Graphical Advice: How Should We Display Data?

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Spring 2018

Abstract

Academic researchers have debated guidelines for making statistical visualizations since visualizations first became a prominent part of statistics. However, little has changed in the way that most graphs are made, and no well-defined theory has come about [24].

This is despite prominent and rigorous work in graphical perception and graphical memory. William Cleveland did ample work in the 1980s on pyschophysics that examined how quickly and accurately we decode the elementary perceptual tasks that are the basic building blocks of graphs. [8]. However, research by Scott Bateman suggests that artistically adorned and perhaps tough-to-read graphs can leave a longer-lasting impact on viewers, in direct conflict with Cleveland's work [1]. Why is there so much disagreement? In this paper, I argue that most graphs can fit into one of two groups, and depending on that classification, there are some guiding principles for their design.

In Section 1, I provide my high-level takeaways from a literature review in data visualization suggestions. I begin with an explanation of why the suggestions are so often contradictory by placing all visualizations into one of two camps: accuracy or storytelling. I then summarize the suggestions for graphs made in each camp. Next, in Section 2, I suggest three papers: the first is the most seminal paper for researchers working the accuracy camp, the second is the most seminal paper for researchers working in the storytelling camp, and the third is a history of data visualization over the last 400 years. Finally, in Section 3, I cite the papers I've read in the structure suggested by the rest of the paper: accuracy suggestions, infographic suggestions, history. The References section lists all these papers again but alphabetically by author's last name. A Google Drive folder of all relevant papers can be found here.

1 Executive Summary

1.1 Two Motivations: Accuracy and Storytelling

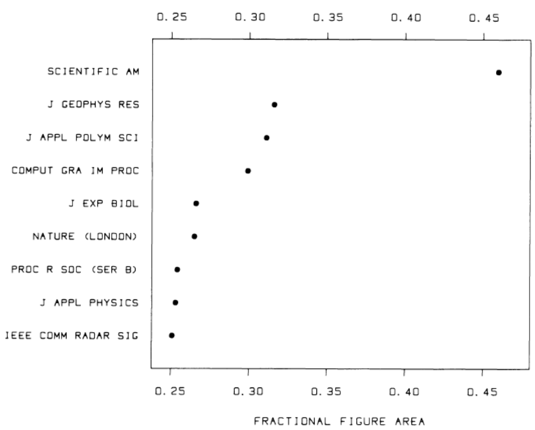

Figure 1: Taken from William Cleveland [5]

Figure 2: Taken from Russell Goldenberg [13]

The two philosophies of graph creation are represented by the two images above. On the left, William Cleveland has plotted the fractions of space devoted to figures (as opposed to text) in major American journals. He uses a dot plot rather than a bar plot because the area enclosed in a rectangle relative to a non-zero indexed axis is meaningless. Viewers will subconsciously assess the area of the bars when what really matters is the position of the end of the bars. Thus, he instead replaced the bars with dots. Furthermore, he avoids color because color has no relevance and could visually distract the viewer.

On the right, Russell Goldenberg presents the quality (as measured by RateBeer) and quantity of microbreweries in cities across the United States in what he terms a "weighted pivot scatter plot." The size and color of the dots, length and orientation of the axes, and list of cities on the right all fluctuate as the user drags the slider between quality and quantity of microbreweries in the city. Some cities perform well when we optimize for quality (Santa Rosa, CA) whereas others perform well when we optimize for quantity (Denver, CO).

Both authors believe their work optimizes for understanding, but the graphs are objectively very different. Cleveland's is simple and static; Goldenberg's is complex and interactive. Each would decry the other's work for disobeying principles they hold dear. I claim this disagreement is not productive because it assumes the graphs seek to achieve the same thing. I contend that a difference in motivation between the authors allows both visualizations to be very successful. Nearly all graphs are (and should be) made to convey information by either optimizing **accuracy** or **storytelling impact**. Theory around successful graphics should be different in each case.

If your goal is to do exploratory analysis for yourself or present in an academic setting (likely because you are a scientist), you fall into the **accuracy** camp. This category includes both graphs explicitly used in analysis—such as residual plots, normal plots, and scagnostics—and any figures created for presentation in an academic journal or classroom. Advances in creating accurate graphs should be driven by theory in graphical perception, such as William Cleveland's work. The results of this research should be integrated into plotting packages in R and Python and highly encouraged (if not mandated) by academic journals. This will prevent researchers from defaulting to flashy, attention-grabbing visuals that don't portray their information as accurately as possible.

If your goal is to drive a point home to a general audience (likely because you are a graphic designer), you fall into the **storytelling** camp. These visualizations are often published in major media outlets that compete for reader attention. Their main goal is to deliver a message using data that sticks with the reader for as long as possible. To do so, using images, vibrant color, or novel graphical methods might be effective. Advances are less clearly defined because each project has its own goals. Of course, this camp cannot falsify or misrepresent data, but if psychophysics research favors one visualization, a graphic designer is still free to use another if they deem it more impactful and memorable.

Cleveland's graph is a success in the accuracy camp. It is clear and displayed in a standard format. It belongs in an academic journal, an R terminal, or a textbook. Goldenberg's visualization is a success in the storytelling camp. It's fun to play with, visually appealing, and experimental. It belongs on a magazine's webpage or in a blog.

1.2 Accuracy Recommendations

What follows are suggestions for scientists creating visualizations in the accuracy camp. These visualizations are for exploration, analysis, or presentation within the academic research community. The findings are based on perception theory.

1.2.1 Color Recommendations

Color should only be used with utmost caution. We do not understand the full emotional effects of various colors, so choosing to color the various portions of a categorical representation (e.g., a bar chart) is ill-advised. However, often color gradients are used to show a gradual change or are otherwise integral in the display. In these cases, color can be effective, and the psychophysics of color perception should inform which to use.

Namely, when adding color to a graph, use Munsell's hue-chroma-luminance (HCL) system [19]. Munsell's breakthrough work created a three-dimensional system with orthogonal components that are absolute across each other:

- Hue - the color (red, green, blue, etc.)
- Chroma - the lightness or darkness of the color
- Luminance - the intensity of the color

Importantly, one should not use the the red-green-blue (RGB) system or the hue-saturation-value (HSV) system. RGB numbers, which are used by computers, are uninterpretable to humans. And unlike the

HSV system, intensities of colors are comparable across hues in the HCL system, which prevents problems like a fully saturated red being way more eye-grabbing than a fully saturated blue.

Munsell's work was popularized in the statistics community by Ithaka [15], and further discussion of selecting colors for graphs is given by Zeilis [25]. An example of how using HCL can prevent misreadings of color is given by Cleveland [6]. Trumbo provides a theory for coloring maps [21].

1.2.2 Structure Recommendations

Choosing which visualization to use (bar graph, line graph, pie chart, etc.) and how to set up axes is a key decision and once again should be based on perception theory. The visualization chosen should optimize for elementary perceptual tasks that can be done quickly and easily. These tasks, as ranked and grouped by Cleveland [8], are as follows:

1. Position along a common scale
2. Positions along nonaligned scales
3. Length, direction, angle
4. Area
5. Volume, curvature
6. Shading, color saturation

Other tips for selecting the structure of the graph include, as also researched by Cleveland [5]:

- If the axis will be broken in such a way to separate data points, fully separate the two portions of the graph into two rectangles rather than only a mark where the axis is broken. This ensures the break will be noticed.
- Dot charts should often be used in place of bar graphs because they highlight that the only perceptual judgment to be made is comparing elements on a common axis and not comparing areas. An example is shown in Figure 1.
- Logarithmic graphs should display their logarithmic axes (perhaps in addition to a standard axis), and bases other than 10 should be considered, such as e or 2. These are more natural in biology and other use cases yet are often not used.

1.3 Storytelling Recommendations

Discovering concrete rules for effective storytelling graphics is challenging in the same way that finding such rules for storytelling itself is challenging. Graphical stories are about compelling the reader to care, convincing them with surprising data, and leaving them with an inspiring message. But as far as concrete rules, there are very few. As such, the readings were significantly more diverse and included both research papers and blogs. Most took the format of an experienced professional outlining their opinions or a recent project.

1.3.1 Research Papers

The two must seminal works in this category are by Tufte and Tukey. Tufte's "The Visual Display of Quantitative Information" seems to be somewhat of a cult classic in creating presentative graphs [22]. Tufte offers many suggestions for creating graphics and usually gives some vague justification, for example that graphs should be wider than they are tall because humans perceive the horizon. Tukey takes on a similar practice discussing how we should think about graphics with the advent of the computer [23].

Bateman's research is worth highlighting. Rather than argue for a certain strategy in making infographics, Bateman instead argues in favor of infographics themselves [1]. He finds that viewers have better long-term recall and message understanding for highly-embellished graphs than for plain graphs.

The final papers in this section were, in my opinion, less interesting. Gelman and Unwin are statisticians who critique infographics in their paper without recognizing their wildly different goals [11]. And Meeusah tries to quantify memorability of different colors and number of topics in a graphic, but the study is too rooted in one type of presentation (namely, bar graphs) to generalize [18].

1.3.2 Blogs

There are many great blogs that regularly publish suggestions and case studies on creating effective data visualizations. Often these blogs get significantly more readership than academic papers, and given the lack of academic research on creating infographics, are defining the dialogue on what are and aren't effective modern, web-based data visualizations.

Two in particular that I read a lot from were The Pudding and Storytelling with Data. The biggest piece of advice both give is exposure to and assessment of many data visualizations. As such, both provide ample examples of data visualizations. Occasionally, they'll provide explicit advice, like how to create a scrollable data visualization [14], how to think about designing for a responsive interface [12], or how to use images in infographics [17].

Aside from well-established blogs, there are a few notable figures who define the dialogue on infographic design. One of the most famous is Mike Bostock, who created the D3.js data visualization library and lead The New York Times's data visualization team. Another is Nigel Holmes, a British graphic designer who has been creating data visualizations for decades.

2 Top Papers

2.1 Accuracy: "Graphical Perception" by Cleveland and McGill [8]

With nearly 1500 citations on Google Scholar, this paper is the seminal work on creating graphs that can be read quickly and accurately. It is a must-read for anyone in the **accuracy** camp. Cleveland and McGill begin by noting that the plethora of treatises on good graph construction are all based on expert opinions without any quantitative underpinning. Cleveland and McGill hypothesize that interpreting a graph fundamentally boils down to basic perception tasks, such as comparing position along a common axis or comparing the areas of two objects, and that our accuracy and speed varies from one perceptual task to another. They define ten elementary perceptual tasks used in graph-reading and design an experiment that tests subjects' ability to make accurate comparisons between two objects that differ in that perceptual way. They find that the ten elementary tasks, grouped and ordered from most to least accurate, are as follows:

1. Position along a common scale
2. Positions along nonaligned scales
3. Length, direction, angle
4. Area
5. Volume, curvature
6. Shading, color saturation

Although they qualify that accuracy of quantitative extraction is not the only factor to consider or theorize about when designing a graph, it should be a main consideration. With these results in hand, they suggest bar graphs should always replace pie graphs, curve difference charts should explicitly plot the difference, and framed rectangle charts should replace shading.

Moreover, this method of using perception theory to design graphs informs much of Cleveland's work, whether it be on defining the shape parameter of a graph [7], the color [6], or more structure decisions [5].

2.2 Storytelling: "Useful Junk?" by Bateman et al. [1]

But what if the goal of the visualization is primarily memorability or conveying a message? Scott Bateman et al. explore how visual embellishment affects the interpretation and recall of a visualization, and it is a must-read for anyone in the **storytelling** camp.

To do so, they compare graphs made by graphic designer Nigel Holmes with reconstructed, simple graphs without embellishment. Study participants were shown either an embellished Holmes graph or a plain graph and asked to explain the graph's subject, noticeable trends, and takeaway message. Then, either immediately or a few weeks after, participants were asked to recall this information about the graphs.

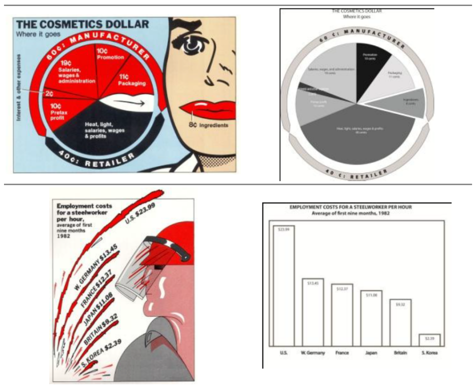

Figure 3: An example of Nigel Holmes original graph with the reconstructed plain graph [1].

Bateman found that viewers were able to read and immediately recall the embellished graphs with equal accuracy to the plain graphs. However, they were able to more accurately discern value messages in and have long-term recall of the embellished graphs significantly better than the plain counterparts.

Of course, we can't draw the general conclusion that any visual embellishment improves the memorability of a graph: these were artistically made graphics by a graphic designer. Instead, Bateman's work suggests that when making graphs to tell a story to a broad audience with limited attention, well-designed, artistic graphs can memorably deliver a message better than a plain graph that is optimized for quick, accurate reading. Even more, all participants surveyed said they preferred the Holmes graphs, so embellishment might attract readers to pay attention in the first place.

I recommend this article because it takes a quantified approach of perception that is very similar to William Cleveland. However, because this design examines memorability rather than quick, accurate perception, it reaches the opposite conclusion! Holmes's graphics have skewed axes, vibrant color, and visual noise that seem to simultaneously reduce quick perception and improve memorability.

2.3 History: "Quantitative Graphics in Statistics" by Beniger and Robyn [2]

Because most papers fit either into the analysis or storytelling camps defined above, picking a third paper was tough. I didn't want to favor either approach by choosing an additional paper.

Thus, I decided to pick a history. It's easy to forget that even a basic bar chart or line graph was invented by someone, and the conventions we don't think twice about today, such as putting time on the x-axis, were decisions made by some researcher. Three of the papers I read ([2], [10], [24]) provided histories of graphs in some ways, and I decided to pick James R. Beniger and Dorothy L. Robyn's. It provides the most structured history with an accompanying timeline.

Beniger and Robyn separate the timeline into four major periods:

- ˜1600-1750: spatial organization for data analysis (line graphs)
- ˜1750-1820: discrete quantitative comparison (bar and pie chart)
- ˜1820-1870: continuous distribution (ogive and histogram)
- ˜1870-1930: multivariate distribution and correlation (contour plots and stereograms)

This development seems both natural and surprising. Natural in that discrete comparisons informed continuous distributions, which in turn informed multivariate distributions. But surprising in their recency: charts seem so integral to how we think about information in our outside world, yet many early scientists and thinkers (like Da Vinci) were only creating diagrams as part of one-off explanations integrated into their work. Charts were not viewed as abstracted ways to present information until the last few centuries.

3 Sources

3.1 Accuracy Camp: Statistical Graphs

3.1.1 Color Recommendations

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5. Zeileis, A., Hornik, K., and Murrell, P. Escaping rgbland: selecting colors for statistical graphics. *Computational Statistics & Data Analysis 53*, 9 (2009), 3259–3270

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2. Cleveland, W. S. Graphical methods for data presentation: Full scale breaks, dot charts, and multibased logging. *The American Statistician 38*, 4 (1984), 270–280

3. Cleveland, W. S., and McGill, R. Graphical perception and graphical methods for analyzing scientific data. *Science 229*, 4716 (1985), 828–833

4. Cleveland, W. S., McGill, M. E., and McGill, R. The shape parameter of a two-variable graph. *Journal of the American Statistical Association 83*, 402 (1988), 289–300

3.2 Storytelling Camp: Infographics

3.2.1 Research Papers

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3. Goldenberg, R. How many users resize their browser?, 2017

4. Goldenberg, R. The making of the weighted pivot scatter plot, 2017

5. Goldenberg, R. Responsive scrollytelling best practices, 2017

6. Knaflic, C. N. Using images, 2018
7. Knaflic, C. N. Area graph to highlight a line, 2018
8. Peltier, J. The problem with marimekkos, 2009

3.3 History

1. Beniger, J. R., and Robyn, D. L. Quantitative graphics in statistics: A brief history. *The American Statistician 32*, 1 (1978), 1–11
2. Fienberg, S. E. Graphical methods in statistics. *The American Statistician 33*, 4 (1979), 165–178
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