Global Extrema Bias Perception and Recall of Average Data Values in Line Charts

Category: Research

Abstract

Experiments in visualization perception demonstrate that people can perceive positions highly accurately. However, position encodings can be susceptible to systematic biases depending on the intrinsic properties of the visualized data, such as its shape and cognitive processes of memory and perception. Using line charts as a case study, we investigate how the shape of data, such as local and global extrema, can bias the perception and recall of average data values. In two studies, participants estimated the average data values in a line chart by adjusting a slider with their mouse. We found that participants' estimates were systematically biased toward the direction of the global extremum. When multiple salient extrema were present, estimates appeared influenced by several extrema simultaneously but ultimately leaned toward the global extremum. Notably, the strength of this bias varied depending on whether participants were perceiving or recalling the mean. This work advances our understanding of how extrema influence perception and memory, potentially exaggerating or underestimating critical trends and contributing to a skewed interpretation of data. These findings offer valuable guidance for the design of narrative visualization tools and data storytelling strategies.

Index Terms: Data visualization, Memory, Perception, Shape, Global Maxima and Minima

1 Introduction

How good are we at remembering the values we see in a visualization? Classic visualization perception work [10, 23] has demonstrated that the position of items in a chart is the most accurately perceived perceptual channel, compared to other channels such as color or size [12]. These findings have inspired best practices to encode data values using positions. However, recent work has shown that perception of position can still be systematically biased: when viewers were asked to indicate the average height of points on a line chart, they consistently recalled the position to be *lower* than it actually was [35]. People can also overweight variability in line patterns, skewing their data value estimates disproportionately toward more variable regions [28].

Despite efforts to model and quantify the degree of bias in position recall, it remains unclear what characteristics of a line in a visualization might be driving this bias. We propose that the shape of the data, which we define as the combined product of the data values and their spatial configuration, plays a key role. In particular, we focus on the extrema. They are points that deviate most from the line's average vertical position. We investigate their influence on viewers' perception and memory of average values. We hypothesize that both global and local extrema can bias average estimates by drawing disproportionate visual attention. This influence likely arises from their high salience due to local contrast with neighboring points [29], which may lead observers to overweight these values during perceptual averaging [20].

We also recognize that in controlled lab studies with human participants, the experimental methodology can have a profound impact on study outcomes [31]. For visualizations, depending on the approaches the researchers took to evaluate the perceptual accuracy of encoding channels such as position and luminance, the resulting rankings of perceptual accuracy affordances can be strikingly different [23, 26, 11]. Therefore, we manipulated whether participants made their responses based on immediate perception or memory (through recall), in order to examine how the elicitation method might influence this bias.

2 Related Work

Data visualizations represent information using a variety of visual encodings such as position, area, and color saturation [3]. These visual encodings have been previously ranked in terms of perceptual precision, with some encoding types (e.g., area and color saturation) being less perceptually precise than others (e.g., position [10]). But perception of visual encodings can also be susceptible to systematic biases. For example, the size of a circle will appear smaller in the context of larger circles than when that same circle is surrounded by smaller circles, and hues can appear darker or lighter depending on their proximity to nearby colors [14]. When people reproduce the average vertical position of a line in a line chart, they consistently underestimate the position to be *lower* than it appeared [35], while simultaneously skewing their estimation towards regions of high variability [28]. People also overestimate smaller data values and underestimate larger data values in bar charts [25] as well as unit charts [36]. In line bisection tasks, for example, participants bias to the left when judging the midpoint of a horizontal line [27]. A similar vertical bias occurs, with participants placing the midpoint higher than the true center [9].

2.1 Shape Perception

Viewers perceive shapes through a combination of bottom-up and top-down processing, in both the perception of natural world objects and data visualizations. They detect low-level visual features while simultaneously drawing on prior knowledge or expectations to interpret the overall structure. This means that how individual elements are arranged can influence how the whole shape is understood and vice versa. In visualizations, this interplay suggests that the perceived 'shape' of data (e.g., a trend line or distribution) may not only reflect the underlying values but also how those values are arranged and interpreted in context.

Neurophysiological studies support this bidirectional process, showing that perception involves recurrent networks that integrate incoming sensory input with top-down modulation [19]. Attention and prior expectations have been shown to change neural responses to visual stimuli, further emphasizing that perception is not purely bottom-up, data-driven. For data visualizations, this suggests that visual encodings are subject to interpretive influences beyond the encoded data itself, such that viewers may 'see' what they expect or what draws their attention, not just what is explicitly shown [37].

In the graphical perception literature, the shape of a visualization has been shown to impact interpretation and memory. For example, the global shape of Directed Acyclic Graphs (DAGs) influences performance in graph similarity tasks [2, 34]. When participants are asked to reconstruct remembered network diagrams, they tend to preserve high-level shape features such as symmetry, orthogonality, and collinearity [24]. These findings demonstrate that people encode and recall structural shape properties from visualizations, suggesting that perceived shape plays a key role in how viewers organize and interpret relational data.

Beyond abstract network diagrams, perceptual studies have shown that shape 'skeletals', which is a set of medial axes abstracted from a shape's boundaries, can modulate attention and bias responses. When asked to tap anywhere on a shape, participants' responses clustered around its skeletal structure, indicating implicit shape-based guidance of spatial attention [15]. Skeletal structures have also been shown to guide similarity judgments: objects sharing skeletal structure are perceived as more similar than those sharing only surface features like contours [22]. These findings are particularly relevant for visualization, where viewers can compare data based on an overall 'gist' rather than specific data points.

Shape-driven biases have also been empirically demonstrated. For example, in bar charts, aspect ratio influences perceived values: viewers tend to underestimate tall bars and overestimate wide bars, suggesting an implicit comparison to a square-shaped prototype [6]. This illustrates how the perceived shape of the encoding itself can systematically bias numerical estimation. Furthermore, the complexity of a shape affects how long viewers study it. Using a measure of skeletal complexity (i.e., the number of structural 'surprises'), studies have shown that people spend more time studying complex shapes when the shape is task-relevant [32]. When shape is irrelevant (e.g., when recalling texture), this effect diminishes.

Together, these lines of work suggest that shape perception is a core mechanism through which viewers process visual information. Since pattern recognition in visualizations often relies on perceived shape (e.g., whether a line curves up or down), and these perceptions can be shaped by both stimulus properties and cognitive expectations. Inspired by this literature, we hypothesize that the data shape can significantly influence how viewers perceive and recall data values. In this work, we test this hypothesis through two controlled experiments designed to isolate and model the role of shape in visualization perception.

2.2 Ensemble Coding, Memory, and Perception

Our perceptual system is highly efficient at extracting abstract representations of spatially distributed visual information [33]. However, extracting 'ensemble' properties affects memory for individual items. For example, a given item seems larger if the aggregate (summary) size estimate for all items of a similar type is larger [4]. When participants are asked to report a summary representation of a scatterplot, their estimated mean of the dots becomes systematically biased towards dots encoded with darker colors [18].

The accuracy of ensemble coding has been linked to its automatic nature. For example, viewers rely more on ensemble representations when memory resources are limited, attention is divided, or uncertainty about individual judgments is high [13]. Increasing the complexity of a visualization while keeping exposure time constant can encourage greater reliance on ensemble perception. As a result, even in complex or noisy displays, people may still accurately extract overall patterns and report summary statistics. On the other hand, as a competing hypothesis, the presence of specific salient features (for example, a salient outlier in a scatterplot) may attenuate this automatic ensemble computation process and lead to an increased reliance on the salient, attention-capturing, visual features of the stimulus. In our study, we test lines with varying numbers of local extrema, which can be thought of as individual "features" in an ensemble. We evaluate the two competing hypotheses by examining whether the number of salient features present (i.e., number of extrema) impacts the accuracy of recall.

Extracting ensemble information from memory interacts with perception [7]. Recent computational models suggest that noise in ensemble computation is impacted by noise at both perceptual and memory levels [30], thereby accounting for the distinction between noise in ensemble statistics accumulated at early and late stages of processing [1]. Extracting ensemble statistics further depends on divided vs focused attention, depending on available cognitive resources such as time to extract information [1]. Specifically, under limited visual processing capacity, we often use focused attention to extract relevant features to compute summaries [5, 8]. Thus, in tasks that require quick extraction of ensemble statistics, salient features of the stimuli may further impact the quality of information extracted.

3 Research Questions and Hypotheses

Perception of position-encoded marks in visualizations can exhibit systematic biases, especially when viewers are asked to reproduce these values from memory [35]. Such biases may be amplified when viewers extract ensemble summaries after brief exposure to visualized data [33]. While prior work has explored biases in spatial encoding and ensemble perception separately, the specific role of data shape on ensemble representations remains largely unexplored. Given the well-documented influence of shape on object perception, we expect that data shape also affects how viewers encode and recall aggregate information in visualizations. Moreover, the cognitive demands of recalling summary statistics from visual memory may further modulate this effect. We therefore investigate how data shape and memory demands jointly influence viewers' estimation of summary statistics. Furthermore, perceptual and memory estimates of summary statistics may be impacted differentially by distributed attention over various salient features of the graph – where recall with limited exposure may rely on salient features more so than perception. To explore this, we study line charts, one of the most common and historically significant forms of visualization [16], and task participants with estimating the average value of a dataset. This experimental design allows us to test the following questions:

Are average position estimates of line charts affected by the shape of the charts? We hypothesize that the overall shape of a line chart influences how viewers recall its average vertical position. Specifically, when a chart contains a salient global extremum, participants will show a systematic bias: they will overestimate the average if the global extremum is a maximum, and underestimate it if the global extremum is a minimum.

How might the presence of local extrema in the direction opposite to a global extremum influence average position estimates? We hypothesize that the presence of local extrema in the opposite direction of the global extremum will pull participants' attention from a single salient feature of the graph and thus will attenuate, but not eliminate, this bias. In such cases, participants' recall of the average position will be more accurate, yet still skewed toward the direction of the global extremum.

Are the average position estimates of lines in a chart perceived or remembered incorrectly? Overall, we expect to find both visual memory and perception of salient shaped line graphs to be similarly biased, with differences in the strength of biases. We did not have an a priori prediction about whether perceptual or memory biases would be stronger.

4 Experiment 1

Participants viewed a series of line charts whose shapes were systematically varied by manipulating the size and number of global and local extrema. Their task was to estimate the average vertical position of each chart. This allowed us to measure how different data shape configurations of extrema influenced perceived positions of data averages.

4.1 Participants

We recruited 13 undergraduate students from University X to participate in this study. All participants provided their informed consent prior to the study and were debriefed about the research question upon completion. All study procedures were approved by the University Institutional Review Board.

4.2 Stimulus Generation Procedure

For the experimental stimuli, we generated multiple types of line charts (See figure 2 for examples). We created **noisy charts** (baseline) by sampling 10,000 points from a normal distribution centered on the experimentally defined mean, then plotting them as a connected line. We generated **extrema-controlled charts** by first specifying anchor points to define the location of extrema and the chart endpoints. For charts with a single extremum, three anchor points were set: the extremum point was positioned 10 units above or below the true mean, while the endpoints were fixed at the true mean. For charts with three extrema (one global extremum and two local extrema), the first and last points were anchored at the true mean. The global extremum was set 20 units above or below the true mean, and the two local extrema were anchored 10 units in the opposite direction of the global extremum[1].

These anchor points were then used as control points for a piecewise cubic interpolator, specifying the first derivatives at each point. This interpolation method allowed us to carefully control the relative heights and widths of the graph features. Finally, the interpolated curves were sampled at 1,000 evenly spaced integer points to generate the final graphical stimuli for each trial.

4.3 Task Design and Procedure

Figure 1 illustrates the design of the experiment. On each trial, participants were first shown a fixation "plus" sign at the center of the screen for 500 ms. Next, they were shown a line chart produced using the procedure described in section 4.2 for 1.5 seconds. The line chart also displayed two y-axis ticks with the lower tick at 0 and the higher at 100. After this, a visual mask (a gray square covering the entire line chart) was presented for 500 ms. Following the visual mask, participants were presented with a blank chart of the same size as the line chart, with the y-axis labeled at the same locations, with 0 at the bottom left corner and 100 at the top left corner. Participants were then prompted to report their estimate of the average y-axis position of the line chart they had seen on the screen before the mask. No other chart labels were presented. To account for any potential effects of stimulus or response onset expectations, all timings (fixation display, stimulus display, and mask display) were jittered by sampling from a normal distribution, with a mean corresponding to the times noted above and a standard deviation of 50 ms.

To estimate the averages of the line charts they saw, participants were shown a horizontal line whose vertical position could be controlled by the mouse. They were then prompted to use the mouse to drag the horizontal line up or down the y-axis until its position reflected their estimate of the mean of the line chart during stimulus presentation. To control for any motor or initial position effects, the initial position of the horizontal line was determined at random. The slider was linked to the vertical component of the mouse trajectory, allowing it to be moved along a single y-axis, and was constrained by the height of the empty graph displayed. Once the participant was satisfied with their estimate of the mean as represented by this vertically adjustable line, they were asked to press the space bar or the enter key to start the next trial.

The end points of all line charts ranged from 36 to 64 units, as defined on the y-axis. All shape-controlled graphs were presented at intervals of 2 units. Overall, participants in this study responded to 145 different charts. The order of stimulus presentation was randomized. Participants were given a self-paced break at the halfway mark. The experiment was scheduled to last up to 30 minutes. To avoid biasing participants with practice responses on the task and to allow us to sample experimental trials in a controlled range, we intentionally did not provide any practice trials. Further, we did not set a response time limit to allow for a clearer grasp of the instructions.

[1]Note that since two opposing local extrema would pull the overall mean, the global extremum necessarily had to be placed farther from the mean in three-extrema graphs

Figure 1: Experiment Design: Participants were shown a line chart with y-axis labeled at 0 and 100. In experiment 1 (top panels), a visual mask following the line chart was shown for around 1.5 seconds. After the visual mask, participants were asked to use their mouse to drag the slider to their estimate of the y-axis average of the line chart. In experiment 2 (bottom panels), the graph remained on screen as participants reported their estimates. The stimulus shown is an example of the noisy graph.

4.4 Experiment 1 Results

We use Bayesian hierarchical linear mixed effects models to conduct all our statistical analyses. To assess participants' biases in estimating the averages, we test their accuracy in responding to all chart types. We fit the following model while allowing for participant-varying effects.

$$errors \sim 0 + shape : direction + (1|participant) \tag{1}$$

We find that participants were accurate in estimating the true means of the viewed noisy chart (*M: .080, 95% HDI: [-0.608, 0.839]*). They were also accurate in their average estimates of graphs with single global extremum (for single global minima graphs: *M=-0.145, 95% HDI:[-0.989, 0.723]* and for single global maxima graphs *M = 0.135, 95% HDI = [-0.650, 0.960]*). On the other hand, the global extremum direction on graphs with three extrema (one global extremum, two local extrema in the opposite direction) were significantly impacted by the direction of the global extremum (for global minimum with local maxima, *M = -4.49, 95% HDI = [-5.344, -3.657]* and for global maximum with local minima, *M = 3.568, 95% HDI = [2.774, 4.371]*. Marginal comparisons between number of extrema reveal that participants' recall estimates were reliably more biased towards the global extremum in three-extrema graphs than single extremum graphs (for global maxima, *M = 3.433, 95% HDI = [2.639, 4.32]*, for global minima, *M = -4.345, 95% HDI = [-5.331, 3.491]*).

Takeaway: Participants' mean estimates were systematically biased toward the direction of the global extremum in graphs where the extremum was sufficiently farther from the true mean. Participants overestimated when the extremum was a maximum and underestimated when it was a minimum. This bias is attenuated when extrema are wider and closer to the true mean, as in the single extremum graphs.

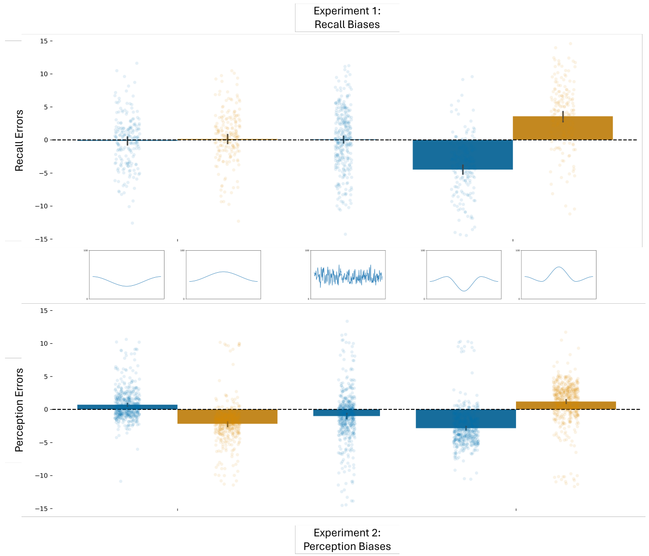

Figure 2: *Left: Experiments 1 Results*. Memory bias *Right: Experiment 2 Results*. Perception bias.

5 Experiment 2

Our previous experiment assessed how people's *recall* was biased by graph shape. We next test whether the effect is in the perception of the stimuli itself.

5.1 Participants, Stimuli, and Methods

We followed the same recruitment protocol and recruited an additional 14 undergraduates to participate. We used the same stimuli generation procedure as before. We made two changes to our experiment: 1) We sampled the vertical space such that the end points of line graphs were fixed from 32 to 68 units with a separation of 1 unit, and 2) We maintained the line charts on the screen while asking participants to adjust a slider estimating the average. Participants thus did not have to rely on their memory to respond.

5.2 Experiment 2 Results

We fit the same statistical model as in experiment 1 to assess the reliability of our data. Interestingly, for all line graphs, participants' perceptual estimates meaningfully differed from their memory estimates in experiment 1. Participants reliably underestimated their averages on noisy graphs when graphs stayed on-screen (*M = -0.988, 95% HDI = [-1.360, -0.638]*). Next, considering shape and direction effects, we find that for graphs with a single global extremum, participants' perceptual estimates were biased in the direction *opposite* of the direction of the extremum (for single global minima graphs: *M=0.728, 95% HDI:[0.366, 1.075]* and for single global maxima graphs *M = -2.162, 95% HDI = [-2.542, 1.831]*). On the other hand, the effects of global extremum direction conformed with our results in experiment 1: reliable overestimation when global extremum is a maximum (M = 1.220, 95%HDI = [0.867, 1.573]) and a reliable underestimation when global extremum is a minimum (M = -2.816, 95%HDI =[-3.183, -2.483]). Marginal comparisons between number of extrema reveal that participants' recall estimates were reliably more biased towards the global extremum in three-extrema graphs than single extremum graphs (for global maxima, *M = 3.382, 95% HDI = [2.968, 3.842]*, for global minima, *M = -3.543, 95% HDI = [-3.995, -3.12]*).

Finally, we performed marginal comparisons between our two experiments. We find that perception of noisy graphs is reliably underestimated than recall (*M=-1.068, 95%HDI = [-1.909, -0.285]*). We also find that recall estimates of three extrema graphs are reliably more biased than perceptual estimates (for graphs with global maxima, *M = 2.349, 95% HDI = [1.484, 3.234]*, for global minima, *M = -1.675, 95% HDI = [-2.646, -0.8]*). Finally, extenuated bias in recall estimates for single global maximum graphs was also reliable (*M=2.297, 95% HDI = [1.42, 3.196]*) whereas it was trending significance for single global minimum graphs (*M=-0.873, 95% HDI = [-1.766, 0.053]*).

6 Discussion and Future Work

We examined how biases arise as a function of data shape and whether participants responded based on immediate perception or memory. Across both studies, we found that when line charts contained three extrema, participants' average estimates (both perceptual and memory-based) were consistently biased toward the direction of the global extremum. In contrast, for graphs with only a single extremum, we observed a different pattern: recall estimates were largely unbiased, while perception estimates showed a bias in the opposite direction of the extremum.

Further examination of the graphs suggests possible explanations for these effects. In the single-extremum graphs, the peak or valley was relatively moderate—approximately 10 points away from the true mean—and the overall height was about 20 points. In contrast, in the three-extrema graphs, the global extremum was more extreme—20 points above or below the mean—but narrower in width. These structural differences may have shaped how participants interpreted the graphs: for single-extremum graphs, participants may have relied on a heuristic of visually bisecting the chart, leading to slight overestimation for minima and underestimation for maxima. In graphs with multiple extrema, however, the greater saliency and complexity of the shape may have prompted stronger reliance on salient points, especially during memory recall.

These results highlight an important distinction between perceptual and memory-based ensemble processing. When perceiving a visualization, participants may integrate multiple cues, including spatial layout and visual balance, leading to different biases than when recalling from memory. At recall, without access to more fine-grained perceptual information, participants may instead rely more heavily on salient features, such as the global extremum, to reconstruct their estimates. This aligns with cognitive theories suggesting that ensemble perception at encoding and feature-based heuristics at recall engage distinct mechanisms, with salience playing a larger role when memory must compensate for missing perceptual detail [17].

Overall, our findings underscore the importance of considering the cognitive demands of a visualization task when interpreting user responses. Whether a viewer is estimating values based on direct perception or memory recall can meaningfully influence bias patterns, particularly in the presence of complex data shapes. Future work should aim to replicate these findings with greater control over stimulus properties and to more precisely dissociate the contributions of perceptual averaging and memory-driven reconstruction in visualization interpretation.

7 Potential Design Guidelines

These biases present an important consideration for visualization design. A single chart can represent a large amount of data encoded through position, and visualization designers should actively account for potential biases. We encourage visualization designers to leverage explicit annotations to communicate key data values, and potentially explore building into visualization tools interventions that specifically address perceptual biases. For example, while displaying a stock price trend graph with significant extrema, it may be a good practice to explicitly state the true aggregate measure along with the graph to avoid reader bias in estimating trends (for more mitigation strategies, see [21]).

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