Angela M. Zoss, Ph.D.

Visualization for Data Science with R

To my family.

I’m so grateful for your support.

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Proposal

Note: This book is a work in progress, with a full draft expected in April of 2022.

This book combines instruction on writing R code with building basic graphic design skills in a way that is unusual in data science literature. The book will guide readers through a series of projects, each designed to cover both how visualizations work in R and how visualizations can be designed to have the greatest impact. Far more than a "do this, then this" checklist, this book will focus on building understanding, confidence, and the ability to transfer skills to other tools and design contexts. It will avoid technical jargon that our target audience is unlikely to have encountered before. To accommodate learners who don't have time to work through an entire book, each chapter will operate independently, covering a specific set of tasks that all make sense together as part of a visualization project. For those who would like extra practice, there will be several types of hands-on exercises, from those that are entirely prescribed to those that allow readers to apply new techniques to problems in their own areas.

The book will have solutions (in the form of completed code and sample output) for all exercises. While not a textbook, the book will also include a brief teacher's guide for courses that might want to use one or more chapters to structure lessons in a course. The book will also have a website, including links to Open Access content, solutions, and related resources like video tutorials.

The target audience of this book would be professionals who are having to learn data science techniques on the job, likely at an under-resourced organization or company. These newly minted data professionals may feel comfortable in Excel but have only just started to learn R for processing data. They have never used a programming language to build a visualization before, and even creating charts in Excel has often been a frustrating and mystifying process. They appreciate that R is freely available and are able to get started on a data science project, but the idea of creating publication-quality visualizations using only code is daunting.

Increasingly, programs of study with a focus on preparing students for professional careers in under-resourced fields, like public policy and even management, include courses on data analysis and communication using freely available software. This book, while not a textbook, could easily be used for a semester-long course, titled something like "Practical data visualization for the modern workforce." A chapter could be covered each week, and larger projects could help learners synthesize chapters into a complete set of analyses and communication materials.

Why read this book

This book will be:

- Written for non-academics, beginning programmers
- Each chapter stands alone
- Covers pressing modern issues, like accessibility and ethics
- Focuses on freely available software
- Combines hands-on exercises with basic graphic design principles

Structure of the book

- Chapter 1: Overview of common visualizations and how to read them
- Chapter 2: Building basic visualizations with ggplot2
- Chapter 3: Working with textual data in ggplot2
- Chapter 4: Customizing the design of ggplot2 visualizations
- Chapter 5: Avoiding unethical design practices
- Chapter 6: Building ggplot2 visualizations into print publications
- Chapter 7: Basic accessibility for static visualizations
- Chapter 8: Exploring interactivity in visualizations with plotly and crosstalk
- Chapter 9: Using RMarkdown to build websites for projects
- Chapter 10: Using RMarkdown to build dashboards for projects
- Chapter 11: Basic usability for interactive visualizations
- Chapter 12: Teacher's guide

Software information and conventions

I used the **knitr** package (Xie, 2015) and the **bookdown** package (Xie, 2021) to compile my book. My R session information is shown below:

```
xfun::session_info()
```

```
## R version 4.1.0 (2021-05-18)
## Platform: x86_64-apple-darwin17.0 (64-bit)
## Running under: macOS Big Sur 10.16
##
## Locale: en_US.UTF-8 / en_US.UTF-8 / en_US.UTF-8 / C / en_US.UTF-
8 / en_US.UTF-8
##
## Package version:
##   base64enc_0.1.3   bookdown_0.23
##   compiler_4.1.0    digest_0.6.27
##   evaluate_0.14     glue_1.4.2
##   graphics_4.1.0    grDevices_4.1.0
##   highr_0.9         htmltools_0.5.1.1
##   jquerylib_0.1.4   jsonlite_1.7.2
##   knitr_1.33        magrittr_2.0.1
##   markdown_1.1      methods_4.1.0
##   mime_0.11         rlang_0.4.11
##   rmarkdown_2.10    rstudioapi_0.13
##   stats_4.1.0       stringi_1.7.3
##   stringr_1.4.0     tinytex_0.33
##   tools_4.1.0       utils_4.1.0
##   xfun_0.25         yaml_2.2.1
```

Package names are in bold text (e.g., **rmarkdown**), and inline code and filenames are formatted in a typewriter font (e.g., `knitr::knit('foo.Rmd')`). Function names are followed by parentheses (e.g., `bookdown::render_book()`).

Angela Zoss

About the Author

FIGURE 1: Angela M. Zoss, Ph.D.

Angela is the Assessment & Data Visualization Analyst[1] in the Assessment & User Experience Department[2] in the Duke University Libraries[3]. She has many years of experience in teaching and training, predominantly focusing on teaching data visualization to university students, faculty, and staff. She is also active in several open source development projects, including FOLIO[4] and Wax[5].

[1] https://library.duke.edu/about/directory/staff/angela.zoss
[2] https://library.duke.edu/about/depts/assessment-user-experience
[3] https://library.duke.edu/
[4] https://github.com/folio-org/
[5] https://github.com/minicomp/wax

1

Overview of common visualizations and how to read them

This book will cover how to create a variety of visualizations using R. One of the first things you should do to improve your skills creating visualizations is to become familiar with the kinds of visualizations that are possible and the different features of each.

Effective visualization design relies on a solid understanding of how data properties, visualization types, and audience characteristics interact to help people make sense of a visualization. In this chapter, we'll look at a series of common visualization types, and we'll break down how each is meant to be read. Understanding these basic visualization types will create a solid foundation for communicating your data science work to a broad audience.

1.1 Visualization components

As we discuss different visualizations, we will also be talking about different components within the visualizations. In figure 1.1 below, the major components of the visualization are labeled: the main title, the subtitle, the x axis title, the y axis title, the panel, the horizontal and vertical gridlines, and the axis labels and tick marks for both axes. Almost all of the visualizations we cover in this book will use these basic components.

In this set of basic visualization components, we see two components labeled as an axis. These axes are called the x and y axes, and they always appear in these positions: the x axis always goes left to right, and the y axis always goes up and down.

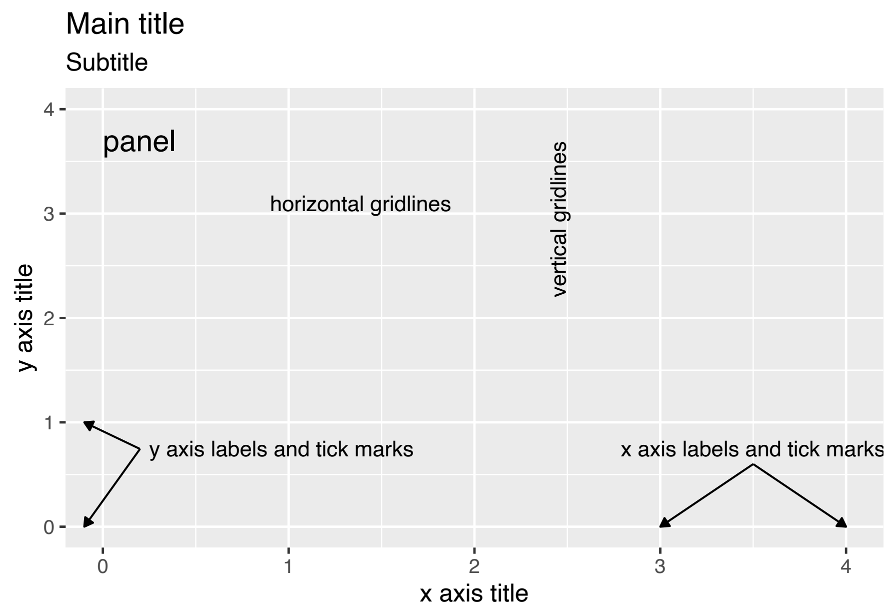


FIGURE 1.1: Visualization components, labeled.

1.2 Bar Chart

The bar chart is possibly the most common type of visualization. In this type of visualization, the basic shape being used to represent data values is a rectangle. In a traditional bar chart, each rectangle (or bar) has exactly the same width, and the height of the bar is representative of some data value. To create a simple bar chart, the data set should have one column that contains textual (or categorical) data and one column that contains numerical data. A common way to create these two columns is to start with one categorical data column and count the number of records for each category to create the numerical column.

In the sample bar chart above, the categorical variable is displayed on the x axis and the numerical variable is displayed on the y axis. This results in a classic style of bar chart where each bar has the same width and the heights are proportionate to a data value. Each bar has a starting value of zero on the y axis. Each bar travels upward from zero and stops at the correct data value.

When reading this visualization, we are comparing the lengths of bars in order to understand patterns within the numerical data values from our data set.

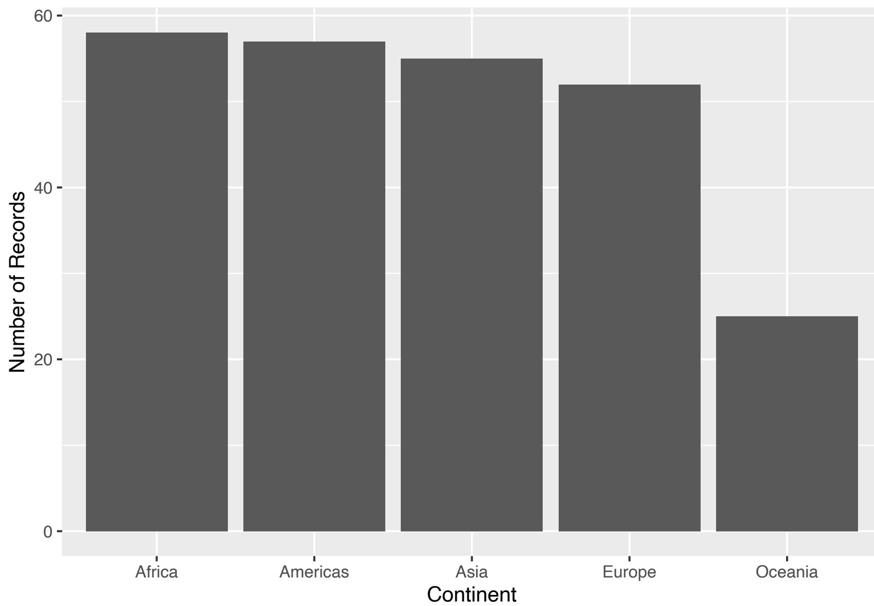


FIGURE 1.2: A sample bar chart.

The power of the bar chart lies in how precisely we can detect differences in the end points of the bars. This is something that people naturally do quite well when all of the bars start at the same lowest point, or baseline.

Bar charts are especially effective if the bars that have small differences in lengths appear close to each other. In the above chart, this is accomplished by arranging the bars so they appear with the highest data values on the left and the lowest data values on the right.

Here is another example of a bar chart where the data values include both positive and negative values. For data values that are negative, the bar travels downward from zero and stops at the correct data value. The x axis title and labels appear at the bottom of the panel, below the lowest data values.

For stylistic reasons, bar charts may also appear with the bars oriented horizontally instead of vertically. In that case, each bar will have the same height, and the widths of the bars will vary based on the data values. The text (or categorical) axis will then be the y axis, and the numerical axis will be the x axis.

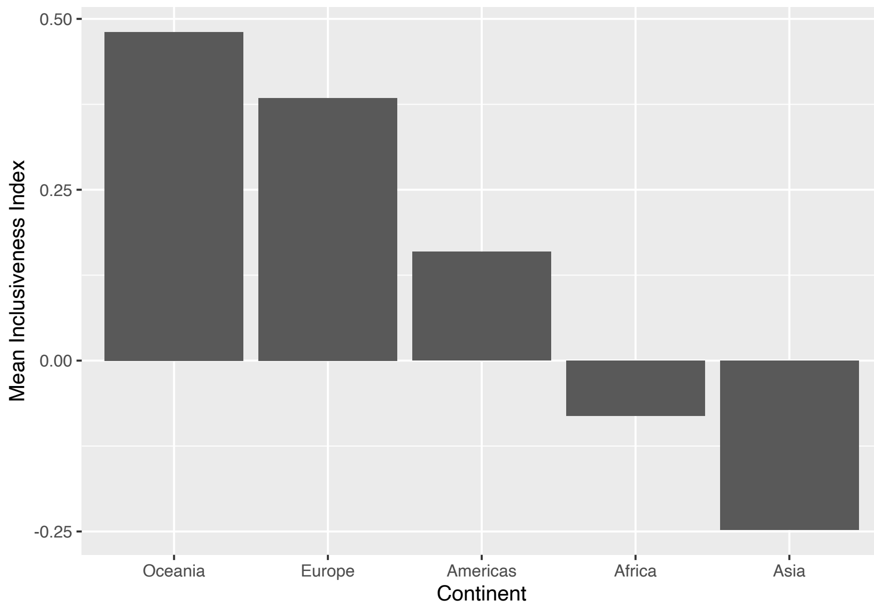


FIGURE 1.3: A sample bar chart with both positive and negative values.

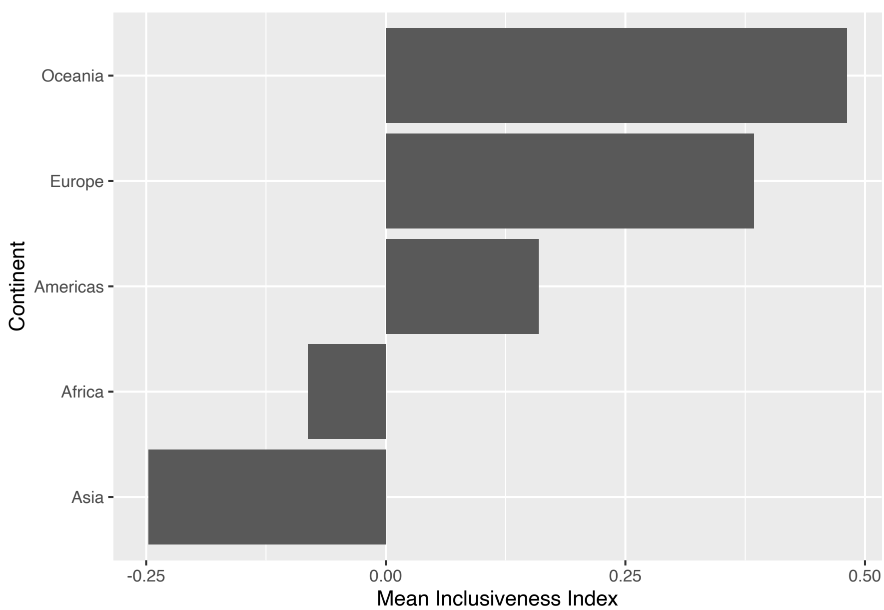


FIGURE 1.4: A sample bar chart, with the bars oriented horizonally.

1.2.1 Variations

The following charts are variations on a bar chart. They either incorporate additional variables, change the basic shape of the chart, or both.

1.2.1.1 Lollipop plot

One quick variation of the bar chart is called the lollipop plot In a lollipop plot, the bars are replace by a long line with a circle at the end, creating something that looks like a lollipop. Apart from the different shapes used, the lollipop plot works just like a bar chart. The circles draw attention to the data value, but the lines extending to the axis reinforce the length comparisons.

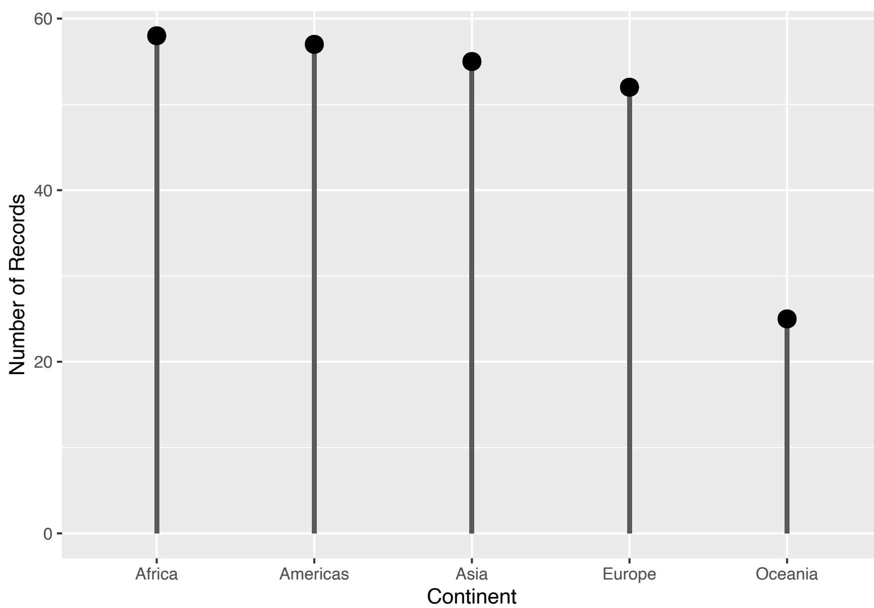


FIGURE 1.5: A sample lollipop plot.

1.2.1.2 Bar charts with color

A simple bar chart includes one categorical variable and one numerical variable. Sometimes, however, it is useful to explore the patterns in relation to a second categorical variable. Adding another categorical variable to a bar chart usually means using color to represent the extra variable.

With a stacked bar chart, the additional variable is used to segment the bars

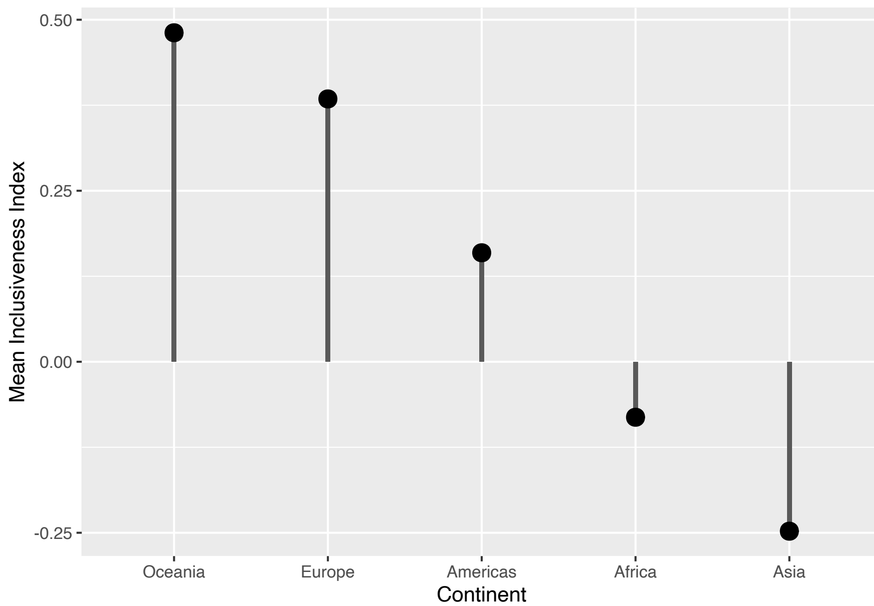


FIGURE 1.6: A sample lollipop plot with both positive and negative values.

into separate, colored regions. In this example, the bar for each continent is subdivided into groups of countries based on their values for Inclusive Index.

With this stacked bar chart, you can still see the total number of records for each Continent, but what happens when you try to compare the different segments inside the bar chart? Starting at the bottom, it seems to work out okay. All of the bars for the "No data" category start at the same baseline (the x axis), and we can read these segments like a normal bar chart. But what happens with the "Low" segments right above them? And the "Medium-Low" segments above those? Every time we have a group of segments that aren't lined up with each other, we have to try to guess how tall the bar is in comparison to the other bars in the group. The farther apart the segments are, the harder it is to make that comparison.

Another variation of the stacked bar chart is the "filled" stacked bar chart. Instead of using the raw counts to determine the lengths of the bars, in the filled stacked bar chart, the full bars are all stretched to have the same height, and each segment becomes the percentage of the records in each bar. (Notice how the y axis changes from "Number" to "Percentage.") This is useful if the percentages matter more than the raw counts, but it doesn't fix any of the concerns with comparing different segments without a common baseline.

An alternative to the stacked bar chart is called the grouped bar chart. In the

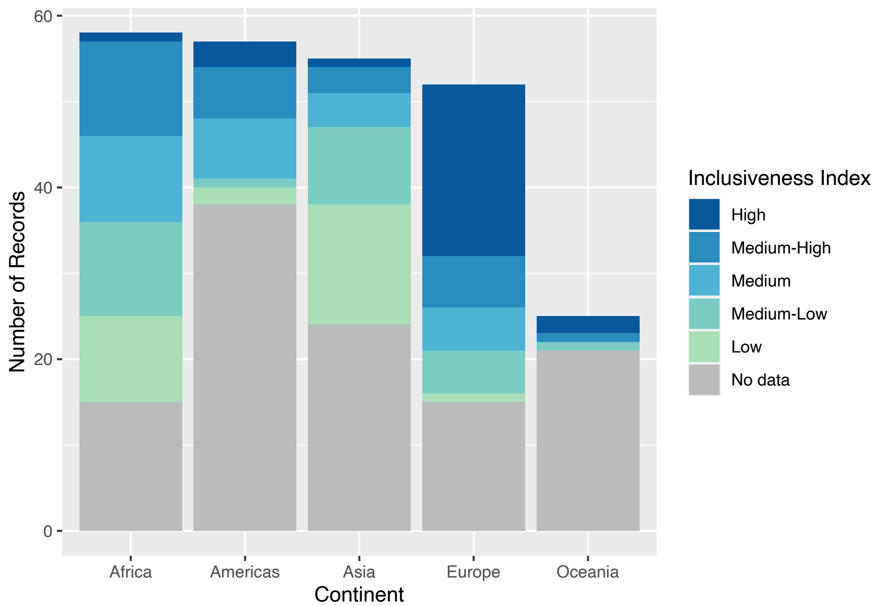


FIGURE 1.7: A sample stacked bar chart.

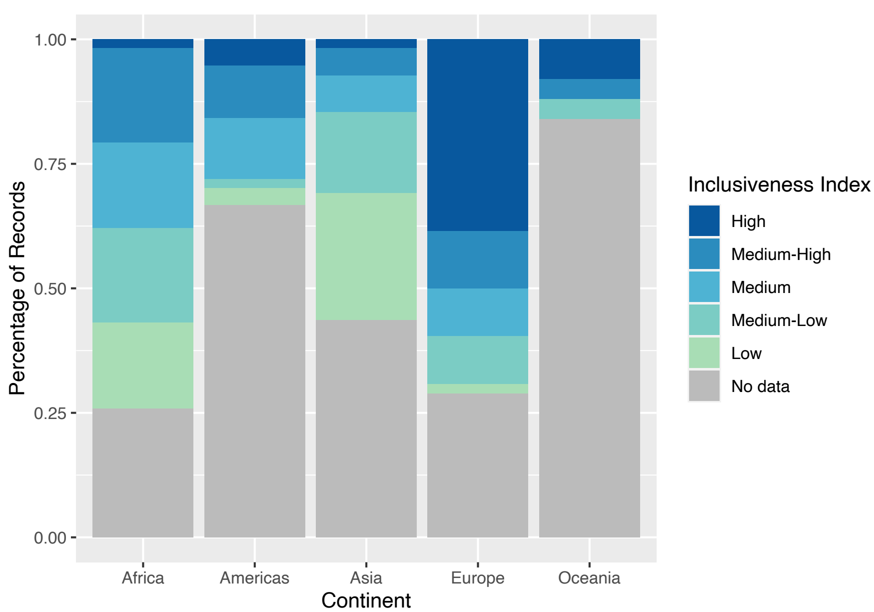


FIGURE 1.8: A sample filled stacked bar chart.

grouped bar chart, every segment starts from the x axis. Each continent forms a group of bars, and each option of the Inclusiveness Index is a separate bar.

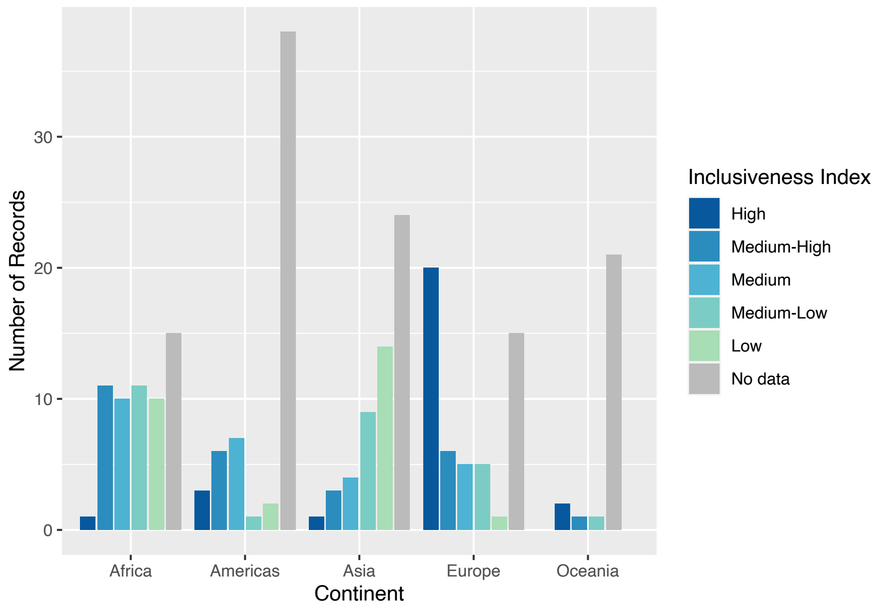


FIGURE 1.9: A sample grouped bar chart.

1.2.1.3 Dumbbell plot

Stacked and grouped bar charts show some of the limitations of bar charts for making complex comparisons. The rectangles in the bar chart take up a large amount of space. Think back to the lollipop plot, where it's the circles that directly represent the data value. Converting bars to something like circles opens up the ability to make more direct comparisons.

For example, let's say we want to compare two continents more directly: Asia and Europe.

This chart groups all of the segments by continent, which makes it easy to compare different Index categories within a single continent. What if we want to bring more attention to the difference between continents for each category? We could always switch which category is the primary division on the x axis and which is represented by color.

This improves our ability to compare the continents directly because the bars are directly next to each other. The amount of space the bars take up is still pretty large, though. If we combine this chart with something like a lollipop plot, we get one last variation: a dumbbell plot.

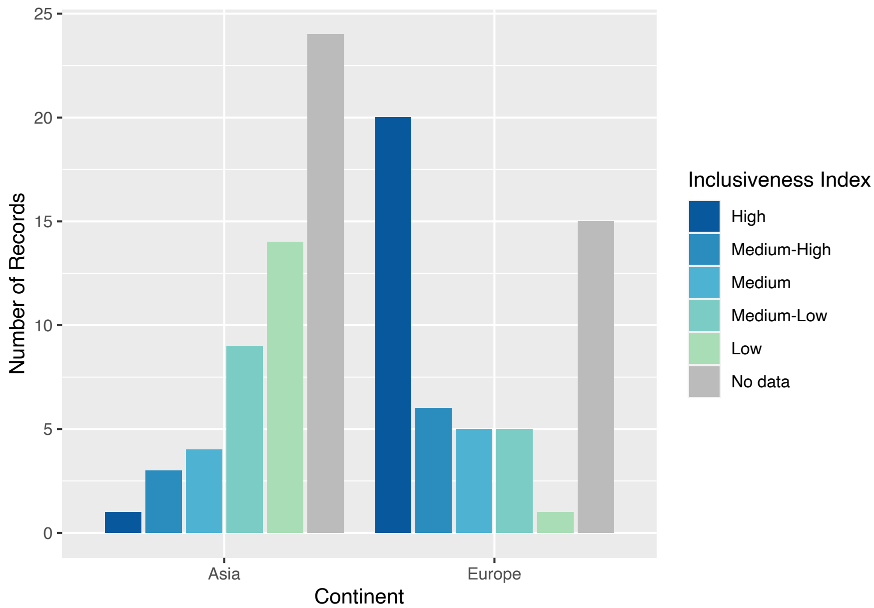


FIGURE 1.10: A grouped bar chart focusing on two continents.

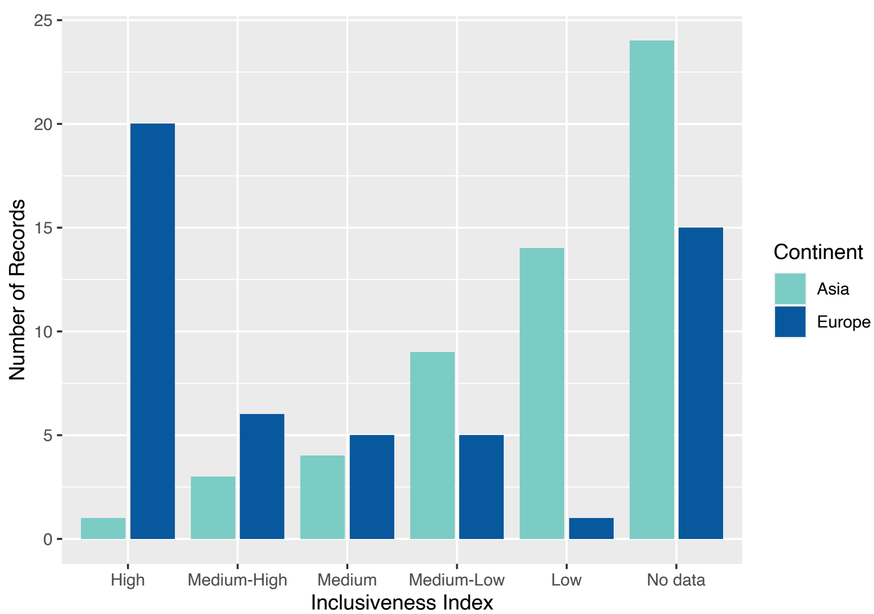


FIGURE 1.11: The same grouped bar chart with a different arrangement of the categorical variables.

With a dumbbell plot, we use a circle to represent the data values, just like the lollipop. Instead of having a line that extends all the way to the axis, though, we use a line to connect the two dots in each category of Inclusiveness Index.

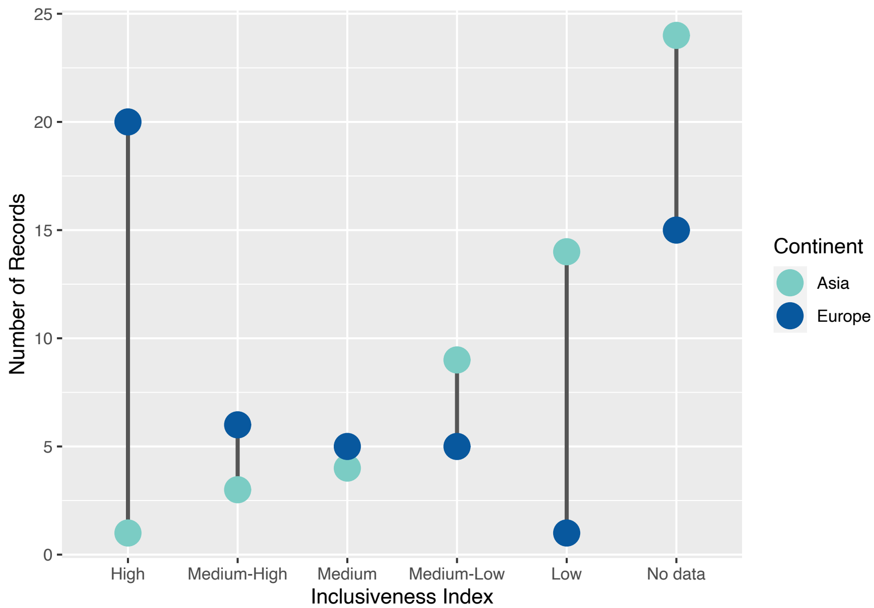


FIGURE 1.12: A dumbbell plot comparing two continents.

With a dumbbell plot, there are three main trends we can explore in the chart. We can focus on the green circles to see the pattern in the Asia data values. We can focus on the blue circles to see the pattern in the Europe data values. Finally, we can focus on the lengths of the lines connecting the circles to compare the continents at each level of the Inclusiveness Index. This chart time is an efficient way to compare these data values, but remember that it can be difficult to compare the lengths of shapes when they don't have the same baseline.

1.3 Scatter Plot

The scatter plot is another common visualization type. This type of visualization displays one circle for each record in the data set. The position of the circle is based on the values of two different numerical variables, one of which is associated with the x axis and the other of which is associated with the y axis.

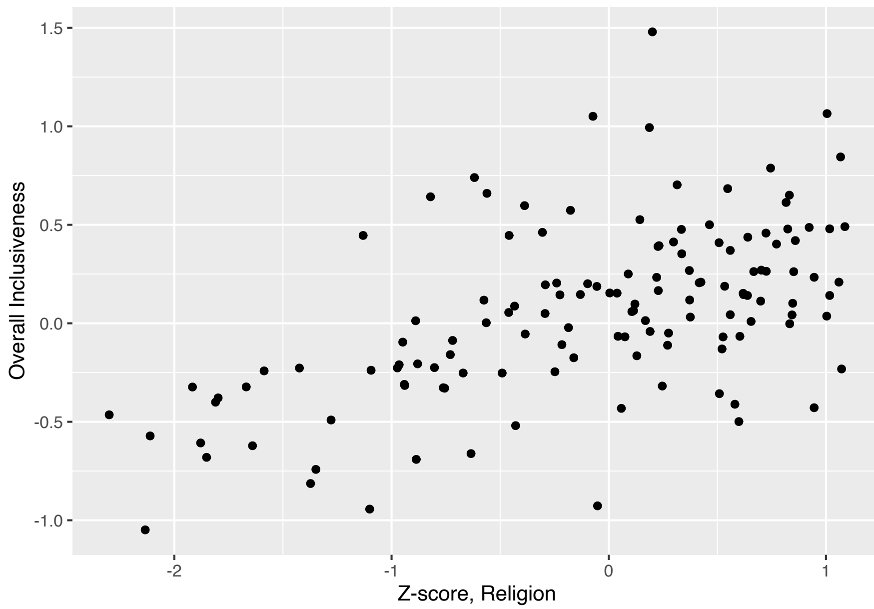


FIGURE 1.13: A sample scatter plot.

This visualization is a way to show a relationship between the two numerical variables displayed on the axes. A relationship between the variables means that a change in one variable would predict a specific kind of change in the other variable. For example, one kind of relationship is a positive correlation, which means that an increase in one variable is associated with an increase in the other variable. Points with higher values on the x axis tend to have higher values on the y axis. Similarly, points with lower values on one axis tend to have lower values on the other axis.

When two numerical variables have a positive correlation, it shows up on the scatter plot as a diagonal pattern of circles, from the bottom left corner of the chart to the upper right corner of the chart. The closer it looks to a straight line, rather than a diffuse pattern, the stronger the relationship is.

There are a few types of patterns that might show up when looking at a scatter plot. Instead of a positive correlation, the variables could have a negative correlation: high values of one variable are associated with low values of the other variable. This relationship shows up on the scatter plot as a diagonal patter from the top left corner to the bottom right corner.

Both positive and negative correlations are linear relationships - they look like lines on the chart. There are also nonlinear relationships that look like different kinds of curves. An exponential relationship looks like a curve that starts mostly horizontal and then curves up dramatically, ending up almost vertical. A logarithmic relationship is a curve that starts mostly vertical and bends over dramatically, ending up almost horizontal. Other curvilinear patterns of dots might be better represented by other mathematical functions.

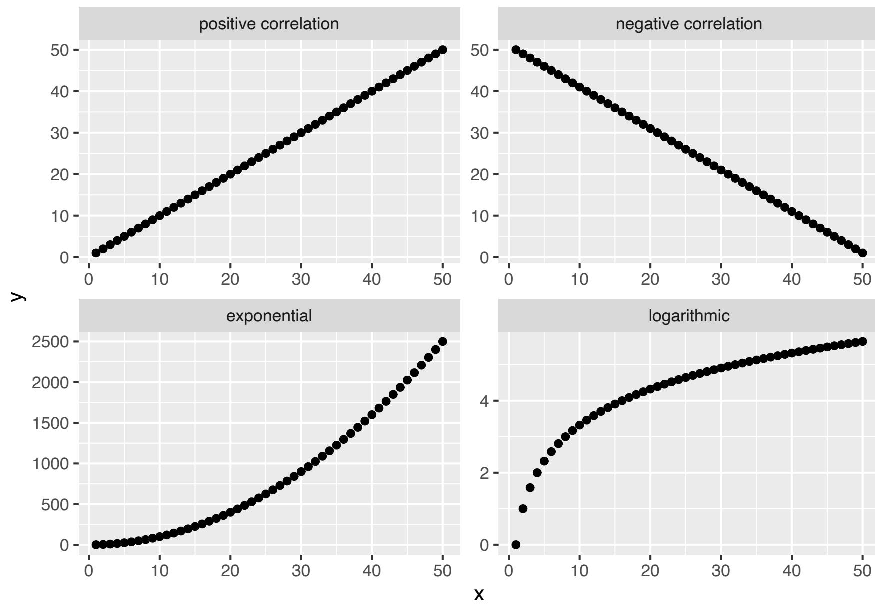


FIGURE 1.14: Different relationships between numerical variables.

What does it mean to see a shape in a scatter plot? A detectable shape in a scatter plot is a suggestion that there might be a statistically powerful relationship between these variables. The chart, however, is not a substitute for a statistical analysis. Using statistical analyses to explore the relationship between two variables is called modeling.

Sometimes a scatter plot will be combined with a statistical model to explore the connection between the data points and an ideal relationship. For example, you may see a scatter plot where there is a correlation between the variables combined with a linear model (represented by a straight line drawn on top of the points).

When you see a line on a scatter plot like this, it is showing the linear model that best represents the relationship between the x and y variables. In this case, the relationship between the variables is not very strong, so the points look more like a cloud than the straight line of the linear model.

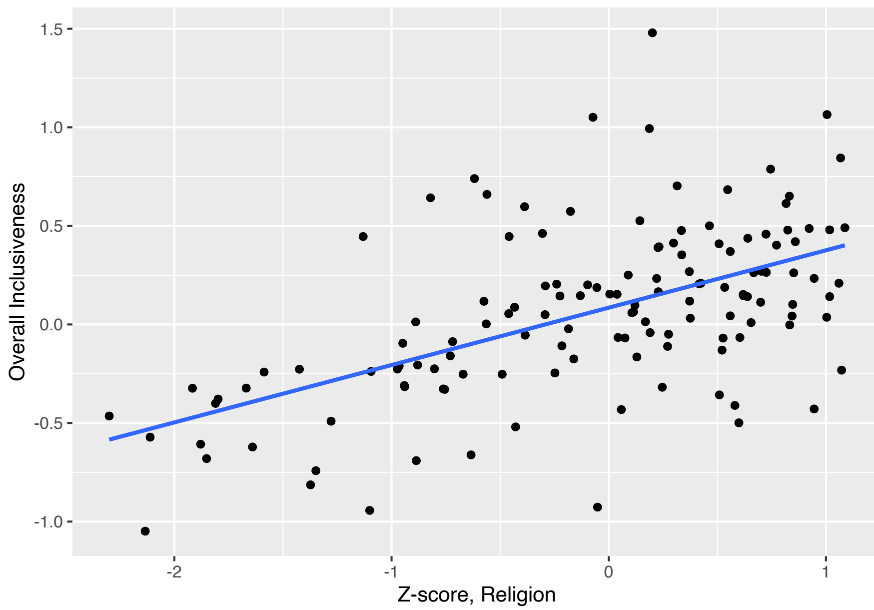


FIGURE 1.15: A sample scatter plot with a linear model overlaid over the points.

1.3.1 Variations

The following charts are variations on a scatter plot. They either summarize the patterns in the data or incorporate additional variables.

1.3.1.1 Contour or density plot

Sometimes a dataset is too large for a scatter plot to be effective. With a large number of data points, there can be too much overlap between the circles to see the dominant patterns. In this instance, it can be helpful to calculate the density of data points across the chart and visualize the density instead of (or in addition to) the points. This is called a contour or density plot.

1.3.1.2 Binned scatter plot

In a contour plot, the density calculation detects regions of high density in a scatter plot. Another way of summarizing the distribution of points across the plot is to divide the plot into an even grid and then to count the points inside each region. This is often called "binning." Common types of binning

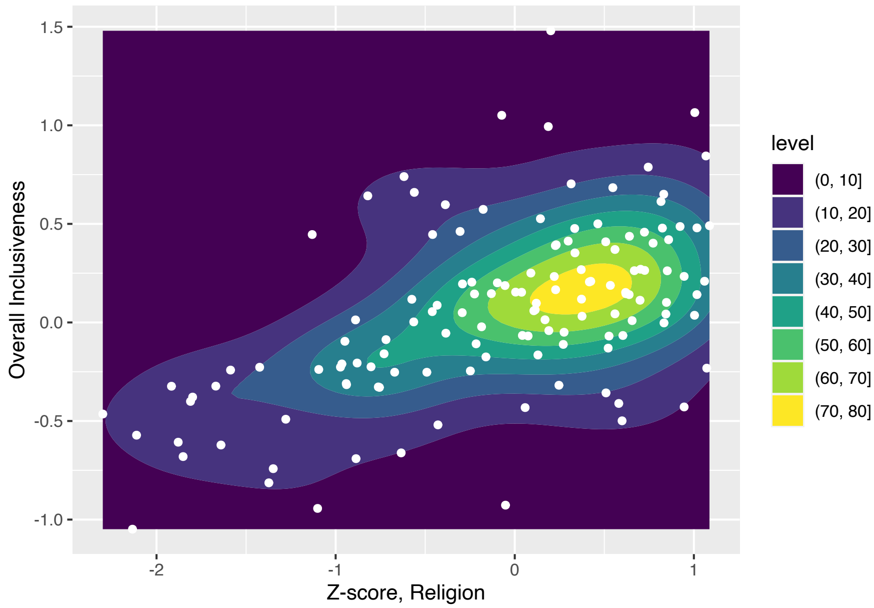


FIGURE 1.16: A sample contour plot with scatter plot points on top.

are rectangular (splitting the plot up using a rectangular grid) and hexagonal (splitting the plot up using a grid of interlocking hexagons).

1.3.1.3 Scatter plot with color

So far, our scatter plots have still only been used to visualize the relationship between two numerical variables. In some datasets, it can be helpful to consider how an additional variable interacts with the scatter plot pattern. One way to incorporate an additional variable is to change the color of the points in the scatter plot according to the third variable. For example, you can associate the color of the points with a categorical variable to show whether different subsets of the points cluster in different parts of the graph.

In the above chart, the color represents the continent; that is, each continent shows as a separate color. We're looking for a relationship between the pattern of the colors and the spatial pattern of the points. In this chart, the points associated with Europe do overall seem to cluster in the upper-right corner of the graph, meaning that on the whole the European countries tend to rate highly on both the Z-score value for religious inclusiveness and the overall inclusiveness score. African countries also tend to have high scores for religious inclusiveness, but they don't rate as highly for overall inclusiveness.

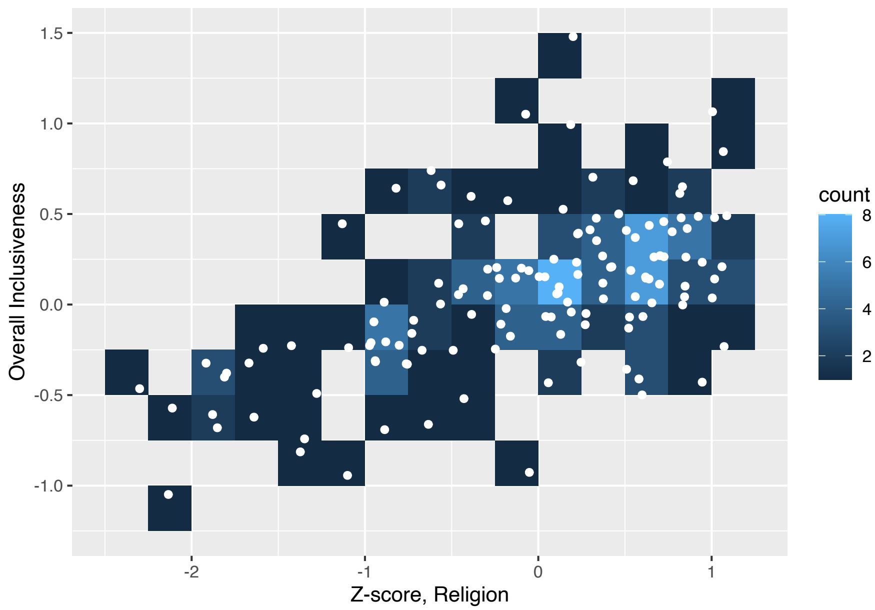


FIGURE 1.17: A sample scatter plot binned with a rectangular grid.

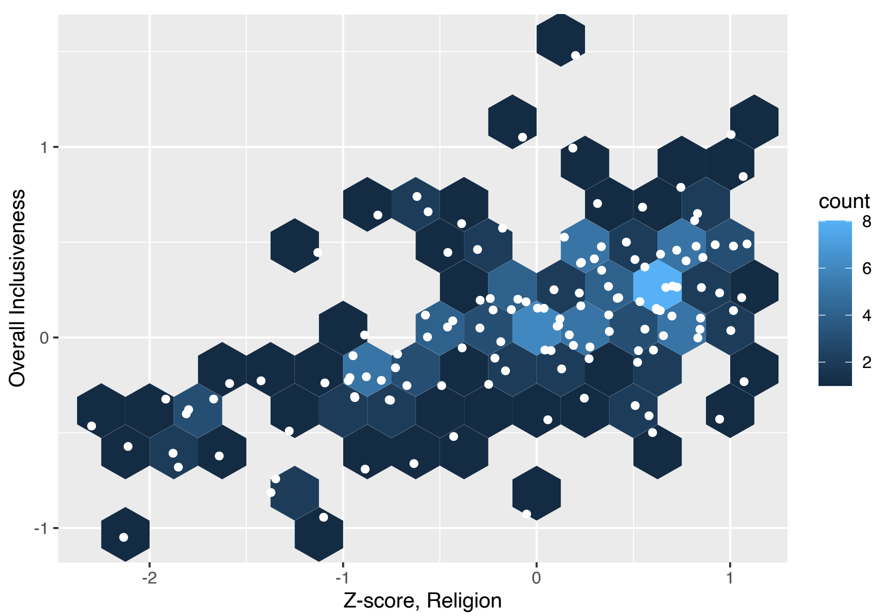


FIGURE 1.18: A sample scatter plot binned with a hexagonal grid.

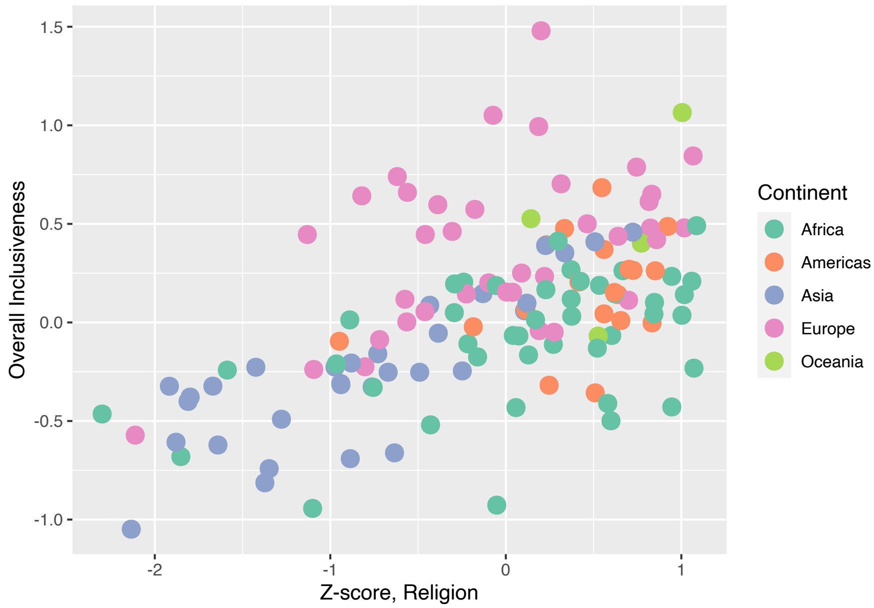


FIGURE 1.19: A sample scatter plot with color categories.

You can also use color to visualize a third numerical variable instead of a categorical variable.

In this chart, the values in the "Z-score, Gender" variable are associated with a color gradient. Positive values of this new variable show in the chart as increasingly darker shades of purple. Negative values show as increasingly darker shades of green.

With any chart, adding more variables runs the risk of creating visual confusion that makes it harder (not easier) to see interesting patterns. For example, in the chart above, we see that purples mostly occur on the top half of the chart and greens on the lower half of the chart. Beyond that, though, it's hard to identify a strong relationship between the strength of the color values and either of the axes. If colors are not concentrating in a particular region of the plot, adding a third variable may not be necessary for this chart.

1.3.1.4 Bubble chart

A bubble chart is another way of adding a third variable to a scatter plot. Unlike adding color to the chart, however, a bubble plot works best when you are adding a third numerical variable. That's because in a bubble plot, the additional variable is represented by changing the size of the bubble. Representing a categorical variable by changing the size of the circle isn't as natural

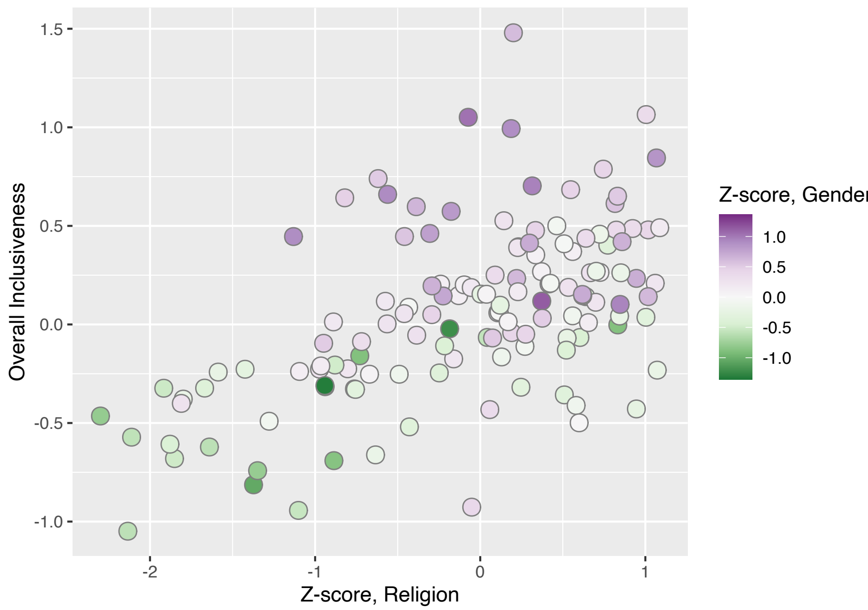


FIGURE 1.20: A sample scatter plot with a color gradient.

as using different colors. It's hard to focus on all of the bubbles of a particular size to try to identify clusters.

If you use a numerical variable to size the bubbles, the goal of the chart becomes similar to when color is used to add a third numerical variable: explore whether the sizes of the bubbles changes in a meaningful way in relation to the axes.

There is one property of bubble charts that is different from scatter plots with added color. When you have a variable that has both positive and negative values, it may be a slightly less natural fit for the size of the bubbles. The size of an object like a circle is naturally a positive value. A circle doesn't itself have negative size. If the variable uses negative and positive in an abstract sense, though, the size of a bubble can still help differentiate low and high values.

With bubble charts, color is still available to display another variable if there is anything else that might interact with the three numerical variables.

Be cautious, again, with adding too many variables to a single chart. If adding a variable doesn't reveal anything new about the data, it is probably getting in the way of a pattern that does exist.

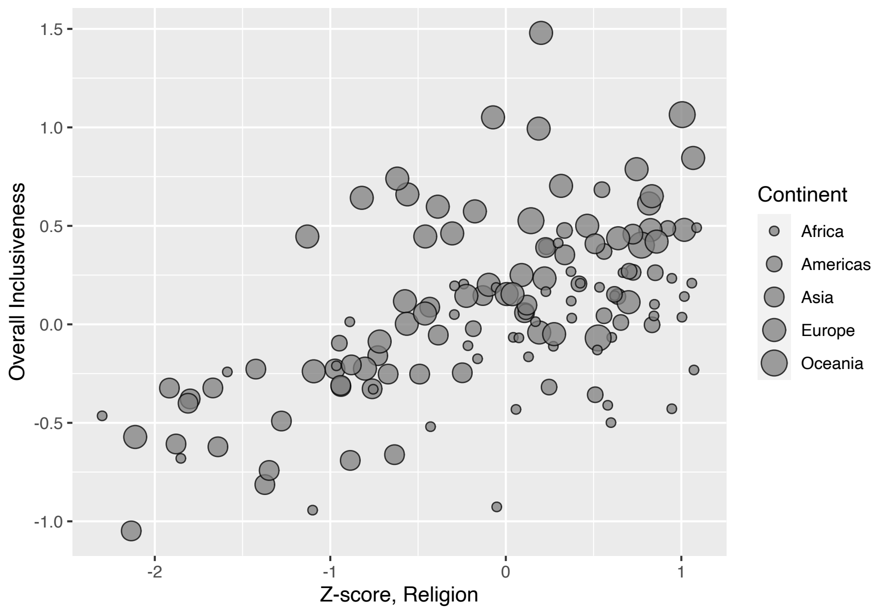


FIGURE 1.21: A sample bubble chart with categories.

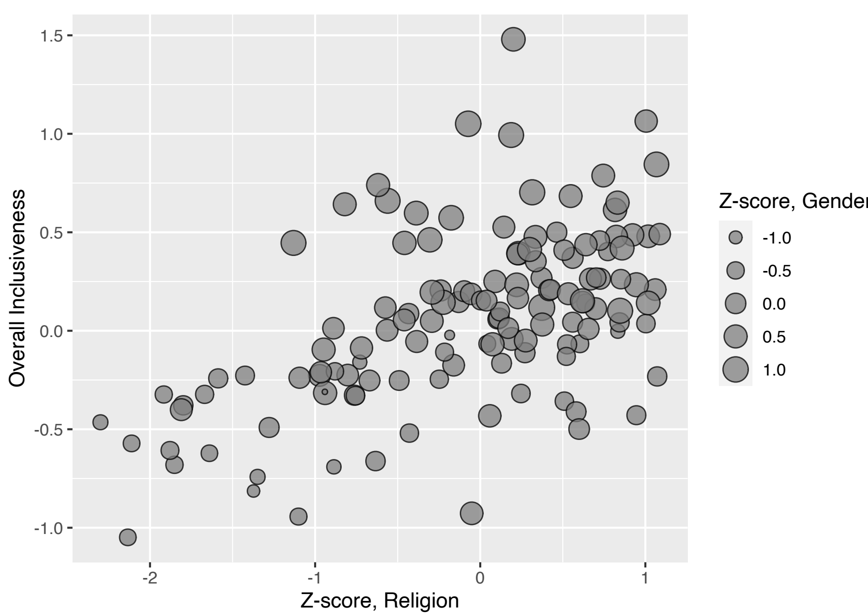


FIGURE 1.22: A sample bubble chart with a size gradient.

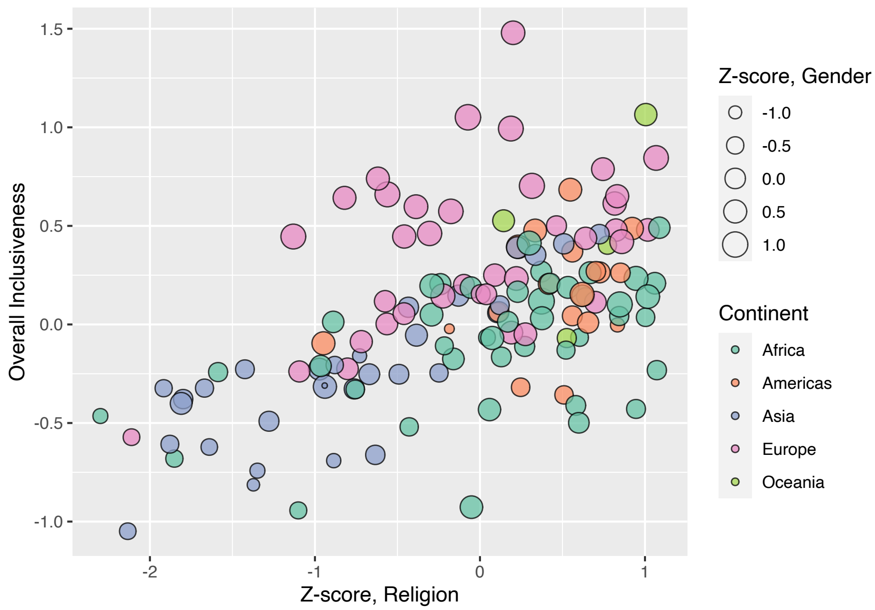
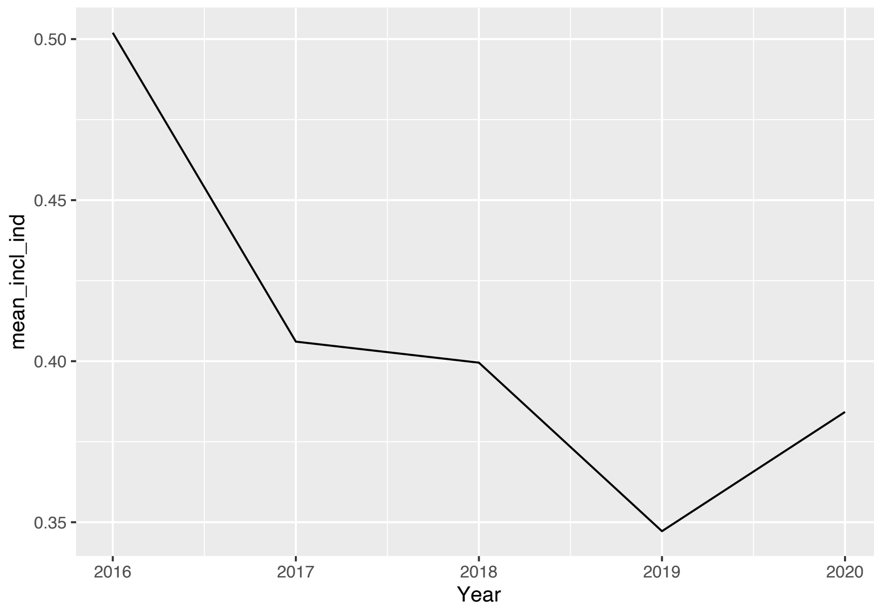


FIGURE 1.23: A sample bubble chart with color categories.

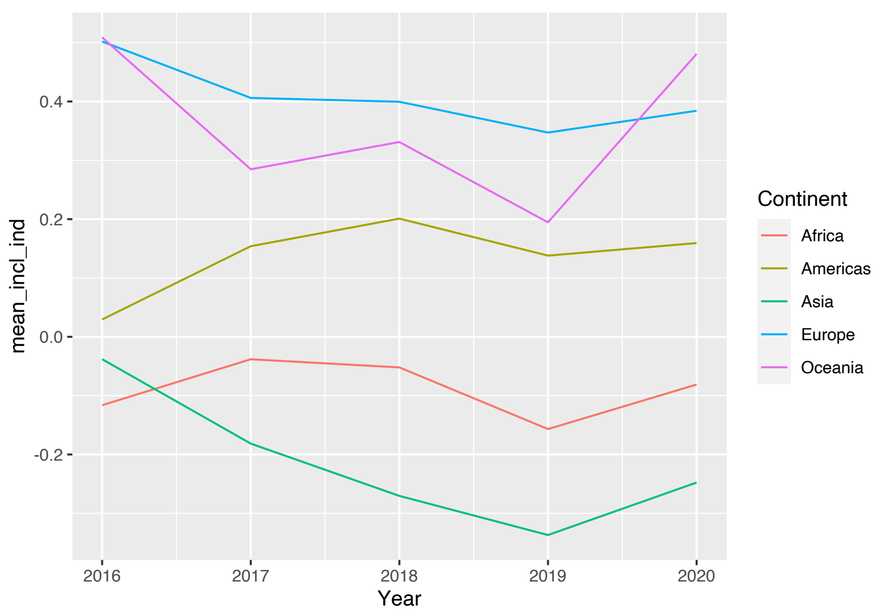
1.4 Line Chart

line chart / area chart

```
## `summarise()` has grouped output by 'Year'. You can override using the `.groups` argument.
```

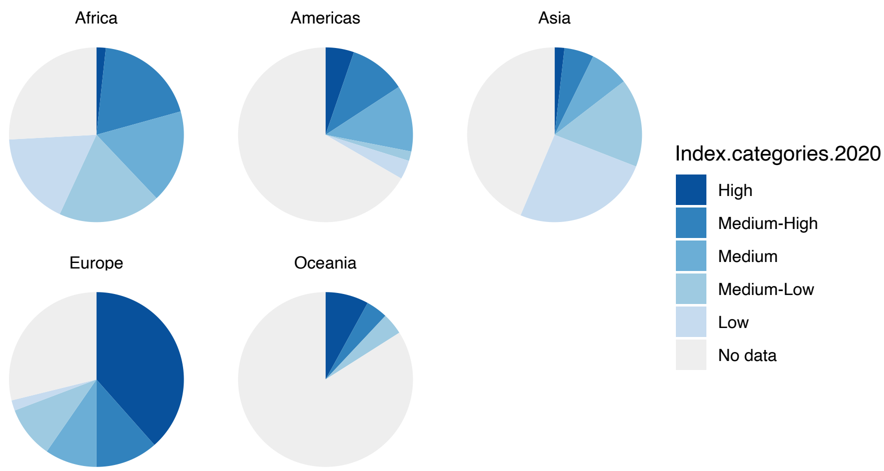



```
## `summarise()` has grouped output by 'Year'. You can override using the `.groups` argument.
```



1.5 Pie Chart

pie chart / donut chart

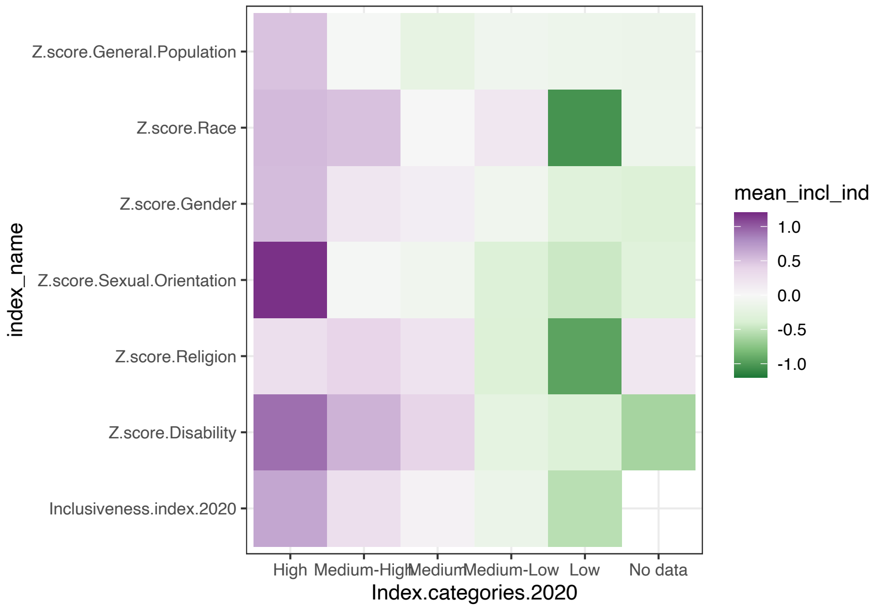


1.6 Heat Map

heat map / matrix / circles with color and size

```
## `summarise()` has grouped output by 'Index.categories.2020'. You can override using the `.groups` ar
```

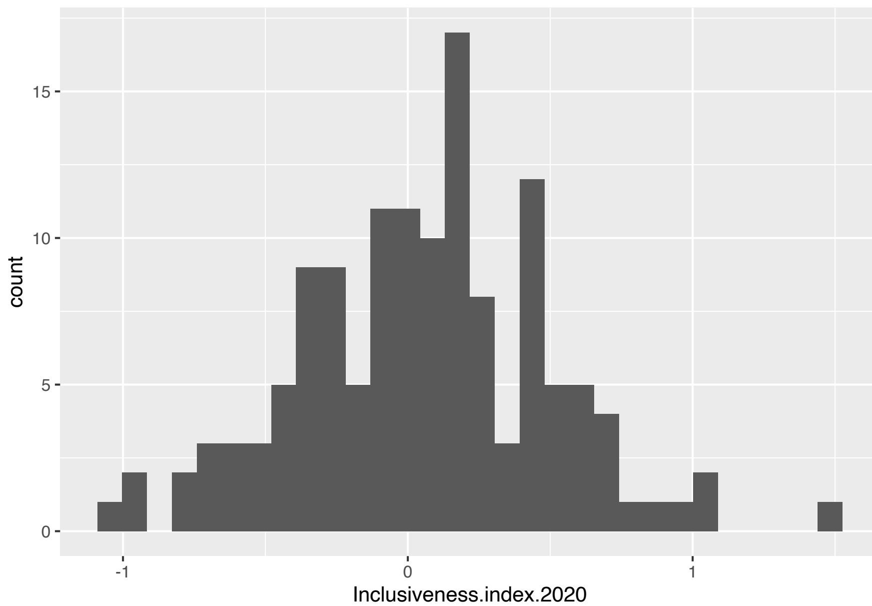
```
## Warning: Unknown levels in `f`:
## Inclusiveness.index.2020
```



1.7 Histogram

histogram / density

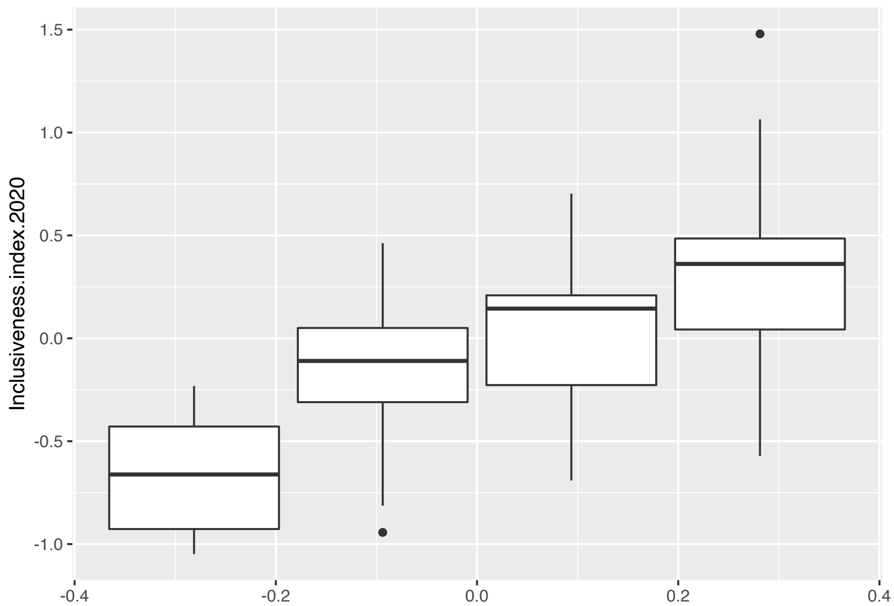
```
## `stat_bin()` using `bins = 30`. Pick better value
## with `binwidth`.
```



1.8 Box Plot

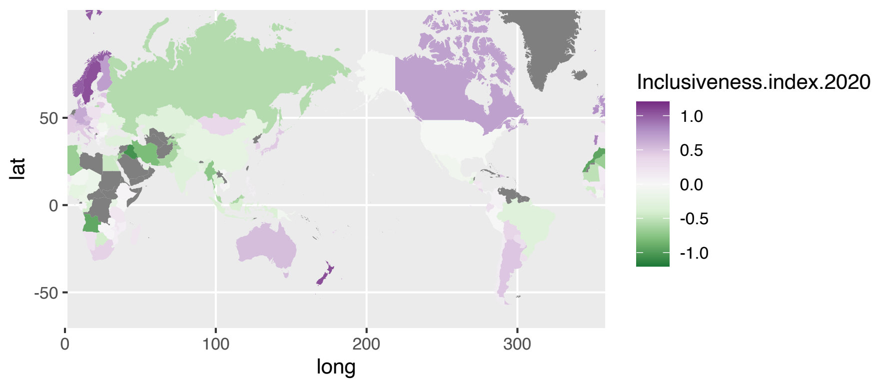
box plot / violin plot / bee swarm

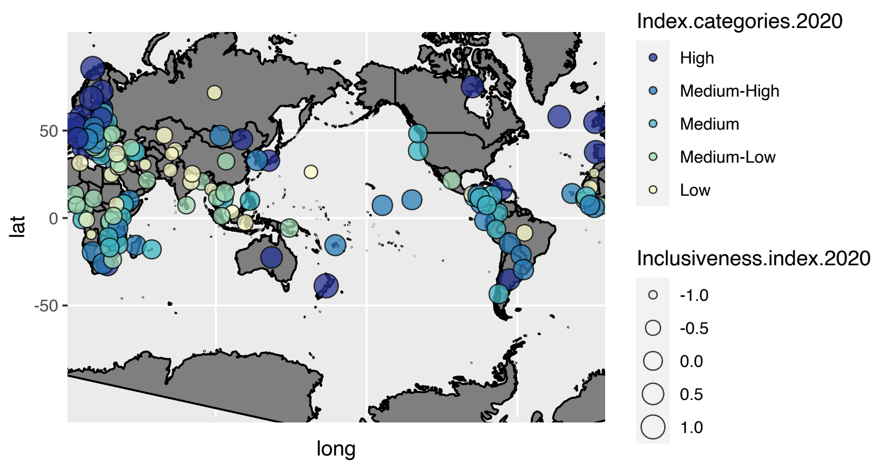
```
## Warning: Removed 113 rows containing non-finite values
## (stat_boxplot).
```



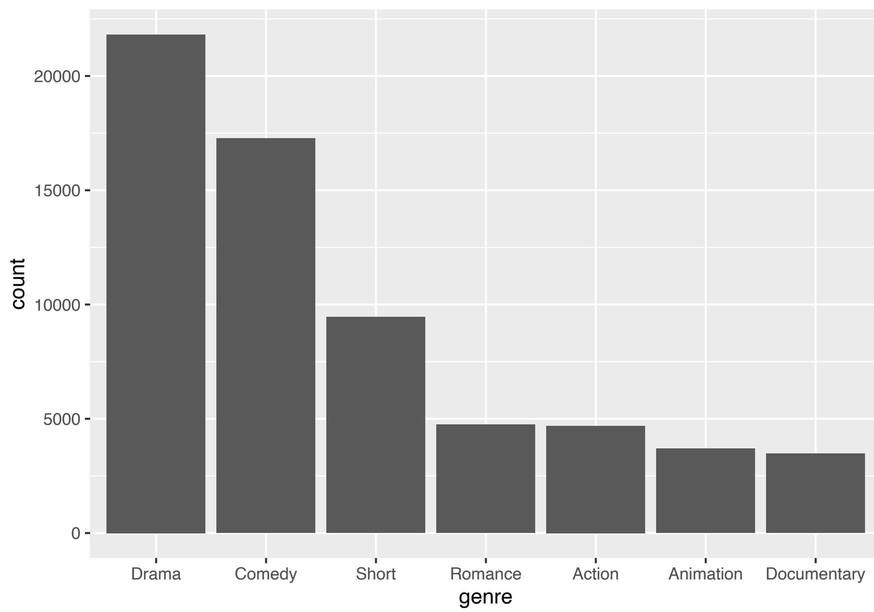
1.9 Maps

choropleth / proportional symbol map

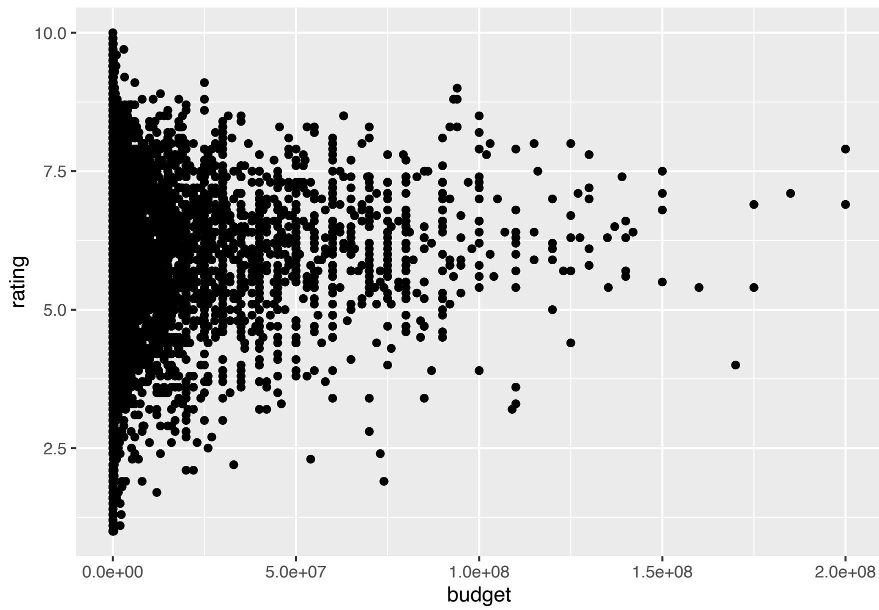

Inclusiveness.index.2020
1.0
0.5
0.0
-0.5
-1.0
lat
long
50
0
-50
0
100
200
300


Index.categories.2020
High
Medium-High
Medium
Medium-Low
Low
Inclusiveness.index.2020
-1.0
-0.5
0.0
0.5
1.0
lat
long
50
0
-50

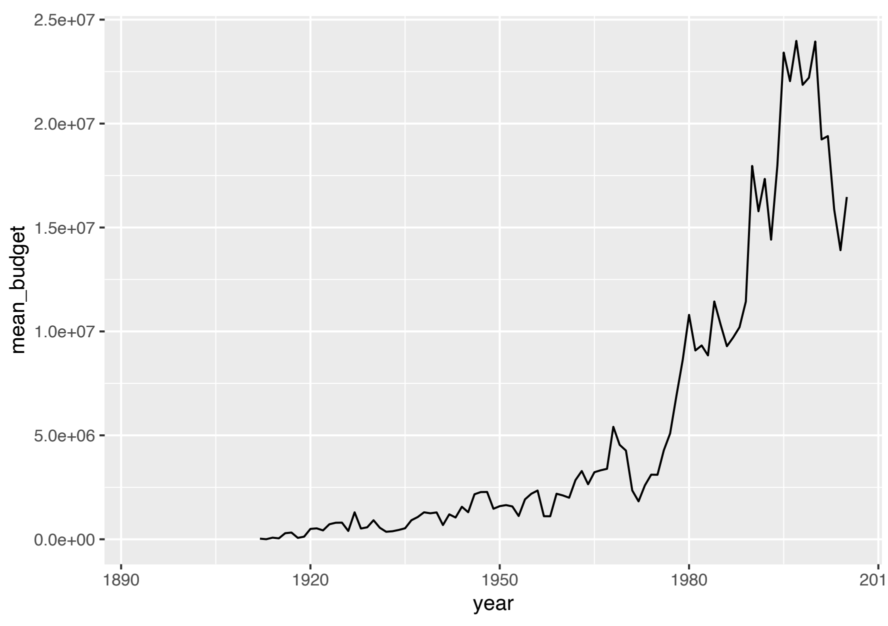
1.10 Movies

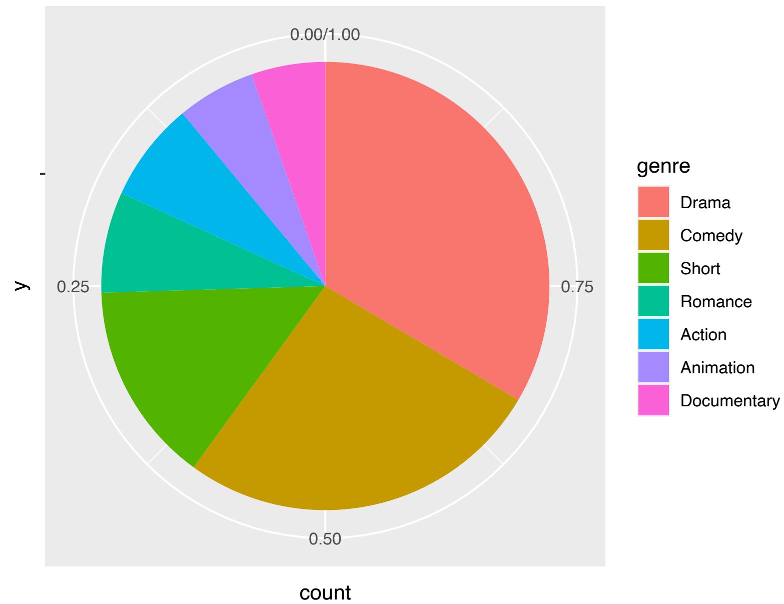



```
## Warning: Removed 53573 rows containing missing values
## (geom_point).
```

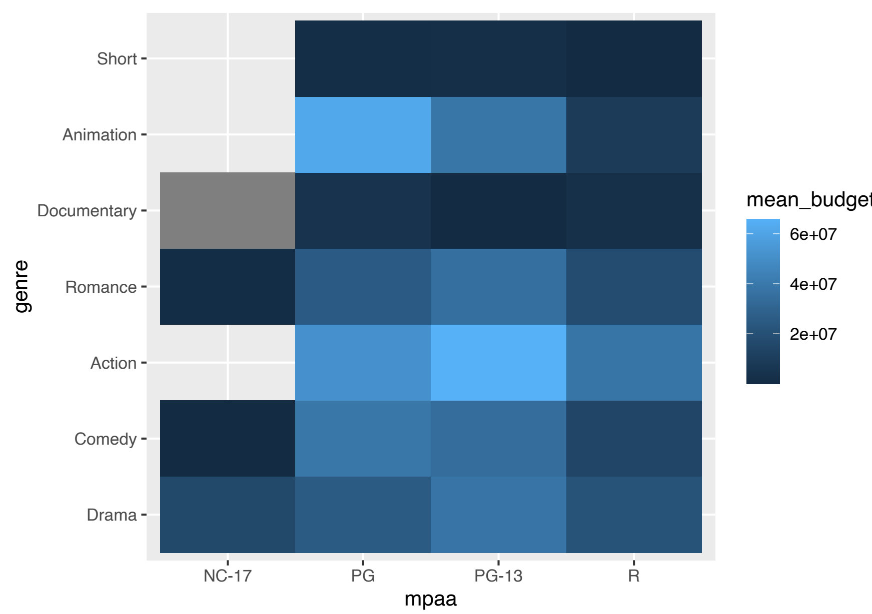



```
## Warning: Removed 10 row(s) containing missing values
## (geom_path).
```

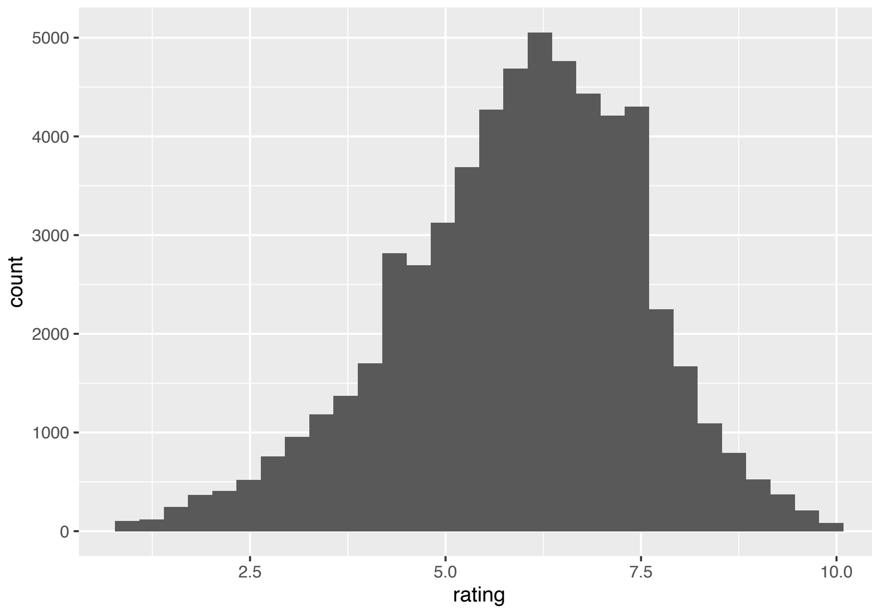


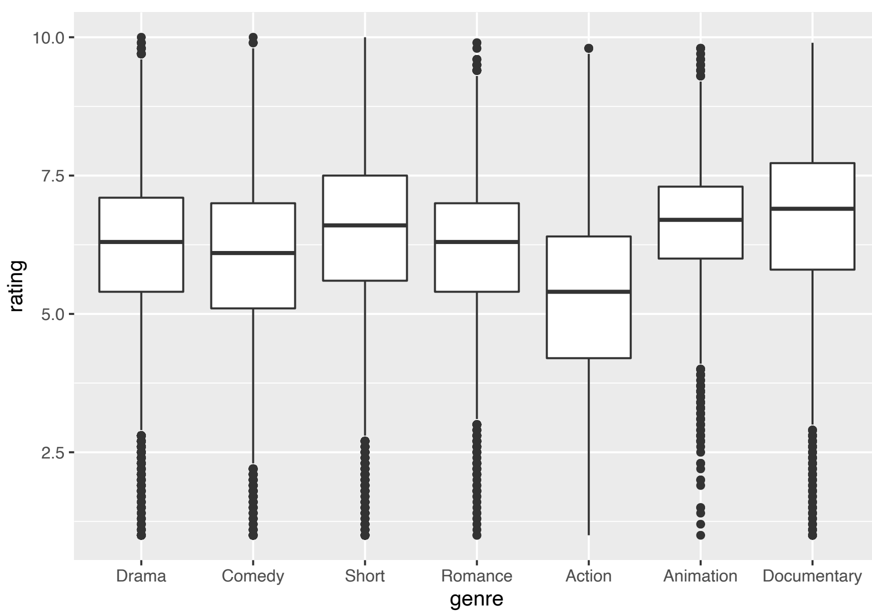



```
## `summarise()` has grouped output by 'mpaa'. You can override using the `.groups` argument.
```




```
## `stat_bin()` using `bins = 30`. Pick better value
## with `binwidth`.
```



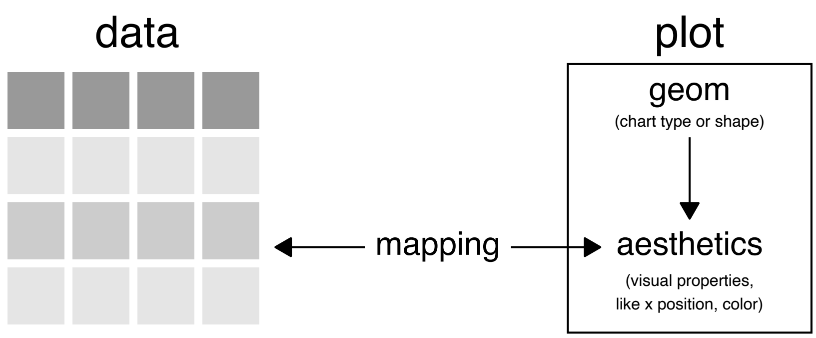


(No maps, but maybe that's okay)

2

Building basic visualizations with ggplot2

2.1 Basic ggplot2 syntax



3

Working with textual data in ggplot2

sample text

Cleaning data: use duke_enrollment (either by status or school) to talk about factors. Have Semester, which is really a time-based variable. Need to combine with Year to get the real sequence of enrollment.

4

Customizing the design of ggplot2 visualizations

sample text

We talk about the *FOO* method in this chapter.

5

Avoiding unethical design practices

sample text

We talk about the *FOO* method in this chapter.

6

Building ggplot2 visualizations into print publications

sample text

We talk about the *FOO* method in this chapter.

7

Basic accessibility for static visualizations

7.1 Low Vision

- Large text
  - "output-examples" file[1]
- High color contrast
  - Both marks/text on background and labels on marks
  - Check with savonliquide package[2]

7.2 Color Vision Deficiency

7.2.1 Dual encoding (never just color)

- Line color – also vary line type
- Point color – also vary point shape
- https://www.youtube.com/watch?v=mbi_JVC1arM

7.2.2 Color palettes

- colorspace package[3]

[1] https://github.com/amzoss/RVis-2Day/blob/master/Day%201/templates/output-examples.md
[2] https://github.com/feddelegrand7/savonliquide
[3] http://colorspace.r-forge.r-project.org/index.html

7.3 Alternative Text for Screen Readers

In R, R Markdown:

- fig.alt[4] in code chunk (new, just for HTML output)
- fig.cap[5] in code chunk as backup
- embedded images: write alt text between square brackets
- New: ggplot2 v3.3.4 adds alt option in labs()[6], with plans to propagate to Rmd, Shiny

Writing good alt text for visualizations[7]

Longer descriptions: savonliquide package[8]

7.4 Converting graphics to sound, touch, text

- sonify package
- tactileR package
- BrailleR package[9]
  - Note: set plot title, subtitle, caption using labs()

Accessible Data Science for the Blind Using R[10]

7.5 Accessibility Resources

- savonliquide package[11]

[4] https://blog.rstudio.com/2021/04/20/knitr-fig-alt/
[5] https://bookdown.org/yihui/rmarkdown/r-code.html
[6] https://ggplot2.tidyverse.org/reference/labs.html
[7] https://nightingaledvs.com/writing-alt-text-for-data-visualization/
[8] https://github.com/feddelegrand7/savonliquide
[9] https://r-resources.massey.ac.nz/BrailleRInAction/GGPlot.html
[10] https://jooyoungseo.com/post/ds4blind/
[11] https://github.com/feddelegrand7/savonliquide

- Making betteR figures: Accessibility and Universal Design[12]
- Highlights from the DVS accessibility fireside chat[13]

[12] https://bookdown.org/ybrandvain/Applied-Biostats/betteRfigs.html#accessibility-and-universal-design

[13] https://nightingaledvs.com/highlights-from-the-dvs-accessibility-fireside-chat/

8

Exploring interactivity in visualizations with plotly and crosstalk

sample text

We talk about the *FOO* method in this chapter.

9

Using RMarkdown to build websites for projects

sample text

We talk about the *FOO* method in this chapter.

10

Using RMarkdown to build dashboards for projects

sample text

We talk about the *FOO* method in this chapter.

11

Basic usability for interactive visualizations

sample text

We talk about the *FOO* method in this chapter.

12

Teacher's guide

sample text

We talk about the *FOO* method in this chapter.

A

Datasets

Duke Enrollment

Duke enrollment[1]

Sample of Duke Enrollment By School dataset, Table A.1.

A.1 Bar Chart

Figure A.1.

[1] https://doi.org/10.7924/r4db82p1j

TABLE A.1: A sample from the Duke Enrollment By School dataset.

Year	Semester	Origin	Region	Sex	School	Count
1970	Fall	Alabama	United States	Female	Trinity	11
1970	Fall	Alabama	United States	Female	Graduate	7
1970	Fall	Alabama	United States	Female	Divinity	1
1970	Fall	Alabama	United States	Female	Law	1
1970	Fall	Alaska	United States	Female	Trinity	1
1970	Fall	Alaska	United States	Female	Graduate	1

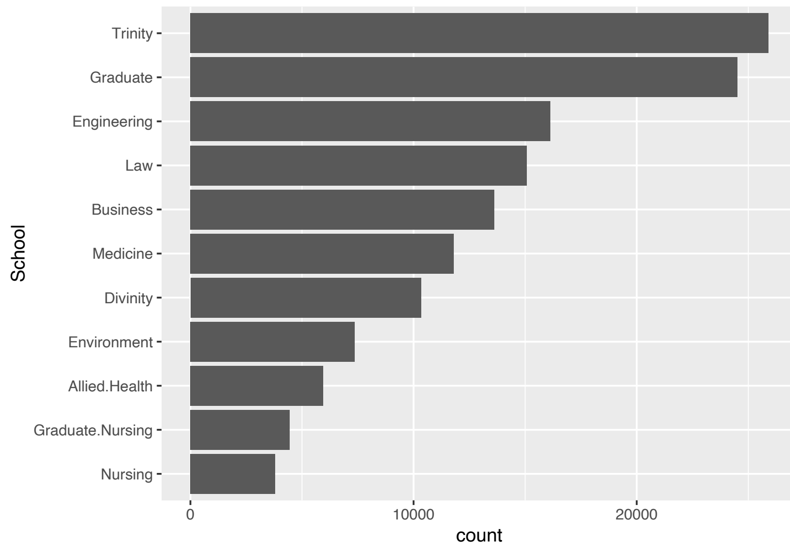


FIGURE A.1: Total Duke Enrollment by School

Coral Resilience Data

Protecting coral reefs[2]

Figure A.2.

```
## Warning: Removed 1 rows containing missing values
## (geom_point).
```

Git Experience

A Behavioral Approach to Understanding the Git Experience[3]

```
## Warning: Removed 1 row(s) containing missing values
## (geom_path).
```

[2] https://doi.org/10.7924/G8348HFP
[3] https://osf.io/57tb8/

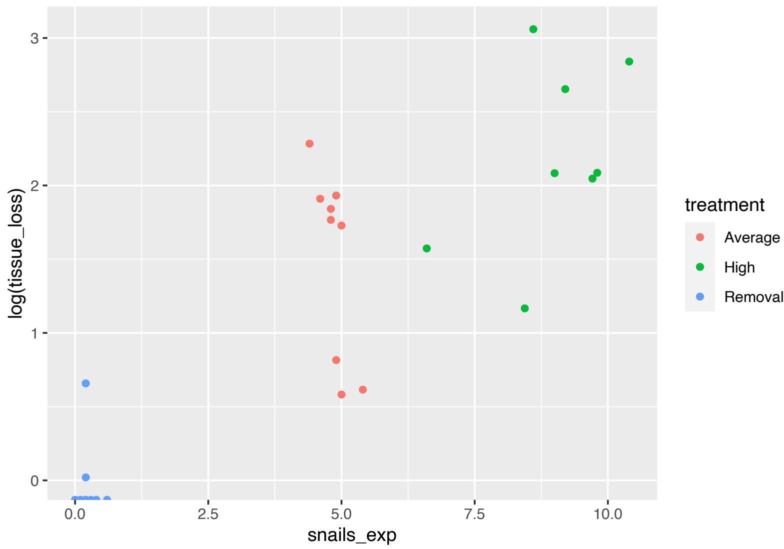
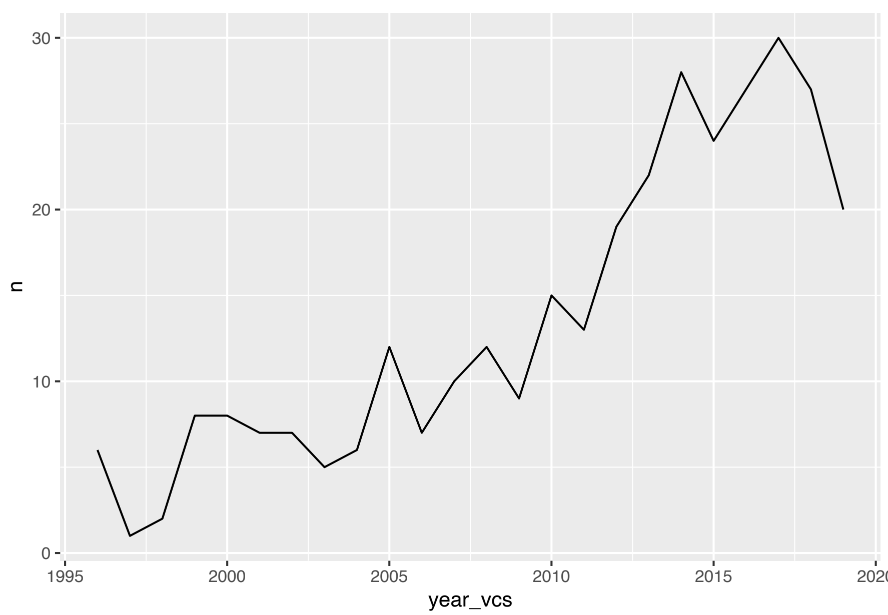
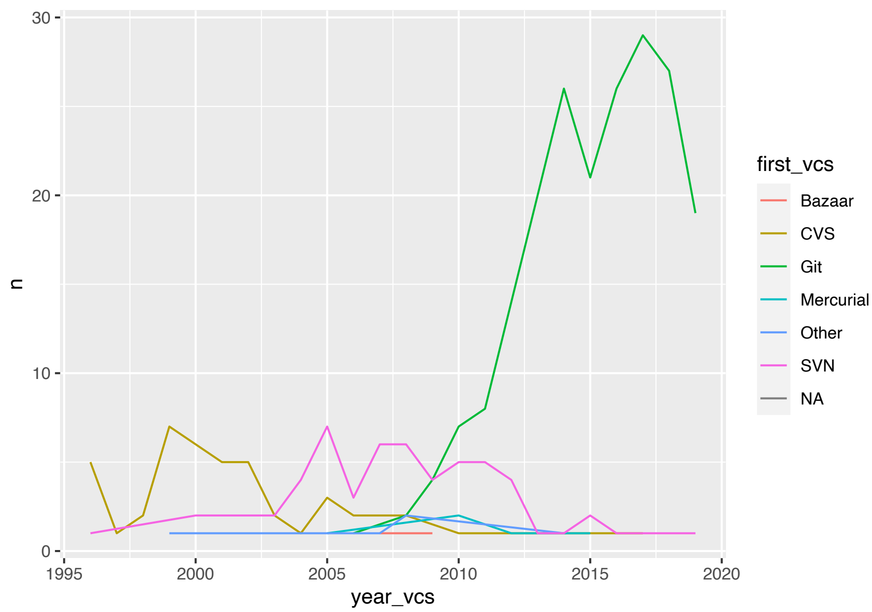


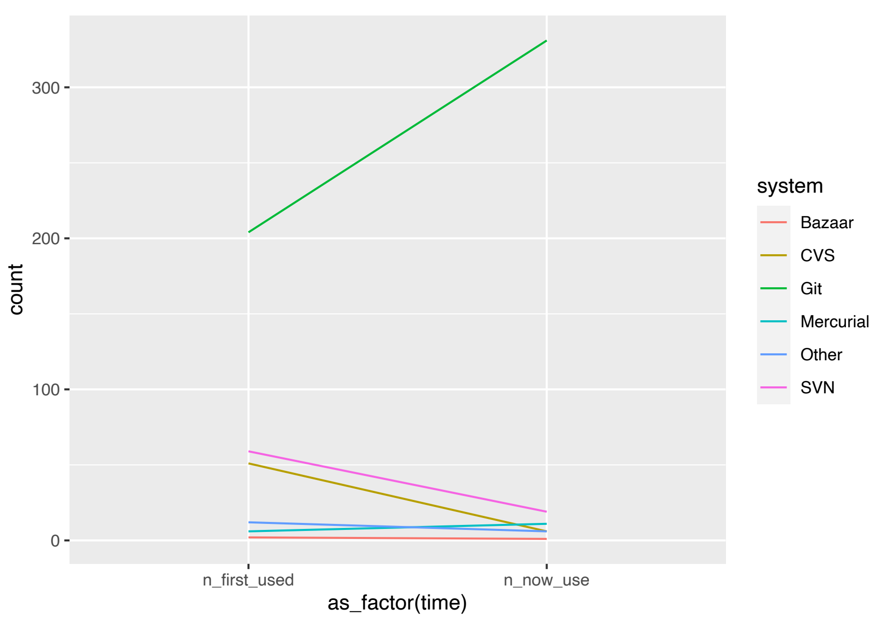
FIGURE A.2: Log of tissue loss by snail density

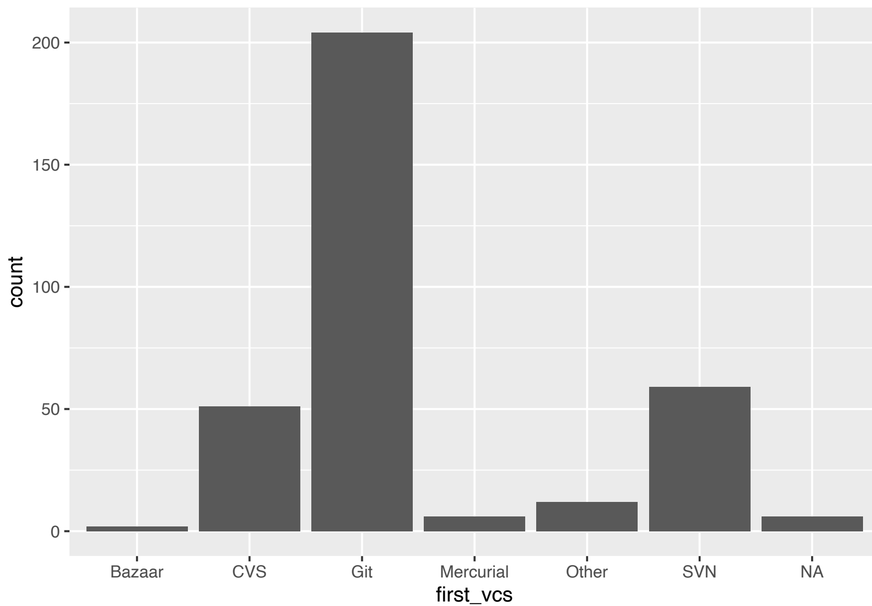



```
## Warning: Removed 3 row(s) containing missing values
## (geom_path).
```

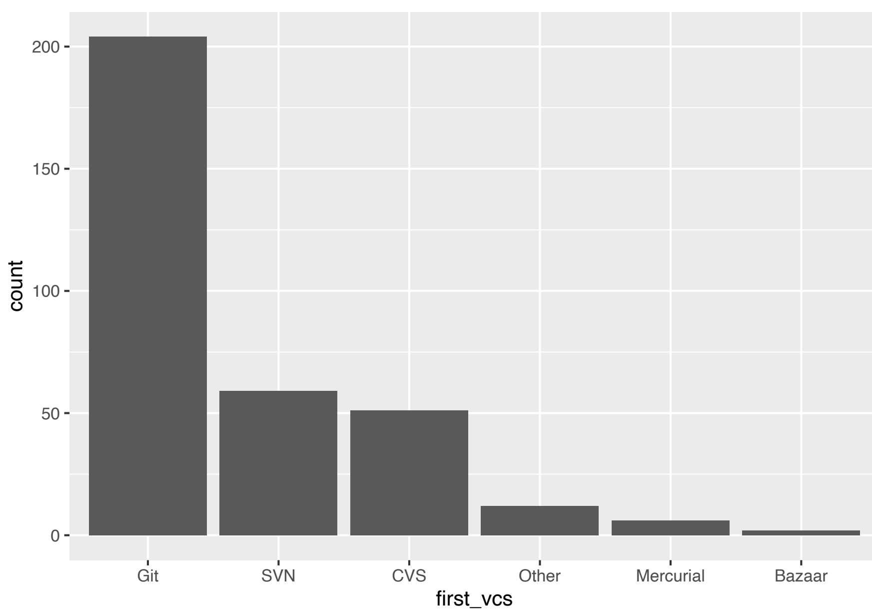



```
## Joining, by = "system"
```

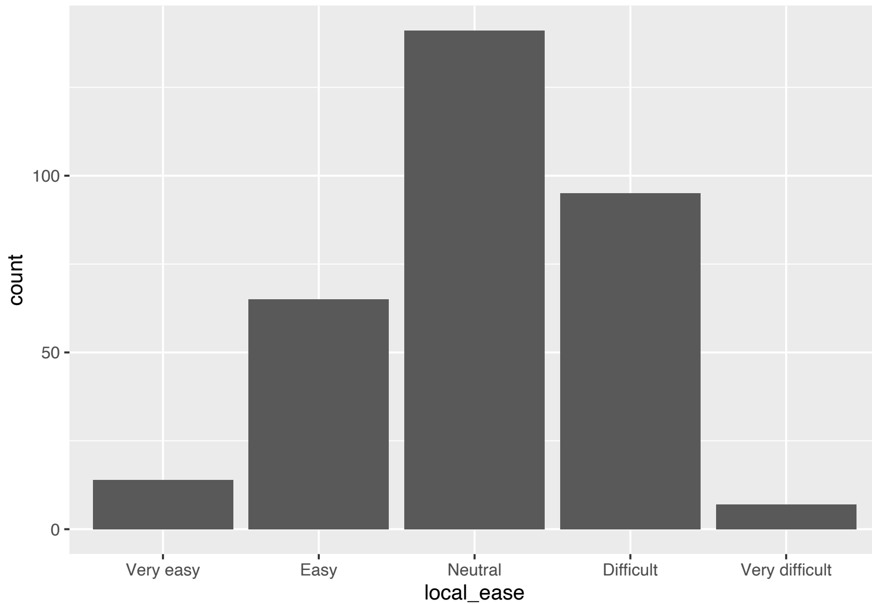


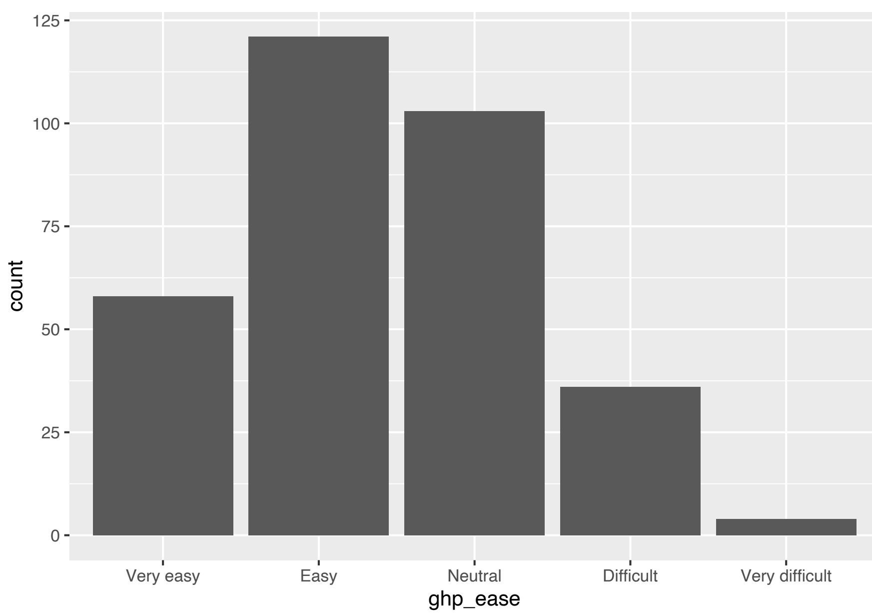


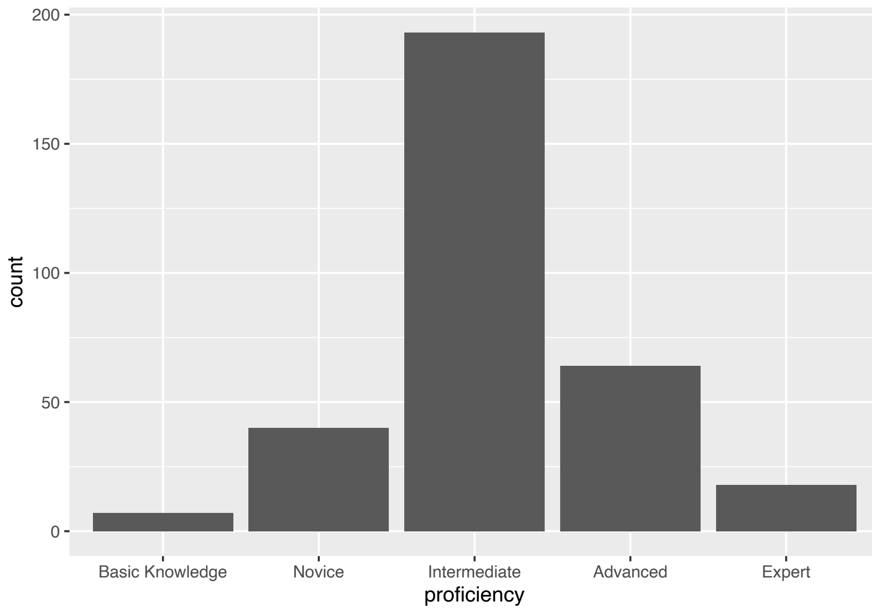
count
200
150
100
50
0
Bazaar
CVS
Git
Mercurial
Other
SVN
NA
first_vcs

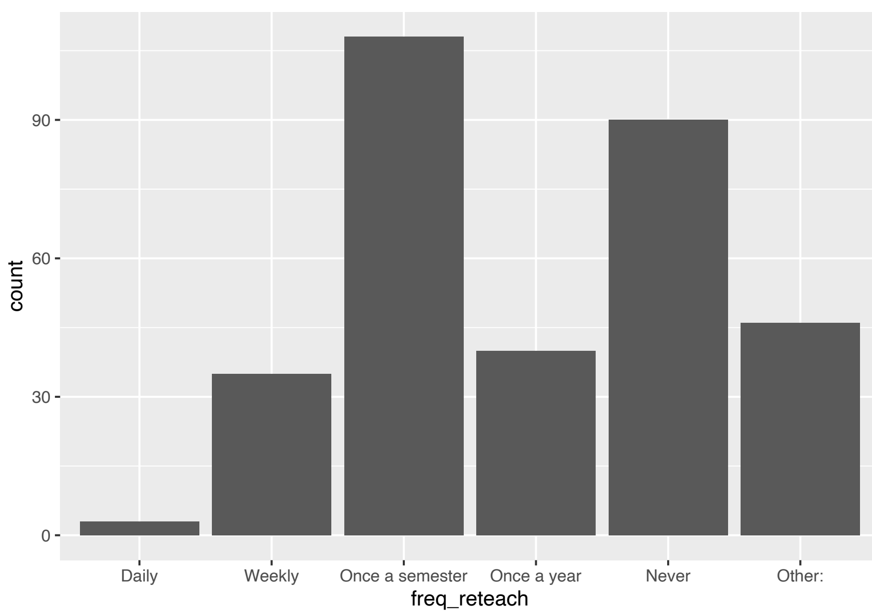


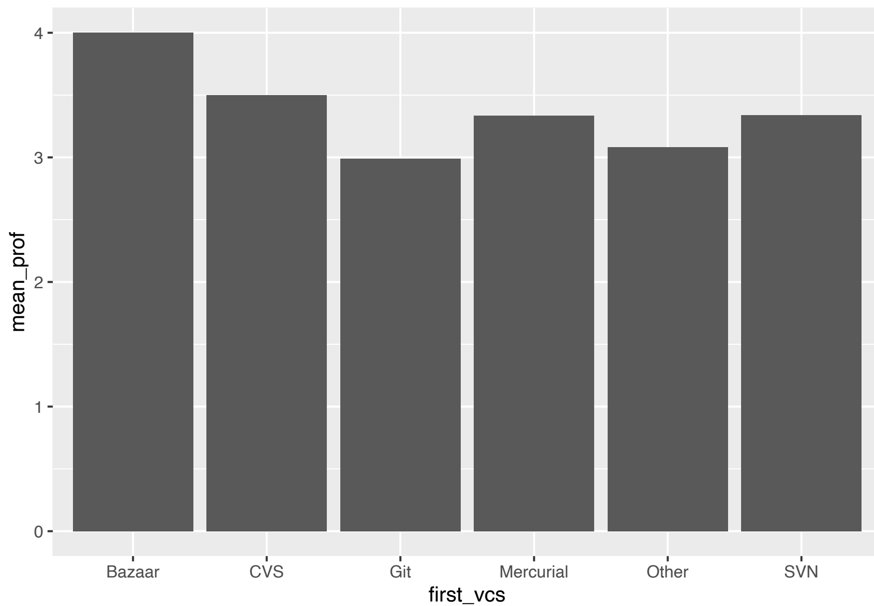
count
200
150
100
50
0
Git
SVN
CVS
Other
Mercurial
Bazaar
first_vcs

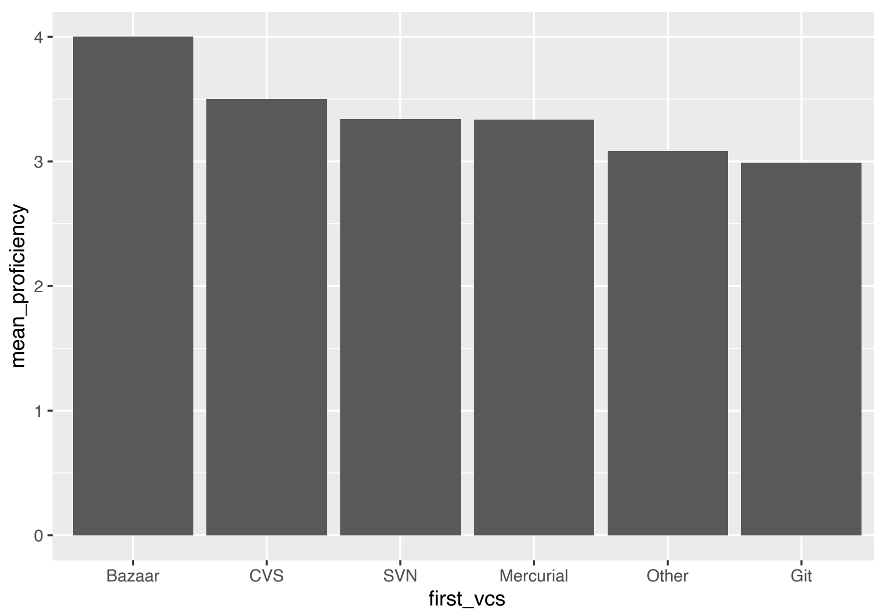

100
50
0
count
Very easy
Easy
Neutral
Difficult
Very difficult
local_ease


125
100
75
50
25
0
count
Very easy
Easy
Neutral
Difficult
Very difficult
ghp_ease

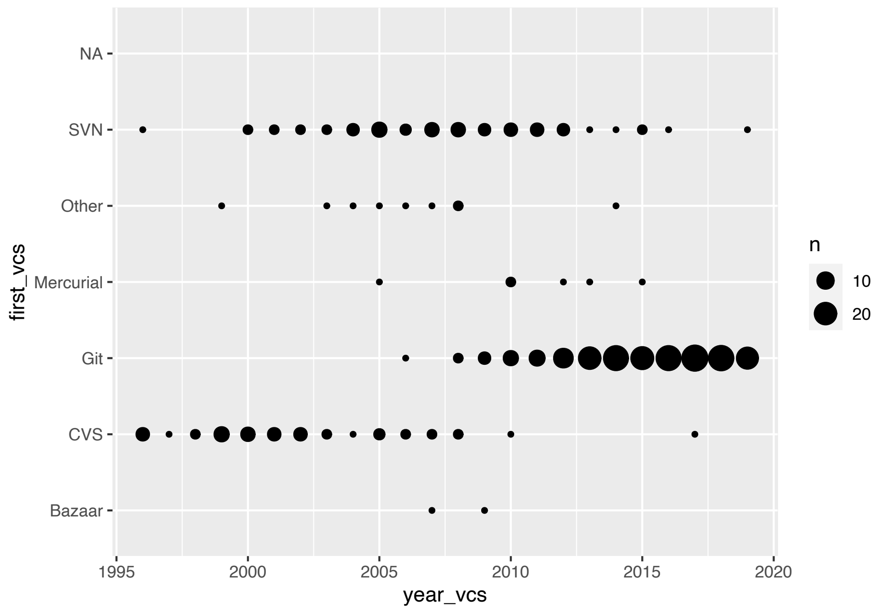

200
150
100
50
0
count
Basic Knowledge
Novice
Intermediate
Advanced
Expert
proficiency


90
60
30
0
count
Daily
Weekly
Once a semester
Once a year
Never
Other:
freq_reteach

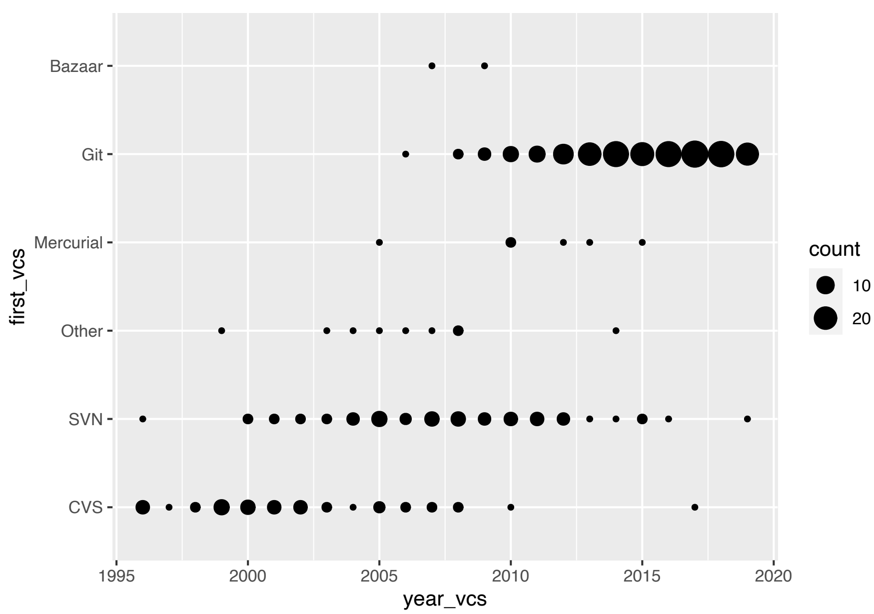




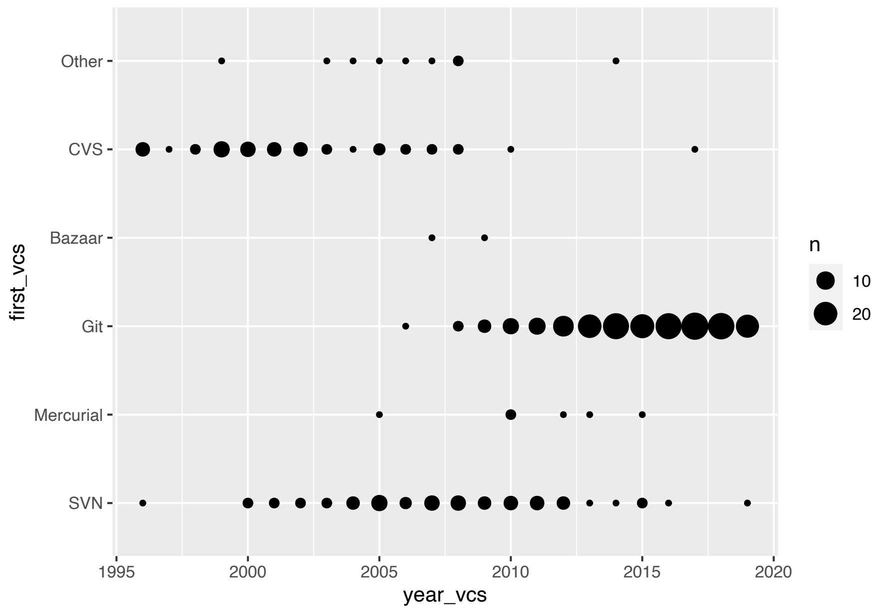

```
## Warning: Removed 15 rows containing non-finite values
## (stat_sum).
```



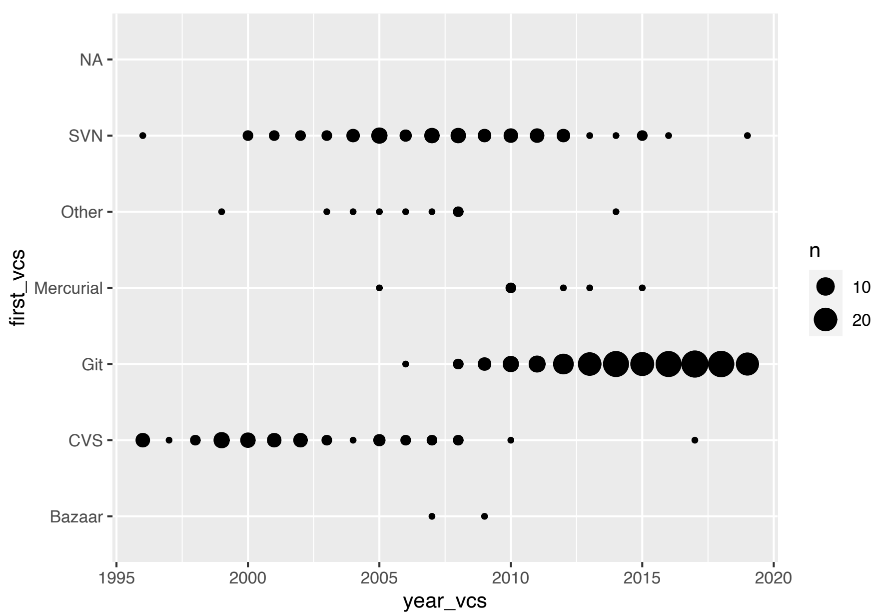

```
## `summarise()` has grouped output by 'year_vcs'. You can override using the `.groups` argument.
```




```
## Warning: Removed 9 rows containing non-finite values
## (stat_sum).
```

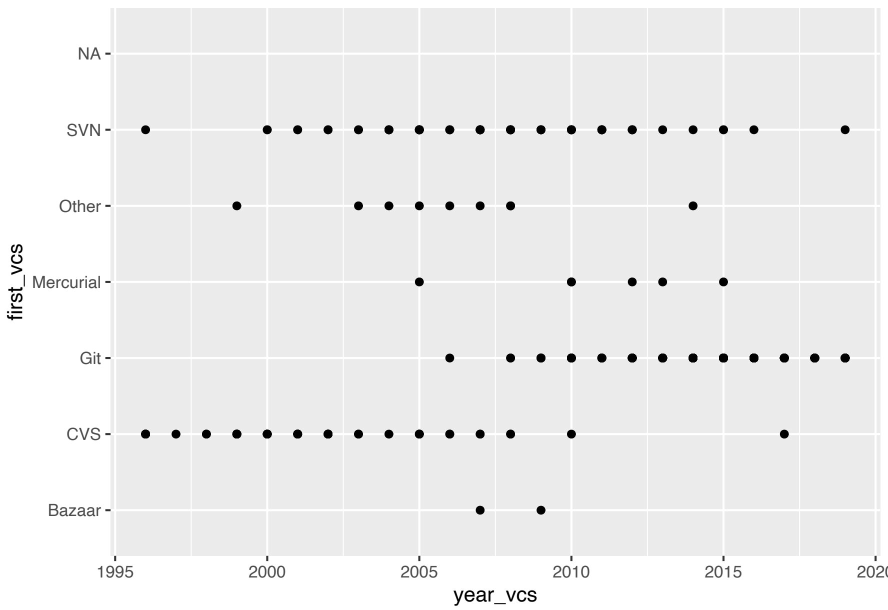



```
## Warning: Removed 3 rows containing missing values
## (geom_point).
```

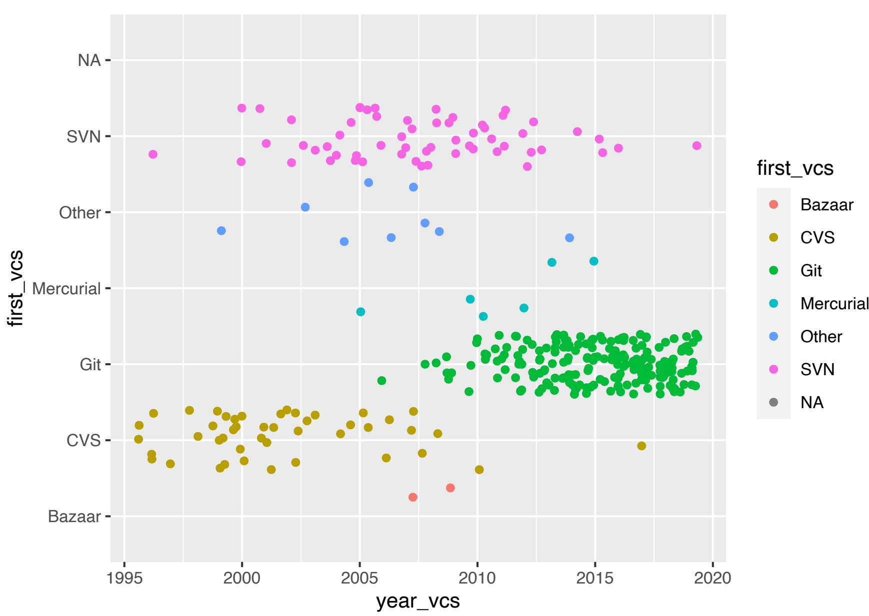



```
## Warning: Removed 15 rows containing missing values
```

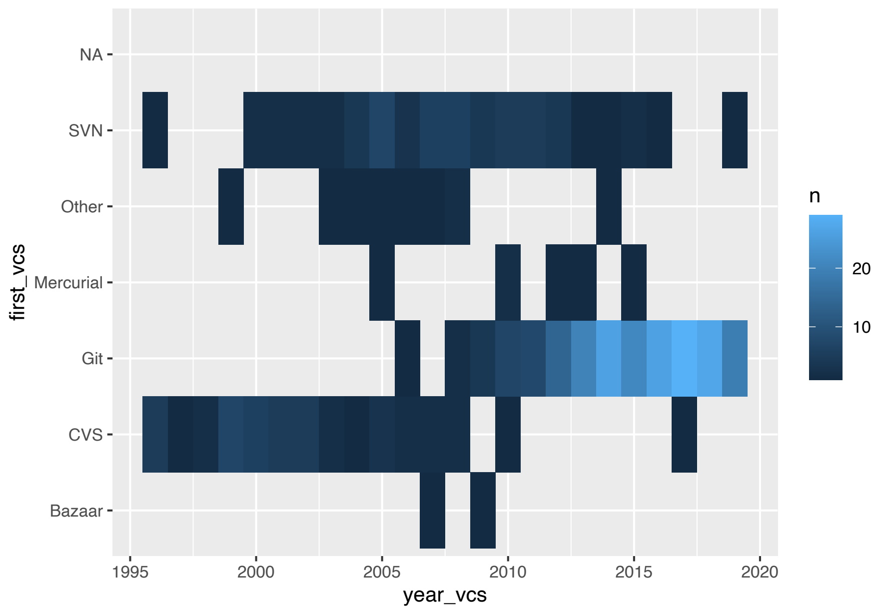
```
## (geom_point).
```

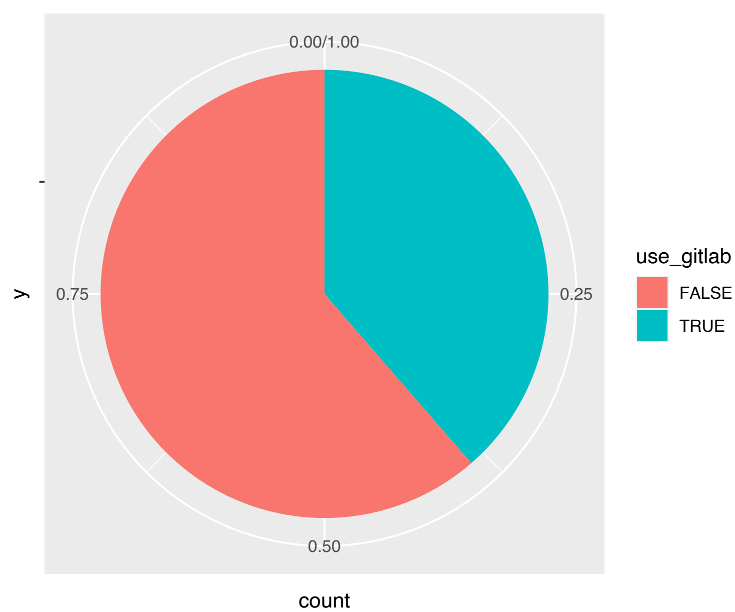



```
## Warning: Removed 15 rows containing missing values
## (geom_point).
```



```
## Warning: Removed 3 rows containing missing values
## (geom_tile).
```





Inclusiveness Index

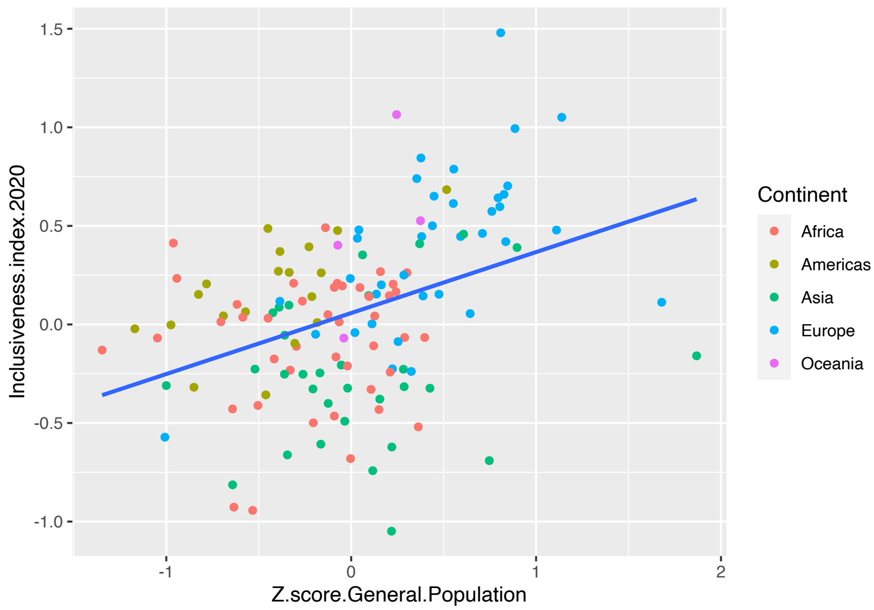
Inclusiveness Index[4]

```
## `geom_smooth()` using formula 'y ~ x'

## Warning: Removed 111 rows containing non-finite values
## (stat_smooth).

## Warning: Removed 111 rows containing missing values
## (geom_point).
```

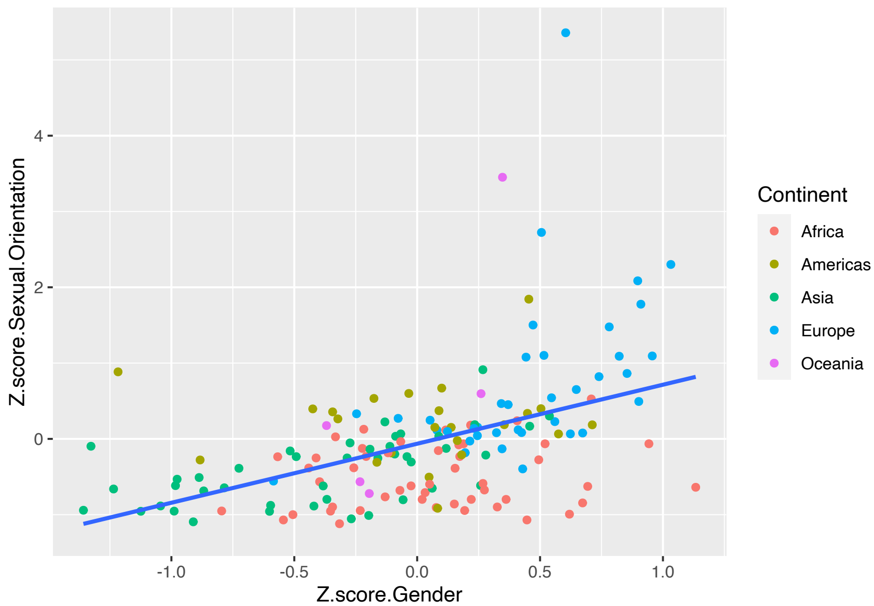

```
## `geom_smooth()` using formula 'y ~ x'

## Warning: Removed 109 rows containing non-finite values
## (stat_smooth).

## Warning: Removed 109 rows containing missing values
## (geom_point).
```

[4] https://belonging.berkeley.edu/inclusivenessindex/data-and-resources

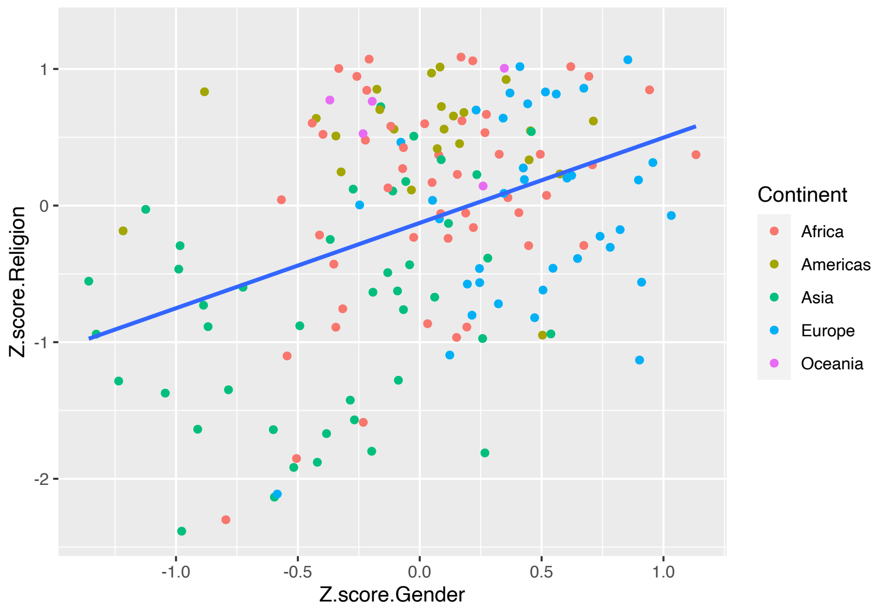

```
## `geom_smooth()` using formula 'y ~ x'

## Warning: Removed 113 rows containing non-finite values
## (stat_smooth).

## Warning: Removed 113 rows containing missing values
## (geom_point).
```



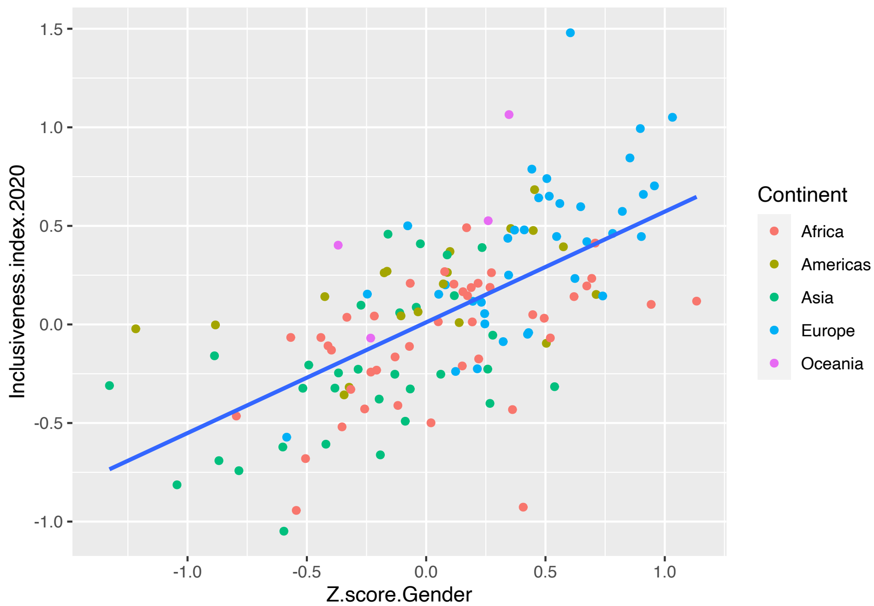

```
## `geom_smooth()` using formula 'y ~ x'

## Warning: Removed 90 rows containing non-finite values
## (stat_smooth).

## Warning: Removed 90 rows containing missing values
## (geom_point).
```



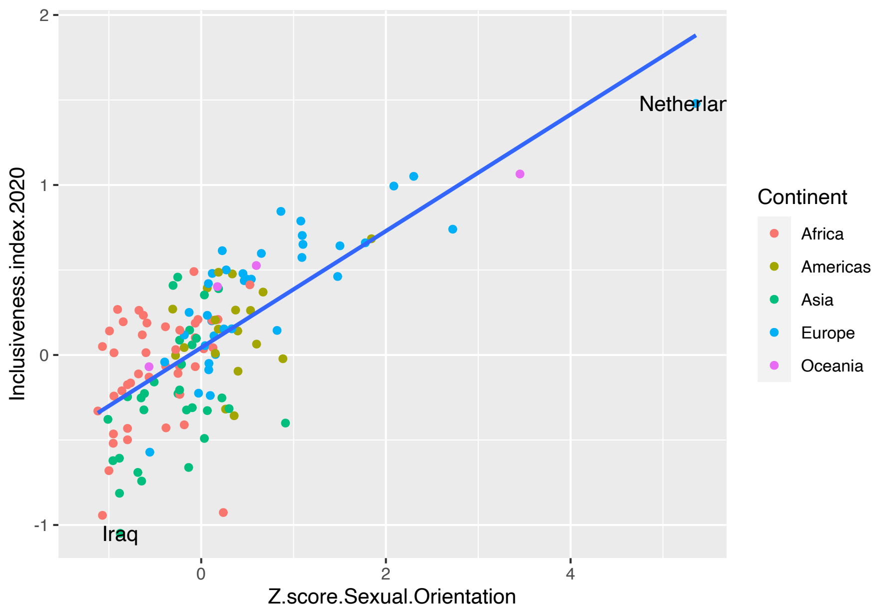

```
## `geom_smooth()` using formula 'y ~ x'

## Warning: Removed 90 rows containing non-finite values
## (stat_smooth).

## Warning: Removed 90 rows containing missing values
## (geom_point).
```



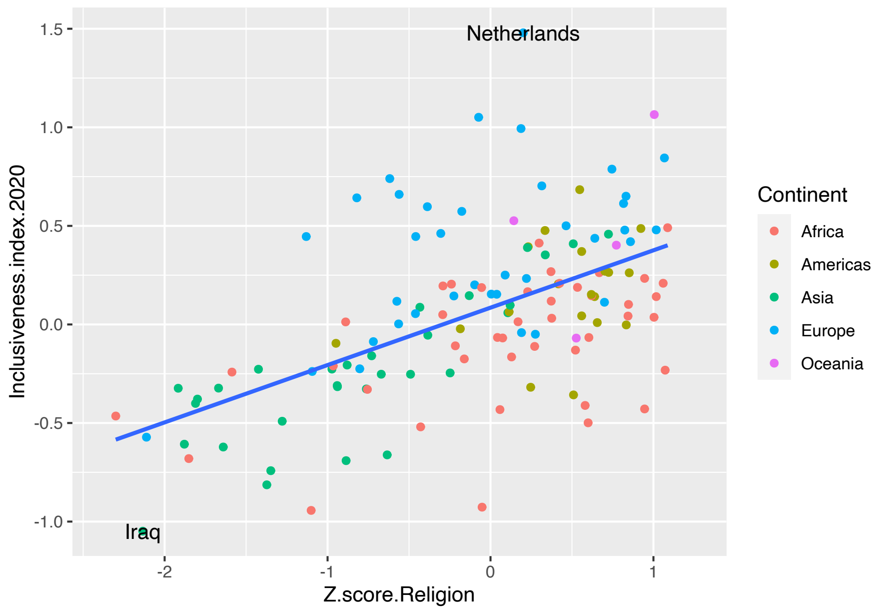

```
## `geom_smooth()` using formula 'y ~ x'

## Warning: Removed 113 rows containing non-finite values
## (stat_smooth).

## Warning: Removed 113 rows containing missing values
## (geom_point).
```



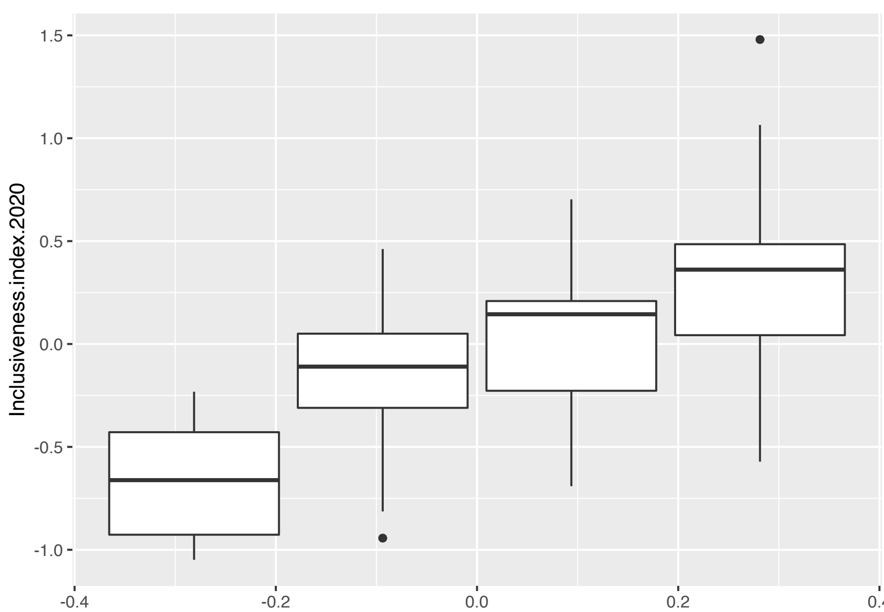

```
## `geom_smooth()` using formula 'y ~ x'

## Warning: Removed 113 rows containing non-finite values
## (stat_smooth).

## Warning: Removed 113 rows containing missing values
## (geom_point).
```




```
## `geom_smooth()` using formula 'y ~ x'

## Warning: Removed 113 rows containing non-finite values
## (stat_smooth).

## Warning: Removed 113 rows containing missing values
## (geom_point).
```




```
## Warning: Removed 113 rows containing non-finite values
## (stat_boxplot).
```



Candidate Demographics

Candidate Demographics[5]

Includes State, Candidate Name, Candidate Party, Office Name, White/Non-White, Race, Gender, Race/Gender Category, Office Level; 4 years (2012, 2014, 2016, 2018), over 40k records

Affinity Spending

Affinity Spending[6]

[5] https://wholeads.us/research/rising-tide-ballot-demographics/
[6] https://github.com/OpportunityInsights/EconomicTracker

Bibliography

Xie, Y. (2015). *Dynamic Documents with R and knitr*. Chapman and Hall/CRC, Boca Raton, Florida, 2nd edition. ISBN 978-1498716963.

Xie, Y. (2021). *bookdown: Authoring Books and Technical Documents with R Markdown*. R package version 0.23.

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