Graphical Perception in Animated Data Visualizations

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Abstract—Interactive visual applications create animations that encode changes in the data. For example, cross-filtering dynamically updates linked visualizations based on the user’s continuous brushing actions. The animated effects resulting from these interactions depends both on how interaction (e.g., brushing speed) controls properties of the animation such as frame rate, as well as how the data that is being explored dictates the data encoded in the animation. Past work has found that frame rate matters to general perception, however a critical question is which of these animation and data properties affects the perceptual accuracy of judgement tasks, and to what extent. Although graphical perception has been well studied for static data visualizations, it is ripe for exploration in the animated setting. We designed two animated judgment tasks of a target bar in an animated bar chart and empirically evaluate the effects of various animations properties—highlighting of the target bar and frame rate—as well as data properties that affect the target bar’s value throughout the animation. In short, we find that the rate and timing of animation changes is easier detected in larger values; that encodings such as color are easier to detect than shapes; and that timing is important—earlier changes were harder to perceive as compared to later changes in the animation. Our results are an initial step to understanding perceptual accuracy for animated data visualizations, both for presentations and ultimately as part of interactive applications.

1 Introduction

Interactive visualizations are an integral part of visual analytics and a predominant method to explore larger, higher dimensional datasets. From Shneiderman’s classic introduction of dynamic queries in HomeFinder [45] to modern cross-filter [42] visualizations, these direct manipulation interfaces dynamically change the visualization in response to user interactions and enable users to rapidly generate and answer hypotheses about the data that cannot be answered by a static table or visualization [9]. Both techniques can translate a single interaction (e.g., brushing motion) into rapid visualization updates and rely on the human’s ability to accurately perceive information encoded in the resulting animation.

For instance, a cross-filtered visualization of flight delays may contain several views of the delay (by week, day, and hour). Dragging a brush in one of the views will update parameters of a filter (e.g., hour ∈ [start, end]) that translate into visual updates in each of the other views. In this case, each pixel of mouse movement defines the subset of data that is shown in an animation frame. Similarly, a user may move her mouse over the west coast of a map visualization to dynamically update a coordinated sales visualization and look for drastic or interesting changes across different counties. In both examples, each animation frame encodes a subset of the database controlled by filtering parameters controlled by the user interaction. This is in contrast to animated transitions [16], which synthesize animations between two separate visualization states for object tracking purposes. User decisions during an interactive session, such as what subset to analyze in detail, rely on making accurate perceptual judgements based on these animations. However, despite the wide deployment and study of dynamic query interactions, the basic factors that affect the user’s graphical perception of dynamically changing data visualizations is still under-explored.

Existing graphical perception research has studied how numerous properties of the visualization, such as the visual encoding, the distractor bars, and the magnitude of the encoded data affect perceptual accuracy. The original Cleveland and McGill [8] studies measured the accuracy that users can perceive differences between pairs of marks under various visual encodings (e.g., length, position, angle). Follow-up work extended the design to crowdsourcing-based experimental platforms [15], studied separation and distractor effects [38], and three-dimensional perspective [48]. Although these works have extended graphical perception in interesting directions, they have focused on pairwise comparison tasks, and static graphics; graphical perception in animated visualizations is ripe for exploration.

A natural question to ask is which factors of the animation, and to what extent do they, affect the accuracy of different perceptual tasks. For instance, does the frame rate always affect user accuracy, or only in certain cases? Are these effects independent of the data that is animated, or are there interactions between these parameters? In order to understand these questions, it is important to perform controlled, replicable studies and study the variation in user judgement accuracy in response to changes in these factors.

Prior studies have compared the effectiveness of animation with static representations of temporal data [33] and found that animation is consistently less accurate. However, these studies do not control for the dataset nor the animation itself, and it is unclear what aspects of the animation contributed to the lower accuracy. Numerous perceptual experiments have studied the mechanisms that affect object tracking accuracy and have found that crowding [44] significantly degrades the ability to track objects, while other factors such as object speed and trajectory changes [39] appear to have minimal effects. Although these provide useful animation guidelines, and have been used to facilitate the design of animated transitions [16], is unclear to how to transfer and quantify the findings for animated data visualization.

This paper extends the graphical perception literature to animated data visualizations and studies the factors that affect perceptual accuracy. We designed and conducted a series of empirical experiments using animated bar charts that broadly surveys three important classes of factors. The first class varies the complexity of the judgment tasks: a simple baseline task that asks users to estimate the maximum height of a target bar and a complex trend estimation task that asks users to reproduce how a target bar’s value changed during the animation by estimating three properties of the trend. The second class of factors evaluates general animation properties such as frame rate and how the target bar is identified. The third class varies the data that is encoded in the visualization; this helps tease apart effects due to the animation as compared to the data being rendered. In addition to the contribution of our experimental design, we seek to address the following questions about perceptual accuracy: 1) how sensitive is perception to the individual factors, and under what conditions? 2) do the factors interact and in what ways? 3) when performing the complex task, how accurate are the individual sub-tasks?

We first present background and motivation, and an overview of our experimental design. We then validate our experimental setup by replicating the prior static visualization studies, report on our experiments, and conclude with implications of our findings as well as future work.
2 Background and Motivation

The studies described in this paper are motivated by our desire to understand the perceptual implications of interactive data visualizations. As background, we first discuss two areas of closely related work—graphical perception studies stemming from the original Cleveland & McGill work [8] and studies of the efficacy and usage of animation in information visualization. We finally describe interactive visualizations systems, the challenges of directly quantifying the effects of interactions on user perception, and its relationship with animation.

Ultimately, a better understanding of perceptually accurate animated visualizations is important for interactive infoviz applications, where the analyst is dynamically sifting through the dataset looking for and quantifying patterns of interest. Understanding what will affect the user’s conclusions is a crucial part of improving future interactive systems.

2.1 Graphical Perception

This paper builds upon theory and experimentation in the areas of psychophysics and graphical perception [8, 10, 37] that study human perceptual accuracy and limitations in decoding visual encodings such as color and position. The most related are a series of graphical perception studies initially performed by Cleveland & McGill. They quantified the accuracy of pairwise comparisons in static data visualizations [8] to gain insight into the effectiveness of different visual encodings.

In their design (Figure 1), users compare the heights of the bars labeled with circles. They argue for this comparison task because the power of a graph is its ability to see patterns and structure not readily revealed by other means of studying data, and that conveying numbers with as many decimal places as possible is best performed using tables [9]. Heer et al. [15] replicate these studies using a crowd-sourced design and a larger variety of visualizations including pie charts and tree maps. Talbot et al. [38] focus specifically on bar charts and study the effects of separation, distractor bars, and participant bias towards multiples of 5. Zacks et al. [49] study the effect of 3D perspective on bar charts.

These studies have followed Cleveland’s original design and focused on static visualization and the same comparison tasks, however numerous challenges arise when translating the ideas to animated visualizations. First, the primary value of exploratory systems is that the exact analyses are not known in advance, so that a static table is not appropriate. Second, naively re-purposing the pairwise comparison task to an animation leads to ill-defined tasks with confounding factors. For example, should the user report on how the comparison changes throughout the animation, or the comparison at a particular instant in the animation? The former approach confounds the effects of the animation due to the changes in the pair of bars, while the latter begs the question of which instant to choose. Ultimately, new task designs are needed in order to quantify graphical perception for animations.

2.2 Animation Studies

Animation simulates continuous visual changes by the rapid sequence of static images. Many original studies were based on principles from cartoon animation [6] and motivated by applications to explain temporal data [35], instructions [22, 50], or state transitions [16]. Animation’s general utility has received mixed reviews. On one hand, it has been found to increase user engagement [40, 41], improve user orientation [40], signal user attention and help group objects through common fate [2]. On the other hand, unnecessary or ill-designed animation can also clutter the information display, and reduce user comprehension. In addition, animations may simply be difficult to perceive [40] and hard to accurately reproduce by the user [20].

There is considerable evidence in the infovis community to use proper static visualization presentation techniques instead of animation for conveying changing data. Tversky’s survey [40] of animation research did not find a use of animation that outperformed a carefully designed static diagram. When studying GapMinder-style animated bubble plots, Robertson et al. [33] found that using animation to convey temporal changes was less accurate and slower than static alternatives through the use of tracks or small multiples. Although some users find animation to convey emotion or be more enjoyable, these are factors that are useful for data presentation, and not necessarily for data exploration.

Animated transitions between two visualization states (e.g., swapping axes, or changing visualization encodings) are a well studied use of animation that is intended to preserve object constancy [32, 34]. Heer et al. [16] develop a taxonomy of transition types that inform a set of animated data visualization transitions and find that a simple, staged approach reduces the error in object tracking, and improves user understanding and engagement. Chevalier et al. [7] present opposing results that staggered animated transitions have negligible utility.

Overall, prior animation research has provided insight into the psychological mechanisms for how we perceive dynamic visualizations, and have provided a number of design guidelines for when to use animation, and what general properties, such as congruence and constancy that are important to preserve. However, there is opportunity to perform detailed studies akin to Cleveland’s graphical perception studies, and quantify the sources of perceptual accuracy, in animated visualizations.

2.3 Interactions and Animation

There has been considerable work on building highly interactive data exploration systems in the recent years. These systems, exemplified by Nanocubes [26] and imMens [28], provide interactive cross-filtering capabilities over million or billion-record datasets. For example, imMens renders histogram summaries as bar and spatial map visualizations; as users move their mouse over marks in the visualization, the charts are dynamically updated to reflect counts of the selected subsets of the data. In effect, continuous user actions can be viewed as the cause of animated changes in a visualization.

In order to best utilize interactions, it is important to understand how users employ interaction and derive conclusions from the animated effects. Interaction taxonomies [17, 23, 24, 47] organize interactions based on e.g., high level goals, user intent, low level operations, and can help narrow the scope of interactions to evaluate. User experiments have varied from qualitative studies of user interaction patterns [11] to the effects of interaction delay [12, 27] on user behavior and decisions. However, detailed studies of the relationship between interaction, or even animation, and perceptual accuracy is still an emerging area; it is unclear how to disentangle the numerous possible confounding factors in a direct interaction experiment.

Consider even a simple controlled design that uses a single interaction (e.g., a slider that dynamically filters a bar chart) and ask the user to perform a single judgement tasks. Even in this simplified case, changes in perceptual accuracy due to the dataset (e.g., how the data changes, noise), the visualization (e.g., visual encoding, number of marks), the animation (e.g., the frame rate), or the user behavior (e.g., where and how often the user chooses to scroll over a region)?

As it is clear that interaction will continue to be an integral part of information visualization, understanding how graphical perception is affected by dynamically changing visualizations is of importance. Animation is arguably the most key visual feedback to the user’s direct manipulation interactions and understanding animation, on its own, affects perception will be a valuable precursor before turning our studies toward interaction.

3 Study Design and Rationale

The goal of our study is to understand how a broad range of factors influence the accuracy of several judgement tasks in short animated visualizations. Our basic task design renders a 2-second bar chart animation and gives visual tests that require estimating values of a single target bar while ignoring other distractor bars. Many of the parameters, such as animation duration, are fixed throughout all experiments, while others, such as frame rate, are tested. We now discuss the rationale behind our task design and the choice of factors that we studied.

3.1 Basic Task Design

When permitted, we chose to remain consistent with the design of prior graphical perception experiments [8, 15, 38]. We positionally encode
the data as bar charts both because of its effectiveness as a visual encoding, and because it is well studied compared to alternative visualization types [8, 15, 38]. In prior static experiment, each chart showed a pair of target bars, along with four distractor bars for each target mark (see Figure 1). To adopt this to our setting, we simplify the chart to contain the single target mark that the user compares across the animation frames, and four distractors (Figure 3).

We assign random heights to the distractor bars in each animation frame [8, 15] in order to avoid inadvertent correlated movements between the target and distractor bars, which may introduce a confounding factor [40]. There is inconclusive evidence about how distractors affect judgement [38], and we do not pursue this aspect in these experiments. All charts are 380 × 380 pixels, without tick marks that may serve as reference points along the x and y axes.

We chose to show short animations based on a simplified model of user interaction \( I = [m_1, \ldots, m_N] \) as a piecewise linear sequence (possibly with gaps) of \( N \) mouse movements \( m_i \). Each \( m_i \) moves at a constant speed \( s_i \) between the time intervals \([t_i', t_i] \). For example, \( m_1 \) may model a single, short, linear scrubbing motion, and the user views the resulting animation \( a_i \). Our tasks focus on varying different properties of this animation unit \( a_i \) and testing users’s ability to accurately perform judgment tasks.

Our choice of the 2-second duration is situated between Newell’s [31] time scales for cognitive operations (e.g., clicking a link) and unit tasks (e.g., making a chess move). This is because the tasks require users to notice and identify patterns, which is deliberate act on the order of 100ms, but also quantify exact amounts, which requires cognitive processing.

3.2 Judgment Tasks

As discussed in Section 2.1, prior judgement tasks for static visualizations studies do not naturally translate to animated data visualizations due to the additional temporal setting. For instance, if the user is asked to perform pair-wise comparisons between a pair of bars, what does the user report? How the comparison changes throughout the animation? Or the largest difference between the pair?

As Cleveland [8] noted, comparison tasks are fundamental to the user of visualizations. Thus, we focus on the comparison of a single bar’s value across animation frames, and ask users to perform judgement tasks that measure different characteristics of the change of a single target bar’s value. For this, we chose two tasks from Yang’s taxonomy [46] of task-oriented visual insights that are used in trend analysis and range from simple to complex.

The baseline extremum task asks users to estimate the value of the target bar at its turning point [4]. Turning points are important in trend analysis because they signify an abrupt and significant change in the trend that can be a candidate for detailed investigation. For the patterns that we study (Section 3.3), this is equivalent to asking users to estimate the maximum value \( v_{\text{max}} \) of the target bar in the animation. This task is of comparable complexity as prior static studies.

The complex trend task is commonly used [33] to characterize the overall shape of the trend (e.g., estimate the target bar’s values that are defined by the curves shown in Figure 2). It is more complex because it requires the user to estimate multiple aspects of the trend such as when it changes, the bar height at the turning point, and how quickly it changes. The bar height estimate is the same as the one in the baseline extremum task, and provides an opportunity to compare the accuracy between the two judgement types.

3.3 Parameters Tested

Animations can be described along two separate dimensions: the data that is encoded in the animation frames (data parameters) and how the animation is styled and rendered (animation parameters). The data dimension defines what is shown, while the animation dimension defines how the animation is styled and played back. We study the effects of both types and describe them below; they are summarized in Table 1.

3.3.1 Data Parameters:

The data parameters define the data that is rendered during the animation. One approach was an ecologically valid design that uses real datasets (e.g., world bank data) to generate the animations [33]. The main limitation is the inability to isolate individual factors such as the magnitude of the values or how the values change over time. We instead used a simple data generation model—the distractor bars are generated randomly (Section 3.1) and the target bar’s height is defined by a trend function \( T \). The trend function must be designed to support a wide variety of patterns yet only require a small number of parameters.

We found that a simple template—variations of a pyramid-shaped pattern containing a single turning point (Figure 2)—revealed interesting insights about the two judgement tasks. Furthermore, complex trend patterns are composed of sequences of turning points, so our results may serve as a baseline future experiments. The key limitation is the difficulty of isolating what parts of the datasets ultimately that affect user judgements.

The trend function \( T(x) \) maps the position of a frame \( x \in [0, 1] \) in the animation to the target’s value. This function can generate variations of a pyramid-shaped pattern by tuning its three parameters: \( v_{\text{max}}, \) \( pos \) and \( k \). The target bar increases from an initial value \( v_i \) to a maximum value \( v_{\text{max}} \), and then decreases to \( v_c \). The frame containing the bar that reaches \( v_{\text{max}} \) is called the maximum position \( pos \in [0, 1] \) and varies from the first to the last frame (Figure 2b,2c). Additionally, trends change at different rates—inflation increases at a constant rate, however the number of edges in a social network increase non-linearly. The exponential term \( k \) models this aspect by controlling the rate of change. When this value is low, the function follows a linear trend, however large values such as 100 approximate an impulse function that has low values at all points except for the frame corresponding to the position parameter \( pos \), where the target value reaches the maximum value \( v_{\text{max}} \) (Figure 2a).

\[
T(x) = \begin{cases} 
(v_{\text{max}} - v_i) \frac{x}{pos} + v_i & \text{if } x \leq pos \\
(v_{\text{max}} - v_c) \frac{1-x}{1-pos} + v_c & \text{otherwise}
\end{cases}
\]

Table 1: Parameters tested in experiments

| Parameter | Type   | Description | Defaults |
|------------|--------|-------------|----------|
| \( mark \in \{0, \ast\} \) | Anim   | Target bar’s marking | color |
| \( fps \in [2, 30] \) | Anim   | Frames per second | 10 |
| \( v_{\text{max}} \in [22, 85] \) | Data   | Maximum value | 22, 32, 47, 69, 85 |
| \( pos \in [0, 1] \) | Data   | Maximum Position | 0, 0.5, 1 |
| \( k \in [1, 100] \) | Data   | Rate of change | 1 |
Finally, trends typically exhibit smaller perturbations in addition to the overall trend shape. To replicate this, we add a small amount of Gaussian noise $N(0, 5)$ to the target bar. In a follow-up study, we specifically analyze the effects of various noise models on user perception in animated visualizations and find that user accuracy is surprisingly robust to the amount of noise. However we use the simple noise model in this paper.

![Fig. 2: Examples of three trend functions along with user input controls for the trend judgement task.](image)

We are careful to ensure the reported errors are due to perceptual inaccuracies rather than an artifact of the experimental design. When varying data and animation parameters, we ensure that the target bar is always within $[5, 95]$, and that the maximum value of the target bar is exactly $v_{\text{max}}$ in a single frame of the animation as defined by the $\text{pos}$ parameter. We also ensure that the inclusion of random noise does not cause the target bar to exceed or equal $v_{\text{max}}$ in any other frame.

![Fig. 3: Examples of frames under different progress and marking conditions. The grey bar at the bottom shows the animation progress. The target bar is marked with color in 3a, 3b, and circle in 3c.](image)

### 3.3.2 Animation Parameters:

The prior graphical perception studies used a circle shape to mark the target bars. The pretentative literature suggests that color identification exhibits “pop-out” that improves tracking performance [13]. For this reason, we study the effects of marking the target bar ($\text{mark}$) using a circle and a colored fill.

In addition, we simulate different speeds of the mouse movement $s_i$ (Section 3.1) by varying the frames-per-second ($\text{fps}$) of the animation. Because we fix the animation to 2-seconds, so changes in the frame rate alter the number of frames sampled from $T$ but not the duration. An alternative design that fixes the number of samples and varies the animation duration is a direction for future studies.

### 3.4 Experimental Overview:

We employ a within-subject format and a custom multi-task interface to manage the multiple judgment tasks in each HIT. We track user progress so users with intermittent connectivity can return to the last incomplete task. Each experiment is a separate HIT deployed on Amazon Mechanical Turk and we pay users using bonuses. Similar to previous studies, subjects must pass several qualification and training tasks before participating in an experiment. We ensure worker comprehension of the task interface by using drastically simplified versions of the tasks as qualification and rejecting subjects that fail the qualification. The qualification task is designed specifically for the experiment and described in the corresponding section. In addition, an initial qualification task renders an animation at 30 frames per second ($\text{fps}$) and terminates the assignment if the true frame rate is below 27 fps; we also track the true fps during an assignment. These measures ensure that the judgments are not biased by the browser’s capability (e.g., a slow browser may render the animation slower than intended.)

The training tasks are the same format as the actual tasks, however we show the correct answer upon submission and do not reject subjects at this point to avoid bias. Workers are presented judgments in random order, and we record auxiliary information such as the browser, display size, and response time. Workers were paid $5c/judgement, including qualification, or $18 - 30/hr (5.5s/extrema, 10s/trend judgement).

Prior to analysis, we filter out incomplete, spammers and outlier responses. We remove spammers whose responses are all nearly identical, based on the difference between maximum and minimum estimates (less than 15 for extrema experiments, less than 50 for trend experiments) and standard derivation of estimates (less than 10). We remove workers whose responses have less than a 0.8 correlation with the true values [38]. Finally, we remove individual responses 3 standard deviations outside of the response mean. Our findings are robust to the specific threshold values.

Log transformation is regularly used in models of human performance [25] to help address skewed residuals that appear in linear models [21]. We similarly compute the user’s absolute error $e_{\text{max}} = |\text{judged val} - \text{true val}|$ and compute its log transform $[8] \log_2(e_{\text{max}} + 1)$, and report the 25% trimmed means along with 95% bootstrapped confidence intervals [38]. We varied the trim percentage to 15% and found our results were robust to this setting.

Due to the unexplored nature of this area of research, we were forced to make a trade off between practical budget limitations and coverage of experiments – we chose to prioritize experimental coverage. For this reason, many of our experiments reflect sample sizes from a modest number of assignments due to many disqualified workers. Despite this, confidence intervals are kept relatively tight in many experiments, and we are still able to draw insights from the results.

The subsequent sections describe the three overarching experiments that we conducted. Section 4 validates our crowd-sourced experimental setup by reproducing prior static graphical perception studies. We then extend the design to animated graphics for the extrema task in Section 5, and the trend characterization task in Section 6.

### 4 Experiment 1: Validating Crowdsourcing Setup

We first demonstrate the consistency of our experimental setup with existing work by re-running prior crowdsourced protocols [15, 38].

#### 4.1 Materials and Procedure

We ask subjects to estimate the height ratio between two target bars in 5 types of bar charts borrowed from Cleveland & McGill [8] (Figure 1). Each chart shows the two bars in addition to additional distractor bars. We study 9 true percentages between the two bars: $22, 26, 32, 39, 47, 55, 69, 85\%$. We ensure that at the same ratio, the compared bars have the same height across all five types of charts. The heights of the randomized distractor bars are constrained such that, for a given true percentage, they are the same between the adjacent and separate chart types (e.g., Figures 1a and 1c), and between the aligned and unaligned stacked charts (e.g., Figures 1b and 1d).

The prior experiments distinguished the target bar by placing a circle or dot in the bar. However, gestalt theory [43] suggests that a colored target bar (e.g., Figure 3a) would be easier to distinguish from the distractors due to pretentative “pop-out” effects—this may have an effect when the bar chart is animated. Although this experiment uses a static image, we additionally test this factor in order to serve as a comparison point for the animation experiments.

The qualification task uses a multiple choice selector where one of the choices is obviously correct. Similar to Talbot [38], we remove incomplete workers and those whose answer correlation with the true percentage is less than 0.8.
4.2 Results
We analyzed 47 and 48 out of 54 completed assignments that passed the correlation threshold for circled and colored markings, respectively. The resulting rankings (Figure 4) are comparable to both the Cleveland & McGill and Heer & Bostock experiments, although the distinctions between each chart type is less pronounced than prior studies. For example, adjacent and aligned stacked bar charts showed similar magnitudes of judgment errors. It is expected that the circle and color mark types exhibited no statistically significant differences in a setting where timing and motion were not a factor.

5 Experiment 2: Reading Extrema Values
Our first animated experiments study user perception of extrema values in animated bar charts. Our key goals are to understand:
1. How is accuracy affected by the target’s marking?
2. Under what conditions does frame-rate affect accuracy?
3. How is accuracy affected by the data that is rendered?

5.1 Procedure
Users were asked to make “quick visual judgements”. When the user clicks the start button, the button is replaced with a three second countdown to ensure that the user is ready. We then render the animation once, along with a gray progress bar at the bottom, and hide the bar down to ensure that the user is ready. We then render the animation.

Users were asked to make “quick visual judgements”. When the user clicks the start button, the button is replaced with a three second countdown to ensure that the user is ready. We then render the animation once, along with a gray progress bar at the bottom, and hide the bar down to ensure that the user is ready. We then render the animation once. Table 2 summarizes the parameter values we used in all animated experiments in this paper, along with the number of experiment once).

5.2 Results
We fit the data using a log-linear model that estimates the log-error of the user estimate $y_{f,u}(e.g., \nu_{max})$—dependent on the estimated parameter value $f$ (e.g., pos) and the user $u$—as a linear combination of the input parameters $p_{i,u}$ (e.g., $p_{pos, u}, p_{v_{max, u}}$). The user specific error $U_u$ is assumed to follow a normal distribution with standard deviation $\sigma_f$ dependent on $f$. The coefficient $\beta_{f,i}$ is the model’s sensitivity to the $i$th parameter, dependent on $f$:

$$\log(y_{f,u}) = \beta_{f,0} + \sum_{i=1}^{n} \beta_{f,i} \times p_{i,u} + U_u$$

$$U_u \sim N(0, \sigma_f)$$

In the text, we use the term error or absolute error to refer to $\epsilon_{v_{max}}$, and log error to refer to its log transformed value.

5 Initial Study

**Initial Study (Initial-study):** Our initial study performed a broad parameter sweep across the frame rate, maximum position, the max value, and the target marking (see Initial-study in Table 2). We ran separate HITs for each marking type. There were 35 and 20 completed assignments, 29 and 17 assignments after removing spammers and outliers, for circle and circle, respectively. An unpoled t-test on log error found a significant effect of mark ($t(1584.4) = 5.336, p = 1e^{-5}$) with an effect size of $0.404$—this is equivalent to $\sim 32\%$ difference in absolute error. These results are consistent with gestalt theory [43] which predicts that color is easier to perceive than shape due to “pop-out” than shape (Figure 6).

| fps | logerror (circle) | logerror (color) | logerror (Heer) |
|-----|------------------|------------------|-----------------|
| 10  | 2.0              | 1.5              | 1.0             |
| 20  | 2.5              | 2.0              | 1.5             |
| 30  | 3.0              | 2.5              | 2.0             |

We then fit the log-linear model to gauge how the accuracy depends on the input parameters. For the circle marking, we found a negative relationship to pos ($\chi^2(1, N = 1285) = 7.9, p = .005, \beta_{pos} = -0.286$). The color marking exhibits a slightly stronger negative relationship with pos ($\chi^2(1, N = 759) = 6.11, p = .01, \beta_{pos} = -0.356$). This means that the log error decreases by $\beta_{pos}$ when the maximum position is at the end of the animation instead of the beginning.

The log-linear fit suggests that peaking later in the animation is slightly easier to detect. We were surprised to find that frame rate did not have a significant impact on the perceived accuracy, which is contrary to common sense expectations. We hypothesize that this is because the linear trend was easily predictable and makes the judgment task simple regardless of frame rate. For this reason, we used the rate of change $k$ parameter and studied non-linear rates of change.

**Frame Rate and Rate of Change (Extrema-fps|k):** In this experiment, we focus on the color marking and increase the granularity of the frame rate $fps$ and rate of change $k$. This results in a 180 factorial design—the large number of judgements resulted in 16 complete assignments, and 15 after filtering.

Figure 7 plots log error against frame rate for each rate of change $k$, and shows that higher frame rates result in higher estimation error, particularly when $k \geq 5$. On average, there is a strong dependence on $k$ ($\chi^2(1, N = 2684) = 34, p = 5e^{-9}, \beta_k = 0.05$), meaning that increasing $k$ by 1 increases the absolute error by 3.5%. There
is a significant dependence on $f_{ps}$ ($\chi^2(1, N = 2684) = 38.1, p = 6e^{-10}, \beta_{f_{ps}} = 0.018$), so that increasing the frame rate by 10 increases absolute error by $\sim 13\%$. We then studied the dependencies conditioned on $k$ and found that there is no dependence on frame rate when $k = 1$. However, when $k = 5, 10$, the absolute error increases by nearly 22% for every increase of the frame rate by 10 ($\beta_{f_{ps}} = 0.029$). This is likely because larger $k$ values more closely approximate an impulse function, and a larger $f_{ps}$ will show the peak for a shorter duration.

Rate of Change (Extrema-$k$): Given the strong dependence on rate of change $k$, we further increased its granularity while fixing the frame rate at $f_{ps} = 30$. In addition, we re-evaluated the effect of the mark types in the context of $k$. Each subject completed 105 judgments and we received 30 and 28 complete assignments for circle and color markings, respectively.

Initially, we found that nearly all of the participants were removed by the correlation threshold as part of spammer and outlier removal. We found that the accuracy degrades by nearly $3 \times$ as the rate of change increases from 5 to 50 and contributed to the low correlation. We concluded that the task is intrinsically difficult when $k \geq 25$. Instead, we only considered user judgements when $k \leq 20$ when applying the correlation-based filter. We ultimately analyzed 20 and 27 assignments for the circle and color markings.

Figure 9 shows that accuracy quickly degrades as the rate of change increases, and converges to a maximum error rate as $k > 25$ for color marking, when the trend appears to approximate an impulse function. We found a statistically significant difference between color and circle

$$t(4429.3) = 9.855, p < 2e^{-16}$$ that is consistent with the initial study. Applying ANOVA, we found a significant effect of $k$ for both circle ($\chi^2(1, N = 2085) = 239, p = 6e^{-54}, \beta_k = 0.016$) and color markings ($\chi^2(1, N = 2813) = 95.1, p = 2e^{-22}, \beta_k = 0.009$). These results motivate our focus on the range of $k \in [0, 25]$ in the subsequent experiments.

Maximum Position (Extrema-pos): This experiment studies sensitivity to the pos parameter at a finer granularity, conditioned on smaller rates of change. We used 10 levels for pos, reduced $k$ to $\{1, 5\}$, fixed $f_{ps} = 10$, and used color marking. Each subject completed 100 judgments, and we analyzed 45 out of 48 complete assignments.
We found that although log error depends on the true height $v_{\text{max}}$. Figure 8 showed that log error appeared constant when $v_{\text{max}} < 40$. This asymmetric distribution is a departure from prior height comparison studies [38] where absolute error peaked when the true percentage was 40. We plotted a histogram (log scale) of all responses from experiments with $pos \in \{0, 5, 1\}$, 30 fps, and color marking. Figure 11 is faceted by the rate of change along the columns and four true $v_{\text{max}}$ values by row. We first note the user bias towards multiples of 5 seen by Talbot et al. [38]. We also find that the distribution of estimates for smaller values is relatively clustered around the true value, while there is a long tail of very small estimates for larger $v_{\text{max}}$ values (e.g., 85). This is most evident when $k = 10$. We verified that the long tail is not related to worker quality, and hypothesize that users are simply more likely to miss the frames containing the maximum value and report a severe underestimate.

A consequence of the experimental design is that the frame containing $v_{\text{max}}$ is always shown, regardless of the frame rate. In practice, say when the user scrubs a slider at different rates, we cannot guarantee the frame will be shown, and expect lower perceived accuracy.

6 Experiment 3: Distribution Characterization

We now turn to the complex trend estimation task (e.g., sales rapidly increased in the 3rd quarter). This task requires multiple simultaneous comparisons of the trend functions parameters $v_{\text{max}}$, $pos$, and $k$. Our key goals are to understand:

1. What parameters most affect accuracy in this task, and how they compare with the sensitivity in the extrema task?
2. How does the estimate of the maximum value in the trend judgment compare with that in the extrema task?

6.1 Materials and Procedure

We use the same materials and procedure as the extrema experiments. The more complex task design require changes to the task interface so that users can input their estimates of the target bar’s trend. One option is to allow the user to directly draw a curve as part of the estimate, however this confounds the input with the user’s expertise and control over the mouse. Instead, we designed a slider-based interface (Fig.12) to specify $k'$, $pos'$, and $v_{\text{max}}$ estimates by interacting with sliders. The interface keeps a visualization of the user’s estimated trend $T'$ up to date (Figure 2). A consequence of this interface is that the user must estimate three different attributes of the animation, including the maximum value, the maximum position and rate of change. One benefit of this design is that it affords us the opportunity to compare the effect of task difficulty on the accuracy of $v_{\text{max}}$ estimates.

We use the Kullback-Leibler (KL) divergence [?], which varies from 0 when the inputs are identical and increases as the inputs diverge, to estimate trend’s similarity to the true trend $T$. We approximate KL by quantizing and comparing $T$ and $T'$ at each of the 380 pixels:

$$kl(T, T') = \sum_{x=0}^{380} T\left(\frac{x}{380}\right) \times \ln \frac{T\left(\frac{x}{380}\right)}{T'\left(\frac{x}{380}\right)}$$

The input interface is more complex, so we used three qualification tasks and three training tasks. The qualification tasks ensure users are able to use the input controls—a static curve is overlaid on the input interface and users must replicate the static curve to within $kl < 0.01$ before they can proceed. The training tasks are identical to a real task users estimate the trend of an animation. On submission, it overlays the true trend over the user’s estimate and encourages the user to re-adjust their submission until satisfaction.

The extrema experiments showed that both data and animation parameters affect user judgement accuracy, while color marking is definitively more accurate. As such, we marked the target bar using color and designed a broad parameter sweep (Table 1) resulting in a 200 factor design. A large number of judgements is likely to overwhelm users [29], so we randomly selected 100 judgments for a given participant, and ran 190 assignments.

6.2 Results

We remove spammers and outliers by separately applying the filtering procedure from Section 5.2 to each of the user’s submissions of $k'$, $pos'$, $v_{\text{max}}$. We remove the result if it is rejected by any of the filters. We found that the existing correlation threshold (0.8) was so stringent that it removed all submitted judgements. This is partly because the task is more difficult—the average judgement time 10s is nearly twice the time for extrema judgements, only 90 of 132 assignments were fully completed, and the correlation was low for all participants. In response, we reduced the correlation threshold to 0, and ultimately analyzed 58 filtered, completed assignments. Our findings are robust to the specific thresholds.

We use a linear model to analyze the $kl$ metric, and the same log-linear model as the extrema experiments for the other user estimates.

Overall Trend Results: Figure 13 compares the KL distance $kl$ and each of the input parameters. Similar with the extrema results, $kl$ increases as the true maximum $v_{\text{max}}$, rate of change $k$, or frame rate $fps$ increase. Interestingly, $k$ is minimized when the target maximum is in the first or last frame (e.g., strictly linear trend functions), and is maximized when the position is early in the animation $pos \in [0, 1, 0.25]$. This relationship is in contrast to the extrema experiments (Figure 10) where judgement was least accurate when $pos = 0$; we study this in depth below.

KL-divergence is a useful summary statistic, however it implicitly assigns importance to the accuracy of each of the estimated data parameters. To better understand the sources of the $kl$ plots, we analyzed how judgements of each parameter are affected by their true values.

Dependence on $v_{\text{max}}$: Figure 14 shows how the user estimates depend on the true maximum value. Although the log error of $v_{\text{max}}$ increases with the true maximum, as in the extrema experiments, the curve is shifted up—the absolute error is $\sim 1.65\times$ larger under the same experimental conditions. We hypothesize this shift is due to the user’s shift of focused attention [13, 14] from specific value of the target bar to its distribution. It is possible that the $v_{\text{max}}$ estimates in the trend experiments may degrade because users estimate using preattentive rather than cognitive processing due to the user’s additional focus on the positional and rate of change aspects of the animation. In contrast, increasing $v_{\text{max}}$ reduces log errors of maximum position and rate of change estimates by nearly 2 and 0.4, respectively. It is possible that the larger value improves the ease of tracking the target bar.

![Figure 11: Histogram (log scale) of judgments for varying rate of change (columns) and true max heights (rows).](image1)

![Figure 12: Example interface for trend judgement task. The right side shows user controls and visualized trend function.](image2)
Dependence on Other Parameters: We found that the log errors were not dependent on $pos$ and $k$ except in three cases, depicted in Figure 15. The first is the dependence on the true maximum position $pos$. We find that neither $v_{max}$ nor $k$ depended on the maximum position; in contrast, the log error of the estimated $pos'$ in Figure 15b is nearly identical to the pattern in Figure 13b, suggesting a causal relationship. To better understand the shape of this curve, we plotted the histogram of $pos'$ estimates for each of the true $pos$ values (Figure 16). Rather than rounding effects [38], which are less likely due to the slider interface, we found considerable bias towards $0$, $0.5$ and $1$. For example, when the true $pos \in \{0.1, 0.25, 0.5\}$, the number of estimates within $0.05$ of the three values constituted $44.6\%$ of all judgments. Some users appear to estimate the true position based on the slight increase in estimates around the true position ($pos = 0.1, 0.25$), however this is dwarfed by the prevalence of the biased estimates.

Discussion: Our analysis used KL divergence as a proxy for overall accuracy, and finds that distribution characterization of a target bar strongly depends on all four data and animation parameters. Interestingly, the relationship between $kl$ and the maximum position is not monotonically increasing, and exhibits a "bump" when $pos \in (0, 0.5]$. This shape may be explained by the relationship between the log error of $pos$ and the true value of the maximum position (Figure 15b).

For the most part, we find that increasing a given data parameter (e.g., $pos$) predominantly affects user judgement of the same parameter, and has minor effect on the other estimated parameters. For example, changes in the maximum position has little effect on the accuracy of $v_{max}$ and $k$. In contrast, increasing $v_{max}$ improves user judgements of $pos$ and $k$, possibly because changes in the target bar are magnified and thus easier to perceive.

On average, shifting the user’s task to distribution characterization reduces the absolute error of the extrema judgement by nearly $1.65 \times$ as compared to the previous experiment that explicitly judges the target bar’s extrema value.

These results show that user perception is highly dependent of the specific data values being animated, as well as the specific aspects of the trend—the overall trend or one of its parameters. One possible use of this result is that, if we know which aspect of the trend the user is focusing on, there may be utility in exaggerating other aspects of the animation to improve the specific task’s perceptual accuracy. For example, in an exploratory setting, a user may first look for candidate patterns by scanning for very rapid changes, and once found, then focus on quantifying values in those patterns. This type of visualization manipulation is similar to fish-eye [36] techniques in interactive visualization, however more studies are needed to understand the utility and whether there are unforeseen side-effects.
7 Limitations and Future Work

To the best of our knowledge, this is the first study that quantitatively measures graphical perceptual accuracy in animated data visualizations. As such, there are a number of limitations that warrant further investigation in order to bridge the gap between our current study and perceptual evaluations in the context of live data visualization interactions. Some of these limitations are due to our choices in experimental design, while we believe others are fundamental to animation and interaction oriented perceptual studies.

One limitation is simply due to our attempt at deriving quantitative results from a finite sample size—given the vast variety of human perceptual systems, backgrounds, experience with data visualizations, viewing conditions, fatigue and other contextual difference, it is difficult to make blanket statements about human perception in general. These are all candidates to study in isolation, however we believe it is still helpful to identify general patterns that may help inform design. Going further, we are excited about the potential for personalized perceptual models that can help tailor interactive interfaces to an individual’s characteristics (e.g., color sensitivity or eyesight).

A second limitation was our choice to fix the animation length while varying the frame rate. By doing so, we were able to control for memory effects. An alternative would be to fix the number of frames and allow the animation length to vary with the frame rate. Both approaches rely on picking a constant (animation length vs # of frames) and it is unclear how this choice would affect our results.

Third, we focused on two simple judgment tasks—extrema and trend distribution—in the context of animation. However, in practice, users may be performing any number or combination of judgement tasks such as comparisons of pairs of marks, or judging multiple visual encodings at the same time (e.g., color and position). We might hypothesize that the user is characterizing the distribution when she rapidly scrolls a scrollbar, however further studies are needed to better predict users’ high level goals [18] – particularly when the goals may be unclear to the user [5, 19]. Understanding the user’s intended tasks will continue to be a valuable direction of work.

Finally, there is still a large gap between the animation-oriented experiments in this paper and understanding the graphical perception of interactions. We made simple assumptions to decompose interactions into short animation units, and evaluated individual animations. However, there is still considerable work to generalize these findings to longer, more complex animations, and finally to interactions.

8 Conclusion

This paper extends graphical perception studies from judgements of static data visualizations to judgments of animated visualizations. We proposed a simple model that decomposes simple direct manipulation interactions (e.g., brushing) into a sequence of elementary animated perceptual chunks that can be parameterized and used in reproducible experiments. We then studied variations of these chunks for two simple judgment tasks—reading the maximum value and the distribution of a target bar throughout the animation.

Our observations verify some known results and also present several new insights. Consistent with the tracking literature, denoting the target using color rather than shapes drastically improves the user’s ability to make quantitative judgements about the target bar. Although larger values improve the ability to detect the rate and timing of changes in an animation, they also increase the error of the estimated bar height. In contrast to values, estimating when the target is maximal is extremely hard to judge. In addition, timing plays an important role: changes earlier in the animation were found to be harder to perceive as compared to changes in the middle or end of an animation.

We believe our work is a promising step towards principled research that combines perception and interactive data visualization systems. Our findings impact two complementary aspects of animated and interactive visualizations spanning both the HCI and systems communities. First, just as the results of static perceptual experiments have been used towards automatic visualization recommendation systems such as APT [3], ShowMe [30], and Voyager [1], we expect our insights to influence how encodings and animation parameters are selected for animated visualizations of a dataset. Second, we believe there is tremendous potential for concrete uses beyond measurements of efficacy between various visual encodings. For example, we hope to embed extensible perceptual models as part of the data visualization system in order to enhance performance while remaining aware of perceptual limitations. In concert, by understanding the user’s sensitivity to various data and animation parameters, we can better design interactive visualizations that are usable, accurate, and performant.
References

[1] John C Anderson, Jose M Andres, McKay Davis, Kayo Fujiiwara, Tie Fung, and Michael Nedbal. 2010. Voyager: an interactive software for visualizing large, geospatial data sets. In *Marine Technology Society Journal*. Marine Technology Society.

[2] Lyn Bartram. 1997. Can motion increase user interface bandwidth in complex systems?. In *TSMC*.

[3] Clifford G Beshers and Steven K Feiner. 1994. Automated design of data visualizations. In *Scientific Visualization*.

[4] M Bianchi, M Boyle, and D Hollingsworth. 1999. A comparison of methods for trend estimation. In *Applied Economics Letters*.

[5] Charles S. Carver and Michael F. Scheier. 2002. Control processes and selforganization as complementary principles underlying behavior. In *Personality and Social Psychology Review*.

[6] Bay-Wei Chang and David Ungar. 1995. Animation: from cartoons to the user interface. In *Sun Microsystems, Inc.*

[7] Fanny Chevalier, Pierre Dracigevic, and Steven Franconeri. 2014. The not-so-staggering effect of staggered animated transitions on visual tracking. In *TVCG*.

[8] William S Cleveland and Robert McGill. 1984. Graphical perception: Theory, experimentiation, and application to the development of graphical methods. In *AS, Taylor & Francis*.

[9] Andrew Samuel Christopher Ehrenberg. 1975. Data reduction: analysing and interpreting statistical data. In *Data reduction: analysing and interpreting statistical data*. John Wiley & Sons.

[10] JC Falmagne. 1971. The generalized Fechner problem and discrimination. In *Journal of Mathematical Psychology*. Elsevier.

[11] David Gotz and Michelle X Zhou. 2008. An empirical study of user interaction behavior during visual analysis. In *IBM Research*.

[12] Wayne D Gray and Deborah A Boehm-Davis. 2000. Milliseconds matter: An introduction to microstrategies and to their use in describing and predicting interactive behavior. In *Journal of Experimental Psychology: Applied*.

[13] Christopher Healey and James Enns. 2012. Attention and Visual Memory in Visualization and Computer Graphics. In *TVCG*.

[14] Christopher G Healey and others. 2007. Perception in visualization. In *Retrieved February*.

[15] Jeffrey Heer and Michael Bostock. 2010. Crowdsourcing Graphical Perception: Using Mechanical Turk to Assess Visualization Design. In *CHI*. http://vis.stanford.edu/papers/crowdsourcing-graphical-perception

[16] Jeffrey Heer and George G Robertson. 2007. Animated transitions in statistical data graphics. In *TVCG*. IEEE.

[17] Jeffrey Heer and Ben Shneiderman. 2012. Interactive dynamics for visual analysis. In *Queue*. ACM.

[18] Eric Horvitz, Jack Breese, David Heckerman, David Hovel, and Koos Rommelse. 1998. The Lumière Project: Bayesian User Modeling for Inferring the Goals and Needs of Software Users. In *UAI*.

[19] Edwin L. Hutchins, James D Hollan, and Donald A Norman. 1985. Direct manipulation interfaces. In *HCI*. Taylor & Francis.

[20] Mary K Kaiser, Dennis R Profitt, Susan M Whelan, and Heiko Hecht. 1992. Influence of animation on dynamical judgments.. In *Journal of Experimental Psychology: Applied*. American Psychological Association.

[21] Matthew Kay and Jeffrey Heer. 2015. Beyond Webberâ€™s Law: A Second Look at Ranking Visualizations of Correlation. In *IEEE*.

[22] Colleen Kehoe, John Stasko, and Ashley Taylor. 2001. Rethinking the evaluation of algorithm animations as learning aids: an observational study. In *International Journal of Human-Computer Studies*. Elsevier.

[23] Daniel A Keim. 2002. Information visualization and visual data mining. In *TVCG*. IEEE.

[24] Heidi Lam. 2008. A framework of interaction costs in information visualization. In *TVCG*. IEEE.

[25] E. Limpert, W. A. Stahel, and M. Abbt. 2001. Log-normal Distributions across the Sciences: Keys and Clues. In *BioScience*.

[26] Lauro Lins, James T Klosowski, and Carlos Scheidegger. 2013. Nanocubes for Real-Time Exploration of Spatiotemporal Datasets. In *TVCG*. IEEE.

[27] Zhicheng Liu and Jeffrey Heer. 2014. The Effects of Interactive Latency on Exploratory Visual Analysis. In *TVCG*. IEEE.

[28] Zhicheng Liu, Biye Jiang, and Jeffrey Heer. 2013. imMens: Real-time Visual Querying of Big Data. In *EuroVis*.

[29] Monicque M Lorist, Merel Klein, Sander Nieuwenhuis, Ritske Jong, Gijsbertus Mulder, and Theo F Meijman. 2000. Mental fatigue and task control: planning and preparation. In *Psychophysiology*. Wiley Online Library.

[30] Jock Mackinlay, Pat Hanrahan, and Chris Stolte. 2007. Show me: Automatic presentation for visual analysis. In *TVCG*. IEEE.

[31] Allen Newell. 1994. *Unified theories of cognition*. Harvard University Press.

[32] Stephen E Palmer. 1999. *Vision science: Photons to phenomenology*. MIT press Cambridge, MA.

[33] George Robertson, Roland Fernandez, Danyel Fisher, Bongshin Lee, and John Stasko. 2008. Effectiveness of animation in trend visualization. In *TVCG*. IEEE.

[34] George G Robertson, Stuart K Card, and Jack D Mackinlay. 1993. Information visualization using 3D interactive animation. In *Communications of the ACM*.

[35] Hans Rosling. 2009. Gapminder. In *GapMinder Foundation*.

[36] Manojit Sarkar and Marc H Brown. 1992. Graphical fisheye views of graphs. In *CHI*.

[37] Stanley S Stevens. 1957. On the psychophysical law.. In *Psychological review*.

[38] Justin Talbot, Vidya Sethur, and Anushka Anand. 2014. Four Experiments on the Perception of Bar Charts. In *TVCG*.

[39] Patrice D Tremoulet and Jacob Feldman. 2000. Perception of animacy from the motion of a single object. In *Perception*. SAGE Publications.

[40] Barbara Tversky, Julie Bauer Morrison, and Mireille Betrancourt. 2002. Animation: can it facilitate?. In *International journal of human-computer studies*. Elsevier.

[41] Martin Wattenberg and Jesse Kriss. 2006. Designing for social data analysis. In *TVCG*.

[42] Chris Weaver. 2010. Cross-filtered views for multidimensional visual analysis. In *TVCG*.

[43] Max Wertheimer and Kurt Riezler. 1944. Gestalt theory. In *Social Research*. JSTOR.

[44] David Whitney and Dennis M Levi. 2011. Visual crowding: A fundamental limit on conscious perception and object recognition. In *Trends in cognitive sciences*. Elsevier.

[45] Christopher Williamson and Ben Shneiderman. 1992. The Dynamic HomeFinder: Evaluating dynamic queries in a real-estate information exploration system. In *SIGIR*.

[46] G. Yang. 2004. The complexity of mining maximal frequent itemsets and maximal frequent patterns. In *KDD*.

[47] JI Soo Yi, Youn ah Kang, John T Stasko, and Julie A Jacko. 2007. Toward a deeper understanding of the role of interaction in information visualization. In *TVCG*. IEEE.

[48] Jeff Zacks, Ellen Levy, Barbara Tversky, and Diane J Schiano. 1998. Reading bar graphs: Effects of extraneous depth cues and graphical context. In *Journal of experimental psychology: Applied*.

[49] Jeffrey M Zacks. 2004. Using movement and intentions to understand simple events. In *Cognitive Science*. Elsevier.

[50] Douglas E Zongker and David H Salesin. 2003. On creating animated simple events. In *Cognitive Science*.