Journal of Experimental Psychology: General

ISSN: 0096-3445

2024, Vol. 153, No. 7, 1699–1704
https://doi.org/10.1037/xge0001604

BRIEF REPORT

Reading a Graph Is Like Reading a Paragraph

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Vision provides rapid processing for some tasks, but encounters strong constraints from others. Although many tasks encounter a capacity limit of processing four visual objects at once, some evidence suggests far lower limits for processing relationships among objects. What is our capacity limit for relational processing? If it is indeed limited, then people may miss important relationships between data values in a graph. To test this question, we asked people to explore graphs of trivially simple 2 × 2 data sets and found that half of the viewers missed surprising and improbable relationships (e.g., a child's height decreasing over time). These relationships were spotted easily in a control condition, which implicitly directed viewers to prioritize inspecting the key relationships. Thus, a severe limit on relational processing, combined with a cascade of other capacity-limited operations (e.g., linking values to semantic content), makes understanding a graph more like slowly reading a paragraph then immediately recognizing an image. These results also highlight the practical importance of "data storytelling" techniques, where communicators design graphs that help their audience prioritize the most important relationships in data.

Public Significance Statement

This study shows that visual processing is drastically limited when processing relationships between objects, such as the bars in a graph. In graphs containing only four values, participants miss surprising relationships at high rates. This highlights the practical importance of designing graphs that guide an audience to process important relationships.

Keywords: data visualization, capacity limits, communication

Supplemental materials: https://doi.org/10.1037/xge0001604.supp

The graph in Figure 1A depicts the height of two children over two different ages. What patterns do you notice? If you are like our participants, then you first noticed that River is taller than Charlie at age 10. Then, Charlie catches up and surpasses River at age 12. But did you notice that River shrinks between ages 10 and 12, which seems improbable? If not, you are like our participants in that regard as well—approximately half of which missed this surprising relationship, even after viewing the graph for 15 s. Why is this relationship so easy to miss? Processing only four visual values is well within capacity estimates of short-term attention and memory, so we might expect to notice such patterns. But extracting those relations requires a cascade of capacity-limited operations that makes reading even a trivially simple graph as slow as reading a paragraph of text (Carpenter & Shah, 1998).

Visual processing can unfold in rapid and powerful ways. We perform impressive operations broadly across the visual field when we visually extract statistics (Haberman & Whitney, 2012), recognize simple features (Wolfe & Horowitz, 2017), or even learn about complex objects (Ahissar & Hochstein, 2004). These operations are similarly powerful when we look at data visualizations (Franconeri et al., 2021; Healey & Enns, 2011; Szafir et al., 2016). But many visual processes encounter strong capacity limitations, such that processing too many objects or features leads to slower or less accurate performance, forcing observers to filter visual input as smaller subsets of information at a time (Franconeri, 2013; Serences & Yantis, 2006). This filtering is guided by not only goal-directed heuristics, but also bottom-up cues to process unique objects, or to simultaneously process objects that are similar in their color, size, spatial proximity, or connectivity (Yu, Tam, & Franconeri, 2019; Yu, Xiao, et al., 2019). Such bottom-up cues can also guide which relationships are prioritized within data visualizations (Bearfield et al., 2023; Xiong et al., 2021).

This article was published Online First May 23, 2024.
Karen Schloss served as action editor.
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This work was supported by the National Science Foundation (NSF; Grants IIS-CHS-1901485 and IIS-HCC-2107490, awarded to Steven Franconeri).

The authors have no conflicts of interest. We thank Amritha Anupindi and members of the Northwestern Visual Thinking Lab for their helpful comments and feedback. Preregistrations, stimuli, data, and other materials are available on the Open Science Framework (OSF) page at https://osf.io/tjbyp/.

Tal Boger served as lead for investigation. Steven Franconeri served as lead for supervision. Tal Boger and Steven Franconeri contributed equally to conceptualization, writing–original draft, writing–review and editing, and methodology.

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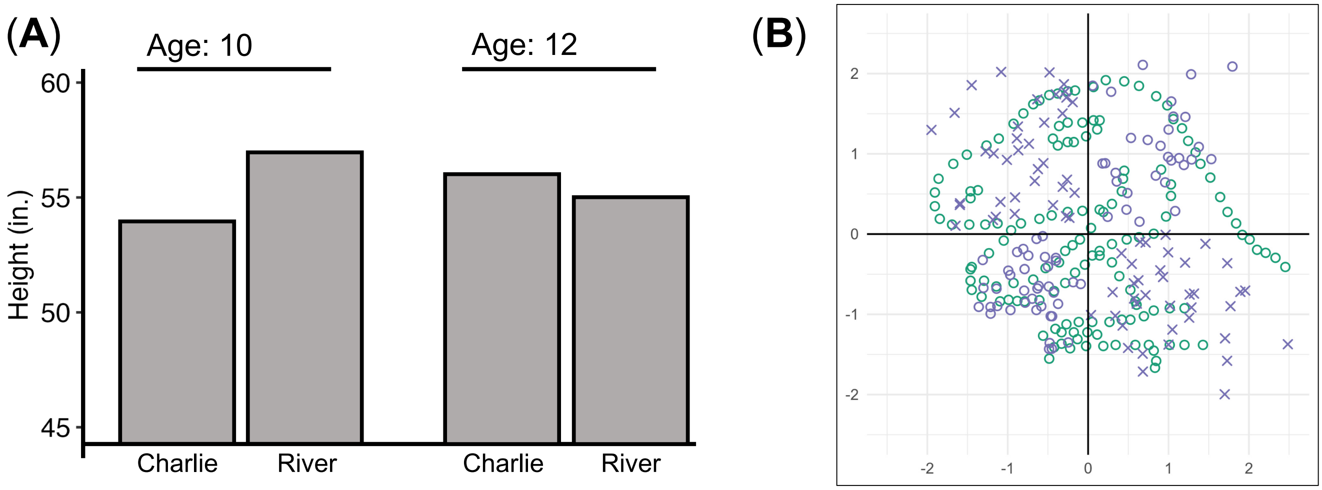
Figure 1

Graphs are Explored Over Time Rather Than Seen in a Single Glance



Note. (A) What patterns do you notice in this graph? Did you notice that River shrinks between ages 10 and 12? Even in graphs like this containing only four values, our participants missed improbable relationships at rates of up to 58%. When participants performed a task that required filtering for the blue Xs in scatterplots like this, more than half missed the appearance of a conspicuous dinosaur formed by the green circles (93% for 1 s presentation, 61% for 2.5 s) in one of the plots. (B) Reproduced from "Jurassic Mark: Inattentional Blindness for a Datasaurus Reveals That Visualizations Are Explored, Not Seen," by T. Boger, S. B. Most, and S. L. Franconeri, *2021 IEEE Visualization Conference (VIS)* (pp. 71–75), 2021. IEEE. Copyright 2021 by the IEEE. See the online article for the color version of this figure.

When information does not match a visual filter, people can fail to notice salient objects, such as motorcycles on a collision course, people holding umbrellas, or even a gorilla (Simons & Chabris, 1999, for review, see Jensen et al., 2011; Most, 2013). A visual filter can have similar effects within data visualizations, with one study finding that 93% of viewers focused on detecting patterns within a scatterplot's blue points failed to notice a salient dinosaur formed by an ignored set of green points (Boger et al., 2021; Figure 1B).

Given these strong capacity limitations, we ask: How limited is relational processing in a realistic case study of processing a simple graph? We choose graph processing because of its critical and ubiquitous role in helping people think about and communicate with quantitative information across science, education, and organizations (Franconeri et al., 2021).

Estimates of visual processing capacity vary, depending on what observers are asked to do. One study proposes a limit of approximately four variables when extracting interactions among variables in a bar graph (Halford et al., 2007). Similarly, when memorizing a list of visual features such as colors or tracking a set of objects, estimates of visual capacity hover around four objects (Brady et al., 2011; Scimeca & Franconeri, 2015). However, when people are asked to remember features not as a simple list, but rather as features linked to specific locations or moving objects, some work shows even lower limits of one to two objects or features (Huang & Pashler, 2007; Saiki, 2002; Scimeca & Franconeri, 2015; Xu & Franconeri, 2015). This limit should apply even for simple static bar graphs, where each object (a bar) might need to be linked to several potential features, including its relative size (the data value), and/or relative spatial position. For those relative sizes or spatial positions alone, one model of visual relationship processing predicts that only a single relationship can be judged at a time between two objects (or statistical summaries of two groups of objects; Franconeri et al., 2012). This may be further limited to relations in a single direction (e.g., extracting that A is larger than B is different than extracting B is smaller than A; Michal et al., 2016) or to within a single feature dimension at a time (e.g., size or contrast, but not both; Michal & Franconeri, 2017). If a 2 × 2 graph presents four data values that presents six possible pairwise relations to its viewer, plus at least two main effects and two interactions. All of those numbers would double if relations are interpreted in a "directional" fashion. While this large space of possibilities should also be drastically reduced by strategic prioritization of which relations to process first, as a product of both current goals and previous experience with graphs, the number of potential relations is daunting.

Understanding a graph requires not only these lower-level perceptual operations, but also connecting those extracted features and relations to their semantic labels and problem context, which should additionally strain capacity limits along a cascade of cognitive operations (Franconeri, 2013). Indeed, in the graph comprehension literature, there is an influential mantra that understanding a graph is more like "reading a paragraph." In other words, reading a graph is a slow and serial extraction of relational "sentences" from the data (Carpenter & Shah, 1998; Shah et al., 2005) rather than an instantaneous and parallel process such as recognizing a picture (Li et al., 2002). Thus, is it possible that our exploration of visualized data could be limited to perhaps a single relationship at any given moment?

The present experiments demonstrate that, even when given time to explore a trivially simple four-value bar graph (within typical estimates of short-term visual processing capacity), participants judge only a small subset of possible relations. We designed graphs that induce viewers to prioritize some relational comparisons over others, by placing some values closer to each other in space, making participants unlikely to compare other values that are farther apart. We then embedded surprising relationships among the far-apart values and asked if participants would notice these surprising relationships. Participants missed these salient patterns at rates as high as 58%. Importantly, participants noticed these patterns at far higher rates when the graph designs highlighted them (again by spatial grouping), suggesting that participants missed the patterns due to limits on relational processing. If reading a graph is like reading a paragraph, then this manipulation should implicitly reorder the sentences of that paragraph, so that in the limited time available, the participant should extract some relations, but not others.

Previous work in data visualization suggests that a demonstration for such a trivially simple graph might be possible. When people were shown relatively complex bar graphs (three values in one factor, three or four values in the other), they were around 3 times more likely to produce descriptions that offered comparisons within local spatial groups, as opposed to within the factor that was interleaved across the local groupings (Shah & Freedman, 2011; Shah et al., 1999, see also Carpenter & Shah, 1998; Shah & Carpenter, 1995). However, these experiments relied on graphs with nine to 12 total data values, which already lay outside typical limits of visual attention and memory, even before considering limits on processing relationships or semantic identities. In other words, any failures to process relationships in these experiments could be due to capacity limits of attention and memory, rather than capacity limits of relational processing. Previous studies also typically use graph designs containing a legend (instead of direct labeling, as used here) which presents an additional working memory load (Lohse, 1993). The graphs used also presented relatively complex topics and potential relationships (e.g., metric, ordinal, or nominal interactions among temperatures and noise levels on test scores). In contrast, the present experiments rely on simple data sets consisting of either one metric and one nominal independent variable, or an even simpler case of two nominal variables, each with only two values. Furthermore, previous work relied on less familiar topics (e.g., population changes across 3 years for four geographic regions), which require higher graphical literacy levels (Shah & Freedman, 2011), as opposed to the present experiments that rely on highly familiar contexts (e.g., children getting taller and comparing battery life for phones).

Finally, in previous work, participants were asked to generate statements about the graph, with the assumption being that more salient descriptions are given first. But a comparison might still have been made and not reported or remembered, even if it is not prioritized (Wolfe, 1999). One solution to this problem is to ensure that a comparison is so surprising that it would surely be reported if it were noticed, such as having a gorilla walk through the middle of a scene (Simons & Chabris, 1999) or a dinosaur appear in a scatterplot (Boger et al., 2021).

Method

Participants

For each of our first three, preregistered vignettes, we recruited 60 unique participants—30 for each graph type. All participants were unique and could only view one type of graph or vignette, meaning we collected data from 180 participants total, all from the online recruiting platform Prolific (for a discussion of the reliability of this subject pool, see Peer et al., 2017). Participants were excluded if they did not submit a full data set, or if they claimed to see a relationship that was in fact not present in the graph (as per their binary responses to such a question).

For our final exploratory vignette (2×2 "age"), we recruited 40 additional unique participants (20 for each graph type).

Stimuli

We created three vignettes and two graph types for each vignette (except for the "age" vignette, which had two graph types for both a 2×3 and a 2×2 vignettes). The vignettes presented either 2×2 or 2×3 (in the case of the third vignette) data sets. The graphs in the first two vignettes were identical, except that the labels and descriptions were interleaved in two ways, one that highlighted and one that hid the improbable relationship.

Design and Procedure

At the start of the experiment, participants read a short vignette describing the context for the graph (these descriptions are available as part of our experimental code in the OSF repository at https://osf.io/tjbyp/). They were told that the graph would appear for 15 s and that they should try to remember at least "two interesting comparisons or patterns that they noticed in the data." Before the graph appeared, the axes were also visible on the screen (with no data present), such that participants could take as much time as they needed to understand the axes and labels. After participants revealed the graph (by pressing the right arrow key on their keyboard) and observed it for 15 s, the graph disappeared, at which point participants were asked to write at least 10 words describing patterns they found to be "most interesting" in the graph.

Following this description, participants had the opportunity to answer a free-response question asking if they saw anything "that didn't make sense in the plot." After these two free-response questions, participants moved on to binary questions. First, they reported whether they noticed the improbable relationship. Then, they reported whether they noticed a second unlikely relationship that was in fact not present in the data (this question was used to exclude participants). For example, this second question (asking about the nonpresent relationship) in the case of the phones vignette asked whether the participant noticed that one of the phones had the same battery life across the two conditions (audio only vs. audio + video). However, the initial graph did not depict this relationship. Therefore, a participant who responds positively (i.e., claims to see this relationship) may falsely report seeing the real, present improbable relationship (probed in the first question) due to a simple bias to respond "yes" to the binary questions. In other words, then, excluding participants in this manner provides an important attention check and ensures that we only analyze participants with trustworthy answers to these binary questions.

Transparency and Openness

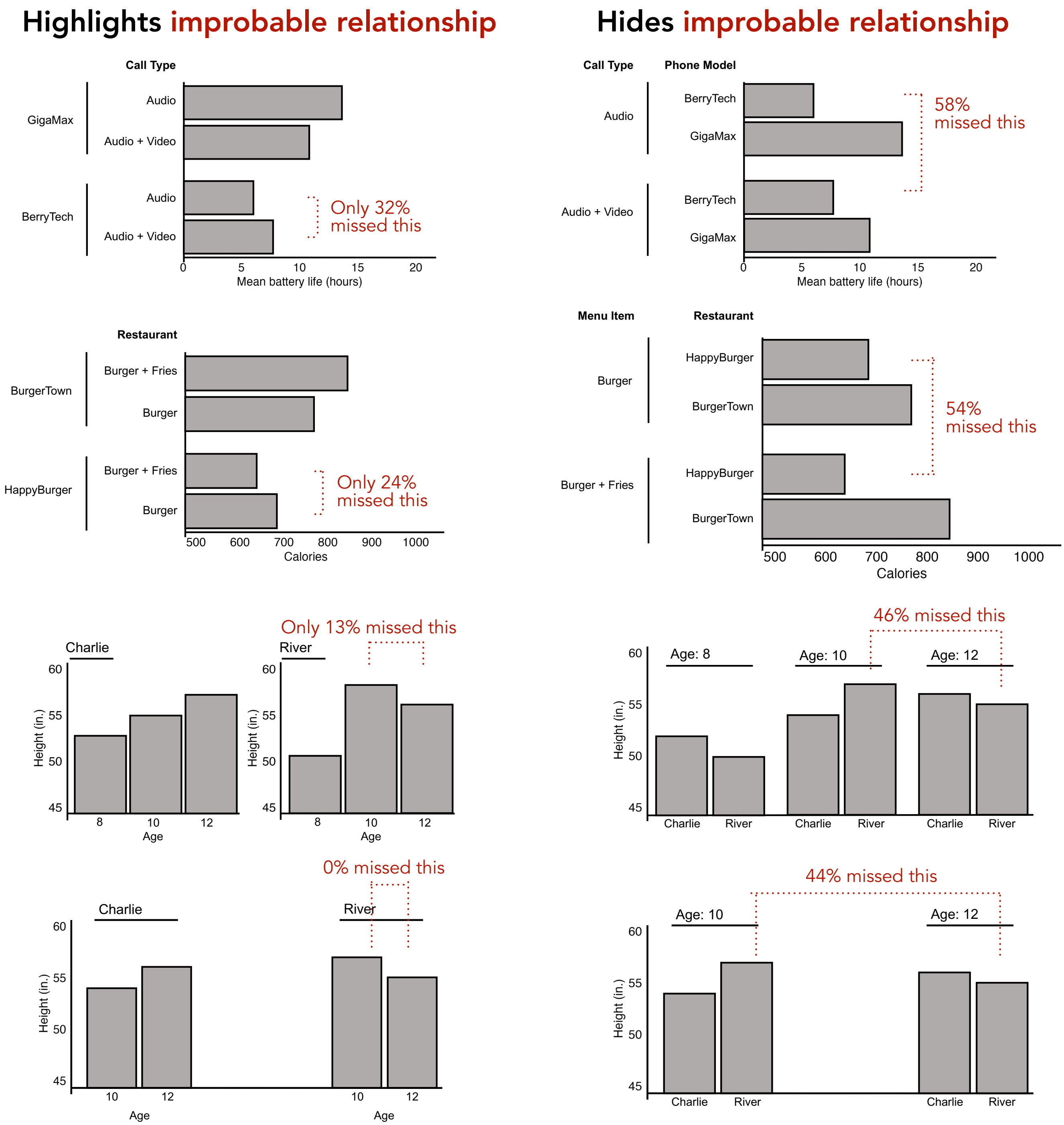
All materials, code, and data are available on the Open Science Framework (OSF) repository at https://osf.io/tjbyp/. Interested readers may view our experiments—exactly as participants did at https://perceptionstudies.github.io/graphs. Our experiments were preregistered, with the exception of a final, exploratory experiment. This is specified later in our methods and in our results.

The Present Experiments

We presented participants with four different data vignettes. Two of the vignettes depict simple 2×2 relationships with four total values, and the third and fourth depict either a 2×3 relationship with six values or a 2×2 relationship with four values[1] (one such

[1] Initially, we preregistered the two 2×2 relationships (phones and restaurants) and one 2×3 relationship (child age). We ran another exploratory experiment in which the same "age" vignette depicts only a 2×2 relationship of the crucial comparison from the 2×3 graphs, and found similar results. However, because this result was not preregistered, we do not include it in our subsequent chi-square test.

Figure 2
Missing Improbable Relationships in Simple Graphs



Note. Participants saw one of these eight graphs for 15 s and were asked to remember at least two "interesting" relationships shown in the plots. Each contained an improbable relationship: a phone battery lasting longer under a tougher task, a larger meal containing fewer calories at a restaurant, or a child shrinking over time. The left column shows the values in a spatial arrangement that was predicted to highlight the improbable relationship by placing the relevant values closer to each other, while the right shows an arrangement that should hide by placing them farther away. The annotations report the percentage of participants who missed the relationship when asked in a binary response whether they noticed the improbable relationship in the plot. See the online article for the color version of this figure.

vignette is depicted in Figure 1A). Within each vignette, participants saw the same bar graph arranged to either implicitly highlight the improbable relationship—by placing that comparison in nearby bars in the graph—or implicitly hide the relationship—by placing that comparison across bars that were more distant from each other. Including a condition where the improbable relation is highlighted serves as evidence that the relationship is salient enough to be detected and reported, and not merely discarded in favor of reporting other potential relationships.

Unique participants viewed the graphs for 15 s before providing typed descriptions of "…the patterns that you see as most interesting within the graphed data." They were then asked: "Did you notice anything that didn't make sense in the plot?" After entering a free-response description to this question, they gave two binary responses. The first asked explicitly if they saw the improbable pattern, and the second asked whether they noticed a pattern that was not actually present; participants who claimed to notice the pattern that was not present were excluded from our analyses (as they may have falsely reported seeing the critical pattern), as per our preregistered analysis plans. Interested readers may try our experiments for themselves at https://perceptionstudies.github.io/graphs. Furthermore, all experimental code, data, and analysis are available on the OSF repository at https://osf.io/tjbyp/.

When the improbable relationship was implicitly highlighted, people were 1.8 ×–3.4 × more likely to find an improbable relationship (Figure 2), $\chi^2(1, 163) = 14.08$, $p < .001$. In a post hoc exploratory analysis, we categorized the sentences that participants typed (before the binary responses) to describe the relationships that they noticed. This revealed that the improbable relationships were far less likely to be described in graph arrangements that hid these relationships and that the arrangement also appeared to highlight or hide other relationships in similar ways, such that values that were closer to one another were more likely to be compared (see Figure S1 in the online supplemental materials).

Conclusion

We show that people miss improbable relationships in trivially simple graphs containing only four objects, even after 15 s of study. Visual processing can be capacity-limited, but a common limit is still around four objects. However, making relational judgments in graphs appears to have far more restrictive limits. These limits start at the perceptual stage, where some models suggest that people can process very few (Hummel, 2000; Wolfe, 1999) or perhaps only one (Franconeri et al., 2012) relationship at a time. These limits should be compounded by the cascade of other cognitive operations that should also be capacity-limited, including tying the extracted relations to their verbal labels and the meaning of those richer relations in context. The present results strongly support the mantra that understanding a graph is not immediate, such as seeing a picture. Rather, it is a slow process that is more akin to reading a paragraph (Carpenter & Shah, 1998; Shah et al., 2005).

These results strongly support an emerging set of guidelines in the practitioner and research literature on effective data communication. First, it strengthens the demonstrations that grouping factors such as spatial proximity, connection (e.g., line graphs), or featural similarity (similar colors or shapes) guide the comparisons that people make in data visualizations (Bearfield et al., 2023; Shah & Carpenter, 1995; Shah & Freedman, 2011; Shah et al., 2005, 1999; Xiong et al., 2021). But because visualization authors often assume that a naive viewer will see the same relationship as they do Xiong et al. (2019), designers should help viewers notice the "right" pattern in a data set by using data storytelling techniques, including highlighting values to be compared and annotating those values with the conclusions drawn from them (Ajani et al., 2021). These steps are important even for trivially simple visualizations. Finally, if a visualization designer can guide a viewer's capacity-limited relationship processing to the "right" pattern, then graphical literacy training should include monitoring for bad actors who use the same technique to guide people to the "wrong pattern" (Ge et al., 2023), much like a magician might use subtle attentional misdirection to hide an action from an audience (Kuhn et al., 2008).

Constraints on Generality

In our experiments, we recruited participants from Prolific, an online recruiting platform (see Peer et al., 2017). The studies were open only to U.S. adults. We do not take it for granted that our findings generalize beyond this group. However, our studies rely on simple questions to probe visual capacity limits that we believe generalize more broadly.

References

Ahissar, M., & Hochstein, S. (2004). The reverse hierarchy theory of visual perceptual learning. *Trends in Cognitive Sciences*, *8*(10), 457–464. https://doi.org/10.1016/j.tics.2004.08.011

Ajani, K., Lee, E., Xiong, C., Knaflic, C. N., Kemper, W., & Franconeri, S. (2021). Declutter and focus: Empirically evaluating design guidelines for effective data communication. *IEEE Transactions on Visualization and Computer Graphics*, *28*(10), 3351–3364. https://doi.org/10.1109/TVCG.2021.3068337

Bearfield, C. X., Stokes, C., Lovett, A., & Franconeri, S. (2023). What does the chart say? Grouping cues guide viewer comparisons and conclusions in bar charts. In *IEEE transactions on visualization and computer graphics*. IEEE. https://doi.org/10.1109/TVCG.2023.3289292

Boger, T., Most, S. B., & Franconeri, S. L. (2021). Jurassic mark: Inattentional blindness for a datasaurus reveals that visualizations are explored, not seen. In *2021 IEEE visualization conference (VIS)* (pp. 71–75). IEEE.

Brady, T. F., Konkle, T., & Alvarez, G. A. (2011). A review of visual memory capacity: Beyond individual items and toward structured representations. *Journal of Vision*, *11*(5), Article 4. https://doi.org/10.1167/11.5.4

Carpenter, P. A., & Shah, P. (1998). A model of the perceptual and conceptual processes in graph comprehension. *Journal of Experimental Psychology: Applied*, *4*(2), 75–100. https://doi.org/10.1037/1076-898X.4.2.75

Franconeri, S. L. (2013). The nature and status of visual resources. In D. Reisberg (Ed.), *Oxford handbook of cognitive psychology* (Vol. 8481, pp. 147–162). Oxford University Press.

Franconeri, S. L., Padilla, L. M., Shah, P., Zacks, J. M., & Hullman, J. (2021). The science of visual data communication: What works. *Psychological Science in the Public Interest*, *22*(3), 110–161. https://doi.org/10.1177/15291006211051956

Franconeri, S. L., Scimeca, J. M., Roth, J. C., Helseth, S. A., & Kahn, L. E. (2012). Flexible visual processing of spatial relationships. *Cognition*, *122*(2), 210–227. https://doi.org/10.1016/j.cognition.2011.11.002

Ge, L., Cui, Y., & Kay, M. (2023, April 23–28). CALVI: Critical thinking assessment for literacy in visualizations. In *Proceedings of the 2023 CHI conference on human factors in computing systems* (pp. 1–18). ACM. https://doi.org/10.1145/3544548.3581406

Haberman, J., & Whitney, D. (2012). Ensemble perception: Summarizing the scene and broadening the limits of visual processing. In J. Wolfe & L. Robertson (Eds.), *From perception to consciousness: Searching with Anne Treisman* (Vol. 33). Oxford University Press.

Halford, G. S., Phillips, S., Wilson, W. H., McCredden, J., Andrews, G., Birney, D., Baker, R., & Bain, J. D. (2007). Relational processing is fundamental to the central executive and is limited to four variables. In N. Osaka, R. H. Logie, & M. D'Esposito (Eds.), *The cognitive neuroscience of working memory* (pp. 261–280). Oxford University Press.

Healey, C., & Enns, J. (2011). Attention and visual memory in visualization and computer graphics. *IEEE Transactions on Visualization and Computer Graphics*, *18*(7), 1170–1188. https://doi.org/10.1109/TVCG.2011.127

Huang, L., & Pashler, H. (2007). A boolean map theory of visual attention. *Psychological Review*, *114*(3), 599–631. https://doi.org/10.1037/0033-295X.114.3.599

Hummel, J. E. (2000). Where view-based theories break down: The role of structure in shape perception and object recognition. In E. Dietrich & A. B. Markman (Eds.), *Cognitive dynamics: Conceptual change in humans and machines* (pp. 157–185). Taylor and Francis.

Jensen, M. S., Yao, R., Street, W. N., & Simons, D. J. (2011). Change blindness and inattentional blindness. *Wiley Interdisciplinary Reviews: Cognitive Science*, *2*(5), 529–546. https://doi.org/10.1002/wcs.130

Kuhn, G., Amlani, A. A., & Rensink, R. A. (2008). Towards a science of magic. *Trends in Cognitive Sciences*, *12*(9), 349–354. https://doi.org/10.1016/j.tics.2008.05.008

Li, F. F., VanRullen, R., Koch, C., & Perona, P. (2002). Rapid natural scene categorization in the near absence of attention. *Proceedings of the National Academy of Sciences of the United States of America*, *99*(14), 9596–9601. https://doi.org/10.1073/pnas.092277599

Lohse, G. L. (1993). A cognitive model for understanding graphical perception. *Human-Computer Interaction*, *8*(4), 353–388. https://doi.org/10.1207/s15327051hci0804_3

Michal, A. L., & Franconeri, S. L. (2017). Visual routines are associated with specific graph interpretations. *Cognitive Research: Principles and Implications*, *2*(1), Article 20. https://doi.org/10.1186/s41235-017-0059-2

Michal, A. L., Uttal, D., Shah, P., & Franconeri, S. L. (2016). Visual routines for extracting magnitude relations. *Psychonomic Bulletin & Review*, *23*(6), 1802–1809. https://doi.org/10.3758/s13423-016-1047-0

Most, S. B. (2013). Setting sights higher: Category-level attentional set modulates sustained inattentional blindness. *Psychological Research*, *77*(2), 139–146. https://doi.org/10.1007/s00426-011-0379-7

Peer, E., Brandimarte, L., Samat, S., & Acquisti, A. (2017). Beyond the Turk: Alternative platforms for crowdsourcing behavioral research. *Journal of Experimental Social Psychology*, *70*, 153–163. https://doi.org/10.1016/j.jesp.2017.01.006

Saiki, J. (2002). Multiple-object permanence tracking: Limitation in maintenance and transformation of perceptual objects. *Progress in Brain Research*, *140*, 133–148. https://doi.org/10.1016/S0079-6123(02)40047-7

Scimeca, J. M., & Franconeri, S. L. (2015). Selecting and tracking multiple objects. *Wiley Interdisciplinary Reviews: Cognitive Science*, *6*(2), 109–118. https://doi.org/10.1002/wcs.1328

Serences, J. T., & Yantis, S. (2006). Selective visual attention and perceptual coherence. *Trends in Cognitive Sciences*, *10*(1), 38–45. https://doi.org/10.1016/j.tics.2005.11.008

Shah, P., & Carpenter, P. A. (1995). Conceptual limitations in comprehending line graphs. *Journal of Experimental Psychology: General*, *124*(1), 43–61. https://doi.org/10.1037/0096-3445.124.1.43

Shah, P., & Freedman, E. G. (2011). Bar and line graph comprehension: An interaction of top-down and bottom-up processes. *Topics in Cognitive Science*, *3*(3), 560–578. https://doi.org/10.1111/tops.2011.3.issue-3

Shah, P., Freedman, E. G., & Vekiri, I. (2005). The comprehension of quantitative information in graphical displays. In P. Shah & A. Miyake (Eds.), *The Cambridge handbook of visuospatial thinking* (pp. 426–476). Cambridge University Press.

Shah, P., Mayer, R. E., & Hegarty, M. (1999). Graphs as aids to knowledge construction: Signaling techniques for guiding the process of graph comprehension. *Journal of Educational Psychology*, *91*(4), Article 690. https://doi.org/10.1037/0022-0663.91.4.690

Simons, D. J., & Chabris, C. F. (1999). Gorillas in our midst: Sustained inattentional blindness for dynamic events. *Perception*, *28*(9), 1059–1074. https://doi.org/10.1068/p281059

Szafir, D. A., Haroz, S., Gleicher, M., & Franconeri, S. (2016). Four types of ensemble coding in data visualizations. *Journal of Vision*, *16*(5), Article 11. https://doi.org/10.1167/16.5.11

Wolfe, J. M. (1999). Inattentional amnesia. In V. Coltheart (Ed.), *Fleeting memories: Cognition of brief visual stimuli* (Vol. 17, No. 5, pp. 71–94). The MIT Press.

Wolfe, J. M., & Horowitz, T. S. (2017). Five factors that guide attention in visual search. *Nature Human Behaviour*, *1*(3), Article 0058. https://doi.org/10.1038/s41562-017-0058

Xiong, C., Setlur, V., Bach, B., Koh, E., Lin, K., & Franconeri, S. (2021). Visual arrangements of bar charts influence comparisons in viewer takeaways. *IEEE Transactions on Visualization and Computer Graphics*, *28*(1), 955–965. https://doi.org/10.1109/TVCG.2021.3114823

Xiong, C., Van Weelden, L., & Franconeri, S. (2019). The curse of knowledge in visual data communication. *IEEE Transactions on Visualization and Computer Graphics*, *26*(10), 3051–3062. https://doi.org/10.1109/TVCG.2945

Xu, Y., & Franconeri, S. L. (2015). Capacity for visual features in mental rotation. *Psychological Science*, *26*(8), 1241–1251. https://doi.org/10.1177/0956797615585002

Yu, D., Tam, D., & Franconeri, S. L. (2019). Gestalt similarity groupings are not constructed in parallel. *Cognition*, *182*, 8–13. https://doi.org/10.1016/j.cognition.2018.08.006

Yu, D., Xiao, X., Bemis, D. K., & Franconeri, S. L. (2019). Similarity grouping as feature-based selection. *Psychological Science*, *30*(3), 376–385. https://doi.org/10.1177/0956797618822798

Received October 4, 2023
Revision received March 21, 2024
Accepted March 29, 2024 ■