

Chapter 0

Literature Review

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1 Motivation and Background

Data visualizations play an essential role in understanding patterns in the structure of data. They allow for a programmatic mapping of data into a “picture” that can be used to gather insight from the viewer (Tukey 1965; Tufte 2001; Wilkinson and Wills 2005). Since the early 20th century, researchers have been exploring the question: what defines a good graph? (Croxtton and Stryker 1927; Croxtton and Stein 1932; Cleveland and McGill 1984; Vanderplas, Cook, and Hofmann 2020). Many attempts to answer this questions have provided good recommendations, but are largely limited to the projection of graphs onto 2-dimensional (2D) surfaces. While this addresses many of the typical use cases for data visualizations, graphs created in our 3-dimensional (3D) world are largely unassessed.

Many charts exist within the confines of a 2D space due to the practicality of computer renderings. These computer-generated graphics are quick and cheap to produce (Tukey 1965), which possibly contributes to their widespread usage. Before computers, hand-drawn and complex printing techniques were common production methods and took time to produce

(Friendly and Wainer 2021; VanderPlas, Ryan, and Hofmann 2019). In contrast, all data physicalizations require additional material resources, increasing the base cost to produce. This results in the majority of modern graphics being produced with 2D representations on digital screens.

Nearly every type of chart can be created by using a programmatic mapping of data and variables to aesthetics and geometries, a process Wilkinson and Wills (2005) referred to as the “Grammar of Graphics.” This has found widespread implementation into numerous software (Wickham 2010; Satyanarayan et al. 2017; “SAS 9.4 ODS Graphics: Procedures Guide, Sixth Edition,” n.d.). For example, consider the chart created in Figure Figure 1. In this figure, the Palmer Penguins dataset (Horst, Hill, and Gorman 2020) is supplied to the `ggplot` function from the `ggplot2` package (Wickham 2016). The x and y axes are mapped to bill length and bill depth, with color and shape being mapped to island. The geometry is given by `geom_point`, which results in a scatter plot that shows each complete data observation. Although the chart would benefit from further customization, it was quick to produce and has instant visual insights.

```
library(tidyverse)

library(palmerpenguins)

ggplot(penguins, mapping = aes(x = bill_length_mm,
                               y = bill_depth_mm,
                               color = island,
                               shape = island)) +
```

```
geom_point()
```

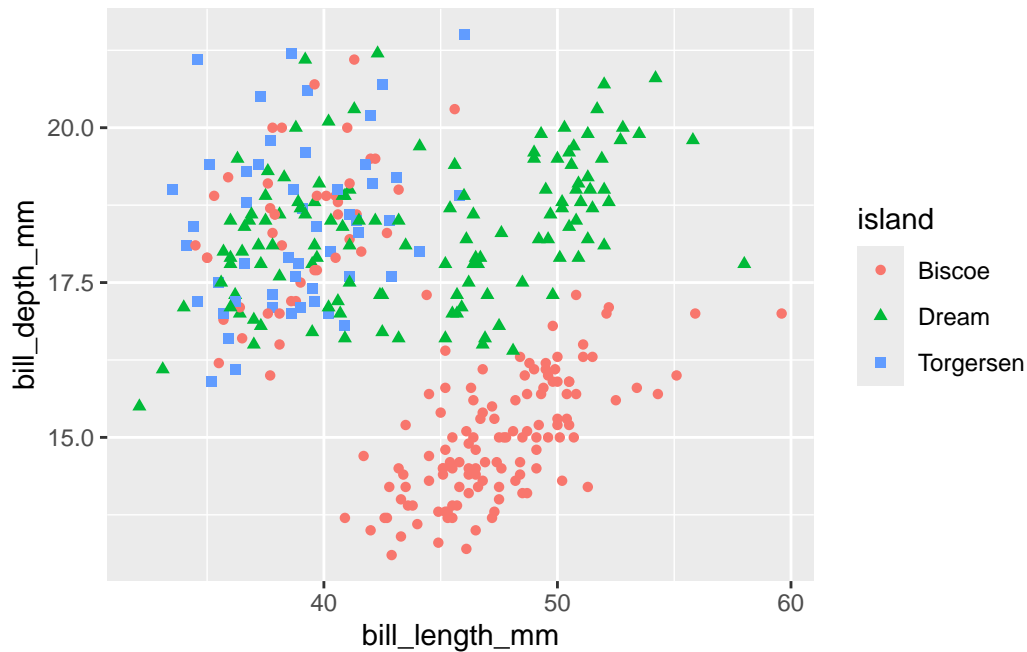


Figure 1: Example of a graphic created using the grammar of graphics.

While there have been many attempts to establish good data visualization practices (Tufte 2001; Vanderplas, Cook, and Hofmann 2020), we do not know how well these recommendations translate from 2D projections into our 3D world. The advent of 3D printing allows us to precisely construct the 3D charts that have widely been studied through their 2D representations (Croxtton and Stein 1932; Barfield and Robless 1989; Zacks et al. 1998). With limited research on 3D-printed data manifestations, we will explore the initial empirical findings of true 3D statistical graphics.

2 Overview of Physical 3D Visualizations

2.1 Creating 3D-Printed Visualizations

The popularity of the 3D printer exploded in the early 2010's as the technology became increasingly available and cheaper. This has led to increase usage of 3D printing in many focus areas, including healthcare (Dodziuk 2016) and engineering (V et al. 2023), but has only seen novel use cases for statistical graphics. Many software programs have the ability to create 3D statistical graphics, but lack the ability to easily export the graphics into files suitable for 3D printing.

Numerous software programs have the can create renderings of 3D charts. Excel (Microsoft Corporation 2025) has native support for creating charts with 3D depth cues, but requires add-ins to produce charts using 3 axes. R (XXX) has a several options for creating 3D charts that have data on 3 axes (e.g., Murdoch and Adler 2024; Morgan-Wall 2024; Sievert 2020), but lacks support for creating depth charts. SAS 9.4 (XXX) has options such as PROC GCHART for adding depth cues and PROC G3D for surface charts. Other popular software programs contain similar capabilities, such as JavaScript libraries, MATLAB, Python, and more.

While a number of tools exist for creating 3D data visualizations, the pipeline of getting these charts into files compatible with 3D printing is not widely automated. For example, R has some options using the `rgl` (Murdoch and Adler 2024) and `rayshader` (Morgan-Wall 2024) packages, but both packages have limited tuning parameters for the resulting output files. Another option is to use 3D software, such as OpenSCAD (Kintel 2023), to manually

create the charts, but these software programs lack the ability to directly integrate statistical information.

Another consideration for 3D-printed charts is the inclusion of text labels. With single-filament 3D printers, text can be incorporated in three primary ways: (1) embossing, in which the text is raised above the surface of the print; (2) engraving, in which the text is recessed into the surface; or (3) applying external labels, such as stickers or ink. Multi-filament 3D printers have the additional option to use a different color to make text labels flush with their surfaces. However, Munzner (n.d.) cautioned that the text of 3D charts will suffer from legibility issues due to the distortion of the text when viewed at an angle.

FIGURE PLACEHOLDER: examples of implementations of text on the charts

2.2 Current use cases

The use of 3D-printed data visualizations for statistical graphics is largely a novelty in the early 21st century. Services such as WhiteClouds (www.whiteclouds.com) offer the ability to create a wide variety of 3D-printed graphics, and more “do-it-yourself” options can be achieved with \$300-\$500 in start-up costs. After acquiring a 3D printer, 1 kilogram rolls of PLA filament cost approximately \$10 on Amazon, resulting in relatively inexpensive charts.

FIGURE PLACEHOLDER: show some examples of 3D printed charts

3 Bar Charts in Research and Practice

One of the most common types of charts is the bar chart, characterized by the use of rectangular geometries. Two variables are mapped to the geometries of the bar chart, where one axis is dedicated to a categorical variable of nominal or ordinal nature, and the other axis is for a continuous variable to denote magnitude or a response. These charts have been used over 200 years, credited to William Playfair in his visualization of trade data (Friendly and Wainer 2021).

The use of 3-dimensional elements in bar charts typically involve converting the rectangular bars into rectangular prisms. The naming convention for these types of charts is not consistent, sometimes referred to as 2.5D charts when the additional dimension does not convey extra information (e.g., Tractinsky and Meyer 1999) or, more commonly, as 3D bar charts (e.g., Zacks et al. 1998; Fischer 2000). All following references to this style of chart will be called “3D bar charts.”

3.1 Against 3D Bar Charts

Tufte (2001) called the use of 3D elements a “fake perspective” in his description of “chart junk”, which is where visual elements add clutter the data visualization. Other researchers (Zacks et al. 1998; Stewart, Cipolla, and Best 2009) have termed the perspective effect “extraneous” when referring to depth cues. The reasoning behind this is fairly intuitive: why include additional noise when simpler alternatives exist?

The seminal work of Cleveland and McGill (1984) theorized that encoding information in volumes would provide worse numerical estimation than for encodings using positions, lengths, and areas. Their reasoning stems from Steven’s Power Law (XXX), a psychophysics formulation that estimates a perceived stimuli magnitude p with the actual magnitude a by $p = ka^\alpha$. The estimation of α provides guidance to what types of stimuli are subject to the most distorted to their true scale when $\alpha = 1$. (alpha for volume estimated to be X, area is Y, and length is Z). While the 3D bar charts do not lose their 2D encodings, they do gain depth, and thus volume encodings. The effect of volume versus area comparisons was noted earlier by Croxton and Stein (1932), where metrics of accuracy were the worst for cubes as compared to bars and circles.

3.2 For 3D Bar Charts

Levy et al. (1996) made an argument for the use of depth cues in certain situations. In a series of three experiments, Levy et al. (1996) tasked over 100 psychology students with selecting one of various 2D and 3D charts that they thought would be best for certain scenarios. What they found was that students tended to pick 3D charts over 2D charts when needing to increase memory recollection of the chart, and about equal preference for 2D and 3D charts when presenting the information to others. Levy et al. (1996) theorized that the depth embellishments in the graphic may increase memorability of the chart by making the chart stand out.

Other types of “chart junk” have shown that additional non-data features can increase rec-

ollection of bar charts at the cost of needing longer processing times (Bateman et al. 2010; Borgo et al. 2012; Peña, Ragan, and Harrison 2020). This increase in time has been shown for 3D bar charts (Siegrist 1996; Fischer 2000; Stewart, Cipolla, and Best 2009), lending some credibility to the argument that 3D depth cues could increase memorability.

3.3 Conflicting Empirical Studies

When accuracy is the goal, 2D is not better than 3D in some cases

Although Tufte (2001) argued against the use of 3D charts when possible, empirical studies involving direct comparisons of 2D and 3D bar charts have shown mixed results. In general, these studies focus on metrics of accuracy and find that 3D bar charts tend to be either less accurate or just as accurate as their 2D counterparts. Another common metric is response time, where 3D charts tend to have longer response times. Overall preference for one style of chart over another is a subjective measurement, but has shown mixed results for the two styles of charts.

3.3.1 Accuracy

Accuracy is a common metric in studies comparing 2D and 3D bar charts, typically measured by either extracting a single numeric estimate or making comparisons between two values. Many studies used controlled environments for constructing stimuli, often displaying one or two stimuli at a time, or controlling non-target stimuli. In practice, charts are often more complex, displaying many stimuli without drawing attention to particular values.

When only measuring accuracy, 3D bar charts tend to be less accurate than their 2D counterparts (Zacks et al. 1998; Stewart, Cipolla, and Best 2009). However, this result is less prominent when introducing time delays (Zacks et al. 1998, Experiment 2) or easier task complexity (Stewart, Cipolla, and Best 2009). Siegrist (1996) noted that bar positions and sizes also affected performance accuracy, emphasizing that other factors contribute to accuracy. It is also important to note that metrics of accuracy are not conclusive, where sometimes there is no evidence of a difference between 2D and 3D bar charts (Melody Carswell, Frankenberger, and Bernhard 1991).

Of course, there are other less-studied factors that could affect perceptual judgments of accuracy in 3D bar charts. In addition to viewing parameters found in 2D bar chart studies (Fischer, Dewulf, and Hill 2005; Rice et al. 2024), adding depth cues are also subject to viewing angles, amount of depth, and field of view parameters. Viewing angle, with respect to the axis, can mislead the reader into overestimating or underestimating numerical quantities (FIGURE X). Zacks et al. (1998) did not find a significant effect for the amount of perception depth, but noted a trend such that increased exaggeration of depth lowered their accuracy metric. Lastly, field of view is fixed for the viewer, but can widely distort 3D renderings (FIGURE X). These factors add additional complexity, but are not widely studied for the use of statistical graphics.

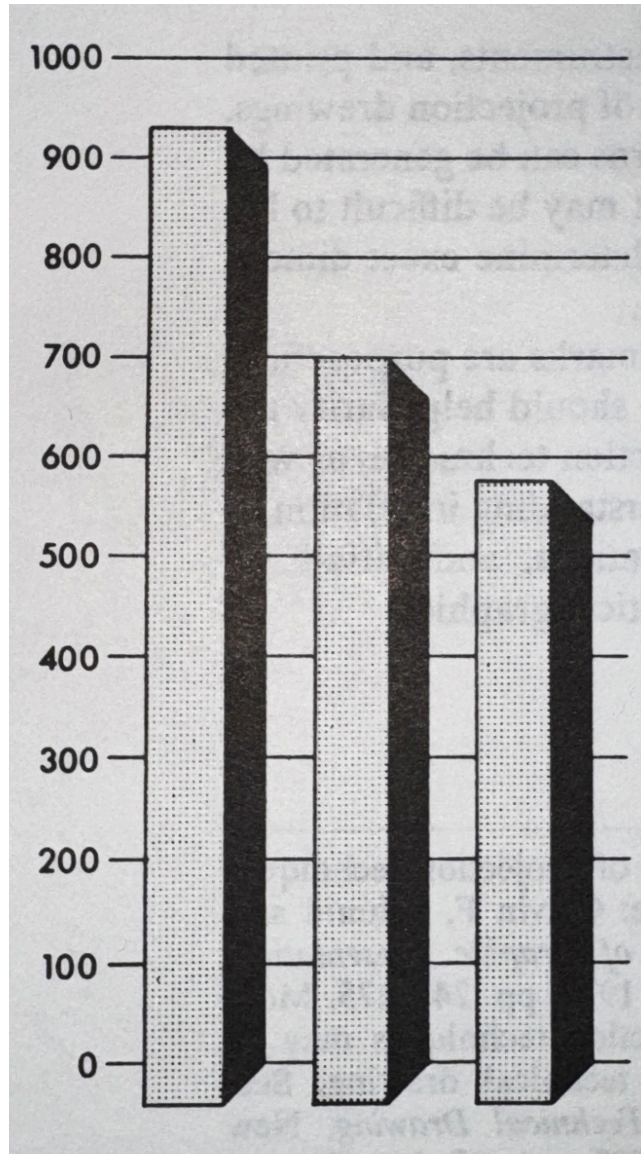
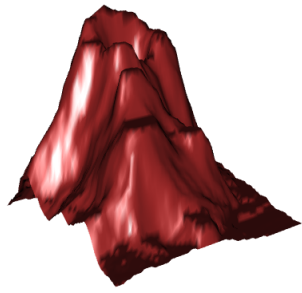


Figure 2: Figure in Statistical Graphics: Design Principles and Practices. The viewing angle for this chart would have viewers overestimate the values of the bars



(a) FOV: 30 degrees



(b) FOV: 60 degrees



(c) FOV: 90 degrees



(d) FOV: 120 degrees



(e) FOV: 150 degrees

Figure 3: Multiple charts of the volcano dataset (R Core Team 2024) rendered using the `rgl` package (Murdoch and Adler 2024) in R. Each chart has a different field-of-view parameter, with the amount of distortion increasing as the field-of-view (FOV) increases.

3.3.2 Response Times

The speed in making perceptual judgments is another common metric in studies comparing types of charts. In theory, charts where questions can be answered more quickly implies that the chart is better at communicating information. However, response time is a poor metric in situations of exploratory data analysis and long term interactions with complex graphics (Vanderplas, Cook, and Hofmann 2020). When a question of interest is known in advance, response time becomes a more viable metric.

Depth cues from 3D bar charts tend to increase the amount of time required to answer questions (Siegrist 1996; Fischer 2000; Stewart, Cipolla, and Best 2009). Intuitively, additional complexity should require additional time to process. For 3D bar charts, viewers need to align the response axis with the rectangular prisms in order to determine the approximate magnitude of the bar. Consider Figure X, where the y-axis denotes magnitude with respect to a hidden face of the bar. In order to extract a numerical quantity, the viewer first has to align the axis with the correct face of the prism before processing the magnitude.

3.3.3 Preference

The debate between whether to use 2D or 3D graphics stems from a wider adoption of 3D charts in practice. Computer graphics have made it easy to produce charts of either dimensionality, resulting in creative liberties for the creation of the chart for publication. Figures X and X showcase two examples of 3D bar charts from the 1978 Handbook of Agricultural Charts

(XXX) where other options exist for displaying the data. Schmid (1983) (Ch. 8) also showcases many other 3D charts published in official reports.

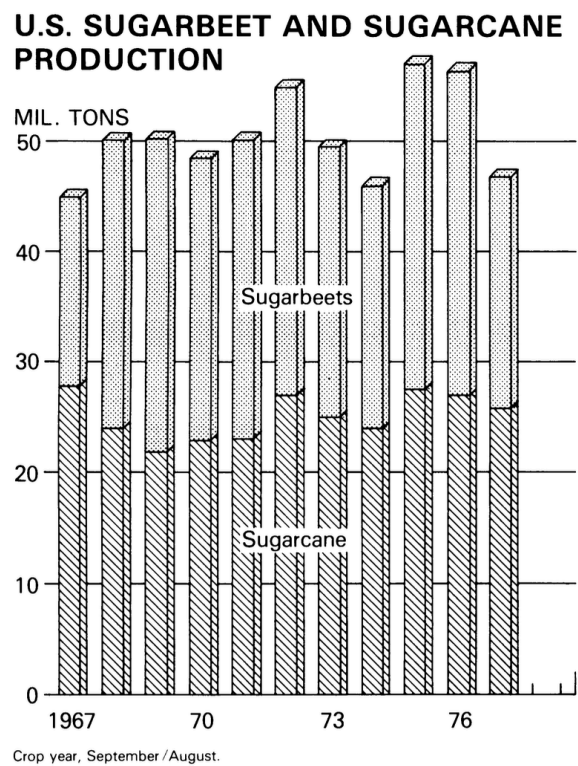
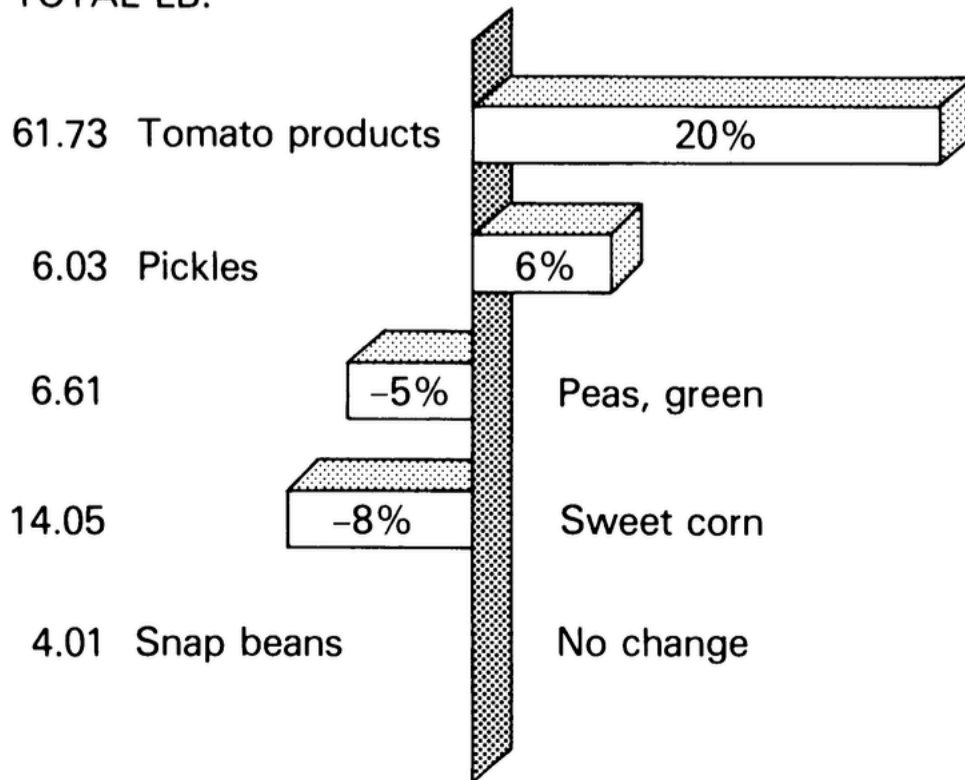


Figure 4: Located from 1978 HANDBOOK OF AGRICULTURAL CHARTS

CHANGES IN CANNED VEGETABLE CONSUMPTION PER CAPITA BETWEEN 1970-72 AND 1975-77

TOTAL LB.



Fresh-weight basis.

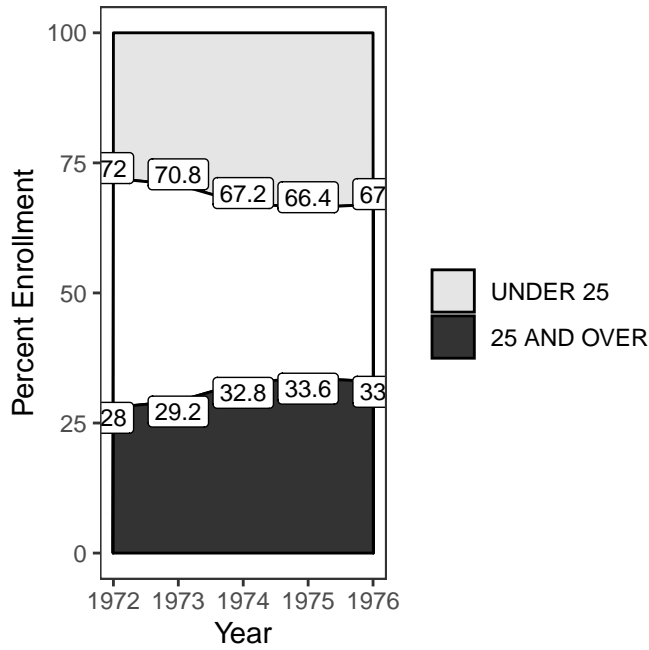
Preference can be broken down into two broad categories: (1) visual appeal, and (2) usefulness.

Visual appeal is where perceptual tasks are not a priority, and the goal is to have an image that is pleasant to the viewer. Usefulness, on the other hand, is a rating of how effective the viewer thought the chart was in order to answer the question. Both are subjective measures

When not tasked with estimating values, 3D bar charts tend to be more visually appealing

(Levy et al. 1996; Fisher, Dempsey, and Marousky 1997; Stewart, Cipolla, and Best 2009).

This may be in part due to the forced illusion of depth which creates additional embellishments that would increase the impression and memorability of the chart, as seen by other types of Tufte’s “chart junk” (Borgo et al. 2012; Peña, Ragan, and Harrison 2020). Despite the visual appeal, 2D charts tend to be chosen for preference and ease of use when making numerical estimations (Levy et al. 1996; Stewart, Cipolla, and Best 2009).



3.4 Construction of 3D Bar Charts

All of the aforementioned studies have one key limitation: they are conducted in environments where the 3D bar charts are projected onto 2D surfaces. An argument could be made that tactile charts created for persons with vision impairments could be considered 3D (Goncu and Marriott 2008; Engel and Weber 2017; Watanabe and Inaba 2018), but current implementa-

tions are vastly different from the typical design of 3D bar charts.

4 Heat Maps in Research and Practice

When creating charts for three or more variables, it becomes increasingly complex to visualize data (Grinstein and Trutschl 2001). One option is to map the additional variables using gestalt principles (Vanderplas, Cook, and Hofmann 2020) (Original citation?), which includes making use of color, size, and/or shapes to denote information. However, not every aesthetic is compatible with every type of variable. Color can be used to map either continuous variables with gradient scales or categorical variables with palettes. Size is typically reserved for continuous variables, where larger values correspond to a larger quantity. Shapes tend to have finite distinguishable representations in order to represent categorical variables. Examples of good and poor cases for each of these aesthetics is presented in Figure Figure 5.

Heat maps are a type of chart that can be used with two variables of any type and a continuous response variable. In two-dimensional formats, color is often used to denote the magnitude of the response, utilizing a gradient scale. When represented in three dimensions, height is the primary mapping of the response of the heat map. Due to the height aesthetic, 3D heat maps are sometimes referred to as “height maps”, particularly when spatial coordinates are involved.

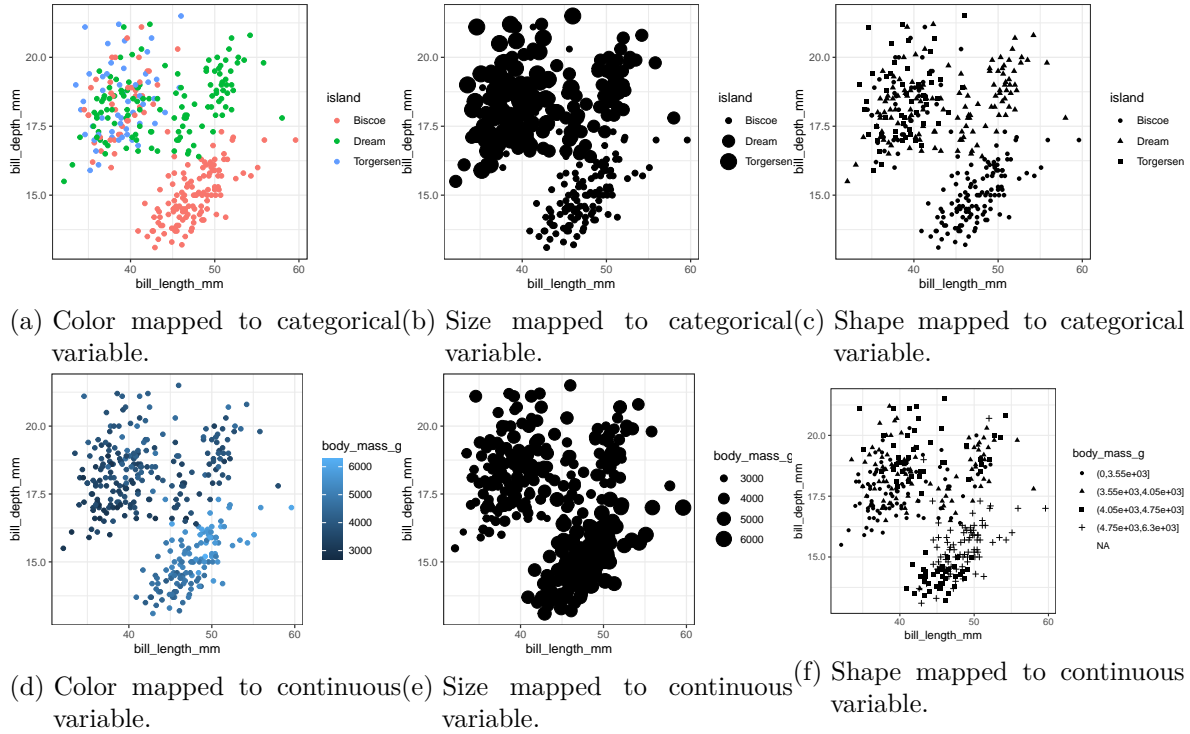
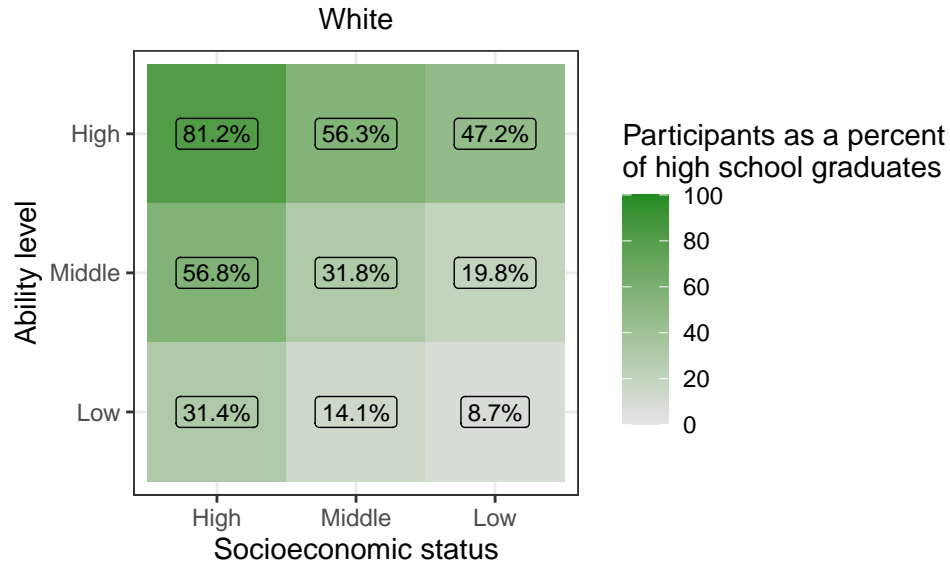
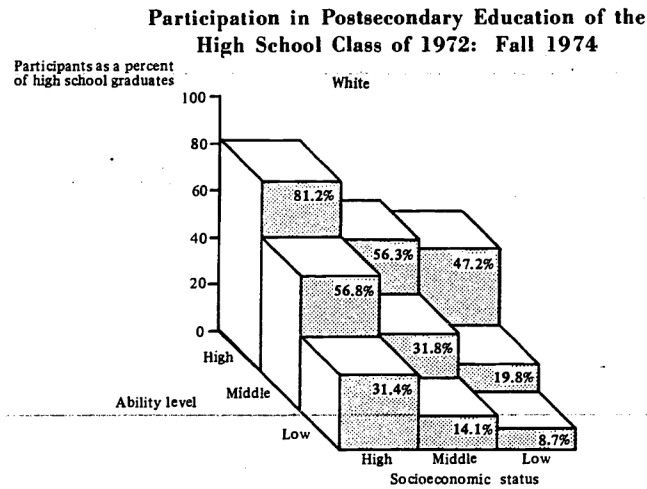


Figure 5: Examples of color, size, and shape for scatterplots of the penguins dataset (Horst, Hill, and Gorman 2020).

Participation in Postsecondary Education of the High School Class of 1972: Fall 1974



(a) 2D heat map



(b) 3D heat map

Figure 6: Heat maps created from with data from (XXX). The 2D heat map represents the percentage of high school graduates using a gradient color scale, whereas the 3D heat map uses height.

4.1 Empirical Studies of 2D and 3D Heat Maps

Unlike 2D and 3D bar charts, the comparison of dimensionality for heat maps has not been widely studied. This may in part be due to the complex nature of color scales (Breslow, Ratwani, and Trafton 2009; Liu and Heer 2018; Reda and Papka 2019). While bar charts simply add a perspective depth cue to increase the dimensionality, the translation of color to height results in numerous considerations, such as the scaling of the height (Figure @fig-color-height).

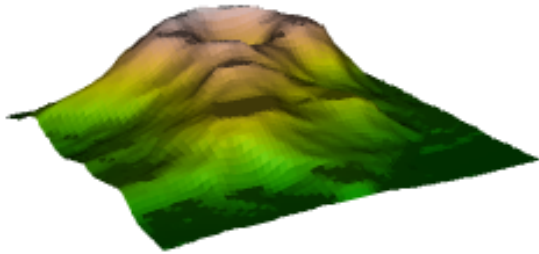
The type of media can affect the perception of 2D and 3D heat maps (Kraus et al. 2020; Jeong et al. 2025).

- Barfield and Robless (1989)
- Kraus et al. (2020)
- Jeong et al. (2025) would be good, but uses VR
- Casali and Gaylin (1988)

5 Methods for Evaluating Visualization Effectiveness

5.1 What makes a good chart?

Vanderplas, Cook, and Hofmann (2020) discussed various approaches to testing graphics, including numerical estimations, speed, and error rates. These metrics are fairly common met-



(a) Flatter height scale



Figure 7: Two figures representing the volcano dataset (R Core Team 2024) using different height scaling factors. Both figures use the same color scale, but there is no “correct” translation of color into the measurable height.

rics when comparing 2D and 3D charts (Croxtton and Stein 1932; Cleveland and McGill 1984; Hughes, n.d.), but do not represent the full picture of what makes a one type of chart better than another. As seen by Levy et al. (1996), the objectives of the chart can determine which type of chart should be used.

Since true 3D charts have limited research compared to 2D representations, it is reasonable to compare how perceptual judgements of numerical estimations compare to earlier studies in statistical graphics.

5.2 Designing studies for numerical estimations

Over 2,500 citations have referenced the work of Cleveland and McGill (1984) when discussing properties of statistical graphics. Since then, the methods of analyzing and conducting studies on statistical graphics have evolved (e.g., Vanderplas, Cook, and Hofmann 2020; Hofmann et al. 2012), but yet the structure of experimental designs involving numerical estimations tend to remain similar. Tasks typically involve the comparison of two stimuli, where the question is “how much bigger/smaller is one value compared to the other?” Care needs to be taken in the phrasing of this question since mental subtractive processes are perceived different from mental ratio processes (Veit, n.d.; Hagerty and Birnbaum 1978).

Cleveland and McGill (1984) asked participants two questions when making comparisons between two values on a chart: (1) which of the two values was the smaller, and (2) what percentage the smaller was of the larger. The first question clarified if the participants were looking at the values correctly for the second questions, and the second question is an estimation of A/B ,

where $A < B$. Accuracy was measured by $\log_2(|\text{True value} - \text{Estimated value}| + 1/8)$, using the trimmed averages when bootstrapping confidence intervals. Cleveland and McGill's experiment was replicated by Heer and Bostock (2010), showing similar results for the experiment's procedure in a crowdsourced environment.

When designing studies for numerical estimation, the choice of A/B and the measure of error are important considerations. Many researchers seemingly choose ratios in an arbitrary fashion or follow previously established work Melody Carswell, Frankenberger, and Bernhard (1991). As for measures of error, several formulations can be used.

- $|\text{Error}|$ for magnitude of error
- Error for direction of error
- $\log |\text{Error}|$

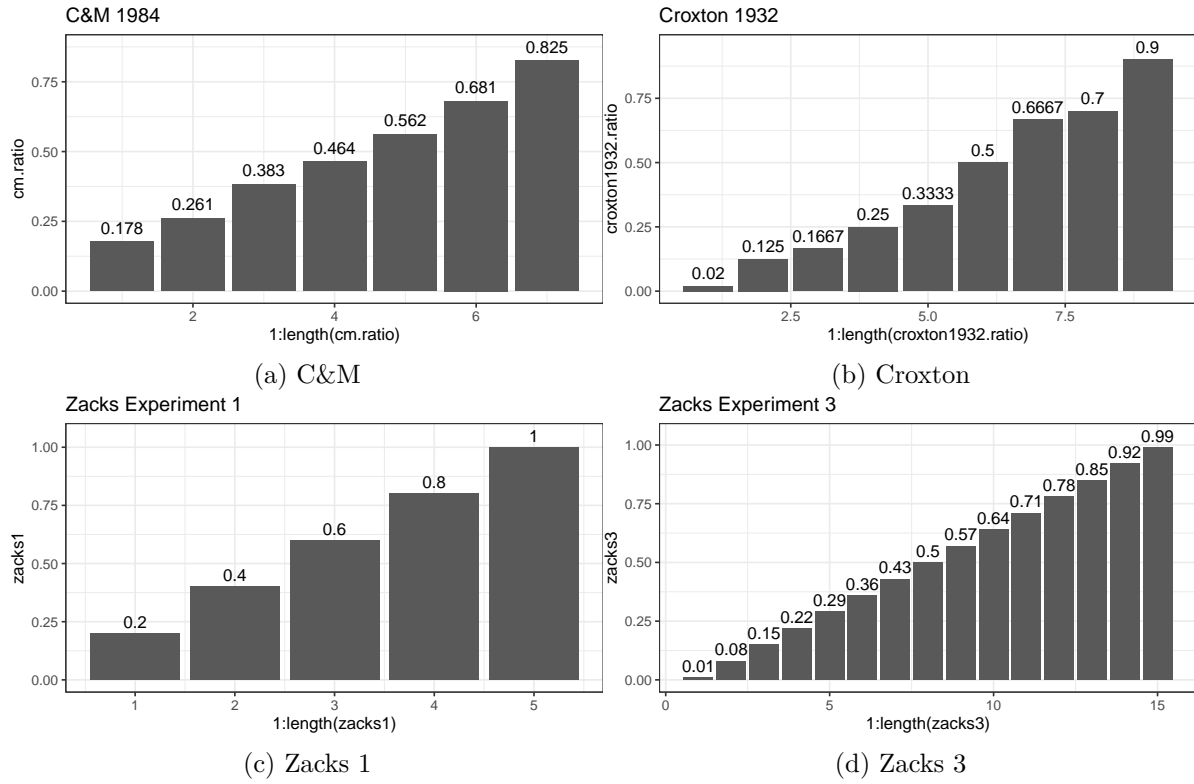


Figure 8: Ratios used by several studies

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