CHAPTER 0

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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 makes a good graph? (Croxton and Stryker 1927; Croxton and Stein 1932; Cleveland and McGill 1984; Vanderplas, Cook, and Hofmann 2020). Many attempts to answer this question 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, the process of creating modern statistical graphics in our 3-dimensional (3D) world is a relatively new phenomenon that does not have widespread usage.

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. Additionally, there are few modern resources that have direct pipelines from data to physical objects. One such example is the rayshader package (Morgan-Wall 2024), although modifications to the resulting stereolithography (STL) file or OBJ file are needed before physicalization can take place. 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 sometimes referred to as the "Grammar of Graphics" (Wilkinson and Wills 2005). 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. Other software packages can create the same chart using a similar process by specifying the axes, colors, and shapes using a point geometry.

```r
library(tidyverse)

library(palmerpenguins)

ggplot(penguins, mapping = aes(x = bill_length_mm,

                               y = bill_depth_mm,

                               color = island,

                               shape = island)) +

  geom_point()
```

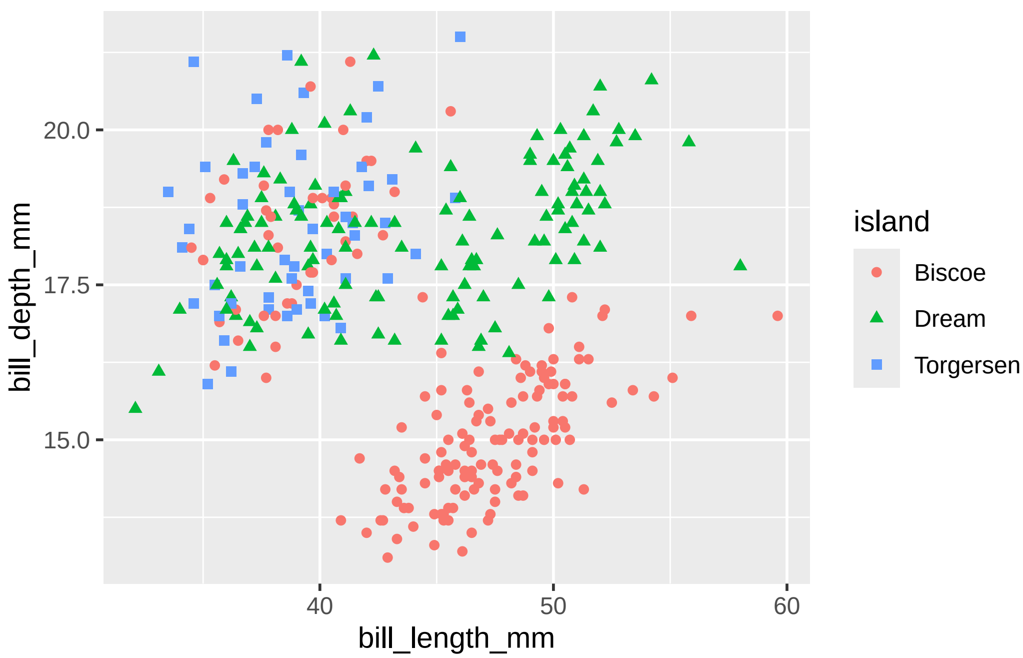


Figure 1: Example of a graphic created using the grammar of graphics.

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 (Croxton and Stein 1932; Barfield and Robless 1989; Zacks et al. 1998). With limited research on 3D-printed data manifestations, we explore the initial empirical findings of true 3D statistical graphics.

2 Overview of Physical 3D Visualizations

Data can be expressed in the physical world through a wide variety of means. In many cases, this can take on artistic expressions, such as encoding information into crocheted blankets or wooden sculptures (Huron et al. 2023). While certainly providing information about the data, these informational art pieces are largely left as display items to promote conversation into the underlying dataset.

Figure 2: 3D-printed treemap created displaying Gross National Income (GNI) for 130 countries (Huron et al. 2023, pg. 217). The two 3D prints on the bottom have additional information overlaid on top of the treemap as 2D displays.

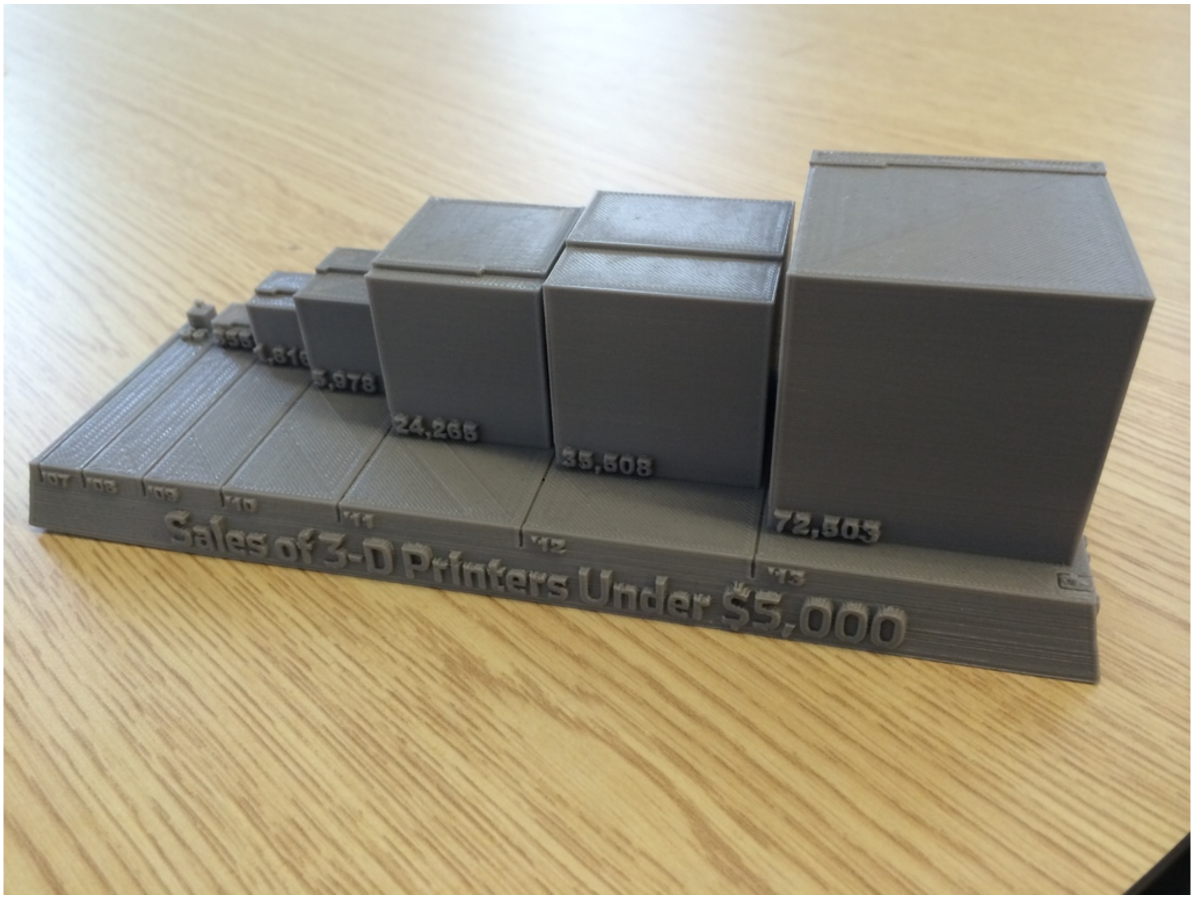
Perhaps one of the most affordable types of data physicalization is through the use of 3D printing. Aside from the startup cost of a 3D-printer, material and labor costs are relatively low. Rolls of PLA filament can be acquired for under $20 and can be used to create multiple charts. Print times vary depending on the size and complexity of the graphic, but smaller charts can be produced in approximately 2 hours. While needing much more time to produce than computer-generated visualizations, the amount of hands-on labor during the 3D-printing process is minimal.

One of the earliest 3D-printed charts was shared in 2014 by the Wall Street Journal, where the print was used to discuss the rising popularity of 3D printers (**graphicsHowDoes3D?**; Thingiverse.com n.d.). Since then, using 3D printers to create statistical graphics has typically been reserved for niche purposes. It is rare to find these types of charts in practice, where images of the charts are often posted to social media or blog posts. This results in limited access to the physical charts, even though source print files can be shared through sites such as thingiverse.com and printables.com.

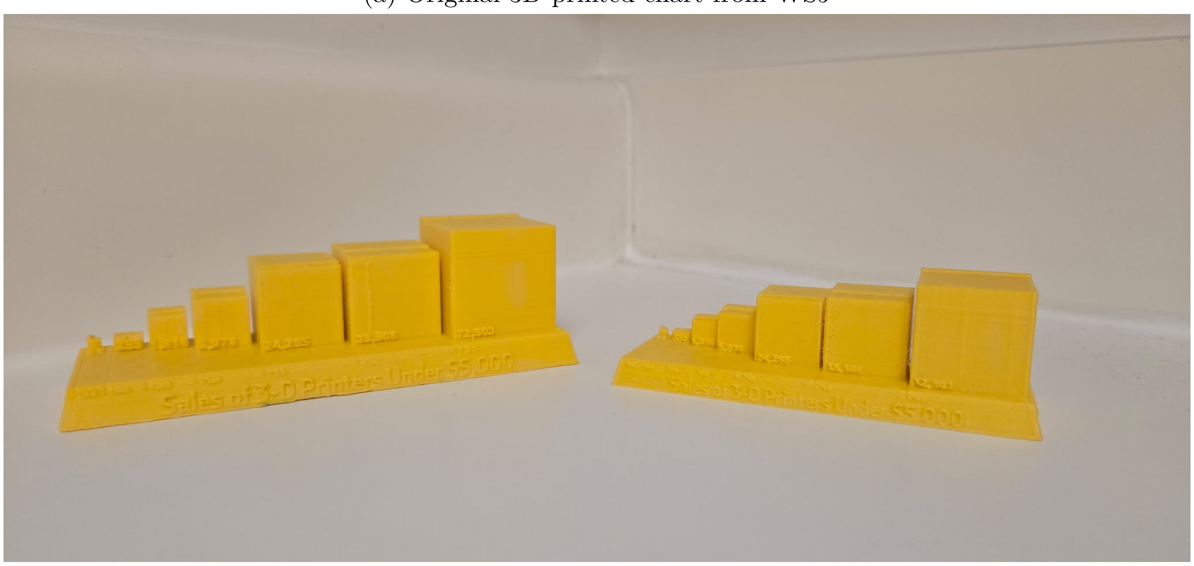
2.1 Creating 3D-Printed Visualizations

The popularity of the 3D printer exploded in the early 2010's as the technology became increasingly available and cheaper. This has led to increased use 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 can create digital 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 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, and Python.



(a) Original 3D printed chart from WSJ



(b) Replicated print created in 2025

Figure 3: 3D-printed volume charts showing the sales of 3D printers under $5,000 (Thingiverse.com n.d.). Figure 3a shows the original WSJ print from 2014. Figure 3b shows two prints created with a Flash Forge Finder 3D Printer, where the smaller chart took 2 hours to print and the larger chart took 6 hours to print.

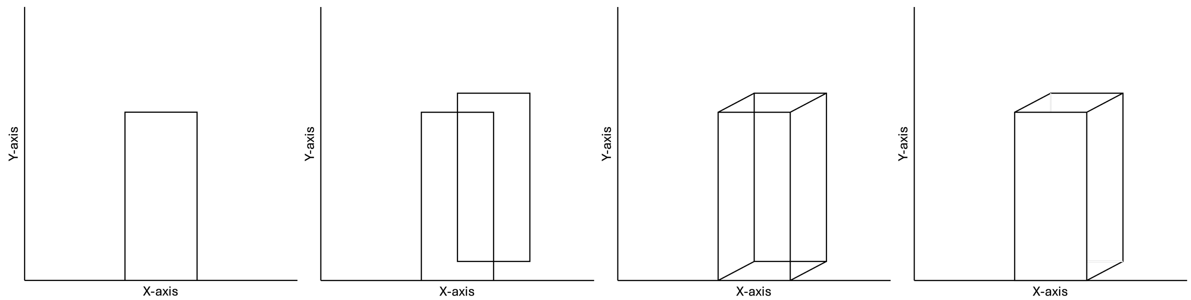
While a number of tools exist for creating 3D data visualizations, the pipeline of getting these charts into files compatible with 3D printing is not widely automated. For example, R has some options using the `rgl` (Murdoch and Adler 2024) and `rayshader` (Morgan-Wall 2024) packages, but both packages 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 in the formulation of the charts.

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.

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 in a 2D space. 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 and remain a popular choice for many modern data visualizations (Friendly and Wainer 2021).

The use of 3-dimensional elements in bar charts typically involve converting the rectangular bars into rectangular prisms. Figure 4 shows an illustration of this transformation.



(a) 2D bar (b) Opposite face (c) Connecting faces (d) Solid object

Figure 4: Construction of depth cues for a 2D bar chart. First, the amount of depth is set by defining the opposite face of the standard 2D rectangular shape. Then the faces are connected and volume is filled in.

The naming convention for these types of bar charts is not consistent. Many researchers in the visualization community call these 3D bar charts due to the portrayal of three-dimensional space (e.g., Zacks et al. 1998; Fischer 2000). Other times, the lack of information in the third dimension results in the charts referred to as 2.5D charts (e.g., Tractinsky and Meyer 1999). To keep a consistent nomenclature, they will be called "3D bar charts" throughout this dissertation.

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 to 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 distortion to their true scale when $\alpha = 1$. 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 accuracy for ratio estimations was worse for cubes as compared to bars and circles.

From an artistic point of view, depth cues can obscure some elements of the chart, resulting in a decrease in readability. For 3D bar charts, this often occurs from the volumetric elements partially covering the response axis. Consider Figure 5 where the y-axis corresponds to the back face of the rectangular prism. In this case, the front and right faces do not directly correspond with the axis, thus making it more difficult to extract values from the chart.

3.2 For 3D Bar Charts

Levy et al. (1996) argued that depth cues can be useful in certain contexts. In three experiments involving over 100 psychology students, participants were asked to select from a range

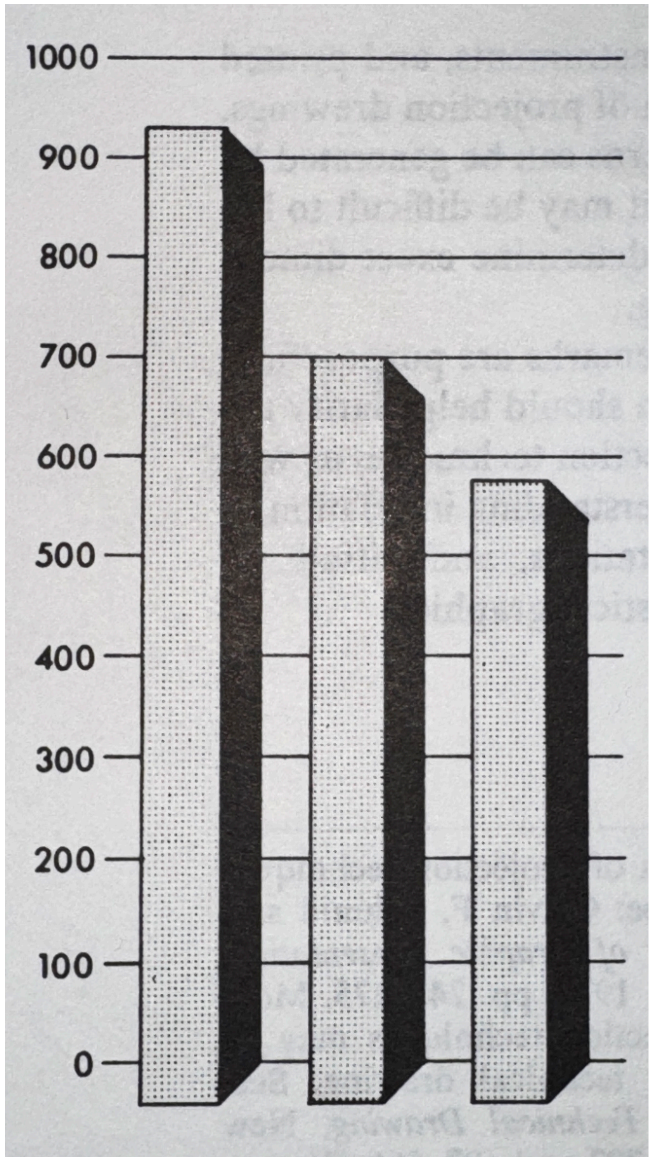


Figure 5: Figure in Statistical Graphics: Design Principles and Practices. The viewing angle for this chart would have viewers overestimate the values of the bars

of 2D and 3D charts for different tasks. Results showed that students more often preferred 3D charts when the goal was to enhance memory of the chart, while preferences were about evenly split between 2D and 3D when the task was to present information to others. Levy et al. (1996) suggested that the depth embellishments in 3D graphics may boost memorability by making charts more visually distinctive.

This idea aligns with broader findings on "chart junk," where non-data elements have been shown to aid recall of bar charts, though often at the cost of longer processing times (Bateman et al. 2010; Borgo et al. 2012; Peña, Ragan, and Harrison 2020). Similar increases in processing time have been reported specifically for 3D bar charts (Siegrist 1996; Fischer 2000; Stewart, Cipolla, and Best 2009), lending some support to the claim that depth cues may improve memorability despite potential cognitive trade-offs.

The persistence of 3D bar charts reflects the influence of artistic preferences in visualization. The added depth can make results appear more striking, giving the impression of visual weight. Such embellishments often appeal to audiences by enhancing visual impact, even when they add little to the clarity of the data itself.

3.3 Conflicting Empirical Studies

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).

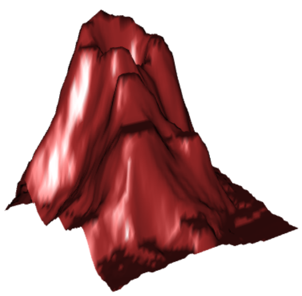
Of course, there are other less-studied factors that could affect perceptual judgments of accuracy in 3D bar charts. In addition to viewing parameters found in 2D bar chart studies

(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 5. 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 6. These factors add additional complexity, but are not widely studied for the use of statistical graphics.

3.3.2 Response Times

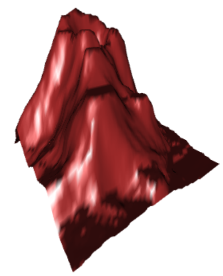
The speed in making perceptual judgments is another common metric in studies comparing types of charts. In theory, charts where questions can be answered more quickly implies that the chart is better at communicating information. However, response time is a poor metric in situations of exploratory data 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



(a) FOV: 30 degrees

(b) FOV: 60 degrees



(c) FOV: 90 degrees

(d) FOV: 120 degrees

(e) FOV: 150 degrees

Figure 6: 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.

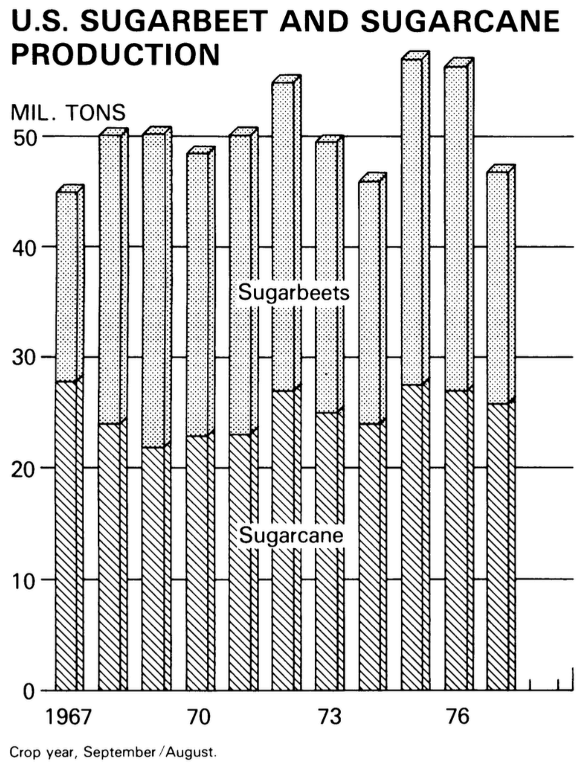
hidden face of the bar. In order to extract a numerical quantity, the viewer first has to align the axis with the correct face of the prism before processing the magnitude.

3.3.3 Preference

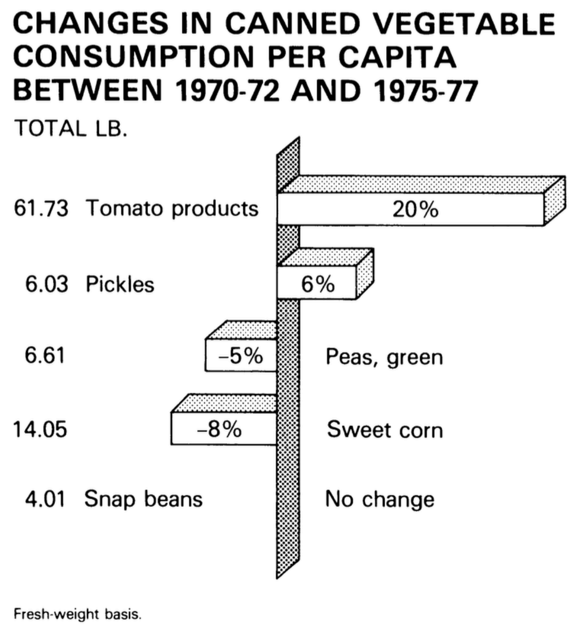
The debate between whether to use 2D or 3D graphics stems from a wider adoption of 3D charts in practice. Computer graphics have made it easy to produce charts of either dimensionality, resulting in creative liberties for the creation of the chart for publication. Figure 7 showcases two examples of 3D bar charts from the 1978 Handbook of Agricultural Charts (**cdi_hathitrust_hathifiles_uva_x030492864?**) where other options exist for displaying the data. Schmid (1983) (Ch. 8) also showcases many other 3D charts published in official reports.

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 that influence the choice

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



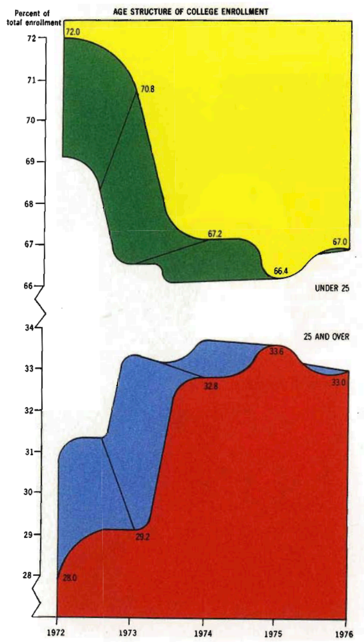
(a) Bar chart with strictly positive values



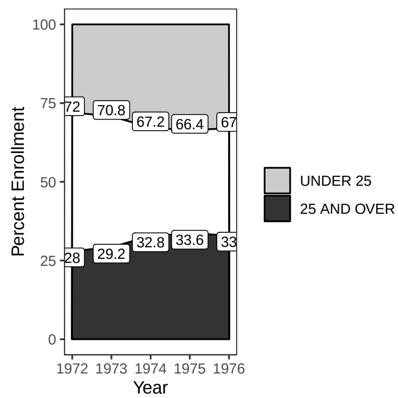
(b) Bar chart with negative values

Figure 7: Two examples of 3D bar charts found in publication (**cdi_hathitrust_hathifiles_uva_x030492864?**). This left image is a stacked bar chart, using shadings to indicate sugarbeats and sugarcane. The image on the right

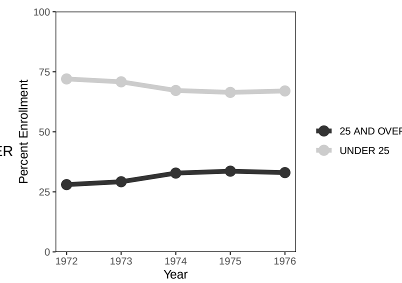
appeal, 2D charts tend to be chosen for preference and ease of use when making numerical estimations (Levy et al. 1996; Stewart, Cipolla, and Best 2009).



(a) 3D volume chart



(a) 2D area chart

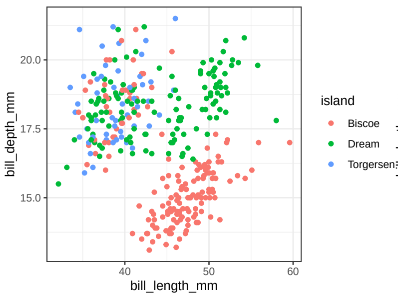


(a) Much better alternative

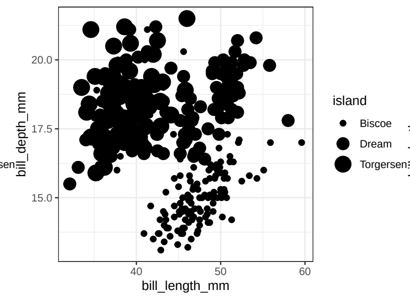
Three examples of chart preferences.

4 Heat Maps in Research and Practice

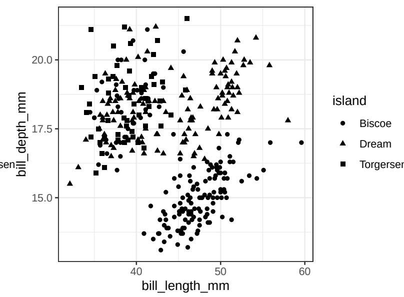
When creating charts for three or more variables, it becomes increasingly complex to visualize data (Grinstein and Trutschl 2001). One option is to map the additional variables to aesthetics using gestalt principles (Vanderplas, Cook, and Hofmann 2020) (Original citation?), which includes making use 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 11.



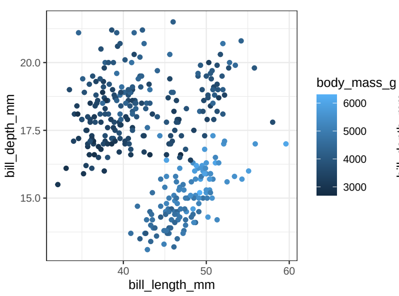
(a) Color mapped to categorical variable.



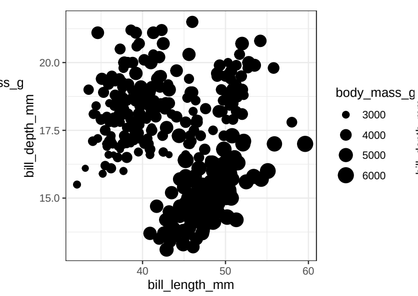
(b) Size mapped to categorical variable.



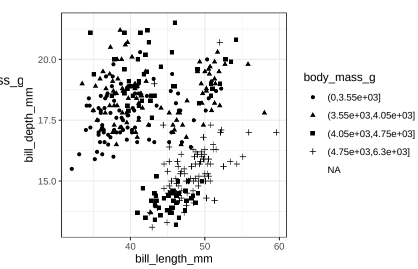
(c) Shape mapped to categorical variable.



(d) Color mapped to continuous variable.



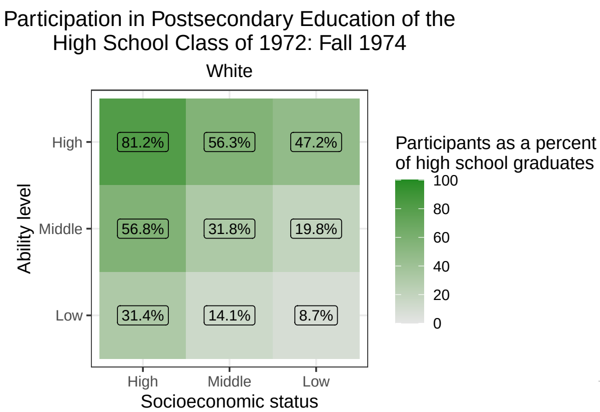
(e) Size mapped to continuous variable.



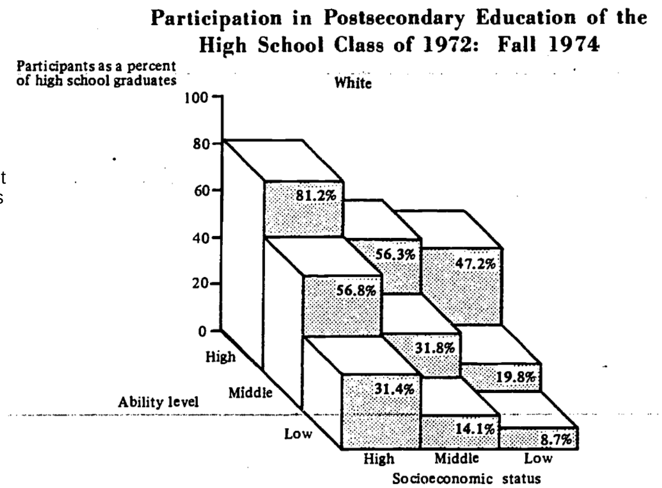
(f) Shape mapped to continuous variable.

Figure 11: Examples of color, size, and shape for scatterplots of the penguins dataset (Horst, Hill, and Gorman 2020).

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, fill colors are often used to denote the magnitude of the responses, 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. Since the color height of the response variable can only be mapped once to each combination of x and y coordinates, heat maps are generally used on the summary of responses, such as averages or single observations. This makes heat maps especially useful for visualizing patterns and trends across large datasets in a compact and interpretable format.



(a) 2D heat map

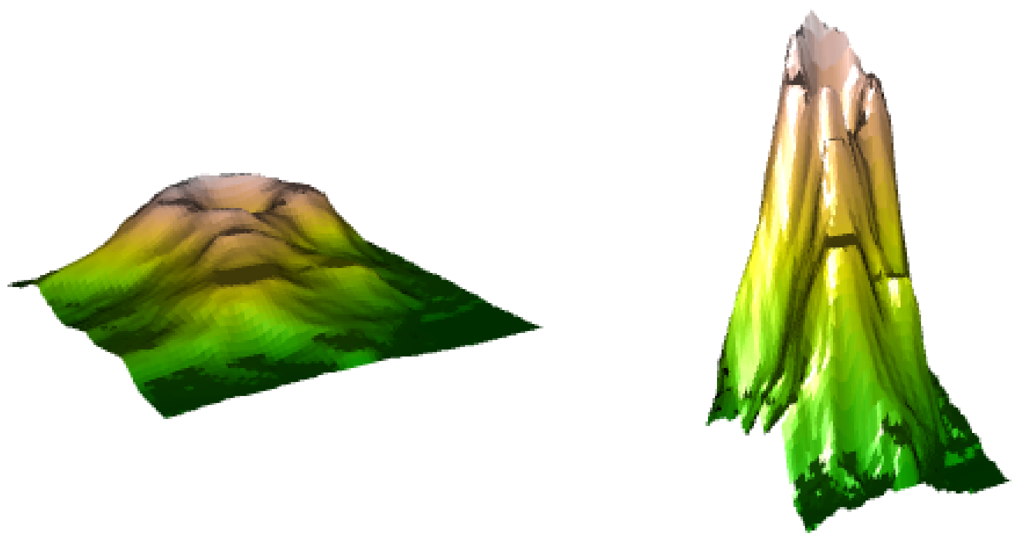


(b) 3D heat map

Figure 12: 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 dimensional comparison for heat maps has not been widely studied. This may be attributed to the complex nature of color scales having an influential role in the perception of heat maps 2D (Breslow, Ratwani, and Trafton 2009; Liu and Heer 2018b; Reda and Papka 2019). Heat maps require a translation of color into height values, a process where designed studies would require multiple considerations. The first consideration is the color palette to use in 2D charts. The next is the physical scaling of color to height. Lastly, the choice to use either solid-colored heights on the 3D charts or to carry over the color scheme from the 2D charts.



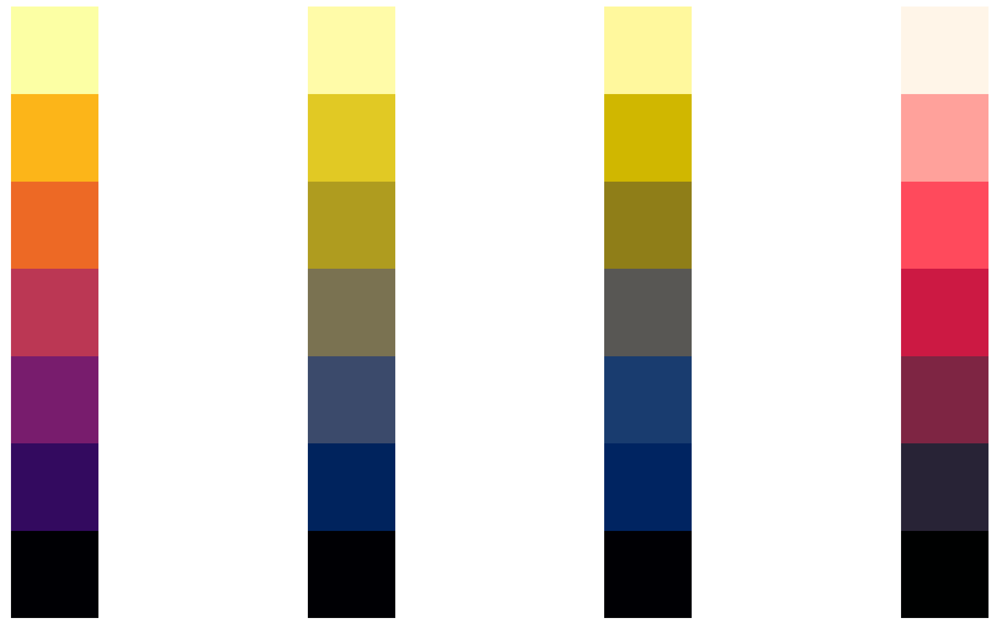
(a) Flatter height scale

(b) Stretched height scale

Figure 13: 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.

In 2D heat maps, the choice of color palettes can influence the perception of numerical estimations (Liu and Heer 2018a; Molina Lopez, Middel Soria, and Vázquez 2023; Zhang et al. 2023). Some color palettes are easier to extract information from than other. An additional consideration is the use of colorblind-friendly palettes for people with color deficiencies. This relationship between color and 2D heat maps contributes to the difficulties with direct translations to 3D heat maps.

Only a few studies have directly compared the dimensionality of statistical graphics (Kraus et



(a) Original palette (b) Deutan (red-green) (c) Protan (red-green) (d) Tritan (blue-yellow)

Figure 14: Effect of color deficiencies on the inferno palette from (**viridis?**).

al. 2020; Jeong et al. 2025). Conducted primarily in virtual reality, these studies suggest that 2D and 3D charts each offer advantages depending on the task. Two-dimensional charts generally produced higher interpretation accuracy and better recognition of overall distributional patterns. In contrast, three-dimensional charts were more effective for estimating single values and supporting long-term recall. Taken together, these findings highlight dimensionality as an important consideration when selecting visual displays for specific analytic goals.

5 State of Data Physicalization in 3D Statistical Graphics

WORK IN PROGRESS

Key ideas

- A few studies have used physical 3D charts
- Not always for statistical graphics, but there are related works

6 Methods for Evaluating Visualization Effectiveness

6.1 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 metrics when comparing 2D and 3D charts (Croxton 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. While many metrics exist, the practical limitation of testing generally allows for only a few metrics to be tested at a given time.

Many studies involving statistical graphics tend to rely on numerical estimations for recommending data visualization practices. This is particular useful given the role that data visualizations play in the understanding of underlying datasets (Tukey 1965).

6.2 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 the structure of experimental designs involving numerical estimations tends 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 differently from mental ratio processes (Veit, n.d.; Hagerty and Birnbaum 1978).

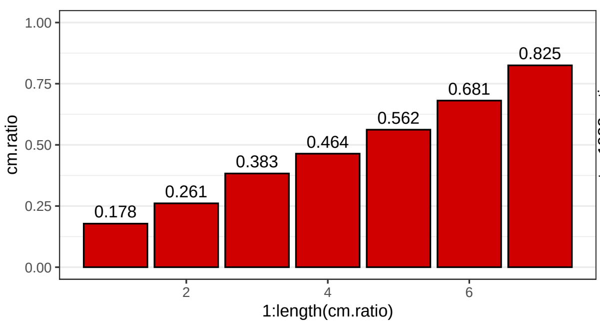
Cleveland and McGill (1984) asked participants two questions when making comparisons between two values on a chart: (1) which of the two values was the smaller, and (2) what percentage the smaller was of the larger. The first question clarified if the participants were looking at the values correctly for the second question, 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). Examples of ratios used in several studies are provided in Figure 15. As for measures of error, several formulations can be used:

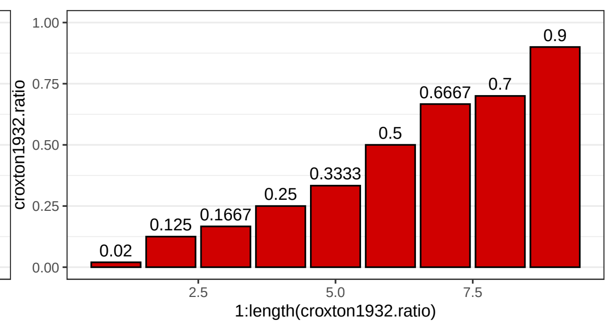
- $|\text{Error}|$ for magnitude of error
- Error for direction of error

- log |Error| for non-linear error estimations

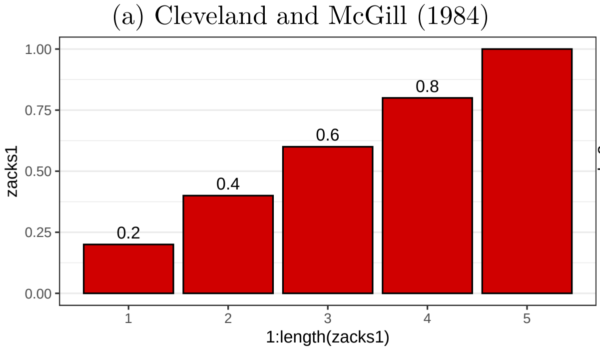
Psychophysics has shown that different estimation tasks affect how participants respond to numerical estimations. Estimations of ratios tend to fall on an exponential scale, where larger differences in stimuli result in smaller differences of estimated ratios. This makes log |Error| a natural choice for measuring ratio estimation tasks, similar to how Cleveland and McGill (1984) measured error. Measurements of differences tend to be estimated linearly, where estimated differences are the same regardless of differences in stimuli. As long as the estimation task is consistent for each trial, statistical methodology can handle the differences in estimation tasks.



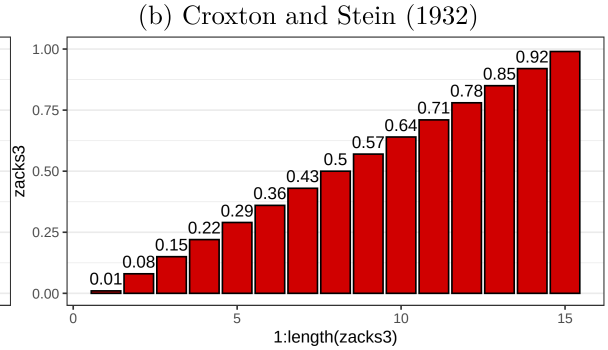
(a) Cleveland and McGill (1984)



(b) Croxton and Stein (1932)



(c) Zacks et al. (1998), Experiment 1



(d) Zacks et al. (1998), Experiment 3

Figure 15: Ratios used by several studies

Barfield, Woodrow, and Robert Robless. 1989. "The Effects of Two- or Three-

Dimensional Graphics on the Problem-Solving Performance of Experienced and Novice Decision Makers." *Behaviour & Information Technology* 8 (5): 369–85. https://doi.org/10.1080/01449298908914567.

Bateman, Scott, Regan L. Mandryk, Carl Gutwin, Aaron Genest, David McDine, and Christopher Brooks. 2010. "CHI '10: CHI Conference on Human Factors in Computing Systems." In, 2573–82. Atlanta Georgia USA: ACM. https://doi.org/10.1145/1753326.1753716.

Borgo, R., A. Abdul-Rahman, F. Mohamed, P. W. Grant, I. Reppa, L. Floridi, and Min Chen. 2012. "An Empirical Study on Using Visual Embellishments in Visualization." *IEEE Transactions on Visualization and Computer Graphics* 18 (12): 2759–68. https://doi.org/10.1109/TVCG.2012.197.

Breslow, Leonard A., Raj M. Ratwani, and J. Gregory Trafton. 2009. "Cognitive Models of the Influence of Color Scale on Data Visualization Tasks." *Human Factors: The Journal of the Human Factors and Ergonomics Society* 51 (3): 321–38. https://doi.org/10.1177/0018720809338286.

Cleveland, William S., and Robert McGill. 1984. "Graphical Perception: Theory, Experimentation, and Application to the Development of Graphical Methods." *Journal of the American Statistical Association* 79 (387): 531–54. https://doi.org/10.1080/01621459.1984.10478080.

Croxton, Frederick E., and Harold Stein. 1932. "Graphic Comparisons by Bars, Squares, Circles, and Cubes." *Journal of the American Statistical Association* 27 (177): 54–60. https://doi.org/10.1080/01621459.1932.10503227.

Croxton, Frederick E., and Roy E. Stryker. 1927. "Bar Charts Versus Circle Diagrams."

Journal of the American Statistical Association 22 (160): 473–82. https://doi.org/10.2307/2276829.

Dodziuk, Helena. 2016. "Applications of 3D Printing in Healthcare." *Polish Journal of Cardio-Thoracic Surgery* 3: 283–93. https://doi.org/10.5114/kitp.2016.62625.

Fischer, Martin H. 2000. "Do Irrelevant Depth Cues Affect the Comprehension of Bar Graphs?" *Applied Cognitive Psychology* 14 (2): 151–62. https://doi.org/10.1002/(SICI)1099-0720(200003/04)14:2%3C151::AID-ACP629%3E3.0.CO;2-Z.

Fischer, Martin H., Nele Dewulf, and Robin L. Hill. 2005. "Designing Bar Graphs: Orientation Matters." *Applied Cognitive Psychology* 19 (7): 953–62. https://doi.org/10.1002/acp.1105.

Fisher, Samuel H., John V. Dempsey, and Robert T. Marousky. 1997. "Data Visualization: Preference and Use of Two-Dimensional and Three-Dimensional Graphs." *Social Science Computer Review* 15 (3): 256–63. https://doi.org/10.1177/089443939701500303.

Friendly, Michael, and Howard Wainer. 2021. *A history of data visualization and graphic communication*. Cambridge, Massachusetts: Harvard University Press.

Grinstein, Georges, and Marjan Trutschl. 2001. "High-Dimensional Visualizations." *In: 7th Data Mining Conference-KDD 2001: San Francisco, California*, January.

Hagerty, Michael, and Michael H. Birnbaum. 1978. "Nonmetric Tests of Ratio Vs. Subtractive Theories of Stimulus Comparison." *Perception & Psychophysics* 24 (2): 121–29. https://doi.org/10.3758/BF03199538.

Heer, Jeffrey, and Michael Bostock. 2010. "CHI '10: CHI Conference on Human Factors in Computing Systems." In, 203–12. Atlanta Georgia USA: ACM. https://doi.org/10.1145/1753326.1753357.

Hofmann, Heike, Lendie Follett, Mahbubul Majumder, and Dianne Cook. 2012. "Graphical Tests for Power Comparison of Competing Designs." *IEEE Transactions on Visualization and Computer Graphics* 18 (12): 2441–48. https://doi.org/10.1109/TVCG.2012.230.

Horst, Allison Marie, Alison Presmanes Hill, and Kristen B Gorman. 2020. *Palmerpenguins: Palmer Archipelago (Antarctica) Penguin Data*. https://doi.org/10.5281/zenodo.3960218.

Hughes, Brian M. n.d. "Just Noticeable Differences in 2D and 3D Bar Charts: A Psychophysical Analysis of Chart Readability."

Huron, Samuel, Till Nagel, Lora Oehlberg, and Wesley Willett, eds. 2023. *Making with Data: Physical Design and Craft in a Data- Driven World*. First edition. AK Peters Visualization Series. Boca Raton: AK Peters : CRC Press.

Jeong, Jongwook, Ayoung Choi, Dongwoo Kang, and Youn Kyu Lee. 2025. "A Comparative Study of 2D Vs. 3D Chart Visualizations in Virtual Reality." *Journal of Visualization* 28 (1): 239–53. https://doi.org/10.1007/s12650-024-01033-6.

Kintel, Marius. 2023. "OpenSCAD. OpenSCAD.org." July 17, 2023. http://openscad.org/documentation.html.

Kraus, Matthias, Katrin Angerbauer, Juri Buchmüller, Daniel Schweitzer, Daniel A. Keim, Michael Sedlmair, and Johannes Fuchs. 2020. "CHI '20: CHI Conference on Human Factors in Computing Systems." In, 1–14. Honolulu HI USA: ACM. https://doi.org/10.1145/3313831.3376675.

Levy, Ellen, Jeff Zacks, Barbara Tversky, and Diane Schiano. 1996. "The SIGCHI Conference." In, 42–49. Vancouver, British Columbia, Canada: ACM Press. https://doi.org/10.1145/238386.238400.

Liu, Yang, and Jeffrey Heer. 2018a. "Somewhere Over the Rainbow: An Empirical Assessment of Quantitative Colormaps." In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 1–12. Montreal QC Canada: ACM. https://doi.org/10.1145/3173574.3174172.

———. 2018b. "CHI '18: CHI Conference on Human Factors in Computing Systems." In, 1–12. Montreal QC Canada: ACM. https://doi.org/10.1145/3173574.3174172.

Melody Carswell, C., Sylvia Frankenberger, and Donald Bernhard. 1991. "Graphing in Depth: Perspectives on the Use of Three-Dimensional Graphs to Represent Lower-Dimensional Data." *Behaviour & Information Technology* 10 (6): 459–74. https://doi.org/10.1080/01449299108924304.

Microsoft Corporation. 2025. "Microsoft Excel." https://office.microsoft.com/excel.

Molina Lopez, Elena, Carolina Middel Soria, and Pere-Pau Vázquez. 2023. "Effect of Color Palettes in Heatmaps Perception: A Study," 5 pages. https://doi.org/10.2312/EVS.20231039.

Morgan-Wall, Tyler. 2024. "Rayshader: Create Maps and Visualize Data in 2D and 3D." https://CRAN.R-project.org/package=rayshader.

Munzner, Tamara. n.d. "Visualization Design and Analysis: Abstractions, Principles, and Methods."

Murdoch, Duncan, and Daniel Adler. 2024. "Rgl: 3D Visualization Using OpenGL." https://CRAN.R-project.org/package=rgl.

Peña, Alyssa, Eric Ragan, and Lane Harrison. 2020. "Memorability of Enhanced Informational Graphics." *Interdisciplinary Journal of Signage and Wayfinding* 4 (1). https://doi.org/10.

15763/issn.2470-9670.2020.v4.i1.a54.

R Core Team. 2024. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Reda, Khairi, and Michael E. Papka. 2019. "2019 IEEE Visualization Conference (VIS)." In, 271–75. https://doi.org/10.1109/VISUAL.2019.8933760.

Rice, Kiegan, Heike Hofmann, Nola Du Toit, and Edward Mulrow. 2024. "Testing Perceptual Accuracy in a U.S. General Population Survey Using Stacked Bar Charts." *Journal of Data Science*, 280–97. https://doi.org/10.6339/24-JDS1121.

"SAS 9.4 ODS Graphics: Procedures Guide, Sixth Edition." n.d.

Satyanarayan, Arvind, Dominik Moritz, Kanit Wongsuphasawat, and Jeffrey Heer. 2017. "Vega-Lite: A Grammar of Interactive Graphics." *IEEE Transactions on Visualization and Computer Graphics* 23 (1): 341–50. https://doi.org/10.1109/TVCG.2016.2599030.

Schmid, Calvin F. 1983. *Statistical graphics: design principles and practices*. A Wiley-interscience publication. New York: Wiley.

Siegrist, Michael. 1996. "The Use or Misuse of Three-Dimensional Graphs to Represent Lower-Dimensional Data." *Behaviour & Information Technology* 15 (2): 96–100. https://doi.org/10.1080/014492996120300.

Sievert, Carson. 2020. "Interactive Web-Based Data Visualization with r, Plotly, and Shiny." https://plotly-r.com.

Stewart, Brandie M., Jessica M. Cipolla, and Lisa A. Best. 2009. "Extraneous Information and Graph Comprehension: Implications for Effective Design Choices." Edited by M. Henderson. *Campus-Wide Information Systems* 26 (3): 191–200. https://doi.org/10.1108/

10650740910967375.

Thingiverse.com. n.d. "Chart: Sales of 3-D Printers Under $5,000 by WSJ." *Thingiverse*. https://www.thingiverse.com/thing:365994. Accessed September 23, 2025.

Tractinsky, Noam, and Joachim Meyer. 1999. "Chartjunk or Goldgraph? Effects of Presentation Objectives and Content Desirability on Information Presentation." *MIS Quarterly* 23 (3): 397–420. https://doi.org/10.2307/249469.

Tufte, Edward R. 2001. *The Visual Display of Quantitative Information*. 2nd ed. Cheshire, Conn: Graphics Press.

Tukey, John W. 1965. "The Technical Tools of Statistics." *The American Statistician* 19 (2): 23–28. https://doi.org/10.2307/2682374.

V, Sundaram, Vidhya Lakshmi Sivakumar, Anand Raju, Saravanan A, and Titus Richard. 2023. "The Role of 3D Printing in Engineering and Its Historical Perspective in Civil Engineering - A Review." *International Journal of Civil Engineering* 10 (12): 58–68. https://doi.org/10.14445/23488352/IJCE-V10I12P107.

Vanderplas, Susan, Dianne Cook, and Heike Hofmann. 2020. "Testing Statistical Charts: What Makes a Good Graph?" *Annual Review of Statistics and Its Application* 7 (1): 61–88. https://doi.org/10.1146/annurev-statistics-031219-041252.

VanderPlas, Susan, Goluch C Ryan, and Heike Hofmann. 2019. "Framed! Reproducing and Revisiting 150-Year-Old Charts." *Journal of Computational and Graphical Statistics* 28 (3): 620–34. https://doi.org/10.1080/10618600.2018.1562937.

Veit, Clairice T. n.d. "Ratio and Subtractive Processes in Psychophysical Judgment."

Wickham, Hadley. 2010. "A Layered Grammar of Graphics." *Journal of Computational and*

Graphical Statistics 19 (1): 3–28. https://www.jstor.org/stable/25651297.

———. 2016. *Ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. https://ggplot2.tidyverse.org.

Wilkinson, Leland, and Graham Wills. 2005. *The Grammar of Graphics*. 2nd ed. Statistics and Computing. New York: Springer.

Zacks, Jeff, Ellen Levy, Barbara Tversky, and Diane J. Schiano. 1998. "Reading Bar Graphs: Effects of Extraneous Depth Cues and Graphical Context." *Journal of Experimental Psychology: Applied* 4 (2): 119–38. https://doi.org/10.1037/1076-898X.4.2.119.

Zhang, Zhao, Xiwu Shang, Guoping Li, and Guozhong Wang. 2023. "Just Noticeable Difference Model for Images with Color Sensitivity." *Sensors* 23 (5): 2634. https://doi.org/10.3390/s23052634.