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Teaching Students to Focus on the Data in Data Visualization

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Abstract

Although most technical communication pedagogy provides students with solid advice on how to visualize particular numerical representations, it underproblematizes the rhetorical decisions we make in choosing which numbers to display in the first place. This pedagogical reflection uses Perelman and Olbrechts-Tyteca's concept of interpretative level to foreground the rhetorical choices that underlie our decisions on how to summarize, aggregate, and synthesize the data we visualize. It then describes two informal classroom activities that emphasize the importance of interpretative level and help students see the recursive nature of data visualization and invention.

Keywords

data visualization, invention

Open any of the large textbooks written for our service technical communication courses (e.g., Anderson, 2011; Johnson-Sheehan, 2015; Lannon &

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Gurak, 2013; Markel, 2012) and you will see a chapter on basic data visualizations. These chapters cover a wide range of territory: They provide guidelines on what types of visualizations are most effective for given types of data, supply advice on how to adapt visualizations for different audiences, and counsel readers on how to ethically represent data. Such topics are covered in further detail in Kostelnick and Robert's (2010) textbook on visual language, which provides useful examples of data visualizations that evolve as their authors refine their rhetorical purpose and adapt their messages for specific audiences and contexts. We also have a wide variety of books that specifically treat data visualization, with a corresponding variety of strengths. Tufte (1983, 1990), of course, is well known, and the elegance of his visualizations sets a standard to aspire to; Kosslyn (2006) did a particularly excellent job summarizing research in cognitive psychology; Yau (2011) provided excellent advice on software for creating data visualizations; and Brasseur (2003) drew our attention to the social elements and distributed cognition embedded in data visualizations.

Despite this wealth of texts to choose from, most gloss over what I consider to be a crucial step in my own experiences of making visual arguments from data I have collected, namely, the need to return to the data to reconsider what data are selected, how they are summarized, and whether they should be synthesized with other data for a more compelling argument. Of course, some books do emphasize this crucial step of returning to the data, but this discussion often requires a level of statistical knowledge that falls outside the comfort zone of many professional and technical communication instructors. Few (2009a), for instance, included an entire chapter on whether to express deviations as percentages versus other units of measure, another on deciding which measures of distribution to visualize, and sections on topics such as deciding whether to display a correlation coefficient or a coefficient of determination. Wainer (2005) likewise included many excellent examples of how data need to be reconceived to avoid the traps of common statistical fallacies.

Although I have learned a lot from these texts, the lesson I want to communicate to students in my technical communication class is much more basic: I want students to consider the various interpretative levels available to them in displaying their data. *Interpretative level* is a concept that Perelman and Olbrechts-Tyteca's (1969) used to describe the act of choosing between competing, valid interpretations. When applied to data, interpretative level describes the choice we make to summarize data on variable x versus variable y versus the intersection of x and y, to present data as

Table 1. Raw Counts of Writing Implements That Female and Male Students Possessed on Given Days.

Gender	November 5	November 19	December 1
Female	15	14	18
Male	21	20	26

Table 2. Average Number of Writing Implements That Female and Male Students Possessed on Given Days.

Gender	November 5	November 19	December 1
Female	2.5	2.8	3.0
Male	1.8	2.0	2.2

averages versus percentages or raw counts, and to base averages or percentages on one value rather than another (e.g., in counting people who use a center, we might choose to focus on either the number of individuals or the number of visits). As Perelman and Olbrechts-Tyteca explained, such choices are acts of "creation, an invention of significance" (p. 121). By foregrounding one interpretation, writers push other interpretations into the shadows (pp. 121–122). Such interpretative choices parallel what Barton and Barton (1993a) described as the rules of inclusion and exclusion that govern which phenomena mapmakers choose to represent in their creations.

To illustrate, consider Table 1, which contains fictional counts of the number of writing implements (pens and pencils) that male and female students brought to class on given days. The author of Table 1 has made a choice to break the data down by gender and date; consequently, based on this display, we know that on November 19, for example, male students had six more writing implements in their possession than did female students. By contrast, the author of Table 2 presents these same data as averages; thus, from this display, we can see that female students, on average, possessed almost one more pen or pencil than male students did. The choice over whether to display these data as raw numbers or averages—as well as the choice to summarize the data by gender—are all choices of interpretative level. And these choices have dramatic consequences for the stories we might tell about data. Not only do the two versions give us different impressions of which gender carries the most writing implements, but they also display two different patterns: Table 1 indicates a slight dip in the overall usage of writing implements on November 19 whereas Table 2 indicates a steady increase. (This simultaneous decrease in the total number of writing implements but increase in their average use can be explained by a dip in student attendance on November 19.) In other words, the different decisions that these authors made about interpretative level forwarded very different interpretations of the data.

Data visualization, then, does not just involve representing a given set of numbers; it involves selecting and rethinking the numbers on which the visualization is based. This point may seem obvious, but in my experience, students—even those in technical fields—fail to think through the numbers when they display data. I want students to realize that part of the argument that they are making involves deciding whether to display data as counts, averages, ratios, or percentages. It involves deciding whether to summarize data based on gender, race, political affiliation, or some other variable. And it often involves creating new variables that aggregate several data points together.

There is also an ethical component to selecting the right numbers to display—a consideration that most data visualization texts fail to foreground. For instance, E. Tufte (1983) stated that "a graphic does not distort if the visual representation of the data is consistent with the numerical representation" (p. 55). Such a definition of distortion understandably causes us to focus on visual effects, such as shifting baselines or perceptual distortions, at the expense of numerical effects. Although Tufte also stated that "graphics must not quote data out of context" (p. 74), he used this precept primarily to warn against data displays that distort because they contain too few data points, thus making an anomaly or small change look like a major trend. Dragga and Voss (2001) extended the conversation on visual ethics to include humanizing displays because they feel that traditional graphics underemphasize the pathos underlying certain stark numbers. But graphics also distort when they rely on wrong numbers. For instance, I would argue that Table 1 is unethical because the author has chosen to summarize the data by gender without providing us with the critical context of the numbers of male and female students. This lack of context encourages readers to make misleading conclusions about gender and behavior. Such reporting of decontextualized numbers is analogous to taking a quote out of context: Yes, the statement may be technically accurate, but it is also misleading.

Interpretative-level data visualization goes beyond what Barton and Barton (1993b) called synoptic versus analytic—and E. Tufte (1983) called macro versus micro—views of data. The synoptic–analytic continuum helps us describe rhetorical choices that govern how much data to display and whether to provide a detailed or a holistic view. But the synoptic–analytic continuum—at least as typically discussed—does not sufficiently account for the complicated choices we make about different types of synoptic or analytic views. There are many ways to summarize or synthesize data that will yield different synoptic views and interpretations of the data. Which methods are best depends on our rhetorical context and purpose.

Our choices about interpretative level go hand in hand with our choices about visualization. As we experiment with different methods for visualizing data, we will often want to reconsider the interpretative level that we are working at. Doing so requires going back to our numbers and thinking about different ways to represent them, a recursive process. But in my experience, students fail to fully consider their options in deciding which numbers to display, with some even worrying that creating new variables to aggregate or synthesize different numbers is a form of cheating.

In calling for technical communication instructors to foreground the invention that occurs when they select and manipulate data, I am not implying that this discussion has been entirely missing from our pedagogy. Sorapure (2010), for instance, provided many lively and interesting exercises in which she requires students to make visual arguments based on data they have collected about their own lives. Although Sorapure's article does not foreground the various interpretative levels that her students must choose between when displaying these data, such discussions surely occur in her classroom. Likewise, while I have several times noted that E. Tufte (1983) failed to problematize the rhetorical act of selecting which numbers to display, he did frequently critique designers for failing to provide numbers adjusted for inflation—a choice that falls under what I have been calling interpretive level. So the discussion of interpretative level is not entirely missing; it just has not often been held up explicitly as an object for analysis.

The following exercises foreground how choices of interpretative level profoundly affect our data displays. In addition, they illustrate the recursive relationship between visualizing data and selecting an appropriate level of interpretation. First I present two low-stakes activities that can be completed in class, and then I describe two formal assignments that build off of these activities.

Olympics Medals Data

I typically teach data visualization in a course unit on writing about data. This unit begins by teaching students to think of data as a story and to identify the stories in various data visualizations. In describing data analysis as

Table 3. 2008 Summer Olympic Medals Sorted by Total Medals.

Country	Gold	Silver	Bronze	Total
United States	36	38	36	110
China	51	21	28	100
Russia	23	21	29	73
Britain	19	13	15	47
Australia	14	15	17	46
Germany	16	10	15	41
France	7	16	18	41

telling a story, I take my lead from well-known statisticians and data analysts who discuss the importance of crafting a "story" or "narrative" (Abelson, 1995; Few, 2009b; McCandless, 2010) out of data. Throughout the unit, I continually ask students to identify the main and secondary stories that a given visualization tells. This storytelling orientation gives us a framework for comparing the various rhetorical choices writers make in presenting their data.

Tables 3 and 4 are particularly useful for getting students to see how seemingly small decisions about visualization can have a major impact on the story that a data set seems to tell. These two tables differ only in the way that the writer has chosen to sort the data—and yet they emphasize two different stories: Table 3 emphasizes that the United States led in total Olympic medals whereas Table 4 emphasizes that China led in gold medals. It is perhaps unsurprising, then, that Table 3 is the data visualization published in most U.S. newspapers whereas Table 4 was published in the rest of the world (Hardaway, 2008; Ruddick, 2008).

Students can quickly point out the main differences between Tables 3 and 4, and the ease with which two different stories can be crafted out of these same data lends itself to these questions: Is either of these two displays the right way to present Olympic winnings? What other methods might we use to present Olympic winnings? Thus, small manipulations in how we present a table open up larger questions about the data and how they should be represented.

In fact, these two tables represent just the tip of a lively controversy over how Olympic winnings should be reported. For instance, in 1908 the British

Table 4. 2008 Summer Olympic Medals Sorted by Gold Medals.

Country	Gold	Silver	Bronze	Total
China	51	21	28	100
United States	36	38	36	110
Russia	23	21	29	73
Britain	19	13	15	47
Germany	16	10	15	41
Australia	14	15	17	46
South Korea	13	10	8	31

press used a point system in which each gold medal ranked five points, each silver medal three, and each bronze medal one (Hardaway, 2008). Such a point system, if applied to Tables 3 and 4, would convey yet a different story about the 2008 Olympics. Others have proposed adjusting the medal tables to account for countries' population size, gross domestic product (GDP), or team size ("Olympics," 2012). These choices all revolve around rhetorical considerations about the appropriate level (or levels) of interpretation for these data.

The Olympic medals data—and the controversies surrounding them—provide good opportunities for students to experiment with interpreting data at different levels and seeing how these choices yield different stories about the data. Raw data on Olympic medals can be obtained from many Web sites, including that of *The Guardian* ("Olympics," 2012), which allows readers to download a spreadsheet with data about Olympic medals, country populations, GDPs, and other metrics. While most Olympic events do not lend themselves to the dramatic differences we obtain just by resorting the 2008 Summer Olympics medal data, I have yet to encounter a year that did not lend itself to a range of interpretations. After downloading the spreadsheet for a given year, students can be prompted to create a visualization that represents the "fairest" view of which countries should be commended for their athleticism. Alternatively, students can be assigned a country and charged to create a data visualization and accompanying text presenting that country in the best possible light while still representing the data ethically, without any distortions meant to mislead readers. Figure 1 illustrates one

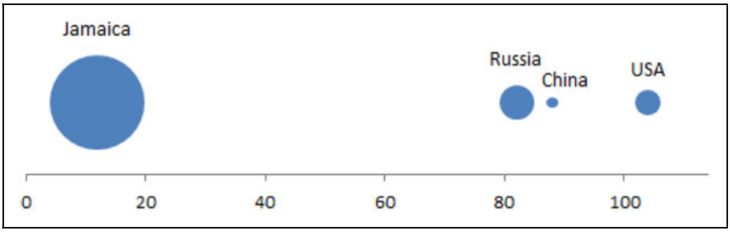

Figure 1. Total number of medals received in the 2012 Olympics. *Note.* Bubble size indicates number of medals per 100,000 residents.

such visualization that foregrounds the relative success of Jamaica in the 2012 Olympics by using the size of bubbles to indicate the number of medals per 100,000 residents. Thus, Figure 1 emphasizes Jamaica's success for its size while it still accurately reports the total number of medals received. Such exercises, which can be completed quickly in class, introduce students to the importance of selecting an appropriate level of interpretation.

Browser Wars

Whenever new browser versions come out, we see various technology reviews on the Internet comparing the browsers on a variety of measures, including start-up speed, memory usage, standards compliance, and the time it takes to load various scripts. These measures provide an opportunity to ask students to critique various data visualizations and attempt to prepare their own visualization. One recent review by MIDAS ("Best Web Browser," 2013), a company providing Web-based scheduling services, used a series of nine bar charts to compare five different Web browsers, with each chart reporting a different measure. Figure 2 shows three of these charts.

By spreading comparisons across nine different charts that cannot fit comfortably on one screen, MIDAS ("Best Web Browser," 2013) provided us with analytic views of individual variables but failed to offer what Barton and Barton (1993b) called a synoptic view of the data. Thus, it is virtually impossible for a reader to assimilate all of the data in order to make a conclusion about which browser has the best overall performance. This task is further inhibited by the use of distracting three-dimensional effects, gridlines, and numbers that extend to as many as three decimal places.

To compensate for the inability of its visualizations to provide a synoptic view of the data, MIDAS returned to the data to create a new

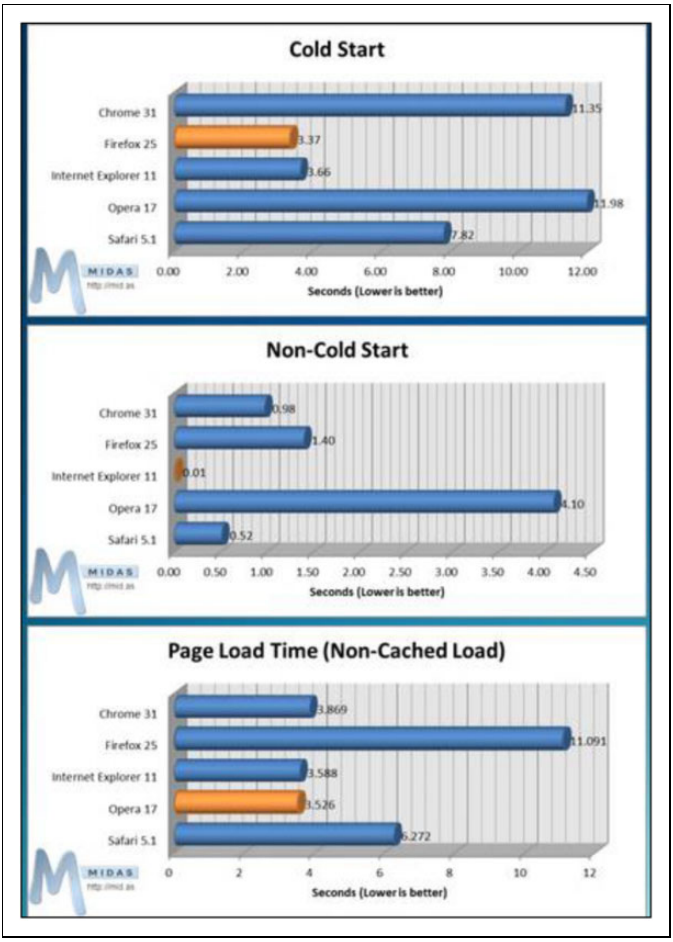

Figure 2. The first three of nine bar charts comparing browser performance ("Best Web Browser," 2013). Reprinted with permission from MIDAS.com.

variable that assigns points based on browsers' rankings on each individual test. Thus, for the cold-start test, Firefox received a score of 1 for coming in first, Internet Explorer (IE) a score of 2 for ranking second, and so forth. For the non–cold-start test, IE received a score of 1, Safari 2, Chrome 3, and so forth. MIDAS then summed these rankings across all tests, concluding that Chrome achieved the best summary score, followed by Opera.

Providing such an overall measure of browser performance is useful, but is MIDAS's method of aggregating rankings on various tests rhetorically appropriate? Are there other ways we might summarize these data to develop a view of which browsers perform best?

Ranking systems have the inherent flaw of not distinguishing between significant and insignificant differences in performance. The difference between first and second place is the same whether the performance differed by a nose or by a mile. Moreover, in the case of MIDAS's data, not all nine tests are equally important to users. MIDAS even tacitly acknowledged these flaws in its conclusion by providing a more nuanced discussion of which browsers its tests might recommend for different types of users.

This is rich data to work with in helping students to see the importance of interpretative level in data visualization. The rhetorical situation calls on writers to compare five items across nine different variables, which have four different measurement scales (e.g., seconds, megabytes, percent of compliance, and JavaScript score). Moreover, the data do not shape up to tell a consistent, clear-cut story. A variety of rhetorical trade-offs must be considered as writers make decisions about how to arrange and aggregate such a complex data set.

I work through this data set with my students, investigating our options in visualizing and interpreting the data and emphasizing the recursive nature of our task. First, since the data consist of different scales of measurement, we are constrained in our choice of visualizations. We start with a table, one of the few visualizations that can handle multiple scales.

Table 5 shows a poorly formatted dump of MIDAS's data ("Best Web Browser," 2013). Such ill-conceived, data-dump tables are depressingly common, and I want students to see how seemingly small formatting choices can make the difference between a potential story and an unintelligible mess. The style of Table 5 is so cluttered that it is nearly impossible to see patterns in the data. Decimal points are misaligned, numbers are inconsistently extended to meaningless decimal places, and gridlines compete with the data for our attention.

In contrast, Table 6 shows what a difference a few simple stylistic and organizational choices can make. The data have been grouped into manageable chunks with headers, indentations, and white space. Clutter has been eliminated by removing extraneous gridlines and decimal places. Numbers are easier to compare because they are now aligned on the decimal point (allowing us to quickly distinguish single-, double-, and triple-digit numbers), and unit information has been moved out of the cells and into row headers. A judicious use of red fonts and bolding adds contrast that helps us see the "winners" in each category.

Table 5. Browser Performance on Nine Different Tasks.

Task	Chrome 31	Firefox 25	IE 11	Opera 17	Safari 5.1
Cold start	11.35s	3.37s	3.66s	11.98s	7.82s
Non–cold start	0.98s	1.40s	0.01s	4.10s	0.52s
Page load time (non–cached load)	3.869s	11.091s	3.588s	3.526s	6.272s
Page load time (reload from cache)	1.638s	5.179s	1.966s	1.685s	3.354s
Base memory usage (blank tab)	99.5mb	49.1mb	29.5mb	91.7mb	35.0mb
Memory usage (10 open tabs)	423.1mb	163.1mb	259.0mb	308.6mb	224.7mb
HTML 5 compliance	93%	82%	70%	88%	56%
CSS3 compliance	57%	53%	57%	58%	45%
JavaScript score	213.88	183.12	165.33	200.03	137.64

Table 6. Browser Performance and Compliance on Various Measures.

Task	Chrome 31	Firefox 25	IE 11	Opera 17	Safari 5.1
Startup speed (in seconds)					
Cold start	11.4	**3.4**	3.7	12.0	7.8
Non–cold start	1.0	1.4	**0.0**	4.1	0.5
Page load speeds (in seconds)					
Non–cached	3.9	11.1	3.6	**3.5**	6.3
Reload from cache	**1.6**	5.2	2.0	1.7	3.4
Memory usage (in megabytes)					
Blank tab	99.5	49.1	**29.5**	91.7	35.0
10 open tabs	423.1	**163.1**	295.0	308.6	224.7
Compliance (in percent)					
HTML 5	**93.0**	82.0	70.0	88.0	56.0
CSS 3	57.0	53.0	57.0	**58.0**	45.0
JavaScript score[a]					
	213.9	183.1	165.3	200.0	137.6

Note. Bold face indicates the top scorer in each category.
[a] See full report for how this item was calculated.

But it is still difficult to see the story in Table 6. Although this table represents a major improvement over Table 5, it is hard to find a pattern in the numbers or derive conclusions about overall browser performance. Moreover, a reader could be forgiven for finding the red fonts distracting: Too many data points are emphasized, creating cacophony rather than coherence.

Table 7. Average Browser Performance on Speed, Memory Use, and Compliance.

Task	Speed (in seconds)	Memory use (in megabytes)	Compliance (in percentages)	JavaScript Score
Chrome 31	4.5	261	**75%**	**213.9**
Firefox 25	5.3	**106**	68%	183.1
IE 11	**2.3**	162	64%	165.3
Opera 17	5.3	200	73%	200.0
Safari 5.1	4.5	130	51%	137.6

Note. Speed was calculated by averaging the speeds of cold start-up, non–cold-start-up, non–cached-page load, and cached-page reload. Memory use was calculated by averaging the memory uses of blank tab and 10 open tabs. Compliance was calculated by averaging HTML 5 and CSS 3 compliance rates. See the full report for an explanation of how the JavaScript score was calculated. Bold face indicates the top scorer in each category.

At this point, we need to return to our data to determine if we can improve our story by selecting different numbers or variables to display. Table 7 provides one such solution by averaging similar data, a consolidation that reduces the number of variables from nine to four—a quantity much easier for readers to hold in their working memory. This consolidation then provides us with a new visualization option: We can now reorient our table so that readers can make comparisons by scanning down columns rather than across rows. Since we are used to seeing numbers arranged in columns, this orientation takes advantage of our existing mental models for reading numbers. Moreover, since we are now emphasizing only four data points instead of nine, the use of contrast in Table 7 is no longer distracting. Thus, our choices about how to summarize the data enable new visualization options.

Now that we have wrangled our data into a manageable format, we can look again to see if we might further clarify our story. For instance, a new column with the textual descriptor "major advantage" could be added to further emphasize the advantages of the different browsers.

Browser performance tests are easy to find (simply google "browser performance test" or "browser performance comparison") and are frequently updated as companies roll out new versions or as operating systems change. Reviews abound across the Web, and different reviewers focus on different measures and comparison points. We can encourage students to critique these reviews and their existing data visualizations before attempting to create their own visualizations.

The Formal Assignment

These short exercises lead up to a formal writing assignment in which I either give students a spreadsheet of data to analyze or have students collect their own data to answer a specific research question. For instance, I have created a spreadsheet containing fictional survey data from 20 employees rating four different software programs on six different criteria that do not all use the same scale. Students have to describe the data and their analytic methods and present a compelling argument to purchase one of the programs in a two-page memo addressed to the company CEO. As an added level of complexity, students must give priority to the opinions of employees from a particular branch of the company. The data are manipulated so that a compelling case can be made for either of two top programs.

The two-page constraint requires students to be creative in selecting and aggregating relevant data so that they can make coherent and comprehensive arguments without overwhelming the reader. For instance, one option students have is to "drill down" by first displaying broad measures for all four programs and then providing more detail for the two programs that can be considered contenders. Other options involve making a case for combining criteria or dropping particular criteria from consideration.

When I have students collect their own data, I ask them to design an experiment to answer a research question related to a communication or usability topic that we have discussed in class. For instance, students have studied user perceptions of fonts in different types of texts, audience recall of PowerPoint slides following different formatting conventions, and the relative performance of mouseover versus point-and-click menu options. To ensure that their data are sufficiently complex, I require that their experiment use, at a minimum, a 3×2 factor design and measure three different variables. In other words, students must focus on two or three factors with different levels and measure different criteria. For instance, the students studying mouseover versus point-and-click menus looked at these two types of menus in three different browsers and measured user speed, accuracy, and preference.

Part of this assignment, of course, requires that students visualize the data they collect, using visuals to tell an interesting, credible, and ethical story about their findings. In fact, the first deliverable for the assignment is just students' data visualizations, which they peer review with their classmates. Students are encouraged to experiment with multiple visualizations of the same data and to use their most effective visualizations to drive the story of their research.

Conclusion

Students in our technical and professional communication courses need much more practice in presenting data to nonexperts (Wolfe, 2009). Such presentations involve not only critical decisions about how to visualize data but also judgments about what numbers to present in the first place. Too often, students think of data as pure, unmodifiable fact rather than as a series of rhetorical choices. The exercises I have discussed here are meant to foreground how the rhetorical choices we make in data visualization need to begin with the data themselves.

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