkaya-Rundel 🔯 cetinkaya.mine@gmail.com 🔄 School of Mathematics, University of Edinburgh, Edinburgh EH9 3FD, UK. © 2020 The Author(s). Published with license by Taylor and Francis Group, LLC.

This is an Open Access article distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0%), which permits unrestricted use, distribution. and reproduction in any medium, provided the original work is properly cited. The moral rights of the named author(s) have been asserted.

Mine Çetinkaya-Rundel & Victoria Ellison (2020)

# A Fresh Look at Introductory **Data Science** Journal of Statistics Education

DOI: 10.1080/10691898.2020.1804497

